INVESTIGATION OF A NEURAL NETWORK METHODOLOGY TO PREDICT TRANSIENT PERFORMANCE IN FMS

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1. Introduction

1.1 Motivation of the Research

In most scientific domains, it is a common practice to build physical or mathematical models to study a system of interest. These models are frequently defined to be a collection of entities (components). These entities act and interact together toward the accomplishment of some logical end [Schmidt and Taylor 1970]. Often, these physical or mathematical models are simplified forms (abstractions) of real systems because it is only necessary to consider those aspects of the system that affect the system behavior under investigation [Banks et al. 1996]. Studying a system model normally provides an opportunity to better understand the relationships among its components or to predict how the system will operate under new policies or new operational conditions [Law and Kelton 1991].

In practice, for many real world systems, building a physical model is often too costly and impractical due to complexity and lengthy development time. Especially when models for the system require a full-scale level of detail, the cost can be prohibitive based on the nature of the system. For this reason, mathematical models are often preferred in many fields to study characteristics or behaviors of the system under given conditions.

System models can be classified into two broad categories based on their use. The first type is an evaluative model. An evaluative model can be used to study a particular system behavior(s) under a set of given configurations and operational parameters. The second type is a generative model. Generative models are built to find a set of optimal decision parameters that can satisfy operational or design objective(s) for the system under given constraints. Evaluative models are designed to provide performance predictions that are essential during the design and operational stages of a system. On the other hand, generative models are extensively used for performance optimization in various operations research (OR) type studies.

Reliable performance prediction for manufacturing systems has been the focus of many industrial and academic research communities. Reliable but easy-to-develop and easy-to-use evaluative models for both design and operation are crucial for operational success. Most evaluative models have focused on long-term steady-state system behaviors rather than short-term transitory behaviors. For this reason, it is not ideal to use them to forecast often volatile transitional short-term behaviors following events that cause disruptions of the steady-state behavior of a system performance indicator. Examples of unexpected events that can cause system disruptions are machine failures, rush orders, and changes in product mix due to part or material shortages.

With the advent of more powerful computer and information technologies, interest in industrial application of on-line decision-making has intensified in recent years. In the area of highly automated production and process controls, on-line decision-making and its associated issues have become prominent research topics. Especially in the area of flexible manufacturing system control, conveying a realistic view of upcoming short-term behavior of the system is vital to building effective control policies to minimize unwanted performance deviation following an unexpected system disruption(s).

1.1.1 Growing Usage of FMS

The most common challenge faced by manufacturers around the world today is to adapt themselves to a rapidly changing operational environment. The demand for highly customized products is on the rise and today's fierce competition in low-cost precision manufacturing is unprecedented. Among many strategies available to deal with these challenges, one approach is to adopt and implement various forms of flexible manufacturing systems (FMSs) as a part of a strategic plan.

There are many definitions of FMS available. Even though they may have some difference in details, all seem to agree on common basic design fundamentals that can be found in the definition given by Groover [1987]**.** According to Groover [1987], an FMS is a fully automated system consisting of functionally similar or dissimilar automated workstations interconnected by means of an automated material handling system and storage system, and controlled by an integrated computer system. The workstations are considered automated cells of computer numerical control (CNC) machines. A similar term, flexible manufacturing cell (FMC), often used in place of FMS, can be defined as follows: a typical FMC comprises a few numerically control (NC) machines, tool magazines, and one or more material handling robots [Narahari and Viswanadham 1989]. According to Groover [1987], a distinction between FMS and FMC can be made based on the number of NC or CNC machines comprised within. Therefore, an FMS can also be formed as a collection of several FMCs. FMSs have various documented and publicized merits such as high adaptability to changes, flexibility in configurations and operations, improved product quality, short lead-time, and high utilization with a relatively low WIP [Groover 1987], [Vollmann et al. 1997].

From a systems perspectives, finding an effective modeling tool for FMSs will likely make contributions to modeling other Discrete Event Dynamic Systems (DEDS) because the system dynamics observed in various FMSs are analogous to those that can be found in many DEDS. In general, DEDS are large scale interconnected systems, driven by the occurrence of discrete events, where their dynamic behavior involves state changes only at discrete points in time [Ho et al.1984].

Complex interactions are often present in the system behaviors of DEDS. Synchronization, concurrency, randomness, and contention for limited resources are common aspects of these interactions [Narahari and Viswanadham 1989]. DEDS can be found almost everywhere in today's modern technological infrastructure. According to Ho et al. [1984], examples of such systems encountered today are communication networks, computer systems, production/assembly lines, traffic systems, and transportation networks. Therefore, an effective modeling methodology for FMS transient behaviors may be applicable to these systems with some modifications.

1.1.2 Known Integration and Performance Modeling Issues with FMS

Despite many publicized FMS merits, there are four well-documented limitations [Huang and Chen 1986] that keep FMSs from being more widely applied in industry. These limitations are:

1. high initial costs,
2. long implementation lead time,
3. uncertainty of a successful FMS interface with the current production system, and
4. control software customization issues based on uniqueness of each installation site.

All of the above limitations except the third, uncertainty of a successful FMS integration, can be naturally resolved as time progresses with little commitment from those who actually operate FMSs on a day-to-day basis. For example, the continuous market growth in FMS installation and ongoing technological innovation will lower the high cost of precision machine tool manufacturing. Thus, FMSs will eventually become an affordable form of automation even to manufacturers without great financial strength. To overcome the uncertainty of successful FMS interface with the current production system, tremendous effort is required from both FMS designers and operators no matter how advanced the supporting technology becomes in the future. Without these efforts, the full potential of FMS may not be realized.

The concept of FMSs can be used within the context of manufacturing cells. Individual cells consist of several workcenters that can carry out similar or dissimilar manufacturing functions. Lin and Chiu [1993] stress that understanding and being able to predict dynamic behavior as well as long term manufacturing cell performance is necessary to better coordinate production among cells. Therefore, knowledge of transient performance behavior as well as steady-state behavior of individual cells can be vital to overcoming the third limitation in adopting FMS. Another research effort points out that the studies done on interactions among FMS resources and impacts brought by random changes in operations are still insufficient [Basnet and Mize 1994]. Random changes during operation, such as resource breakdowns and rush orders, are normally responsible for unanticipated system interruptions.

Traditional performance modeling approaches, such as analytical and simulation modeling, constantly rely on human intelligence and modeling skills to create and maintain effective evaluative power. On a busy shop floor, especially for a highly utilized FMS, the ability to make instantaneous decision to effectively handle a wide range of critical disruptions using an effective short-term evaluative model can be highly beneficial. For example, evaluative models based on steady-state performance can help an operator select a proper operational strategy in order to reach an optimal production level based on a long term production schedule. On the other hand, an effective short-term look head capability can help an operator choose a proper short term remedy to handle the day-to-day operational problems without compromising the long-term performance goal. However, due to its dependency on human intelligence and expertise, occasional off-line maintenance is required when there are significant changes to the system configurations and operation rules. For example, adding new part type, AGV or machine center to the existing system requires redefining its state space in a Markov chain model. Lacking self-maintainable modeling capability in a highly dynamic operational environment can sometimes result in a costly impact to the rest of production line.

Utilizing transient analysis to measure impacts on a performance indicator following one or more disruptions will provide an FMS operator the opportunity to assess the situation and help him/her make the best operational choice so that the impact to the other parts of the production line can be minimized. The proper balancing between short-term and long-term performance look-ahead capability through efficient evaluative models is one crucial key for seamless integration between FMSs and traditional production systems since the return on investment on an FMS is initially much lower than other forms of automation. This is necessary to avoid creating another costly "automated island". As applications of FMSs continue to grow, successfully integrating FMSs with other types of production systems become more critical.

1.1.3 Importance of Performance Predictor in On-line Controller

The continuous improvement and new development of on-line as well as off-line production flow optimization schemes under different planning time horizons for a dynamic system has been a primary focus for many FMS researchers. These schemes are developed using various operations research, mathematical programming, and artificial intelligence (AI) techniques with a well-constructed evaluative model.

There are important distinctions between off-line flow and on-line production flow optimization schemes in typical shop floor control environments. Off-line schemes are typically used to perform planning, scheduling and routing functions through periodic interactions with a human supervisor. On the other hand, on-line schemes are used by automatic control devices such as PLCs to continuously optimize hardware performance and to perform schedule and route changes due to resource failures, rush orders, and major deviations in the original production plans. If the predetermined schedule is carried out as planned, on-line controllers are required only for the actual implementation of control procedures, such as downloading of CNC programs. In such cases, off-line schemes are used at predetermined time intervals and the resulting schedules are implemented.

However, a perfect adherence to predefined schedules is almost never realized in practice due to exceptions known as disruptions or unexpected events that cause deviations of the shop floor behavior from the manager’s expectation [Katz and Manivannan 1993]. Katz and Manivannan [1993] acknowledge a great need for architecture to analyze complex patterns of on-line events caused by possible production disruptions. On-line simulation is proposed as one way to obtain information about foreseeable detailed behavior of the manufacturing system within a specified length of time in which a control decision has to be made (also known as the control horizon).

For on-line FMS control, devising fast and reliable evaluation models in a disruption handling architecture is crucial because most decision-making regarding unexpected on-line events takes place within a matter of seconds or minutes. Lin and Cochran [1990] state, “For shop floor control in real time, not only long term steady-state performance is important, short-term dynamic performance of the production line is of even greater interest, since many unexpected events can be vital.”

The majority of analytical model developments for FMS operations are based on long-term system behaviors using steady-state analysis. However, in reality most of these systems never reach steady state because of their highly dynamic operational nature [Buzacott and Yao 1986]. For people who operate FMSs on shop floors as a means to meet daily production goals, a comprehensive system model to depict realistic transient behaviors accompanied by possible, but unscheduled, disruptions is more meaningful to make control decision within a small time horizon.

1.1.4 Simulation Modeling versus Metamodeling

Simulation modeling is an evaluative technique to study a system of interest. Simulation is normally conducted by a digital computer numerically exercising a model for the inputs in question to see how they affect the output measures of performance [Law and Kelton 1991]. Often, a well-built simulation model provides realistic views of system behaviors of interest. Thus, one can extensively study behaviors of a real world system without modifying an actual system for different baseline characteristics. Although most simulation models are simpler than the real world system they model, it is still a complex way to study systems behaviors because building a valid simulation model takes a considerable amount of expertise, effort, and time.

The time and effort to build and validate such models, especially under time pressure, often leads users to switch to other forms of evaluative models, such as analytical models, or to choose a hybrid model that combines analytical and simulation models to avoid lengthy computation time. Metamodeling is a supplementary way to map target system input to corresponding output in simpler manner using simulation experimental design and mathematical techniques like regression analysis or time series analysis. Well-built metamodels often provide the speed of analytical models with the fidelity of a carefully executed simulation study. The usefulness of regression-based metamodels has been investigated in several studies [Friedman 1989], [Friedman and Pressman 1988], [Kleijnen 1979].

Typical metamodels are approximation formulas that map different combinations of input values to associated output values normally obtained through a full execution of a simulation experimental design. In most cases, non-terminating simulation is used for each run in the experimental design. A terminating simulation is one for that runs for some duration of time T_E, where E is a particular event (or set of events) which stops the simulation. On the contrary, non-terminating simulation is one for which there is no particular event E to specify the length of a run**.** Typically, a performance measure for such a simulation is said to be a steady-state parameter if the output stochastic process of interest $Y_1, Y_2, \cdots$ exhibits a steady-state (or near steady-state) distribution.

Relying on the traditional terminating simulation method to investigate transitional behaviors of a manufacturing system can be expensive and often impractical for real time production control [Lin and Cochran 1990], [Lin and Cochran 1990], [Lin and Chiu 1993], [Lin et al. 1998]. Thus, constructing metamodels using stochastic discrete event simulation and mathematical formulation as an evaluative modeling tool to forecast possible transient behaviors of a complex-manufacturing system under various scenarios has been shown to be a highly effective and practical approach [Lin and Chiu 1993].

1.1.5 Artificial Neural Network Based Metamodeling vs. Regression Based Metamodeling Approach

Artificial neural networks are widely used in many fields as a prominent artificial intelligent tool when rapid computation, adaptability, and robustness are required [Padgett and Roppel 1992]. Typically, neural network applications require fewer assumptions and less accurate data to model unknown functions. Using artificial neural networks as a non-parametric approximation methodology has been shown to be highly effective in the area of metamodeling compared to traditional regression type approaches [Kilmer 1994]. This is especially true, when the system contains a significant amount of the “noise” which is often present in many stochastically transitional systems [Kilmer

1994]. The number of different types of artificial neural networks is almost unlimited based on different design architectures and their application areas. Alternative design architectures are discussed more fully in Chapter 3.

Regression analysis is the part of statistics that deals with investigation of the relationship between two or more variables related in a nondeterministic fashion. Regression models can be grouped into linear and non-linear regression models. Non-linear regression functions can have many different forms. A polynomial regression function is one common possible form. If there is more than one independent variable related to dependent variables, the model is called a multiple regression model.

In general, neural networks appear to perform better than ordinary regression techniques in statistical approximation of unknown functions [Kilmer 1994]. The implementation of most regression techniques depends on two critical statistical assumptions about the model errors. These assumptions are:

1. errors must be independent, and
2. errors must be normally distributed with a zero mean and a constant variance [Miller et al. 1990].

Nam and Schaefer [1995] identify three reasons to move away from a traditional regression approach in practical forecasting. First, even though the accuracy of regression models is not significantly compromised when there are small departures from these assumptions, the performance of the model can deteriorate when the assumptions are violated. Such deviations from the assumptions can generally only be detected after the construction of the model. Second, past observations regarding the unknown function often contain complex patterns. Third, there is no way of being certain that the choice of a given regression technique provides the best result.

Alternatively, neural networks can learn from experience, move to new generalizations from previous ones, and abstract essential characteristics from somewhat noisy and incomplete inputs [Wasserman 1989]. In addition, neural networks do not require the same assumptions about the underlying distribution, as do many regression techniques. Therefore, artificial neural networks can be an effective alternative to most regression type approaches.

Lin and Cochran [1990] utilize time series regression analysis and stochastic simulation in their metamodels to predict transient behaviors of a flow shop system. Since their modeling scheme relies on the modeler's ability to classify and synthesize various functional elements to make a proper time series model for a given unknown performance function, it is difficult to transform the scheme into an effective automated modeling framework. Based on the pattern of the transitional behavior following a disruption(s), building a prediction model through ad hoc combinations of time series analysis and a linear equation with a particular part arrival or departure rate can be cumbersome. Compared to the traditional regression method, properly configured artificial neural networks can learn and capture any unknown functions with almost no human intervention. It has also been shown that artificial neural networks can effectively approximate behaviors of many non-linear dynamic systems with a relatively small error

[Narendra and Parthasarathy 1990].

Since the development of reliable and easy-to-use performance prediction tools for a control mechanism is essential for wide acceptance of FMS in industry, constructing metamodels using an efficient artificial neural network design will be a stepping stone to building a truly practical disruption handler in future FMS control environments.

1.2 Problem Statement

Thorough understanding of possible dynamic transient behaviors of a typical FMS under pre-selected disruption scenarios utilizing an artificial neural networks (ANN) based metamodeling framework is the motivation behind this research. The need for this research is based on a proposition made by Buzacott and Yao [1986] who argue that in reality, most FMSs never reach steady state because of their highly dynamic nature. Most rapid analytical evaluative models for FMSs are based on their steady-state performance. This argument supports a need to develop robust, easy to construct, and transportable transient-performance evaluative models for FMSs. Thus, building hybrid type evaluative models (metamodels) using artificial neural networks and stochastic simulations, which can capture realistic but general transient behaviors of an FMS under a set of typical operational scenarios, will help shop floor managers to successfully manage day-to-day FMS operations in a tightly integrated manner.

The primary objective of this research is to define an artificial neural network

(ANN) based metamodeling methodology for FMS transient behavior prediction. The proposed ANN based meta-modeling scheme consists of a hierarchical taxonomy of clustered ANNs. Each cluster of ANNs collectively represents a different system knowledge domain. This taxonomically structured arrangement of ANNs overcomes shortcomings often found in single ANN based meta-modeling schemes. These shortcomings are generally related to the limited knowledge acquisition capability of these schemes.

The advantage of neural network based prediction models lies in their capability to capture not only time based one-to-one expected performance but also an overall dynamic behavioral pattern of a particular performance index during a transition caused by a disruption. The proposed ANN based transient performance model is designed to provide better knowledge for an automated disruption handler or FMS operator to discriminatorily react to controllable performance deteriorations. The captured dynamic behavioral pattern of interest may show gradual or sudden shifting of the average performance value over a given time horizon, as well as an expected duration of such behavior. This feature will provide a decision-maker with the capability of conducting intelligent disruption diagnosis for a discriminatory remedial control action(s) based on unique post-disruption system behavior. This capability will enhance the adaptability of FMSs in a highly dynamic manufacturing environment with a minimal performance disruption by providing shop production control a “look-ahead” capability in order to make event-dependent and timely control decisions.

Defining an effective modeling framework to intelligently activate corresponding metamodels based on the nature of the disruption event and characteristics of behavioral patterns will be another contribution that makes this study practical in terms of real world application. Identifying and selecting significant operational factors as system input as well as performance indicators as meaningful system output, is done before the actual model construction process starts.

Modeling an FMS with a common configuration and testing it under realistic operational scenarios are important tasks. In return, these well-designed simulation experiments should closely capture common dynamic characteristics for the majority of FMSs that this research intends to represent. This will assure that pursuing an ANN based transient metamodeling approach is a viable alternative to devise a short-term performance forecasting feature in on-line disruption handlers for many industries that operate similar types of FMSs in volatile day-to-day production environments. Needless to say, designing and conducting verifiable simulation experiments and proper post simulation analysis are essential for the success of this research effort.

1.3 Scope of the Research

The goal of this research is to demonstrate that ANN based metamodel consisting of a hierarchical taxonomy of ANNs can be an effective modeling alternative to regression based metamodels to forecast FMS transient behaviors following a random disruption event(s). This research is proposed under the partially verified hypothesis that artificial neural network based metamodels of stochastic simulations generally appear to perform better than regression based counterparts [Kilmer 1994]. In Kilmer's study [Kilmer 1994], ANN based metamodels are built to approximate an unknown response surface given by a set of alternative input parameters. The procedure, often called response surface methods (RMS) [Box and Wilson 1951], is used to find the levels of the experimental factors that yield the best value of the response (or output) of a system. Such ANN based metamodels deal only with steady-state performance parameters of stochastic discrete event simulations. However, for this research, ANN based metamodels deal with transient performances depicted by non-terminating simulations with imposed resource failures because the focus is on transitional behaviors (deviations from steady state) after the disruption(s).

Even though the ultimate use of these ANN based models is for on-line disruption control, FMS control is not the focus of this research. Therefore, any technical issues regarding the actual FMS control are beyond the scope of this study. This study is intended to develop a new methodology for forecasting short-term transient performance in a timely manner.

In contrast to typical ANN applications in time series modeling trained with actual data points, individual ANNs from the proposed modeling framework will be trained with selected time average resource utilizations and coefficients from selected polynomial regression models found on a limited number of data points generated from various simulation experiments. These non-terminating stochastic simulations will be carefully designed and chosen to represent various unique post-disruption behavior patterns. Therefore, independent experimental factors for FMS transient behaviors are carefully identified, screened, and structured for a valid design of experiments. Then a manageable subset is selected for experimentation. Although this study extensively uses simulation, it is not an intention of this study to extensively review traditional issues associated with simulation modeling, validation, verification, and post-statistical analysis processes.

Finding justifiable reasons to choose particular artificial neural network design architecture over others is another crucial objective of this research. The choice of possible variations within a particular architecture and training method, for example, the number of nodes, the number of hidden layers, the type of transfer function, selection of training data set, training methods, and the length of training period etc., must be identified. Finally, a taxonomical arrangement of individual neural networks that are designed to capture and approximate various parts of the desired system knowledge domain is to be presented and examined.

1.4 Anticipated Contributions

The primary contribution of this research is the conceptualization of a system modeling framework that can provide self-organizing and pattern based transient behavior forecasting. The proposed system modeling framework maps various short-term transient behavior patterns over the chosen performance indexes by utilizing taxonomically structured ANN based metamodeling. The transient behavior forecasting is based on both the initial reaction path following a disruption and a unique relationship to a corresponding disruption scenario.

The majority of ANN based time series modeling approaches presented to date in the literature have focused on a single function realization. However, this study intends to provide a means to store more than one post-disruption system behavior function under various disruption scenarios and make them retrievable by providing a nonparametric relationship between a functional domain and a range of unknown post-disruption system behavior prediction functions. Because the proposed framework will be designed to capture unknown transient behavior prediction functions in a simple form using independent variables, spline modeling, using such techniques as polynomial regression analysis can be useful to extract the unique characteristics of many non-linear transient behaviors.

Secondly, since the proposed approach is aimed toward online application, the practicality of a proposed modeling approach as an on-line modeling scheme can be partially verified through limited controlled tests. Thirdly, the simulation study of a given FMS model will provide a better understanding of how other tightly coupled systems would react to a disruption under similar circumstances. This will also help to verify if there are signs of any overreactions or under-reaction from recovery actions taken by the control system, if not, how closely these reactions will follow a monotonic behavior patterns discussed in some studies [Suri 1985], [Shanthikumar and Yao 1987]. Furthermore, this study provides a chance to closely examine methods and issues involved in quantification of non-monotonic system behaviors compared to typical monotonic transition behaviors.

If there exist any non-monotonic transient behaviors following a disruption, this study will provide a better knowledge of when these behaviors can be triggered and under which system conditions. Finally, the study will examine the overall effectiveness of the proposed system-modeling framework as a “look ahead” tool. In other words, the study will examine if an automated system modeling approach such as the one in this study is practical and reliable enough to provide an effective look-ahead function for a fully automated production control environment.

1.5 Overview of the Dissertation

The remainder of this dissertation is presented in seven chapters plus five appendices and a bibliography.   Chapter Two reviews the literature in several major evaluative modeling methods commonly used in both steady-state and transient FMS performance analysis. Topics such as artificial neural networks and time series analysis are discussed extensively in Chapter Three since they are closely related to the proposed modeling methodology. Chapter Three presents the FMS under study and proposed modeling approach. This includes detailed descriptions of the hardware configuration, operational rules, operational scenarios, and system parameters relevant to the hypothetical FMS under study. The rest of Chapter Three is allocated to elaboration of the proposed modeling framework. Chapter Four presents the research goal, objectives, assumptions, and limitations. Chapter Five outlines the research tasks, research methodology, and execution plan. Chapter Six discusses the design of simulation experiments, results analysis, classification of primary transient behavior patterns, configuration of input and target vectors, and configuration of the proposed taxonomically organized ANN modeling scheme for this study. Chapter Seven covers the training and construction of individual ANNs and evaluates the performance of the proposed ANN based metamodeling approach. Chapter Eight summarizes findings, draws conclusions, presents concerning issues, and discusses future research directions and opportunities.

2. Literature Review

The primary objective of this research is to explore artificial neural networks as a non-parametric and non-regression based technique to build metamodels for time series so that the model can effectively predict short-term transient behavior of an FMS after a disruption(s). The literature review focuses on several major FMS evaluative modeling methods that are useful for transient performance analysis. These techniques have evolved from major steady-state based evaluative modeling approaches. Therefore, there is a need to briefly review what has been done in the area of FMS performance modeling.

This literature review covers not only specific transient performance models but also the steady-state performance models on which these transient performance models are based. Major evaluative modeling approaches in FMS are queuing networks, Markov chain, metamodels, stochastic Petri nets, and simulation. Basic theoretical foundations of these modeling approaches used for both FMSs transient performance analysis and steady-state analysis are briefly discussed. Common modeling assumptions for both steady and transient performance analyses using a particular modeling approach are identified and discussed. Typical of these modeling assumptions are that a model's theoretical foundation is based on a steady-state Markovian stochastic process, a common underlining probabilistic distribution for arrival and service processes, no resource failure, no blocking, and deterministic part routings.

Significant breakthroughs in each modeling approach are reviewed. If there are several variations in a particular modeling approach, they are identified and their merits, compared to the original modeling approaches, are briefly discussed. Finally, the potential for adapting the particular approach for transient analysis is discussed. If there are already established ways to conduct transient analysis through the particular modeling approach, the literature review introduces the concepts and addresses their usefulness and concerning issues. A brief review of major developments in artificial neural networks is provided in Chapter 3 in addition to the proposed design architecture for this research.

2.1 Queueing Network Approaches

2.1.1 Summary of Major Developments

Queueing networks (QNs) are the most frequently used analytical form among various FMS evaluative modeling approaches. In general, queueing networks can be formed to study aggregate system behaviors of clustered interactive queues, often "a machine shop" consisting of several departments [Jackson 1957]. Each department is considered a multi-server or single-server queueing system (or a node within a queueing network) with an exponential service time distribution(s) and a single waiting line.

There are two major types of queueing networks based upon whether or not the total number of parts or pallets circulating in the network remains the same at any point in time during a normal operating cycle. The first type is open queueing networks (OQNs), also called Jackson networks [Jackson 1957], do not maintain a fixed number of parts in the network at any given time. The second type of queueing networks, called closed queueing networks (CQNs) [Gorden and Newell 1967], always maintain a constant number of parts. Despite the fact that the majority of analytical evaluative models for FMSs are based on CQN [Buzacott and Yao 1986], both the CQN and the OQN approaches are equally perceived as an effective way to model steady-state performance for various FMSs. For example, Buzacott and Shanthikumar [1980] model an FMS as an OQN where the scope of the model is expanded to include the jobs waiting for release to the FMS in a dispatching area. This study demonstrates the benefits of balanced workload, diversity in job routings with adequate control of job release to the system, and the superiority of common storage over local storage at each machine. Yao and Buzacott [1985] develop an OQN model to evaluate the performance of an FMS with general service times and limited local buffers. The model demonstrates that the arrival process can be formulated in terms of blocking probability on each station using renewal approximation by Whitt [1982].

Since most FMSs with limited local buffers tend to maintain a fixed number of pallets or parts in the system in order to avoid blocking, CQNs were initially perceived as an ideal type of queueing network model to depict behaviors of such FMSs. Formation of a CQN analytic model can result in either a product form solution with a normalization constant or non-product form solution for the equilibrium joint distribution of pallets or parts. If the FMS CQN has a small number of nodes (workstations), the product form final solution of the equilibrium joint distribution can be easily estimated through an algebraic approach to finding the normalization constant. Several basic assumptions have to be made in order to have a product form solution.

1. The balance equations of part arrival rate are based on steady-state behaviors of the system.
2. The system consists of m interconnected stages of service. The number of parts (or pallets) n remains constant throughout the entire operational life cycle.
3. The service time distributions on each server are exponentially distributed.
4. The routing can be determined according to a discrete time Markov chain.

The advantage of the closed queueing network approach is the ability to approximate the joint probability distribution of parts (or pallets) in the system using a separation of variables technique.

When the number of nodes (workstations or cells) in the network (FMS) gets large, finding the normalizing constant, which is essential for finding the equilibrium joint probability of pallets in the system, becomes computationally challenging due to its permutable nature. The technique has been further improved by a computational algorithm to calculate the normalizing constant in a recursive manner [Buzen 1973]. This enables analytic CQN analysis to be a practical approach for a real production environment, especially for complex systems that require prompt decision-making.

The first successful adaptation of product form CQN in FMS was with a convolution technique, which is called CAN-Q [Solberg 1977]. This model was initially developed to handle only single-part-type FMSs with a central server (typically a material handling system) that every part must pass through. Later, CAN-Q was extended by Stecke [1981] to handle multiple part type FMSs. The performance of this analytical model depends on the assumption that the processing times at each first-come-first-serve (FCFS) station are independent of the part type. If the assumption is satisfied, the convolution algorithm can deliver the exact solution. Otherwise, only an approximation can be made.

Additional study done on a similar model suggested that the model would not perform satisfactorily if all the servers use an FCFS queue discipline and non-exponential service time distributions [Chandy and Sauer 1978]. Dallery [1986] has also shown that the product form FMS CQN model with a single part type is not well suited for performance prediction of multiple-part-type FMSs with universal pallets and prescribed production ratios. Despite its known limitations, CQNs have been widely used for preliminary design and studying some operational issues in production planning for FMSs because of the speed and accuracy with which they can be evaluated once a model is correctly built. In the area of FMS production planning the CAN-Q model is extensively used to study the effect of various operational strategies on system throughput.

The class of product form CQNs was substantially extended and presented in a unified fashion [Baskett et al. 1975]. This triggered a rapid growth of applying CQN analysis in various FMS analytic models so that CQN analysis grew to handle problems that were initially thought to be unsolvable due to their deviations from the original assumptions. Assumptions such as a single part type and exponential service time distributions are commonly used in Gordon and Newell type network analysis. To overcome limitations of one of these assumptions, CQN with non-exponential service times, an "exponentialization" approach was introduced. This allows a CQN with general service times to be solvable, substituting general service times with equivalent exponential times so that the final product form can be still maintained [Yao and Buzacott 1986].

In practice, QNs with exponential arrival and service time distributions are not robust enough to capture realistic behaviors of various forms of FMSs in which the machine times are often known quite accurately [Pratt 1992]. Most workstations in an FMS, except for those that are failure prone, behave almost in a deterministic manner with very small variance especially when the system is fed with pre-selected part types, tightly integrated, and controlled by a computer. In some cases, time duration for individual part movements on predetermined part routes as well as processing in individual workstations is highly consistent and has much smaller variation than those with exponential probability distributions. Similarly, modeling failure-prone FMSs using QNs with an exponential time assumption, which usually have larger variance than those of exponential systems, can also be misleading. Thus, modeling such FMSs using QN with G/G/c/N queues is a more realistic approach. Yao and Buzacott [1985] model a workstation of an FMS using diffusion approximation (a recursive algorithm) in which the queueing process is formulated as a G/G/c/N queue. They found that a $C_2/C_2/c/N$ queue and Coxian phases are appropriate for modeling queueing processes that represent workstations of an FMS with inter-arrival service time distributions having squared coefficients of variation of less than 0.05.

Kamath [1989] found that most behaviors of asynchronous automated assembly systems (AASs) do not satisfy the assumption of exponential processing times made by closed form QN analysis and often the analysis can be misleading by such an assumption. These asynchronous automated assembly systems are also known as flexible assembly systems and represent a large and important subset of FMSs. Thus, it is necessary to use a method that can handle general service time distributions at each server for such AAMs [Kamath 1989].

Whitt [1993] studies a deterministic multiclass single-server OQN and has shown that feedback with class-dependent service times, and FIFO discipline can dramatically increase a chance for sudden large fluctuations on the sample paths of the queue-waiting processes with some initial conditions, which is highly conceivable in some FMS models. Suri [1985] has shown that a homogeneous service time (HST) CQN with exponentially distributed service times exhibits monotonicity throughout their performance measures depending only on the number of jobs present in the system. A HST workstation implies that the service time distribution at the workstation remains consistent across different numbers of jobs present in the system. However, the monotonicity property cannot be satisfied unless all service times are exponentially distributed. Therefore, it is less likely for any CQN or OQN with non-exponential service times to exhibit monotonic behavior after a sudden disruption.

Yao and Buzacott [1986] use product form CQNs to study the performance of FMSs with unlimited local buffers compared to FMSs with limited local buffers under three possible operational scenarios. Three possible operational scenarios to deal with any blocking are fixed routing, fixed loading, and dynamic routing. They conclude that dynamic routing has clear advantage in increasing throughputs when local buffers have limited capacities. Other studies [Kimemia and Gershwin 1985], [Shalev-Oren et al. 1985] used non-product form CQNs as an evaluative tool to test their new operational policies such as loading/routing and scheduling schemes. Several researchers used a non-product form CQN framework to study common behaviors of FMSs under a different set of system constraints or variables such as workstation breakdowns and limited buffers on each node so even blocking can be considered.

Other studies extended the scope of QN modeling for FMSs even to those that are traditionally considered FMS supporting systems such as maintenance float networks and control systems. Lin et al.[1994] used CQNs with Buzen's recursive algorithm to model a maintenance float network problem for FMSs.

Based on the approach taken to solve the product form of the equilibrium probability distribution, CQN can be further broken down into several subclasses. According to Seidmann et al. [1987], there are three subclasses for CQN analytic models. These are mean value analysis (MVA), the convolution technique (an extension of Buzen's [Buzen 1973] recursive algorithm), and approximate mean value analysis (PMVA). CAN-Q uses the convolution technique. But, most other models are solved by either MVA or approximate MVA depending on whether or not the model will have a final product form as its equilibrium probability distribution of parts or pallets over the network. If the analytic CQN model results in a non-product form, the approximate MVA is applied. On the contrary, if a product form solution is found, either the convolution technique or mean value analysis can be applied.

Mean value analysis (MVA) is a simplified technique to solve a CQN for a limited set of quantities, such as mean queue sizes, mean waiting times, utilizations, and throughputs, in a recursive manner without calculating normalization constants and product form joint distributions. MVA reduces a significant amount of the computational burden associated with complex CQN problems.

In reality, the joint equilibrium distribution often contains far more detail than is needed for practical analysis. As matters of fact, the computational burden of calculating the normalization constants can easily outpace the efficiency of CQN analysis as the system gets more complex. Thus, a simplified way to get the most common performance measures was needed for larger scale product form CQN problems without going through the somewhat tedious computational steps in traditional CQN analysis [Reiser and Lavenberg 1980].

MVA is based on a relationship between the mean waiting time and the mean queue size of a system with one less job. This relationship is also called the arrival theorem. The distribution of the network state seen by a job arriving at any node in the network is the same as the distribution of the network state a random observer would see with $(n-1)$ parts circulating in the network.

Several assumptions must be initially made in order to apply MVA to analyze CQN type FMSs. Some of these assumptions are: (a) the processing time of a part at each workstation has an exponential distribution, (b) the routing of parts to the next machine is chosen probabilistically, and (c) all workstations choose their next part according to the FCFS queue discipline. In reality, these assumptions have to be relaxed somewhat because there are many different classes of FMSs in existence based on their configuration and operational characteristics. Three major classes of FMSs are identified based on their modeling constraints such as pallet type, queue discipline, and prescribed production ratios [Dallery 1986]. These classes are monoclass models, multiclass models with fixed queueing disciplines, and multiclass models with prescribed relative throughputs.

Viswanadham and Narahari [1992] identify nine common characteristics of automated manufacturing systems that could lead an FMS CQN model to a non-product form. These are: (1) non-exponential service time distributions, (2) scheduling discipline other than FCFS, (3) different processing priorities among multiple part types, (4) new production control policies such as a pull system, (5) assembly operations (joining of parts), (6) breakdowns, (7) dynamic routing such as shortest queue routing (SQR), (8) blocking, and (9) multiple resource holding such as a part seizing a fixture, a pallet, a machine, and a set of tools in order to be processed. For example, a non-product form solution would result from an FMS where the routing is predetermined and the processing times at some workstations are not exponentially distributed. Another non-product form characteristic that is quite common is for each workstation to have a queue discipline other than FCFS. For this reason, Cavaille and Dubois [1982] proposed a heuristic based on MVA, called the approximate MVA method, to model an FMS with near deterministic service times using MVA with an additional approximation term. The FMS model used in the Cavaille and Dubois's study has FCFS servers where the various part types may require distinct service time and routing requirements. Approximate MVA methods have been extended to handle FMSs with priority scheduling disciplines [Shalev-Oren et al. 1985].

The first successful computerized MVA application in overall production planning and control problems includes two different decision categories [Hildebrant 1980]. The first category deals with resource decisions and the second category deals with temporal decisions. Resource decisions are concerned with choices among different resources and temporal decisions deal with job sequencing and scheduling issues. This model was subsequently further improved to demonstrate its accuracy and robustness even on larger scale models [Suri and Hildebrant 1984].

Zhuang and Hindi [1990] developed an extended MVA approach that can handle multiple class queueing networks with limited queue capacities to model an FMS with a central material handling system (MHS) and exponential service time distributions including one by the MHS. Zhuang and Hindi also develop an approximate MVA to evaluate an FMS with a single cart MHS, the assumption of exponential service time distribution, and limited local buffers which leads to block and wait mechanisms. Tetzalff [1996] utilizes approximate MVA to evaluate the performance of a tool management system in an FMS. The part transportation system is modeled as a product form CQN and the tool delivery system is model as a non-product form CQN.

As an indirect way to study transient behavior of FMSs using QN, Chance [1993] studies the relationships among various conjectured upper bounds on transient mean total waiting times in OQNs with some assumptions such as Poisson arrival process, exponential service time distribution, and multi-server queue nodes within the network. He concludes that after some small initial period, transient mean total waiting times in the Jackson network are bounded above by the weighted sum of expected waiting times in queues. The expected network waiting time can be found from simulation and the expected waiting times for queue can be estimated through the program described in Kelton and Law [1985]. These conjectured upper bounds provide the lower bounds on the time required for the transient mean to approach its steady-state value. However, this method can be applied only to OQNs with exponential service times. Also there is a significant drawback that the author acknowledges. The gap between the conjectured upper bound and actual transient mean on total waiting time grows wider as the network gets larger, which implies that the method is not robust enough to be applied on large scale networks.

The study done by Suri [1985] supports the position that any OQNs with exponential service time distribution and some specified initial conditions are most likely to behave in a monotonic way during their transient period. Conversely, this implies that there may be a chance for either a CQN or an OQN with non-exponential service time distribution to exhibit non-monotonic behavior during the transient period after a disruption on its sample paths. Thus, a transient analysis approach by asymptotically connecting individual steady-state values approximated for the particular number of jobs that can be present in the system during the transition period may not always provide a realistic view of true system behavior during a short time window. This issue leaves an open question for further research investigation.

2.1.2 Conclusion

Table 1 summarizes the previously discussed major developments in QN analysis of FMSs. Most works are focused on steady-state behavior of the system.

Table 1. Major Developments in FMS Performance Study Using QN Analysis

Title of Method/ Study	Author(s) Year	Type of QN (Approx. Method)	Limits /Restrictions	Type of Analysis	Focus of Study/ Findings
CAN-Q	Solberg 1977	CQN	-Single part with a central servers -Necessary assumptions for a product form solution	Steady-State Analysis	To study effects of various operational strategies (production planning) on system throughput
Models for understand ing FMSs	Buzacott, Shanthikumar 1980	OQN	-Basic OQN assumptions	Steady-State Analysis	To evaluate FMS with jobs waiting for release in the dispatching area
MVA (earlier version of MVAQ)	Hildebrant 1980	CQN (MVA)	-Exponential processing times -Probabilistic routings -FCFS queue discipline	Steady-State Analysis	To study production planning and control issues related to failure prone FMSs
CAN-Q (extended)	Stecke 1981	CQN	-Multiple part type -Processing times at each FCFS station are independent of Part Type	Steady-State Analysis	Effect of various operational strategies on system throughput of FMS with multiple part type
Heuristic methods based on MVA	Cavaille Dubois 1982	CQN (Approximat e MVA)	-FCFS servers various part types require distinct service time and routing requirements	Steady-State Analysis	To study the performance of FMS with predetermined part routings and non-exponential service times
MVAQ	Suri, Hildebrant 1984	CQN (MVA)	-Exponential Service times -Probabilistic routings -Multiple part type modeled -Proven robustness on larger scale models	Steady-State Analysis	To use MVA for practical planning and control of an FMS
The method of Coaxian Phases	Yao, Buzacott, 1985	OQN	-General service times -Limited local buffers	Steady-State Analysis	To evaluate the performance of an FMS with general service times and limited local buffers

Table 1 (continued). Major Developments in FMS Performance Study Using QN Analysis

Title of Method/ Study	Author(s) Year	Type of QN (Approx. Method)	Limits /Restrictions	Type of Analysis	Focus of Study/ Findings
Diffusion approximation	Yao Buzacott 1985	CQN	-Coefficients of variation of inter-arrival and service time distributions is less than 0.05	Steady-state Analysis	To approximate the behavior of FMS with non-exponential workstations
Approximate MVA (extended)	Shalev-Oren, Seidmann, Schweitzer 1985	CQN (Approximate MVA)	-Similar to Cavaille and Dubois's approximate MVA assumptions	Steady-state Analysis	To study impact of priority scheduling discipline
Heuristic based approximation of MVA	Kimemia, Gershwin 1985	CQN (Approximate MVA)	-Similar to Cavaille and Dubois's approximate MVA assumptions	Steady-state Analysis	To optimize the flow of the operation
Exponentialization	Yao, Buzacott 1986	CQN	-Necessary assumptions for a product form solution except general service times	Steady-state Analysis	To evaluate the performance of FMS with general service times using a product form CQN analysis
ON modeling FMSs using CQNs	Dallery 1986	CQN(MVA) CQN(Approximate MVA)	-Necessary assumptions for product form CQN analysis, MVA, and approximate MVA	Steady-state Analysis	Identified three major classes of QN based FMS models
Models of FMSs (with various configurations) with limited local buffers	Yao, Buzacott 1986	CQN	-Various non-exponential service time vs. exponential service time distributions -Dynamic routing vs. fixed one -Unlimited vs. limited local buffers	Steady-state Analysis	FMS with small local buffers are robust to various non-exponential processing time distributions
MVA (extended)	Zhuang, Hindi 1990	CQN (MVA)	-Limited queue capacity -exponential service times -A central server (material handling system) -multiple part types	Steady-state Analysis	To extended MVA approach to multiple part type FMS with finite queue capacity
Approximate MVA	Zhuang, Hindi 1991	CQN (approximate MVA)	-Exponential service times -limited local buffers -A single cart MHS (block and wait mechanisms)	Steady-state Analysis	To study behavior FMS with a single cart MHS

Table 1 (continued). Major Developments in FMS Performance Study Using QN Analysis

Title of Method/ Study	Author(s) Year	Type of QN (Approx. Method)	Limits /Restrictions	Type of Analysis	Focus of Study/ Findings
Conjectured upper bounds on transient mean total waiting times in QNs	Chance 1993	OQN	-Poisson arrival process -Exponential service time multi server queues -Size of the network	Transient Analysis	To find conjectured upper bound on the mean total waiting time in Jackson Networks (applicable to some FMS)
A maintenance float network problem	Lin, Madu, Kuei 1994	CQN	Necessary assumptions for product form CQN analysis	Steady-state Analysis	To find the optimal capacity of redundant system for a failure prone FMS
A QN model for FMSs with tool management	Tetzalff 1996	CQN (approximate MVA)	-Product form CQN requirements for MHS -Non product form CQN for the tool delivery system	Steady-state Analysis	To study the performance of a tool management system in an FMS

The QN approach is generally not an effective way to study detailed behavior of the system within a short time horizon. Instead it provides an idealistic picture of long-term behavior if the system reaches steady state. The most critical role of transient study in an on-line decision making environment is not only to detect any possible disturbances in steady-state performance but also to investigate the detailed nature of the system reactions brought by such disturbances. The detailed nature of such system behavior consists of the duration of a transient state, the magnitude of any reaction, under or over reaction if any, and the value of the new steady-state mean. Using this knowledge the decision-maker can proactively engage in any remedial action to minimize or prevent the negative impact caused by such a disturbance in steady-state sample paths.

Since queueing networks are an aggregated form to represent interactive neighboring queueing systems as a whole, the equilibrium conditions for the entire network must be satisfied in order to directly or indirectly estimate the network performance. Even transient analysis on OQNs such as the one proposed by Chance [1993] to conjecture the upper bounds for the sample paths of total mean waiting time of the network during a transient period, has many limitations as a robust means to facilitate on-line transient analysis. Therefore, we can conclude that instantaneous transient analysis through ordinary QN analysis is practically infeasible because any exact or approximated behaviors of an individual or aggregated queue(s) using QN analysis can be derived only under the steady-state assumption.

However, QN's speed, reliability, and intuitive details are appealing to many researchers and industry users who are primarily interested in steady-state performance of FMSs. The QN approach can be extensively used during planning and designing stages of an FMS. However, it appears ill suited for online based transient analysis.

2.2 Markov Chain Models

2.2.1 Summary of Major developments

Markov chain modeling provides fundamental foundations to many analytical evaluative models. Markov models are based on a stochastic process called a Markov process that has a unique mathematical property in which any future state of the system depends on the past state of the system only through the present state. Markov chains can be effectively used to capture stochastic dynamics of many discrete event systems with a finite state space such as manufacturing systems. Despite their well-known drawbacks as an analytical evaluative modeling tool, such as exponential growth in modeling complexity as the size of the state space (a collection of all possible system states) gets larger, Markov chain analysis can be an appropriate way to study many special cases of FMS operations.

Each state in a Markov chain model usually represents a possible discrete state of the stochastic process during its life cycle. Markov chains can be grouped into either discrete time or continuous time processes. Between the two types of Markov chains, Continuous Time Markov chains (CTMC) have been extensively used to analyze dynamic behaviors of many automated manufacturing systems [Viswanadham and Narahari 1992]. For example, studying the overall impact of a certain control mechanism over the entire system and a machine repair system with a redundant resource backup system are popular areas to apply CTMC analysis. CTMCs also provide theoretical grounds for birth and death processes and time reversible Markov chains. Time reversibility is a necessary condition for product form QN analysis.

Several foreseeable computational issues in CTMC modeling as the complexity of the problem grows can be identified. These issues are size, ill conditioning, and stiffness. The size issue arises when there is an exponential growth in the size of the state space as the number of available resources increases in the given system. In other words, the computational burden to calculate the coefficient matrix will rise rapidly as the state space gains more possible states. The second issue, ill conditioning, is based on the fact that small changes in the coefficient matrix can lead to large changes in the solution vector. Stiffness is a consequence of having transition rates of significantly different orders of magnitude among states. For example, for a certain CTMC, for particular states the transition rates among them can be significantly higher than the rest of transition rates among other states, which implies faster transitions between those particular states compared to other states. This can create stiffness during the computation.

There are two ways, namely uniformization and numerical ordinary differential equation (ODE) solution, to solve these types of differential equations. Reibman and Trivedi [1988] conducted a survey of three numerical methods for transient analysis, uniformization, RKF45, and TR-BDF2. They found that two numerical approaches, ODE RKF45 and TR-BDF2, work well only for certain types of problems. On the other hand, uniformization works well for typical problems with more accuracy and efficiency.

Gross and Miller [1984] extend the randomization technique to Markov processes with infinite state spaces. The randomization technique was originally proposed by Grassmann [1977] and is a general non-numerical method based technique to compute transient probabilities of Markov processes with finite state spaces through a probabilistic interpretation. Gross and Miller [1984] present an approach called SERT utilizing a generalized randomization procedure in an algorithmic way to model a continuous parameter Markov processes. SERT stands for state space (S), event set (E), rate vectors (R), and target vectors (T) that can collectively describe a general class of Markov processes. Upon successful completion of the randomization, closed form formulas for expected time averages, first passage time distribution, and expected number of events of a certain type occurring for a time interval can be constructed. This approach promises substantial relief from the computational burden associated with traditional transient Markov processes whose state spaces are quite large.

The part selection policy for a flexible manufacturing cell is studied to minimize the expected shortage penalty per unit time using a semi-Markovian process [Seidmann and Schweitzer 1984]. For an FMS with block and recirculate, the workstations with finite buffers are modeled as a Markov chain model and solved even though one with a central buffer becomes substantially complicated to model [Viswanadham and Narahari 1992].

Another major achievement in the study of FMS transient behavior by a Markov chain based analytical modeling approach is performability analysis. The notion of performability was first used by Meyer [1980] in the study of a degradable computing system performance. Performability analysis is a combined form of performance and reliability analysis. Performability modeling is used to study the overall impact brought by constituent subsystem failures on a particular system performance index over a finite time horizon.

Performability analysis was originally designed to investigate performance-related reliability for fault-tolerant computing systems. Later the same technique was applied to automated manufacturing systems (AMSs). Even though the majority of performability studies use continuous time Markov chains with the deterministic reward structure consisting of a number of transient states and a single absorbing state, discrete time Markov chains with random rewards were later introduced [Mallubhatla and Pattipati 1994]. The notion of a Markov reward often implies the cost or reward incurred from being in a particular state at a given time.

The first application of performability modeling in manufacturing systems appears in a work by Viswanadham et al. [1991]. This modeling was focused on AMSs producing a single part type. A subsequent study [Viswanadham et al. 1993] was done on AMSs producing multiple part types using continuous time Markov reward models.

Most automated manufacturing systems consist of numerous constituent subsystems. In reality, even the most reliable and well-designed AMSs are subject to unscheduled and unexpected subsystem failures due to many complex mechanical interactions and functional dependencies. Especially for an FMS, a proper functioning of individual resources within the system is highly critical to its operational success because the role of each resource is often uniquely defined and tightly integrated with others to complete any planned operations. Even if the frequency of these failures is very low, most of these AMSs are built with a certain degree of redundancy so that highly expensive systems like FMSs will not be sitting idle in case of any unscheduled subsystem failures. We call these types of manufacturing systems fault-tolerant systems. They are built with a certain degree of flexibility in both operation and capacity to handle limited multiple resource failures simultaneously.

Due to natural time scale differences in frequencies of failure, repairs, and reconfigurations and of the part processing events, a performability model is often hierarchically devised: a higher level (longer-time scale) dependability model and a set of lower level (shorter-time scale) performance models. The study done by Viswanandham et al. [1995] shows that the accumulated reward over a given time interval is a solution of a set of forward or adjoint multidimensional linear hyperbolic partial differential equations. They also proposed efficient numerical methods for computing the distribution of the cumulative operational time, and the mean and variance of the cumulative production over a given time interval. One of the common difficulties in this approach lies in efficient numerical methods to solve the partial differential equations in order to find the distribution of accumulated production over $[0, t]$.

After occurrences of these resource failures, the system often goes through a series of possible intermediate transient states during the recovery process. The complex dynamics of the state transitions can be captured via the structure state process (SSP). The SSP is to describe the system evolution as influenced only by failures, repairs, and reconfigurations. In each structure state, the system can be associated with a different performance measure such as lead time, throughput, and work in process.

The formal definitions of a structure state process and performability can be given as follows.

Definition: Let $Z(u)$ be the structure state of the manufacturing system at time $u \geq 0$. Then the family of random variables $\{Z(u), u \geq 0\}$ having state space $S = \{0,1,2,\ldots,m\}$ is called the structure state process.

If we let $f_0, f_1, \ldots, f_m$ be rewards in the individual structure states and $Y_t(s)$ be a random variable over an observed period $[0, t]$ with initial structure state given as $s \in S$, the performability can be given as

$$Y_t(s) = \sum_{i=0}^{m} f_i \tau_i$$

where τ_i is the total sojourn time of the SSP during $[0, t]$ in state i.

The SSP can be modeled using CTMC, queueing networks, or stochastic Petri Nets. Viswanadham and Ram [1994] use both CTMC and Pertri nets to model performability of a flexible manufacturing cell (FMC) and suggest techniques for computing statistical moments of certain cumulative performance measures. Three measures: performability distribution, steady-state performability, and interval performability, are focuses of interest in performability analysis.

The structure state of the SSP is a vector whose components describe the status of its constituent subsystems. The SSP is a collection of all possible structure states in which the sequence of transitions among all-possible states can be logically captured to reflect the evolution of the system during a given time horizon. Any failure prone AMS can go through a series of individual structure states within a given length of time following a resource failure. This combines both the performance and the reliability aspects of the system. Typically a part of the vector representation of the components in each state contains the total number of available machines at any point during a given time period. The current structure state changes due to failures and repairs as time progresses. A well-illustrated SSP model for a degradable (non-repairable) fault-tolerant FMS with a central server and m identical machines is provided by Viswanadham and Narahari [1992].

Gershwin's study [Gershwin 1992] argues that the estimation of variability of production is an important measure of interest to the manufacturer. Furthermore, his study shows that the coefficient of variation of production in an actual AMS can exceed 0.1, which is considered unacceptable since high variability can cause over and under production by creating either unnecessary inventory or material shortage. Therefore, finding higher statistical moments for the performability distribution is highly critical.

The performability distribution is a cumulative distribution function of the performability $Y_t(s)$, i.e., $P\{Y_t(s) \le x\}$ for $x \in R$. The performability distribution and its statistical moments are used to quantify the performance and reliability of the system. A closed form expression for the performability distribution and its moments and recursive formulas to compute the moments for an n-process system are found using a sum of simple exponential terms and double Laplace-Stieltjes transformations by Donatiello and Iyer [1987].

Typically when a system with non-homogeneous components (e.g., different types of machines) is modeled using a Markov process, the number of states in the system is the product of the number of different type components. Hence the total number of structure states n can be very large. Finding statistical moments for the performability distribution is a useful way to approximate the distribution especially when the time complexity for computing the coefficients of the distribution becomes too expensive as the number of structure states grows. The same framework to find an analytical solution for the distribution of performability can be applicable to non-repairable systems as long as the transitions between states are modeled by an acyclic Markov chain.

A similar but improved modeling approach was proposed by Rupe and Kuo [2003] in order to lessen the complexity of the traditional performability model by separately modeling independent failure and repair processes of each system and combining the results at the conclusion. This approach is designed to provide an efficient general architecture to be applied to a wide variety of FMS configurations including spare part inventory to repair down machines. Despite their promising findings, the complexity of the model can still grow significantly if each machine type has different failure and repair processes.

2.2.2 Conclusion

Markov chain models are based on either Markov or semi-Markov processes that are the two most important subclasses of stochastic processes. Markov processes provide underlying theoretical foundations for many queueing theory based analytical modeling approaches. Significant contributions in FMS transient analysis are made by Viswanadham et al. [1991], Viswanadham [1992], Viswanadham and Ram [1994], Gross and Miller [1984].

In general, Markov chain models are intuitive and easy to understand. However, there are a few major drawbacks as Narahari and Viswanadham [1989] point out. These drawbacks are: (1) when the size of the physical system grows, the number of states in the Markov chain grows exponentially and this makes Markov analysis computationally expensive; (2) as the number and complexity of interactions increases, visualizing the Markov chain states and the transitions among states becomes difficult; (3) the existence of two or more time scales can cause tremendous computational difficulties.

Solving Chapman-Kolmogorov equations that correspond to first order linear differential equations with constant coefficients, provides closed form solutions to approximate individual transition probabilities or the state probabilities as functions of time. There are basically two ways to find the solution for these first order differential equations. The first method is a numerical method based technique and the second one is non-numerical method based technique. With either technique, finding closed form solutions can become problematic as the size of the state space grows. Also, building a Markov chain model using a predefined state space, which often focuses on one aspect of the system performance, still requires intuitive and creative modeling efforts.

Shifting focus from one to the other or changing configuration of the system often requires redefining of the state space which can result in rebuilding the entire model. This process requires a significant amount of human modeler’s analytical skills and modeling expertise. Hence, this cannot be easily transportable to a fully automated system with a non-interactive modeling environment. Unless the system configuration never changes, in other words, the state space (dynamics of the model) remain unchanged and only the associated transition probabilities (performance parameters) change, reconfiguration of model on the fly will be challenging for on-line transient analysis. Therefore, it can be concluded that constructing Markov chains is not a practical approach to building a rapidly re-configurable online evaluative model focusing on transient behavior of a dynamic system.

2.3 Simulation Modeling

2.3.1 Summary of Major Developments

During the past several decades, computer simulation has been an indispensable tool for many system engineers to numerically study the behavior of complex discrete and non-discrete (continuous) event systems. Since many improvements have been made in simulation technology, such as improved usability, modeling power, and speed, simulation analysis has received greater attention as an effective modeling tool. Despite the availability of many effective system modeling methods, simulation modeling frequently becomes a favorable choice over other evaluative tools because it gives invaluable understanding of how the system operates as opposed to how everybody thinks it does [Pegden et al.1990].

In general, simulation should be used whenever detailed results are needed such as in a transient behavior study. The price to be paid for being detailed is that simulation takes a relatively longer time to develop, usually requires more input data than other analytical evaluative modeling approaches and often requires a great deal of computation time [Suri and Hildebrant 1984]. In addition, a steady-state analysis of a system by the simulation modeling approach requires a statistically valid output analysis to find true steady-state means if there exists a significant initial bias on its outputs due to the model's startup conditions, often called a warm-up period.

Because of this time consuming modeling process and cumbersome output analysis, the simulation modeling approach has shown only limited application in on-line decision making schemes such as online production control systems. Nevertheless, a great deal of research and efforts have been put into the area of on-line simulation as a viable approach to predict the short-term system behavior for untested operational scenarios in typical manufacturing control environments. Especially with the current pace of progress in parallel and distributed computation, processing speed of inexpensive CPUs, and various model simplification techniques, simulation modeling to study detailed behavior of a system within a given time window has a promising future as a practical online based system modeling approach.

Traditionally, simulation modeling has been extensively used in design, planning, scheduling, and control of FMSs. These studies typically seek the optimal configuration for a hypothetical system or the best operational policy for an existing system. The modeling oriented languages, such as GPSS/H, SLAM II, SIMAN, SIMSCRIPT, and ARENA, etc., have been favored over general programming languages by many simulation practitioners. Most of these modeling oriented languages possess realistic abstraction capability for individual behavior and interactions among various modeling entities, automatic statistic collection features, extensive run-time error detection, many built-in sophisticated event handling mechanisms, and powerful add-in animation features. However, there is some modeling inefficiency associated with these general purpose simulation languages to model complex manufacturing systems like FMSs because they are designed to model a wide variety of discrete event systems as well as manufacturing systems using generic building blocks.

As Rolston [1985] points out, modeling FMSs with a general purpose simulation language often requires highly trained programming skills to conceptualize the entire system in terms of entities, queues, servers, and resources. For this reason, dedicated simulation languages for various manufacturing systems were developed, such as MAP/1 [Rolston 1985], GPSS/H [Schriber 1985], XCELL+ [Conway et al. 1987], WITNESS [Gilman and Billingham 1989], and MAST [Lenz 1989]. Fixtures, conditional part routing, and conveyers often require special modeling elements to capture their unique behaviors. For example, a conveyor belt is a material handing system but often acts as a finite storage buffer. Also, based on the way of the conveyer belt is used in the system, securing consecutive spaces on the conveyor belt is crucial for undisrupted traffic of a particular group of parts. MAP/1 is a simulation language that has been developed to capture such unique behaviors of FMSs [Rolston 1985].

Similarly, a GPSS/H model is proposed to represent a hypothetical FMS using a modular design approach to explore the concept of a universally applicable simulation model with minimal modifications possible for various FMSs [Schriber 1985]. For the GPSS/H model, some simplifying assumptions have to be made. These assumptions are no machine breakdowns, negligible part travel time between any two points in the system, and no traffic congestion.

Because of the complexity of most simulation models, a formal scheme to convey the underlying logic of the system using common words is needed. An activity cycle diagram is a graphical presentation to describe the underlying logic of a discrete event system that can be easily understood by non-experts. Despite this effective formalism to depict the dynamics of a complex manufacturing system such as an FMS, the influence of a particular simulation language used to construct the models based on the activity cycle diagram can be found. Hlupic and Paul [1994] build a conceptual FMS simulation model using activity cycles diagrams to conduct a comparative study to show the apparent influence of the simulation package used for the model construction.

There are two ways for simulation to be used in production control and planning environment: the first is on-line based simulation analysis and the second is off-line based. Most simulation modeling efforts in FMS operation management have concentrated on off-line steady-state analysis. Simulation modeling has been extensively used as an evaluation tool to test whether a suggested dispatching rule or schedule really works better than other alternatives. The schedule or dispatching rule in an FMS normally determines which parts are introduced into the system at what time and which part to load next into a particular machine. Comprehensive literature reviews on FMS scheduling using off-line simulation as an evaluative tool can be found in [Gupta et al. 1989; Hutchison 1991; Basnet and Mize 1994].

The other prominent application area for off-line based simulation study is FMS design. Abdin and Mohamed [1986] conduct a simulation study to examine FMS design issues regarding the maximum number of pallets for each part type and the optimal conveyor speed under two distinctive job sequencing rules, namely the LPT and PROB rules. LPT gives the job with longest processing time the highest priority while the PROB rule orders work pieces according to their highest content in the work-in-process. The study concludes that for that particular cell configuration LPT is favorable over PROB and allocating four pallets of each part type can ensure a smooth production against various changes.

A significant number of recent research efforts using simulation applications in FMS production planning and control have shifted their focuses to on-line and real-time applications. M. Kim and Y. Kim [1994] propose simulation-based real-time scheduling for an FMS. In this study, they argue that the dynamic and uncertain nature of system states may make off-line scheduling impractical for most FMSs. In general, FMSs are more sensitive to system disruptions than conventional manufacturing systems because of their tighter synchronization, system integration, and interdependencies among many automated system components. Hence, FMSs require an immediate response to changes in their system states, and this can be achieved through implementing on-line scheduling and control.

Harmonosky [1993] addresses two key issues, the simulation run length issue and look-ahead horizon assumptions, for using simulation for real-time production control. In this study, Harmonosky identifies the types of manufacturing systems suited to pursuing simulation as a real-time control aid: systems with longer average processing time, WIP performance measures, and high flow shop characteristics are believed to take smaller CPU time and fall into this category. The biggest obstacle for simulation to become a practical on-line evaluative tool in real-time decision making environments has been its lengthy execution time. In addition to a rapid improvement in the speed of inexpensive CPUs, there have been many ongoing research efforts to make simulation experimentation a more practical methodology for on-line use. In order to shorten the lengthy execution time of simulation without compromising statistical precision, the majority of on-line steady-state simulation analysis schemes have adopted a form of execution-time reduction techniques, such as concurrent simulation, distributed simulation, model simplification, and the reverse simulation method. Each of these are discussed more fully below.

A concurrent simulation means that a separate, independent processor is dedicated to running a simulation under each set of input parameters. Concurrent simulation is proposed as a primary analysis tool to evaluate candidate schedules in on-line production control environment. It utilizes parallel computing techniques to mathematically decomposing a scheduling problem into a parallel hierarchy [Davis and Jones 1988]. The success of this conceptual scheduling algorithm lies in the integration and development of key technologies, such as compromise analysis, conflict resolution, and efficiency of concurrent simulation techniques. Also, the authors acknowledge that the optimality of the found schedule cannot be guaranteed and the probability of exact implementation of the suggested schedule is close to zero due to the tradeoff between a guarantee of feasibility and operational efficiency.

Different from concurrent simulation, distributed simulation uses a technique to partition a single simulation run into several independently executable small components (routines) using parallel computation techniques. Distributed simulation focuses more on a distributed simulation algorithm (software) using parallel computation techniques rather than employing multiple processors (hardware) to host multiple simulation runs. In other words, a sound simulation model of concurrency is more important than the multi-processor hardware itself. Traditional discrete event simulation is designed to be executed by a single processor sequentially following an event calendar as the single stepping clock advances. On the contrary, for distributed simulation each simulation component is run concurrently and brought together to collectively present the overall behavior of the system. A distributed simulation system must explicitly coordinate the advance of time in order to maintain temporal consistency among its components. There are two distinct tasks to maintain time among distributed simulation components: the movement of time and the coordination of time movement. Based on methods to coordinate time advances between concurrent simulation components, distributed simulation algorithms can be classified into two classes.

The first class is Chandy-Misra (CM) simulation, also called pessimistic simulation [Peacock et al. 1979; Chandy and Misra 1981]. The mechanism holds back processing because it assumes that components will communicate out of sequence. The CM algorithm does not prevent simulation-induced deadlock. Thus, CM works best in tightly coupled simulations where objects are highly synchronous. The second class is Time Warp (TW) simulation, sometimes referred to as optimistic simulation [Jefferson 1985; Jefferson and Sowizral 1985]. It relies on the ability of an object to rollback its present state to that of some previous time. Time Warp is good for loosely coupled, highly asynchronous systems but is inefficient when models have mixed time scales or diverse interaction behaviors.

McAffer [1990] proposes the Unified Distributed Simulation (USD) algorithm as a compromising approach. This approach is loosely based on the Time Warp algorithm. By explicitly defining risk and aggressiveness parameters for each model, simulation models with different behaviors can be mixed within one simulation. Prassad and Deo [1991] propose a parallel algorithm for discrete event simulation on exclusive-read exclusive-write parallel random-access machines (EREW PRAM). The proposed algorithm uses a parallel data structure as an event queue, called a parallel heap, which allows simultaneous insertions and deletions of messages maintaining priorities among messages in a reasonably small amount of time using multiple processors.

Another way to use simulation for real time scheduling, control, and monitoring was proposed by Harmonosky [1990]. Instead of adopting a concurrent simulation approach, she suggests interfacing simulation with the physical system to run two separate modes. Figure 1 depicts the structure for such an approach. The first mode is a monitoring mode. It is used when the model is directly linked to the physical system, continuously receiving status information from various system elements. The second mode is a decision-making mode and is used when the model evaluates different control decision options through traditional off-line runs. The issues regarding this approach are how to balance the tradeoff between a long enough time horizon to obtain statistically valid results and a shorter response time required to make prompt decisions.

A similar approach interfacing a SIMAN based simulation model to a real-time control database is proposed to evaluate work order release sequences based on measure of performance by Muller et al. [1990]. Unlike most simulation studies, the evaluation is based on the transient behavior of the system and not steady-state performance. The control system looks at the time window in which the work order is predicted to be completed in order to determine if a particular work order sequence meets due date requirements set in advance by the MRP system. Ten replications are made to construct the confidence intervals (CI) on the completion time for a work order in order to be compared with actual data. Surprisingly, results indicate that only 43.6% of actual completion times occur within these estimated CI. The authors attribute the occurrences of work orders outside the confidence interval mainly to the uncertainty at the finishing cell.

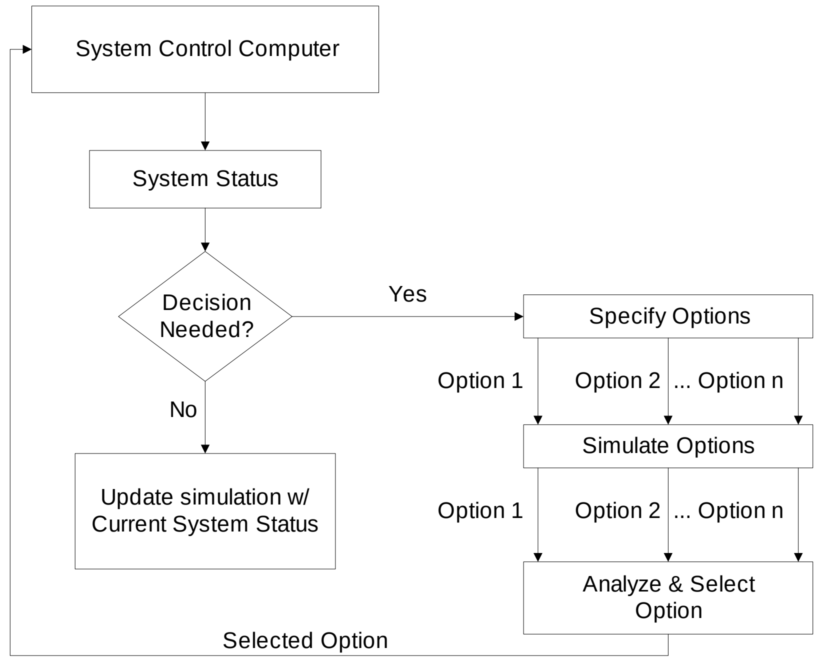


Figure 1. Scenario for Interfacing Simulation with Physical System for Real-time Control [Harmonosky 1990]

Even though the study done by Sims [1997] does not directly discuss the application of real-time simulation, he argues that, for any scheduling problem with a short-term goal, running simplified simulation models with deterministic values would provide a realistic view and a faster response. Reverse simulation is used when the desirable range of values of the performance measure are known and used as inputs to the model so that the steady-state mean for the performance measure can be reached at a faster rate with fewer samplings. Lee et al. [1997] propose a single run optimization method to take advantage of the reduced execution time using the reverse simulation technique and chaos theory.

As discussed in Chapter 1, simulation can be classified into two categories: terminating and non-terminating. Non-terminating simulations are sometimes called steady-state simulations. Terminating simulations are run only until some stopping criterion is met. The stopping criterion is normally set as a system event that is designed to end the simulation run based on the nature of system or the purpose of analysis. On the contrary, non-terminating simulations can conceptually run indefinitely after they reach a steady-state or stationary pattern of behavior. With use of a proper warm-up period deletion technique, most non-terminating simulations can be stopped at the point where there are sufficient observations for statistical accuracy and the least significant amount of influence from the truncated initial bias, often called the warm up condition.

Most simulation languages have some form of built-in statistical output analyzers. These built-in statistical output analyzers are often inaccurate and misleading because they tend to ignore common startup problems and autocorrelation among observations [Seila 1990]. A simulation experiment without a valid statistical output analysis is meaningless. There are clearly two different classes of output analysis that can be applied to find statistical means based on whether the simulation is terminating or non-terminating. Different types of output analysis are covered in detail in several works [Seila 1990; Law and Kelton 1991; Banks et al. 1996].

Typically, a steady-state simulation with particular input parameters can be carried out by a single but reasonably lengthy replication with an output analysis using a technique like the batch means method. These techniques find statistically valid steady-state means from a stochastic process that represents a particular performance measure. On the other hand, the run length in a terminating simulation is dictated by the terminating event or condition and this event or condition often limits the number of observations that can be collected from a single replication for the statistical output analysis. For a statistically valid output analysis one cannot depend on a highly autocorrelated sequence of a limited number of observations from a single run. Therefore, repeating a single run a total of R times is required for terminating simulation to have n_r observations in each replication r so that it can have statistically independent and identically distributed R sample means.

Terminating simulation can be effectively used as a look-ahead performance evaluator in an on-line production control environment. The chronologically captured behavior of a particular performance measure from a terminating simulation during the transition period following an unexpected disruption may provide realistic and meaningful information to on-line based decision making for automated disruption handling. Such attempts can be accomplished by adopting a hybrid modeling approach, often called metamodeling. Metamodeling maps simulation output to a corresponding mathematical model using techniques such as regression or time series analysis. Lin and Cochran [Lin and Cochran 1990; Lin and Cochran 1990; Lin et al. 1998] proposed a metamodeling approach using terminating simulation. They argue that relying on the traditional terminating simulation method to investigate transitional behaviors of a manufacturing system can be expensive and impractical for real time production control.

2.3.2 Conclusion

Many researchers and systems engineers studying the detailed behavior of complex systems such as FMSs have favored discrete event simulation as their preferred modeling tool. However, its limitations as an evaluative modeling tool, such as lengthy model development time, detailed input data requirement, lengthy simulation execution time, and necessary but cumbersome statistical output analysis procedures have kept simulation from becoming a practical analysis tool for on-line decision making. Recent improvements in simulation usability, modeling power, and speed have started receiving increased attention from both the research community and industry. In addition to these improvements, there have been considerable on-going research efforts to make a simulation run faster and shorter using techniques such as distributed simulation, concurrent simulation, model simplification, and reverse simulation. There are clear differences between terminating simulation and non-terminating (steady state) simulation analyses. Non-terminating simulation is often useful to predict short-term effects of disruption(s) on a particular system behavior. The majority of simulation modeling approaches proposed and explored so far within a framework of online decision-making, including online production control systems, have focused only on steady-state simulation. Even for a dynamic production environment, such attempts tend to focus only on the newly shifted steady-state mean after the disruption rather than intermediate transitional behaviors.

Using terminating simulation in a traditional way is very costly and impractical as a part of an on-line production control system such as a disruption handler. Applying a hybrid method such as metamodeling proposed by Lin [1990] combining terminating simulation and mathematical modeling is one way to effectively apply terminating simulation in such an on-line decision making support system.

The drawback of such approach is the difficulty encountered as an online based non-interactive model constructor to choose the right time series model to represent dynamic characteristics and the complexity of the system's possible volatile behavior following the disruption. This can become a critical issue especially when a composite model, a linear combination of several mathematical models, has to be built. Thus, in order to effectively use Lin's approach for the fully automated and self-contained FMS online controller there is a need to adopt a non-parametric method to build the model, such as applying effective neural network architecture.

2.4 Stochastic Petri Nets

2.4.1 Summary of Major Developments

This study presents a brief history of Petri net based approaches in systems modeling and focuses on their applications in FMS transient and steady-state performance analysis. First, we need to look at some elementary definitions in classical Petri nets and other subclasses such as Stochastic Petri nets (SPNs) before discussing major developments in this area.

Petri nets (PNs), also known as place-transition nets (PTNs), were proposed to graphically model discrete event dynamic systems by Carl Adam Petri [1962]. Petri nets were designed to model systems with deterministic behaviors. Classical Petri nets are useful for investigating qualitative or logical properties of concurrent systems, such as mutual exclusion and presence or absence of deadlocks. Recently, PNs have emerged as a powerful performance modeling tool by incorporating stochastic time functions for analyzing asynchronous concurrent systems that exhibit non-deterministic behaviors. As Kamath and Viswanadham [1986] point out, Petri nets have some noticeable advantages over other system modeling approaches. These advantages are: (1) easy visualization of complex systems using a powerful graphical presentation scheme, (2) modeling capability for hierarchical decompositions, (3) relatively well-developed analysis techniques, (4) well-formulated schemes for system design and synthesis, and (5) dual analysis capability for both quantitative (performance evaluation) and qualitative (deadlock detection) characteristics using timed Petri nets.

Formally, a Petri net is a bipartie graph (a graph with two types of nodes) and can be presented by three types of objects, namely places, transitions, and directed arcs connecting places to transitions and transitions to places. Pictorially, places are depicted as circles, transitions are depicted as boxes or bars. A place is an input place if there exists a directed arc connecting the place to a transition. A place is an output place if there exists a directed arc connecting a transition to the place. Typically, places represent preconditions or postconditions and transitions represent events. The presence of a token (a black dot) inside a place often indicates that the condition is satisfied. For example, input places may represent the availability of particular resources, transitions represent their use, output places represent release of the resources.

Over the years Petri nets have been enhanced to improve their somewhat limited initial modeling capability. For example, to overcome shortcoming of being unmanageably large and complex in modeling of a concurrent system using a place-transition net (PTN), colored Petri nets (CPNs) are introduced to maintain a manageable size of the net [Jensen 1981]. Representation of an equivalent model of a traditionally large and complex system using CPN is simpler and more concise in comparison to using a traditional PTN. In addition, CPNs are capable of capturing complex functional dependencies between the color of transition firing and colors of required tokens.

By changing the placement of tokens on possible subsets of places, which may reflect the occurrence of events or execution of operations, one can capture and investigate dynamic behavior of the modeled system. The flow of tokens is governed by both enabling rules and firing rules.

There are several key structural properties that can be exhibited by a certain class of Petri nets. These structural properties for Petri nets are: pure, boundedness, safe, live, dead, deadlock, mutual exclusion, reversibility, home state, concurrency, conflict, asynchronous, nondeterminism, instantaneous, and union of Petri nets. The detailed definitions for such properties can be found in various articles [Peterson 1977; Agerwala 1979; Kamath and Viswanadham 1986; Zurawski and Zhou 1994]. Among these properties, pureness, boundness, and liveness are necessary properties to capture important qualitative characteristic such as presence of deadlock in a Petri net model of any asynchronous concurrent system.

To conduct quantitative performance evaluation for a system during time evolution, the concept of time has been added to the definition of Petri nets. There are two ways to introduce the time elements to a Petri net: the first one is to attach time to transitions [Ramchandani 1973; Ramamoorthy and Ho 1980; Zuberek 1980; Molloy 1982]; second one is to associate time with places [Sifakis 1977; Bruno and Biglia 1985]. The choice of associating time with transitions is more popular in the literature than associating time with places [Viswanadham and Narahari 1992]. Petri nets with time functions are called timed Petri nets. There are two types of timed Petri nets based on the nature of the time function: one is deterministic timed Petri nets; and the other is stochastic timed Petri nets. Early work related to timed Petri nets is mostly confined to deterministic timed Petri nets [Ramchandani 1973; Sifakis 1977]. Later, the concept has been expanded to include random time duration [Natkin 1980; Molloy 1981]. We call Petri nets with random time delay for their transitions Stochastic Petri nets (SPNs).

When random variables representing time delay are of general distribution rather than exponential, the resulting net model can not be solved analytically as we have seen in similar queueing network models with non-exponential service times. Thus, simulation or approximation methods are required to analyze the model. However, when the time delay for each transition is assumed to be stochastic and exponential, the resulting net can be analytically solved. These Petri nets are called exponential timed Petri nets (ETPNs) [Viswanadham and Narahari 1992]. When ETPN models allow for immediate (zero time delay) transitions, we call these SPNs generalized SPNs (GSPNs). Studies individually done by Natkin [1980] and Molloy [1981] have shown that the marking process of an exponential (or geometric) timed Petri net is a continuous time Markov chain (CTMC). Thus, both ETPN and GSPN models, including extensions such as priority transitions, inhibitor arcs, and probabilistic arcs can be directly converted into their equivalent continuous time Markov chain (CTMC) models, and analyzed using a Markovian analysis method.

As we discussed earlier in Section 2.2 Makov Chain Models, the CTMC modeling approach has its own inherent shortcomings as an effective online-based transient performance analysis tool in addition to drawbacks typically associated with Markov chain models. These shortcomings are associated with solving Kolmogorov backward or forward differential equations in the form of first order linear differential equations to find a closed form solution to approximate individual transition probabilities or state probabilities as a function of time.

As Molloy mentions [Molloy 1985], for quantitative analysis of system performance, stochastic Petri nets do not provide more modeling power than Markov chains, but they provide a better human interface. By using a GSPN representation on appropriate discrete event dynamic systems, Markov chains may be generated and solved automatically. The clear advantage of using GSPN over Markov chains lies in enabling the system designer to specify the system operation in a concise form that can be verified during the generation of the reachable tree. In comparison to product form queueing networks, GSPNs are more powerful because they can represent non-product form features [Narahari and Viswanadham 1989].

Despite its continuous expansion and enhancement in modeling capability and flexibility, the abstraction power of ordinary Petri nets is not sufficient to capture many complex industrial systems, such as manufacturing and communication systems which require the flow of different resources or messages within the system.

One way to model such systems is to construct a model in such a way that the flow of each resource or message is confined within a dedicated subnet. In large-scale systems, a number of resources or messages often share the same system that can be modeled as a single subnet. When this subnet is duplicated to model the entire system for different resources and messages, the overall model that may contain multiple replications of the same subnet may result in unmanageable graphical complexity. To resolve this issue, several methods for tokens to have distinct identity are proposed and they are often referred to as high-level Petri nets. In high-level Petri nets, a token can be a compound object carrying data in forms of integers, reals, text strings, records, lists and tuples. High-level Petri nets typically include predicate-transition nets [Genrich and Lautenbach 1991], colored nets [Jensen 1981], object-oriented nets, and nets with individual tokens [Reisig 1983].

Colored Petri nets (CPNs) were introduced to represent a complex system in a compact and manageable manner by maintaining distinct token identity through associating different colors [Jensen 1981]. In CPNs, a set of colors is associated with each place and each transition. The set of colors associated with a place indicates the color of tokens that can be placed at the place. Similarly a transition can fire based on each of its assigned colors. When a transition is fired, corresponding colored tokens are removed and added at its appropriate input and output places respectively according to the functional dependency specified between the color of the transition firing and the colors of the involved tokens.

Petri nets have gained popularity as a versatile modeling and analysis tool for addressing design issues related to FMSs [Silva and Valette 1990; Zhou 1995].

Typically, most ordinary PTN models have been used in the area of control system design, validation, and implementation. However, as Kamath and Viswanadham [1986] point out, the number of related studies in FMS performance modeling using Petri nets has been somewhat limited due to the limited availability of proper performance evaluation techniques for various PTN classes.

A predominant number of FMS performance modeling attempts using Petri nets are based on Stochastic Petri nets with Markov chain analysis. Since k-bounded SPN models with exponentially distributed transition rates are isomorphic to Markov process models with a state space consisting of possible markings, a direct conversion to an equivalent Markov model can be easily achieved if the model is not too complex. Moreover, analytically evaluating equivalent Markov chain models is not a computationally difficult task as long as the level of complexity is kept minimal. As previously discussed, studying transient behavior of the given Markov chain requires finding equilibrium distributions in terms of time t. To find these distributions, solving Chapman-Kolmogorov equations in the form of first order differential equations either in a backward or forward form is necessary. The complexity of solving these equations can vary based on the different types of mathematical techniques that are applied.

A simple SPN can also be easily converted to a simulation model as a non-analytical form of performance evaluation. A transition state analysis by simulation is a more feasible approach to understand quantitative behaviors of the net than Markov chain analysis especially when the complexity of the given net is no longer considered moderate. For FMS performance modeling using PTNs, converting PTNs to valid simulation models is a better approach for on-line production control. However, technical difficulties in conducting a reliable and fast online simulation study can still be problematic as discussed in the previous section.

The majority of PTN modeling in FMS performance evaluation is based on the steady-state behavior of the given FMS. An initial investigation of applications of timed PTNs in FMS real-time control and performance evaluation can be found in the work by Dubois and Stecke [1983]. The study has concluded that timed PTN is a useful means to assess the steady-state performance as well as to detect any sequence of events which can result in deadlock in FMS real-time control.

However, in reality ordinary SPN models for FMSs can become highly complex due to the fact that most control logic or operational sequences in many FMSs consists of resources that have a high degree of interaction. This type of systems is viewed as a system composed of many replications of a few basic common components. In most cases, these common components behave in a similar manner.

Different arrangements of these basic components can represent various system conditions (status) and subsequent events for the given FMS. Utilizing Colored Petri nets in conjunction with SPNs is proposed as a powerful tool to verify the control logic through investigating the presence of deadlock in an FMS [Kamath and Viswanadham 1986]. Kamath and Viswanadham [1986] have shown the feasibility of direct transformation of CPNs to effective simulation models. Aside from the traditional linear algebraic methods, the fast and efficient way to compute invariants of a PTN model for an FMS is found by taking the union of invariants of smaller and simpler underlying PTNs [Narahari and Viswanadham 1984].

Another study [Micovsky et al. 1990] has demonstrated that a CPN approach to validate a deadlock free design for an FMS control system utilizing a dedicated object-oriented programming tool with an incorporated simulation method is a highly effective way to prototype a new control system. A similar study [Venkatesh and Ilyas 1995] is done for modeling, controlling, and evaluating local area networks in FMSs using real-time timed PNs (RTPNs). In an RTPN, the standard TPN is augmented with two extra tuples, namely input signal vector and output signal vector, to read inputs from the system and send outputs to the system in real time. Venkatesh, Zhou, and Kaighobadi et al. [1996] find that TPNs are effective tools to study optimal operational parameters for a flexible factory automated system (FFAS) under both 'push' and 'pull' paradigms. FFASs typically comprise a strategic arrangement of flexible manufacturing systems (FMSs) and flexible assembly systems (FASs) to meet dynamically changing orders. The study shows that the configuration can result in the minimum buffer sizes and maximum system utilization when output rate is considered as the optimal solution under each paradigm. The study also concludes that the "push" paradigm performs better than the "pull" one for the steady-state performance of the given FFAS.

Despite a powerful formalism of CPNs, converting a complex large-scale stochastic Petri net not only to a valid but also to a computationally efficient simulation model is a challenging task. Gaeta [1996] proposes three approaches to improve simulation efficiency: first, use of an efficient algorithm for the computation of the occurrence of a transition in a given marking; second, reduction of the amount of work needed to schedule or preempt the occurrence of a transition as a consequence of a marking change; third, reduction of the average length of the event list in the case of symmetric models where the symbolic simulation techniques applies. The symbolic simulation technique is to collapse all the equivalent events of the set FIRING (a set of firable color instances) into a single symbolic event.

Yim and Barta [1994] propose a system architecture for a Petri net based on-line simulator that can be utilized in both design and operating phases for FMSs. This architecture separates a simulation model into hardware and control systems to achieve a more realistic and easier modeling process. The hardware components, including low-level control functions, are modeled by Petri nets objects such as places and tokens. Cell control functions such as part dispatching, routing, real-time scheduling, and part monitoring are modeled separately as subnets and integrated into a Petri net model. For operating an FMS using this architecture, the current state of a system should be mapped to the Petri net model by assigning initial tokens accordingly and an integrated decision maker issues a proper operational decision based on the automatically collected Petri net simulation results. Since a simulation study is used as a means to quantitatively analyze the performance of the given net, the Petri net model utilizing simulation can provide a framework for a realistic transient performance analysis for the given FMS.

Hastono et al. [1991] propose an online-based performance modeling method using SPNs to schedule FMSs. This method uses both continuous time and discrete time stochastic Petri nets with hierarchical structure to model an FMS under uncertainty, such as machine tool failures and variations of processing time. Simulations on SPNs are conducted to evaluate the performance of the given rule base. The whole model is partitioned into two parts: the transporting level model represented by discrete-time SPNs and the processing level model represented by continuous-time SPNs. The biggest advantage of this approach is that the final simulation model generated from the given SPN can be simple since the overall model is built considering the processing level models as the submodels of the transporting level models.

2.4.2 Conclusion

Traditionally, Pertri nets have been effective graphical modeling tools in studying qualitative aspects of system behaviors such as presence or absence of deadlocks. However, after the emergence of new classes, such as stochastic and colored Petri nets, and new performance evaluation techniques in Petri nets, Petri nets are now considered powerful system performance evaluation tools to investigate quantitative aspects of many concurrent systems. Since FMSs are tightly coupled concurrent asynchronous systems that typically have complex interactions among their sub-components, Petri net modeling is an ideal way to conduct control system design, validation, and implementation in FMSs.

There are typically two ways to conduct performance evaluation on a given Petri net: the first one is converting a given net to an equivalent Markov chain model by making a set of all possible markings as a state space of the Markov chain and conducting a conventional algebraic Markov chain analysis for the steady-state performance of the given net; the second one is to build a simulation model directly out of a given Petri net model if the net maintains its moderate complexity. Despite a powerful formalism of CPN, a direct conversion of a complex stochastic net to a computationally efficient simulation model is a challenging task. Use of efficient algorithms for the computation of the occurrence of a transition in a given marking, model simplification, and utilizing symbolic simulation techniques are proposed to improve simulation efficiency.

For the Markov chain model directly converted from a given Petri net model, conducting a transient performance analysis on the net requires solving Chapman-Kolmogorov equations, first order differential equations, to find equilibrium distributions in terms of time t. This can become problematic based on the degree of complexity of the equation and types of mathematical techniques to be applied. On the other hand, running a simulation model that is directly derived from the given SPN is relatively easier and realistic enough to be used as a framework to evaluate the transient performance of the given net. However, building an efficient simulation model when the net becomes highly complex is still a difficult task. Furthermore, for modeling a system that changes its configuration during its lifecycle, an automatic adjustment or modification of the given SPN model based on the new system configuration requirements is still a challenging task. Yet there are continuous efforts and interests in the research community to incorporate SPNs as the backbone performance evaluation tool to handle both steady and transient performance, a part of online decision-making mechanism in FMS controls. This is mainly due to the unique capability of Petri net modeling, such as simultaneous quantitative and qualitative assessment capability.

2.5 Summary

Four major evaluative modeling approaches are commonly used to study FMS behavior. These approaches are: queueing networks, Markov chains, simulation, and Petri nets. The majority of studies done in FMS performance modeling used Queueing Networks analysis. However, they tend to focus on the steady-state system performance under a specific operational strategy rather than transient behaviors followed by a disruption. The QN approach is generally not an effective way to study detailed behavior of the system within a short-term time interval.

Markov chain models are based on either Markov or semi-Markov processes that are the two most important subclasses of stochastic processes. Markov processes provide the underlying theoretical foundations for many queueing theory-based analytical modeling approaches. Markov chain modeling approach is more suitable for off-line decision making process. Reconfiguration of the model on the fly can be problematic if the system configuration changes during the course of operation.

The most promising analytical model based transient performance analysis method is performability modeling using either continuous or discrete time Markov reward processes. Performability analysis combines both performance and reliability aspects of a system. Furthermore, this provides a critical insight into higher moments of the performability distribution. Useful expected values such as the expected instantaneous reward (selected performance measures) vector at time t as well as cumulative reward over $[0, t]$ for a given part type can be found through this approach. Despite its promising effectiveness as a transient performance analysis tool, the technique still heavily relies on the assumption of exponential processing times. This can be a problem for many asynchronous systems like FMSs with non-exponential service time distributions. Aside from this biggest drawback, the method also relies on human analytical skills and modeling expertise, which can become a hindrance to be a fully automated modeling scheme with no or less human interventions during the model's life cycle.

Many studies show that simulation is the most widely used as an off-line based evaluative modeling tool to study the impact of a new control policy or scheduling algorithm/heuristic. However, its limitations as an evaluative modeling tool, such as lengthy model development time, detailed input data requirement, lengthy simulation execution time, and necessary but cumbersome statistical output analysis procedures have kept discrete event simulation from becoming a practical analysis tool for on-line decision making. However, there have been considerable on-going research efforts in recent years to make a simulation run faster and shorter using techniques such as distributed simulation, concurrent simulation, model simplification, and reverse simulation. The majority of simulation modeling approaches proposed for online decision making relies on steady-state performance analysis.

Using terminating simulation in a traditional way can be costly and impractical especially for real time disruption detection and diagnosis under on-line production control. Applying a hybrid method such as the meta-modeling, which combines terminating simulation and mathematical modeling, is one way to effectively apply terminating simulation in an on-line decision making support system.

After the emergence of new Petri net classes, such as stochastic and colored Petri nets, as well as new performance evaluation techniques using Petri nets, Petri nets are now considered a powerful system performance evaluation tool to investigate quantitative aspects of many concurrent systems. There are many efforts in the research community to incorporate Stochastic Petri-nets as the backbone performance evaluation tool to handle both steady and transient performance. This is mainly due to several unique capabilities of Petri net modeling, such as simultaneous quantitative and qualitative assessment capability.

3. Problem Settings and Systems Description

In this chapter the FMS chosen for this study is presented. Since using a time series model can easily render predictions on quantified system performance of an FMS, a basic review of conventional approaches, regression based time series modeling, is provided. As a means to capture various system behavior patterns under the new transient performance-modeling framework proposed in this study, ANN based time series modeling is closely investigated as an alternative to its regression based counterpart.

3.1 FMS

3.1.1 System Description

The flexible manufacturing system (FMS) used in this study is an ideal system that is realistic enough to represent many currently deployed real-world systems but also can be analyzed within a reasonable amount of time and effort. The focus of the experiments to be conducted is to explore the possibility of artificial neural networks as an effective baseline technique to capture realistic transient behaviors of an FMS. The neural network based transient performance model should provide better knowledge for both an operator and automated disruption handler to selectively react to controllable performance deteriorations. Typically, transient behaviors in the form of overreaction can bring a negative impact on the overall system performance. Over-reactive transient behaviors often result in system nervousness.

System nervousness can be defined as a system phenomenon that can be characterized by hypersensitiveness to changes caused by unexpected event(s). System nervousness can be worsened by overbearing corrective or preventive measures. This phenomenon is commonly found in tightly coupled automated manufacturing systems with self-guided system performance monitoring and control system such as FMSs [Kim and Kim 1994]. Thus, the system studied in this research should exhibit similar behaviors during its transient states following unexpected disruptions of its steady-state.

The proposed FMS model is based on a real world FMS, the Caterpillar system, which can be found in a simulation study by Stecke and Solberg [1981]. Some system configuration and operational rules used with the original model are modified here to create the desired system conditions and level of complexity needed for this research.

The FMS consists of eight machining stations with an automatic tool changer, one loading station, one unloading station, and three automated guided cart systems as shown in Figure 2. Each machining station has a limited capacity tool magazine that holds machining tools required by various operations assigned to the machine. Thus, each machine stations can perform more than one type of similar machining operation. The eight machining stations can be grouped into four machine groups based on the similarity in their primary machining operations. Machine grouping is for functional redundancy and even machine loading. There are three automated guided carts that run on a straight track connecting all machining stations in tandem, carrying a loaded part fixture among machining stations and loading/unloading stations. There are ten universal part fixtures. Each part fixture is designed to hold a mixture of different part types that share similar machining requirements.

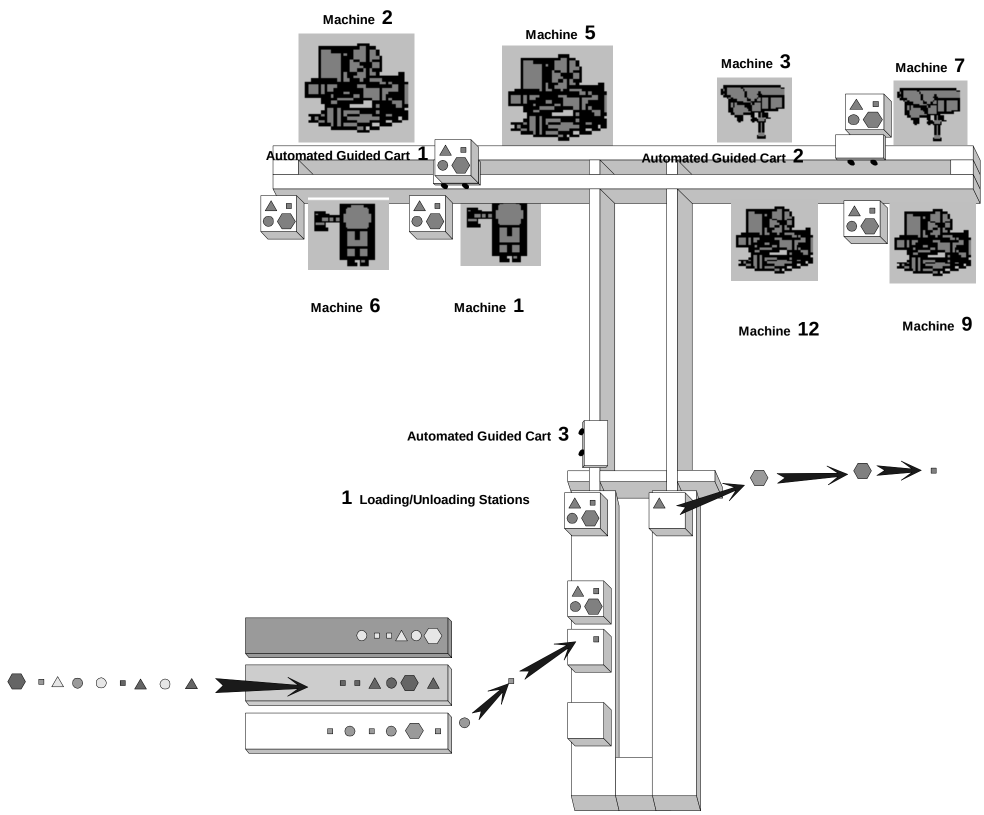


Figure 2. Physical layout of the FMS under study

3.1.2 Parts

The FMS under study is a subsystem of a make-to-order part production system. There are maximum of 12 different part types that can be handled by the FMS. In a normal operation mode, continuous inflow of similar part orders from the main production plan is assumed. Each production plan requires multiple orders of four to five unique part types. Table 2 illustrates how individual orders may look like under a single production plan. For this study, five is the maximum number of different part types to be allowed in a single order. Equal proportion of selected part types will be fed into the system during the course of a given production plan. An unplanned shift from four part types to five part type or vice versa can be considered as a form of disruption scenarios to be studied in this experiment.

Table 2. Sample orders with four part types under a production plan

Order No.	No. of Parts per each order	Part Type (% of the given order)											
		1	2	3	4	5	6	7	8	9	10	11	12
1	1324	25				25		25				25	
2	1056	25				25		25				25	
3	999	25				25		25				25	
4	1320	25				25		25				25	
5	1406	25				25		25				25	
6	1320	25				25		25				25	

The chance to detect upcoming changes in demand for a particular product type that requires a particular combination of various part types is presumed to be small due to its volatile nature. Each part type has the same inter-arrival time that is sampled from an exponential distribution with either mean of 2.3 or 2.4 minutes.

Steps to pick these two numbers are explained in Chapter 6. A group of similar part types require a set of similar machine operations that can be provided by one or more machining groups. The following table provides exemplary part types with corresponding arrival times and required machining sequences.

Table 3. Inter-arrival Time and Machining Process Requirements for Different Part Types

Part Type	Machining Process Requirement in the sequence of 1st ->2nd->3rd		
	1st	2nd	3rd
Part Type 1	*P1*	*P4*	*P9*
Part Type 2	*P2*	*P3*	*P9*
Part Type 3	*P1*	*P5*	*P10*
Part Type 4	*P1*	*p3*	*P9*
Part Type 5	*P2*	*P7*	*P9*
Part Type 6	*P1*	*P6*	*P10*
Part Type 7	*P1*	*P8*	*P9*
Part Type 8	*P2*	*P7*	*P9*
Part Type 9	*P3*	*P7*	*P9*
Part Type 10	*P4*	*P6*	*P10*
Part Type 11	*P5*	*P7*	*P9*
Part Type 12	*P3*	*P8*	*P9*

Incoming parts are fed into one of three conveyor belt systems based on similar machining process requirements before they actually enter the system. These conveyor belts provide a presorting capability as well as three separate waiting areas. Consequently, certain part types share the same conveyor belt due to similar machining requirements (refer to Table 4).

Table 4. Pre-sort Conveyor Belts and Possible Part Types

Pre-sort Conveyor Belt (prior to fixture loading)	Admissible Part Types			
	1st	2nd	3rd	4th
Belt 1	*Part Type 1*	*Part Type 2*	*Part Type 3*	*Part Type 4*
Belt 2	*Part Type 5*	*Part Type 6*	*Part Type 7*	*Part Type 8*
Belt 3	*Part Type 9*	*Part Type 10*	*Part Type 11*	*Part Type 12*

The loading station continuously monitors individual queue length of the three conveyor belts and services the conveyor belt with the longest queue buildup. Then parts from the selected conveyor belt are loaded into the first available universal part fixture one by one in the order of their arrivals until the fixture becomes full. Then the current loading stops until a next fixture becomes available in the loading/unloading area.

Each part type comes in different sizes and shapes and they are to be equally well distributed in the incoming part flow. Consequently, the total number of incoming parts to be loaded onto a particular fixture cannot be known until the fixture is actually loaded. The number of parts to be loaded into a next available fixture can be determined by the sum of individual part sizes taken from parts waiting on the selected conveyor belt.

The loaded fixture is delivered to a machine center by an automated guided vehicle if a machine center from the desired machine group is available. Each machine group provides a unique set of machining operations. Otherwise the loaded fixture waits in the loading/unloading area until a machine station from the desired machine group becomes available. If there are multiple fixtures from the same part group competing for one available machine group, the fixture with the shortest processing time will take the first available machine from the group by the rule of STP (Shortest Processing Time First).

Table 5. Relative Part Size for Different Part Types

Part Type	Relative Part Size when the fixture size = 15
Part Type 1	*3*
Part Type 2	*5*
Part Type 3	*2*
Part Type 4	*4*
Part Type 5	*3*
Part Type 6	*5*
Part Type 7	*2*
Part Type 8	*4*
Part Type 9	*3*
Part Type 10	*5*
Part Type 11	*2*
Part Type 12	*4*

ex) a possible fixture load, 3 x part type 1 and 3 x part type 3
= 3*3 +3*2= 9 + 6 = 15 <= 15 (maximum fixture capacity)

However, when there are two or more fixtures from different part groups competing for the same machine group, the fixture with the shorted processing time divided by the total estimated processing time of the particular part groups waiting in the loading/unloading area will take the first available machine. The rule of STP/TOT, the shortest processing time for the operation divided by the total processing time for the job, will guarantee the best production rate under most circumstances according to the study done by Stecke and Solberg [1981].

When two or more machines from the same machine group become available, the machine with the longer idle time will process the next available fixture. A machine group can provide more than one unique machining operation. Some of machine centers within a group can actually perform identical machining operations even though their average processing time against the same part type may not be the same.

An operational sequence to process each part type is predefined but the actual machine assignment is not made until the fixture containing the particular part types is ready to be dispatched. The number of different operations that can be performed by a particular machining center from a given machine group is often restricted by the tools currently available to the machining center. Table 6 summarizes four machine groups and their capable machining operations.

The system is designed with some degree of functional redundancy within each machine group to allow alternative routings in case of any machine failures. Many argue that FMSs deployed today behave more in a deterministic manner due to their rigid computer control. But there is still a room for stochastic behaviors that could result from interactions with their neighboring production systems that exhibit stochastic natures. Moreover, one of intentions for this study is to extend the applicability of ANN based transient performance modeling methodology to other asynchronous concurrent systems. Therefore, the suggested FMS should represent broader system characteristics of many asynchronous concurrent systems. In order to achieve this objective, stochastic elements are introduced in the proposed system, which may distance itself from the realistic modeling perspective of most real-world FMSs.

Table 6. Part Groups and Machine Process Capability

Machine Group	Individual Machines in a Group	
	1st	2nd
Group 1	*M1*	*M6*
Group 2	*M2*	*M5*
Group 3	*M3*	*M7*
Group 4	*M9*	*M12*

Machine Process	Capable Machine Group
P1	*Group1*
P2	*Group1*
P3	*Group2*
P4	*Group2*
P5	*Group2*
P6	*Group3*
P7	*Group3*
P8	*Group3*
P9	*Group4*
P10	*Group4*

Setup times between different part types for machining stations are considered significant and are counted toward to the average processing time for each part type. The order for processing individual parts within a given fixture is to start from the part type with the shorted processing time (SPT) and then move onto parts with the next shortest processing time. Naturally, if different part types loaded into a given fixture came from only one or two type, the average processing time to process the entire fixture will have small variances. On the contrary, if the number of different part types from incoming fixtures is high, the average processing time to process individual fixtures will have a relatively larger variance. Estimated processing time distributions by each machining stations for various part types are summarized in Table 7.

Actual machine assignments are not made until the parts actually enter the system. The controller determines proper machine loading assignments based on the current workload of individual machine centers within a group. This loading policy is based on the pooling strategy in which machines from the same machine group can perform similar machining processes even though there is a slight difference in terms of speed. This would also guarantee the best performance in terms of balanced loadings among machines according to the Stecke and Solberg's [1981] study.

Table 7. Service Time Distributions for Individual Part Types

Part Type	Machining Time Distribution							
	M1	*M6*	*M2*	*M5*	*M3*	*M7*	*M9*	*M12*
Part Type 1	*triang (1.7, 3.6, 2.5)*	*triang (2.3, 5.5, 3.2)*	*triang (2.2, 4.4, 3)*	*triang (2, 5.5, 3.5)*	*N/A*	*N/A*	*triang (2.2, 5, 3.4)*	*triang (1.7, 3.2, 2.5)*
Part Type 2	*triang (1.3, 3.7, 2.3)*	*triang (2, 5, 3.5)*	*triang (2, 4, 3.2)*	*triang (2.5, 5.5, 3.9)*	*N/A*	*N/A*	*triang (2.2, 4.5, 3)*	*triang (1.5, 3.5, 2)*
Part Type 3	*triang (1.5, 3, 2.2)*	*triang (2.3, 5, 3.3)*	*triang (2, 5, 3.7)*	*triang (1.7, 3.5, 2.3)*	*N/A*	*N/A*	*triang (1.2, 3.5, 2.3)*	*triang (3, 5, 3.6)*
Part Type 4	*triang (2, 5, 3.2)*	*triang (3, 5, 4.2)*	*triang (2.7, 4.3, 3.5)*	*triang (2.5, 4.5, 3)*	*N/A*	*N/A*	*triang (2, 4.5, 3.1)*	*triang (3, 5, 3.6)*
Part Type 5	*triang (2, 5, 3.2)*	*triang (2, 5.5, 3.3)*	*N/A*	*N/A*	*triang (1.8, 3.8, 2.4)*	*triang (2.5, 5.5, 3)*	*triang (1, 3, 2)*	*triang (2, 5, 3)*
Part Type 6	*triang (2.5, 4, 3)*	*triang (2, 4.3, 3.5)*	*N/A*	*N/A*	*triang (1.9, 3.4, 2)*	*triang (4, 6, 5)*	*triang (1, 3, 2)*	*triang (2, 3.5, 2.5)*
Part Type 7	*triang (1.7, 2.6, 2.1)*	*triang (1.7, 4.3, 3.5)*	*N/A*	*N/A*	*triang (2, 5, 3.5)*	*triang (3, 6, 4)*	*triang (1, 3, 2)*	*triang (1, 3, 2)*
Part Type 8	*triang (2.2, 4.8, 3)*	*triang (3, 5, 4.5)*	*N/A*	*N/A*	*triang (4, 7, 5.5)*	*triang (5, 8, 6)*	*triang (1, 3, 2)*	*triang (3, 5, 4)*
Part Type 9	*N/A*	*N/A*	*triang (1.5, 4.5, 3)*	*triang (2, 5, 4)*	*triang (2, 5, 3.5)*	*triang (3, 6, 4)*	*triang (2.5, 5.5, 3.5)*	*triang (1, 3, 2)*
Part Type 10	*N/A*	*N/A*	*triang (0.5, 4.5, 3)*	*triang (2.3, 5.3, 4.3)*	*triang (1.5, 5.5, 3)*	*triang (2.5, 5.5, 3.8)*	*triang (2.5, 5.5, 3.5)*	*triang (3, 5, 4)*
Part Type 11	*N/A*	*N/A*	*triang (2, 5, 3.5)*	*triang (2.5, 5.5, 4.5)*	*triang (2.5, 5.5, 4)*	*triang (3.5, 6.5, 4.5)*	*triang (3, 6, 4)*	*triang (1.5, 3.5, 2.5))*
Part Type 12	*N/A*	*N/A*	*triang (2.5, 5.5, 4)*	*triang (3, 6, 5)*	*triang (3, 6, 4.5)*	*triang (4, 7, 5)*	*triang (3.5, 6.5, 4.5)*	*triang (2, 4, 3)*

A rough order of magnitude estimate of an overall efficiency of the proposed FMS system in a steady-state condition is necessary to verify the simulation model later. In this case, a simple queueing approximation can be used to estimate the average utilization. The whole system needs to be simplified and some fundamental operational rules have to be modified to use the queueing approximation. One such example is machine processing time distribution. They need to be presumed as exponential rather than the original triangular distributions. A second assumption is no competition among loaded fixtures over AGVs and machining stations due to the fact that only two fixtures are allowed to circulate in the system to undergo various machining operations at any given time.

Individual parts have to be loaded onto a single fixture in order to undergo designated machining operations based on common machining requirements. Thus, mean arrival time of individual parts to the system can be actually viewed as mean time between fixture loading completions. On average about six parts are loaded into a single fixture, which can be approximated by six times the mean arrival times of 2.3 or 2.4 minutes. Then, the whole system can be viewed as a single M/M/2 system where a service consists of three distinctive operations provided by four machine groups and each machine group consists of two machines that can perform identical operations. Two AGVs can be also viewed as an additional operation. This over-simplistic picture makes the queueing approximation possible for the model. Otherwise the modeling using traditional queueing approximation can be highly challenging. The approximation result can be later used as a verification measure for the simulation model.

Since the average utilization of M/M/c can be found using a relationship of $\rho = \frac{\lambda}{c\mu}$ where c = number of servers that can provide the identical service, λ = mean arrival time, and μ =mean service time. The relationship of ρ becomes $\rho =$

$$\frac{\text{mean arrival time of fixture to the first machine}}{2 \times \text{total mean service time of three wighted machine operations plus average transportation}}$$

Finally, approximated $\rho \cong \frac{2.3*6}{2*11.424} = 0.603939$ where 6 is the estimated average number of incoming parts that can fit into a single fixture and 11.424 is the weighted average of total machine processing (three operations) and transportation time based on different part mix.

3.2 Time Series Analysis

Forecasting through a regression based time series modeling is closely examined in this chapter to devise it as a benchmark for the new transient modeling approach . The term, forecasting, is extensively used in many scientific disciplines, referring to a systematic approach to predict the future outcome of either a known or unknown process through analyzing its past behaviors or attributes. Forecasting in time series analysis typically means an accurate prediction of the short-term evolution of a given time series process [Weigend and Gershenfeld 1992].

Even though there is no universally applicable forecasting procedure, many types of forecasting procedures can be classified into three broad categories: 1) forecasting procedures are considered subjective if predictions are made on a subjective basis using judgment, intuition, commercial knowledge and any other relevant information; 2) forecasting procedures are considered univariate if predictions are made based entirely on past observations in a given time series, by fitting a model to the data and extrapolating; 3) forecasting procedures are called multivariate if predictions are made by taking observations on other variables into account as well as utilizing their past observations. A common form of univariate models is a regression model. These are frequently used as econometric models.

For long-term forecasting, a univariate forecasting procedure such as extrapolation of trend curves is useful to fit a curve to historic yearly totals and extrapolate. Harrison and Pearce [1972] indicate that the forecasting lead time should not exceed half the number of past years. The method is simple, fairly crude, but robust and economical for long-term forecasting where complicated models can seldom be fitted to past data. One drawback is that there is no logical basis for choosing among different curves except by goodness of fit.

In 1958, C. C. Holt suggested exponential smoothing, another univariate forecasting procedure using weighted sum of past observations. Exponential smoothing can be applied to any stationary series that does not contain a trend or seasonal pattern. The procedure that generalized exponential smoothing to deal with time series containing trend and seasonal variation is called Holt-Winters procedure [Winters 1960]. Holt-Winters procedure introduces trend and seasonal terms that can be updated by the exponential smoothing.

Box and Jenkins [1968] create the most popular univariate forecasting procedure, the Box and Jenkins procedure. This procedure is based on fitting an autoregressive integrated moving average (ARIMA) model to a given set of data and taking conditional expectations. The procedure starts with model identification, examining the data to see which member of the ARIMA process classes is the most appropriate model. Then the procedure requires estimation of parameters of the chosen model by minimizing the sum of least squares. As a next step the procedure examines the residuals from the fitted model. As a last step in the procedure, continuous considerations of alternative models are necessary until the chosen model appears to be adequate.

One of major drawbacks of Box and Jenkins procedure is the difficulty to fully automate the entire procedure. Granger and Newbold [1977] propose a procedure called step-wise autoregression that can be considered a subset of the Box-Jenkins procedure. Since autoregressive (AR) models are much easier to fit than moving average (MA) or mixed autoregressive-moving average (ARMA) models, the step-wise autoregression has the advantage of being fully automatic in contrast with the Box-Jenkins procedure. However, the step-wise autoregression requires additional parameters to closely fit given data.

The majority of quantitative techniques used to build a mathematical model for a series of values collected at different points in time utilize statistical means. This section reviews some of fundamentals of the set of techniques classified as time series analysis. A time series is a collection of quantitative observations made sequentially in time [Chatfield 1984]. If a time series can be predicted exactly, it is said to be deterministic. However, most time series are stochastic. This means the future can be only partially determined by past values. For stochastic series, exact predictions are difficult to make and must be estimated based on the fact that future values have a probability distribution.

Mathematically, a stochastic process may be defined as a collection of random variables $\{X(t), t \in T\}$, where T denotes the set of time-points at which the process is defined. One common way to describe a stochastic process is to find the statistical moments of the underlying probability distributions for the process, particularly the first and second moments (which are called the mean and variance) and autocovariance functions. Mathematical notation for the first and second moments for a stochastic process with discrete time observations follows.

The first moment, the mean function, of the underlying probability distribution at time t, $\mu(t)$, is defined by

$$\mu(t) = E(X_t) .$$

The second moment, the variance function at time t, $\sigma^2(t)$, is defined by

$$\sigma^2(t) = Var(X_t) = E[X_t - \mu(t)].$$

The autocovariance function between time t and $t+k$ of the underlying probability distributions is defined by

$$\gamma(k) = COV(X_t, X_{t+k}) = E\{[X_t - \mu(t)][X_t - \mu(t+k)]\}$$

where $k = 0 \pm 1, \pm 2, \ldots$.

In most statistical problems, estimating the properties of a population from a sample is of primary interest. In time series analysis, however, it is often impossible to make more than one observation at a given time. Thus, only one observation on the random variable can be obtained at a time. Nevertheless we may regard the observed time series as just one sample of the infinite set of time series that we might have observed. This infinite set of time series is called the ensemble. Every member of the ensemble is a possible realization of the stochastic process. The observed time series can be regarded as one particular realization, and will be denoted by $x(t)$ for $(0 \le t \le T)$ if observations are continuous and by x_t for $t = 1, \ldots, N$, if observations are discrete.

One unique feature of stochastic time series, which distinguishes time series from common statistical data, is the correlation among the observed values of the series at different time instants. If we let X_t be a random variable from either a multivariate or a univariate stochastic process at different discrete times $t = 0, 1, 2, 3, \ldots n,$ then the random variable X_t will be correlated with the random variables $X_{t-1}, X_{t-2}, X_{t-3}, \ldots,$ and

$X_{t-1}, X_{t-2}, X_{t-3}, \ldots$. The covariance between successive observations is called autocovariance. The autocorrelation coefficient between observations a distance k apart, is given by

$$r_k = \frac{\sum_{t=1}^{N-k}(x_t - \bar{x})(x_{t+k} - \bar{x})}{\sum_{t=1}^{N}(x_t - \bar{x})^2}$$

where $\bar{x}$ is the sample mean for x_t.

Typically autocorrelation coefficients are calculated by computing the series of autocovariance coefficients, $\{c_k \mid c_k = \frac{1}{N}\sum_{t=1}^{N-k}(x_t - \bar{x})(x_{t+k} - \bar{x})\}$, which can be obtained from the usual covariance formula [Chatfield 1984]. Then the autocorrelation coefficient at lag k can be calculated by finding $r_k = \frac{c_k}{c_0}$, which is the ratio between autocovariance coefficient at lag k and at lag 0.

A time series is said to be strictly stationary (also called first-order stationary) if the joint distribution of $X(t_1), \ldots, X(t_n)$ is the same as the joint distribution of $X(t_1 + k), \ldots, X(t_n + k)$ for all $t_1, t_2, \ldots, t_n, k$. This implies that shifting the time origin by an amount k has no effect on the joint distribution at different times but rather the joint distribution depends only on the intervals between $t_1, t_2, \ldots, t_n$. Furthermore, when $n = 1$, the above definition implies that the distribution of $X(t)$ must be the same for all t so that $\mu_{X(t)}$ and $\sigma^2_{X(t)}$ are both constants which do not depend on the value of t.

When $n = 2$ or higher, the joint distribution of two random variables at different time instances depends only on the difference between two time instances and the difference is called the lag.

A time series is said to be weakly stationary (also called second-order stationary) if its mean is constant and its autocovariance function depends only on the lag, so that

$$E[X(t)] = \mu$$

and

$$COV[X(t), X(t+\tau)] = \gamma(\tau).$$

This weaker definition of stationarity is more commonly used than the first-order definition since many of the properties of stationary processes depend only on the structure of the process as specified by its first and second moments [Bartlett 1966]. There are four main types of univariate probability models for a time series, namely AR, MA, ARMA, and ARIMA.

Suppose that $\{Z_t\}$ is a discrete random process. A discrete random process $\{Z_t\}$ is called a purely random process if the random variables $\{Z_t\}$ are a sequence of mutually independent, identically distributed variables. This implies that the process has constant mean and variance such that

$$\gamma(k) = COV(Z_t, Z_{t+k}) = 0 \text{ for } k = \pm 1, \pm 2, \ldots \, .$$

Since the mean and autocovariance function do not depend on time, the process is first-order stationary as well as second-order stationary. The autocorrelation function is given by

$$\rho(k) = \begin{cases} 1 & k = 0 \\ 0 & k = \pm 1, \pm 2, \ldots \end{cases}$$

Suppose that $\{Z_t\}$ is a purely random process with mean zero and variance σ_z^2. Then a process $\{Z_t\}$ is called a moving average process of order q and also abbreviated to MA(q) if

$$X_t = \beta_0 Z_t + \beta_1 Z + \ldots + \beta_q Z_{t-q} \tag{3.2.1}$$

where $\{\beta_i\}$ are constants. For a given MA, we can verify that $E(X_t) = 0$ and

$Var(X_t) = \sigma_z^2 \sum_{i=0}^{q} \beta_i^2$.

The autocorrelation function of the MA(q) is given by

$$\rho(k) = \begin{cases} 1 & k = 0 \\ \sum_{i=0}^{q-k} \beta_i \beta_{i+k} / \sum_{i=0}^{q} \beta_i^2 & k = 1, \ldots, q \\ 0 & k > q \\ \rho(-k) & k < 0 \end{cases}$$

Although no restrictions on the $\{\beta_i\}$ are required for a MA process to be stationary, Box and Jenkins [1970] propose restrictions on the $\{\beta_i\}$ to ensure 'invertability'. This property ensures that there is a unique MA process for a given autocorrelation function. The invertability condition for the general order MA process can be expressed by using the backward shift operator, denoted by B, which is defined by

$$B^j X_t = X_{t-j} \qquad \text{for all } j.$$

Then equation (3.2.1) can be written as

$$X_t = (\beta_0 + \beta_1 B + \ldots + \beta_q B^q) Z_t = \theta(B) Z_t$$

where $\theta(B)$ is a polynomial of order q in B. An MA process of order q is invertible if the roots of the polynomial

$$\theta(B) = \beta_0 + \beta_1 B + \ldots + \beta_q B^q = 0$$

all lie outside the unit circle [Box 1970].

Suppose that $\{Z_t\}$ is a purely random process with mean zero and variance σ_Z^2. Then a process $\{X_t\}$ is said to be an autoregressive process of order p if

$$X_t = \alpha_1 X_{t-1} + \ldots + \alpha_p X_{t-p} + Z_t . \qquad (3.2.2)$$

This is similar to a multiple regression model, but X_t is regressed not on independent variables but on past X_t's. The autoregressive model in (3.2.2) is called an autoregressive process of order p and also denoted by AR(p). For example, when $p = 1$, it is called a first order AR process such that

$$X_t = \alpha X_{t-1} + Z_t . \qquad (3.2.3)$$

By successive substitution of X_{t-1} in (3.2.3)

$$X_t = \alpha(\alpha X_{t-2} + Z_{t-1}) + Z_t$$

$$= \alpha(\alpha(X_{t-3} + Z_{t-2}) + Z_{t-1}) + Z_t$$

and eventually X_t can be expressed as an infinite-order MA process in the form

$$X_t = Z_t + \alpha Z_{t-1} + \alpha^2 Z_{t-2} + \ldots \text{ where } -1 < \alpha < +1.$$

This property is called duality between AR and MA processes. If we use the backward shift operator B rather than successive substitution of X_{t-1}, then equation (3.2.3) can be written

$$(1-\alpha B)X_t = Z_t$$

so that

$$X_t = Z_t/(1-\alpha B)$$

$$= (1+\alpha B+\alpha^2 B^2+\ldots)Z_t$$

$$= Z_t + \alpha Z_{t-1} + \alpha^2 Z_{t-2} + \ldots .$$

The mean and variance for process $\{X_t\}$ are

$$E(X_t) = 0$$

and

$$Var(X_t) = \sigma_Z^2(1+\alpha^2+\alpha^4+\ldots) \ .$$

When $|\alpha|<1$, $(1+\alpha^2+\alpha^4+\ldots)$ converges and can be replaced with $1/(1-\alpha^2)$ so that

$$Var(X_t) = \sigma_X^2 = \sigma_Z^2/(1-\alpha^2)\,.$$

The autocovariance function is given by

$$\gamma(k) = E[X_t X_{t+k}]$$

$$= E\{[\sum \alpha^i Z_{t-1}][\sum \alpha^j Z_{t+k-j}]\}$$

$$= \sigma_Z^2 \sum_{i=0}^{\infty} \alpha^i \alpha^{k+i} \qquad \text{(for } k \geq 0\text{)}$$

which converges for $|\alpha|<1$ to

$$\gamma(k) = \alpha^k \sigma_Z^2/(1-\alpha^2)$$

$$= \alpha^k \sigma_X^2$$

The autocorrelation function is given by

$$\rho(k) = \frac{\gamma(k)}{\gamma(0)} = \frac{\alpha^k \sigma_X^2}{\alpha^0 \sigma_X^2} = \alpha^k \quad (k = 0,\ 1,\ 2,\ \ldots)$$

which can be rewritten for all integer lag k

$$\rho(k) = \alpha^{|k|} \qquad\qquad (k = 0,\ \pm 1,\ \pm 2,\ \ldots)$$

For the general order case where $q > 1$, by using the backward shift operator, equation (3.2.2) can be written as

$$(1 - \alpha_1 B - \ldots - \alpha_p B^p) X_t = Z_t$$

which can also be written as

$$X_t = Z_t / (1 - \alpha_1 B - \ldots - \alpha_p B^p)^{-1}$$

$$= f(B) Z_t$$

where $f(B) = (1 - \alpha_1 B - \ldots - \alpha_p B^p)^{-1}$

$$= (1 + \beta_1 B + \beta_2 B^2 + \ldots)$$

The autocovariance function is given by

$$\gamma(k) = \sigma_Z^2 \sum_{i=0}^{\infty} \beta_i \beta_{i+k} \qquad \text{(where } \beta_0 = 1\text{)}$$

A sufficient condition for this to converge is that $\sum |\beta_i|$ converges, so it satisfies stationarity for the process. However, finding the $\{\beta_i\}$ is algebraically hard. The alternative way to determine if the process is stationary is to multiply (3.2.2) by X_{t-k}, take expectations, and divide by σ_X^2 assuming that the variance of X_t is finite. Then we can find

$$\rho(k) = \alpha_1 \rho(k-1) + \ldots + \alpha_p \rho(k-p) \text{ for all } k > 0.$$

In order for AR(p) to meet the stationary condition the roots of the equation

$$\phi(B) = 1 - \alpha_1 B - \ldots - \alpha_p B^p = 0$$

must lie outside the unit circle.

For those processes with non-zero mean, equation (3.2.2) can be rewritten in the form

$$X_t - \mu = \alpha_1 (X_{t-1} - \mu) + \ldots + \alpha_p (X_{t-p} - \mu) + Z_t.$$

Combining MA and AR processes can form a useful class of time series models. This class is called a mixed autoregressive-moving average process containing p AR terms and q MA terms, abbreviated to an ARMA (p, q), which can be expressed as

$$X_t = \alpha_1 X_{t-1} + \ldots + \alpha_p X_{t-p} + Z_t + \beta_1 Z_{t-1} + \ldots + \beta_q Z_{t-q} \qquad (3.2.4)$$

Using the backward shift operator B, equation (3.2.4) can be written in the form

$$\phi(B) X_t = \theta(B) Z_t$$

where $\phi(B)$, $\theta(B)$ are polynomials of order p and q respectively, such that

$$\phi(B) = 1 - \alpha_1 B - \ldots - \alpha_p B^p$$

and

$$\theta(B) = 1 + \beta_1 B + \ldots + \beta_q B^q.$$

Any stationary ARMA process must have values of $\{\alpha_i\}$ which are the roots of $\phi(B) = 0$ and lie outside the unit circle. When values of $\{\beta_i\}$ are the roots of $\theta(B) = 0$ which lie outside of the unit circle, the process is invertible. The importance of

ARMA processes is that describing a stationary time series by an ARMA model requires fewer parameters than one described by an MA or AR process [Chatfield 1984]. Even though finding an autocorrelation function of an ARMA process is fairly straightforward, it is algebraically tedious.

In practice most time series are non-stationary. In order to fit a stationary model, such as AR, MA, or ARMA, it is necessary to remove sources of variation. If the observed time series is non-stationary in the mean then we can still model the process using a stationary model by differencing the series. Differencing is a special type of filtering technique. It is particularly useful for removing a trend. It is based on applying a differencing operator repeatedly until the time series becomes stationary. For example, second order differencing of X_{t+2} can be expressed by

$$\nabla^2 X_{t+2} = \nabla X_{t+2} - \nabla X_{t+1} = X_{t+2} - 2X_{t+1} + X_t$$

where

$$\nabla X_t = X_t - X_{t-1}$$

By replacing X_t with $\nabla^d X_t$ (dth order differencing of X_t) in equation (3.2.4) we have a model capable of describing certain types of non-stationary series. Such a model is called an autoregressive integrated moving average process (also abbreviated ARIMA) and can be written

$$W_t = \alpha_1 W_{t-1} + \ldots + \alpha_p W_{t-p} + Z_t + \ldots + \beta_q Z_{t-q} \qquad (3.2.5)$$

where

$$W_t = \nabla^d X_t \text{ (}d\text{th difference of } X_t\text{)}.$$

To this point, mathematical models that are available to describe various time series have been discussed. These models are classified as a general class of linear models. Linear time series models have two distinct advantages over their non-linear counterparts: they can be understood in great detail and they are easy to implement [Weigend and Gershenfeld 1992]. Linear time series also have one major drawback. They are inappropriate to represent even moderately complicated systems. Identifying an appropriate model for a given time series is challenging because it requires more subjective judgment and practical experience than a clear-cut heuristic method.

Typically plotting an accurate correlogram, a graph in which r_k is plotted against the lag k, based on the time series is the right start for time series analysis. Figures 9 and 10 illustrate how correlograms may be different under stationary and non-stationary time series. The correlogram of the stationary process from Figure 3 clearly shows how quickly the autocorrelation function decays compared to that of the non-stationary process shown in Figure 4 despite its seasonal short-term fluctuations. On the other hand the correlogram in Figure 4 indicates that the values of r_k will not come down to zero except for large values of the lag. In fact various trend removal techniques, such as curve fitting, filtering, or differencing, are necessary to remove the underlying trend before calculating $\{r_k\}$. One popular filtering technique is the moving average method that is discussed in detail in [Kendall 1976] and [Law and Kelton 1991].

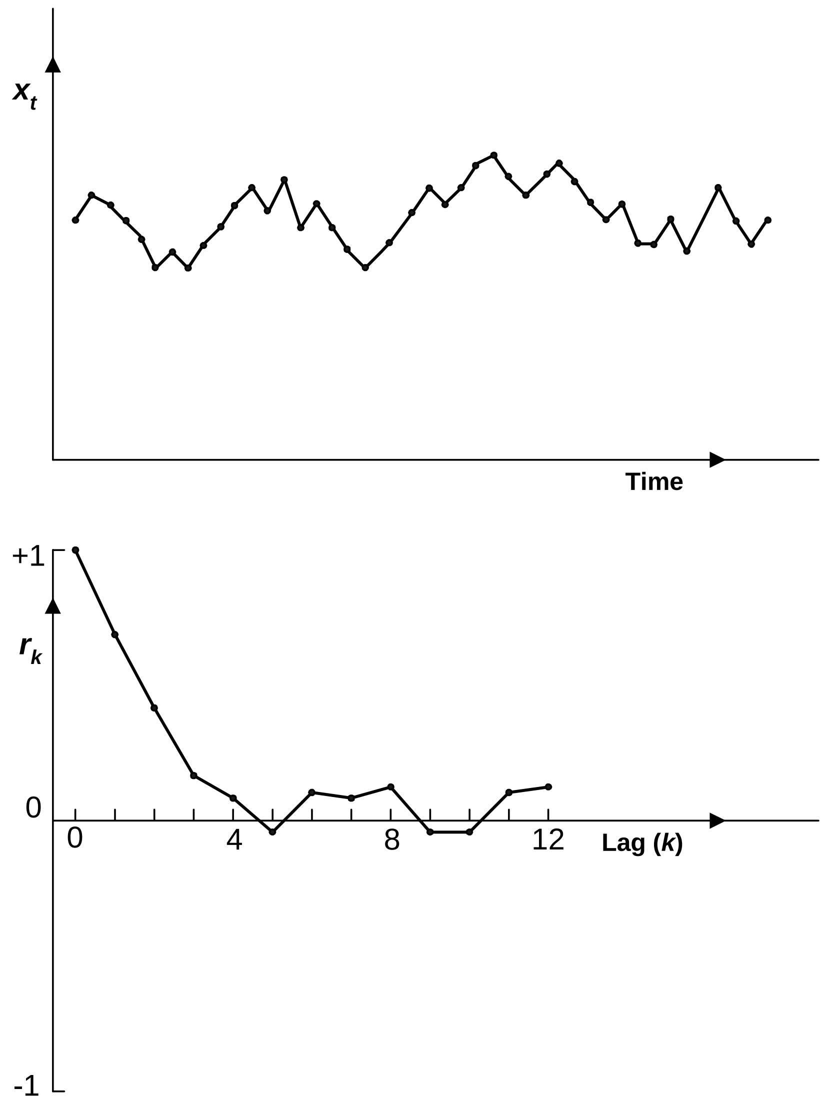


Figure 3. A stationary time series showing short-term correlation with its correlogram

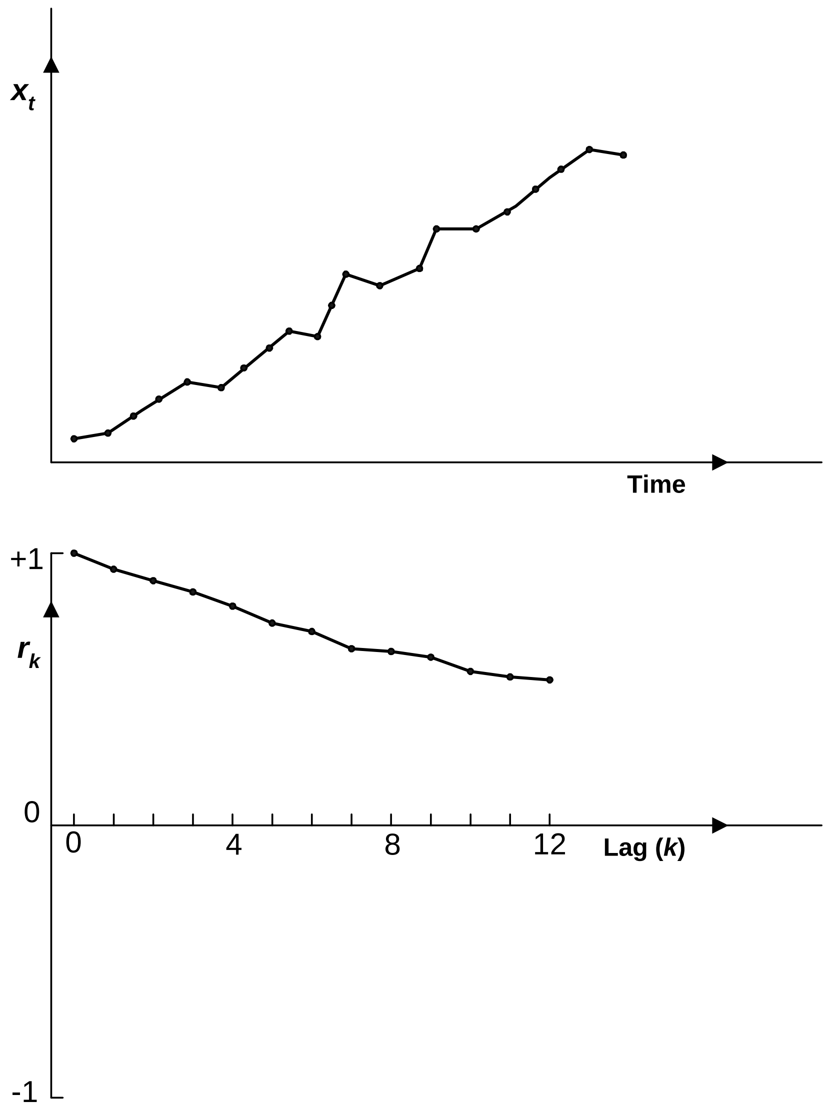


Figure 4. A non-stationary time series together with its correlograms

The correlogram is helpful in identifying which type of ARIMA model gives the best representation of an observed time series. A correlogram like that in Figure 4, where the values of r_k do not come down to zero quickly, indicates that the series is non-stationary and needs to be differenced so that an ARIMA model can be constructed. For stationary series, the correlogram of the observed series is compared to the theoretical $\{r_k\}$ of different ARMA processes in order to choose the most appropriate model.

The autocorrelation function, r_k, of a MA(q) process is relatively easier to recognize since it drops to zero and flattens out at lag q whereas the autocorrelation function of an AR(p) approaches zero more slowly. This is due to the fact that it is a mixture of dampened exponentials and sinusoids. The autocorrelation function of mixed ARMA model also dies out gradually rather than having a sudden drop.

If r_1 of an observed time series is significantly different from zero but the subsequent values of r_k are all close to zero then an moving average model of order 1, MA(1), is indicated. Alternatively, if r_1, r_2, r_3, … appear to be decreasing exponentially then an AR(1) model may be appropriate.

The interpretation of correlograms is one of the hardest aspects of time-series analysis and this is where practical experience must come to play [Chatfield 1984].

After identifying the type of ARIMA model that gives the best presentation of the observed time series, the detail of the selected model such as the order and parameters of the process must be found. For an AR process of order p with mean μ, the series can be expressed by

$$X_t - \mu = \alpha_1 (X_{t-1} - \mu) + \ldots + \alpha_p (X_{t-p} - \mu) + Z_t$$

If we let $1 \le p < N$, for given N observations, $x_1, \ldots, x_N$, then the parameters μ, $\alpha_1, \ldots, \alpha_p$, can be estimated by minimizing the least square equation

$$S = \sum_{t=p+1}^{N} [x_t - \mu - \alpha_1 (x_{t-1} - \mu) - \ldots - \alpha_p (x_{t-p} - \mu)]^2 \qquad (3.2.6)$$

with respect to μ, $\alpha_1, \ldots, \alpha_p$. If the Z_t process is normal, then the least squares are in fact maximum likelihood estimates [Jenkins and Watts 1968].

In the first order case, with $p = 1$, minimizing (3.2.6) results in

$$\hat{\mu} = \frac{\bar{x}_{(2)} - \hat{\alpha}_1 \bar{x}_{(1)}}{1 - \hat{\alpha}_1} \qquad (3.2.7)$$

and

$$\hat{\alpha}_1 = \frac{\sum_{t=1}^{N-1} (x_t - \hat{\mu})(x_{t+1} - \hat{\mu})}{\sum_{t=1}^{N-1} (x_t - \hat{\mu})^2} \qquad (3.2.8)$$

where $\bar{x}_{(1)}, \bar{x}_{(2)}$ are the means of the first and last ($N-1$) observations. Since $\bar{x}$ is the unbiased estimator for $\hat{\mu}$ and

$$\bar{x}_{(1)} \cong \bar{x}_{(2)} \cong \bar{x},$$

$\hat{\mu}$ can be replaced by $\bar{x}$.

Now equation (3.2.8) becomes

$$\hat{\alpha}_1 = \frac{\sum_{t=1}^{N-1}(x_t - \bar{x})(x_{t+1} - \bar{x})}{\sum_{t=1}^{N-1}(x_t - \bar{x})^2}, \tag{3.2.9}$$

which is approximately equivalent to an autocorrelation function at lag 1. Thus, equation (3.2.9) becomes

$$\hat{\alpha}_1 \cong \frac{c_1}{c_0} = r_1.$$

Similarly, for a second-order AR process ($p = 2$) minimizing (3.2.6) gives

$$\hat{\mu} \cong \bar{x}$$

$$\hat{\alpha}_1 \cong \frac{r_1(1 - r_2)}{(1 - r_1^2)}$$

$$\hat{\alpha}_2 \cong \frac{(r_2 - r_1^2)}{(1 - r_1^2)}.$$

For higher order AR processes two alternative approximate methods are commonly used. The first method fits data to equation (3.2.6), treating it as if it is an ordinary regression model. The second method is to substitute ρ 's with the sample autocorrelation coefficients in the first p Yule and Walker equations, which are denoted by

$$\rho(k) = \alpha_1\rho(k-1) + \ldots + \alpha_p\rho(k-p) \qquad \text{for all } k > 0,$$

and solve for $(\hat{\alpha}_1, \ldots, \hat{\alpha}_p)$. In order to solve for $(\hat{\alpha}_1, \ldots, \hat{\alpha}_p)$, Yule and Walker equations can be expressed in matrix form

$$\mathbf{R}\hat{\boldsymbol{\alpha}} = \mathbf{r}$$

where

$$\mathbf{R} = \begin{pmatrix} 1 & r_1 & r_2 & \cdots & r_{p-1} \\ r_1 & 1 & r_1 & \cdots & r_{p-2} \\ r_2 & r_1 & 1 & \cdots & r_{p-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ r_{p-1} & r_{p-2} & r_{p-3} & \cdots & 1 \end{pmatrix}$$

$$\hat{\boldsymbol{\alpha}}^T = (\hat{\alpha}_1, \ldots, \hat{\alpha}_p)$$

and

$$\mathbf{r}^T = (r_1, \ldots, r_p).$$

For reasonably large N , both methods will give close approximated values to the least squares estimates for which $\hat{\mu}$ is close to but not necessarily equal to $\bar{x}$ [Chatfield 1984].

It is difficult to determine the order of an AR process from the sample autocorrelation function alone. For example, the theoretical autocorrelation function for a first-order process decreases exponentially and the sample function should exhibit a similar pattern. On the other hand, most theoretical autocorrelation functions for higher order processes have a mixture pattern of damped exponential or sinusoidal functions and they are difficult to identify. One approach is to fit AR processes of progressively higher order, calculating the residual sum of squares for each value of p and plotting this against p [Chatfield 1984]. Then it is possible to find the proper value of p where the curve of the residual sum of squares against each value of p levels off. Typically, the addition of extra parameters gives little improvement in fit. There are several other approaches, such as one approach by Box and Jenkins [1970] using the partial autocorrelation function, and two alternative methods each based on the inverse autocorrelation function [Chatfield 1979] and Akaike's information criterion [Akaike 1978]. One drawback of these heuristics is that they rely heavily on the linearity of the model and on assumptions about the distribution from which the errors drawn [Weigend and Gershenfeld 1992].

Estimating the parameters of an MA process is more difficult than an AR process because efficient explicit estimators cannot be found. Suppose we have an AR process of order of 1, with mean μ, given by

$$X_t = \mu + Z_t + \beta_1 Z_{t-1} \qquad (3.2.10)$$

where μ, β_1 are constants and Z_t denotes a purely random process. If we write the residual sum of squares, $\sum Z_t^2$, solely in terms of x's and the parameters μ, and β_1, and differentiate with respect to μ and β_1, as we did for the AR process in order to find the least-squares estimates, the residual sum of squares is not a quadratic function of the parameters. Thus, explicit least-squares estimates cannot be found.

Box and Jenkins [1970] propose one way to calculate the corresponding residual sum of squares using a recursive form of (3.2.10)

$$Z_t = X_t - \mu - \beta_1 Z_{t-1} \qquad (3.2.11)$$

First, select suitable starting values for μ and β_1 such as $\mu = \bar{x}$ and β_1, which would satisfy the theoretical first-order autocorrelation coefficients

$r_1 = \dfrac{\hat{\beta}_1}{(1+\hat{\beta}_1^2)}$ where $\left|\hat{\beta}_1\right| < 1$.

Then, Z_t's for $t = 1,\ 2,\ \ldots,\ N$ where $z_0 = 0$

become

$z_1 = x_1 - \mu,\ \ z_2 = x_2 - \mu - \beta_1 z_1,\ \ldots,\ z_N = x_N - \mu - \beta_1 z_{N-1}$.

Finally, the residual sum of squares, $\sum_{t=1}^{N} Z_t^2$, can be calculated. These steps can be repeated for other values of μ and β_1 to find corresponding sum of squares. Then the computed $\sum_{t=1}^{N} Z_t^2$ can be plotted against the (μ, β_1) plane. Finally, find the least square estimates in terms of μ and β_1, which minimize $\sum_{t=1}^{N} Z_t^2$. These are maximum likelihood estimates. For higher order processes a similar type of iterative procedure can be applied. Estimating the appropriate order of the process can be done through looking for a 'cut off' point, lag q, beyond which the values of the sample autocorrelation function remain close to zero.

So far we have focused on the sample autocorrelation function as the primary diagnostic tool to gain insight into the probability model of an unknown time series process. Inference based on this function is often called an analysis in the time domain. There is another useful tool, called the spectral density function, to investigate the frequency properties of a time series. Inference regarding this function is called an analysis in the frequency domain. The frequency domain is the counter part of the time domain. Thus, from a practical stand point, the spectral density function is considered complementary to the sample autocorrelation function. However, both functions contain the same information regarding a stationary stochastic process but express it in different ways. In order to understand the spectral density function, we must first look into a function called the spectral distribution function.

The formal representation of the spectral distribution function can be given

$$X_t = R\cos(\omega t + \theta) + Z_t \tag{3.2.12}$$

where ω is called frequency of the periodic variation (also called the angular frequency), R is called the amplitude of the variation, θ is called the phase, and Z_t denotes a stationary random series. A graphical example of (3.2.12) is shown in Figure 5.

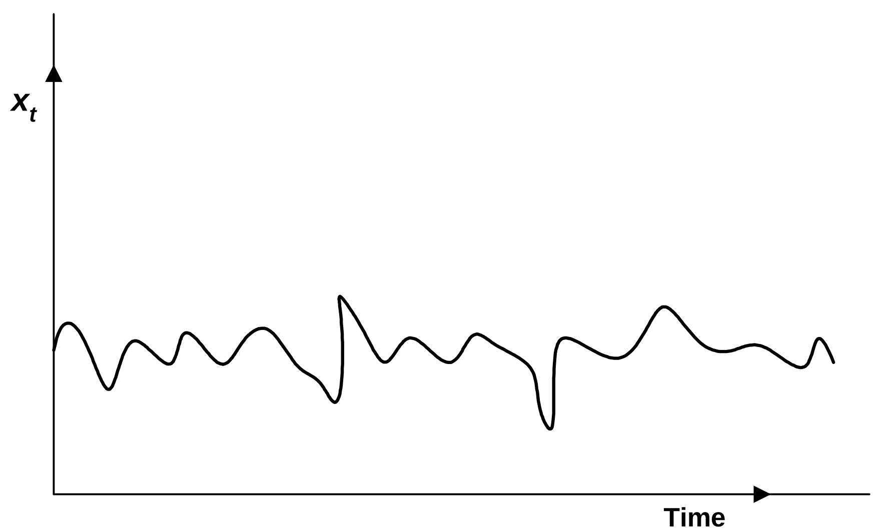


Figure 5. A time series contains a periodic component

. The frequency of the periodic variation, ω, is the number of radians per unit time. However, by some authors [Jenkins and Watts 1968], the frequency is often referred as the number of cycles per unit time and expressed by

$$f = \frac{\omega}{2\pi}$$

Then the period of a sinusoidal cycle, called λ the wavelength, can be denoted by

$$\lambda = \frac{1}{f} = \frac{2\pi}{\omega}.$$

A time series model expressed in (3.2.12) is simple but not realistic in practice. Since it is highly likely for a given time series to have variation at several different frequencies, a generalized form of the model can be found

$$X_t = \sum_{j=1}^{k} R_j \cos(\omega_j t + \theta_j) + Z_t \qquad (3.2.13)$$

Since $\cos(\omega t + \theta) = \cos\omega t \cos\theta - \sin\omega t \sin\theta$, model (3.2.13) can be rewritten as a sum of sine and cosine terms in the form

$$X_t = \sum_{j=1}^{k} (a_j \cos\omega_j t + b_j \sin\omega_j t) + Z_t \qquad (3.2.14)$$

where $a_j = R_j \cos\theta_j$

and $b_j = -R_j \sin\theta_j$.

If we let $k \to \infty$, the work of Wiener and others has shown that any discrete stationary process measured at unit intervals can be represented in the form

$$X_t = \int_0^{\pi} \cos\omega t \, du(\omega) + \int_0^{\pi} \sin\omega t \, dv(\omega) \qquad (3.2.15)$$

where $u(\omega)$ and $v(\omega)$ are uncorrelated continuous processes with orthogonal increments for all w in the range $(0, \pi)$. For a continuous process, the upper limits would be ∞, but for a discrete process measured at unit intervals of time there is no loss of generality in restricting frequency ω to the range $(0,\ \pi)$ since

$$\cos(\omega t + k\pi t) = \begin{cases} \cos\omega & k,\ t \text{ integers with } k \text{ even} \\ \cos(\pi - \omega)t & k,\ t \text{ integers with } k \text{ odd} \end{cases}$$

The sinusoidal model (3.2.15) is called the spectral representation of the process. In practice, processes $u(\omega)$ and $v(\omega)$ hold no direct significance in terms of characterization of a given time series. Instead, a function, $F(\omega)$ which is called the power spectral distribution function, can be used. The spectral distribution function arises from the Wiener-Khintchine theorem (see Section 6.1 of [Bartlett 1966]) and is related to $u(\omega)$ and $v(\omega)$. The theorem says that for any stationary stochastic process with autocovariance function $\gamma(k)$, there exists a monotonically increasing function, $F(\omega)$, such that

$$\gamma(k) = \int_0^\pi \cos\omega k \, dF(\omega) \qquad (3.2.16)$$

Equation (3.2.16) is called the spectral representation of the autocovariance function. A normalized form of the spectral distribution function, symbolically $F^*(\omega)$, can be found by

$$F^*(\omega) = \frac{F(\omega)}{\sigma_X^2} \qquad (3.2.17)$$

which is the proportion of variance accounted for by frequencies in the range $(0, \pi)$. Since $F^*(\pi) = 1$ and $F^*(\omega)$ is monotonically increasing in the range $(0, \pi)$, $F^*(\omega)$ behaves almost as a cumulative distribution function.

For a purely stochastic discrete stationary process, the spectral distribution function $F(\omega)$ is continuous in $(0,\pi)$ and therefore, it can be differentiated with respect to ω in $(0,\omega)$. Thus, the derivative of the spectral distribution function, $f(\omega)$, can be denoted by

$$f(\omega) = \frac{\mathrm{d}F(\omega)}{\mathrm{d}\omega}$$

and called the power spectral density function or simply the spectrum.

When $f(\omega)$ exists for a stationary stochastic process, autocovariance equation (3.2.16) for the process can be expressed in the form

$$\gamma(k) = \int_0^\pi \cos\omega k \; f(\omega)\mathrm{d}\omega \qquad (3.2.18)$$

When $k = 0$, then equation (3.2.18) becomes

$$\gamma(0) = \sigma_X^2 = \int_0^\pi f(\omega)\mathrm{d}\omega = F(\pi) \qquad (3.2.19)$$

The relationship between the spectral distribution function and the spectral density function is somewhat similar to that of between the probability density function and the corresponding continuous probability function [Chatfield 1984]. An example of a spectrum with the corresponding normalized spectral distribution function is shown in Figure 6. A peak in the spectrum indicates an important contribution to variance at given frequencies. The spectrum that is concentrated at low frequency and reaches 0 relatively faster is often the result of a smooth stationary time series.

In some situations a time-domain approach based on the autocovariance function is more useful while in other situations a frequency-domain approach is preferable. For example, spectral analysis, which is the general term given to methods estimating the spectral density function or spectrum, is at its most useful to access often hidden frequency components from stationary non-deterministic time series with no obvious trend or seasonal variation. On the other hand, the autocovariance function can be applied to either stationary or non-stationary processes. Equation (3.2.18) is expressed in an inverse form in terms of $\gamma(k)$:

$$f(\omega) = \frac{1}{\pi}\sum_{k=-\infty}^{\infty}\gamma(k)e^{-i\omega k} \qquad (3.2.20)$$

Since $\gamma(k)$ is a symmetric function, equation (3.2.20) is often written in the equivalent form

$$f(\omega) = \frac{1}{\pi}\left[\gamma(0) + 2\sum_{k=1}^{\infty}\gamma(k)\cos\omega k\right] \qquad (3.2.21)$$

Using (3.2.21), we can verify that the spectrum is the Fourier transformation of the autocovariance function.

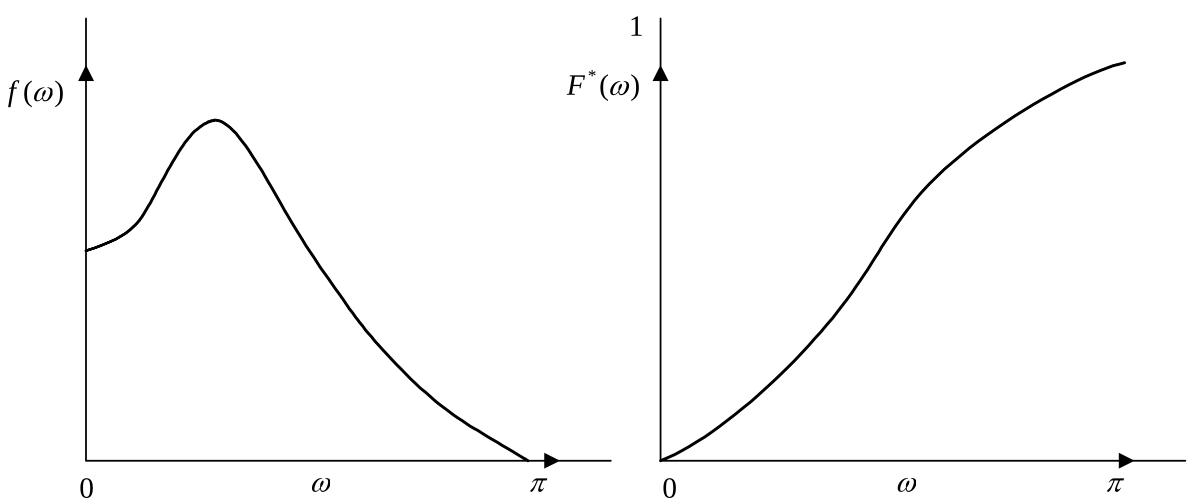


Figure 6. A spectrum with the corresponding normalized spectral distribution function

Thus far, we have only focused on analyzing a single time series. In some cases observations must be made on two or more time series to find the relationship among them. We call these multivariate processes. When observations are made on two time series, we call it a bivariate process. Jenkins and Watts [1968] distinguish two types of bivariate situation. The first one is designed for a time series on equal time intervals and the correlation between them is the primary concern. The second one is to deal with a set of time series in which the series are casually related. For the second type one series is regarded as the input to a linear system, while other is considered the output to the other. For a bivariate process, a new function, called the cross-covariance function, is introduced in addition to the statistical moments up to second order, namely the mean and autocovariance functions of each of the two series. The cross-covariance function can be denoted by

$$\gamma_{xy}(t,\tau) = \mathrm{Cov}(X_t, Y_{t+\tau}).$$

The cross-covariance function differs from the autocovariance function in a way that it is not an even function unlike autocovariance, since

$$\gamma_{xy}(\tau) = \gamma_{yx}(-\tau).$$

The cross-correlation function, $\rho_{xy}(\tau)$, can also be defined by

$$\rho_{xy}(\tau) = \gamma_{xy}(\tau) / \sqrt{[\gamma_{xx}(0)\gamma_{yy}(0)]}.$$

The cross-spectrum of a discrete bivariate process measured over the range $(0,\pi)$ can be expressed in the form

$$f_{xy}(\omega) = \frac{1}{\pi}\left[\sum_{k=-\infty}^{\infty}\gamma_{xy}(k)e^{-i\omega k}\right] \qquad (3.2.22)$$

Again, cross-spectrum (3.2.22) can be written in the form

$$f_{xy}(\omega) = \frac{1}{2\pi}\left[\sum_{k=-\infty}^{\infty} \gamma_{xy}(k) e^{-i\omega k}\right] \tag{3.2.23}$$

over the range $(-\pi, \pi)$, which is preferred by most authors. Equation (3.2.23) has a simple inverse relationship to $\gamma_{xy}(k)$ such that

$$\gamma_{xy}(k) = \int_{-\pi}^{\pi} e^{i\omega k} f_{xy}(\omega) \mathrm{d}\omega .$$

There are several functions that can be derived from various forms denoting the same cross-spectrum function. These functions are used to describe unique relationships between two series in the frequency domain. For example, (3.2.22) can be expressed in the form of a complex function

$$f_{xy}(\omega) = c(\omega) - iq(\omega) \tag{3.2.24}$$

where

$c(\omega)$ is the real part of the f_{xy} such that

$$c(\omega) = \frac{1}{\pi}\left[\sum_{k=-\infty}^{\infty} \gamma_{xy}(k) \cos \omega k\right] \tag{3.2.25}$$

$$= \frac{1}{\pi}\left\{\gamma_{xy}(0) + \sum_{k=1}^{\infty} \left[\gamma_{xy}(k) + \gamma_{yx}(k)\right] \cos \omega k\right\}$$

and $q(\omega)$ is the complex part of the f_{xy} such that

$$q(\omega) = \frac{1}{\pi}\left[\sum_{k=-\infty}^{\infty} \gamma_{xy}(k) \sin \omega k\right] \tag{3.2.26}$$

$$= \frac{1}{\pi}\left\{\sum_{k=1}^{\infty} \left[\gamma_{xy}(k) - \gamma_{yx}(k)\right] \sin \omega k\right\}$$

Equation (3.2.25) is called the co-spectrum and equation (3.2.26) is called the quadrature spectrum. The third way of expressing cross-spectrum function (3.2.22) is to use the form

$$f_{xy}(\omega) = \alpha_{xy}(\omega) e^{i\phi_{xy}(\omega)} \tag{3.2.27}$$

where $\alpha_{xy}(\omega) =$ cross-amplitude spectrum

$$= \sqrt{\left[c^2(\omega) + q^2(\omega)\right]} \tag{3.2.28}$$

and $\phi_{xy} =$ phase spectrum

$$= \tan^{-1}[-q(\omega)/c(\omega)] \tag{3.2.29}$$

Another useful function derived from the cross-spectrum is the squared coherency which is found by

$$C(\omega) = \left[c^2(\omega) + q^2(\omega)\right] / \left[f_x(\omega) f_y(\omega)\right] \tag{3.2.30}$$

$$= \alpha_{xy}^2(\omega) / f_x(\omega) f_y(\omega)$$

where $f_x(\omega)$, $f_y(\omega)$ are the power spectra of the individual stochastic processes, X_t and Y_t. It can be shown that $0 \le C(\omega) \le 1$. The squared coherency measures the linear correlation between the two components of the bivariate process at frequency ω. The closer $C(\omega)$ is to one, more closely the processes are related at frequency ω. Lastly a function called the gain spectrum is given by

$$G_{xy}(\omega) = \sqrt{\left[f_y(\omega) C(\omega) / f_x(\omega)\right]}$$

$$= \alpha_{xy}(\omega) / f_x(\omega) \tag{3.2.31}$$

Equation (3.2.31) is in fact the regression coefficient of the process Y_t on the process X_t at frequency ω. Interpreting a cross-spectrum is a challenging task compared to interpreting an autospectrum [Chatfield 1984]. Usually three functions out of above six functions have to be plotted against frequency to describe the relationship between two series. For example, the coherency, phase, and cross-amplitude are suitable for certain bivaritate processes, while the co-quadrature and coherency spectra are most suitable for different bivariate processes. Granger and Hughes [1964] have carried out a simulation study on some short series with cross-spectral estimators.

Most theories available for time series analysis can be applied only if the process is stable. However, many time series in real life do change with time even though they change slowly. We previously discussed some ways of transforming data to achieve stationarity, such as differencing, so that the theories can be applied and a stationary model can be fit. However, it is often more important to describe the non-stationary features of the series, such as trends and seasonality, rather than the properties of the stationary residuals. One way to capture slowly-changing series is to fit a time-dependent spectrum called an evolutionary spectrum, where the frequency properties are examined for overlapping segments [Priestley 1981].

3.3 Artificial Neural Networks

This section presents artificial neural networks as a general non-parametric transient performance prediction tool. Before introducing the ANN model to be used in this research, fundamentals and a brief history of ANNs are reviewed. A well-known ANN architecture, a multilayer ANN and its training algorithms are also discussed to help readers who are new to ANNs.

3.3.1 Background

Artificial neural networks (ANNs), also known as parallel processing elements or connectionist networks, are computational paradigms that mimic simplified models of their biological counterparts, biological neural networks. Biological neural networks are the local assemblies of neurons and their dendritic connections that form a human brain. As shown in Figure 7 [Hagan et al. 1996], most biological neurons consist of a cell body plus one axon and many dendrites. The axon is a protuberance that delivers the neuron's output to connections with other neurons. Dendrites are protuberances that provide a wide surface area, facilitating connection with the axons of neighboring neurons. A neuron does nothing unless the collective influence of all its inputs reaches a threshold level. Whenever that threshold is reached, a neuron produces a full-strength output in the form of narrow pulse that transmits from the cell body, down the axon, and into the axon's branches. When this happens, the neuron is said to fire. Since a neuron either fires or does nothing, it is said to be an all-or-none device [Winston 1992].

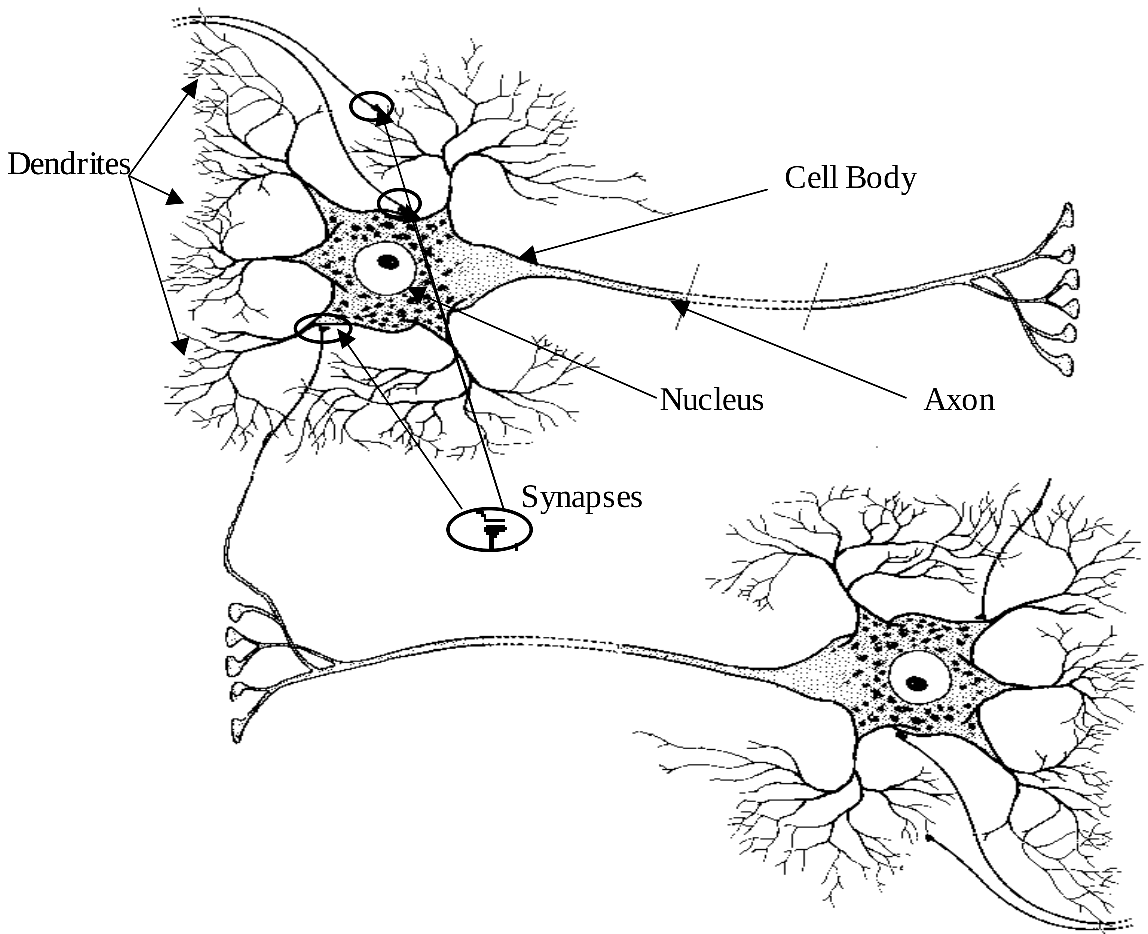
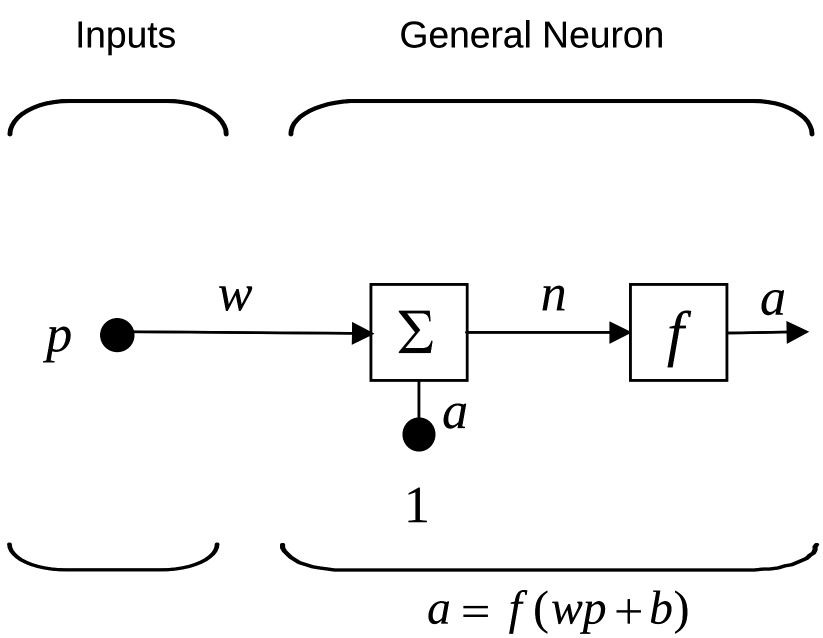


Figure 7. Anatomical illustration of biological neurons [Hagan et al. 1996]

Axons influence dendrites over narrow gaps called synapses. Stimulation at some synapses encourages neurons to fire. At the same time stimulation at others discourages neurons from firing. It is widely believed that learning takes place in the vicinity of synapses and has something to do with the intensity level to which synapses translate the pulse traveling down one neuron's axon into excitation or inhibition of the next neuron.

Artificial neural networks typically consist of simulated neurons like the one shown in Figure 8. The simulated neuron is viewed as a node connected to other nodes via links that correspond to axon-synapse-dendrite connections.



$\sum$ - summation

f - transfer function – a linear or a nonlinear function of n

$a, b, n, p, w,$ - scalars

Figure 8. Single-Input Neuron

A weight is associated with each link. Like a synapse, the weight for a given node determines the strength of the node's influence on another. More specifically, one node's influence on another is the product of the influencing neuron's output value times the connecting link's weight. For example, a large positive weight corresponds to a strong excitation, or a small negative weight corresponds to weak inhibition.

The work of McCulloch and Pitts [1943] introduces the first mathematical model of a neuron, in which a weighted sum of input signals is compared to a threshold value to determine whether or not to fire the neuron. Their work is acknowledged as the origin of the modern view of neural networks and demonstrates that networks of artificial neurons are capable of handling a broad range of arithmetic or logical functions. In 1949, Hebb [1949] proposed one of the first learning rules of biological neurons, which explained a mechanism for learning at the cellular level.

The first practical application of ANNs appeared in the late 1950s and for the first time, neural networks demonstrated their pattern recognition capability. This was enabled by the invention of the perceptron network and associated learning rule by Rosenblatt [1958]. Despite its limited capability, the success of the perceptron created a great deal of enthusiasm among many neural network researchers. In 1960 Widrow and Hoff [1960] introduced a perceptron-like network with an adaptive learning capability. They assumed that the system has inputs and a desired output classification for each input, and that the system can calculate the error between the actual and target output. By using a gradient descent method, the weights are adjusted in order to minimize the mean square error. The learning algorithm is also known as Least Mean Square (LMS) algorithm.

Minsky and Parpert [1969] publicized the first comprehensive analysis of perceptron networks. In this book they point out the inherent limitations of perceptrons. One of the limitations is that a given perception-learning rule is not guaranteed to converge to a solution in a finite number of steps, unless the given input space (or vector) is linearly separable. This rather pessimistic view discouraged many potential new developments in the area and put most of the neural network research community into silence for the following ten years.

Even during this period of silence, some notable works were published. For example, Kohonen [1972] proposed a correlation model for associative memory. The model was trained, using the outer product rule, also known as the Hebb rule [Hebb 1949], to learn an association between input and output vectors. Almost at the same time Anderson [1972] independently proposed a "linear associator" model for associative memory. The model was trained in a similar manner as a generalized approach to the Hebb rule so that it learned an association between input and output vectors.

During the 1980s many of earlier limitations in the field, such as absence of powerful computers and fresh insights into the problems, dissipated. Research in neural networks rapidly expanded during this period. The introduction of desktop personal computers and powerful workstations fueled this phenomenon. Two notable concepts were introduced during this period. The first was the work done by Hopfield [1982] to explain the operation of a certain class of recurrent networks, using statistical mechanics as an associative memory. The second one was the introduction of the back propagation algorithm, which was discovered by several independent researchers including Rumelhart and McClelland [1986] for training multi-layer perceptron networks.

During the 1990's there was a rapid growth of public interest, more widespread industrial applications, and an explosion of research publications in the area of artificial neural networks. As Hagan et al. [1996] point out, these renewed interests in ANNs have much to do with new concepts, such as innovative architectures and training rules. But these phenomena have also resulted from an improvement in the average computer processor speed and a growing public interest in information technology in general. Further breakthroughs in the field are likely as progress is made in our understanding of biological neural networks.

ANNs are typically used in pattern recognition, where a collection of numerically translated features such as an image is presented to the networks, and the task is to let the networks get familiar with the translated features through a course of training so that it can categorize the input feature pattern to one or more distinguishable classes. Another principal use for ANNs is nonlinear regression, where the task is to find a smooth interpolation between points. In both cases, all the relevant information is presented to the network simultaneously. In contrast, time series prediction using neural networks involves processing of patterns that evolves over time to predict future observations, which implies continuous feeding of its predicted observations (outputs) as a part of past observations (inputs).

The simplest way to teach a network about the past is to provide time-delayed samples to its input layer. The network predicts the future not only based on the present but also on the past. Mozer [1992] argues that conventional neural network architectures are not suited for patterns that vary over time. He identifies two necessary architectural elements, short-term memory and a generic predictor, in temporal sequence processing using neural networks. Furthermore, three dimensions along which neural net temporal memory models vary are identified: memory form (delay line, exponential trace, gamma trace), content (input, transformed input, transformed input and state, output, transformed output, and transformed output and state), and adaptability (static, adaptive).

The simplest form of memory is a buffer containing the n most recent inputs. Such a memory is often called a tapped delay-line model because the buffer can be formed by a series of delay lines. It provides the basis for traditional statistical autoregressive (AR) models. Tapped delay models are more common in neural network architectures than other forms of short-term memory such as exponential trace or gamma memory. Unlike the delay-line memory, the exponential trace memory does not sharply drop off at a fixed point in time; rather the strength of an input decays exponentially. This implies that more recent inputs will always have greater strength than distant inputs.

de Vries and Principe [1991] use two dimensions, depth and resolution, to characterize the tapped delay-line and exponential trace memories. In general, the term, "depth" in memory, refers to how far into the past the memory stores information in relation to the memory size. A high-depth memory easily holds information distant in the past, whereas a low-depth memory only holds recent information. The second term, "resolution", refers to the degree to which information concerning the individual elements of the input sequence is preserved. A high-resolution memory can reconstruct the actual elements of the input sequence; low-resolution memory holds distorted information about the sequence. Memory models that generalize across delay lines and exponential traces are gamma memories. Gamma memories allow a continuum of memory forms covering all levels of depth and resolution combinations. Gamma memories use the gamma density function as the corresponding kernel for discrete-time memories.

Elman and Zisper [1988] propose a neural net architecture consisting of input as its memory content and delay line as its memory form, often called I-delay memory. The I-delay memory is the simplest class and corresponds to a feedforward network with a delay space embedded in the input sequence. A similar architecture is also found in other papers [Lapedes and Farber 1987], [Zhang and Hutchinson 1992]. The TI-delay architecture, a combination of transformed input and tapped delay line, has been extensively used in physical science oriented neural net application [Kleinfeld 1986], [Sompolinksy and Kanter 1986]. In this architecture, each hidden unit, which is a nonlinear transformation of the input, maintains a history of its n most recent values, and all these hidden values are available to the next layer.

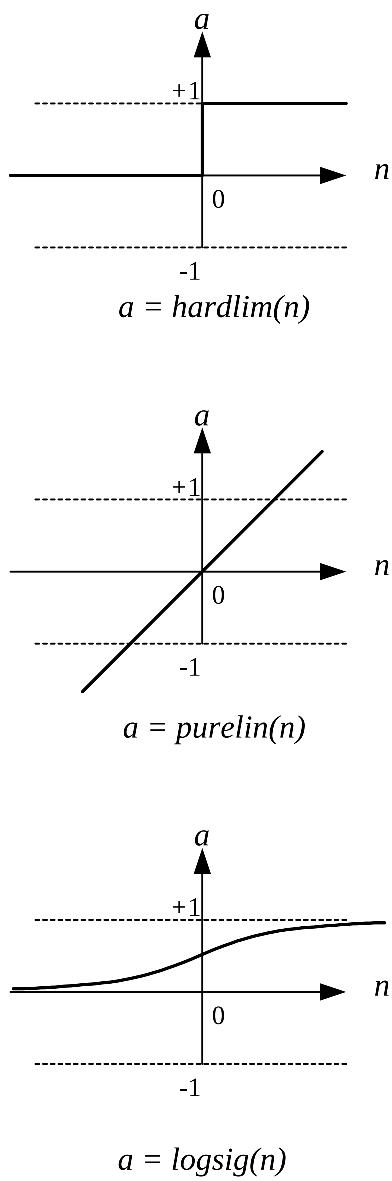
TI-delay memories are the basis of the time-delay neural networks (TDNN) [Waibel et al. 1989] and finite impulse responses (FIR) neural network [Wan 1992]. Herz [1991] proposes a TIS-delay memory, a combination of transformed input and state as its memory content and delay line as its memory form. TIS-delay memories are designed for networks whose dynamics are governed by a Lyapunov function under certain symmetry conditions on the time delayed weights. Connor et al. [1992] studied a nonlinear neural network based ARMA model, whose MA component is constructed from outputs. Their study shows that nonlinear MA(q) models can be constructed using O-delay memories, a combination of output as its memory content and delay line as its memory form.

Among all possible architectures using Mozer's three dimensions, those that utilize non-delay line type memory forms which are widely studied in other literature are: TI-exponential (transformed input as memory content and exponential trace as its memory form) [Elman and Zipser 1988], [Lapedes and Farber 1987], [Zhang and Hutchinson 1992], TIS-exponential memory (transformed input and state as its memory content and exponential trace memory as its memory form) [Mozer 1992], O-exponential (output as its memory content and exponential trace memory as its memory form) [Jordan 1987], and I-gamma memory (input as its memory content and gamma trace memory as its memory form) [de Vries and Principe 1991]. Mozer [1992] uses a TIS-exponential memory to create a multiscale integration model. His work is to design recurrent hidden units that have different time constants of integration. In Mozer's model, the slow integrators form a coarse but global sequence memory and the fast integrators form a fine-gained but local memory. Jordan [1987] uses an O-exponential memory to create a sequence production network.

3.3.2 Multilayer Neural Network Architecture and Training Methods

This section presents a brief review of the most common form of neural networks, multilayer neural networks, and its training algorithms. According to Hagan, Demuth, and Beale [1996], despite ANN's fast growing popularity and applications in many diverse fields, there has been a lack of cohesion in standard mathematical notation and architectural representations of ANNs. To make the matter simpler, through the rest of this section, scalar inputs are represented in small italic letters such as *a*, *b*, and *c*. On the other hand, vector inputs are expressed in small bold nonitalic letters such as **a**, **b**, and **c**. Weights on connections between input(s) and neuron(s) are often expressed in a matrix form and these matrices are expressed in capital bold nonitalic letters such as **A**, **B**, and **C**. The output of a single simulated neuron as shown in Figure 8 (Page 123) is the result of a transfer function of the summation output *n*. A transfer function may be a linear or nonlinear function of *n* (a sum of weighted inputs **Wp** or *wp* where **W** is a weight matrix, **p** is a input vector, and *w* and *p* are scalar parameters).

There are three primary types of transfer functions – hard limit transfer function, linear transfer function, and log-sigmoid transfer function. The hard limit transfer function, shown in the top of Figure 9, sets the output of the neuron to 0 if the function argument is less than 0, or 1 if its argument is greater than or equal to 0.



$$\begin{cases} a = 0 & \text{when } n < 0 \\ a = 1 & \text{when } n \geq 0 \end{cases}$$

$$a = n \quad \text{for all } n$$

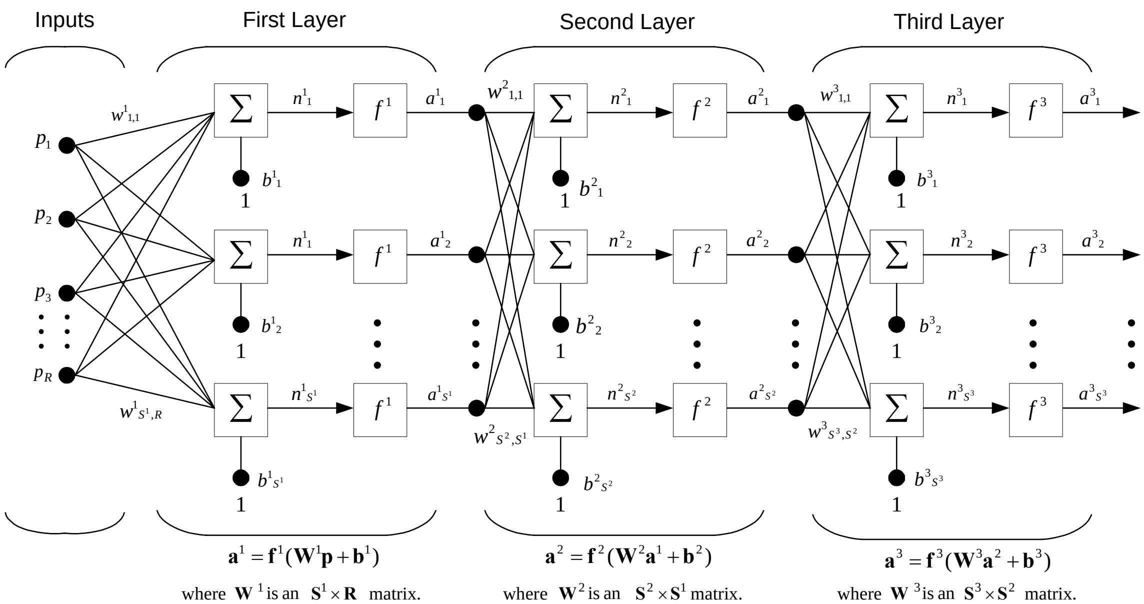
$$a = \frac{1}{1 + e^{-n}} \quad \text{for all } n$$

Figure 9. Typical Transfer functions

This function is commonly used to create neurons that classify inputs into two distinct categories. Whereas, the linear transfer function, shown in the middle of Figure 9, sets the output of the neuron to the same value as the input. The log-sigmoid transfer function, shown in the bottom of Figure 9, converts the input into the output that ranges from 0 to 1.

Neurons are the smallest building block of a neural network. More than one neuron can be used to construct a layer of a neural network. Furthermore, a network can be constructed with more than one layer of multiple neurons. These are called multi-layer networks. Each layer has its own weight matrix $\mathbf{W}$, its own bias vector $\mathbf{b}$, a net input vector $\mathbf{n}$ and an output vector $\mathbf{a}$. In addition, superscript numbers are appended to each of these variables to distinguish a particular variable for a given layer. For example, the weight matrix for the first layer is written as $\mathbf{W^1}$, and the one for the second layer is written as $\mathbf{W^2}$. Using this notation, a three-layer network can be illustrated as in Figure 10.

As shown in Figure 10, for the first layer, the input vector $\mathbf{p}$ has dimension R and there are S^1 summation nodes, the weight matrix $\mathbf{W^1}$ becomes a $S^1 \times R$ matrix. Consequently, the output vector $\mathbf{a^1}$ for the first layer has the dimensions of S^1. The output for first layer is the input for the second layer. Similarly, the second layer output is the third layer input. Therefore, the weight matrix $\mathbf{W}^2$ and $\mathbf{W}^3$ have the dimension of $S^2 \times S^1$ and $S^3 \times S^2$ respectively. These dimensional parameters can be found in the shorthand notation where the number of inputs is followed by the number of neurons in each layer. This notation is used to identify the structure of a multilayer network. Such a shorthand notation for the three-layer network in Figure 10 is $R - S^1 - S^2 - S^3$.



$$\mathbf{a}^3 = \mathbf{f}^3(\mathbf{W}^3\mathbf{f}^2(\mathbf{W}^2\mathbf{f}^1(\mathbf{W}^1\mathbf{p} + \mathbf{b}^1) + \mathbf{b}^2) + \mathbf{b}^3)$$

Figure 10. Three-layer network

The transfer functions for a multi layer network can be chosen based on the primary use of the net. If the net is for pattern classification, transfer functions such as Hard Limit (refer to Figure 9) are typical. If the net is for function approximation, a combination of Log-sigmoid and Linear transfer function is useful. Determination of the proper number of nodes in hidden layers is more critical in the case of function approximation. The number of nodes in hidden layers such as first and second layers in

Figure 10, has to be large enough to capture a realistic view of the unknown target function but also small enough to result in a reasonable training length and ease of training. The number of hidden layers is also critical to reliable performance of the net. For a network to be able to generalize, the network should have fewer parameters to train than the number of data points in the training set. Hornik et al. [1989] have shown that two-layer feedforward networks, with sigmoid transfer functions in the hidden layer and linear transfer functions in the output layer, can approximate virtually any integrable function of interest to any degree of accuracy.

The most popular algorithms to train multilayer networks are backpropagation algorithms. The concept of "backpropagation" first appeared in the thesis of Werbos [1974] and was independently rediscovered and revived during the mid 1980s by several researchers [Le Cun 1985; Parker 1985; Rumelhart and McClelland 1986]. Today, the word "backpropagation algorithm" refers to any *supervised learning* (see [Hagan et al. 1996]) algorithm in which derivatives of transfer functions are recursively calculated from the last layer to the first layer of the network and used to update weights and bias in order to train the network to perform a given task. Existing backpropagation algorithms differ based on the way in which the resulting derivatives are used.

The backpropagation algorithm uses the same performance index as the LMS (least mean square algorithm). The algorithm is provided with Q pairs of input and output vectors consisting of training points:

$$\{\mathbf{p}_1, \mathbf{t}_1\},\ \{\mathbf{p}_2, \mathbf{t}_2\},\ \ldots,\ \{\mathbf{p}_Q, \mathbf{t}_Q\} \tag{3.3.1}$$

where $\mathbf{p}_q$ is a qth input vector to the network, and $\mathbf{t}_q$ is the corresponding target output vector. These vectors comprise a subset of the true functional domain and range. The training procedure starts with a feed forward process first. As a single input vector $\mathbf{p}$ is applied to the network and propagated to the last layer, the final network output vector $\mathbf{a}$ is compared to the corresponding target vector $\mathbf{t}$. Then the algorithm adjusts the network parameters such as weights and biases using a backpropagation process in order to minimize the mean square error:

$$F(\mathbf{x}) = E(e^2) = E[(t-a)^2] \qquad (3.3.2)$$

where $\mathbf{x}$ is the vector of network weights and biases. Since both t and a are vectors, the equation (3.3.2) can be generalized to

$$F(\mathbf{x}) = E[\mathbf{e}^T\mathbf{e}] = E[(\mathbf{t}-\mathbf{a})^T(\mathbf{t}-\mathbf{a})]. \qquad (3.3.3)$$

As with the LMS algorithm, (3.3.3) can be approximated by

$$\hat{F}(\mathbf{x}) = (\mathbf{t}(k)-\mathbf{a}(k))^T(\mathbf{t}(k)-\mathbf{a}(k)) = \mathbf{e}^T(k)\mathbf{e}(k). \qquad (3.3.4)$$

Now, the steepest descent algorithm (see [Hagan et al. 1996]) for $\hat{F}(\mathbf{x})$ is used to update the weights and biases at each iteration k. The steepest descent algorithm for the approximate mean square error is

$$w_{i,j}^m(k+1) = w_{i,j}^m(k) - \alpha\frac{\partial\hat{F}}{\partial w_{i,j}^m}, \qquad (3.3.5)$$

$$b_i^m(k+1) = b_i^m(k) - \alpha\frac{\partial\hat{F}}{\partial b_i^m}, \qquad (3.3.6)$$

where α is a fixed learning rate. A stable learning rate α should be between 0 and $2/\lambda_{\max}$ where $\lambda_{\max}$ is the maximum eigenvalue of the Hessian matrix. The next step of the algorithm is to calculate the partial derivatives. For a multilayer network calculating the partial derivatives is not trivial, since the function (3.3.4) is not an explicit function of the weights and biases in the hidden layers. Thus, the partial derivatives in (3.3.5) and (3.3.6) should be solved using the chain rule:

$$\frac{\partial \hat{F}}{\partial w_{i,j}^m} = \frac{\partial \hat{F}}{\partial n_i^m} \times \frac{\partial n_i^m}{\partial w_{i,j}^m}, \tag{3.3.7}$$

$$\frac{\partial \hat{F}}{\partial b_i^m} = \frac{\partial \hat{F}}{\partial n_i^m} \times \frac{\partial n_i^m}{\partial b_i^m}. \tag{3.3.8}$$

Since

$$n_i^m = \sum_{j=1}^{S^{m-1}} w_{i,j}^m a_j^{m-1} + b_i^m, \tag{3.3.9}$$

the second term in each of equation (3.3.7) and (3.3.8) can be calculated as

$$\frac{\partial n_i^m}{\partial w_{i,j}^m} = a_j^{m-1}, \quad \frac{\partial n_i^m}{\partial b_i^m} = 1. \tag{3.3.10}$$

If we let $\frac{\partial \hat{F}}{\partial n_i^m} = s_i^m$, where s_i^m is the sensitivity of $\hat{F}$ to changes in the i th element of the net input at layer m, equation (3.3.7) and (3.3.8) can be simplified to

$$\frac{\partial \hat{F}}{\partial w_{i,j}^m} = s_i^m a_j^{m-1}, \tag{3.3.11}$$

$$\frac{\partial \hat{F}}{\partial b_i^m} = s_i^m. \tag{3.3.12}$$

Now, the equation (3.3.5) and (3.3.6) can be expressed as

$$w_{i,j}^m(k+1) = w_{i,j}^m(k) - \alpha s_i^m a_j^{m-1}, \tag{3.3.13}$$

$$b_i^m(k+1) = b_i^m(k) - \alpha s_i^m. \tag{3.3.14}$$

This can be generalized in matrix form:

$$\mathbf{W}^m(k+1) = \mathbf{W}^m(k) - \alpha \mathbf{s}^m (\mathbf{a}^{\mathbf{m-1}})^T, \tag{3.3.15}$$

$$\mathbf{b}^m(k+1) = \mathbf{b}^m(k) - \alpha \mathbf{s}^m, \tag{3.3.16}$$

where

$$\mathbf{s}^m \equiv \frac{\partial \hat{F}}{\partial \mathbf{n}^m} = \begin{bmatrix} \frac{\partial \hat{F}}{\partial n_1^m} \\ \frac{\partial \hat{F}}{\partial n_2^m} \\ \vdots \\ \frac{\partial \hat{F}}{\partial n_{s^m}^m} \end{bmatrix}. \tag{3.3.17}$$

The sensitivities $\mathbf{s}^m$ can be calculated using a chain rule. By using the Jacobian matrix $\frac{\partial \mathbf{n}^{m+1}}{\partial \mathbf{n}^m}$, the equation (3.3.17) can be written

$$\mathbf{s}^m = \frac{\partial \hat{F}}{\partial \mathbf{n}^=} = \left(\frac{\partial \mathbf{n}^{m+1}}{\partial \mathbf{n}^m} \right)^T \frac{\partial \hat{F}}{\partial \mathbf{n}^{\mathbf{m+1}}}. \tag{3.3.18}$$

Since

$$\frac{\partial n_i^{m+1}}{\partial n_j^m} = \frac{\partial \left(\sum_{l=1}^{s^m} w_{i,l}^{m+1} a_l^m + b_i^{m+1} \right)}{\partial n_j^m} = \frac{\partial \left(\sum_{l=1}^{s^m} w_{i,l}^{m+1} f^m(n_l^m) + b_i^{m+1} \right)}{\partial n_j^m} \tag{3.3.19}$$

$$= w_{i,j}^{m+1} \frac{\partial f^m(n_j^m)}{\partial n_j^m} = w_{i,j}^{m+1} \dot{f}^m(n_j^m),$$

the Jacobian matrix can be written

$$\frac{\partial \mathbf{n}^{m+1}}{\partial \mathbf{n}^m} = \mathbf{W}^{m+1} \dot{\mathbf{F}}^m(\mathbf{n}^{\mathbf{m}}), \tag{3.3.20}$$

where

$$\dot{\mathbf{F}}^m(\mathbf{n}^m) = \begin{bmatrix} \dot{f}^m(n_1^m) & 0 & \cdots & 0 \\ 0 & \dot{f}^m(n_2^m) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \dot{f}^m(n_{s^m}^m) \end{bmatrix} \tag{3.3.21}$$

$$= \begin{bmatrix} \dfrac{\partial f^m(n_1^m)}{\partial n_1^m} & 0 & \cdots & 0 \\ 0 & \dfrac{\partial f^m(n_2^m)}{\partial n_2^m} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \dfrac{\partial f^m(n_{s^m}^m)}{\partial n_{s^m}^m} \end{bmatrix}.$$

The equation (3.3.18) can be rewritten using equation (3.3.20)

$$\mathbf{s}^m = \frac{\partial \hat{F}}{\partial \mathbf{n}^=} = \left(\frac{\partial \mathbf{n}^{m+1}}{\partial \mathbf{n}^m}\right)^T \frac{\partial \hat{F}}{\partial \mathbf{n}^{\mathbf{m+1}}} = \dot{\mathbf{F}}^m(\mathbf{n}^m)(\mathbf{W}^{m+1})^T \frac{\partial \hat{F}}{\partial \mathbf{n}^{m+1}} \tag{3.3.22}$$

$$= \dot{\mathbf{F}}^m(\mathbf{n}^m)(\mathbf{W}^{m+1})^T \mathbf{s}^{m+1}$$

The recursive relationship in which the sensitivity at layer m is computed from the sensitivity at layer $m+1$ leads to the term backpropagation. The equation (3.3.22) can be used to calculate sensitivities for the first layer and all hidden layers. However, a different equation is required to calculate the sensitivity for the last layer $\mathbf{s}^M$. Since $\hat{F} = (\mathbf{t} - \mathbf{a})^T(\mathbf{t} - \mathbf{a})$ and $\dfrac{\partial a_i}{\partial n_i^M}$ can be calculated using a similar Jacobian matrix as seen in (3.3.21), the sensitivity for the final layer $\mathbf{s}^M$ can be expressed as

$$\mathbf{s}^M = \frac{\partial \hat{F}}{\partial \mathbf{n}^M} = -2\dot{\mathbf{F}}^M(\mathbf{n}^M)(\mathbf{t} - \mathbf{a}). \tag{3.3.23}$$

A summary of the backpropagation algorithm for an M layer network can be given as follows.

1. Propagate the input forward (from the first layer to the last layer) through the network:

$$\mathbf{a}^0 = \mathbf{p}, \tag{3.3.24}$$

$$\mathbf{a}^{m+1} = \mathbf{f}^{m+1}(\mathbf{W}^{m+1}\mathbf{a}^m + \mathbf{b}^{m+1}) \text{ for } m = 0, 2, \ldots, M-1, \tag{3.3.25}$$

$$\mathbf{a} = \mathbf{a}^M. \tag{3.3.26}$$

2. Propagate the sensitivities backward (from the last layer to the first layer) through the network:

$$\mathbf{s}^M = -2\dot{\mathbf{F}}^M(\mathbf{n}^M)(\mathbf{t}-\mathbf{a}) \text{ for the last layer,} \tag{3.3.27}$$

$$\mathbf{s}^m = \dot{\mathbf{F}}^m(\mathbf{n}^m)(\mathbf{W}^{m+1})^T\mathbf{s}^{m+1} \text{ for } m = M-1, \ldots, 2, 1. \tag{3.3.28}$$

3. Finally, update the weights and biases at each iteration using the approximate steepest descent rule:

$$\mathbf{W}^m(k+1) = \mathbf{W}^m(k) - \alpha\mathbf{s}^m(\mathbf{a}^{m-1})^T, \tag{3.3.29}$$

$$\mathbf{b}^m(k+1) = \mathbf{b}^m(k) - \alpha\mathbf{s}^m. \tag{3.3.30}$$

One of the major drawbacks in the basic backpropagation algorithm using the steepest descent algorithm is the long training time. There are two types of variations on backpropagation to improve the performance of the algorithm: heuristic modifications and standard numerical optimization techniques. The first method, heuristic modifications, is the use of momentum [Vogl et al. 1988]. This method is based on the fact that convergence to a global minimum might be improved if the oscillations in the trajectory are reduced. It is a common phenomenon in neural network training that increasing the learning rate will make the algorithm unstable when the algorithm reaches steeper portions of the performance surface $\hat{F}$. A momentum filter can be added to the parameter changes in order to reduce the side effect of using a higher learning rate. If we let

$$\mathbf{W}^m(k+1) - \mathbf{W}^m(k) = \Delta\mathbf{W}^m(k) \text{ and}$$

$$\mathbf{b}^m(k+1) - \mathbf{b}^m(k) = \Delta\mathbf{b}^m(k) \ ,$$

then equations (3.3.29) and (3.3.30) become

$$\Delta\mathbf{W}^m(k) = -\alpha\mathbf{s}^m(\mathbf{a}^{m-1})^T , \quad (3.3.31)$$

$$\Delta\mathbf{b}^m(k) = -\alpha\mathbf{s}^m . \quad (3.3.32)$$

The modified parameter update equations for the backpropagation algorithm can be expressed using a recursive relationship and introducing a momentum coefficient γ:

$$\Delta\mathbf{W}^m(k) = \gamma\Delta\mathbf{W}^m(k-1) - (1-\gamma)\alpha\mathbf{s}^m(\mathbf{a}^{m-1})^T , \quad (3.3.33)$$

$$\Delta\mathbf{b}^m(k) = \gamma\Delta\mathbf{b}^m(k-1) - (1-\gamma)\alpha\mathbf{s}^m , \quad (3.3.34)$$

In a modified backpropagation algorithm using momentum, the parameters $\mathbf{W}^m$ and $\mathbf{b}^m$ are updated only after the entire training set has been presented. By using momentum, we can use a larger learning rate and accelerate convergence without making the algorithm unstable when the trajectory is moving in a consistent direction. The modified backpropagation algorithm using momentum, sometimes called MOBP, is simple to implement and significantly faster than the steepest descent backpropagation (SDBP). It can also be used either in batch mode or incremental mode.

The second method in heuristic modifications of the basic backpropagation algorithm is to use a variable learning rate. We can speed up convergence if we increase the learning rate on flat surfaces of the performance surface and decrease the learning rate on the non-flat surfaces. There are many variations on this variable learning rate backpropagation (VLBP) algorithm. Vogl et al. [1988] propose a batching procedure, where the learning rate is varied according to the performance (the squared error) of the algorithm. For example, when the square error exceeds more than some set percentage ζ after a weight update, the weight update should be discarded and a lower learning rate should be applied, multiplying the learning rate by some factor $0 < \rho < 1$ and setting the momentum coefficient γ to zero. On the contrary when the square error decreases after a weight update, the update is accepted and an increased learning rate should be applied, multiplying the learning rate by some factor $\eta > 1$ and setting the momentum coefficient γ to its original value.

However, when the squared error increases by less than ζ, the weight update is accepted and the current learning rate and momentum should be used for the next iteration. Jacobs [1988] proposed the *delta-bar-delta* learning rule, in which each network weight or bias has its own learning rate. The algorithm increases the learning rate for a network weight or bias if the weight or bias change has been in the same direction for several iterations. If the weight or bias change has not been in the same direction, then the learning rate is reduced.

In general, the algorithm using a variable learning rate is faster than the backpropagation using momentum and also reasonably robust [Hagan et al. 1996]. But, it must be used in batch mode; therefore it takes more intermediate computation storage. It also has a limit of selecting a total of five parameters, and the choice of the parameters can affect the convergence speed.

There are two methods based on numerical optimization techniques that can be used as an enhancement for the backpropagation algorithm. They are conjugate gradient and Newton's method. The steepest descent algorithm is the simplest algorithm, but it is often slow in converging to a global minimum. On the contrary, Newton's method is much faster in converging, but it requires the Hessian matrix (a second derivative) and its calculated inverse.

The conjugate gradient algorithm comes as a compromise of the steepest descent algorithm and Newton's method. The conjugate algorithm does not require the calculation of second derivative, and yet it has the quadratic convergence property. For quadratic performance functions the algorithm will converge to the minimum in at most n iterations where n is equal to the number of parameters being optimized [Scales 1985]. However, for multilayer networks the conjugate algorithm would not converge in n iterations because the mean squared error performance index for multilayer networks is not quadratic. To overcome this problem, modifications have to be made to continue the search for the global minimum. There have been a few methods suggested, but the simplest way is to reset the search direction to the steepest descent direction after n

iterations [Scales 1985]. In addition, a method called the Golden Section Search is added to the conjugate gradient backpropagation algorithm (see [Scales 1985] or [Hagan et al. 1996] for details) for the smaller linear search size at each iteration. Conjugate gradient back propagation (CGBP) is a batch mode algorithm and generally faster than VLBP. But its memory requirement is no greater than VLBP.

The second numerical optimization technique to improve the backpropagation algorithm is the Levenberg-Marquardt algorithm. The Levenberg-Marquardt algorithm (see [Scales 1985]) is a variation of Newton's method that is a simple technique to obtain faster convergence to the minimizing points for sums of squares of nonlinear functions. The Levenberg-Marquardt backpropagation (LMBP) alogrithm uses the Gauss-Newton method that does not require calculation of the second derivatives. The algorithm uses the assumption to converge when the norm of the gradient is less than some predetermined value or when the sum of squares has been reduced below the target error. The LMBP is the fastest algorithm for training multilayer networks of moderate size according to [Hagan et al. 1996]. The major drawback is its heavy memory burden for a matrix inversion at each iteration. When the size of a network becomes large (more than a few thousand parameters to train), the algorithm can become impractical because of this computational burden.

3.3.3 Proposed Neural Network based metamodeling framework

A preliminary study and experiment were conducted to decide on a final form of ANN based meta-modeling framework for this research. The study concluded that most existing ANN based metamodeling frameworks utilize a single ANN to be trained on a single functional domain of interest. As previously discussed, the idea to use multiple ANNs is not new. It was inspired by the way the human brain works. Collective neurons can store a single knowledge domain represented by a complex pattern. An array of multiple neurons form a group to collectively store and retrieve information through a repetitive neurological stimulation process called learning. The effective use of well organized multiple ANNs can be as powerful as human neurons.

The modeling framework for multiple ANNs is to increase modeling economy and flexibility so that it can collectively store more than one functional domain, such as time average machine utilizations and time series models for time-in-system (TIS) under distinctive disruption patterns. It is also intended for improved accuracy of individual ANNs, future expandability, and potential automation. Therefore, several methods to effectively integrate multiple ANNs were examined. One such framework is to store individually trained ANNs in a single database. But the preliminary study concluded that using a database along with ANNs can be problematic due to the complexity of maintenance and future expandability issues. The study found that, based on modeling efficiency, the logical branching to taxonomically interconnect individual ANNs trained on more than one modeling domain is a highly economical approach for the proposed system.

The proposed ANN based meta-modeling scheme consists of a hierarchical taxonomy of multi-layer ANNs that can individually adapt to different systems modeling domains. As shown in Figure 11, the top level multi-layer ANN is designed to detect and classify distinctive post-disruption system behaviors upon 44 x 1 input vector utilizing pattern matching. A 44 x 1 input vector is designed to feed the ANNs with a snapshot of the system's key operational conditions as well as disruption itself. For instance, time averaged utilization of each machine stations prior to a particular disruption event are a part of input elements in such vector. The output of the top level ANN can be either 3 x 1 or 2 x 1 vector that is designed to represent various distinctive transient behavior pattern types. Most post-disruption system behaviors can be classified into several distinctive transient behavior pattern types. Each transient behavior pattern type can be coded into either a three-digit or two-digit binary number. The length of binary number can be determined by the number of distinctive system behavior pattern types that can be produced under current system configurations and operational conditions. For example, the output vector 100, represents the pattern type class number four.

The second (or low) level multi-layer ANNs are designed to capture significant variations within a selected transient behavior pattern type. Even though second level ANNs share the same input vector that is fed to the first level, output vectors used by second level ANNs are different from one network to another network based on one's need to capture unique mathematical properties of each transient behavior pattern under focus. For example, for post-disruption system behaviors that exhibit a common curve pattern and can also be generalized by a similar parametric time series model, approximated coefficients for a pre-selected high degree polynomial regression model can be a part of elements in expected output vectors from a trained second level ANN. The Figure 11 illustrates how the taxonomically structured ANN based Meta-modeling scheme can deliver a post-disruption performance prediction upon feeding pre-disruption system conditions.

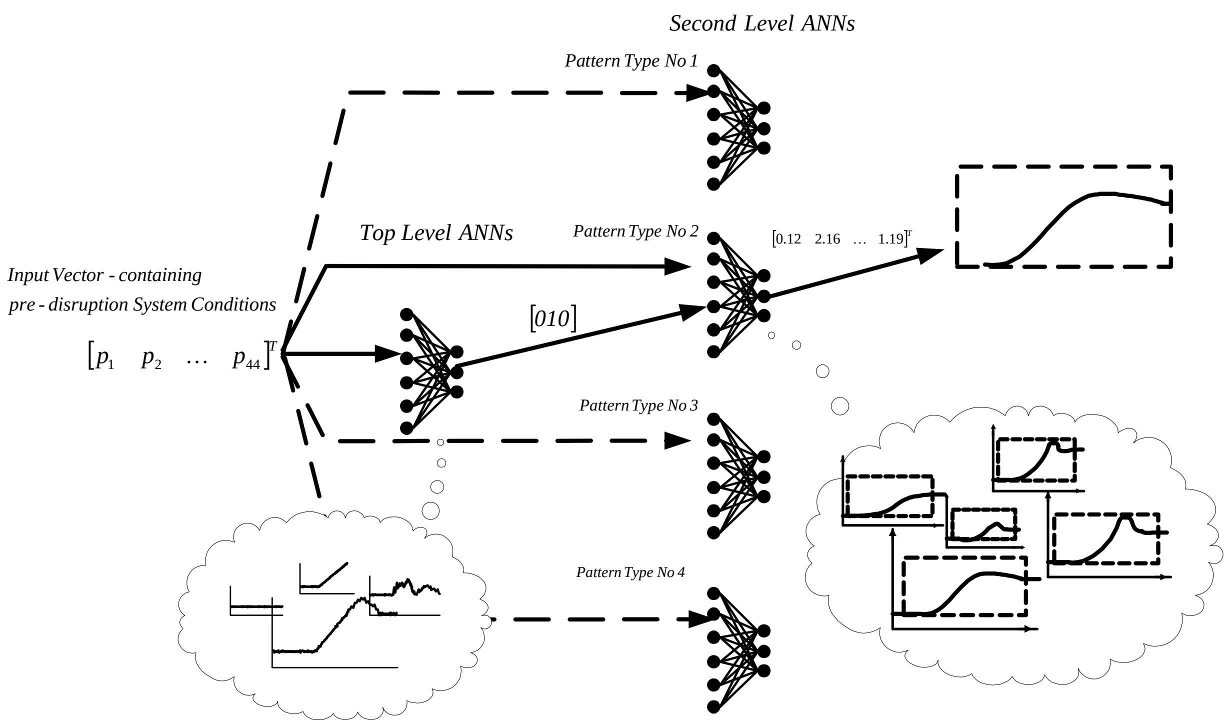


Figure 11. Proposed ANN based Metamodeling scheme

To construct a parametric time series model, various time series approximation methods such as regression methods, moving average methods, or exponential smoothing methods, can be used to mathematically capture the unknown transient performance function. In addition to underlying time series models, some quantitative aspects of the transient behavior, such as the estimated time from the occurrence of a disruptive event to the emergence of the first sign of performance deterioration and variance changes during a transient state, can be predicted in output vectors.

Prior to a full investigation of various transient behavior patterns of the FMS under study using computer simulation, we could scientifically guess the basic behavior patterns of the target system performance index such as time in system based on a study of most common types of any time series. According to Chatfield [1984], there are three basic types of time series characteristics: constant process, linear and quadratic trends, and cyclic or periodic variation. Thus, it is theoretically possible to have a time series in combined forms of these three basic patterns.

4. Statement of Research

4.1 Research Goal

The primary goal of this research is to demonstrate that a hierarchically organized ANN based metamodeling framework is a viable means to provide an effective "lookahead" performance modeling capability to a non-human controller as well as human operator in case there is an unanticipated performance disruption. The proposed ANN based metamodeling framework is a pattern based knowledge system that consists of independently trained multiple ANNs in a taxonomical arrangement. These individual ANNs are designed to work together to cover different areas in the functional range of an unknown transient system performance prediction function. This is a feasibility study of such a performance-modeling framework. The research comprises six major objectives: (1) a simulation study on a hypothetical FMS model with limited operational characteristics and scenarios to identify a unique set of possible transient system behavior patterns under pre-selected disruption scenarios, (2) identification of the input space and output space of an unknown transient performance prediction function, (3) identification of a proper logical taxonomy that can logically connect multiple ANNs, making them work collectively to capture various transient behaviors, (4) identification of design architecture for individual ANNs and their proper training methods, (5) validation and performance assessment of the final model through comparisons with simulation results,

(6) recommendations for further improvements of the proposed modeling framework in future research.

4.2 Research Objectives

To achieve the research goal, six research objectives have been identified and need to be pursued:

<u>Objective 1- Construct a simulation model and identify an appropriate experimental design to study various transient system behaviors of the proposed FMS.</u> A discrete event simulation model is built using Extend [1987-2001] to study various transient behaviors of the proposed FMS. The model is built and studied according to the steps in a simulation study suggested in Banks et al. (p13 –p18) [1996]. The simulation model is constructed in such way that a single resource failure can be scheduled at a precise moment during a single run. Key performance indexes such as time averaged utilization of each machine stations and AGV are recorded prior and after a scheduled disruption. Limited pilot runs of the model with selected ranges for system operational parameters of interest are used to finalize the experimental design. The main focus of these pilot runs is to test which set of operational parameters could provide better samples for distinctive post-disruption transient behaviors. Individual workstation process time distributions under each part type are also selected to meet desired average system utilization throughout the system. A valid experimental design is identified based on the results from these pilot runs. Experimental factors, the number of levels of each

experimental factor, and the total number of different experiment is described in depth in Section 4.3

Objective 2 - identify a domain (input space) and range (output space) of an unknown transient performance prediction function to be modeled by the proposed ANN based meta-modeling framework.

Major system performance indexes prior to an operational disruption such as time averaged utilization for each machine stations and the AGVs can be a part of the functional domain. These selected indexes can help an unknown transient performance prediction function to map and distinguish various post-disruption system behaviors based on their unique input space value pattern after the mapping is finished. Among various system performance indexes, those that exhibit clear changes after a given disruption can be considered as candidate elements for the functional domain as well as functional range. The other significant part of functional range is aimed to capture an unknown time series function of key performance index of primary interest to depict the detail transient behavior such as time-in-system of individual incoming parts.

Objective 3 - identify proper taxonomical logic structure to loosely connect multiple ANNs to predict an unknown transient performance prediction function.

A branch logic structure where each branch uses individually trained ANNs and predicts a mutually exclusive area of the functional range of the unknown transient performance prediction function is to be identified. Questions such as what part of the functional range to capture by the top level ANN and how many levels of branch logic are needed in order to predict the entire functional range are investigated. A pictorial presentation of a proposed modeling scheme can be found in Figure 17 (page 156) from the previous chapter. Major design principles of the proposed taxonomical logic structure are:

- Top level branch logic is to map an appropriate set of subsequent ANNs so that they can collectively predict a detail transient behavior after the top level ANN distinguishes its overall transient behavior pattern class.
- The depth of levels in the taxonomical structure can be adjusted based on the number of unique transient system behavior patterns and the number of key indexes and parameters to be modeled.
- The structure of taxonomical branch logic should be designed in such way to comprehensively cover all possible transient system behaviors of the proposed FMS under given disruption scenarios and future expansion of the model can be accommodated.

<u>Objective 4 - identify appropriate ANN architecture and training strategy for individual ANNs to be used in overall meta-modeling framework.</u>

First, an appropriate artificial neural network design architecture to cover different parts of a functional range of the unknown transient performance prediction function needs to be selected. Second, a choice of possible network configurations and a training method for individual ANNs need to be made. For example, the number of nodes, the number of hidden layers, the type of transfer function, selection of training data set, training methods, and the length of training period need to be identified.

Objective 5 - Validate the proposed ANN based metamodeling framework using the simulation model developed in Objective and selected disruption scenarios.

The overall effectiveness of the proposed modeling framework can be judged through a controlled simulation study. A portion of experimental design from Objective 1 can be used to evaluate the effectiveness of the model. The effectiveness test consists of three major parts. The first part is to evaluate the fidelity of the distinctive transient system behavior pattern classification by the trained top-level ANNs. The second part is to assess the accuracy of individual key performance index predictions such as time averaged resource utilizations. The third part is to assess the accuracy of the approximated coefficients of an unknown time series function of key performance indexes of primary interest.

Objective 6 – Make recommendations for the future research based on outcomes of this study.

Based on the outcome of the study, three courses of action can be taken. The first course of action is that the anticipated performance is fully met and no other improvement is necessary. In this case, the automation of the proposed FMS transient performance-modeling scheme can be suggested as a possible topic for the future research. Also, a generalization of the proposed methodology can be made so that it can be applied to other similar asynchronous concurrent system control environments. The second case is that the anticipated performance is partially met and some improvement is necessary. In such case, possible candidates for further improvement can be identified and a possible remedy can be suggested for the future research. The third case is that the outcome has completely failed to meet the anticipated performance. Therefore, possible causes for failure have to be identified. If there is evidence that theoretically incorrect assumptions were made or inappropriate concepts were used for either the study or methodology itself, they need to be identified and discussed.

4.3 Assumptions and limitations

The performance prediction scheme using ANNs is to provide a lower level FMS controller its most needed "lookahead" capability. The performance index of primary interest is the average time in the system for individual parts. The maximum performance forecasting time horizon for "lookahead" feature in this hypothetical control system has no need to exceed 15 working days. However, the minimum performance forecasting time horizon should be at least five working days. Each working day has 14 hours of operational time for the proposed FMS.

The mean and variance of the unknown distribution of the average time in the system need to be measured during the experiment. Machining time distributions are assumed to be triangular distributions. Despite the almost deterministic operational nature of most FMSs, non-deterministic service times are chosen for this study mainly due to setup time variability caused by the random sequence of part types in a loaded fixture. Inter-arrival times for individual part types can be adjusted during pilot runs to achieve the desired overall system utilization level. Since this research is intended to validate a new metamodeling framework, the simulation study only focuses on a small set of single event disruption scenarios to keep the experiment size manageable. Single discrete events such as part mix changes, introduction of new product, machine center breakdown, and AGV breakdown are assumed to be the only source of disruptions under study.

No more than one machine or AGV breakdown is allowed to take place at any given time. Even though actual machine center breakdown and AGV failure are random in nature, for the purpose of this study, a single disruption event is scheduled to take place at a particular point during a single non-terminating simulation run. During pilot runs, the event trigger time for both machine center breakdown and AGV failure needs to be carefully selected so that a resource failure can only happen after a particular performance index has passed its initial warm-up period and reached its steady-state.

4.4 Summary

The primary goal of this research is to demonstrate that a group of taxonomically organized ANNs can collectively provide a post-disruption "lookahead" capability on a selected performance index. The proposed ANN based metamodeling approach is a pattern based performance modeling system utilizing both regression and simulation data. The six major research objectives are: (1) a simulation study on a hypothetical FMS model with a limited capability of fault tolerance, (2) identification of the functional domain and range of an unknown transient performance prediction function, (3) identification of a proper taxonomical framework that logically combines individual ANNs, (4) identification of proper design architecture of individual ANNs and their training methods, (5) validation and performance assessment of the final metamodel, (6) identification of future improvements and opportunities regarding the proposed metamodeling approach. Assumptions and limitations regarding the hypothetical FMS were also identified.

5. Research Methodology

This chapter outlines major research tasks, their execution plans, and necessary methodology to achieve the goal and objectives defined in Chapter 4.

5.1 Research Tasks

There are ten major tasks identified. Task 1 is to construct a valid simulation model based on the proposed FMS that can facilitate a single scheduled resource failure during its run time. Task 2 is to finalize appropriate values for key system parameters such as interarrival mean time for incoming parts and mean service times for each part type at particular machine centers to obtain a desired level of system wide utilization through pilot runs. Task 3 is to finalize key performance indexes and experimental factors to create limited disruption scenarios that can be used for development and validation of an ANN based transient performance metamodeling framework. Task 3 must provide two separate scenarios, one for the steady state performance analysis and the other for the transient state performance analysis using a single resource failure.

Task 4 conducts a simulation experiment using the two separate scenarios defined in Task 3 to find values for various elements in both the functional domain and range of an unknown transient performance prediction function. Collecting steady state as well as transient performance values for chosen key performance indexes and constructing individual time series approximation models to capture detail transient behaviors of the primary performance index such as time-in-system are key steps under this task.

Task 5 is to prepare data generated from simulation experiments for the ANN application. Appropriate structures for both input and output vectors are identified during this process. Individually constructed time series approximation functions for the primary performance index under a given disruption scenario need to be carefully converted to a group of elements in a single output (target) column vector so that they can be fed into a corresponding ANN during its training. During input and output data preparation for ANN training, a data conditioning method such as moving average method is employed to minimize unwanted noise and help to capture only essential trend information in time series performance data. This makes the individual network training easier and faster and also improve its overall prediction accuracy. Task 6 identifies and constructs appropriate neural networks for various parts of the proposed ANN based metamodeling scheme based on their input space and output space vector configurations. A proper configuration for each neural network is identified through both theoretical and empirical approaches. Task 7 trains and validates neural networks using mutually exclusive subsets of data collected from Task 4. The entire neural network training and simulation are done using MATLAB [1984-2000].

Task 8 is to construct proper branch logic to taxonomically organize various ANNs to map selected members of the functional domain to a proper part of the functional range. Conceptualization and design of the overall logical framework is started as early as when Task 3 starts. The entire logic and input and output interfaces are written in MATLAB language. Task 9 is to assess the effectiveness of the proposed ANN based metamodeling framework under selected sets of simulated shop-floor disruption scenarios found in Task 3. Task 10 does continuous write-up as the research progresses. Task 11 summarizes the findings and makes recommendations based on the outcomes from Task 9.

Task 1: constructs a valid simulation model based on the proposed FMS in Chapter 3. A discrete event simulation model is constructed using Extend to run non-terminating simulations with a single-resource failure to generate time series performance data for a primary key performance index such as mean time-in-system. The model consists of three major functional elements. The first element is a part type and attribute allocation module where a part type is probabilistically generated from an empirical discrete distribution and necessary parameters for individual machining time distributions are automatically assigned to an incoming part as its attributes. The second element is a part routing and AGV handling logic that controls the bypass and pass-through track at each machine stations based on the current machine status and machine operation requirements by the incoming loaded fixture. The third element is a resource failure trigger mechanism that allows a user to selectively pick the resource to fail, the failure start time, and the duration of failure. System configuration parameters such as mean part inter-arrival time and relative part sizes for individual part types can be selected during pilot runs. The model validation needs to be done to see if the model closely follows the system descriptions given in Chapter 3.

Task 2: executes ten pilot runs (10 independent reps) with two sets of part mixes to finalize key system parameters. Part mix one consists of part type 1 (25%), part type 5 (25%), part type 8 (25%), and part type 11 (25%). Part mix two consists of part type 1 (20%), part type 4 (20%), part type 5 (20%), part type 11 (20%), and part type 12 (20%). Pilot runs are also to finalize key system parameters, such as inter-arrival mean time for different part types and mean service time by a particular machine center for a specific part type. Furthermore, Identifies ranges for the mean service time by each AGV should be determined to obtain a desired average system utilization level.

Task 3: finalizes experimental factors to create initial disruption scenarios. Refer to Section 5.2 for more details.

Task 4: conducts simulation experiments using two separate scenarios to find both steady state performance values and transient state patterns for the chosen performance index. Also Task 4 identifies the following system parameters:

- common warm up period for all steady state scenarios under study,
- least amount of time duration required to observe any transient impact following a particular disruption over the target performance index,

- maximum deviation of the target performance index at a given time from its steady state value prior to a particular disruption,
- maximum duration of any transient behavior under each scenario.

Task 5: identifies a proper input and output vector space to represent both functional domain and range of an unknown transient system performance function. Properly configured input and output column vectors can be fed to a loosely connected group of individually trained ANNs in a taxonomical manner in order to predict the transient system behavior following a single performance disruption.

Task 6: identifies, constructs and trains individual ANNs comprising the proposed ANN based metamodeling scheme for both steady state and transient state performance predictions. A proper training method for individual ANN shall be selected. Refer to Section 3.3.2 and 3.3.3 for ANN based methodology.

Task 7: trains and validates individual ANNs in the proposed ANN based metamodeling scheme using input and output vectors constructed from the performance data collected from Task 4.

Task 8: constructs proper branch logic that is to loosely connect individual ANNs in taxonomical manner to map various parts of the functional domain to the intended functional response of an unknown transient performance function. This needs to be all done using MATLAB.

Task 9: assesses the overall effectiveness of the proposed ANN based metamodeling framework under a selected set of disruption scenarios found in Task 3.

Task 10: does continuous write-up as the research progresses.

Task 11: summarizes findings based on outcomes from Task9 and makes final recommendations for possible future research.

5.2 Simulation Based Disruption Scenarios

Single discrete events such as part mix changes, introduction of new product, machine center breakdown, and AGV breakdown are considered experimental factors of this study. Even though we consider part mix change a single discrete event, in reality, there are more than single part percentages affected by a part mix change. A new part introduction to the current production flow is an inclusive form of part mix change. There can be many different combinations to form a part mix change. For this research, only one set of part mix changes is studied.

Factor 1: A part mix change can be characterized by changes in the percentage combination of individual part types across presently available part types under the current production order. Unexpected change in the current production plan can result in a part mix change. In addition, introduction of a new product can result in a shift in part mix. The table below illustrates three possible part mix scenarios that are used in this experiment.   A disruption can be caused by a sudden shift from one part mix to the other. As result there can be three possible disruption scenarios, namely Part Mix 1 → Part Mix 2 and Part Mix 2 → Part Mix 1, which can be caused by changes in part mix.

Table 8. Part Types and Possible Part Mix Change Scenarios

	Part Type 1	Part Type 4	Part Type 5	Part Type 8	Part Type 11	Part Type 12
Part Mix1	25%		25%	25%	25%	
Part Mix2	20%	20%	20%		20%	20%

	Part Mix Change
Case 1	None
Case 2	Part Mix1 → Part Mix2
Case 3	Part Mix2 → Part Mix1

Factor 2: A single machine center breakdown or recovery can be characterized by adding or removing a specific machine center to a particular machine group. Since performance of each machine center differs even among the same machine group, which machine to breaks down can be critical to substantiate the impact. The following Table 9 contains seven distinctive machine breakdown scenarios that are used for this experiment.

Table 9. Possible Single Machine Failure Scenarios

	Failed Machine from Machine Group 1	Failed Machine from Machine Group 2	Failed Machine from Machine Group 3
Case 1	None	None	None
Case 2	M1		
Case 3	M6		
Case 4		M2	
Case 5		M5	
Case 6			M3
Case 7			M7

Factor 3: Single AGV failure can be characterized in the same way as the machine center breakdown.

Table 10. Possible Single AGV Failure Scenarios

	Failed AGV
Case 1	None
Case 2	AGV1 or AGV2

Thus, the total number of levels in the experimental design is

$$Nc_{PM \times PA} \times N_{ind\ \ rep} \times (1 + Nf_{AGV} + Nf_{machine} + Nch_{PM}) = total\ \ number\ \ of\ \ levels$$

$4 \times 5 \times (1+1+6+1) = 180$

$$where \begin{cases} Nc_{PM \times PA} & \begin{array}{l} Number\ of\ different\ blocking\ factors\ by \\ part\ mix\ and\ part\ arrival\ time\ combinations \end{array} \\ N_{ind\ rep} & Number\ of\ independent\ replications \\ 1 & No\ disruption \\ Nf_{AGV} & Number\ of\ a\ single\ AGV\ failutre \\ Nf_{machine} & Number\ of\ a\ single\ machine\ failure \\ Nch_{PM} & Number\ of\ part\ mix\ change - 1 (double\ factor\ adjuster) \end{cases}.$$

Each level in this experimental design represents various single source disruption scenarios derived from four steady states pre-disruption conditions (see Table 11). Total eight single source disruptions are identified for this experiment. These single source disruptions are designed to create various transient performance behaviors from a steady state condition. Through early pilot runs, two distinctive types of pre-disruption steady state condition are identified. Because of their behavioral similarity to the physical equilibrium, the notion of "equilibrium" in physics is used throughout the study to describe these two types of pre-disruption steady state conditions.

In physics, there are two types of equilibrium, stable and unstable. As shown in Figure 12, a stable equilibrium can be considered the lowest point in a valley where a ball can remain still unless some external force acts on it. Even after applying some force on the ball, the ball tends to roll back to the same lowest point after a period of pendulum movements. An unstable equilibrium can be considered the highest point on a peak where the ball can slide off in either direction after applying a little external force.
A pre-disruption steady state followed by no or very little change after the disruption can be considered to be in a state of stable equilibrium. Whereas, a pre-disruption steady

state followed by a significant change after the disruption can be considered to be in a state of unstable equilibrium.

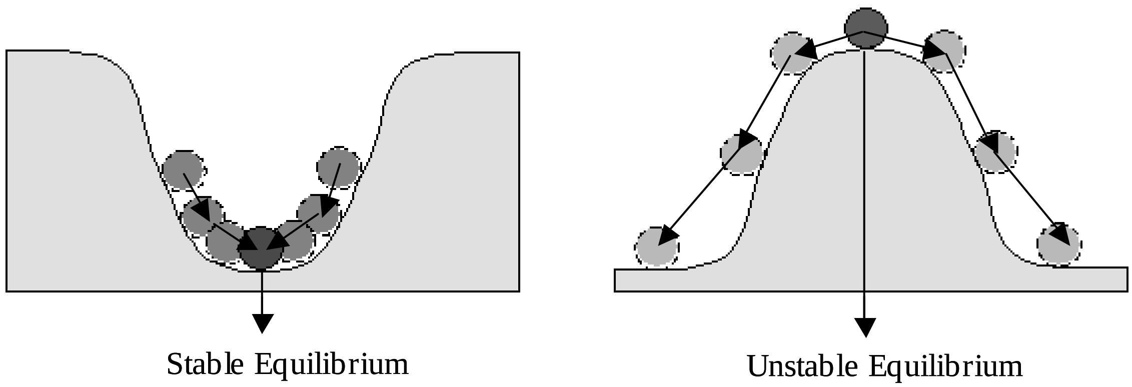


Figure 12. Graphical Representation of Stable and Unstable Equilibrium

The purpose of this simulation experiment is to investigate transient behaviors of the target performance index after a single disruptive event occurs during its simulation time. Thus, four different steady state system settings formed by unique combinations between a particular part mix and a specific part arrival time can be followed by a single disruptive event to simulate each single disruption scenarios. The following table illustrates how these nine single event based disruption scenarios can be formed. For example, the first disruption scenario is based on a part mix change during a production cycle from a part mix consisted of part type 1, 5, 8, and 11 to a part mix consisted of part type 1, 4, 5, 11, and 12.

Table 11. Possible Single Resource Failure Scenarios

Disruption Scenario No	Part Type 1	Part Type 4	Part Type 5	Part Type 8	Part Type 11	Part Type 12	Failed Machine from Machine Group 1	Failed Machine from Machine Group 2	Failed Machine from Machine Group 3	Failed AGV
1	25%		25%	25%	25%					
	20%	20%	20%		20%	20%				
2	20%	20%	20%		20%	20%				
	25%		25%	25%	25%					
3							M1			
4							M6			
5								M2		
6								M5		
7									M3	
8									M7	
9										1

Thus, nine independent single even disruption scenarios plus one steady state scenario with 20 independent replications (except for part mix changes) per scenario can create 180 independent simulation runs. The total size of experiments can be increased as necessary by adding more independent replications under each scenario.

5.3 Summary

This chapter identifies ten major research tasks. A simulation tool, Extend, was selected to conduct a simulation study on the proposed FMS. MATLAB and MATLAB Neural Network Toolbox are used to construct ANNs components and the metamodel execution framework. It also identifies types of performance disruption events that can take place under the current operational environment by the hypothetical FMS. Only limited part mix, a single machine, or AGV failure is allowed to be a factor for disruption event scenarios. Based on these limited sources for performance disruption, an initial design of experiments was identified.

6. Problem Development – Pilot Experiments

The proposed modeling framework requires a carefully planned data collection of the selected performance index by the system. The successful construction of a good evaluative model lies on realistic data the model is derived from. We assume that such raw data can be acquired through an effective simulation model that can replicate realistic behaviors of the intended system. Structures and compositions of input and output vectors need for ANN training are identified. Data processing activities required to construct such input and target vector sets for the proposed taxonomically organized ANN are discussed in detail. This chapter closely examines modeling issues involved with creating a realistic simulation model. The configuration and training of individual ANNs and hierarchical modeling relationships among ANNs is also discussed.

6.1 Development of a Computer Simulation Model

The simulation model of the proposed FMS is written in Extend. Extend is a block diagram based simulation tool that allows a user to easily model a complex discrete/non-discrete event system in a relatively short amount of time compared to many conventional simulation modeling tools. It also provides unlimited hierarchical decompositions of a model, which helps the readability of a complex model. In addition, it provides simple animation and run-time block statistics monitoring capability that are useful for verification purposes.

The simulation model consists of three major functional components. The first functional component is to assign individual part attributes such as processing time (Table 7 on page 88) and relative part size (Table 5 on page 85). As shown in Figure 13, this functionality is built with a collection of modeling components such as Set Attributes, Get Attributes, and DE Outputs in a hierarchical structure. The second component is the part routing and AGV handling logic that control and regulate the movement of a loaded/unloaded fixture based on its common part process requirements and target machine center conditions.

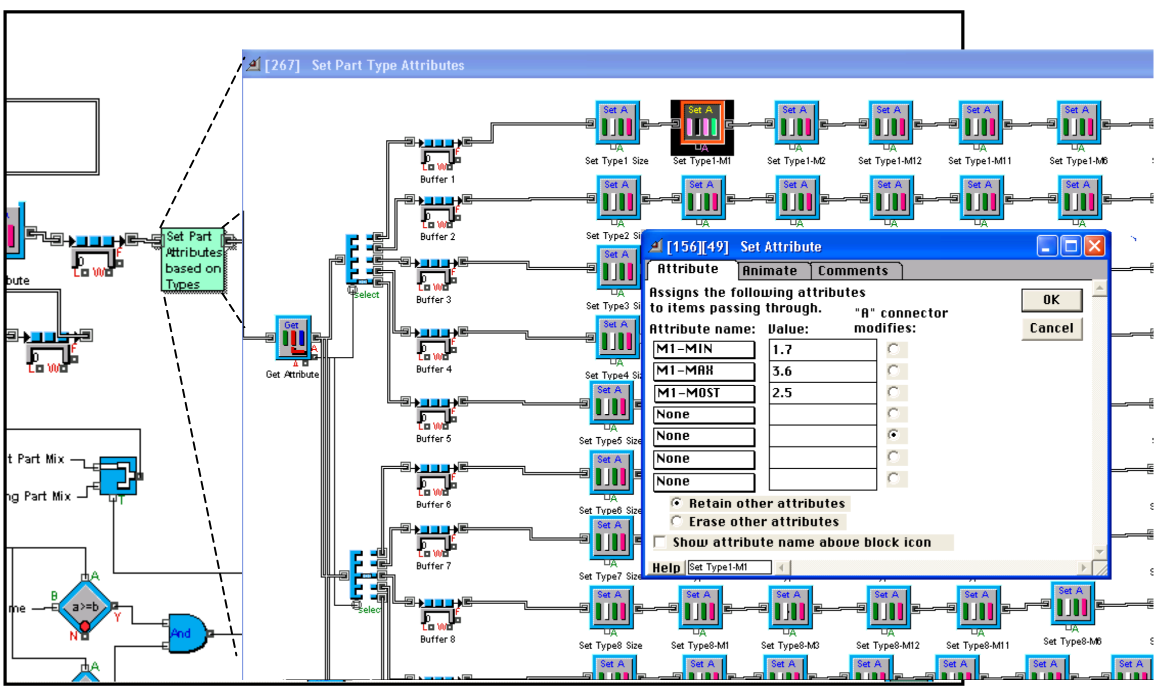


Figure 13. Set Part Type Attribute Block

As shown in Figure 14, the logic consists of various modeling components such as Select DE Output, Get Attributes, Decision, Logical OR, Logical AND, and Batch. The third component is the resource failure trigger mechanism that allows the user to select a single resource to fail and adjust timing and duration of the failure. As shown in Figure 15, this component consists of various modeling components such as Decision, Logical AND, and Logical OR.

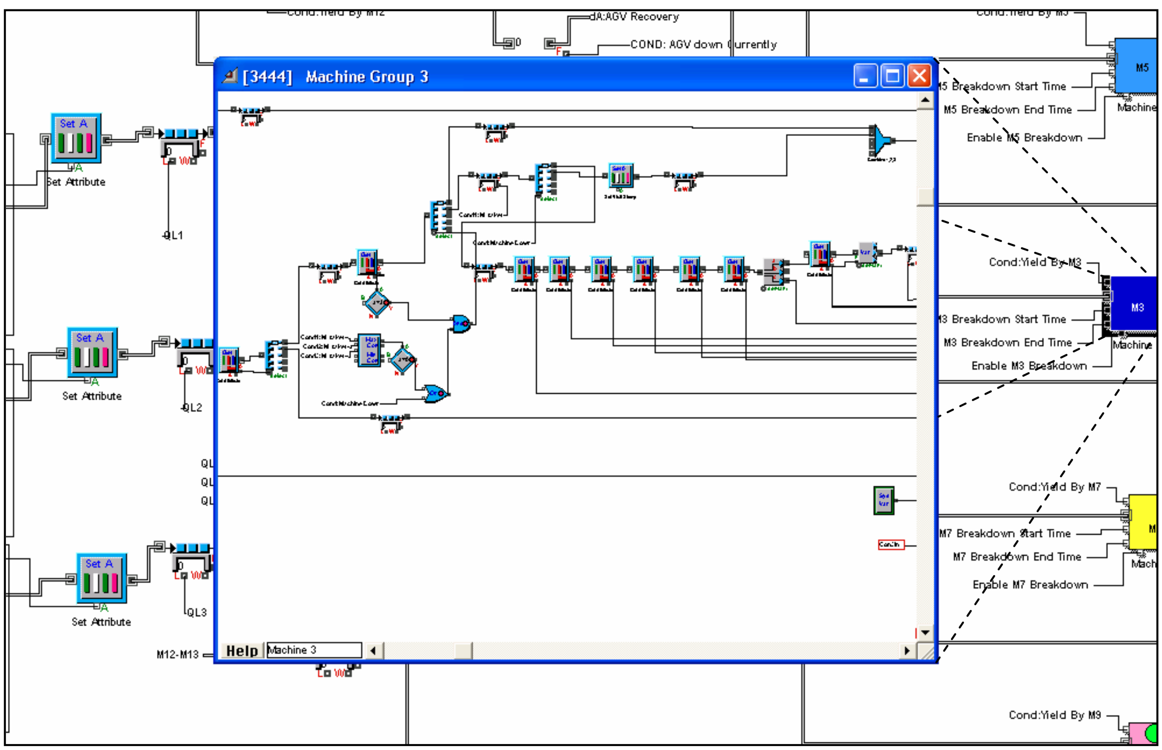


Figure 14. Part Routing and AGV Control Logic

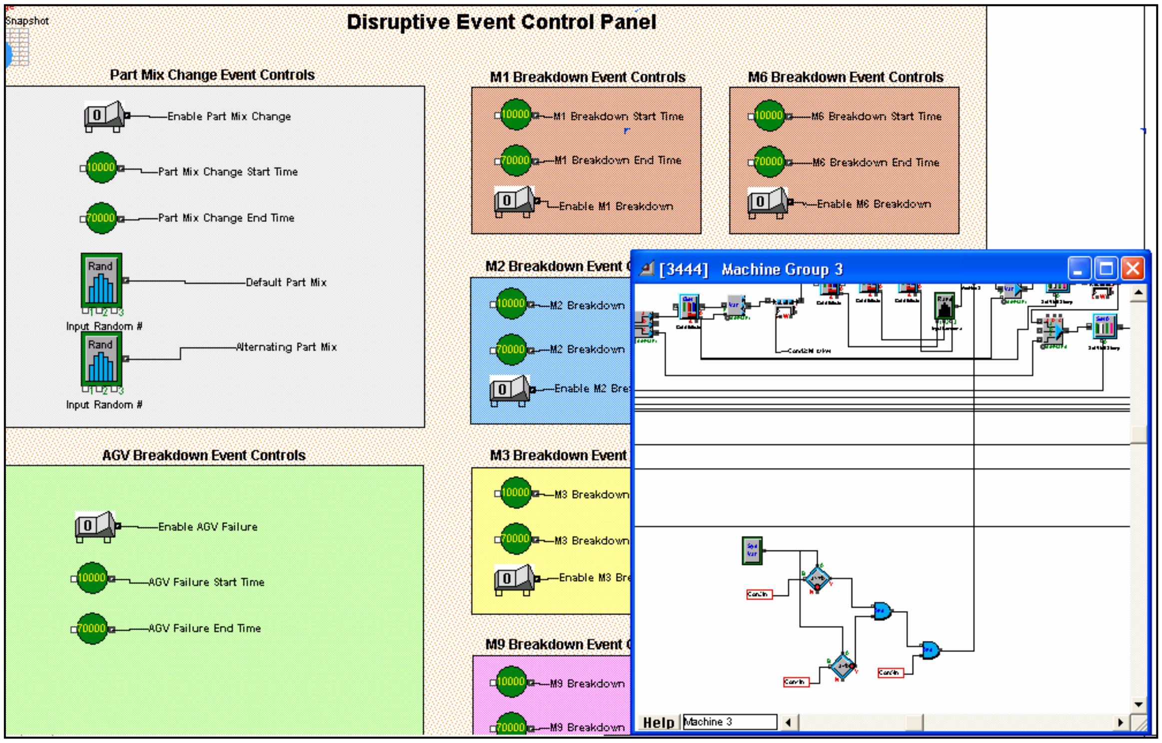


Figure 15. Single Resource Failure Scheduling and Control

6.2 Initial Experiments and Findings

To study the system wide best average utilization under selected steady state performance scenarios and develop control limits to detect the post-disruption impact, five independent non-terminating simulation runs will be executed for 70,000 minutes under four distinctive steady state operational settings. Because the simulation models starts from an empty and idle state, the presence of substantial warm-up periods in simulation results was examined under four different steady state operational scenarios. Welch's graphical method [Welch 1981; Law et al. 1991] was chosen to detect and remove the warm-up period from simulation results.

Results from the five replications of four individual no-disruption scenarios were averaged at individual observations to create four averaged time-in-system processes. It was difficult to find any visible signs of a warm up period from both raw and averaged time-in-system observation processes without applying a moving average filtration due to the high content of random noise among individual observations. Numerous moving average filtrations with various widths were applied to find a proper moving average width (or interval) that can minimize unwanted high frequency random noises without compromising the resolution for the low-frequency oscillations (long-run trend of interest). A moving average width of 50 observations was found to be good enough to detect a warm-up period on a limited initial data set from individual averaged time-in-system processes under four steady state scenarios. Even after applying moving average filtration with a width of 50 observations, four averaged TIS processes still exhibit a considerable amount of high-frequency noises. The length of the individual warm-up period from four moving average filtered mean TIS processes varies slightly.

As shown in Table 12, no warm-up period is greater than 130 observations. Later the study found a need for a greater moving average width to be applied on entire observations (about 30000 consecutive observations) from each averaged time-in-system processes. Therefore, the size of warm up period, 130 observations or less is found to be rather insignificant even compared to a newer moving average width of 500 observations. As result, the warm-up period from each pre-disruption data is to be ignored during this study.

Table 12. Four Steady State Scenarios and Their Warm-up Periods

Steady State Performance Scenario No	Part Mix Type	Mean Part Interarrival Time	Exp NO. (independent run #)	Warm-up Period Ends	
				Observation Count (from 1st observation)	Simulation Time in Minutes (from 0)
1	PM1	2.2	1 2 3 4 5	70	171.1136
2	PM1	2.3	91 92 93 94 95	100	240.5254
3	PM2	2.2	96 97 98 99 100	80	186.1029
4	PM2	2.3	101 102 103 104 105	65	153.117

Throughout the study a common single disruption event trigger time was chosen at 10,000 minutes because it is well beyond any potential influence by relatively small warm-up periods under four steady state scenarios. To approximate steady state means in TIS observations, the replication and deletion method has been used [Law and Kelton 1991]. Since the presence of a warm-up period was decided to be ignored, five independent replications of each steady state scenarios are averaged to approximate a corresponding steady state mean of TIS observations of parts in chronological order.

As shown in Figure 16, row TIS observations from a single realization contain a significant amount of high frequency noise due to unanticipated travels of parts within the model. In this time series (TIS observations), we are interested in detecting any low frequency oscillations or long-term trend rather than high frequency oscillations or noises in consecutive observations.

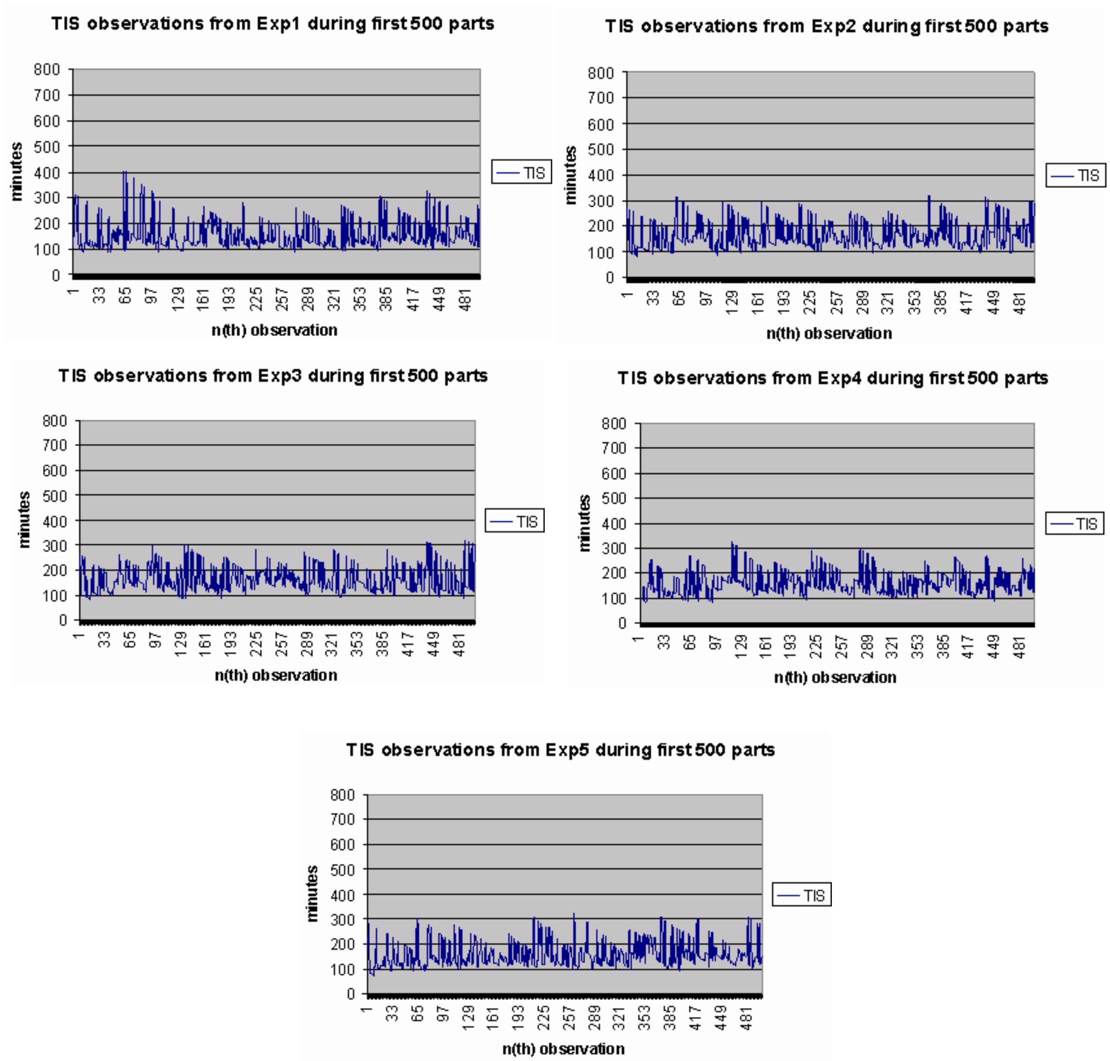


Figure 16. Row TIS Observations during First 500 Parts under the First Steady State Scenario with No Disruption

To smooth out these high-frequency oscillations in TIS observations, the moving average filtering technique has been used to treat raw TIS observations [Law and Kelton 1991]. A width (or interval) of moving average, $w = 500$, was selected through a trial and error method. The term width is used in place of the interval throughout the study. The criteria to select a proper width for the moving average filtering depends on a balancing act where a chosen moving average width will not oversimplify the long-term trend but smooth out high frequency noises.

A series of simulation experiments were performed to find two proper mean inter-arrival times. Initial pilot runs show that mean arrival times ranging between 1.8 and 2.5 show similar overall average utilization and performance without creating a infinite queue in front of the proposed system during the normal run without a disruption. Then an interval reduction technique was used to selectively screen potential mean arrival times so that a small set of essential mean arrival times between 1.8 and 2.5 can be tested in order to rule out any mean arrival time that can result in a post-disruption condition where every runs show either no changes or infinite growth of its queue length under all single disruptions. As result, mean part inter-arrival time 2.2 and 2.3 minutes were selected for steady state scenarios in order to facilitate an unknown optimal response surface area that exhibits both stable and unstable equilibrium characteristics in the event of a single performance disruption. Since each part type group has its own unique process requirements involving three different machine groups and no waiting queues are available in between the machining stations, the proposed FMS simulation model exhibits unique characteristics somewhat different than those that exist in typical closed queuing network models. Based on these unique operational characteristics and results from early test runs, an upper bound for the presumed optimal system wide utilization level is found to be lower than expected in theoretical queuing network models. Results from 20 independent pilot runs under four different steady state (no-disruption) scenarios in Table 13 show that the mean utilization over all eight machining stations averaged approximately 60% under four different steady state scenarios, which matches the result of queuing approximation estimate from the preliminary analysis in Chapter 3 page 89 thru 90. Results also show that two AGVs were utilized on average around 30% under steady state scenarios. Since two AGVs serve as necessary transporters as well as buffers among machining stations, it is not fair to judge the overall utilization solely based on individual machining stations. As result, the actual system utilization may be even higher than 60% on average.

In order to capture a diverse transient behavior population, an ideal system wide utilization level for this experiment must contain a substantial portion of “tipping points” that can lead to both unstable and stable state in the event of a single disruption. The control limits are used in this experiment to determine the approximate starting point of suspected post disruption behavior that is usually characterized as an obvious deviation from the pre-disruption steady state mean. Using three-sigma control limits is one way to detect that such deviation took place or is possibly underway in the current process.

$\overline{X}$ control limits can be constructed based on the assumption that $\overline{\overline{X}}$ and $\overline{R}$ are unbiased estimators for μ and σ of the steady state process. The lower and upper control limits for $\overline{X}$ can be found using A_2 where $A_2 = \dfrac{3}{d_2\sqrt{n}}$ and n is the size of subgroups.

Table 13. Individual System Resource Utilization Rates under Four Steady State Scenarios

Scenario No.	Exp No.	Time Average Resource Utilization										
		M1	M6	M2	M5	M3	M7	M9	M12	Mean	AGV	Fixture
1	1	0.67	0.50	0.49	0.31	0.78	0.72	0.75	0.66	*0.61*	0.41	0.62
	2	0.66	0.48	0.50	0.31	0.78	0.70	0.72	0.62	*0.60*	0.36	0.59
	3	0.68	0.49	0.51	0.29	0.78	0.72	0.74	0.66	*0.61*	0.41	0.62
	4	0.66	0.48	0.49	0.30	0.78	0.71	0.75	0.63	*0.60*	0.39	0.60
	5	0.65	0.49	0.49	0.32	0.77	0.70	0.72	0.63	*0.60*	0.35	0.59
	Mean	**0.66**	**0.49**	**0.50**	**0.31**	**0.78**	**0.71**	**0.74**	**0.64**	***0.60***	**0.38**	**0.60**
2	91	0.63	0.46	0.48	0.29	0.76	0.68	0.72	0.60	*0.58*	0.33	0.57
	92	0.65	0.47	0.47	0.29	0.77	0.70	0.73	0.63	*0.59*	0.36	0.58
	93	0.65	0.47	0.48	0.30	0.76	0.67	0.72	0.61	*0.58*	0.34	0.57
	94	0.65	0.46	0.48	0.29	0.76	0.68	0.72	0.62	*0.58*	0.34	0.57
	95	0.64	0.47	0.49	0.29	0.77	0.70	0.74	0.62	*0.59*	0.35	0.58
	Mean	**0.64**	**0.47**	**0.48**	**0.29**	**0.76**	**0.69**	**0.72**	**0.62**	***0.58***	**0.34**	**0.57**
3	96	0.57	0.34	0.72	0.64	0.66	0.47	0.81	0.71	*0.62*	0.44	0.64
	97	0.58	0.32	0.72	0.63	0.65	0.45	0.80	0.69	*0.60*	0.41	0.62
	98	0.57	0.33	0.72	0.63	0.66	0.46	0.82	0.70	*0.61*	0.45	0.64
	99	0.57	0.32	0.72	0.64	0.66	0.46	0.81	0.69	*0.61*	0.42	0.63
	100	0.57	0.32	0.71	0.64	0.66	0.45	0.80	0.69	*0.61*	0.42	0.62
	Mean	**0.57**	**0.32**	**0.72**	**0.64**	**0.66**	**0.46**	**0.81**	**0.70**	***0.61***	**0.43**	**0.63**
4	101	0.56	0.31	0.69	0.60	0.64	0.42	0.78	0.66	0.58	0.36	0.58
	102	0.55	0.31	0.70	0.59	0.64	0.42	0.79	0.65	0.58	0.36	0.58
	103	0.55	0.30	0.70	0.60	0.65	0.43	0.79	0.66	0.58	0.36	0.58
	104	0.56	0.31	0.69	0.61	0.64	0.41	0.78	0.66	0.58	0.36	0.58
	105	0.57	0.30	0.70	0.60	0.63	0.42	0.80	0.67	0.59	0.36	0.58
	Mean	**0.56**	**0.31**	**0.70**	**0.60**	**0.64**	**0.42**	**0.79**	**0.66**	***0.58***	**0.36**	**0.58**

A value for d_2 can be found in any statistical process control book. In this experiment, since the subgroup size n is 5, the value 2.326 can be found for d_2 from Table C of App.3. in Grant's book [Grant et al. 1988]. Thus, upper control limit (UCL) and lower control limit (LCL) for four steady state scenarios can be calculated as in Table 14. Table 14 summarizes the results of 20 pilot runs where unique combinations of mean inter-arrival time and type of part mix were tested with five independent runs.

Table 14. Four Steady State Scenarios and Their Control Limits

Steady State Performance Scenario No	**Part Mix Type**	**Mean Part Interarrival Time**	**Exp NO.** (independent run #)	**Mean TIS**	**UCI** (95%)	**LCI** (95%)	**UCL**	**LCL**
1	PM1	2.2	1 2 3 4 5	163.4984	164.3	162.6968	171.6962	155.3006
2	PM1	2.3	91 92 93 94 95	161.6357	162.2448	161.0266	166.8541	156.4173
3	PM2	2.2	96 97 98 99 100	149.9076	152.0061	147.809	159.2466	140.5685
4	PM2	2.3	101 102 103 104 105	147.2282	147.6567	146.7996	153.6755	140.7808

To find lower and upper bound values within the range of inter-arrival times, time between individual part arrivals were also tested during the pilot run. Figure 17 graphically shows results of five independent replications of the steady state scenarios number one

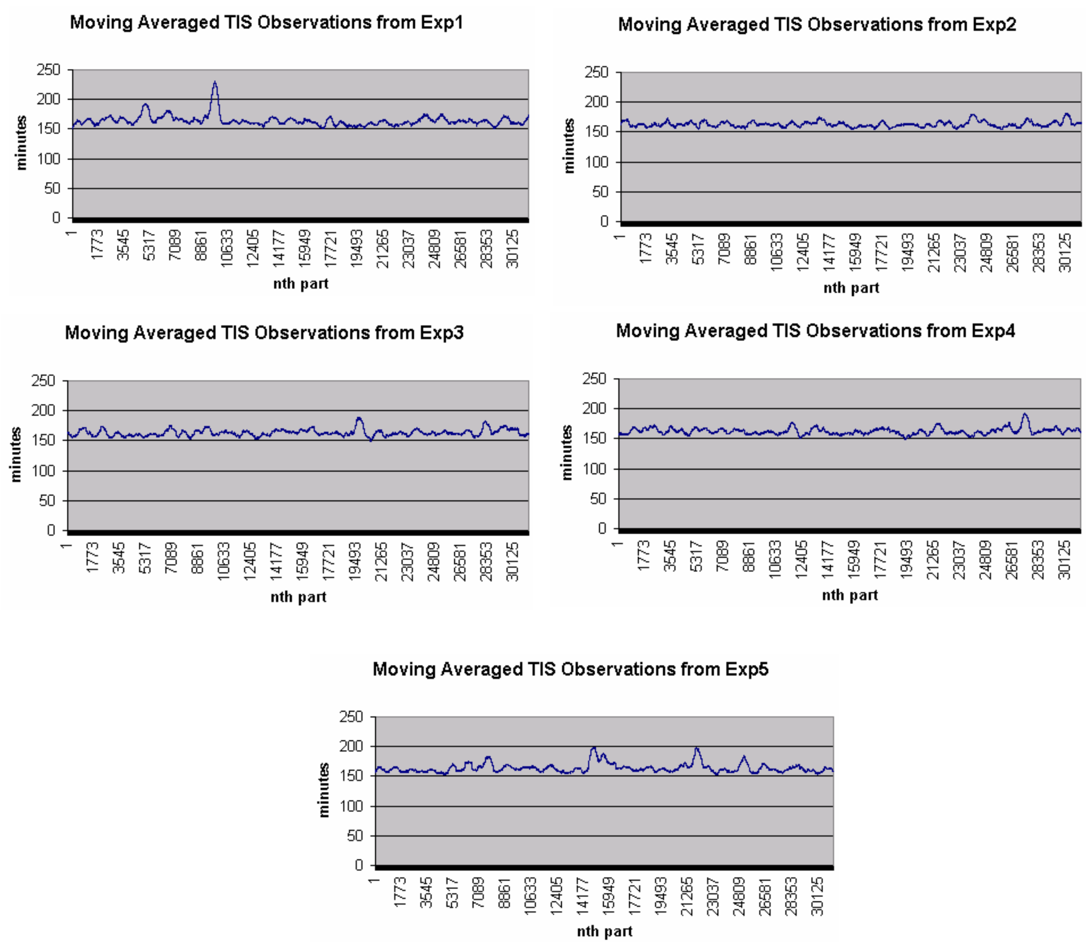


Figure 17. Moving Average Filtered TIS Observations under the First Steady State Scenario with No Disruption

The pilot results indicate that mean inter-arrival time 2.2 and 2.3 minutes are ideal values in order to exhibit both stable and unstable equilibrium transient behaviors under selected part mix Type 1 and 2. After finding UCL and LCL for each steady state scenario as criteria to decide the presence of any disruption impacts in their post-disruption behaviors, five independent replications of each disruption scenarios found in

Table 11 (see page 166 in Chapter 5) were conducted under four steady state scenarios as its pre-disruption condition.

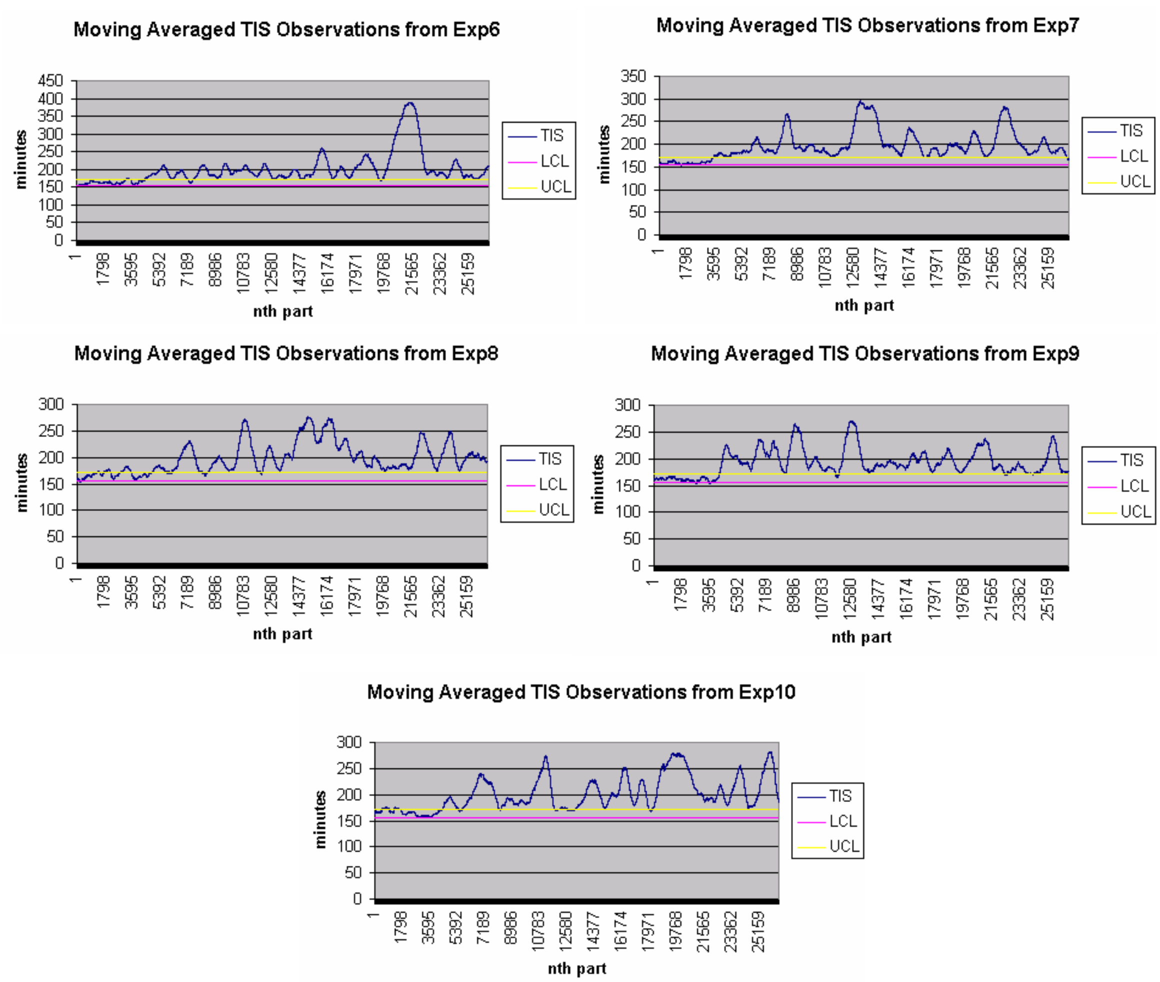


Figure 18. Moving Average Filtered TIS Observations under the First Steady State Scenario with Machine M6 Failure Took Place at 10000

For example, Figure 18 on the previous page shows five independent replications of the disruption scenario number four under the steady state scenario number one as its pre-disruption scenario. A point where the disruption behavior becomes apparent on each graph differs slightly since a number of parts processed at the end of 10,000 minutes vary from run to run due to the randomness of stochastic process.

6.3 Initial Simulation Experiment Sets and Data Processing Procedures

The final set of initial experiments is shown in Table 15. A total of 180 independent runs were conducted. Each run is marked with a unique experiment number that was assigned arbitrarily. After each run, key statistical indexes such as time-average utilizations of each resource before and after a scheduled disruption were recorded and TIS for each part accompanied by its entry time and departure time were generated and saved as a text file. The order in which values of individual TIS observations were saved was based on their departure time from the system.

There are two parts of data processing required in this study to construct an ANN based metamodel. The first part of data processing is called the pre-processing and is designed to prepare raw TIS observation data in a proper form to detect the presence of any transient behavior after the disruption and classify its behavior pattern. The second part is called the post-processing and is designed to extract essential mathematical properties from a formatted TIS observation data, such as variance changes, and to find coefficients of a designated parametric mathematical model, such as a polynomial.

Table 15. Initial Experiment Set

Scenario Index	Single Event Disruption Scenario (Triggered at 10000 minutes)			Steady State Scenario (pre-disruption)		Exp. No.
	Part Mix Change	Machine Breakdown	AGV Breakdown	Mean Interarrival Time (minutes)	Part Mix	
1	PM1 → PM2			2.2	PM1	11
	PM1 → PM2			2.2	PM1	12
	PM1 → PM2			2.2	PM1	13
	PM1 → PM2			2.2	PM1	14
	PM1 → PM2			2.2	PM1	15
2	PM1 → PM2			2.3	PM1	111
	PM1 → PM2			2.3	PM1	112
	PM1 → PM2			2.3	PM1	113
	PM1 → PM2			2.3	PM1	114
	PM1 → PM2			2.3	PM1	115
3	PM2 → PM1			2.2	PM2	56
	PM2 → PM1			2.2	PM2	57
	PM2 → PM1			2.2	PM2	58
	PM2 → PM1			2.2	PM2	59
	PM2 → PM1			2.2	PM2	60
4	PM2 → PM1			2.3	PM2	116
	PM2 → PM1			2.3	PM2	117
	PM2 → PM1			2.3	PM2	118
	PM2 → PM1			2.3	PM2	119
	PM2 → PM1			2.3	PM2	120
5			3 → 2	2.2	PM1	66
			3 → 2	2.2	PM1	67
			3 → 2	2.2	PM1	68
			3 → 2	2.2	PM1	69
			3 → 2	2.2	PM1	70
6			3 → 2	2.3	PM1	121
			3 → 2	2.3	PM1	122
			3 → 2	2.3	PM1	123
			3 → 2	2.3	PM1	124
			3 → 2	2.3	PM1	125
7			3 → 2	2.2	PM2	61
			3 → 2	2.2	PM2	62
			3 → 2	2.2	PM2	63
			3 → 2	2.2	PM2	64
			3 → 2	2.2	PM2	65
8			3 → 2	2.3	PM2	126
			3 → 2	2.3	PM2	127
			3 → 2	2.3	PM2	128
			3 → 2	2.3	PM2	129
			3 → 2	2.3	PM2	130

Table 15 (continued). Initial Experiment Set

Scenario Index	Single Event Disruption Scenario (Triggered at 10000 minutes)			Steady State Scenario (pre-disruption)		Exp. No.
	Part Mix Change	Machine Breakdown	AGV Breakdown	Mean Interarrival Time (minutes)	Part Mix	
9		M1		2.2	PM1	16
		M1		2.2	PM1	17
		M1		2.2	PM1	18
		M1		2.2	PM1	19
		M1		2.2	PM1	20
10		M1		2.3	PM1	131
		M1		2.3	PM1	132
		M1		2.3	PM1	133
		M1		2.3	PM1	134
		M1		2.3	PM1	135
11		M1		2.2	PM2	21
		M1		2.2	PM2	22
		M1		2.2	PM2	23
		M1		2.2	PM2	24
		M1		2.2	PM2	25
12		M1		2.3	PM2	136
		M1		2.3	PM2	137
		M1		2.3	PM2	138
		M1		2.3	PM2	139
		M1		2.3	PM2	140
13		M6		2.2	PM1	6
		M6		2.2	PM1	7
		M6		2.2	PM1	8
		M6		2.2	PM1	9
		M6		2.2	PM1	10
14		M6		2.3	PM1	141
		M6		2.3	PM1	142
		M6		2.3	PM1	143
		M6		2.3	PM1	144
		M6		2.3	PM1	145
15		M6		2.2	PM2	71
		M6		2.2	PM2	72
		M6		2.2	PM2	73
		M6		2.2	PM2	74
		M6		2.2	PM2	75
16		M6		2.3	PM2	106
		M6		2.3	PM2	107
		M6		2.3	PM2	108
		M6		2.3	PM2	109
		M6		2.3	PM2	110
17		M2		2.2	PM1	46
		M2		2.2	PM1	47
		M2		2.2	PM1	48
		M2		2.2	PM1	49
		M2		2.2	PM1	50

Table 15 (continued). Initial Experiment Set

Scenario Index	Single Event Disruption Scenario (Triggered at 10000 minutes)			Steady State Scenario (pre-disruption)		Exp. No.
	Part Mix Change	Machine Breakdown	AGV Breakdown	Mean Interarrival Time (minutes)	Part Mix	
18		M2		2.3	PM1	146
		M2		2.3	PM1	147
		M2		2.3	PM1	148
		M2		2.3	PM1	149
		M2		2.3	PM1	150
19		M2		2.2	PM2	26
		M2		2.2	PM2	27
		M2		2.2	PM2	28
		M2		2.2	PM2	29
		M2		2.2	PM2	30
20		M2		2.3	PM2	151
		M2		2.3	PM2	152
		M2		2.3	PM2	153
		M2		2.3	PM2	154
		M2		2.3	PM2	155
21		M5		2.2	PM1	51
		M5		2.2	PM1	52
		M5		2.2	PM1	53
		M5		2.2	PM1	54
		M5		2.2	PM1	55
22		M5		2.3	PM1	156
		M5		2.3	PM1	157
		M5		2.3	PM1	158
		M5		2.3	PM1	159
		M5		2.3	PM1	160
23		M5		2.2	PM2	31
		M5		2.2	PM2	32
		M5		2.2	PM2	33
		M5		2.2	PM2	34
		M5		2.2	PM2	35
24		M5		2.3	PM2	161
		M5		2.3	PM2	162
		M5		2.3	PM2	163
		M5		2.3	PM2	164
		M5		2.3	PM2	165
25		M3		2.2	PM1	76
		M3		2.2	PM1	77
		M3		2.2	PM1	78
		M3		2.2	PM1	79
		M3		2.2	PM1	80
26		M3		2.3	PM1	166
		M3		2.3	PM1	167
		M3		2.3	PM1	168
		M3		2.3	PM1	169
		M3		2.3	PM1	170

Table 15 (continued). Initial Experiment Set

Scenario Index	Single Event Disruption Scenario (Triggered at 10000 minutes)			Steady State Scenario (pre-disruption)		Exp. No.
	Part Mix Change	Machine Breakdown	AGV Breakdown	Mean Interarrival Time (minutes)	Part Mix	
27		M3		2.2	PM2	36
		M3		2.2	PM2	37
		M3		2.2	PM2	38
		M3		2.2	PM2	39
		M3		2.2	PM2	40
28		M3		2.3	PM2	171
		M3		2.3	PM2	172
		M3		2.3	PM2	173
		M3		2.3	PM2	174
		M3		2.3	PM2	175
29		M7		2.2	PM1	81
		M7		2.2	PM1	82
		M7		2.2	PM1	83
		M7		2.2	PM1	84
		M7		2.2	PM1	85
30		M7		2.3	PM1	86
		M7		2.3	PM1	87
		M7		2.3	PM1	88
		M7		2.3	PM1	89
		M7		2.3	PM1	90
31		M7		2.2	PM2	41
		M7		2.2	PM2	42
		M7		2.2	PM2	43
		M7		2.2	PM2	44
		M7		2.2	PM2	45
32		M7		2.3	PM2	176
		M7		2.3	PM2	177
		M7		2.3	PM2	178
		M7		2.3	PM2	179
		M7		2.3	PM2	180
33				2.2	PM1	1
				2.2	PM1	2
				2.2	PM1	3
				2.2	PM1	4
				2.2	PM1	5
34				2.3	PM1	91
				2.3	PM1	92
				2.3	PM1	93
				2.3	PM1	94
				2.3	PM1	95
35				2.2	PM2	96
				2.2	PM2	97
				2.2	PM2	98
				2.2	PM2	99
				2.2	PM2	100

Table 15 (continued). Initial Experiment Set

Scenario Index	Single Event Disruption Scenario (Triggered at 10000 minutes)			Steady State Scenario (pre-disruption)		Exp. No.
	Part Mix Change	Machine Breakdown	AGV Breakdown	Mean Interarrival Time (minutes)	Part Mix	
36				2.3	PM2	101
				2.3	PM2	102
				2.3	PM2	103
				2.3	PM2	104
				2.3	PM2	105

During the pre-processing process, individual TIS values from a single simulation run were sorted again based on a part's arrival time rather than their departure time. Then TIS observation time series from five independent replications under the same disruption scenario are averaged to get a stochastic process of $\overline{Y}_j$ for $1 \ldots m$ observations where $\overline{Y}_j = \dfrac{Y_{ij}}{n}$ for $i = 1 \ldots n$ independent replications and $Y_{ij} = j$ th observation of TIS in the i th independent replication. This procedure is similar to one from Welch's graphical procedure to detect and eliminate a warm up period from a stochastic process. A moving average filtering is also applied to smooth out any noise found in the time series of mean TIS observations at observation t from five independent simulation replications under a single disruption scenario.

To avoid oversimplification of any major low frequency trends that may exist in the mean TIS time series, plots of unfiltered TIS time series and corresponding MA filtered TIS time series with a width of 500 observations were compared. This process helps the modeler to visually verify the overall resemblance of any major trends existing in filtered and unfiltered observation processes, which also verifies a proper width for the moving average filtering.

If the comparison shows no sign of over-filtering, then corresponding control limits are applied to detect that a transient behavior exists in the moving average filtered mean TIS data. Such plots can be shown as in Figure 18 (see page 180) for both moving average filtered mean TIS data and control limits found from the corresponding steady state scenario. A presumed starting point for the probable transient behavior can be identified using these three plots. Figure 19 summarizes the sequence of pre-processing steps designed for stochastic mean TIS data from independent simulation replications under individual disruption scenarios throughout the rest of this study. The post-processing will be discussed in the following section.

6.4 Post Disruption Behavior Pattern Classification

After conducting 180 independent simulation runs (36 disruption scenarios $\times$ five independent replications of each scenario) and necessary pre-processing on stochastic mean TIS data, individual plots for moving average filtered mean TIS time series are carefully studied to identify common transient behavior patterns among them after a single event disruption.

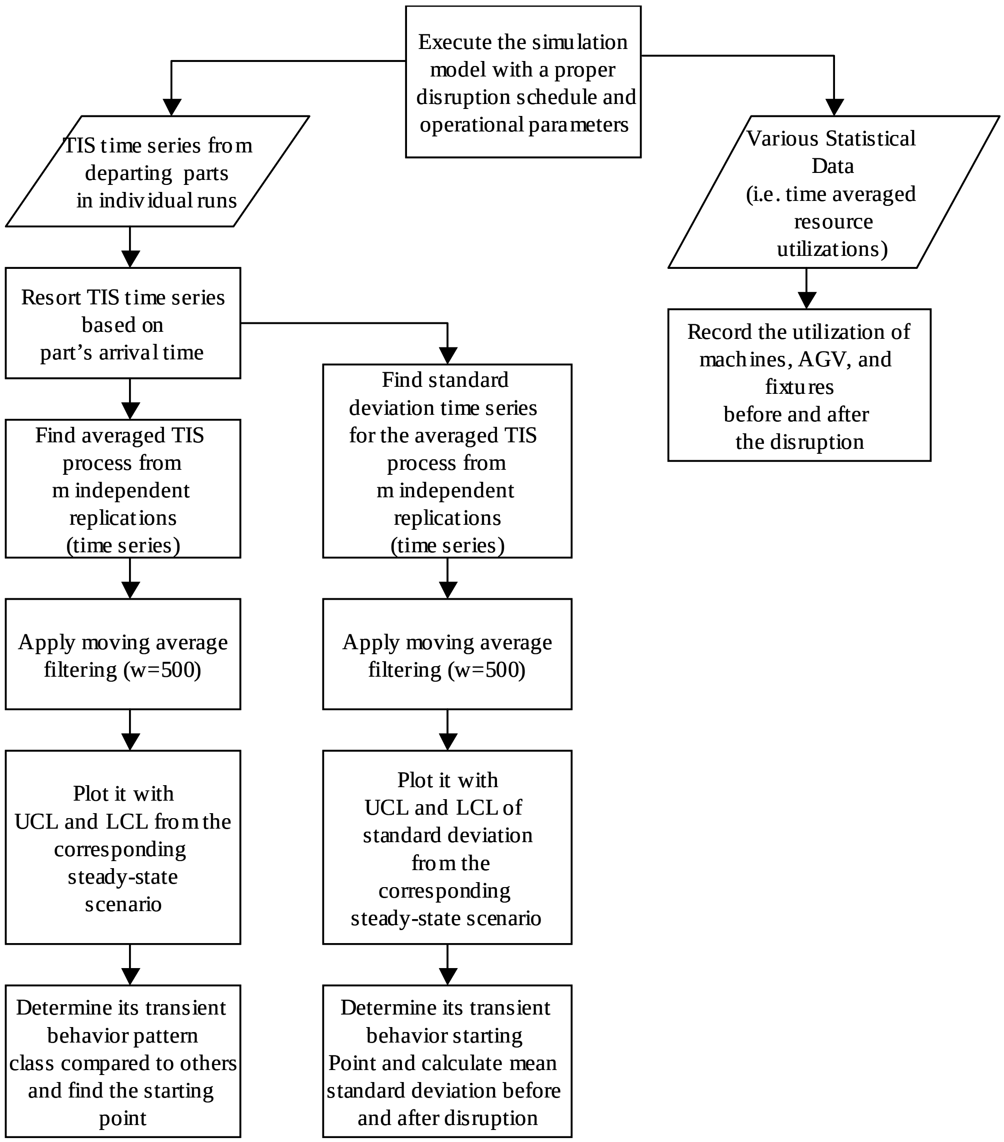


Figure 19. Pre-process Steps

Grouping various post disruption transient behaviors into several distinctive pattern classes is necessary to construct a proper ANN based metamodel. By doing so, it helps identify both a functional domain and functional range of an unknown transient behavior prediction function, which is a crucial step in constructing a training set for the ANN based modeling. In addition, key mathematical properties such as the highest order of a proper polynomial can be identified and factored into the construction of proper baseline parametric models.

During the post-process, each filtered mean TIS time series is used to approximate a selected mathematical parametric function for the selected pattern class. Selected mathematical parametric functions can be polynomial, exponential, or logarithmic. Approximated coefficients of the selected parametric function can be used to construct a corresponding target output vector for the designated ANN based metamodel.

Initial findings indicate that there are four different major types of post-disruption transient behavior that exist among the 180 independent TIS observation time series. For this study, the number of post-disruption transient behavior patterns was not solely determined by its graphical distinctiveness but rather driven by their mathematical modeling needs and efficiency. For example, even though there may be more than one type of transient behavior pattern that exists under a pattern class based on their graphical distinctiveness, the need for using the same order of univariate polynomial regression model forces them to be under the same transient behavior pattern class.

Type 0 pattern class as shown in Figure 20 is a collection of transient patterns where there is no visible sign of change in their post-disruption mean TIS stochastic patterns. In other words, there is no shift in the trend of the process (average TIS). For this type of post-disruption transient behaviors, the system may have operated near the stable equilibrium system condition during the pre-disruption period. The unique combination of each resource conditions (idle or not idle) followed by a sequence of system events before and after the time of scheduled resource failure can characterize these pre-disruption system conditions such as unstable/stable equilibrium.

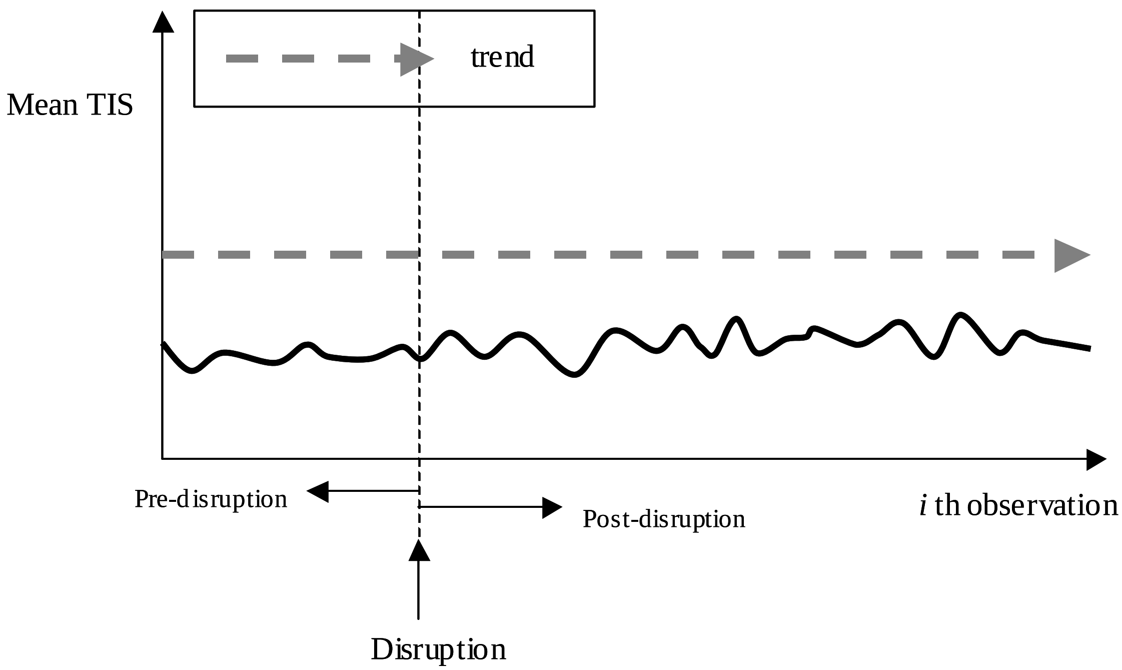


Figure 20. Type 0 (no change) Transient Behavior Pattern Class

Type 1 pattern class as shown in Figure 21 is a collection of transient patterns where there is a clear indication of an infinite linear growth by the target performance index during a post-disruption period. This type of post-disruption behavior may result from the near-unstable equilibrium system condition during the pre-disruption period.

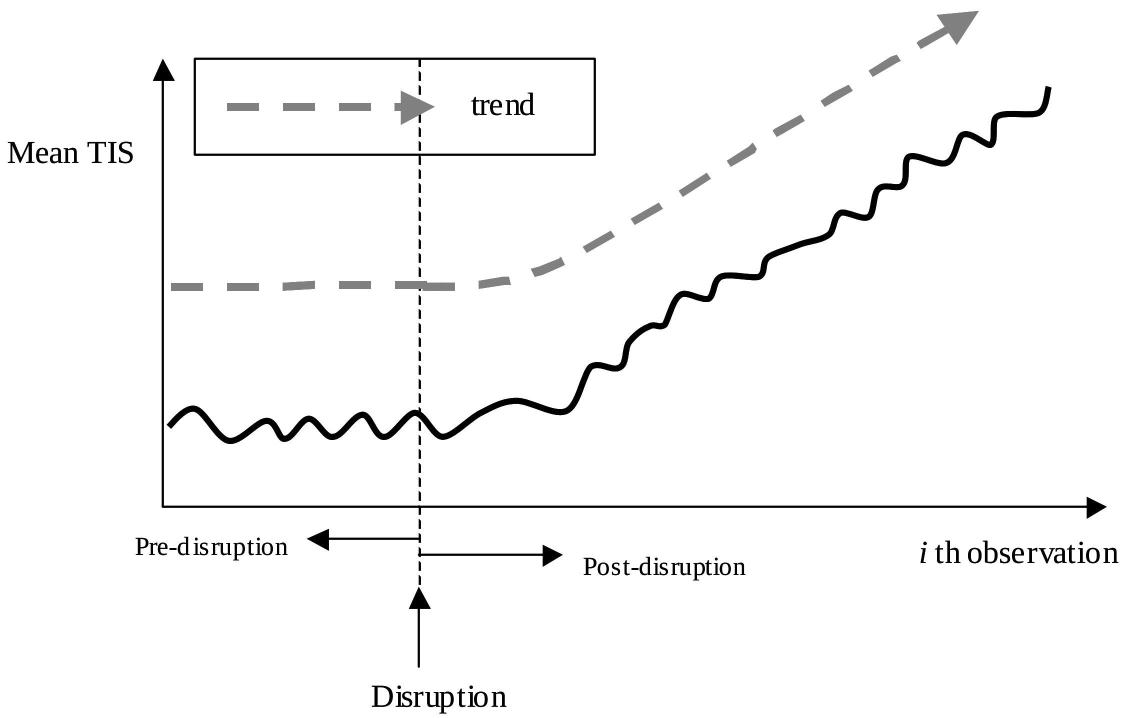


Figure 21. Type 1 (an infinite linear growth) Transient Behavior Pattern Class

Type 2 pattern class, as shown in Figure 22, is a collection of transient patterns where there is a clear indication of an infinite non-linear growth by the target performance index in post-disruption behavior. This type of post-disruption behavior may result from the near-unstable equilibrium system condition during the pre-disruption period.

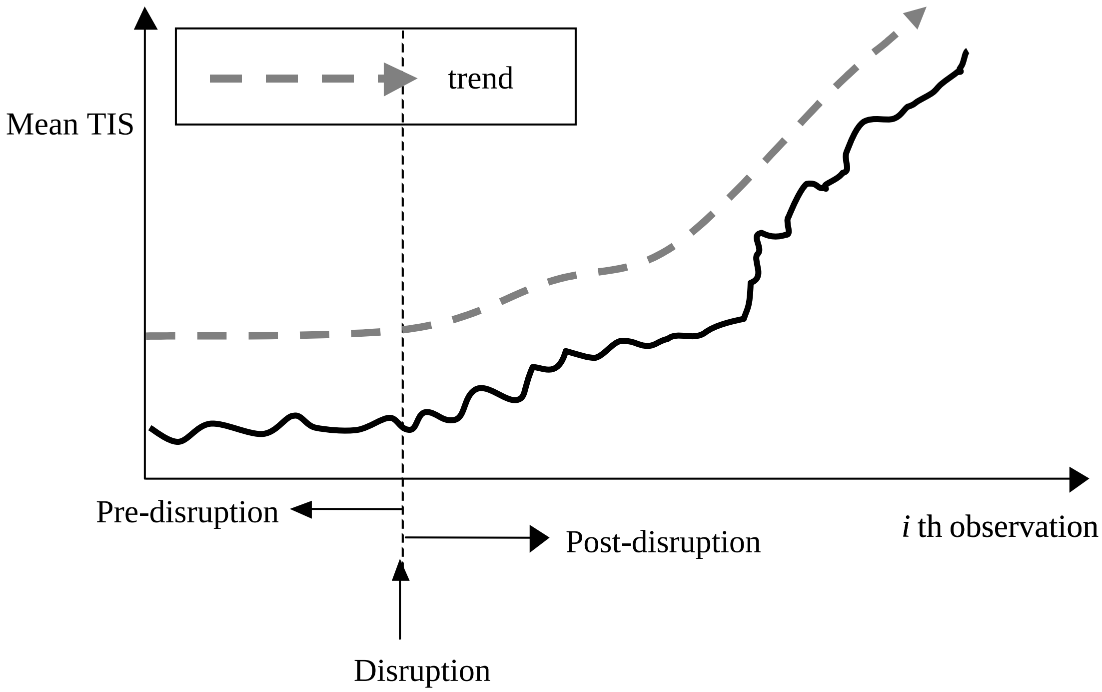


Figure 22. Type 2 (an infinite non-linear growth) Transient Behavior Pattern Class

Type 3 pattern class as shown in Figure 23 is a collection of transient patterns where there is a clear indication of a temporary finite non-linear growth followed by stabilization to a new steady state during its post-disruption period. This type of post-disruption behavior can be resulted by the near-stable equilibrium during the pre-disruption period.

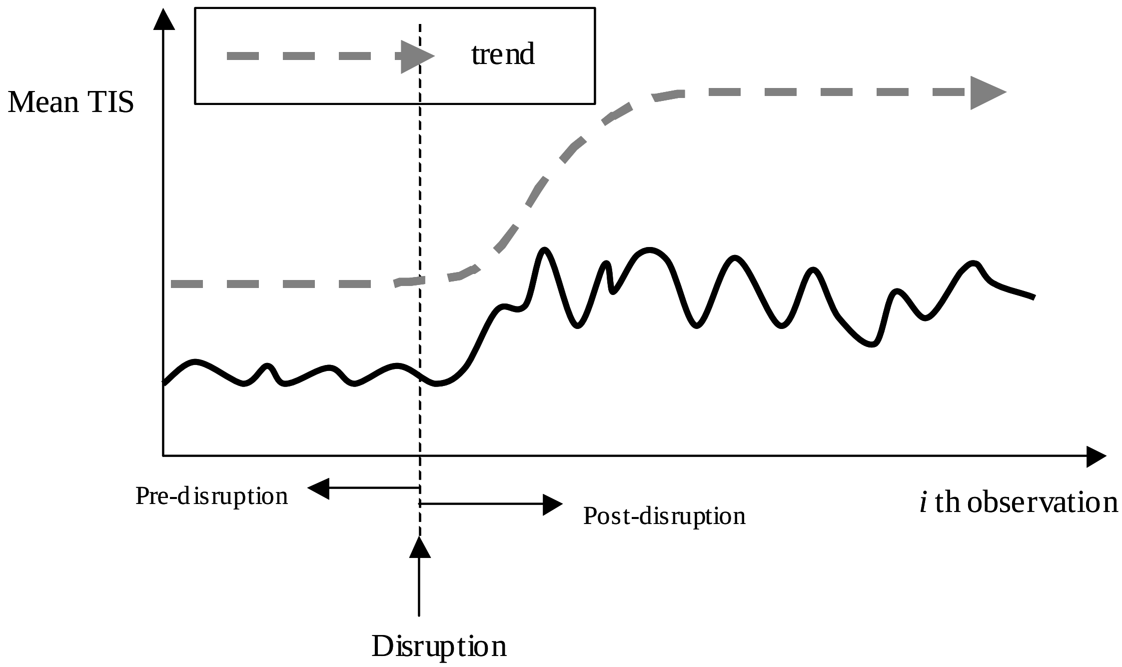


Figure 23. Type 3 (a finite growth to a new steady state) Transient Behavior Pattern Class

After 180 individual runs, the makeup of four transient behavior patterns among resulting MA filtered mean TIS time series was found and is shown in Table 16. As can be seen from the table, every post-disruption transient behavior accompanies a form of deviation from their pre-disruption TIS means. Scenario 33, 34, 35 and 36 are steady state scenarios without a disruption.

Table 16. Makeup for Four Transient Pattern Types

Transient Pattern Type	% Makeup from 36 scenarios (total 180 independent runs)	Scenarios Index No
Type 0 – "no change"	11%	33, 34, 35, 36
Type 1 – "an infinite linear growth"	22%	19, 20, 25, 26, 27, 28, 29, 30
Type 2 – "an infinite non-linear growth"	11%	7, 15, 31, 32
Type 3 – "a finite growth to a new steady state"	56%	1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 16, 17, 18, 21, 22, 23, 24

The structure for both input (functional domain) and output (functional range) vector spaces for each transient behavior pattern type had to be individually identified in order to map input and output spaces of an unknown transient performance prediction function. As one of the assumptions for this study states, the primary index of interest is average time-in-system (TIS) of departing parts. Thus, the majority of vector elements in the output vectors are used to capture functional characteristics of an unknown transient TIS time series during the 10,000 minutes time horizon after a single disruption.

We can closely examine the process of determining the transient behavior pattern type for scenario No.19 consisting of independent experiments 26, 27, 28, 29, and 30 as an example. The five moving average (w = 500) filtered TIS data plots of the independent simulation replications, Exp.26, 27, 28, 29, and 30 under scenarios No.19 in Figure 24 clearly show a distinctive infinite linear growth in four out of five plots. Only Exp.30 shows a different pattern, a finite growth to a new steady state.

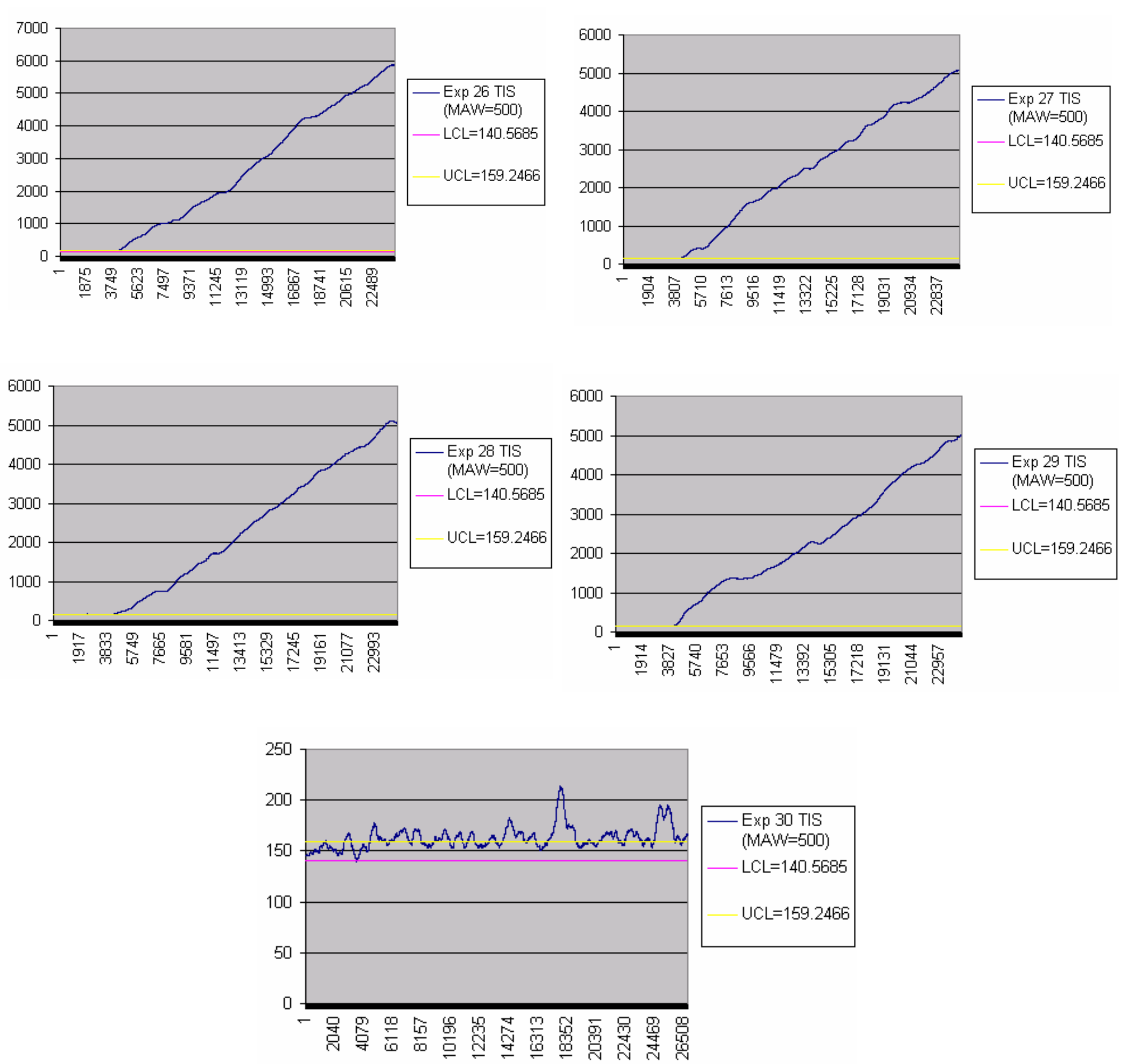


Figure 24. Individual Moving Average Filtered TIS plots under Scenario No.19

Using the entire data points collected during the first 10,000 minutes after a disruption event is a computationally inefficient way to construct a regression model. Especially when neighboring data points from a substantially smaller time window than

10,000 minutes contains no significant seasonal patterns but rather they are noisy and redundant. Fewer data points can replace the entire set of data to construct a relatively realistic regression based model without causing a computational burden.

A proper width of sampling interval was carefully selected through several different disruption scenarios so that a resulting regression model with fewer data points would not inhibit any major frequency trends in a given time series. Throughout this study, a width of 100 data points has been selected as a sampling interval for data reduction. Every 100th point of the moving average filtered mean TIS values from the point of disruption to 10,000 minutes is collected to estimate an unknown polynomial function of relative time index X ,

$X = \{x_i \mid x_i = x_{i-1} + \Delta x \text{ where } \Delta x \text{ is a constant and } i = 0 \ldots n\}$.

In Figure 25, the plot of a moving average (w=500) filtered time series of mean TIS from the five independent replications clearly shows an infinite linear growth. Thus, the overall transient pattern type for Scenario No.19 is considered an infinite linear growth type.

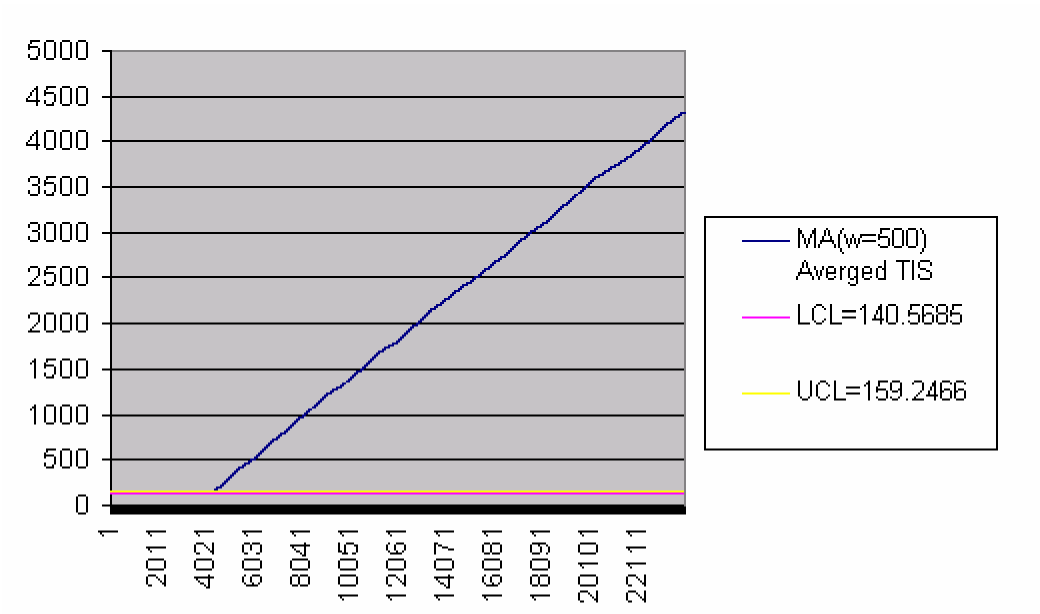


Figure 25. Moving Average Filtered Mean TIS Plots under Scenario No.19

A close-up view of the plot of every 100th MA filtered mean TIS observations after the point of disruption in Figure 26 shows a sign of slight non-linear trend during first 300 observations after which the disruption follows a linear trend. This phenomenon was found in all Type 1 behaviors. After a certain number of initial observations, the trend maintains its linearity throughout remaining observations. Therefore, the post-transient behavior for Type 1 can be modeled with a two-phase function that consists of two regression-based functions covering two different observation periods.

The first one is a second-order polynomial (quadratic) during a given number of initial observations and the second one is a linear function for the remaining observations.

These two regression-based functions can be mathematically found using a regression of Y (time-in-system) on X (number of observations since $\Delta x \equiv 1$).

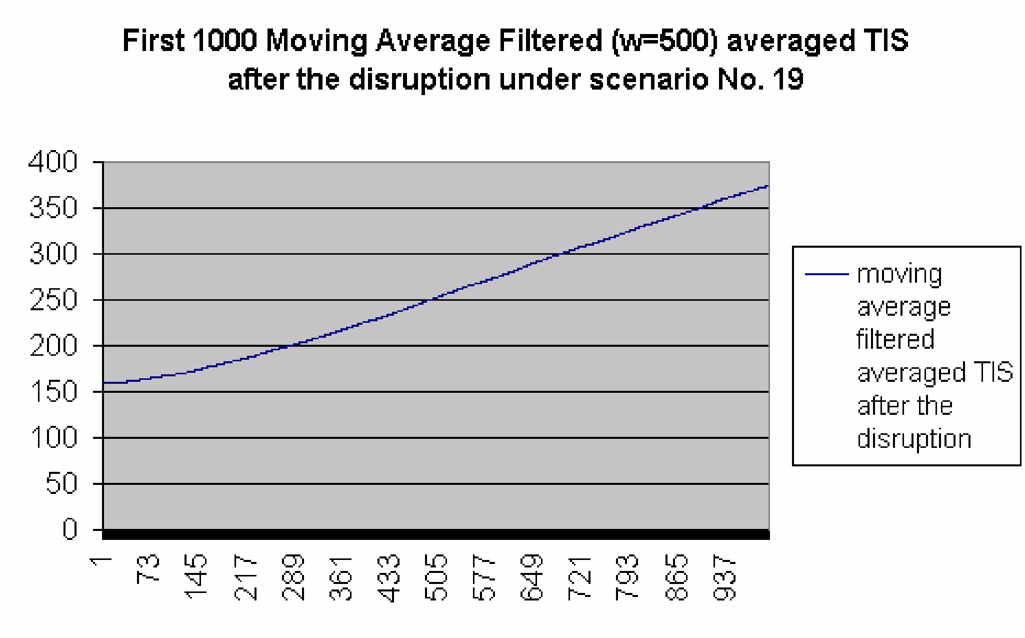


Figure 26. A Close-up View of Moving Average Filtered Mean TIS Plots under Scenario No.19

For higher order polynomial regressions, computational simplicity and a balanced growth of polynomial coefficients during the approximation are two key factors to determine the proper size of Δx of X. By selecting the proper size of Δx, we can avoid a large variations among individual coefficients of unknown high order polynomial during approximation, which in turn will result in a better training performance for the ANN based metamodeling approach.

For a relatively simple implementation and future automation purpose, the polynomial regression was selected to approximate all three post-disruption transient behaviors. A single nth order polynomial or combination of more than one polynomial functions in a multiphased functional form was used to capture each post-disruption transient behavior.

6.5 Identification of Input and Output Vectors

The input and output vectors for the unknown ANN based transient performance function need to be identified. As the proposed ANN based meta-modeling scheme was briefly discussed in 3.3.3, it consists of several multilayer ANNs that logically comprise a hierarchical modeling taxonomy. Each ANN has its own location in the hierarchy to independently or dependently map a different part of the functional domain to a group of corresponding target values.

As shown in Figure 11 (see page 146 in Chapter 3), the top level multilayer ANN is designed to detect and classify major post-disruption patterns existing in TIS of departing parts. A series of ANNs position in the second level is to provide an actual performance model of interest. The final design layout of the proposed hierarchically organized ANN based transient system performance modeling framework is detailed in later in this chapter (refer to Figure 27 on page 211).

A single configuration for input vectors is used in this experiment. The design goal of input vector is to differentiate various pre-disruption system conditions that result in the same post-disruption system behavior pattern. Input vector, $\mathbf{p}$, consists of 44 elements that are designed to feed the ANNs in both top and second levels with a snapshot of the pre-disruption system condition such as time average machine utilizations as well as the type of disruption itself. The configuration of the 44×1 input vector is illustrated as follows:

A common input vector $\mathbf{p}$ is such that

$$\mathbf{p} = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_{44} \end{bmatrix} \text{ where } p_1,\ p_2,\ \dots\ p_{44} \text{ are as shown in Table 16.}$$

Exemplary vector elements used in Table 17 indicate that a single event disruption was triggered by a machine center M1 failure. It also shows that the current disruption scenario is based on a steady state with the mean part arrival time of 2.2 minutes and part mix Type 2. Even though the main configuration of output vector carries the same vector space organization, the length and location of individual vector elements may differ based on the characteristics of a selected approximation function for the given transient behavior pattern type.

Table 17. Semantics of Common Input Vector p

Vector Element	Description	*Example*
p_1	Mean Arrival Time of Parts (2.2 or 2.3 minutes)	2.2
p_2	M1 Time Average Utilization prior to a disruptive event (1/100%)	0.5589
p_3	M6 Time Average Utilization prior to a disruptive event (1/100%)	0.3312
p_4	M2 Time Average Utilization prior to a disruptive event (1/100%)	0.7297
p_5	M5 Time Average Utilization prior to a disruptive event (1/100%)	0.6565
p_6	M3 Time Average Utilization prior to a disruptive event (1/100%)	0.6649
p_7	M7 Time Average Utilization prior to a disruptive event (1/100%)	0.4577
p_8	M9 Time Average Utilization prior to a disruptive event (1/100%)	0.813
p_9	M12 Time Average Utilization prior to a disruptive event (1/100%)	0.6984
p_{10}	AGV Time Average Utilization prior to a disruptive event (1/100%)	0.4527
p_{11}	Fixture Time Average Utilization prior to a disruptive event (1/100%)	0.6411
p_{12}	Start% Makeup of Part Type1 (1/100%)	0.2
p_{13}	Start% Makeup of Part Type2 (1/100%)	0
p_{14}	Start% Makeup of Part Type3 (1/100%)	0
p_{15}	Start% Makeup of Part Type4 (1/100%)	0.2
p_{16}	Start% Makeup of Part Type5 (1/100%)	0.2
p_{17}	Start% Makeup of Part Type6 (1/100%)	0
p_{18}	Start% Makeup of Part Type7 (1/100%)	0
p_{19}	Start% Makeup of Part Type8 (1/100%)	0
p_{20}	Start% Makeup of Part Type9 (1/100%)	0
p_{21}	Start% Makeup of Part Type10 (1/100%)	0
p_{22}	Start% Makeup of Part Type11 (1/100%)	0.2
p_{23}	Start% Makeup of Part Type12 (1/100%)	0.2
p_{24}	% Change in Part Type1 (1/100%)	0
p_{25}	% Change in Part Type2 (1/100%)	0
p_{26}	% Change in Part Type3 (1/100%)	0
p_{27}	% Change in Part Type4 (1/100%)	0
p_{28}	% Change in Part Type5 (1/100%)	0
p_{29}	% Change in Part Type6 (1/100%)	0
p_{30}	% Change in Part Type7 (1/100%)	0
p_{31}	% Change in Part Type8 (1/100%)	0

Table 17 (continued). Semantics of Common Input Vector p

p_{32}	% Change in Part Type9 (1/100%)	0
p_{33}	% Change in Part Type10 (1/100%)	0
p_{34}	% Change in Part Type11 (1/100%)	0
p_{35}	% Change in Part Type12 (1/100%)	0
p_{36}	Status of M1 Failure (0 = false; 1 = true)	1
p_{37}	Status of M6 Failure (0 = false; 1 = true)	0
p_{38}	Status of M2 Failure (0 = false; 1 = true)	0
p_{39}	Status of M5 Failure (0 = false; 1 = true)	0
p_{40}	Status of M3 Failure (0 = false; 1 = true)	0
p_{41}	Status of M7 Failure (0 = false; 1 = true)	0
p_{42}	Status of M9 Failure (0 = false; 1 = true)	0
p_{43}	Status of M12 Failure (0 = false; 1 = true)	0
p_{44}	Status of Single AGV Failure (0 = false; 1 = true)	0

Since there are only four major transient behavior pattern classes identified in this study, output vector $\mathbf{a}^1$ for the top level ANN is designed to capture class numbers in two digit binary numbers such as 00_2, 01_2, 10_2, and 11_2. Output vector $\mathbf{a}^1$ is such that $\mathbf{a}^1 = \begin{bmatrix} a_1^1 \\ a_2^1 \end{bmatrix}$ where individual elements, a_1^1 and a_2^1, can be summarized in Table 18.

Table 18. Semantics of First Output Vector $\mathbf{a}^1$ from the Top Level ANN

Vector Element	Description	*Example*
a_1^1	Coefficient c_0 of two digit binary number $c_1c_{0(2)} = c_1 \times 2^1 + c_0 \times 2^0$ to represent a post-disruption transient behavior pattern type	1
a_2^1	Coefficient c_1 of two digit binary number $c_1c_{0(2)} = c_1 \times 2^1 + c_0 \times 2^0$ to represent a post-disruption transient behavior pattern type	1

In order to satisfy Research Object No. 2 identified in Chapter 3, the following output vectors for the three different transient behavior pattern types were carefully designed. Output vectors for the second level ANNs were designed to capture detail functional information about the primary performance index as well as performance changes in other indexes of choice such as time-average utilization of various resources.

Semantics for individual vector elements in output vector $\mathbf{a}^{2,1}$ are described in Table 18. The first ten elements, from $a_1^{2,1}$ to $a_{10}^{2,1}$, were designed to capture individual time average utilizations of ten resources in the system since t = 0. A function that depicts mean TIS behavior after the disruption consists of a two-phase function of index numbers for a TIS observation process. A period of disruption impact delay $a_{11}^{2,1}$ is followed by the first phase of an unknown transient function of the disruption impact on mean TIS characterized by a second order polynomial. The quadratic function consists of $a_{12}^{2,1}$, $a_{13}^{2,1}$, and $a_{14}^{2,1}$ such that $y = a_{14}^{2,1}t^2 + a_{13}^{2,1}t + a_{12}^{2,1}$ where y is the approximated mean TIS at observation index t and $t = 0 \ldots 299$ is the tth TIS observation upon departing parts after the delay of $a_{11}^{2,1}$ observations. After 300 TIS observations denoted by $a_{15}^{2,1}$, the second phase of transient function, a linear infinite growth represented by two vector elements, $a_{16}^{2,1}$ and $a_{17}^{2,1}$ such that $y = a_{17}^{2,1}t + a_{16}^{2,1}$ where y is the approximated mean TIS at observation index t and $t = 0,1,\ldots n$ (in reality $t =$ 301,302….300+n) is the tth observation on departing parts after first 300 parts after disruption until the elapse of 10,000 minutes. The remaining elements from $a_{18}^{2,1}$ to $a_{27}^{2,1}$ cover the trend of standard deviations of moving average (w=500) mean TIS during 10,000 minutes after the disruption, which was captured in a eighth order polynomial.

In Figure 27 (see page 211), the output vector for first three multilayer ANNs in the second level, namely $net\_2\_1\_1$, $net\_2\_1\_2$, and $net\_2\_1\_3$, collectively representing the transient behavior pattern Type 1, is symbolically denoted as:

$\mathbf{a}^{2,1} = \begin{bmatrix} a_1^{2,1} \\ a_2^{2,1} \\ \vdots \\ a_{27}^{2,1} \end{bmatrix}$ where individual elements, $a_1^{2,1}, a_2^{2,1} \ldots, a_{27}^{2,1}$, can be summarized in Table 19.

Table 19. Semantics of Output Vector $\mathbf{a}^{2,1}$ from First Three ANNs in the Second Level ANNs to Approximate Transient Behavior Pattern Type No. 1

Vector Element	Description	*Example*
$a_1^{2,1}$	M1 Utilization after the disruptive event	0.5451
$a_2^{2,1}$	M6 Utilization after the disruptive event	0.265
$a_3^{2,1}$	M2 Utilization after the disruptive event	0.1194
$a_4^{2,1}$	M5 Utilization after the disruptive event	0.8425
$a_5^{2,1}$	M3 Utilization after the disruptive event	0.6858
$a_6^{2,1}$	M7 Utilization after the disruptive event	0.6708
$a_7^{2,1}$	M9 Utilization after the disruptive event	0.75
$a_8^{2,1}$	M12 Utilization after the disruptive event	0.6111
$a_9^{2,1}$	AGV Utilization after the disruptive event	0.8784
$a_{10}^{2,1}$	Fixture Utilization after the disruptive event	0.931
$a_{11}^{2,1}$	Disruption Impact Delay (estimated lag to the first part of transient)	192
$a_{12}^{2,1}$	A0 (first coefficient approx. for the quadratic trend in TIS)	158.55
$a_{13}^{2,1}$	A1 (second coefficient approx. for the quadratic trend in TIS)	0.069713

Table 19 (continued). Semantics of Output Vector $\mathbf{a}^{2,1}$ from First Three ANNs in the Second Level ANNs to Approximate Transient Behavior Pattern Type No. 1

Vector Element	Description	*Example*
$a_{14}^{2,1}$	A2 (third coefficient approx. for the quadratic trend in TIS)	0.000284
$a_{15}^{2,1}$	Starting point of the linear trend (second part) of TIS	300
$a_{16}^{2,1}$	A0 (first coefficient approx. for the linear trend in TIS)	207.56
$a_{17}^{2,1}$	A1 (second coefficient approx. for the linear trend in TIS)	0.22251
$a_{18}^{2,1}$	Mean Sigma of TIS during pre-disruption (assuming stationary condition)	37.31739
$a_{19}^{2,1}$	A0 (first coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	46.912
$a_{20}^{2,1}$	A1 (second coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	102.28
$a_{21}^{2,1}$	A2 (third coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	1943.5
$a_{22}^{2,1}$	A3 (forth coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	-7734.3
$a_{23}^{2,1}$	A4 (fifth coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	13632
$a_{24}^{2,1}$	A5 (sixth coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	-12717
$a_{25}^{2,1}$	A6 (seventh coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	6516.9
$a_{26}^{2,1}$	A7 (eighth coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	-1733.1
$a_{27}^{2,1}$	A8 (ninth coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	186.97

A period of disruption impact delay $a_{11}^{2,2}$ is followed by a cubic transient function of the disruption impact on mean TIS. The reason to pick a third order polynomial is to capture the overall steepness, as well as, the contour of the non-linear growth in a relatively simple way without sacrificing its mathematical credibility. Also, the training burden of the ANN, often followed by an erratic behavior and large error of ANN due to its relatively smaller training set, can be lessened using smaller target vectors. A cubic function consists of four polynomial coefficients, $a_{12}^{2,2}, a_{13}^{2,2}, a_{14}^{2,2}$, and $a_{15}^{2,2}$ such that

$y = a_{15}^{2,2} t^3 + a_{14}^{2,2} t^2 + a_{13}^{2,2} t + a_{12}^{2,2}$ where y is the approximated mean TIS at observation index t and $t = 0,1,2,\ldots n$ is the t th TIS observation upon departing parts after the delay of $a_{11}^{2,2}$ observations. The actual increment of t used for the third order polynomial is 0.0005 rather than one for the evenly scaled growth of its coefficients during the polynomial regression. Thus, the actual values of t are $t = 0, 0.0005, 0.0010, \ldots n$.

The remaining elements from $a_{16}^{2,2}$ to $a_{20}^{2,2}$ cover the trend of standard deviations of moving average (w=500) filtered mean TIS before and after the disruption. The mean standard deviation prior to the disruption was captured by a single value, $a_{16}^{2,2}$. The post-disruption mean standard deviation was captured by a cubic function with coefficients, $a_{17}^{2,2}, a_{18}^{2,2}, a_{19}^{2,2}$ and $a_{20}^{2,2}$ such that $y = a_{20}^{2,2} t^3 + a_{19}^{2,2} t^2 + a_{18}^{2,2} t + a_{17}^{2,2}$ where y is the approximated standard deviation of moving average (w=500) mean TIS at observation index t and $t = 0,1,2,\ldots n$ is the t th TIS observation upon departing parts after the disruption. Again the actual increment of t is 0.0005 rather than one so values for t are $t = 0, 0.0005, 0.0010, \ldots n$.

As shown in Figure 27 on page 211, the output vector for the second group of three multilayer ANNs in the second level, namely $net\_2\_2\_1$, $net\_2\_2\_2$, and $net\_2\_2\_3$, collectively representing the transient behavior pattern Type 2, is symbolically denoted as:

$\mathbf{a}^{2,2} = \begin{bmatrix} a_1^{2,2} \\ a_2^{2,2} \\ \vdots \\ a_{20}^{2,2} \end{bmatrix}$ where individual elements, $a_1^{2,2}, a_2^{2,2} \ldots, a_{20}^{2,2}$, can be summarized in Table 20.

Table 20. Semantics of Output Vector $\mathbf{a}^{2,2}$ from Second Group of Three ANNs in the Second Level ANNs to Approximate Transient Behavior Pattern Type No. 2

Vector Element	Description	*Example*
$a_1^{2,2}$	M1 Utilization after the disruptive event	0.56526
$a_2^{2,2}$	M6 Utilization after the disruptive event	0.29298
$a_3^{2,2}$	M2 Utilization after the disruptive event	0.69212
$a_4^{2,2}$	M5 Utilization after the disruptive event	0.59026
$a_5^{2,2}$	M3 Utilization after the disruptive event	0.80704
$a_6^{2,2}$	M7 Utilization after the disruptive event	0.0701
$a_7^{2,2}$	M9 Utilization after the disruptive event	0.767
$a_8^{2,2}$	M12 Utilization after the disruptive event	0.6572
$a_9^{2,2}$	AGV Utilization after the disruptive event	0.88234
$a_{10}^{2,2}$	Fixture Utilization after the disruptive event	0.94158
$a_{11}^{2,2}$	Disruption Impact Delay (estimated lag to transient)	112
$a_{12}^{2,2}$	A0 (first coefficient approx. for the eighth order polynomial trend in TIS)	158.32
$a_{13}^{2,2}$	A1 (second coefficient approx. for the eighth order polynomial trend in TIS)	87.177
$a_{14}^{2,2}$	A2 (third coefficient approx. for the eighth order polynomial trend in TIS)	2080.3
$a_{15}^{2,2}$	A3 (forth coefficient approx. for the eighth order polynomial trend in TIS)	-5572.9
$a_{16}^{2,2}$	Mean Sigma of TIS during pre-disruption (assuming stationary condition)	36.36818
$a_{17}^{2,2}$	A0 (first coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	45.496
$a_{18}^{2,2}$	A1 (second coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	355.31
$a_{19}^{2,2}$	A2 (third coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	-194.23
$a_{20}^{2,2}$	A3 (forth coefficient of the eighth order polynomial trend in σ of moving average TIS during post-disruption period)	495.38

Semantics for individual vector elements in output vector $\mathbf{a}^{2,3}$ are described in Table 20 on page 207. Similar to the two previous transient behavior pattern types, the first ten elements, from $a_1^{2,3}$ to $a_{10}^{2,3}$, were designed to capture individual time average utilizations of ten resources in the system since t = 0. A function that depicts mean TIS behavior after the disruption consists of a single eighth order polynomial based on TIS observation index after a disruption.

Different from the second transient pattern type, a period of disruption impact delay $a_{11}^{2,3}$ is followed by an eighth order polynomial transient function of the disruption impact on mean TIS. The reason to pick eighth order polynomial was based on its modeling efficiency and easiness of ANN training. The eighth order polynomial consists of nine polynomial coefficients, $a_{12}^{2,3}, a_{13}^{2,3}, a_{14}^{2,3}, a_{15}^{2,3}, a_{16}^{2,3}$, $a_{17}^{2,3}, a_{18}^{2,3}, a_{19}^{2,3}$ and $a_{20}^{2,3}$ such that $y = a_{20}^{2,3}t^8 + a_{19}^{2,3}t^7 + a_{18}^{2,3}t^6 + a_{17}^{2,3}t^5 + a_{16}^{2,3}t^4 + a_{15}^{2,3}t^3 + a_{14}^{2,3}t^2 + a_{13}^{2,3}t + a_{12}^{2,3}$ where y is the approximated mean TIS at observation index t and $t = 0,1,2,\ldots n$ is the t th TIS observation upon departing parts after the delay of $a_{11}^{2,3}$ observations. The actual increment of t used for the eighth order polynomial is 0.0005 rather than one due to a large uneven growth-scale disparity among nine coefficients of t during the polynomial regression.

In other words, since the variation tends to remain consistent, there is no increase or decrease in the variance of TIS; three constant values $a_{21}^{2,3}, a_{22}^{2,3}$, and $a_{23}^{2,3}$ can cover the trend of standard deviations of moving average (w=500) mean TIS before and after the disruption. The mean standard deviation prior to the disruption was captured by first single value $a_{21}^{2,3}$. Second single vector element, $a_{22}^{2,3}$, captured the mean standard deviation during transient. The post-transient mean standard deviation was captured by third single element $a_{23}^{2,3}$. As shown in Figure 27 on page 211, the output vector for third group of two multilayer ANNs in the second level, namely $net\_2\_3\_1$ and $net\_2\_3\_2$, collectively representing the transient behavior pattern Type 3, is denoted as:

$\mathbf{a}^{2,3} = \begin{bmatrix} a_1^{2,3} \\ a_2^{2,3} \\ \vdots \\ a_{23}^{2,3} \end{bmatrix}$ where individual elements, $a_1^{2,3}, a_2^{2,3} \ldots, a_{23}^{2,3}$, can be summarized in Table 21.

A logical framework ties various trained ANNs into a single meta-modeling scheme. The principal design objective for this logical framework is to organize individual ANNs in such way that these ANNs can collectively map functional range of an unknown transient performance functions. Different areas of an unknown functional range can be captured via training designated ANNs under the transient behavior pattern it belongs to. The captured transient function can be realized via simulating the same set of ANNs under a particular transient behavior pattern.

The basic control flow of the proposed branch logic structure is illustrated in Figure 27. The detail logical structure for a MATLAB based program can be found in

Appendix B. Detail views of individual ANNs are provided later in Figure 28, Figure 29, Figure 30, and Figure 31 in Chapter 7.

Table 21. Semantics of Output Vector $\mathbf{a}^{2,3}$ from Third Group of Two ANNs in the Second Level ANNs to Approximate Transient Behavior Pattern Type No. 3

Vector Element	Description	*Example*
$a_1^{2,3}$	M1 Utilization after the disruptive event	0.092444
$a_2^{2,3}$	M6 Utilization after the disruptive event	0.717588
$a_3^{2,3}$	M2 Utilization after the disruptive event	0.565373
$a_4^{2,3}$	M5 Utilization after the disruptive event	0.674801
$a_5^{2,3}$	M3 Utilization after the disruptive event	0.75937
$a_6^{2,3}$	M7 Utilization after the disruptive event	0.684116
$a_7^{2,3}$	M9 Utilization after the disruptive event	0.714482
$a_8^{2,3}$	M12 Utilization after the disruptive event	0.612693
$a_9^{2,3}$	AGV Utilization after the disruptive event	0.475533
$a_{10}^{2,3}$	Fixture Utilization after the disruptive event	0.720063
$a_{11}^{2,3}$	Disruption Impact Delay (estimated lag to transient)	222
$a_{12}^{2,3}$	A0 (first coefficient approx. for the eighth order polynomial trend in TIS)	166.22
$a_{13}^{2,3}$	A1 (second coefficient approx. for the eighth order polynomial trend in TIS)	138.95
$a_{14}^{2,3}$	A2 (third coefficient approx. for the eighth order polynomial trend in TIS)	-587.97
$a_{15}^{2,3}$	A3 (forth coefficient approx. for the eighth order polynomial trend in TIS)	1341.1
$a_{16}^{2,3}$	A4 (fifth coefficient approx. for the eighth order polynomial trend in TIS)	-1786.8
$a_{17}^{2,3}$	A5 (sixth coefficient approx. for the eighth order polynomial trend in TIS)	1411.7
$a_{18}^{2,3}$	A6 (seventh coefficient approx. for the eighth order polynomial trend in TIS)	-644.23
$a_{19}^{2,3}$	A7 (eighth coefficient approx. for the eighth order polynomial trend in TIS)	155.63
$a_{20}^{2,3}$	A8 (ninth coefficient approx. for the eighth order polynomial trend in TIS)	-15.302
$a_{21}^{2,3}$	Mean σ of TIS during pre-disruption (assuming stationary condition)	54.23641
$a_{22}^{2,3}$	Mean σ of TIS during transient (average)	53.60903
$a_{23}^{2,3}$	Mean σ of TIS during post-transient (assuming stationary condition)	53.75352

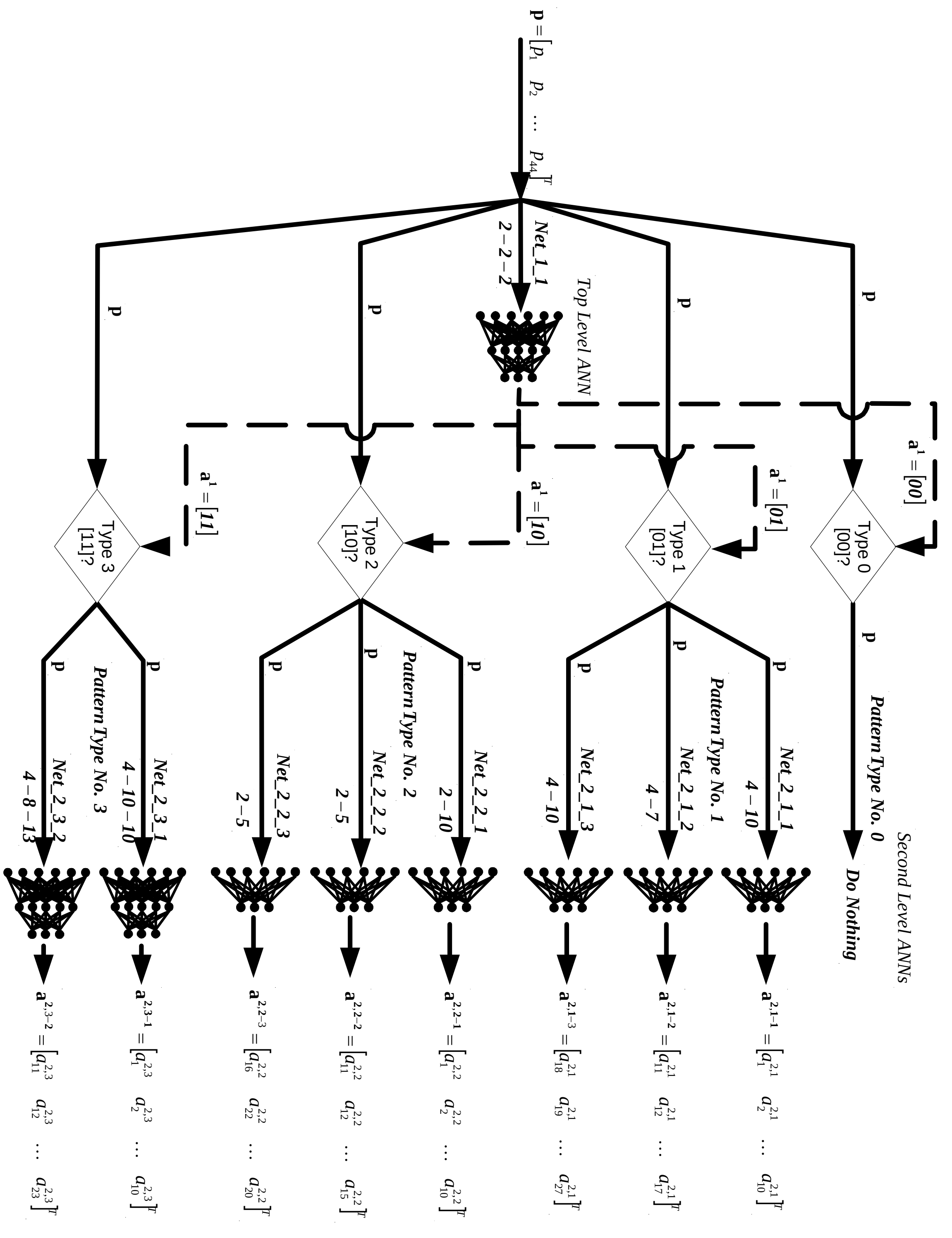


Figure 27. Proposed Two-Level Deep Taxonomically Organized ANN Based Transient Performance Model

As shown in Figure 27, the top level multilayer ANN is designed to classify distinctive post-disruption transient behavior patterns that can be encoded into a two digit binary number. Upon predicting a particular post-disruption transient pattern, the same system input vector is fed into a group of multilayer ANNs in the second level predestined by the proposed branch logic.

As we can see from Figure 27, Type 1 input vectors are simultaneously fed into three multilayer networks in the second level, namely Net_2_1_1, Net_2_1_2, and Net_2_1_3. Breaking output vectors under a particular transient type into smaller ones using two or three ANNs rather than a single large one is mainly due to the ease of training and better performance of smaller networks.

Especially when the dimension (or size) of an output vector from a particular transient behavior pattern type is large in relation to its total number of training output vectors, breaking an output vector into several smaller ones based on their similar scale of individual vector elements and letting those smaller ANNs collectively approximate an unknown function is a more efficient way to handle a large dimension output approximation without increasing the number of actual training vectors. Otherwise, training such an ANN with a large size outer layer can be quite difficult. Even if one can manage to train such a large network, the reliability and performance of the ANN will be very poor due to its significantly large number of weights and biases.

As shown in Figure 27, the first type transient behavior output vector in the second level, $\mathbf{a}^{2,1}$, is broken into $\mathbf{a}^{2,1-1}$, $\mathbf{a}^{2,1-2}$, and $\mathbf{a}^{2,1-3}$ based on similarity in individual vector element scales and their positions in the final output vector. The first sub-output vector, $\mathbf{a}^{2,1-1}$, contains the first element, $a_1^{2,1}$, thru the tenth element, $a_{10}^{2,1}$, from the original output vector, $\mathbf{a}^{2,1}$. The second sub-output vector, $\mathbf{a}^{2,1-2}$, contains the 11th element, $a_{11}^{2,1}$, thru the 17th element, $a_{17}^{2,1}$, from the original output vector. The third sub-output vector, $\mathbf{a}^{2,1-3}$, contains the 18th element, $a_{18}^{2,1}$, thru the 27th element, $a_{18}^{2,1}$, from the original output vector, $\mathbf{a}^{2,1}$.

Similarly, the second type transient behavior output vector in the second level, $\mathbf{a}^{2,2}$, is broken into three sub-output vectors, namely $\mathbf{a}^{2,2-1}$, $\mathbf{a}^{2,2-2}$, and $\mathbf{a}^{2,2-3}$. The first sub-output, $\mathbf{a}^{2,2-1}$, contains the first thru tenth elements from $\mathbf{a}^{2,2}$. The second sub-output, $\mathbf{a}^{2,2-2}$, contains the 11th thru 20th elements from $\mathbf{a}^{2,2}$. The third sub-output, $\mathbf{a}^{2,2-3}$, contains the 21st thru 30th elements from $\mathbf{a}^{2,2}$.

The third type transient behavior output vector in the second level, $\mathbf{a}^{2,3}$, is broken into two sub-output vectors, $\mathbf{a}^{2,3-1}$ and $\mathbf{a}^{2,3-1}$. The first sub-output, $\mathbf{a}^{2,3-1}$, contains the first thru tenth elements from $\mathbf{a}^{2,3}$. The second sub-output, $\mathbf{a}^{2,3-2}$, contains the 11th thru 23rd elements from $\mathbf{a}^{2,3}$.

6.6 Summary

This chapter provides an overview of simulation modeling using Extend, expansion of initial design of experiments, post-simulation data processing, and construction of input and target vectors for the proposed ANN based metamodeling approach. The simulation model was designed to reflect various aspects of asynchronous and tightly coupled FMS behaviors with a built-in resource failure scheduler. The study concluded that the initial experiment set was not large enough to produce an acceptable ANN training performance; therefore, increasing the number of total experiments was necessary. Results from simulation experiments and analysis show that there are four major transient behavior pattern types based on graphical similarity and modeling requirements by the polynomial regression. The study found that about half of experiments fell under Type 3 post-disruption behavior, namely a finite growth to a new steady state. Data processing activities are divided into two phases, pre and post. The pre-process is to prepare raw TIS data to detect the presence of transient behaviors and classify them accordingly. The post-process involves extracting various mathematical properties from the underlying TIS observation time series process to construct necessary target vectors.

7. Experimental Results

The performance of the proposed ANN based meta model is discussed in this chapter. Steps for training and validation of individual ANNs are also presented. Performances of prediction results by both individual regression models and the proposed ANN based model on selected disruption scenarios are compared to actual observations from simulation experiments to evaluate the overall effectiveness of the proposed modeling scheme.

7.1 Construction and training of Individual ANNs

Upon completing construction of input and output vectors from all 180 initial experiments, individual ANNs comprising the proposed taxonomically-organized ANN based meta model can be constructed. Various output vector sizes for both first and second level ANNs help us to determine right configurations of individual ANNs.

Since output vectors for three transient performance functions were broken into eight smaller sub-output vectors, the configuration of outer layer of individual ANN in the second level can be determined accordingly. The first ANN, *Net_1_1*, in the top level has 44 dimension input and two dimension output vectors and its final configuration of the network was decided as an $2 \times 2 \times 2$ network after several trials. The diagram of this ANN is illustrated in Figure 28. The transfer function for both the first and second layer is Hyperbolic Tangent Sigmoid. The transfer function for the last (outer) layer is Linear. Justifications to choose these two types of transfer function are given in an earlier chapter (refer to section 3.3.2 in Chapter 3).

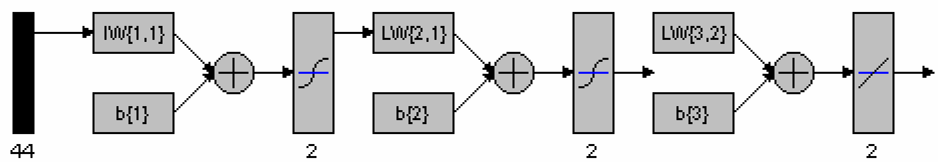
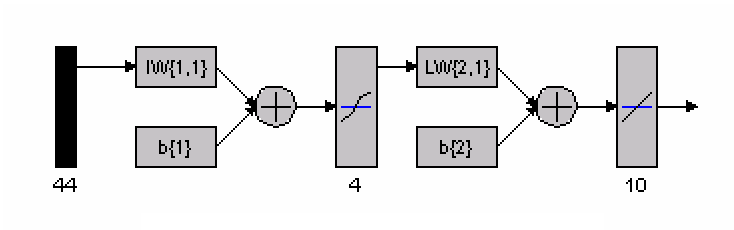


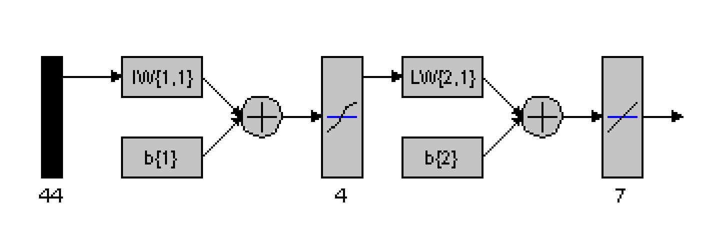
Figure 28. Network Diagram of *Net_1_1* in the Top Level

One hundred eighty input and corresponding output vectors were equally divided into four mutually exclusive subsets. The training vector set including both input and matching output vectors consists of two groups. The first group is made of every forth vector starting from the first one such as 1, 5, 9, and 13 … 177. Since actual sequences of both input and output vectors are identical to the sequence of actual experiment numbers listed in Table 15 in Chapter 6, the actual sequence of equivalent experiment numbers from the table is 11, 15, 114, and 58, …102. The second group consists of every forth vector starting from the third one such as 3, 7, 11, and 15 … 179. The actual sequence of equivalent experiment numbers from the table is 13, 112, 56, and 60 …104. The remaining two vector sets were used for validation and testing.

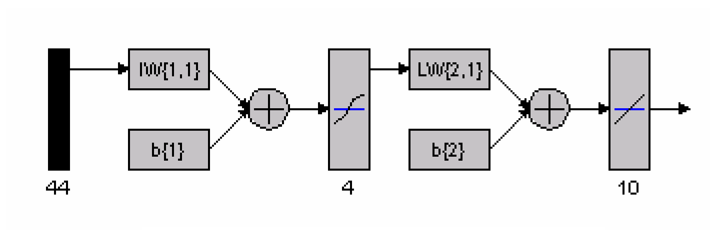
For a collective approximation of Type one post-disruption behavior, three sub-ANNs from the second level, *Net_2_1_1*, *Net_2_1_2*, and *Net_2_1_3*, share 44 dimension input vectors. They respectively use ten, seven, and ten dimension output vectors. The final configurations of these networks were decided as 4×10, 4×7, and 4×10 network after several trials. Diagrams of these ANNs are illustrated in Figure 29. The transfer function for the first layer is Hyperbolic Tangent Sigmoid. The transfer function for last (outer) layer is Linear.



Net_2_1_1



Net_2_1_2



Net_2_1_3

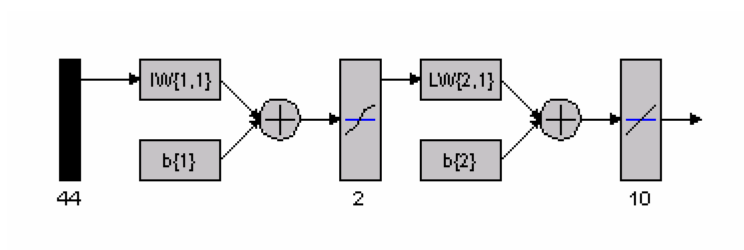
Figure 29. Individual Network Diagram of Type One Transient Behavior Approximation sub-ANNs in the Second Level

Forty input and corresponding separate output vectors for each sub-ANN were equally divided into four mutually exclusive subsets. These input and output vectors are from scenarios that may result in Type 1 post-disruption behavior patterns. Numbers for these scenarios are 19, 20, 25, 26, 27, 28, 29, and 30 as shown in Table 15 in Chapter 6.

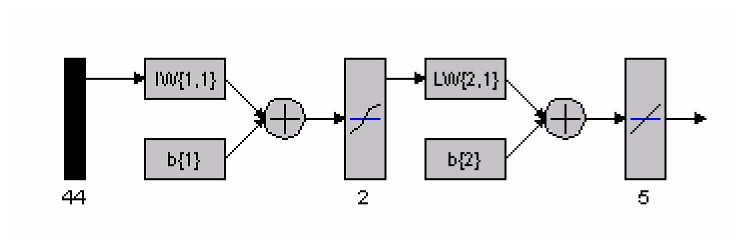
As seen in the configuration of the training vector set for the fist ANN, the training vector set including both input and matching output vectors is made of two groups. The first group is made of every forth vector such as 1, 5, 9, 13, …, and 37. Since the first experiment in the first group starts with 26, the actual sequence of experiment numbers is 26, 30, 154, …, and 87. Likewise, the second group is made of every forth vector starting from experiment number 28. The actual sequence of experiment numbers in the final training set is made of these two groups in a sequential manner, such as 26, 30, 154, …, 87, 28, 152, 76, …, 89. The remaining vectors was used for validation and testing.

For a collective approximation of type two post-disruption behavior, three sub-ANNs from the second level, *Net_2_2_1* covering output vector elements from $a_1^{2,2}$ thru $a_{10}^{2,2}$, *Net_2_2_2* covering output vector elements from $a_{11}^{2,2}$ thru $a_{15}^{2,2}$, and *Net_2_2_3* covering output vector elements from $a_{16}^{2,2}$ thru $a_{20}^{2,2}$, share 44 dimension input vectors. The final configurations of these networks were decided as 2×10, 2×5, and 2×5 network after several trials. The diagrams of these ANNs can be illustrated in Figure 30. The transfer function for the first layers is Hyperbolic Tangent Sigmoid. The transfer function for the last (outer) layers is Linear.

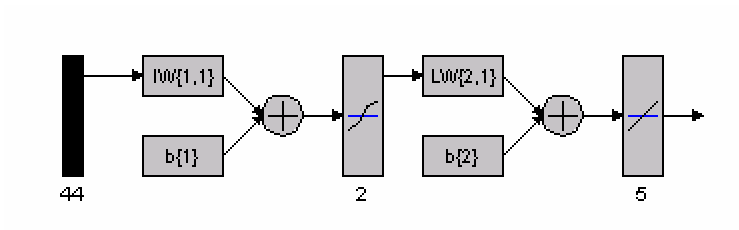
Twenty input and corresponding twenty output vectors were equally divided into four mutually exclusive subsets for training, validation and testing. Each individual input vectors are constructed from experiment scenarios that may result in type two post-disruption behavior patterns. Numbers of these scenarios are 7, 15, 31, and 32 as shown in Table 15 in Chapter 6. Each scenario consists of five independent experiments.



Net_2_2_1



Net_2_2_2



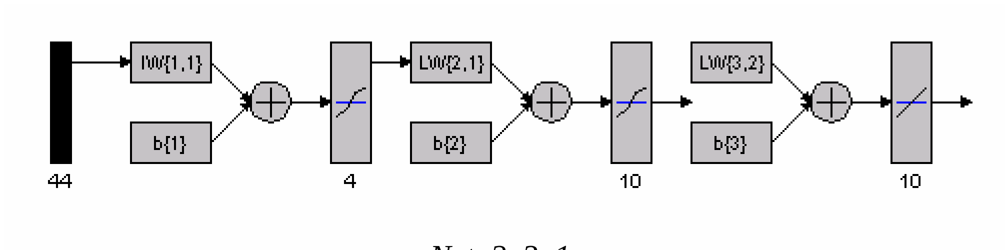
Net_2_2_3

Figure 30. Individual Network Diagram of Type Two Transient Behavior Approximation Sub-ANNs in the Second Level

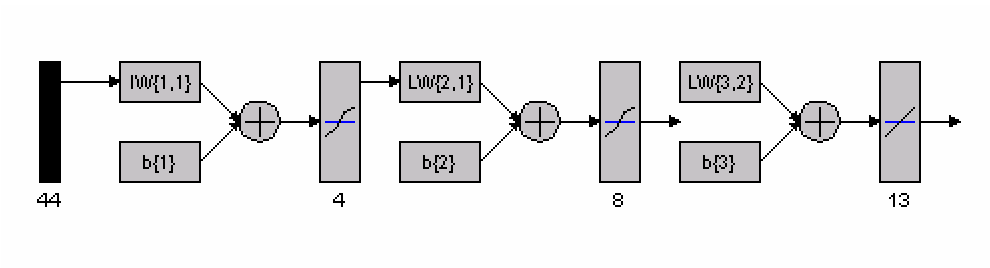
Similar to the configuration of training vector sets for the previous set of ANNs, the training vector set for each sub-ANN including common input and matching output vectors can be divided into two groups. The first group is made of every forth vector starting from experiment number 61, such as 61, 65, 179, 63, 72. The second group is made of every forth vector starting from experiment number 63 such as 63, 177, 61, 65, 74. The final training vector set can be put together, combining the first and second group back to back such that the final sequence of input vectors can be 61, 65, 179, 63, 72, 63, 177, 61, 65, and 74. The rest of remaining vectors was used for validation and testing purposes.

For a collective approximation of type three post-disruption behavior, sub-ANNs, *Net_2_3_1* and *Net_2_3_2* in the second level share 44 dimension input and each uses ten and thirteen dimension output vectors. The final configurations of these networks were decided as $4\times10\times10$ and $4\times8\times13$ network after several trials. The diagrams of these ANNs can be illustrated in Figure 31. The transfer function for the first and second layers is Hyperbolic Tangent Sigmoid. The transfer function for the last (outer) layers is Linear.

One hundred input and corresponding output vectors for two sub-ANNs were equally divided into four mutually exclusive subsets. These input and output vectors are from scenarios that result in type two post-disruption behavior patterns. Numbers for these scenarios are 1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 16, 17, 18, 21, 22, 23, and 24 as shown in Table 15 in Chapter 6.



Net_2_3_1



Net_2_3_2

Figure 31. Individual Network Diagram of Type Three Transient Behavior Approximation sub-ANNs in the Second Level

As seen in configuration of training vector sets for previous ANNs, the training vector set for each sub-ANN including common input and matching output vectors can be divided into two groups. The first group is made of every forth vector starting from experiment number 11. The second group is made of every forth vector starting from experiment number 13. The remaining vectors were prepared for validation and testing.

The type of backpropagation training algorithm used throughout this study is Bayesian regularization based on the Bayesian framework of Mackay [1992]. This function can be callable through the MATLAB neural network toolbox. Regularization is a method used to improve the generalization of feedforward neural networks such as those in this study by modifying its performance function. The typical performance function used for training feedforward neural networks can be expressed as the mean sum of squares of the network errors:

$$F = mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2$$

Regularization can be achieved by adding a term that consists of the mean of the sum of squares of the network weights and biases

$$msereg = \gamma mse + (1-\gamma)msw$$

where γ is the performance ratio, and

$$msw = \frac{1}{n}\sum_{j=1}^{n} w_j^2$$

Minimizing this performance function will help the network to maintain smaller weights and biases during its training, which in return will force the network response to be smoother and less likely to overfit. Bayesian regularization updates the weights and biases according to Levenberg-Marquardt optimization (see Section 3.3.2 for details).

Training of individual neural networks was set to stop when it reaches maximum 100 epochs, an error goal of 0.01, or any other stopping conditions imposed by Bayesian regularization. It is also set to display their sum of squared errors on test, validation, and training at every fifth epoch during the training.

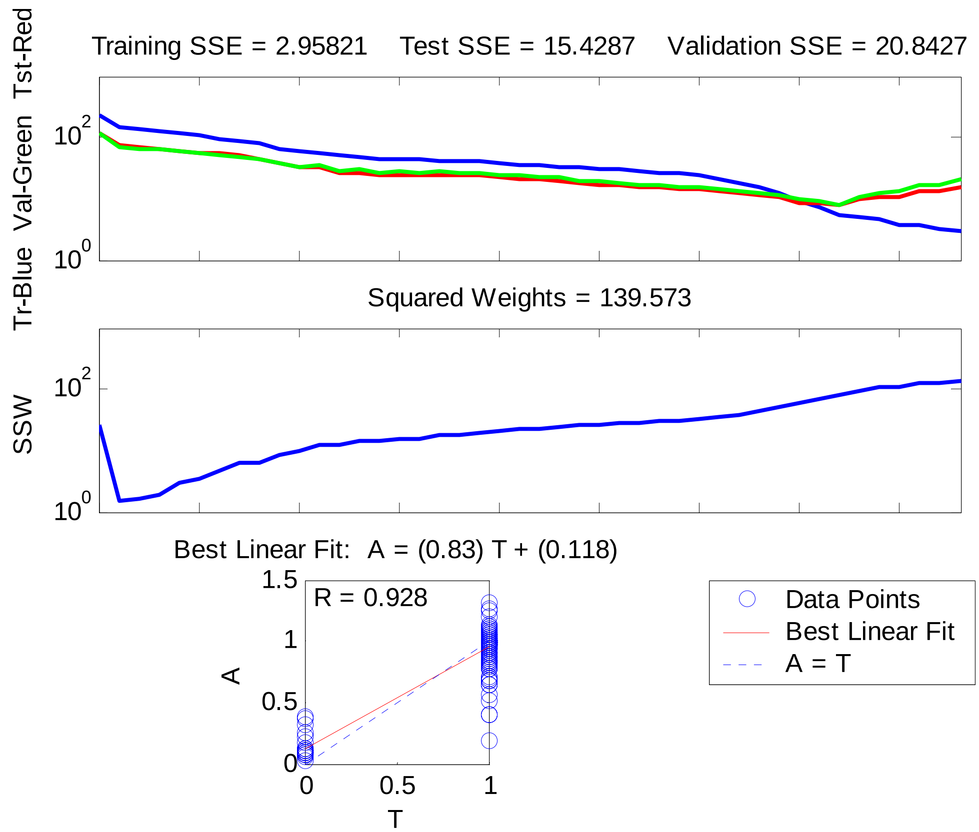


Figure 32. Performance Plots of the Top Level ANN *Net_1_1* during Its Initial training with 90 Input and Output

The results of initial training of the top level ANN with 90 input and output vectors exhibits a performance of SSE = 2.95821 as shown in Figure 32. However, a test performances index, test SEE, climbed to 15.4287. The training was prematurely terminated at the 43rd epoch by reaching the point where the sum of squared errors cannot be further reduced by moving into neighboring points on a descending terrain of the performance surface, or perhaps it might have stuck in a plateau of the performance surface. Other trainings of sub-neural networks such as *Net_2_1_1*, *Net_2_1_2*, *Net_2_1_3*, *Net_2_2_2*, *Net_2_2_2* and *Net_2_3_1* were successful since both their test and validation SSE were below one as shown in Table 22.

Table 22. Training and Testing Performance Indexes from Individual Neural Networks with 90 training and 45 Testing Input and Output Vectors (original experiment set)

Sub-network	Training SSE	Test SSE	Validation SSE
Net_1_1	2.95821	15.4287	20.8427
Net_2_1_1	0.0773568	0.0362079	0.0553606
Net_2_1_2	0.386327	0.280162	0.268072
Net_2_1_3	0.398952	0.188614	0.199922
Net_2_2_1	1.15518	1.0123	0.570032
Net_2_2_2	0.616456	0.481829	0.313887
Net_2_2_3	0.186616	0.257429	0.40057
Net_2_3_1	0.00673646	0.0102034	0.0117372
Net_2_3_2	2.71756	4.09792	9.8713

The rest of sub-neural networks (those marked with the gray color in Table), *net_2_2_1*, *net_2_3_2*, and *net_1_1* exhibit relatively poor test performance despite multiple attempts of training. In each training attempt, a slightly different training and test performance were observed because the starting condition of the same neural network may change per each training cycle by automatically selecting different initial values for weights and biases unless they are given. In other words, if you compare the training process of an ANN to a 3D terrain navigation of the performance surface to find a point that typically minimizes the overall training error represented by the training SSE, a different starting point of the performance surface in each training cycle may result in a slightly different performance result. Individual training and testing plots for each sub-ANN can be found in Appendix D.

7.2 Expansion of the Initial Experiment Size

After careful review of configurations of individual ANNs and possibility of using different training methods, increasing the number of input and output data points become an effective choice to improve the poor performance of three sub-ANNs *net_1_1*, *net_2_2_1*, and *net_2_3_2*, in both training and testing as well as boost the overall performance of the collective framework. The number of entire input and output vectors was to be tripled by adding ten more independent replications under each disruption scenarios.

The new extended experiment set similar to Table 14 on page 178 can be found in Appendix A. Since values for individual output vectors were derived from the average values of all experiments under a particular scenario, recalculations were necessary for all 36 scenarios after 360 additional simulation runs (ten additional runs for 36 scenarios).

Individual values for input and output vectors for the first level and second level ANNs can be found in Appendix C. Results from training ANNs with an extended vector set (total 540 vectors) are summarized in Table 23.

Table 23. Training, Test, and Validation Performances from Individual Sub-ANNs under New Extended Training, Test and Validation Vector Sets vs. Those under Old Training, Test, and Validation Vector Sets

	Training SSE		Test SSE		Validation SSE	
Sub-network	Under 180 Original Exp Set	Under 540 New Exp Set	Under 180 Original Exp Set	Under 540 New Exp Set	Under 180 Original Exp Set	Under 540 New Exp Set
Net_1_1	2.95821	0.219501	15.4287	0.114293	20.8427	0.148303
Net_2_1_1	0.0773568	0.238701	0.0362079	0.114738	0.0553606	0.127628
Net_2_1_2	0.386327	1.32545	0.280162	0.683936	0.268072	0.73432
Net_2_1_3	0.398952	0.563311	0.188614	0.294714	0.199922	0.304855
Net_2_2_1	1.15518	3.6151	1.0123	1.93986	0.570032	1.80218
Net_2_2_2	0.616456	1.75279	0.481829	0.968875	0.313887	0.931073
Net_2_2_3	0.186616	0.606394	0.257429	0.322154	0.40057	0.334161
Net_2_3_1	0.00673646	0.0932927	0.0102034	0.0511311	0.0117372	0.0466751
Net_2_3_2	2.71756	1.19486	4.09792	0.608019	9.8713	0.606891

Contrary to the prior expectation, using the extended experiment set did not improve the performance of every sub-ANNs. In fact, for some sub-ANNs, the performance in all three training, test, and validation, has shown a slight degradation. But, these performance degradations are acceptable because the overall improvement made by other sub-ANNs is greater.

On the other hand, the testing and validation performances by both Net_1_1 and Net_2_3_2 showed significant improvements under the new extended training, test, and validation vector sets against the old ones. As seen in Figure 33, improvements made by these two sub-ANNs under the new extended training and validation vector sets are significant enough to justify the additional 360 experiments to the original experiment set.

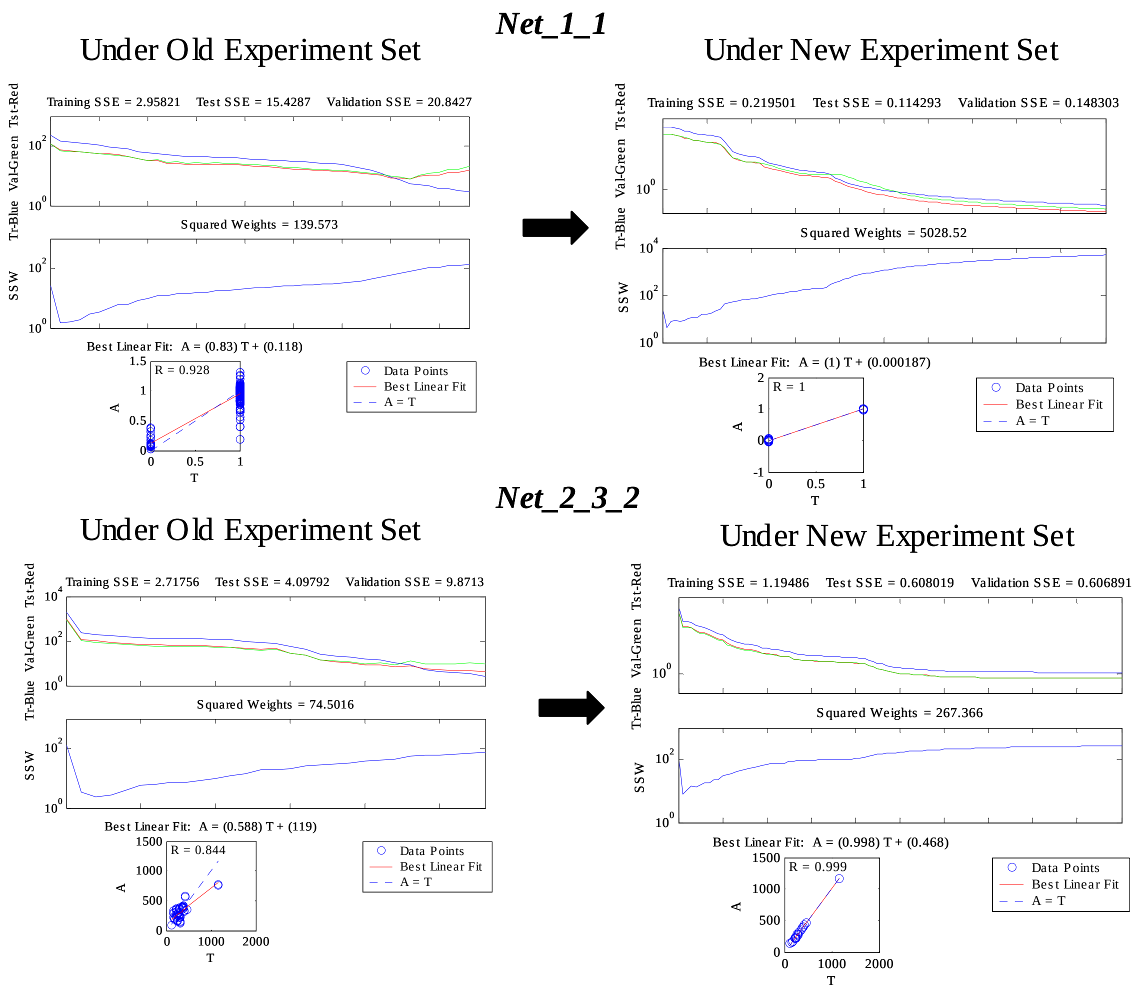


Figure 33. Comparative Performance plots of sub- ANNs, *Net_1_1 and Net_2_3_2*, under Old and New Training, Test, and Validation Vector Sets

The remaining individual plots show the chronological progression of the sum of squared errors (SSE), squared weights of each neurons and the effective number of parameters against the number of epochs for each sub-ANN under both experiment sets can be found in Appendix D.

7.3 Performance Evaluation of Proposed Modeling Scheme

For this study, the standard error of estimate was chosen to measure the performance of the proposed ANN based meta model on selected input vectors (experiments) due to its computational simplicity and closeness to the scale of actual RAW time-in-system data. If we let $\hat{y}_i$ be an unbiased estimator for y_i (time-in-system for i th part), the standard error of estimate can be stated as

$S_e = \sqrt{\frac{1}{n-(k+1)}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$ where $\hat{y}_i$ is y_i's unbiased estimator in k th degree polynomial.

For simplicity and economic reasons, a total 18 out of 540 experiments were selected to benchmark their standard error of estimate by the proposed ANN based meta model against those estimated by corresponding univariate regression models based on its MA TIS (moving average filtered time-in-system) and MA scenario average TIS (out of fifteen independent runs). Six experiments from each post-disruption behavior types were carefully selected. Selection criteria were based on the size of the sum of squared errors (SSE) between the approximation made by an univariate regression model based on moving average filtered TIS (MA TIS) time series and the approximation made by the proposed ANN based meta model.

Among six experiments under each post-disruption behavior type, first one third (two) comprises two best cases in terms of its least size of sum of squared errors (SSE). The second one-third represents two average cases in its sum of squared errors. The remaining one-third represents the two worst cases in its sum of squared errors. Even though two post-disruption behavior types, Type 1 and Type 2, are not covariance stationary stochastic processes, we assume that actual performance of the proposed ANN based meta model on a individual input vector basis can be judged by finding the standard error of TIS estimates by the ANN based meta model against actual (RAW) time-in-system (TIS) values and moving averaged (MA) TIS values. These standard error of estimates by the ANN based meta model are then compared to similar standard error of estimates made by the univariate regression model based on MA TIS and by the univariate regression model based on moving average filtered scenario average TIS.

For example, Exp 438 was picked as the best case under Type 1 post-transient behavior based on its smallest deviation between approximations by the regression model based on MA scenario average TIS and approximations by the proposed ANN based meta model. On actual RAW TIS data, the post-disruption event took place somewhere around 4297th part observation/entry that marks simulation time 10,000 minutes. Therefore, we can assume the same part observation/entry number for the disruption event time on approximated MA TIS points by both the regression model based on MA scenario average TIS and ANN generated regression model.

Since Type 1 post-disruption behavior exhibits a short duration of non-linear behavior at the beginning followed by a steady linear behavior, two different starting times for both non-linear and linear behavior, 4353 and 4753 for experiment no. 438, need to be specified in terms of relative part observation/entry count. Following are three tables summarizing different start times in the form of absolute observation count for 18 selected experiments on MA TIS observations from RAW data, approximated MA TIS observations by the regression model based on moving average filtered (MA) scenario average TIS, and approximated MA TIS observations by the ANN generated regression model. As shown, Table 24, Table 25, and Table 26 share the same disruption event time.

Table 24. Major Event Start Times on MA TIS Observations from 18 Selected Experiment RAW Data

	Type 1 Post-disruption Behavior				Type 2 Post-disruption Behavior			Type 3 Post-disruption Behavior		
	Exp No.	Disruption Event Time (n th observation)	Non-linear Behavior Start Time (n th observation)	Linear Behavior Start Time (n th observation)	Exp No.	Disruption Event Time (n th observation)	Non-linear Behavior Start Time (n th observation)	Exp No.	Disruption Event Time (n th observation)	Non-linear Behavior Start Time (n th observation)
Best	438	4297	4353	4753	73	4379	4474	275	4299	4515
	436	4324	4356	4856	71	4464	4747	356	4332	4979
Average	85	4536	4654	5054	62	4600	5191	349	4430	4694
	470	4567	4595	4995	487	4541	4689	346	4620	4938
Worst	453	4319	4389	4789	500	4406	4606	213	4270	4521
	175	4408	4477	4877	498	4420	4662	211	4344	4410

Table 25. Major Event Start Times on Approximated TIS Observations Rendered by Regression Models Based on MA Scenario Average TIS Observations from 18 Selected Experiments

	Type 1 Post-disruption Behavior				Type 2 Post-disruption Behavior			Type 3 Post-disruption Behavior		
	Exp No.	Disruption Event Time (n th observation)	Non-linear Behavior Start Time (n th observation)	Linear Behavior Start Time (n th observation)	Exp No.	Disruption Event Time (n th observation)	Non-linear Behavior Start Time (n th observation)	Exp No.	Disruption Event Time (n th observation)	Non-linear Behavior Start Time (n th observation)
Best	438	4297	4339	4639	73	4379	4557	275	4299	4521
	436	4324	4366	4666	71	4464	4642	356	4332	4623
Average	85	4536	4554	4954	62	4600	4977	349	4430	4710
	470	4567	4580	4980	487	4541	4653	346	4620	4900
Worst	453	4319	4387	4787	500	4406	4619	213	4270	4497
	175	4408	4476	4876	498	4420	4633	211	4344	4571

Table 26. Major Event Start Times on Approximated TIS Observations Rendered by ANN Generated Regression Models for 18 Selected Experiments

	Type 1 Post-disruption Behavior				Type 2 Post-disruption Behavior			Type 3 Post-disruption Behavior		
	Exp No.	Disruption Event Time (n th observation)	Non-linear Behavior Start Time (n th observation)	Linear Behavior Start Time (n th observation)	Exp No.	Disruption Event Time (n th observation)	Non-linear Behavior Start Time (n th observation)	Exp No.	Disruption Event Time (n th observation)	Non-linear Behavior Start Time (n th observation)
Best	438	4297	4334	4631	73	4379	4559	275	4299	4512
	436	4324	4361	4658	71	4464	4643	356	4332	4637
Average	85	4536	4562	4965	62	4600	4979	349	4430	4707
	470	4567	4588	4990	487	4541	4658	346	4620	4897
Worst	453	4319	4379	4777	500	4406	4614	213	4270	4508
	175	4408	4469	4867	498	4420	4627	211	4344	4582

Figure 34 illustrates how closely the plot of MA (w= 500) TIS observations resembles the actual RAW TIS plot. It is obvious that variances among observations (covariance) prior to the disruption event have increased after the disruption. A close up view of the early post-disruption observations marked by a square box within the plot figure also help us to confirm the existence of a short lasting non-linear behavior trend during the early post-disruption stage that is followed by a dominant steady linear trend. The duration of these initial non-linear trends varies but usually lasts about 300 to 400 observations depending on each disruption scenarios. Only under Type 1 post-disruption behavior, these initial non-linear behavior trends are modeled as a part of the metamodel because they are followed by long lasting linear-trends.

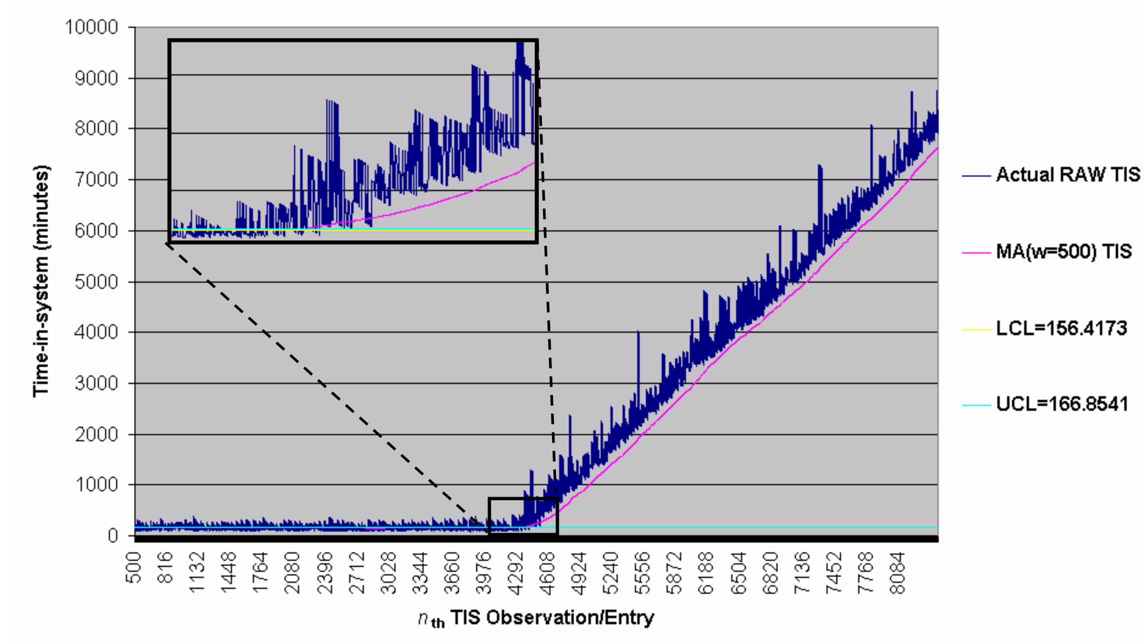


Figure 34. RAW TIS and Moving Average Filtered (MA) TIS Plots of Exp No. 438 (Post-disruption Type 1 Behavior)

First, the MA TIS based metamodel using univariate regression was constructed. The first observation of TIS that can be considered the starting point of post-disruption impact was found on 4353rd TIS observation. As discussed in the previous chapter, the detection of the starting point of the non-steady state process utilizes both Welch's graphic method and control limit theorem.

The post-disruption TIS trend for Type 1 behavior was modeled to generate elements for a proper target vector using a composite function combining two separate univariate polynomial models. We are to use a similar modeling approach against MA TIS from individual experiments to benchmark the approximation performance by corresponding ANN generated regression models. The first phase of the model is a nonlinear univariate regression model using a quadratic function and then the second phase of the model is a linear regression model.

The same least square fit method and fixed-interval data sampling technique used to render both quadratic and linear regression models for MA TIS are also used to construct baseline regression models for the ANN training target vector construction. As seen in Figure 35, MA TIS from Exp No. 438 exhibits nonlinear trend during its first 400 TIS observations from index 4353 to index 4752. The resulting univariate quadratic model to represent the first phase of post-disruption behavior is $y = 0.001605(t-4353)^2 + 0.31045(t-4353) + 169.31$ where t is tth TIS observation index such that $t = 4353 \ldots 4752$.

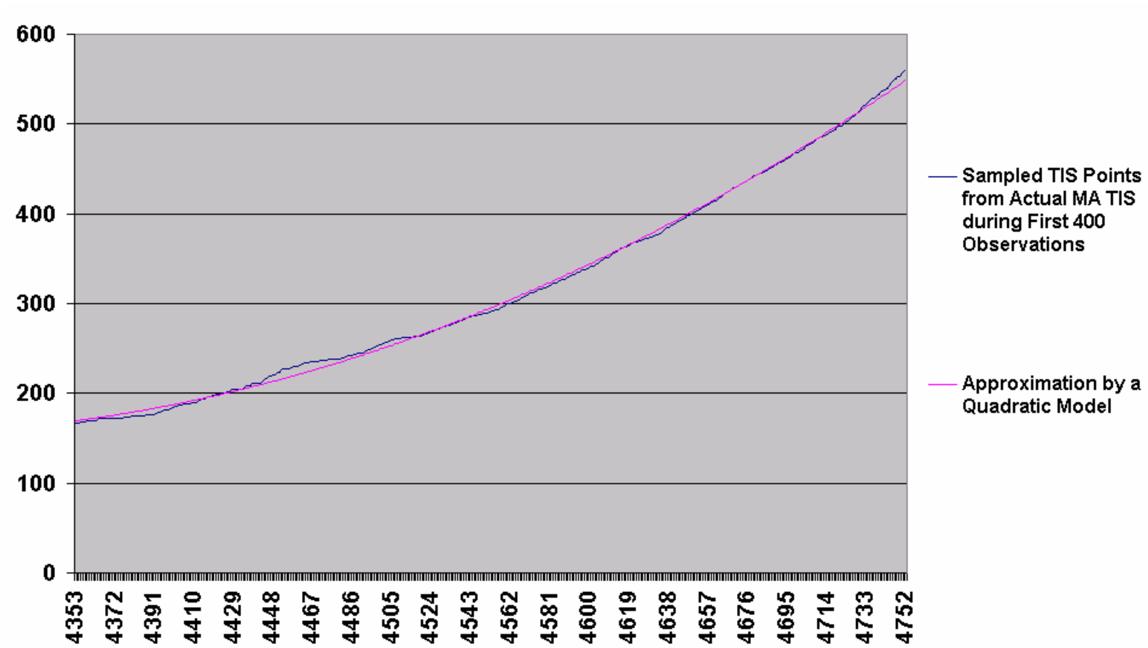


Figure 35. Moving Average Filtered (MA) TIS vs. Approximations by a Quadratic Model for TISs during First 400 Post-disruption Observations

The second univariate regression model was constructed using a linear model on sampled TISs at every 100th observation from 4753rd to 8653rd, which is to cover the remainder of first 10,000 minutes from the point of the disruption event hit.

The resulting univariate regression model to represent the second phase of post-disruption behavior is $y = 1.8951(t - 4753) + 508.2$ where t is tth TIS observation index such that $t = 4753 \ldots 8653$.

Thus, the final form of a composite univariate regression model based on actual MA TIS is:

$$f_{\bar{x}}(t)_{\text{MA TIS}} = \begin{cases} 0.001605(t-4353)^2 + 0.31045(t-4353) + 169.31 & \text{if } 4353 \le t < 4753 \\ 1.8951(t-4753) + 508.2 & \text{if } 4753 \le t < 8654 \end{cases} \tag{7.3.1}$$

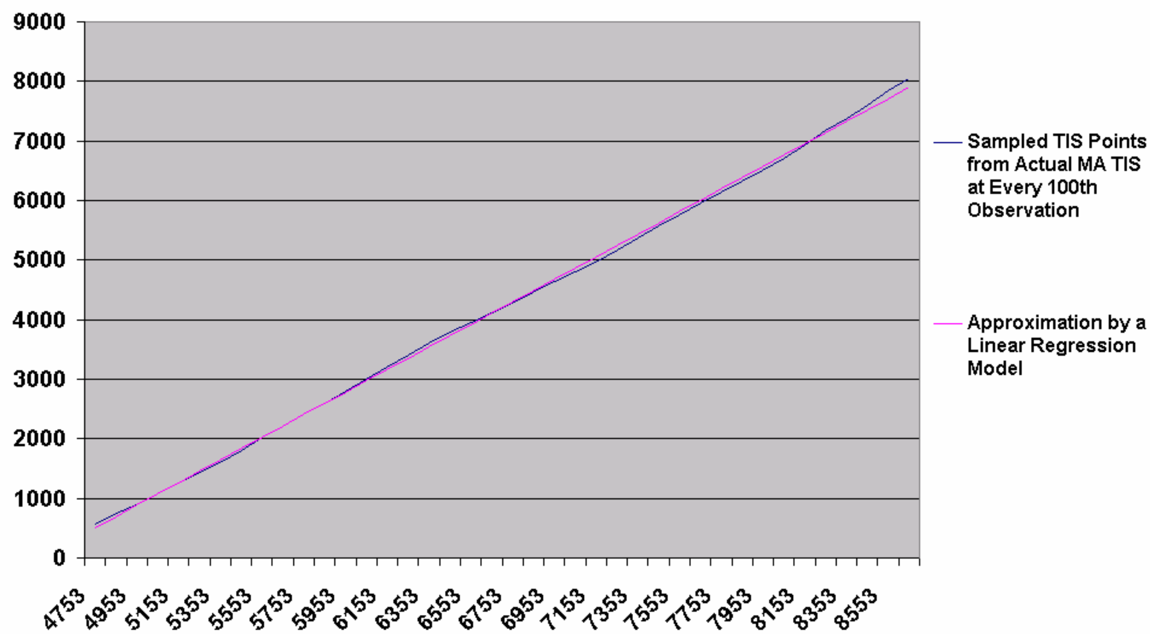


Figure 36. Moving Average Filtered (MA) TIS vs. Approximations by a Linear Regression Model for TISs from 4753rd to 8653rd Observation

Figure 37 summarizes the overall accuracy of the two-phase regression model to actual MA(w=500) TIS. Figure 38 shows the trend of standard deviation among five hundreds adjacent TIS points, which is a meaningful measure to see any change in dispersion of 500 moving consecutive individual TIS observations (equal to the width of the moving average filter) before and after the disruption hit.

As we can verify from Figure 38, there was a big jump in the standard deviation of moving average filtration with a width of 500 observations around the observation index 4297. This clearly indicates that there is an obvious shift in the variance among 500 moving consecutive TIS observations after the disruption hit the system.

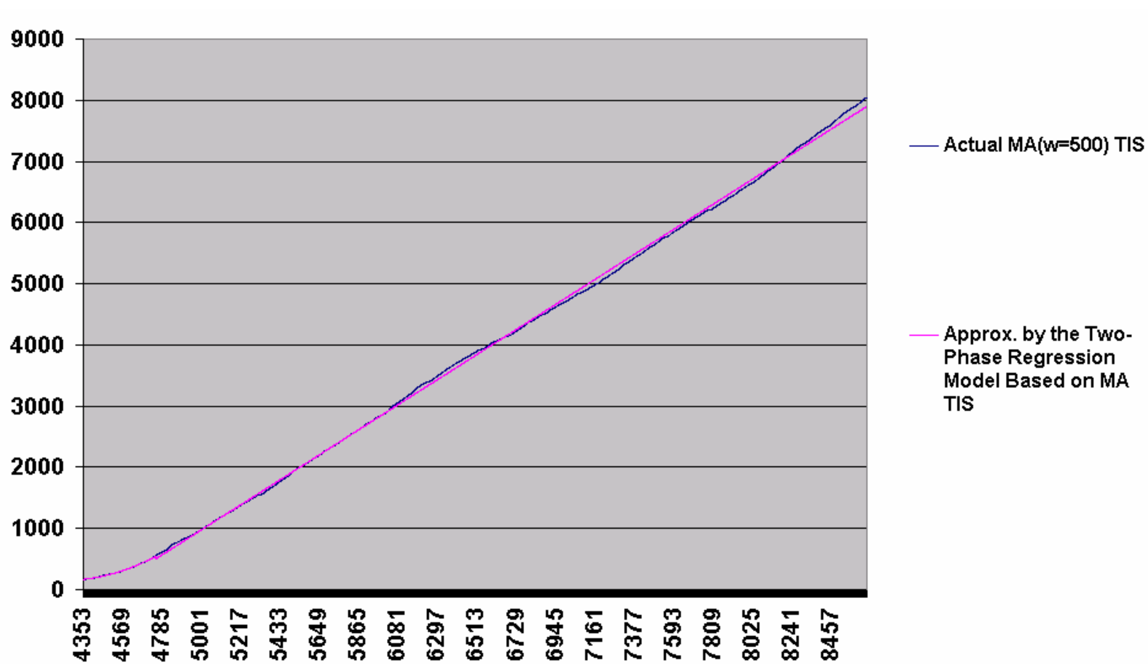


Figure 37: Moving Average Filtered (MA) TIS vs. Approximations by the final Composite Regression Model for TISs from 4353rd to 8653rd Observation

The post-disruption behavior of standard deviation of moving average filtration oscillates around 400 minutes but maintains its overall steady trend for the remainder, which also confirms a predominantly steady linear growth of TIS after the disruption under Type 1 post-disruption behavior.

Since experiment no. 438 belongs to disruption scenario number 26, the proposed ANN based metamodel is supposed to generate a similar composite polynomial based regression model constructed with the moving average filtered (MA) scenario average TIS data. Thus, it is necessary to compare the accuracy of stochastic process of MA TIS approximated by the composite regression model generated from the ANN based meta-model to ones by the composite regression model (7.3.1) based on actual MA TIS and ones by the composite regression model (7.3.2) found on MA scenario average TIS data.

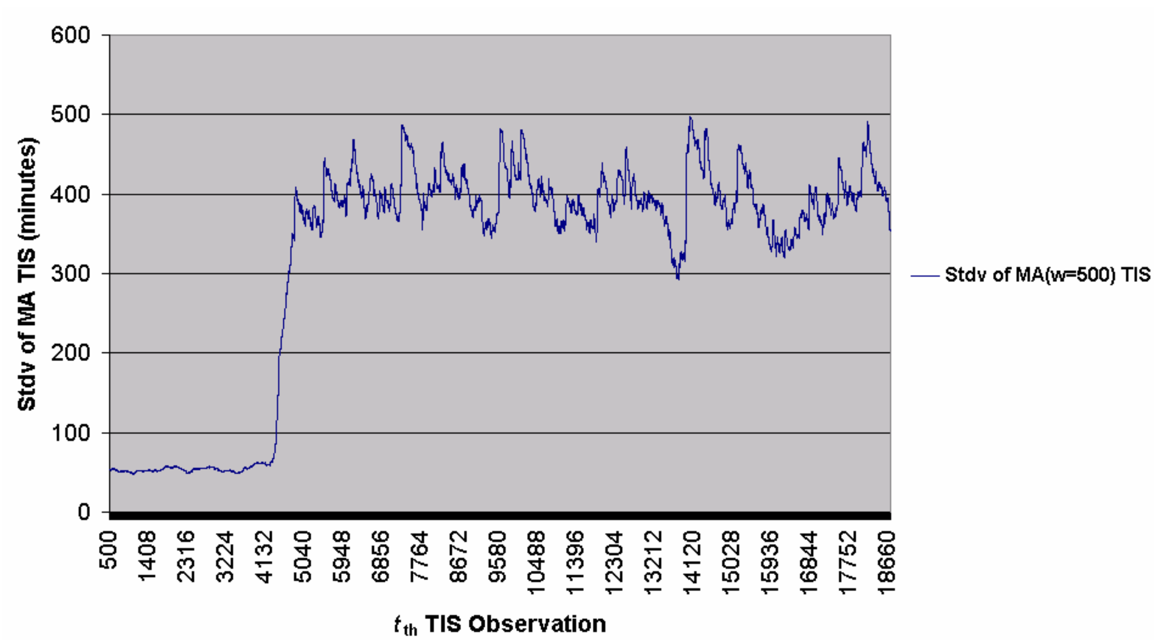


Figure 38. Trend Plot of Standard Deviation of Moving Average (w=500) Filtered TIS observations before and after the disruption and Comparative Plots of Standard Deviation Regression Models

The two-phase regression model found on MA scenario average TIS data can be stated as follows:

$$f_{\bar{x}}(t)_{\text{scenario AVE}} = \begin{cases} 0.0016802(t-4339)^2 + 0.23289(t-4339) + 181.48 & \text{if } 4339 \le t < 4639 \\ 1.8306(t-4639) + 337.94 & \text{if } 4639 \le t < 8654 \end{cases}$$

(7.3.2)

The equivalent two-phase regression model rendered from the proposed ANN based meta-model to find a point estimate of MA TIS (w=500) value at observation t, namely $\hat{\mu}_{f_{\bar{x}} \cdot t}$, can be stated as follows:

$$f_{\bar{x}}(t)_{\text{ANN}} = \begin{cases} 0.0016197(t-4334)^2 + 0.23319(t-4334) + 180.21 & \text{if } 4334 \le t < 4631 \\ 1.8306(t-4631) + 337.94 & \text{if } 4631 \le t < 8654 \end{cases}$$

(7.3.3)

Other target vectors and corresponding ANN approximations to construct the rest of univariate polynomial regression models can be found in Appendix C.

Figure 39 shows a slight disparity between two regression models, (7.3.2) and (7.3.3) as well as disparity with both actual TIS and MA(w=500) TIS plots during the 10,000-minute forecasting horizon. As shown on Figure 43, the closeness to actual (RAW) TIS and MA TIS from above three approximation plots, (7.3.1), (7.3.2), and (7.3.3), are difficult to visually assess.

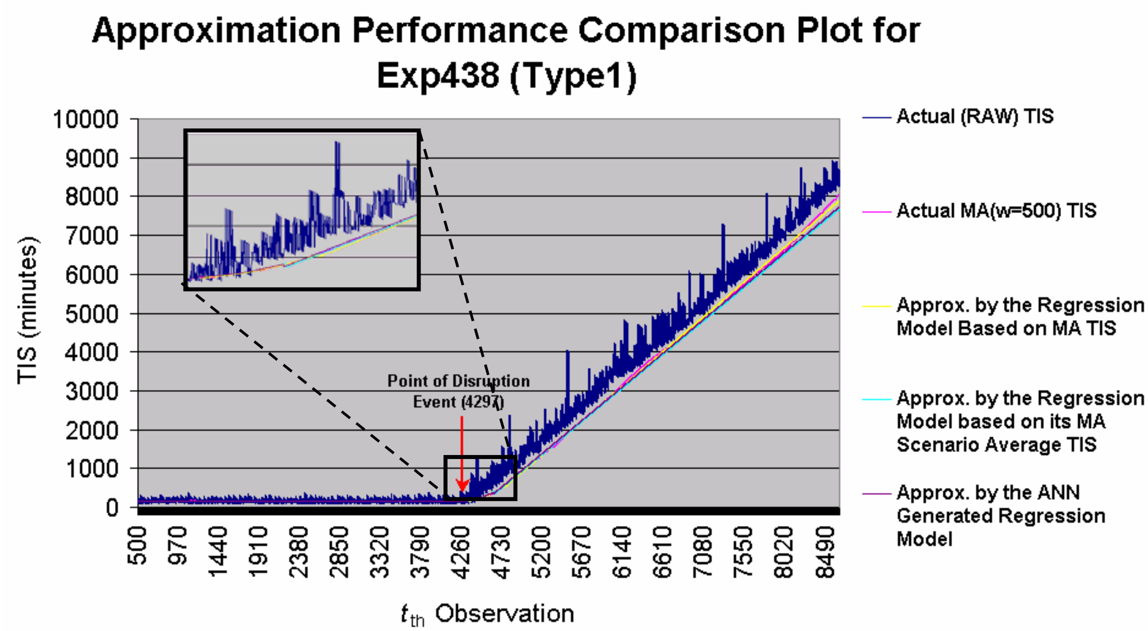


Figure 39. Comparative Plots of Mean TIS Approximations by Various Regression Based Models for Exp438 (Type1)

Thus, an accuracy measure such as a standard error of estimate

($S_e = \sqrt{\dfrac{1}{n-(k+1)}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$ where $\hat{y}_i$ is y_i's unbiased estimator in kth degree polynomial) can be used to estimate individual average proximity to both RAW TIS and MA (w=500) TIS processes from approximated MA TIS stochastic processes by two composite polynomial models and one ANN generated composite polynomial model.

Since metamodeling is a deterministic modeling technique, the trade-offs involve imprecision and simplification can be compensated in some degree by introducing surrogate stochastic elements such as a confidence interval. As discussed in a previous chapter, a point estimator of standard deviation for the moving average filtration consisting of consecutive 500 TIS observations was modeled as a part of the target vector to provide an estimated standard deviation of estimated TIS at observation t.

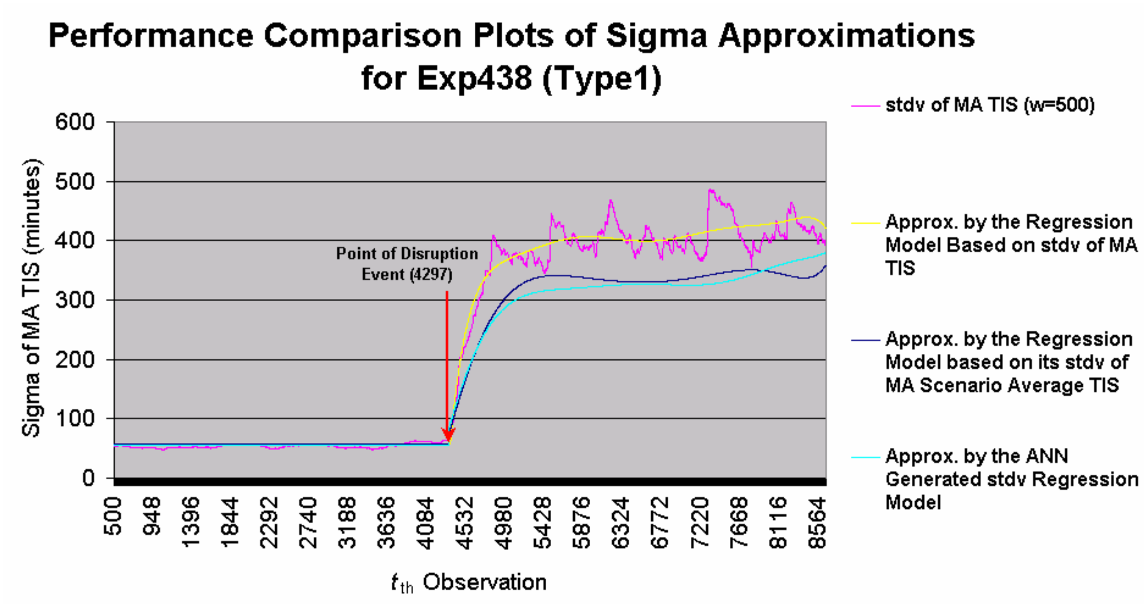


Figure 40. Comparative Plots of Sigma Approximations by Various Regression Based Models for Exp438 (Type1)

Since estimated coefficients for the regression model was based on MA filtered TIS points sampled from fixed intervals of 100 observations rather than entire RAW TIS, a traditional unbiased estimator for the standard deviation of a point estimate of MA TIS at observation t, $\hat{\mu}_{f_{\bar{x}} \cdot t}$ can grossly underestimate the true standard deviation of a point estimate of $\hat{\mu}_{f_{\bar{x}} \cdot t}$ approximated by ANN. Thus, a point estimate of standard deviation from consecutive 500 TIS observations up to t th observation using a univariate polynomial regression model constructed with ANN estimated coefficients is used as the estimated standard deviation of point t in conjunction with the standard deviation of all

ts to construct a confidence interval for $\hat{\mu}_{f_{\bar{x}} \cdot t}$. Figure 40 illustrates the proximity among various standard deviation approximation functions of t using a polynomial regression model.

The first eighth-order polynomial was derived from the actual standard deviation stochastic process of MA (w=500) TIS process to predict chronological behavior of standard deviation after the disruption. A formal notation of this polynomial can be presented as follows: if we assume $E(\hat{\sigma}_t)_{\text{MA TIS}}$ to be an unbiased estimator of standard deviation of moving average TIS at observation t where all $t \geq 4353$ and let 0.0005 be a scaling factor for t to avoid a large disparity among eight coefficients during the regression analysis prior to the ANN training,

$$\begin{aligned} E(\sigma_t)_{\text{MA TIS}} = f_\sigma(t) = 66.641 + 3027.2[(t-4353)\times 0.0005] - 13298[(t-4353)\times 0.0005]^2 \\ + 32604[(t-4353)\times 0.0005]^3 - 46433[(\text{t} - 4353)\times 0.0005]^4 \\ + 39070[(t-4353)\times 0.0005]^5 - 19102[(t-4353)\times 0.0005]^6 \\ + 5012[(t-4353)\times 0.0005]^7 - 545.48[(t-4353)\times 0.0005]^8 \end{aligned} \tag{7.3.4}$$

The second eighth-order polynomial was found on standard deviations of MA scenario average TIS to approximate standard deviations of the MA scenario average TIS at observation t where all $t \geq 4339$:

$$\begin{aligned} E(\sigma_t)_{\text{scenario AVE}} = f_\sigma(t) = 76.98 + 1035.7[(t-4339)\times 0.0005] - 484.92[(t-4339)\times 0.0005]^2 \\ - 3627.1[(t-4339)\times 0.0005]^3 + 8258.9[(t-4339)\times 0.0005]^4 \\ - 8348.6[(t-4339)\times 0.0005]^5 + 4595.7[(t-4339)\times 0.0005]^6 \\ - 1335.7[(t-4339)\times 0.0005]^7 + 160.17[(t-4339)\times 0.0005]^8 \end{aligned} \tag{7.3.5}$$

The third eighth-order polynomial was found on regression coefficients estimated by the ANN to approximate the standard deviation of MA TIS at every observation t where all $t \geq 4334$:

$$
\begin{aligned}
E(\sigma_t)_{\text{ANN}} = f_\sigma(t) = 84.79 + 1017.9[(t-4334)\times 0.0005] - 833.57[(t-4334)\times 0.0005]^2 \\
- 3139.1[(t-4334)\times 0.0005]^3 + 8739.4[(\text{t - }4334)\times 0.0005]^4 \\
- 9567.8[(t-4334)\times 0.0005]^5 + 5383.7[(t-4334)\times 0.0005]^6 \\
- 1535[(\text{t - }4334)\times 0.0005]^7 + 175.61[(t-4334)\times 0.0005]^8
\end{aligned}
\tag{7.3.6}
$$

Since the standard deviation of ANN's MA TIS approximation at observation t can be estimated by using (7.3.6) and standard error of estimate S_e by the regression model can be calculated, the 95% confidence interval for MA TIS at observation t by the ANN generated regression model, $\mu_{f_{\bar{x}}\cdot t}$, can be stated:

$$
f_{\bar{x}}(t) - t_{0.025,n-(k+1)}\left\{s_e^2 + f_\sigma(t)^2\right\}^{1/2} < \mu_{f_{\bar{x}}\cdot t} < f_{\bar{x}}(t) + t_{0.025,n-(k+1)}\left\{s_e^2 + f_\sigma(t)^2\right\}^{1/2} \tag{7.3.7}
$$

where $k = k$ th order polynomial and n = total number of estimates.

The accuracy of this confidence interval for MA TIS at observation t will hold as along as distributions from both actual and approximated MA TIS points hold normality. For instance an estimated 95% prediction interval for MA TIS when t = 5428 can be stated as:

$$
f_{\bar{x}}(5428) \pm t_{0.025,n-(k+1)}\left\{s_e^2 + f_\sigma(5428)\right\}^{1/2}. \tag{7.3.8}
$$

Since $f_{\bar{x}}(5428) = 1811.48$, $s_e^2 = 435.96^2 = 190061.12$, $t_{0.025,8153}$ = 1.96, and $f_\sigma(5428)^2 = 317.11^2$ = 100558.75, the interval (7.3.8) becomes: (756.83, 2866.11).

However, following normality tests, Figure 41 and Figure 42 on both RAW and MA TIS data prior to the point of disruption event shows both populations do not hold characteristics of a normal distribution. Both distributions are positively skewed. Therefore, the accuracy of the prediction interval may not be as accurate as it was intended but still provides a good ballpark estimate of the range where the predicted MA TIS may lie.

Comparative performance plots of MA TIS for the remaining 17 experiments can be found in Appendix E. As we can see from these plots, the proposed ANN based transient modeling technique for various disruption scenarios, especially under post-disruption behavior pattern Type 1 and 3, provides relatively close approximations even compared to its individual regression based counter parts. On the other hand, approximations rendered by the ANN for disruption scenarios classified under post-disruption behavior pattern Type 2 exhibit relatively large discrepancies from their counter parts as well as RAW TIS and MA TIS observations.

Two main causes for such discrepancies were identified. The first cause was a relatively large variation among individual experiments under a single post-disruption behavior scenario from Type 2 compared to those from Type 1 and 3. The second cause was an insufficient modeling capability of a cubic function as the baseline regression modeling technique to capture the non-linear functional TIS trend and construct target vectors for ANN based approximations.

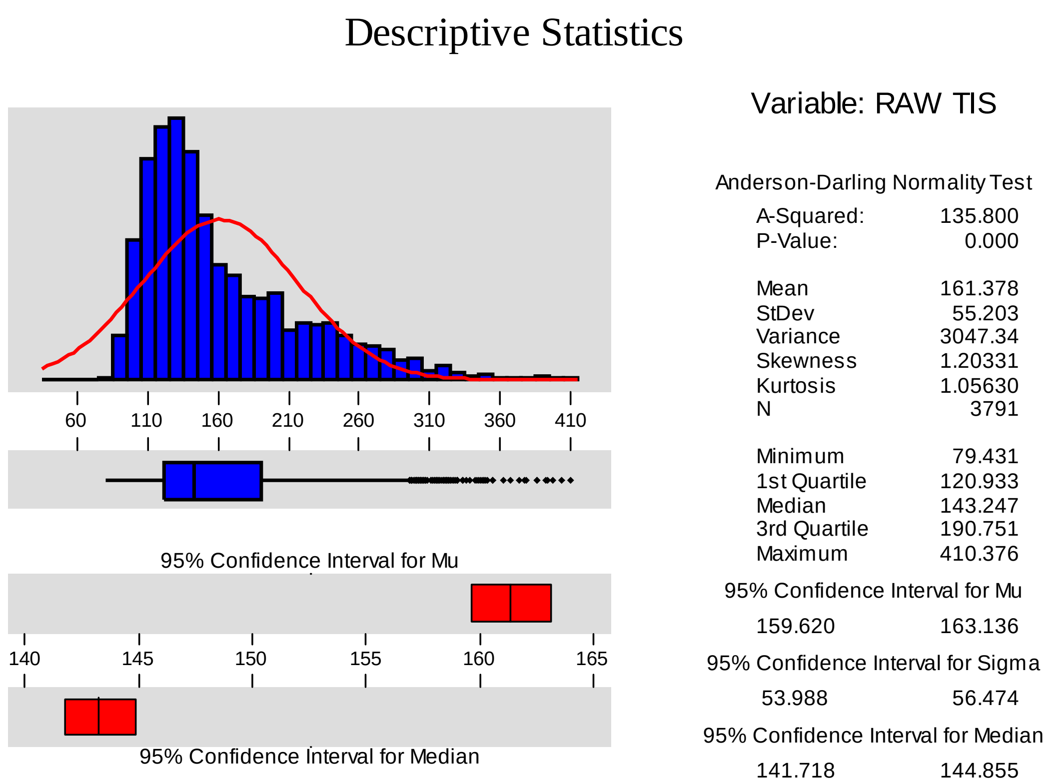


Figure 41. Descriptive Statistics and Normality Test on RAW TIS data from Pre-disruption Period of Exp438

Another finding was that the trend of standard deviations on MA TIS time series under the post-disruption behavior pattern Type 1 is still noisy but stable as shown in Figure 40 on page 239. However, it is visible that there was a significant shift in the overall mean standard deviation after the disruption hit. Unfortunately, this shift in a mean standard deviation plot is not always obvious in some experiments from post-disruption behavior pattern Type 2 and 3 such as Exp62 (Type2), Exp275, Exp356, Exp349, and Exp346.

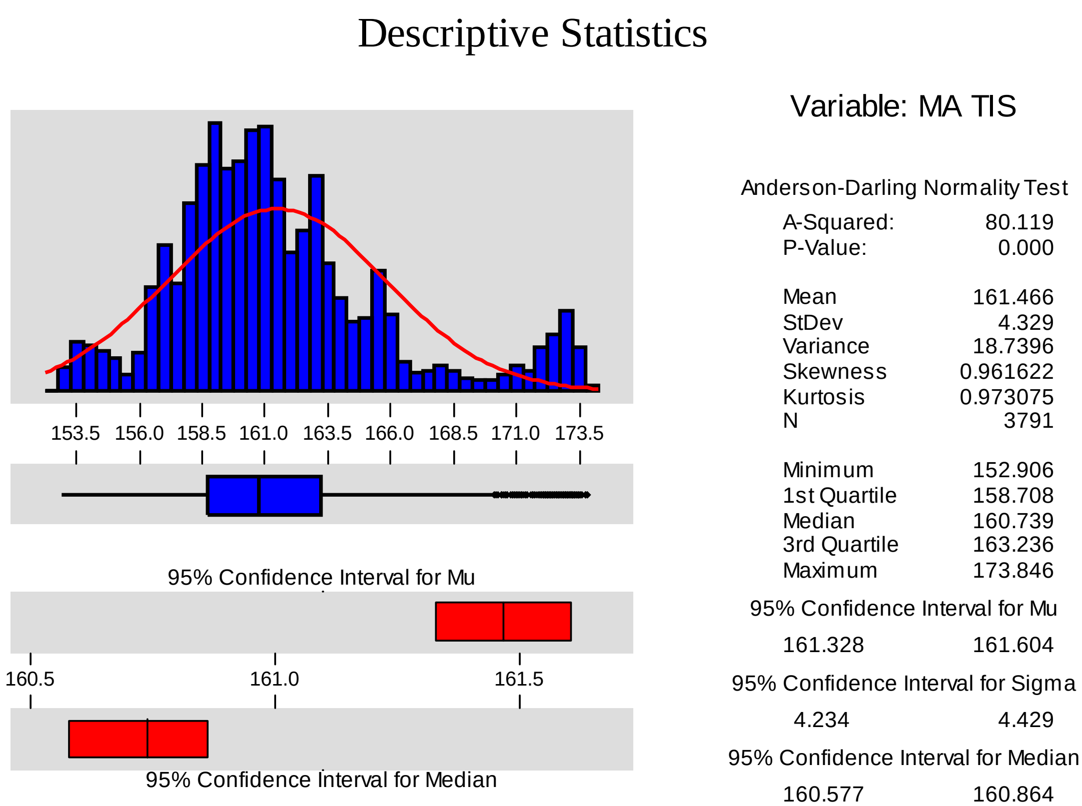


Figure 42. Descriptive Statistics and Normality Test on MA TIS data from Pre-disruption Period of Exp438

The study found that there are more signs of pattern discrepancy and high variation in post-disruption behavior of MA sigma estimates compared to MA scenarios average TIS estimates on individual experiments under Type 2 and 3. As a result, current baseline regression models, a cubic function for Type 2 and constant value function for Type 3, are found to be not robust enough to produce a desired level of prediction accuracy. The study found a higher polynomial model such as the eighth order polynomial used for type 1-disruption scenarios is suitable to approximate individual sigma of MA TIS for all three post-disruption behavior types.

Table 23 summarizes standard errors of MA TIS estimates from all 18 selected experiments. Approximations made by the regression model based on MA TIS outperforms approximations by regression models based on both MA scenarios average TIS and ANN in most selected experiments except Exp436 and Exp85 in comparison to RAW TIS. We can statistically test to see if there is a significant difference between S_e by $f_{\bar{x}}(t)_{\text{ANN}}$ and S_e by $f_{\bar{x}}(t)_{\text{MATIS}}$ against both RAW TIS and MA TIS and also see if there is a significant difference between S_e by $f_{\bar{x}}(t)_{\text{scenario AVE}}$ and S_e by $f_{\bar{x}}(t)_{\text{ANN}}$ against both RAW TIS and MA TIS on each experiment using a hypothesis test concerning two variances with a F-test.

The null hypothesis $H_0 : \sigma_1^2 = \sigma_2^2$ if $F = \dfrac{s_1^2}{s_2^2} > F_\alpha(\nu_1, \nu_2)$ where ν_1 = degrees of freedom from s_1^2 and ν_1 = degrees of freedom from s_1^2 will be rejected in favor of the alternative hypothesis $H_a : \sigma_1^2 > \sigma_2^2$. Since $F_{0.05}(\nu_1 > 100, \nu_2 > 100) \cong 1$, for any s_1^2 and s_2^2 that satisfy $F = \dfrac{s_1^2}{s_2^2} > 1$ equality $\sigma_1^2 > \sigma_2^2$ must exist.

This hypothesis test can be done visually by comparing two standard errors of estimate against both MA TIS and RAW TIS. For example, the mean proximity to both RAW TIS and MA (w=500) TIS processes approximated by $f_{\bar{x}}(t)_{\text{ANN}}$ did not outperform those approximated by $f_{\bar{x}}(t)_{\text{MA TIS}}$, since S_e by $f_{\bar{x}}(t)_{\text{ANN}}$ against RAW TIS is 435.96 minutes which is larger than 403.89 minutes by $f_{\bar{x}}(t)_{\text{MA TIS}}$ against RAW TIS and S_e by $f_{\bar{x}}(t)_{\text{ANN}}$ against MA TIS is 65.50 minutes which is larger than 36.43 minutes by $f_{\bar{x}}(t)_{\text{MA TIS}}$ against MA TIS. However, approximations by $f_{\bar{x}}(t)_{\text{ANN}}$ outperformed approximations by $f_{\bar{x}}(t)_{\text{scenario AVE}}$ against both RAW TIS and actual MA TIS as S_e by $f_{\bar{x}}(t)_{\text{ANN}}$ against both RAW TIS and MA TIS are slightly smaller than S_e by $f_{\bar{x}}(t)_{\text{scenario AVE}}$ against both RAW TIS and MA TIS (S_e by $f_{\bar{x}}(t)_{\text{scenario AVE}}$ against both RAW TIS = 458.98 minutes and S_e by $f_{\bar{x}}(t)_{\text{scenario AVE}}$ against both MA TIS = 84.55 minutes).

As shown in Figure 26, approximations by ANN generated regression models against RAW TIS outperforms approximations by regression models based on MA scenario average TIS in nine out of 18 experiments, 50%, in terms of smaller standard error of estimate. Even in Exp436 and Exp85, approximations by ANN outperformed those by the regression models directly driven from their MA TIS. However, in approximations against MA TIS, only eight out of 18 experiments by ANN approximations outperform approximations done by regression models based on MA scenario average TIS, which accounts for only 44%.

Table 27. TIS Transient Behavior Prediction Performance Table for Selected Experiments under Three Post-disruption Behavior Types

Post-disruption Behavior Type	Performance Rank based on polynomial coefficients approximation for the unknown disruption function by ANN	Exp No.	Std Error of Estimate (minutes): Against Actual (RAW) TIS: Approximation by the regression model based on MA TIS	Against Actual (RAW) TIS: Approximation by the regression model based on MA scenario average TIS	Against Actual (RAW) TIS: Approximation by ANN generated regression model	Against MA TIS: Approximation by the regression model based on MA TIS	Against MA TIS: Approximation by the regression model based on MA scenario average TIS	Against MA TIS: Approximation by ANN generated regression model
Type 1	**Best**	438	403.89	458.98	435.96	36.43	84.55	65.50
		436	382.15	309.05	289.77	33.70	121.41	142.10
	Average	85	288.93	212.06	185.25	32.75	128.82	173.30
		470	318.19	383.67	341.32	20.44	87.64	36.26
	Worst	453	200.46	202.81	228.94	34.72	122.60	66.50
		175	215.02	312.46	308.29	21.25	130.29	125.98
Type 2	**Best**	73	59.87	68.76	68.11	12.27	33.35	31.50
		71	55.31	63.14	58.92	10.11	26.21	18.01
	Average	62	59.21	83.33	92.25	28.29	58.92	70.01
		487	110.73	135.22	138.41	17.96	61.65	54.51
	Worst	500	111.58	157.00	181.28	24.90	136.87	167.98
		498	122.61	135.14	137.20	30.17	63.71	79.85
Type 3	**Best**	275	54.90	55.11	55.11	2.97	6.36	6.59
		356	60.95	61.03	61.18	5.30	7.38	8.10
	Average	349	71.53	87.58	86.00	16.49	56.50	53.86
		346	60.24	61.23	61.98	4.61	12.47	15.65
	Worst	213	45.80	45.88	46.82	4.18	4.96	10.73
		211	45.76	45.82	46.57	2.45	3.11	8.32

Despite this study's limited performance analysis over 18 selected experiments and the proposed modeling scheme's disappointing approximation accuracy as those by traditional regression models based on MA scenario average TIS, the study concludes that this modeling method is still worth investigating and developing in order to materialize its full potential as an automated post-disruption system behavior modeling technique. The biggest modeling advantage of this proposed modeling scheme is its ability to approximate functional targets that were associated with data points never trained with or regressed on.

Appendix B contains sample screen shots of the actual user interface displaying prediction results for Exp438 (see Section B.2). The user interface for the proposed transient behavior prediction system consists of two parts. The first part is to let a user enter actual pre-disruption system conditions and a disruption event itself. It was designed to walk a user through a series of questions asking pre-disruption conditions, various operational parameters, and the nature of disruption. The logic checks behind the user interface keep the user from entering invalid values or out of range values in order to prevent the system from predicting an area that it was never trained to handle. The second part is to present prediction results in English using mathematical notations. It was also designed to display predicted results as an original column vector.

7.4 Summary

This chapter covers results and findings from the experiments designed to test the prediction performance of the proposed ANN based metamodel. Since the current MATLAB based application does not have a fully automated model construction feature and plotting function for point estimates, a comparative plotting of point estimates and actual values can be cost prohibitive for all 540 independent experiments. Therefore, a smaller test set of 18 experiments, two best, two average, and two worst-case TIS observation processes, were selected and evaluated against RAW TIS and MA TIS processes under three post-disruption behavior pattern types. The measure of accuracy used is the standard error of estimates.

The study found that the accuracy of predictions by ANN driven regression models in collective-form predictions using more than one output vector elements, such as coefficients of unknown TIS polynomial approximation function at time t after the disruption, is 50% better than its counter part, regression models based on MA scenarios average TIS. However, in its single-element predictions, such as individual machine utilizations at time t after the disruption, the proposed modeling approach has demonstrated its strength. The study also concludes that despite its somewhat mixed prediction performance results by the proposed modeling approach; the proposed metamodeling methodology is worth further research due to its modeling economy, flexibility, and automation potentials.

8. Summary and Conclusions

Based on findings from the experimental results, weakness and strength of the proposed ANN based performance modeling approach are identified and discussed. The future research directions and opportunities are also presented and discussed for the possible enhancement of the proposed methodology.

8.1 Overview of Research Objectives and Accomplishments

The research identified six major objectives: (1) a simulation study on a hypothetical FMS model with limited operational characteristics and scenarios to identify a unique set of possible transient system behavior patterns under pre-selected disruption scenarios, (2) identification of the input space and output space of an unknown transient performance prediction function, (3) identification of a proper logical taxonomy that can logically connect multiple ANNs, making them work collectively to capture various transient behaviors, (4) identification of design architecture for individual ANNs and their proper training methods, (5) validation and performance assessment of the final model through comparisons with simulation results, (6) recommendations for further improvements of the proposed modeling framework in future research.

In order to satisfy Objective 1, a discrete event simulation model was built using Extend [1987-2001] to study various transient behaviors of the proposed FMS. The model was built and studied. The model was constructed in such way that a single resource failure could be scheduled at a precise moment during a single run. Key performance indexes such as time averaged utilization of each machine stations and AGV are recorded prior and after a scheduled disruption. Limited pilot runs of the model with selected ranges for system operational parameters of interest are used to finalize the experimental design. Individual workstation process time distributions under each part type were also selected to meet desired average system utilization throughout the system. Finally, a valid experimental design was identified and expanded for the analysis.

In order to satisfy Objective 2, major system performance indexes such as time averaged utilization for each machine stations and the AGVs and average TIS for parts were identified through sensitive analysis and used for a part of input space vector. These selected indexes can help an unknown transient performance prediction function to map and distinguish various post-disruption system behaviors based on their unique input space value pattern after the mapping is finished. The other significant part of output space was allocated to capture an unknown time series function of key performance index such as time-in-system of departing parts.

In order to satisfy Objective 3, a branch logic structure was identified based on a number of sub-ANNs and their functional roles. The branch logic helps to taxonomically connect individually trained ANNs so that they can collectively predicts a mutually exclusive area of the functional range of the unknown transient performance prediction function.

In order to satisfy Objective 4, total nine multi-layer ANNs were identified. Based on their primary functional role, a different number of inner layers and number of neurons on the outer layer were identified. Bayesian regularization was chosen as a backpropagation training algorithm. Regularization is a method used to improve the generalization of feedforward neural networks.

In order to satisfy Objective 5, the overall effectiveness of the proposed modeling framework was judged through a combined simulation study and regression analysis. The fidelity of the distinctive transient system behavior pattern classification by the trained top-level ANNs was tested. The accuracy of individual key performance index predictions such as time averaged resource utilizations was tested by comparing prediction data to the target data collected from the regression model. The approximated coefficients of an unknown time series function of TIS (time-in-system) were also compared to actual coefficients from the underlying regression model.

In order to satisfy Objective 6, the study drew a conclusion that the accuracy of predictions by ANN driven regression models is not significantly better than its counter part, regression models based on MA scenarios average TIS. However, the proposed metamodeling methodology has its merits such as modeling economy and automation potentials. Therefore, a further research was recommended to improve its accuracy and expand it applicability.

8.2 The major contributions of this research

Despite the somewhat disappointing performance of the proposed ANN based metamodeling approach, in terms of its accuracy compared to its traditional regression based approach, this study still holds merit as a first attempt to develop a transient system behavior based evaluative performance model utilizing artificial neural networks, discrete event simulation model, and regression analysis. Upon identification of the overall post-disruption behavior pattern, a group of trained ANNs is to collectively construct a univariate regression based prediction model for a selected performance index and predict a series of post-disruption average resource utilizations. Thus far the majority of ANN based performance prediction models have been focused on a single function realization. Under the proposed ANN based metamodeling approach, multiple function realization is possible without storing individual math models in any form of file or database for later use.

Upon analyzing performance disruption scenarios of a known system, a proper degree of polynomial regression model can be determined based on a limited number of trials and the magnitude of error by its point estimates. This also helps to determine the dimension of target vectors that can be used to train individual ANNs. An input vector for the unknown transient performance function is a function of pre-disruption individual resource utilizations and disruption events represented by a single column vector consisting of binary, integer and real numbers. Half of the target vector elements were used to capture the essence of the underlying changes of the target performance index over time by observing a few select data in a fixed interval.

Processing an entire RAW TIS observation data could have been computationally problematic under a data rich environment such as a stochastic process of TIS observation in this study. Individual realizations of unknown TIS point estimation function are possible through learning the changes on each coefficients of a selected polynomial regression model rather than directly approximating an unknown TIS stochastic series.

Utilizing hierarchical inter-relationships and interactions among individual ANNs within the proposed metamodeling framework are another contribution to show how individual ANN can work together to collectively approximate a complex function in a nonparametric way. The top-level ANN is to identify a primary transient behavior pattern exhibited by the suspected process under a given disruption scenario and to invoke only necessary ANNs from the second level to construct corresponding polynomial regression models for both mean TIS and its sigma, as well as, post-disruption time average resource utilization factors. Since the proposed metamodeling scheme does not approximate the point estimate of unknown TIS process at observation t directly, rather it generates an approximation function in the form of a polynomial regression model, the structure of target vectors can be easily customized for future needs. As long as deviations among different sets of coefficients representing independent TIS processes under a specific post-disruption behavior pattern type are kept minimal, the overall accuracy of the proposed metamodeling approach can stay relatively high.

The study found that there are four key factors to determine the final performance of the proposed metamodeling framework. The first factor is whether there are enough independent target performance index observations such as TIS under a specific transient behavior type to train hierarchically organized ANNs within the framework. The second is the proximity of independent target performance index observation processes under a disruption scenario in terms of a small sum of deviations in their estimates and resemblance of their individual functional trend patterns. The third is the robustness of a chosen polynomial regression model to represent various unique trends of each scenario is average performance index observation processes under a particular transient behavior pattern type. Finally, the forth is the modeling effectiveness of individual ANNs and their training method.

The devised metamodeling framework can easily work with an unmanned online controller providing a short-term look-ahead capability. Especially if there is a high chance for any resource failure during the production cycle, this look-ahead capability will become a vital part of intelligent production management techniques. After reasonable coverage of the unknown functional domain and matching range areas, the proposed metamodel can sustain itself with very little human intervention.

The current user interface can be replaced with several branch logics and I/O modules to let the system directly feed its system status and nature of the disruption to the model itself without going through any manual input. Similarly, the current output screen can be replaced with several modules that can directly pass the expected point estimates of TIS at observation t and other performance estimates to the main operation controller to quickly respond with a post-disruption remedial action. The remedial action is designed to reduce any unwanted negative effects caused by the disruption on the selected performance index. When the controller sees the current value of a selected performance index sustainable within a tolerable range, then a remedial action can be dispatched. If the current value of the target performance index is not sustainable within a tolerable range, an urgent warning message can be issued to the operator so that quick intervention can minimize any potential negative impact.

The study provides an opportunity to investigate complex behavior of FMS especially after a single event disruption. The FMS in this study was designed with some level of functional redundancy to cope with a limited resource failure and contention so that re-routing parts is possible when necessary. Even with such functional redundancy, the system remained fault tolerant 55.56% of time. The study verified a presence of two different regions in near equilibrium operation, namely stable equilibrium and unstable equilibrium. Based on current level of individual resource utilizations and nature of disruption event, categorized as unstable equilibrium or stable equilibrium, a different post-disruption state can be reached when a single event disruption hits. This study identified three major patterns of post-disruption system behavior based on modeling efficiency and effectiveness, namely infinite linear growth, infinite non-linear growth, and finite growth to a new steady-state. The study found that 54% of independent TIS observation processes exhibit characteristics of finite growth to a new steady-state.

8.3 The Strength and Weakness of the Proposed Modeling Approach

The study found several strengths of the proposed ANN based metamodeling approach for transient behavior predictions compared to a traditional regression based modeling approach. Under a data rich environment such as the TIS observation process from a suggested FMS, training a group of dedicated ANNs with polynomial regression coefficients from individual performance index observation processes is an economical way to model various time series with a similar overall pattern. By using hierarchical organization and firing of only relevant ANNs under a primary pattern classification, training difficulties and accuracy issues, often faced by a similar functional approximation using single ANN can be resolved. Traditionally more than one time series with a slight difference in individual patterns may require dedicated ANNs or time series models for each in order to maintain a certain level of modeling accuracy. Under the proposed approach, more than one time series such as TIS process can be modeled under a single dedicated ANN.

The proposed metamodeling approach focuses on a transient process such as the post-disruption system behavior on a particular performance aspect. As one of the well-known benefits of neural network application in point estimation of unknown function, it has the capability of predicting points never trained on. In other words, with a comprehensive training of similar transient behavior patterns expressed by a series of coefficients from a carefully selected polynomial regression model, many post-disruption processes with similar system conditions can be predicted. Since the proposed metamodeling approach uses input and target vectors consisting of a series of predefined numerical elements and not all vector elements are mathematically dependent on each other, an expansion of the input and output vectors by adding additional elements is relatively easy.

The followings are some of weaknesses the study found. First, a comprehensive set of possible transient behavior pattern types must be studied. In order to do that, constructing a faithful simulation model or collecting comprehensive data is necessary, which can represent various disruption scenarios under a specific post-disruption behavior pattern. A successful training of various ANNs within the framework relies on effective input and target vectors. Therefore, a well-designed experiment is needed to construct effect training input and target vectors.

A successful classification of different primary behavior patterns for the ANN in the first level relies on the modeler's intuition and experiences. Each primary pattern should be defined in such way where all individual observation processes of a target performance index can have the least amount of deviation from each other when they are expressed with a series of coefficients from a polynomial regression model. The smaller the deviation among individual observation processes, the better it is for modeling accuracy and better prediction performance. Accuracy in the final model may suffer when the training size is too small, the order of the selected polynomial regression model is inappropriate, or deviations among individual post-disruption behaviors are relatively big. The accuracy of estimated confidence interval of mean value for the selected performance index at observation t can also suffer when distributions of standard error of point estimate fails to hold the normality.

8.4 Future Research Directions and Opportunities

The primary focus of any future research is to improve the accuracy of the proposed modeling approach using different baseline mathematical models to construct more efficient target vectors so that a better training result can be achieved. Also, enhancing the current input and output data format in such way that a machine interpretation of prediction outcomes will be feasible. Third, find a method to automate both target vector constructions and individual ANN trainings so that the entire methodology truly will become an automated modeling process. Forth, expand the application beyond the boundary of manufacturing systems. For example, other discrete event dynamic systems such as communication/computer network, computer systems, and transformation networks can be good candidate areas to test the effectiveness of the proposed methodology when unscheduled system performance disruptions are a daily phenomenon.

8.5 Summary

As stated in Chapter 1, most FMSs never reach their steady state in reality because of their highly dynamic nature and operational environment, conventional evaluative model approaches utilizing steady-state analysis often provide their controller very little help to assess a short-term performance after an unscheduled disruption. Such situations often require direct human intervention to adjust various control parameters including some low-level operational rules of individual resources, which can cause a momentary shut down of the entire system. The capability to provide a short-term look ahead may reduce costly downtime of an expensive FMS. Furthermore, it may help run the overall production system more efficiently.

The proposed ANN based metamodeling approach using multiple ANNs, in a taxonomically organized modeling structure, is an efficient way to capture multiple target performance index observation processes with a similar overall post-disruption behavior pattern. Despite its mixed performance results, this methodology was proven especially effective when it had to deal with noisy time series such as TIS at observation t under a data rich environment. The study was done to prove that the proposed methodology could be a viable means to model transient system behaviors especially where the selfmaintainability and modeling economy are the key focus. As long as individual observation processes of the selected performance index can keep their variances smaller among themselves, the accuracy of the overall model would be acceptable. This non-parametric performance modeling technique using hierarchically organized multiple ANNs, is worth further investigation.

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Appendix A

Extended Design of Experiments

Scenario Index	Single Event Disruption Scenario (Triggered at 10000 minutes)			Steady State Scenario (pre-disruption)		Exp. No.
	Part Mix Change	Machine Breakdown	AGV Breakdown	Mean Interarrival Time (minutes)	Part Mix	
1	PM1 → PM2			2.2	PM1	11
	PM1 → PM2			2.2	PM1	12
	PM1 → PM2			2.2	PM1	13
	PM1 → PM2			2.2	PM1	14
	PM1 → PM2			2.2	PM1	15
	PM1 → PM2			2.2	PM1	181
	PM1 → PM2			2.2	PM1	182
	PM1 → PM2			2.2	PM1	183
	PM1 → PM2			2.2	PM1	184
	PM1 → PM2			2.2	PM1	185
	PM1 → PM2			2.2	PM1	186
	PM1 → PM2			2.2	PM1	187
	PM1 → PM2			2.2	PM1	188
	PM1 → PM2			2.2	PM1	189
	PM1 → PM2			2.2	PM1	190
2	PM1 → PM2			2.3	PM1	111
	PM1 → PM2			2.3	PM1	112
	PM1 → PM2			2.3	PM1	113
	PM1 → PM2			2.3	PM1	114
	PM1 → PM2			2.3	PM1	115
	PM1 → PM2			2.3	PM1	191
	PM1 → PM2			2.3	PM1	192
	PM1 → PM2			2.3	PM1	193
	PM1 → PM2			2.3	PM1	194
	PM1 → PM2			2.3	PM1	195
	PM1 → PM2			2.3	PM1	196
	PM1 → PM2			2.3	PM1	197
	PM1 → PM2			2.3	PM1	198
	PM1 → PM2			2.3	PM1	199
	PM1 → PM2			2.3	PM1	200
3	PM2 → PM1			2.2	PM2	56
	PM2 → PM1			2.2	PM2	57
	PM2 → PM1			2.2	PM2	58
	PM2 → PM1			2.2	PM2	59
	PM2 → PM1			2.2	PM2	60
	PM2 → PM1			2.2	PM2	201
	PM2 → PM1			2.2	PM2	202
	PM2 → PM1			2.2	PM2	203
	PM2 → PM1			2.2	PM2	204
	PM2 → PM1			2.2	PM2	205
	PM2 → PM1			2.2	PM2	206

	PM2 → PM1			2.2	PM2	207
	PM2 → PM1			2.2	PM2	208
	PM2 → PM1			2.2	PM2	209
	PM2 → PM1			2.2	PM2	210
4	PM2 → PM1			2.3	PM2	116
	PM2 → PM1			2.3	PM2	117
	PM2 → PM1			2.3	PM2	118
	PM2 → PM1			2.3	PM2	119
	PM2 → PM1			2.3	PM2	120
	PM2 → PM1			2.3	PM2	211
	PM2 → PM1			2.3	PM2	212
	PM2 → PM1			2.3	PM2	213
	PM2 → PM1			2.3	PM2	214
	PM2 → PM1			2.3	PM2	215
	PM2 → PM1			2.3	PM2	216
	PM2 → PM1			2.3	PM2	217
	PM2 → PM1			2.3	PM2	218
	PM2 → PM1			2.3	PM2	219
	PM2 → PM1			2.3	PM2	220
5			3 → 2	2.2	PM1	66
			3 → 2	2.2	PM1	67
			3 → 2	2.2	PM1	68
			3 → 2	2.2	PM1	69
			3 → 2	2.2	PM1	70
			3 → 2	2.2	PM1	221
			3 → 2	2.2	PM1	222
			3 → 2	2.2	PM1	223
			3 → 2	2.2	PM1	224
			3 → 2	2.2	PM1	225
			3 → 2	2.2	PM1	226
			3 → 2	2.2	PM1	227
			3 → 2	2.2	PM1	228
			3 → 2	2.2	PM1	229
			3 → 2	2.2	PM1	230
6			3 → 2	2.3	PM1	121
			3 → 2	2.3	PM1	122
			3 → 2	2.3	PM1	123
			3 → 2	2.3	PM1	124
			3 → 2	2.3	PM1	125
			3 → 2	2.3	PM1	231
			3 → 2	2.3	PM1	232
			3 → 2	2.3	PM1	233
			3 → 2	2.3	PM1	234
			3 → 2	2.3	PM1	235
			3 → 2	2.3	PM1	236
			3 → 2	2.3	PM1	237
			3 → 2	2.3	PM1	238
			3 → 2	2.3	PM1	239
			3 → 2	2.3	PM1	240
7			3 → 2	2.2	PM2	61

			$3 \rightarrow 2$	2.2	PM2	62
			$3 \rightarrow 2$	2.2	PM2	63
			$3 \rightarrow 2$	2.2	PM2	64
			$3 \rightarrow 2$	2.2	PM2	65
			$3 \rightarrow 2$	2.2	PM2	241
			$3 \rightarrow 2$	2.2	PM2	242
			$3 \rightarrow 2$	2.2	PM2	243
			$3 \rightarrow 2$	2.2	PM2	244
			$3 \rightarrow 2$	2.2	PM2	245
			$3 \rightarrow 2$	2.2	PM2	246
			$3 \rightarrow 2$	2.2	PM2	247
			$3 \rightarrow 2$	2.2	PM2	248
			$3 \rightarrow 2$	2.2	PM2	249
			$3 \rightarrow 2$	2.2	PM2	250
8			$3 \rightarrow 2$	2.3	PM2	126
			$3 \rightarrow 2$	2.3	PM2	127
			$3 \rightarrow 2$	2.3	PM2	128
			$3 \rightarrow 2$	2.3	PM2	129
			$3 \rightarrow 2$	2.3	PM2	130
			$3 \rightarrow 2$	2.3	PM2	251
			$3 \rightarrow 2$	2.3	PM2	252
			$3 \rightarrow 2$	2.3	PM2	253
			$3 \rightarrow 2$	2.3	PM2	254
			$3 \rightarrow 2$	2.3	PM2	255
			$3 \rightarrow 2$	2.3	PM2	256
			$3 \rightarrow 2$	2.3	PM2	257
			$3 \rightarrow 2$	2.3	PM2	258
			$3 \rightarrow 2$	2.3	PM2	259
			$3 \rightarrow 2$	2.3	PM2	260
9		M1		2.2	PM1	16
		M1		2.2	PM1	17
		M1		2.2	PM1	18
		M1		2.2	PM1	19
		M1		2.2	PM1	20
		M1		2.2	PM1	261
		M1		2.2	PM1	262
		M1		2.2	PM1	263
		M1		2.2	PM1	264
		M1		2.2	PM1	265
		M1		2.2	PM1	266
		M1		2.2	PM1	267
		M1		2.2	PM1	268
		M1		2.2	PM1	269
		M1		2.2	PM1	270
10		M1		2.3	PM1	131
		M1		2.3	PM1	132
		M1		2.3	PM1	133
		M1		2.3	PM1	134
		M1		2.3	PM1	135
		M1		2.3	PM1	271
		M1		2.3	PM1	272

		M1		2.3	PM1	273
		M1		2.3	PM1	274
		M1		2.3	PM1	275
		M1		2.3	PM1	276
		M1		2.3	PM1	277
		M1		2.3	PM1	278
		M1		2.3	PM1	279
		M1		2.3	PM1	280
		M1		2.2	PM2	21
		M1		2.2	PM2	22
		M1		2.2	PM2	23
		M1		2.2	PM2	24
		M1		2.2	PM2	25
		M1		2.2	PM2	281
		M1		2.2	PM2	282
11		M1		2.2	PM2	283
		M1		2.2	PM2	284
		M1		2.2	PM2	285
		M1		2.2	PM2	286
		M1		2.2	PM2	287
		M1		2.2	PM2	288
		M1		2.2	PM2	289
		M1		2.2	PM2	290
		M1		2.3	PM2	136
		M1		2.3	PM2	137
		M1		2.3	PM2	138
		M1		2.3	PM2	139
		M1		2.3	PM2	140
		M1		2.3	PM2	291
		M1		2.3	PM2	292
12		M1		2.3	PM2	293
		M1		2.3	PM2	294
		M1		2.3	PM2	295
		M1		2.3	PM2	296
		M1		2.3	PM2	297
		M1		2.3	PM2	298
		M1		2.3	PM2	299
		M1		2.3	PM2	300
		M6		2.2	PM1	6
		M6		2.2	PM1	7
		M6		2.2	PM1	8
		M6		2.2	PM1	9
		M6		2.2	PM1	10
		M6		2.2	PM1	301
		M6		2.2	PM1	302
13		M6		2.2	PM1	303
		M6		2.2	PM1	304
		M6		2.2	PM1	305
		M6		2.2	PM1	306
		M6		2.2	PM1	307
		M6		2.2	PM1	308
		M6		2.2	PM1	309
		M6		2.2	PM1	310

14		M6		2.3	PM1	141
		M6		2.3	PM1	142
		M6		2.3	PM1	143
		M6		2.3	PM1	144
		M6		2.3	PM1	145
		M6		2.3	PM1	311
		M6		2.3	PM1	312
		M6		2.3	PM1	313
		M6		2.3	PM1	314
		M6		2.3	PM1	315
		M6		2.3	PM1	316
		M6		2.3	PM1	317
		M6		2.3	PM1	318
		M6		2.3	PM1	319
		M6		2.3	PM1	320
15		M6		2.2	PM2	71
		M6		2.2	PM2	72
		M6		2.2	PM2	73
		M6		2.2	PM2	74
		M6		2.2	PM2	75
		M6		2.2	PM2	321
		M6		2.2	PM2	322
		M6		2.2	PM2	323
		M6		2.2	PM2	324
		M6		2.2	PM2	325
		M6		2.2	PM2	326
		M6		2.2	PM2	327
		M6		2.2	PM2	328
		M6		2.2	PM2	329
		M6		2.2	PM2	330
16		M6		2.3	PM2	106
		M6		2.3	PM2	107
		M6		2.3	PM2	108
		M6		2.3	PM2	109
		M6		2.3	PM2	110
		M6		2.3	PM2	331
		M6		2.3	PM2	332
		M6		2.3	PM2	333
		M6		2.3	PM2	334
		M6		2.3	PM2	335
		M6		2.3	PM2	336
		M6		2.3	PM2	337
		M6		2.3	PM2	338
		M6		2.3	PM2	339
		M6		2.3	PM2	340
17		M2		2.2	PM1	46
		M2		2.2	PM1	47
		M2		2.2	PM1	48
		M2		2.2	PM1	49
		M2		2.2	PM1	50
		M2		2.2	PM1	341
		M2		2.2	PM1	342
		M2		2.2	PM1	343

		M2		2.2	PM1	344
		M2		2.2	PM1	345
		M2		2.2	PM1	346
		M2		2.2	PM1	347
		M2		2.2	PM1	348
		M2		2.2	PM1	349
		M2		2.2	PM1	350
18		M2		2.3	PM1	146
		M2		2.3	PM1	147
		M2		2.3	PM1	148
		M2		2.3	PM1	149
		M2		2.3	PM1	150
		M2		2.3	PM1	351
		M2		2.3	PM1	352
		M2		2.3	PM1	353
		M2		2.3	PM1	354
		M2		2.3	PM1	355
		M2		2.3	PM1	356
		M2		2.3	PM1	357
		M2		2.3	PM1	358
		M2		2.3	PM1	359
		M2		2.3	PM1	360
19		M2		2.2	PM2	26
		M2		2.2	PM2	27
		M2		2.2	PM2	28
		M2		2.2	PM2	29
		M2		2.2	PM2	30
		M2		2.2	PM2	361
		M2		2.2	PM2	362
		M2		2.2	PM2	363
		M2		2.2	PM2	364
		M2		2.2	PM2	365
		M2		2.2	PM2	366
		M2		2.2	PM2	367
		M2		2.2	PM2	368
		M2		2.2	PM2	369
		M2		2.2	PM2	370
20		M2		2.3	PM2	151
		M2		2.3	PM2	152
		M2		2.3	PM2	153
		M2		2.3	PM2	154
		M2		2.3	PM2	155
		M2		2.3	PM2	371
		M2		2.3	PM2	372
		M2		2.3	PM2	373
		M2		2.3	PM2	374
		M2		2.3	PM2	375
		M2		2.3	PM2	376
		M2		2.3	PM2	377
		M2		2.3	PM2	378
		M2		2.3	PM2	379
		M2		2.3	PM2	380
21		M5		2.2	PM1	51

		M5		2.2	PM1	52
		M5		2.2	PM1	53
		M5		2.2	PM1	54
		M5		2.2	PM1	55
		M5		2.2	PM1	381
		M5		2.2	PM1	382
		M5		2.2	PM1	383
		M5		2.2	PM1	384
		M5		2.2	PM1	385
		M5		2.2	PM1	386
		M5		2.2	PM1	387
		M5		2.2	PM1	388
		M5		2.2	PM1	389
		M5		2.2	PM1	390
		M5		2.3	PM1	156
		M5		2.3	PM1	157
		M5		2.3	PM1	158
		M5		2.3	PM1	159
		M5		2.3	PM1	160
		M5		2.3	PM1	391
		M5		2.3	PM1	392
22		M5		2.3	PM1	393
		M5		2.3	PM1	394
		M5		2.3	PM1	395
		M5		2.3	PM1	396
		M5		2.3	PM1	397
		M5		2.3	PM1	398
		M5		2.3	PM1	399
		M5		2.3	PM1	400
		M5		2.2	PM2	31
		M5		2.2	PM2	32
		M5		2.2	PM2	33
		M5		2.2	PM2	34
		M5		2.2	PM2	35
		M5		2.2	PM2	401
		M5		2.2	PM2	402
23		M5		2.2	PM2	403
		M5		2.2	PM2	404
		M5		2.2	PM2	405
		M5		2.2	PM2	406
		M5		2.2	PM2	407
		M5		2.2	PM2	408
		M5		2.2	PM2	409
		M5		2.2	PM2	410
24		M5		2.3	PM2	161
		M5		2.3	PM2	162
		M5		2.3	PM2	163
		M5		2.3	PM2	164
		M5		2.3	PM2	165
		M5		2.3	PM2	411
		M5		2.3	PM2	412
		M5		2.3	PM2	413
		M5		2.3	PM2	414

		M5		2.3	PM2	415
		M5		2.3	PM2	416
		M5		2.3	PM2	417
		M5		2.3	PM2	418
		M5		2.3	PM2	419
		M5		2.3	PM2	420
25		M3		2.2	PM1	76
		M3		2.2	PM1	77
		M3		2.2	PM1	78
		M3		2.2	PM1	79
		M3		2.2	PM1	80
		M3		2.2	PM1	421
		M3		2.2	PM1	422
		M3		2.2	PM1	423
		M3		2.2	PM1	424
		M3		2.2	PM1	425
		M3		2.2	PM1	426
		M3		2.2	PM1	427
		M3		2.2	PM1	428
		M3		2.2	PM1	429
		M3		2.2	PM1	430
26		M3		2.3	PM1	166
		M3		2.3	PM1	167
		M3		2.3	PM1	168
		M3		2.3	PM1	169
		M3		2.3	PM1	170
		M3		2.3	PM1	431
		M3		2.3	PM1	432
		M3		2.3	PM1	433
		M3		2.3	PM1	434
		M3		2.3	PM1	435
		M3		2.3	PM1	436
		M3		2.3	PM1	437
		M3		2.3	PM1	438
		M3		2.3	PM1	439
		M3		2.3	PM1	440
27		M3		2.2	PM2	36
		M3		2.2	PM2	37
		M3		2.2	PM2	38
		M3		2.2	PM2	39
		M3		2.2	PM2	40
		M3		2.2	PM2	441
		M3		2.2	PM2	442
		M3		2.2	PM2	443
		M3		2.2	PM2	444
		M3		2.2	PM2	445
		M3		2.2	PM2	446
		M3		2.2	PM2	447
		M3		2.2	PM2	448
		M3		2.2	PM2	449
		M3		2.2	PM2	450
28		M3		2.3	PM2	171
		M3		2.3	PM2	172

		M3		2.3	PM2	173
		M3		2.3	PM2	174
		M3		2.3	PM2	175
		M3		2.3	PM2	451
		M3		2.3	PM2	452
		M3		2.3	PM2	453
		M3		2.3	PM2	454
		M3		2.3	PM2	455
		M3		2.3	PM2	456
		M3		2.3	PM2	457
		M3		2.3	PM2	458
		M3		2.3	PM2	459
		M3		2.3	PM2	460
29		M7		2.2	PM1	81
		M7		2.2	PM1	82
		M7		2.2	PM1	83
		M7		2.2	PM1	84
		M7		2.2	PM1	85
		M7		2.2	PM1	461
		M7		2.2	PM1	462
		M7		2.2	PM1	463
		M7		2.2	PM1	464
		M7		2.2	PM1	465
		M7		2.2	PM1	466
		M7		2.2	PM1	467
		M7		2.2	PM1	468
		M7		2.2	PM1	469
		M7		2.2	PM1	470
30		M7		2.3	PM1	86
		M7		2.3	PM1	87
		M7		2.3	PM1	88
		M7		2.3	PM1	89
		M7		2.3	PM1	90
		M7		2.3	PM1	471
		M7		2.3	PM1	472
		M7		2.3	PM1	473
		M7		2.3	PM1	474
		M7		2.3	PM1	475
		M7		2.3	PM1	476
		M7		2.3	PM1	477
		M7		2.3	PM1	478
		M7		2.3	PM1	479
		M7		2.3	PM1	480
31		M7		2.2	PM2	41
		M7		2.2	PM2	42
		M7		2.2	PM2	43
		M7		2.2	PM2	44
		M7		2.2	PM2	45
		M7		2.2	PM2	481
		M7		2.2	PM2	482
		M7		2.2	PM2	483
		M7		2.2	PM2	484
		M7		2.2	PM2	485

		M7		2.2	PM2	486
		M7		2.2	PM2	487
		M7		2.2	PM2	488
		M7		2.2	PM2	489
		M7		2.2	PM2	490
32		M7		2.3	PM2	176
		M7		2.3	PM2	177
		M7		2.3	PM2	178
		M7		2.3	PM2	179
		M7		2.3	PM2	180
		M7		2.3	PM2	491
		M7		2.3	PM2	492
		M7		2.3	PM2	493
		M7		2.3	PM2	494
		M7		2.3	PM2	495
		M7		2.3	PM2	496
		M7		2.3	PM2	497
		M7		2.3	PM2	498
		M7		2.3	PM2	499
		M7		2.3	PM2	500
33				2.2	PM1	1
				2.2	PM1	2
				2.2	PM1	3
				2.2	PM1	4
				2.2	PM1	5
				2.2	PM1	501
				2.2	PM1	502
				2.2	PM1	503
				2.2	PM1	504
				2.2	PM1	505
				2.2	PM1	506
				2.2	PM1	507
				2.2	PM1	508
				2.2	PM1	509
				2.2	PM1	510
34				2.3	PM1	91
				2.3	PM1	92
				2.3	PM1	93
				2.3	PM1	94
				2.3	PM1	95
				2.3	PM1	511
				2.3	PM1	512
				2.3	PM1	513
				2.3	PM1	514
				2.3	PM1	515
				2.3	PM1	516
				2.3	PM1	517
				2.3	PM1	518
				2.3	PM1	519
				2.3	PM1	520
35				2.2	PM2	96
				2.2	PM2	97
				2.2	PM2	98

				2.2	PM2	99
				2.2	PM2	100
				2.2	PM2	521
				2.2	PM2	522
				2.2	PM2	523
				2.2	PM2	524
				2.2	PM2	525
				2.2	PM2	526
				2.2	PM2	527
				2.2	PM2	528
				2.2	PM2	529
				2.2	PM2	530
36				2.3	PM2	101
				2.3	PM2	102
				2.3	PM2	103
				2.3	PM2	104
				2.3	PM2	105
				2.3	PM2	531
				2.3	PM2	532
				2.3	PM2	533
				2.3	PM2	534
				2.3	PM2	535
				2.3	PM2	536
				2.3	PM2	537
				2.3	PM2	538
				2.3	PM2	539
				2.3	PM2	540

Appendix B

B.1 MATLAB Source Code for Training Individual ANNs

```
%ANN based FMS Transient Performance Model Training Session

%
figure(gcf)
clf;
echo on
clc

%    ============================================================
%    ANN based FMS Transient Performance Model Training Session
%    ============================================================

%    PRESTD  - Normalize data for zero mean and unity standard deviation.
%    PREPCA  - Principal components analysis.
%    NEWFF   - Inititializes feed-forward networks.
%    TRAIN   - Trains a network.
%    SIM     - Simulates networks.
%    POSTSTD - Inverts PRESTD to convert network outputs to original units.
%    POSTREG - Linear regression between targets and trained network outputs.

%    NONLINEAR REGRESSION:

%    Using the above functions a feed-forward network is trained
%    to perform a nonlinear regression between predisruption system conditions
%    and postdiruption system conditions.  The final network is analyzed to
%    investigate overall performance.

pause % Strike any key to continue...
clc

%    DEFINING THE PROBLEM
%    ====================

%    The .mat file FMStransientModel contains matrices
%    P and T.  The P matrix contains the network inputs,
%    which are 15 independent measured spectral components of 36 different system disruption scenarios.
%    The T matrix contains the corresponding targets, which are
%    individual machine utilization levels after a disruption and estimated regression paramenters for the
unknown transient function.

% Load in the data file
%load choles_all
load training_data_1_1;
p=inputs_1_1;
t=outputs_1_1;

% Normalize the inputs and targets so that they have
% zero mean and unity variance.
[pn,minp,maxp,tn,mint,maxt] = premnmx(p,t);

% Perform a principal component analysis and remove those
% components which account for less than 0.1% of the variation.
%[ptrans,transMat] = prepca(pn,0.001);
ptrans=pn;
pause % Strike any key to divide the data...
clc
```

```
% Divide the data up into training, validation and test sets.
% The testing set will start with the second point and take
% every fourth point.  The validation set will start with the
% fourth point and take every fourth point.  The training set
% will take the remaining points.
[R,Q] = size(ptrans);
iitst = 2:4:Q;
iival = 4:4:Q;
iitr = [1:4:Q 3:4:Q];
validation.P = ptrans(:,iival);
validation.T = tn(:,iival);
testing.P = ptrans(:,iitst);
testing.T = tn(:,iitst);
ptr = ptrans(:,iitr);
ttr = tn(:,iitr);

pause % Strike any key to define the network...
clc
%    DEFINING THE NETWORK
%    ===================

% Create a feedforward network with 4 hidden neurons, 2 output
% neurons, TANSIG hidden neurons and linear output neurons.  Here
% we assign the Bayesian Regulation training function - TRAINBR.  You
% can replace TRAINBR with any training function you desire. The NEWFF
% command will also initialize the weights in the network.
net = newff(minmax(ptr),[2 2 2],{'tansig' 'tansig' 'purelin'},'trainbr');

pause % Strike any key to train the network...
clc

%    TRAINING THE NETWORK
%    ===================

% Before training the network you may want to change some of the training
% parameters from their default values.  Here we change only the
% show parameter.
net.trainParam.show = 5;    % Show intermediate results every five iterations.
%net.trainParam.epochs = 150;
%    Training begins...please wait...

% Train the network.  We use early stopping, so we are passing the
% validation data.  We also want the errors computed on a test
% set, so we are passing the testing data.
[net,tr]=train(net,ptr,ttr,[],[],validation,testing);

pause % Strike any key to test the networks...
clc
%    TESTING THE NETWORK
%    ===================

% Plot the training, validation and test errors.
plot(tr.epoch,tr.perf,'r',tr.epoch,tr.vperf,':g',tr.epoch,tr.tperf,'-.b')
legend('Training','Validation','Test',-1);
ylabel('Squared Error')

% Simulate the trained network.
an = sim(net,ptrans);

% Convert the output of the network back into the original units
% of the targets.  Since the targets were transformed using PRESTD so
```

```
% that the mean was 0 and the standard deviation was 1, we need to
% use POSTSTD (the inverse of PRESTD) and the original mean and standard
% deviation to transform the network outputs back into the original units.
a = postmnmx(an,mint,maxt);

pause % Strike any key to display the regression analysis...
clc
%    DISPLAY RESULTS
%    ===============

%    We will now display plots showing regression analyses between the
%    network outputs and the corresponding targets (in original units).


for i=1:1

   pause % Strike any key to display the next output...
   clc
         [m(i),b(i),r(i)] = postreg(a(i,:),t(i,:));


end

echo off
                           disp('End of ANN based FMS Transient model training')
```

MATLAB Source Code for Simulating A Taxonomically Organized ANN based Transient Behavior Prediction Model

```
%ANN based FMS Transient Performance Model Training Session

%
%echo on
%clc


load trained_transient_SM;
disp ('what is a mean part arrival time to the system? ')
n = input ('Enter 1 for 2.2min or 2 for 2.3min: ');
while (n ~= 1) & (n ~= 2)
disp ('warning: digits 1 and 2 are only acceptable.');
n = input ('Enter 1 for 2.2min or 2 for 2.3min: ');
end
if n == 1
  mparrv = 2.2;
else
  mparrv = 2.3;
end
disp ('Following time averaged utilizations of each machine stations prior to')
disp ('a disruptive event are needed as a part of the input vector. ')
disp (' ')
disp (' ')
disp ('What is time averaged utilization of Machine#1 prior to a disruptive event? ')
disp ('A desirable value should be between 0.4382 and 0.68303. ')
u1 = input ('Enter M1 Utilization prior to a disruption:');
while (u1 < 0.4) | (u1> 0.75)
  if (u1 < 0.4)
     disp ('warning: the value is too low to generate a valid prediction. ')
     disp ('A desirable value should be between 0.4382 and 0.68303. ')
     u1 = input ('Enter M1 Utilization prior to a disruption:');
  else
     disp ('warning: the value is too high to generate a valid prediction. ')
     disp ('A desirable value should be between 0.4382 and 0.68303. ')
     u1 = input ('Enter M1 Utilization prior to a disruption:');
  end
end
disp (' ')
disp (' ')
disp ('What is time averaged utilization of Machine#6 prior to a disruptive event? ')
disp ('A desirable value should be between 0.2649 and 0.80999. ')
u6 = input ('Enter M6 Utilization prior to a disruption:');
while (u6 < 0.2) | (u6 > 0.85)
  if (u6 < 0.2)
     disp ('warning: the value is too low to generate a valid prediction. ');
     disp ('A desirable value should be between 0.2649 and 0.80999. ')
     u6 = input ('Enter M6 Utilization prior to a disruption:');
  else
     disp ('warning: the value is too high to generate a valid prediction. ');
     disp ('A desirable value should be between 0.2649 and 0.80999. ')
     u6 = input ('Enter M6 Utilization prior to a disruption:');
  end
end
disp (' ')
disp (' ')
```

```
disp ('What is time averaged utilization of Machine#2 prior to a disruptive event? ')
disp ('A desirable value should be between 0.44374 and 0.74975. ')
u2 = input ('Enter M2 Utilization prior to a disruption:');
while (u2 < 0.4) | (u2 > 0.80)
   if (u2 < 0.4)
      disp ('warning: the value is too low to generate a valid prediction. ')
      disp ('A desirable value should be between 0.44374 and 0.74975. ')
      u2 = input ('Enter M2 Utilization prior to a disruption:');
   else
      disp ('warning: the value is too high to generate a valid prediction. ')
      disp ('A desirable value should be between 0.44374 and 0.74975. ')
      u2 = input ('Enter M2 Utilization prior to a disruption:');
   end
end
disp (' ')
disp (' ')
disp ('What is time averaged utilization of Machine#5 prior to a disruptive event? ')
disp ('A desirable value should be between 0.23492 and 0.67018. ')
u5 = input ('Enter M5 Utilization prior to a disruption: ');
while (u5 < 0.2) | (u5 > 0.7)
   if (u5 < 0.2)
      disp ('warning: the value is too low to generate a valid prediction. ')
      disp ('A desirable value should be between 0.23492 and 0.67018. ')
      u5 = input ('Enter M5 Utilization prior to a disruption: ');
   else
      disp ('warning: the value is too high to generate a valid prediction. ')
      disp ('A desirable value should be between 0.23492 and 0.67018. ')
      u5 = input ('Enter M5 Utilization prior to a disruption: ');
   end
end
disp (' ')
disp (' ')
disp ('What is time averaged utilization of Machine#3 prior to a disruptive event? ')
disp ('A desirable value should be between 0.357 and 0.8041. ')
u3 = input ('Enter M3 Utilization prior to a disruption: ');
while (u3 < 0.3) | (u3 > 0.83)
   if (u3 < 0.3)
      disp ('warning: the value is too low to generate a valid prediction. ')
      disp ('A desirable value should be between 0.357 and 0.8041. ')
      u3 = input ('Enter M3 Utilization prior to a disruption: ');
   else
      disp ('warning: the value is too high to generate a valid prediction. ')
      disp ('A desirable value should be between 0.357 and 0.8041. ')
      u3 = input ('Enter M3 Utilization prior to a disruption: ');
   end
end
disp (' ')
disp (' ')
disp ('What is time averaged utilization of Machine#7 prior to a disruptive event? ')
disp ('A desirable value should be between 0.36168 and 0.7649. ')
u7 = input ('Enter M7 Utilization prior to a disruption: ');
while (u7 < 0.3) | (u7 > 0.8)
   if (u7 < 0.3)
      disp ('warning: the value is too low to generate a valid prediction. ')
      disp ('A desirable value should be between 0.36168 and 0.7649. ')
      u7 = input ('Enter M7 Utilization prior to a disruption: ');
   else
      disp ('warning: the value is too high to generate a valid prediction. ')
      disp ('A desirable value should be between 0.36168 and 0.7649. ')
      u7 = input ('Enter M7 Utilization prior to a disruption: ');
   end
end
```

```
disp (' ')
disp (' ')
disp ('What is time averaged utilization of Machine#9 prior to a disruptive event? ')
disp ('A desirable value should be between 0.28211 and 0.8268. ')
u9 = input ('Enter M9 Utilization prior to a disruption: ');
while (u9 < 0.2) | (u9 > 0.85)
  if (u9 < 0.2)
      disp ('warning: the value is too low to generate a valid prediction. ')
      disp ('A desirable value should be between 0.28211 and 0.8268. ')
      u9 = input ('Enter M9 Utilization prior to a disruption: ');
  else
      disp ('warning: the value is too high to generate a valid prediction. ')
      disp ('A desirable value should be between 0.28211 and 0.8268. ')
      u9 = input ('Enter M9 Utilization prior to a disruption: ');
  end
end
disp (' ')
disp (' ')
disp ('What is time averaged utilization of Machine#12 prior to a disruptive event? ')
disp ('A desirable value should be between 0.54538 and 0.72847. ')
u12 = input ('Enter M12 Utilization prior to a disruption: ');
while (u12 < 0.5) | (u12 > 0.75)
  if (u12 < 0.5)
      disp ('warning: the value is too low to generate a valid prediction. ')
      disp ('A desirable value should be between 0.54538 and 0.72847. ')
      u12 = input ('Enter M12 Utilization prior to a disruption: ');
  else
      disp ('warning: the value is too high to generate a valid prediction. ')
      disp ('A desirable value should be between 0.54538 and 0.72847. ')
      u12 = input ('Enter M12 Utilization prior to a disruption: ');
  end
end
disp (' ')
disp (' ')
disp ('What is time averaged utilization of AGV prior to a disruptive event? ')
disp ('A desirable value should be between 0.27854 and 0.60651. ')
uav = input ('Enter AGV Utilization prior to a disruption: ');
while (uav < 0.2) | (uav > 0.65)
  if (uav < 0.2)
      disp ('warning: the value is too low to generate a valid prediction. ')
      disp ('A desirable value should be between 0.27854 and 0.60651. ')
      uav = input ('Enter AGV Utilization prior to a disruption: ');
  else
      disp ('warning: the value is too high to generate a valid prediction. ')
      disp ('A desirable value should be between 0.27854 and 0.60651. ')
      uav = input ('Enter AGV Utilization prior to a disruption: ');
  end
end
disp (' ')
disp (' ')
disp ('What is time averaged utilization of Fixture prior to a disruptive event? ')
disp ('A desirable value should be between 0.52744 and 0.676. ')
ufx = input ('Enter Fixture Utilization prior to a disruption: ');
while (ufx < 0.5) | (ufx > 0.7)
  if (ufx < 0.5)
      disp ('warning: the value is too low to generate a valid prediction. ')
      disp ('A desirable value should be between 0.52744 and 0.676. ')
      ufx = input ('Enter Fixture Utilization prior to a disruption: ');
  else
      disp ('warning: the value is too high to generate a valid prediction. ')
      disp ('A desirable value should be between 0.52744 and 0.676. ')
      ufx = input ('Enter Fixture Utilization prior to a disruption: ');
```

```
  end
end
putil = [mparrv u1 u6 u2 u5 u3 u7 u9 u12 uav ufx];
disp (' ')
disp (' ')
disp ('Possible operational disruption scenarios are based on only two types of single disruption event.')
disp ('A part mix change and single resource failure are two preselected types of single disruption event.')
disp ('What type of disruptive event took place? If it was a part mix change, enter 1. ')
disp ('if it was a resource failure, enter 2.')
dstype = input ('Enter 1 or 2 for a part mix change or a resource failure: ');
while (dstype ~= 1) & (dstype ~= 2)
     disp ('warning: invalid value. A number 1 or 2 is only allowed.')
     dstype = input ('Enter 1 or 2 for a part mix change or a resource failure: ');
end
disp (' ')
disp (' ')
if (dstype == 1)
   disp ('Select an appropriate part mix change from the below.')
   disp ('Part Mix Type 1: P1=25% P5=25% P8=25% P11=25%')
   disp ('Part Mix Type 2: P1=20% P4=20% P5=25% P11=20% P12=20%')
   disp ('Enter 1 if a disruption is resulted by Part Mix Type 1 => Part Mix Type 2 ')
   disp ('Otherwise enter 2 for the disruption is resulted by Part Mix Type 2 => Part Mix Type 1 ')
   pmdstype = input('Enter only 1 or 2 for a part mix change PM1 => PM2 or PM2 => PM1:  ');
   while (pmdstype ~= 1) & (pmdstype ~= 2)
     disp ('warning: invalid value. A number 1 or 2 is only allowed.')
     pmdstype = input ('Enter only 1 or 2 for a part mix change PM1 => PM2 or PM2 => PM1:  ');
   end
   if pmdstype == 1
     pmxtype  = 1;
     pdisevnt = [0.25 0 0 0 0.25 0 0 0.25 0 0 0.25 0 -0.05 0 0 0.2 -0.05 0 0 -0.25 0 0 -0.05 0.2 0 0 0 0 0 0 0 0 0
0];
   else
     pmxtype = 2;
     pdisevnt = [0.2 0 0 0.2 0.2 0 0 0 0 0 0.2 0.2 0.05 0 0 -0.2 0.05 0 0 0.25 0 0 0.05 -0.2 0 0 0 0 0 0 0 0 0];
   end
   pnew = [putil pdisevnt]'
else
   disp ('What is the current part mix type for the system?');
   disp ('Part Mix Type 1: P1=25% P5=25% P8=25% P11=25%')
   disp ('Part Mix Type 2: P1=20% P4=20% P5=20% P11=20% P12=20%')
   pmxtype = input('Enter only 1 or 2 for Part Mix Type 1 or Part Mix Type 2:  ');
   while (pmxtype ~= 1) & (pmxtype ~= 2)
     disp ('warning: invalid value. A number 1 or 2 is only allowed.')
     pmxtype = input ('Enter only 1 or 2 for Part Mix Type 1 or Part Mix Type 2:  ');
   end
   if pmxtype == 1
     pmx = [0.25 0 0 0 0.25 0 0 0.25 0 0 0.25 0 0 0 0 0 0 0 0 0 0 0 0 0];
   else
     pmx = [0.2 0 0 0.2 0.2 0 0 0 0 0 0.2 0.2 0 0 0 0 0 0 0 0 0 0 0 0];
   end
   disp (' ')
   disp (' ')
   disp ('Select a single resource that failed and caused a disruption during the operation.')
   disp ('Enter 1 for machine 1 breakdown, 6 for machine 6 breakdown, 2 for machine 2 breakdown, ')
   disp ('5 for machine 5 breakdown, 3 for machine 3 breakdown, 7 for machine 7 breakdown, ')
   disp ('or 99 for a single AGV failure.')
   psrftype = input ('Enter only 1, 6, 2, 5, 3, 7, or 99 for a single resource failure:  ');
   while (psrftype ~= 1) & (psrftype ~= 6) & (psrftype ~= 2) & (psrftype ~= 5) & (psrftype ~= 3) & (psrftype ~=
7) & (psrftype ~= 99)
      disp ('warning: invalide number. A number should be either 1, 6, 2, 5, 3, 7, or 99. ')
      psrftype = input ('Enter only 1, 6, 2, 5, 3, 7, or 99 for a single resource failure:  ');
   end
```

```
    if (psrftype == 1)
        psrf = [1 0 0 0 0 0 0 0 0 ];
    elseif (psrftype == 6)
        psrf = [0 1 0 0 0 0 0 0 0 ];
    elseif (psrftype == 2)
        psrf = [0 0 1 0 0 0 0 0 0 ];
    elseif (psrftype == 5)
        psrf = [0 0 0 1 0 0 0 0 0 ];
    elseif (psrftype == 3)
        psrf = [0 0 0 0 1 0 0 0 0];
    elseif (psrftype == 7)
        psrf = [0 0 0 0 0 1 0 0 0];
    elseif (psrftype == 99)
        psrf = [0 0 0 0 0 0 0 0 1];
    end
    pnew = [putil pmx psrf]'
end
pnewn1 = tramnmx(pnew,minp_1_1,maxp_1_1);
anewn1 = sim(net_1_1,pnewn1);
anew1 = postmnmx(anewn1,mint_1_1,maxt_1_1);
ptype = round(anew1(1)^2+anew1(2)^2*2);
if ptype == 1
    pnewn2_1=tramnmx(pnew,minp_2_1_1,maxp_2_1_1);
    anewn2_1_1 =sim(net_2_1_1,pnewn2_1);
    anew2_1_1 = postmnmx(anewn2_1_1,mint_2_1_1,maxt_2_1_1);
    anewn2_1_2 =sim(net_2_1_2,pnewn2_1);
    anew2_1_2 = postmnmx(anewn2_1_2,mint_2_1_2,maxt_2_1_2);
    anewn2_1_3 =sim(net_2_1_3,pnewn2_1);
    anew2_1_3 = postmnmx(anewn2_1_3,mint_2_1_3,maxt_2_1_3);
    anew = [anew2_1_1' anew2_1_2' anew2_1_3']';
elseif ptype == 2
    pnewn2_2=tramnmx(pnew,minp_2_2_1,maxp_2_2_1);
    anewn2_2_1 =sim(net_2_2_1,pnewn2_2);
    anew2_2_1 = postmnmx(anewn2_2_1,mint_2_2_1,maxt_2_2_1);
    anewn2_2_2 =sim(net_2_2_2,pnewn2_2);
    anew2_2_2 = postmnmx(anewn2_2_2,mint_2_2_2,maxt_2_2_2);
    anewn2_2_3 =sim(net_2_2_3,pnewn2_2);
    anew2_2_3 = postmnmx(anewn2_2_3,mint_2_2_3,maxt_2_2_3);
    anew = [anew2_2_1' anew2_2_2' anew2_2_3']';
elseif ptype == 3
    pnewn2_3=tramnmx(pnew,minp_2_3_1,maxp_2_3_1);
    anewn2_3_1 =sim(net_2_3_1,pnewn2_3);
    anew2_3_1 = postmnmx(anewn2_3_1,mint_2_3_1,maxt_2_3_1);
    anewn2_3_2 =sim(net_2_3_2,pnewn2_3);
    anew2_3_2 = postmnmx(anewn2_3_2,mint_2_3_2,maxt_2_3_2);
    anew = [anew2_3_1' anew2_3_2']';
end
disp (' ')
disp (' ')
disp ('Predicted transient system behavior pattern type is:      ')
disp (ptype)
disp (' ')
if ptype == 0
    disp ('There is no sign of a significant change in the system behavior.')
else
    disp ('Approximated post disruption system behavior vector is      ')
    disp (anew)
    disp (' ')
    disp ('***********  Post-Disruption System Behavior Prediction Report *************' )
    disp ('******************************************************************************' )
    disp (' ')
    disp (' ')
```

```
    disp ('Following time averaged utilizations of each machine stations are')
    disp ('approximated as a part of post-disruption system behavior. ')
    disp (' ')
end
if ptype == 1
    tanew = anew';
    psutil = tanew(1:10);
    psdely = tanew(11);
    psnlmean = tanew(12:14);
    pslstp = tanew(15);
    pslmean = tanew(16:17);
    pssgmpre = tanew(18);
    pssgmpst = tanew(19:27);
    disp (['**The expected final time averaged utilization for Machine#1 is ' num2str(psutil(1))])
    disp (['**The expected final time averaged utilization for Machine#6 is ' num2str(psutil(2))])
    disp (['**The expected final time averaged utilization for Machine#2 is ' num2str(psutil(3))])
    disp (['**The expected final time averaged utilization for Machine#5 is ' num2str(psutil(4))])
    disp (['**The expected final time averaged utilization for Machine#3 is ' num2str(psutil(5))])
    disp (['**The expected final time averaged utilization for Machine#7 is ' num2str(psutil(6))])
    disp (['**The expected final time averaged utilization for Machine#9 is ' num2str(psutil(7))])
    disp (['**The expected final time averaged utilization for Machine#12 is ' num2str(psutil(8))])
    disp (['**The expected final time averaged utilization for AGV is ' num2str(psutil(9))])
    disp (['**The expected final time averaged utilization for Fixture is ' num2str(psutil(10))])
    disp (['**The expected disruption impact delay in terms of # of parts/independent TIS observations is '
num2str(ceil(psdely)) ])
    disp ('   parts/observations from the moment of disruption hit. ')
    disp ('**Only one TIS observation on each departing part is allowed.')
    disp (' ')
    disp (' ')
    if (mparrv == 2.2) & (pmxtype == 1)
      disp ('If there was no performance disruption, ')
      disp ('the approximated steady-state mean time-in-system would be 163.4984 minutes ')
      stsmean = 163.4984;
      disp ('with the approximated upper control limit of 171.6962 minutes and ')
      stsucl = 171.6962;
      disp ('with the approximated lower control limit of 155.3006 minutes.')
      stslcl = 155.3006;
    elseif (mparrv == 2.2) & (pmxtype == 2)
      disp ('If there was no performance disruption, ')
      disp ('the approximated steady-state mean time-in-system would be 149.9076 minutes ')
      stsmean = 149.9076;
      disp ('with the approximated upper control limit of 159.2466 minutes and ')
      stsucl = 159.2466;
      disp ('with the approximated lower control limit of 140.5685 minutes.')
      stslcl = 140.5685;
    elseif (mparrv == 2.3) & (pmxtype == 1)
      disp ('If there was no performance disruption, ')
      disp ('the approximated steady-state mean time-in-system would be 161.6357 minutes ')
      stsmean = 161.6357;
      disp ('with the approximated upper control limit of 166.8541 minutes and ')
      stsucl = 166.8541;
      disp ('with the approximated lower control limit of 156.4173 minutes.')
      stslcl = 156.4173;
    elseif (mparrv == 2.3) & (pmxtype == 2)
      disp ('If there was no performance disruption, ')
      disp ('the approximated steady-state mean time-in-system would be 147.2282 minutes ')
      stsmean = 147.2282;
      disp ('with the approximated upper control limit of 153.6755 minutes and ')
      stsucl = 153.6755;
      disp ('with the approximated lower control limit of 140.7808 minutes.')
      stslcl = 140.7808;
    end
```

```
    disp (' ')
    disp (' ')
    disp ('Following 2nd order polynomial regression model is to forecast ')
    disp (['the behavior of moving averaged (w=500) mean TIS (time-in-system) for first ' num2str(ceil(pslstp))
' parts'])
    disp (['after the disruption delay of ' num2str(ceil(psdely)) ' parts. '])
    disp ('An independent variable t is t-th part entering the system after the disruption impact delay. ')
    disp ('An dependent variable y1 is an estimated mean total minutes spent in the system by t-th part after ')
    disp ('a period of impact delay elapses.')
    disp (['Values for t are 0, 1, 2,...' num2str(ceil(pslstp)) 'th part entering the system after the disruption
impact delay.'])
    disp (' ')
    disp (['y1 = ' num2str(psnlmean(1)) ' + ' num2str(psnlmean(2)) 't + ' num2str(psnlmean(3)) 't^2 '])
    disp (' ')
    disp (' ')
    disp ('Following linear model is to forecast')
    disp ('the behavior of moving averaged (w=500) mean TIS (time-in-system) of parts ')
    disp (['entering the system after first ' num2str(ceil(psdely)+ceil(pslstp)) ' parts from the moment of
disruption hit'])
    disp (' but no later than 10000 minutes after the disruption hit. ')
    disp (['An independent variable t is t-th part entering the system after the first '
num2str(ceil(psdely)+ceil(pslstp)) ' parts'])
    disp (' from the moment of disruption hit.')
    disp ('An dependent variable y2 is an estimated mean total minutes spent in the system by t-th part after ')
    disp ('a period of impact delay and non-linear trend. ')
    disp (['Values for t are 0, 1, 2,...n th part entering the system after first ' num2str(ceil(psdely)+ceil(pslstp)) '
parts'])
    disp ('following the disruption but their arrival time should less than 10,000 minutes ')
    disp ('from the moment of disruption hit. ')
    disp (' ')
    disp (['y2 = ' num2str(pslmean(1)) ' + ' num2str(pslmean(2)) 't '])
    disp (' ')
    disp (' ')
    disp (['The mean sigma of TIS during the pre-disruption period is ' num2str(pssgmpre) ' minutes'])
    disp ('Following 8th order polynomial regression model is to')
    disp ('forecast the behavior of sigma of moving averaged (w=500) mean TIS of parts entering the system
during ')
    disp ('10000 minutes from the moment of the disruption hit. ')
    disp (['An independent variable t is t-th part entering the system after the impact delay of '
num2str(ceil(psdely)) ' parts.'])
    disp ('An dependent variable y_sigma is an estimated mean sigma of TIS by t-th part after ')
    disp ('a period of impact delay elapses. ')
    disp ('Values for t = 0, 1, 2,...n were substituted with t = 0, 0.0005, 0.0010, 0.0015,...n ')
    disp ('in order to avoid a large scale magnitude disparity among coefficients in a polynomial ')
    disp ('during the regression analysis.')
    disp (['( t=0 is the first departing part after the disruption impact delay of ' num2str(ceil(psdely)) ' parts)'])
    disp (' ')
    disp (['y_sigma = ' num2str(pssgmpst(1)) ' + ' num2str(pssgmpst(2)) 't + ' num2str(pssgmpst(3)) 't^2 + '
num2str(pssgmpst(4)) 't^3 + ' num2str(pssgmpst(5)) 't^4 + ' num2str(pssgmpst(6)) 't^5 + '
num2str(pssgmpst(7)) 't^6 + ' num2str(pssgmpst(8)) 't^7 + ' num2str(pssgmpst(9)) 't^8'])
    disp (' ')
    disp (' ')
elseif ptype == 2
    tanew = anew';
    psutil = tanew(1:10);
    psdely = tanew(11);
    psmean = tanew(12:15);
    pssgmpre = tanew(16);
    pssgmpst = tanew(17:20);
    disp (['**The expected final time averaged utilization for Machine#1 is ' num2str(psutil(1))])
    disp (['**The expected final time averaged utilization for Machine#6 is ' num2str(psutil(2))])
    disp (['**The expected final time averaged utilization for Machine#2 is ' num2str(psutil(3))])
```

```
   disp (['**The expected final time averaged utilization for Machine#5 is ' num2str(psutil(4))])
   disp (['**The expected final time averaged utilization for Machine#3 is ' num2str(psutil(5))])
   disp (['**The expected final time averaged utilization for Machine#7 is ' num2str(psutil(6))])
   disp (['**The expected final time averaged utilization for Machine#9 is ' num2str(psutil(7))])
   disp (['**The expected final time averaged utilization for Machine#12 is ' num2str(psutil(8))])
   disp (['**The expected final time averaged utilization for AGV is ' num2str(psutil(9))])
   disp (['**The expected final time averaged utilization for Fixture is ' num2str(psutil(10))])
   disp (['**The expected disruption impact delay in terms of # of parts/independent TIS observations is '
num2str(ceil(psdely)) ])
   disp ('   parts/observations from the moment of disruption hit. ')
   disp ('**Only one TIS observation on each departing part is allowed.')
   disp (' ')
   disp (' ')
   if (mparrv == 2.2) & (pmxtype == 1)
      disp ('If there were no performance disruptions, ')
      disp ('the approximated steady-state mean time-in-system would be 163.4984 minutes ')
      stsmean = 163.4984;
      disp ('with the approximated upper control limit of 171.6962 minutes and ')
      stsucl = 171.6962;
      disp ('with the approximated lower control limit of 155.3006 minutes.')
      stslcl = 155.3006;
   elseif (mparrv == 2.2) & (pmxtype == 2)
      disp ('If there were no performance disruptions, ')
      disp ('the approximated steady-state mean time-in-system would be 149.9076 minutes ')
      stsmean = 149.9076;
      disp ('with the approximated upper control limit of 159.2466 minutes and ')
      stsucl = 159.2466;
      disp ('with the approximated lower control limit of 140.5685 minutes.')
      stslcl = 140.5685;
   elseif (mparrv == 2.3) & (pmxtype == 1)
      disp ('If there were no performance disruptions, ')
      disp ('the approximated steady-state mean time-in-system would be 161.6357 minutes ')
      stsmean = 161.6357;
      disp ('with the approximated upper control limit of 166.8541 minutes and ')
      stsucl = 166.8541;
      disp ('with the approximated lower control limit of 156.4173 minutes.')
      stslcl = 156.4173;
   elseif (mparrv == 2.3) & (pmxtype == 2)
      disp ('If there were no performance disruptions, ')
      disp ('the approximated steady-state mean time-in-system would be 147.2282 minutes ')
      stsmean = 147.2282;
      disp ('with the approximated upper control limit of 153.6755 minutes and ')
      stsucl = 153.6755;
      disp ('with the approximated lower control limit of 140.7808 minutes.')
      stslcl = 140.7808;
   end
   disp (' ')
   disp (' ')
   disp ('Following 8th order polynomial regression model is to forecast')
   disp ('the behavior of moving averaged (w=500) mean TIS (time-in-system)on parts entering the system ')
   disp ('during 10000 minutes from the moment of disruption hit. ')
   disp (['An independent variable t is t-th part entering the system after the impact delay of'
num2str(ceil(psdely)) ' parts.'])
   disp ('An dependent variable y is an estimated mean total minutes spent in the system by t-th part after ')
   disp (['the impact delay of ' num2str(ceil(psdely)) ' parts.'])
   disp ('Values for t = 0, 1, 2,...n are to be substituted with t = 0, 0.0005, 0.0010, 0.0015,...n ')
   disp ('in order to avoid a large scale magnitude disparity among coefficients in a polynomial during the
regression analysis.')
   disp (['( t=0 is the first TIS observation after ' num2str(ceil(psdely)) ' parts from the moment of disruption
event hit)'])
   disp (' ')
```

```
    disp (['y = ' num2str(psmean(1)) ' + ' num2str(psmean(2)) 't + ' num2str(psmean(3)) 't^2 + '
num2str(psmean(4)) 't^3 '])
    disp (' ')
    disp (' ')
    disp (['The average sigma of TIS during the pre-disruption period is ' num2str(pssgmpre) ' parts.'])
    disp ('Following 8th order polynomial regression model is to forecast')
    disp ('the behavior of moving averaged (w=500) mean sigma of TIS of parts entering the system ')
    disp ('during 10000 minutes from the moment of disruption hit. ')
    disp (['An independent variable t is t-th part entering the system after the impact delay of '
num2str(ceil(psdely)) ' parts.'])
    disp ('An dependent variable y is an estimated mean sigma of TIS by t-th part after ')
    disp (['the impact delay of ' num2str(ceil(psdely)) ' parts.'])
    disp ('Values for t = 0, 1, 2,...n were substituted with t = 0, 0.0005, 0.0010, 0.0015,...n ')
    disp ('in order to avoid a large scale magnitude disparity among coefficients in a polynomial during the
regression analysis.')
    disp (['( t=0 is the first sigma observation after ' num2str(ceil(psdely)) ' parts from the moment of disruption
event hit)'])
    disp (' ')
    disp (['y = ' num2str(pssgmpst(1)) ' + ' num2str(pssgmpst(2)) 't + ' num2str(pssgmpst(3)) 't^2 + '
num2str(pssgmpst(4)) 't^3 '])
    disp (' ')
    disp (' ')
elseif ptype == 3
    tanew = anew';
    psutil = tanew(1:10);
    psdely = tanew(11);
    psmean = tanew(12:20);
    pssgmpre = tanew(21);
    pssgmtsn = tanew(22);
    pssgmpst = tanew(23);
    disp (['**The expected final time averaged utilization for Machine#1 is ' num2str(psutil(1))])
    disp (['**The expected final time averaged utilization for Machine#6 is ' num2str(psutil(2))])
    disp (['**The expected final time averaged utilization for Machine#2 is ' num2str(psutil(3))])
    disp (['**The expected final time averaged utilization for Machine#5 is ' num2str(psutil(4))])
    disp (['**The expected final time averaged utilization for Machine#3 is ' num2str(psutil(5))])
    disp (['**The expected final time averaged utilization for Machine#7 is ' num2str(psutil(6))])
    disp (['**The expected final time averaged utilization for Machine#9 is ' num2str(psutil(7))])
    disp (['**The expected final time averaged utilization for Machine#12 is ' num2str(psutil(8))])
    disp (['**The expected final time averaged utilization for AGV is ' num2str(psutil(9))])
    disp (['**The expected final time averaged utilization for Fixture is ' num2str(psutil(10))])
    disp (['**The expected disruption impact delay in terms of # of parts/independent TIS observations is '
num2str(ceil(psdely)) ])
    disp ('    parts/observations from the moment of disruption hit. ')
    disp ('**Only one TIS observation on each departing part is allowed.')
    disp (' ')
    disp (' ')
    if (mparrv == 2.2) & (pmxtype == 1)
      disp ('If there were no performance disruptions, ')
      disp ('the approximated steady-state mean time-in-system would be 163.4984 minutes ')
      stsmean = 163.4984;
      disp ('with the approximated upper control limit of 171.6962 minutes and ')
      stsucl = 171.6962;
      disp ('with the approximated lower control limit of 155.3006 minutes.')
      stslcl = 155.3006;
    elseif (mparrv == 2.2) & (pmxtype == 2)
      disp ('If there were no performance disruptions, ')
      disp ('the approximated steady-state mean time-in-system would be 149.9076 minutes ')
      stsmean = 149.9076;
      disp ('with the approximated upper control limit of 159.2466 minutes and ')
      stsucl = 159.2466;
      disp ('with the approximated lower control limit of 140.5685 minutes.')
      stslcl = 140.5685;
```

```
    elseif (mparrv == 2.3) & (pmxtype == 1)
      disp ('If there were no performance disruptions, ')
      disp ('the approximated steady-state mean time-in-system would be 161.6357 minutes ')
      stsmean = 161.6357;
      disp ('with the approximated upper control limit of 166.8541 minutes and ')
      stsucl = 166.8541;
      disp ('with the approximated lower control limit of 156.4173 minutes.')
      stslcl = 156.4173;
    elseif (mparrv == 2.3) & (pmxtype == 2)
      disp ('If there were no performance disruptions, ')
      disp ('the approximated steady-state mean time-in-system would be 147.2282 minutes ')
      stsmean = 147.2282;
      disp ('with the approximated upper control limit of 153.6755 minutes and ')
      stsucl = 153.6755;
      disp ('with the approximated lower control limit of 140.7808 minutes.')
      stslcl = 140.7808;
    end
    disp (' ')
    disp (' ')
    disp ('Following 8th order polynomial regression model is to forecast')
    disp ('the behavior of moving averaged (w=500) mean TIS (time-in-system)on parts entering the system ')
    disp ('during 10000 minutes from the moment of disruption hit. ')
    disp (['An independent variable t is t-th part entering the system after the impact delay of'
num2str(ceil(psdely)) ' parts.'])
    disp ('An dependent variable y is an estimated mean total minutes spent in the system by t-th part after ')
    disp (['the impact delay of ' num2str(ceil(psdely)) ' parts.'])
    disp ('Values for t = 0, 1, 2,...n were substituted with t = 0, 0.0005, 0.0010, 0.0015,...n ')
    disp ('in order to avoid a large scale magnitude disparity among coefficients in a polynomial during the
regression analysis.')
    disp (['( t=0 is the first observation after ' num2str(ceil(psdely)) ' parts from the moment of disruption event
hit)'])
    disp (' ')
    disp (['y = ' num2str(psmean(1)) ' + ' num2str(psmean(2)) 't + ' num2str(psmean(3)) 't^2 + '
num2str(psmean(4)) 't^3 + ' num2str(psmean(5)) 't^4 + ' num2str(psmean(6)) 't^5 + ' num2str(psmean(7))
't^6 + ' num2str(psmean(8)) 't^7 + ' num2str(psmean(9)) 't^8'])
    disp (' ')
    disp (' ')
    disp (['The average sigma of TIS during the pre-disruption period is ' num2str(pssgmpre)])
    disp (['The average sigma of TIS during the transient period is ' num2str(pssgmtsn)])
    disp (['The average sigma of TIS after the transient period is ' num2str(pssgmpst)])
end


%echo off
```

B.2 Transient Behavior Prediction User Interface in MATLAB

The user interface for the proposed transient behavior prediction system consists of two parts. The first part is to let a user to enter actual pre-disruption system conditions and a disruption event itself. It was designed to walk through a user a series of questions asking pre-disruption conditions, various operational parameters, and the nature of disruption. The logic checks behind the user interface keep the user from entering invalid values or out of range values in order to prevent the system to predict the area that was never trained to handle. The second part is to present prediction results in English using mathematical notations. It was also designed to display predicted results as an original column vector.

```
>> what is a mean part arrival time to the system?
Enter 1 for 2.2min or 2 for 2.3min: 2
Following time averaged utilizations of each machine stations prior to
a disruptive event are needed as a part of the input vector.


What is time averaged utilization of Machine#1 prior to a disruptive event?
A desirable value should be between 0.4382 and 0.68303.
Enter M1 Utilization prior to a disruption:0.626092724


What is time averaged utilization of Machine#6 prior to a disruptive event?
A desirable value should be between 0.2649 and 0.80999.
Enter M6 Utilization prior to a disruption:0.451223542


What is time averaged utilization of Machine#2 prior to a disruptive event?
A desirable value should be between 0.44374 and 0.74975.
Enter M2 Utilization prior to a disruption:0.476030228


What is time averaged utilization of Machine#5 prior to a disruptive event?
A desirable value should be between 0.23492 and 0.67018.
Enter M5 Utilization prior to a disruption: 0.294553065


What is time averaged utilization of Machine#3 prior to a disruptive event?
A desirable value should be between 0.357 and 0.8041.
Enter M3 Utilization prior to a disruption: 0.753000501


What is time averaged utilization of Machine#7 prior to a disruptive event?
A desirable value should be between 0.36168 and 0.7649.
Enter M7 Utilization prior to a disruption: 0.654717144
```

What is time averaged utilization of Machine#9 prior to a disruptive event?
A desirable value should be between 0.28211 and 0.8268.
Enter M9 Utilization prior to a disruption: 0.685214836

What is time averaged utilization of Machine#12 prior to a disruptive event?
A desirable value should be between 0.54538 and 0.72847.
Enter M12 Utilization prior to a disruption: 0.598174323

What is time averaged utilization of AGV prior to a disruptive event?
A desirable value should be between 0.27854 and 0.60651.
Enter AGV Utilization prior to a disruption: 0.330983599

What is time averaged utilization of Fixture prior to a disruptive event?
A desirable value should be between 0.52744 and 0.676.
Enter Fixture Utilization prior to a disruption: 0.558691709

Possible operational disruption scenarios are based on only two types of single disruption event.
A part mix change and single resource failure are two pre-selected types of single disruption event.
What type of disruptive event took place? If it was a part mix change, enter 1.
if it was a resource failure, enter 2.
Enter 1 or 2 for a part mix change or a resource failure: 2

What is the current part mix type for the system?
Part Mix Type 1: P1=25% P5=25% P8=25% P11=25%
Part Mix Type 2: P1=20% P4=20% P5=20% P11=20% P12=20%
Enter only 1 or 2 for Part Mix Type 1 or Part Mix Type 2: 1

Select a single resource that failed and caused a disruption during the operation.
Enter 1 for machine 1 breakdown, 6 for machine 6 breakdown, 2 for machine 2 breakdown,
5 for machine 5 breakdown, 3 for machine 3 breakdown, 7 for machine 7 breakdown,
or 99 for a single AGV failure.
Enter only 1, 6, 2, 5, 3, 7, or 99 for a single resource failure: 3

```
pnew =

    2.3
 0.62609
 0.45122
 0.47603
 0.29455
   0.753
 0.65472
 0.68521
 0.59817
 0.33098
 0.55869
    0.25
       0
       0
```

```
         0
       0.25
         0
         0
       0.25
         0
         0
       0.25
         0
         0
         0
         0
         0
         0
         0
         0
         0
         0
         0
         0
         0
         0
         0
         0
         0
         1
         0
         0
         0
         0

Warning: Some maximums and minimums are equal. Those inputs won't be transformed.
> In C:\MATLAB6p5\toolbox\nnet\nnet\tramnmx.m at line 65
  In C:\MATLAB6p5\work\FMS_transient_model\simulating_ANN_FMS_final.m at line 257
Warning: Some maximums and minimums are equal. Those inputs won't be transformed.
> In C:\MATLAB6p5\toolbox\nnet\nnet\tramnmx.m at line 65
  In C:\MATLAB6p5\work\FMS_transient_model\simulating_ANN_FMS_final.m at line 262


Predicted transient system behavior pattern type is:
     1


Approximated post disruption system behavior vector is
      0.44885
      0.22148
      0.35227
      0.10633
      0.10795
      0.86862
      0.54445
      0.24624
      0.89735
      0.93568
       36.508
       180.21
```

0.23319
0.0016197
296.22
347.23
1.8372
56.32
84.79
1017.9
-833.57
-3139.1
8739.4
-9567.8
5383.7
-1535
175.61

*********** Post-Disruption System Behavior Prediction Report *************
****

Following time averaged utilizations of each machine stations are
approximated as a part of post-disruption system behavior.

**The expected final time averaged utilization for Machine#1 is 0.44885
**The expected final time averaged utilization for Machine#6 is 0.22148
**The expected final time averaged utilization for Machine#2 is 0.35227
**The expected final time averaged utilization for Machine#5 is 0.10633
**The expected final time averaged utilization for Machine#3 is 0.10795
**The expected final time averaged utilization for Machine#7 is 0.86862
**The expected final time averaged utilization for Machine#9 is 0.54445
**The expected final time averaged utilization for Machine#12 is 0.24624
**The expected final time averaged utilization for AGV is 0.89735
**The expected final time averaged utilization for Fixture is 0.93568
**The expected disruption impact delay in terms of # of parts/independent TIS observations is 37 parts/observations from the moment of disruption hit.
**Only one TIS observation on each departing part is allowed.

If there was no performance disruption,
the approximated steady-state mean time-in-system would be 161.6357 minutes
with the approximated upper control limit of 166.8541 minutes and
with the approximated lower control limit of 156.4173 minutes.

Following 2nd order polynomial regression model is to forecast
the behavior of moving averaged (w=500) mean TIS (time-in-system) for first 297 parts
after the disruption delay of 37 parts.
An independent variable t is t-th part entering the system after the disruption impact delay.
An dependent variable y1 is an estimated mean total minutes spent in the system by t-th part
after
a period of impact delay elapses.
Values for t are 0, 1, 2,...297th part entering the system after the disruption impact delay.

y1 = 180.2144 + 0.23319t + 0.0016197t^2

Following linear model is to forecast
the behavior of moving averaged (w=500) mean TIS (time-in-system) of parts
entering the system after first 334 parts from the moment of disruption hit
but no later than 10000 minutes after the disruption hit.
An independent variable t is t-th part entering the system after the first 334 parts
from the moment of disruption hit.
An dependent variable y2 is an estimated mean total minutes spent in the system by t-th part after
a period of impact delay and non-linear trend.
Values for t are 0, 1, 2,...n th part entering the system after first 334 parts
following the disruption but their arrival time should less than 10,000 minutes
from the moment of disruption hit.
y2 = 347.2306 + 1.8372t

The mean sigma of TIS during the pre-disruption period is 56.3196 minutes
Following eighth order polynomial regression model is to
forecast the behavior of sigma of moving averaged (w=500) mean TIS of parts entering the system during
10000 minutes from the moment of the disruption hit.
An independent variable t is t-th part entering the system after the impact delay of 37 parts.
An dependent variable y_sigma is an estimated mean sigma of TIS by t-th part after
a period of impact delay elapses.
Values for t = 0, 1, 2,...n were substituted with t = 0, 0.0005, 0.0010, 0.0015,...n
in order to avoid a large scale magnitude disparity among coefficients in a polynomial
during the regression analysis.
(t=0 is the first departing part after the disruption impact delay of 37 parts)

y_sigma = 84.7898 + 1017.8832t + -833.567t^2 + -3139.0915t^3 + 8739.393t^4 + -9567.8327t^5 + 5383.7241t^6 + -1534.9745t^7 + 175.6123t^8

>>

Appendix C

C.1 Input Vectors for Post-disruption Type 1 ANNs, *Net_2_1_1, Net_2_1_2*, and *Net_2_1_3,* from the second level

Vector Number	1	2	3	4	5
Experiment Number	26	27	28	29	30
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.5691	0.5742	0.5611	0.5595	0.574
M6 Utilization prior to a disruptive event	0.3107	0.3299	0.3265	0.3169	0.3346
M2 Utilization after the disruptive event	0.7165	0.7183	0.7159	0.7179	0.7219
M5 Utilization after the disruptive event	0.6044	0.6376	0.6259	0.6429	0.652
M3 Utilization after the disruptive event	0.6495	0.6375	0.6682	0.6814	0.6401
M7 Utilization after the disruptive event	0.4269	0.454	0.4188	0.4356	0.4835
M9 Utilization after the disruptive event	0.7922	0.823	0.8018	0.8119	0.8037
M12 Utilization after the disruptive event	0.6723	0.694	0.6921	0.6902	0.7208
AGV Utilization prior to a disruptive event	0.3943	0.4164	0.4104	0.4407	0.4483
Fixture Utilization prior to a disruptive event	0.6	0.622	0.6154	0.6295	0.6398
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	6	7	8	9	10
Experiment Number	361	362	363	364	365
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.582776	0.562458	0.570406	0.571675	0.575603
M6 Utilization prior to a disruptive event	0.341366	0.340468	0.316389	0.350731	0.334205
M2 Utilization after the disruptive event	0.727723	0.729239	0.717601	0.735131	0.711751
M5 Utilization after the disruptive event	0.624124	0.643452	0.655262	0.609895	0.641717
M3 Utilization after the disruptive event	0.652436	0.659866	0.645179	0.656263	0.642764
M7 Utilization after the disruptive event	0.430753	0.456683	0.423908	0.439148	0.45063
M9 Utilization after the disruptive event	0.807627	0.802697	0.803454	0.813373	0.818583
M12 Utilization after the disruptive event	0.712979	0.697367	0.694246	0.702171	0.686715
AGV Utilization prior to a disruptive event	0.492819	0.438983	0.463142	0.407906	0.503775
Fixture Utilization prior to a disruptive event	0.665442	0.631676	0.660212	0.618978	0.67114
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	11	12	13	14	15
Experiment Number	366	367	368	369	370
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.573699	0.587348	0.565462	0.578984	0.548044
M6 Utilization prior to a disruptive event	0.322995	0.331095	0.318834	0.342501	0.306456
M2 Utilization after the disruptive event	0.729903	0.72643	0.725383	0.706664	0.726917
M5 Utilization after the disruptive event	0.628643	0.635704	0.608563	0.638898	0.628959
M3 Utilization after the disruptive event	0.650164	0.658219	0.659886	0.645754	0.682696
M7 Utilization after the disruptive event	0.423669	0.454859	0.44937	0.427496	0.442881
M9 Utilization after the disruptive event	0.806581	0.802852	0.794495	0.789501	0.801783
M12 Utilization after the disruptive event	0.676967	0.695837	0.707753	0.697269	0.696915
AGV Utilization prior to a disruptive event	0.418178	0.443037	0.419303	0.40981	0.420427
Fixture Utilization prior to a disruptive event	0.617551	0.635113	0.621011	0.616064	0.619406
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	16	17	18	19	20
Experiment Number	151	152	153	154	155
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.5521	0.5631	0.5648	0.5639	0.5609
M6 Utilization prior to a disruptive event	0.2931	0.2953	0.2961	0.2943	0.311
M2 Utilization after the disruptive event	0.7005	0.6842	0.7133	0.708	0.7026
M5 Utilization after the disruptive event	0.605	0.5959	0.5797	0.5965	0.6055
M3 Utilization after the disruptive event	0.6424	0.6359	0.624	0.6326	0.6316
M7 Utilization after the disruptive event	0.4115	0.4098	0.4361	0.4148	0.4281
M9 Utilization after the disruptive event	0.7718	0.7923	0.7939	0.8047	0.7813
M12 Utilization after the disruptive event	0.6525	0.6482	0.6605	0.6685	0.665
AGV Utilization prior to a disruptive event	0.3701	0.3567	0.3657	0.3765	0.3639
Fixture Utilization prior to a disruptive event	0.5822	0.5761	0.5829	0.5914	0.5838
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	21	22	23	24	25
Experiment Number	371	372	373	374	375
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.539217	0.551178	0.556399	0.556903	0.531574
M6 Utilization prior to a disruptive event	0.283345	0.290708	0.301712	0.313209	0.3052
M2 Utilization after the disruptive event	0.680426	0.695021	0.683285	0.717908	0.683042
M5 Utilization after the disruptive event	0.609767	0.569018	0.616235	0.585337	0.573535
M3 Utilization after the disruptive event	0.622022	0.622174	0.665023	0.652131	0.625638
M7 Utilization after the disruptive event	0.440866	0.403306	0.377653	0.427751	0.396955
M9 Utilization after the disruptive event	0.772435	0.77612	0.785979	0.786974	0.772983
M12 Utilization after the disruptive event	0.635416	0.645439	0.65234	0.676115	0.622663
AGV Utilization prior to a disruptive event	0.35322	0.35478	0.344413	0.361206	0.306328
Fixture Utilization prior to a disruptive event	0.571209	0.567506	0.572776	0.586375	0.546805
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	26	27	28	29	30
Experiment Number	376	377	378	379	380
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.558849	0.555124	0.543481	0.553872	0.545576
M6 Utilization prior to a disruptive event	0.294346	0.305517	0.283934	0.304938	0.295965
M2 Utilization after the disruptive event	0.699725	0.683074	0.701531	0.686373	0.679336
M5 Utilization after the disruptive event	0.591282	0.596874	0.586352	0.587959	0.609671
M3 Utilization after the disruptive event	0.648858	0.620462	0.641526	0.630924	0.642279
M7 Utilization after the disruptive event	0.420769	0.395861	0.40421	0.399937	0.427938
M9 Utilization after the disruptive event	0.781706	0.771371	0.778102	0.776553	0.78296
M12 Utilization after the disruptive event	0.654271	0.652465	0.631374	0.639726	0.664085
AGV Utilization prior to a disruptive event	0.353638	0.338974	0.327866	0.31314	0.356343
Fixture Utilization prior to a disruptive event	0.576975	0.564535	0.560072	0.555561	0.577314
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	31	32	33	34	35
Experiment Number	76	77	78	79	80
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.6501	0.6477	0.6643	0.6577	0.6728
M6 Utilization prior to a disruptive event	0.4892	0.5302	0.5071	0.4967	0.5034
M2 Utilization after the disruptive event	0.4754	0.5064	0.5266	0.4842	0.5221
M5 Utilization after the disruptive event	0.3358	0.3165	0.3026	0.3096	0.2919
M3 Utilization after the disruptive event	0.7739	0.7885	0.8024	0.7895	0.7867
M7 Utilization after the disruptive event	0.7049	0.7283	0.7114	0.7278	0.7055
M9 Utilization after the disruptive event	0.7297	0.7485	0.7432	0.7195	0.7471
M12 Utilization after the disruptive event	0.6499	0.6706	0.6561	0.6604	0.6451
AGV Utilization prior to a disruptive event	0.3829	0.4145	0.4098	0.3931	0.3933
Fixture Utilization prior to a disruptive event	0.6029	0.6258	0.6224	0.6108	0.6133
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	36	37	38	39	40
Experiment Number	421	422	423	424	425
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.639625	0.661991	0.669953	0.675276	0.653102
M6 Utilization prior to a disruptive event	0.500858	0.516474	0.50123	0.49579	0.475612
M2 Utilization after the disruptive event	0.499459	0.50859	0.506268	0.503767	0.519447
M5 Utilization after the disruptive event	0.287602	0.321762	0.308831	0.3142	0.234918
M3 Utilization after the disruptive event	0.766204	0.79237	0.793638	0.799413	0.777226
M7 Utilization after the disruptive event	0.697327	0.742347	0.754623	0.738019	0.689154
M9 Utilization after the disruptive event	0.722731	0.727176	0.749144	0.743666	0.747591
M12 Utilization after the disruptive event	0.634504	0.658856	0.691392	0.659287	0.621284
AGV Utilization prior to a disruptive event	0.386468	0.40931	0.444843	0.411648	0.37607
Fixture Utilization prior to a disruptive event	0.596948	0.623384	0.644748	0.624347	0.591607
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	41	42	43	44	45
Experiment Number	426	427	428	429	430
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.668062	0.66536	0.670213	0.65847	0.661217
M6 Utilization prior to a disruptive event	0.53094	0.512431	0.481376	0.496144	0.486901
M2 Utilization after the disruptive event	0.482139	0.498873	0.515374	0.489653	0.493766
M5 Utilization after the disruptive event	0.326858	0.300658	0.279456	0.322946	0.300125
M3 Utilization after the disruptive event	0.784047	0.780248	0.762789	0.789744	0.78773
M7 Utilization after the disruptive event	0.738686	0.700655	0.716233	0.724088	0.731507
M9 Utilization after the disruptive event	0.736807	0.74974	0.732754	0.729825	0.723371
M12 Utilization after the disruptive event	0.663764	0.653111	0.640879	0.668222	0.645903
AGV Utilization prior to a disruptive event	0.412401	0.410903	0.365488	0.395434	0.426561
Fixture Utilization prior to a disruptive event	0.625057	0.618919	0.595752	0.61463	0.622368
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	46	47	48	49	50
Experiment Number	166	167	168	169	170
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.6364	0.6469	0.6402	0.6281	0.629299
M6 Utilization prior to a disruptive event	0.4645	0.4739	0.4503	0.475	0.456523
M2 Utilization after the disruptive event	0.4704	0.4986	0.4611	0.4949	0.466021
M5 Utilization after the disruptive event	0.2764	0.2819	0.3098	0.2522	0.255774
M3 Utilization after the disruptive event	0.7456	0.7473	0.7423	0.7457	0.735005
M7 Utilization after the disruptive event	0.6599	0.6817	0.6739	0.6704	0.637509
M9 Utilization after the disruptive event	0.7312	0.7299	0.7219	0.7023	0.688435
M12 Utilization after the disruptive event	0.5763	0.6129	0.6123	0.5916	0.575633
AGV Utilization prior to a disruptive event	0.3294	0.3429	0.3128	0.3228	0.309791
Fixture Utilization prior to a disruptive event	0.5592	0.5745	0.5578	0.5582	0.541442
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	51	52	53	54	55
Experiment Number	431	432	433	434	435
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.639275	0.656848	0.632854	0.652036	0.649348
M6 Utilization prior to a disruptive event	0.438512	0.491406	0.482928	0.476244	0.455358
M2 Utilization after the disruptive event	0.46827	0.474673	0.472562	0.496716	0.478457
M5 Utilization after the disruptive event	0.264605	0.284414	0.307061	0.321355	0.29936
M3 Utilization after the disruptive event	0.740446	0.755671	0.738409	0.766869	0.755428
M7 Utilization after the disruptive event	0.675147	0.661022	0.66847	0.701012	0.658142
M9 Utilization after the disruptive event	0.680076	0.737244	0.725661	0.723639	0.692149
M12 Utilization after the disruptive event	0.573567	0.64275	0.608454	0.640138	0.608183
AGV Utilization prior to a disruptive event	0.306674	0.356697	0.318633	0.355629	0.332161
Fixture Utilization prior to a disruptive event	0.543788	0.584222	0.56304	0.589229	0.563831
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	56	57	58	59	60
Experiment Number	436	437	438	439	440
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.635772	0.638215	0.626093	0.641604	0.653065
M6 Utilization prior to a disruptive event	0.461588	0.467516	0.451224	0.481895	0.472174
M2 Utilization after the disruptive event	0.492611	0.481857	0.47603	0.491285	0.498982
M5 Utilization after the disruptive event	0.293756	0.269195	0.294553	0.299897	0.27602
M3 Utilization after the disruptive event	0.754487	0.74448	0.753001	0.762473	0.770828
M7 Utilization after the disruptive event	0.633084	0.66311	0.654717	0.659551	0.666818
M9 Utilization after the disruptive event	0.714326	0.687658	0.685215	0.742188	0.724884
M12 Utilization after the disruptive event	0.595934	0.585418	0.598174	0.63584	0.620026
AGV Utilization prior to a disruptive event	0.326327	0.352748	0.330984	0.346802	0.342151
Fixture Utilization prior to a disruptive event	0.559768	0.56564	0.558692	0.581309	0.575689
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	61	62	63	64	65
Experiment Number	36	37	38	39	40
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.5684	0.5969	0.5701	0.5703	0.5795
M6 Utilization prior to a disruptive event	0.3277	0.3277	0.3031	0.339	0.3003
M2 Utilization after the disruptive event	0.7219	0.7264	0.6936	0.739	0.7027
M5 Utilization after the disruptive event	0.6312	0.6563	0.6278	0.6474	0.6177
M3 Utilization after the disruptive event	0.6678	0.676	0.6627	0.6701	0.6674
M7 Utilization after the disruptive event	0.4548	0.4229	0.4149	0.4719	0.4185
M9 Utilization after the disruptive event	0.7968	0.8268	0.7946	0.8164	0.794
M12 Utilization after the disruptive event	0.7012	0.7242	0.6682	0.7056	0.679
AGV Utilization prior to a disruptive event	0.4278	0.4607	0.3726	0.4651	0.3845
Fixture Utilization prior to a disruptive event	0.6292	0.6467	0.5928	0.656	0.5997
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	66	67	68	69	70
Experiment Number	441	442	443	444	445
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.561783	0.569936	0.58556	0.567526	0.568909
M6 Utilization prior to a disruptive event	0.32166	0.321085	0.329597	0.350447	0.309942
M2 Utilization after the disruptive event	0.707333	0.701493	0.731295	0.722101	0.702135
M5 Utilization after the disruptive event	0.648703	0.631989	0.670175	0.64227	0.609802
M3 Utilization after the disruptive event	0.633942	0.645612	0.669545	0.652775	0.628775
M7 Utilization after the disruptive event	0.457144	0.442502	0.443026	0.453203	0.453878
M9 Utilization after the disruptive event	0.783357	0.779454	0.808878	0.817709	0.794271
M12 Utilization after the disruptive event	0.678231	0.678283	0.72847	0.702346	0.684573
AGV Utilization prior to a disruptive event	0.386625	0.384281	0.494227	0.496566	0.373561
Fixture Utilization prior to a disruptive event	0.604245	0.601162	0.674243	0.67092	0.594785
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	71	72	73	74	75
Experiment Number	446	447	448	449	450
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.567495	0.557642	0.55678	0.563496	0.573795
M6 Utilization prior to a disruptive event	0.313296	0.336975	0.31478	0.332866	0.341161
M2 Utilization after the disruptive event	0.71582	0.724785	0.694735	0.740699	0.728095
M5 Utilization after the disruptive event	0.611957	0.622824	0.626596	0.63141	0.660553
M3 Utilization after the disruptive event	0.640215	0.655183	0.622042	0.670598	0.672003
M7 Utilization after the disruptive event	0.453886	0.421909	0.462765	0.443627	0.439999
M9 Utilization after the disruptive event	0.788418	0.800804	0.784802	0.805072	0.801616
M12 Utilization after the disruptive event	0.678232	0.687156	0.659474	0.691983	0.707262
AGV Utilization prior to a disruptive event	0.379073	0.381565	0.411695	0.423698	0.441528
Fixture Utilization prior to a disruptive event	0.598352	0.602294	0.61095	0.626253	0.641956
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	76	77	78	79	80
Experiment Number	171	172	173	174	175
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.5784	0.5366	0.555	0.546	0.5189
M6 Utilization prior to a disruptive event	0.2815	0.2931	0.2729	0.3102	0.3329
M2 Utilization after the disruptive event	0.7008	0.6734	0.6824	0.6813	0.6823
M5 Utilization after the disruptive event	0.569	0.5877	0.5817	0.5915	0.573
M3 Utilization after the disruptive event	0.6235	0.6369	0.6332	0.623	0.6338
M7 Utilization after the disruptive event	0.3879	0.375	0.3782	0.3945	0.3819
M9 Utilization after the disruptive event	0.7663	0.7557	0.7587	0.7667	0.7643
M12 Utilization after the disruptive event	0.6493	0.6223	0.628	0.6369	0.6827
AGV Utilization prior to a disruptive event	0.3255	0.3	0.351	0.33	0.3364
Fixture Utilization prior to a disruptive event	0.5577	0.5426	0.5619	0.5595	0.5604
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	81	82	83	84	85
Experiment Number	451	452	453	454	455
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.541662	0.539492	0.552771	0.519733	0.538742
M6 Utilization prior to a disruptive event	0.325065	0.293204	0.297831	0.292288	0.322272
M2 Utilization after the disruptive event	0.700702	0.70633	0.710789	0.664109	0.688098
M5 Utilization after the disruptive event	0.594773	0.564725	0.585556	0.571558	0.604046
M3 Utilization after the disruptive event	0.640744	0.624431	0.607406	0.638309	0.629086
M7 Utilization after the disruptive event	0.432465	0.412768	0.430801	0.408581	0.430007
M9 Utilization after the disruptive event	0.783929	0.76193	0.793417	0.761042	0.773765
M12 Utilization after the disruptive event	0.676027	0.636734	0.647871	0.615931	0.643884
AGV Utilization prior to a disruptive event	0.343238	0.318372	0.369161	0.324708	0.358793
Fixture Utilization prior to a disruptive event	0.577549	0.554445	0.57969	0.550321	0.577163
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	86	87	88	89	90
Experiment Number	456	457	458	459	460
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.567066	0.554087	0.544884	0.544752	0.566372
M6 Utilization prior to a disruptive event	0.305373	0.310284	0.294966	0.315611	0.312408
M2 Utilization after the disruptive event	0.710802	0.711072	0.671107	0.708667	0.702286
M5 Utilization after the disruptive event	0.58521	0.576564	0.579202	0.592542	0.609736
M3 Utilization after the disruptive event	0.629242	0.653537	0.61414	0.633535	0.622178
M7 Utilization after the disruptive event	0.410761	0.393922	0.404245	0.43817	0.421616
M9 Utilization after the disruptive event	0.77508	0.769405	0.74669	0.802131	0.791679
M12 Utilization after the disruptive event	0.650028	0.652903	0.630694	0.660683	0.671399
AGV Utilization prior to a disruptive event	0.347721	0.325931	0.297618	0.382855	0.366004
Fixture Utilization prior to a disruptive event	0.573402	0.565358	0.541524	0.59209	0.587061
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	1	1	1	1	1
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	91	92	93	94	95
Experiment Number	81	82	83	84	85
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.6585	0.6437	0.6613	0.6687	0.6623
M6 Utilization prior to a disruptive event	0.4739	0.5193	0.5209	0.5187	0.4796
M2 Utilization after the disruptive event	0.5084	0.5234	0.5264	0.4842	0.5071
M5 Utilization after the disruptive event	0.3073	0.2768	0.3076	0.3357	0.3008
M3 Utilization after the disruptive event	0.7686	0.7761	0.7923	0.7904	0.7985
M7 Utilization after the disruptive event	0.6872	0.721	0.751	0.734	0.7087
M9 Utilization after the disruptive event	0.7247	0.7453	0.7609	0.746	0.7348
M12 Utilization after the disruptive event	0.6422	0.6482	0.6767	0.671	0.6373
AGV Utilization prior to a disruptive event	0.37	0.3992	0.4368	0.4759	0.3914
Fixture Utilization prior to a disruptive event	0.5959	0.613	0.6395	0.6592	0.6071
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	1	1	1	1	1
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	96	97	98	99	100
Experiment Number	461	462	463	464	465
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.64396	0.658707	0.656176	0.68004	0.673582
M6 Utilization prior to a disruptive event	0.4969	0.480005	0.483261	0.527957	0.494239
M2 Utilization after the disruptive event	0.511422	0.450022	0.479428	0.497705	0.504509
M5 Utilization after the disruptive event	0.299503	0.328437	0.337675	0.349626	0.294859
M3 Utilization after the disruptive event	0.78566	0.784147	0.785387	0.781403	0.787457
M7 Utilization after the disruptive event	0.712103	0.692829	0.728125	0.740741	0.724711
M9 Utilization after the disruptive event	0.737566	0.702857	0.732397	0.748445	0.738424
M12 Utilization after the disruptive event	0.621763	0.63533	0.6369	0.689243	0.662426
AGV Utilization prior to a disruptive event	0.379932	0.37197	0.385451	0.421564	0.434779
Fixture Utilization prior to a disruptive event	0.601734	0.591369	0.606447	0.640899	0.632866
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	1	1	1	1	1
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	101	102	103	104	105
Experiment Number	466	467	468	469	470
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.647538	0.65225	0.69292	0.661303	0.667638
M6 Utilization prior to a disruptive event	0.514105	0.479357	0.736	0.46408	0.495874
M2 Utilization after the disruptive event	0.511951	0.513433	0.632155	0.493606	0.498801
M5 Utilization after the disruptive event	0.309617	0.311962	0.369642	0.296822	0.294949
M3 Utilization after the disruptive event	0.770903	0.767096	0.597194	0.79421	0.768626
M7 Utilization after the disruptive event	0.708777	0.69292	0.764897	0.668702	0.746056
M9 Utilization after the disruptive event	0.717194	0.736	0.74299	0.74756	0.732562
M12 Utilization after the disruptive event	0.638589	0.632155	0.633922	0.655091	0.66504
AGV Utilization prior to a disruptive event	0.390765	0.369642	0.41635	0.389253	0.388933
Fixture Utilization prior to a disruptive event	0.60588	0.597194	0.624776	0.603447	0.609885
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	1	1	1	1	1
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	106	107	108	109	110
Experiment Number	86	87	88	89	90
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.657	0.6321	0.6366	0.6308	0.6426
M6 Utilization prior to a disruptive event	0.4511	0.4694	0.4779	0.4465	0.4443
M2 Utilization after the disruptive event	0.4799	0.4673	0.4779	0.457	0.4711
M5 Utilization after the disruptive event	0.2797	0.2886	0.2667	0.2811	0.2929
M3 Utilization after the disruptive event	0.7642	0.7487	0.7749	0.7742	0.7695
M7 Utilization after the disruptive event	0.6762	0.6417	0.6435	0.6741	0.6532
M9 Utilization after the disruptive event	0.7075	0.6977	0.7005	0.7227	0.7104
M12 Utilization after the disruptive event	0.5816	0.578	0.6053	0.5951	0.6067
AGV Utilization prior to a disruptive event	0.337	0.2897	0.3246	0.3307	0.3353
Fixture Utilization prior to a disruptive event	0.5657	0.5421	0.5598	0.5614	0.5634
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	1	1	1	1	1
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	111	112	113	114	115
Experiment Number	471	472	473	474	475
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.656192	0.627104	0.642606	0.636233	0.63902
M6 Utilization prior to a disruptive event	0.445354	0.452161	0.444494	0.469743	0.492858
M2 Utilization after the disruptive event	0.473797	0.481727	0.475736	0.498785	0.465314
M5 Utilization after the disruptive event	0.279714	0.272272	0.286951	0.294641	0.334203
M3 Utilization after the disruptive event	0.767914	0.748408	0.740687	0.747077	0.779604
M7 Utilization after the disruptive event	0.669654	0.666665	0.684721	0.638764	0.690794
M9 Utilization after the disruptive event	0.701962	0.715248	0.693023	0.714304	0.729415
M12 Utilization after the disruptive event	0.593294	0.595798	0.589104	0.603915	0.632259
AGV Utilization prior to a disruptive event	0.321225	0.333011	0.335007	0.31922	0.36754
Fixture Utilization prior to a disruptive event	0.558845	0.559541	0.561717	0.559625	0.592434
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	1	1	1	1	1
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	116	117	118	119	120
Experiment Number	476	477	478	479	480
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.654796	0.650438	0.632682	0.649816	0.64002
M6 Utilization prior to a disruptive event	0.455436	0.481477	0.467371	0.46606	0.456218
M2 Utilization after the disruptive event	0.480964	0.466497	0.499482	0.478932	0.47195
M5 Utilization after the disruptive event	0.295839	0.275358	0.248078	0.314478	0.311315
M3 Utilization after the disruptive event	0.764733	0.750624	0.740982	0.774153	0.750354
M7 Utilization after the disruptive event	0.644976	0.705466	0.668993	0.700444	0.684848
M9 Utilization after the disruptive event	0.701946	0.714349	0.7018	0.704475	0.702776
M12 Utilization after the disruptive event	0.597553	0.610525	0.58921	0.619274	0.588869
AGV Utilization prior to a disruptive event	0.314528	0.347528	0.314664	0.349347	0.329807
Fixture Utilization prior to a disruptive event	0.556923	0.575826	0.552601	0.580649	0.56363
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	1	1	1	1	1
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

C.2 Input Vectors for Post-disruption Type 2 ANNs, *Net_2_2_1, Net_2_2_2*, and *Net_2_2_3,* from the second level

Vector Number	1	2	3	4	5
Experiment Number	26	27	28	29	30
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.5691	0.5742	0.5611	0.5595	0.574
M6 Utilization prior to a disruptive event	0.3107	0.3299	0.3265	0.3169	0.3346
M2 Utilization after the disruptive event	0.7165	0.7183	0.7159	0.7179	0.7219
M5 Utilization after the disruptive event	0.6044	0.6376	0.6259	0.6429	0.652
M3 Utilization after the disruptive event	0.6495	0.6375	0.6682	0.6814	0.6401
M7 Utilization after the disruptive event	0.4269	0.454	0.4188	0.4356	0.4835
M9 Utilization after the disruptive event	0.7922	0.823	0.8018	0.8119	0.8037
M12 Utilization after the disruptive event	0.6723	0.694	0.6921	0.6902	0.7208
AGV Utilization prior to a disruptive event	0.3943	0.4164	0.4104	0.4407	0.4483
Fixture Utilization prior to a disruptive event	0.6	0.622	0.6154	0.6295	0.6398
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	6	7	8	9	10
Experiment Number	481	482	483	484	485
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.585643	0.577422	0.559058	0.551772	0.572294
M6 Utilization prior to a disruptive event	0.34277	0.335614	0.324101	0.331044	0.339059
M2 Utilization after the disruptive event	0.725939	0.739512	0.717956	0.702132	0.725544
M5 Utilization after the disruptive event	0.640529	0.628539	0.656036	0.603162	0.622692
M3 Utilization after the disruptive event	0.658381	0.666634	0.672477	0.657959	0.651766
M7 Utilization after the disruptive event	0.417882	0.422525	0.454031	0.41892	0.44832
M9 Utilization after the disruptive event	0.81136	0.818156	0.807335	0.782153	0.81038
M12 Utilization after the disruptive event	0.700409	0.695289	0.700071	0.665314	0.687531
AGV Utilization prior to a disruptive event	0.462295	0.408566	0.460743	0.368725	0.442698
Fixture Utilization prior to a disruptive event	0.639504	0.61916	0.643303	0.589621	0.634542
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	1	1	1	1	1
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	11	12	13	14	15
Experiment Number	486	487	488	489	490
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.56835	0.598555	0.570005	0.577344	0.574573
M6 Utilization prior to a disruptive event	0.328241	0.308505	0.325471	0.328863	0.307762
M2 Utilization after the disruptive event	0.721673	0.723798	0.722002	0.718844	0.710834
M5 Utilization after the disruptive event	0.616914	0.628681	0.649902	0.609549	0.618473
M3 Utilization after the disruptive event	0.647185	0.642922	0.638599	0.649033	0.64333
M7 Utilization after the disruptive event	0.434408	0.426645	0.459867	0.42815	0.426295
M9 Utilization after the disruptive event	0.807576	0.814755	0.799566	0.793437	0.79576
M12 Utilization after the disruptive event	0.684376	0.688071	0.695439	0.703581	0.675617
AGV Utilization prior to a disruptive event	0.41574	0.425663	0.418309	0.396523	0.38991
Fixture Utilization prior to a disruptive event	0.615141	0.620964	0.621777	0.607631	0.601563
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	1	1	1	1	1
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	16	17	18	19	20
Experiment Number	176	177	178	179	180
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.5527	0.5477	0.5581	0.5488	0.554
M6 Utilization prior to a disruptive event	0.2649	0.2948	0.298	0.3262	0.3018
M2 Utilization after the disruptive event	0.7007	0.676	0.7218	0.6976	0.6967
M5 Utilization after the disruptive event	0.5738	0.5867	0.5818	0.5891	0.588
M3 Utilization after the disruptive event	0.6425	0.6119	0.643	0.6317	0.631
M7 Utilization after the disruptive event	0.3664	0.4174	0.439	0.4437	0.4101
M9 Utilization after the disruptive event	0.7465	0.7674	0.7876	0.7874	0.7842
M12 Utilization after the disruptive event	0.6352	0.6316	0.6579	0.6413	0.6323
AGV Utilization prior to a disruptive event	0.3218	0.3374	0.3714	0.3502	0.3367
Fixture Utilization prior to a disruptive event	0.5487	0.5603	0.5876	0.5781	0.5675
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	1	1	1	1	1
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	21	22	23	24	25
Experiment Number	491	492	493	494	495
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.56774	0.553634	0.556317	0.563774	0.562929
M6 Utilization prior to a disruptive event	0.306456	0.329846	0.313569	0.321932	0.304986
M2 Utilization after the disruptive event	0.724067	0.691922	0.689599	0.700576	0.682083
M5 Utilization after the disruptive event	0.601778	0.604111	0.596558	0.571748	0.64044
M3 Utilization after the disruptive event	0.659945	0.64004	0.650962	0.612788	0.672843
M7 Utilization after the disruptive event	0.415193	0.378439	0.396055	0.428758	0.381551
M9 Utilization after the disruptive event	0.776602	0.792282	0.796547	0.762175	0.783035
M12 Utilization after the disruptive event	0.679826	0.655324	0.640549	0.643739	0.63617
AGV Utilization prior to a disruptive event	0.411858	0.346128	0.341633	0.322106	0.342428
Fixture Utilization prior to a disruptive event	0.612132	0.573153	0.571737	0.561197	0.575462
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	1	1	1	1	1
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	26	27	28	29	30
Experiment Number	496	497	498	499	500
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization prior to a disruptive event	0.551616	0.537422	0.568375	0.559583	0.564917
M6 Utilization prior to a disruptive event	0.315825	0.307702	0.301971	0.299181	0.297309
M2 Utilization after the disruptive event	0.693317	0.690909	0.695808	0.688633	0.710079
M5 Utilization after the disruptive event	0.593319	0.593022	0.622481	0.589774	0.601837
M3 Utilization after the disruptive event	0.626406	0.642144	0.644544	0.625951	0.656602
M7 Utilization after the disruptive event	0.404649	0.425615	0.436387	0.419936	0.42381
M9 Utilization after the disruptive event	0.77211	0.773748	0.801211	0.772958	0.784627
M12 Utilization after the disruptive event	0.652113	0.667231	0.667361	0.634166	0.672315
AGV Utilization prior to a disruptive event	0.335272	0.362504	0.392547	0.329989	0.389012
Fixture Utilization prior to a disruptive event	0.5667	0.579553	0.602162	0.562861	0.597679
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	1	1	1	1	1
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	31	32	33	34	35
Experiment Number	61	62	63	64	65
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.5688	0.5823	0.5751	0.5542	0.561
M6 Utilization prior to a disruptive event	0.3373	0.3334	0.3294	0.3452	0.3455
M2 Utilization after the disruptive event	0.7177	0.7152	0.7391	0.7245	0.725
M5 Utilization after the disruptive event	0.6601	0.6393	0.6101	0.6148	0.6408
M3 Utilization after the disruptive event	0.6686	0.6626	0.6416	0.6555	0.6494
M7 Utilization after the disruptive event	0.4262	0.4454	0.4758	0.4318	0.4914
M9 Utilization after the disruptive event	0.8004	0.7992	0.809	0.7909	0.8239
M12 Utilization after the disruptive event	0.7071	0.6946	0.6914	0.6904	0.7176
AGV Utilization prior to a disruptive event	0.4616	0.4157	0.51	0.425	0.4305
Fixture Utilization prior to a disruptive event	0.644	0.6232	0.6721	0.6224	0.634
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	36	37	38	39	40
Experiment Number	241	242	243	244	245
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.541744	0.559142	0.55872	0.565226	0.565411
M6 Utilization prior to a disruptive event	0.318522	0.325116	0.346884	0.3462	0.340512
M2 Utilization after the disruptive event	0.702559	0.720469	0.706103	0.704333	0.721111
M5 Utilization after the disruptive event	0.590933	0.620046	0.636223	0.644082	0.622684
M3 Utilization after the disruptive event	0.641433	0.667292	0.655415	0.644659	0.649061
M7 Utilization after the disruptive event	0.410215	0.411475	0.446831	0.461448	0.44926
M9 Utilization after the disruptive event	0.773086	0.796951	0.798235	0.801439	0.800348
M12 Utilization after the disruptive event	0.6567	0.680412	0.688087	0.687903	0.703614
AGV Utilization prior to a disruptive event	0.365635	0.395148	0.40818	0.418368	0.407074
Fixture Utilization prior to a disruptive event	0.580062	0.604663	0.61514	0.620628	0.615737
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	41	42	43	44	45
Experiment Number	246	247	248	249	250
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.554446	0.561928	0.570418	0.581979	0.562081
M6 Utilization prior to a disruptive event	0.348064	0.33032	0.333024	0.300225	0.317857
M2 Utilization after the disruptive event	0.727662	0.705694	0.706002	0.715088	0.712045
M5 Utilization after the disruptive event	0.629213	0.618109	0.602167	0.620834	0.617249
M3 Utilization after the disruptive event	0.633912	0.655267	0.665156	0.647108	0.657707
M7 Utilization after the disruptive event	0.491066	0.433186	0.426488	0.457043	0.404824
M9 Utilization after the disruptive event	0.803464	0.777936	0.794813	0.794819	0.770769
M12 Utilization after the disruptive event	0.715429	0.664046	0.68439	0.695071	0.676004
AGV Utilization prior to a disruptive event	0.469416	0.423588	0.36742	0.398959	0.394387
Fixture Utilization prior to a disruptive event	0.651923	0.619006	0.594711	0.608873	0.598595
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	46	47	48	49	50
Experiment Number	71	72	73	74	75
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.561	0.5752	0.5441	0.552	0.568
M6 Utilization prior to a disruptive event	0.3281	0.2975	0.3257	0.328	0.3119
M2 Utilization after the disruptive event	0.7141	0.7308	0.7101	0.7205	0.6946
M5 Utilization after the disruptive event	0.6077	0.6327	0.5835	0.6311	0.6202
M3 Utilization after the disruptive event	0.6702	0.6616	0.6518	0.643	0.6553
M7 Utilization after the disruptive event	0.3952	0.4435	0.4004	0.4615	0.4074
M9 Utilization after the disruptive event	0.7962	0.7876	0.7805	0.8116	0.7788
M12 Utilization after the disruptive event	0.6754	0.6957	0.6598	0.6935	0.6784
AGV Utilization prior to a disruptive event	0.367	0.4099	0.3988	0.4106	0.4037
Fixture Utilization prior to a disruptive event	0.5917	0.6137	0.5951	0.6152	0.6024
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	51	52	53	54	55
Experiment Number	321	322	323	324	325
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.584543	0.556711	0.569236	0.566144	0.53839
M6 Utilization prior to a disruptive event	0.318782	0.323765	0.347178	0.342456	0.337727
M2 Utilization after the disruptive event	0.727184	0.693702	0.713561	0.70771	0.713336
M5 Utilization after the disruptive event	0.627908	0.622712	0.633409	0.640404	0.656183
M3 Utilization after the disruptive event	0.62468	0.654839	0.637193	0.65142	0.691672
M7 Utilization after the disruptive event	0.442609	0.412044	0.442414	0.444611	0.413648
M9 Utilization after the disruptive event	0.79889	0.775422	0.811423	0.801315	0.8057
M12 Utilization after the disruptive event	0.683395	0.667074	0.679375	0.677368	0.684186
AGV Utilization prior to a disruptive event	0.405291	0.375347	0.398029	0.432376	0.416582
Fixture Utilization prior to a disruptive event	0.611351	0.592271	0.610633	0.62577	0.619682
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	56	57	58	59	60
Experiment Number	326	327	328	329	330
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization prior to a disruptive event	0.599594	0.571423	0.591404	0.565983	0.574875
M6 Utilization prior to a disruptive event	0.304593	0.307313	0.329111	0.327438	0.322635
M2 Utilization after the disruptive event	0.714816	0.71887	0.715664	0.715938	0.722671
M5 Utilization after the disruptive event	0.633395	0.633886	0.648341	0.615209	0.63274
M3 Utilization after the disruptive event	0.631941	0.64859	0.663697	0.662646	0.659992
M7 Utilization after the disruptive event	0.440965	0.461492	0.42859	0.443749	0.441053
M9 Utilization after the disruptive event	0.793772	0.801878	0.804345	0.782538	0.800373
M12 Utilization after the disruptive event	0.660924	0.70008	0.703737	0.689649	0.696304
AGV Utilization prior to a disruptive event	0.398385	0.444858	0.43458	0.393018	0.421875
Fixture Utilization prior to a disruptive event	0.607884	0.631853	0.63418	0.60696	0.620461
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

C.3 Input Vectors for Post-disruption Type 3 ANNs, *Net_2_3_1* and *Net_2_3_2*, from the second level

Vector Number	1	2	3	4	5
Experiment Number	21	22	23	24	25
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.5589	0.564	0.5763	0.5658	0.5955
M6 Utilization after the disruptive event	0.3312	0.342	0.3264	0.3548	0.3266
M2 Utilization after the disruptive event	0.7297	0.7206	0.7294	0.7105	0.7302
M5 Utilization after the disruptive event	0.6565	0.66	0.6102	0.6222	0.6313
M3 Utilization after the disruptive event	0.6649	0.6737	0.6656	0.6415	0.6502
M7 Utilization after the disruptive event	0.4577	0.4341	0.4419	0.4324	0.4579
M9 Utilization after the disruptive event	0.813	0.803	0.8081	0.7935	0.8037
M12 Utilization after the disruptive event	0.6984	0.7136	0.6922	0.7054	0.7035
AGV Utilization prior to a disruptive event	0.4527	0.4676	0.4178	0.4142	0.4579
Fixture Utilization prior to a disruptive event	0.6411	0.6453	0.6209	0.6158	0.6413
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	6	7	8	9	10
Experiment Number	281	282	283	284	285
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.567442	0.565995	0.58365	0.574319	0.58088
M6 Utilization after the disruptive event	0.326845	0.326903	0.325382	0.320929	0.344083
M2 Utilization after the disruptive event	0.726893	0.716068	0.746134	0.710382	0.712695
M5 Utilization after the disruptive event	0.622859	0.648382	0.649455	0.603689	0.603311
M3 Utilization after the disruptive event	0.655925	0.646406	0.682143	0.639585	0.66737
M7 Utilization after the disruptive event	0.455007	0.463444	0.455075	0.464107	0.411493
M9 Utilization after the disruptive event	0.796229	0.807589	0.80727	0.776196	0.795527
M12 Utilization after the disruptive event	0.704497	0.698563	0.72707	0.684373	0.694974
AGV Utilization prior to a disruptive event	0.397085	0.412257	0.487893	0.384935	0.390872
Fixture Utilization prior to a disruptive event	0.613735	0.619282	0.660443	0.601766	0.607101
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	11	12	13	14	15
Experiment Number	286	287	288	289	290
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.574703	0.566147	0.568707	0.543816	0.560413
M6 Utilization after the disruptive event	0.32841	0.30888	0.301363	0.337282	0.345357
M2 Utilization after the disruptive event	0.711897	0.730163	0.710758	0.713493	0.720804
M5 Utilization after the disruptive event	0.644757	0.639958	0.603417	0.62242	0.647035
M3 Utilization after the disruptive event	0.661676	0.644267	0.634648	0.65963	0.667188
M7 Utilization after the disruptive event	0.425693	0.511211	0.43972	0.453601	0.425185
M9 Utilization after the disruptive event	0.794775	0.797866	0.764466	0.779679	0.811918
M12 Utilization after the disruptive event	0.701141	0.696222	0.660871	0.673394	0.685696
AGV Utilization prior to a disruptive event	0.392462	0.428412	0.372134	0.386511	0.428073
Fixture Utilization prior to a disruptive event	0.608785	0.627946	0.588685	0.603716	0.625906
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	16	17	18	19	20
Experiment Number	6	7	8	9	10
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.6669	0.6703	0.6621	0.6563	0.6459
M6 Utilization after the disruptive event	0.5236	0.5008	0.4914	0.5083	0.4873
M2 Utilization after the disruptive event	0.5066	0.4919	0.4962	0.4819	0.4872
M5 Utilization after the disruptive event	0.344	0.3202	0.3055	0.2736	0.3148
M3 Utilization after the disruptive event	0.8041	0.7885	0.7877	0.7802	0.7751
M7 Utilization after the disruptive event	0.7105	0.7266	0.7583	0.7106	0.7169
M9 Utilization after the disruptive event	0.7339	0.7285	0.7374	0.7191	0.7267
M12 Utilization after the disruptive event	0.6669	0.6396	0.6424	0.6345	0.6262
AGV Utilization prior to a disruptive event	0.4261	0.4084	0.4562	0.3673	0.3844
Fixture Utilization prior to a disruptive event	0.6338	0.6177	0.6393	0.5931	0.6011
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	21	22	23	24	25
Experiment Number	301	302	303	304	305
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.661476	0.653703	0.663217	0.657403	0.652618
M6 Utilization after the disruptive event	0.473886	0.525272	0.497646	0.47119	0.493349
M2 Utilization after the disruptive event	0.47762	0.486455	0.497039	0.500365	0.518085
M5 Utilization after the disruptive event	0.286377	0.337406	0.284598	0.282666	0.295067
M3 Utilization after the disruptive event	0.76812	0.789941	0.78427	0.796185	0.779412
M7 Utilization after the disruptive event	0.667118	0.729466	0.704593	0.690185	0.729231
M9 Utilization after the disruptive event	0.709782	0.752416	0.730767	0.739204	0.728084
M12 Utilization after the disruptive event	0.607685	0.674029	0.642714	0.623729	0.652126
AGV Utilization prior to a disruptive event	0.349142	0.425367	0.374665	0.363561	0.42054
Fixture Utilization prior to a disruptive event	0.574966	0.630237	0.599357	0.590026	0.620904
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	26	27	28	29	30
Experiment Number	306	307	308	309	310
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.663945	0.659712	0.65141	0.648365	0.668175
M6 Utilization after the disruptive event	0.471146	0.471636	0.461377	0.494619	0.526385
M2 Utilization after the disruptive event	0.491695	0.506208	0.467195	0.492412	0.485359
M5 Utilization after the disruptive event	0.295767	0.29064	0.319225	0.304036	0.304815
M3 Utilization after the disruptive event	0.77843	0.764941	0.782505	0.77253	0.774296
M7 Utilization after the disruptive event	0.686461	0.733721	0.706162	0.683554	0.757036
M9 Utilization after the disruptive event	0.741909	0.750007	0.695396	0.733374	0.749489
M12 Utilization after the disruptive event	0.622364	0.637784	0.605064	0.631229	0.661431
AGV Utilization prior to a disruptive event	0.346325	0.409312	0.326315	0.36615	0.42323
Fixture Utilization prior to a disruptive event	0.584204	0.614901	0.570437	0.590943	0.627619
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	31	32	33	34	35
Experiment Number	11	12	13	14	15
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.6659	0.6701	0.6504	0.6651	0.6586
M6 Utilization after the disruptive event	0.5001	0.5009	0.484	0.4841	0.5195
M2 Utilization after the disruptive event	0.5063	0.4812	0.5032	0.4863	0.4624
M5 Utilization after the disruptive event	0.3198	0.3059	0.288	0.287	0.3129
M3 Utilization after the disruptive event	0.7945	0.7754	0.7698	0.7645	0.7951
M7 Utilization after the disruptive event	0.7065	0.7129	0.709	0.7251	0.726
M9 Utilization after the disruptive event	0.7491	0.7439	0.734	0.7493	0.7206
M12 Utilization after the disruptive event	0.6573	0.6368	0.6284	0.6354	0.6544
AGV Utilization prior to a disruptive event	0.4483	0.3842	0.39	0.3881	0.4157
Fixture Utilization prior to a disruptive event	0.6402	0.6043	0.6017	0.6035	0.6174
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0.2	0.2	0.2	0.2	0.2
% change in Part Type 5	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	-0.25	-0.25	-0.25	-0.25	-0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 12	0.2	0.2	0.2	0.2	0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	36	37	38	39	40
Experiment Number	181	182	183	184	185
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.661617	0.661837	0.655067	0.670649	0.666781
M6 Utilization after the disruptive event	0.481173	0.519278	0.502821	0.499558	0.482849
M2 Utilization after the disruptive event	0.491228	0.501196	0.509556	0.493205	0.483592
M5 Utilization after the disruptive event	0.309834	0.293162	0.31953	0.310635	0.304412
M3 Utilization after the disruptive event	0.792532	0.755743	0.781344	0.772305	0.785783
M7 Utilization after the disruptive event	0.706474	0.707818	0.720021	0.725124	0.71217
M9 Utilization after the disruptive event	0.723643	0.731288	0.739254	0.757426	0.741255
M12 Utilization after the disruptive event	0.64985	0.639977	0.676679	0.675541	0.64892
AGV Utilization prior to a disruptive event	0.354804	0.396703	0.406849	0.467078	0.377899
Fixture Utilization prior to a disruptive event	0.593324	0.608046	0.621026	0.649453	0.603503
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0.2	0.2	0.2	0.2	0.2
% change in Part Type 5	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	-0.25	-0.25	-0.25	-0.25	-0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 12	0.2	0.2	0.2	0.2	0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	41	42	43	44	45
Experiment Number	186	187	188	189	190
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.664914	0.645717	0.652086	0.683032	0.680276
M6 Utilization after the disruptive event	0.505806	0.537288	0.49345	0.482536	0.490994
M2 Utilization after the disruptive event	0.479757	0.506426	0.497055	0.477138	0.492783
M5 Utilization after the disruptive event	0.335107	0.307433	0.324065	0.311012	0.322372
M3 Utilization after the disruptive event	0.77946	0.79247	0.757056	0.791011	0.778084
M7 Utilization after the disruptive event	0.721131	0.716477	0.717571	0.715266	0.746111
M9 Utilization after the disruptive event	0.74093	0.75485	0.744352	0.730932	0.729768
M12 Utilization after the disruptive event	0.667212	0.679527	0.633015	0.661317	0.652367
AGV Utilization prior to a disruptive event	0.43021	0.439809	0.373251	0.392498	0.397992
Fixture Utilization prior to a disruptive event	0.632451	0.637045	0.60075	0.609061	0.616254
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0.2	0.2	0.2	0.2	0.2
% change in Part Type 5	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	-0.25	-0.25	-0.25	-0.25	-0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 12	0.2	0.2	0.2	0.2	0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	46	47	48	49	50
Experiment Number	16	17	18	19	20
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.642	0.6583	0.6453	0.6629	0.6631
M6 Utilization after the disruptive event	0.4886	0.482	0.5075	0.5297	0.4905
M2 Utilization after the disruptive event	0.4943	0.4891	0.4851	0.5028	0.5363
M5 Utilization after the disruptive event	0.3181	0.287	0.3202	0.3315	0.2652
M3 Utilization after the disruptive event	0.7989	0.7756	0.78	0.7912	0.7774
M7 Utilization after the disruptive event	0.6586	0.6979	0.6985	0.7417	0.7216
M9 Utilization after the disruptive event	0.7301	0.6902	0.7225	0.7745	0.7543
M12 Utilization after the disruptive event	0.6188	0.6207	0.6416	0.6839	0.6303
AGV Utilization prior to a disruptive event	0.3335	0.3703	0.3661	0.4757	0.389
Fixture Utilization prior to a disruptive event	0.579	0.5867	0.5951	0.661	0.607
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	51	52	53	54	55
Experiment Number	261	262	263	264	265
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.675977	0.666174	0.665985	0.654207	0.670743
M6 Utilization after the disruptive event	0.493626	0.47828	0.522087	0.480376	0.504007
M2 Utilization after the disruptive event	0.484131	0.474281	0.485873	0.493489	0.501929
M5 Utilization after the disruptive event	0.308102	0.306169	0.316386	0.300821	0.307309
M3 Utilization after the disruptive event	0.772391	0.765565	0.78958	0.774451	0.776599
M7 Utilization after the disruptive event	0.735019	0.715051	0.724779	0.700544	0.754216
M9 Utilization after the disruptive event	0.731181	0.71302	0.735926	0.735413	0.753314
M12 Utilization after the disruptive event	0.659324	0.626014	0.681902	0.619149	0.65131
AGV Utilization prior to a disruptive event	0.414315	0.353037	0.431414	0.375542	0.441768
Fixture Utilization prior to a disruptive event	0.620289	0.586044	0.630721	0.594953	0.635487
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	56	57	58	59	60
Experiment Number	266	267	268	269	270
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.669441	0.65407	0.653893	0.664374	0.662162
M6 Utilization after the disruptive event	0.527301	0.502899	0.481924	0.503637	0.492429
M2 Utilization after the disruptive event	0.507898	0.514332	0.468548	0.529248	0.499454
M5 Utilization after the disruptive event	0.297502	0.262677	0.320542	0.285518	0.2833
M3 Utilization after the disruptive event	0.7873	0.772444	0.778333	0.781232	0.762238
M7 Utilization after the disruptive event	0.750177	0.714906	0.720352	0.717156	0.710955
M9 Utilization after the disruptive event	0.73694	0.751757	0.721638	0.72151	0.728904
M12 Utilization after the disruptive event	0.636796	0.642693	0.648693	0.64585	0.636757
AGV Utilization prior to a disruptive event	0.476978	0.404115	0.378973	0.380234	0.36157
Fixture Utilization prior to a disruptive event	0.652722	0.611059	0.599672	0.604821	0.591287
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	61	62	63	64	65
Experiment Number	31	32	33	34	35
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.5776	0.5793	0.5523	0.567	0.5564
M6 Utilization after the disruptive event	0.3377	0.3277	0.3046	0.3042	0.3336
M2 Utilization after the disruptive event	0.7249	0.7221	0.6927	0.715	0.7166
M5 Utilization after the disruptive event	0.6507	0.6317	0.6169	0.6204	0.5944
M3 Utilization after the disruptive event	0.6514	0.6517	0.6422	0.6661	0.6357
M7 Utilization after the disruptive event	0.4613	0.4353	0.4074	0.4409	0.4535
M9 Utilization after the disruptive event	0.8111	0.7916	0.7735	0.7843	0.7981
M12 Utilization after the disruptive event	0.7194	0.6969	0.664	0.6771	0.6659
AGV Utilization prior to a disruptive event	0.4964	0.4964	0.3458	0.3458	0.4152
Fixture Utilization prior to a disruptive event	0.6588	0.6588	0.5746	0.5746	0.6191
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	66	67	68	69	70
Experiment Number	401	402	403	404	405
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.570931	0.578057	0.571823	0.571952	0.567189
M6 Utilization after the disruptive event	0.349944	0.342822	0.307735	0.332152	0.311188
M2 Utilization after the disruptive event	0.723142	0.729135	0.718396	0.725357	0.715348
M5 Utilization after the disruptive event	0.651995	0.641376	0.598875	0.641153	0.631254
M3 Utilization after the disruptive event	0.675185	0.65429	0.654619	0.648969	0.632454
M7 Utilization after the disruptive event	0.428529	0.464104	0.419061	0.460796	0.457639
M9 Utilization after the disruptive event	0.808432	0.799255	0.799199	0.810768	0.813241
M12 Utilization after the disruptive event	0.709457	0.704337	0.658615	0.698714	0.674125
AGV Utilization prior to a disruptive event	0.469944	0.462951	0.375586	0.443095	0.408805
Fixture Utilization prior to a disruptive event	0.647597	0.647068	0.59238	0.63457	0.612217
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	71	72	73	74	75
Experiment Number	406	407	408	409	410
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.571524	0.549566	0.552784	0.582101	0.548114
M6 Utilization after the disruptive event	0.317994	0.313427	0.328734	0.315125	0.348202
M2 Utilization after the disruptive event	0.702871	0.714011	0.701435	0.720822	0.696657
M5 Utilization after the disruptive event	0.614283	0.617852	0.592223	0.633412	0.605269
M3 Utilization after the disruptive event	0.65048	0.655722	0.636354	0.653075	0.631375
M7 Utilization after the disruptive event	0.408012	0.433495	0.412725	0.446914	0.432027
M9 Utilization after the disruptive event	0.792292	0.769124	0.773352	0.789428	0.777118
M12 Utilization after the disruptive event	0.668268	0.677442	0.674633	0.711877	0.667763
AGV Utilization prior to a disruptive event	0.395525	0.386137	0.363638	0.435557	0.381857
Fixture Utilization prior to a disruptive event	0.600144	0.596892	0.583331	0.630326	0.5935
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	76	77	78	79	80
Experiment Number	46	47	48	49	50
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.6392	0.6712	0.6588	0.6469	0.6552
M6 Utilization after the disruptive event	0.4854	0.4882	0.5161	0.4703	0.5294
M2 Utilization after the disruptive event	0.4888	0.5037	0.5046	0.4856	0.5176
M5 Utilization after the disruptive event	0.2838	0.2913	0.3123	0.2825	0.2892
M3 Utilization after the disruptive event	0.7682	0.7729	0.797	0.7874	0.7699
M7 Utilization after the disruptive event	0.7121	0.7193	0.7393	0.6795	0.6969
M9 Utilization after the disruptive event	0.7399	0.7248	0.7565	0.745	0.7259
M12 Utilization after the disruptive event	0.6238	0.6121	0.6715	0.6229	0.6343
AGV Utilization prior to a disruptive event	0.4019	0.3691	0.4243	0.3677	0.386
Fixture Utilization prior to a disruptive event	0.6061	0.5966	0.6322	0.5884	0.6054
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	81	82	83	84	85
Experiment Number	341	342	343	344	345
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.66307	0.660106	0.658157	0.663248	0.667058
M6 Utilization after the disruptive event	0.527974	0.491633	0.473391	0.498154	0.517002
M2 Utilization after the disruptive event	0.489609	0.499853	0.493447	0.472437	0.500787
M5 Utilization after the disruptive event	0.321244	0.301585	0.302906	0.307444	0.303813
M3 Utilization after the disruptive event	0.785058	0.769253	0.764968	0.764018	0.766986
M7 Utilization after the disruptive event	0.741677	0.712827	0.727191	0.715701	0.744736
M9 Utilization after the disruptive event	0.727826	0.732904	0.715828	0.719577	0.727499
M12 Utilization after the disruptive event	0.628018	0.642036	0.636244	0.642708	0.658508
AGV Utilization prior to a disruptive event	0.429182	0.389678	0.368239	0.380864	0.404761
Fixture Utilization prior to a disruptive event	0.628649	0.606493	0.59314	0.60017	0.617529
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	86	87	88	89	90
Experiment Number	346	347	348	349	350
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.667716	0.668367	0.635764	0.649938	0.674913
M6 Utilization after the disruptive event	0.497473	0.488269	0.521527	0.487124	0.461154
M2 Utilization after the disruptive event	0.503415	0.485885	0.521685	0.476189	0.49919
M5 Utilization after the disruptive event	0.349227	0.301826	0.288826	0.299874	0.274712
M3 Utilization after the disruptive event	0.772958	0.774417	0.786586	0.775668	0.775906
M7 Utilization after the disruptive event	0.727223	0.695568	0.732959	0.68774	0.701305
M9 Utilization after the disruptive event	0.751827	0.736386	0.745903	0.725364	0.718883
M12 Utilization after the disruptive event	0.67876	0.625547	0.653867	0.635002	0.619735
AGV Utilization prior to a disruptive event	0.389435	0.38637	0.398093	0.377155	0.372273
Fixture Utilization prior to a disruptive event	0.619427	0.60202	0.615249	0.592193	0.591288
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	91	92	93	94	95
Experiment Number	51	52	53	54	55
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.6608	0.6562	0.6706	0.6532	0.659
M6 Utilization after the disruptive event	0.5249	0.5061	0.5383	0.4969	0.4956
M2 Utilization after the disruptive event	0.5072	0.5138	0.5246	0.5111	0.5715
M5 Utilization after the disruptive event	0.2884	0.275	0.2931	0.3146	0.4897
M3 Utilization after the disruptive event	0.7912	0.7913	0.7891	0.7901	0.4897
M7 Utilization after the disruptive event	0.7116	0.7386	0.735	0.7318	0.7398
M9 Utilization after the disruptive event	0.7536	0.7479	0.7171	0.7371	0.7313
M12 Utilization after the disruptive event	0.6504	0.6492	0.6579	0.6424	0.6377
AGV Utilization prior to a disruptive event	0.4331	0.4048	0.4174	0.4104	0.3841
Fixture Utilization prior to a disruptive event	0.6303	0.6167	0.625	0.6187	0.6454
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	96	97	98	99	100
Experiment Number	381	382	383	384	385
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.66499	0.672513	0.664077	0.664626	0.641557
M6 Utilization after the disruptive event	0.51086	0.490657	0.485896	0.483096	0.471194
M2 Utilization after the disruptive event	0.494423	0.495068	0.497832	0.494625	0.46614
M5 Utilization after the disruptive event	0.307831	0.277423	0.283694	0.262309	0.293599
M3 Utilization after the disruptive event	0.792695	0.778364	0.787844	0.767084	0.765363
M7 Utilization after the disruptive event	0.728095	0.707822	0.735714	0.726923	0.692521
M9 Utilization after the disruptive event	0.741578	0.714962	0.751457	0.70793	0.691087
M12 Utilization after the disruptive event	0.659397	0.610343	0.668064	0.62854	0.606639
AGV Utilization prior to a disruptive event	0.4214	0.393149	0.42598	0.353627	0.352098
Fixture Utilization prior to a disruptive event	0.629256	0.602052	0.622898	0.584841	0.573672
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	101	102	103	104	105
Experiment Number	386	387	388	389	390
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.663507	0.66487	0.661924	0.659319	0.660541
M6 Utilization after the disruptive event	0.495329	0.52199	0.490797	0.497069	0.479579
M2 Utilization after the disruptive event	0.493733	0.50929	0.48734	0.491138	0.485686
M5 Utilization after the disruptive event	0.321086	0.277131	0.300365	0.302702	0.30785
M3 Utilization after the disruptive event	0.790799	0.778415	0.788183	0.776396	0.785345
M7 Utilization after the disruptive event	0.732961	0.755221	0.704004	0.705021	0.711714
M9 Utilization after the disruptive event	0.70299	0.743649	0.726414	0.742061	0.740085
M12 Utilization after the disruptive event	0.635648	0.676092	0.616356	0.626889	0.623838
AGV Utilization prior to a disruptive event	0.393829	0.434706	0.380319	0.357506	0.399561
Fixture Utilization prior to a disruptive event	0.609166	0.634536	0.598894	0.592754	0.608214
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	106	107	108	109	110
Experiment Number	56	57	58	59	60
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.5674	0.6182	0.566	0.5785	0.5736
M6 Utilization after the disruptive event	0.3206	0.3391	0.3106	0.6446	0.3455
M2 Utilization after the disruptive event	0.7053	0.7046	0.7082	0.7223	0.4839
M5 Utilization after the disruptive event	0.6323	0.6502	0.6058	0.6326	0.5308
M3 Utilization after the disruptive event	0.6421	0.6638	0.357	0.6723	0.6514
M7 Utilization after the disruptive event	0.7639	0.4124	0.3961	0.441	0.4651
M9 Utilization after the disruptive event	0.7998	0.792	0.7871	0.8028	0.8241
M12 Utilization after the disruptive event	0.6991	0.7113	0.6745	0.7129	0.7006
AGV Utilization prior to a disruptive event	0.4331	0.4413	0.4413	0.4477	0.4383
Fixture Utilization prior to a disruptive event	0.6202	0.6339	0.6339	0.6368	0.6341
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0.05	0.05	0.05	0.05	0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	-0.2	-0.2	-0.2	-0.2	-0.2
% change in Part Type 5	0.05	0.05	0.05	0.05	0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0.25	0.25	0.25	0.25	0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0.05	0.05	0.05	0.05	0.05
% change in Part Type 12	-0.2	-0.2	-0.2	-0.2	-0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	111	112	113	114	115
Experiment Number	201	202	203	204	205
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.580314	0.574311	0.561773	0.558985	0.546739
M6 Utilization after the disruptive event	0.320274	0.312427	0.32054	0.342362	0.358161
M2 Utilization after the disruptive event	0.735312	0.744549	0.707989	0.711755	0.720743
M5 Utilization after the disruptive event	0.612093	0.657406	0.619185	0.633082	0.627262
M3 Utilization after the disruptive event	0.67636	0.655833	0.658813	0.665735	0.66894
M7 Utilization after the disruptive event	0.411711	0.491958	0.436052	0.41477	0.461576
M9 Utilization after the disruptive event	0.823698	0.799596	0.792361	0.804438	0.790265
M12 Utilization after the disruptive event	0.688988	0.71464	0.674051	0.685418	0.68942
AGV Utilization prior to a disruptive event	0.423402	0.459202	0.415401	0.42301	0.437618
Fixture Utilization prior to a disruptive event	0.622821	0.651066	0.613402	0.619263	0.629646
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0.05	0.05	0.05	0.05	0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	-0.2	-0.2	-0.2	-0.2	-0.2
% change in Part Type 5	0.05	0.05	0.05	0.05	0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0.25	0.25	0.25	0.25	0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0.05	0.05	0.05	0.05	0.05
% change in Part Type 12	-0.2	-0.2	-0.2	-0.2	-0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	116	117	118	119	120
Experiment Number	206	207	208	209	210
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.563215	0.57545	0.57378	0.572605	0.569526
M6 Utilization after the disruptive event	0.337581	0.323807	0.327987	0.335749	0.313243
M2 Utilization after the disruptive event	0.725053	0.702996	0.721817	0.722385	0.716179
M5 Utilization after the disruptive event	0.649525	0.632491	0.644125	0.653393	0.629543
M3 Utilization after the disruptive event	0.65955	0.599137	0.653144	0.655433	0.659612
M7 Utilization after the disruptive event	0.493555	0.444725	0.421732	0.457341	0.440383
M9 Utilization after the disruptive event	0.803087	0.804989	0.806402	0.806186	0.79885
M12 Utilization after the disruptive event	0.696842	0.704799	0.70264	0.689138	0.695851
AGV Utilization prior to a disruptive event	0.463024	0.483099	0.428761	0.44776	0.421196
Fixture Utilization prior to a disruptive event	0.647975	0.65991	0.630083	0.640492	0.620452
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0.05	0.05	0.05	0.05	0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	-0.2	-0.2	-0.2	-0.2	-0.2
% change in Part Type 5	0.05	0.05	0.05	0.05	0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0.25	0.25	0.25	0.25	0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0.05	0.05	0.05	0.05	0.05
% change in Part Type 12	-0.2	-0.2	-0.2	-0.2	-0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	121	122	123	124	125
Experiment Number	66	67	68	69	70
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.6499	0.6722	0.6626	0.666	0.6571
M6 Utilization after the disruptive event	0.5119	0.5068	0.4811	0.4808	0.4456
M2 Utilization after the disruptive event	0.4965	0.4827	0.5116	0.488	0.4968
M5 Utilization after the disruptive event	0.3009	0.3044	0.2834	0.2817	0.2994
M3 Utilization after the disruptive event	0.7867	0.7833	0.7526	0.7763	0.7673
M7 Utilization after the disruptive event	0.7304	0.7254	0.7134	0.7175	0.7325
M9 Utilization after the disruptive event	0.7346	0.7389	0.7395	0.728	0.7198
M12 Utilization after the disruptive event	0.6534	0.6519	0.6398	0.6202	0.6166
AGV Utilization prior to a disruptive event	0.4009	0.4284	0.3956	0.379	0.3805
Fixture Utilization prior to a disruptive event	0.6147	0.6249	0.6055	0.5968	0.5951
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	126	127	128	129	130
Experiment Number	221	222	223	224	225
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.658841	0.67662	0.680877	0.664158	0.667464
M6 Utilization after the disruptive event	0.515128	0.503028	0.502464	0.510077	0.48716
M2 Utilization after the disruptive event	0.52412	0.514909	0.503496	0.487559	0.48519
M5 Utilization after the disruptive event	0.273037	0.290009	0.298673	0.327187	0.304751
M3 Utilization after the disruptive event	0.787197	0.787147	0.786033	0.774006	0.782936
M7 Utilization after the disruptive event	0.709753	0.741245	0.747235	0.731661	0.704796
M9 Utilization after the disruptive event	0.733194	0.742926	0.747893	0.740079	0.760946
M12 Utilization after the disruptive event	0.658214	0.648749	0.653219	0.65454	0.650329
AGV Utilization prior to a disruptive event	0.414314	0.417171	0.432822	0.406302	0.418675
Fixture Utilization prior to a disruptive event	0.618797	0.624496	0.635644	0.618401	0.621725
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	131	132	133	134	135
Experiment Number	226	227	228	229	230
Elements					
Mean Arrival Time	2.2	2.2	2.2	2.2	2.2
M1 Utilization after the disruptive event	0.660039	0.663758	0.677186	0.667357	0.654986
M6 Utilization after the disruptive event	0.482183	0.479781	0.526093	0.485485	0.48109
M2 Utilization after the disruptive event	0.484692	0.497336	0.508567	0.483352	0.475678
M5 Utilization after the disruptive event	0.304797	0.299998	0.332792	0.316205	0.332661
M3 Utilization after the disruptive event	0.765391	0.786866	0.793205	0.775793	0.76583
M7 Utilization after the disruptive event	0.716239	0.730224	0.763549	0.699753	0.708439
M9 Utilization after the disruptive event	0.735045	0.734616	0.771131	0.724498	0.71988
M12 Utilization after the disruptive event	0.644354	0.634706	0.666416	0.631402	0.627015
AGV Utilization prior to a disruptive event	0.353062	0.399054	0.477445	0.370895	0.36886
Fixture Utilization prior to a disruptive event	0.591288	0.612322	0.66167	0.597056	0.59301
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	136	137	138	139	140
Experiment Number	106	107	108	109	110
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.5592	0.5627	0.5648	0.5571	0.5383
M6 Utilization after the disruptive event	0.3142	0.3052	0.3072	0.3051	0.2972
M2 Utilization after the disruptive event	0.6762	0.6845	0.6827	0.6902	0.6943
M5 Utilization after the disruptive event	0.6046	0.6139	0.6079	0.6065	0.5808
M3 Utilization after the disruptive event	0.6241	0.6464	0.6302	0.6056	0.6297
M7 Utilization after the disruptive event	0.4184	0.4255	0.428	0.4392	0.3943
M9 Utilization after the disruptive event	0.7848	0.7975	0.7871	0.7947	0.775
M12 Utilization after the disruptive event	0.649	0.6519	0.6533	0.6472	0.6334
AGV Utilization prior to a disruptive event	0.3211	0.3606	0.3628	0.3448	0.3361
Fixture Utilization prior to a disruptive event	0.5632	0.5839	0.5822	0.5736	0.5602
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	141	142	143	144	145
Experiment Number	331	332	333	334	335
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.545729	0.555551	0.534249	0.554531	0.547331
M6 Utilization after the disruptive event	0.29364	0.316001	0.330401	0.32666	0.321577
M2 Utilization after the disruptive event	0.716163	0.708627	0.698035	0.711006	0.693169
M5 Utilization after the disruptive event	0.588044	0.608723	0.606876	0.611284	0.58846
M3 Utilization after the disruptive event	0.638117	0.659655	0.631517	0.646265	0.616934
M7 Utilization after the disruptive event	0.448263	0.381144	0.417023	0.41196	0.458272
M9 Utilization after the disruptive event	0.769872	0.79232	0.776657	0.78949	0.777028
M12 Utilization after the disruptive event	0.658963	0.658593	0.660556	0.666371	0.652126
AGV Utilization prior to a disruptive event	0.356292	0.352895	0.359609	0.370371	0.348907
Fixture Utilization prior to a disruptive event	0.579394	0.58053	0.579749	0.590837	0.576352
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	146	147	148	149	150
Experiment Number	336	337	338	339	340
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.553689	0.547112	0.568418	0.536828	0.568847
M6 Utilization after the disruptive event	0.286163	0.31611	0.290631	0.297026	0.287312
M2 Utilization after the disruptive event	0.677493	0.70077	0.692784	0.66837	0.70594
M5 Utilization after the disruptive event	0.594898	0.564548	0.59368	0.549325	0.585506
M3 Utilization after the disruptive event	0.635062	0.627733	0.636667	0.6171	0.615152
M7 Utilization after the disruptive event	0.390927	0.434767	0.418514	0.380699	0.434349
M9 Utilization after the disruptive event	0.779746	0.764222	0.785533	0.745778	0.783256
M12 Utilization after the disruptive event	0.634848	0.652505	0.658856	0.617303	0.643205
AGV Utilization prior to a disruptive event	0.329804	0.318928	0.341294	0.30859	0.3237
Fixture Utilization prior to a disruptive event	0.559771	0.560958	0.57171	0.538125	0.563499
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	151	152	153	154	155
Experiment Number	111	112	113	114	115
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.6317	0.6227	0.6614	0.6474	0.657
M6 Utilization after the disruptive event	0.4825	0.4683	0.4421	0.4477	0.4208
M2 Utilization after the disruptive event	0.478	0.5101	0.4631	0.4924	0.4843
M5 Utilization after the disruptive event	0.3006	0.2452	0.2955	0.2635	0.2511
M3 Utilization after the disruptive event	0.7592	0.7598	0.7536	0.7512	0.7502
M7 Utilization after the disruptive event	0.6899	0.6577	0.657	0.6503	0.6611
M9 Utilization after the disruptive event	0.7128	0.7071	0.6966	0.7061	0.6861
M12 Utilization after the disruptive event	0.6046	0.6072	0.5901	0.5647	0.5863
AGV Utilization prior to a disruptive event	0.3435	0.3122	0.3121	0.3078	0.3129
Fixture Utilization prior to a disruptive event	0.5736	0.5577	0.5554	0.5484	0.5474
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0.2	0.2	0.2	0.2	0.2
% change in Part Type 5	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	-0.25	-0.25	-0.25	-0.25	-0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 12	0.2	0.2	0.2	0.2	0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	156	157	158	159	160
Experiment Number	191	192	193	194	195
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.647781	0.645972	0.639256	0.662002	0.658688
M6 Utilization after the disruptive event	0.503736	0.449544	0.4476	0.451645	0.484092
M2 Utilization after the disruptive event	0.473523	0.486215	0.469808	0.497433	0.469039
M5 Utilization after the disruptive event	0.286823	0.288794	0.252023	0.302259	0.279545
M3 Utilization after the disruptive event	0.757356	0.752958	0.749488	0.761922	0.752905
M7 Utilization after the disruptive event	0.699307	0.680441	0.664175	0.695907	0.687096
M9 Utilization after the disruptive event	0.718026	0.736903	0.710483	0.721111	0.707425
M12 Utilization after the disruptive event	0.624574	0.612471	0.577539	0.637503	0.584377
AGV Utilization prior to a disruptive event	0.37118	0.340829	0.320342	0.342338	0.338316
Fixture Utilization prior to a disruptive event	0.589095	0.572842	0.550518	0.580341	0.567899
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0.2	0.2	0.2	0.2	0.2
% change in Part Type 5	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	-0.25	-0.25	-0.25	-0.25	-0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 12	0.2	0.2	0.2	0.2	0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	161	162	163	164	165
Experiment Number	196	197	198	199	200
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.667749	0.630304	0.63691	0.633813	0.645354
M6 Utilization after the disruptive event	0.481681	0.486927	0.46639	0.467716	0.442626
M2 Utilization after the disruptive event	0.506648	0.472789	0.503751	0.478836	0.46793
M5 Utilization after the disruptive event	0.29831	0.292558	0.285143	0.277112	0.24726
M3 Utilization after the disruptive event	0.782791	0.763684	0.748876	0.750467	0.740858
M7 Utilization after the disruptive event	0.692446	0.645888	0.670105	0.6714	0.673981
M9 Utilization after the disruptive event	0.739549	0.725697	0.71066	0.677501	0.701179
M12 Utilization after the disruptive event	0.642485	0.593037	0.607904	0.607436	0.563517
AGV Utilization prior to a disruptive event	0.396188	0.314799	0.340216	0.330992	0.316668
Fixture Utilization prior to a disruptive event	0.615346	0.559049	0.570051	0.559401	0.547822
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0.2	0.2	0.2	0.2	0.2
% change in Part Type 5	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	-0.25	-0.25	-0.25	-0.25	-0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	-0.05	-0.05	-0.05	-0.05	-0.05
% change in Part Type 12	0.2	0.2	0.2	0.2	0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	166	167	168	169	170
Experiment Number	116	117	118	119	120
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.5403	0.5382	0.5457	0.5653	0.5642
M6 Utilization after the disruptive event	0.3187	0.3201	0.3158	0.2792	0.2847
M2 Utilization after the disruptive event	0.6861	0.6912	0.7022	0.6697	0.6785
M5 Utilization after the disruptive event	0.6083	0.5869	0.6018	0.6	0.6069
M3 Utilization after the disruptive event	0.651	0.6536	0.6202	0.6345	0.6275
M7 Utilization after the disruptive event	0.4123	0.401	0.4405	0.3996	0.4007
M9 Utilization after the disruptive event	0.7782	0.7806	0.771	0.7851	0.7867
M12 Utilization after the disruptive event	0.6659	0.6592	0.6626	0.6327	0.644
AGV Utilization prior to a disruptive event	0.3597	0.3765	0.3415	0.3214	0.3613
Fixture Utilization prior to a disruptive event	0.5806	0.5858	0.5734	0.5591	0.5777
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0.05	0.05	0.05	0.05	0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	-0.2	-0.2	-0.2	-0.2	-0.2
% change in Part Type 5	0.05	0.05	0.05	0.05	0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0.25	0.25	0.25	0.25	0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0.05	0.05	0.05	0.05	0.05
% change in Part Type 12	-0.2	-0.2	-0.2	-0.2	-0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	171	172	173	174	175
Experiment Number	211	212	213	214	215
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.552792	0.551022	0.552235	0.538211	0.53924
M6 Utilization after the disruptive event	0.307534	0.313744	0.282113	0.315755	0.301271
M2 Utilization after the disruptive event	0.67242	0.687635	0.681086	0.687459	0.692594
M5 Utilization after the disruptive event	0.606508	0.609454	0.582956	0.595947	0.584745
M3 Utilization after the disruptive event	0.64123	0.618776	0.630473	0.622441	0.626983
M7 Utilization after the disruptive event	0.552792	0.420368	0.552235	0.424967	0.53924
M9 Utilization after the disruptive event	0.307534	0.778665	0.282113	0.767368	0.301271
M12 Utilization after the disruptive event	0.67242	0.633928	0.681086	0.636791	0.692594
AGV Utilization prior to a disruptive event	0.606508	0.356905	0.582956	0.348591	0.584745
Fixture Utilization prior to a disruptive event	0.64123	0.574039	0.630473	0.568667	0.626983
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0.05	0.05	0.05	0.05	0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	-0.2	-0.2	-0.2	-0.2	-0.2
% change in Part Type 5	0.05	0.05	0.05	0.05	0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0.25	0.25	0.25	0.25	0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0.05	0.05	0.05	0.05	0.05
% change in Part Type 12	-0.2	-0.2	-0.2	-0.2	-0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	176	177	178	179	180
Experiment Number	216	217	218	219	220
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.549453	0.554215	0.539457	0.438203	0.557304
M6 Utilization after the disruptive event	0.288178	0.314933	0.302702	0.809987	0.310749
M2 Utilization after the disruptive event	0.676642	0.685433	0.707995	0.685705	0.697957
M5 Utilization after the disruptive event	0.599659	0.582784	0.603416	0.393505	0.606323
M3 Utilization after the disruptive event	0.644133	0.633678	0.668292	0.604563	0.638139
M7 Utilization after the disruptive event	0.382485	0.411218	0.438203	0.423491	0.450777
M9 Utilization after the disruptive event	0.781397	0.776242	0.809987	0.778594	0.798721
M12 Utilization after the disruptive event	0.636134	0.651435	0.685705	0.651208	0.651854
AGV Utilization prior to a disruptive event	0.330035	0.360354	0.393505	0.34814	0.341947
Fixture Utilization prior to a disruptive event	0.559604	0.576287	0.604563	0.570176	0.579506
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0.05	0.05	0.05	0.05	0.05
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	-0.2	-0.2	-0.2	-0.2	-0.2
% change in Part Type 5	0.05	0.05	0.05	0.05	0.05
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0.25	0.25	0.25	0.25	0.25
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0.05	0.05	0.05	0.05	0.05
% change in Part Type 12	-0.2	-0.2	-0.2	-0.2	-0.2
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	181	182	183	184	185
Experiment Number	121	122	123	124	125
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.6499	0.6501	0.6514	0.6596	0.6502
M6 Utilization after the disruptive event	0.4802	0.4332	0.4865	0.4724	0.4398
M2 Utilization after the disruptive event	0.4786	0.4722	0.4836	0.474	0.4755
M5 Utilization after the disruptive event	0.3035	0.2873	0.2786	0.2865	0.269
M3 Utilization after the disruptive event	0.7486	0.7459	0.769	0.7565	0.7614
M7 Utilization after the disruptive event	0.7109	0.6576	0.6483	0.686	0.6351
M9 Utilization after the disruptive event	0.7552	0.6832	0.7081	0.6982	0.6897
M12 Utilization after the disruptive event	0.6339	0.596	0.6065	0.6104	0.5971
AGV Utilization prior to a disruptive event	0.3971	0.3137	0.3375	0.3214	0.3109
Fixture Utilization prior to a disruptive event	0.6019	0.5495	0.5688	0.5631	0.5484
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	186	187	188	189	190
Experiment Number	231	232	233	234	235
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.6487	0.628096	0.660209	0.651281	0.655171
M6 Utilization after the disruptive event	0.458854	0.472638	0.489637	0.457838	0.495435
M2 Utilization after the disruptive event	0.49534	0.487647	0.480241	0.482653	0.488876
M5 Utilization after the disruptive event	0.276632	0.288154	0.289582	0.296372	0.284308
M3 Utilization after the disruptive event	0.762906	0.769157	0.779185	0.754114	0.758376
M7 Utilization after the disruptive event	0.683273	0.628404	0.698943	0.674139	0.675243
M9 Utilization after the disruptive event	0.716431	0.720516	0.717358	0.710356	0.708296
M12 Utilization after the disruptive event	0.604457	0.62083	0.624475	0.606484	0.611859
AGV Utilization prior to a disruptive event	0.323978	0.334847	0.365259	0.314805	0.387102
Fixture Utilization prior to a disruptive event	0.564763	0.566394	0.590389	0.560578	0.596062
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	191	192	193	194	195
Experiment Number	236	237	238	239	240
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.644684	0.658269	0.637704	0.665152	0.635014
M6 Utilization after the disruptive event	0.462895	0.420544	0.41131	0.44109	0.46601
M2 Utilization after the disruptive event	0.473258	0.454394	0.456669	0.450595	0.486282
M5 Utilization after the disruptive event	0.288068	0.27855	0.268436	0.296691	0.265146
M3 Utilization after the disruptive event	0.760625	0.753959	0.731085	0.757772	0.740876
M7 Utilization after the disruptive event	0.686237	0.659564	0.658548	0.679207	0.658481
M9 Utilization after the disruptive event	0.728918	0.707009	0.705129	0.736378	0.703942
M12 Utilization after the disruptive event	0.611022	0.57209	0.568154	0.602778	0.600241
AGV Utilization prior to a disruptive event	0.352237	0.321857	0.293378	0.343219	0.324435
Fixture Utilization prior to a disruptive event	0.577188	0.551029	0.534218	0.570625	0.557819
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	196	197	198	199	200
Experiment Number	126	127	128	129	130
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.5471	0.5368	0.5464	0.5573	0.5579
M6 Utilization after the disruptive event	0.3132	0.2934	0.3199	0.309	0.311
M2 Utilization after the disruptive event	0.7001	0.6946	0.7147	0.6871	0.6973
M5 Utilization after the disruptive event	0.5958	0.5531	0.6038	0.6038	0.6165
M3 Utilization after the disruptive event	0.6248	0.6144	0.6307	0.6212	0.6517
M7 Utilization after the disruptive event	0.4261	0.4028	0.4415	0.4418	0.4077
M9 Utilization after the disruptive event	0.7824	0.7694	0.779	0.7967	0.7799
M12 Utilization after the disruptive event	0.6715	0.6244	0.6671	0.6683	0.6529
AGV Utilization prior to a disruptive event	0.3514	0.3167	0.3571	0.3785	0.3536
Fixture Utilization prior to a disruptive event	0.5773	0.5483	0.5829	0.59	0.5786
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	201	202	203	204	205
Experiment Number	251	252	253	254	255
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.554723	0.568041	0.568861	0.555056	0.529192
M6 Utilization after the disruptive event	0.326257	0.331027	0.286663	0.30725	0.292678
M2 Utilization after the disruptive event	0.705256	0.719644	0.699523	0.706211	0.680456
M5 Utilization after the disruptive event	0.588825	0.612649	0.586067	0.582345	0.590392
M3 Utilization after the disruptive event	0.645627	0.642904	0.634785	0.62972	0.665341
M7 Utilization after the disruptive event	0.394707	0.432049	0.394277	0.416874	0.393364
M9 Utilization after the disruptive event	0.784212	0.781128	0.768918	0.786033	0.784635
M12 Utilization after the disruptive event	0.665879	0.672683	0.639419	0.660102	0.635303
AGV Utilization prior to a disruptive event	0.354159	0.412402	0.333987	0.340074	0.359927
Fixture Utilization prior to a disruptive event	0.578978	0.609319	0.563545	0.57179	0.572158
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	206	207	208	209	210
Experiment Number	256	257	258	259	260
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.529167	0.537751	0.540511	0.541449	0.551879
M6 Utilization after the disruptive event	0.29398	0.284679	0.303322	0.314657	0.292471
M2 Utilization after the disruptive event	0.698132	0.686963	0.687288	0.678919	0.680141
M5 Utilization after the disruptive event	0.578396	0.576691	0.593817	0.580777	0.576386
M3 Utilization after the disruptive event	0.634048	0.626918	0.608111	0.611083	0.633188
M7 Utilization after the disruptive event	0.410123	0.407237	0.415803	0.439212	0.401721
M9 Utilization after the disruptive event	0.789613	0.771148	0.76374	0.745346	0.76114
M12 Utilization after the disruptive event	0.635867	0.640893	0.632245	0.636703	0.644441
AGV Utilization prior to a disruptive event	0.330543	0.328618	0.312799	0.347995	0.317786
Fixture Utilization prior to a disruptive event	0.561404	0.556483	0.551423	0.566193	0.553934
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	1	1	1	1	1

Vector Number	211	212	213	214	215
Experiment Number	131	132	133	134	135
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.657	0.6485	0.6466	0.6359	0.6458
M6 Utilization after the disruptive event	0.4728	0.4712	0.46	0.46	0.4611
M2 Utilization after the disruptive event	0.4633	0.4815	0.4591	0.4694	0.4946
M5 Utilization after the disruptive event	0.2904	0.2815	0.2703	0.2604	0.2789
M3 Utilization after the disruptive event	0.7528	0.7551	0.7468	0.7426	0.7765
M7 Utilization after the disruptive event	0.6866	0.6913	0.6666	0.6976	0.6692
M9 Utilization after the disruptive event	0.7007	0.7119	0.7127	0.7142	0.7296
M12 Utilization after the disruptive event	0.5986	0.6022	0.6025	0.59	0.6194
AGV Utilization prior to a disruptive event	0.3533	0.326	0.3353	0.3254	0.3337
Fixture Utilization prior to a disruptive event	0.5743	0.5668	0.5622	0.5577	0.5708
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	216	217	218	219	220
Experiment Number	271	272	273	274	275
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.6412	0.6372	0.6461	0.6469	0.6505
M6 Utilization after the disruptive event	0.4393	0.4741	0.4704	0.4568	0.4456
M2 Utilization after the disruptive event	0.5093	0.4653	0.5241	0.5118	0.4923
M5 Utilization after the disruptive event	0.2816	0.3096	0.2605	0.2398	0.2660
M3 Utilization after the disruptive event	0.7334	0.7537	0.7697	0.7737	0.7437
M7 Utilization after the disruptive event	0.6717	0.6706	0.7051	0.6501	0.6736
M9 Utilization after the disruptive event	0.7333	0.7303	0.7266	0.7064	0.7251
M12 Utilization after the disruptive event	0.6174	0.6268	0.6089	0.6034	0.6243
AGV Utilization prior to a disruptive event	0.3320	0.3362	0.3350	0.3338	0.3328
Fixture Utilization prior to a disruptive event	0.5663	0.5716	0.5752	0.5633	0.5662
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	221	222	223	224	225
Experiment Number	276	277	278	279	280
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.6626	0.6566	0.6429	0.6557	0.6249
M6 Utilization after the disruptive event	0.4466	0.4627	0.4378	0.4559	0.4715
M2 Utilization after the disruptive event	0.4721	0.4811	0.4510	0.4825	0.4958
M5 Utilization after the disruptive event	0.2969	0.2907	0.2995	0.2983	0.2717
M3 Utilization after the disruptive event	0.7714	0.7481	0.7482	0.7495	0.7513
M7 Utilization after the disruptive event	0.6735	0.6811	0.6543	0.6883	0.6726
M9 Utilization after the disruptive event	0.7157	0.7083	0.7202	0.7220	0.7247
M12 Utilization after the disruptive event	0.6257	0.6042	0.5740	0.5984	0.6043
AGV Utilization prior to a disruptive event	0.3663	0.3225	0.2978	0.3339	0.3194
Fixture Utilization prior to a disruptive event	0.5858	0.5635	0.5449	0.5694	0.5611
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	226	227	228	229	230
Experiment Number	136	137	138	139	140
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.5461	0.56	0.5425	0.5593	0.5529
M6 Utilization after the disruptive event	0.3066	0.2968	0.3132	0.2813	0.3054
M2 Utilization after the disruptive event	0.6804	0.6946	0.668	0.6945	0.7073
M5 Utilization after the disruptive event	0.5999	0.614	0.6022	0.6167	0.6095
M3 Utilization after the disruptive event	0.6331	0.6308	0.6289	0.6497	0.6526
M7 Utilization after the disruptive event	0.414	0.4089	0.414	0.4073	0.4487
M9 Utilization after the disruptive event	0.7769	0.7617	0.7685	0.7736	0.7877
M12 Utilization after the disruptive event	0.6464	0.6384	0.6383	0.6572	0.6797
AGV Utilization prior to a disruptive event	0.3464	0.3353	0.3253	0.3532	0.3783
Fixture Utilization prior to a disruptive event	0.5697	0.5663	0.5604	0.5762	0.5951
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	231	232	233	234	235
Experiment Number	291	292	293	294	295
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.5417	0.5742	0.5313	0.5147	0.5540
M6 Utilization after the disruptive event	0.3127	0.2777	0.3117	0.3064	0.3149
M2 Utilization after the disruptive event	0.6836	0.6791	0.6758	0.6861	0.7056
M5 Utilization after the disruptive event	0.5703	0.6014	0.5783	0.5731	0.5963
M3 Utilization after the disruptive event	0.6398	0.6205	0.6076	0.6335	0.6190
M7 Utilization after the disruptive event	0.3935	0.3617	0.4146	0.4037	0.4416
M9 Utilization after the disruptive event	0.7642	0.7585	0.7594	0.7858	0.7810
M12 Utilization after the disruptive event	0.6301	0.6403	0.6255	0.6259	0.6435
AGV Utilization prior to a disruptive event	0.3202	0.3182	0.3317	0.3420	0.3657
Fixture Utilization prior to a disruptive event	0.5539	0.5519	0.5552	0.5622	0.5820
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	236	237	238	239	240
Experiment Number	296	297	298	299	300
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.5490	0.5439	0.5767	0.5236	0.5660
M6 Utilization after the disruptive event	0.2843	0.3014	0.2685	0.3112	0.3256
M2 Utilization after the disruptive event	0.7181	0.7091	0.6872	0.6782	0.6951
M5 Utilization after the disruptive event	0.5783	0.6079	0.6049	0.6094	0.6063
M3 Utilization after the disruptive event	0.6603	0.6409	0.6414	0.6389	0.6209
M7 Utilization after the disruptive event	0.4018	0.4347	0.3969	0.3960	0.4192
M9 Utilization after the disruptive event	0.7666	0.7918	0.7861	0.7710	0.7928
M12 Utilization after the disruptive event	0.6492	0.6525	0.6370	0.6348	0.6514
AGV Utilization prior to a disruptive event	0.3354	0.3522	0.3202	0.3397	0.3739
Fixture Utilization prior to a disruptive event	0.5664	0.5798	0.5602	0.5641	0.5864
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	1	1	1	1	1
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	241	242	243	244	245
Experiment Number	141	142	143	144	145
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.6414	0.6657	0.6341	0.6344	0.6464
M6 Utilization after the disruptive event	0.4414	0.4418	0.4625	0.4701	0.4281
M2 Utilization after the disruptive event	0.4558	0.4797	0.4923	0.4723	0.4722
M5 Utilization after the disruptive event	0.3217	0.2691	0.2921	0.2885	0.2964
M3 Utilization after the disruptive event	0.7556	0.7664	0.7441	0.7682	0.754
M7 Utilization after the disruptive event	0.6799	0.6553	0.6592	0.6954	0.65
M9 Utilization after the disruptive event	0.6958	0.7079	0.7324	0.7257	0.7006
M12 Utilization after the disruptive event	0.5908	0.5837	0.6322	0.6133	0.6139
AGV Utilization prior to a disruptive event	0.3036	0.3167	0.3459	0.3689	0.3194
Fixture Utilization prior to a disruptive event	0.5528	0.5561	0.5732	0.5841	0.5558
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	246	247	248	249	250
Experiment Number	311	312	313	314	315
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.6434	0.6596	0.6468	0.6366	0.6508
M6 Utilization after the disruptive event	0.4572	0.4315	0.4696	0.4709	0.5009
M2 Utilization after the disruptive event	0.4877	0.4750	0.4652	0.4871	0.5126
M5 Utilization after the disruptive event	0.2776	0.2877	0.3210	0.2812	0.2974
M3 Utilization after the disruptive event	0.7723	0.7567	0.7703	0.7458	0.7597
M7 Utilization after the disruptive event	0.6952	0.6637	0.6645	0.6710	0.7125
M9 Utilization after the disruptive event	0.7210	0.7345	0.7356	0.7231	0.7435
M12 Utilization after the disruptive event	0.6069	0.6108	0.6271	0.5921	0.6561
AGV Utilization prior to a disruptive event	0.3548	0.3535	0.3474	0.3526	0.4092
Fixture Utilization prior to a disruptive event	0.5783	0.5740	0.5789	0.5724	0.6186
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	251	252	253	254	255
Experiment Number	316	317	318	319	320
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.6402	0.6366	0.6401	0.6379	0.6446
M6 Utilization after the disruptive event	0.4614	0.4607	0.4336	0.4234	0.4525
M2 Utilization after the disruptive event	0.4739	0.4724	0.4778	0.4900	0.4559
M5 Utilization after the disruptive event	0.2459	0.2765	0.2717	0.2567	0.2912
M3 Utilization after the disruptive event	0.7487	0.7630	0.7451	0.7416	0.7395
M7 Utilization after the disruptive event	0.6714	0.6639	0.6570	0.6598	0.6588
M9 Utilization after the disruptive event	0.7157	0.6939	0.7229	0.7180	0.6834
M12 Utilization after the disruptive event	0.5883	0.5683	0.5894	0.5725	0.5924
AGV Utilization prior to a disruptive event	0.3067	0.3080	0.3035	0.2984	0.3164
Fixture Utilization prior to a disruptive event	0.5494	0.5491	0.5481	0.5433	0.5514
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	1	1	1	1	1
M2 Breakdown	0	0	0	0	0
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	256	257	258	259	260
Experiment Number	146	147	148	149	150
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.645800	0.662100	0.639900	0.659000	0.657700
M6 Utilization after the disruptive event	0.454900	0.429300	0.490200	0.445100	0.482300
M2 Utilization after the disruptive event	0.474100	0.459100	0.474500	0.495700	0.480900
M5 Utilization after the disruptive event	0.276600	0.319500	0.302500	0.269000	0.320600
M3 Utilization after the disruptive event	0.749700	0.769600	0.774200	0.766300	0.761500
M7 Utilization after the disruptive event	0.643200	0.670400	0.685700	0.692400	0.688400
M9 Utilization after the disruptive event	0.699300	0.695500	0.708900	0.716200	0.722600
M12 Utilization after the disruptive event	0.592700	0.592200	0.615600	0.593700	0.611400
AGV Utilization prior to a disruptive event	0.299000	0.325600	0.373600	0.339900	0.376700
Fixture Utilization prior to a disruptive event	0.546700	0.561400	0.589200	0.570600	0.594200
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	261	262	263	264	265
Experiment Number	351	352	353	354	355
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.660716	0.652571	0.641024	0.649251	0.667915
M6 Utilization after the disruptive event	0.446940	0.464114	0.474254	0.474763	0.449636
M2 Utilization after the disruptive event	0.485139	0.482187	0.491150	0.473626	0.475576
M5 Utilization after the disruptive event	0.269422	0.305539	0.284878	0.279310	0.284817
M3 Utilization after the disruptive event	0.764474	0.757344	0.753473	0.766721	0.763420
M7 Utilization after the disruptive event	0.656676	0.697083	0.700607	0.678039	0.689065
M9 Utilization after the disruptive event	0.722228	0.705092	0.723799	0.702311	0.716683
M12 Utilization after the disruptive event	0.613584	0.596841	0.607023	0.587075	0.612497
AGV Utilization prior to a disruptive event	0.328633	0.354870	0.355016	0.337449	0.345516
Fixture Utilization prior to a disruptive event	0.564670	0.578732	0.577718	0.567280	0.574204
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	266	267	268	269	270
Experiment Number	356	357	358	359	360
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.633299	0.639764	0.646191	0.633399	0.642182
M6 Utilization after the disruptive event	0.480540	0.493703	0.473930	0.479126	0.477424
M2 Utilization after the disruptive event	0.465445	0.445727	0.468646	0.492256	0.492603
M5 Utilization after the disruptive event	0.312356	0.333778	0.304284	0.291573	0.276182
M3 Utilization after the disruptive event	0.757381	0.768962	0.765635	0.747342	0.755391
M7 Utilization after the disruptive event	0.662688	0.683369	0.707817	0.645172	0.675608
M9 Utilization after the disruptive event	0.706259	0.720622	0.733030	0.723635	0.711999
M12 Utilization after the disruptive event	0.610604	0.627629	0.613313	0.580202	0.600001
AGV Utilization prior to a disruptive event	0.335989	0.348711	0.361480	0.330217	0.335952
Fixture Utilization prior to a disruptive event	0.568939	0.580026	0.587316	0.563816	0.568163
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	1	1	1	1	1
M5 Breakdown	0	0	0	0	0
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	271	272	273	274	275
Experiment Number	156	157	158	159	160
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.651500	0.639000	0.649900	0.653300	0.666900
M6 Utilization after the disruptive event	0.484300	0.464800	0.457600	0.461300	0.437900
M2 Utilization after the disruptive event	0.496400	0.468600	0.463700	0.454600	0.466800
M5 Utilization after the disruptive event	0.276200	0.272100	0.284700	0.292200	0.284100
M3 Utilization after the disruptive event	0.761500	0.719100	0.740300	0.770500	0.754200
M7 Utilization after the disruptive event	0.675900	0.676600	0.660800	0.677600	0.676600
M9 Utilization after the disruptive event	0.711700	0.684700	0.698200	0.710800	0.717900
M12 Utilization after the disruptive event	0.627100	0.608800	0.575900	0.597400	0.596300
AGV Utilization prior to a disruptive event	0.350600	0.305900	0.310700	0.343400	0.332700
Fixture Utilization prior to a disruptive event	0.578700	0.548000	0.550600	0.569700	0.564200
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	276	277	278	279	280
Experiment Number	391	392	393	394	395
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.661587	0.653007	0.643907	0.645807	0.660868
M6 Utilization after the disruptive event	0.436610	0.464983	0.463792	0.439446	0.481575
M2 Utilization after the disruptive event	0.468465	0.477599	0.487951	0.443735	0.478721
M5 Utilization after the disruptive event	0.270474	0.258937	0.292833	0.298173	0.291315
M3 Utilization after the disruptive event	0.750541	0.768408	0.763106	0.742482	0.772322
M7 Utilization after the disruptive event	0.637785	0.676072	0.666780	0.639510	0.704071
M9 Utilization after the disruptive event	0.705858	0.718115	0.731966	0.696283	0.730692
M12 Utilization after the disruptive event	0.595190	0.623308	0.616277	0.612796	0.629154
AGV Utilization prior to a disruptive event	0.323667	0.337279	0.348397	0.315506	0.379762
Fixture Utilization prior to a disruptive event	0.554017	0.569727	0.575753	0.550228	0.596259
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	281	282	283	284	285
Experiment Number	396	397	398	399	400
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.638942	0.629522	0.660312	0.632358	0.652056
M6 Utilization after the disruptive event	0.425554	0.416378	0.460578	0.446797	0.469520
M2 Utilization after the disruptive event	0.486618	0.465597	0.477129	0.469698	0.493101
M5 Utilization after the disruptive event	0.254809	0.268111	0.296879	0.276927	0.257051
M3 Utilization after the disruptive event	0.755954	0.734666	0.758713	0.760014	0.745633
M7 Utilization after the disruptive event	0.637861	0.634512	0.700941	0.664398	0.667848
M9 Utilization after the disruptive event	0.715837	0.703139	0.730332	0.712322	0.705365
M12 Utilization after the disruptive event	0.581146	0.563399	0.645026	0.599054	0.609239
AGV Utilization prior to a disruptive event	0.310076	0.278538	0.370416	0.322203	0.337509
Fixture Utilization prior to a disruptive event	0.546545	0.527744	0.591109	0.556884	0.566392
Start % of Part Type 1	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0	0	0	0	0
Start % of Part Type 5	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.25	0.25	0.25	0.25	0.25
Start % of Part Type 12	0	0	0	0	0
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	286	287	288	289	290
Experiment Number	161	162	163	164	165
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.549500	0.542800	0.536800	0.553500	0.553900
M6 Utilization after the disruptive event	0.309500	0.341200	0.290600	0.305700	0.326900
M2 Utilization after the disruptive event	0.696500	0.682400	0.691100	0.676300	0.707000
M5 Utilization after the disruptive event	0.579400	0.586100	0.592100	0.577900	0.580700
M3 Utilization after the disruptive event	0.635900	0.611100	0.660800	0.645500	0.654500
M7 Utilization after the disruptive event	0.419100	0.437900	0.402700	0.368200	0.397200
M9 Utilization after the disruptive event	0.748700	0.774600	0.789300	0.768700	0.768200
M12 Utilization after the disruptive event	0.650800	0.635200	0.630900	0.628500	0.656600
AGV Utilization prior to a disruptive event	0.335800	0.341100	0.343100	0.316500	0.336700
Fixture Utilization prior to a disruptive event	0.564600	0.568400	0.568000	0.552500	0.571200
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	291	292	293	294	295
Experiment Number	411	412	413	414	415
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.536324	0.555203	0.540118	0.545308	0.539721
M6 Utilization after the disruptive event	0.322706	0.317632	0.289858	0.294539	0.306239
M2 Utilization after the disruptive event	0.679824	0.704081	0.679939	0.688671	0.673188
M5 Utilization after the disruptive event	0.563372	0.597469	0.579957	0.598838	0.594921
M3 Utilization after the disruptive event	0.639782	0.634564	0.608403	0.632347	0.627728
M7 Utilization after the disruptive event	0.425156	0.406330	0.404840	0.420869	0.424706
M9 Utilization after the disruptive event	0.782989	0.778293	0.766103	0.774628	0.783450
M12 Utilization after the disruptive event	0.639907	0.671575	0.607775	0.641915	0.652646
AGV Utilization prior to a disruptive event	0.354297	0.377323	0.301190	0.335259	0.335316
Fixture Utilization prior to a disruptive event	0.571917	0.588549	0.541963	0.565582	0.566073
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

Vector Number	296	297	298	299	300
Experiment Number	416	417	418	419	420
Elements					
Mean Arrival Time	2.3	2.3	2.3	2.3	2.3
M1 Utilization after the disruptive event	0.556658	0.569354	0.553769	0.554748	0.538768
M6 Utilization after the disruptive event	0.284905	0.269616	0.305117	0.297102	0.323796
M2 Utilization after the disruptive event	0.680014	0.698698	0.697187	0.703981	0.686957
M5 Utilization after the disruptive event	0.593075	0.628040	0.588340	0.591791	0.593926
M3 Utilization after the disruptive event	0.629217	0.669350	0.662584	0.640310	0.630711
M7 Utilization after the disruptive event	0.379350	0.372936	0.402171	0.443906	0.414368
M9 Utilization after the disruptive event	0.774255	0.776052	0.786835	0.780409	0.777051
M12 Utilization after the disruptive event	0.638679	0.659063	0.645748	0.652537	0.657408
AGV Utilization prior to a disruptive event	0.323740	0.331018	0.359248	0.352537	0.351382
Fixture Utilization prior to a disruptive event	0.554957	0.567984	0.578536	0.578076	0.572967
Start % of Part Type 1	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 2	0	0	0	0	0
Start % of Part Type 3	0	0	0	0	0
Start % of Part Type 4	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 5	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 6	0	0	0	0	0
Start % of Part Type 7	0	0	0	0	0
Start % of Part Type 8	0	0	0	0	0
Start % of Part Type 9	0	0	0	0	0
Start % of Part Type 10	0	0	0	0	0
Start % of Part Type 11	0.2	0.2	0.2	0.2	0.2
Start % of Part Type 12	0.2	0.2	0.2	0.2	0.2
% change in Part Type 1	0	0	0	0	0
% change in Part Type 2	0	0	0	0	0
% change in Part Type 3	0	0	0	0	0
% change in Part Type 4	0	0	0	0	0
% change in Part Type 5	0	0	0	0	0
% change in Part Type 6	0	0	0	0	0
% change in Part Type 7	0	0	0	0	0
% change in Part Type 8	0	0	0	0	0
% change in Part Type 9	0	0	0	0	0
% change in Part Type 10	0	0	0	0	0
% change in Part Type 11	0	0	0	0	0
% change in Part Type 12	0	0	0	0	0
M1 Breakdown	0	0	0	0	0
M6 Breakdown	0	0	0	0	0
M2 Breakdown	0	0	0	0	0
M5 Breakdown	1	1	1	1	1
M3 Breakdown	0	0	0	0	0
M7 Breakdown	0	0	0	0	0
M9 Breakdown	0	0	0	0	0
M12 Breakdown	0	0	0	0	0
Single AGV Failure	0	0	0	0	0

C.4 Output Vectors for *Net_1_1*

Vector Number	1		2		3		4		5	
Experiment Number	21		22		23		24		25	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99965	1	0.99894	1	0.99914	1	0.99892	1	0.99897
1st digit	1	1.0029	1	1.0029	1	1.0029	1	1.0029	1	1.0029
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	6		7		8		9		10	
Experiment Number	281		282		283		284		285	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99978	1	0.99991	1	0.99874	1	0.99986	1	0.99901
1st digit	1	1.0029	1	1.0029	1	1.0029	1	1.0029	1	1.0029
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	11		12		13		14		15	
Experiment Number	286		287		288		289		290	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99978	1	1.0001	1	1.0002	1	1	1	0.99936
1st digit	1	1.0029	1	1.0029	1	1.0029	1	1.0029	1	1.0029
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	16		17		18		19		20	
Experiment Number	6		7		8		9		10	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0003	1	1.0003	1	1.0003	1	1.0002	1	1.0004
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	21		22		23		24		25	
Experiment Number	301		302		303		304		305	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0004	1	1.0002	1	1.0003	1	1.0004	1	1.0004
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	306		307		308		309		310	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0004	1	1.0004	1	1.0003	1	1.0004	1	1.0001
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	11		12		13		14		15	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0004	1	1.0003	1	1.0005	1	1.0003	1	1.0002
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	181		182		183		184		185	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0003	1	1.0004	1	1.0003	1	1.0003	1	1.0003
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	186		187		188		189		190	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0002	1	1.0003	1	1.0004	1	1.0001	1	1.0002
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	16		17		18		19		20	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0005	1	1.0004	1	1.0004	1	1.0003	1	1.0005
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	261		262		263		264		265	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0002	1	1.0003	1	1.0002	1	1.0005	1	1.0003
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	266		267		268		269		270	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0004	1	1.0004	1	1.0003	1	1.0004	1	1.0004
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	31		32		33		34		35	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99865	1	0.99931	1	1.0006	1	0.99951	1	1.0001
1st digit	1	1.0029	1	1.0029	1	1.0029	1	1.0029	1	1.0029
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	401		402		403		404		405	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99875	1	0.99929	1	0.99976	1	0.99949	1	1.0001
1st digit	1	1.0029	1	1.0029	1	1.0029	1	1.0029	1	1.0029
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	406		407		408		409		410	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99957	1	0.99997	1	0.9997	1	0.99968	1	0.9996
1st digit	1	1.0029	1	1.0029	1	1.0029	1	1.0029	1	1.0029
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	46		47		48		49		50	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99989	1	0.99979	1	0.99967	1	0.99987	1	0.99983
1st digit	1	1.0027	1	1.0027	1	1.0027	1	1.0027	1	1.0027
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	341		342		343		344		345	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99971	1	0.9998	1	0.99978	1	0.99967	1	0.99965
1st digit	1	1.0027	1	1.0027	1	1.0027	1	1.0027	1	1.0027
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	346		347		348		349		350	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99972	1	0.99978	1	0.99983	1	0.99979	1	0.99979
1st digit	1	1.0027	1	1.0027	1	1.0027	1	1.0027	1	1.0027
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	51		52		53		54		55	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0003	1	1.0003	1	1.0002	1	1.0004	1	1.001
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	381		382		383		384		385	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0002	1	1.0003	1	1.0002	1	1.0002	1	1.0004
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	386		387		388		389		390	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0003	1	1.0002	1	1.0003	1	1.0003	1	1.0004
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	56		57		58		59		60	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99996	1	1.0009	1	1.0051	1	0.9929	1	1.0026
1st digit	1	1.0029	1	1.0029	1	1.003	1	1.0028	1	1.0029
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	201		202		203		204		205	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0009	1	1.002	1	1.0015	1	1.0011	1	1.0009
1st digit	1	1.0029	1	1.0029	1	1.0029	1	1.0029	1	1.0029
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	206		207		208		209		210	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0015	1	1.0026	1	1.0018	1	1.0017	1	1.0016
1st digit	1	1.0029	1	1.0029	1	1.0029	1	1.0029	1	1.0029
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Experiment Number	66		67		68		69		70	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0003	1	1.0002	1	1.0004	1	1.0003	1	1.0004
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	126		127		128		129		130	
Experiment Number	221		222		223		224		225	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0003	1	1.0003	1	1.0002	1	1.0002	1	1.0003
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	131		132		133		134		135	
Experiment Number	226		227		228		229		230	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0003	1	1.0003	1	1.0002	1	1.0003	1	1.0003
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	136		137		138		139		140	
Experiment Number	106		107		108		109		110	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.98155	1	0.98076	1	0.98047	1	0.98154	1	0.98032
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	141		142		143		144		145	
Experiment Number	331		332		333		334		335	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.98055	1	0.97979	1	0.97976	1	0.9795	1	0.98047
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0025	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	146		147		148		149		150	
Experiment Number	336		337		338		339		340	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.98145	1	0.98036	1	0.98065	1	0.98018	1	0.98163
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	151		152		153		154		155	
Experiment Number	111		112		113		114		115	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99957	1	0.9997	1	0.9995	1	0.99971	1	0.99959
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	156		157		158		159		160	
Experiment Number	191		192		193		194		195	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99942	1	0.99959	1	0.99962	1	0.99947	1	0.99946
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	161		162		163		164		165	
Experiment Number	196		197		198		199		200	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99946	1	0.99962	1	0.99969	1	0.99957	1	0.99961
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	166		167		168		169		170	
Experiment Number	116		117		118		119		120	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0127	1	1.0127	1	1.0127	1	1.0127	1	1.0127
1st digit	1	1.0031	1	1.0031	1	1.0031	1	1.0031	1	1.0031
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	171		172		173		174		175	
Experiment Number	211		212		213		214		215	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0126	1	1.0127	1	1.0126	1	1.0127	1	1.0126
1st digit	1	1.0031	1	1.0031	1	1.0031	1	1.0031	1	1.0031
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	176		177		178		179		180	
Experiment Number	216		217		218		219		220	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0127	1	1.0127	1	1.0127	1	1.0123	1	1.0127
1st digit	1	1.0031	1	1.0031	1	1.0031	1	1.0031	1	1.0031
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	181		182		183		184		185	
Experiment Number	121		122		123		124		125	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99948	1	0.99956	1	0.99951	1	0.99939	1	0.99956
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	186		187		188		189		190	
Experiment Number	231		232		233		234		235	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99954	1	0.99965	1	0.99936	1	0.99952	1	0.99952
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	191		192		193		194		195	
Experiment Number	236		237		238		239		240	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99951	1	0.99954	1	0.99965	1	0.99941	1	0.99963
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	196		197		198		199		200	
Experiment Number	126		127		128		129		130	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.9806	1	0.98092	1	0.98056	1	0.98034	1	0.9807
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	201		202		203		204		205	
Experiment Number	251		252		253		254		255	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.97919	1	0.978	1	0.98111	1	0.98056	1	0.98036
1st digit	1	1.0025	1	1.0025	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)*2) + Round(0th digit)*2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	206		207		208		209		210	
Experiment Number	256		257		258		259		260	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.98152	1	0.98144	1	0.98233	1	0.98075	1	0.98143
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)*2) + Round(0th digit)*2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	211		212		213		214		215	
Experiment Number	131		132		133		134		135	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99949	1	0.99954	1	0.99954	1	0.99959	1	0.99959
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)*2) + Round(0th digit)*2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	216		217		218		219		220	
Experiment Number	271		272		273		274		275	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99976	1	0.99955	1	0.99964	1	0.99969	1	0.9996
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)*2) + Round(0th digit)*2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	221		222		223		224		225	
Experiment Number	276		277		278		279		280	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99949	1	0.99954	1	0.99963	1	0.99959	1	0.99971
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)*2) + Round(0th digit)*2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	226		227		228		229		230	
Experiment Number	136		137		138		139		140	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0126	1	1.0127	1	1.0127	1	1.0127	1	1.0126
1st digit	1	1.0031	1	1.0031	1	1.0031	1	1.0031	1	1.0031
Decimal Equivalence 2*Round((1st digit)*2) + Round(0th digit)*2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	231		232		233		234		235	
Experiment Number	291		292		293		294		295	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0126	1	1.0127	1	1.0126	1	1.0126	1	1.0126
1st digit	1	1.0031	1	1.0031	1	1.0031	1	1.0031	1	1.0031
Decimal Equivalence 2*Round((1st digit)*2) + Round(0th digit)*2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	236		237		238		239		240	
Experiment Number	296		297		298		299		300	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0126	1	1.0126	1	1.0127	1	1.0126	1	1.0126
1st digit	1	1.0031	1	1.0031	1	1.0031	1	1.0031	1	1.0031
Decimal Equivalence 2*Round((1st digit)*2) + Round(0th digit)*2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	241		242		243		244		245	
Experiment Number	141		142		143		144		145	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99952	1	0.99952	1	0.99964	1	0.99953	1	0.99957
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	246		247		248		249		250	
Experiment Number	311		312		313		314		315	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99954	1	0.99955	1	0.99948	1	0.99967	1	0.99949
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	251		252		253		254		255	
Experiment Number	316		317		318		319		320	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99954	1	0.99961	1	0.99964	1	0.99972	1	0.99953
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	256		257		258		259		260	
Experiment Number	146		147		148		149		150	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0002	1	1.0001	1	1.0001	1	1.0001	1	1.0001
1st digit	1	1.0027	1	1.0027	1	1.0027	1	1.0027	1	1.0027
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	261		262		263		264		265	
Experiment Number	351		352		353		354		355	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0001	1	1.0001	1	1.0001	1	1.0001	1	0.99999
1st digit	1	1.0027	1	1.0027	1	1.0027	1	1.0027	1	1.0027
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	266		267		268		269		270	
Experiment Number	356		357		358		359		360	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0001	1	0.99996	1	1	1	1.0003	1	1.0001
1st digit	1	1.0027	1	1.0027	1	1.0027	1	1.0027	1	1.0027
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	271		272		273		274		275	
Experiment Number	156		157		158		159		160	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99948	1	0.9995	1	0.99954	1	0.99942	1	0.99945
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	276		277		278		279		280	
Experiment Number	391		392		393		394		395	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99953	1	0.99941	1	0.99957	1	0.99948	1	0.99937
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	281		282		283		284		285	
Experiment Number	396		397		398		399		400	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.9997	1	0.99973	1	0.99937	1	0.99958	1	0.99953
1st digit	1	1.0026	1	1.0026	1	1.0026	1	1.0026	1	1.0026
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	286		287		288		289		290	
Experiment Number	161		162		163		164		165	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0126	1	1.0126	1	1.0126	1	1.0126	1	1.0126
1st digit	1	1.0031	1	1.0031	1	1.0031	1	1.0031	1	1.0031
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	291		292		293		294		295	
Experiment Number	411		412		413		414		415	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0126	1	1.0126	1	1.0127	1	1.0127	1	1.0127
1st digit	1	1.0031	1	1.0031	1	1.0031	1	1.0031	1	1.0031
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	296		297		298		299		300	
Experiment Number	416		417		418		419		420	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0127	1	1.0127	1	1.0126	1	1.0126	1	1.0126
1st digit	1	1.0031	1	1.0031	1	1.0031	1	1.0031	1	1.0031
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00

Vector Number	301		302		303		304		305	
Experiment Number	26		27		28		29		30	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99771	1	0.99771	1	0.99771	1	0.99771	1	0.99771
1st digit	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	306		307		308		309		310	
Experiment Number	361		362		363		364		365	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99771	1	0.99771	1	0.99771	1	0.99771	1	0.99771
1st digit	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	311		312		313		314		315	
Experiment Number	366		367		368		369		370	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99771	1	0.99771	1	0.99771	1	0.99771	1	0.99771
1st digit	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	316		317		318		319		320	
Experiment Number	151		152		153		154		155	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99771	1	0.99771	1	0.99771	1	0.99771	1	0.99771
1st digit	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	321		322		323		324		325	
Experiment Number	371		372		373		374		375	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99771	1	0.99771	1	0.99771	1	0.99771	1	0.99771
1st digit	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	326		327		328		329		330	
Experiment Number	376		377		378		379		380	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99771	1	0.99771	1	0.99771	1	0.99771	1	0.99771
1st digit	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728	0	-0.0067728
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	331		332		333		334		335	
Experiment Number	76		77		78		79		80	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0005	1	1.0005	1	1.0005	1	1.0005	1	1.0005
1st digit	0	-0.00683	0	-0.0068309	0	-0.0068309	0	-0.0068306	0	-0.0068308
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	336		337		338		339		340	
Experiment Number	421		422		423		424		425	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0005	1	1.0005	1	1.0006	1	1.0005	1	1.0005
1st digit	0	-0.0068306	0	-0.0068308	0	-0.006831	0	-0.0068308	0	-0.0068308
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	341		342		343		344		345	
Experiment Number	426		427		428		429		430	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1.0005	1	1.0005	1	1.0005	1	1.0005	1	1.0005
1st digit	0	-0.006831	0	-0.0068309	0	-0.0068304	0	-0.0068305	0	-0.0068308
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	346		347		348		349		350	
Experiment Number	166		167		168		169		170	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99918	1	0.99919	1	0.99916	1	0.99919	1	0.99918
1st digit	0	-0.0068023	0	-0.0068025	0	-0.0068018	0	-0.0068024	0	-0.0068022
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	351		352		353		354		355	
Experiment Number	431		432		433		434		435	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99917	1	0.99922	1	0.99917	1	0.99919	1	0.99918
1st digit	0	-0.006802	0	-0.006803	0	-0.006802	0	-0.0068024	0	-0.0068023
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	356		357		358		359		360	
Experiment Number	436		437		438		439		440	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99918	1	0.9992	1	0.99917	1	0.99919	1	0.9992
1st digit	0	-0.0068021	0	-0.0068026	0	-0.006802	0	-0.0068025	0	-0.0068027
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	361		362		363		364		365	
Experiment Number	36		37		38		39		40	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1	1	1	1	1	1	1	1	1
1st digit	0	-0.0068213	0	-0.0068213	0	-0.0068213	0	-0.0068213	0	-0.0068213
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	366		367		368		369		370	
Experiment Number	441		442		443		444		445	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1	1	1	1	1	1	1	1	1
1st digit	0	-0.0068213	0	-0.0068213	0	-0.0068213	0	-0.0068213	0	-0.0068213
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	371		372		373		374		375	
Experiment Number	446		447		448		449		450	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1	1	1	1	1	1	1	1	1
1st digit	0	-0.0068213	0	-0.0068213	0	-0.0068213	0	-0.0068213	0	-0.0068213
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	376		377		378		379		380	
Experiment Number	171		172		173		174		175	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1	1	1	1	1	1	1	1	1
1st digit	0	-0.0068213	0	-0.0068212	0	-0.0068212	0	-0.0068212	0	-0.0068213
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	381		382		383		384		385	
Experiment Number	451		452		453		454		455	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1	1	1	1	1	1	1	1	1
1st digit	0	-0.0068213	0	-0.0068212	0	-0.0068212	0	-0.0068212	0	-0.0068212
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	386		387		388		389		390	
Experiment Number	456		457		458		459		460	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	1	1	1	1	1	1	1	1	1
1st digit	0	-0.0068213	0	-0.0068213	0	-0.0068213	0	-0.0068212	0	-0.0068213
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	391		392		393		394		395	
Experiment Number	81		82		83		84		85	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99993	1	0.99993	1	0.99993	1	0.99993	1	0.99993
1st digit	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	396		397		398		399		400	
Experiment Number	461		462		463		464		465	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99993	1	0.99993	1	0.99993	1	0.99993	1	0.99993
1st digit	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	401		402		403		404		405	
Experiment Number	466		467		468		469		470	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99993	1	0.99993	1	0.99993	1	0.99993	1	0.99993
1st digit	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	406		407		408		409		410	
Experiment Number	86		87		88		89		90	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99993	1	0.99993	1	0.99993	1	0.99993	1	0.99993
1st digit	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	411		412		413		414		415	
Experiment Number	471		472		473		474		475	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99993	1	0.99993	1	0.99993	1	0.99993	1	0.99993
1st digit	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	416		417		418		419		420	
Experiment Number	476		477		478		479		480	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	1	0.99993	1	0.99993	1	0.99993	1	0.99993	1	0.99993
1st digit	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818	0	-0.006818
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Vector Number	421		422		423		424		425	
Experiment Number	1		2		3		4		5	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	-0.00030229	0	-0.0015612	0	-0.0010977	0	-0.0012777	0	-0.0013137
1st digit	0	0.014189	0	0.014216	0	0.014206	0	0.01421	0	0.01421
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	426		427		428		429		430	
Experiment Number	501		502		503		504		505	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	-0.0010874	0	-0.00064061	0	-0.0014201	0	-0.0010013	0	-0.0014993
1st digit	0	0.014206	0	0.014196	0	0.014213	0	0.014204	0	0.014214
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	431		432		433		434		435	
Experiment Number	506		507		508		509		510	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	-0.00079347	0	-0.0009247	0	-0.00091272	0	-0.00072683	0	-0.00085094
1st digit	0	0.014199	0	0.014202	0	0.014202	0	0.014198	0	0.014201
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	436		437		438		439		440	
Experiment Number	91		92		93		94		95	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.00253	0	0.0025204	0	0.0020101	0	0.0019118	0	0.0017827
1st digit	0	0.01413	0	0.01413	0	0.014141	0	0.014143	0	0.014145
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	441		442		443		444		445	
Experiment Number	511		512		513		514		515	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.0012353	0	0.0021108	0	0.0020285	0	0.0021102	0	0.0020061
1st digit	0	0.014157	0	0.014138	0	0.01414	0	0.014138	0	0.014141
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	446		447		448		449		450	
Experiment Number	516		517		518		519		520	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.0020146	0	0.001329	0	0.0026295	0	0.0020766	0	0.0020853
1st digit	0	0.014141	0	0.014155	0	0.014128	0	0.014139	0	0.014139
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	451		452		453		454		455	
Experiment Number	96		97		98		99		100	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.043885	0	0.045231	0	0.044764	0	0.044287	0	0.044089
1st digit	0	0.013259	0	0.013231	0	0.013241	0	0.013251	0	0.013255
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	456		457		458		459		460	
Experiment Number	521		522		523		524		525	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.044545	0	0.04535	0	0.045667	0	0.043303	0	0.04421
1st digit	0	0.013245	0	0.013228	0	0.013222	0	0.013271	0	0.013252
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	461		462		463		464		465	
Experiment Number	526		527		528		529		530	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.044478	0	0.044564	0	0.043499	0	0.044952	0	0.043406
1st digit	0	0.013247	0	0.013245	0	0.013267	0	0.013237	0	0.013269
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	466		467		468		469		470	
Experiment Number	101		102		103		104		105	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	-0.044504	0	-0.044996	0	-0.045193	0	-0.046241	0	-0.046112
1st digit	0	0.015115	0	0.015126	0	0.01513	0	0.015152	0	0.015149
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	471		472		473		474		475	
Experiment Number	531		532		533		534		535	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	-0.045557	0	-0.046331	0	-0.04487	0	-0.045592	0	-0.044245
1st digit	0	0.015137	0	0.015154	0	0.015123	0	0.015138	0	0.01511
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	476		477		478		479		480	
Experiment Number	536		537		538		539		540	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	-0.045523	0	-0.044721	0	-0.044488	0	-0.04465	0	-0.046168
1st digit	0	0.015137	0	0.01512	0	0.015115	0	0.015118	0	0.01515
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Vector Number	481		482		483		484		485	
Experiment Number	41		42		43		44		45	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.00059814	0	-0.0012186	0	-0.0011497	0	0.00032623	0	-0.00015732
1st digit	1	0.98506	1	0.98502	1	0.98503	1	0.98505	1	0.98504
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Vector Number	486		487		488		489		490	
Experiment Number	481		482		483		484		485	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	-0.0020227	0	-0.00037377	0	0.00097319	0	-0.00041333	0	-0.00084242
1st digit	1	0.98501	1	0.98504	1	0.98506	1	0.98504	1	0.98503
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Vector Number	491		492		493		494		495	
Experiment Number	486		487		488		489		490	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.0002265	0	-0.00249	0	-0.00066484	0	-0.0059834	0	-0.00048606
1st digit	1	0.98505	1	0.985	1	0.98503	1	0.98494	1	0.98504
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Vector Number	496		497		498		499		500	
Experiment Number	176		177		178		179		180	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.0066616	0	0.0015988	0	0.001548	0	-0.00092446	0	0.0029879
1st digit	1	0.98514	1	0.98506	1	0.98506	1	0.98501	1	0.98508
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Vector Number	501		502		503		504		505	
Experiment Number	491		492		493		494		495	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	-3.44E-06	0	0.00035051	0	-0.0001419	0	-0.0039211	0	0.00030296
1st digit	1	0.98503	1	0.98504	1	0.98503	1	0.98496	1	0.98504
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Vector Number	506		507		508		509		510	
Experiment Number	496		497		498		499		500	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	-9.51E-05	0	-0.00037634	0	-0.0028796	0	-0.0006151	0	-0.0015933
1st digit	1	0.98503	1	0.98502	1	0.98498	1	0.98502	1	0.985
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Vector Number	511		512		513		514		515	
Experiment Number	61		62		63		64		65	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	-0.0064953	0	0.01332	0	0.0010491	0	-0.018328	0	-0.0023562
1st digit	1	0.98655	1	0.98687	1	0.98667	1	0.98636	1	0.98662
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Vector Number	516		517		518		519		520	
Experiment Number	241		242		243		244		245	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.016828	0	-0.0024834	0	0.004123	0	0.0092615	0	-0.0121
1st digit	1	0.98693	1	0.98661	1	0.98672	1	0.9868	1	0.98646
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Vector Number	521		522		523		524		525	
Experiment Number	246		247		248		249		250	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.0038251	0	0.024226	0	0.0051997	0	0.028283	0	-0.0014632
1st digit	1	0.98672	1	0.98705	1	0.98674	1	0.98711	1	0.98663
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Vector Number	526		527		528		529		530	
Experiment Number	71		72		73		74		75	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	-0.0044027	0	0.0067264	0	-0.053414	0	-0.00056196	0	-0.010832
1st digit	1	0.98658	1	0.98676	1	0.98579	1	0.98665	1	0.98648
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Vector Number	531		532		533		534		535	
Experiment Number	321		322		323		324		325	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.0042204	0	0.030793	0	-0.0037661	0	-0.012858	0	0.0052427
1st digit	1	0.98672	1	0.98715	1	0.98659	1	0.98645	1	0.98674
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

Vector Number	536		537		538		539		540	
Experiment Number	326		327		328		329		330	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
0th digit	0	0.040057	0	-0.00067636	0	0.0015791	0	-0.0049032	0	-0.028867
1st digit	1	0.9873	1	0.98664	1	0.98668	1	0.98658	1	0.98619
Decimal Equivalence 2*Round((1st digit)^2) + Round(0th digit)^2)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

C.5 Output Vectors for *Net_2_1_1*

Count	1		2		3		4		5	
Exp. NO	26		27		28		29		30	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.55955734	0.55898	0.55955734	0.55904	0.55955734	0.55899	0.55955734	0.55898	0.55955734	0.55901
M6 Utilization after the disruptive event	0.311439216	0.31096	0.311439216	0.31093	0.311439216	0.31094	0.311439216	0.31094	0.311439216	0.31094
M2 Utilization after the disruptive event	0.108812053	0.10706	0.108812053	0.10748	0.108812053	0.10721	0.108812053	0.10724	0.108812053	0.10731
M5 Utilization after the disruptive event	0.835583828	0.83726	0.835583828	0.83791	0.835583828	0.83749	0.835583828	0.83739	0.835583828	0.83766
M3 Utilization after the disruptive event	0.682427409	0.68457	0.682427409	0.68462	0.682427409	0.68446	0.682427409	0.68445	0.682427409	0.68452
M7 Utilization after the disruptive event	0.691421008	0.69037	0.691421008	0.6902	0.691421008	0.69046	0.691421008	0.69041	0.691421008	0.69038
M9 Utilization after the disruptive event	0.760225893	0.75985	0.760225893	0.76013	0.760225893	0.75995	0.760225893	0.75992	0.760225893	0.76002
M12 Utilization after the disruptive event	0.633609831	0.63472	0.633609831	0.63515	0.633609831	0.63487	0.633609831	0.63482	0.633609831	0.63498
AGV Utilization after the disruptive event	0.849047008	0.84894	0.849047008	0.84891	0.849047008	0.84894	0.849047008	0.84895	0.849047008	0.84894
Fixture Utilization after the disruptive event	0.920178086	0.92024	0.920178086	0.92023	0.920178086	0.92024	0.920178086	0.92024	0.920178086	0.92024

Count	6		7		8		9		10	
Exp. NO	361		362		363		364		365	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.55955734	0.55897	0.55955734	0.55897	0.55955734	0.55905	0.55955734	0.55897	0.55955734	0.55895
M6 Utilization after the disruptive event	0.311439216	0.31092	0.311439216	0.31095	0.311439216	0.31083	0.311439216	0.31098	0.311439216	0.3109
M2 Utilization after the disruptive event	0.108812053	0.10731	0.108812053	0.10709	0.108812053	0.10823	0.108812053	0.10691	0.108812053	0.10744
M5 Utilization after the disruptive event	0.835583828	0.83737	0.835583828	0.83718	0.835583828	0.83837	0.835583828	0.83715	0.835583828	0.83721
M3 Utilization after the disruptive event	0.682427409	0.68422	0.682427409	0.68444	0.682427409	0.68436	0.682427409	0.68448	0.682427409	0.68431
M7 Utilization after the disruptive event	0.691421008	0.69062	0.691421008	0.69047	0.691421008	0.69007	0.691421008	0.69057	0.691421008	0.69036
M9 Utilization after the disruptive event	0.760225893	0.75992	0.760225893	0.75983	0.760225893	0.76039	0.760225893	0.75979	0.760225893	0.75989
M12 Utilization after the disruptive event	0.633609831	0.63481	0.633609831	0.63468	0.633609831	0.63552	0.633609831	0.63463	0.633609831	0.63475
AGV Utilization after the disruptive event	0.849047008	0.84897	0.849047008	0.84896	0.849047008	0.84891	0.849047008	0.84896	0.849047008	0.84897
Fixture Utilization after the disruptive event	0.920178086	0.92026	0.920178086	0.92025	0.920178086	0.92023	0.920178086	0.92025	0.920178086	0.92025

Count	11		12		13		14		15	
Exp. NO	366		367		368		369		370	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.55955734	0.55901	0.55955734	0.55894	0.55955734	0.55898	0.55955734	0.55898	0.55955734	0.55901
M6 Utilization after the disruptive event	0.311439216	0.31092	0.311439216	0.31096	0.311439216	0.31097	0.311439216	0.31095	0.311439216	0.31094
M2 Utilization after the disruptive event	0.108812053	0.10743	0.108812053	0.10698	0.108812053	0.10704	0.108812053	0.10709	0.108812053	0.10728
M5 Utilization after the disruptive event	0.835583828	0.83768	0.835583828	0.83688	0.835583828	0.83734	0.835583828	0.83728	0.835583828	0.83761
M3 Utilization after the disruptive event	0.682427409	0.68451	0.682427409	0.68446	0.682427409	0.68449	0.682427409	0.68447	0.682427409	0.6845
M7 Utilization after the disruptive event	0.691421008	0.69029	0.691421008	0.69044	0.691421008	0.69053	0.691421008	0.69047	0.691421008	0.69041
M9 Utilization after the disruptive event	0.760225893	0.76004	0.760225893	0.75972	0.760225893	0.75987	0.760225893	0.75986	0.760225893	0.76
M12 Utilization after the disruptive event	0.633609831	0.63501	0.633609831	0.6345	0.633609831	0.63476	0.633609831	0.63473	0.633609831	0.63495
AGV Utilization after the disruptive event	0.849047008	0.84893	0.849047008	0.84897	0.849047008	0.84896	0.849047008	0.84895	0.849047008	0.84894
Fixture Utilization after the disruptive event	0.920178086	0.92023	0.920178086	0.92025	0.920178086	0.92025	0.920178086	0.92024	0.920178086	0.92024

Count	16		17		18		19		20	
Exp. NO	151		152		153		154		155	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.556183095	0.55685	0.556183095	0.55685	0.556183095	0.55687	0.556183095	0.55688	0.556183095	0.55686
M6 Utilization after the disruptive event	0.299049472	0.29958	0.299049472	0.29959	0.299049472	0.2996	0.299049472	0.29957	0.299049472	0.2996
M2 Utilization after the disruptive event	0.099206206	0.10125	0.099206206	0.10118	0.099206206	0.10118	0.099206206	0.10139	0.099206206	0.10117
M5 Utilization after the disruptive event	0.831467948	0.82915	0.831467948	0.82913	0.831467948	0.82923	0.831467948	0.82943	0.831467948	0.82916
M3 Utilization after the disruptive event	0.665711648	0.66325	0.665711648	0.66329	0.665711648	0.66337	0.665711648	0.66323	0.665711648	0.66333
M7 Utilization after the disruptive event	0.681291027	0.68234	0.681291027	0.68233	0.681291027	0.6823	0.681291027	0.68234	0.681291027	0.68233
M9 Utilization after the disruptive event	0.754747463	0.75509	0.754747463	0.75508	0.754747463	0.75511	0.754747463	0.7552	0.754747463	0.75509
M12 Utilization after the disruptive event	0.621647636	0.62013	0.621647636	0.62011	0.621647636	0.62017	0.621647636	0.62031	0.621647636	0.62013
AGV Utilization after the disruptive event	0.827852254	0.82798	0.827852254	0.82798	0.827852254	0.82798	0.827852254	0.82797	0.827852254	0.82798
Fixture Utilization after the disruptive event	0.905907306	0.90585	0.905907306	0.90584	0.905907306	0.90584	0.905907306	0.90584	0.905907306	0.90585

Count	21		22		23		24		25	
Exp. NO	371		372		373		374		375	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.556183095	0.55685	0.556183095	0.55687	0.556183095	0.55685	0.556183095	0.55686	0.556183095	0.55685
M6 Utilization after the disruptive event	0.299049472	0.29957	0.299049472	0.2996	0.299049472	0.29958	0.299049472	0.29963	0.299049472	0.2996
M2 Utilization after the disruptive event	0.099206206	0.10128	0.099206206	0.10114	0.099206206	0.10123	0.099206206	0.10103	0.099206206	0.10108
M5 Utilization after the disruptive event	0.831467948	0.82911	0.831467948	0.82926	0.831467948	0.82914	0.831467948	0.82912	0.831467948	0.82907
M3 Utilization after the disruptive event	0.665711648	0.66328	0.665711648	0.66332	0.665711648	0.66321	0.665711648	0.66343	0.665711648	0.66332
M7 Utilization after the disruptive event	0.681291027	0.68226	0.681291027	0.68239	0.681291027	0.68238	0.681291027	0.68233	0.681291027	0.68236
M9 Utilization after the disruptive event	0.754747463	0.75509	0.754747463	0.75511	0.754747463	0.75509	0.754747463	0.75506	0.754747463	0.75505
M12 Utilization after the disruptive event	0.621647636	0.62011	0.621647636	0.62017	0.621647636	0.62012	0.621647636	0.62009	0.621647636	0.62006
AGV Utilization after the disruptive event	0.827852254	0.82798	0.827852254	0.82797	0.827852254	0.82798	0.827852254	0.82799	0.827852254	0.82797
Fixture Utilization after the disruptive event	0.905907306	0.90584	0.905907306	0.90584	0.905907306	0.90584	0.905907306	0.90585	0.905907306	0.90584

Count	26		27		28		29		30	
Exp. NO	376		377		378		379		380	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.556183095	0.55685	0.556183095	0.55687	0.556183095	0.55685	0.556183095	0.55685	0.556183095	0.55687
M6 Utilization after the disruptive event	0.299049472	0.29961	0.299049472	0.29959	0.299049472	0.29958	0.299049472	0.2996	0.299049472	0.2996
M2 Utilization after the disruptive event	0.099206206	0.1011	0.099206206	0.10121	0.099206206	0.10126	0.099206206	0.10113	0.099206206	0.10117
M5 Utilization after the disruptive event	0.831467948	0.82903	0.831467948	0.82929	0.831467948	0.82915	0.831467948	0.8291	0.831467948	0.82921
M3 Utilization after the disruptive event	0.665711648	0.66337	0.665711648	0.66325	0.665711648	0.66328	0.665711648	0.66332	0.665711648	0.66334
M7 Utilization after the disruptive event	0.681291027	0.6823	0.681291027	0.6824	0.681291027	0.68229	0.681291027	0.68233	0.681291027	0.68233
M9 Utilization after the disruptive event	0.754747463	0.75504	0.754747463	0.75513	0.754747463	0.7551	0.754747463	0.75506	0.754747463	0.7551
M12 Utilization after the disruptive event	0.621647636	0.62005	0.621647636	0.6202	0.621647636	0.62013	0.621647636	0.62008	0.621647636	0.62016
AGV Utilization after the disruptive event	0.827852254	0.82799	0.827852254	0.82797	0.827852254	0.82798	0.827852254	0.82797	0.827852254	0.82798
Fixture Utilization after the disruptive event	0.905907306	0.90585	0.905907306	0.90584	0.905907306	0.90584	0.905907306	0.90584	0.905907306	0.90584

Count	31		32		33		34		35	
Exp. NO	76		77		78		79		80	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.452328936	0.45011	0.452328936	0.4502	0.452328936	0.45016	0.452328936	0.45018	0.452328936	0.45014
M6 Utilization after the disruptive event	0.224876288	0.22609	0.224876288	0.2262	0.224876288	0.22616	0.224876288	0.22619	0.224876288	0.22614
M2 Utilization after the disruptive event	0.360598807	0.3627	0.360598807	0.36205	0.360598807	0.36236	0.360598807	0.36212	0.360598807	0.36244
M5 Utilization after the disruptive event	0.113371845	0.11773	0.113371845	0.11825	0.113371845	0.11795	0.113371845	0.11813	0.113371845	0.11787
M3 Utilization after the disruptive event	0.11224654	0.11171	0.11224654	0.11203	0.11224654	0.11197	0.11224654	0.11205	0.11224654	0.11191
M7 Utilization after the disruptive event	0.877756316	0.87708	0.877756316	0.8774	0.877756316	0.87714	0.877756316	0.87729	0.877756316	0.87711
M9 Utilization after the disruptive event	0.551349698	0.55011	0.551349698	0.55019	0.551349698	0.55014	0.551349698	0.55016	0.551349698	0.55013
M12 Utilization after the disruptive event	0.254703872	0.2586	0.254703872	0.25879	0.254703872	0.25867	0.254703872	0.25874	0.254703872	0.25864
AGV Utilization after the disruptive event	0.90757421	0.90805	0.90757421	0.908	0.90757421	0.90804	0.90757421	0.90801	0.90757421	0.90804
Fixture Utilization after the disruptive event	0.943365168	0.9431	0.943365168	0.94309	0.943365168	0.9431	0.943365168	0.94309	0.943365168	0.9431

Count	36		37		38		39		40	
Exp. NO	421		422		423		424		425	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.452328936	0.45018	0.452328936	0.45016	0.452328936	0.45019	0.452328936	0.45015	0.452328936	0.45019
M6 Utilization after the disruptive event	0.224876288	0.22617	0.224876288	0.22617	0.224876288	0.2262	0.224876288	0.22616	0.224876288	0.22619
M2 Utilization after the disruptive event	0.360598807	0.36217	0.360598807	0.36228	0.360598807	0.36212	0.360598807	0.36237	0.360598807	0.36207
M5 Utilization after the disruptive event	0.113371845	0.11815	0.113371845	0.11795	0.113371845	0.1182	0.113371845	0.11789	0.113371845	0.11823
M3 Utilization after the disruptive event	0.11224654	0.11191	0.11224654	0.11205	0.11224654	0.11211	0.11224654	0.11201	0.11224654	0.112
M7 Utilization after the disruptive event	0.877756316	0.87739	0.877756316	0.87713	0.877756316	0.87726	0.877756316	0.87708	0.877756316	0.8774
M9 Utilization after the disruptive event	0.551349698	0.55017	0.551349698	0.55013	0.551349698	0.55019	0.551349698	0.55013	0.551349698	0.55018
M12 Utilization after the disruptive event	0.254703872	0.25874	0.254703872	0.25867	0.254703872	0.25878	0.254703872	0.25865	0.254703872	0.25877
AGV Utilization after the disruptive event	0.90757421	0.90801	0.90757421	0.90804	0.90757421	0.90802	0.90757421	0.90804	0.90757421	0.908
Fixture Utilization after the disruptive event	0.943365168	0.94309	0.943365168	0.9431	0.943365168	0.94309	0.943365168	0.9431	0.943365168	0.94308

Count	41		42		43		44		45	
Exp. NO	426		427		428		429		430	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.452328936	0.45019	0.452328936	0.45017	0.452328936	0.45014	0.452328936	0.45016	0.452328936	0.45016
M6 Utilization after the disruptive event	0.224876288	0.2262	0.224876288	0.22616	0.224876288	0.22613	0.224876288	0.22615	0.224876288	0.22617
M2 Utilization after the disruptive event	0.360598807	0.36204	0.360598807	0.36224	0.360598807	0.36248	0.360598807	0.36234	0.360598807	0.36229
M5 Utilization after the disruptive event	0.113371845	0.11814	0.113371845	0.11807	0.113371845	0.11789	0.113371845	0.11801	0.113371845	0.11794
M3 Utilization after the disruptive event	0.11224654	0.11208	0.11224654	0.11191	0.11224654	0.11188	0.11224654	0.11194	0.11224654	0.11202
M7 Utilization after the disruptive event	0.877756316	0.87732	0.877756316	0.87731	0.877756316	0.87712	0.877756316	0.8772	0.877756316	0.87714
M9 Utilization after the disruptive event	0.551349698	0.55015	0.551349698	0.55016	0.551349698	0.55014	0.551349698	0.55015	0.551349698	0.55013
M12 Utilization after the disruptive event	0.254703872	0.25873	0.254703872	0.25871	0.254703872	0.25866	0.254703872	0.2587	0.254703872	0.25867
AGV Utilization after the disruptive event	0.90757421	0.90801	0.90757421	0.90802	0.90757421	0.90803	0.90757421	0.90803	0.90757421	0.90803
Fixture Utilization after the disruptive event	0.943365168	0.94309	0.943365168	0.94309	0.943365168	0.9431	0.943365168	0.9431	0.943365168	0.9431

Count	46		47		48		49		50	
Exp. NO	166		167		168		169		170	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.446721508	0.44885	0.446721508	0.44887	0.446721508	0.44887	0.446721508	0.44888	0.446721508	0.44888
M6 Utilization after the disruptive event	0.222856091	0.22149	0.222856091	0.22151	0.222856091	0.22147	0.222856091	0.22155	0.222856091	0.22153
M2 Utilization after the disruptive event	0.35399585	0.35214	0.35399585	0.35205	0.35399585	0.35245	0.35399585	0.35167	0.35399585	0.35183
M5 Utilization after the disruptive event	0.110789559	0.10624	0.110789559	0.10646	0.110789559	0.10646	0.110789559	0.10647	0.110789559	0.10651
M3 Utilization after the disruptive event	0.107360805	0.10806	0.107360805	0.10799	0.107360805	0.10813	0.107360805	0.10795	0.107360805	0.10801
M7 Utilization after the disruptive event	0.868383053	0.86856	0.868383053	0.86878	0.868383053	0.86834	0.868383053	0.86909	0.868383053	0.86892
M9 Utilization after the disruptive event	0.543197147	0.5444	0.543197147	0.54445	0.543197147	0.54452	0.543197147	0.5444	0.543197147	0.54443
M12 Utilization after the disruptive event	0.250053411	0.24617	0.250053411	0.24627	0.250053411	0.24634	0.250053411	0.2462	0.250053411	0.24625
AGV Utilization after the disruptive event	0.897805272	0.89734	0.897805272	0.89733	0.897805272	0.89733	0.897805272	0.89731	0.897805272	0.89731
Fixture Utilization after the disruptive event	0.935392661	0.93567	0.935392661	0.93567	0.935392661	0.93567	0.935392661	0.93566	0.935392661	0.93566

Count	51		52		53		54		55	
Exp. NO	431		432		433		434		435	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.446721508	0.44884	0.446721508	0.44892	0.446721508	0.44887	0.446721508	0.44885	0.446721508	0.44885
M6 Utilization after the disruptive event	0.222856091	0.22151	0.222856091	0.22157	0.222856091	0.22148	0.222856091	0.22148	0.222856091	0.22148
M2 Utilization after the disruptive event	0.35399585	0.35201	0.35399585	0.35155	0.35399585	0.35228	0.35399585	0.35222	0.35399585	0.35224
M5 Utilization after the disruptive event	0.110789559	0.10613	0.110789559	0.10689	0.110789559	0.10646	0.110789559	0.10633	0.110789559	0.10628
M3 Utilization after the disruptive event	0.107360805	0.10806	0.107360805	0.10794	0.107360805	0.10806	0.107360805	0.10795	0.107360805	0.10796
M7 Utilization after the disruptive event	0.868383053	0.86863	0.868383053	0.86933	0.868383053	0.86854	0.868383053	0.86867	0.868383053	0.86862
M9 Utilization after the disruptive event	0.543197147	0.54434	0.543197147	0.54451	0.543197147	0.54449	0.543197147	0.54444	0.543197147	0.54443
M12 Utilization after the disruptive event	0.250053411	0.24608	0.250053411	0.24641	0.250053411	0.24631	0.250053411	0.24623	0.250053411	0.24621
AGV Utilization after the disruptive event	0.897805272	0.89734	0.897805272	0.89728	0.897805272	0.89733	0.897805272	0.89735	0.897805272	0.89735
Fixture Utilization after the disruptive event	0.935392661	0.93567	0.935392661	0.93565	0.935392661	0.93567	0.935392661	0.93568	0.935392661	0.93568

Count	56		57		58		59		60	
Exp. NO	436		437		438		439		440	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.446721508	0.44885	0.446721508	0.44885	0.446721508	0.44885	0.446721508	0.44889	0.446721508	0.44888
M6 Utilization after the disruptive event	0.222856091	0.22145	0.222856091	0.22152	0.222856091	0.22148	0.222856091	0.2215	0.222856091	0.22153
M2 Utilization after the disruptive event	0.35399585	0.3525	0.35399585	0.3518	0.35399585	0.35227	0.35399585	0.35212	0.35399585	0.35182
M5 Utilization after the disruptive event	0.110789559	0.10636	0.110789559	0.10628	0.110789559	0.10633	0.110789559	0.10671	0.110789559	0.10648
M3 Utilization after the disruptive event	0.107360805	0.10797	0.107360805	0.1079	0.107360805	0.10795	0.107360805	0.10796	0.107360805	0.10793
M7 Utilization after the disruptive event	0.868383053	0.86844	0.868383053	0.86901	0.868383053	0.86862	0.868383053	0.86884	0.868383053	0.86902
M9 Utilization after the disruptive event	0.543197147	0.5445	0.543197147	0.54435	0.543197147	0.54445	0.543197147	0.54454	0.543197147	0.54442
M12 Utilization after the disruptive event	0.250053411	0.2463	0.250053411	0.24612	0.250053411	0.24624	0.250053411	0.24641	0.250053411	0.24624
AGV Utilization after the disruptive event	0.897805272	0.89735	0.897805272	0.89733	0.897805272	0.89735	0.897805272	0.89732	0.897805272	0.89732
Fixture Utilization after the disruptive event	0.935392661	0.93568	0.935392661	0.93567	0.935392661	0.93568	0.935392661	0.93567	0.935392661	0.93567

Count	61		62		63		64		65	
Exp. NO	36		37		38		39		40	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.475764164	0.47536	0.475764164	0.47537	0.475764164	0.47535	0.475764164	0.47533	0.475764164	0.47536
M6 Utilization after the disruptive event	0.20468378	0.20541	0.20468378	0.20537	0.20468378	0.20538	0.20468378	0.20537	0.20468378	0.2054
M2 Utilization after the disruptive event	0.592916668	0.59366	0.592916668	0.59395	0.592916668	0.59384	0.592916668	0.59395	0.592916668	0.59373
M5 Utilization after the disruptive event	0.430365812	0.4303	0.430365812	0.43055	0.430365812	0.43032	0.430365812	0.43011	0.430365812	0.43035
M3 Utilization after the disruptive event	0.099066555	0.09797	0.099066555	0.097838	0.099066555	0.097821	0.099066555	0.097891	0.099066555	0.097892
M7 Utilization after the disruptive event	0.82212507	0.82273	0.82212507	0.82272	0.82212507	0.82273	0.82212507	0.82254	0.82212507	0.82276
M9 Utilization after the disruptive event	0.686013787	0.68596	0.686013787	0.68608	0.686013787	0.68599	0.686013787	0.68594	0.686013787	0.68599
M12 Utilization after the disruptive event	0.468782583	0.46946	0.468782583	0.46964	0.468782583	0.46949	0.468782583	0.4694	0.468782583	0.46949
AGV Utilization after the disruptive event	0.899299233	0.89952	0.899299233	0.89951	0.899299233	0.89951	0.899299233	0.89954	0.899299233	0.89951
Fixture Utilization after the disruptive event	0.94181668	0.94168	0.94181668	0.94168	0.94181668	0.94168	0.94181668	0.9417	0.94181668	0.94168

Count	66		67		68		69		70	
Exp. NO	441		442		443		444		445	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.475764164	0.47535	0.475764164	0.47535	0.475764164	0.47532	0.475764164	0.47532	0.475764164	0.47539
M6 Utilization after the disruptive event	0.20468378	0.20536	0.20468378	0.2054	0.20468378	0.20531	0.20468378	0.20535	0.20468378	0.20541
M2 Utilization after the disruptive event	0.592916668	0.59399	0.592916668	0.59372	0.592916668	0.59437	0.592916668	0.59404	0.592916668	0.59367
M5 Utilization after the disruptive event	0.430365812	0.4303	0.430365812	0.43027	0.430365812	0.43022	0.430365812	0.43008	0.430365812	0.43056
M3 Utilization after the disruptive event	0.099066555	0.097803	0.099066555	0.097892	0.099066555	0.097734	0.099066555	0.097806	0.099066555	0.097927
M7 Utilization after the disruptive event	0.82212507	0.82264	0.82212507	0.82274	0.82212507	0.82243	0.82212507	0.82255	0.82212507	0.82283
M9 Utilization after the disruptive event	0.686013787	0.68601	0.686013787	0.68596	0.686013787	0.68604	0.686013787	0.68595	0.686013787	0.68605
M12 Utilization after the disruptive event	0.468782583	0.4695	0.468782583	0.46945	0.468782583	0.46953	0.468782583	0.4694	0.468782583	0.4696
AGV Utilization after the disruptive event	0.899299233	0.89952	0.899299233	0.89951	0.899299233	0.89955	0.899299233	0.89955	0.899299233	0.89949
Fixture Utilization after the disruptive event	0.94181668	0.94168	0.94181668	0.94168	0.94181668	0.9417	0.94181668	0.9417	0.94181668	0.94167

Count	71		72		73		74		75	
Exp. NO	446		447		448		449		450	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.475764164	0.47537	0.475764164	0.47538	0.475764164	0.47533	0.475764164	0.47536	0.475764164	0.47534
M6 Utilization after the disruptive event	0.20468378	0.20541	0.20468378	0.2054	0.20468378	0.20537	0.20468378	0.2054	0.20468378	0.20536
M2 Utilization after the disruptive event	0.592916668	0.59368	0.592916668	0.59371	0.592916668	0.59391	0.592916668	0.59378	0.592916668	0.59399
M5 Utilization after the disruptive event	0.430365812	0.43039	0.430365812	0.43055	0.430365812	0.43014	0.430365812	0.43031	0.430365812	0.43022
M3 Utilization after the disruptive event	0.099066555	0.097935	0.099066555	0.097892	0.099066555	0.097812	0.099066555	0.097915	0.099066555	0.097832
M7 Utilization after the disruptive event	0.82212507	0.82276	0.82212507	0.82283	0.82212507	0.82264	0.82212507	0.82269	0.82212507	0.8226
M9 Utilization after the disruptive event	0.686013787	0.68599	0.686013787	0.68605	0.686013787	0.68595	0.686013787	0.68598	0.686013787	0.68598
M12 Utilization after the disruptive event	0.468782583	0.46951	0.468782583	0.4696	0.468782583	0.46941	0.468782583	0.46948	0.468782583	0.46947
AGV Utilization after the disruptive event	0.899299233	0.89951	0.899299233	0.8995	0.899299233	0.89953	0.899299233	0.89952	0.899299233	0.89953
Fixture Utilization after the disruptive event	0.94181668	0.94168	0.94181668	0.94167	0.94181668	0.94169	0.94181668	0.94169	0.94181668	0.94169

Count	76		77		78		79		80	
Exp. NO	171		172		173		174		175	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.473728461	0.4745	0.473728461	0.47449	0.473728461	0.47448	0.473728461	0.4745	0.473728461	0.47458
M6 Utilization after the disruptive event	0.202262291	0.20137	0.202262291	0.20136	0.202262291	0.20135	0.202262291	0.20137	0.202262291	0.20144
M2 Utilization after the disruptive event	0.589311314	0.5882	0.589311314	0.58826	0.589311314	0.58833	0.589311314	0.58818	0.589311314	0.58754
M5 Utilization after the disruptive event	0.425745817	0.42526	0.425745817	0.42515	0.425745817	0.42512	0.425745817	0.42522	0.425745817	0.42588
M3 Utilization after the disruptive event	0.089976937	0.091265	0.089976937	0.09128	0.089976937	0.091224	0.089976937	0.091249	0.089976937	0.091141
M7 Utilization after the disruptive event	0.82002485	0.81948	0.82002485	0.81938	0.82002485	0.81939	0.82002485	0.8195	0.82002485	0.82028
M9 Utilization after the disruptive event	0.682852665	0.68306	0.682852665	0.68303	0.682852665	0.68303	0.682852665	0.68304	0.682852665	0.68314
M12 Utilization after the disruptive event	0.463540989	0.46222	0.463540989	0.46217	0.463540989	0.46217	0.463540989	0.4622	0.463540989	0.46244
AGV Utilization after the disruptive event	0.891505529	0.8912	0.891505529	0.89121	0.891505529	0.89121	0.891505529	0.8912	0.891505529	0.89114
Fixture Utilization after the disruptive event	0.935793675	0.93596	0.935793675	0.93597	0.935793675	0.93597	0.935793675	0.93596	0.935793675	0.93594

Count	81		82		83		84		85	
Exp. NO	451		452		453		454		455	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.473728461	0.47452	0.473728461	0.4745	0.473728461	0.4745	0.473728461	0.47451	0.473728461	0.47449
M6 Utilization after the disruptive event	0.202262291	0.20139	0.202262291	0.20137	0.202262291	0.20135	0.202262291	0.20139	0.202262291	0.20137
M2 Utilization after the disruptive event	0.589311314	0.58796	0.589311314	0.58815	0.589311314	0.58832	0.589311314	0.58801	0.589311314	0.58814
M5 Utilization after the disruptive event	0.425745817	0.42542	0.425745817	0.42526	0.425745817	0.42521	0.425745817	0.42524	0.425745817	0.42518
M3 Utilization after the disruptive event	0.089976937	0.091207	0.089976937	0.091257	0.089976937	0.091259	0.089976937	0.091268	0.089976937	0.091213
M7 Utilization after the disruptive event	0.82002485	0.81977	0.82002485	0.81953	0.82002485	0.81938	0.82002485	0.81961	0.82002485	0.81956
M9 Utilization after the disruptive event	0.682852665	0.68307	0.682852665	0.68305	0.682852665	0.68306	0.682852665	0.68302	0.682852665	0.68302
M12 Utilization after the disruptive event	0.463540989	0.46226	0.463540989	0.46221	0.463540989	0.46222	0.463540989	0.46218	0.463540989	0.46217
AGV Utilization after the disruptive event	0.891505529	0.89118	0.891505529	0.8912	0.891505529	0.89121	0.891505529	0.89119	0.891505529	0.8912
Fixture Utilization after the disruptive event	0.935793675	0.93596	0.935793675	0.93596	0.935793675	0.93597	0.935793675	0.93596	0.935793675	0.93597

Count	86		87		88		89		90	
Exp. NO	456		457		458		459		460	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.473728461	0.47449	0.473728461	0.4745	0.473728461	0.47451	0.473728461	0.4745	0.473728461	0.47449
M6 Utilization after the disruptive event	0.202262291	0.20136	0.202262291	0.20138	0.202262291	0.20138	0.202262291	0.20137	0.202262291	0.20135
M2 Utilization after the disruptive event	0.589311314	0.58823	0.589311314	0.58808	0.589311314	0.58811	0.589311314	0.58815	0.589311314	0.58832
M5 Utilization after the disruptive event	0.425745817	0.42518	0.425745817	0.42527	0.425745817	0.42525	0.425745817	0.42528	0.425745817	0.42521
M3 Utilization after the disruptive event	0.089976937	0.09122	0.089976937	0.091187	0.089976937	0.091312	0.089976937	0.091198	0.089976937	0.091227
M7 Utilization after the disruptive event	0.82002485	0.81949	0.82002485	0.81966	0.82002485	0.81949	0.82002485	0.8196	0.82002485	0.81942
M9 Utilization after the disruptive event	0.682852665	0.68303	0.682852665	0.68304	0.682852665	0.68304	0.682852665	0.68305	0.682852665	0.68306
M12 Utilization after the disruptive event	0.463540989	0.46218	0.463540989	0.4622	0.463540989	0.4622	0.463540989	0.46222	0.463540989	0.46222
AGV Utilization after the disruptive event	0.891505529	0.89121	0.891505529	0.8912	0.891505529	0.89119	0.891505529	0.8912	0.891505529	0.89121
Fixture Utilization after the disruptive event	0.935793675	0.93597	0.935793675	0.93597	0.935793675	0.93596	0.935793675	0.93597	0.935793675	0.93597

Count	91		92		93		94		95	
Exp. NO	81		82		83		84		85	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.48582661	0.4903	0.48582661	0.49029	0.48582661	0.49028	0.48582661	0.49024	0.48582661	0.49027
M6 Utilization after the disruptive event	0.280949766	0.27983	0.280949766	0.27989	0.280949766	0.27988	0.280949766	0.27985	0.280949766	0.27986
M2 Utilization after the disruptive event	0.387833404	0.38926	0.387833404	0.38864	0.387833404	0.38868	0.387833404	0.38887	0.387833404	0.38889
M5 Utilization after the disruptive event	0.144511031	0.13464	0.144511031	0.13442	0.144511031	0.13436	0.144511031	0.13411	0.144511031	0.13425
M3 Utilization after the disruptive event	0.851020128	0.84758	0.851020128	0.84743	0.851020128	0.8474	0.851020128	0.84734	0.851020128	0.8475
M7 Utilization after the disruptive event	0.102809956	0.10494	0.102809956	0.10549	0.102809956	0.10548	0.102809956	0.10533	0.102809956	0.10517
M9 Utilization after the disruptive event	0.584862809	0.58726	0.584862809	0.58709	0.584862809	0.58708	0.584862809	0.58702	0.584862809	0.58708
M12 Utilization after the disruptive event	0.323322607	0.31497	0.323322607	0.31473	0.323322607	0.3147	0.323322607	0.3146	0.323322607	0.31468
AGV Utilization after the disruptive event	0.904871391	0.90432	0.904871391	0.90432	0.904871391	0.90433	0.904871391	0.90435	0.904871391	0.90433
Fixture Utilization after the disruptive event	0.941544988	0.94183	0.941544988	0.94183	0.941544988	0.94183	0.941544988	0.94184	0.941544988	0.94183

Count	96		97		98		99		100	
Exp. NO	461		462		463		464		465	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.48582661	0.49026	0.48582661	0.49027	0.48582661	0.49026	0.48582661	0.49027	0.48582661	0.49026
M6 Utilization after the disruptive event	0.280949766	0.27986	0.280949766	0.27987	0.280949766	0.27985	0.280949766	0.27985	0.280949766	0.27987
M2 Utilization after the disruptive event	0.387833404	0.38893	0.387833404	0.38884	0.387833404	0.38905	0.387833404	0.38896	0.387833404	0.38876
M5 Utilization after the disruptive event	0.144511031	0.13422	0.144511031	0.13426	0.144511031	0.13423	0.144511031	0.13435	0.144511031	0.13426
M3 Utilization after the disruptive event	0.851020128	0.84752	0.851020128	0.84754	0.851020128	0.84759	0.851020128	0.84746	0.851020128	0.8474
M7 Utilization after the disruptive event	0.102809956	0.10511	0.102809956	0.10516	0.102809956	0.10495	0.102809956	0.10521	0.102809956	0.10539
M9 Utilization after the disruptive event	0.584862809	0.58707	0.584862809	0.58707	0.584862809	0.5871	0.584862809	0.58712	0.584862809	0.58706
M12 Utilization after the disruptive event	0.323322607	0.31467	0.323322607	0.31468	0.323322607	0.3147	0.323322607	0.31474	0.323322607	0.31466
AGV Utilization after the disruptive event	0.904871391	0.90433	0.904871391	0.90432	0.904871391	0.90433	0.904871391	0.90433	0.904871391	0.90433
Fixture Utilization after the disruptive event	0.941544988	0.94183	0.941544988	0.94183	0.941544988	0.94183	0.941544988	0.94184	0.941544988	0.94184

Count	101		102		103		104		105	
Exp. NO	466		467		468		469		470	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.48582661	0.49027	0.48582661	0.4903	0.48582661	0.49029	0.48582661	0.49031	0.48582661	0.49029
M6 Utilization after the disruptive event	0.280949766	0.27986	0.280949766	0.27982	0.280949766	0.27987	0.280949766	0.27985	0.280949766	0.27989
M2 Utilization after the disruptive event	0.387833404	0.38886	0.387833404	0.38935	0.387833404	0.38883	0.387833404	0.38911	0.387833404	0.38867
M5 Utilization after the disruptive event	0.144511031	0.13433	0.144511031	0.13459	0.144511031	0.13451	0.144511031	0.13477	0.144511031	0.13442
M3 Utilization after the disruptive event	0.851020128	0.84745	0.851020128	0.84761	0.851020128	0.84744	0.851020128	0.84754	0.851020128	0.84752
M7 Utilization after the disruptive event	0.102809956	0.10527	0.102809956	0.10483	0.102809956	0.10536	0.102809956	0.10514	0.102809956	0.10537
M9 Utilization after the disruptive event	0.584862809	0.5871	0.584862809	0.58726	0.584862809	0.58715	0.584862809	0.58728	0.584862809	0.5871
M12 Utilization after the disruptive event	0.323322607	0.31472	0.323322607	0.31495	0.323322607	0.31481	0.323322607	0.315	0.323322607	0.31473
AGV Utilization after the disruptive event	0.904871391	0.90433	0.904871391	0.90432	0.904871391	0.90431	0.904871391	0.90431	0.904871391	0.90431
Fixture Utilization after the disruptive event	0.941544988	0.94183	0.941544988	0.94183	0.941544988	0.94183	0.941544988	0.94183	0.941544988	0.94183

Count	106		107		108		109		110	
Exp. NO	86		87		88		89		90	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.496848861	0.49173	0.496848861	0.4918	0.496848861	0.49178	0.496848861	0.49179	0.496848861	0.49183
M6 Utilization after the disruptive event	0.27417547	0.27541	0.27417547	0.27538	0.27417547	0.27546	0.27417547	0.27542	0.27417547	0.27538
M2 Utilization after the disruptive event	0.395505919	0.39423	0.395505919	0.39459	0.395505919	0.39392	0.395505919	0.39428	0.395505919	0.39467
M5 Utilization after the disruptive event	0.139979476	0.15112	0.139979476	0.15188	0.139979476	0.15145	0.139979476	0.15167	0.139979476	0.15223
M3 Utilization after the disruptive event	0.844093762	0.84799	0.844093762	0.84791	0.844093762	0.8481	0.844093762	0.84804	0.844093762	0.84799
M7 Utilization after the disruptive event	0.095762681	0.093056	0.095762681	0.093093	0.095762681	0.093274	0.095762681	0.093138	0.095762681	0.093072
M9 Utilization after the disruptive event	0.595851361	0.59313	0.595851361	0.59343	0.595851361	0.59319	0.595851361	0.59332	0.595851361	0.59356
M12 Utilization after the disruptive event	0.312061082	0.32158	0.312061082	0.32205	0.312061082	0.32172	0.312061082	0.32189	0.312061082	0.32226
AGV Utilization after the disruptive event	0.894139541	0.89478	0.894139541	0.89474	0.894139541	0.89476	0.894139541	0.89475	0.894139541	0.89473
Fixture Utilization after the disruptive event	0.935961807	0.93564	0.935961807	0.93563	0.935961807	0.93563	0.935961807	0.93563	0.935961807	0.93562

Count	111		112		113		114		115	
Exp. NO	471		472		473		474		475	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.496848861	0.49176	0.496848861	0.49184	0.496848861	0.49179	0.496848861	0.49188	0.496848861	0.49179
M6 Utilization after the disruptive event	0.27417547	0.27542	0.27417547	0.27539	0.27417547	0.27538	0.27417547	0.27534	0.27417547	0.27542
M2 Utilization after the disruptive event	0.395505919	0.39427	0.395505919	0.39463	0.395505919	0.3946	0.395505919	0.39512	0.395505919	0.39433
M5 Utilization after the disruptive event	0.139979476	0.1514	0.139979476	0.15232	0.139979476	0.15181	0.139979476	0.15284	0.139979476	0.15168
M3 Utilization after the disruptive event	0.844093762	0.84802	0.844093762	0.84801	0.844093762	0.84797	0.844093762	0.84791	0.844093762	0.84803
M7 Utilization after the disruptive event	0.095762681	0.093078	0.095762681	0.093104	0.095762681	0.093013	0.095762681	0.093008	0.095762681	0.093116
M9 Utilization after the disruptive event	0.595851361	0.59323	0.595851361	0.59358	0.595851361	0.59341	0.595851361	0.59382	0.595851361	0.59333
M12 Utilization after the disruptive event	0.312061082	0.32174	0.312061082	0.32231	0.312061082	0.32202	0.312061082	0.32267	0.312061082	0.32191
AGV Utilization after the disruptive event	0.894139541	0.89477	0.894139541	0.89472	0.894139541	0.89475	0.894139541	0.89471	0.894139541	0.89476
Fixture Utilization after the disruptive event	0.935961807	0.93564	0.935961807	0.93562	0.935961807	0.93563	0.935961807	0.93562	0.935961807	0.93563

Count	116		117		118		119		120	
Exp. NO	476		477		478		479		480	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.496848861	0.49181	0.496848861	0.49174	0.496848861	0.4918	0.496848861	0.49176	0.496848861	0.49178
M6 Utilization after the disruptive event	0.27417547	0.27537	0.27417547	0.27548	0.27417547	0.27543	0.27417547	0.27542	0.27417547	0.27537
M2 Utilization after the disruptive event	0.395505919	0.39468	0.395505919	0.39374	0.395505919	0.39424	0.395505919	0.39429	0.395505919	0.39471
M5 Utilization after the disruptive event	0.139979476	0.15197	0.139979476	0.15103	0.139979476	0.15178	0.139979476	0.1514	0.139979476	0.15178
M3 Utilization after the disruptive event	0.844093762	0.84794	0.844093762	0.84813	0.844093762	0.84807	0.844093762	0.84805	0.844093762	0.84792
M7 Utilization after the disruptive event	0.095762681	0.093032	0.095762681	0.093234	0.095762681	0.093168	0.095762681	0.093039	0.095762681	0.092973
M9 Utilization after the disruptive event	0.595851361	0.59347	0.595851361	0.59303	0.595851361	0.59335	0.595851361	0.59323	0.595851361	0.59341
M12 Utilization after the disruptive event	0.312061082	0.32212	0.312061082	0.32146	0.312061082	0.32195	0.312061082	0.32175	0.312061082	0.32202
AGV Utilization after the disruptive event	0.894139541	0.89475	0.894139541	0.89477	0.894139541	0.89475	0.894139541	0.89477	0.894139541	0.89476
Fixture Utilization after the disruptive event	0.935961807	0.93563	0.935961807	0.93564	0.935961807	0.93563	0.935961807	0.93564	0.935961807	0.93563

C.6 Output Vectors for *Net_2_1_2*

Count	1		2		3		4		5	
Exp. NO	41		42		43		44		45	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	112	116.49	112	117.05	112	116.81	112	116.83	112	116.35
A0 (non-linear trend mu)	135.61	130.22	135.61	130.2	135.61	130.17	135.61	130.2	135.61	130.18
A1 (non-linear trend mu)	464.63	481.22	464.63	480.87	464.63	481.27	464.63	481.04	464.63	481.59
A2 (non-linear trend mu)	269.21	237.53	269.21	237.57	269.21	237.78	269.21	237.58	269.21	237.78
A3 (non-linear trend mu)	-68.44	-64.783	-68.44	-64.816	-68.44	-64.867	-68.44	-64.812	-68.44	-64.847

Count	6		7		8		9		10	
Exp. NO	481		482		483		484		485	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	112	116.66	112	116.64	112	116.61	112	117.46	112	116.85
A0 (non-linear trend mu)	135.61	130.18	135.61	130.2	135.61	130.2	135.61	130.13	135.61	130.17
A1 (non-linear trend mu)	464.63	481.28	464.63	481.17	464.63	481.22	464.63	480.9	464.63	481.21
A2 (non-linear trend mu)	269.21	237.69	269.21	237.58	269.21	237.6	269.21	237.87	269.21	237.75
A3 (non-linear trend mu)	-68.44	-64.836	-68.44	-64.804	-68.44	-64.809	-68.44	-64.917	-68.44	-64.86

Count	11		12		13		14		15	
Exp. NO	486		487		488		489		490	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	112	116.93	112	116.61	112	116.46	112	116.93	112	116.99
A0 (non-linear trend mu)	135.61	130.14	135.61	130.17	135.61	130.19	135.61	130.19	135.61	130.14
A1 (non-linear trend mu)	464.63	481.3	464.63	481.42	464.63	481.41	464.63	481.03	464.63	481.25
A2 (non-linear trend mu)	269.21	237.89	269.21	237.79	269.21	237.68	269.21	237.64	269.21	237.88
A3 (non-linear trend mu)	-68.44	-64.9	-68.44	-64.86	-68.44	-64.824	-68.44	-64.831	-68.44	-64.902

Count	16		17		18		19		20	
Exp. NO	176		177		178		179		180	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	213	208.69	213	208.38	213	207.31	213	207.76	213	208.02
A0 (non-linear trend mu)	120.4	127.17	120.4	127.14	120.4	127.19	120.4	127.17	120.4	127.16
A1 (non-linear trend mu)	441.36	419.42	441.36	419.9	441.36	420.49	441.36	420.28	441.36	420.12
A2 (non-linear trend mu)	201.23	240.94	201.23	241.18	201.23	241.03	201.23	241.12	201.23	241.14
A3 (non-linear trend mu)	-64.83	-69.42	-64.83	-69.475	-64.83	-69.39	-64.83	-69.432	-64.83	-69.449

Count	21		22		23		24		25	
Exp. NO	491		492		493		494		495	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	213	207.09	213	207.86	213	208.01	213	207.96	213	207.37
A0 (non-linear trend mu)	120.4	127.21	120.4	127.15	120.4	127.16	120.4	127.18	120.4	127.18
A1 (non-linear trend mu)	441.36	420.56	441.36	420.29	441.36	420.13	441.36	420.04	441.36	420.51
A2 (non-linear trend mu)	201.23	240.94	201.23	241.21	201.23	241.15	201.23	241.03	201.23	241.08
A3 (non-linear trend mu)	-64.83	-69.356	-64.83	-69.461	-64.83	-69.449	-64.83	-69.415	-64.83	-69.407

Count	26		27		28		29		30	
Exp. NO	496		497		498		499		500	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	213	207.91	213	207.94	213	206.68	213	207.92	213	207.12
A0 (non-linear trend mu)	120.4	127.16	120.4	127.17	120.4	127.18	120.4	127.16	120.4	127.2
A1 (non-linear trend mu)	441.36	420.18	441.36	420.11	441.36	421.13	441.36	420.14	441.36	420.62
A2 (non-linear trend mu)	201.23	241.13	201.23	241.08	201.23	241.2	201.23	241.11	201.23	241.02
A3 (non-linear trend mu)	-64.83	-69.441	-64.83	-69.429	-64.83	-69.411	-64.83	-69.435	-64.83	-69.379

Count	31		32		33		34		35	
Exp. NO	61		62		63		64		65	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	377	378.74	377	378.75	377	378.92	377	379.08	377	378.55
A0 (non-linear trend mu)	162.09	159.67	162.09	159.75	162.09	159.6	162.09	159.57	162.09	159.65
A1 (non-linear trend mu)	57.698	65.386	57.698	64.847	57.698	65.67	57.698	65.712	57.698	65.673
A2 (non-linear trend mu)	36.271	21.943	36.271	21.448	36.271	22.335	36.271	22.477	36.271	22.091
A3 (non-linear trend mu)	-17.24	-15.553	-17.24	-15.417	-17.24	-15.669	-17.24	-15.715	-17.24	-15.587

Count	36		37		38		39		40	
Exp. NO	241		242		243		244		245	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	377	379.48	377	379.06	377	378.93	377	378.81	377	378.85
A0 (non-linear trend mu)	162.09	159.31	162.09	159.56	162.09	159.55	162.09	159.55	162.09	159.62
A1 (non-linear trend mu)	57.698	67.003	57.698	65.783	57.698	65.943	57.698	66.086	57.698	65.573
A2 (non-linear trend mu)	36.271	23.956	36.271	22.534	36.271	22.595	36.271	22.651	36.271	22.191
A3 (non-linear trend mu)	-17.24	-16.141	-17.24	-15.73	-17.24	-15.741	-17.24	-15.752	-17.24	-15.626

Count	41		42		43		44		45	
Exp. NO	246		247		248		249		250	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	377	378.76	377	379.21	377	379.15	377	378.78	377	379.16
A0 (non-linear trend mu)	162.09	159.59	162.09	159.55	162.09	159.59	162.09	159.7	162.09	159.6
A1 (non-linear trend mu)	57.698	65.867	57.698	65.709	57.698	65.499	57.698	65.129	57.698	65.441
A2 (non-linear trend mu)	36.271	22.408	36.271	22.563	36.271	22.323	36.271	21.733	36.271	22.277
A3 (non-linear trend mu)	-17.24	-15.683	-17.24	-15.744	-17.24	-15.675	-17.24	-15.497	-17.24	-15.662

Count	46		47		48		49		50	
Exp. NO	**71**		**72**		**73**		**74**		**75**	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	178	178.69	178	177.21	178	179.63	178	177.44	178	178.61
A0 (non-linear trend mu)	176.48	178.57	176.48	178.64	176.48	178.53	176.48	178.57	176.48	178.56
A1 (non-linear trend mu)	130.46	122.06	130.46	122.9	130.46	121.48	130.46	123.15	130.46	122.15
A2 (non-linear trend mu)	-70.55	-58.128	-70.55	-58.321	-70.55	-58.042	-70.55	-57.931	-70.55	-58.096
A3 (non-linear trend mu)	16.131	14.639	16.131	14.751	16.131	14.577	16.131	14.634	16.131	14.633

Count	51		52		53		54		55	
Exp. NO	**321**		**322**		**323**		**324**		**325**	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	178	177.23	178	178.74	178	177.57	178	177.78	178	177.94
A0 (non-linear trend mu)	176.48	178.59	176.48	178.56	176.48	178.56	176.48	178.57	176.48	178.58
A1 (non-linear trend mu)	130.46	123.22	130.46	122.06	130.46	123.09	130.46	122.81	130.46	122.63
A2 (non-linear trend mu)	-70.55	-58.006	-70.55	-58.092	-70.55	-57.898	-70.55	-58.022	-70.55	-58.09
A3 (non-linear trend mu)	16.131	14.664	16.131	14.627	16.131	14.62	16.131	14.646	16.131	14.658

Count	56		57		58		59		60	
Exp. NO	**326**		**327**		**328**		**329**		**330**	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	178	177.35	178	177.3	178	177.17	178	178.05	178	177.39
A0 (non-linear trend mu)	176.48	178.6	176.48	178.6	176.48	178.62	176.48	178.62	176.48	178.61
A1 (non-linear trend mu)	130.46	123.04	130.46	123.08	130.46	123.09	130.46	122.3	130.46	122.92
A2 (non-linear trend mu)	-70.55	-58.089	-70.55	-58.091	-70.55	-58.174	-70.55	-58.322	-70.55	-58.187
A3 (non-linear trend mu)	16.131	14.681	16.131	14.684	16.131	14.712	16.131	14.718	16.131	14.707

C.7 Output Vectors for *Net_2_1_3*

Count	1		2		3		4		5	
Exp. NO	26		27		28		29		30	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	37.31739182	37.294	37.31739182	37.272	37.31739182	37.291	37.31739182	37.294	37.31739182	37.279
sigma post-distruption A0	46.912	47.557	46.912	47.555	46.912	47.572	46.912	47.552	46.912	47.548
sigma post-distruption A1	102.28	100.78	102.28	99.733	102.28	100.31	102.28	100.89	102.28	100.22
sigma post-distruption A2	1943.5	1922.8	1943.5	1929.2	1943.5	1926.6	1943.5	1921.8	1943.5	1925.8
sigma post-distruption A3	-7734.3	-7689.5	-7734.3	-7707.9	-7734.3	-7702.2	-7734.3	-7686	-7734.3	-7697.1
sigma post-distruption A4	13632	13617	13632	13644	13632	13637	13632	13611	13632	13627
sigma post-distruption A5	-12717	-12753	-12717	-12776	-12717	-12772	-12717	-12748	-12717	-12761
sigma post-distruption A6	6516.9	6551.3	6516.9	6562	6516.9	6560.2	6516.9	6548.7	6516.9	6554.9
sigma post-distruption A7	-1733.1	-1742.9	-1733.1	-1745.5	-1733.1	-1745.2	-1733.1	-1742.3	-1733.1	-1743.8
sigma post-distruption A8	186.97	187.72	186.97	187.97	186.97	187.94	186.97	187.65	186.97	187.8

Count	6		7		8		9		10	
Exp. NO	361		362		363		364		365	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	37.31739182	37.3	37.31739182	37.3	37.31739182	37.261	37.31739182	37.297	37.31739182	37.301
sigma post-distruption A0	46.912	47.668	46.912	47.568	46.912	47.618	46.912	47.609	46.912	47.685
sigma post-distruption A1	102.28	98.447	102.28	100.83	102.28	97.661	102.28	99.727	102.28	98.088
sigma post-distruption A2	1943.5	1944.1	1943.5	1923.1	1943.5	1946.1	1943.5	1932.4	1943.5	1947.3
sigma post-distruption A3	-7734.3	-7764.2	-7734.3	-7691.4	-7734.3	-7764.7	-7734.3	-7723.3	-7734.3	-7775.4
sigma post-distruption A4	13632	13743	13632	13621	13632	13738	13632	13674	13632	13762
sigma post-distruption A5	-12717	-12867	-12717	-12757	-12717	-12859	-12717	-12805	-12717	-12884
sigma post-distruption A6	6516.9	6606.9	6516.9	6553.5	6516.9	6602.1	6516.9	6576.5	6516.9	6615.2
sigma post-distruption A7	-1733.1	-1757	-1733.1	-1743.5	-1733.1	-1755.6	-1733.1	-1749.3	-1733.1	-1759.1
sigma post-distruption A8	186.97	189.15	186.97	187.78	186.97	189	186.97	188.37	186.97	189.37

Count	11		12		13		14		15	
Exp. NO	366		367		368		369		370	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	37.31739182	37.287	37.31739182	37.301	37.31739182	37.287	37.31739182	37.297	37.31739182	37.282
sigma post-distruption A0	46.912	47.55	46.912	47.606	46.912	47.566	46.912	47.601	46.912	47.508
sigma post-distruption A1	102.28	100.62	102.28	99.971	102.28	100.24	102.28	99.881	102.28	101.38
sigma post-distruption A2	1943.5	1923.4	1943.5	1930.8	1943.5	1926.8	1943.5	1931.1	1943.5	1916.2
sigma post-distruption A3	-7734.3	-7690.4	-7734.3	-7718.2	-7734.3	-7702	-7734.3	-7718.5	-7734.3	-7664.5
sigma post-distruption A4	13632	13617	13632	13666	13632	13637	13632	13666	13632	13573
sigma post-distruption A5	-12717	-12753	-12717	-12798	-12717	-12771	-12717	-12797	-12717	-12713
sigma post-distruption A6	6516.9	6551.1	6516.9	6573.2	6516.9	6559.7	6516.9	6572.9	6516.9	6531.5
sigma post-distruption A7	-1733.1	-1742.9	-1733.1	-1748.5	-1733.1	-1745	-1733.1	-1748.4	-1733.1	-1737.9
sigma post-distruption A8	186.97	187.7	186.97	188.29	186.97	187.93	186.97	188.27	186.97	187.2

Count	16		17		18		19		20	
Exp. NO	151		152		153		154		155	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.62650105	34.598	34.62650105	34.615	34.62650105	34.597	34.62650105	34.592	34.62650105	34.605
sigma post-distruption A0	38.472	38.751	38.472	38.98	38.472	38.725	38.472	38.683	38.472	38.842
sigma post-distruption A1	263.26	267.02	263.26	265.62	263.26	267	263.26	267.46	263.26	266.35
sigma post-distruption A2	-99.701	-79.685	-99.701	-74.801	-99.701	-78.794	-99.701	-82.37	-99.701	-76.655
sigma post-distruption A3	-56.126	-77.158	-56.126	-87.488	-56.126	-81.043	-56.126	-68.882	-56.126	-85.245
sigma post-distruption A4	242.07	222.11	242.07	233.77	242.07	229.61	242.07	209.39	242.07	233.72
sigma post-distruption A5	-457.64	-411.96	-457.64	-417.63	-457.64	-419.47	-457.64	-401.68	-457.64	-420.65
sigma post-distruption A6	395.92	370.6	395.92	370.79	395.92	374.67	395.92	366.18	395.92	373.91
sigma post-distruption A7	-152.77	-148.49	-152.77	-147.79	-152.77	-149.63	-152.77	-147.55	-152.77	-149.05
sigma post-distruption A8	21.705	21.785	21.705	21.624	21.705	21.913	21.705	21.71	21.705	21.809

Count	21		22		23		24		25	
Exp. NO	371		372		373		374		375	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.62650105	34.591	34.62650105	34.599	34.62650105	34.619	34.62650105	34.611	34.62650105	34.615
sigma post-distruption A0	38.472	38.662	38.472	38.751	38.472	39.067	38.472	38.91	38.472	38.976
sigma post-distruption A1	263.26	267.62	263.26	266.85	263.26	265.49	263.26	265.8	263.26	265.6
sigma post-distruption A2	-99.701	-83.08	-99.701	-77.664	-99.701	-77.417	-99.701	-73.145	-99.701	-73.716
sigma post-distruption A3	-56.126	-67.087	-56.126	-84.746	-56.126	-74.733	-56.126	-96.315	-56.126	-92.036
sigma post-distruption A4	242.07	206.88	242.07	235.43	242.07	208.9	242.07	251.28	242.07	241.92
sigma post-distruption A5	-457.64	-399.85	-457.64	-424.26	-457.64	-392.67	-457.64	-435.39	-457.64	-425.26
sigma post-distruption A6	395.92	365.51	395.92	376.8	395.92	357.18	395.92	380.57	395.92	374.7
sigma post-distruption A7	-152.77	-147.45	-152.77	-150.11	-152.77	-143.95	-152.77	-150.57	-152.77	-148.82
sigma post-distruption A8	21.705	21.707	21.705	21.955	21.705	21.188	21.705	21.945	21.705	21.736

Count	26		27		28		29		30	
Exp. NO	376		377		378		379		380	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.62650105	34.611	34.62650105	34.604	34.62650105	34.596	34.62650105	34.617	34.62650105	34.602
sigma post-distruption A0	38.472	38.927	38.472	38.847	38.472	38.745	38.472	39.017	38.472	38.81
sigma post-distruption A1	263.26	265.91	263.26	266.5	263.26	267.34	263.26	265.51	263.26	266.76
sigma post-distruption A2	-99.701	-75.437	-99.701	-78.55	-99.701	-83.541	-99.701	-75.144	-99.701	-80.283
sigma post-distruption A3	-56.126	-87.034	-56.126	-78.008	-56.126	-62.639	-56.126	-85.034	-56.126	-72.502
sigma post-distruption A4	242.07	234.48	242.07	220.87	242.07	196.74	242.07	228.41	242.07	212.22
sigma post-distruption A5	-457.64	-419.47	-457.64	-408.66	-457.64	-388.61	-457.64	-411.83	-457.64	-401.49
sigma post-distruption A6	395.92	372.33	395.92	367.81	395.92	358.88	395.92	367.43	395.92	364.61
sigma post-distruption A7	-152.77	-148.36	-152.77	-147.45	-152.77	-145.45	-152.77	-146.79	-152.77	-146.73
sigma post-distruption A8	21.705	21.705	21.705	21.639	21.705	21.466	21.705	21.506	21.705	21.576

Count	31		32		33		34		35	
Exp. NO	76		77		78		79		80	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	55.20239941	55.433	55.20239941	55.434	55.20239941	55.434	55.20239941	55.434	55.20239941	55.434
sigma post-distruption A0	66.261	60.642	66.261	60.639	66.261	60.648	66.261	60.646	66.261	60.644
sigma post-distruption A1	1022.9	1023.9	1022.9	1023.8	1022.9	1023.8	1022.9	1023.8	1022.9	1023.8
sigma post-distruption A2	133.33	162.24	133.33	160.28	133.33	162.82	133.33	162.09	133.33	161.73
sigma post-distruption A3	-7502.1	-7667.8	-7502.1	-7658.8	-7502.1	-7669.4	-7502.1	-7666.2	-7502.1	-7664.8
sigma post-distruption A4	17229	17400	17229	17384	17229	17402	17229	17397	17229	17394
sigma post-distruption A5	-18172	-18139	-18172	-18124	-18172	-18141	-18172	-18136	-18172	-18134
sigma post-distruption A6	10098	9993.8	10098	9986.4	10098	9994.9	10098	9992.4	10098	9991.2
sigma post-distruption A7	-2855.5	-2814.9	-2855.5	-2813	-2855.5	-2815.2	-2855.5	-2814.5	-2855.5	-2814.2
sigma post-distruption A8	323.69	319.36	323.69	319.15	323.69	319.38	323.69	319.31	323.69	319.28

Count	36		37		38		39		40	
Exp. NO	421		422		423		424		425	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	55.20239941	55.435	55.20239941	55.434	55.20239941	55.434	55.20239941	55.434	55.20239941	55.435
sigma post-distruption A0	66.261	60.657	66.261	60.644	66.261	60.638	66.261	60.635	66.261	60.654
sigma post-distruption A1	1022.9	1023.8	1022.9	1023.7	1022.9	1023.8	1022.9	1023.8	1022.9	1023.8
sigma post-distruption A2	133.33	165.69	133.33	161.45	133.33	160.16	133.33	159.29	133.33	164.67
sigma post-distruption A3	-7502.1	-7681.5	-7502.1	-7663.4	-7502.1	-7658.2	-7502.1	-7654.7	-7502.1	-7677.1
sigma post-distruption A4	17229	17424	17229	17392	17229	17383	17229	17377	17229	17416
sigma post-distruption A5	-18172	-18161	-18172	-18132	-18172	-18124	-18172	-18118	-18172	-18154
sigma post-distruption A6	10098	10005	10098	9990.1	10098	9986	10098	9983.2	10098	10001
sigma post-distruption A7	-2855.5	-2817.7	-2855.5	-2813.9	-2855.5	-2812.8	-2855.5	-2812.1	-2855.5	-2816.8
sigma post-distruption A8	323.69	319.65	323.69	319.25	323.69	319.14	323.69	319.06	323.69	319.55

Count	41		42		43		44		45	
Exp. NO	426		427		428		429		430	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	55.20239941	55.434	55.20239941	55.434	55.20239941	55.434	55.20239941	55.434	55.20239941	55.435
sigma post-distruption A0	66.261	60.631	66.261	60.641	66.261	60.646	66.261	60.642	66.261	60.652
sigma post-distruption A1	1022.9	1023.7	1022.9	1023.8	1022.9	1023.9	1022.9	1023.8	1022.9	1023.7
sigma post-distruption A2	133.33	157.42	133.33	160.7	133.33	163.19	133.33	161.62	133.33	163.67
sigma post-distruption A3	-7502.1	-7646.2	-7502.1	-7660.3	-7502.1	-7671.5	-7502.1	-7664.7	-7502.1	-7672.6
sigma post-distruption A4	17229	17362	17229	17387	17229	17406	17229	17394	17229	17408
sigma post-distruption A5	-18172	-18104	-18172	-18127	-18172	-18145	-18172	-18134	-18172	-18146
sigma post-distruption A6	10098	9976.3	10098	9987.7	10098	9996.7	10098	9991.3	10098	9997.4
sigma post-distruption A7	-2855.5	-2810.3	-2855.5	-2813.3	-2855.5	-2815.6	-2855.5	-2814.2	-2855.5	-2815.8
sigma post-distruption A8	323.69	318.86	323.69	319.18	323.69	319.44	323.69	319.29	323.69	319.45

Count	46		47		48		49		50	
Exp. NO	166		167		168		169		170	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	56.92089532	56.415	56.92089532	56.361	56.92089532	56.323	56.92089532	56.39	56.92089532	56.383
sigma post-distruption A0	76.98	86.332	76.98	85.455	76.98	84.935	76.98	85.858	76.98	85.778
sigma post-distruption A1	1035.7	1011.9	1035.7	1015.1	1035.7	1017.7	1035.7	1013.2	1035.7	1013.9
sigma post-distruption A2	-484.92	-838.99	-484.92	-833.69	-484.92	-840.57	-484.92	-829.96	-484.92	-834.02
sigma post-distruption A3	-3627.1	-3065.9	-3627.1	-3115.4	-3627.1	-3106.2	-3627.1	-3116.8	-3627.1	-3104.1
sigma post-distruption A4	8258.9	8567.2	8258.9	8678.6	8258.9	8676.6	8258.9	8670.3	8258.9	8650.2
sigma post-distruption A5	-8348.6	-9374	-8348.6	-9496.6	-8348.6	-9506.1	-8348.6	-9480.1	-8348.6	-9463.3
sigma post-distruption A6	4595.7	5267.9	4595.7	5340	4595.7	5350.7	4595.7	5327.1	4595.7	5319.5
sigma post-distruption A7	-1335.7	-1499.8	-1335.7	-1521.4	-1335.7	-1525.8	-1335.7	-1516.7	-1335.7	-1515
sigma post-distruption A8	160.17	171.32	160.17	173.93	160.17	174.59	160.17	173.29	160.17	173.14

Count	51		52		53		54		55	
Exp. NO	431		432		433		434		435	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	56.92089532	56.377	56.92089532	56.436	56.92089532	56.366	56.92089532	56.352	56.92089532	56.358
sigma post-distruption A0	76.98	85.695	76.98	86.67	76.98	85.59	76.98	85.352	76.98	85.431
sigma post-distruption A1	1035.7	1014.3	1035.7	1010.3	1035.7	1014.9	1035.7	1015.7	1035.7	1015.5
sigma post-distruption A2	-484.92	-834.78	-484.92	-837.07	-484.92	-838.42	-484.92	-836.8	-484.92	-837.65
sigma post-distruption A3	-3627.1	-3103.9	-3627.1	-3061.2	-3627.1	-3092.6	-3627.1	-3106.8	-3627.1	-3101.6
sigma post-distruption A4	8258.9	8652.2	8258.9	8549.1	8258.9	8634.7	8258.9	8666.4	8258.9	8655.3
sigma post-distruption A5	-8348.6	-9467	-8348.6	-9349.5	-8348.6	-9452.8	-8348.6	-9487.5	-8348.6	-9475.7
sigma post-distruption A6	4595.7	5322.4	4595.7	5251.6	4595.7	5316.3	4595.7	5336.5	4595.7	5329.7
sigma post-distruption A7	-1335.7	-1516	-1335.7	-1494.4	-1335.7	-1514.7	-1335.7	-1520.8	-1335.7	-1518.8
sigma post-distruption A8	160.17	173.28	160.17	170.63	160.17	173.18	160.17	173.91	160.17	173.67

Count	56		57		58		59		60	
Exp. NO	436		437		438		439		440	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	56.92089532	56.328	56.92089532	56.398	56.92089532	56.32	56.92089532	56.357	56.92089532	56.407
sigma post-distruption A0	76.98	84.965	76.98	85.965	76.98	84.79	76.98	85.451	76.98	86.208
sigma post-distruption A1	1035.7	1017.5	1035.7	1012.9	1035.7	1017.9	1035.7	1015.3	1035.7	1012.3
sigma post-distruption A2	-484.92	-838.25	-484.92	-830.24	-484.92	-833.57	-484.92	-837.14	-484.92	-837.57
sigma post-distruption A3	-3627.1	-3115	-3627.1	-3112.6	-3627.1	-3139.1	-3627.1	-3102	-3627.1	-3075.4
sigma post-distruption A4	8258.9	8691.8	8258.9	8660.2	8258.9	8739.4	8258.9	8654.9	8258.9	8587.3
sigma post-distruption A5	-8348.6	-9519.7	-8348.6	-9468.6	-8348.6	-9567.8	-8348.6	-9474.6	-8348.6	-9395.3
sigma post-distruption A6	4595.7	5357.4	4595.7	5320.1	4595.7	5383.7	4595.7	5328.8	4595.7	5280.1
sigma post-distruption A7	-1335.7	-1527.5	-1335.7	-1514.6	-1335.7	-1535	-1335.7	-1518.5	-1335.7	-1503.3
sigma post-distruption A8	160.17	174.76	160.17	173.03	160.17	175.61	160.17	173.62	160.17	171.74

Count	61		62		63		64		65	
Exp. NO	36		37		38		39		40	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	37.15268077	37.28	37.15268077	37.243	37.15268077	37.262	37.15268077	37.27	37.15268077	37.263
sigma post-distruption A0	44.777	41.57	44.777	41.551	44.777	41.565	44.777	41.565	44.777	41.57
sigma post-distruption A1	490.8	484.86	490.8	482.91	490.8	483.94	490.8	484.25	490.8	483.96
sigma post-distruption A2	1712.8	1665.9	1712.8	1671.6	1712.8	1670.1	1712.8	1667.1	1712.8	1670.8
sigma post-distruption A3	-9163.5	-9181.5	-9163.5	-9189.9	-9163.5	-9191.7	-9163.5	-9181.8	-9163.5	-9195.1
sigma post-distruption A4	16804	16972	16804	16979	16804	16986	16804	16970	16804	16992
sigma post-distruption A5	-16009	-16165	-16009	-16167	-16009	-16176	-16009	-16162	-16009	-16181
sigma post-distruption A6	8430.1	8477.5	8430.1	8476.9	8430.1	8482.1	8430.1	8475.6	8430.1	8485
sigma post-distruption A7	-2320.2	-2321	-2320.2	-2320.5	-2320.2	-2322	-2320.2	-2320.4	-2320.2	-2322.8
sigma post-distruption A8	260.26	259.05	260.26	258.96	260.26	259.15	260.26	258.97	260.26	259.23

Count	66		67		68		69		70	
Exp. NO	441		442		443		444		445	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	37.15268077	37.259	37.15268077	37.278	37.15268077	37.233	37.15268077	37.272	37.15268077	37.24
sigma post-distruption A0	44.777	41.594	44.777	41.57	44.777	41.642	44.777	41.58	44.777	41.574
sigma post-distruption A1	490.8	483.62	490.8	484.8	490.8	481.43	490.8	484.09	490.8	482.57
sigma post-distruption A2	1712.8	1679	1712.8	1666.7	1712.8	1698.7	1712.8	1669.6	1712.8	1678.8
sigma post-distruption A3	-9163.5	-9227.4	-9163.5	-9184.1	-9163.5	-9294.1	-9163.5	-9191.5	-9163.5	-9218.1
sigma post-distruption A4	16804	17048	16804	16976	16804	17157	16804	16987	16804	17027
sigma post-distruption A5	-16009	-16231	-16009	-16168	-16009	-16327	-16009	-16177	-16009	-16210
sigma post-distruption A6	8430.1	8509.7	8430.1	8479.2	8430.1	8556.2	8430.1	8483.2	8430.1	8498.5
sigma post-distruption A7	-2320.2	-2329.2	-2320.2	-2321.4	-2320.2	-2340.9	-2320.2	-2322.3	-2320.2	-2326
sigma post-distruption A8	260.26	259.9	260.26	259.1	260.26	261.1	260.26	259.18	260.26	259.55

Count	71		72		73		74		75	
Exp. NO	446		447		448		449		450	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	37.15268077	37.264	37.15268077	37.269	37.15268077	37.282	37.15268077	37.286	37.15268077	37.268
sigma post-distruption A0	44.777	41.583	44.777	41.584	44.777	41.584	44.777	41.582	44.777	41.584
sigma post-distruption A1	490.8	483.95	490.8	484.21	490.8	484.91	490.8	485.25	490.8	484.08
sigma post-distruption A2	1712.8	1674.3	1712.8	1673.3	1712.8	1669.3	1712.8	1667.8	1712.8	1673
sigma post-distruption A3	-9163.5	-9209.8	-9163.5	-9207.6	-9163.5	-9196.3	-9163.5	-9192.6	-9163.5	-9205.4
sigma post-distruption A4	16804	17018	16804	17015	16804	16998	16804	16993	16804	17011
sigma post-distruption A5	-16009	-16205	-16009	-16203	-16009	-16189	-16009	-16185	-16009	-16199
sigma post-distruption A6	8430.1	8496.8	8430.1	8496	8430.1	8489.5	8430.1	8487.6	8430.1	8493.9
sigma post-distruption A7	-2320.2	-2325.8	-2320.2	-2325.7	-2320.2	-2324.1	-2320.2	-2323.7	-2320.2	-2325.1
sigma post-distruption A8	260.26	259.55	260.26	259.54	260.26	259.39	260.26	259.35	260.26	259.48

Count	76		77		78		79		80	
Exp. NO	171		172		173		174		175	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.72114909	34.615	34.72114909	34.616	34.72114909	34.616	34.72114909	34.616	34.72114909	34.616
sigma post-distruption A0	44.814	47.455	44.814	47.461	44.814	47.463	44.814	47.453	44.814	47.455
sigma post-distruption A1	279.4	282.68	279.4	282.69	279.4	282.68	279.4	282.73	279.4	282.72
sigma post-distruption A2	3991	4004.2	3991	4004.4	3991	4006.2	3991	4002.5	3991	4004.3
sigma post-distruption A3	-17592	-17551	-17592	-17552	-17592	-17559	-17592	-17544	-17592	-17551
sigma post-distruption A4	30967	30868	30967	30870	30967	30883	30967	30856	30967	30869
sigma post-distruption A5	-28529	-28476	-28529	-28478	-28529	-28490	-28529	-28465	-28529	-28477
sigma post-distruption A6	14495	14498	14495	14499	14495	14505	14495	14492	14495	14499
sigma post-distruption A7	-3846.9	-3855.2	-3846.9	-3855.4	-3846.9	-3857.1	-3846.9	-3853.8	-3846.9	-3855.4
sigma post-distruption A8	416.69	418.16	416.69	418.18	416.69	418.35	416.69	418	416.69	418.18

Count	81		82		83		84		85	
Exp. NO	451		452		453		454		455	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.72114909	34.615	34.72114909	34.616	34.72114909	34.615	34.72114909	34.617	34.72114909	34.616
sigma post-distruption A0	44.814	47.443	44.814	47.458	44.814	47.444	44.814	47.456	44.814	47.447
sigma post-distruption A1	279.4	282.76	279.4	282.68	279.4	282.73	279.4	282.75	279.4	282.78
sigma post-distruption A2	3991	4000.4	3991	4005.7	3991	4003.4	3991	4002.4	3991	4000.7
sigma post-distruption A3	-17592	-17535	-17592	-17557	-17592	-17547	-17592	-17543	-17592	-17537
sigma post-distruption A4	30967	30841	30967	30880	30967	30863	30967	30855	30967	30844
sigma post-distruption A5	-28529	-28451	-28529	-28487	-28529	-28471	-28529	-28465	-28529	-28454
sigma post-distruption A6	14495	14486	14495	14503	14495	14496	14495	14492	14495	14487
sigma post-distruption A7	-3846.9	-3852	-3846.9	-3856.6	-3846.9	-3854.7	-3846.9	-3853.7	-3846.9	-3852.4
sigma post-distruption A8	416.69	417.81	416.69	418.31	416.69	418.1	416.69	418	416.69	417.85

Count	86		87		88		89		90	
Exp. NO	456		457		458		459		460	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.72114909	34.615	34.72114909	34.616	34.72114909	34.616	34.72114909	34.615	34.72114909	34.614
sigma post-distruption A0	44.814	47.451	44.814	47.457	44.814	47.456	44.814	47.44	44.814	47.441
sigma post-distruption A1	279.4	282.73	279.4	282.71	279.4	282.71	279.4	282.78	279.4	282.74
sigma post-distruption A2	3991	4002.5	3991	4003	3991	4003.5	3991	4000.4	3991	4001.1
sigma post-distruption A3	-17592	-17544	-17592	-17546	-17592	-17548	-17592	-17535	-17592	-17538
sigma post-distruption A4	30967	30856	30967	30859	30967	30863	30967	30841	30967	30846
sigma post-distruption A5	-28529	-28465	-28529	-28468	-28529	-28472	-28529	-28452	-28529	-28456
sigma post-distruption A6	14495	14493	14495	14494	14495	14496	14495	14486	14495	14488
sigma post-distruption A7	-3846.9	-3853.8	-3846.9	-3854.2	-3846.9	-3854.7	-3846.9	-3852.1	-3846.9	-3852.6
sigma post-distruption A8	416.69	418.01	416.69	418.04	416.69	418.1	416.69	417.83	416.69	417.88

Count	91		92		93		94		95	
Exp. NO	81		82		83		84		85	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
sigma pre-distruption	54.48581117	54.657	54.48581117	54.682	54.48581117	54.68	54.48581117	54.695	54.48581117	54.675
sigma post-distruption A0	57.73	56.782	57.73	56.934	57.73	56.923	57.73	57.041	57.73	56.895
sigma post-distruption A1	1068.6	1087.7	1068.6	1085.5	1068.6	1085.5	1068.6	1083.9	1068.6	1086.2
sigma post-distruption A2	-747.63	-494.5	-747.63	-477.88	-747.63	-480.83	-747.63	-466.04	-747.63	-484.33
sigma post-distruption A3	-5032.3	-5254.1	-5032.3	-5311.3	-5032.3	-5298.7	-5032.3	-5350.9	-5032.3	-5288.1
sigma post-distruption A4	13794	13216	13794	13313	13794	13291	13794	13379	13794	13273
sigma post-distruption A5	-15282	-14326	-15282	-14413	-15282	-14393	-15282	-14472	-15282	-14377
sigma post-distruption A6	8624.3	8103.6	8624.3	8146.3	8624.3	8136	8624.3	8174.7	8624.3	8128.4
sigma post-distruption A7	-2445.1	-2332.5	-2445.1	-2343.1	-2445.1	-2340.4	-2445.1	-2350.1	-2445.1	-2338.6
sigma post-distruption A8	276.5	269.73	276.5	270.79	276.5	270.51	276.5	271.49	276.5	270.33

Count	96		97		98		99		100	
Exp. NO	461		462		463		464		465	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
sigma pre-distruption	54.48581117	54.677	54.48581117	54.68	54.48581117	54.671	54.48581117	54.679	54.48581117	54.685
sigma post-distruption A0	57.73	56.904	57.73	56.935	57.73	56.874	57.73	56.948	57.73	56.967
sigma post-distruption A1	1068.6	1086.1	1068.6	1085.8	1068.6	1086.4	1068.6	1085	1068.6	1085
sigma post-distruption A2	-747.63	-482.8	-747.63	-481.05	-747.63	-488.17	-747.63	-478.66	-747.63	-473.89
sigma post-distruption A3	-5032.3	-5294	-5032.3	-5299.1	-5032.3	-5272.9	-5032.3	-5304.2	-5032.3	-5324.6
sigma post-distruption A4	13794	13283	13794	13291	13794	13247	13794	13299	13794	13335
sigma post-distruption A5	-15282	-14387	-15282	-14393	-15282	-14353	-15282	-14399	-15282	-14433
sigma post-distruption A6	8624.3	8133.1	8624.3	8136.1	8624.3	8116.3	8624.3	8138.7	8624.3	8155.7
sigma post-distruption A7	-2445.1	-2339.8	-2445.1	-2340.4	-2445.1	-2335.4	-2445.1	-2341	-2445.1	-2345.4
sigma post-distruption A8	276.5	270.45	276.5	270.51	276.5	270	276.5	270.55	276.5	271.02

Count	101		102		103		104		105	
Exp. NO	466		467		468		469		470	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
sigma pre-distruption	54.48581117	54.678	54.48581117	54.657	54.48581117	54.69	54.48581117	54.66	54.48581117	54.675
sigma post-distruption A0	57.73	56.902	57.73	56.779	57.73	56.904	57.73	56.814	57.73	56.897
sigma post-distruption A1	1068.6	1086.2	1068.6	1087.7	1068.6	1086	1068.6	1087.2	1068.6	1085.9
sigma post-distruption A2	-747.63	-481.58	-747.63	-495.46	-747.63	-484.95	-747.63	-492.42	-747.63	-483.38
sigma post-distruption A3	-5032.3	-5299.8	-5032.3	-5250.2	-5032.3	-5285.5	-5032.3	-5259.6	-5032.3	-5289.9
sigma post-distruption A4	13794	13294	13794	13209	13794	13270	13794	13224	13794	13276
sigma post-distruption A5	-15282	-14397	-15282	-14320	-15282	-14376	-15282	-14333	-15282	-14379
sigma post-distruption A6	8624.3	8138.2	8624.3	8100.6	8624.3	8128.1	8624.3	8106.8	8624.3	8129.2
sigma post-distruption A7	-2445.1	-2341.1	-2445.1	-2331.7	-2445.1	-2338.5	-2445.1	-2333.2	-2445.1	-2338.7
sigma post-distruption A8	276.5	270.6	276.5	269.65	276.5	270.32	276.5	269.79	276.5	270.34

Count	106		107		108		109		110	
Exp. NO	86		87		88		89		90	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
sigma pre-distruption	54.36520858	54.496	54.36520858	54.444	54.36520858	54.526	54.36520858	54.441	54.36520858	54.387
sigma post-distruption A0	231.07	229.81	231.07	229.64	231.07	229.93	231.07	229.64	231.07	229.21
sigma post-distruption A1	223.22	227.88	223.22	226.59	223.22	228.55	223.22	226.2	223.22	226.9
sigma post-distruption A2	-1470.1	-1428	-1470.1	-1416.1	-1470.1	-1434.8	-1470.1	-1413	-1470.1	-1407.4
sigma post-distruption A3	6627.4	6587.6	6627.4	6548	6627.4	6611.4	6627.4	6537.3	6627.4	6508.1
sigma post-distruption A4	-14444	-14576	-14444	-14511	-14444	-14616	-14444	-14493	-14444	-14435
sigma post-distruption A5	16212	16452	16212	16393	16212	16489	16212	16377	16212	16317
sigma post-distruption A6	-9720.9	-9867.9	-9720.9	-9838.1	-9720.9	-9886.8	-9720.9	-9830.2	-9720.9	-9796
sigma post-distruption A7	2965.8	3002.9	2965.8	2995	2965.8	3008	2965.8	2993	2965.8	2982.9
sigma post-distruption A8	-361.94	-364.97	-361.94	-364.1	-361.94	-365.53	-361.94	-363.89	-361.94	-362.69

Count	111		112		113		114		115	
Exp. NO	471		472		473		474		475	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
sigma pre-distruption	54.36520858	54.454	54.36520858	54.381	54.36520858	54.405	54.36520858	54.33	54.36520858	54.461
sigma post-distruption A0	231.07	229.72	231.07	228.9	231.07	229.03	231.07	228.83	231.07	229.87
sigma post-distruption A1	223.22	226.39	223.22	228.63	223.22	228.94	223.22	226.63	223.22	225.27
sigma post-distruption A2	-1470.1	-1416.1	-1470.1	-1409.3	-1470.1	-1414.3	-1470.1	-1395.1	-1470.1	-1412.2
sigma post-distruption A3	6627.4	6549.5	6627.4	6501.5	6627.4	6520.5	6627.4	6457.7	6627.4	6541.2
sigma post-distruption A4	-14444	-14515	-14444	-14412	-14444	-14445	-14444	-14343	-14444	-14505
sigma post-distruption A5	16212	16398	16212	16287	16212	16319	16212	16228	16212	16393
sigma post-distruption A6	-9720.9	-9841	-9720.9	-9776.9	-9720.9	-9793.5	-9720.9	-9748.2	-9720.9	-9840.8
sigma post-distruption A7	2965.8	2996	2965.8	2976.8	2965.8	2981.4	2965.8	2969.5	2965.8	2996.5
sigma post-distruption A8	-361.94	-364.23	-361.94	-361.92	-361.94	-362.44	-361.94	-361.16	-361.94	-364.34

Count	116		117		118		119		120	
Exp. NO	476		477		478		479		480	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
sigma pre-distruption	54.36520858	54.411	54.36520858	54.513	54.36520858	54.443	54.36520858	54.446	54.36520858	54.412
sigma post-distruption A0	231.07	229.5	231.07	230.1	231.07	229.19	231.07	229.57	231.07	229.26
sigma post-distruption A1	223.22	226.05	223.22	225.72	223.22	229.49	223.22	226.94	223.22	227.83
sigma post-distruption A2	-1470.1	-1409.5	-1470.1	-1417.4	-1470.1	-1421	-1470.1	-1415.7	-1470.1	-1414.4
sigma post-distruption A3	6627.4	6524.3	6627.4	6558.8	6627.4	6544.3	6627.4	6542.8	6627.4	6530.4
sigma post-distruption A4	-14444	-14470	-14444	-14534	-14444	-14486	-14444	-14499	-14444	-14471
sigma post-distruption A5	16212	16355	16212	16420	16212	16357	16212	16379	16212	16348
sigma post-distruption A6	-9720.9	-9818.4	-9720.9	-9855.5	-9720.9	-9813.3	-9720.9	-9830.2	-9720.9	-9811.3
sigma post-distruption A7	2965.8	2989.6	2965.8	3000.7	2965.8	2986.9	2965.8	2992.7	2965.8	2986.8
sigma post-distruption A8	-361.94	-363.5	-361.94	-364.84	-361.94	-363.05	-361.94	-363.83	-361.94	-363.1

C.8 Output Vectors for *Net_2_2_1*

Count	1		2		3		4		5	
Exp. NO	41		42		43		44		45	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.549860918	0.54804	0.549860918	0.54799	0.549860918	0.54804	0.549860918	0.54811	0.549860918	0.54804
M6 Utilization after the disruptive event	0.277092867	0.25509	0.277092867	0.25559	0.277092867	0.25503	0.277092867	0.25448	0.277092867	0.25503
M2 Utilization after the disruptive event	0.677818611	0.68043	0.677818611	0.68021	0.677818611	0.68043	0.677818611	0.6807	0.677818611	0.68039
M5 Utilization after the disruptive event	0.560617624	0.56579	0.560617624	0.56535	0.560617624	0.56579	0.560617624	0.56632	0.560617624	0.5657
M3 Utilization after the disruptive event	0.817353798	0.81879	0.817353798	0.81892	0.817353798	0.81887	0.817353798	0.81865	0.817353798	0.81905
M7 Utilization after the disruptive event	0.06463676	0.063605	0.06463676	0.06327	0.06463676	0.063492	0.06463676	0.063991	0.06463676	0.063178
M9 Utilization after the disruptive event	0.750875829	0.74724	0.750875829	0.74718	0.750875829	0.74724	0.750875829	0.74732	0.750875829	0.74721
M12 Utilization after the disruptive event	0.626440027	0.61866	0.626440027	0.61858	0.626440027	0.61863	0.626440027	0.61874	0.626440027	0.61857
AGV Utilization after the disruptive event	0.891270772	0.88578	0.891270772	0.88579	0.891270772	0.8858	0.891270772	0.88578	0.891270772	0.88584
Fixture Utilization after the disruptive event	0.942661103	0.9426	0.942661103	0.94252	0.942661103	0.94264	0.942661103	0.9427	0.942661103	0.9427

Count	6		7		8		9		10	
Exp. NO	481		482		483		484		485	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.549860918	0.54801	0.549860918	0.54805	0.549860918	0.5481	0.549860918	0.54799	0.549860918	0.54801
M6 Utilization after the disruptive event	0.277092867	0.25529	0.277092867	0.25499	0.277092867	0.25456	0.277092867	0.25559	0.277092867	0.25532
M2 Utilization after the disruptive event	0.677818611	0.68028	0.677818611	0.68045	0.677818611	0.68065	0.677818611	0.68023	0.677818611	0.6803
M5 Utilization after the disruptive event	0.560617624	0.5655	0.560617624	0.56582	0.560617624	0.56623	0.560617624	0.5654	0.560617624	0.56553
M3 Utilization after the disruptive event	0.817353798	0.81907	0.817353798	0.81887	0.817353798	0.81871	0.817353798	0.81884	0.817353798	0.81895
M7 Utilization after the disruptive event	0.06463676	0.063086	0.06463676	0.063495	0.06463676	0.063877	0.06463676	0.063408	0.06463676	0.063279
M9 Utilization after the disruptive event	0.750875829	0.74718	0.750875829	0.74724	0.750875829	0.7473	0.750875829	0.7472	0.750875829	0.7472
M12 Utilization after the disruptive event	0.626440027	0.61855	0.626440027	0.61863	0.626440027	0.61872	0.626440027	0.61861	0.626440027	0.61859
AGV Utilization after the disruptive event	0.891270772	0.88583	0.891270772	0.8858	0.891270772	0.88579	0.891270772	0.88577	0.891270772	0.88581
Fixture Utilization after the disruptive event	0.942661103	0.94264	0.942661103	0.94265	0.942661103	0.9427	0.942661103	0.94249	0.942661103	0.94259

Count	11		12		13		14		15	
Exp. NO	486		487		488		489		490	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.549860918	0.54802	0.549860918	0.54808	0.549860918	0.54805	0.549860918	0.54802	0.549860918	0.54805
M6 Utilization after the disruptive event	0.277092867	0.2553	0.277092867	0.25466	0.277092867	0.255	0.277092867	0.25527	0.277092867	0.25495
M2 Utilization after the disruptive event	0.677818611	0.68032	0.677818611	0.68056	0.677818611	0.68044	0.677818611	0.68032	0.677818611	0.68047
M5 Utilization after the disruptive event	0.560617624	0.56557	0.560617624	0.56604	0.560617624	0.56581	0.560617624	0.56557	0.560617624	0.56587
M3 Utilization after the disruptive event	0.817353798	0.81891	0.817353798	0.81893	0.817353798	0.81888	0.817353798	0.81896	0.817353798	0.81884
M7 Utilization after the disruptive event	0.06463676	0.063343	0.06463676	0.06348	0.06463676	0.063474	0.06463676	0.06327	0.06463676	0.063561
M9 Utilization after the disruptive event	0.750875829	0.74721	0.750875829	0.74726	0.750875829	0.74724	0.750875829	0.7472	0.750875829	0.74725
M12 Utilization after the disruptive event	0.626440027	0.6186	0.626440027	0.61863	0.626440027	0.61863	0.626440027	0.61859	0.626440027	0.61865
AGV Utilization after the disruptive event	0.891270772	0.8858	0.891270772	0.88583	0.891270772	0.88581	0.891270772	0.88581	0.891270772	0.8858
Fixture Utilization after the disruptive event	0.942661103	0.94259	0.942661103	0.94275	0.942661103	0.94265	0.942661103	0.94261	0.942661103	0.94265

Count	16		17		18		19		20	
Exp. NO	176		177		178		179		180	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.541804321	0.54437	0.541804321	0.54431	0.541804321	0.54435	0.541804321	0.54431	0.541804321	0.54432
M6 Utilization after the disruptive event	0.268018709	0.29693	0.268018709	0.29749	0.268018709	0.29701	0.268018709	0.29751	0.268018709	0.29737
M2 Utilization after the disruptive event	0.668755722	0.66603	0.668755722	0.66581	0.668755722	0.66597	0.668755722	0.66581	0.668755722	0.66585
M5 Utilization after the disruptive event	0.543489214	0.53819	0.543489214	0.53774	0.543489214	0.53806	0.543489214	0.53776	0.543489214	0.53783
M3 Utilization after the disruptive event	0.816671732	0.81251	0.816671732	0.81257	0.816671732	0.81265	0.816671732	0.81251	0.816671732	0.81257
M7 Utilization after the disruptive event	0.058882379	0.064242	0.058882379	0.063997	0.058882379	0.063982	0.058882379	0.064092	0.058882379	0.064033
M9 Utilization after the disruptive event	0.739801734	0.74505	0.739801734	0.74499	0.739801734	0.74502	0.739801734	0.745	0.739801734	0.745
M12 Utilization after the disruptive event	0.607182984	0.61836	0.607182984	0.6183	0.607182984	0.6183	0.607182984	0.61832	0.607182984	0.61831
AGV Utilization after the disruptive event	0.875899882	0.88278	0.875899882	0.88277	0.875899882	0.88281	0.875899882	0.88276	0.875899882	0.88278
Fixture Utilization after the disruptive event	0.930486157	0.92985	0.930486157	0.92973	0.930486157	0.92988	0.930486157	0.92971	0.930486157	0.92976

Count	21		22		23		24		25	
Exp. NO	491		492		493		494		495	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.541804321	0.54434	0.541804321	0.54428	0.541804321	0.54431	0.541804321	0.5443	0.541804321	0.54434
M6 Utilization after the disruptive event	0.268018709	0.29698	0.268018709	0.29773	0.268018709	0.29743	0.268018709	0.29757	0.268018709	0.29713
M2 Utilization after the disruptive event	0.668755722	0.66591	0.668755722	0.66567	0.668755722	0.66581	0.668755722	0.66573	0.668755722	0.6659
M5 Utilization after the disruptive event	0.543489214	0.53792	0.543489214	0.53746	0.543489214	0.53775	0.543489214	0.5376	0.543489214	0.53792
M3 Utilization after the disruptive event	0.816671732	0.81293	0.816671732	0.81274	0.816671732	0.81263	0.816671732	0.81272	0.816671732	0.81273
M7 Utilization after the disruptive event	0.058882379	0.063504	0.058882379	0.063644	0.058882379	0.063911	0.058882379	0.06372	0.058882379	0.063812
M9 Utilization after the disruptive event	0.739801734	0.74497	0.739801734	0.74495	0.739801734	0.74499	0.739801734	0.74496	0.739801734	0.745
M12 Utilization after the disruptive event	0.607182984	0.61821	0.607182984	0.61823	0.607182984	0.61829	0.607182984	0.61825	0.607182984	0.61827
AGV Utilization after the disruptive event	0.875899882	0.88287	0.875899882	0.8828	0.875899882	0.88279	0.875899882	0.8828	0.875899882	0.88282
Fixture Utilization after the disruptive event	0.930486157	0.92999	0.930486157	0.92973	0.930486157	0.92977	0.930486157	0.92976	0.930486157	0.92988

Count	26		27		28		29		30	
Exp. NO	496		497		498		499		500	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.541804321	0.5443	0.541804321	0.54433	0.541804321	0.54433	0.541804321	0.54432	0.541804321	0.54435
M6 Utilization after the disruptive event	0.268018709	0.29756	0.268018709	0.29734	0.268018709	0.29713	0.268018709	0.29733	0.268018709	0.29695
M2 Utilization after the disruptive event	0.668755722	0.66575	0.668755722	0.66588	0.668755722	0.66583	0.668755722	0.66584	0.668755722	0.66594
M5 Utilization after the disruptive event	0.543489214	0.53764	0.543489214	0.5379	0.543489214	0.53778	0.543489214	0.53781	0.543489214	0.53798
M3 Utilization after the disruptive event	0.816671732	0.81265	0.816671732	0.81248	0.816671732	0.81299	0.816671732	0.81266	0.816671732	0.81286
M7 Utilization after the disruptive event	0.058882379	0.063837	0.058882379	0.064186	0.058882379	0.06337	0.058882379	0.063885	0.058882379	0.063636
M9 Utilization after the disruptive event	0.739801734	0.74497	0.739801734	0.74502	0.739801734	0.74495	0.739801734	0.74499	0.739801734	0.74499
M12 Utilization after the disruptive event	0.607182984	0.61827	0.607182984	0.61834	0.607182984	0.61818	0.607182984	0.61828	0.607182984	0.61823
AGV Utilization after the disruptive event	0.875899882	0.88279	0.875899882	0.88276	0.875899882	0.88287	0.875899882	0.8828	0.875899882	0.88285
Fixture Utilization after the disruptive event	0.930486157	0.92974	0.930486157	0.92974	0.930486157	0.92997	0.930486157	0.9298	0.930486157	0.92997

Count	31		32		33		34		35	
Exp. NO	61		62		63		64		65	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.548951876	0.54837	0.548951876	0.54838	0.548951876	0.54838	0.548951876	0.54838	0.548951876	0.54838
M6 Utilization after the disruptive event	0.30893964	0.30096	0.30893964	0.30092	0.30893964	0.30094	0.30893964	0.3011	0.30893964	0.30101
M2 Utilization after the disruptive event	0.689521564	0.69046	0.689521564	0.69047	0.689521564	0.69047	0.689521564	0.69049	0.689521564	0.69048
M5 Utilization after the disruptive event	0.589411283	0.59123	0.589411283	0.59126	0.589411283	0.59126	0.589411283	0.59131	0.589411283	0.59128
M3 Utilization after the disruptive event	0.709573238	0.71073	0.709573238	0.71074	0.709573238	0.71071	0.709573238	0.71041	0.709573238	0.71058
M7 Utilization after the disruptive event	0.239517471	0.23816	0.239517471	0.23815	0.239517471	0.2382	0.239517471	0.23868	0.239517471	0.2384
M9 Utilization after the disruptive event	0.763057251	0.76178	0.763057251	0.76178	0.763057251	0.76178	0.763057251	0.76182	0.763057251	0.7618
M12 Utilization after the disruptive event	0.656462388	0.65366	0.656462388	0.65366	0.656462388	0.65367	0.656462388	0.65377	0.656462388	0.65371
AGV Utilization after the disruptive event	0.862804585	0.86114	0.862804585	0.86114	0.862804585	0.86114	0.862804585	0.86107	0.862804585	0.86111
Fixture Utilization after the disruptive event	0.893027154	0.8934	0.893027154	0.89342	0.893027154	0.8934	0.893027154	0.89326	0.893027154	0.89334

Count	36		37		38		39		40	
Exp. NO	241		242		243		244		245	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.548951876	0.54839	0.548951876	0.54839	0.548951876	0.54837	0.548951876	0.54837	0.548951876	0.54837
M6 Utilization after the disruptive event	0.30893964	0.3011	0.30893964	0.30095	0.30893964	0.3011	0.30893964	0.30111	0.30893964	0.30105
M2 Utilization after the disruptive event	0.689521564	0.69056	0.689521564	0.69055	0.689521564	0.69047	0.689521564	0.69044	0.689521564	0.69047
M5 Utilization after the disruptive event	0.589411283	0.59145	0.589411283	0.59142	0.589411283	0.59127	0.589411283	0.5912	0.589411283	0.59125
M3 Utilization after the disruptive event	0.709573238	0.71015	0.709573238	0.71041	0.709573238	0.71048	0.709573238	0.71059	0.709573238	0.71057
M7 Utilization after the disruptive event	0.239517471	0.23913	0.239517471	0.23871	0.239517471	0.23856	0.239517471	0.23837	0.239517471	0.23841
M9 Utilization after the disruptive event	0.763057251	0.76187	0.763057251	0.76183	0.763057251	0.76181	0.763057251	0.76179	0.763057251	0.7618
M12 Utilization after the disruptive event	0.656462388	0.65386	0.656462388	0.65378	0.656462388	0.65374	0.656462388	0.6537	0.656462388	0.65371
AGV Utilization after the disruptive event	0.862804585	0.86101	0.862804585	0.86107	0.862804585	0.86108	0.862804585	0.86111	0.862804585	0.8611
Fixture Utilization after the disruptive event	0.893027154	0.89316	0.893027154	0.89329	0.893027154	0.89328	0.893027154	0.89332	0.893027154	0.89332

Count	41		42		43		44		45	
Exp. NO	246		247		248		249		250	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.548951876	0.54837	0.548951876	0.54838	0.548951876	0.54838	0.548951876	0.54839	0.548951876	0.54839
M6 Utilization after the disruptive event	0.30893964	0.30111	0.30893964	0.30101	0.30893964	0.30102	0.30893964	0.30076	0.30893964	0.30094
M2 Utilization after the disruptive event	0.689521564	0.69045	0.689521564	0.69052	0.689521564	0.6905	0.689521564	0.69054	0.689521564	0.69054
M5 Utilization after the disruptive event	0.589411283	0.59122	0.589411283	0.59136	0.589411283	0.59133	0.589411283	0.59139	0.589411283	0.5914
M3 Utilization after the disruptive event	0.709573238	0.71056	0.709573238	0.71044	0.709573238	0.71048	0.709573238	0.71073	0.709573238	0.71047
M7 Utilization after the disruptive event	0.239517471	0.23842	0.239517471	0.23866	0.239517471	0.23858	0.239517471	0.23821	0.239517471	0.23862
M9 Utilization after the disruptive event	0.763057251	0.7618	0.763057251	0.76183	0.763057251	0.76182	0.763057251	0.7618	0.763057251	0.76183
M12 Utilization after the disruptive event	0.656462388	0.65372	0.656462388	0.65376	0.656462388	0.65375	0.656462388	0.65368	0.656462388	0.65376
AGV Utilization after the disruptive event	0.862804585	0.8611	0.862804585	0.86108	0.862804585	0.86108	0.862804585	0.86115	0.862804585	0.86109
Fixture Utilization after the disruptive event	0.893027154	0.8933	0.893027154	0.89329	0.893027154	0.8933	0.893027154	0.89345	0.893027154	0.89332

Count	46		47		48		49		50	
Exp. NO	71		72		73		74		75	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.575376028	0.57565	0.575376028	0.57567	0.575376028	0.57565	0.575376028	0.57565	0.575376028	0.57565
M6 Utilization after the disruptive event	0.046176337	0.051136	0.046176337	0.050895	0.046176337	0.051188	0.046176337	0.051124	0.046176337	0.051095
M2 Utilization after the disruptive event	0.808724444	0.80797	0.808724444	0.80801	0.808724444	0.80798	0.808724444	0.80796	0.808724444	0.80795
M5 Utilization after the disruptive event	0.82561415	0.82413	0.82561415	0.82421	0.82561415	0.82415	0.82561415	0.82412	0.82561415	0.82408
M3 Utilization after the disruptive event	0.624935715	0.62461	0.624935715	0.6248	0.624935715	0.6245	0.624935715	0.62465	0.624935715	0.62475
M7 Utilization after the disruptive event	0.446730926	0.44684	0.446730926	0.44657	0.446730926	0.44702	0.446730926	0.44677	0.446730926	0.44661
M9 Utilization after the disruptive event	0.79496267	0.7956	0.79496267	0.79559	0.79496267	0.79562	0.79496267	0.7956	0.79496267	0.79558
M12 Utilization after the disruptive event	0.697180888	0.69863	0.697180888	0.69857	0.697180888	0.69866	0.697180888	0.69861	0.697180888	0.69858
AGV Utilization after the disruptive event	0.851943099	0.85297	0.851943099	0.85302	0.851943099	0.85295	0.851943099	0.85298	0.851943099	0.853
Fixture Utilization after the disruptive event	0.926695924	0.92646	0.926695924	0.92659	0.926695924	0.92641	0.926695924	0.92648	0.926695924	0.92652

Count	51		52		53		54		55	
Exp. NO	321		322		323		324		325	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.575376028	0.57564	0.575376028	0.57565	0.575376028	0.57564	0.575376028	0.57564	0.575376028	0.57566
M6 Utilization after the disruptive event	0.046176337	0.051108	0.046176337	0.051152	0.046176337	0.05124	0.046176337	0.051169	0.046176337	0.051088
M2 Utilization after the disruptive event	0.808724444	0.80791	0.808724444	0.80796	0.808724444	0.80789	0.808724444	0.80792	0.808724444	0.80801
M5 Utilization after the disruptive event	0.82561415	0.824	0.82561415	0.82412	0.82561415	0.82397	0.82561415	0.82403	0.82561415	0.82422
M3 Utilization after the disruptive event	0.624935715	0.62489	0.624935715	0.62462	0.624935715	0.62476	0.624935715	0.62475	0.624935715	0.62452
M7 Utilization after the disruptive event	0.446730926	0.44637	0.446730926	0.44683	0.446730926	0.44657	0.446730926	0.4466	0.446730926	0.44701
M9 Utilization after the disruptive event	0.79496267	0.79556	0.79496267	0.7956	0.79496267	0.79557	0.79496267	0.79558	0.79496267	0.79562
M12 Utilization after the disruptive event	0.697180888	0.69853	0.697180888	0.69862	0.697180888	0.69857	0.697180888	0.69858	0.697180888	0.69866
AGV Utilization after the disruptive event	0.851943099	0.85303	0.851943099	0.85297	0.851943099	0.853	0.851943099	0.853	0.851943099	0.85295
Fixture Utilization after the disruptive event	0.926695924	0.92657	0.926695924	0.92646	0.926695924	0.92649	0.926695924	0.9265	0.926695924	0.92644

Count	56		57		58		59		60	
Exp. NO	326		327		328		329		330	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.575376028	0.57565	0.575376028	0.57566	0.575376028	0.57564	0.575376028	0.57566	0.575376028	0.57565
M6 Utilization after the disruptive event	0.046176337	0.051023	0.046176337	0.050996	0.046176337	0.051071	0.046176337	0.051058	0.046176337	0.051032
M2 Utilization after the disruptive event	0.808724444	0.80793	0.808724444	0.80797	0.808724444	0.8079	0.808724444	0.80798	0.808724444	0.80796
M5 Utilization after the disruptive event	0.82561415	0.82403	0.82561415	0.82411	0.82561415	0.82398	0.82561415	0.82415	0.82561415	0.82409
M3 Utilization after the disruptive event	0.624935715	0.62495	0.624935715	0.62483	0.624935715	0.62498	0.624935715	0.62469	0.624935715	0.62482
M7 Utilization after the disruptive event	0.446730926	0.44628	0.446730926	0.4465	0.446730926	0.44623	0.446730926	0.44673	0.446730926	0.44651
M9 Utilization after the disruptive event	0.79496267	0.79555	0.79496267	0.79558	0.79496267	0.79555	0.79496267	0.79559	0.79496267	0.79557
M12 Utilization after the disruptive event	0.697180888	0.69851	0.697180888	0.69856	0.697180888	0.6985	0.697180888	0.6986	0.697180888	0.69856
AGV Utilization after the disruptive event	0.851943099	0.85305	0.851943099	0.85302	0.851943099	0.85305	0.851943099	0.85299	0.851943099	0.85302
Fixture Utilization after the disruptive event	0.926695924	0.92661	0.926695924	0.92658	0.926695924	0.92661	0.926695924	0.92651	0.926695924	0.92656

C.9 Output Vectors for *Net_2_2_2*

Count	1		2		3		4		5	
Exp. NO	41		42		43		44		45	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	112	116.49	112	117.05	112	116.81	112	116.83	112	116.35
A0 (non-linear trend mu)	135.61	130.22	135.61	130.2	135.61	130.17	135.61	130.2	135.61	130.18
A1 (non-linear trend mu)	464.63	481.22	464.63	480.87	464.63	481.27	464.63	481.04	464.63	481.59
A2 (non-linear trend mu)	269.21	237.53	269.21	237.57	269.21	237.78	269.21	237.58	269.21	237.78
A3 (non-linear trend mu)	-68.44	-64.783	-68.44	-64.816	-68.44	-64.867	-68.44	-64.812	-68.44	-64.847

Count	6		7		8		9		10	
Exp. NO	481		482		483		484		485	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	112	116.66	112	116.64	112	116.61	112	117.46	112	116.85
A0 (non-linear trend mu)	135.61	130.18	135.61	130.2	135.61	130.2	135.61	130.13	135.61	130.17
A1 (non-linear trend mu)	464.63	481.28	464.63	481.17	464.63	481.22	464.63	480.9	464.63	481.21
A2 (non-linear trend mu)	269.21	237.69	269.21	237.58	269.21	237.6	269.21	237.87	269.21	237.75
A3 (non-linear trend mu)	-68.44	-64.836	-68.44	-64.804	-68.44	-64.809	-68.44	-64.917	-68.44	-64.86

Count	11		12		13		14		15	
Exp. NO	486		487		488		489		490	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	112	116.93	112	116.61	112	116.46	112	116.93	112	116.99
A0 (non-linear trend mu)	135.61	130.14	135.61	130.17	135.61	130.19	135.61	130.19	135.61	130.14
A1 (non-linear trend mu)	464.63	481.3	464.63	481.42	464.63	481.41	464.63	481.03	464.63	481.25
A2 (non-linear trend mu)	269.21	237.89	269.21	237.79	269.21	237.68	269.21	237.64	269.21	237.88
A3 (non-linear trend mu)	-68.44	-64.9	-68.44	-64.86	-68.44	-64.824	-68.44	-64.831	-68.44	-64.902

Count	16		17		18		19		20	
Exp. NO	176		177		178		179		180	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	213	208.69	213	208.38	213	207.31	213	207.76	213	208.02
A0 (non-linear trend mu)	120.4	127.17	120.4	127.14	120.4	127.19	120.4	127.17	120.4	127.16
A1 (non-linear trend mu)	441.36	419.42	441.36	419.9	441.36	420.49	441.36	420.28	441.36	420.12
A2 (non-linear trend mu)	201.23	240.94	201.23	241.18	201.23	241.03	201.23	241.12	201.23	241.14
A3 (non-linear trend mu)	-64.83	-69.42	-64.83	-69.475	-64.83	-69.39	-64.83	-69.432	-64.83	-69.449

Count	21		22		23		24		25	
Exp. NO	491		492		493		494		495	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	213	207.09	213	207.86	213	208.01	213	207.96	213	207.37
A0 (non-linear trend mu)	120.4	127.21	120.4	127.15	120.4	127.16	120.4	127.18	120.4	127.18
A1 (non-linear trend mu)	441.36	420.56	441.36	420.29	441.36	420.13	441.36	420.04	441.36	420.51
A2 (non-linear trend mu)	201.23	240.94	201.23	241.21	201.23	241.15	201.23	241.03	201.23	241.08
A3 (non-linear trend mu)	-64.83	-69.356	-64.83	-69.461	-64.83	-69.449	-64.83	-69.415	-64.83	-69.407

Count	26		27		28		29		30	
Exp. NO	496		497		498		499		500	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	213	207.91	213	207.94	213	206.68	213	207.92	213	207.12
A0 (non-linear trend mu)	120.4	127.16	120.4	127.17	120.4	127.18	120.4	127.16	120.4	127.2
A1 (non-linear trend mu)	441.36	420.18	441.36	420.11	441.36	421.13	441.36	420.14	441.36	420.62
A2 (non-linear trend mu)	201.23	241.13	201.23	241.08	201.23	241.2	201.23	241.11	201.23	241.02
A3 (non-linear trend mu)	-64.83	-69.441	-64.83	-69.429	-64.83	-69.411	-64.83	-69.435	-64.83	-69.379

Count	31		32		33		34		35	
Exp. NO	61		62		63		64		65	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	377	378.74	377	378.75	377	378.92	377	379.08	377	378.55
A0 (non-linear trend mu)	162.09	159.67	162.09	159.75	162.09	159.6	162.09	159.57	162.09	159.65
A1 (non-linear trend mu)	57.698	65.386	57.698	64.847	57.698	65.67	57.698	65.712	57.698	65.673
A2 (non-linear trend mu)	36.271	21.943	36.271	21.448	36.271	22.335	36.271	22.477	36.271	22.091
A3 (non-linear trend mu)	-17.24	-15.553	-17.24	-15.417	-17.24	-15.669	-17.24	-15.715	-17.24	-15.587

Count	36		37		38		39		40	
Exp. NO	241		242		243		244		245	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	377	379.48	377	379.06	377	378.93	377	378.81	377	378.85
A0 (non-linear trend mu)	162.09	159.31	162.09	159.56	162.09	159.55	162.09	159.55	162.09	159.62
A1 (non-linear trend mu)	57.698	67.003	57.698	65.783	57.698	65.943	57.698	66.086	57.698	65.573
A2 (non-linear trend mu)	36.271	23.956	36.271	22.534	36.271	22.595	36.271	22.651	36.271	22.191
A3 (non-linear trend mu)	-17.24	-16.141	-17.24	-15.73	-17.24	-15.741	-17.24	-15.752	-17.24	-15.626

Count	41		42		43		44		45	
Exp. NO	246		247		248		249		250	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	377	378.76	377	379.21	377	379.15	377	378.78	377	379.16
A0 (non-linear trend mu)	162.09	159.59	162.09	159.55	162.09	159.59	162.09	159.7	162.09	159.6
A1 (non-linear trend mu)	57.698	65.867	57.698	65.709	57.698	65.499	57.698	65.129	57.698	65.441
A2 (non-linear trend mu)	36.271	22.408	36.271	22.563	36.271	22.323	36.271	21.733	36.271	22.277
A3 (non-linear trend mu)	-17.24	-15.683	-17.24	-15.744	-17.24	-15.675	-17.24	-15.497	-17.24	-15.662

Count	46		47		48		49		50	
Exp. NO	71		72		73		74		75	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	178	178.69	178	177.21	178	179.63	178	177.44	178	178.61
A0 (non-linear trend mu)	176.48	178.57	176.48	178.64	176.48	178.53	176.48	178.57	176.48	178.56
A1 (non-linear trend mu)	130.46	122.06	130.46	122.9	130.46	121.48	130.46	123.15	130.46	122.15
A2 (non-linear trend mu)	-70.55	-58.128	-70.55	-58.321	-70.55	-58.042	-70.55	-57.931	-70.55	-58.096
A3 (non-linear trend mu)	16.131	14.639	16.131	14.751	16.131	14.577	16.131	14.634	16.131	14.633

Count	51		52		53		54		55	
Exp. NO	321		322		323		324		325	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	178	177.23	178	178.74	178	177.57	178	177.78	178	177.94
A0 (non-linear trend mu)	176.48	178.59	176.48	178.56	176.48	178.56	176.48	178.57	176.48	178.58
A1 (non-linear trend mu)	130.46	123.22	130.46	122.06	130.46	123.09	130.46	122.81	130.46	122.63
A2 (non-linear trend mu)	-70.55	-58.006	-70.55	-58.092	-70.55	-57.898	-70.55	-58.022	-70.55	-58.09
A3 (non-linear trend mu)	16.131	14.664	16.131	14.627	16.131	14.62	16.131	14.646	16.131	14.658

Count	56		57		58		59		60	
Exp. NO	326		327		328		329		330	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	178	177.35	178	177.3	178	177.17	178	178.05	178	177.39
A0 (non-linear trend mu)	176.48	178.6	176.48	178.6	176.48	178.62	176.48	178.62	176.48	178.61
A1 (non-linear trend mu)	130.46	123.04	130.46	123.08	130.46	123.09	130.46	122.3	130.46	122.92
A2 (non-linear trend mu)	-70.55	-58.089	-70.55	-58.091	-70.55	-58.174	-70.55	-58.322	-70.55	-58.187
A3 (non-linear trend mu)	16.131	14.681	16.131	14.684	16.131	14.712	16.131	14.718	16.131	14.707

C.10 Output Vectors for *Net_2_2_3*

Count	1		2		3		4		5	
Exp. NO	41		42		43		44		45	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	36.368	36.374	36.368	36.374	36.368	36.373	36.368	36.373	36.368	36.374
sigma post-distruption A0	48.676	48.638	48.676	48.639	48.676	48.635	48.676	48.635	48.676	48.639
sigma post-distruption A1	361.06	366.91	361.06	366.83	361.06	366.95	361.06	366.93	361.06	366.79
sigma post-distruption A2	-252.7	-250.99	-252.7	-250.92	-252.7	-251.02	-252.7	-251.01	-252.7	-250.89
sigma post-distruption A3	68.11	66.917	68.11	66.9	68.11	66.925	68.11	66.921	68.11	66.891

Count	6		7		8		9		10	
Exp. NO	481		482		483		484		485	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	36.368	36.376	36.368	36.375	36.368	36.373	36.368	36.372	36.368	36.374
sigma post-distruption A0	48.676	48.647	48.676	48.642	48.676	48.637	48.676	48.632	48.676	48.64
sigma post-distruption A1	361.06	366.75	361.06	366.83	361.06	366.88	361.06	366.97	361.06	366.88
sigma post-distruption A2	-252.7	-250.84	-252.7	-250.92	-252.7	-250.96	-252.7	-251.05	-252.7	-250.96
sigma post-distruption A3	68.11	66.883	68.11	66.901	68.11	66.911	68.11	66.929	68.11	66.911

Count	11		12		13		14		15	
Exp. NO	486		487		488		489		490	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	36.368	36.374	36.368	36.374	36.368	36.373	36.368	36.374	36.368	36.372
sigma post-distruption A0	48.676	48.638	48.676	48.64	48.676	48.637	48.676	48.64	48.676	48.633
sigma post-distruption A1	361.06	366.9	361.06	366.92	361.06	366.88	361.06	366.76	361.06	366.98
sigma post-distruption A2	-252.7	-250.98	-252.7	-250.99	-252.7	-250.97	-252.7	-250.86	-252.7	-251.05
sigma post-distruption A3	68.11	66.915	68.11	66.92	68.11	66.911	68.11	66.885	68.11	66.932

Count	16		17		18		19		20	
Exp. NO	176		177		178		179		180	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.571	34.553	34.571	34.552	34.571	34.555	34.571	34.554	34.571	34.553
sigma post-distruption A0	40.83	40.918	40.83	40.916	40.83	40.927	40.83	40.923	40.83	40.919
sigma post-distruption A1	349.3	333.1	349.3	333.12	349.3	333.07	349.3	333.1	349.3	333.13
sigma post-distruption A2	-231.5	-235.74	-231.5	-235.76	-231.5	-235.71	-231.5	-235.73	-231.5	-235.77
sigma post-distruption A3	55.769	58.864	55.769	58.869	55.769	58.859	55.769	58.865	55.769	58.872

Count	21		22		23		24		25	
Exp. NO	491		492		493		494		495	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.571	34.557	34.571	34.555	34.571	34.554	34.571	34.555	34.571	34.554
sigma post-distruption A0	40.83	40.934	40.83	40.927	40.83	40.923	40.83	40.926	40.83	40.923
sigma post-distruption A1	349.3	332.92	349.3	332.95	349.3	333.09	349.3	333.04	349.3	333.13
sigma post-distruption A2	-231.5	-235.58	-231.5	-235.61	-231.5	-235.72	-231.5	-235.68	-231.5	-235.76
sigma post-distruption A3	55.769	58.829	55.769	58.833	55.769	58.862	55.769	58.852	55.769	58.871

Count	26		27		28		29		30	
Exp. NO	496		497		498		499		500	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.571	34.554	34.571	34.554	34.571	34.555	34.571	34.553	34.571	34.556
sigma post-distruption A0	40.83	40.923	40.83	40.922	40.83	40.926	40.83	40.92	40.83	40.93
sigma post-distruption A1	349.3	332.99	349.3	332.97	349.3	333.04	349.3	333.13	349.3	333
sigma post-distruption A2	-231.5	-235.65	-231.5	-235.63	-231.5	-235.68	-231.5	-235.77	-231.5	-235.64
sigma post-distruption A3	55.769	58.842	55.769	58.838	55.769	58.853	55.769	58.872	55.769	58.844

Count	31		32		33		34		35	
Exp. NO	61		62		63		64		65	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	35.667	35.653	35.667	35.652	35.667	35.651	35.667	35.651	35.667	35.651
sigma post-distruption A0	45.375	45.458	45.375	45.455	45.375	45.451	45.375	45.45	45.375	45.452
sigma post-distruption A1	47.287	33.426	47.287	33.522	47.287	33.532	47.287	33.448	47.287	33.445
sigma post-distruption A2	15.178	11.359	15.178	11.278	15.178	11.263	15.178	11.329	15.178	11.335
sigma post-distruption A3	-6.96	-4.2343	-6.96	-4.2143	-6.96	-4.2127	-6.96	-4.2307	-6.96	-4.2311

Count	36		37		38		39		40	
Exp. NO	241		242		243		244		245	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	35.667	35.645	35.667	35.649	35.667	35.65	35.667	35.65	35.667	35.652
sigma post-distruption A0	45.375	45.423	45.375	45.443	45.375	45.447	45.375	45.447	45.375	45.453
sigma post-distruption A1	47.287	33.538	47.287	33.517	47.287	33.493	47.287	33.517	47.287	33.439
sigma post-distruption A2	15.178	11.216	15.178	11.264	15.178	11.288	15.178	11.271	15.178	11.341
sigma post-distruption A3	-6.96	-4.2146	-6.96	-4.2167	-6.96	-4.2214	-6.96	-4.2164	-6.96	-4.2324

Count	41		42		43		44		45	
Exp. NO	246		247		248		249		250	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	35.667	35.651	35.667	35.648	35.667	35.65	35.667	35.649	35.667	35.649
sigma post-distruption A0	45.375	45.45	45.375	45.439	45.375	45.445	45.375	45.442	45.375	45.443
sigma post-distruption A1	47.287	33.391	47.287	33.577	47.287	33.51	47.287	33.546	47.287	33.51
sigma post-distruption A2	15.178	11.374	15.178	11.209	15.178	11.272	15.178	11.239	15.178	11.27
sigma post-distruption A3	-6.96	-4.2427	-6.96	-4.2045	-6.96	-4.2181	-6.96	-4.2108	-6.96	-4.2183

Count	46		47		48		49		50	
Exp. NO	71		72		73		74		75	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.724	34.753	34.724	34.755	34.724	34.753	34.724	34.753	34.724	34.753
sigma post-distruption A0	41.824	41.69	41.824	41.695	41.824	41.686	41.824	41.687	41.824	41.69
sigma post-distruption A1	108.83	134.22	108.83	134.28	108.83	134.46	108.83	134.22	108.83	134.23
sigma post-distruption A2	-81.83	-75.189	-81.83	-75.233	-81.83	-75.394	-81.83	-75.194	-81.83	-75.204
sigma post-distruption A3	21.577	16.734	21.577	16.748	21.577	16.786	21.577	16.734	21.577	16.738

Count	51		52		53		54		55	
Exp. NO	321		322		323		324		325	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.724	34.755	34.724	34.752	34.724	34.754	34.724	34.755	34.724	34.753
sigma post-distruption A0	41.824	41.695	41.824	41.683	41.824	41.694	41.824	41.696	41.824	41.689
sigma post-distruption A1	108.83	134.25	108.83	134.53	108.83	134.2	108.83	134.3	108.83	134.2
sigma post-distruption A2	-81.83	-75.211	-81.83	-75.453	-81.83	-75.17	-81.83	-75.25	-81.83	-75.176
sigma post-distruption A3	21.577	16.742	21.577	16.8	21.577	16.731	21.577	16.753	21.577	16.73

Count	56		57		58		59		60	
Exp. NO	326		327		328		329		330	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
sigma pre-distruption	34.724	34.754	34.724	34.754	34.724	34.757	34.724	34.755	34.724	34.756
sigma post-distruption A0	41.824	41.692	41.824	41.692	41.824	41.704	41.824	41.695	41.824	41.7
sigma post-distruption A1	108.83	135.12	108.83	134.18	108.83	133.62	108.83	134.08	108.83	133.96
sigma post-distruption A2	-81.83	-75.911	-81.83	-75.156	-81.83	-74.687	-81.83	-75.071	-81.83	-74.97
sigma post-distruption A3	21.577	16.926	21.577	16.726	21.577	16.608	21.577	16.705	21.577	16.681

C.11 Output Vectors for *Net_2_3_1*

Count	1		2		3		4		5	
Exp. NO	21		22		23		24		25	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.086	0.086101	0.086	0.086028	0.086	0.086074	0.086	0.08597	0.086	0.086051
M6 Utilization after the disruptive event	0.6858	0.68582	0.6858	0.68584	0.6858	0.68582	0.6858	0.68584	0.6858	0.68583
M2 Utilization after the disruptive event	0.7968	0.79744	0.7968	0.79744	0.7968	0.79745	0.7968	0.79745	0.7968	0.79744
M5 Utilization after the disruptive event	0.8038	0.80411	0.8038	0.80415	0.8038	0.80414	0.8038	0.80419	0.8038	0.80414
M3 Utilization after the disruptive event	0.6427	0.64266	0.6427	0.64267	0.6427	0.64265	0.6427	0.64266	0.6427	0.64267
M7 Utilization after the disruptive event	0.4528	0.45318	0.4528	0.4532	0.4528	0.45316	0.4528	0.45318	0.4528	0.45319
M9 Utilization after the disruptive event	0.7983	0.79839	0.7983	0.79838	0.7983	0.79839	0.7983	0.79838	0.7983	0.79838
M12 Utilization after the disruptive event	0.7006	0.70059	0.7006	0.70057	0.7006	0.70059	0.7006	0.70056	0.7006	0.70058
AGV Utilization after the disruptive event	0.7416	0.74162	0.7416	0.74166	0.7416	0.74164	0.7416	0.74168	0.7416	0.74164
Fixture Utilization after the disruptive event	0.863	0.86283	0.863	0.86286	0.863	0.86284	0.863	0.86289	0.863	0.86285

Count	6		7		8		9		10	
Exp. NO	281		282		283		284		285	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.086	0.086069	0.086	0.086104	0.086	0.086064	0.086	0.086025	0.086	0.08601
M6 Utilization after the disruptive event	0.6858	0.68581	0.6858	0.68581	0.6858	0.68583	0.6858	0.68581	0.6858	0.68582
M2 Utilization after the disruptive event	0.7968	0.79746	0.7968	0.79745	0.7968	0.79744	0.7968	0.79747	0.7968	0.79745
M5 Utilization after the disruptive event	0.8038	0.80415	0.8038	0.80412	0.8038	0.80413	0.8038	0.80419	0.8038	0.80418
M3 Utilization after the disruptive event	0.6427	0.64265	0.6427	0.64266	0.6427	0.64267	0.6427	0.64264	0.6427	0.64265
M7 Utilization after the disruptive event	0.4528	0.45315	0.4528	0.45317	0.4528	0.45319	0.4528	0.45314	0.4528	0.45316
M9 Utilization after the disruptive event	0.7983	0.79839	0.7983	0.79839	0.7983	0.79838	0.7983	0.79839	0.7983	0.79839
M12 Utilization after the disruptive event	0.7006	0.70059	0.7006	0.70059	0.7006	0.70058	0.7006	0.70058	0.7006	0.70057
AGV Utilization after the disruptive event	0.7416	0.74164	0.7416	0.74163	0.7416	0.74164	0.7416	0.74166	0.7416	0.74167
Fixture Utilization after the disruptive event	0.863	0.86284	0.863	0.86283	0.863	0.86284	0.863	0.86286	0.863	0.86287

Count	11		12		13		14		15	
Exp. NO	286		287		288		289		290	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.086	0.086079	0.086	0.086137	0.086	0.086036	0.086	0.086063	0.086	0.08609
M6 Utilization after the disruptive event	0.6858	0.68582	0.6858	0.6858	0.6858	0.68582	0.6858	0.68581	0.6858	0.68583
M2 Utilization after the disruptive event	0.7968	0.79745	0.7968	0.79746	0.7968	0.79745	0.7968	0.79746	0.7968	0.79744
M5 Utilization after the disruptive event	0.8038	0.80413	0.8038	0.80412	0.8038	0.80417	0.8038	0.80417	0.8038	0.80411
M3 Utilization after the disruptive event	0.6427	0.64266	0.6427	0.64264	0.6427	0.64265	0.6427	0.64264	0.6427	0.64267
M7 Utilization after the disruptive event	0.4528	0.45318	0.4528	0.45314	0.4528	0.45316	0.4528	0.45314	0.4528	0.45319
M9 Utilization after the disruptive event	0.7983	0.79839	0.7983	0.7984	0.7983	0.79839	0.7983	0.7984	0.7983	0.79839
M12 Utilization after the disruptive event	0.7006	0.70059	0.7006	0.7006	0.7006	0.70058	0.7006	0.70059	0.7006	0.70059
AGV Utilization after the disruptive event	0.7416	0.74164	0.7416	0.74162	0.7416	0.74166	0.7416	0.74165	0.7416	0.74163
Fixture Utilization after the disruptive event	0.863	0.86284	0.863	0.86281	0.863	0.86286	0.863	0.86284	0.863	0.86283

Count	16		17		18		19		20	
Exp. NO	6		7		8		9		10	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6266	0.6263	0.6266	0.62627	0.6266	0.62622	0.6266	0.62617	0.6266	0.62627
M6 Utilization after the disruptive event	0.0744	0.073296	0.0744	0.073281	0.0744	0.073313	0.0744	0.073354	0.0744	0.073295
M2 Utilization after the disruptive event	0.6028	0.60285	0.6028	0.60289	0.6028	0.60291	0.6028	0.60292	0.6028	0.60287
M5 Utilization after the disruptive event	0.7294	0.72784	0.7294	0.72784	0.7294	0.72784	0.7294	0.72783	0.7294	0.72784
M3 Utilization after the disruptive event	0.7787	0.77845	0.7787	0.77844	0.7787	0.77843	0.7787	0.77842	0.7787	0.77844
M7 Utilization after the disruptive event	0.7296	0.73041	0.7296	0.73038	0.7296	0.73034	0.7296	0.73032	0.7296	0.73038
M9 Utilization after the disruptive event	0.7333	0.73323	0.7333	0.73323	0.7333	0.73322	0.7333	0.73322	0.7333	0.73323
M12 Utilization after the disruptive event	0.6465	0.64661	0.6465	0.6466	0.6465	0.64659	0.6465	0.64658	0.6465	0.6466
AGV Utilization after the disruptive event	0.6606	0.66067	0.6606	0.66067	0.6606	0.66069	0.6606	0.66071	0.6606	0.66067
Fixture Utilization after the disruptive event	0.8229	0.82273	0.8229	0.82273	0.8229	0.82276	0.8229	0.82279	0.8229	0.82273

Count	21		22		23		24		25	
Exp. NO	301		302		303		304		305	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6266	0.62627	0.6266	0.62625	0.6266	0.62624	0.6266	0.62629	0.6266	0.62626
M6 Utilization after the disruptive event	0.0744	0.07334	0.0744	0.073319	0.0744	0.073318	0.0744	0.073259	0.0744	0.073328
M2 Utilization after the disruptive event	0.6028	0.60282	0.6028	0.60289	0.6028	0.60288	0.6028	0.60288	0.6028	0.60285
M5 Utilization after the disruptive event	0.7294	0.72784	0.7294	0.72784	0.7294	0.72784	0.7294	0.72784	0.7294	0.72784
M3 Utilization after the disruptive event	0.7787	0.77845	0.7787	0.77844	0.7787	0.77843	0.7787	0.77844	0.7787	0.77845
M7 Utilization after the disruptive event	0.7296	0.73041	0.7296	0.73038	0.7296	0.73036	0.7296	0.73039	0.7296	0.73039
M9 Utilization after the disruptive event	0.7333	0.73323	0.7333	0.73323	0.7333	0.73322	0.7333	0.73323	0.7333	0.73323
M12 Utilization after the disruptive event	0.6465	0.6466	0.6465	0.6466	0.6465	0.64659	0.6465	0.6466	0.6465	0.6466
AGV Utilization after the disruptive event	0.6606	0.66065	0.6606	0.66071	0.6606	0.66068	0.6606	0.66064	0.6606	0.66067
Fixture Utilization after the disruptive event	0.8229	0.82273	0.8229	0.82277	0.8229	0.82275	0.8229	0.82271	0.8229	0.82274

Count	26		27		28		29		30	
Exp. NO	306		307		308		309		310	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6266	0.62631	0.6266	0.62628	0.6266	0.62626	0.6266	0.62629	0.6266	0.6262
M6 Utilization after the disruptive event	0.0744	0.073258	0.0744	0.073295	0.0744	0.073254	0.0744	0.073315	0.0744	0.073322
M2 Utilization after the disruptive event	0.6028	0.60286	0.6028	0.60285	0.6028	0.60294	0.6028	0.60282	0.6028	0.60292
M5 Utilization after the disruptive event	0.7294	0.72784	0.7294	0.72784	0.7294	0.72785	0.7294	0.72784	0.7294	0.72784
M3 Utilization after the disruptive event	0.7787	0.77845	0.7787	0.77844	0.7787	0.77843	0.7787	0.77846	0.7787	0.77842
M7 Utilization after the disruptive event	0.7296	0.7304	0.7296	0.73039	0.7296	0.73035	0.7296	0.73042	0.7296	0.73033
M9 Utilization after the disruptive event	0.7333	0.73323	0.7333	0.73323	0.7333	0.73323	0.7333	0.73323	0.7333	0.73322
M12 Utilization after the disruptive event	0.6465	0.6466	0.6465	0.6466	0.6465	0.6466	0.6465	0.64661	0.6465	0.64659
AGV Utilization after the disruptive event	0.6606	0.66063	0.6606	0.66064	0.6606	0.66069	0.6606	0.66065	0.6606	0.66071
Fixture Utilization after the disruptive event	0.8229	0.8227	0.8229	0.82272	0.8229	0.82275	0.8229	0.82272	0.8229	0.82278

Count	31		32		33		34		35	
Exp. NO	11		12		13		14		15	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
M1 Utilization after the disruptive event	0.5843	0.58459	0.5843	0.58456	0.5843	0.58458	0.5843	0.58454	0.5843	0.58447
M6 Utilization after the disruptive event	0.3535	0.35468	0.3535	0.35466	0.3535	0.35467	0.3535	0.35466	0.3535	0.35465
M2 Utilization after the disruptive event	0.6852	0.68529	0.6852	0.68532	0.6852	0.6853	0.6852	0.68533	0.6852	0.68542
M5 Utilization after the disruptive event	0.5825	0.58235	0.5825	0.58239	0.5825	0.58236	0.5825	0.5824	0.5825	0.58252
M3 Utilization after the disruptive event	0.6747	0.67459	0.6747	0.67456	0.6747	0.67458	0.6747	0.67455	0.6747	0.67451
M7 Utilization after the disruptive event	0.4895	0.49026	0.4895	0.49019	0.4895	0.49023	0.4895	0.49015	0.4895	0.49001
M9 Utilization after the disruptive event	0.7951	0.79542	0.7951	0.79541	0.7951	0.79542	0.7951	0.79541	0.7951	0.7954
M12 Utilization after the disruptive event	0.6929	0.69271	0.6929	0.6927	0.6929	0.6927	0.6929	0.69269	0.6929	0.69267
AGV Utilization after the disruptive event	0.419	0.41874	0.419	0.41877	0.419	0.41875	0.419	0.41878	0.419	0.41887
Fixture Utilization after the disruptive event	0.6233	0.62325	0.6233	0.62322	0.6233	0.62323	0.6233	0.62321	0.6233	0.62321

Count	36		37		38		39		40	
Exp. NO	181		182		183		184		185	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
M1 Utilization after the disruptive event	0.5843	0.58455	0.5843	0.58458	0.5843	0.58458	0.5843	0.58453	0.5843	0.58454
M6 Utilization after the disruptive event	0.3535	0.35465	0.3535	0.35468	0.3535	0.35467	0.3535	0.35468	0.3535	0.35465
M2 Utilization after the disruptive event	0.6852	0.68533	0.6852	0.6853	0.6852	0.68531	0.6852	0.68535	0.6852	0.68534
M5 Utilization after the disruptive event	0.5825	0.58241	0.5825	0.58235	0.5825	0.58237	0.5825	0.58242	0.5825	0.58242
M3 Utilization after the disruptive event	0.6747	0.67456	0.6747	0.67459	0.6747	0.67459	0.6747	0.67456	0.6747	0.67455
M7 Utilization after the disruptive event	0.4895	0.49018	0.4895	0.49025	0.4895	0.49024	0.4895	0.49015	0.4895	0.49015
M9 Utilization after the disruptive event	0.7951	0.79542	0.7951	0.79541	0.7951	0.79542	0.7951	0.79541	0.7951	0.79541
M12 Utilization after the disruptive event	0.6929	0.6927	0.6929	0.6927	0.6929	0.69271	0.6929	0.69269	0.6929	0.69269
AGV Utilization after the disruptive event	0.419	0.41878	0.419	0.41874	0.419	0.41876	0.419	0.4188	0.419	0.41879
Fixture Utilization after the disruptive event	0.6233	0.62323	0.6233	0.62325	0.6233	0.62325	0.6233	0.62325	0.6233	0.62322

Count	41		42		43		44		45	
Exp. NO	186		187		188		189		190	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
M1 Utilization after the disruptive event	0.5843	0.58455	0.5843	0.58454	0.5843	0.58462	0.5843	0.58453	0.5843	0.58456
M6 Utilization after the disruptive event	0.3535	0.35467	0.3535	0.35467	0.3535	0.35467	0.3535	0.35466	0.3535	0.35465
M2 Utilization after the disruptive event	0.6852	0.68535	0.6852	0.68535	0.6852	0.68526	0.6852	0.68535	0.6852	0.68532
M5 Utilization after the disruptive event	0.5825	0.58242	0.5825	0.58241	0.5825	0.5823	0.5825	0.58244	0.5825	0.58239
M3 Utilization after the disruptive event	0.6747	0.67457	0.6747	0.67456	0.6747	0.67461	0.6747	0.67454	0.6747	0.67456
M7 Utilization after the disruptive event	0.4895	0.49018	0.4895	0.49017	0.4895	0.49033	0.4895	0.49012	0.4895	0.4902
M9 Utilization after the disruptive event	0.7951	0.79541	0.7951	0.79541	0.7951	0.79543	0.7951	0.79541	0.7951	0.79542
M12 Utilization after the disruptive event	0.6929	0.6927	0.6929	0.6927	0.6929	0.69272	0.6929	0.69269	0.6929	0.6927
AGV Utilization after the disruptive event	0.419	0.41879	0.419	0.41879	0.419	0.4187	0.419	0.41882	0.419	0.41876
Fixture Utilization after the disruptive event	0.6233	0.62325	0.6233	0.62324	0.6233	0.62325	0.6233	0.62321	0.6233	0.62322

Count	46		47		48		49		50	
Exp. NO	16		17		18		19		20	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
M1 Utilization after the disruptive event	0.0997	0.098201	0.0997	0.098134	0.0997	0.09815	0.0997	0.098141	0.0997	0.098196
M6 Utilization after the disruptive event	0.7414	0.74027	0.7414	0.74026	0.7414	0.74026	0.7414	0.74026	0.7414	0.74027
M2 Utilization after the disruptive event	0.5944	0.5925	0.5944	0.5926	0.5944	0.59258	0.5944	0.59259	0.5944	0.5925
M5 Utilization after the disruptive event	0.7107	0.70886	0.7107	0.70888	0.7107	0.70888	0.7107	0.70888	0.7107	0.70886
M3 Utilization after the disruptive event	0.781	0.78104	0.781	0.78097	0.781	0.78099	0.781	0.78098	0.781	0.78102
M7 Utilization after the disruptive event	0.7323	0.73251	0.7323	0.73238	0.7323	0.73242	0.7323	0.7324	0.7323	0.73248
M9 Utilization after the disruptive event	0.7359	0.73585	0.7359	0.73586	0.7359	0.73586	0.7359	0.73586	0.7359	0.73585
M12 Utilization after the disruptive event	0.6526	0.65266	0.6526	0.65265	0.6526	0.65266	0.6526	0.65265	0.6526	0.65265
AGV Utilization after the disruptive event	0.576	0.57588	0.576	0.57602	0.576	0.57597	0.576	0.57599	0.576	0.57588
Fixture Utilization after the disruptive event	0.7927	0.79276	0.7927	0.79286	0.7927	0.79284	0.7927	0.79285	0.7927	0.79276

Count	51		52		53		54		55	
Exp. NO	261		262		263		264		265	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
M1 Utilization after the disruptive event	0.0997	0.098113	0.0997	0.098129	0.0997	0.098102	0.0997	0.098178	0.0997	0.098143
M6 Utilization after the disruptive event	0.7414	0.74025	0.7414	0.74026	0.7414	0.74025	0.7414	0.74027	0.7414	0.74026
M2 Utilization after the disruptive event	0.5944	0.59263	0.5944	0.5926	0.5944	0.59265	0.5944	0.59253	0.5944	0.59258
M5 Utilization after the disruptive event	0.7107	0.70888	0.7107	0.70888	0.7107	0.70889	0.7107	0.70887	0.7107	0.70887
M3 Utilization after the disruptive event	0.781	0.78096	0.781	0.78097	0.781	0.78095	0.781	0.78101	0.781	0.78098
M7 Utilization after the disruptive event	0.7323	0.73235	0.7323	0.73238	0.7323	0.73233	0.7323	0.73245	0.7323	0.73239
M9 Utilization after the disruptive event	0.7359	0.73586	0.7359	0.73586	0.7359	0.73587	0.7359	0.73586	0.7359	0.73586
M12 Utilization after the disruptive event	0.6526	0.65265	0.6526	0.65265	0.6526	0.65265	0.6526	0.65266	0.6526	0.65265
AGV Utilization after the disruptive event	0.576	0.57605	0.576	0.57601	0.576	0.57608	0.576	0.57593	0.576	0.57599
Fixture Utilization after the disruptive event	0.7927	0.79288	0.7927	0.79285	0.7927	0.7929	0.7927	0.7928	0.7927	0.79284

Count	56		57		58		59		60	
Exp. NO	266		267		268		269		270	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
M1 Utilization after the disruptive event	0.0997	0.098127	0.0997	0.098146	0.0997	0.098104	0.0997	0.098177	0.0997	0.098151
M6 Utilization after the disruptive event	0.7414	0.74025	0.7414	0.74026	0.7414	0.74025	0.7414	0.74026	0.7414	0.74026
M2 Utilization after the disruptive event	0.5944	0.5926	0.5944	0.59257	0.5944	0.59264	0.5944	0.59253	0.5944	0.59257
M5 Utilization after the disruptive event	0.7107	0.70888	0.7107	0.70887	0.7107	0.70889	0.7107	0.70887	0.7107	0.70887
M3 Utilization after the disruptive event	0.781	0.78097	0.781	0.78098	0.781	0.78095	0.781	0.78101	0.781	0.78099
M7 Utilization after the disruptive event	0.7323	0.73237	0.7323	0.73239	0.7323	0.73234	0.7323	0.73246	0.7323	0.73241
M9 Utilization after the disruptive event	0.7359	0.73586	0.7359	0.73586	0.7359	0.73587	0.7359	0.73586	0.7359	0.73586
M12 Utilization after the disruptive event	0.6526	0.65265	0.6526	0.65265	0.6526	0.65265	0.6526	0.65266	0.6526	0.65265
AGV Utilization after the disruptive event	0.576	0.576	0.576	0.57599	0.576	0.57607	0.576	0.57592	0.576	0.57597
Fixture Utilization after the disruptive event	0.7927	0.79285	0.7927	0.79284	0.7927	0.79289	0.7927	0.79279	0.7927	0.79283

Count	61		62		63		64		65	
Exp. NO	31		32		33		34		35	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6084	0.61003	0.6084	0.61004	0.6084	0.61004	0.6084	0.61003	0.6084	0.61006
M6 Utilization after the disruptive event	0.5401	0.54246	0.5401	0.54249	0.5401	0.54246	0.5401	0.54238	0.5401	0.54248
M2 Utilization after the disruptive event	0.657	0.65919	0.657	0.65919	0.657	0.65917	0.657	0.65917	0.657	0.65915
M5 Utilization after the disruptive event	0.094	0.095586	0.094	0.095579	0.094	0.095618	0.094	0.095642	0.094	0.095632
M3 Utilization after the disruptive event	0.7153	0.71598	0.7153	0.71598	0.7153	0.71596	0.7153	0.71597	0.7153	0.71595
M7 Utilization after the disruptive event	0.6858	0.68586	0.6858	0.68586	0.6858	0.68584	0.6858	0.68583	0.6858	0.68582
M9 Utilization after the disruptive event	0.8011	0.80152	0.8011	0.80154	0.8011	0.80154	0.8011	0.80152	0.8011	0.80156
M12 Utilization after the disruptive event	0.6992	0.69874	0.6992	0.69876	0.6992	0.69876	0.6992	0.69873	0.6992	0.69878
AGV Utilization after the disruptive event	0.6473	0.64737	0.6473	0.64735	0.6473	0.64732	0.6473	0.64734	0.6473	0.64727
Fixture Utilization after the disruptive event	0.8014	0.80117	0.8014	0.80119	0.8014	0.80115	0.8014	0.80111	0.8014	0.80115

Count	66		67		68		69		70	
Exp. NO	401		402		403		404		405	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6084	0.61003	0.6084	0.61004	0.6084	0.61003	0.6084	0.61003	0.6084	0.61003
M6 Utilization after the disruptive event	0.5401	0.54245	0.5401	0.54245	0.5401	0.54241	0.5401	0.54243	0.5401	0.5424
M2 Utilization after the disruptive event	0.657	0.65919	0.657	0.65917	0.657	0.65918	0.657	0.65918	0.657	0.65918
M5 Utilization after the disruptive event	0.094	0.095592	0.094	0.09561	0.094	0.095617	0.094	0.09561	0.094	0.095612
M3 Utilization after the disruptive event	0.7153	0.71598	0.7153	0.71597	0.7153	0.71597	0.7153	0.71597	0.7153	0.71598
M7 Utilization after the disruptive event	0.6858	0.68586	0.6858	0.68584	0.6858	0.68584	0.6858	0.68585	0.6858	0.68585
M9 Utilization after the disruptive event	0.8011	0.80152	0.8011	0.80153	0.8011	0.80152	0.8011	0.80152	0.8011	0.80151
M12 Utilization after the disruptive event	0.6992	0.69874	0.6992	0.69875	0.6992	0.69873	0.6992	0.69874	0.6992	0.69873
AGV Utilization after the disruptive event	0.6473	0.64737	0.6473	0.64733	0.6473	0.64735	0.6473	0.64735	0.6473	0.64736
Fixture Utilization after the disruptive event	0.8014	0.80116	0.8014	0.80115	0.8014	0.80113	0.8014	0.80114	0.8014	0.80113

Count	71		72		73		74		75	
Exp. NO	406		407		408		409		410	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6084	0.61003	0.6084	0.61004	0.6084	0.61005	0.6084	0.61004	0.6084	0.61005
M6 Utilization after the disruptive event	0.5401	0.54244	0.5401	0.54246	0.5401	0.54249	0.5401	0.54247	0.5401	0.54249
M2 Utilization after the disruptive event	0.657	0.65918	0.657	0.65916	0.657	0.65916	0.657	0.65917	0.657	0.65916
M5 Utilization after the disruptive event	0.094	0.0956	0.094	0.095624	0.094	0.095613	0.094	0.095609	0.094	0.09562
M3 Utilization after the disruptive event	0.7153	0.71598	0.7153	0.71596	0.7153	0.71596	0.7153	0.71597	0.7153	0.71595
M7 Utilization after the disruptive event	0.6858	0.68585	0.6858	0.68584	0.6858	0.68584	0.6858	0.68584	0.6858	0.68583
M9 Utilization after the disruptive event	0.8011	0.80152	0.8011	0.80154	0.8011	0.80155	0.8011	0.80154	0.8011	0.80155
M12 Utilization after the disruptive event	0.6992	0.69874	0.6992	0.69876	0.6992	0.69878	0.6992	0.69876	0.6992	0.69878
AGV Utilization after the disruptive event	0.6473	0.64735	0.6473	0.64731	0.6473	0.6473	0.6473	0.64733	0.6473	0.64729
Fixture Utilization after the disruptive event	0.8014	0.80116	0.8014	0.80115	0.8014	0.80116	0.8014	0.80116	0.8014	0.80116

Count	76		77		78		79		80	
Exp. NO	46		47		48		49		50	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.659	0.65948	0.659	0.65952	0.659	0.6595	0.659	0.65951	0.659	0.6595
M6 Utilization after the disruptive event	0.5	0.50052	0.5	0.50058	0.5	0.50053	0.5	0.50054	0.5	0.5006
M2 Utilization after the disruptive event	0.0708	0.070257	0.0708	0.070256	0.0708	0.070263	0.0708	0.070256	0.0708	0.07025
M5 Utilization after the disruptive event	0.6812	0.68206	0.6812	0.68195	0.6812	0.68202	0.6812	0.68202	0.6812	0.68197
M3 Utilization after the disruptive event	0.8219	0.82102	0.8219	0.82103	0.8219	0.82102	0.8219	0.82102	0.8219	0.82103
M7 Utilization after the disruptive event	0.8179	0.81936	0.8179	0.81936	0.8179	0.81936	0.8179	0.81936	0.8179	0.81936
M9 Utilization after the disruptive event	0.7361	0.73559	0.7361	0.73558	0.7361	0.73559	0.7361	0.73559	0.7361	0.73558
M12 Utilization after the disruptive event	0.6475	0.64765	0.6475	0.64764	0.6475	0.64765	0.6475	0.64765	0.6475	0.64765
AGV Utilization after the disruptive event	0.589	0.58946	0.589	0.58947	0.589	0.58947	0.589	0.58948	0.589	0.58948
Fixture Utilization after the disruptive event	0.7854	0.78556	0.7854	0.78553	0.7854	0.78556	0.7854	0.78556	0.7854	0.78554

Count	81		82		83		84		85	
Exp. NO	341		342		343		344		345	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.659	0.6595	0.659	0.6595	0.659	0.6595	0.659	0.65948	0.659	0.65949
M6 Utilization after the disruptive event	0.5	0.50055	0.5	0.50057	0.5	0.50055	0.5	0.50052	0.5	0.50054
M2 Utilization after the disruptive event	0.0708	0.070261	0.0708	0.070255	0.0708	0.07026	0.0708	0.070261	0.0708	0.07026
M5 Utilization after the disruptive event	0.6812	0.68201	0.6812	0.682	0.6812	0.68201	0.6812	0.68207	0.6812	0.68204
M3 Utilization after the disruptive event	0.8219	0.82102	0.8219	0.82103	0.8219	0.82102	0.8219	0.82102	0.8219	0.82102
M7 Utilization after the disruptive event	0.8179	0.81936	0.8179	0.81936	0.8179	0.81936	0.8179	0.81936	0.8179	0.81936
M9 Utilization after the disruptive event	0.7361	0.73558	0.7361	0.73558	0.7361	0.73559	0.7361	0.73559	0.7361	0.73559
M12 Utilization after the disruptive event	0.6475	0.64765	0.6475	0.64765	0.6475	0.64765	0.6475	0.64765	0.6475	0.64765
AGV Utilization after the disruptive event	0.589	0.58946	0.589	0.58948	0.589	0.58948	0.589	0.58947	0.589	0.58947
Fixture Utilization after the disruptive event	0.7854	0.78555	0.7854	0.78555	0.7854	0.78556	0.7854	0.78557	0.7854	0.78556

Count	86		87		88		89		90	
Exp. NO	346		347		348		349		350	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.659	0.65952	0.659	0.6595	0.659	0.6595	0.659	0.65949	0.659	0.65951
M6 Utilization after the disruptive event	0.5	0.50063	0.5	0.50057	0.5	0.50055	0.5	0.50054	0.5	0.50055
M2 Utilization after the disruptive event	0.0708	0.070258	0.0708	0.070254	0.0708	0.07026	0.0708	0.070257	0.0708	0.070255
M5 Utilization after the disruptive event	0.6812	0.68192	0.6812	0.68199	0.6812	0.68201	0.6812	0.68205	0.6812	0.682
M3 Utilization after the disruptive event	0.8219	0.82104	0.8219	0.82103	0.8219	0.82102	0.8219	0.82102	0.8219	0.82102
M7 Utilization after the disruptive event	0.8179	0.81937	0.8179	0.81936	0.8179	0.81936	0.8179	0.81936	0.8179	0.81936
M9 Utilization after the disruptive event	0.7361	0.73558	0.7361	0.73558	0.7361	0.73558	0.7361	0.73559	0.7361	0.73558
M12 Utilization after the disruptive event	0.6475	0.64766	0.6475	0.64765	0.6475	0.64765	0.6475	0.64766	0.6475	0.64765
AGV Utilization after the disruptive event	0.589	0.58951	0.589	0.58948	0.589	0.58947	0.589	0.58949	0.589	0.58948
Fixture Utilization after the disruptive event	0.7854	0.78554	0.7854	0.78555	0.7854	0.78555	0.7854	0.78557	0.7854	0.78555

Count	91		92		93		94		95	
Exp. NO	51		52		53		54		55	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6719	0.67151	0.6719	0.67155	0.6719	0.67153	0.6719	0.6716	0.6719	0.67159
M6 Utilization after the disruptive event	0.5681	0.56805	0.5681	0.56805	0.5681	0.56806	0.5681	0.56811	0.5681	0.56828
M2 Utilization after the disruptive event	0.4909	0.49103	0.4909	0.49108	0.4909	0.49105	0.4909	0.49108	0.4909	0.49082
M5 Utilization after the disruptive event	0.0717	0.072839	0.0717	0.072734	0.0717	0.072781	0.0717	0.072618	0.0717	0.072713
M3 Utilization after the disruptive event	0.8258	0.82593	0.8258	0.8259	0.8258	0.82591	0.8258	0.82588	0.8258	0.82587
M7 Utilization after the disruptive event	0.819	0.81802	0.819	0.81798	0.819	0.81799	0.819	0.81792	0.819	0.81787
M9 Utilization after the disruptive event	0.7333	0.73323	0.7333	0.73323	0.7333	0.73323	0.7333	0.73324	0.7333	0.73322
M12 Utilization after the disruptive event	0.6481	0.64821	0.6481	0.64821	0.6481	0.64821	0.6481	0.64821	0.6481	0.64819
AGV Utilization after the disruptive event	0.6355	0.63526	0.6355	0.6353	0.6355	0.63529	0.6355	0.6354	0.6355	0.63548
Fixture Utilization after the disruptive event	0.7854	0.78542	0.7854	0.78543	0.7854	0.78543	0.7854	0.78544	0.7854	0.78533

Count	96		97		98		99		100	
Exp. NO	381		382		383		384		385	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6719	0.67151	0.6719	0.67153	0.6719	0.67151	0.6719	0.67151	0.6719	0.67149
M6 Utilization after the disruptive event	0.5681	0.56803	0.5681	0.56806	0.5681	0.56804	0.5681	0.56802	0.5681	0.56803
M2 Utilization after the disruptive event	0.4909	0.49106	0.4909	0.49105	0.4909	0.49106	0.4909	0.49106	0.4909	0.49104
M5 Utilization after the disruptive event	0.0717	0.072846	0.0717	0.072782	0.0717	0.072846	0.0717	0.072845	0.0717	0.072904
M3 Utilization after the disruptive event	0.8258	0.82593	0.8258	0.82591	0.8258	0.82593	0.8258	0.82593	0.8258	0.82595
M7 Utilization after the disruptive event	0.819	0.81803	0.819	0.81799	0.819	0.81803	0.819	0.81803	0.819	0.81806
M9 Utilization after the disruptive event	0.7333	0.73323	0.7333	0.73323	0.7333	0.73324	0.7333	0.73323	0.7333	0.73324
M12 Utilization after the disruptive event	0.6481	0.64822	0.6481	0.64821	0.6481	0.64822	0.6481	0.64821	0.6481	0.64822
AGV Utilization after the disruptive event	0.6355	0.63525	0.6355	0.63528	0.6355	0.63528	0.6355	0.63523	0.6355	0.63525
Fixture Utilization after the disruptive event	0.7854	0.78544	0.7854	0.78542	0.7854	0.78545	0.7854	0.78543	0.7854	0.78544

Count	101		102		103		104		105	
Exp. NO	386		387		388		389		390	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6719	0.67157	0.6719	0.67146	0.6719	0.67157	0.6719	0.67159	0.6719	0.67158
M6 Utilization after the disruptive event	0.5681	0.56808	0.5681	0.56799	0.5681	0.56809	0.5681	0.5681	0.5681	0.56809
M2 Utilization after the disruptive event	0.4909	0.49108	0.4909	0.49104	0.4909	0.49107	0.4909	0.49108	0.4909	0.49107
M5 Utilization after the disruptive event	0.0717	0.072701	0.0717	0.072965	0.0717	0.072682	0.0717	0.072634	0.0717	0.072677
M3 Utilization after the disruptive event	0.8258	0.8259	0.8258	0.82596	0.8258	0.82589	0.8258	0.82588	0.8258	0.82589
M7 Utilization after the disruptive event	0.819	0.81797	0.819	0.81808	0.819	0.81795	0.819	0.81793	0.819	0.81795
M9 Utilization after the disruptive event	0.7333	0.73324	0.7333	0.73323	0.7333	0.73323	0.7333	0.73323	0.7333	0.73323
M12 Utilization after the disruptive event	0.6481	0.64822	0.6481	0.64822	0.6481	0.64821	0.6481	0.64821	0.6481	0.64822
AGV Utilization after the disruptive event	0.6355	0.63535	0.6355	0.63518	0.6355	0.63535	0.6355	0.63537	0.6355	0.63537
Fixture Utilization after the disruptive event	0.7854	0.78545	0.7854	0.78544	0.7854	0.78543	0.7854	0.78543	0.7854	0.78544

Count	106		107		108		109		110	
Exp. NO	56		57		58		59		60	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6483	0.64756	0.6483	0.64775	0.6483	0.64781	0.6483	0.64775	0.6483	0.64693
M6 Utilization after the disruptive event	0.4779	0.47586	0.4779	0.47611	0.4779	0.47624	0.4779	0.47609	0.4779	0.47556
M2 Utilization after the disruptive event	0.5321	0.53154	0.5321	0.5313	0.5321	0.5312	0.5321	0.5313	0.5321	0.53214
M5 Utilization after the disruptive event	0.3558	0.35541	0.3558	0.35491	0.3558	0.35476	0.3558	0.3549	0.3558	0.35694
M3 Utilization after the disruptive event	0.7647	0.76465	0.7647	0.76503	0.7647	0.76536	0.7647	0.76502	0.7647	0.76454
M7 Utilization after the disruptive event	0.6834	0.68106	0.6834	0.68187	0.6834	0.68245	0.6834	0.68186	0.6834	0.6802
M9 Utilization after the disruptive event	0.7539	0.75376	0.7539	0.75373	0.7539	0.75367	0.7539	0.75372	0.7539	0.75362
M12 Utilization after the disruptive event	0.6621	0.66224	0.6621	0.6623	0.6621	0.66231	0.6621	0.66229	0.6621	0.66209
AGV Utilization after the disruptive event	0.4109	0.41095	0.4109	0.41085	0.4109	0.41066	0.4109	0.41078	0.4109	0.41115
Fixture Utilization after the disruptive event	0.6242	0.62413	0.6242	0.62457	0.6242	0.62501	0.6242	0.62455	0.6242	0.62432

Count	111		112		113		114		115	
Exp. NO	201		202		203		204		205	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6483	0.64777	0.6483	0.64777	0.6483	0.64771	0.6483	0.64774	0.6483	0.64769
M6 Utilization after the disruptive event	0.4779	0.47611	0.4779	0.47609	0.4779	0.47606	0.4779	0.47609	0.4779	0.47604
M2 Utilization after the disruptive event	0.5321	0.53127	0.5321	0.5313	0.5321	0.53135	0.5321	0.53131	0.5321	0.53137
M5 Utilization after the disruptive event	0.3558	0.35483	0.3558	0.35491	0.3558	0.35502	0.3558	0.35493	0.3558	0.35508
M3 Utilization after the disruptive event	0.7647	0.76501	0.7647	0.765	0.7647	0.76498	0.7647	0.76501	0.7647	0.76496
M7 Utilization after the disruptive event	0.6834	0.68187	0.6834	0.68185	0.6834	0.68174	0.6834	0.68183	0.6834	0.6817
M9 Utilization after the disruptive event	0.7539	0.75373	0.7539	0.75375	0.7539	0.75372	0.7539	0.75373	0.7539	0.75373
M12 Utilization after the disruptive event	0.6621	0.66229	0.6621	0.66231	0.6621	0.66228	0.6621	0.66229	0.6621	0.66228
AGV Utilization after the disruptive event	0.4109	0.41082	0.4109	0.4108	0.4109	0.41085	0.4109	0.41084	0.4109	0.41084
Fixture Utilization after the disruptive event	0.6242	0.62452	0.6242	0.62454	0.6242	0.62451	0.6242	0.62454	0.6242	0.62451

Count	116		117		118		119		120	
Exp. NO	206		207		208		209		210	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6483	0.64773	0.6483	0.64768	0.6483	0.64777	0.6483	0.64777	0.6483	0.64773
M6 Utilization after the disruptive event	0.4779	0.47605	0.4779	0.47607	0.4779	0.47611	0.4779	0.47609	0.4779	0.47608
M2 Utilization after the disruptive event	0.5321	0.53134	0.5321	0.53137	0.5321	0.53129	0.5321	0.53129	0.5321	0.53133
M5 Utilization after the disruptive event	0.3558	0.35501	0.3558	0.35512	0.3558	0.35489	0.3558	0.35489	0.3558	0.35498
M3 Utilization after the disruptive event	0.7647	0.76497	0.7647	0.76505	0.7647	0.76504	0.7647	0.76501	0.7647	0.76499
M7 Utilization after the disruptive event	0.6834	0.68174	0.6834	0.68182	0.6834	0.6819	0.6834	0.68186	0.6834	0.68178
M9 Utilization after the disruptive event	0.7539	0.75374	0.7539	0.75371	0.7539	0.75373	0.7539	0.75374	0.7539	0.75373
M12 Utilization after the disruptive event	0.6621	0.66229	0.6621	0.66228	0.6621	0.6623	0.6621	0.6623	0.6621	0.66229
AGV Utilization after the disruptive event	0.4109	0.41082	0.4109	0.41081	0.4109	0.41081	0.4109	0.41079	0.4109	0.41085
Fixture Utilization after the disruptive event	0.6242	0.62451	0.6242	0.62464	0.6242	0.62458	0.6242	0.62454	0.6242	0.62452

Count	121		122		123		124		125	
Exp. NO	66		67		68		69		70	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.653	0.65333	0.653	0.65335	0.653	0.65326	0.653	0.65332	0.653	0.65325
M6 Utilization after the disruptive event	0.5107	0.51029	0.5107	0.51024	0.5107	0.51068	0.5107	0.51035	0.5107	0.5106
M2 Utilization after the disruptive event	0.5013	0.50086	0.5013	0.50085	0.5013	0.50085	0.5013	0.50086	0.5013	0.50087
M5 Utilization after the disruptive event	0.3065	0.30672	0.3065	0.30678	0.3065	0.30625	0.3065	0.30663	0.3065	0.30631
M3 Utilization after the disruptive event	0.7782	0.77824	0.7782	0.77825	0.7782	0.77819	0.7782	0.77822	0.7782	0.77818
M7 Utilization after the disruptive event	0.7282	0.72777	0.7282	0.7278	0.7282	0.72765	0.7282	0.72773	0.7282	0.72762
M9 Utilization after the disruptive event	0.7373	0.73718	0.7373	0.73719	0.7373	0.73715	0.7373	0.73717	0.7373	0.73715
M12 Utilization after the disruptive event	0.6588	0.65892	0.6588	0.65893	0.6588	0.65886	0.6588	0.6589	0.6588	0.65885
AGV Utilization after the disruptive event	0.7301	0.72996	0.7301	0.72996	0.7301	0.73006	0.7301	0.72999	0.7301	0.73005
Fixture Utilization after the disruptive event	0.7065	0.70661	0.7065	0.70666	0.7065	0.70649	0.7065	0.70657	0.7065	0.70645

Count	126		127		128		129		130	
Exp. NO	221		222		223		224		225	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.653	0.65332	0.653	0.65328	0.653	0.65332	0.653	0.65327	0.653	0.65331
M6 Utilization after the disruptive event	0.5107	0.51043	0.5107	0.5105	0.5107	0.51036	0.5107	0.51054	0.5107	0.51043
M2 Utilization after the disruptive event	0.5013	0.50084	0.5013	0.50086	0.5013	0.50086	0.5013	0.50086	0.5013	0.50085
M5 Utilization after the disruptive event	0.3065	0.30655	0.3065	0.30643	0.3065	0.30662	0.3065	0.30641	0.3065	0.30655
M3 Utilization after the disruptive event	0.7782	0.77823	0.7782	0.77819	0.7782	0.77822	0.7782	0.77821	0.7782	0.77822
M7 Utilization after the disruptive event	0.7282	0.72774	0.7282	0.72766	0.7282	0.72773	0.7282	0.72768	0.7282	0.72773
M9 Utilization after the disruptive event	0.7373	0.73717	0.7373	0.73716	0.7373	0.73717	0.7373	0.73716	0.7373	0.73717
M12 Utilization after the disruptive event	0.6588	0.6589	0.6588	0.65887	0.6588	0.6589	0.6588	0.65888	0.6588	0.6589
AGV Utilization after the disruptive event	0.7301	0.73	0.7301	0.73002	0.7301	0.72998	0.7301	0.73001	0.7301	0.73001
Fixture Utilization after the disruptive event	0.7065	0.7066	0.7065	0.70649	0.7065	0.70656	0.7065	0.70651	0.7065	0.70658

Count	131		132		133		134		135	
Exp. NO	226		227		228		229		230	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.653	0.65329	0.653	0.65329	0.653	0.65325	0.653	0.65326	0.653	0.65324
M6 Utilization after the disruptive event	0.5107	0.51046	0.5107	0.51044	0.5107	0.51063	0.5107	0.51062	0.5107	0.51069
M2 Utilization after the disruptive event	0.5013	0.50086	0.5013	0.50087	0.5013	0.50087	0.5013	0.50086	0.5013	0.50087
M5 Utilization after the disruptive event	0.3065	0.30651	0.3065	0.30651	0.3065	0.30628	0.3065	0.30631	0.3065	0.30623
M3 Utilization after the disruptive event	0.7782	0.77821	0.7782	0.7782	0.7782	0.77818	0.7782	0.77819	0.7782	0.77818
M7 Utilization after the disruptive event	0.7282	0.7277	0.7282	0.72769	0.7282	0.72763	0.7282	0.72765	0.7282	0.72763
M9 Utilization after the disruptive event	0.7373	0.73716	0.7373	0.73716	0.7373	0.73715	0.7373	0.73715	0.7373	0.73714
M12 Utilization after the disruptive event	0.6588	0.65889	0.6588	0.65888	0.6588	0.65885	0.6588	0.65886	0.6588	0.65885
AGV Utilization after the disruptive event	0.7301	0.73	0.7301	0.73	0.7301	0.73003	0.7301	0.73003	0.7301	0.73005
Fixture Utilization after the disruptive event	0.7065	0.70653	0.7065	0.70651	0.7065	0.70643	0.7065	0.70647	0.7065	0.70644

Count	136		137		138		139		140	
Exp. NO	106		107		108		109		110	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.5525	0.5514	0.5525	0.55138	0.5525	0.5514	0.5525	0.55137	0.5525	0.55139
M6 Utilization after the disruptive event	0.0436	0.042253	0.0436	0.042237	0.0436	0.042246	0.0436	0.042219	0.0436	0.042228
M2 Utilization after the disruptive event	0.7849	0.78389	0.7849	0.78391	0.7849	0.78389	0.7849	0.78392	0.7849	0.7839
M5 Utilization after the disruptive event	0.7993	0.79782	0.7993	0.79782	0.7993	0.79782	0.7993	0.79781	0.7993	0.79782
M3 Utilization after the disruptive event	0.6211	0.62158	0.6211	0.62158	0.6211	0.62159	0.6211	0.6216	0.6211	0.6216
M7 Utilization after the disruptive event	0.4183	0.41766	0.4183	0.41767	0.4183	0.41767	0.4183	0.41769	0.4183	0.41769
M9 Utilization after the disruptive event	0.779	0.7792	0.779	0.77919	0.779	0.77919	0.779	0.77918	0.779	0.77918
M12 Utilization after the disruptive event	0.6585	0.65849	0.6585	0.65849	0.6585	0.65849	0.6585	0.65848	0.6585	0.65848
AGV Utilization after the disruptive event	0.6837	0.68377	0.6837	0.68379	0.6837	0.68378	0.6837	0.6838	0.6837	0.68379
Fixture Utilization after the disruptive event	0.812	0.812	0.812	0.81201	0.812	0.81201	0.812	0.81202	0.812	0.81202

Count	141		142		143		144		145	
Exp. NO	331		332		333		334		335	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.5525	0.55139	0.5525	0.55136	0.5525	0.5514	0.5525	0.55138	0.5525	0.55141
M6 Utilization after the disruptive event	0.0436	0.042252	0.0436	0.042196	0.0436	0.042247	0.0436	0.042216	0.0436	0.042281
M2 Utilization after the disruptive event	0.7849	0.78389	0.7849	0.78394	0.7849	0.78389	0.7849	0.78392	0.7849	0.78386
M5 Utilization after the disruptive event	0.7993	0.79782	0.7993	0.7978	0.7993	0.79782	0.7993	0.79781	0.7993	0.79783
M3 Utilization after the disruptive event	0.6211	0.62158	0.6211	0.62161	0.6211	0.62159	0.6211	0.6216	0.6211	0.62157
M7 Utilization after the disruptive event	0.4183	0.41766	0.4183	0.41771	0.4183	0.41768	0.4183	0.4177	0.4183	0.41764
M9 Utilization after the disruptive event	0.779	0.7792	0.779	0.77917	0.779	0.77919	0.779	0.77918	0.779	0.77921
M12 Utilization after the disruptive event	0.6585	0.65849	0.6585	0.65847	0.6585	0.6585	0.6585	0.65848	0.6585	0.65851
AGV Utilization after the disruptive event	0.6837	0.68377	0.6837	0.68384	0.6837	0.68377	0.6837	0.68381	0.6837	0.68372
Fixture Utilization after the disruptive event	0.812	0.812	0.812	0.81204	0.812	0.81201	0.812	0.81202	0.812	0.81198

Count	146		147		148		149		150	
Exp. NO	336		337		338		339		340	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.5525	0.55139	0.5525	0.55142	0.5525	0.55139	0.5525	0.55144	0.5525	0.55136
M6 Utilization after the disruptive event	0.0436	0.042234	0.0436	0.042294	0.0436	0.042239	0.0436	0.042296	0.0436	0.042211
M2 Utilization after the disruptive event	0.7849	0.7839	0.7849	0.78385	0.7849	0.7839	0.7849	0.78383	0.7849	0.78393
M5 Utilization after the disruptive event	0.7993	0.79782	0.7993	0.79783	0.7993	0.79782	0.7993	0.79784	0.7993	0.7978
M3 Utilization after the disruptive event	0.6211	0.62159	0.6211	0.62157	0.6211	0.62159	0.6211	0.62158	0.6211	0.62159
M7 Utilization after the disruptive event	0.4183	0.41768	0.4183	0.41764	0.4183	0.41767	0.4183	0.41766	0.4183	0.41768
M9 Utilization after the disruptive event	0.779	0.77919	0.779	0.77921	0.779	0.77919	0.779	0.77922	0.779	0.77918
M12 Utilization after the disruptive event	0.6585	0.65849	0.6585	0.65851	0.6585	0.65849	0.6585	0.65852	0.6585	0.65847
AGV Utilization after the disruptive event	0.6837	0.68379	0.6837	0.68371	0.6837	0.68379	0.6837	0.68369	0.6837	0.68381
Fixture Utilization after the disruptive event	0.812	0.81202	0.812	0.81197	0.812	0.81201	0.812	0.81198	0.812	0.81202

Count	151		152		153		154		155	
Exp. NO	111		112		113		114		115	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.5678	0.56741	0.5678	0.56742	0.5678	0.56742	0.5678	0.56745	0.5678	0.5674
M6 Utilization after the disruptive event	0.3276	0.32693	0.3276	0.32692	0.3276	0.32694	0.3276	0.32697	0.3276	0.32694
M2 Utilization after the disruptive event	0.6654	0.66641	0.6654	0.66641	0.6654	0.66639	0.6654	0.66632	0.6654	0.66641
M5 Utilization after the disruptive event	0.5526	0.55269	0.5526	0.55269	0.5526	0.55267	0.5526	0.55258	0.5526	0.55269
M3 Utilization after the disruptive event	0.6555	0.65469	0.6555	0.6547	0.6555	0.6547	0.6555	0.65472	0.6555	0.65469
M7 Utilization after the disruptive event	0.4526	0.45271	0.4526	0.45271	0.4526	0.45273	0.4526	0.4528	0.4526	0.45269
M9 Utilization after the disruptive event	0.7746	0.77387	0.7746	0.77386	0.7746	0.77387	0.7746	0.77387	0.7746	0.77386
M12 Utilization after the disruptive event	0.6516	0.65208	0.6516	0.65208	0.6516	0.65208	0.6516	0.65208	0.6516	0.65207
AGV Utilization after the disruptive event	0.3535	0.35346	0.3535	0.35347	0.3535	0.35345	0.3535	0.3534	0.3535	0.35348
Fixture Utilization after the disruptive event	0.5784	0.5785	0.5784	0.57853	0.5784	0.5785	0.5784	0.57847	0.5784	0.57849

Count	156		157		158		159		160	
Exp. NO	191		192		193		194		195	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.5678	0.56739	0.5678	0.56743	0.5678	0.56739	0.5678	0.56742	0.5678	0.5674
M6 Utilization after the disruptive event	0.3276	0.3269	0.3276	0.32695	0.3276	0.32692	0.3276	0.32695	0.3276	0.32693
M2 Utilization after the disruptive event	0.6654	0.66646	0.6654	0.66637	0.6654	0.66642	0.6654	0.66637	0.6654	0.66641
M5 Utilization after the disruptive event	0.5526	0.55277	0.5526	0.55264	0.5526	0.55272	0.5526	0.55265	0.5526	0.5527
M3 Utilization after the disruptive event	0.6555	0.65468	0.6555	0.6547	0.6555	0.65468	0.6555	0.6547	0.6555	0.65469
M7 Utilization after the disruptive event	0.4526	0.45264	0.4526	0.45275	0.4526	0.45266	0.4526	0.45275	0.4526	0.45269
M9 Utilization after the disruptive event	0.7746	0.77386	0.7746	0.77387	0.7746	0.77386	0.7746	0.77387	0.7746	0.77386
M12 Utilization after the disruptive event	0.6516	0.65207	0.6516	0.65208	0.6516	0.65206	0.6516	0.65208	0.6516	0.65207
AGV Utilization after the disruptive event	0.3535	0.35352	0.3535	0.35343	0.3535	0.3535	0.3535	0.35343	0.3535	0.35348
Fixture Utilization after the disruptive event	0.5784	0.57853	0.5784	0.57848	0.5784	0.57849	0.5784	0.57848	0.5784	0.57849

Count	161		162		163		164		165	
Exp. NO	196		197		198		199		200	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.5678	0.56742	0.5678	0.56743	0.5678	0.56745	0.5678	0.5674	0.5678	0.56739
M6 Utilization after the disruptive event	0.3276	0.32693	0.3276	0.32694	0.3276	0.32696	0.3276	0.32691	0.3276	0.32692
M2 Utilization after the disruptive event	0.6654	0.6664	0.6654	0.66637	0.6654	0.66634	0.6654	0.66644	0.6654	0.66643
M5 Utilization after the disruptive event	0.5526	0.55267	0.5526	0.55264	0.5526	0.5526	0.5526	0.55274	0.5526	0.55272
M3 Utilization after the disruptive event	0.6555	0.6547	0.6555	0.65471	0.6555	0.65473	0.6555	0.65469	0.6555	0.65468
M7 Utilization after the disruptive event	0.4526	0.45274	0.4526	0.45276	0.4526	0.45281	0.4526	0.45267	0.4526	0.45265
M9 Utilization after the disruptive event	0.7746	0.77387	0.7746	0.77387	0.7746	0.77387	0.7746	0.77386	0.7746	0.77386
M12 Utilization after the disruptive event	0.6516	0.65208	0.6516	0.65208	0.6516	0.65209	0.6516	0.65207	0.6516	0.65206
AGV Utilization after the disruptive event	0.3535	0.35344	0.3535	0.35343	0.3535	0.3534	0.3535	0.3535	0.3535	0.3535
Fixture Utilization after the disruptive event	0.5784	0.57852	0.5784	0.5785	0.5784	0.5785	0.5784	0.57854	0.5784	0.57849

Count	166		167		168		169		170	
Exp. NO	116		117		118		119		120	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6316	0.63214	0.6316	0.63214	0.6316	0.63217	0.6316	0.63216	0.6316	0.63218
M6 Utilization after the disruptive event	0.44	0.44113	0.44	0.44112	0.44	0.44116	0.44	0.44117	0.44	0.44119
M2 Utilization after the disruptive event	0.5127	0.51187	0.5127	0.51188	0.5127	0.51183	0.5127	0.51184	0.5127	0.5118
M5 Utilization after the disruptive event	0.3319	0.33165	0.3319	0.33169	0.3319	0.33156	0.3319	0.33154	0.3319	0.33151
M3 Utilization after the disruptive event	0.7433	0.74404	0.7433	0.74405	0.7433	0.74405	0.7433	0.74403	0.7433	0.74407
M7 Utilization after the disruptive event	0.6376	0.63859	0.6376	0.63858	0.6376	0.63864	0.6376	0.63862	0.6376	0.63868
M9 Utilization after the disruptive event	0.73	0.73077	0.73	0.73076	0.73	0.73077	0.73	0.73077	0.73	0.73076
M12 Utilization after the disruptive event	0.6206	0.62007	0.6206	0.62006	0.6206	0.62008	0.6206	0.62007	0.6206	0.62007
AGV Utilization after the disruptive event	0.3396	0.33979	0.3396	0.33981	0.3396	0.33976	0.3396	0.33977	0.3396	0.33977
Fixture Utilization after the disruptive event	0.5727	0.57199	0.5727	0.57201	0.5727	0.57199	0.5727	0.57195	0.5727	0.57198

Count	171		172		173		174		175	
Exp. NO	211		212		213		214		215	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6316	0.63185	0.6316	0.6322	0.6316	0.63183	0.6316	0.63216	0.6316	0.63186
M6 Utilization after the disruptive event	0.44	0.44057	0.44	0.44121	0.44	0.44052	0.44	0.44116	0.44	0.44058
M2 Utilization after the disruptive event	0.5127	0.51237	0.5127	0.51178	0.5127	0.51242	0.5127	0.51184	0.5127	0.51235
M5 Utilization after the disruptive event	0.3319	0.33311	0.3319	0.33144	0.3319	0.33325	0.3319	0.33158	0.3319	0.33309
M3 Utilization after the disruptive event	0.7433	0.74403	0.7433	0.74407	0.7433	0.74403	0.7433	0.74405	0.7433	0.74405
M7 Utilization after the disruptive event	0.6376	0.63806	0.6376	0.63871	0.6376	0.63801	0.6376	0.63863	0.6376	0.6381
M9 Utilization after the disruptive event	0.73	0.73073	0.73	0.73077	0.73	0.73073	0.73	0.73077	0.73	0.73073
M12 Utilization after the disruptive event	0.6206	0.62004	0.6206	0.62007	0.6206	0.62004	0.6206	0.62007	0.6206	0.62004
AGV Utilization after the disruptive event	0.3396	0.34017	0.3396	0.33974	0.3396	0.34021	0.3396	0.33978	0.3396	0.34018
Fixture Utilization after the disruptive event	0.5727	0.57242	0.5727	0.57197	0.5727	0.57246	0.5727	0.57199	0.5727	0.57244

Count	176		177		178		179		180	
Exp. NO	216		217		218		219		220	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6316	0.63217	0.6316	0.63214	0.6316	0.63213	0.6316	0.63194	0.6316	0.63216
M6 Utilization after the disruptive event	0.44	0.44119	0.44	0.44113	0.44	0.44113	0.44	0.44069	0.44	0.44118
M2 Utilization after the disruptive event	0.5127	0.51182	0.5127	0.51187	0.5127	0.51188	0.5127	0.51223	0.5127	0.51183
M5 Utilization after the disruptive event	0.3319	0.33152	0.3319	0.33166	0.3319	0.33164	0.3319	0.33278	0.3319	0.33151
M3 Utilization after the disruptive event	0.7433	0.74405	0.7433	0.74405	0.7433	0.74402	0.7433	0.74402	0.7433	0.74402
M7 Utilization after the disruptive event	0.6376	0.63865	0.6376	0.63859	0.6376	0.63856	0.6376	0.63815	0.6376	0.63861
M9 Utilization after the disruptive event	0.73	0.73076	0.73	0.73076	0.73	0.73077	0.73	0.73074	0.73	0.73078
M12 Utilization after the disruptive event	0.6206	0.62007	0.6206	0.62006	0.6206	0.62007	0.6206	0.62004	0.6206	0.62007
AGV Utilization after the disruptive event	0.3396	0.33977	0.3396	0.33981	0.3396	0.33979	0.3396	0.34008	0.3396	0.33975
Fixture Utilization after the disruptive event	0.5727	0.57196	0.5727	0.572	0.5727	0.57196	0.5727	0.5723	0.5727	0.57193

Count	181		182		183		184		185	
Exp. NO	121		122		123		124		125	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6439	0.64341	0.6439	0.64343	0.6439	0.64343	0.6439	0.64342	0.6439	0.64346
M6 Utilization after the disruptive event	0.469	0.46957	0.469	0.46961	0.469	0.46959	0.469	0.46944	0.469	0.4695
M2 Utilization after the disruptive event	0.4841	0.48493	0.4841	0.48492	0.4841	0.48491	0.4841	0.48495	0.4841	0.48491
M5 Utilization after the disruptive event	0.286	0.28578	0.286	0.28574	0.286	0.28575	0.286	0.28592	0.286	0.28586
M3 Utilization after the disruptive event	0.7619	0.76122	0.7619	0.76123	0.7619	0.76124	0.7619	0.76124	0.7619	0.76125
M7 Utilization after the disruptive event	0.6813	0.68248	0.6813	0.68249	0.6813	0.68249	0.6813	0.68251	0.6813	0.68253
M9 Utilization after the disruptive event	0.7167	0.71655	0.7167	0.71655	0.7167	0.71655	0.7167	0.71656	0.7167	0.71656
M12 Utilization after the disruptive event	0.618	0.6181	0.618	0.6181	0.618	0.6181	0.618	0.61811	0.618	0.61812
AGV Utilization after the disruptive event	0.6366	0.63641	0.6366	0.63644	0.6366	0.6364	0.6366	0.63635	0.6366	0.6364
Fixture Utilization after the disruptive event	0.6008	0.60095	0.6008	0.60097	0.6008	0.60096	0.6008	0.60097	0.6008	0.60102

Count	186		187		188		189		190	
Exp. NO	231		232		233		234		235	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6439	0.64333	0.6439	0.64344	0.6439	0.64344	0.6439	0.64334	0.6439	0.64348
M6 Utilization after the disruptive event	0.469	0.46971	0.469	0.4697	0.469	0.46931	0.469	0.46978	0.469	0.46949
M2 Utilization after the disruptive event	0.4841	0.48496	0.4841	0.48489	0.4841	0.48496	0.4841	0.48494	0.4841	0.48489
M5 Utilization after the disruptive event	0.286	0.28561	0.286	0.28564	0.286	0.28607	0.286	0.28554	0.286	0.28587
M3 Utilization after the disruptive event	0.7619	0.76118	0.7619	0.76124	0.7619	0.76125	0.7619	0.76118	0.7619	0.76127
M7 Utilization after the disruptive event	0.6813	0.68238	0.6813	0.68249	0.6813	0.68255	0.6813	0.68238	0.6813	0.68257
M9 Utilization after the disruptive event	0.7167	0.71654	0.7167	0.71655	0.7167	0.71656	0.7167	0.71654	0.7167	0.71655
M12 Utilization after the disruptive event	0.618	0.61806	0.618	0.6181	0.618	0.61812	0.618	0.61806	0.618	0.61812
AGV Utilization after the disruptive event	0.6366	0.63641	0.6366	0.63646	0.6366	0.6363	0.6366	0.63644	0.6366	0.63636
Fixture Utilization after the disruptive event	0.6008	0.60082	0.6008	0.60096	0.6008	0.60101	0.6008	0.60082	0.6008	0.60103

Count	191		192		193		194		195	
Exp. NO	236		237		238		239		240	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6439	0.64342	0.6439	0.6434	0.6439	0.64342	0.6439	0.6434	0.6439	0.64347
M6 Utilization after the disruptive event	0.469	0.46945	0.469	0.46952	0.469	0.46953	0.469	0.46946	0.469	0.46954
M2 Utilization after the disruptive event	0.4841	0.48495	0.4841	0.48495	0.4841	0.48493	0.4841	0.48496	0.4841	0.4849
M5 Utilization after the disruptive event	0.286	0.28591	0.286	0.28582	0.286	0.28582	0.286	0.2859	0.286	0.28582
M3 Utilization after the disruptive event	0.7619	0.76123	0.7619	0.76121	0.7619	0.76122	0.7619	0.76122	0.7619	0.76126
M7 Utilization after the disruptive event	0.6813	0.6825	0.6813	0.68246	0.6813	0.68248	0.6813	0.68247	0.6813	0.68254
M9 Utilization after the disruptive event	0.7167	0.71656	0.7167	0.71655	0.7167	0.71655	0.7167	0.71656	0.7167	0.71655
M12 Utilization after the disruptive event	0.618	0.61811	0.618	0.6181	0.618	0.6181	0.618	0.6181	0.618	0.61811
AGV Utilization after the disruptive event	0.6366	0.63636	0.6366	0.6364	0.6366	0.6364	0.6366	0.63638	0.6366	0.63639
Fixture Utilization after the disruptive event	0.6008	0.60097	0.6008	0.60093	0.6008	0.60095	0.6008	0.60094	0.6008	0.60101

Count	196		197		198		199		200	
Exp. NO	126		127		128		129		130	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.5478	0.5482	0.5478	0.54821	0.5478	0.54814	0.5478	0.5482	0.5478	0.5481
M6 Utilization after the disruptive event	0.312	0.31154	0.312	0.31147	0.312	0.31168	0.312	0.3115	0.312	0.31174
M2 Utilization after the disruptive event	0.6981	0.69727	0.6981	0.69729	0.6981	0.69724	0.6981	0.69728	0.6981	0.69723
M5 Utilization after the disruptive event	0.5972	0.59732	0.5972	0.59737	0.5972	0.59716	0.5972	0.59735	0.5972	0.59708
M3 Utilization after the disruptive event	0.6324	0.63314	0.6324	0.63314	0.6324	0.63311	0.6324	0.63313	0.6324	0.63311
M7 Utilization after the disruptive event	0.4219	0.42111	0.4219	0.42111	0.4219	0.42107	0.4219	0.42111	0.4219	0.42106
M9 Utilization after the disruptive event	0.7814	0.7817	0.7814	0.7817	0.7814	0.78168	0.7814	0.7817	0.7814	0.78167
M12 Utilization after the disruptive event	0.6651	0.66488	0.6651	0.66488	0.6651	0.66484	0.6651	0.66488	0.6651	0.66482
AGV Utilization after the disruptive event	0.6691	0.66929	0.6691	0.66931	0.6691	0.66925	0.6691	0.6693	0.6691	0.66925
Fixture Utilization after the disruptive event	0.6313	0.63117	0.6313	0.63123	0.6313	0.63102	0.6313	0.6312	0.6313	0.63096

Count	201		202		203		204		205	
Exp. NO	251		252		253		254		255	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.5478	0.54818	0.5478	0.54813	0.5478	0.54812	0.5478	0.54816	0.5478	0.54821
M6 Utilization after the disruptive event	0.312	0.31159	0.312	0.31172	0.312	0.31169	0.312	0.3116	0.312	0.31145
M2 Utilization after the disruptive event	0.6981	0.69725	0.6981	0.69722	0.6981	0.69724	0.6981	0.69726	0.6981	0.6973
M5 Utilization after the disruptive event	0.5972	0.59725	0.5972	0.5971	0.5972	0.59713	0.5972	0.59724	0.5972	0.5974
M3 Utilization after the disruptive event	0.6324	0.63313	0.6324	0.63313	0.6324	0.63312	0.6324	0.63312	0.6324	0.63313
M7 Utilization after the disruptive event	0.4219	0.42111	0.4219	0.4211	0.4219	0.42109	0.4219	0.42109	0.4219	0.4211
M9 Utilization after the disruptive event	0.7814	0.78169	0.7814	0.78167	0.7814	0.78167	0.7814	0.78169	0.7814	0.7817
M12 Utilization after the disruptive event	0.6651	0.66486	0.6651	0.66483	0.6651	0.66483	0.6651	0.66486	0.6651	0.66488
AGV Utilization after the disruptive event	0.6691	0.66928	0.6691	0.66925	0.6691	0.66927	0.6691	0.66928	0.6691	0.66932
Fixture Utilization after the disruptive event	0.6313	0.63112	0.6313	0.63098	0.6313	0.63101	0.6313	0.6311	0.6313	0.63125

Count	206		207		208		209		210	
Exp. NO	256		257		258		259		260	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.5478	0.54815	0.5478	0.54822	0.5478	0.54816	0.5478	0.54829	0.5478	0.54824
M6 Utilization after the disruptive event	0.312	0.31159	0.312	0.31146	0.312	0.31163	0.312	0.3113	0.312	0.31139
M2 Utilization after the disruptive event	0.6981	0.69727	0.6981	0.69729	0.6981	0.69725	0.6981	0.69733	0.6981	0.69731
M5 Utilization after the disruptive event	0.5972	0.59725	0.5972	0.5974	0.5972	0.59721	0.5972	0.59759	0.5972	0.59748
M3 Utilization after the disruptive event	0.6324	0.63311	0.6324	0.63314	0.6324	0.63312	0.6324	0.63315	0.6324	0.63314
M7 Utilization after the disruptive event	0.4219	0.42108	0.4219	0.42111	0.4219	0.42109	0.4219	0.42114	0.4219	0.42112
M9 Utilization after the disruptive event	0.7814	0.78169	0.7814	0.7817	0.7814	0.78168	0.7814	0.78173	0.7814	0.78172
M12 Utilization after the disruptive event	0.6651	0.66485	0.6651	0.66489	0.6651	0.66485	0.6651	0.66493	0.6651	0.66491
AGV Utilization after the disruptive event	0.6691	0.66928	0.6691	0.66932	0.6691	0.66927	0.6691	0.66933	0.6691	0.66933
Fixture Utilization after the disruptive event	0.6313	0.6311	0.6313	0.63125	0.6313	0.63108	0.6313	0.63141	0.6313	0.63131

Count	211		212		213		214		215	
Exp. NO	131		132		133		134		135	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.0924	0.093303	0.0924	0.09332	0.0924	0.093286	0.0924	0.093282	0.0924	0.093353
M6 Utilization after the disruptive event	0.7176	0.71765	0.7176	0.71764	0.7176	0.71765	0.7176	0.71763	0.7176	0.71764
M2 Utilization after the disruptive event	0.5654	0.5664	0.5654	0.56637	0.5654	0.56642	0.5654	0.56642	0.5654	0.56633
M5 Utilization after the disruptive event	0.6748	0.67563	0.6748	0.67562	0.6748	0.67564	0.6748	0.67564	0.6748	0.67561
M3 Utilization after the disruptive event	0.7594	0.75983	0.7594	0.75984	0.7594	0.75982	0.7594	0.75981	0.7594	0.75986
M7 Utilization after the disruptive event	0.6841	0.68344	0.6841	0.68345	0.6841	0.68341	0.6841	0.6834	0.6841	0.68349
M9 Utilization after the disruptive event	0.7145	0.71463	0.7145	0.71462	0.7145	0.71463	0.7145	0.71463	0.7145	0.71462
M12 Utilization after the disruptive event	0.6127	0.6126	0.6127	0.61259	0.6127	0.6126	0.6127	0.61259	0.6127	0.61259
AGV Utilization after the disruptive event	0.4755	0.47569	0.4755	0.47564	0.4755	0.47573	0.4755	0.47571	0.4755	0.47562
Fixture Utilization after the disruptive event	0.7201	0.71982	0.7201	0.71979	0.7201	0.71985	0.7201	0.71984	0.7201	0.71977

Count	216		217		218		219		220	
Exp. NO	271		272		273		274		275	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.0924	0.09344	0.0924	0.09333	0.0924	0.093372	0.0924	0.093356	0.0924	0.093348
M6 Utilization after the disruptive event	0.7176	0.71766	0.7176	0.71765	0.7176	0.71763	0.7176	0.71765	0.7176	0.71765
M2 Utilization after the disruptive event	0.5654	0.56621	0.5654	0.56636	0.5654	0.5663	0.5654	0.56632	0.5654	0.56633
M5 Utilization after the disruptive event	0.6748	0.67559	0.6748	0.67563	0.6748	0.6756	0.6748	0.67562	0.6748	0.67562
M3 Utilization after the disruptive event	0.7594	0.75992	0.7594	0.75986	0.7594	0.75987	0.7594	0.75986	0.7594	0.75986
M7 Utilization after the disruptive event	0.6841	0.6836	0.6841	0.68348	0.6841	0.6835	0.6841	0.68349	0.6841	0.68349
M9 Utilization after the disruptive event	0.7145	0.71462	0.7145	0.71463	0.7145	0.71461	0.7145	0.71462	0.7145	0.71463
M12 Utilization after the disruptive event	0.6127	0.6126	0.6127	0.6126	0.6127	0.61258	0.6127	0.6126	0.6127	0.6126
AGV Utilization after the disruptive event	0.4755	0.47553	0.4755	0.47565	0.4755	0.47556	0.4755	0.47564	0.4755	0.47565
Fixture Utilization after the disruptive event	0.7201	0.7197	0.7201	0.7198	0.7201	0.71973	0.7201	0.71978	0.7201	0.71979

Count	221		222		223		224		225	
Exp. NO	276		277		278		279		280	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.0924	0.093308	0.0924	0.093359	0.0924	0.093369	0.0924	0.093387	0.0924	0.093358
M6 Utilization after the disruptive event	0.7176	0.71765	0.7176	0.71765	0.7176	0.71764	0.7176	0.71764	0.7176	0.71765
M2 Utilization after the disruptive event	0.5654	0.56639	0.5654	0.56632	0.5654	0.5663	0.5654	0.56628	0.5654	0.56632
M5 Utilization after the disruptive event	0.6748	0.67563	0.6748	0.67561	0.6748	0.67561	0.6748	0.6756	0.6748	0.67561
M3 Utilization after the disruptive event	0.7594	0.75984	0.7594	0.75987	0.7594	0.75987	0.7594	0.75988	0.7594	0.75987
M7 Utilization after the disruptive event	0.6841	0.68345	0.6841	0.6835	0.6841	0.68351	0.6841	0.68353	0.6841	0.6835
M9 Utilization after the disruptive event	0.7145	0.71463	0.7145	0.71462	0.7145	0.71462	0.7145	0.71462	0.7145	0.71462
M12 Utilization after the disruptive event	0.6127	0.6126	0.6127	0.61259	0.6127	0.61259	0.6127	0.61259	0.6127	0.61259
AGV Utilization after the disruptive event	0.4755	0.47569	0.4755	0.4756	0.4755	0.4756	0.4755	0.47556	0.4755	0.47561
Fixture Utilization after the disruptive event	0.7201	0.71982	0.7201	0.71976	0.7201	0.71975	0.7201	0.71973	0.7201	0.71976

Count	226		227		228		229		230	
Exp. NO	136		137		138		139		140	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.0785	0.079172	0.0785	0.079248	0.0785	0.079156	0.0785	0.079246	0.0785	0.079231
M6 Utilization after the disruptive event	0.6564	0.6576	0.6564	0.65759	0.6564	0.6576	0.6564	0.65759	0.6564	0.65758
M2 Utilization after the disruptive event	0.7743	0.77431	0.7743	0.77429	0.7743	0.77432	0.7743	0.7743	0.7743	0.77431
M5 Utilization after the disruptive event	0.7687	0.76917	0.7687	0.76912	0.7687	0.76918	0.7687	0.76913	0.7687	0.76915
M3 Utilization after the disruptive event	0.6329	0.63243	0.6329	0.63245	0.6329	0.63242	0.6329	0.63244	0.6329	0.63242
M7 Utilization after the disruptive event	0.4151	0.41549	0.4151	0.41553	0.4151	0.41548	0.4151	0.41552	0.4151	0.41548
M9 Utilization after the disruptive event	0.7796	0.77945	0.7796	0.77945	0.7796	0.77945	0.7796	0.77946	0.7796	0.77946
M12 Utilization after the disruptive event	0.6577	0.65774	0.6577	0.65775	0.6577	0.65774	0.6577	0.65776	0.6577	0.65775
AGV Utilization after the disruptive event	0.5862	0.58594	0.5862	0.58593	0.5862	0.58593	0.5862	0.58596	0.5862	0.58593
Fixture Utilization after the disruptive event	0.7747	0.77503	0.7747	0.77501	0.7747	0.77502	0.7747	0.77502	0.7747	0.77501

Count	231		232		233		234		235	
Exp. NO	291		292		293		294		295	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.0785	0.079137	0.0785	0.079159	0.0785	0.079092	0.0785	0.07914	0.0785	0.079222
M6 Utilization after the disruptive event	0.6564	0.6576	0.6564	0.65764	0.6564	0.65763	0.6564	0.6576	0.6564	0.65759
M2 Utilization after the disruptive event	0.7743	0.77431	0.7743	0.77429	0.7743	0.77431	0.7743	0.77431	0.7743	0.77429
M5 Utilization after the disruptive event	0.7687	0.76918	0.7687	0.76915	0.7687	0.7692	0.7687	0.76918	0.7687	0.76913
M3 Utilization after the disruptive event	0.6329	0.63242	0.6329	0.63246	0.6329	0.63243	0.6329	0.63242	0.6329	0.63244
M7 Utilization after the disruptive event	0.4151	0.41548	0.4151	0.41556	0.4151	0.41549	0.4151	0.41548	0.4151	0.41551
M9 Utilization after the disruptive event	0.7796	0.77945	0.7796	0.77944	0.7796	0.77944	0.7796	0.77945	0.7796	0.77945
M12 Utilization after the disruptive event	0.6577	0.65773	0.6577	0.65774	0.6577	0.65773	0.6577	0.65773	0.6577	0.65774
AGV Utilization after the disruptive event	0.5862	0.58592	0.5862	0.58598	0.5862	0.58594	0.5862	0.58593	0.5862	0.58591
Fixture Utilization after the disruptive event	0.7747	0.77502	0.7747	0.77506	0.7747	0.77504	0.7747	0.77503	0.7747	0.775

Count	236		237		238		239		240	
Exp. NO	296		297		298		299		300	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.0785	0.07924	0.0785	0.079289	0.0785	0.079311	0.0785	0.079169	0.0785	0.079203
M6 Utilization after the disruptive event	0.6564	0.65758	0.6564	0.65756	0.6564	0.65756	0.6564	0.65761	0.6564	0.65761
M2 Utilization after the disruptive event	0.7743	0.7743	0.7743	0.77429	0.7743	0.77429	0.7743	0.77431	0.7743	0.77429
M5 Utilization after the disruptive event	0.7687	0.76913	0.7687	0.76911	0.7687	0.7691	0.7687	0.76916	0.7687	0.76913
M3 Utilization after the disruptive event	0.6329	0.63244	0.6329	0.63244	0.6329	0.63244	0.6329	0.63244	0.6329	0.63245
M7 Utilization after the disruptive event	0.4151	0.4155	0.4151	0.4155	0.4151	0.41551	0.4151	0.41551	0.4151	0.41553
M9 Utilization after the disruptive event	0.7796	0.77945	0.7796	0.77945	0.7796	0.77945	0.7796	0.77945	0.7796	0.77944
M12 Utilization after the disruptive event	0.6577	0.65775	0.6577	0.65775	0.6577	0.65776	0.6577	0.65774	0.6577	0.65774
AGV Utilization after the disruptive event	0.5862	0.58593	0.5862	0.58591	0.5862	0.58592	0.5862	0.58595	0.5862	0.58594
Fixture Utilization after the disruptive event	0.7747	0.775	0.7747	0.77498	0.7747	0.77499	0.7747	0.77503	0.7747	0.77502

Count	241		242		243		244		245	
Exp. NO	141		142		143		144		145	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6169	0.61823	0.6169	0.61827	0.6169	0.61828	0.6169	0.61821	0.6169	0.61826
M6 Utilization after the disruptive event	0.0648	0.067211	0.0648	0.067232	0.0648	0.067286	0.0648	0.067257	0.0648	0.067269
M2 Utilization after the disruptive event	0.5667	0.56767	0.5667	0.56761	0.5667	0.56753	0.5667	0.56765	0.5667	0.56758
M5 Utilization after the disruptive event	0.6824	0.68519	0.6824	0.68518	0.6824	0.68518	0.6824	0.68519	0.6824	0.68518
M3 Utilization after the disruptive event	0.7527	0.75253	0.7527	0.75254	0.7527	0.75256	0.7527	0.75253	0.7527	0.75255
M7 Utilization after the disruptive event	0.681	0.68085	0.681	0.68088	0.681	0.68091	0.681	0.68084	0.681	0.68089
M9 Utilization after the disruptive event	0.7115	0.71152	0.7115	0.71152	0.7115	0.71152	0.7115	0.71152	0.7115	0.71152
M12 Utilization after the disruptive event	0.6085	0.60842	0.6085	0.60842	0.6085	0.60843	0.6085	0.60841	0.6085	0.60842
AGV Utilization after the disruptive event	0.5229	0.52282	0.5229	0.52279	0.5229	0.52277	0.5229	0.52285	0.5229	0.5228
Fixture Utilization after the disruptive event	0.731	0.73121	0.731	0.73119	0.731	0.73119	0.731	0.73125	0.731	0.73121

Count	246		247		248		249		250	
Exp. NO	311		312		313		314		315	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6169	0.61823	0.6169	0.61827	0.6169	0.61825	0.6169	0.61828	0.6169	0.61825
M6 Utilization after the disruptive event	0.0648	0.06723	0.0648	0.06725	0.0648	0.067239	0.0648	0.067267	0.0648	0.067281
M2 Utilization after the disruptive event	0.5667	0.56766	0.5667	0.56758	0.5667	0.56762	0.5667	0.56755	0.5667	0.56758
M5 Utilization after the disruptive event	0.6824	0.68519	0.6824	0.68518	0.6824	0.68519	0.6824	0.68518	0.6824	0.68518
M3 Utilization after the disruptive event	0.7527	0.75253	0.7527	0.75255	0.7527	0.75254	0.7527	0.75255	0.7527	0.75255
M7 Utilization after the disruptive event	0.681	0.68085	0.681	0.68089	0.681	0.68087	0.681	0.6809	0.681	0.68087
M9 Utilization after the disruptive event	0.7115	0.71152	0.7115	0.71152	0.7115	0.71152	0.7115	0.71152	0.7115	0.71152
M12 Utilization after the disruptive event	0.6085	0.60842	0.6085	0.60842	0.6085	0.60842	0.6085	0.60843	0.6085	0.60842
AGV Utilization after the disruptive event	0.5229	0.52282	0.5229	0.52278	0.5229	0.5228	0.5229	0.52277	0.5229	0.52281
Fixture Utilization after the disruptive event	0.731	0.73122	0.731	0.73119	0.731	0.73121	0.731	0.73118	0.731	0.73122

Count	251		252		253		254		255	
Exp. NO	316		317		318		319		320	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6169	0.61822	0.6169	0.61825	0.6169	0.61827	0.6169	0.61829	0.6169	0.61823
M6 Utilization after the disruptive event	0.0648	0.067268	0.0648	0.067235	0.0648	0.067244	0.0648	0.067234	0.0648	0.067297
M2 Utilization after the disruptive event	0.5667	0.56763	0.5667	0.56764	0.5667	0.56759	0.5667	0.56758	0.5667	0.56758
M5 Utilization after the disruptive event	0.6824	0.68518	0.6824	0.68518	0.6824	0.68518	0.6824	0.68518	0.6824	0.68518
M3 Utilization after the disruptive event	0.7527	0.75254	0.7527	0.75254	0.7527	0.75255	0.7527	0.75255	0.7527	0.75254
M7 Utilization after the disruptive event	0.681	0.68085	0.681	0.68086	0.681	0.68089	0.681	0.6809	0.681	0.68087
M9 Utilization after the disruptive event	0.7115	0.71152	0.7115	0.71152	0.7115	0.71152	0.7115	0.71152	0.7115	0.71152
M12 Utilization after the disruptive event	0.6085	0.60841	0.6085	0.60842	0.6085	0.60842	0.6085	0.60843	0.6085	0.60842
AGV Utilization after the disruptive event	0.5229	0.52284	0.5229	0.52281	0.5229	0.52278	0.5229	0.52276	0.5229	0.52283
Fixture Utilization after the disruptive event	0.731	0.73124	0.731	0.73121	0.731	0.73119	0.731	0.73117	0.731	0.73124

Count	256		257		258		259		260	
Exp. NO	146		147		148		149		150	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6462	0.64561	0.6462	0.64562	0.6462	0.64561	0.6462	0.64563	0.6462	0.64561
M6 Utilization after the disruptive event	0.4651	0.46454	0.4651	0.46457	0.4651	0.46448	0.4651	0.46455	0.4651	0.46459
M2 Utilization after the disruptive event	0.0682	0.068794	0.0682	0.068803	0.0682	0.068798	0.0682	0.068804	0.0682	0.068797
M5 Utilization after the disruptive event	0.6511	0.65019	0.6511	0.65012	0.6511	0.65025	0.6511	0.65012	0.6511	0.6501
M3 Utilization after the disruptive event	0.7997	0.80059	0.7997	0.80059	0.7997	0.80058	0.7997	0.80059	0.7997	0.8006
M7 Utilization after the disruptive event	0.7839	0.78245	0.7839	0.78245	0.7839	0.78246	0.7839	0.78244	0.7839	0.78245
M9 Utilization after the disruptive event	0.7159	0.71635	0.7159	0.71634	0.7159	0.71635	0.7159	0.71634	0.7159	0.71634
M12 Utilization after the disruptive event	0.6122	0.61207	0.6122	0.61206	0.6122	0.61207	0.6122	0.61206	0.6122	0.61206
AGV Utilization after the disruptive event	0.4854	0.48503	0.4854	0.48502	0.4854	0.48502	0.4854	0.48501	0.4854	0.48502
Fixture Utilization after the disruptive event	0.7196	0.71942	0.7196	0.71939	0.7196	0.71944	0.7196	0.71939	0.7196	0.71938

Count	261		262		263		264		265	
Exp. NO	351		352		353		354		355	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6462	0.64562	0.6462	0.64562	0.6462	0.64562	0.6462	0.64562	0.6462	0.64562
M6 Utilization after the disruptive event	0.4651	0.46453	0.4651	0.46457	0.4651	0.46455	0.4651	0.4645	0.4651	0.4645
M2 Utilization after the disruptive event	0.0682	0.068796	0.0682	0.0688	0.0682	0.0688	0.0682	0.068801	0.0682	0.068802
M5 Utilization after the disruptive event	0.6511	0.65019	0.6511	0.65012	0.6511	0.65015	0.6511	0.65021	0.6511	0.6502
M3 Utilization after the disruptive event	0.7997	0.80059	0.7997	0.80059	0.7997	0.80059	0.7997	0.80058	0.7997	0.80058
M7 Utilization after the disruptive event	0.7839	0.78245	0.7839	0.78245	0.7839	0.78245	0.7839	0.78245	0.7839	0.78245
M9 Utilization after the disruptive event	0.7159	0.71635	0.7159	0.71634	0.7159	0.71634	0.7159	0.71635	0.7159	0.71635
M12 Utilization after the disruptive event	0.6122	0.61207	0.6122	0.61206	0.6122	0.61206	0.6122	0.61207	0.6122	0.61207
AGV Utilization after the disruptive event	0.4854	0.48502	0.4854	0.48501	0.4854	0.48502	0.4854	0.48501	0.4854	0.48502
Fixture Utilization after the disruptive event	0.7196	0.71942	0.7196	0.71939	0.7196	0.7194	0.7196	0.71942	0.7196	0.71942

Count	266		267		268		269		270	
Exp. NO	356		357		358		359		360	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6462	0.6456	0.6462	0.64561	0.6462	0.64562	0.6462	0.64561	0.6462	0.64561
M6 Utilization after the disruptive event	0.4651	0.46452	0.4651	0.46447	0.4651	0.46449	0.4651	0.46466	0.4651	0.46455
M2 Utilization after the disruptive event	0.0682	0.068794	0.0682	0.068801	0.0682	0.068805	0.0682	0.068791	0.0682	0.068797
M5 Utilization after the disruptive event	0.6511	0.65021	0.6511	0.65025	0.6511	0.65021	0.6511	0.65003	0.6511	0.65015
M3 Utilization after the disruptive event	0.7997	0.80059	0.7997	0.80058	0.7997	0.80058	0.7997	0.8006	0.7997	0.80059
M7 Utilization after the disruptive event	0.7839	0.78246	0.7839	0.78246	0.7839	0.78245	0.7839	0.78245	0.7839	0.78245
M9 Utilization after the disruptive event	0.7159	0.71635	0.7159	0.71635	0.7159	0.71635	0.7159	0.71633	0.7159	0.71634
M12 Utilization after the disruptive event	0.6122	0.61207	0.6122	0.61207	0.6122	0.61207	0.6122	0.61205	0.6122	0.61206
AGV Utilization after the disruptive event	0.4854	0.48503	0.4854	0.48503	0.4854	0.48501	0.4854	0.48502	0.4854	0.48502
Fixture Utilization after the disruptive event	0.7196	0.71943	0.7196	0.71944	0.7196	0.71942	0.7196	0.71935	0.7196	0.7194

Count	271		272		273		274		275	
Exp. NO	156		157		158		159		160	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6574	0.65747	0.6574	0.65742	0.6574	0.65749	0.6574	0.6575	0.6574	0.65752
M6 Utilization after the disruptive event	0.5269	0.52664	0.5269	0.5266	0.5269	0.52666	0.5269	0.52664	0.5269	0.52668
M2 Utilization after the disruptive event	0.4767	0.47638	0.4767	0.47636	0.4767	0.47639	0.4767	0.4764	0.4767	0.47641
M5 Utilization after the disruptive event	0.0396	0.038295	0.0396	0.038421	0.0396	0.038233	0.0396	0.038248	0.0396	0.038178
M3 Utilization after the disruptive event	0.7951	0.79504	0.7951	0.79506	0.7951	0.79502	0.7951	0.79503	0.7951	0.79501
M7 Utilization after the disruptive event	0.7693	0.77027	0.7693	0.77032	0.7693	0.77025	0.7693	0.77026	0.7693	0.77023
M9 Utilization after the disruptive event	0.7137	0.71366	0.7137	0.71366	0.7137	0.71366	0.7137	0.71366	0.7137	0.71366
M12 Utilization after the disruptive event	0.609	0.6089	0.609	0.6089	0.609	0.6089	0.609	0.6089	0.609	0.6089
AGV Utilization after the disruptive event	0.4903	0.49044	0.4903	0.49039	0.4903	0.49047	0.4903	0.49046	0.4903	0.49049
Fixture Utilization after the disruptive event	0.7103	0.71035	0.7103	0.71035	0.7103	0.71034	0.7103	0.71035	0.7103	0.71034

Count	276		277		278		279		280	
Exp. NO	391		392		393		394		395	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6574	0.65747	0.6574	0.65746	0.6574	0.65751	0.6574	0.65742	0.6574	0.6575
M6 Utilization after the disruptive event	0.5269	0.52665	0.5269	0.52662	0.5269	0.52668	0.5269	0.52661	0.5269	0.52664
M2 Utilization after the disruptive event	0.4767	0.47638	0.4767	0.47639	0.4767	0.4764	0.4767	0.47637	0.4767	0.4764
M5 Utilization after the disruptive event	0.0396	0.038294	0.0396	0.038334	0.0396	0.038183	0.0396	0.038407	0.0396	0.038251
M3 Utilization after the disruptive event	0.7951	0.79503	0.7951	0.79505	0.7951	0.79501	0.7951	0.79506	0.7951	0.79503
M7 Utilization after the disruptive event	0.7693	0.77027	0.7693	0.77029	0.7693	0.77022	0.7693	0.77031	0.7693	0.77026
M9 Utilization after the disruptive event	0.7137	0.71366	0.7137	0.71366	0.7137	0.71366	0.7137	0.71366	0.7137	0.71366
M12 Utilization after the disruptive event	0.609	0.6089	0.609	0.6089	0.609	0.6089	0.609	0.6089	0.609	0.6089
AGV Utilization after the disruptive event	0.4903	0.49045	0.4903	0.49042	0.4903	0.4905	0.4903	0.4904	0.4903	0.49045
Fixture Utilization after the disruptive event	0.7103	0.71034	0.7103	0.71035	0.7103	0.71034	0.7103	0.71035	0.7103	0.71035

Count	281		282		283		284		285	
Exp. NO	396		397		398		399		400	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.6574	0.6575	0.6574	0.6575	0.6574	0.65748	0.6574	0.65749	0.6574	0.65745
M6 Utilization after the disruptive event	0.5269	0.52668	0.5269	0.52668	0.5269	0.52664	0.5269	0.52665	0.5269	0.52663
M2 Utilization after the disruptive event	0.4767	0.47639	0.4767	0.47639	0.4767	0.47639	0.4767	0.47639	0.4767	0.47637
M5 Utilization after the disruptive event	0.0396	0.038203	0.0396	0.038213	0.0396	0.03829	0.0396	0.038268	0.0396	0.038332
M3 Utilization after the disruptive event	0.7951	0.79502	0.7951	0.79502	0.7951	0.79504	0.7951	0.79503	0.7951	0.79504
M7 Utilization after the disruptive event	0.7693	0.77023	0.7693	0.77023	0.7693	0.77027	0.7693	0.77026	0.7693	0.77028
M9 Utilization after the disruptive event	0.7137	0.71366	0.7137	0.71366	0.7137	0.71366	0.7137	0.71366	0.7137	0.71366
M12 Utilization after the disruptive event	0.609	0.6089	0.609	0.6089	0.609	0.6089	0.609	0.6089	0.609	0.6089
AGV Utilization after the disruptive event	0.4903	0.49049	0.4903	0.49049	0.4903	0.49044	0.4903	0.49045	0.4903	0.49043
Fixture Utilization after the disruptive event	0.7103	0.71034	0.7103	0.71034	0.7103	0.71035	0.7103	0.71035	0.7103	0.71034

Count	286		287		288		289		290	
Exp. NO	161		162		163		164		165	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.585	0.58335	0.585	0.58334	0.585	0.58332	0.585	0.58334	0.585	0.58334
M6 Utilization after the disruptive event	0.5061	0.50393	0.5061	0.50393	0.5061	0.50391	0.5061	0.50393	0.5061	0.50392
M2 Utilization after the disruptive event	0.6484	0.64636	0.6484	0.64636	0.6484	0.64637	0.6484	0.64637	0.6484	0.64637
M5 Utilization after the disruptive event	0.0843	0.083003	0.0843	0.082999	0.0843	0.083011	0.0843	0.082987	0.0843	0.082995
M3 Utilization after the disruptive event	0.6919	0.69112	0.6919	0.69112	0.6919	0.69113	0.6919	0.69113	0.6919	0.69113
M7 Utilization after the disruptive event	0.6446	0.64453	0.6446	0.64452	0.6446	0.64454	0.6446	0.64454	0.6446	0.64453
M9 Utilization after the disruptive event	0.7819	0.78143	0.7819	0.78143	0.7819	0.78141	0.7819	0.78142	0.7819	0.78142
M12 Utilization after the disruptive event	0.6596	0.66	0.6596	0.65999	0.6596	0.65998	0.6596	0.65999	0.6596	0.65999
AGV Utilization after the disruptive event	0.5346	0.53454	0.5346	0.53453	0.5346	0.53456	0.5346	0.53456	0.5346	0.53455
Fixture Utilization after the disruptive event	0.7312	0.73149	0.7312	0.73147	0.7312	0.73145	0.7312	0.73148	0.7312	0.73147

Count	291		292		293		294		295	
Exp. NO	411		412		413		414		415	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.585	0.58336	0.585	0.58334	0.585	0.58333	0.585	0.58333	0.585	0.58335
M6 Utilization after the disruptive event	0.5061	0.50394	0.5061	0.50393	0.5061	0.50391	0.5061	0.50392	0.5061	0.50393
M2 Utilization after the disruptive event	0.6484	0.64634	0.6484	0.64638	0.6484	0.64638	0.6484	0.64637	0.6484	0.64635
M5 Utilization after the disruptive event	0.0843	0.083017	0.0843	0.082969	0.0843	0.082987	0.0843	0.083005	0.0843	0.083016
M3 Utilization after the disruptive event	0.6919	0.6911	0.6919	0.69114	0.6919	0.69114	0.6919	0.69113	0.6919	0.69112
M7 Utilization after the disruptive event	0.6446	0.64451	0.6446	0.64455	0.6446	0.64454	0.6446	0.64454	0.6446	0.64452
M9 Utilization after the disruptive event	0.7819	0.78144	0.7819	0.78141	0.7819	0.78141	0.7819	0.78142	0.7819	0.78144
M12 Utilization after the disruptive event	0.6596	0.66001	0.6596	0.65998	0.6596	0.65997	0.6596	0.65999	0.6596	0.66001
AGV Utilization after the disruptive event	0.5346	0.53449	0.5346	0.5346	0.5346	0.53457	0.5346	0.53456	0.5346	0.53453
Fixture Utilization after the disruptive event	0.7312	0.73148	0.7312	0.7315	0.7312	0.73146	0.7312	0.73146	0.7312	0.73148

Count	296		297		298		299		300	
Exp. NO	416		417		418		419		420	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
M1 Utilization after the disruptive event	0.585	0.58333	0.585	0.58331	0.585	0.58333	0.585	0.58333	0.585	0.58335
M6 Utilization after the disruptive event	0.5061	0.50392	0.5061	0.50389	0.5061	0.50391	0.5061	0.50391	0.5061	0.50393
M2 Utilization after the disruptive event	0.6484	0.64638	0.6484	0.6464	0.6484	0.64637	0.6484	0.64637	0.6484	0.64636
M5 Utilization after the disruptive event	0.0843	0.082976	0.0843	0.082991	0.0843	0.083002	0.0843	0.083017	0.0843	0.082993
M3 Utilization after the disruptive event	0.6919	0.69115	0.6919	0.69116	0.6919	0.69113	0.6919	0.69113	0.6919	0.69113
M7 Utilization after the disruptive event	0.6446	0.64455	0.6446	0.64457	0.6446	0.64454	0.6446	0.64453	0.6446	0.64454
M9 Utilization after the disruptive event	0.7819	0.7814	0.7819	0.78139	0.7819	0.78141	0.7819	0.78142	0.7819	0.78143
M12 Utilization after the disruptive event	0.6596	0.65998	0.6596	0.65996	0.6596	0.65998	0.6596	0.65999	0.6596	0.66
AGV Utilization after the disruptive event	0.5346	0.53461	0.5346	0.53464	0.5346	0.53456	0.5346	0.53455	0.5346	0.53456
Fixture Utilization after the disruptive event	0.7312	0.73148	0.7312	0.73146	0.7312	0.73146	0.7312	0.73145	0.7312	0.73149

C.12 Output Vectors for *Net_2_3_2*

Count	1		2		3		4		5	
Exp. NO	21		22		23		24		25	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	223	233.32	223	233.59	223	233.08	223	233.28	223	233.4
A0 (8th order polynomial's coefficient)	161.43	161.37	161.43	161.38	161.43	161.36	161.43	161.37	161.43	161.36
A1	2.717	6.664	2.717	6.0511	2.717	7.1798	2.717	6.6929	2.717	6.5437
A2	1170.2	1156.5	1170.2	1159.4	1170.2	1154	1170.2	1156.3	1170.2	1157.1
A3	-4615	-4711.5	-4615	-4718.6	-4615	-4705.5	-4615	-4711.1	-4615	-4713
A4	7930.2	8159.7	7930.2	8169.2	7930.2	8151.8	7930.2	8159.5	7930.2	8161.4
A5	-7243	-7402.3	-7243	-7409.6	-7243	-7396.4	-7243	-7402.6	-7243	-7403.2
A6	3645.6	3668.5	3645.6	3671.7	3645.6	3666	3645.6	3668.9	3645.6	3668.6
A7	-952.85	-939.38	-952.85	-940.13	-952.85	-938.83	-952.85	-939.55	-952.85	-939.34
A8	100.88	97.145	100.88	97.217	100.88	97.095	100.88	97.17	100.88	97.133
sigma pre-disruption	34.14754404	34.375	34.14754404	34.394	34.14754404	34.36	34.14754404	34.378	34.14754404	34.373
sigma transient	55.05299785	56.042	55.05299785	56.038	55.05299785	56.044	55.05299785	56.041	55.05299785	56.041
sigma post-transient	58.1883331	56.641	58.1883331	56.638	58.1883331	56.642	58.1883331	56.64	58.1883331	56.64

Count	6		7		8		9		10	
Exp. NO	281		282		283		284		285	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	223	233.23	223	233.09	223	233.85	223	233.11	223	232.97
A0 (8th order polynomial's coefficient)	161.43	161.36	161.43	161.36	161.43	161.38	161.43	161.37	161.43	161.35
A1	2.717	6.8357	2.717	7.1496	2.717	5.5911	2.717	7.0157	2.717	7.3998
A2	1170.2	1155.7	1170.2	1154.2	1170.2	1161.7	1170.2	1154.7	1170.2	1152.9
A3	-4615	-4709.5	-4615	-4705.8	-4615	-4724.1	-4615	-4707.2	-4615	-4702.9
A4	7930.2	8157.1	7930.2	8152.2	7930.2	8176	7930.2	8154.6	7930.2	8148.5
A5	-7243	-7400.5	-7243	-7396.7	-7243	-7414.1	-7243	-7399.3	-7243	-7394.1
A6	3645.6	3667.8	3645.6	3666.1	3645.6	3673.2	3645.6	3667.7	3645.6	3665.2
A7	-952.85	-939.24	-952.85	-938.85	-952.85	-940.34	-952.85	-939.33	-952.85	-938.68
A8	100.88	97.134	100.88	97.097	100.88	97.221	100.88	97.157	100.88	97.086
sigma pre-disruption	34.14754404	34.37	34.14754404	34.36	34.14754404	34.4	34.14754404	34.373	34.14754404	34.355
sigma transient	55.05299785	56.042	55.05299785	56.044	55.05299785	56.036	55.05299785	56.043	55.05299785	56.045
sigma post-transient	58.1883331	56.641	58.1883331	56.642	58.1883331	56.637	58.1883331	56.642	58.1883331	56.643

Count	11		12		13		14		15	
Exp. NO	286		287		288		289		290	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	223	233.14	223	233.36	223	233.12	223	233.11	223	233.06
A0 (8th order polynomial's coefficient)	161.43	161.36	161.43	161.37	161.43	161.37	161.43	161.37	161.43	161.36
A1	2.717	7.0562	2.717	6.5387	2.717	6.9788	2.717	6.9779	2.717	7.2168
A2	1170.2	1154.6	1170.2	1157.1	1170.2	1154.8	1170.2	1154.8	1170.2	1153.8
A3	-4615	-4707	-4615	-4712.8	-4615	-4707.5	-4615	-4707.5	-4615	-4705
A4	7930.2	8153.7	7930.2	8161.7	7930.2	8155.3	7930.2	8155.3	7930.2	8151.2
A5	-7243	-7397.7	-7243	-7404	-7243	-7400	-7243	-7400.2	-7243	-7396
A6	3645.6	3666.5	3645.6	3669.4	3645.6	3668.1	3645.6	3668.3	3645.6	3665.8
A7	-952.85	-938.92	-952.85	-939.61	-952.85	-939.47	-952.85	-939.53	-952.85	-938.79
A8	100.88	97.102	100.88	97.17	100.88	97.174	100.88	97.182	100.88	97.093
sigma pre-disruption	34.14754404	34.362	34.14754404	34.381	34.14754404	34.376	34.14754404	34.378	34.14754404	34.359
sigma transient	55.05299785	56.043	55.05299785	56.041	55.05299785	56.043	55.05299785	56.043	55.05299785	56.045
sigma post-transient	58.1883331	56.642	58.1883331	56.641	58.1883331	56.642	58.1883331	56.642	58.1883331	56.643

Count	16		17		18		19		20	
Exp. NO	6		7		8		9		10	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	258	251.54	258	251.5	258	251.81	258	251.63	258	251.6
A0 (8th order polynomial's coefficient)	173.91	173.97	173.91	173.97	173.91	173.97	173.91	173.97	173.91	173.97
A1	-50.131	-54.315	-50.131	-54.308	-50.131	-54.024	-50.131	-54.161	-50.131	-54.199
A2	1232.3	1255.6	1232.3	1255.5	1232.3	1254.6	1232.3	1255	1232.3	1255.1
A3	-4982.5	-4892.5	-4982.5	-4892.3	-4982.5	-4889.8	-4982.5	-4890.9	-4982.5	-4891.3
A4	9030.7	8742	9030.7	8741.9	9030.7	8736.2	9030.7	8739	9030.7	8739.8
A5	-8543.4	-8310.7	-8543.4	-8310.9	-8543.4	-8303.3	-8543.4	-8307.2	-8543.4	-8308.1
A6	4382.2	4336.3	4382.2	4336.6	4382.2	4331.3	4382.2	4334.1	4382.2	4334.7
A7	-1157.1	-1172.7	-1157.1	-1172.8	-1157.1	-1171.1	-1157.1	-1172	-1157.1	-1172.2
A8	123.45	128.57	123.45	128.58	123.45	128.35	123.45	128.48	123.45	128.5
sigma pre-disruption	52.87843603	52.964	52.87843603	52.964	52.87843603	52.96	52.87843603	52.962	52.87843603	52.962
sigma transient	70.67626315	70.041	70.67626315	70.037	70.67626315	70.11	70.67626315	70.07	70.67626315	70.062
sigma post-transient	73.04227531	74.23	73.04227531	74.224	73.04227531	74.311	73.04227531	74.264	73.04227531	74.254

Count	21		22		23		24		25	
Exp. NO	301		302		303		304		305	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	258	251.52	258	251.5	258	251.45	258	251.32	258	251.86
A0 (8th order polynomial's coefficient)	173.91	173.97	173.91	173.97	173.91	173.97	173.91	173.97	173.91	173.97
A1	-50.131	-54.262	-50.131	-54.318	-50.131	-54.35	-50.131	-54.462	-50.131	-54.003
A2	1232.3	1255.3	1232.3	1255.6	1232.3	1255.7	1232.3	1256	1232.3	1254.5
A3	-4982.5	-4891.8	-4982.5	-4892.4	-4982.5	-4892.6	-4982.5	-4893.6	-4982.5	-4889.7
A4	9030.7	8741.1	9030.7	8742.1	9030.7	8742.8	9030.7	8745.1	9030.7	8735.7
A5	-8543.4	-8310	-8543.4	-8311.1	-8543.4	-8312.1	-8543.4	-8315.3	-8543.4	-8302.4
A6	4382.2	4336	4382.2	4336.7	4382.2	4337.4	4382.2	4339.7	4382.2	4330.6
A7	-1157.1	-1172.7	-1157.1	-1172.9	-1157.1	-1173.1	-1157.1	-1173.9	-1157.1	-1170.8
A8	123.45	128.56	123.45	128.59	123.45	128.62	123.45	128.72	123.45	128.32
sigma pre-disruption	52.87843603	52.963	52.87843603	52.964	52.87843603	52.964	52.87843603	52.966	52.87843603	52.959
sigma transient	70.67626315	70.044	70.67626315	70.035	70.67626315	70.024	70.67626315	69.992	70.67626315	70.122
sigma post-transient	73.04227531	74.232	73.04227531	74.223	73.04227531	74.21	73.04227531	74.172	73.04227531	74.324

Count	26		27		28		29		30	
Exp. NO	306		307		308		309		310	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	258	251.04	258	251.41	258	251.61	258	251.42	258	251.43
A0 (8th order polynomial's coefficient)	173.91	173.97	173.91	173.97	173.91	173.97	173.91	173.97	173.91	173.97
A1	-50.131	-54.711	-50.131	-54.392	-50.131	-54.171	-50.131	-54.379	-50.131	-54.366
A2	1232.3	1256.9	1232.3	1255.8	1232.3	1255	1232.3	1255.8	1232.3	1255.7
A3	-4982.5	-4895.7	-4982.5	-4893	-4982.5	-4891	-4982.5	-4892.9	-4982.5	-4892.8
A4	9030.7	8750.1	9030.7	8743.6	9030.7	8739.3	9030.7	8743.4	9030.7	8743.1
A5	-8543.4	-8322.1	-8543.4	-8313.2	-8543.4	-8307.6	-8543.4	-8312.9	-8543.4	-8312.6
A6	4382.2	4344.4	4382.2	4338.2	4382.2	4334.4	4382.2	4338	4382.2	4337.8
A7	-1157.1	-1175.5	-1157.1	-1173.4	-1157.1	-1172.1	-1157.1	-1173.3	-1157.1	-1173.2
A8	123.45	128.93	123.45	128.66	123.45	128.49	123.45	128.65	123.45	128.64
sigma pre-disruption	52.87843603	52.969	52.87843603	52.965	52.87843603	52.962	52.87843603	52.965	52.87843603	52.965
sigma transient	70.67626315	69.926	70.67626315	70.013	70.67626315	70.065	70.67626315	70.016	70.67626315	70.02
sigma post-transient	73.04227531	74.095	73.04227531	74.197	73.04227531	74.258	73.04227531	74.2	73.04227531	74.204

Count	31		32		33		34		35	
Exp. NO	11		12		13		14		15	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	243	195.53	243	195.55	243	195.53	243	195.54	243	195.52
A0 (8th order polynomial's coefficient)	155.39	155.66	155.39	155.66	155.39	155.66	155.39	155.66	155.39	155.66
A1	-111.88	-121.95	-111.88	-121.96	-111.88	-121.97	-111.88	-121.94	-111.88	-121.97
A2	670.09	651.3	670.09	651.29	670.09	651.47	670.09	651.19	670.09	651.55
A3	-1772.5	-1679.3	-1772.5	-1679.1	-1772.5	-1680	-1772.5	-1678.8	-1772.5	-1680.5
A4	2440.1	2329	2440.1	2328.3	2440.1	2330.3	2440.1	2327.7	2440.1	2331.6
A5	-1895	-1841.3	-1895	-1840.3	-1895	-1842.8	-1895	-1839.8	-1895	-1844.4
A6	840.8	832.02	840.8	831.4	840.8	832.95	840.8	831.09	840.8	833.95
A7	-199.46	-200.25	-199.46	-200.05	-199.46	-200.54	-199.46	-199.96	-199.46	-200.86
A8	19.667	19.937	19.667	19.911	19.667	19.971	19.667	19.901	19.667	20.011
sigma pre-disruption	53.09362062	53.007	53.09362062	53.007	53.09362062	53.007	53.09362062	53.007	53.09362062	53.007
sigma transient	35.13792688	35.251	35.13792688	35.252	35.13792688	35.248	35.13792688	35.253	35.13792688	35.245
sigma post-transient	34.43157757	34.346	34.43157757	34.347	34.43157757	34.342	34.43157757	34.349	34.43157757	34.339

Count	36		37		38		39		40	
Exp. NO	181		182		183		184		185	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	243	195.54	243	195.53	243	195.53	243	195.53	243	195.54
A0 (8th order polynomial's coefficient)	155.39	155.66	155.39	155.66	155.39	155.66	155.39	155.66	155.39	155.66
A1	-111.88	-121.98	-111.88	-121.95	-111.88	-121.98	-111.88	-121.9	-111.88	-121.95
A2	670.09	651.48	670.09	651.3	670.09	651.54	670.09	650.97	670.09	651.27
A3	-1772.5	-1680	-1772.5	-1679.3	-1772.5	-1680.3	-1772.5	-1678.1	-1772.5	-1679.1
A4	2440.1	2330.1	2440.1	2329	2440.1	2330.8	2440.1	2326.7	2440.1	2328.3
A5	-1895	-1842.5	-1895	-1841.3	-1895	-1843.4	-1895	-1838.9	-1895	-1840.4
A6	840.8	832.72	840.8	832.04	840.8	833.28	840.8	830.63	840.8	831.49
A7	-199.46	-200.46	-199.46	-200.26	-199.46	-200.64	-199.46	-199.84	-199.46	-200.08
A8	19.667	19.961	19.667	19.938	19.667	19.983	19.667	19.887	19.667	19.915
sigma pre-disruption	53.09362062	53.007	53.09362062	53.007	53.09362062	53.007	53.09362062	53.007	53.09362062	53.007
sigma transient	35.13792688	35.248	35.13792688	35.251	35.13792688	35.247	35.13792688	35.256	35.13792688	35.252
sigma post-transient	34.43157757	34.342	34.43157757	34.345	34.43157757	34.341	34.43157757	34.351	34.43157757	34.347

Count	41		42		43		44		45	
Exp. NO	186		187		188		189		190	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	243	195.53	243	195.52	243	195.55	243	195.54	243	195.54
A0 (8th order polynomial's coefficient)	155.39	155.66	155.39	155.66	155.39	155.66	155.39	155.66	155.39	155.66
A1	-111.88	-121.95	-111.88	-121.95	-111.88	-121.98	-111.88	-121.98	-111.88	-121.98
A2	670.09	651.26	670.09	651.31	670.09	651.42	670.09	651.52	670.09	651.47
A3	-1772.5	-1679.2	-1772.5	-1679.5	-1772.5	-1679.6	-1772.5	-1680.1	-1772.5	-1679.9
A4	2440.1	2328.8	2440.1	2329.4	2440.1	2329.1	2440.1	2330.3	2440.1	2329.9
A5	-1895	-1841.1	-1895	-1841.8	-1895	-1841.2	-1895	-1842.7	-1895	-1842.1
A6	840.8	831.92	840.8	832.42	840.8	831.94	840.8	832.85	840.8	832.51
A7	-199.46	-200.22	-199.46	-200.38	-199.46	-200.21	-199.46	-200.5	-199.46	-200.39
A8	19.667	19.933	19.667	19.953	19.667	19.93	19.667	19.966	19.667	19.953
sigma pre-disruption	53.09362062	53.007	53.09362062	53.007	53.09362062	53.007	53.09362062	53.007	53.09362062	53.007
sigma transient	35.13792688	35.251	35.13792688	35.25	35.13792688	35.25	35.13792688	35.248	35.13792688	35.249
sigma post-transient	34.43157757	34.346	34.43157757	34.344	34.43157757	34.345	34.43157757	34.342	34.43157757	34.343

Count	46		47		48		49		50	
Exp. NO	16		17		18		19		20	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	286	282.37	286	284.85	286	283.52	286	283.06	286	282.39
A0 (8th order polynomial's coefficient)	169.81	169.71	169.81	169.7	169.81	169.7	169.81	169.71	169.81	169.71
A1	231.44	237.64	231.44	236.92	231.44	237.31	231.44	237.43	231.44	237.63
A2	-1317.2	-1301.7	-1317.2	-1299.3	-1317.2	-1300.7	-1317.2	-1301.4	-1317.2	-1301.9
A3	3378.4	3216.4	3378.4	3213.1	3378.4	3215.1	3378.4	3217.2	3378.4	3217.4
A4	-4308.6	-4057.1	-4308.6	-4058.3	-4308.6	-4058.2	-4308.6	-4061	-4308.6	-4059.2
A5	2896	2770.9	2896	2778.1	2896	2774.8	2896	2776.6	2896	2773.2
A6	-1010.1	-1014.2	-1010.1	-1020.9	-1010.1	-1017.7	-1010.1	-1018.2	-1010.1	-1015.6
A7	159.95	178.98	159.95	181.51	159.95	180.24	159.95	180.29	159.95	179.37
A8	-6.8952	-10.691	-6.8952	-11.041	-6.8952	-10.864	-6.8952	-10.859	-6.8952	-10.737
sigma pre-disruption	52.90986767	53.209	52.90986767	53.221	52.90986767	53.215	52.90986767	53.213	52.90986767	53.21
sigma transient	53.6043572	53.785	53.6043572	53.878	53.6043572	53.827	53.6043572	53.805	53.6043572	53.782
sigma post-transient	54.9617507	54.11	54.9617507	54.221	54.9617507	54.16	54.9617507	54.135	54.9617507	54.107

Count	51		52		53		54		55	
Exp. NO	261		262		263		264		265	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	286	283.62	286	283.22	286	284.12	286	282.89	286	283.12
A0 (8th order polynomial's coefficient)	169.81	169.7	169.81	169.7	169.81	169.7	169.81	169.7	169.81	169.71
A1	231.44	237.27	231.44	237.39	231.44	237.13	231.44	237.49	231.44	237.42
A2	-1317.2	-1300.7	-1317.2	-1301.1	-1317.2	-1300.2	-1317.2	-1301.3	-1317.2	-1301.2
A3	3378.4	3215.8	3378.4	3216	3378.4	3214.8	3378.4	3216.1	3378.4	3216.5
A4	-4308.6	-4060	-4308.6	-4059	-4308.6	-4059.5	-4308.6	-4058.1	-4308.6	-4059.7
A5	2896	2776.9	2896	2775	2896	2777.6	2896	2773.2	2896	2775.4
A6	-1010.1	-1019	-1010.1	-1017.4	-1010.1	-1019.9	-1010.1	-1016.1	-1010.1	-1017.6
A7	159.95	180.64	159.95	180.11	159.95	181.03	159.95	179.64	159.95	180.12
A8	-6.8952	-10.912	-6.8952	-10.841	-6.8952	-10.968	-6.8952	-10.779	-6.8952	-10.84
sigma pre-disruption	52.90986767	53.216	52.90986767	53.214	52.90986767	53.218	52.90986767	53.212	52.90986767	53.213
sigma transient	53.6043572	53.828	53.6043572	53.815	53.6043572	53.848	53.6043572	53.803	53.6043572	53.81
sigma post-transient	54.9617507	54.162	54.9617507	54.146	54.9617507	54.186	54.9617507	54.132	54.9617507	54.14

Count	56		57		58		59		60	
Exp. NO	266		267		268		269		270	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	286	284.34	286	283.36	286	283.88	286	283.5	286	283.04
A0 (8th order polynomial's coefficient)	169.81	169.7	169.81	169.71	169.81	169.7	169.81	169.7	169.81	169.71
A1	231.44	237.07	231.44	237.35	231.44	237.2	231.44	237.31	231.44	237.44
A2	-1317.2	-1300.2	-1317.2	-1301	-1317.2	-1300.4	-1317.2	-1300.8	-1317.2	-1301.3
A3	3378.4	3215.8	3378.4	3216.5	3378.4	3214.7	3378.4	3215.5	3378.4	3216.5
A4	-4308.6	-4062.2	-4308.6	-4060.5	-4308.6	-4058.6	-4308.6	-4058.9	-4308.6	-4059.5
A5	2896	2780.9	2896	2777	2896	2776.1	2896	2775.5	2896	2775.1
A6	-1010.1	-1021.9	-1010.1	-1018.7	-1010.1	-1018.7	-1010.1	-1018	-1010.1	-1017.3
A7	159.95	181.68	159.95	180.52	159.95	180.64	159.95	180.35	159.95	180.04
A8	-6.8952	-11.049	-6.8952	-10.893	-6.8952	-10.918	-6.8952	-10.876	-6.8952	-10.83
sigma pre-disruption	52.90986767	53.22	52.90986767	53.215	52.90986767	53.217	52.90986767	53.215	52.90986767	53.213
sigma transient	53.6043572	53.852	53.6043572	53.818	53.6043572	53.841	53.6043572	53.826	53.6043572	53.807
sigma post-transient	54.9617507	54.191	54.9617507	54.15	54.9617507	54.177	54.9617507	54.159	54.9617507	54.137

Count	61		62		63		64		65	
Exp. NO	31		32		33		34		35	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	241	245.52	241	245.41	241	245.65	241	245.75	241	245.71
A0 (8th order polynomial's coefficient)	157.31	157.26	157.31	157.26	157.31	157.26	157.31	157.26	157.31	157.26
A1	288.96	284.11	288.96	284.3	288.96	283.91	288.96	283.73	288.96	283.81
A2	-1897	-1902.8	-1897	-1904	-1897	-1901.8	-1897	-1900.6	-1897	-1901.2
A3	5669.3	5788.1	5669.3	5791.2	5669.3	5785.8	5669.3	5782.7	5669.3	5784.4
A4	-9041.9	-9261.7	-9041.9	-9265.3	-9041.9	-9259.9	-9041.9	-9256.1	-9041.9	-9258.3
A5	8191.1	8321.3	8191.1	8323.3	8191.1	8321.5	8191.1	8319.1	8191.1	8320.7
A6	-4211.2	-4219.7	-4211.2	-4220.1	-4211.2	-4220.6	-4211.2	-4219.9	-4211.2	-4220.6
A7	1141.8	1127	1141.8	1127	1141.8	1127.5	1141.8	1127.5	1141.8	1127.6
A8	-126.57	-123.23	-126.57	-123.21	-126.57	-123.3	-126.57	-123.31	-126.57	-123.31
sigma pre-disruption	34.69555187	34.591	34.69555187	34.592	34.69555187	34.588	34.69555187	34.587	34.69555187	34.587
sigma transient	48.98767989	49.738	48.98767989	49.729	48.98767989	49.744	48.98767989	49.753	48.98767989	49.749
sigma post-transient	51.23305812	50.712	51.23305812	50.701	51.23305812	50.72	51.23305812	50.732	51.23305812	50.726

Count	66		67		68		69		70	
Exp. NO	401		402		403		404		405	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	241	245.62	241	245.62	241	245.94	241	245.77	241	245.94
A0 (8th order polynomial's coefficient)	157.31	157.26	157.31	157.26	157.31	157.26	157.31	157.26	157.31	157.26
A1	288.96	283.94	288.96	283.94	288.96	283.41	288.96	283.68	288.96	283.41
A2	-1897	-1901.8	-1897	-1901.8	-1897	-1898.7	-1897	-1900.3	-1897	-1898.7
A3	5669.3	5785.7	5669.3	5785.7	5669.3	5778.3	5669.3	5782	5669.3	5778.1
A4	-9041.9	-9259.1	-9041.9	-9259.1	-9041.9	-9251.4	-9041.9	-9255.1	-9041.9	-9251.1
A5	8191.1	8320.2	8191.1	8320.2	8191.1	8317.1	8191.1	8318.4	8191.1	8316.9
A6	-4211.2	-4219.7	-4211.2	-4219.7	-4211.2	-4220	-4211.2	-4219.7	-4211.2	-4219.9
A7	1141.8	1127.2	1141.8	1127.2	1141.8	1127.8	1141.8	1127.4	1141.8	1127.7
A8	-126.57	-123.26	-126.57	-123.26	-126.57	-123.37	-126.57	-123.31	-126.57	-123.36
sigma pre-disruption	34.69555187	34.589	34.69555187	34.589	34.69555187	34.584	34.69555187	34.587	34.69555187	34.584
sigma transient	48.98767989	49.745	48.98767989	49.745	48.98767989	49.767	48.98767989	49.756	48.98767989	49.767
sigma post-transient	51.23305812	50.721	51.23305812	50.721	51.23305812	50.749	51.23305812	50.735	51.23305812	50.75

Count	71		72		73		74		75	
Exp. NO	406		407		408		409		410	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	241	245.77	241	245.36	241	245.51	241	245.58	241	245.51
A0 (8th order polynomial's coefficient)	157.31	157.26	157.31	157.26	157.31	157.26	157.31	157.26	157.31	157.26
A1	288.96	283.69	288.96	284.39	288.96	284.14	288.96	284.02	288.96	284.14
A2	-1897	-1900.4	-1897	-1904.6	-1897	-1903.1	-1897	-1902.3	-1897	-1903.2
A3	5669.3	5782.5	5669.3	5792.7	5669.3	5789.1	5669.3	5786.8	5669.3	5789.3
A4	-9041.9	-9256	-9041.9	-9267.3	-9041.9	-9263.4	-9041.9	-9260.3	-9041.9	-9263.8
A5	8191.1	8319.4	8191.1	8324.6	8191.1	8323	8191.1	8320.8	8191.1	8323.3
A6	-4211.2	-4220.2	-4211.2	-4220.5	-4211.2	-4220.6	-4211.2	-4219.7	-4211.2	-4220.7
A7	1141.8	1127.6	1141.8	1127.1	1141.8	1127.3	1141.8	1127.2	1141.8	1127.3
A8	-126.57	-123.32	-126.57	-123.21	-126.57	-123.26	-126.57	-123.25	-126.57	-123.26
sigma pre-disruption	34.69555187	34.586	34.69555187	34.593	34.69555187	34.59	34.69555187	34.59	34.69555187	34.59
sigma transient	48.98767989	49.754	48.98767989	49.724	48.98767989	49.734	48.98767989	49.741	48.98767989	49.734
sigma post-transient	51.23305812	50.733	51.23305812	50.694	51.23305812	50.708	51.23305812	50.717	51.23305812	50.707

Count	76		77		78		79		80	
Exp. NO	46		47		48		49		50	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	280	276.88	280	276.42	280	276.61	280	276.59	280	276.71
A0 (8th order polynomial's coefficient)	171.93	171.76	171.93	171.77	171.93	171.77	171.93	171.77	171.93	171.77
A1	96.409	85.197	96.409	84.943	96.409	85.026	96.409	84.938	96.409	85.072
A2	230.6	183.88	230.6	185.78	230.6	185.17	230.6	185.84	230.6	184.82
A3	-1835.4	-1594	-1835.4	-1599.7	-1835.4	-1597.9	-1835.4	-1599.8	-1835.4	-1596.8
A4	3696.2	3441.2	3696.2	3450.7	3696.2	3447.5	3696.2	3450.4	3696.2	3445.7
A5	-3594.4	-3535.9	-3594.4	-3545	-3594.4	-3541.8	-3594.4	-3544.1	-3594.4	-3540
A6	1874.7	1915.9	1874.7	1920.9	1874.7	1919.1	1874.7	1920.1	1874.7	1918.1
A7	-505.4	-528.58	-505.4	-529.99	-505.4	-529.46	-505.4	-529.71	-505.4	-529.18
A8	55.388	58.593	55.388	58.756	55.388	58.693	55.388	58.717	55.388	58.66
sigma pre-disruption	53.67390616	52.668	53.67390616	52.668	53.67390616	52.668	53.67390616	52.668	53.67390616	52.668
sigma transient	68.82688312	69.394	68.82688312	69.364	68.82688312	69.378	68.82688312	69.38	68.82688312	69.385
sigma post-transient	73.0252017	72.917	73.0252017	72.882	73.0252017	72.899	73.0252017	72.901	73.0252017	72.906

Count	81		82		83		84		85	
Exp. NO	341		342		343		344		345	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	280	276.82	280	276.69	280	276.93	280	276.82	280	276.83
A0 (8th order polynomial's coefficient)	171.93	171.76	171.93	171.77	171.93	171.77	171.93	171.76	171.93	171.76
A1	96.409	85.11	96.409	85.024	96.409	85.023	96.409	85.104	96.409	85.108
A2	230.6	184.55	230.6	185.19	230.6	185.23	230.6	184.59	230.6	184.56
A3	-1835.4	-1596	-1835.4	-1597.9	-1835.4	-1598	-1835.4	-1596.1	-1835.4	-1596.1
A4	3696.2	3444.3	3696.2	3447.4	3696.2	3446.8	3696.2	3444.4	3696.2	3444.3
A5	-3594.4	-3538.5	-3594.4	-3541.4	-3594.4	-3540.1	-3594.4	-3538.6	-3594.4	-3538.5
A6	1874.7	1917.2	1874.7	1918.8	1874.7	1917.7	1874.7	1917.2	1874.7	1917.2
A7	-505.4	-528.91	-505.4	-529.34	-505.4	-528.94	-505.4	-528.91	-505.4	-528.89
A8	55.388	58.628	55.388	58.677	55.388	58.622	55.388	58.628	55.388	58.625
sigma pre-disruption	53.67390616	52.668	53.67390616	52.668	53.67390616	52.668	53.67390616	52.668	53.67390616	52.668
sigma transient	68.82688312	69.393	68.82688312	69.385	68.82688312	69.407	68.82688312	69.393	68.82688312	69.394
sigma post-transient	73.0252017	72.916	73.0252017	72.906	73.0252017	72.933	73.0252017	72.916	73.0252017	72.917

Count	86		87		88		89		90	
Exp. NO	346		347		348		349		350	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	280	276.27	280	276.47	280	276.84	280	276.96	280	276.72
A0 (8th order polynomial's coefficient)	171.93	171.77	171.93	171.77	171.93	171.76	171.93	171.77	171.93	171.77
A1	96.409	84.77	96.409	84.928	96.409	85.117	96.409	85.025	96.409	85.007
A2	230.6	187.09	230.6	185.9	230.6	184.49	230.6	185.22	230.6	185.33
A3	-1835.4	-1603.6	-1835.4	-1600.1	-1835.4	-1595.8	-1835.4	-1597.9	-1835.4	-1598.3
A4	3696.2	3456.7	3696.2	3451	3696.2	3443.9	3696.2	3446.6	3696.2	3447.8
A5	-3594.4	-3550.3	-3594.4	-3545.1	-3594.4	-3538.1	-3594.4	-3539.8	-3594.4	-3541.7
A6	1874.7	1923.6	1874.7	1920.9	1874.7	1917	1874.7	1917.5	1874.7	1918.8
A7	-505.4	-530.69	-505.4	-529.95	-505.4	-528.85	-505.4	-528.87	-505.4	-529.33
A8	55.388	58.831	55.388	58.749	55.388	58.62	55.388	58.613	55.388	58.673
sigma pre-disruption	53.67390616	52.668	53.67390616	52.668	53.67390616	52.668	53.67390616	52.668	53.67390616	52.668
sigma transient	68.82688312	69.357	68.82688312	69.369	68.82688312	69.395	68.82688312	69.41	68.82688312	69.388
sigma post-transient	73.0252017	72.875	73.0252017	72.888	73.0252017	72.918	73.0252017	72.936	73.0252017	72.911

Count	91		92		93		94		95	
Exp. NO	51		52		53		54		55	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	392	385.25	392	385.26	392	385.4	392	385.3	392	384.87
A0 (8th order polynomial's coefficient)	171.17	171.36	171.17	171.36	171.17	171.36	171.17	171.36	171.17	171.36
A1	107.09	107.33	107.09	107.32	107.09	107.15	107.09	107.27	107.09	107.59
A2	-46.838	-50.504	-46.838	-50.464	-46.838	-49.576	-46.838	-50.209	-46.838	-51.472
A3	-1170.3	-1184.1	-1170.3	-1184.2	-1170.3	-1186.3	-1170.3	-1184.8	-1170.3	-1182.5
A4	3563	3599.8	3563	3599.8	3563	3602.1	3563	3600.5	3563	3598.5
A5	-4457.1	-4480	-4457.1	-4480.1	-4457.1	-4481.1	-4457.1	-4480.3	-4457.1	-4479.9
A6	2791.7	2792.2	2791.7	2792.2	2791.7	2792.3	2791.7	2792.2	2791.7	2792.6
A7	-865.32	-862.27	-865.32	-862.27	-865.32	-862.17	-865.32	-862.23	-865.32	-862.47
A8	105.75	105.15	105.75	105.15	105.75	105.13	105.75	105.14	105.75	105.18
sigma pre-disruption	53.2012826	53.316	53.2012826	53.316	53.2012826	53.317	53.2012826	53.316	53.2012826	53.312
sigma transient	72.47915978	71.723	72.47915978	71.723	72.47915978	71.727	72.47915978	71.724	72.47915978	71.728
sigma post-transient	75.4297058	76.114	75.4297058	76.114	75.4297058	76.118	75.4297058	76.115	75.4297058	76.12

Count	96		97		98		99		100	
Exp. NO	381		382		383		384		385	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	392	385.26	392	385.28	392	385.31	392	385.31	392	385.41
A0 (8th order polynomial's coefficient)	171.17	171.36	171.17	171.36	171.17	171.36	171.17	171.36	171.17	171.36
A1	107.09	107.31	107.09	107.31	107.09	107.27	107.09	107.28	107.09	107.2
A2	-46.838	-50.458	-46.838	-50.457	-46.838	-50.221	-46.838	-50.315	-46.838	-49.971
A3	-1170.3	-1184.2	-1170.3	-1184.2	-1170.3	-1184.8	-1170.3	-1184.5	-1170.3	-1185.2
A4	3563	3599.8	3563	3599.7	3563	3600.4	3563	3600.1	3563	3600.8
A5	-4457.1	-4480	-4457.1	-4480	-4457.1	-4480.3	-4457.1	-4480.2	-4457.1	-4480.4
A6	2791.7	2792.2	2791.7	2792.2	2791.7	2792.2	2791.7	2792.2	2791.7	2792.2
A7	-865.32	-862.26	-865.32	-862.25	-865.32	-862.24	-865.32	-862.25	-865.32	-862.2
A8	105.75	105.15	105.75	105.15	105.75	105.14	105.75	105.14	105.75	105.13
sigma pre-disruption	53.2012826	53.316	53.2012826	53.316	53.2012826	53.316	53.2012826	53.316	53.2012826	53.317
sigma transient	72.47915978	71.723	72.47915978	71.722	72.47915978	71.724	72.47915978	71.723	72.47915978	71.722
sigma post-transient	75.4297058	76.114	75.4297058	76.113	75.4297058	76.114	75.4297058	76.113	75.4297058	76.113

Count	101		102		103		104		105	
Exp. NO	386		387		388		389		390	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	392	385.39	392	385.35	392	385.21	392	385.09	392	385.2
A0 (8th order polynomial's coefficient)	171.17	171.36	171.17	171.36	171.17	171.36	171.17	171.36	171.17	171.36
A1	107.09	107.19	107.09	107.22	107.09	107.37	107.09	107.49	107.09	107.39
A2	-46.838	-49.83	-46.838	-49.962	-46.838	-50.801	-46.838	-51.335	-46.838	-50.865
A3	-1170.3	-1185.6	-1170.3	-1185.4	-1170.3	-1183.4	-1170.3	-1182.2	-1170.3	-1183.2
A4	3563	3601.3	3563	3601.1	3563	3598.9	3563	3597.7	3563	3598.8
A5	-4457.1	-4480.7	-4457.1	-4480.6	-4457.1	-4479.6	-4457.1	-4479.1	-4457.1	-4479.5
A6	2791.7	2792.2	2791.7	2792.3	2791.7	2792.1	2791.7	2792.2	2791.7	2792.1
A7	-865.32	-862.18	-865.32	-862.21	-865.32	-862.29	-865.32	-862.37	-865.32	-862.3
A8	105.75	105.13	105.75	105.14	105.75	105.15	105.75	105.17	105.75	105.16
sigma pre-disruption	53.2012826	53.317	53.2012826	53.317	53.2012826	53.315	53.2012826	53.314	53.2012826	53.315
sigma transient	72.47915978	71.725	72.47915978	71.725	72.47915978	71.722	72.47915978	71.721	72.47915978	71.721
sigma post-transient	75.4297058	76.116	75.4297058	76.116	75.4297058	76.112	75.4297058	76.111	75.4297058	76.112

Count	106		107		108		109		110	
Exp. NO	56		57		58		59		60	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	309	306.6	309	307.25	309	307.49	309	307.09	309	308.2
A0 (8th order polynomial's coefficient)	159.45	159.62	159.45	159.58	159.45	159.57	159.45	159.58	159.45	159.59
A1	61.334	68.878	61.334	67.855	61.334	67.583	61.334	68.045	61.334	67.122
A2	-338.1	-302.62	-338.1	-296.62	-338.1	-295.3	-338.1	-297.55	-338.1	-294.3
A3	827.39	749.55	827.39	735.73	827.39	733.5	827.39	737.38	827.39	736.02
A4	-1029.1	-979.44	-1029.1	-966.42	-1029.1	-966.09	-1029.1	-966.83	-1029.1	-979.29
A5	703.39	719.73	703.39	716.61	703.39	719.27	703.39	714.93	703.39	739.25
A6	-268.56	-303.71	-268.56	-306.32	-268.56	-309.1	-268.56	-304.48	-268.56	-323.1
A7	53.936	69.493	53.936	71.229	53.936	72.323	53.936	70.493	53.936	77.009
A8	-4.4647	-6.7468	-4.4647	-7.0402	-4.4647	-7.1946	-4.4647	-6.9356	-4.4647	-7.8003
sigma pre-disruption	35.79828161	35.807	35.79828161	35.791	35.79828161	35.788	35.79828161	35.793	35.79828161	35.79
sigma transient	54.13263771	52.396	54.13263771	52.43	54.13263771	52.445	54.13263771	52.419	54.13263771	52.501
sigma post-transient	53.24013617	54.329	53.24013617	54.375	53.24013617	54.395	53.24013617	54.361	53.24013617	54.464

Count	111		112		113		114		115	
Exp. NO	201		202		203		204		205	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	309	307.47	309	306.85	309	307.08	309	307.16	309	306.75
A0 (8th order polynomial's coefficient)	159.45	159.57	159.45	159.6	159.45	159.6	159.45	159.59	159.45	159.61
A1	61.334	67.581	61.334	68.408	61.334	68.204	61.334	68.068	61.334	68.643
A2	-338.1	-295.2	-338.1	-299.66	-338.1	-298.86	-338.1	-298.02	-338.1	-301.24
A3	827.39	733.03	827.39	742.17	827.39	741.42	827.39	739.4	827.39	746.34
A4	-1029.1	-965.1	-1029.1	-971.22	-1029.1	-972.97	-1029.1	-970.86	-1029.1	-976.35
A5	703.39	718.19	703.39	715.79	703.39	720.03	703.39	719.18	703.39	718.89
A6	-268.56	-308.46	-268.56	-303.4	-268.56	-306.83	-268.56	-306.92	-268.56	-304.22
A7	53.936	72.133	53.936	69.832	53.936	71.064	53.936	71.216	53.936	69.864
A8	-4.4647	-7.1719	-4.4647	-6.826	-4.4647	-6.9918	-4.4647	-7.0213	-4.4647	-6.8108
sigma pre-disruption	35.79828161	35.788	35.79828161	35.798	35.79828161	35.797	35.79828161	35.795	35.79828161	35.803
sigma transient	54.13263771	52.443	54.13263771	52.407	54.13263771	52.423	54.13263771	52.426	54.13263771	52.403
sigma post-transient	53.24013617	54.393	53.24013617	54.344	53.24013617	54.364	53.24013617	54.369	53.24013617	54.339

Count	116		117		118		119		120	
Exp. NO	206		207		208		209		210	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	309	306.92	309	307.12	309	307.24	309	307.21	309	307.07
A0 (8th order polynomial's coefficient)	159.45	159.6	159.45	159.59	159.45	159.58	159.45	159.59	159.45	159.59
A1	61.334	68.373	61.334	68.122	61.334	67.911	61.334	67.962	61.334	68.169
A2	-338.1	-299.65	-338.1	-298.34	-338.1	-297.02	-338.1	-297.33	-338.1	-298.54
A3	827.39	742.66	827.39	740.13	827.39	736.87	827.39	737.64	827.39	740.39
A4	-1029.1	-972.86	-1029.1	-971.55	-1029.1	-967.97	-1029.1	-968.79	-1029.1	-971.32
A5	703.39	718.01	703.39	719.35	703.39	717.71	703.39	718.06	703.39	718.57
A6	-268.56	-304.89	-268.56	-306.79	-268.56	-306.73	-268.56	-306.72	-268.56	-306.11
A7	53.936	70.315	53.936	71.126	53.936	71.302	53.936	71.251	53.936	70.876
A8	-4.4647	-6.8874	-4.4647	-7.006	-4.4647	-7.0445	-4.4647	-7.0342	-4.4647	-6.9719
sigma pre-disruption	35.79828161	35.799	35.79828161	35.796	35.79828161	35.792	35.79828161	35.793	35.79828161	35.796
sigma transient	54.13263771	52.412	54.13263771	52.425	54.13263771	52.43	54.13263771	52.428	54.13263771	52.421
sigma post-transient	53.24013617	54.351	53.24013617	54.367	53.24013617	54.374	53.24013617	54.373	53.24013617	54.363

Count	121		122		123		124		125	
Exp. NO	66		67		68		69		70	
	Target	Approx. by ANN	Target	Approx. by ANN	Acutal	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	427	436.71	427	436.67	427	436.63	427	436.63	427	436.7
A0 (8th order polynomial's coefficient)	171.29	171.18	171.29	171.19	171.29	171.19	171.29	171.19	171.29	171.19
A1	39.064	39.477	39.064	39.471	39.064	39.432	39.064	39.45	39.064	39.431
A2	349.44	337.19	349.44	337.38	349.44	337.85	349.44	337.69	349.44	337.66
A3	-2005.3	-1993.2	-2005.3	-1993.8	-2005.3	-1995.3	-2005.3	-1994.8	-2005.3	-1994.6
A4	4119.4	4118.2	4119.4	4119	4119.4	4120.9	4119.4	4120.3	4119.4	4120.2
A5	-4198.2	-4207.3	-4198.2	-4207.7	-4198.2	-4209	-4198.2	-4208.5	-4198.2	-4208.8
A6	2283	2291	2283	2291.1	2283	2291.5	2283	2291.3	2283	2291.6
A7	-635.44	-638.04	-635.44	-638.02	-635.44	-638.07	-635.44	-638.04	-635.44	-638.16
A8	71.285	71.581	71.285	71.575	71.285	71.574	71.285	71.572	71.285	71.589
sigma pre-disruption	53.48945338	53.714	53.48945338	53.713	53.48945338	53.713	53.48945338	53.713	53.48945338	53.714
sigma transient	70.66307026	72.637	70.66307026	72.64	70.66307026	72.645	70.66307026	72.644	70.66307026	72.643
sigma post-transient	78.95320149	76.964	78.95320149	76.968	78.95320149	76.974	78.95320149	76.972	78.95320149	76.972

Count	126		127		128		129		130	
Exp. NO	221		222		223		224		225	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	427	436.74	427	436.6	427	436.58	427	436.61	427	436.55
A0 (8th order polynomial's coefficient)	171.29	171.18	171.29	171.19	171.29	171.18	171.29	171.19	171.29	171.19
A1	39.064	39.483	39.064	39.455	39.064	39.498	39.064	39.425	39.064	39.436
A2	349.44	337.03	349.44	337.75	349.44	337.41	349.44	337.99	349.44	338.08
A3	-2005.3	-1992.7	-2005.3	-1995	-2005.3	-1994	-2005.3	-1995.7	-2005.3	-1996
A4	4119.4	4117.5	4119.4	4120.4	4119.4	4118.9	4119.4	4121.5	4119.4	4121.8
A5	-4198.2	-4206.8	-4198.2	-4208.5	-4198.2	-4207.3	-4198.2	-4209.4	-4198.2	-4209.4
A6	2283	2290.9	2283	2291.2	2283	2290.7	2283	2291.6	2283	2291.4
A7	-635.44	-638.04	-635.44	-637.98	-635.44	-637.86	-635.44	-638.07	-635.44	-637.99
A8	71.285	71.584	71.285	71.563	71.285	71.551	71.285	71.572	71.285	71.558
sigma pre-disruption	53.48945338	53.714	53.48945338	53.712	53.48945338	53.712	53.48945338	53.712	53.48945338	53.712
sigma transient	70.66307026	72.633	70.66307026	72.646	70.66307026	72.643	70.66307026	72.649	70.66307026	72.65
sigma post-transient	78.95320149	76.96	78.95320149	76.975	78.95320149	76.971	78.95320149	76.979	78.95320149	76.979

Count	131		132		133		134		135	
Exp. NO	226		227		228		229		230	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	427	436.56	427	436.63	427	436.53	427	436.59	427	436.64
A0 (8th order polynomial's coefficient)	171.29	171.19	171.29	171.19	171.29	171.19	171.29	171.19	171.29	171.19
A1	39.064	39.417	39.064	39.459	39.064	39.461	39.064	39.412	39.064	39.395
A2	349.44	338.21	349.44	337.59	349.44	337.9	349.44	338.17	349.44	338.16
A3	-2005.3	-1996.4	-2005.3	-1994.5	-2005.3	-1995.5	-2005.3	-1996.3	-2005.3	-1996.2
A4	4119.4	4122.4	4119.4	4119.8	4119.4	4121	4119.4	4122.3	4119.4	4122.4
A5	-4198.2	-4209.9	-4198.2	-4208.2	-4198.2	-4208.7	-4198.2	-4209.9	-4198.2	-4210.2
A6	2283	2291.7	2283	2291.2	2283	2291.1	2283	2291.8	2283	2292
A7	-635.44	-638.04	-635.44	-638.02	-635.44	-637.9	-635.44	-638.09	-635.44	-638.19
A8	71.285	71.564	71.285	71.571	71.285	71.549	71.285	71.571	71.285	71.585
sigma pre-disruption	53.48945338	53.712	53.48945338	53.713	53.48945338	53.712	53.48945338	53.712	53.48945338	53.713
sigma transient	70.66307026	72.651	70.66307026	72.644	70.66307026	72.651	70.66307026	72.651	70.66307026	72.65
sigma post-transient	78.95320149	76.98	78.95320149	76.972	78.95320149	76.981	78.95320149	76.981	78.95320149	76.981

Count	136		137		138		139		140	
Exp. NO	106		107		108		109		110	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	180	173.14	180	173.18	180	173.09	180	173.11	180	172.95
A0 (8th order polynomial's coefficient)	151.28	151.42	151.28	151.42	151.28	151.42	151.28	151.42	151.28	151.43
A1	208.85	203.49	208.85	203.47	208.85	203.64	208.85	203.56	208.85	203.92
A2	-685.23	-735.23	-685.23	-735.15	-685.23	-735.82	-685.23	-735.49	-685.23	-736.86
A3	1438.8	1504	1438.8	1504	1438.8	1505.4	1438.8	1504.5	1438.8	1507.4
A4	-1822.2	-1827	-1822.2	-1827.7	-1822.2	-1829.4	-1822.2	-1827.7	-1822.2	-1831.5
A5	1357.6	1344.6	1357.6	1345.8	1357.6	1347.1	1357.6	1345.2	1357.6	1348.3
A6	-583.3	-590.31	-583.3	-591.21	-583.3	-591.73	-583.3	-590.58	-583.3	-592.06
A7	134.52	142.72	134.52	143.02	134.52	143.15	134.52	142.78	134.52	143.17
A8	-12.983	-14.652	-12.983	-14.692	-12.983	-14.704	-12.983	-14.659	-12.983	-14.702
sigma pre-disruption	33.69582299	33.564	33.69582299	33.564	33.69582299	33.56	33.69582299	33.563	33.69582299	33.555
sigma transient	55.56822264	56.179	55.56822264	56.185	55.56822264	56.191	55.56822264	56.181	55.56822264	56.197
sigma post-transient	60.61177818	59.292	60.61177818	59.299	60.61177818	59.305	60.61177818	59.294	60.61177818	59.31

Count	141		142		143		144		145	
Exp. NO	331		332		333		334		335	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	180	172.84	180	172.95	180	172.85	180	172.91	180	173.01
A0 (8th order polynomial's coefficient)	151.28	151.43	151.28	151.42	151.28	151.43	151.28	151.42	151.28	151.43
A1	208.85	204.19	208.85	203.84	208.85	204.13	208.85	203.97	208.85	203.84
A2	-685.23	-737.91	-685.23	-736.57	-685.23	-737.67	-685.23	-737.06	-685.23	-736.56
A3	1438.8	1509.8	1438.8	1506.6	1438.8	1509.2	1438.8	1507.8	1438.8	1507
A4	-1822.2	-1835	-1822.2	-1830	-1822.2	-1833.9	-1822.2	-1831.8	-1822.2	-1831.5
A5	1357.6	1351.4	1357.6	1346.5	1357.6	1350.2	1357.6	1348.2	1357.6	1348.8
A6	-583.3	-593.74	-583.3	-590.96	-583.3	-593	-583.3	-591.94	-583.3	-592.55
A7	134.52	143.66	134.52	142.82	134.52	143.43	134.52	143.11	134.52	143.37
A8	-12.983	-14.759	-12.983	-14.658	-12.983	-14.731	-12.983	-14.693	-12.983	-14.729
sigma pre-disruption	33.69582299	33.549	33.69582299	33.557	33.69582299	33.551	33.69582299	33.554	33.69582299	33.556
sigma transient	55.56822264	56.212	55.56822264	56.187	55.56822264	56.206	55.56822264	56.196	55.56822264	56.199
sigma post-transient	60.61177818	59.327	60.61177818	59.3	60.61177818	59.32	60.61177818	59.309	60.61177818	59.314

Count	146		147		148		149		150	
Exp. NO	336		337		338		339		340	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	180	173.1	180	172.91	180	173.02	180	172.94	180	173.04
A0 (8th order polynomial's coefficient)	151.28	151.42	151.28	151.43	151.28	151.42	151.28	151.43	151.28	151.42
A1	208.85	203.61	208.85	204	208.85	203.72	208.85	203.99	208.85	203.65
A2	-685.23	-735.67	-685.23	-737.16	-685.23	-736.13	-685.23	-737.12	-685.23	-735.84
A3	1438.8	1505	1438.8	1508.1	1438.8	1505.8	1438.8	1508.1	1438.8	1505.1
A4	-1822.2	-1828.6	-1822.2	-1832.3	-1822.2	-1829.4	-1822.2	-1832.7	-1822.2	-1828.2
A5	1357.6	1346.1	1357.6	1348.8	1357.6	1346.4	1357.6	1349.5	1357.6	1345.2
A6	-583.3	-591.14	-583.3	-592.25	-583.3	-591.12	-583.3	-592.81	-583.3	-590.41
A7	134.52	142.96	134.52	143.22	134.52	142.91	134.52	143.41	134.52	142.7
A8	-12.983	-14.681	-12.983	-14.706	-12.983	-14.672	-12.983	-14.732	-12.983	-14.646
sigma pre-disruption	33.69582299	33.561	33.69582299	33.553	33.69582299	33.559	33.69582299	33.553	33.69582299	33.561
sigma transient	55.56822264	56.186	55.56822264	56.199	55.56822264	56.187	55.56822264	56.203	55.56822264	56.181
sigma post-transient	60.61177818	59.3	60.61177818	59.313	60.61177818	59.3	60.61177818	59.318	60.61177818	59.294

Count	151		152		153		154		155	
Exp. NO	111		112		113		114		115	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	112	162.9	112	162.86	112	162.78	112	162.73	112	162.91
A0 (8th order polynomial's coefficient)	156.52	156.21	156.52	156.21	156.52	156.21	156.52	156.21	156.52	156.21
A1	-80.863	-73.262	-80.863	-73.246	-80.863	-73.226	-80.863	-73.212	-80.863	-73.263
A2	339.08	350.07	339.08	350.01	339.08	349.96	339.08	349.91	339.08	350.07
A3	-885.37	-912.18	-885.37	-912.4	-885.37	-913.04	-885.37	-913.35	-885.37	-912.06
A4	1397.9	1402.6	1397.9	1403.9	1397.9	1406.7	1397.9	1408.1	1397.9	1402.2
A5	-1301.2	-1294.1	-1301.2	-1296	-1301.2	-1300.3	-1301.2	-1302.5	-1301.2	-1293.5
A6	693.97	695.14	693.97	696.53	693.97	699.53	693.97	701.14	693.97	694.68
A7	-195.65	-198.86	-195.65	-199.33	-195.65	-200.34	-195.65	-200.89	-195.65	-198.7
A8	22.58	23.319	22.58	23.382	22.58	23.513	22.58	23.585	22.58	23.299
sigma pre-disruption	53.67848612	53.656	53.67848612	53.656	53.67848612	53.657	53.67848612	53.657	53.67848612	53.656
sigma transient	33.21783913	33.897	33.21783913	33.888	33.21783913	33.869	33.21783913	33.859	33.21783913	33.9
sigma post-transient	33.27588112	32.608	33.27588112	32.597	33.27588112	32.574	33.27588112	32.562	33.27588112	32.612

Count	156		157		158		159		160	
Exp. NO	191		192		193		194		195	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	112	162.91	112	162.71	112	162.81	112	162.8	112	162.8
A0 (8th order polynomial's coefficient)	156.52	156.21	156.52	156.21	156.52	156.21	156.52	156.21	156.52	156.21
A1	-80.863	-73.266	-80.863	-73.206	-80.863	-73.234	-80.863	-73.234	-80.863	-73.235
A2	339.08	350.08	339.08	349.89	339.08	349.98	339.08	349.99	339.08	349.99
A3	-885.37	-912.08	-885.37	-913.55	-885.37	-912.75	-885.37	-912.93	-885.37	-912.86
A4	1397.9	1402.2	1397.9	1409	1397.9	1405.4	1397.9	1406	1397.9	1405.8
A5	-1301.2	-1293.5	-1301.2	-1303.8	-1301.2	-1298.4	-1301.2	-1299.3	-1301.2	-1298.9
A6	693.97	694.67	693.97	702.06	693.97	698.21	693.97	698.82	693.97	698.54
A7	-195.65	-198.7	-195.65	-201.2	-195.65	-199.9	-195.65	-200.1	-195.65	-200.01
A8	22.58	23.299	22.58	23.625	22.58	23.456	22.58	23.482	22.58	23.47
sigma pre-disruption	53.67848612	53.656	53.67848612	53.657	53.67848612	53.656	53.67848612	53.656	53.67848612	53.656
sigma transient	33.21783913	33.9	33.21783913	33.853	33.21783913	33.877	33.21783913	33.874	33.21783913	33.875
sigma post-transient	33.27588112	32.612	33.27588112	32.554	33.27588112	32.584	33.27588112	32.58	33.27588112	32.582

Count	161		162		163		164		165	
Exp. NO	196		197		198		199		200	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	112	162.79	112	162.68	112	162.88	112	163.08	112	162.82
A0 (8th order polynomial's coefficient)	156.52	156.21	156.52	156.21	156.52	156.21	156.52	156.21	156.52	156.21
A1	-80.863	-73.233	-80.863	-73.196	-80.863	-73.255	-80.863	-73.315	-80.863	-73.238
A2	339.08	349.99	339.08	349.86	339.08	350.05	339.08	350.23	339.08	349.99
A3	-885.37	-913.02	-885.37	-913.72	-885.37	-912.31	-885.37	-910.77	-885.37	-912.67
A4	1397.9	1406.4	1397.9	1409.9	1397.9	1403.3	1397.9	1396.3	1397.9	1405
A5	-1301.2	-1299.8	-1301.2	-1305.2	-1301.2	-1295.2	-1301.2	-1284.4	-1301.2	-1297.8
A6	693.97	699.17	693.97	703.04	693.97	695.9	693.97	688.22	693.97	697.77
A7	-195.65	-200.22	-195.65	-201.54	-195.65	-199.12	-195.65	-196.52	-195.65	-199.75
A8	22.58	23.497	22.58	23.669	22.58	23.353	22.58	23.014	22.58	23.436
sigma pre-disruption	53.67848612	53.657	53.67848612	53.657	53.67848612	53.656	53.67848612	53.655	53.67848612	53.656
sigma transient	33.21783913	33.871	33.21783913	33.847	33.21783913	33.892	33.21783913	33.941	33.21783913	33.88
sigma post-transient	33.27588112	32.577	33.27588112	32.547	33.27588112	32.602	33.27588112	32.662	33.27588112	32.588

Count	166		167		168		169		170	
Exp. NO	116		117		118		119		120	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	227	235.25	227	235.29	227	235.13	227	235.21	227	235.19
A0 (8th order polynomial's coefficient)	153.63	153.3	153.63	153.3	153.63	153.3	153.63	153.29	153.63	153.29
A1	110.28	120.5	110.28	120.44	110.28	120.65	110.28	120.39	110.28	120.49
A2	-458.71	-381.14	-458.71	-380.92	-458.71	-381.75	-458.71	-380.85	-458.71	-381.19
A3	859.66	678.95	859.66	678.45	859.66	680.06	859.66	678.81	859.66	679.31
A4	-860.11	-693.02	-860.11	-692.36	-860.11	-693.94	-860.11	-693.8	-860.11	-693.96
A5	496.12	414.61	496.12	414.11	496.12	414.79	496.12	416.09	496.12	415.77
A6	-168.77	-145.98	-168.77	-145.75	-168.77	-145.79	-168.77	-147.06	-168.77	-146.7
A7	32.481	28.922	32.481	28.867	32.481	28.804	32.481	29.284	32.481	29.144
A8	-2.8349	-2.5957	-2.8349	-2.5904	-2.8349	-2.5766	-2.8349	-2.6419	-2.8349	-2.6227
sigma pre-disruption	33.73967282	34.013	33.73967282	34.013	33.73967282	34.011	33.73967282	34.019	33.73967282	34.016
sigma transient	54.21850305	53.108	54.21850305	53.106	54.21850305	53.108	54.21850305	53.109	54.21850305	53.11
sigma post-transient	53.58052519	55.544	53.58052519	55.542	53.58052519	55.543	53.58052519	55.549	53.58052519	55.548

Count	171		172		173		174		175	
Exp. NO	211		212		213		214		215	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	227	237.11	227	235.21	227	237.12	227	235.3	227	236.97
A0 (8th order polynomial's coefficient)	153.63	153.48	153.63	153.3	153.63	153.49	153.63	153.3	153.63	153.49
A1	110.28	119.82	110.28	120.5	110.28	119.86	110.28	120.41	110.28	120.05
A2	-458.71	-377.13	-458.71	-381.2	-458.71	-377.25	-458.71	-380.82	-458.71	-377.97
A3	859.66	667.23	859.66	679.28	859.66	667.08	859.66	678.34	859.66	668.28
A4	-860.11	-673.49	-860.11	-693.81	-860.11	-672.43	-860.11	-692.49	-860.11	-673.09
A5	496.12	396.17	496.12	415.56	496.12	394.5	496.12	414.46	496.12	394.1
A6	-168.77	-136.3	-168.77	-146.56	-168.77	-135.12	-168.77	-146.04	-168.77	-134.48
A7	32.481	26.302	32.481	29.103	32.481	25.907	32.481	28.969	32.481	25.631
A8	-2.8349	-2.3109	-2.8349	-2.6178	-2.8349	-2.2601	-2.8349	-2.6038	-2.8349	-2.2199
sigma pre-disruption	33.73967282	33.965	33.73967282	34.015	33.73967282	33.962	33.73967282	34.014	33.73967282	33.959
sigma transient	54.21850305	53.094	54.21850305	53.11	54.21850305	53.089	54.21850305	53.107	54.21850305	53.087
sigma post-transient	53.58052519	55.496	53.58052519	55.547	53.58052519	55.489	53.58052519	55.544	53.58052519	55.485

Count	176		177		178		179		180	
Exp. NO	216		217		218		219		220	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	227	235.23	227	235.24	227	235.17	227	235.58	227	235.11
A0 (8th order polynomial's coefficient)	153.63	153.29	153.63	153.3	153.63	153.3	153.63	153.31	153.63	153.29
A1	110.28	120.42	110.28	120.47	110.28	120.58	110.28	120.03	110.28	120.56
A2	-458.71	-380.9	-458.71	-381.05	-458.71	-381.49	-458.71	-379.17	-458.71	-381.5
A3	859.66	678.68	859.66	678.81	859.66	679.75	859.66	673.91	859.66	680.09
A4	-860.11	-693.13	-860.11	-692.91	-860.11	-694.11	-860.11	-684.91	-860.11	-695.14
A5	496.12	415.11	496.12	414.59	496.12	415.5	496.12	406.75	496.12	416.83
A6	-168.77	-146.39	-168.77	-145.99	-168.77	-146.4	-168.77	-141.61	-168.77	-147.24
A7	32.481	29.066	32.481	28.93	32.481	29.028	32.481	27.651	32.481	29.293
A8	-2.8349	-2.6144	-2.8349	-2.597	-2.8349	-2.6068	-2.8349	-2.4457	-2.8349	-2.6392
sigma pre-disruption	33.73967282	34.017	33.73967282	34.014	33.73967282	34.013	33.73967282	34.015	33.73967282	34.016
sigma transient	54.21850305	53.107	54.21850305	53.107	54.21850305	53.111	54.21850305	53.078	54.21850305	53.113
sigma post-transient	53.58052519	55.545	53.58052519	55.543	53.58052519	55.547	53.58052519	55.507	53.58052519	55.552

Count	181		182		183		184		185	
Exp. NO	121		122		123		124		125	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	1161	1160.2	1161	1161.6	1161	1160.8	1161	1160.8	1161	1161.4
A0 (8th order polynomial's coefficient)	165.83	165.84	165.83	165.86	165.83	165.84	165.83	165.84	165.83	165.85
A1	118.49	117.49	118.49	117.42	118.49	117.46	118.49	117.46	118.49	117.43
A2	-830.25	-833.71	-830.25	-834.35	-830.25	-834	-830.25	-833.99	-830.25	-834.27
A3	2295.9	2315	2295.9	2320.1	2295.9	2317.2	2295.9	2317.2	2295.9	2319.2
A4	-3388.1	-3410.3	-3388.1	-3423.6	-3388.1	-3415.7	-3388.1	-3416.1	-3388.1	-3421.1
A5	2910.6	2915	2910.6	2931.6	2910.6	2921.6	2910.6	2922.2	2910.6	2928.2
A6	-1453.8	-1447.2	-1453.8	-1457.9	-1453.8	-1451.4	-1453.8	-1451.9	-1453.8	-1455.7
A7	390.09	386.11	390.09	389.54	390.09	387.45	390.09	387.6	390.09	388.8
A8	-43.361	-42.711	-43.361	-43.143	-43.361	-42.878	-43.361	-42.899	-43.361	-43.048
sigma pre-disruption	54.25918345	54.205	54.25918345	54.2	54.25918345	54.203	54.25918345	54.203	54.25918345	54.201
sigma transient	55.23906401	55.191	55.23906401	55.235	55.23906401	55.207	55.23906401	55.21	55.23906401	55.223
sigma post-transient	54.52549896	54.606	54.52549896	54.657	54.52549896	54.624	54.52549896	54.628	54.52549896	54.643

Count	186		187		188		189		190	
Exp. NO	231		232		233		234		235	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	1161	1160.4	1161	1161.1	1161	1160.8	1161	1160.3	1161	1161.4
A0 (8th order polynomial's coefficient)	165.83	165.84	165.83	165.85	165.83	165.85	165.83	165.84	165.83	165.85
A1	118.49	117.47	118.49	117.44	118.49	117.46	118.49	117.48	118.49	117.43
A2	-830.25	-833.82	-830.25	-834.13	-830.25	-833.97	-830.25	-833.76	-830.25	-834.24
A3	2295.9	2315.7	2295.9	2317.9	2295.9	2317.3	2295.9	2315.2	2295.9	2319.5
A4	-3388.1	-3412	-3388.1	-3417.4	-3388.1	-3416.7	-3388.1	-3410.6	-3388.1	-3422.4
A5	2910.6	2917	2910.6	2923.5	2910.6	2923.2	2910.6	2915.1	2910.6	2930.4
A6	-1453.8	-1448.4	-1453.8	-1452.6	-1453.8	-1452.6	-1453.8	-1447.3	-1453.8	-1457.2
A7	390.09	386.5	390.09	387.8	390.09	387.84	390.09	386.11	390.09	389.34
A8	-43.361	-42.759	-43.361	-42.921	-43.361	-42.931	-43.361	-42.71	-43.361	-43.12
sigma pre-disruption	54.25918345	54.205	54.25918345	54.203	54.25918345	54.202	54.25918345	54.205	54.25918345	54.2
sigma transient	55.23906401	55.195	55.23906401	55.209	55.23906401	55.216	55.23906401	55.189	55.23906401	55.236
sigma post-transient	54.52549896	54.61	54.52549896	54.626	54.52549896	54.635	54.52549896	54.604	54.52549896	54.658

Count	191		192		193		194		195	
Exp. NO	236		237		238		239		240	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	1161	1160.5	1161	1160.5	1161	1160.7	1161	1159.5	1161	1161.3
A0 (8th order polynomial's coefficient)	165.83	165.84	165.83	165.84	165.83	165.84	165.83	165.83	165.83	165.85
A1	118.49	117.47	118.49	117.47	118.49	117.46	118.49	117.52	118.49	117.43
A2	-830.25	-833.88	-830.25	-833.86	-830.25	-833.97	-830.25	-833.43	-830.25	-834.24
A3	2295.9	2316.3	2295.9	2316	2295.9	2316.5	2295.9	2312.5	2295.9	2318.9
A4	-3388.1	-3413.5	-3388.1	-3412.5	-3388.1	-3413.6	-3388.1	-3403.3	-3388.1	-3420.1
A5	2910.6	2918.8	2910.6	2917.6	2910.6	2918.6	2910.6	2906	2910.6	2926.9
A6	-1453.8	-1449.6	-1453.8	-1448.8	-1453.8	-1449.3	-1453.8	-1441.3	-1453.8	-1454.8
A7	390.09	386.88	390.09	386.61	390.09	386.75	390.09	384.2	390.09	388.51
A8	-43.361	-42.807	-43.361	-42.772	-43.361	-42.787	-43.361	-42.469	-43.361	-43.011
sigma pre-disruption	54.25918345	54.204	54.25918345	54.205	54.25918345	54.205	54.25918345	54.208	54.25918345	54.202
sigma transient	55.23906401	55.2	55.23906401	55.195	55.23906401	55.193	55.23906401	55.163	55.23906401	55.218
sigma post-transient	54.52549896	54.616	54.52549896	54.611	54.52549896	54.608	54.52549896	54.574	54.52549896	54.637

Count	196		197		198		199		200	
Exp. NO	126		127		128		129		130	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	350	351.05	350	350.73	350	351.2	350	350.79	350	351.02
A0 (8th order polynomial's coefficient)	154.85	154.9	154.85	154.9	154.85	154.91	154.85	154.89	154.85	154.9
A1	-41.897	-38.837	-41.897	-38.253	-41.897	-39.115	-41.897	-38.348	-41.897	-38.717
A2	1274.8	1294	1274.8	1290.9	1274.8	1295.5	1274.8	1291.5	1274.8	1293.7
A3	-5271.4	-5331	-5271.4	-5323.6	-5271.4	-5334.7	-5271.4	-5324.8	-5271.4	-5330.8
A4	9350.4	9417.1	9350.4	9408.1	9350.4	9421.7	9350.4	9409.4	9350.4	9417.2
A5	-8691.9	-8716.2	-8691.9	-8710.5	-8691.9	-8719.1	-8691.9	-8711.1	-8691.9	-8716.4
A6	4424.6	4417.9	4424.6	4416.1	4424.6	4418.8	4424.6	4416.1	4424.6	4418
A7	-1167.3	-1160.8	-1167.3	-1160.6	-1167.3	-1160.9	-1167.3	-1160.5	-1167.3	-1160.8
A8	124.79	123.62	124.79	123.62	124.79	123.62	124.79	123.61	124.79	123.62
sigma pre-disruption	33.62758936	33.639	33.62758936	33.631	33.62758936	33.644	33.62758936	33.624	33.62758936	33.626
sigma transient	44.6405642	43.708	44.6405642	43.702	44.6405642	43.716	44.6405642	43.692	44.6405642	43.707
sigma post-transient	39.12306178	39.93	39.12306178	39.921	39.12306178	39.94	39.12306178	39.91	39.12306178	39.928

Count	201		202		203		204		205	
Exp. NO	251		252		253		254		255	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	350	351.02	350	351.4	350	350.94	350	350.89	350	350.75
A0 (8th order polynomial's coefficient)	154.85	154.9	154.85	154.91	154.85	154.9	154.85	154.89	154.85	154.91
A1	-41.897	-38.757	-41.897	-39.522	-41.897	-38.572	-41.897	-38.502	-41.897	-38.297
A2	1274.8	1293.6	1274.8	1297.6	1274.8	1292.8	1274.8	1292.3	1274.8	1291.4
A3	-5271.4	-5330.1	-5271.4	-5339.6	-5271.4	-5328.5	-5271.4	-5326.9	-5271.4	-5325.1
A4	9350.4	9415.9	9350.4	9427.5	9350.4	9414.2	9350.4	9411.9	9350.4	9410.1
A5	-8691.9	-8715.4	-8691.9	-8722.8	-8691.9	-8714.4	-8691.9	-8712.8	-8691.9	-8712
A6	4424.6	4417.6	4424.6	4420	4424.6	4417.3	4424.6	4416.7	4424.6	4416.7
A7	-1167.3	-1160.7	-1167.3	-1161	-1167.3	-1160.7	-1167.3	-1160.6	-1167.3	-1160.7
A8	124.79	123.61	124.79	123.61	124.79	123.62	124.79	123.61	124.79	123.62
sigma pre-disruption	33.62758936	33.632	33.62758936	33.655	33.62758936	33.624	33.62758936	33.624	33.62758936	33.635
sigma transient	44.6405642	43.699	44.6405642	43.725	44.6405642	43.699	44.6405642	43.69	44.6405642	43.719
sigma post-transient	39.12306178	39.919	39.12306178	39.954	39.12306178	39.917	39.12306178	39.906	39.12306178	39.943

Count	206		207		208		209		210	
Exp. NO	256		257		258		259		260	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	350	350.69	350	350.87	350	350.86	350	350.93	350	350.79
A0 (8th order polynomial's coefficient)	154.85	154.89	154.85	154.9	154.85	154.9	154.85	154.92	154.85	154.9
A1	-41.897	-38.139	-41.897	-38.506	-41.897	-38.452	-41.897	-38.776	-41.897	-38.381
A2	1274.8	1290.5	1274.8	1292.4	1274.8	1292.2	1274.8	1293.4	1274.8	1291.6
A3	-5271.4	-5322.8	-5271.4	-5327.3	-5271.4	-5327	-5271.4	-5329.2	-5271.4	-5325.3
A4	9350.4	9407.2	9350.4	9412.9	9350.4	9412.4	9350.4	9414.7	9350.4	9410.2
A5	-8691.9	-8709.9	-8691.9	-8713.7	-8691.9	-8713.4	-8691.9	-8714.6	-8691.9	-8711.8
A6	4424.6	4415.9	4424.6	4417.2	4424.6	4417.1	4424.6	4417.4	4424.6	4416.5
A7	-1167.3	-1160.5	-1167.3	-1160.7	-1167.3	-1160.7	-1167.3	-1160.7	-1167.3	-1160.6
A8	124.79	123.62	124.79	123.62	124.79	123.62	124.79	123.62	124.79	123.62
sigma pre-disruption	33.62758936	33.621	33.62758936	33.638	33.62758936	33.629	33.62758936	33.663	33.62758936	33.634
sigma transient	44.6405642	43.696	44.6405642	43.715	44.6405642	43.707	44.6405642	43.732	44.6405642	43.706
sigma post-transient	39.12306178	39.913	39.12306178	39.938	39.12306178	39.927	39.12306178	39.961	39.12306178	39.927

Count	211		212		213		214		215	
Exp. NO	131		132		133		134		135	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	222	212.65	222	212.23	222	212.68	222	212.68	222	212.12
A0 (8th order polynomial's coefficient)	166.22	166.47	166.22	166.46	166.22	166.47	166.22	166.47	166.22	166.45
A1	138.95	137.26	138.95	137.03	138.95	137.1	138.95	137.12	138.95	136.96
A2	-587.97	-602.09	-587.97	-600.62	-587.97	-600.77	-587.97	-600.94	-587.97	-600.12
A3	1341.1	1369.1	1341.1	1363	1341.1	1364.3	1341.1	1365	1341.1	1361
A4	-1786.8	-1775	-1786.8	-1761.6	-1786.8	-1766.5	-1786.8	-1767.7	-1786.8	-1757.3
A5	1411.7	1369.8	1411.7	1354	1411.7	1361.4	1411.7	1362.6	1411.7	1349.1
A6	-644.23	-622.08	-644.23	-612.22	-644.23	-617.54	-644.23	-618.2	-644.23	-609.17
A7	155.63	153.19	155.63	150.08	155.63	151.91	155.63	152.1	155.63	149.13
A8	-15.302	-15.749	-15.302	-15.361	-15.302	-15.601	-15.302	-15.624	-15.302	-15.243
sigma pre-disruption	54.23640573	54.296	54.23640573	54.3	54.23640573	54.298	54.23640573	54.298	54.23640573	54.301
sigma transient	53.60903218	53.434	53.60903218	53.378	53.60903218	53.43	53.60903218	53.431	53.60903218	53.362
sigma post-transient	53.75352384	54.312	53.75352384	54.246	53.75352384	54.307	53.75352384	54.309	53.75352384	54.228

Count	216		217		218		219		220	
Exp. NO	271		272		273		274		275	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	222	212.08	222	212.21	222	212.04	222	212.89	222	212.36
A0 (8th order polynomial's coefficient)	166.22	166.45	166.22	166.45	166.22	166.45	166.22	166.47	166.22	166.46
A1	138.95	136.88	138.95	136.95	138.95	137	138.95	137.21	138.95	136.97
A2	-587.97	-599.56	-587.97	-600.02	-587.97	-600.51	-587.97	-601.49	-587.97	-600.04
A3	1341.1	1358.9	1341.1	1360.8	1341.1	1362.3	1341.1	1367.3	1341.1	1361.1
A4	-1786.8	-1753.2	-1786.8	-1757.4	-1786.8	-1759.2	-1786.8	-1773	-1786.8	-1758.9
A5	1411.7	1344.7	1411.7	1349.6	1411.7	1350.5	1411.7	1369.1	1411.7	1351.9
A6	-644.23	-606.65	-644.23	-609.68	-644.23	-609.74	-644.23	-622.37	-644.23	-611.41
A7	155.63	148.38	155.63	149.33	155.63	149.24	155.63	153.43	155.63	149.93
A8	-15.302	-15.153	-15.302	-15.272	-15.302	-15.25	-15.302	-15.792	-15.302	-15.351
sigma pre-disruption	54.23640573	54.302	54.23640573	54.301	54.23640573	54.301	54.23640573	54.296	54.23640573	54.3
sigma transient	53.60903218	53.354	53.60903218	53.371	53.60903218	53.355	53.60903218	53.458	53.60903218	53.389
sigma post-transient	53.75352384	54.218	53.75352384	54.238	53.75352384	54.219	53.75352384	54.34	53.75352384	54.259

Count	221		222		223		224		225	
Exp. NO	276		277		278		279		280	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	222	212.45	222	212.12	222	211.75	222	211.79	222	212.43
A0 (8th order polynomial's coefficient)	166.22	166.47	166.22	166.45	166.22	166.44	166.22	166.45	166.22	166.46
A1	138.95	137.19	138.95	136.99	138.95	136.73	138.95	136.9	138.95	136.98
A2	-587.97	-601.71	-587.97	-600.4	-587.97	-598.67	-587.97	-599.97	-587.97	-600.09
A3	1341.1	1367.4	1341.1	1362.1	1341.1	1355.2	1341.1	1359.9	1341.1	1361.4
A4	-1786.8	-1770.8	-1786.8	-1759.2	-1786.8	-1744.5	-1786.8	-1753.4	-1786.8	-1759.8
A5	1411.7	1364.5	1411.7	1350.9	1411.7	1334.1	1411.7	1343.3	1411.7	1353.3
A6	-644.23	-618.62	-644.23	-610.18	-644.23	-599.82	-644.23	-605.03	-644.23	-612.37
A7	155.63	152.07	155.63	149.42	155.63	146.19	155.63	147.72	155.63	150.25
A8	-15.302	-15.606	-15.302	-15.276	-15.302	-14.877	-15.302	-15.057	-15.302	-15.393
sigma pre-disruption	54.23640573	54.298	54.23640573	54.301	54.23640573	54.305	54.23640573	54.303	54.23640573	54.3
sigma transient	53.60903218	53.409	53.60903218	53.363	53.60903218	53.311	53.60903218	53.323	53.60903218	53.398
sigma post-transient	53.75352384	54.283	53.75352384	54.229	53.75352384	54.167	53.75352384	54.181	53.75352384	54.269

Count	226		227		228		229		230	
Exp. NO	136		137		138		139		140	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	155	143.54	155	143.62	155	143.38	155	143.71	155	143.88
A0 (8th order polynomial's coefficient)	152.58	152.62	152.58	152.62	152.58	152.62	152.58	152.62	152.58	152.62
A1	249.66	242.91	249.66	242.74	249.66	243.22	249.66	242.59	249.66	242.34
A2	-924.4	-925.15	-924.4	-924.29	-924.4	-926.74	-924.4	-923.58	-924.4	-922.4
A3	2065	2220.2	2065	2218	2065	2223.9	2065	2216.5	2065	2214.2
A4	-3295.9	-3606.4	-3295.9	-3603.3	-3295.9	-3611	-3295.9	-3601.9	-3295.9	-3600.3
A5	3425.1	3624.1	3425.1	3621.6	3425.1	3627	3425.1	3621.2	3425.1	3621.6
A6	-2071.2	-2092.2	-2071.2	-2091.1	-2071.2	-2093.2	-2071.2	-2091.4	-2071.2	-2092.4
A7	651.87	631.61	651.87	631.35	651.87	631.73	651.87	631.5	651.87	632
A8	-82.243	-77.066	-82.243	-77.04	-82.243	-77.067	-82.243	-77.067	-82.243	-77.142
sigma pre-disruption	33.70934345	33.567	33.70934345	33.57	33.70934345	33.562	33.70934345	33.573	33.70934345	33.578
sigma transient	43.69499375	43.695	43.69499375	43.691	43.69499375	43.695	43.69499375	43.695	43.69499375	43.707
sigma post-transient	41.18283	41.806	41.18283	41.801	41.18283	41.805	41.18283	41.807	41.18283	41.822

Count	231		232		233		234		235	
Exp. NO	291		292		293		294		295	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	155	143.59	155	143.53	155	143.79	155	143.55	155	143.62
A0 (8th order polynomial's coefficient)	152.58	152.62	152.58	152.61	152.58	152.62	152.58	152.62	152.58	152.62
A1	249.66	242.81	249.66	242.78	249.66	242.5	249.66	242.91	249.66	242.76
A2	-924.4	-924.67	-924.4	-924.37	-924.4	-923.21	-924.4	-925.2	-924.4	-924.43
A3	2065	2219	2065	2217.2	2065	2216.1	2065	2220.4	2065	2218.5
A4	-3295.9	-3604.7	-3295.9	-3600.1	-3295.9	-3602.6	-3295.9	-3607	-3295.9	-3604.5
A5	3425.1	3622.8	3425.1	3616.9	3425.1	3622.9	3425.1	3624.8	3425.1	3623
A6	-2071.2	-2091.7	-2071.2	-2087.8	-2071.2	-2092.8	-2071.2	-2092.8	-2071.2	-2092
A7	651.87	631.48	651.87	630.23	651.87	632.02	651.87	631.77	651.87	631.62
A8	-82.243	-77.054	-82.243	-76.896	-82.243	-77.137	-82.243	-77.086	-82.243	-77.075
sigma pre-disruption	33.70934345	33.569	33.70934345	33.566	33.70934345	33.577	33.70934345	33.568	33.70934345	33.569
sigma transient	43.69499375	43.694	43.69499375	43.668	43.69499375	43.707	43.69499375	43.699	43.69499375	43.696
sigma post-transient	41.18283	41.804	41.18283	41.773	41.18283	41.822	41.18283	41.811	41.18283	41.807

Count	236		237		238		239		240	
Exp. NO	296		297		298		299		300	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	155	143.98	155	143.47	155	142.84	155	143.69	155	143.35
A0 (8th order polynomial's coefficient)	152.58	152.62	152.58	152.61	152.58	152.6	152.58	152.62	152.58	152.61
A1	249.66	242.08	249.66	243	249.66	244.03	249.66	242.67	249.66	243.17
A2	-924.4	-921.03	-924.4	-925.57	-924.4	-930.57	-924.4	-924.02	-924.4	-926.38
A3	2065	2210.5	2065	2220.8	2065	2231.4	2065	2217.8	2065	2222.4
A4	-3295.9	-3594.9	-3295.9	-3606.4	-3295.9	-3616.3	-3295.9	-3604.3	-3295.9	-3607.4
A5	3425.1	3616.9	3425.1	3623.1	3425.1	3626	3425.1	3623.6	3425.1	3622.7
A6	-2071.2	-2090.1	-2071.2	-2091.3	-2071.2	-2090	-2071.2	-2092.7	-2071.2	-2090.5
A7	651.87	631.38	651.87	631.25	651.87	630.21	651.87	631.89	651.87	630.88
A8	-82.243	-77.076	-82.243	-77.016	-82.243	-76.835	-82.243	-77.113	-82.243	-76.961
sigma pre-disruption	33.70934345	33.582	33.70934345	33.564	33.70934345	33.542	33.70934345	33.573	33.70934345	33.56
sigma transient	43.69499375	43.697	43.69499375	43.686	43.69499375	43.657	43.69499375	43.703	43.69499375	43.677
sigma post-transient	41.18283	41.81	41.18283	41.795	41.18283	41.756	41.18283	41.817	41.18283	41.783

Count	241		242		243		244		245	
Exp. NO	141		142		143		144		145	
	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	156	157.79	156	157.72	156	157.77	156	157.86	156	157.83
A0 (8th order polynomial's coefficient)	166.46	166.47	166.46	166.45	166.46	166.46	166.46	166.48	166.46	166.47
A1	142.66	145.7	142.66	145.46	142.66	145.69	142.66	145.92	142.66	145.88
A2	-808.08	-817.89	-808.08	-816.5	-808.08	-817.76	-808.08	-819.14	-808.08	-818.85
A3	2718	2648.4	2718	2644.1	2718	2647.7	2718	2652.3	2718	2651.1
A4	-5019.2	-4857.5	-5019.2	-4850	-5019.2	-4855.6	-5019.2	-4864.1	-5019.2	-4861.6
A5	5139.6	5035.8	5139.6	5028.4	5139.6	5033.5	5139.6	5042.4	5139.6	5039.4
A6	-2912.3	-2902	-2912.3	-2897.9	-2912.3	-2900.5	-2912.3	-2905.7	-2912.3	-2903.8
A7	854.27	864.02	854.27	862.8	854.27	863.53	854.27	865.1	854.27	864.5
A8	-101.17	-103.45	-101.17	-103.31	-101.17	-103.39	-101.17	-103.58	-101.17	-103.5
sigma pre-disruption	54.26455008	54.243	54.26455008	54.243	54.26455008	54.243	54.26455008	54.243	54.26455008	54.243
sigma transient	59.86187348	59.101	59.86187348	59.075	59.86187348	59.092	59.86187348	59.124	59.86187348	59.113
sigma post-transient	61.42112155	62.059	61.42112155	62.028	61.42112155	62.048	61.42112155	62.086	61.42112155	62.072

Count	246		247		248		249		250	
Exp. NO	311		312		313		314		315	
	Acutal	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN	Target	Approx. by ANN
Disruption Impact Delay (estimated lag)	156	157.83	156	157.72	156	157.71	156	157.79	156	157.81
A0 (8th order polynomial's coefficient)	166.46	166.47	166.46	166.45	166.46	166.45	166.46	166.47	166.46	166.47
A1	142.66	145.81	142.66	145.45	142.66	145.43	142.66	145.71	142.66	145.7
A2	-808.08	-818.51	-808.08	-816.45	-808.08	-816.34	-808.08	-817.92	-808.08	-817.87
A3	2718	2650.4	2718	2644	2718	2643.6	2718	2648.4	2718	2648.6
A4	-5019.2	-4860.9	-5019.2	-4849.6	-5019.2	-4849.1	-5019.2	-4857.2	-5019.2	-4858.1
A5	5139.6	5039.2	5139.6	5028	5139.6	5027.5	5139.6	5035.4	5139.6	5036.7
A6	-2912.3	-2904	-2912.3	-2897.6	-2912.3	-2897.4	-2912.3	-2901.7	-2912.3	-2902.7
A7	854.27	864.59	854.27	862.73	854.27	862.67	854.27	863.91	854.27	864.24
A8	-101.17	-103.52	-101.17	-103.3	-101.17	-103.29	-101.17	-103.43	-101.17	-103.48
sigma pre-disruption	54.26455008	54.243	54.26455008	54.243	54.26455008	54.243	54.26455008	54.243	54.26455008	54.244
sigma transient	59.86187348	59.113	59.86187348	59.073	59.86187348	59.072	59.86187348	59.099	59.86187348	59.105
sigma post-transient	61.42112155	62.073	61.42112155	62.027	61.42112155	62.025	61.42112155	62.057	61.42112155	62.064

Count	251		252		253		254		255	
Exp. NO	316		317		318		319		320	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	156	157.76	156	157.83	156	157.7	156	157.72	156	157.88
A0 (8th order polynomial's coefficient)	166.46	166.46	166.46	166.47	166.46	166.45	166.46	166.45	166.46	166.48
A1	142.66	145.62	142.66	145.83	142.66	145.44	142.66	145.48	142.66	146.03
A2	-808.08	-817.4	-808.08	-818.57	-808.08	-816.36	-808.08	-816.58	-808.08	-819.72
A3	2718	2646.7	2718	2650.4	2718	2643.5	2718	2644.1	2718	2653.9
A4	-5019.2	-4854	-5019.2	-4860.7	-5019.2	-4848.4	-5019.2	-4849.6	-5019.2	-4866.4
A5	5139.6	5032	5139.6	5038.9	5139.6	5026.5	5139.6	5027.6	5139.6	5044.3
A6	-2912.3	-2899.7	-2912.3	-2903.7	-2912.3	-2896.6	-2912.3	-2897.3	-2912.3	-2906.6
A7	854.27	863.31	854.27	864.48	854.27	862.41	854.27	862.6	854.27	865.32
A8	-101.17	-103.36	-101.17	-103.5	-101.17	-103.26	-101.17	-103.28	-101.17	-103.6
sigma pre-disruption	54.26455008	54.243	54.26455008	54.243	54.26455008	54.243	54.26455008	54.243	54.26455008	54.243
sigma transient	59.86187348	59.087	59.86187348	59.111	59.86187348	59.067	59.86187348	59.071	59.86187348	59.13
sigma post-transient	61.42112155	62.042	61.42112155	62.071	61.42112155	62.019	61.42112155	62.024	61.42112155	62.092

Count	256		257		258		259		260	
Exp. NO	146		147		148		149		150	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	291	304.11	291	303.9	291	304.72	291	303.73	291	303.58
A0 (8th order polynomial's coefficient)	165.79	165.72	165.79	165.73	165.79	165.75	165.79	165.72	165.79	165.72
A1	97.585	107.71	97.585	107.89	97.585	108.14	97.585	107.78	97.585	107.83
A2	-342.79	-309.51	-342.79	-311.04	-342.79	-312.58	-342.79	-310.28	-342.79	-310.74
A3	656.04	458.41	656.04	463.67	656.04	470.54	656.04	460.65	656.04	462.08
A4	-863.77	-612.41	-863.77	-620.91	-863.77	-637.4	-863.77	-614.65	-863.77	-616.48
A5	817.91	719.32	817.91	726.67	817.91	747.06	817.91	719.67	817.91	720.72
A6	-492.08	-510.65	-492.08	-514.16	-492.08	-527.34	-492.08	-509.93	-492.08	-510.13
A7	159.38	180.79	159.38	181.66	159.38	185.9	159.38	180.36	159.38	180.32
A8	-20.767	-24.646	-20.767	-24.735	-20.767	-25.272	-20.767	-24.575	-20.767	-24.562
sigma pre-disruption	53.88363684	54.358	53.88363684	54.356	53.88363684	54.35	53.88363684	54.358	53.88363684	54.358
sigma transient	62.41560531	62.11	62.41560531	62.094	62.41560531	62.178	62.41560531	62.076	62.41560531	62.063
sigma post-transient	64.72764533	64.391	64.72764533	64.373	64.72764533	64.472	64.72764533	64.352	64.72764533	64.337

Count	261		262		263		264		265	
Exp. NO	351		352		353		354		355	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	291	303.65	291	304.1	291	304.1	291	304.24	291	303.71
A0 (8th order polynomial's coefficient)	165.79	165.71	165.79	165.74	165.79	165.73	165.79	165.73	165.79	165.72
A1	97.585	107.62	97.585	107.98	97.585	107.88	97.585	107.92	97.585	107.77
A2	-342.79	-309.05	-342.79	-311.65	-342.79	-310.84	-342.79	-311.08	-342.79	-310.2
A3	656.04	456.03	656.04	466.19	656.04	463.24	656.04	464.32	656.04	460.3
A4	-863.77	-605.85	-863.77	-626.47	-863.77	-621.1	-863.77	-623.76	-863.77	-613.9
A5	817.91	710.56	817.91	733.16	817.91	727.84	817.91	731.19	817.91	718.83
A6	-492.08	-504.73	-492.08	-518.2	-492.08	-515.28	-492.08	-517.47	-492.08	-509.42
A7	159.38	178.83	159.38	182.93	159.38	182.1	159.38	182.8	159.38	180.2
A8	-20.767	-24.394	-20.767	-24.893	-20.767	-24.796	-20.767	-24.887	-20.767	-24.556
sigma pre-disruption	53.88363684	54.361	53.88363684	54.354	53.88363684	54.356	53.88363684	54.355	53.88363684	54.359
sigma transient	62.41560531	62.064	62.41560531	62.116	62.41560531	62.113	62.41560531	62.127	62.41560531	62.074
sigma post-transient	64.72764533	64.338	64.72764533	64.398	64.72764533	64.395	64.72764533	64.412	64.72764533	64.349

Count	266		267		268		269		270	
Exp. NO	356		357		358		359		360	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	291	304.45	291	304	291	303.61	291	303.55	291	304.16
A0 (8th order polynomial's coefficient)	165.79	165.74	165.79	165.73	165.79	165.72	165.79	165.71	165.79	165.73
A1	97.585	107.93	97.585	107.85	97.585	107.76	97.585	107.59	97.585	107.84
A2	-342.79	-311.09	-342.79	-310.7	-342.79	-310.19	-342.79	-308.87	-342.79	-310.5
A3	656.04	464.69	656.04	462.57	656.04	460.12	656.04	455.22	656.04	462.08
A4	-863.77	-625.45	-863.77	-619.43	-863.77	-613.09	-863.77	-603.9	-863.77	-619.33
A5	817.91	733.89	817.91	725.73	817.91	717.52	817.91	708.12	817.91	726.42
A6	-492.08	-519.46	-492.08	-513.91	-492.08	-508.46	-492.08	-503.16	-492.08	-514.67
A7	159.38	183.49	159.38	181.65	159.38	179.87	159.38	178.32	159.38	181.96
A8	-20.767	-24.978	-20.767	-24.74	-20.767	-24.512	-20.767	-24.329	-20.767	-24.785
sigma pre-disruption	53.88363684	54.354	53.88363684	54.356	53.88363684	54.359	53.88363684	54.362	53.88363684	54.356
sigma transient	62.41560531	62.147	62.41560531	62.103	62.41560531	62.064	62.41560531	62.054	62.41560531	62.118
sigma post-transient	64.72764533	64.435	64.72764533	64.384	64.72764533	64.338	64.72764533	64.326	64.72764533	64.401

Count	271		272		273		274		275	
Exp. NO	156		157		158		159		160	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	467	465.29	467	465.41	467	465.2	467	465.17	467	465.12
A0 (8th order polynomial's coefficient)	167.08	167.02	167.08	167.02	167.08	167.02	167.08	167.02	167.08	167.02
A1	26.194	25.706	26.194	25.771	26.194	25.668	26.194	25.773	26.194	25.606
A2	427.78	444.33	427.78	443.68	427.78	444.78	427.78	444.08	427.78	445.36
A3	-2617.6	-2594.8	-2617.6	-2592.8	-2617.6	-2596.5	-2617.6	-2594.5	-2617.6	-2598.3
A4	5757.3	5664.2	5757.3	5661.3	5757.3	5667.1	5757.3	5664.2	5757.3	5669.9
A5	-6241.5	-6162.9	-6241.5	-6160.7	-6241.5	-6165.7	-6241.5	-6163.3	-6241.5	-6167.9
A6	3585.9	3566.1	3585.9	3565.2	3585.9	3567.7	3585.9	3566.6	3585.9	3568.6
A7	-1047.5	-1049.9	-1047.5	-1049.7	-1047.5	-1050.3	-1047.5	-1050	-1047.5	-1050.5
A8	122.6	123.75	122.6	123.73	122.6	123.79	122.6	123.77	122.6	123.81
sigma pre-disruption	54.83098455	54.685	54.83098455	54.685	54.83098455	54.686	54.83098455	54.684	54.83098455	54.686
sigma transient	61.36139379	60.721	61.36139379	60.717	61.36139379	60.717	61.36139379	60.72	61.36139379	60.719
sigma post-transient	61.6804937	62.469	61.6804937	62.465	61.6804937	62.464	61.6804937	62.468	61.6804937	62.467

Count	276		277		278		279		280	
Exp. NO	391		392		393		394		395	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	467	465.26	467	465.27	467	465.2	467	465.35	467	465.14
A0 (8th order polynomial's coefficient)	167.08	167.02	167.08	167.02	167.08	167.02	167.08	167.02	167.08	167.02
A1	26.194	25.595	26.194	25.735	26.194	25.559	26.194	25.669	26.194	25.774
A2	427.78	445.24	427.78	444.12	427.78	445.6	427.78	444.6	427.78	444.05
A3	-2617.6	-2597.7	-2617.6	-2594.4	-2617.6	-2598.8	-2617.6	-2595.6	-2617.6	-2594.4
A4	5757.3	5668.7	5757.3	5664	5757.3	5670.2	5757.3	5665.5	5757.3	5664
A5	-6241.5	-6166.7	-6241.5	-6163.2	-6241.5	-6167.8	-6241.5	-6164	-6241.5	-6163.1
A6	3585.9	3568	3585.9	3566.5	3585.9	3568.4	3585.9	3566.7	3585.9	3566.4
A7	-1047.5	-1050.3	-1047.5	-1050	-1047.5	-1050.4	-1047.5	-1050	-1047.5	-1050
A8	122.6	123.79	122.6	123.77	122.6	123.8	122.6	123.76	122.6	123.76
sigma pre-disruption	54.83098455	54.686	54.83098455	54.686	54.83098455	54.686	54.83098455	54.685	54.83098455	54.684
sigma transient	61.36139379	60.72	61.36139379	60.712	61.36139379	60.724	61.36139379	60.723	61.36139379	60.717
sigma post-transient	61.6804937	62.468	61.6804937	62.458	61.6804937	62.473	61.6804937	62.472	61.6804937	62.464

Count	281		282		283		284		285	
Exp. NO	396		397		398		399		400	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	467	465.28	467	465.29	467	465.2	467	465.29	467	465.33
A0 (8th order polynomial's coefficient)	167.08	167.02	167.08	167.02	167.08	167.02	167.08	167.02	167.08	167.02
A1	26.194	25.567	26.194	25.557	26.194	25.707	26.194	25.713	26.194	25.714
A2	427.78	445.41	427.78	445.5	427.78	444.47	427.78	444.33	427.78	444.21
A3	-2617.6	-2598.2	-2617.6	-2598.5	-2617.6	-2595.4	-2617.6	-2595	-2617.6	-2594.5
A4	5757.3	5669.5	5757.3	5670.1	5757.3	5665.4	5757.3	5664.8	5757.3	5663.8
A5	-6241.5	-6167.4	-6241.5	-6168.1	-6241.5	-6164	-6241.5	-6163.7	-6241.5	-6162.8
A6	3585.9	3568.3	3585.9	3568.7	3585.9	3566.8	3585.9	3566.7	3585.9	3566.2
A7	-1047.5	-1050.4	-1047.5	-1050.5	-1047.5	-1050	-1047.5	-1050	-1047.5	-1049.9
A8	122.6	123.8	122.6	123.82	122.6	123.77	122.6	123.77	122.6	123.75
sigma pre-disruption	54.83098455	54.687	54.83098455	54.687	54.83098455	54.685	54.83098455	54.685	54.83098455	54.686
sigma transient	61.36139379	60.718	61.36139379	60.717	61.36139379	60.72	61.36139379	60.719	61.36139379	60.716
sigma post-transient	61.6804937	62.466	61.6804937	62.464	61.6804937	62.467	61.6804937	62.467	61.6804937	62.463

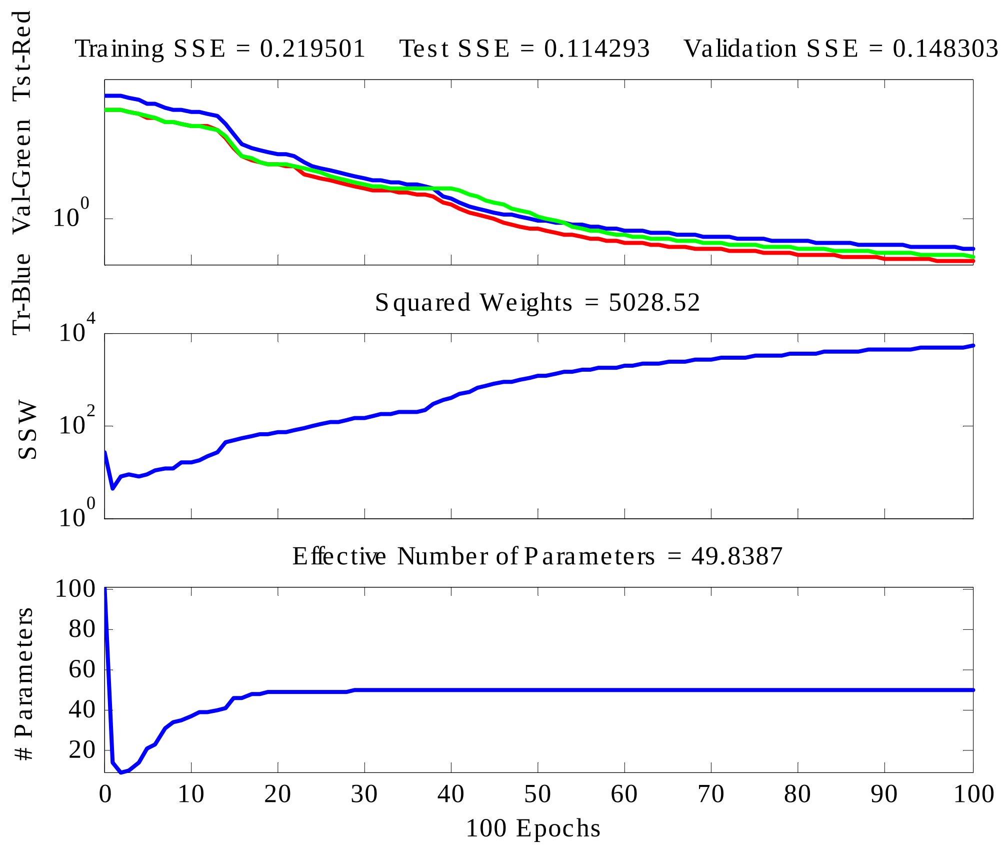
Count	286		287		288		289		290	
Exp. NO	161		162		163		164		165	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	383	379.34	383	379.18	383	379.11	383	379.21	383	379.18
A0 (8th order polynomial's coefficient)	155.08	155.1	155.08	155.08	155.08	155.08	155.08	155.07	155.08	155.08
A1	-18.024	-22.139	-18.024	-22.545	-18.024	-22.588	-18.024	-22.699	-18.024	-22.5
A2	358.32	299.15	358.32	301.61	358.32	301.76	358.32	302.76	358.32	301.38
A3	-1384.2	-1318.5	-1384.2	-1327.3	-1384.2	-1327.8	-1384.2	-1331.4	-1384.2	-1326.6
A4	2697.1	2716.8	2697.1	2734.6	2697.1	2736.1	2697.1	2742.1	2697.1	2733.5
A5	-2882.7	-2930.4	-2882.7	-2950.3	-2882.7	-2952.4	-2882.7	-2957.9	-2882.7	-2949.3
A6	1686.7	1702.4	1686.7	1714.4	1686.7	1715.9	1686.7	1718.7	1686.7	1713.9
A7	-504.77	-504.11	-504.77	-507.82	-504.77	-508.33	-504.77	-509.07	-504.77	-507.67
A8	60.312	59.69	60.312	60.146	60.312	60.212	60.312	60.294	60.312	60.13
sigma pre-disruption	33.17731134	33.128	33.17731134	33.136	33.17731134	33.137	33.17731134	33.137	33.17731134	33.135
sigma transient	42.16671367	43.098	42.16671367	43.041	42.16671367	43.027	42.16671367	43.033	42.16671367	43.043
sigma post-transient	43.14094484	42.45	43.14094484	42.384	43.14094484	42.368	43.14094484	42.374	43.14094484	42.386

Count	291		292		293		294		295	
Exp. NO	411		412		413		414		415	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	383	379.31	383	379.19	383	379.22	383	379.14	383	379.21
A0 (8th order polynomial's coefficient)	155.08	155.08	155.08	155.09	155.08	155.07	155.08	155.08	155.08	155.08
A1	-18.024	-22.394	-18.024	-22.365	-18.024	-22.695	-18.024	-22.519	-18.024	-22.571
A2	358.32	300.78	358.32	300.47	358.32	302.72	358.32	301.37	358.32	301.85
A3	-1384.2	-1324.1	-1384.2	-1323.4	-1384.2	-1331.2	-1384.2	-1326.5	-1384.2	-1328.1
A4	2697.1	2727.6	2697.1	2727.4	2697.1	2741.7	2697.1	2733.4	2697.1	2735.9
A5	-2882.7	-2941.9	-2882.7	-2942.8	-2882.7	-2957.4	-2882.7	-2949.4	-2882.7	-2951.4
A6	1686.7	1709	1686.7	1710.1	1686.7	1718.3	1686.7	1714	1686.7	1714.9
A7	-504.77	-506.11	-504.77	-506.54	-504.77	-508.97	-504.77	-507.75	-504.77	-507.94
A8	60.312	59.931	60.312	59.993	60.312	60.28	60.312	60.141	60.312	60.158
sigma pre-disruption	33.17731134	33.132	33.17731134	33.133	33.17731134	33.137	33.17731134	33.136	33.17731134	33.136
sigma transient	42.16671367	43.074	42.16671367	43.056	42.16671367	43.034	42.16671367	43.037	42.16671367	43.044
sigma post-transient	43.14094484	42.422	43.14094484	42.401	43.14094484	42.376	43.14094484	42.38	43.14094484	42.387

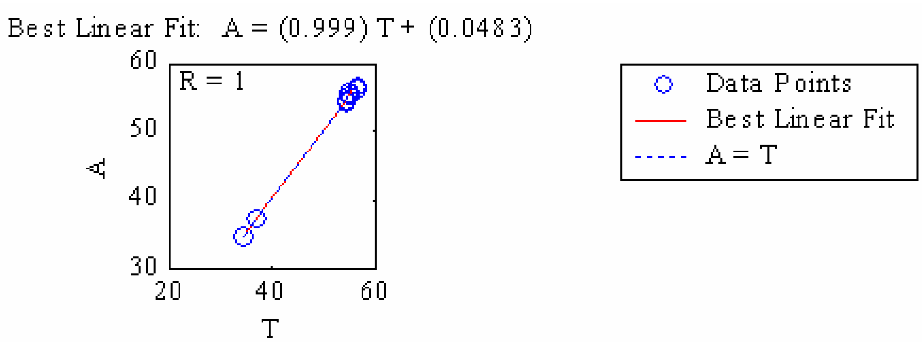
Count	296		297		298		299		300	
Exp. NO	416		417		418		419		420	
	Target	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**	**Target**	**Approx. by ANN**
Disruption Impact Delay (estimated lag)	383	379.16	383	378.92	383	379.07	383	379.05	383	379.27
A0 (8th order polynomial's coefficient)	155.08	155.07	155.08	155.07	155.08	155.08	155.08	155.08	155.08	155.09
A1	-18.024	-22.714	-18.024	-22.744	-18.024	-22.573	-18.024	-22.496	-18.024	-22.386
A2	358.32	302.8	358.32	302.57	358.32	301.61	358.32	301.04	358.32	300.73
A3	-1384.2	-1331.6	-1384.2	-1331.1	-1384.2	-1327.4	-1384.2	-1325.4	-1384.2	-1324.1
A4	2697.1	2743	2697.1	2744	2697.1	2735.7	2697.1	2732.1	2697.1	2728
A5	-2882.7	-2959.3	-2882.7	-2962.4	-2882.7	-2952.4	-2882.7	-2948.8	-2882.7	-2942.7
A6	1686.7	1719.7	1686.7	1722.4	1686.7	1716	1686.7	1714.1	1686.7	1709.6
A7	-504.77	-509.42	-504.77	-510.45	-504.77	-508.42	-504.77	-507.85	-504.77	-506.33
A8	60.312	60.339	60.312	60.483	60.312	60.227	60.312	60.161	60.312	59.961
sigma pre-disruption	33.17731134	33.138	33.17731134	33.141	33.17731134	33.138	33.17731134	33.137	33.17731134	33.132
sigma transient	42.16671367	43.024	42.16671367	42.984	42.16671367	43.021	42.16671367	43.025	42.16671367	43.068
sigma post-transient	43.14094484	42.364	43.14094484	42.318	43.14094484	42.362	43.14094484	42.366	43.14094484	42.415

Appendix D

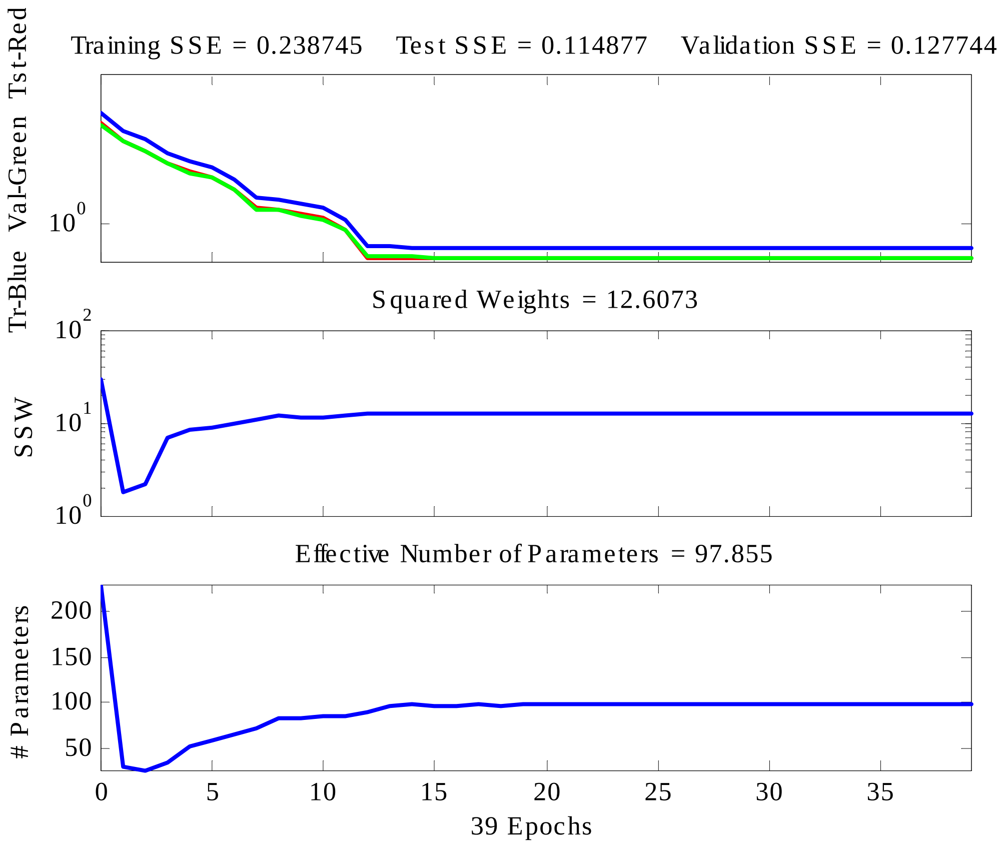
Training, Testing & Validation Plots for ANN_1_1



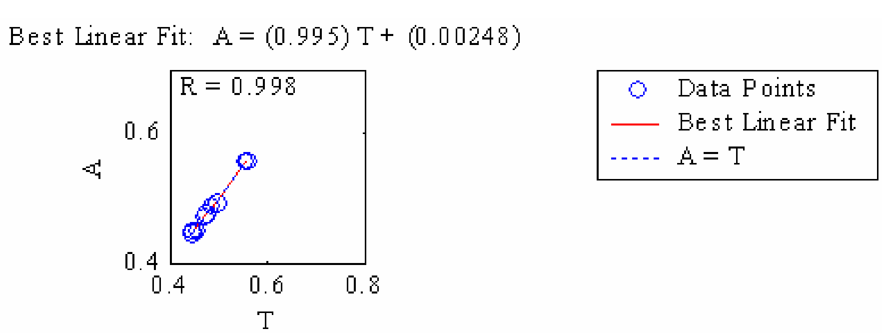
Approximations of First Element in Output Vectors



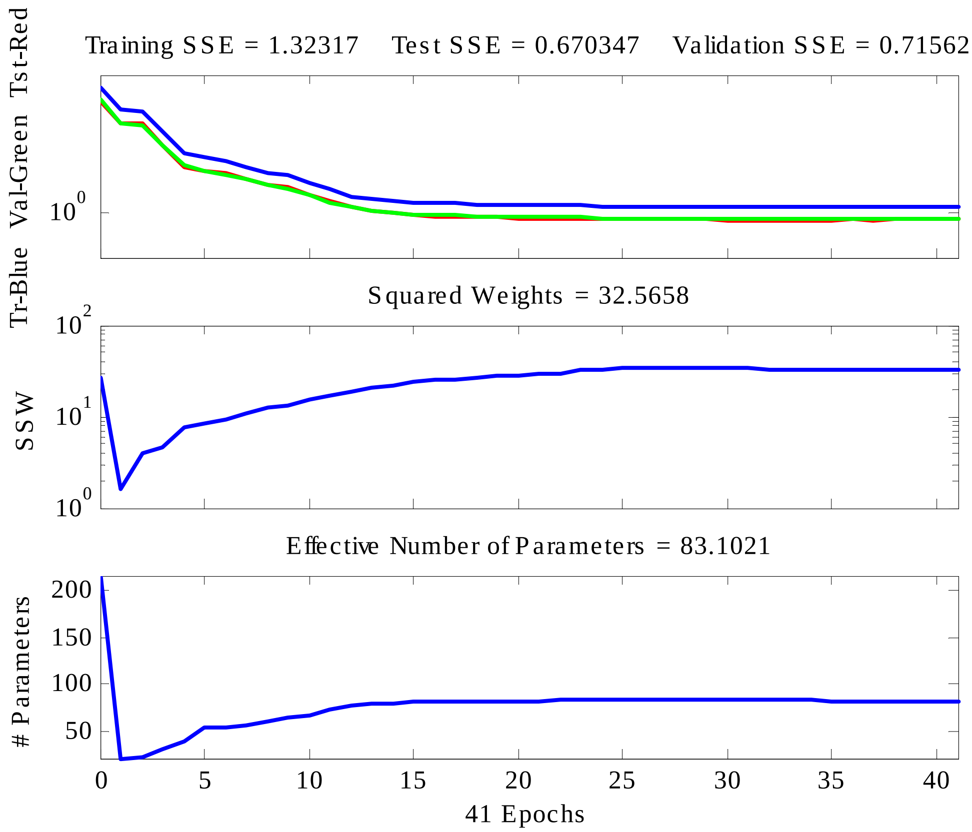
Training, Testing & Validation Plots for ANN_2_1_1



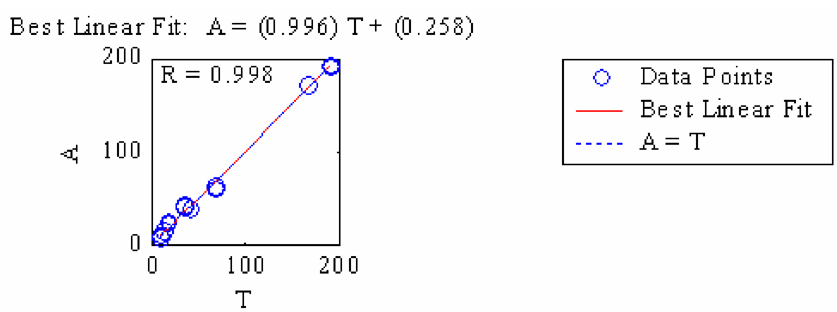
Approximations of First Element in Output Vectors



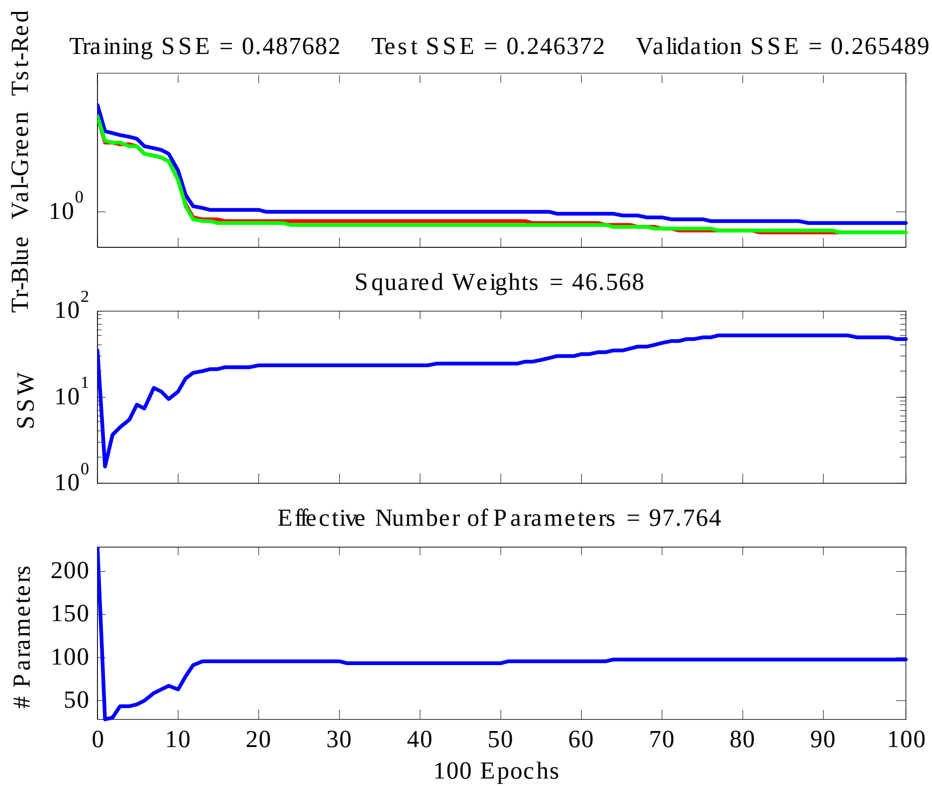
Training, Testing & Validation Plots for ANN_2_1_2



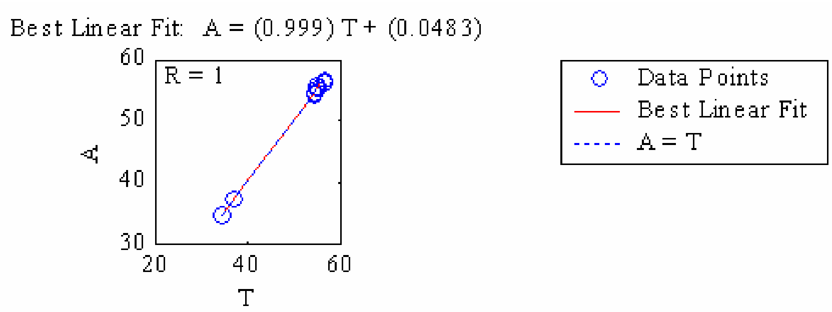
Approximations of First Element in Output Vectors



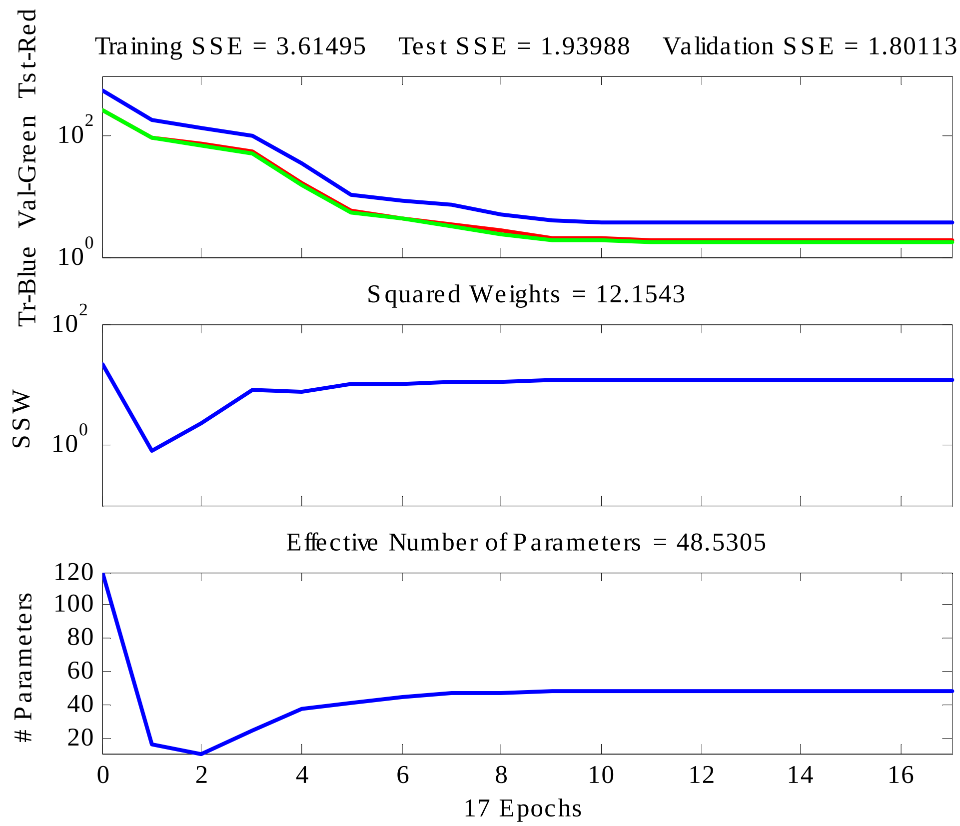
Training, Testing & Validation Plots for ANN_2_1_3



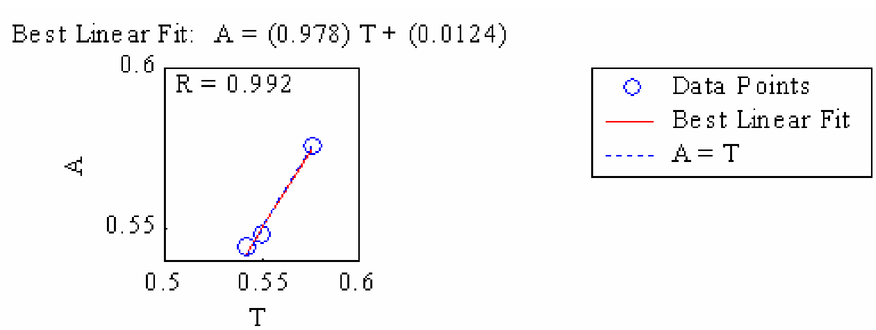
Approximations of First Element in Output Vectors



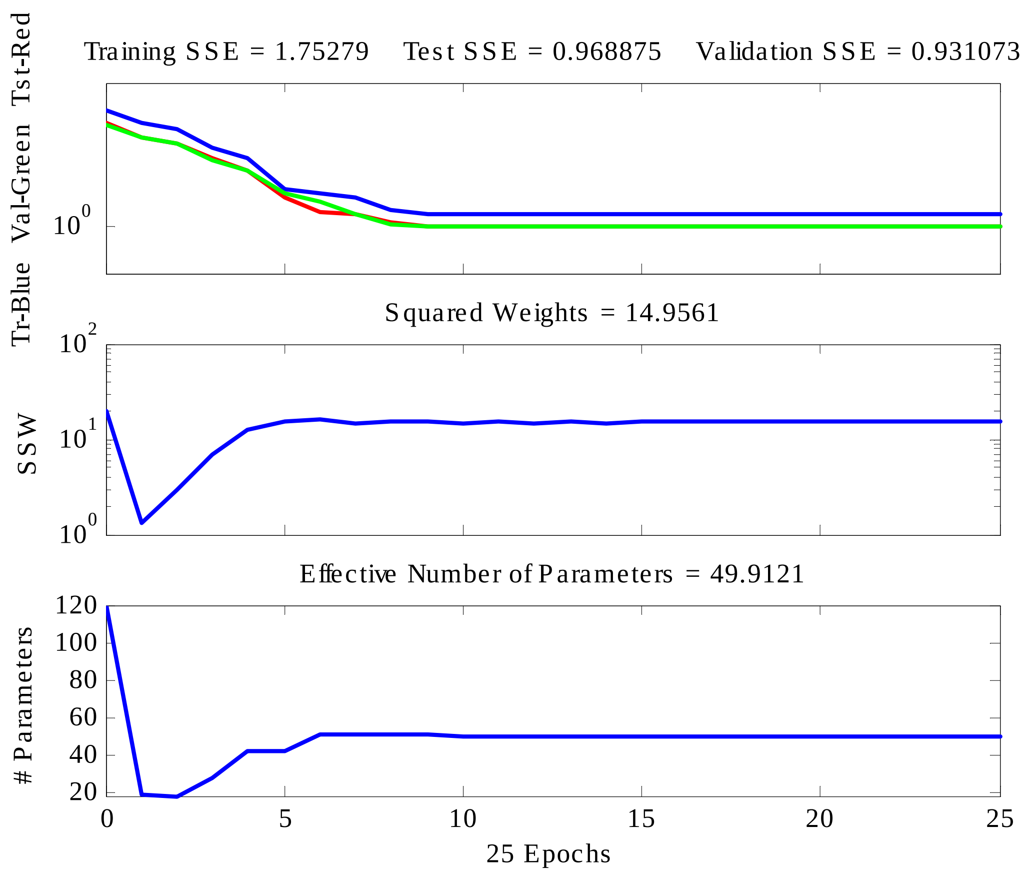
Training, Testing & Validation Plots for ANN_2_2_1



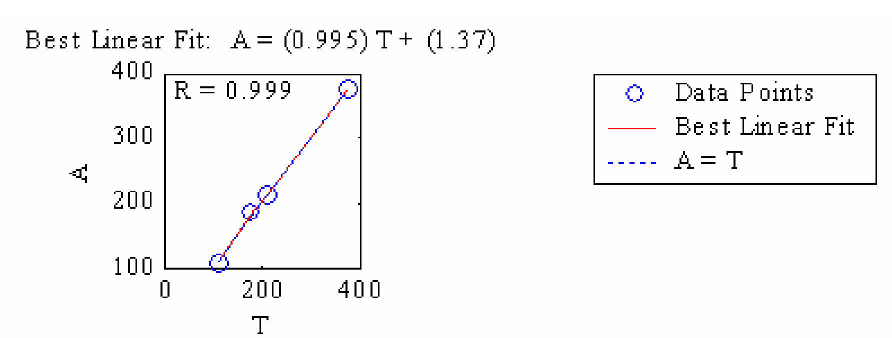
Approximations of First Element in Output Vectors



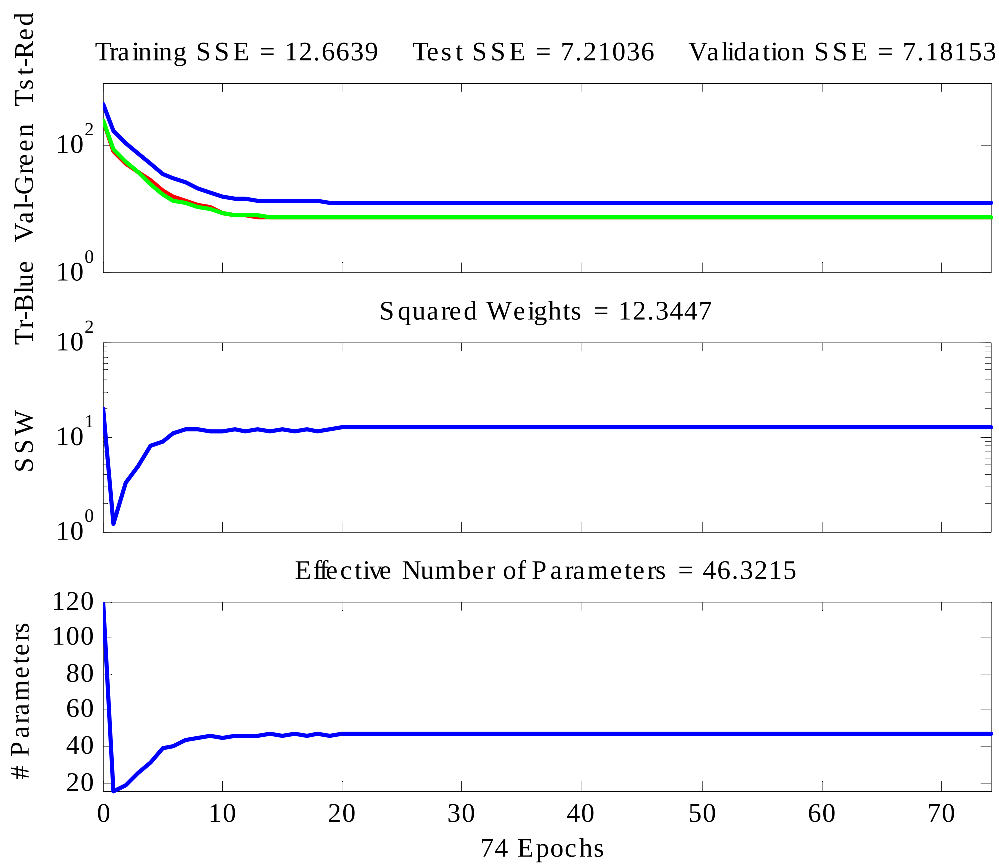
Training, Testing & Validation Plots for ANN_2_2_2



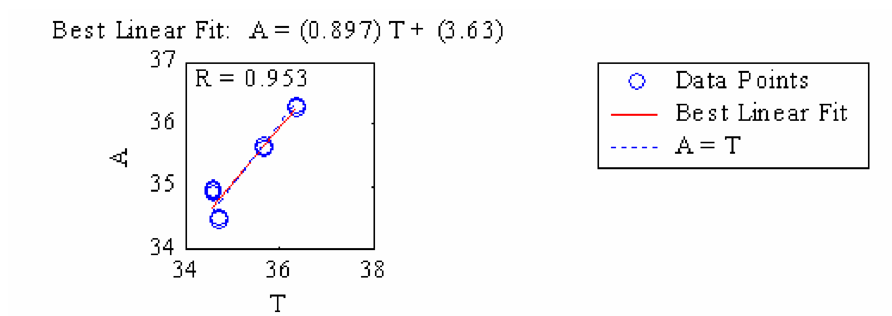
Approximations of First Element in Output Vectors



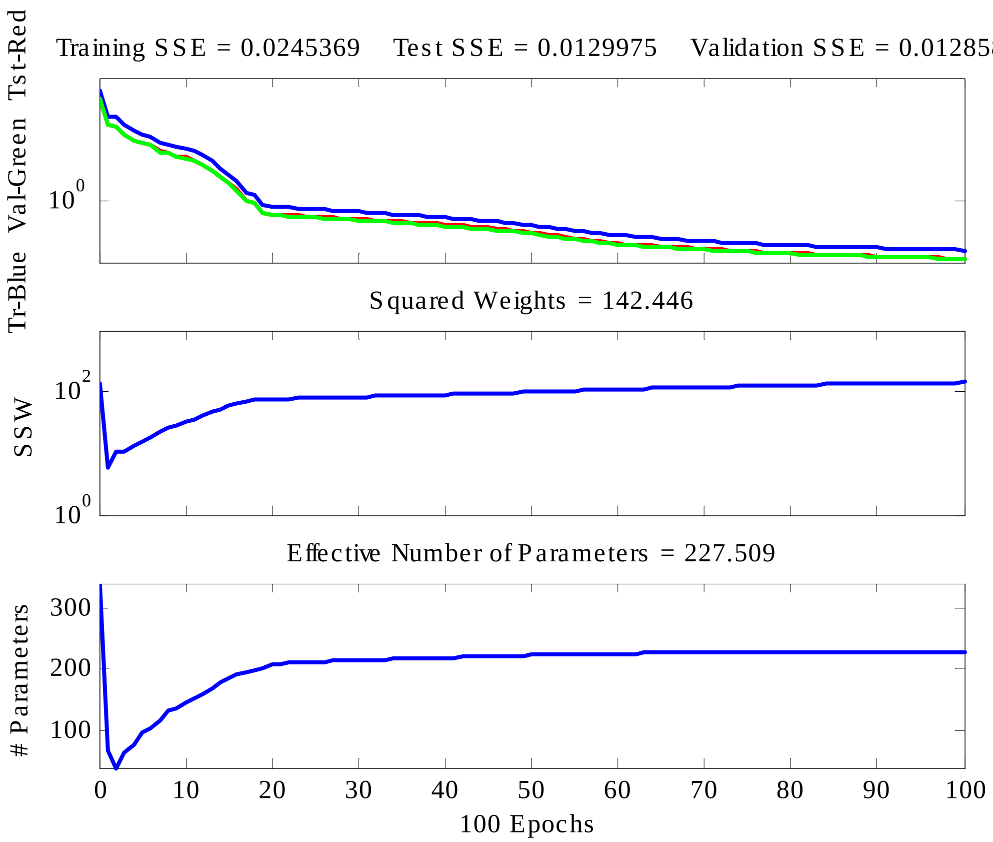
Training, Testing & Validation Plots for ANN_2_2_3



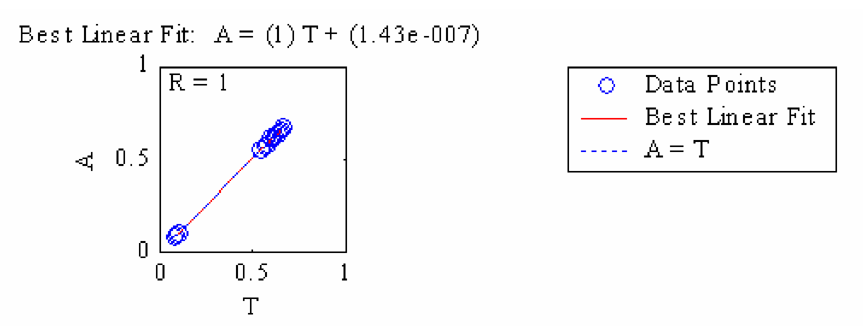
Approximations of First Element in Output Vectors



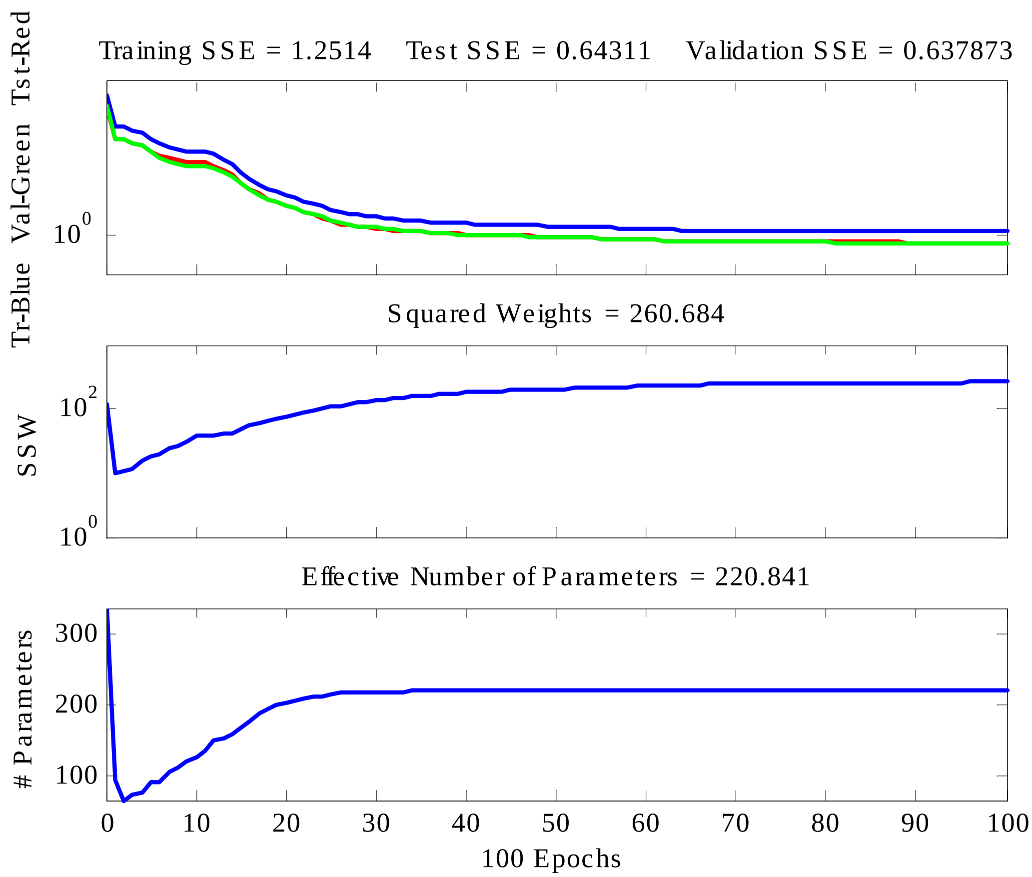
Training, Testing & Validation Plots for ANN_2_3_1



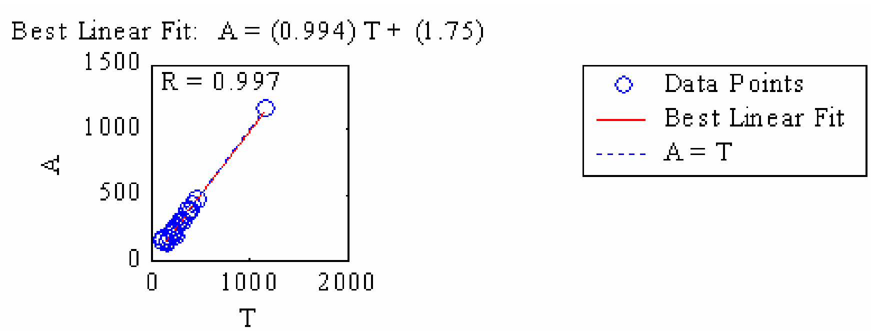
Approximations of First Element in Output Vectors



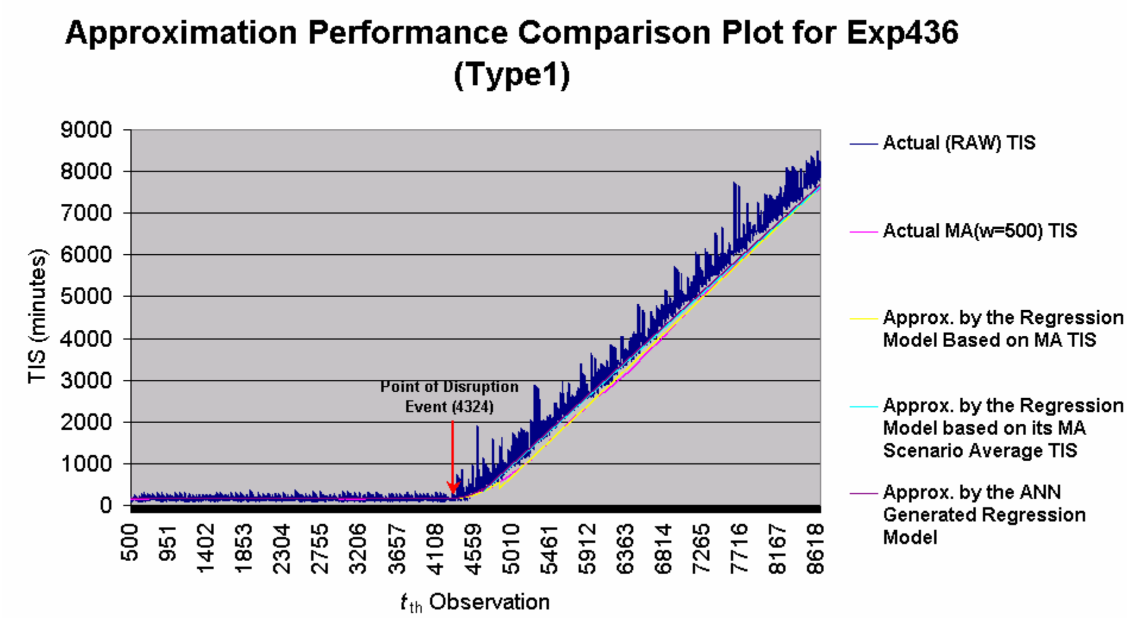
Training, Testing & Validation Plots for ANN_2_3_2

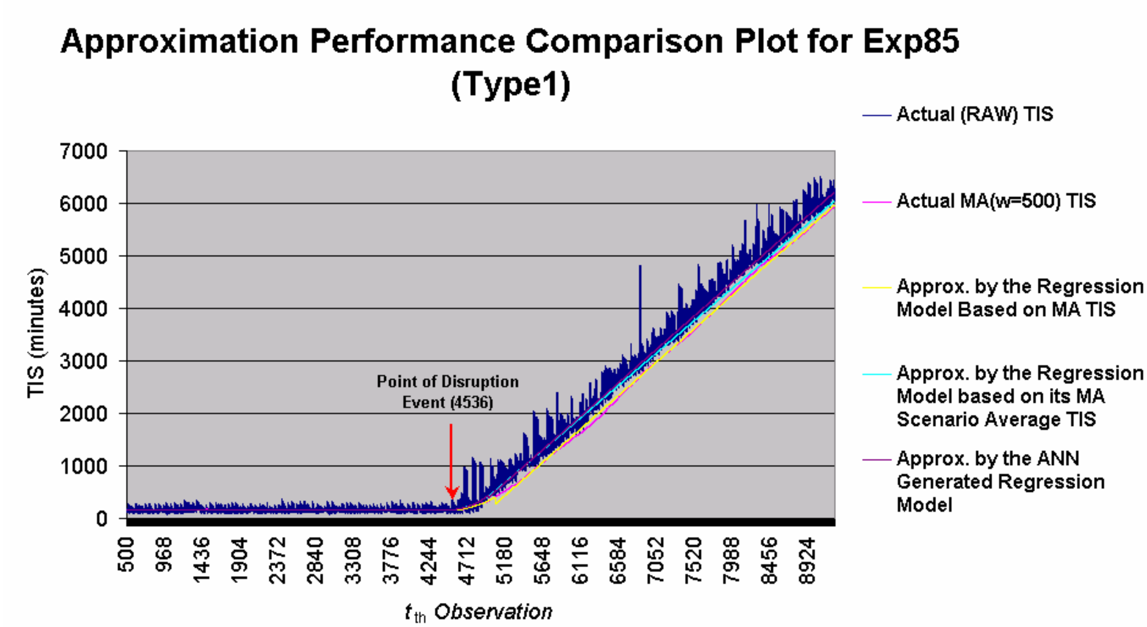


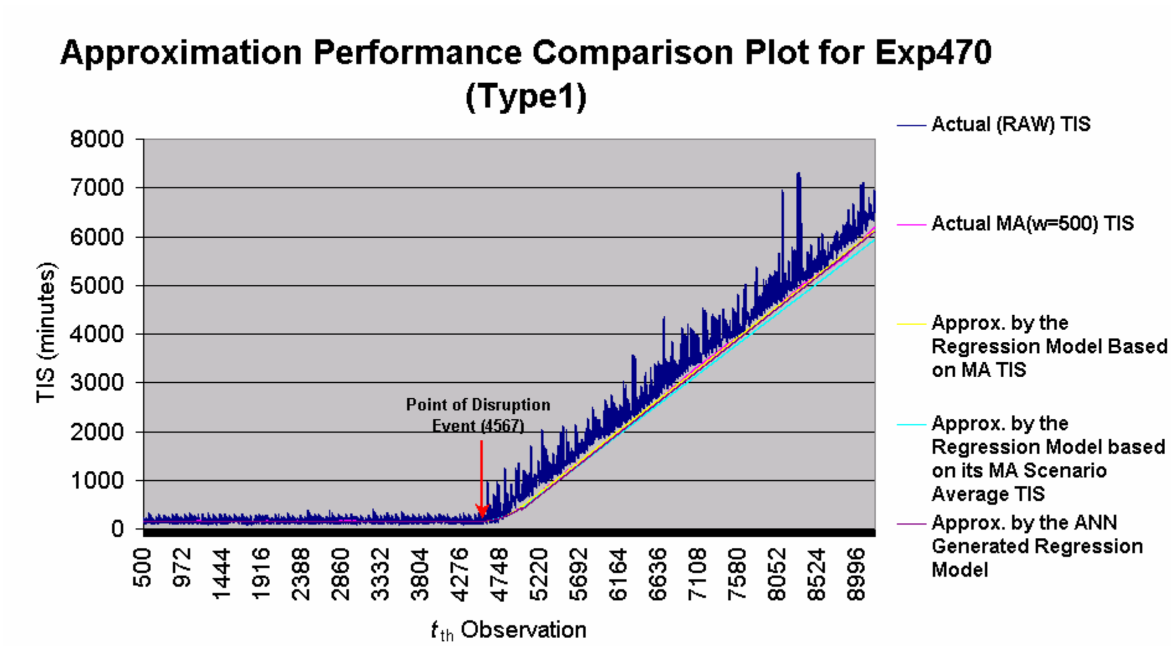
Approximations of First Element in Output Vectors



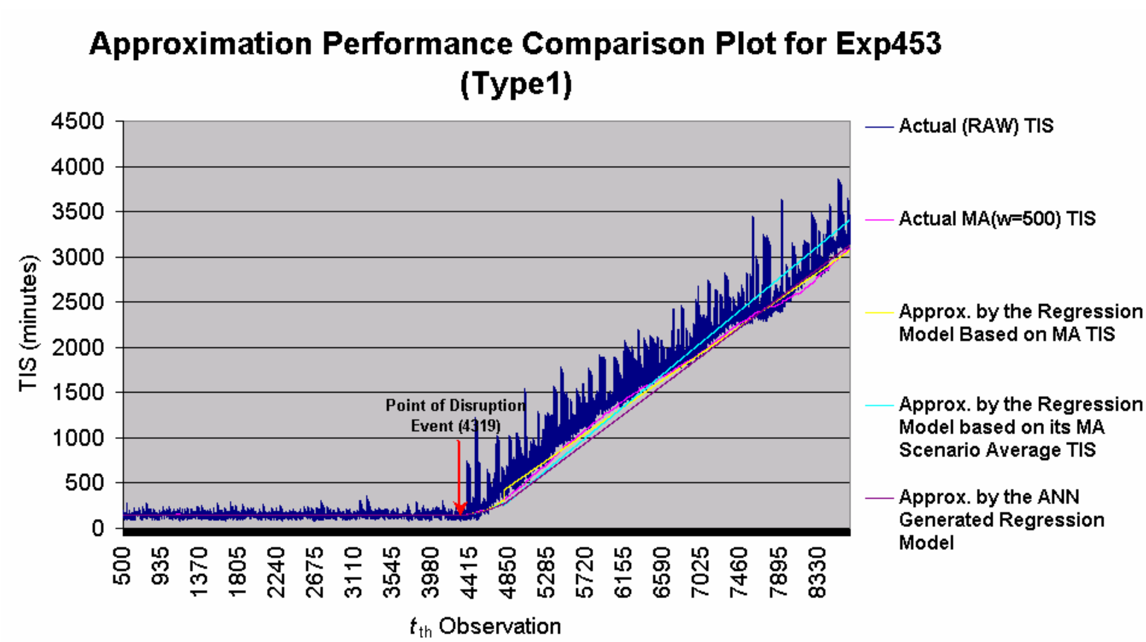
Appendix E


Approximation Performance Comparison Plot for Exp436 (Type1)
TIS (minutes)
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
Point of Disruption Event (4324)
500
951
1402
1853
2304
2755
3206
3657
4108
4559
5010
5461
5912
6363
6814
7265
7716
8167
8618
t th Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model

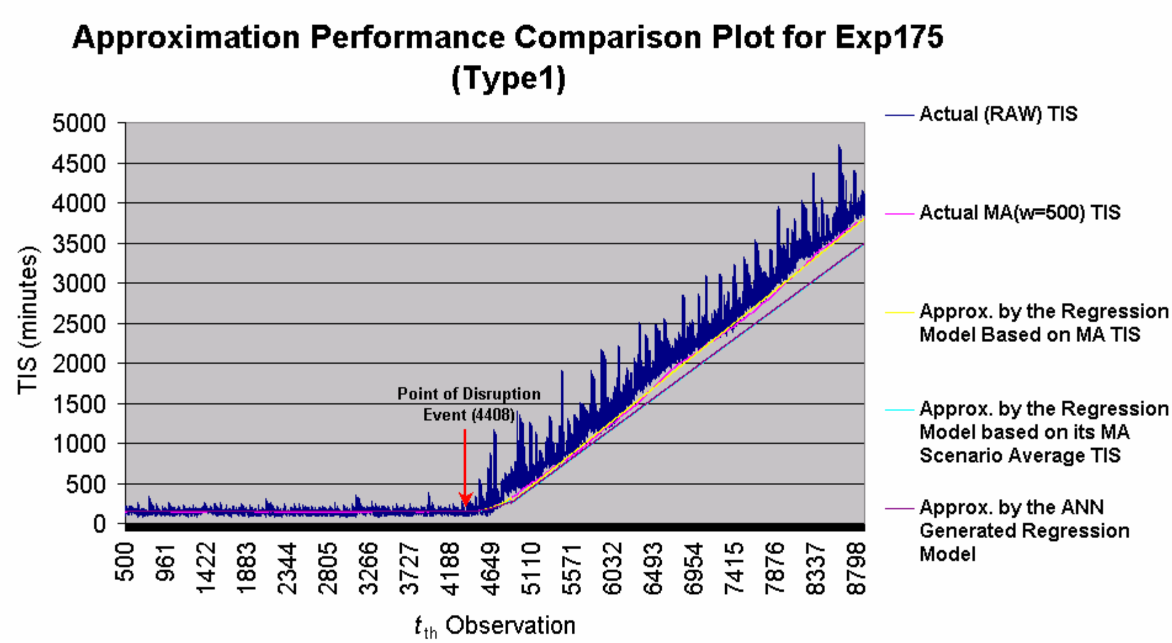

Approximation Performance Comparison Plot for Exp85 (Type1)
TIS (minutes)
7000
6000
5000
4000
3000
2000
1000
0
Point of Disruption Event (4536)
500
968
1436
1904
2372
2840
3308
3776
4244
4712
5180
5648
6116
6584
7052
7520
7988
8456
8924
t th Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model

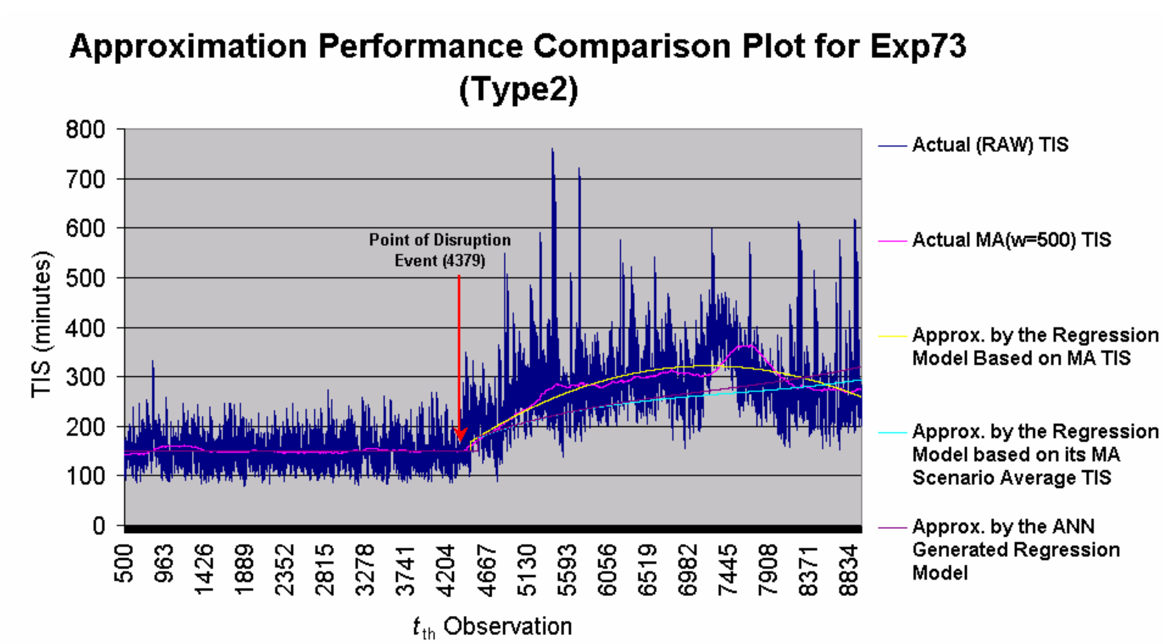


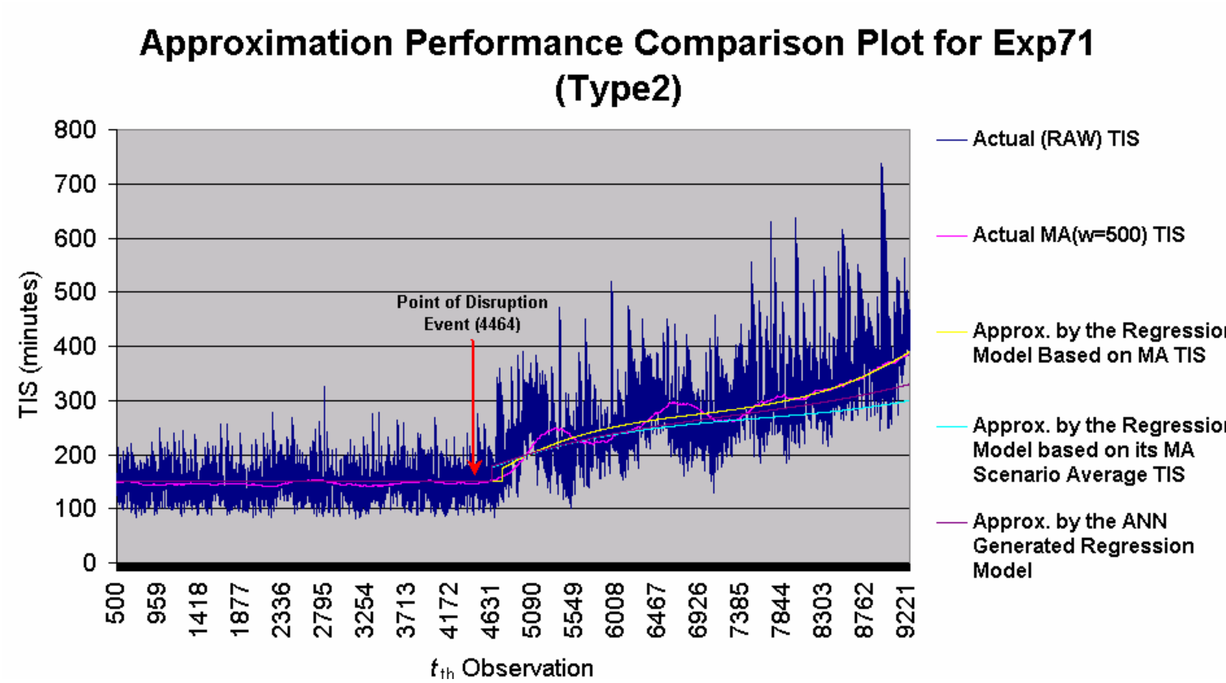
Approximation Performance Comparison Plot for Exp470 (Type1)
8000
7000
6000
5000
4000
3000
2000
1000
0
TIS (minutes)
Point of Disruption Event (4567)
500
972
1444
1916
2388
2860
3332
3804
4276
4748
5220
5692
6164
6636
7108
7580
8052
8524
8996
f th Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model

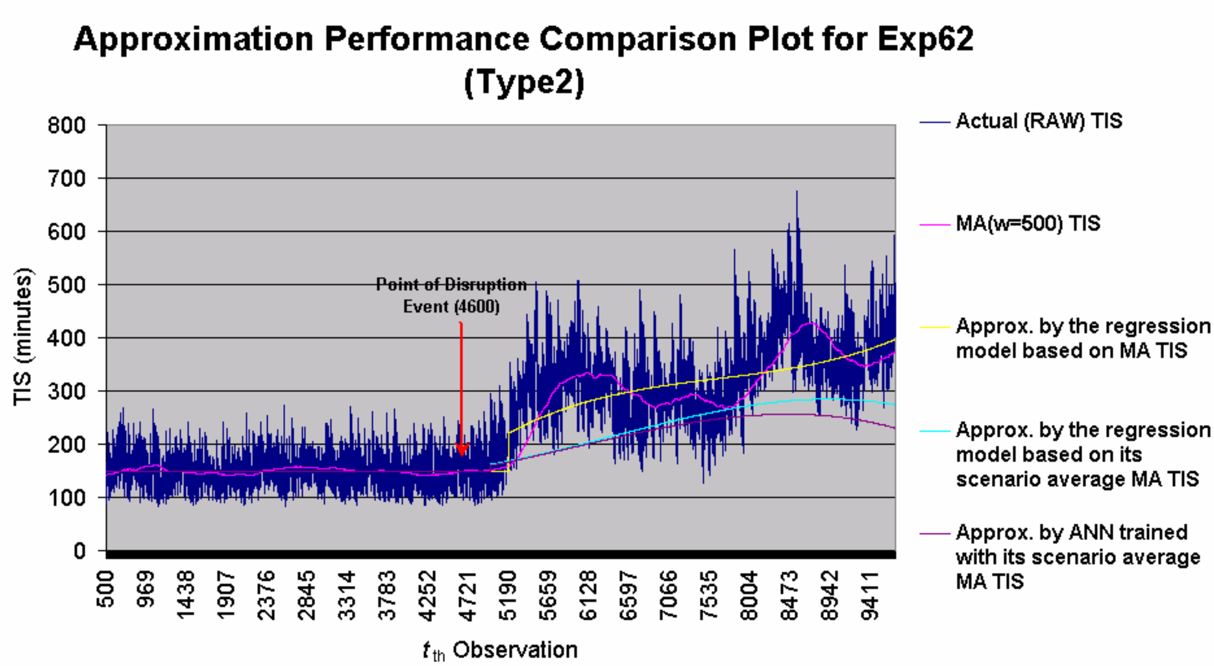


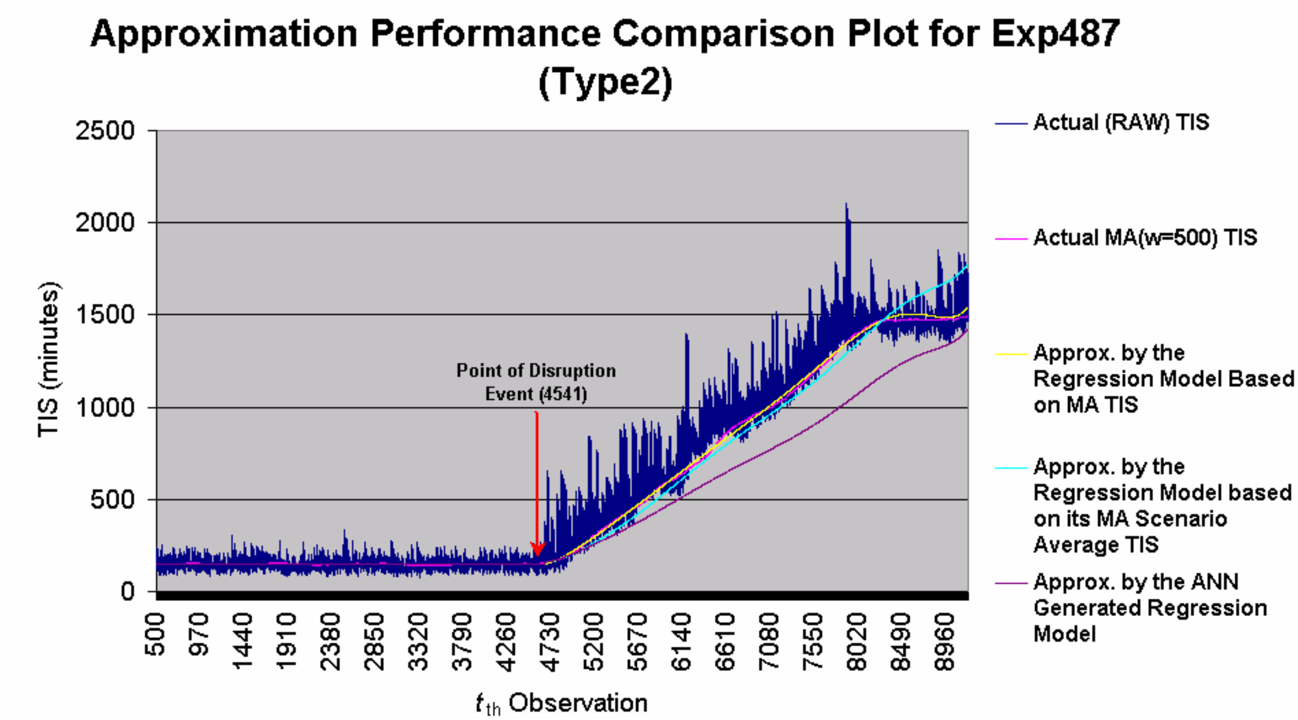
Approximation Performance Comparison Plot for Exp453 (Type1)
4500
4000
3500
3000
2500
2000
1500
1000
500
0
TIS (minutes)
Point of Disruption Event (4319)
500
935
1370
1805
2240
2675
3110
3545
3980
4415
4850
5285
5720
6155
6590
7025
7460
7895
8330
f th Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model

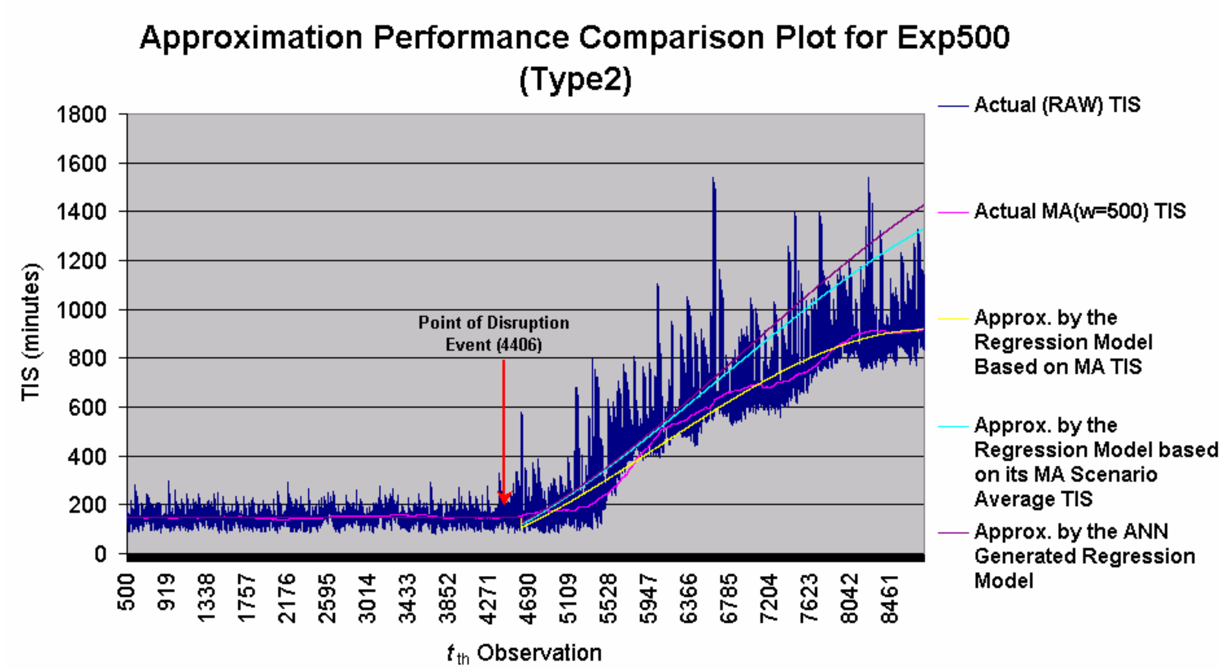

Approximation Performance Comparison Plot for Exp175 (Type1)
TIS (minutes)
5000
4500
4000
3500
3000
2500
2000
1500
1000
500
0
Point of Disruption Event (4408)
500
961
1422
1883
2344
2805
3266
3727
4188
4649
5110
5571
6032
6493
6954
7415
7876
8337
8798
t_{th} Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model

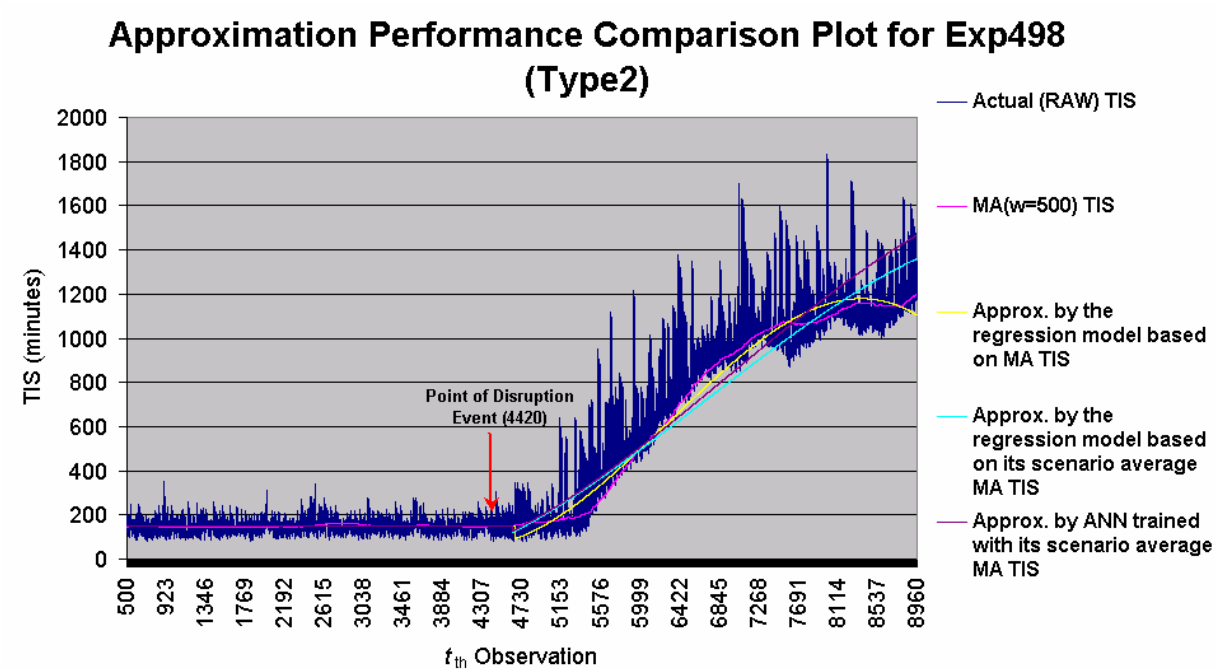

Approximation Performance Comparison Plot for Exp73 (Type2)
TIS (minutes)
800
700
600
500
400
300
200
100
0
Point of Disruption Event (4379)
500
963
1426
1889
2352
2815
3278
3741
4204
4667
5130
5593
6056
6519
6982
7445
7908
8371
8834
t_{th} Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model

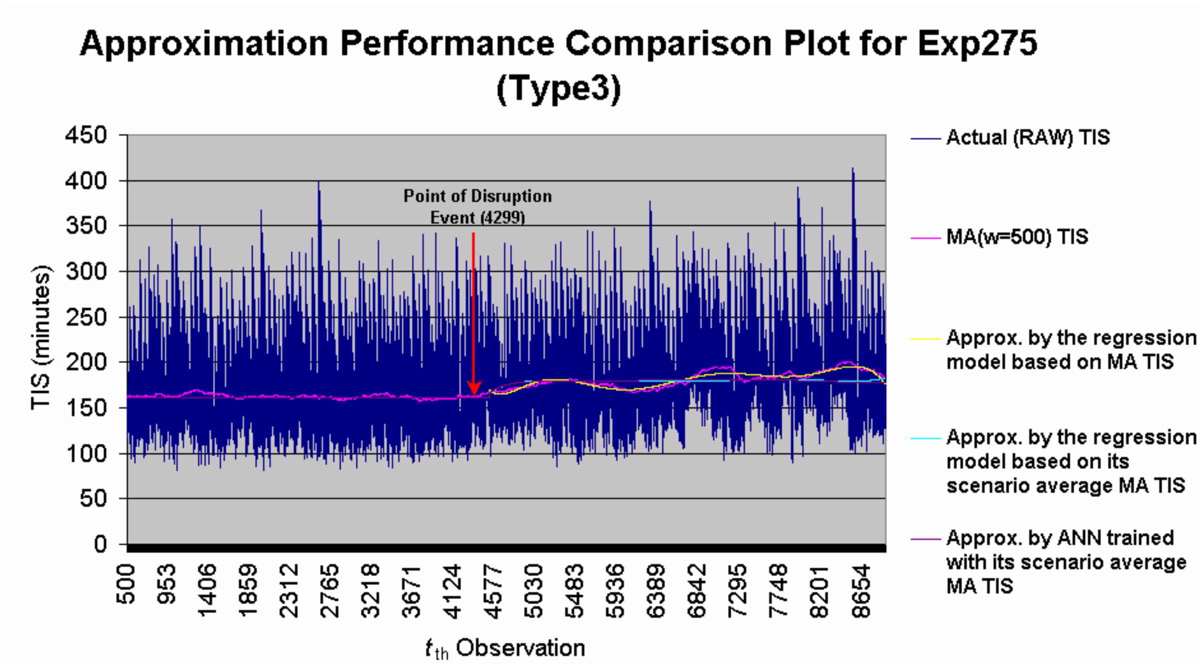

Approximation Performance Comparison Plot for Exp71 (Type2)
800
700
600
500
400
300
200
100
0
TIS (minutes)
Point of Disruption Event (4464)
500
959
1418
1877
2336
2795
3254
3713
4172
4631
5090
5549
6008
6467
6926
7385
7844
8303
8762
9221
t th Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model

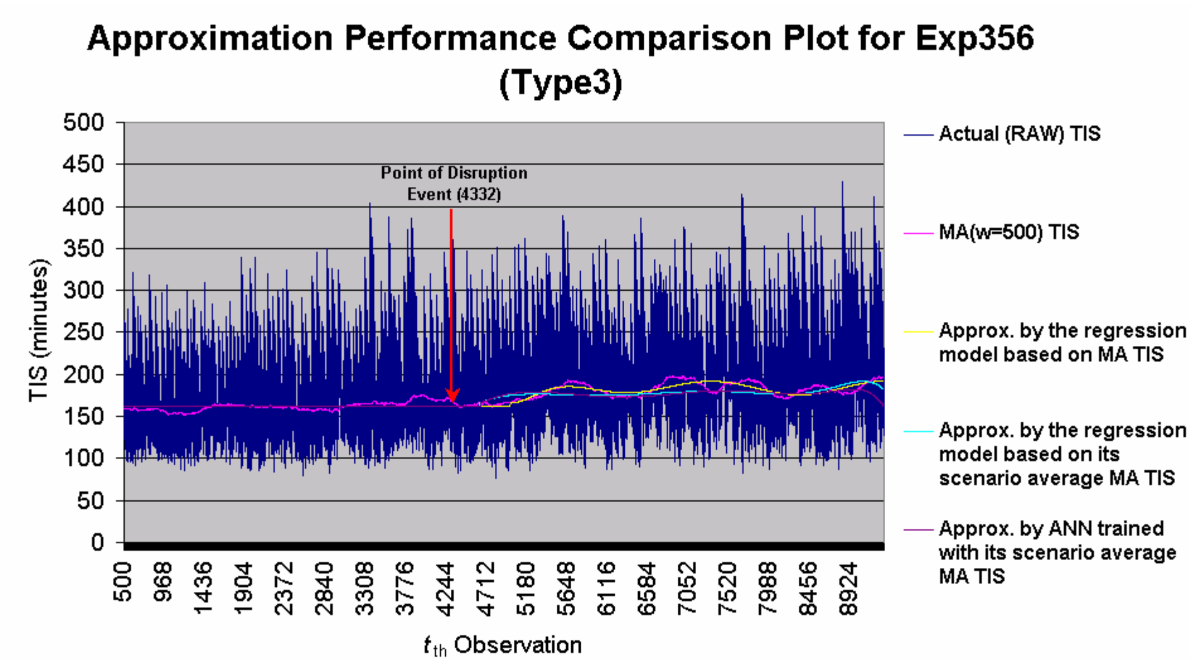

Approximation Performance Comparison Plot for Exp62 (Type2)
800
700
600
500
400
300
200
100
0
TIS (minutes)
Point of Disruption Event (4600)
500
969
1438
1907
2376
2845
3314
3783
4252
4721
5190
5659
6128
6597
7066
7535
8004
8473
8942
9411
t th Observation
Actual (RAW) TIS
MA(w=500) TIS
Approx. by the regression model based on MA TIS
Approx. by the regression model based on its scenario average MA TIS
Approx. by ANN trained with its scenario average MA TIS

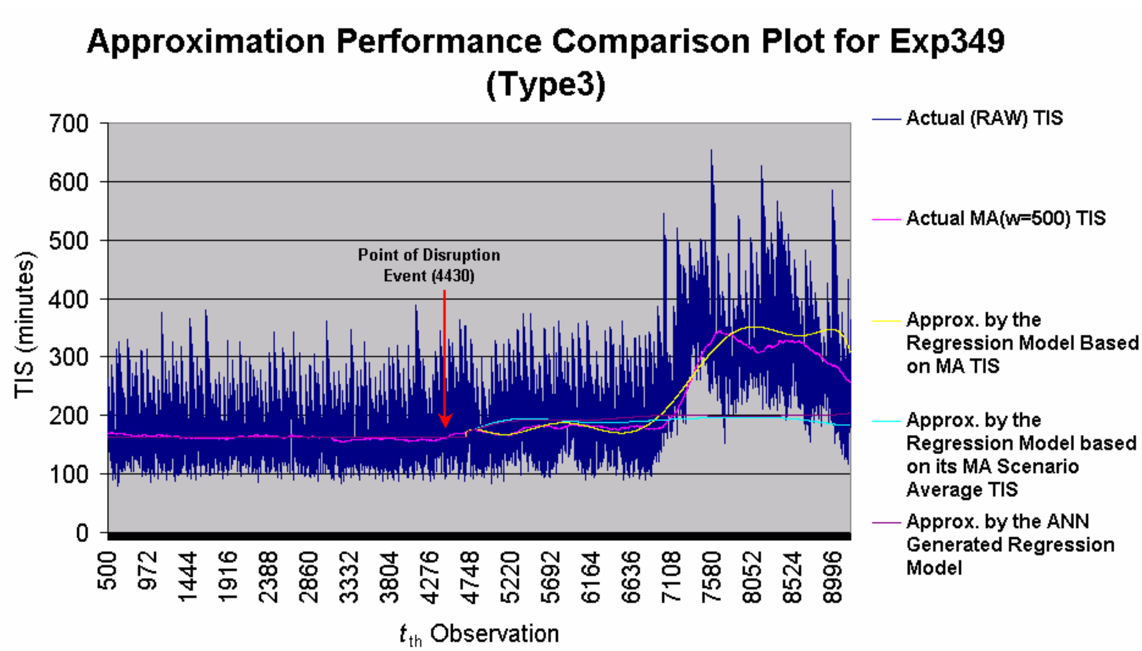

Approximation Performance Comparison Plot for Exp487 (Type2)
TIS (minutes)
2500
2000
1500
1000
500
0
Point of Disruption Event (4541)
500
970
1440
1910
2380
2850
3320
3790
4260
4730
5200
5670
6140
6610
7080
7550
8020
8490
8960
t_{th} Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model

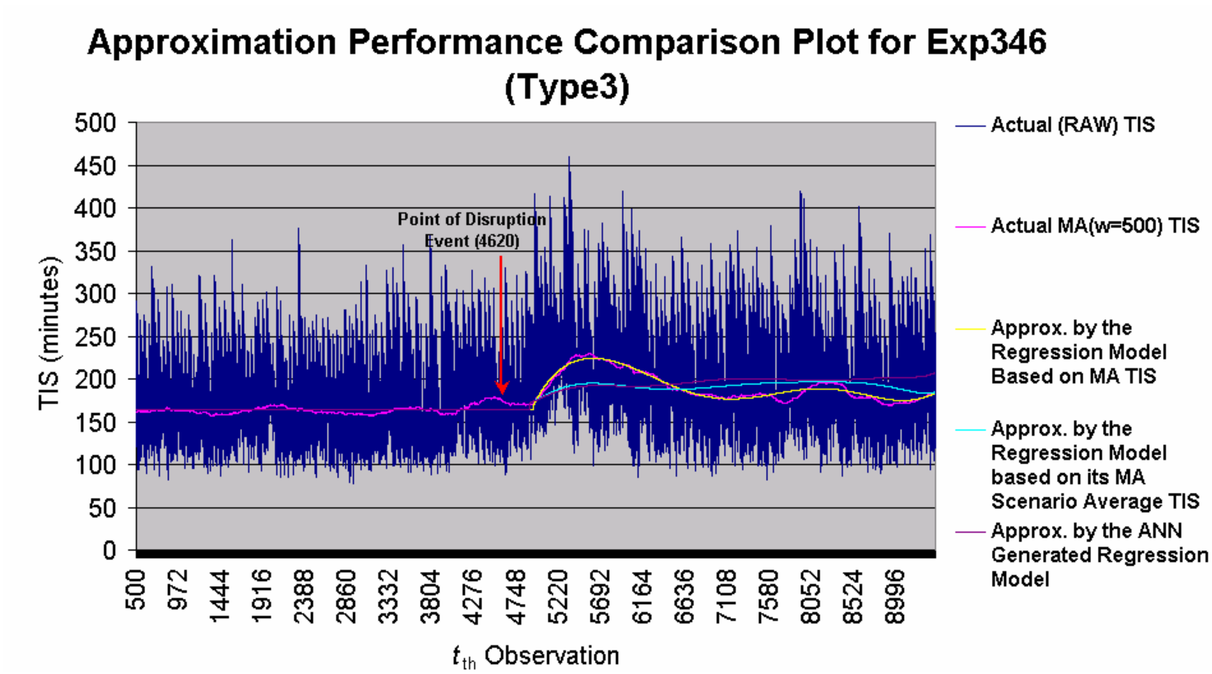

Approximation Performance Comparison Plot for Exp500 (Type2)
TIS (minutes)
1800
1600
1400
1200
1000
800
600
400
200
0
Point of Disruption Event (4406)
500
919
1338
1757
2176
2595
3014
3433
3852
4271
4690
5109
5528
5947
6366
6785
7204
7623
8042
8461
t_{th} Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model


Approximation Performance Comparison Plot for Exp498 (Type2)
TIS (minutes)
2000
1800
1600
1400
1200
1000
800
600
400
200
0
Point of Disruption Event (4420)
500
923
1346
1769
2192
2615
3038
3461
3884
4307
4730
5153
5576
5999
6422
6845
7268
7691
8114
8537
8960
t_{th} Observation
Actual (RAW) TIS
MA(w=500) TIS
Approx. by the regression model based on MA TIS
Approx. by the regression model based on its scenario average MA TIS
Approx. by ANN trained with its scenario average MA TIS

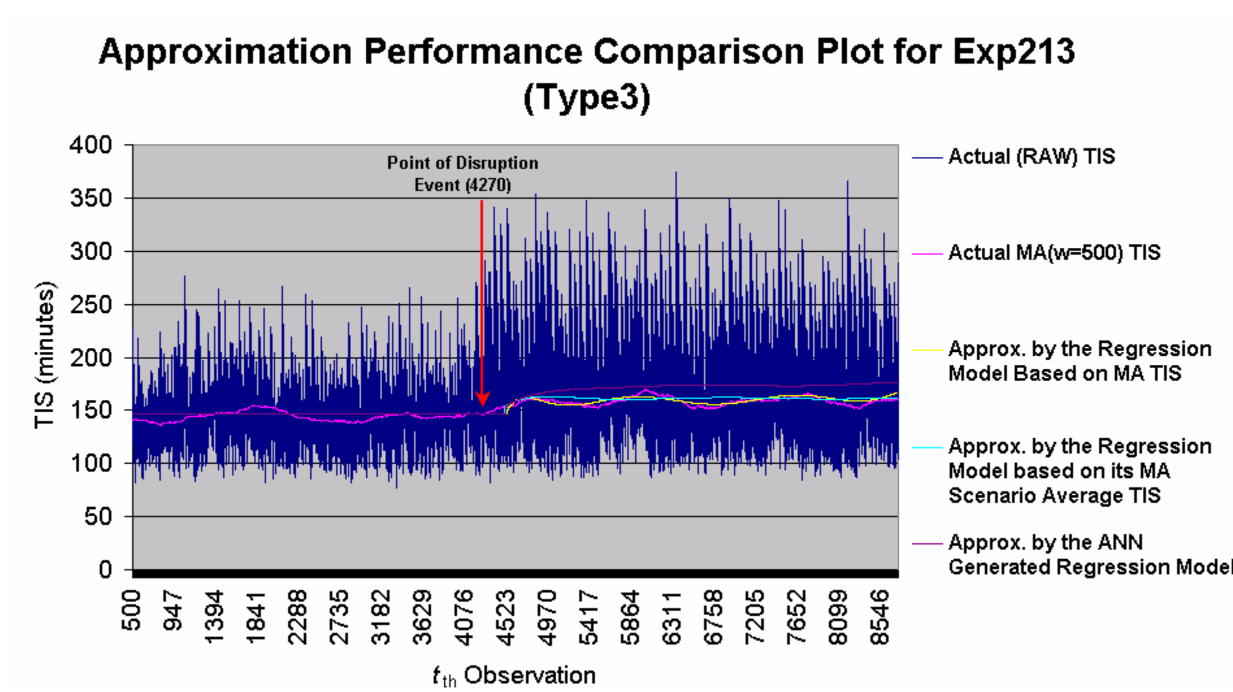

Approximation Performance Comparison Plot for Exp275 (Type3)
TIS (minutes)
450
400
350
300
250
200
150
100
50
0
Point of Disruption Event (4299)
500
953
1406
1859
2312
2765
3218
3671
4124
4577
5030
5483
5936
6389
6842
7295
7748
8201
8654
t_{th} Observation
Actual (RAW) TIS
MA(w=500) TIS
Approx. by the regression model based on MA TIS
Approx. by the regression model based on its scenario average MA TIS
Approx. by ANN trained with its scenario average MA TIS


Approximation Performance Comparison Plot for Exp356 (Type3)
Point of Disruption Event (4332)
TIS (minutes)
t_{th} Observation
Actual (RAW) TIS
MA(w=500) TIS
Approx. by the regression model based on MA TIS
Approx. by the regression model based on its scenario average MA TIS
Approx. by ANN trained with its scenario average MA TIS
0
50
100
150
200
250
300
350
400
450
500
500
968
1436
1904
2372
2840
3308
3776
4244
4712
5180
5648
6116
6584
7052
7520
7988
8456
8924

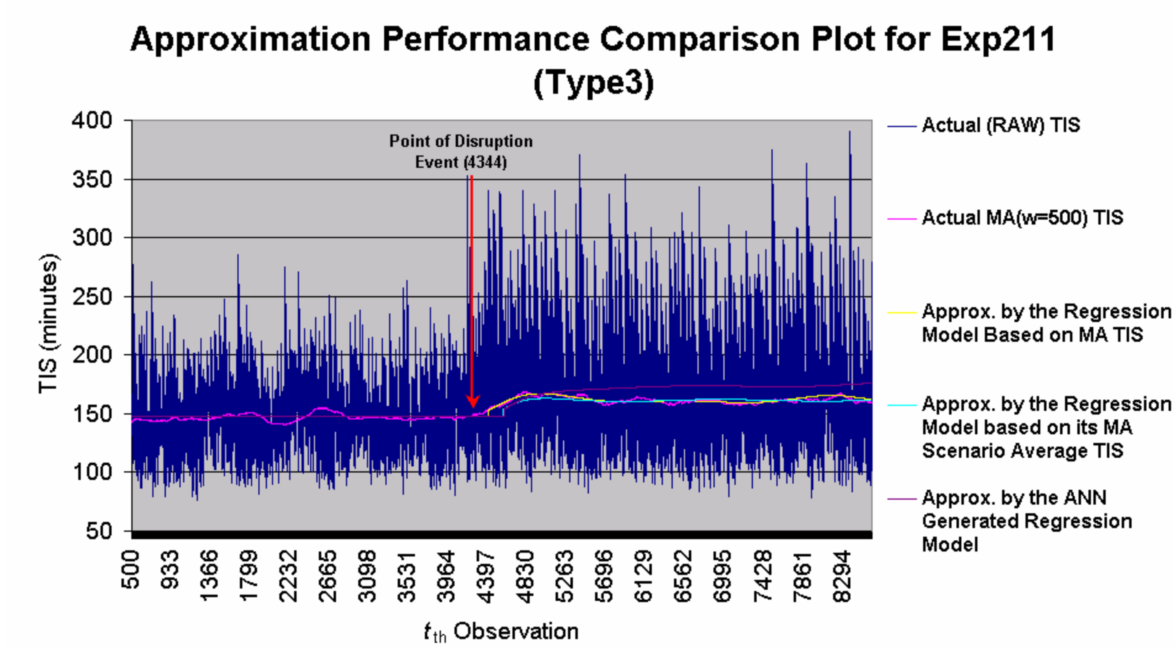

Approximation Performance Comparison Plot for Exp349 (Type3)
Point of Disruption Event (4430)
TIS (minutes)
t_{th} Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model
0
100
200
300
400
500
600
700
500
972
1444
1916
2388
2860
3332
3804
4276
4748
5220
5692
6164
6636
7108
7580
8052
8524
8996



Approximation Performance Comparison Plot for Exp346 (Type3)
Point of Disruption Event (4620)
TIS (minutes)
500
450
400
350
300
250
200
150
100
50
0
500
972
1444
1916
2388
2860
3332
3804
4276
4748
5220
5692
6164
6636
7108
7580
8052
8524
8996
t_{th} Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model



Approximation Performance Comparison Plot for Exp213 (Type3)
Point of Disruption Event (4270)
TIS (minutes)
400
350
300
250
200
150
100
50
0
500
947
1394
1841
2288
2735
3182
3629
4076
4523
4970
5417
5864
6311
6758
7205
7652
8099
8546
t_{th} Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model


Approximation Performance Comparison Plot for Exp211 (Type3)
TIS (minutes)
400
350
300
250
200
150
100
50
Point of Disruption Event (4344)
500
933
1366
1799
2232
2665
3098
3531
3964
4397
4830
5263
5696
6129
6562
6995
7428
7861
8294
t th Observation
Actual (RAW) TIS
Actual MA(w=500) TIS
Approx. by the Regression Model Based on MA TIS
Approx. by the Regression Model based on its MA Scenario Average TIS
Approx. by the ANN Generated Regression Model

Appendix F

Additional definitions and descriptions of evaluative models

Queueing Network:

In general, queueing networks can be formed to study aggregate system behaviors of clustered interactive queues, often “a machine shop” consisting of several departments [Jackson 1957]. Each department is considered a multi-server or single-server queueing system (or a node within a queueing network) with an exponential service time distribution(s) and a single waiting line. Typically, each department is connected to other departments in a way in which finished jobs can be sent out either to designated department(s) based on the given set of routing probabilities or outside the shop. Similarly, new jobs can arrive either from outside the shop or from other department(s) within the shop according to the probability associated with the particular incoming route to the department. A simplified QN to illustrate possible paths for a part within a network is shown in Figure 43.

The total arrival rate to any given department can be calculated by summing its external (from outside the QN) and internal (from other departments within the QN) job arrival rates. If we let Γ_m be the total arrival rate of parts (customers) at Department m for $m = 1, 2, 3, \ldots, M$ (M = the total number of departments in the network), then the traffic equation for node m is given by

$$\Gamma_m = \lambda_m + \sum_k P_{km} \Gamma_k .$$

Where

λ_m : external arrival rate to Department m and

P_{km} : routing probability from Department k to Department m.

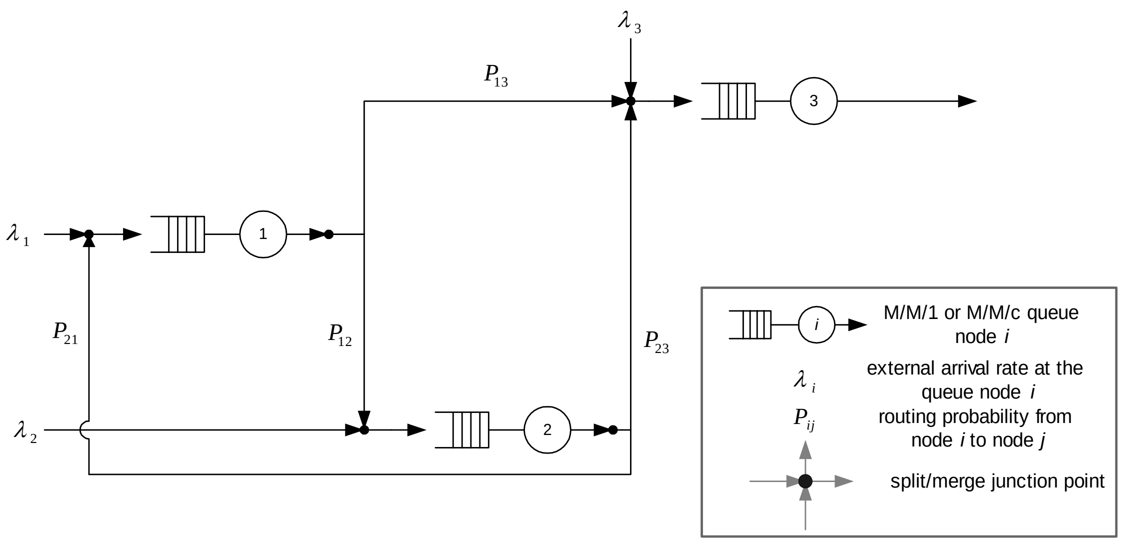


Figure 43. Open Queueing Network

The steady-state performance indices, such as mean waiting time in the queue and average number in the system, for each queue can be individually determined using the total arrival rate. The final product form probability distribution, called the equilibrium joint probability distribution, for the QN can be found as follows using steady-state probabilities of individual queues with a specific number of parts or pallets.

$$P(k_1, k_2, \ldots, k_M) = P_{k_1}{}^1 P_{k_2}{}^2 \cdots P_{k_M}{}^M$$

where

$$P_k{}^m = \begin{cases} P_0{}^m (\Gamma_m / \mu_m)^k / k!, & (k = 0,1,\cdots,n_m) \\ P_0{}^m (\Gamma_m / \mu_m)^k / n_m!(n_m)^{k-n_m} & (k = n_m, n_{m+1}, \cdots) \end{cases}$$

and

$P_k{}^m$: steady-state probability of having exactly k number of parts (or customers) at the queue node m.

The final steady state joint probability can be expressed as

$$\pi(k_0, k_1, ..., k_m) = \frac{1}{C(n)} \prod_{i=0}^{m} \rho_i^{k_i} \qquad k_i : \text{ number of parts (pallets) at } i \text{ th node}$$

where

$$\rho_i = \frac{\upsilon_i}{\mu_i}; \quad i = 0,1,...,m$$

m : total number of nodes

υ_i : average number of visits to i th node

μ_i : mean service rate at i th node

ρ_i : utilization of i th node

and the normalization constant $C(n)$ is given by

$$C(n) = \sum_{all\ n} \prod_{i=0}^{m} \rho_i^{k_i} \quad \text{where } n = \text{all the feasible states.}$$

Markov Chain:

Discrete time Markov chains (DTMCs): for a given discrete time stochastic process (DTSP) $\{X_n, n = 0,1,\ldots\}$, there exists a countable state space that can be expressed as $\{i_0, i_1, \ldots, i_{n-1}, i, j\}$ where X_n represents a possible state of a discrete system at discrete time n. If a stochastic process satisfies the following condition, often called the *Markov* Property:

for all $n \geq 0$ and all states $i_0, i_1, \ldots, i_{n-1}, i, j$,

$$P\{X_{n+1} = j / X_0 = i_0, X_1 = i_1, \ldots, X_{n-1} = i_{n-1}, X_n = i\} = P\{X_{n+1} = j / X_n = i\}$$

where n can be considered the present state and

$n+1$ can be considered the future state,

then it is called a discrete time Markov chain (DTMC).

Continuous time Markov chains (CTMCs): for a given continuous time stochastic process (CTSP), there exists a state space similar to those of DTSP, which can be expressed as $\{X(t), t \geq 0\}$ where $X(t)$ represents a possible state of a discrete system at continuous time $t \geq 0$. A stochastic process is then called a continuous time Markov chain (CTMC) if it satisfies the following condition, often called the *memoryless* property:

for all $s \geq 0, u \geq 0, t \geq 0$, and $i, j, x(u) \in S$,

$$P\{X(t+s) = j / X(s) = i, X(u) = x(u) \text{ for } 0 \leq u \leq s\} = P\{X(t+s) = j / X(s) = i\}.$$

If we let p_{ij} be the transition probability from state i to state j, the time reversibility of the CTMC can be expressed as $\pi_i q_{ij} = \pi_j q_{ji}$ where π_i is the stationary probability of state i, $q_{ij} = \dfrac{p_{ij}}{m_i}$ for all states i and j. Also note that m_i is the mean sojourn time of state i and so $(1/m_i)$ will be the rate at which the CTMC leaves state i.

The most important underlying theoretical grounds for queueing models are birth and death processes that are based on CTMCs. The state space for such CTMCs consists of a number of customers in the system and transitions between states are limited only to immediate neighboring states based on time independent arrival and service rates. According to Viswanadham and Narahari [1992], if a finite and irreducible birth and death process always satisfies the following two conditions,

$$(1)\ \sum_j \left(\lambda_j \frac{\lambda_0 \ldots \lambda_{j-1}}{\mu_1 \ldots \mu_j} \right)^{-1} = \infty \text{ and } \ (2)\ \sum_j \frac{\lambda_0 \ldots \lambda_{j-1}}{\mu_1 \ldots \mu_j} < \infty,$$

then it is positive recurrent. Hence a unique steady-state probability distribution is guaranteed. Therefore, we can confirm that queueing theory captures steady-state behaviors of CTMCs.

The bases for CTMC analysis are the Chapman-Kolmogorov equations and the Kolmogorov differential equations. If we let s and t be time parameters for all $s \geq 0$ and

$t \geq 0$, the stationary (homogeneous CTMC) transition probability from state i to state j in time $t+s$ can be written as

$$p_{ij}(t+s) = \sum_{k=0}^{\infty} p_{ik}(t)\, p_{kj}(s)\,,\;\; p(t+s) = p(t)\, p(s)\,;$$

$$p(0) = I\,,$$

which are called Chapman-Kolmogorov equations. The Kolmogorov differential equations consist of forward and backward equations. The Kolmogorov backward equations can be written as:

$$\frac{dH(t)}{dt} = QH(t);\;\; H(0) = I$$

where $H(t)$ is a transition probability matrix such that

$$H(t) = \lfloor p_{ij}(t) \rfloor\,,$$

Q is the rate or intensity matrix. The above equation can be rewritten in terms of individual elements of transition probability matrix $H(t)$ as:

$$\frac{dp_{ij}(t)}{dt} = q_{ii}\, p_{ij}(t) + \sum_{k \neq i} q_{ik}\, p_{kj}(t)$$

where the transition probability from state i to state j in time t can be expressed as

$$p_{ij}(t) = P\{X(t) = j \,|\, X(0) = i\}\,.$$

The Kolmogorov forward equations can be given as:

$$\frac{dH(t)}{dt} = H(t)Q;\;\; H(0) = I\,.$$

Similarly these equations can be written in terms of individual elements of $H(t)$ as:

$$\frac{dp_{ij}(t)}{dt} = q_{jj}\, p_{ij}(t) + \sum_{k \neq j} q_{kj}\, p_{ik}(t)\,.$$

Solving either the Kolmogorov backward or forward differential equations, first order linear differential equations with constant coefficients, provides a closed form solution

$$H(t) = \exp(Qt)$$

or

$$\prod(t) = \prod(0)\exp(Qt)$$

where

$$\prod(t) = \left[p_0(t) \quad p_1(t) \quad p_2(t) \quad \cdots \quad p_N(t)\right]$$

$$p_j(t) = P\{X(t) = j\}$$

to approximate individual transition probabilities or the state probabilities as a function of time [Viswanadham and Narahari 1992].

Unbiased Estimators of the Sample Mean:

An unbiased estimator of the sample mean θ over a simulation time interval $\left[0, T_E\right]$:

If we let $\hat{\theta}_r$ be a sample mean for each replication r

where $\hat{\theta}_r = \dfrac{1}{n_r}\sum_{i=1}^{n_r} Y_{ri}$, $r = 1, \ldots, R$,

R : the total number of simulation run ,

n_r : the sample size per each replication r , then R sample means $\hat{\theta}_1, \ldots, \hat{\theta}_R$ become statistically independent and identically distributed and an unbiased estimators of the sample mean θ over a simulation time interval $[0, T_E]$ such that

$\theta = E\left(\frac{1}{n}\sum_{i=1}^{n} Y_i\right)$ where

terminating simulation results in observations $Y_i = Y_1, \ldots, Y_n$.

Petri Nets:

A pictorial example of a Petri net is shown in Figure 44. The net in Figure 44 consists of five places (circles), four transitions (horizontal bars), one token (black dot) and ten directed arcs (arrows) connecting places and transitions. In this net, p_1 is an input place of transition t_1. A black dot inside p_1 indicates that the precondition p_1 is satisfied at present state. Places p_2 and p_3 are output places of transition t_1. At the same time place p_2 is also an input place of transition t_2 and place p_3 is also an input place of transition t_3. In a similar manner, all places in this net are input places as well as output places to their corresponding transitions that are directly connected by either incoming or outgoing arcs. Later, for the modeling convenience, the connecting rule between a place and a transition has been extended to permit a place to use more than one arc directed from it or toward it so that it can contribute or receive more than one token from the firing of a transition. These types of PTNs are often called generalized Petri nets (GPNs). To incorporate the priority rule among enabled transitions, inhibitor arcs are introduced [Peterson 1977].

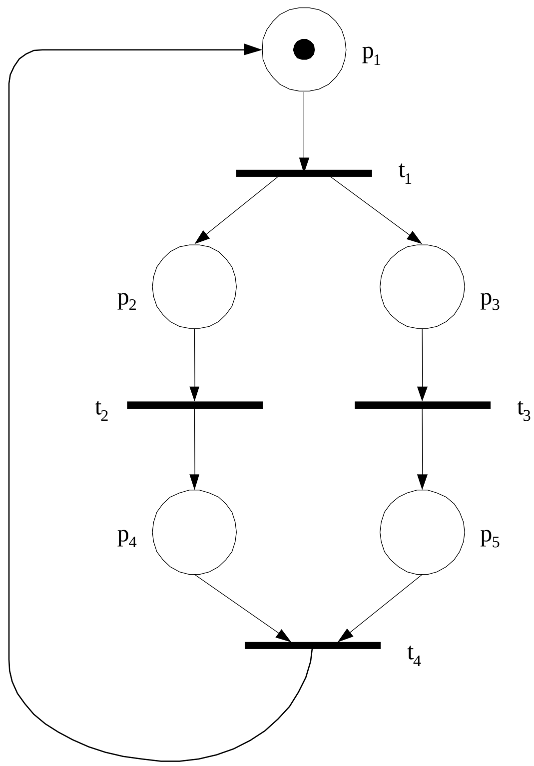


Figure 44. Example of graphical representation of a Petri net [Zurawski and Zhou 1994].

Formal definitions in classical Petri nets are given as follows [Zurawski and Zhou 1994]:

Definition: If we let **N** be a set of nonnegative integers, a Petri net is a five-tuple (P, T, I, O, M_0) where

1. $P = \{p_1, p_2, p_3, \ldots, p_m\}$ is a finite set of places,

2. $T = \{t_1, t_2, t_3, \ldots, t_n\}$ is a finite set of transitions,

   $P \bigcup T \neq \phi$, and $P \bigcap T = \phi$,

3. $I : (P \times T) \rightarrow$ **N** is an *input function* that defines directed arcs from places to transitions,

4. $O : (P \times T) \rightarrow$ **N** is an *output function* that defines directed arcs from transitions to places, and

5. $M_0 : P \rightarrow$ **N** is the initial marking.

A unique distribution of tokens among places or on a given place can be expressed as a marking M. The initial marking, M_0, denotes the initial placement of tokens upon all places at time 0.

Enabling Rule: A transition t_j is said to be enabled in a marking M if each input place p_i of t_j contains at least the number of tokens equal to the weight (multiplicity factor permitting k arcs to exist between a place and a transition) of the directed arc connecting p_i to t_j, which can be symbolically expressed as

$M(p_i) \geq I(p_i, t_j) \;\; \forall p_i \in IP(t_j)$ where

$IP(t_j) = \{p_i \in P : \;\; I(p_i, t_j) \neq 0\}$ ($IP(t_j)$ is the set of input places of t_j).

Firing Rule: A firing of an enabled transition t_j in a marking M removes the number of tokens equal to the weight of the directed arc connecting p_i to t_j from each input place p_i. At the same time, a firing deposits in each output place p_i the number of tokens equal to the weight of the directed are connecting t_j to p_i, which implies that a new marking M' has been reached. This can be symbolically represented as

$$M'(p_i) = M(p_i) + O(p_i, t_j) - I(p_i, t_j) \quad \forall p_i \in P \text{ where}$$

$$M(p_i) = \begin{cases} 1 \text{ if the number of tokens in } p_i = \sum I(p_i, t_j) \text{ for } \forall t_j \in T_1 \\ 0 \text{ if the number of tokens in } p_i \neq \sum I(p_i, t_j) \text{ for } \forall t_j \in T_1 \end{cases}.$$

and $T_1 \subset T$ such that $T_1 = \{t_j \mid \text{for every } t_j \in T_1, I(p_i, t_j) \neq 0\}$.

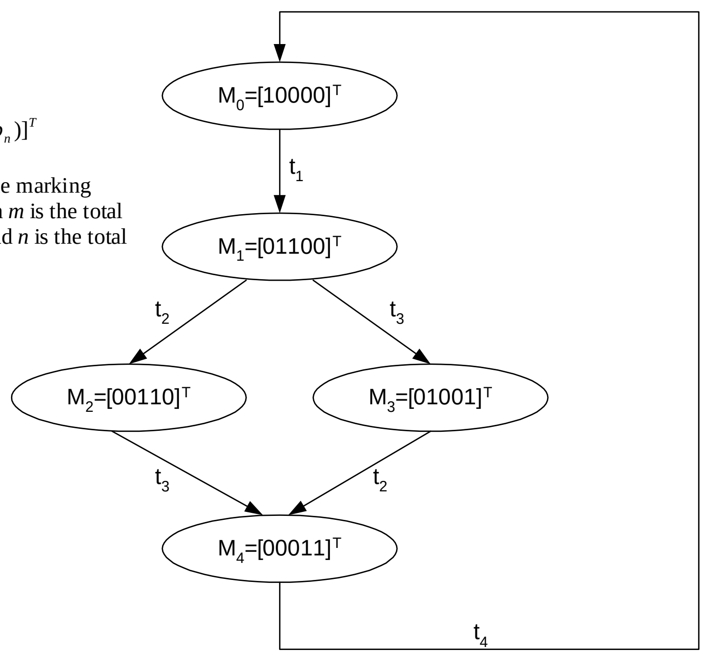
If the above expression is true, then we can say that a new marking M' is reachable from the present marking M and write $M \xrightarrow{t_j} M'$.

The transitive closure of the reachability relation, which comprises all markings reachable from the initial marking M_0 by firing one or more transitions, is called the reachability set of a Petri net within initial marking M_0. This can be expressed as $R(M_0)$. An example of a reachability set for a given Petri net with initial marking M_0 is illustrated in Figure 45.

A PTN is said to be pure or self-loop free if no place is an output place and an input place for the same transition. A pure net can be completely defined by its incidence matrix. An incident matrix is defined by an $n \times m$ matrix, $\mathbf{C}$, whose ij th element, c_{ij} is equal to 0 if no arc exists between place p_i and transition t_j; is equal to $-k$ if an input arc with multiplicity factor k exists between place p_i and transition t_j; is equal to $+k$ if an output arc with multiplicity factor k exists between place p_i and transition t_j. For example, an appropriate (5×4) incident matrix, $\mathbf{C}$, for the PTN from Figure 44 can be given by

$$C = \begin{array}{c} \begin{array}{cccc} t_1 & t_2 & t_3 & t_4 \end{array} \\ \begin{bmatrix} -\mathbf{1} & \mathbf{0} & \mathbf{0} & \mathbf{1} \\ \mathbf{1} & -\mathbf{1} & \mathbf{0} & \mathbf{0} \\ \mathbf{1} & \mathbf{0} & -\mathbf{1} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} & \mathbf{0} & -\mathbf{1} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} & -\mathbf{1} \end{bmatrix} \end{array} \begin{array}{c} \\ p_1 \\ p_2 \\ p_3 \\ p_4 \\ p_5 \end{array}$$

Through this given incident matrix we can verify the net given in Figure 44 to be pure.



$M_i = [M(p_1), M(p_2), \ldots, M(p_n)]^T$

where *i* is the number of unique marking takes on value 0, 1,…, *m* when *m* is the total number of unique markings and *n* is the total number of places.

e.g.) $M_0 = [10000]^T$

Figure 45. Reachability tree of the model in Figure 44

A place in a marked Petri net is said to be k bounded if and only if there exists a positive integer k such that the place never simultaneously contains more than k tokens throughout all markings contained in the nets reachability set. If $k = 1$ for a single place, that particular place can be said to be safe but if it is true for all the places then the PTN itself is said to be safe. Boundedness refers to a finite requirement of resources and infers absence of overflows in buffers. Boundedness also implies a finite reachability set. This is an important requirement for conducting performance analysis using PN models.

Place Invariants of a Petri Net:

Finding a valid incident matrix is an essential part of P-invariant analysis that is helpful for establishing net properties, such as boundness, liveness, and conservativeness. Place invariants, often called P-Invariants, can be defined as follows:

Definition : If we let G be a pure Petri net, $\mathbf{C}$ the incident matrix of G and n the number of places, a $(1 \times n)$ row-vector $\mathbf{x}$ is said to be a place invariant (P-invariant) of G if and only if $\mathbf{x} \cdot \mathbf{C} = \phi$ where $\phi = \text{zero row-vector}$.

If $\mathbf{x}$ is a P-invariant for all reachable markings with the weights given by the place invariant, the weighted sum of tokens within the places is a constant such that

$$\sum_{i=1}^{n} x_i M(p_i) = k$$

where k is a constant, $\mathbf{x} = [x_1, x_2, \ldots x_n]$, and $n =$ the total number of places in Petri net G.

Conservativeness of a Petri Net:

A conservative PTN means that the number of tokens in the net is conserved. This implies that each transition in a conservative net is conservative so that the number of inputs of each enabled transition is equal to the number of outputs of that transition. To prove a Petri net $G \equiv (P, T, I, O)$ to be conservative, finding a P-invariant all of whose entries are equal to unity can be used such that

$$\sum_{j=1}^{n} M(p_j) = k \text{ for all } M \in R[M_0]$$

where $k =$ constant. Also finding P-invariants can be useful to verify if a given Petri net $G \equiv (P, T, I, O)$ is bounded. If there exists a place invariant $\mathbf{x}$ where all of its n entries are strictly positive then Petri net G can be said to be bounded.

Liveness of a Petri Net:

A formal definition for liveness of a Petri net as well as its transitions can be given as follows [Viswanadham and Narahari 1992]:

Definition: A transition t_j of a marked Petri net is said to be live under a marking M_0 if, for all markings $M \in R[M_0]$, there exists a sequence of transition firings which results in a marking that enables t_j. A Petri net is said to be live if all its transactions are live.

If a Petri net is live, it indicates that the entire net is free of deadlock. On the contrary, if there is at least one transition that is not live, it implies that there might be a chance for a possible deadlock for the system going through a corresponding sequence of transition firings.

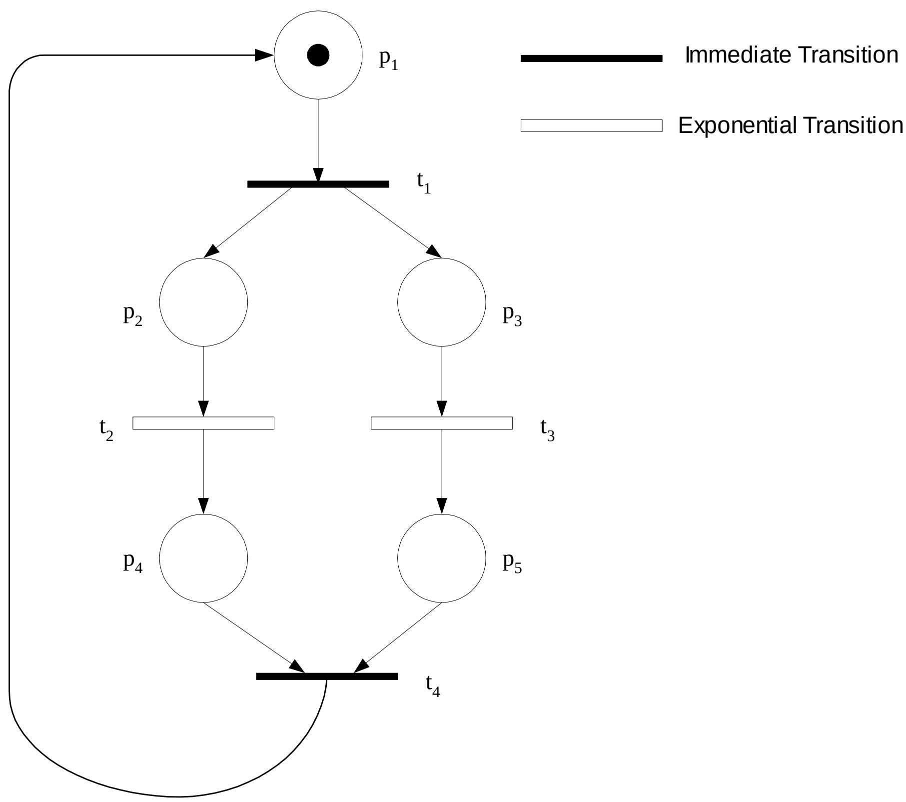


Figure 46. GSPN model of Figure 44 with given exponential and immediate transition times

Figure 47 shows an equivalent CTMC model for the GSPN model given in Figure 46 which has an identical PN model to that of Figure 44 with the addition of arbitrary exponentially distributed time delays.

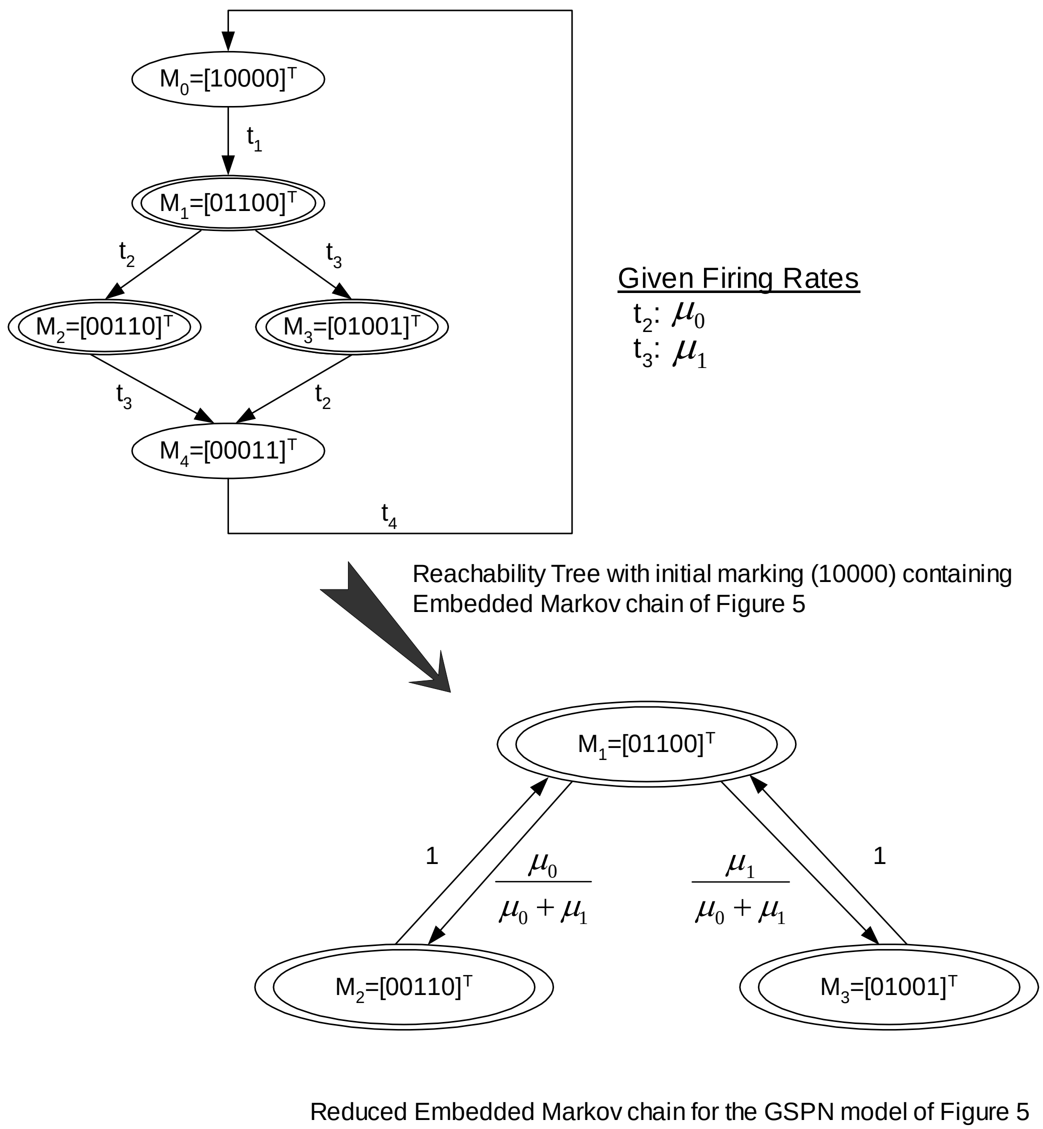


Figure 47. Finding an equivalent CTMC for GSPN model given in Figure 46

Stochastic Petri Net:

According to Viswanadham [1992], the formal definition of SPN can be given as follows:

Definition: An SPN is a sex-tuple (P, T, I, O, M_0, F) in which (P, T, I, O, M_0) is a Petri net and F is a function with domain $(R[M_0] \times T)$, which associates with each transition in each reachable marking, a random variable. The function F is the firing function and the random variable $F(M,t)$ for $M \in R[M_0]$ and $t \in T$ is the firing time of transition t in the marking M. Hence the firing time of a transition in an SPN is in general marking dependent. In an SPN, when t is enabled in M, the tokens remain in the input places of t, $IP(t)$, during the time of $F(M,t)$. At the end of the time $F(M,t)$, tokens are removed from the input places of t, $IP(t)$ and deposited in the output places of t, $OP(t)$.

Colored Petri Net:

The formal definition of CPNs can be given as follows:

Definition: if we let $\mathbf{N}$ and $\mathbf{Z}$ be nonempty sets and $C(p)$ and $C(t)$ be the sets of colors attached to p and t respectively, A colored Petri net is a 5-tuple

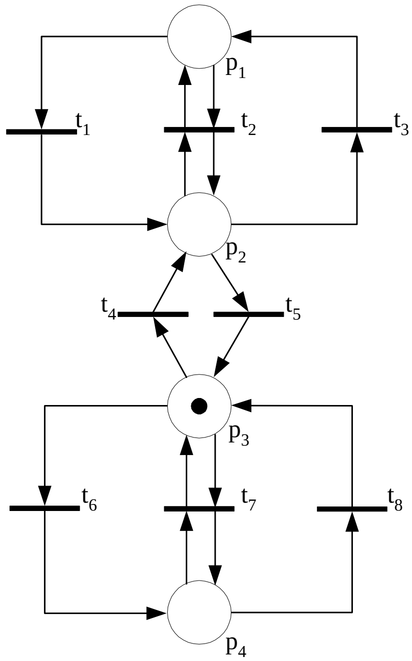
$\text{CPN} = (P, T, C, W, m_0)$, where

1. $P = \{p_1, p_2, p_3, \ldots, p_m\}$ is a finite set of places,
2. $T = \{t_1, t_2, t_3, \ldots, t_n\}$ is a finite set of transitions,
3. $P \cap T = \phi$, $P \cup T \neq \phi$,
4. C is the *color-function* defined from $P \cup T$ into nonempty sets,
5. W is the *incident-function* defined on $P \times T$ such that $W(p,t) \in$

   $[C(t) \rightarrow [C(p) \rightarrow \mathbf{Z}]_f\,]$ for all $(p,t) \in P \times T$,
6. m_0, the *initial marking*, is a function defined on P, such that

   $m(p) \in [C(p) \rightarrow \mathbf{N}]_f$ for all $p \in P$.

The definitions of liveness, boundness, P-invariants and other properties in CPNs are similar to that in PTNs. However, invariant computation is somewhat complicated since the elements of the incident matrix are functions rather than integers. The clear advantage of using CPN over PTN is its compactness of the model as we can see from a comparative pictorial, Figure 48.



An ordinary PN model of the FCFS Queueing Discipline with two job classes

For a given ordinary PN

<u>Places</u> : $\mathbf{P_1}$: buffer places free for a type 1 job
$\mathbf{P_2}$: buffer places full by a type 1 job
$\mathbf{P_3}$: buffer places free for a type 2 job
$\mathbf{P_4}$: buffer places free by a type 2 job

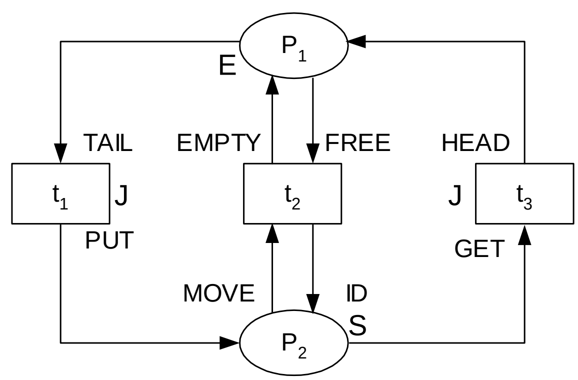
<u>Transitions</u> : $\mathbf{t_1}$: add a type 1 job to the buffer
$\mathbf{t_2}$: move a type 1 job one place ahead in the queue and free the place which was occupied by it
$\mathbf{t_3}$: remove a type 1 job from the buffer
$\mathbf{t_4}$: Enter a type 1 job as a next job
$\mathbf{t_5}$: Enter a type 2 job as a next job
$\mathbf{t_6}$: add a type 2 job to the buffer
$\mathbf{t_7}$: move a type 2 job one place ahead in the queue and free the place which was occupied by it
$\mathbf{t_8}$: remove a type 2 job from the buffer

The Given CPN Model

<u>Places:</u> $\mathbf{P_1}$: buffer places free; $\mathbf{P_2}$: buffer places full;
<u>Transitions:</u> $\mathbf{t_1}$: add a job to the buffer; $\mathbf{t_2}$: move a job one place ahead in the queue and free the place which was occupied by it; $\mathbf{t_3}$: remove a job from the buffer
<u>Color sets</u>: **E** : $\{e_k \mid k=1,2,..., n\}$; a token of color e_k indicates that the kth place in the buffer is empty
J : $\{j_i \mid i=1, 2, ..., p\}$; a set of job classes
Q : $\{<j_i, e_k> \mid i=1, 2, ..., p; k=2, ..., n\}$; a token of color $<j_i, e_k>$ represents a situation in which a job belonging to class j_i is occupying the kth place in the buffer
S : Q U $\{<j_i, e_k> \mid i= 1, 2, ..., p\}$; similar to the set Q; in addition to the elements of the set Q, the set S also contains the details of the job occupying the first place in the buffer

Color Functions :

$HEAD(j_i)=e_1$; $TAIL(j_i)=e_n$;
$PUT(j_i)=<j_i, e_n>$; $GET(j_i)=<j_i, e_1>$;
$ID(<j_i, e_k>)=k$; $FREE(<j_i, e_k>)=e_k$;
$EMPTY(<j_i, e_k>)=e_{k-1}$; $MOVE(<j_i, e_k>)=<j_i, e_{k-1}>$



Equivalent CPN model of the FCFS queueing Discipline within multiple Job classes [Kamath and Viswanadham, 1986]

Figure 48. A conversion from an ordinary PN of the FCFS queueing discipline with two job classes to an equivalent CPN

VITA

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