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MODELING AND MEASURING RESILIENCE: APPLICATIONS IN SUPPLIER SELECTION AND CRITICAL INFRASTRUCTURE

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SCHOOL OF INDUSTRIAL AND SYSTEMS ENGINEERING

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Dedicated to my adorable parents and lovely wife

You are truly an inspiration to my life I know I did never be where

I am today without your constant love, support and unending faith in me

Thank you for holding my hands and making my path easy from hurdle during my research

I feel myself lucky that I have adorable parents and Lovely wife

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ABSTRACT

Nowadays, infrastructure systems such as transportation, telecommunications, water supply, and electrical grids, are considerably facing the exposure of disruptive events such as natural disasters, manmade accidents, malevolent attacks, and common failures due to their size, complexity, and interconnectedness nature. For example fragile design of supply chain infrastructure might collapses because the consequences of a failure can propagate easily through the layers of supply chains, especially for large interconnected networks. Previously, owners and operators of infrastructure systems focused to design cost-efficient, competitive and sustainable ones; however the need for design of resilient infrastructure systems is inevitable.

Infrastructure systems must be designed in such a way so that they are resistant enough to withstand and recover quickly from disruptions. The consequences of disruptive events on infrastructures ranging from energy systems (e.g., electrical power network, natural gas pipeline) to transportation systems (e.g., food supply chain, public transportation) cannot only impacted on individuals, but also on communities, governments and economics.

The goal of this dissertation is to (i) identify the resilience capacities of infrastructure systems; in particular inland waterway ports, and supply chain systems, (ii) quantify and analyze the resilience value of critical infrastructure systems (CIs), (iii) improve the resilience of CIs by simulating different disruptive scenarios, and (iv) recommend managerial implications to help owners and operators of CIs for timely response, preparedness, and quick recovery against disruptive events.

This research first identifies the resilience capacity of CIs, in particular, inland waterway, supply chain and electrical power plant. The resilience capacity of CIs is modeled in terms of their absorptive capacity, adaptive capacity and restorative capacity. A new resilience metric is developed to quantify the resilience of CIs. The metric captures the causal relationship among the characteristics of CIs and characteristics of disruptive events including intensity and detection of disruption likelihood of disruptive events. The proposed resilience metric is generic, meaning that can be applied across variety of CIs. The proposed metric measures the system resilience as the sum of degree of achieving successful mitigation and contingency strategies. The resilience metric accounts for subjectivity aspect of disruptive events (e.g., late disruption detection, very intense disruption, etc.). Additionally, the proposed resilience metric is capable of modeling multiple disruptive events occurring simultaneously.

This research study further explores how to model the resilience of CIs using graphical probabilistic approach, known as Bayesian Networks (BN). BN model is developed to not only quantify the resilience of CIs but also to predict the behavior of CIs against different disruptive scenarios using special case of inference analysis called forward propagation analysis (FPA), and improvement scenarios on resilience of CIs are examined through backward propagation analysis (BPA), a unique features of BN that cannot be implemented by any other methods such as classical regression analysis, optimization, etc.

Of interest in this work are inland waterway ports, suppliers and electrical power plant. Examples of CIs are inland waterway ports, which are critical elements of global supply chain as well as civil infrastructure. They facilitate a cost-effective flow of roughly $150 billion worth of freights annually across different industries and locations. Stoppage of inland waterway ports can poses huge disruption costs to the nation's economic. Hence, a series of questions arise in the context of resilience of inland waterway ports.

How the resilience of inland waterway ports can be modeled and quantified? How to simulate impact of potential disruptive events on the resilience of inland waterway ports? What are the factors contributing to the resilience capacity of inland waterway ports? How the resilience of inland waterway can be improved?

CHAPTER

1

INTRODUCTION

Critical infrastructures (CIs), such as energy, supply chain, manufacturing, communication, public transportation provide necessary commodities and services and have been described as the “backbone of a nation’s economy, security, and health” (U.S. Department of Homeland Security 2014). Any type of permanent or temporary disruption can leads to significant impact and consequences on society, individuals, governments, economics. Hence, protecting CIs is a vital component of national security activities in countries across the globe (Vugrin et al. 2014).

Historically, the owners and operators of CIs attempt to prevent and minimize the occurrence of disruptive events by reinforcing their infrastructures through physical protection activities. However, over the past decade, the owners and operators of CIs realized that prevention of all threats, especially innovative ones such as terrorist attacks, ecological disasters are impossible. Hence, recently more attention is given to the quick responding and recovery to the disruptive events such as hurricane, tornado, malevolent attacks, etc. Consequently, the importance of design for resilience infrastructures is emerged.

An important challenge in the context of resilience modeling is that the existing metrics for measuring the resilience of CIs are not generic, in the sense that it can be only used for a specific system. For example, resilience metrics that have been developed to measure the resiliency of transportation systems cannot be easily used to quantify the resilience of an inland waterway port. In addition to this, many of existing resilience metrics are deterministic while resilience is a concept with stochastic nature due to the random and unpredicted nature of disruptive events. Moreover, in reality, the severity of some of the disruptive events such as storm, fire or manmade attacks cannot be easily measured but instead can be expressed and analyzed using linguistic variables (e.g., huge storm). One of the aims in this dissertation is to propose a new resilience metric that has the following features:

1. Accounting for uncertainty associated with the likelihood and severity of disruptive events.
2. Usability across different infrastructure systems including power grids, inland waterway port, manufacturing systems, among others.
3. Utilizing linguistic variables to express subjectivity aspect of disruption characteristics.
4. Integrating historical data with expert knowledge to estimate disruption characteristics.

This dissertation also aims to quantify, analyze and improve the resilience of CIs through a graphical probabilistic method, known as Bayesian network (BN). BNs can be used to describe the casual relationship among the characteristics of system. For example, the causal relationship between the likelihood of a disruptive event (cause) can be captured and modeled. BNs are powerful technology for handling risk assessment, decision making under uncertainty. BNs are capable of handling both types of qualitative and quantitative variables. Hence, this dissertation seeks to present mainstream penetration of BN tools in the context of resilience modeling. The rest of this dissertation is organized as follows:

Chapter 2 reviews definitions and measures of system resilience. A Classification review of resilience metrics is presented in Chapter 2. A BN model is developed in Chapter 3 to model the resilience of inland waterway port as critical element of critical infrastructure. The developed BN model describes how the resilience of inland waterway can be measured through its absorptive capacity, adaptive capacity and restorative capacity. Different disruption scenarios have been implemented to simulate the impacts of disruptions on the resilience of inland waterway port using forward propagation analysis (FPA). Sensitivity analysis has been also performed to determine the importance of factors contributing to the resilience of inland waterway port. Chapter 4 presents a novel BN model for resilience-based supplier selection. The factors related to the resilience of supplier selection problem are first identified, and then a BN is developed to select the best supplier in terms of resilience, green and primary criteria. Chapter 5 proposes a mixed integer programming model based on the concept of resilience capacity of suppliers. Resilience capacity of supplier is further decomposed to the absorptive capacity and adaptive capacity.

CHAPTER

2

A REVIEW OF QUANTIFICATION APPROACHES FOR MEASURING SYSTEM RESILIENCE[†]

ABSTRACT

Modeling and evaluating the resilience of systems, potentially complex and large-scale in nature, has recently raised significant interest among both practitioners and researchers. This recent interest has resulted in several definitions of the concept of resilience and several approaches to measuring this concept, across several application domains. As such, this paper presents a comprehensive review of research articles related to modeling and quantifying of resilience in various disciplines. To the best of our knowledge, this is the first comprehensive review that addresses quantitative research related to the subject of resilience. We classify the literature of resilience into three categories: qualitative, quantitative, and solution based approaches based on the resilience measurement concept. The review is highlighted by three factors: extensive coverage of the literature, exploration of current gaps and challenges, and recommendation of directions for future research.

[†] This chapter has been published at the journal of Reliability Engineering and System Safety. A review of definitions and measures of system resilience. *Reliability Engineering & System Safety* 2016, 145: 47-61.

Keywords: Resilience, Engineering systems

2.1 Introduction

Historically, the primary questions asked during a risk assessment study are: (i) what can go wrong?, (ii) what is the likelihood of such a disruptive scenario?, and (iii) what are the consequences of such a scenario? (Kaplan 1981). Risk management strategies have traditionally focused on reducing the likelihood of disruptive events and reducing the potential consequences of the event, as well as some synthesis of both. As such, risk management strategies often emphasized mitigation options in the form of prevention and protection: designing systems to avoid or absorb undesired events from occurring. The main objective of protection strategy is to detect the adversary early and defer the adversary long enough for an appropriate respond. While a protection strategy is critical to prevent undesired events or consequences, however recent events suggested that not all undesired events can be prevent. Hurricane Sandy, which devastated NY/NJ in 2012, is among the more recent examples of a disruptive event that adversely impacted multiple networked systems (e.g., months after the storm, power had not been restored to all communities in the NY/NJ area (Manual 2013), one million cubic yards of debris impeded transportation networks (Lipton 2013). Plenty of other disruptions have highlighted the resilience, or lack thereof, of networked systems: the August 2003 US blackout that caused transportation and economic network disruptions (Minkel 2008), Hurricane Isabel devastated the transportation system of the Hampton Roads, VA, region in 2003 and overwhelmed emergency response (Smith and Graffeo 2005), the 2011 9.0 magnitude earthquake and tsunami that struck Japan, causing over 15,000 confirmed deaths and disrupting global supply chain networks (MacKenzie et al. 2012).

It is because of these recent large-scale events that the Department of Homeland Security, among others, has placed emphasis on resilience through preparedness, response, and recovery (Department of Homeland Security 2013, Department of Homeland Security 2014).

The term *resilience* has increasingly been seen in the research literature (Park et al. 2013) and popular science literature (Zoli and Healy 2013) due to its role in reducing the risks associated with the inevitable disruption of systems. This paper presents a comprehensive review of resilience in various disciplines, published in 2000 to 2014. In this paper, we primarily focus on the quantitative perspective of modeling resilience, distinguishing our work from existing excellent review papers (Bhamra and Burnard 2011). Several definitions of resilience have been offered. Many are similar, though many overlap with a number of already existing concepts such as *robustness*, *fault-tolerance, flexibility*, *survivability*, and *agility*, among others.

The concept of resilience is a multidisciplinary notion that has been considered in different context and domains of applications, including psychology, ecology, enterprises and business among others. Variety of definitions for the notion of resilience has been proposed by many researchers and organizations. We identify four domains of resilience: engineering, organizational, social, and economic. Note that this classification may vary depending on researcher’s perspective. We provide a variety of definitions of resilience according to four aforementioned groups.

2.1.1 Engineering domain

The concept of resilience in engineering domain is relatively new in compared to non-engineering domains. Engineering domain includes technical systems designed by engineers that interact with computer systems, and humans such as power gird electrical systems. Hollnagel and Prologue (Hollnagel and Prologue 2010) pointed out that for resilience engineering, understanding of the normal functioning of a technical system is important as well as understanding how it fails. Dinh et al. (Dinh et al. 2012) identified six factors that enhance the resilience engineering of industrial processes, including minimization of failure, limitation of effects, administrative controls/procedures, flexibility, controllability, and early detection.

2.1.2 Organizational domain

In organizational science, resilience of an organization is defined by Sheffi (2005) as inherent ability to keep or recover a steady state, thereby allowing it to continue normal operations after a disruptive event or in presence of continuous stress. Vogus and Sutcliffe (2007) defined organizational resilience as "the ability of an organization to absorb strain and improve functioning despite the presence of adversity". Sheffi (2006) defined the resilience for companies as "the company's ability to, and speed at which they can, return to their normal performance level (e.g., inventory, capacity, service rate) following by disruptive event". McDonald (2010) defined resilience in the context of organizations as "the properties of being able to adapt to the requirements of the environment and being able to manage the environments variability". Patterson et al. (2007) highlighted that collaborative cross-checking can greatly enhance the resilience of organizations. Collaborative cross-checking is an enhanced resilience strategy in which at least two groups or individuals with different viewpoints investigate the others' activations to evaluate accuracy or validity. By implementing collaborative cross-checking, erroneous actions can be detected quickly enough to mitigate adverse consequences.

2.1.3 Economic domain

The concept of resilience in the domain of economic has received a fair share of consideration by researchers. Rose and Liao (2005) described economic resilience as the “inherent ability and adaptive response that enables firms and regions to avoid maximum potential losses”. Static economic resilience is referred by Rose (2007) as the capability of an entity or system to continue its functionality like producing when faces with a sever shock, while dynamic economic is defined by the same author as the speed at which a system recovers from a sever shock to achieve a steady state. A more specific definition of economic resilience is presented by Martin (2012) as “the capacity to reconfigure, that is adapt, its structure (firms, industries, technologies, institutions) so as to maintain an acceptable growth path in output, employment and wealth over time”.

Infrastructure systems such as water distribution systems, nuclear plants, transportation systems, water dams among others can be considered as subdomain of engineering domain, because these systems are founded based on engineering knowledge, and their restoration need technical efforts. Infrastructures are also considered as subdomain of social domain in which the lack of its resiliency can lead to negative impacts on society and the life of humans. Ouyang and Wang (2015) assessed the resilience of interdependent infrastructure systems. Their research focused on modeling and resilience analysis of interdependent power and gas system in Houston, Texas, USA when multiple hazards are taken into account. Their major finding of their research is that the interdependent restoration strategy and the power first and gas second restoration strategy generate the largest resilience value for the power system. The unique aspect of their research is that interdependency between two infrastructure systems are modeled and analyzed for a real case study.

Some more general definitions of resilience are also presented by researchers and organizations. For example, Allenby and Fink (2000) defined resilience as the "capability of system to maintain its function and structure against internal and external changes and downgrade the performance of system when it must." Pregenzer (2011) defined resilience as the "measure of a system's ability to absorb continuous and unpredictable change and still maintain its vital functions." Haimes (2009) defined the resilience as the "ability of system to withstand a major disruption within acceptable degradation parameters and to recover with a suitable time and reasonable costs and risks." Disaster resilience is characterized by Infrastructure Security Partnership (2006) as the capability to prevent or protect against significant multi-hazard threats and incidents, including terrorist attacks, and to recover and reconstitute critical services with minimum devastation to public safety and health. Vugrin et al. (2010) defined system resilience as: "Given the occurrence of a particular disruptive event (or set of events), the resilience of a system to that event (or events) is that system's ability to reduce efficiently both the magnitude and duration of deviation from targeted system performance levels." Two elements of this definition are noted: system impact, the negative impact that a disruption imposes to a system and measured by the difference between targeted and disrupted performance level of system, and total recovery efforts, the amount of resources expended to recover the disrupted system.

2.1.4 Social domain

The social domain looks at the resilience capacities of individuals, groups, community, environment and country. Community and Regional Resilience Institute (2009) defined the resilience as the capability to predict risk, restrict adverse consequences, and return rapidly through survival, adaptability, and growth in the face of turbulent changes. Keck and Sakdapolrak (2013) defined social resilience as comprised of three dimensions: coping capacities, adaptive capacities, and transformative capacities.

2.1.5 Analysis of resilience definition

The review of resilience definitions indicates that there is no unique insight about how to define the resilience, however several similarities can be observed across these resilience definitions. The main highlights of resilience definitions reviewed above are summarized as follows:

- Some of reviewed definitions does not specify mechanisms to achieve resilience; however many of them focus on the capability of system to “absorb”, “adapt” from disruptive events and recovery is considered as the critical part of resilience.
- For engineered systems such as nuclear and power plant systems, reliability is extremely important feature. The definition of resilience in engineering systems is established based on the reliability of system.
- Some definitions, such as Sheffi (2005) and ASME (2009) emphasize that returning to steady state performance level is needed for resilience, while other definitions do not impose the entity (e.g., infrastructure, enterprise, community, etc) return to pre-disaster state.

- Definition represented by Haimes (2009) highlights that resiliency must be achieved by less cost, energy, time and labor efforts. This definition points out the two main features of recovery: recovery time and speed of recovery. As a result, recovery activities with shorter time and high speed are more desirable.
- Some definitions such as Allenby and Fink (2000), and Pregenzer (2011) defined resilience in terms of preparedness (pre-disaster) activities, while the role of recovery (post-disaster) activities are discarded. Definitions presented by organizations such as National Infrastructure Advisory Council (NIAC), 2009 emphasized on the role of both preparedness and recovery activities to achieve resilience.

2.2 Literature Review Methodology

In this section, we discuss framework we used to identify resilience-related literature. We also report, to the extent that we can, the distribution of literature by domains, years of publication, and journals.

To present a breadth coverage of literature review of resilience study, we developed a framework of five steps: (i) online database searching and information clustering, (ii) citation and sample refinement, (iii) abstract review refinement, (iv) full-text review refinement, and (v) final sort. The Web of Science database, one of the most comprehensive multidisciplinary content search platforms for academic researchers (Web of Science), was searched to identify the papers.

Using keywords to conduct the search, we selected those papers only relevant to modeling and measuring resilience in engineering fields, including engineering design, supply chain, infrastructure systems, and physical networks, and non-engineering fields, including enterprises/organizations, social networks, and economics. Journal papers were filtered with such keywords as *resilience modeling*, *resilience quantification*, *resilience metrics*, *design resilience*, *disaster resilience*, and *engineering resilience*. This approach was applied to the papers published from 2000 to 2014, though we focus primarily on recent papers.

2.2.1 Distribution by Domain

CiteSpace (Chen 2006), a well-known visualization tool, was used to visualize and analyze trends in the resilience literature. As shown in Figure 2.1, the application of resilience in each discipline is represented by a cluster. The largest cluster is dedicated to the *Psychology* domain, followed by the *Environmental, Social, & Ecology* domain. The size of cluster of a discipline is relates to the number of papers published in that discipline. Meanwhile, a lesser proportion of resilience-related research exists in the engineering domain, suggesting that greater strides in defining and quantifying resilience have historically been made in non-engineering contexts. As such, opportunities exist in impacting resilience in the engineering domain (e.g., engineering design).

2.2.2 Distribution by Journal

A decent number of different journals from different disciplines related to resilience quantification approaches were included in this literature review. Table 2.1 lists the first fourteen journals that contributed more than one article. Among these, *Reliability Engineering & Systems Safety* is the most significant source of articles related to the resilience research, with *Risk Analysis*, *International Journal of Production Research*, and *Procedia Computer Science* following. The application of resilience in organizations, enterprises, business management, and logistics engineering are mostly published in *International Journal of Production Research*. Mathematical modeling based resilience work is mostly published in *Computers & Operations Research*, *Transportation Research-Part B*, and *Transportation Research-Part E*.

2.2.3 Distribution by Year of Publication

The distribution of resilience-related archival journal articles by year from 2000 to April 2015 is represented in Figure 2.2, using Web of Science (WoS). The recent government and policy emphasis on resilience is also seen in academic research, according to the increasing appearance of resilience-related research.

2.3 Resilience Assessment Methodologies

In general, the resilience evaluation procedure can be separated into two major categories: qualitative and quantitative. Qualitative category includes methods that tend to assess the resilience of system qualitatively. The qualitative category itself divides into two sub-categories: conceptual framework, and semi-qualitative. The quantitative methods including two sub-categories of generic resilience metrics and structural-based modeling aim to measure the resilience value of system qualitatively. The classification scheme of resilience assessment approaches is visually represented in Figure 2.3. Note that the focus of this paper is on qualitative approaches and qualitative assessment methodology is not the point of our interest. Interested readers in qualitative contributions to resilience research can refer to (Ungar 2015; Sarre et al. 2014).

Qualitative Assessment Methodology

2.3.1 Conceptual Framework

Conceptual framework is one of the most common qualitative approaches for assessing the system resilience. Conceptual framework is usually generic but can be extended to different types of systems. For example, Resilience Alliance (2007) proposed a generic framework for evaluating the resilience of social-ecological systems, composed of seven steps: (i) defining and understanding the system under study, (ii) identifying appropriate scale to evaluate resilience, (iii) identifying the system drivers and external and internal disturbance, (iv) identifying the key players in the system, including people and governance, (v) developing conceptual models for identifying necessary recovery activities, (vi) implementing the results of step 5 to inform policymaker, and (vii) incorporating the findings of the previous step. Speranza et al. (2014) developed a notional framework for analyzing resilience of livelihoods, or the "resources that people have and the strategies they adopt to make a living." The framework provides a few attributes of three dimension of resilience: buffer capacity (the amount of change a system can undergo), self-organization (the emergence of society through inherent social structure), and capacity for learning (an ability to adapt). In a homeland security context, Kahan et al. (2009) proposed a broad conceptual framework for system resilience using eight guiding principles: (i) threat and hazard assessment, (ii) robustness, (iii) consequence mitigation, (iv) adaptability, (v) risk-informed planning, (vi) risk-informed investment, (vii) harmonization of purposes, and (viii) comprehensive of scope.

Semi-quantitative index approach is usually constructed based on two steps. In the first step, a set of questions are designed and then answered by the experts of related domain. The answered questions are then scored by a value between 0 to 10 or 0 to 100, and finally these scores can be used in some manner to quantify the resilience value. It is noteworthy to mention that indicators of resilience can be identified without questionnaire. The commonality across those papers used SQI approach is that they found major indicators of resilience and then assign score to them and finally measure the resilience by aggregating scored indicators in some manner like weighted sum approach. These indicators may vary from one paper to another but are usually general like redundancy, robustness, resourcefulness among others. For example, Cutter et al. (2008) fist identified 36 resilience variables of communities to natural disasters, including redundancy, resourcefulness, and robustness. Each variable was then scored between 0 and 100 according to the data observation from a government source. These 36 variables were grouped into five sub-indices, including economic, infrastructure, social, community capital, and institutional. The score for each sub-index was calculated using an unweighted average of each variable, and the total score was calculated by taking unweighted average of all sub-index scores. Pettit et al. (2010) distilled the two key drivers of resilience in an industrial supply chain: (i) level of the supply chain's vulnerability, and (ii) capability of the supply chain to withstand and recover from disruption. The authors measured vulnerability and capability of supply chains by providing a set of 152 questions divided into six sections of vulnerability and 15 sections of capability.

2.3.2 Generic Resilience Metric

Generic resilience metric is a quantitative way to assess the resilience by measuring performance of system, regardless of the structure of system. These metrics are comparable across different system contexts with similar underlying logic. The generic resilience metrics determine the resilience by comparing the performance of system before and after disruption without concentrate on understanding and developing of general structure of system under study. It should be noted that although the generic resilience metrics do not concentrate on understanding and developing of the general structure of a system, however a quantitative examination compels attentive thinking about behavior of system to deal with disruptions. Generic resilience metrics can be either deterministic or probabilistic. Deterministic and probabilistic metrics can be further divided into either static or dynamic states. Performance-based approaches can be classified in the following ways:

- *Dynamic vs. static*: A dynamic performance-based approach accounts for time-dependent behavior, while a static performance-based approach is free of time dependent measures of resilience.
- *Deterministic vs. probabilistic*: A deterministic performance-approach does not incorporate uncertainty (e.g., probability of disruption) into the metric, while probabilistic performance-based approach captures the stochasticity associated with system behavior.

Bruneau et al. (2003) defined four dimensions for resilience in the well-known *resilience* triangle model in civil infrastructure: (i) robustness, the strength of system, or its ability to prevent damage propagation through the system in the presence of disruptive event, (ii) rapidity, the speed or rate at which a system could return to its original state or at least an acceptable level of functionality after the occurrence of disruption, (iii) resourcefulness, the level of capability in applying material (i.e., information, technological, physical) and human resources (i.e., labor) to respond to a disruptive event, and (iv) redundancy, the extent to which carries by a system to minimize the likelihood and impact of disruption.

Bruneau et al. (2003) then proposed a deterministic static metric for measuring the *resilience loss* of a community to an earthquake with Equation 2.1. The time at which the disruption occurs is t_0, and the time at which the community returns to its normal pre-disruption state is t_1. The quality of the community infrastructure at time t, which could represent several different kinds of performance measures, is denoted with $Q(t)$.

$$RL = \int_{t_0}^{t_1} [100 - Q(t)]dt \tag{2.1}$$

In this approach, the quality of degraded infrastructure is compared to the as-planned infrastructure quality (100) during the recovery period. *RL* can be illustrated as the shaded area in Figure 2.4. Larger *RL* values indicate lower resilience while smaller *RL* imply higher resilience. The privilege of this method is its general applicability. Although this approach is utilized for the context of earthquake; however it can be extended to any systems, because quality is a general concept and can be applied to almost any system. Therefore, the general applicability is the most important advantage of this metric.

Henry and Ramirez-Marquez (2012) developed a time-dependent resilience metric that quantifies resilience as ratio of recovery to loss. Given that the performance of the system at a point in time is measured with performance function $\varphi(t)$, three system states that are important in quantifying resilience are represented in Figure 2.5: (i) the *stable original state* which represents normal functionally of a system before disruption occurs, starts from time t_0 and ends by time t_e, (ii) the *disrupted state,* which is brought about by a disruptive event (e^j) at time t_e whose effects set in until time t_d, describes the performance of the system from time t_d to t_s, (iii) the *stable recovered state* which refers to the new steady state performance level once the recovery action initiated at time t_s is over. Important dimensions of resilience that are depicted in Figure 2.5. include reliability, or the ability of the system to maintain typical operation prior to a disruption, vulnerability, or the ability of the system to stave off initial impacts after event e^j, and recoverability, or the ability of the system to recover in a timely manner from e^j. The time-dependent measure of resilience is defined in Equation 2.2, noting that resilient behavior is a function of e^j. Notation $Я(t|e^j)$ was adopted by Whitson and Ramirez-Marquez (2009), as *R* is commonly reserved for reliability.

$$Я_\varphi(t|e^j) = \frac{\varphi(t|e^j) - \varphi(t_d|e^j)}{\varphi(t_0) - \varphi(t_d|e^j)} \tag{2.2}$$

As it explained above, the numerator of this metric implies recovery up to time t, while the denominator refers to the total loss due to disruption e^j. The authors also calculated the total cost of recovered system followed by disruption as sum of implementing cost for resilience action and loss cost incurred due to system’s non-operability due to disruption. Several subsequent developments in the context of resilience measurement and planning (Barker et al. 2013; Pant et al. 2014) are based on the system state transition represented in Figure 2.5 and the metric in Equation 2.2 by Henry and Ramirez-Marquez (2012). The main advantage of metric proposed by Whitson and Ramirez-Marquez (2009) is its simplicity and practicality; however it presents the following drawbacks: I) the metric does not include preparedness (pre-disaster) activities. II) the system’s resilience is measured based on only single performance function $\varphi(t)$, while in real case study, a system may have multiple performance functions. III) System's property did not incorporate into the resilience formulation.

Chen and Miller-Hooks (2012) introduced an indicator for measuring resilience in transportation networks. The resilience indicator, represented in Equation 2.3, quantifies the post-disruption expected fraction of demand that, for a given network, can be satisfied within pre-determined recovery budgets. Parameter d_w quantifies the maximum demand that can be satisfied for origin-destination (O-D) pair *w* following a disruption, and D_w is demand that can be satisfied for O-D pair *w* prior to the disruption.

$$\text{Resilience} = E\left(\sum_{w \in W} d_w \Big/ \sum_{w \in W} D_w\right) = \frac{1}{\sum_{w \in W} D_w} E\left(\sum_{w \in W} d_w\right) \tag{2.3}$$

Chang and Shinozuka (2004) introduced a probabilistic approach for assessing resilience, measured with two elements: (i) loss of performance and (ii) length of recovery. Resilience is defined as the probability of the initial system performance loss after a disruption being less than the maximum acceptable performance loss and the time to full recovery being less than the maximum acceptable disruption time. This measure is represented in Equation 2.4, where A represents the set of performance standards for maximum acceptable loss of system performance, $r^\star$, and maximum acceptable recovery time, $t^\star$, for a disruption of magnitude i.

$$R = P(A|i) = P(r_0 < r^\star \text{ and } t_1 < t^\star) \tag{2.4}$$

Hashimoto et al. (1982) defined the resilience of a system as conditional probability of a satisfactory (i.e., non-failure) state in time period $t + 1$ given an unsatisfactory state in time period t, shown in Equation 2.5. $S(t)$ is the state of the system at time t, and NF and F represent non-failure and failure states, respectively.

$$R = P\{S(t+1) \in NF | S(t) \in F\} \tag{2.5}$$

Franchin and Cavalieri (2015) introduced a probabilistic metric for assessing infrastructure resilience in the presence of earthquake. Their definition of resilience is based on the efficiency of the spatial distribution of an infrastructure network. The efficiency of two nodes in an infrastructure network is defined as being inversely proportional to their shortest distance. The resilience metric is provided in Equation 2.6, where P_D is the fraction of displaced population, E_0 is the efficiency of the city network before the earthquake, P_r is the measure of progress of recovery, and $E(P_r)$ is the recovery curve of the fraction of the displaced population. In their study, the efficiency of a city road network is measured in terms of population density.

$$R = \frac{1}{P_D E_0} \int_0^{P_D} E(P_r)\, dP_r \tag{2.6}$$

Barker et al. (2013) proposed two stochastic resilience-based component importance measures (CIMs) for identifying the primary contributors to network resilience. The modeling of these two metrics is devoted to vulnerability and recoverability in a network following a disruption. The first CIM metric, analogous to the risk reduction worth importance measure in the reliability engineering field, quantifies the proportion of restoration time attributed to each network component. The second resilience-based CIM, similar to the reliability achievement worth importance measure, quantifies how network resilience is improved if a specific network component is invulnerable. The authors then concluded that the network resilience can be obtained in the form of two ways: vulnerability reduction strategy or accelerating the speed of recovery activities through evaluating CIM metrics.

2.4 Structural Based Modeling Approach

The structural based approaches examine how the structure of a system impacts on its resilience. To investigate the resilience using structure based approach, the general behavior of systems must be observed and characteristics of a system must be modeled or simulated. The structural based approach can be thought of as anticipation of how a system could represent resilience but generic resilience metrics validate resilience value, or how much of resilience is actually presented. Three approaches have been used by researchers to model the structure of systems for purpose of resilience examination including optimization modeling, simulation modeling and fuzzy modeling.

2.4.1 Optimization-Based Approach

Faturechi et al. (2014) proposed a mathematical model for evaluating and optimizing airport resilience, aiming to maximize the resilience of an airport's runway and taxiway network. The main strategy used in their mathematical model is the quick restoration of post-event take-off and landing capacities to the level of capacities before disruption by taking into account time, physical, operational, space, resource, and budget restrictions. Two types of decision variables, including pre-event and post-event decisions, were considered. The main feature of their work is that preparedness and recovery activities are taken into account in the stochastic integer model. Besides that, multiple damage scenarios are considered.

Alderson et al. (2014) proposed a mixed integer non-linear programming (MINLP) to quantify the operational resilience of critical infrastructures. Resilience is defined in terms of defense strategies with little attention given to the important recovery dimension of resilience found in most works. Their proposed model aims to find out the best defense strategy in the case of attacks such that the total cost of the defense strategy is minimized. The concentration of MINLP model is on preparedness actions but not on recovery which necessities further improvement.

2.4.2 Simulation-Based Approach

Albores and Shaw (2008) proposed a discrete event simulation model to evaluate the preparedness of a fire and rescue service department in the presence of terrorist attacks. The authors considered preparedness as key driving factor of pre-event disruption resilience. Two simulation models were: (i) the first model mimics the mass decontamination of a population following a terrorist attack, while (ii) the second model deals with the harmonization of resource allocation across regions.

Carvalho et al. (2012) applied discrete event simulation to assess the resilience of a supply chain. Two strategies of flexibility and redundancy are taken into account as elements of resilience in their simulation model. Redundancy is modeled by keeping additional inventory to successfully withstand disruptions, and flexibility is modeled by restricting the extent of the disrupted transportation system. Six different scenarios are investigated with the simulation model. There are several limitations for this research study. First, the results found in this research may not be universally applicable across different sectors, because redundancy strategy may not be a cost-efficient solution in compared to flexibility strategy to some supplier due to high inventory holding costs or vice versa. The simulation model dose not embedded automaker supply chain entirely. The results obtained are highly dependent on the supply chain parameters. Finally, the behavior of automaker is not simulated.

2.4.3 Fuzzy-Based Approaches

Aleksic et al. (2013) proposed a fuzzy model for assessing organizational resilience. Fuzzy linguistic variables were used to express the relative importance of the organizational resilience factors. Muller (2012) presented a fuzzy architecture (FA) for assessing the resilience of critical infrastructure. Redundancy and adaptability were considered to be the primary components of infrastructure resilience. The redundancy and adaptability inputs of the FA, and the resilience output, are expressed using linguistic variables. Tadic et al. (2014) integrated fuzzy forms of the Analytic Hierarchical Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for evaluating and ranking organizational resilience based on qualitative assessments. The approach was used to rank several resilience factors including (i) planning strategies, (ii) capability and capacity of internal resources, (iii) internal situation monitoring and reporting, (iv) human factors, (v) quality, (vi) external situation monitoring and reporting, (vii) capability and capacity of external resources, (viii) design factors, (ix) detection potential, and (x) emergency response.

2.5 Concluding Remarks

Over the past decade, the significance of the concept of resilience has been well recognized among researchers and practitioners. Many efforts have been devoted to measure resilience of systems but this area is still challenging. The objective of this research is to provide a vision about quantification approaches of system resilience. In this paper, we first classified four domains for definitions of resilience including engineering, organizational, social and economic. A variety of resilience definitions presented by researchers and related organizations such as ASME, NIAC and others are reviewed. The traditional definitions of resilience concentrates on the inherent ability of systems to absorb shocks of disruptions which refers to preparedness activity but more recent definitions presented by organizations like ASME and NIAC focus on not only preparedness but also recovery aspect of resilience. The main similarity that can be observed across the definitions of resilience is the lack of proposing a mechanism for preparedness and recovery aspects. Follows by definitions of resilience, the quantifications of resilience have been classified and analyzed. We classified the resilience quantification approaches into two classes: quantitative and qualitative approaches. Qualitative approach includes conceptual framework and semi-quantitative methods. Conceptual frameworks provide insights about the notion of resilience but do not provide quantitative value of system resilience. Semi-quantitative is usually composed of two steps: first is to conduct a survey questions to identify the indicators of resilience and second step is to aggregate scored indicators into a single one using sum method like sum weighted approach in order to measure of resilience. Quantitative assessment category consists of two sub-categories: general resilience metric and structural resilience based approach. General resilience metrics itself divided into two groups: deterministic and probabilistic. Our findings indicate that the metrics used to measure resilience is established based on the definition of resilience. For example, Henry and Ramirez-Marques (2012) measured resilience as ratio of recovery to loss of system's performance because they considered recovery as lever of resilience while

Francis and Bekera (2014) considered preparedness in addition to recovery. Indeed different perspectives on quantifying resilience emanate from inconsistency that exists in resilience concepts and definitions. The similarity that can be observed across the resilience metrics is that they assess the resilience by comparing the performance of system before and after disruption. The generic metrics basically uses only single performance for a system while in a real world cases; there might be multiple system performances for a system. The future potential studies must consider this issue by proposing metrics that has capability of measuring multiple performance functions simultaneously. Another major critic on the existing metrics is that they do not incorporate the economic impact like recovery costs into their resilience metrics. Hence, future researchers can focus on economic feature of resilience. Our findings show that the earlier development of resilience metrics were more deterministic while recent trend is focused more on stochastic resilience metrics. We predict that the future researches would be concentrated more on developing stochastic resilience metrics like the one presented by Barker et al. (2013) due to stochastic nature of resilience concept. Different consideration can be taken in order to create stochastic resilience metrics such as considering stochastic restoration time, probability of disruption occurrence, probability of system failing due to disruption, and interdependency probability between failures. We finally analyzed the structural based approach for assessing the resilience of systems. In this approach, in order to assess the resilience, characteristics and general behavior of systems must be modeled or simulated.

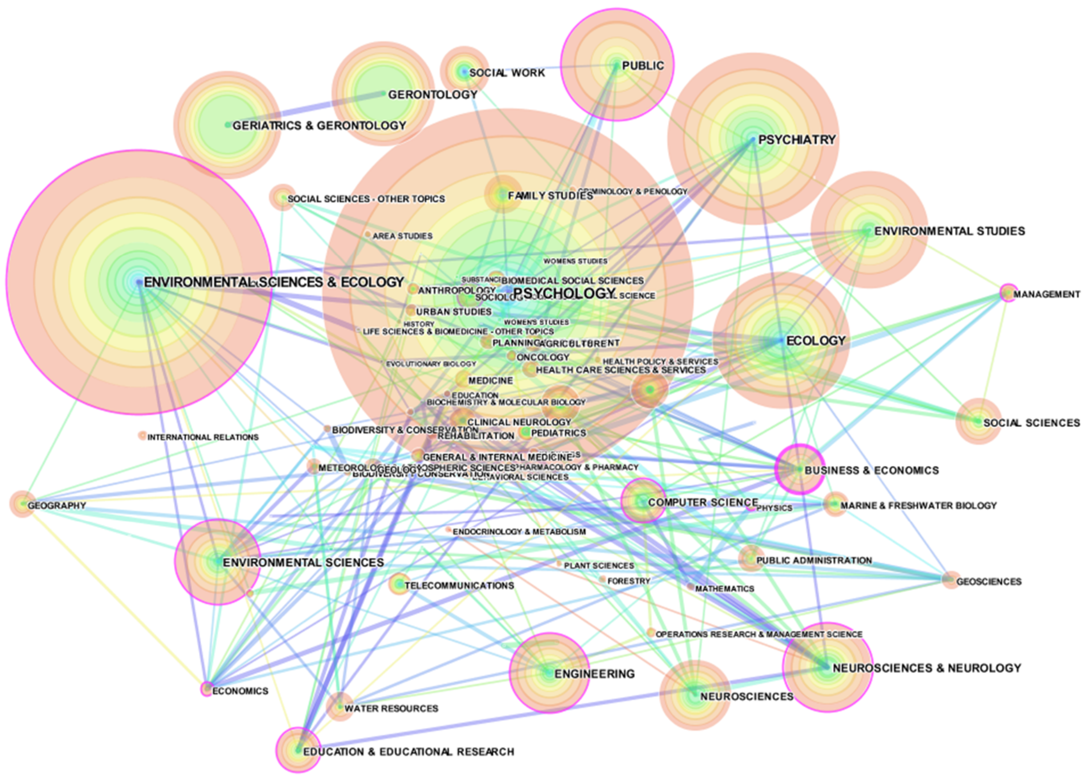

Figure 2.1 A snapshot of clusters based on category, created by CiteSpace

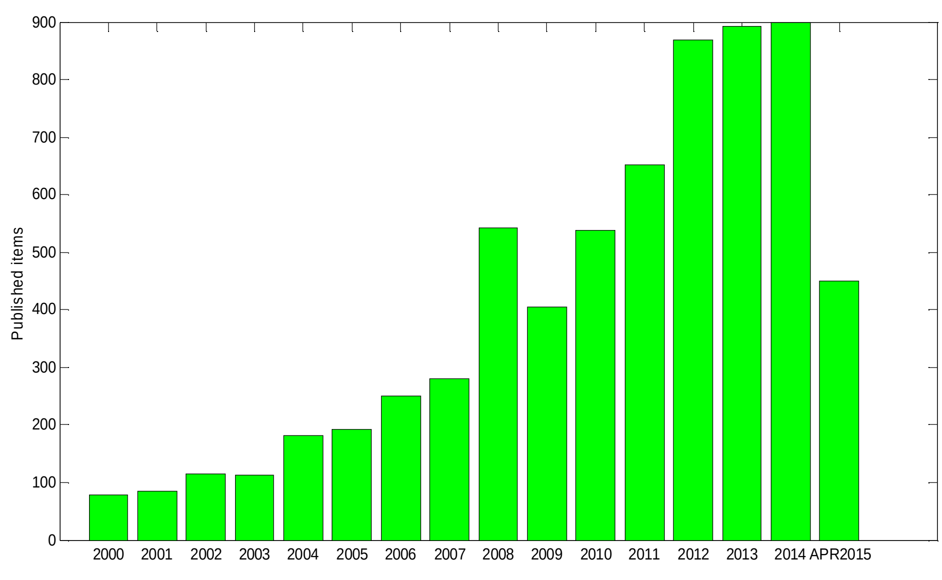

Figure 2.2 Distribution of papers by year of publication, as of April 2015

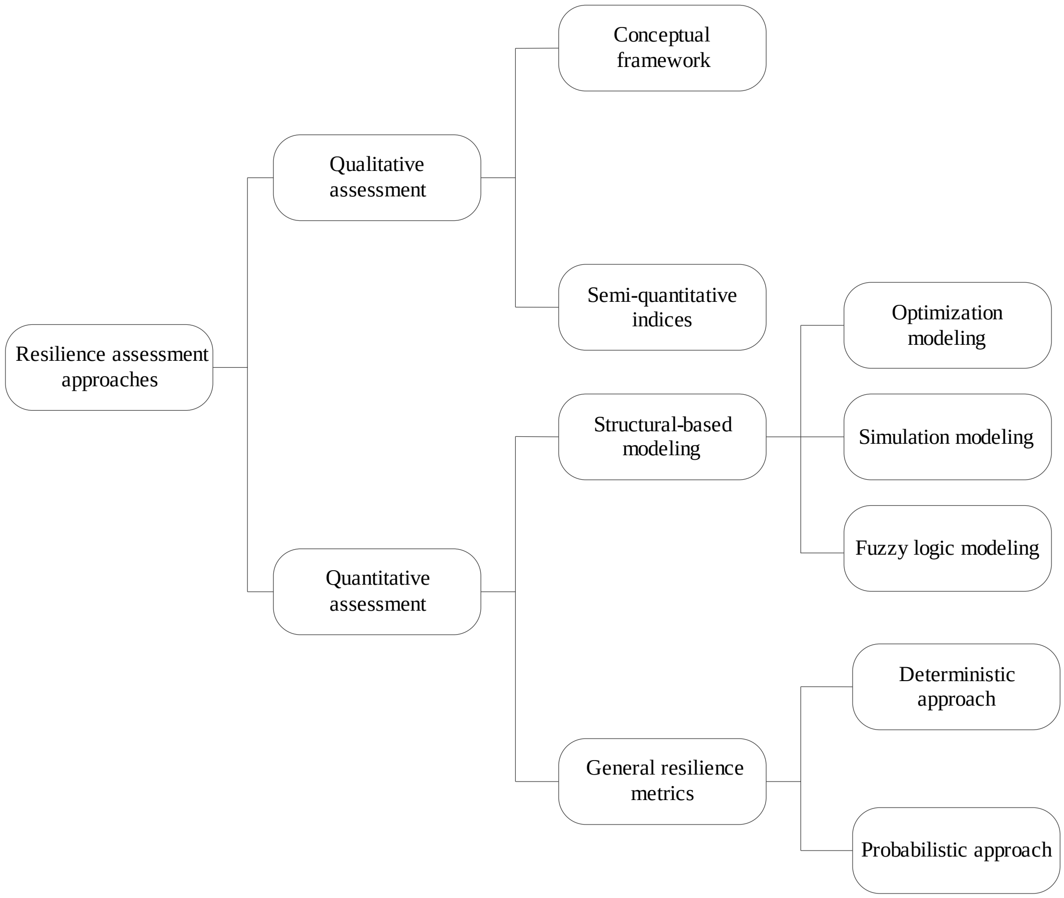

Figure 2.3 Classification scheme of resilience assessment methodologies

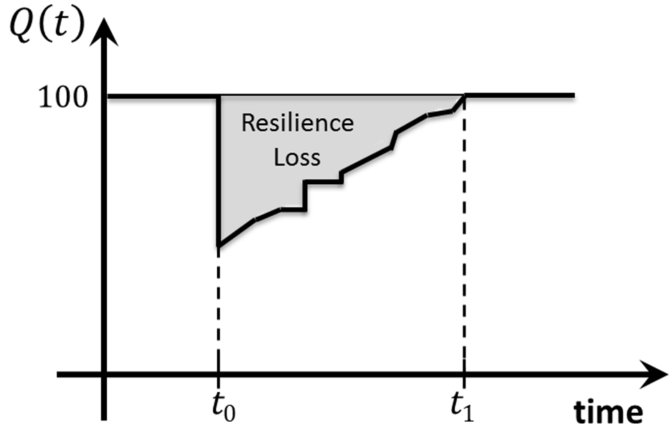

Figure 2.4 Resilience loss measurement from the resilience triangle (adapted from Bruneau et al. 2003)

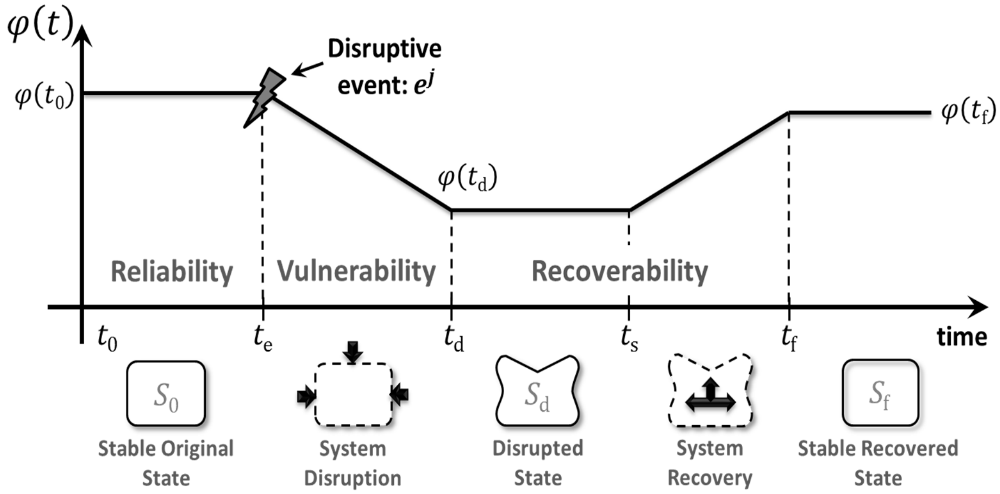

Figure 2.5 System performance and state transition to describe resilience (adapted from Henery and Ramirez-Marquez 2012)

Table 2.1 Top journal sources of resilience research output, as of April 2015.

No.	Journal title	No. of papers
1	Reliability Engineering & Systems Safety	9
2	Risk Analysis	5
3	International Journal of Production Research	4
4	Procedia Computer Science	3
5	Computers & Operations Research	3
6	Safety Science	3
7	Transportation Research-Part B	2
8	Transportation Research-Part E	2
9	Bioscience	2
10	European Management Journal	2
11	Earthquake Spectra	2
12	Computers & Industrial Engineering	2
13	Process Safety Progress	2
14	Structural Safety	2
15	IEEE Systems Journal	2
16	International Journal of Critical Infrastructures	2
17	Journal of Loss Prevention in the Process Industries	2
18	Process Safety and Environmental Protection	2
19	Transportation Research-Part A	2
20	Expert Systems with Applications	2
21	Electrical Power and Energy Systems	2
22	Global Environmental Change	2

CHAPTER

3

MODELING INFRASTRUCTURE RESILIENCE USING BAYESIAN NETWORKS[‡]

ABSTRACT

Infrastructure systems, including transportation, telecommunications, water supply, and electric power networks, are faced with growing number of disruptions such as natural disasters, malevolent attacks, human-made accidents, and common failures, due to their age, condition, and interdependence with other infrastructures. Risk planners, previously concerned with protection and prevention, are now more interested in the ability of such infrastructures to withstand and recover from disruptions in the form of resilience building strategies. This paper offers a means to quantify resilience as a function of absorptive, adaptive, and restorative capacities with Bayesian networks. A popular tool to structure relationships among several variables, the Bayesian network model allows for the analysis of different resilience building strategies through forward and backward propagation. The use of Bayesian networks to quantify resilience is

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demonstrated with the example of an inland waterway port, an important component in the intermodal transportation network.

Keywords: Resilience, Bayesian network, Transportation

3.1 Introduction

Infrastructure systems are faced with growing number of disruptions due to their age, condition, and interdependence with other infrastructures. These systems are subject to common cause failure, but also natural disasters that are becoming more frequent and more impactful (e.g., Hurricane Sandy in 2012, the Japanese earthquake and tsunami of 2011, the Haiti earthquake in 2010, Hurricane Katrina in 2005).

The resilience of infrastructure systems in the face of the variety of disruptive events and resulting consequence has become an increasingly important topic among planners. Infrastructure systems must be designed in a way so that they are resistant enough to withstand and recover quickly from disruptions. Previously, the emphasis of preparedness planning dealt with protection and prevention of disruptive events. Such strategies may not be sufficient to withstand disruptive events, particularly for uncharacteristically devastating events, because it is almost impossible in practice to harden infrastructure systems against all types of disruptive events. Accordingly, the concept of resilience emerged to supplement a mitigation-focused philosophy, recognizing the significance and need for timely response and recovery from disruptions. Activities that account for response and recovery are commonly referred to as post-disruption or contingency strategies. A suitable resilience strategy for a critical infrastructure might be different from one to another. For example, rerouting alternative is a suitable resilience strategy for transportation and communication networks when the connectivity and redundancy degree of networks are high, however having a high degree of connectivity is not suitable for power grid systems where the cascading failures are common.

In this chapter, we propose the novel quantification of resilience with Bayesian networks, a technique that has found popularity in such fields as reliability engineering but with little application in resilience modeling. Bayesian networks can model the causal relationships among various aspects of resilience and are especially useful when varying levels of data describing those relationships are known (e.g., data sets describing commodity flows through a port, expert elicitation of the effects of a natural hazard on the condition of dock-specific equipment). Different disruptive scenarios, as well as different resilience building strategies, can be simulated, and a sensitivity analysis of parameters can be performed for a robust analysis.

To illustrate the proposed quantification approach, we use an inland waterway port case study. Inland ports play a vital role in intermodal transportation networks by maintaining the flow of commodities among industries and regions. The disruption of ports can have significant adverse impacts on supply and demand, ultimately affecting productivity. U.S. inland waterway infrastructure was recently given the grade of D- (American Society of Civil Engineers 2013), with locks and dams increasingly vulnerable to common cause failure and natural disasters that could exploit their state of repair. Port closures could result in cargo congestion at the gates, vessel queuing, backlogs at warehousing transloading facilities, and manufacturing production stoppages (National Cooperative Freight Research Program 2014). For example, the impact of a 10-day shutdown of West Coast port could be approximately $2.1 billion per day on the overall economy (Reuters Feb 7, 2015). Closures to inland waterway ports can have significant regional impacts (Pant et al. 2014; Pant et al. 2015).

3.2 Literature Review

This section offers some background on the study of resilience, as well as the use of Bayesian networks, which will be used to quantify resilience in this paper.

3.2.1 Quantifying Resilience

Despite the extensive research recently on the subject of resilience, most work in infrastructure systems deal with system vulnerability (withstanding a disruption) rather than system resilience (withstanding then recovering) (Wang et al. 2010; Johansson et al. 2013; Johansson et al. 2010; Eusgeld et al. 2009). Various general metrics have been defined to measure the resilience that is applicable to the infrastructure systems (Chang and Shinozuka 2004; Vugrin et al. 2014; Muller 2012; Carvalho et al. 2012; Jain and Bhunya 2010; Hashimoto et al. 1982; Losada and Scaparra 2012). Hosseini et al. (2016) classified the literature related to the resilience measurement approaches into two groups: qualitative based approach and quantitative based approach. Qualitative assessment was further divided into conceptual frameworks and semi-qualitative indices, while quantitative assessment was further divided into general measures which contain probabilistic and deterministic approaches; and structural-based models which contain optimization, simulation and fuzzy logic models.

Several works have focused on transportation and logistics systems, in particular. Omer et al. (2014) introduced a metric for infrastructure system resilience, measuring the closeness centrality of network before and after a disruptive event. Soni et al. (2014) proposed a deterministic modeling approach based on graph theory to measure supply chain resilience. Their proposed approach is able to capture dynamic nature of environment for handling disruptive events in supply chains. Carvalho et al. (2012) applied discrete event simulation technique to assess alternative supply chain scenarios for improving supply chain resilience. The authors considered two performance measures including lead time ration and total cost for comparing the merit of alternatives. Rajesh and Ravi (2015) addressed the enablers of supply chain risk mitigation and then proposed a Grey theory and DEMATEL approaches to explore cause/effect among the enablers of supply chain risk mitigation. Faturechi et al. (2014) proposed a mathematical model to evaluate and optimize airport resilience, focusing on the quick restoration of post-event take-off and landing capacities to the level of pre-disruption capacities. Vugrin et al. (2014) proposed a multi-objective optimization model for transportation network recovery, designed as a lower-level problem that involves solving a regular network flow problem and an upper-level problem that explores the optimal recovery sequences and modes. The objective of the optimization model presented by Vugrin et al. (2014) is to maximize the resilience of disrupted transportation networks. Their proposed model was applied to two networks: a maximum flow network and a complex congested traffic flow network for recovery task sequencing. Khaled et al. (2015) proposed a mixed integer nonlinear programming problem and heuristic solution approach for evaluating critical railroad infrastructures to maximize rail network resilience. Reyes Levalle and Nof (2015) proposed an approach based on fault tolerance by teaming principle of collaborative control theory for design and operation of resilient supply networks. Their proposed approach is capable of achieving higher fault tolerance with fewer resources in the case of disruptions.

Note that many of the previous approaches to quantifying resilience focus solely on modeling system reliability, whereas more recent methods also account for system recovery. Such a trend aligns with the comprehensive definition of infrastructure resilience is presented by National Infrastructure Advisory Council (NIAC) (2009) which defines the resilience as the ability to predict, adapt and/or quickly recover from a disruptive event. Given this definition, we are primarily motivated by the time-dependent resilience measure proposed by Henry and Ramirez-Marquez (2012) which represents resilience metric at time t, $Я(\mathbf{t})$, as ratio of recovery to loss at time t. The performance of a system over time, $\boldsymbol{\varphi(t)}$, is generally represented in Figure 3.1. Three transition states have been defined in which a system can operate: (i) $\boldsymbol{S_0}$, the baseline or steady state when system operates under normal conditions until disruptive event $\boldsymbol{e^j}$ occurs at time $\boldsymbol{t_e}$, (ii) $\boldsymbol{S_d}$, the disrupted state at time $\boldsymbol{t_d}$ due to disruptive event $\boldsymbol{e^j}$ disrupting the performance of system, and (iii) $\boldsymbol{S_f}$, the recovered state at time $\boldsymbol{t_f}$, resulting from recovery activities triggered at time $\boldsymbol{t_s}$.

Depicted in Figure 3.1, the system operates normally with service function of $\varphi(t_0)$ (e.g., inventory rate, capacity level) within time interval $[t_0, t_\mathrm{e}]$. With presence of disruption event e^j at time t_e the system service function reduces from $\varphi(t_0)$ to $\varphi(t_\mathrm{d})$ at time t_d. The system service function remains constant from time t_d to time t_s until the resilience action takes place in time t_s, then the system service function gradually increases and reaches a new steady state at time t_f. Based on description, system resilience given in Equation 3.1 read the resilience of system at a given disruptive event e^j at time t, $t \in [t_\mathrm{s}, t_\mathrm{f}]$ describes the ratio of recovery to loss at such point in time.

$$Я\left(t \middle| e^j\right) = \frac{\varphi\left(t \middle| e^j\right) - \varphi\left(t_d \middle| e^j\right)}{\varphi(t_0) - \varphi\left(t_d \middle| e^j\right)} \tag{3.1}$$

Barker et al. (2013) proposed a resilience-based component importance measures for infrastructure networks which quantify the (i) potential adverse impact on system resilience from a disruption affecting link i, and (ii) potential positive impact on system resilience when link i cannot be disrupted. Pant et al. (Pant et al. 2014) proposed a stochastic resilience measure based on proposed metric in Equation 3.1 to evaluate the system resilience under uncertainty by including time to total system restoration, time to full system service resilience, and time to $\alpha\%$-resilience, applied to quantify resilience of inland waterway ports.

3.3 Bayesian Networks

Bayesian networks (BNs) are structured based on Bayes' theorem, capable of updating the prior probability of some unknown variable when some evidence describing that variable exists. In real world applications of risk analysis, there are frequently many unknown variables and many distinct pieces of evidence, some of which may be linked. BNs can graphically represent such problems where uncertain variables are represented as vertices (nodes), with an edge representing the causal relationship between two vertices, forming a directed graph in which cycles are not allowed. BNs are an excellent tool for computing the posterior probability distribution of unobserved variables conditioned on some variables that have been observed, encoding both quantitative and qualitative information in a conditional probability format (*e.g.*, variables could be Boolean (yes/no), qualitative (low/medium/high), or continuous, among others). The ability to model variables of several types is the main property of BN that motivates us to employ it for quantifying of system resilience.

Consider a large interconnected network like power grids where the failure of a component could possibly trigger the failure of successive components. BNs can be used to quantify the resilience of such systems due to their interconnected structure among their components. The application of BN in modeling resilience of critical infrastructures is underdeveloped. For example, Asriana Sutrisnowati et al. (2014) proposed a novel BN model from event log for analyzing the lateness probability in port logistics. The proposed BN model is constructed by decomposition of a dependency graph that generated from event log in port management systems. The proposed BN model can provide valid inference for activity lateness probabilities and also beneficial recommendations to port managers for improving existing activities.

Let $V = \{X_1, X_2, \dots, X_n\}$ be the set of variables in a BN whose structure specifies conditional independence. An outgoing edge from X_i to X_j indicates a relationship that value of variable X_j is dependent of the value of X_i variable. If there is outgoing edge from X_i to X_j then X_i is the parent node of X_j and X_j is a child node of X_i.Three classes of nodes exist in BN: (i) nodes without a child node are called *leaf nodes*, (ii) nodes without a parent node are called *root nodes*, and (iii) nodes with parent and child nodes are called *intermediate nodes*. For example, in Figure 3.2, nodes X_1 and X_2, called as root node, in which are parents of nodes X_3, X_4, and X_5 (intermediate nodes). Finally, Nodes X_6 and X_7 are called as leaf nodes.

The causal relationships among variables of a BN are measured by conditional probability distributions. The full joint probability distribution of a BN consisting of *n* variables $X_1, X_2, \dots, X_n$ is found in Equation 3.2.

$$P(X_1, X_2, \dots, X_n) = P(X_1|X_2, X_3, \dots, X_n)P(X_2|X_3, \dots, X_n) \cdots P(X_{n-1}|X_n)P(X_n)$$

$$= \prod_{i=1}^{n} P(X_i|X_{i+1}, \dots, X_n) \quad (3.2)$$

However, Equation 3.2 can be further simplified with knowledge of what the parents of each node are. For example, if we know that node X_1 has exactly two parents, X_2 and X_4, then the part of joint probability distribution $\mathsf{P}(\mathsf{X}_1|\mathsf{X}_2, \dots, \mathsf{X}_\mathsf{n})$ can be replaced with $\mathsf{P}(\mathsf{X}_1|\mathsf{X}_2, \mathsf{X}_4)$, as only X_2 and X_4 affect the occurrence of X_1. As such, the joint probability of distribution of a BN can be written using parent nodes of each node. Suppose that Parents (X_i) denote the set of parent nodes of node X_i, then the joint probability distribution of the BN can be simplified in Equation 3.3.

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i|Parents(X_i)) \quad (3.3)$$

A BN can consist of continuous, discrete, or mixed variables. Conditional distributions are commonly referred to as conditional probability tables (CPT). The causal relationship between variables and corresponding CPT are determined based on expert knowledge.

An illustrative example of BN with seven variables as depicted in Figure 3.2. The corresponding decomposition of the joint distribution of variables is given by Equation 3.4.

$$P(X_1, X_2, \dots, X_7)$$

$$= P(X_1)P(X_2)P(X_3|X_1)P(X_4|X_1, X_2)P(X_5|X_2)P(X_6|X_3, X_4)P(X_7|X_3, X_4, X_5) \quad (3.4)$$

It is clear that to calculate the joint distribution, $P(X_1, X_2, \dots, X_7)$, the unconditional probabilities of $P(X_1)$ and $P(X_2)$, as well as the conditional probabilities of

$P(X_3|X_1), P(X_4|X_1,X_2)$, $P(X_5|X_2)$, $P(X_6|X_3,X_4)$, and $P(X_7|X_3,X_4,X_5)$, must be determined.

An important property of BN is the ability to update belief propagation or forward propagation, or the ability to update marginal probabilities, $P(X_i)$, after observing other variables. For example, the conditional probability for variable X_3 given evidence e, ($e = \{X_1, X_2, X_4, X_5, X_6, X_7\}$) can be calculated with Equation 3.5.

$$P(X_3|e) = \frac{P(X_1,X_2,X_3,X_4,X_5,X_6,X_7)}{P(X_1,X_2,X_4,X_5,X_6,X_7)} = \frac{P(X_1,X_2,X_3,X_4,X_5,X_6,X_7)}{\sum_{X_3} P(X_1,X_2,X_4,X_5,X_6,X_7)} \tag{3.5}$$

The calculation represented by Equation 3.5 is not computationally efficient and can be simplified with Equation 3.6.

$$\begin{aligned} &P(X_3|e) \\ &= \frac{P(X_1)P(X_2)P(X_3|X_1)P(X_4|X_1,X_2)P(X_5|X_2)P(X_6|X_3,X_4)P(X_7|X_3,X_4,X_5)}{\sum_{X_3} P(X_1)P(X_2)P(X_3|X_1)P(X_4|X_1,X_2)P(X_5|X_2)P(X_6|X_3,X_4)P(X_7|X_3,X_4,X_5)} \\ &= \frac{P(X_3|X_1)P(X_6|X_3,X_4)P(X_7|X_3,X_4,X_5)}{\sum_{X_3} P(X_3|X_1)P(X_6|X_3,X_4)P(X_7|X_3,X_4,X_5)} \end{aligned} \tag{3.6}$$

3.4 Elements of Inland Waterway Resilience

A case study of the Port of Catoosa, an inland waterway port in the Mississippi River Navigation System located near Tulsa, Oklahoma, is used to illustrate the measurement of resilience using Bayesian networks. We choose this case study because inland waterway ports play a crucial role in the U.S. economy. These ports serve as hubs that connect components of intermodal transportation systems, including barge, train, truck transportation modes (MacKenzie et al. 2012). According to Waterborne Commerce Statistics Center (Waterborne Commerce Statistics Center 2009), approximately one billion tons of cargo or 40% of U.S. waterway commerce traverse through inland port

(Waterborne Commerce Statistics Center 2009). Ninety percent of this cargo consists of coal and petroleum products and crude materials, all of which are important commodities for U.S. manufacturing and production (MacKenzie et al. 2012) and are primary commodities at the Port of Catoosa. The impact of disruptive events on inland ports can be devastating and could barricade production at many industries in the U.S.

The Port of Catoosa is the largest port in Oklahoma and is the largest inland waterway port in the U.S. by land area. Over 2.8 million tons of different types of commodities, including fertilizers, chemicals, grains, and metal products were shipped imported and exported through the port in 2014. Industries in many states, including Alabama, Arkansas, Iowa, Illinois, Kentucky, Louisiana, Mississippi, Oklahoma, Ohio, and Texas, are served by the Port of Catoosa.

The Port of Catoosa consists of four major docks, each of which deals with a specific commodity type (Pant et al. 2015). The Liquid Bulk dock is used for moving different types of liquids, including asphalt, chemicals, and refined petroleum products. The Grains dock handles agricultural products such as corn, wheat, and soybeans. The Dry Bulk dock moves a variety of loose commodities such as sands, gravel, and fertilizer that can be handled by conveyer. The Dry Cargo dock loads and unloads large items, primarily iron, steel, and machinery. This study concentrates on the Dry Cargo dock, whose products are categorized by the North American Industry Classification System (NAICS) economic sectors: Fabricated metals, Machinery, Primary metals, and Miscellaneous manufacturing.

3.4.1 Port Disruptions

Natural disasters (e.g., floods, tornados) and hazardous material threats (e.g., fires, explosions, liquid spills) are the primary disruption concerns of decision makers at the Port of Catoosa. As such, natural disasters and hazardous material threats are considered in the BN model as major sources of vulnerability at the port. Hazardous material threats are considered short-term in their disruptive consequences, where natural disasters may have more extended consequences.

3.4.2 Resilience Capacity

Resilience capacity is the resilience enhancement features that could increase the ability of system to absorb, adapt, and restore from disruptions. Biringer et al. (2013) proposed the concept of resilience capacity with three categories that each represents temporal attributes before, during, and after a disruptive event: absorptive capacity, adaptive capacity, and restorative capacity. These categories are discussed below in the context of the inland waterway port, and they appear in Figure 3.3.

Absorptive capacity is the capability of the system to absorb or withstand the impact of disruptive events and minimize the consequences, akin to *robustness* in the resilience triangle literature (Vugrin et al. 2011; Bruneau et al. 2003). Absorptive capacity refers to all activities that need to be taken to absorb shocks of disruptions in advance. We identified five features of absorptive capacity that are effective for our case study (National Cooperative Freight Research Program 2014; Sturgis et al. 2014).

- *Backup utility systems*. Having backup power generators can be viewed as an absorptive feature of resilience capacity to maintain continuity of port operations. Power system failure is a common failure in the observation of port disruptions, as a number of the 17 ports interviewed by the U.S. Government

Accounting Office (Government Accountability Office 2007) reported that the purchase of redundant back-up power generation is critical in the case of emergencies.

- *Extra cargo handling equipment*. Redundant cargo handling facilities, including cranes and reach stackers, can reduce the impact of disruptions to the Dry Cargo dock. Further, extra fuel availability is a related option to improve absorptive capacity.
- *Storm surge protection*. Physical protection, called as storm surge protection (e.g., barge channel protection) can improve the port's robustness to flood damage.
- *Skilled labor and management.* Training operators and managers to react to and control a disruption to maintain continuity is an absorptive measure. In addition, the use of skilled labor reduces the time of loading and unloading tasks by fully utilizing equipment such as cranes and reach stackers.
- *Communication and coordination*. An effective flow of information and coordination before disruption triggers between National Weather Service, port staff, dock operators, utility operators, vessel operators, shipping agents, regulatory agencies, and emergency agencies can reduce the impact of disruptions. A report related to the port resilience released by Center for a New American Security (Sturgis et al. 2014) highlighted that communication and coordination between the members of the port community of New York and New Jersey during Hurricane Sandy was one the most influential recovery efforts that has been made. Hence, through the lessons learned from the Port of

New York and New Jersey, it is not hard to look at communication and coordination between the members of port community as the backbone of port resilience planning.

- *Space utilization*. For example, for a port terminal with two berths and four cranes receiving an oversized vessel, the terminal has no alternative but to allow the unused capacity to remain idle. Therefore, a balance for the usage of berth and cranes can be made by larger facility in contiguous dock space by minimizing capacity waste.
- *Maintenance and reliability*. Port maintenance activities, including on-time repair scheduling of cargo handling equipment and availability of spare equipment, strengthen a port's ability to withstand disruptions. The reliability of a port, defined as the probability that port continues its normal operations for a given time interval under normal operating conditions, is a measure of the effectiveness of port maintenance.

Adaptive capacity is the capability of system to adapt itself and attempt to overcome a disruption without any recovery activity (Vugrin et al. 2011). It refers to the ability of a system to be reorganized and perform efficiently with some extra effort and cost in response to a disruption. Design for adaptive capacity can enhance the resilience of infrastructure systems. Three features of adaptive capacity are identified as contributors to the resilience of inland waterway ports (National Cooperative Freight Research Program 2014; Sturgis et al. 2014).

- *Repositioning*. It is common for containers to be stacked at dock locations, however repositioning containers and large items on the ground in the case of natural disasters can be useful. The impact of repositioning has been recognized in the aftermath of Hurricane Sandy at Port of New York and New Jersey, where a large number of containerized cargo could have been saved if they had been repositioned at the yard.

- *Mode flexibility.* In the case of a port disruption, shipping at ports for a specific transportation mode (e.g., waterway) can be congested and delayed.
- *Quick evacuation*. Time response evacuation of cargo and facilities in the case of disruption can enhance the resilience of port operations. For example, thousands of new vehicles stored at the port of New Jersey and New York were flooded and ruined following Hurricane Sandy because their engines burned due to exposure to salt water. In contrast, other East Coast ports responded to Hurricane Sandy with evacuation very quickly and sustained minimal damage (National Cooperative Freight Research Program 2014).

Restorative capacity refers to the ability of a system to repair or restore damages from a disruption (Vugrin et al. 2011). Restorative capacity is different from adaptive capacity in the sense that it is considered to be a permanent feature of system resilience, while adaptive capacity is a temporary feature (i.e., repairing equipment permanently in place versus ensuring continuity through a nonstandard manner that results in an increase in service cost or time). Note that the repair of port facilities during the recovery period may not necessarily restore performance to its pre-damaged state and may exceed prior performance capabilities.

Two components of budget restoration and resource restoration, including technical and equipment restoration have been found as major contribution into the restorative capacity of our case study.

- *Budget restoration*: In the context of port recovery, the damaged equipment (e.g., crane, power generator) can be repaired or restored depending on the severity of disruption but also on budget availability. Budget limitations are the primary driver of resilience enhancing investments (Haimes 2009).
- *Resource restoration*: Resource restoration includes the availability of human-based resources (e.g., skilled labors, technical engineers), and non-human-based resources (e.g., repair equipment).

3.5 Quantifying Resilience Capacity with Bayesian Networks

In this section, we employ a Bayesian network to quantify system resilience as a function of the various elements of resilience capacity shown in Figure 3.3. We illustrate with the inland waterway port example. The graphical model of proposed BN is depicted in Figure 3.4.

3.5.1 Type of Variables

Three types of variables were used to model the various elements of resilience capacity, depending on how each are measured: (i) Boolean variables that measure a dichotomous response (true/false, yes/no, on/fail), (ii) qualitative variables that measure ordinal categories used for weights of factors contributed to the absorptive, adaptive, and restorative capacities, and (iii) continuous variables that measure random variables with a known probability distribution. Much of the works in applying BNs use only Boolean variables (Trucco et al. 2008), though many characteristics of a system require a more sophisticated representation. Also many analyses are hindered by the types of variables allowed by particular BN software called AgenaRisk (Fenton and Neil 2013).

The majority of discrete variables or Boolean variables are defined in the form of two states: the *True* state represents the success state (or positive outcome), and the *False* state represents the fail state (or negative outcome). Similarly, Boolean states (*Yes* and *No*) of the *Resilience improvement* variable and states (*On* and *Fail*) of the *Reliability* variable are the counterparts of *True* and *False* states. For example, the probability table for *Maintenance and inspection* variable includes *True* = 0.7982 and *False* = 0.2017, suggesting that the maintenance and inspection of the port's facilities are successful 79.82% of the time, while such activities fail 20.17% of the time. Another example is the prior distribution of the *storm surge protection* variable with two states of *True* = 0.84 and *False* = 0.16, which refers to a 84% chance that storm surge protection implemented by port authorities may successfully succeed to hinder the negative impacts of disruptive events according to historical data, while there's a 16% chance that it may fail.

An example of a continuous variable is the one that describes *Availability of spare equipment*, which is modeled using a truncated normal distribution denoted by TNORM with a mean of 87%, and variance of 3%, lower and upper bounds of 50% and 100% respectively as represented in Equation 3.7. Note that that the lower bound and upper bound show that the availability of spare equipment in the worst and best possible scenario may not be below 50% and beyond 100%, respectively. All prior probability distributions of continuous variables in this work are generated using TNORM.

$$\text{Availability of spare equipment} \sim TNORM(\mu = 0.87, \sigma^2 = 0.03, LB = 0.5, UB = 1.0) \quad (3.7)$$

Note that the parameters of the variables with continuous distributions can be generally obtained through collecting and evaluating historical data. Generally, the truncated normal distribution is an appropriate distribution as it is confined to lie between two determined lower and upper bound values, especially for modeling the amount of cargo handling or similar variables.

3.5.2 Modeling Vulnerability through Absorptive Capacity

Discussed previously, eight important factors were identified as contributors to the port's absorptive capacity. The prior probability distribution for six of variables, including space utilization, storm surge protection, communication and coordination, backup utility system, skilled labor and management and extra cargo handling, are represented by two states of either False or True as can be seen on the left side of Figure 3.6. The posterior probability distribution for the *Reliability* and *Maintenance* variables are obtained by Boolean logic rules.

To calculate port reliability, we considered the time to failure or closure/stoppage of the port in terms of operation hours, denoted by time to failure (TTF). TTF can be simply obtained by historical data. If the TTF is greater than or equal to the expected TTF of port, then the port is reliable (On state) and fails (Fail state) otherwise. Similar logic has been used to determine the posterior probability distribution for the on-time repair scheduling variable. The Boolean expressions for these two variables are presented in Table 3.1. The procedure for calculating reliability is depicted in Figure 3.4.

The posterior probability distribution of absorptive capacity node is determined by the weighted sum of probabilities of its parent nodes. The weight of each factor represents the importance of that factor in achieving the port's absorptive capacity. To calculate the probability of absorptive capacity, a labelled type node called *Weights of factors contributed to absorptive capacity* is defined to incorporate the weight of each factor. Such weights can be obtained from decision makers using any of a number of decision analysis techniques (e.g., Analytic Hierarchy Process, swing weights). The weighted mean (WMEAN) function is shown in Eq. (8), where i is the number of variables connected (eight in this case) to the weighted average node (*Absorptive capacity* in Figure 6 in this case), and $\boldsymbol{w_i}$ is the weight associated with *i*th variable. This same weighted average method has been used for adaptive capacity and restorative capacity variables.

$$\text{WMEAN} = \sum_i w_i X_i\,, \qquad \forall i = 1, \ldots n, \qquad 0 < w_i < 1, \qquad \sum_i w_i = 1 \tag{3.8}$$

The logic used to determine the posterior probability distribution of absorptive capacity is based on Boolean logic discussed earlier. For example, the expression used to tie the relationship between the *Absorptive capacity* node and *Maintenance* node is IF (maintenance =“True”, “True”, “False”), which denotes that absorptive capacity can be achieved when maintenance is successfully achieved. The similar interpretation can be used for other contributors of absorptive capacity since their achievement will eventually contributed positively to the achievement of absorptive capacity.

Discussed previously, the adaptive capacity and restorative capacity of a system reflect the capability of system to recover its lost capacity after experiencing a disruptive event. Adaptive capacity refers to the temporary solutions to recover the lost capacity (lost cargo handling) of the system, like repositioning of containers and equipment. Restorative capacity refers to the permanent activities to fully restore damaged infrastructure impacted by disruption, such as dock berth and equipment restoration. Adaptive and restorative capacities are modeled similarly to absorptive capacity, as shown in Figure 3.6.

3.5.3 Modeling Recoverability through Adaptive and Restorative Capacities

Adaptive capacity and restorative capacity both contribute to the system's recoverability; however their impacts may be different. Adaptive capacity, or temporary solutions to recover lost capacity, can be viewed as a second line of defense if absorptive capacity is not strong enough to withstand a disruption. Restorative capacity, or permanent activities to fully restore damaged infrastructure impacted by disruption, can be thought of third line of defense. The practical experience of planning for disruptions, specifically natural disasters (Lucena-Moya et al. 2013), indicate that ports with higher restorative capacity (relative to adaptive capacity) are more resilient, suggesting the need to model the link between a post-disaster strategy and its causal factors. The key assumption throughout the Bayesian network model is the conditional independence between the causal factors, but this assumption can be relaxed by introducing links between them. Although the Boolean expression can be used to express the causal relationship between post-disaster strategy and its contributing factors, (adaptive capacity and restorative capacity), there may be a more effective means to account for the uncertainty associated with a successful post-disaster strategy even if adaptive and restorative capacities are both at their True settings. As such, we address this uncertainty with the NoisyOR function, which allows for a probability of resilient strategy failure even when the contributing conditions are met.

To model the causal influences on post-disaster strategy, we use the NoisyOR function. Suppose that there are n causal factors, $X_1, \dots, X_n$ of a condition, Y, with a probability value for Y being true when one and only one X_1 is true, and all causes other than X_1 are false. The NoisyOR function is defined Equation 3.9, where for each i, $v_i = P(Y = \text{true} | X_i = \text{true}, X_j = \text{false}, \text{for each } j \neq i)$ is the probability of the conditional being true if and only if that causal factor is true (Fenton and Neil 2013).

$$\text{NoisyOR}(X_1, v_1, X_2, v_2, \dots, X_n, v_n, l) \tag{3.9}$$

Term l is the leak factor representing the probability that Y will be true when all of its causal factors are false, as shown in Equation 3.10.

$$l = P(Y = \text{true} | X_1 = \text{false}, X_2 = \text{false}, \dots, X_n = \text{false}) \tag{3.10}$$

In general the conditional probability of Y obtained with the NoisyOR function can be represented with Equation 3.11.

$$P(Y = \text{True} | X_1, \dots, X_n) = 1 - \prod_{i=1}^{n} [(1 - P(Y = \text{True} | X_i = \text{True})(1 - P(l))] \tag{3.11}$$

The NoisyOR function used in this paper to calculate the conditional probability of post-disaster strategy is defined in Equation 3.12, which suggests that the chance of successful achievement of a post-disaster strategy is 70% if only adaptive capacity is met, while this value increases to 95% when only restorative capacity is met, where the leak probability is only 0.02. Equation 3.12 follows the approach by Vugrin et al. (2011), who suggest that adaptive capacity (e.g., repositioning, rerouting) can achieve some level of recoverability, while restorative capacity (e.g., repair) is required to achieve more.

$$\text{NoisyOR}(\text{Adaptive capacity}, 0.7, \text{Restorative capacity}, 0.95, 0.02) \quad (3.12)$$

3.5.4 Modeling Resilience Capacity

Inspired by Equation 3.1, resilience is modeled as the ratio of recoverability to vulnerability, or the ratio of recovered cargo handling capacity to the lost cargo handling capacity resulting from a disruptive event. Vulnerability is achieved through absorptive capacity, and recoverability is achieved with a combination of adaptive and restorative capacity. The resilience node is represented by in Figure 3.7. The lost capacity of the *Cargo handling* variable is conditioned on expected inbound and outbound cargo handling under normal operating conditions (NOC), and inbound and outbound cargo handling under disrupted operating conditions (DOC). The partitioned expression in Table 3.2 was used to define the probability of inbound and outbound cargo facility under DOC.

It is assumed that the port's absorptive capacity can fully absorb the shocks from a disruptive event if it is in its True state, and as a result, its inbound and outbound cargo handling capacity under DOC would be the same under NOC. That is, when absorptive capacity is in its True state, inbound and outbound cargo handling is assumed to follow a truncated normal distribution, TNORM (69000, 150, 62000, 72000), which suggests that monthly tonnage has an average of 69000 with standard deviation of 150, with minimum and maximum tonnage of 62000 and 75000 tons, respectively, due to restrictions on yard space and cargo handling equipment. When the absorptive capacity is in its False state, the amount of inbound and outbound cargo handling in terms of monthly tonnage follows TNORM (45000, 200, 0, 75000). The lost capacity of cargo handling in terms of tonnage can be obtained by calculating the difference between the inbound and outbound cargo handling under DOC and NOC as represented in Equation 3.13.

$$\max\{0,\ \text{difference between inbound and outbound cargo handling under DOC and NOC} \tag{3.13}$$

Note that the estimated resilience distribution is bimodal because resilience is calculated as a function of lost and recovered cargo handling capacity. Lost capacity of cargo handling is conditioned on inbound and outbound cargo handling. Inbound and outbound cargo handling itself determined depending whether absorptive capacity is on either False state or True state which results in two different modes.

3.5.5 Improving Resilience Capacity

The ultimate usefulness of the Bayesian network approach to modeling resilience capacity is to determine the efficacy of different strategies to strengthen absorptive, adaptive, and restorative capacities. This is addressed through a set of hypotheses that determine how similar desired resilience, $0 < Я_{\text{desired}} \leq 1$, is to the actual resilience, $Я_{\text{actual}}$, calculated from the Bayesian network. The null hypothesis is that desired and actual resilience are similar to each other, that is the difference between $Я_{\text{desired}}$ and $Я_{\text{actual}}$ (as the ratio of recovered to lost cargo handling capacity follows a probability distribution) is within ε, a small acceptable threshold. Alternatively, the difference between $Я_{\text{desired}}$ and $Я_{\text{actual}}$ would be sufficiently large to conclude that the simulated strategy does not meet the desired resilience level. These hypotheses are found in Equation 3.14, the notation used by (Fenton and Neil 2013).

$$\begin{cases} H_0: & Я_{\text{desired}} - Я_{\text{actual}} \leq \varepsilon \\ H_1: & Я_{\text{desired}} - Я_{\text{actual}} > \varepsilon \end{cases} \tag{3.14}$$

In this study, $Я_{\text{desired}}$ is generated by TNORM (μ =0.85, σ^2 =0.01, LB=0, UB=1), and ε is set to 0.05, as represented in Figure 3.8.

For the example in Figure 3.8, it is found that with probability of 73.7%, the current port resilience strategy being analyzed may not necessarily need any urgent improvement actions to enhance resilience. However, with probability of 26.3% the port's resilience strategy should be improved.

3.5.6 Sensitivity Analysis

A useful means to examine the validity of an expert-built model is to perform sensitivity analysis, whereby it is possible to graphically analyze the greatest impact of a set of variables on a selected (target) node. To analyze the impact of causal factors of *Absorptive capacity*, we set the *Absorptive capacity* to be the target node, and the impacts of its factors are measured in term of conditional probability. The sensitivity analysis of *Absorptive capacity*'s factors is represented in Figures 3.9 and 3.10. From a purely visual inspection, we can think of the length of the bars in the tornado graphs as being the measure of the impact of that variable on absorptive capacity. Figure 3.9 illustrates the impacts of a set of selected nodes including reliability, maintenance, communication and coordination, skilled labor and management, extra cargo handling, and space utilization on the absorptive capacity when absorptive capacity is being "False". Figure 3.10 shows the impacts of those variables when the absorptive capacity is being "True." From these figures, it is obvious that reliability and space utilization have the greatest and lowest impact on the absorptive capacity, respectively. The formal interpretation is that the probability of adaptive capacity given the result of reliability goes from 0.649 (when reliability is “Fail”) to 0.899 (when reliability is “On”), shown in Figure 3.10. Despite the wide impactful range of reliability, the impact of space utilization is limited to narrow range, from 0.846 to 0.876. This implies that improvement in port reliability will have an impact on improving the absorptive capacity of port, while this impact would be negligible for utilizing the space of ports.

The sensitivity analysis of the lost capacity of cargo handling in respect to six contributors of port’s absorptive capacity is illustrated in Figure 3.11. Note that the lost capacity of cargo handling drastically drops when the state of reliability variable changes from Fail to On, which points out the high impacts of reliability on reduction of lost cargo facility, while the range of changes on lost capacity of cargo handling slightly varies for the space utilization variable which indicates the low impact of this variable on the loss of capacity of cargo handling.

Forward Propagation Analysis

A useful feature of Bayesian networks is the ability to propagate the effect of evidence through the network, referred to as “propagation analysis” (Fenton and Neil 2013). Forward propagation implies the propagation of an observed variable and measures its impact on the target variable. If there exists enough evidence that an observation occurs, then the observation can be entered into the model, and the probabilities of all unobserved variables can be updated. The junction tree algorithm (Jensen 1996) is used for propagation analysis, where the joint probability for the model from the Bayesian network’s conditional probability structure is calculated in a computationally efficient manner.

Four different forward propagation scenarios were designed, with results reported in Table 3.3. Four decision variables were chosen such that contributions were believed to be significant to the port resilience: *Maintenance*, *Backup utility system*, *Quick evacuation*, and *Restoration resource*. Variables were chosen to fall into each of absorptive (*Maintenance*, *Backup utility system*), adaptive (*Quick evacuation*), and restorative (*Restoration resource*) capacities.

The first scenario refers to the case when there observation is made that *Maintenance* is not successful (its “False” state), which eventually increased the lost capacity of cargo handling. In scenario 2, two failure events of *Maintenance* and *Restoration resource* are assumed, leading to a reduction recovered capacity due to the reduction in restorative capacity which eventually results in reduction of expected port’s resilience. Scenario 3 simulates the impacts of failures of *Backup utility system* and *Quick evacuation*, and results indicate that the reduction in restorative capacity has a larger adverse impact on resilience compared to adaptive capacity as the resilience value of Scenario 2 drops to 67% when the restoration resource fails, while in Scenario 3 this value reduces to 76% when quick evacuation is not successful. Scenario 4 accounts for failure of all four variables, dropping the expected resilience of the port to 55%. The results of observations generated by those aforementioned scenarios on absorptive capacity, adaptive capacity, restorative capacity and finally expected resilience of port are determined and summarized in Table 3.3.

A comparison of the forward propagation analysis scenarios 1, 3, and 4 is illustrated in Figure 3.12. The absorptive, adaptive, and restorative capacities of those four scenarios are visually illustrated in Figure 3.14. Figure 3.15 shows the comparison of the probability distributions of port resilience among scenarios 1, 3, and 4. We can conclude that the distribution of resilience is skewed to the left when adaptive and restorative capacities are reduced, suggesting that adaptive and restorative strategies are important to building resilience.

Two key results are gathered from the propagation analysis discussed above:

- Setting any contributor to the absorptive capacity to be “False” or “Fail” will reduce the “True” probability of absorptive capacity.

- Setting any contributor to the adaptive and restorative capacities to be “False” will reduce the “True” probability of absorptive and restorative capacity, respectively.

Backward Propagation Analysis

Backward propagation is another useful feature of Bayesian networks. In backward propagation, observation is made for a specific variable, usually a target variable (e.g., the resilience node in this study) and then the Bayesian network calculates the marginal probabilities of unobserved variables by propagating the impact of the observed variable through the network in a backward fashion. For example, if the resilience value is set to 90%, as shown in Figure 3.13, that the adaptive capacity should enhance from 82.75% to 85.47%% and the restorative capacity from 82.5% to 88.29% under such a scenario. Several analyses could be performed for different desired outcomes.

3.5.7 Concluding Remarks

The importance of resilience in the context of planning for infrastructure systems is inescapable. Infrastructure systems such as electric power, communication, and supply chains, among others, are dealing with different types of threats ranging from natural disasters to malevolent human-made events to accidents, and hence are required to be rigorously designed to withstand and recover from disruptions rapidly and efficiently. This is especially true of the components of an intermodal transportation network, including inland waterway ports.

In this paper, we relate the resilience capacity of an inland port to the three components of absorptive capacity (a means to withstand a disruptive event, or a reduction in vulnerability), adaptive capacity (a means to temporarily adapt to maintain performance), and restorative capacity (a means to restore performance in a long term manner, which with adaptive capacity constitutes recoverability). Various pre-disaster and post-disaster strategies can improve the three capacities to varying extents, all combining to improve the resilience capacity of the port.

We employ Bayesian networks to quantify the resilience capacity of an inland waterway network. Bayesian networks have the ability to combine historical data and expert knowledge, using calculation of prior and posterior conditional probability. Bayesian networks provide a rigorous tool for handling risks and decision making under uncertainty environments based on configuration of graphical framework. Although the Bayesian networks have been applied in a number of fields, their application to quantifying resilience is sparse. Our motivating example is the Port of Catoosa, among the ports along the Mississippi River Navigation System and located in Tulsa, Oklahoma.

The objective of this work is to provide an initial framework for studying resilience with a Bayesian network, highlighting areas for data or expert elicitation and demonstrating how sensitivity analyses can help guide and compare pre-disaster and post-disaster strategies for building resilience. Reports released by the National Cooperative Freight Research Program (NCFRP) (2014) highlight that many contributors to resilience are qualitative in nature (e.g., maintaining frequent communication and information flow, skilled level of port's labor and management, physical protection), rather than quantitative. Quantifying and assessing resilience from such qualitative variables are difficult when relying on the result of a mathematical optimization model, though such a task is relatively straightforward in a Bayesian network (when underlying variables are effectively assessed).

Bayesian network are also powerful tools for generating risk scenarios. Backward propagation scenario analysis is especially beneficial for the port authority in the sense that it gives insights to them which factors must be fortified significantly to achieve a specific level of resilience.

Table 3.1 Boolean expressions used to define posterior probability distribution of the Reliability and Maintenance variables

Variable name	Boolean expression	Meaning
Reliability	IF (TTF ≥ 7500, "On", "Fail")	If time to failure (closure/stoppage) of port is greater than or equal to 7500 hrs (expected time to failure), then port is reliable (On state), otherwise not (Fail state)
Maintenance	IF (on time repair scheduling ≥ 85% || Availability of spare equipment ≥ 85%, "True", "False")	If the probability of on time repair scheduling is greater than or equal to 85% AND the probability of availability of spare equipment is greater than 85%, then maintenance mission is successes (True state), otherwise not (False state)

Table 3.2 The conditional probability table for inbound and outbound cargo handling under DOC

	False	True
Absorptive capacity	TNORM (45000, 200, 0, 75000)	TNORM (69000, 150, 62000, 75000)

Table 3.3 Forward propagation analysis

Scenario	Maintenance	Backup utility	Restoration resource	Quick evacuation	Absorptive capacity	Adaptive capacity	Restorative capacity	Expected resilience	Failure events
1	F	-	-	-	0.56	0.83	0.83	0.81	One
2	F	-	F	-	0.56	0.83	0.40	0.67	Two
3	-	F	-	F	0.62	0.47	0.83	0.76	Two
4	F	F	F	F	0.43	0.46	0.40	0.55	Four

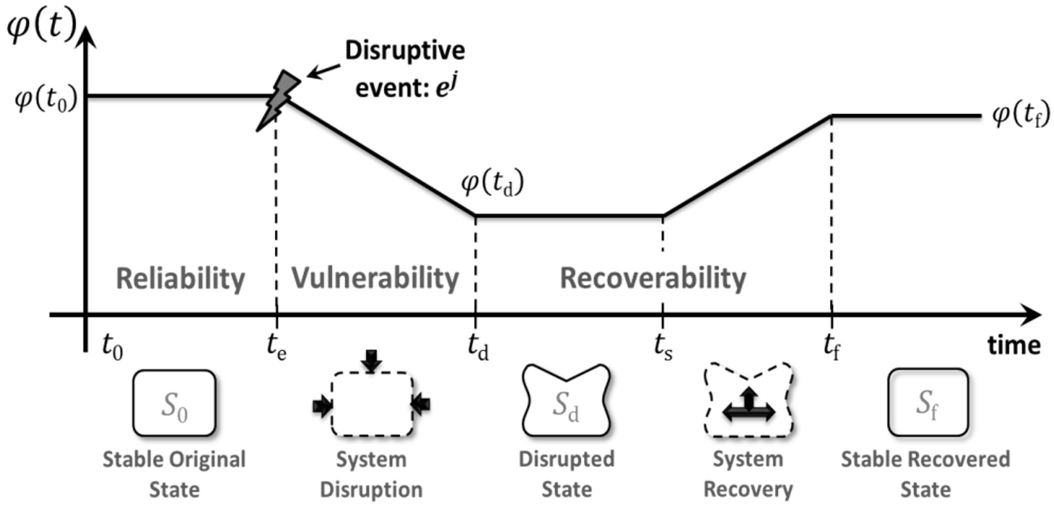


Figure 3.1 System performance and state transition to describe resilience (adapted from Henry and Ramirez-Marquez 2012)

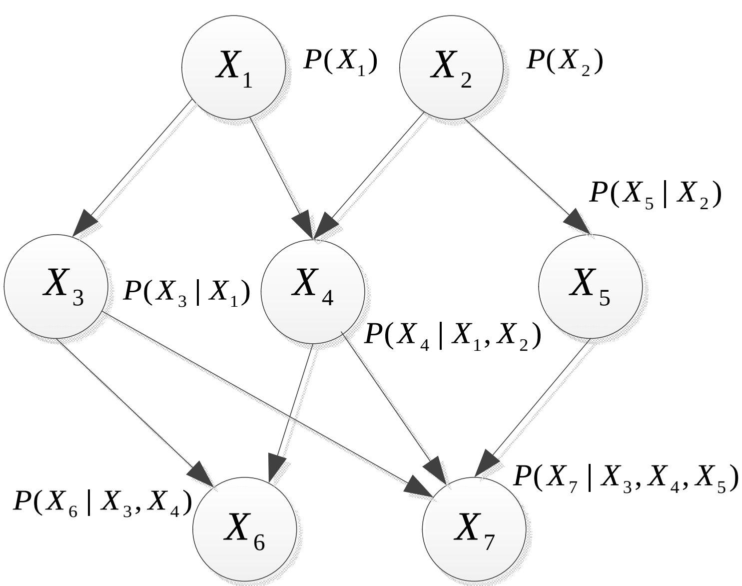


Figure 3.2 An example of BN with seven variables

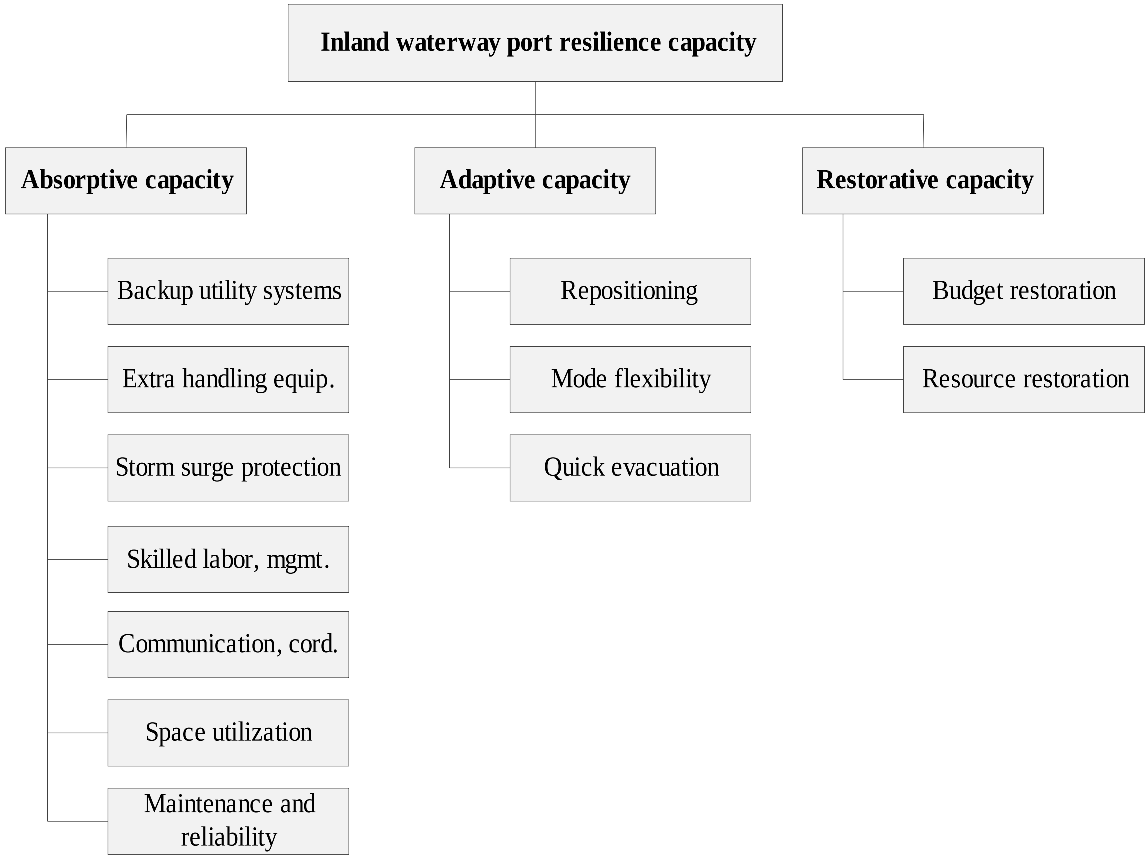
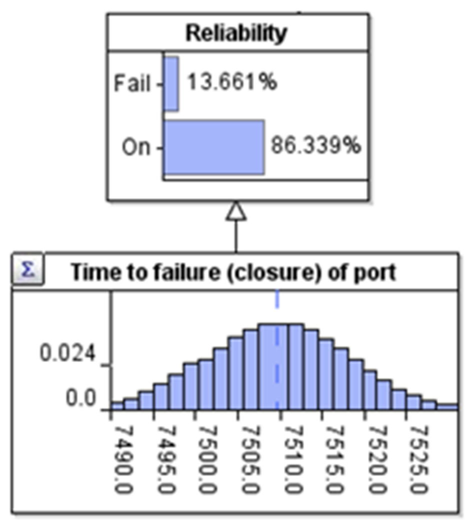


Figure 3.3 Resilience capacity characteristics of an inland waterway port

IF (TTF $\geq$ 7500, "On", "Fail")



TTF~TNORM (μ =7510, σ^2 =70, LB=0, UB=8200)

Figure 3.4 Calculating the value of Reliability at the port

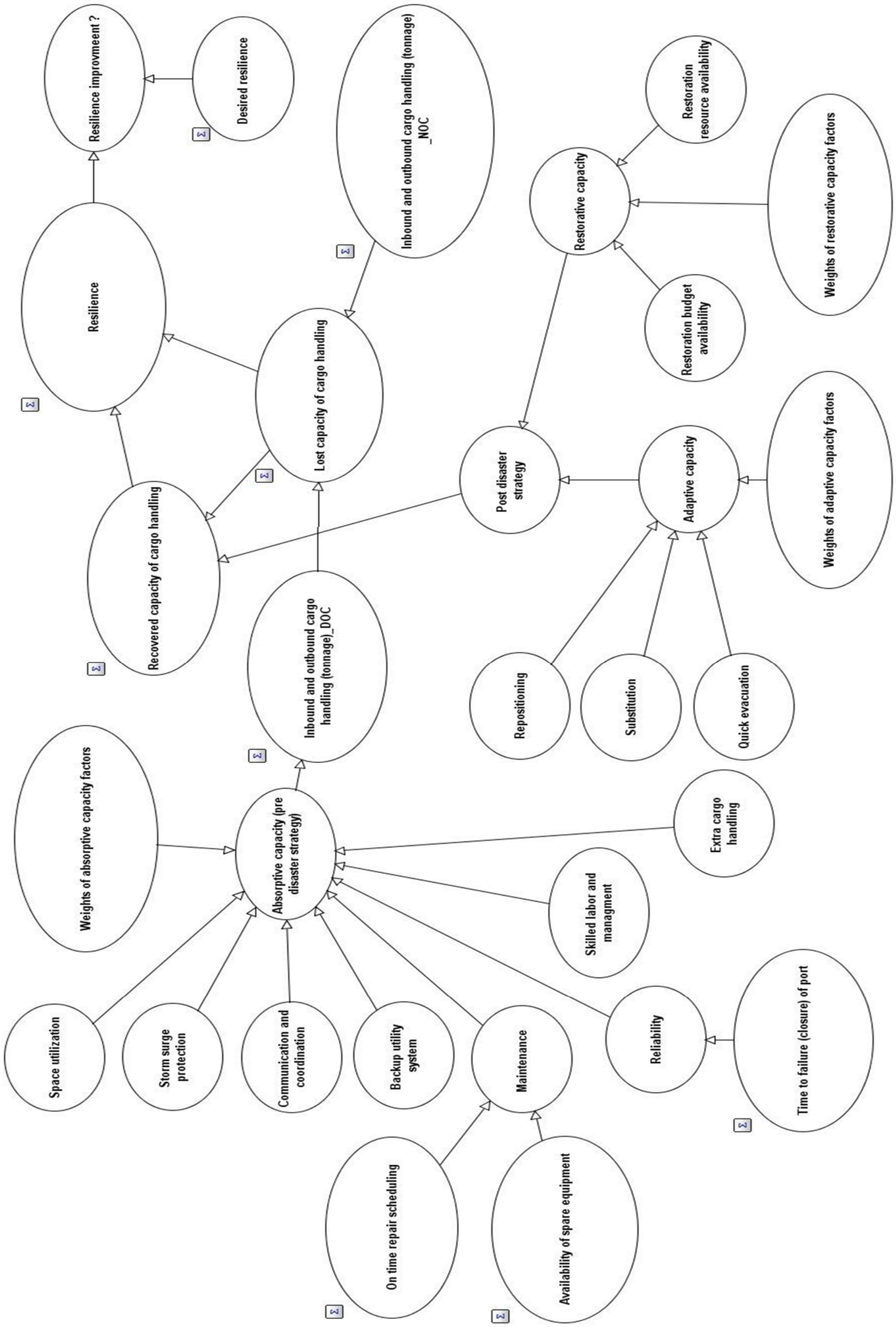


Figure 3.5 The graphical depiction of the proposed Bayesian network model

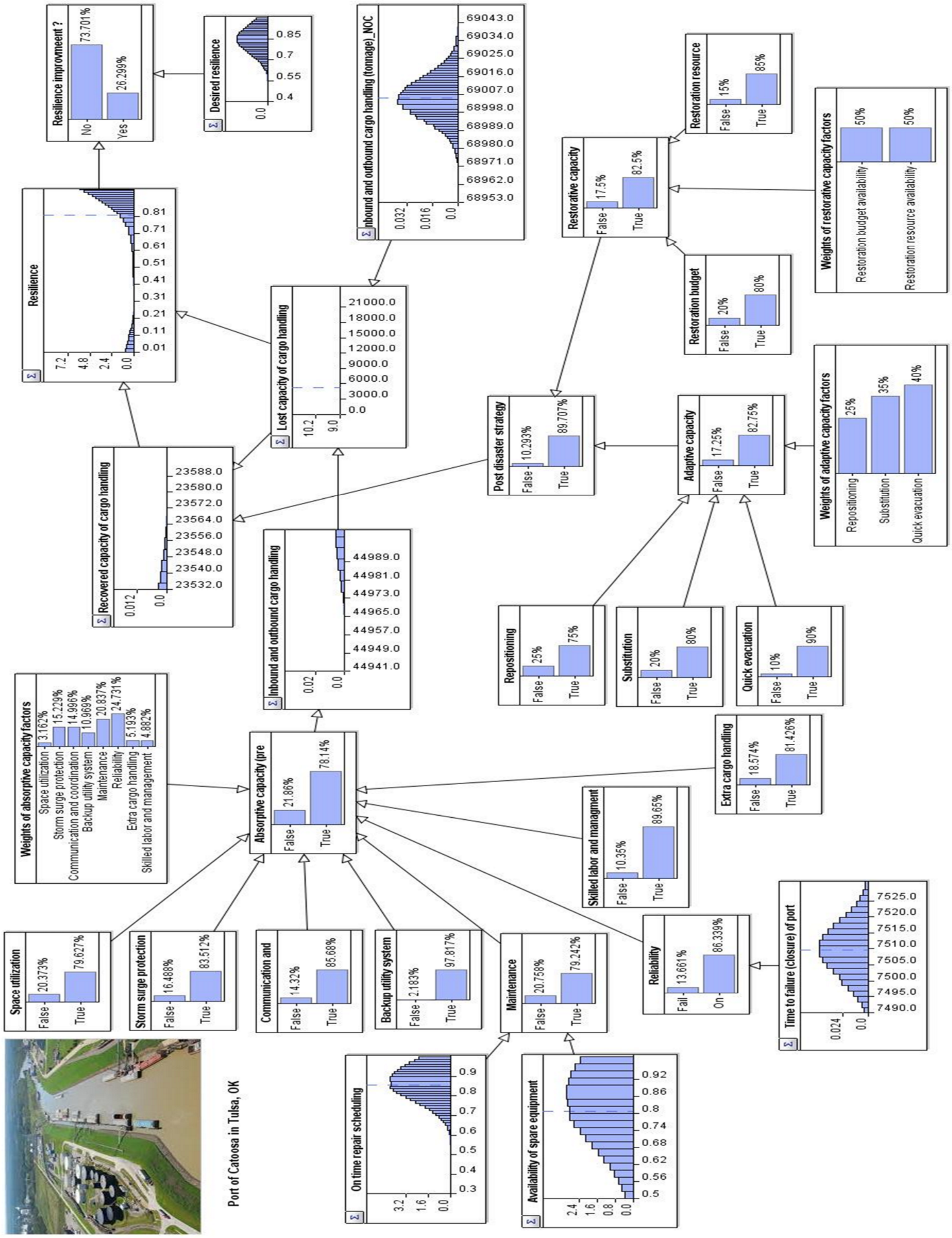


Figure 3.6 Baseline Bayesian network for measuring resilience

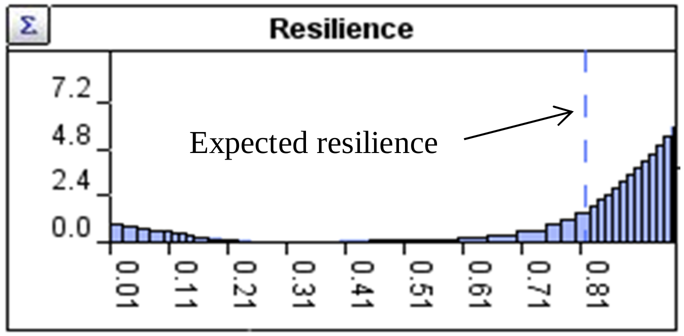


Figure 3.7 The resilience value measured for the baseline model

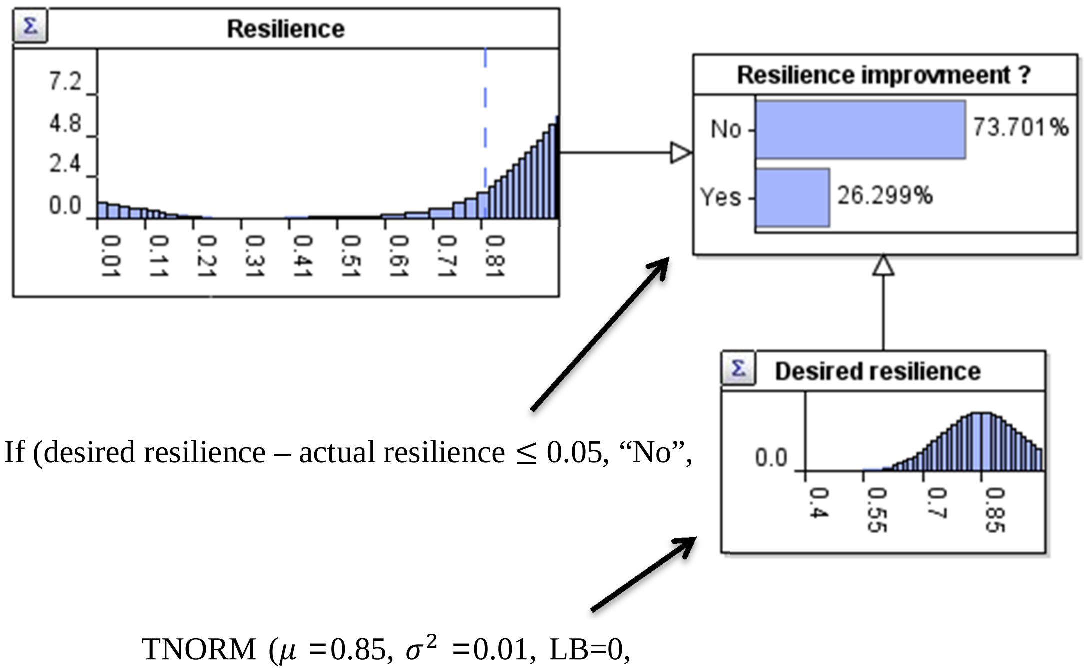


Figure 3.8 Hypothesis modeling through Bayesian networks to determine the efficacy of port resilience strategies

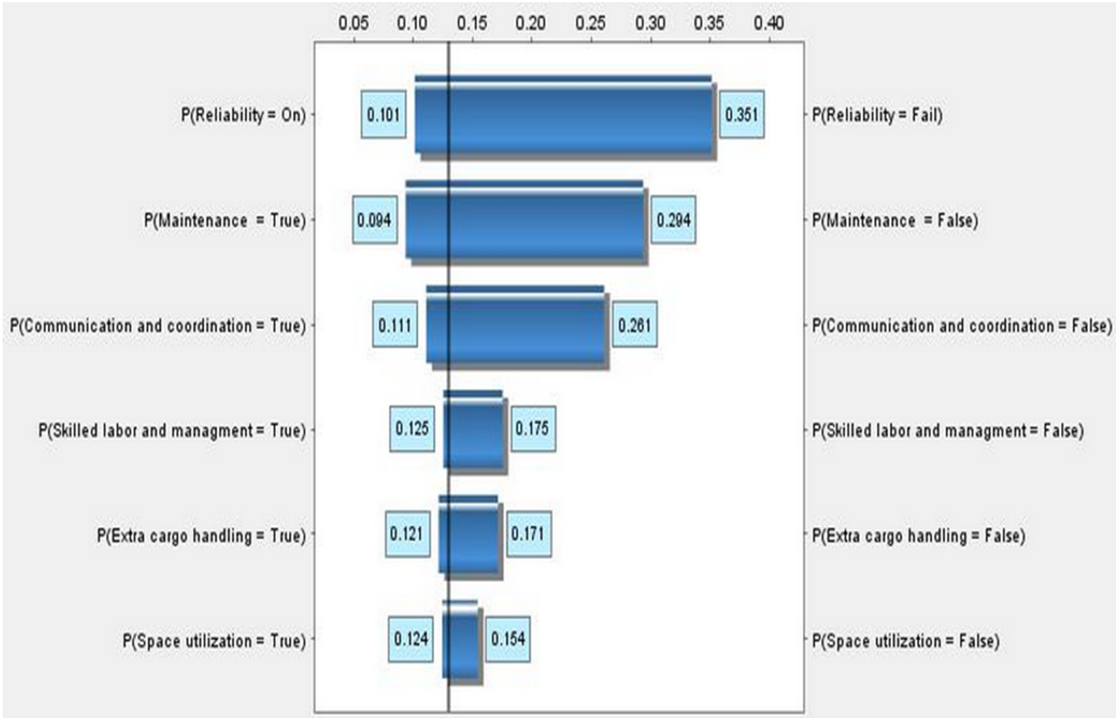


Figure 3.9 Tornado graph depicting the impact on several variables when Absorptive capacity is set to "False"

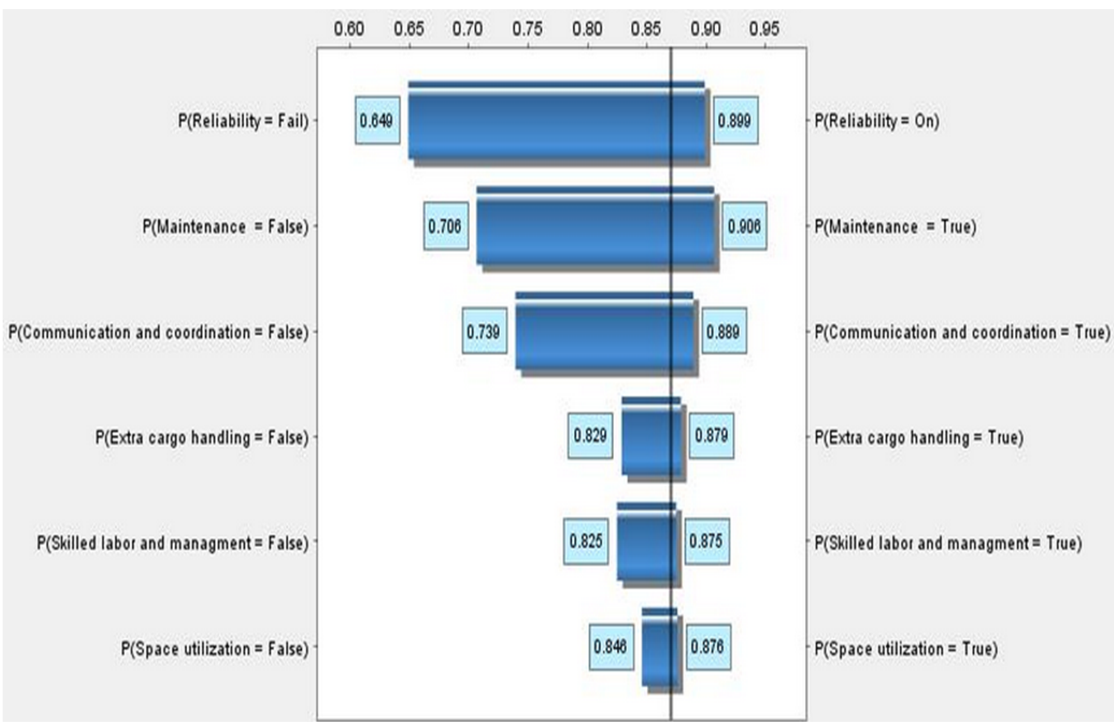
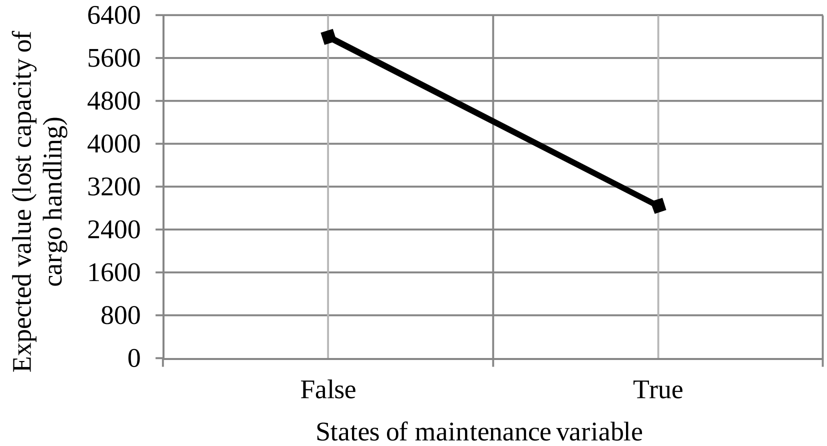
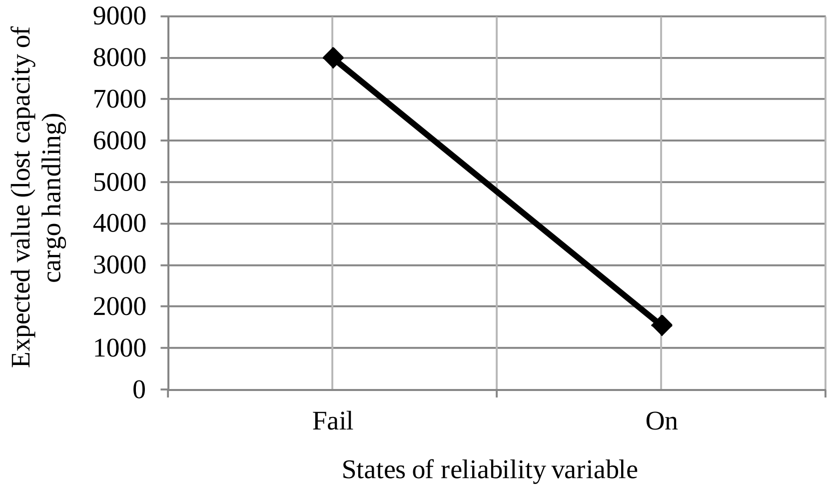


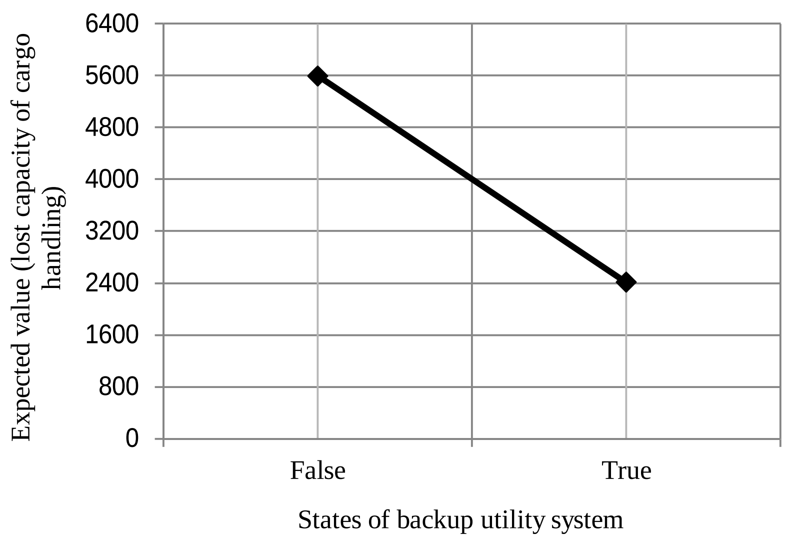
Figure 3.10 Tornado graph depicting the impact on several variables when Absorptive capacity is set to "True"



6400
5600
4800
4000
3200
2400
1600
800
0
Expected value (lost capacity of cargo handling)
False
True
States of maintenance variable



9000
8000
7000
6000
5000
4000
3000
2000
1000
0
Expected value (lost capacity of cargo handling)
Fail
On
States of reliability variable



6400
5600
4800
4000
3200
2400
1600
800
0
Expected value (lost capacity of cargo handling)
False
True
States of backup utility system

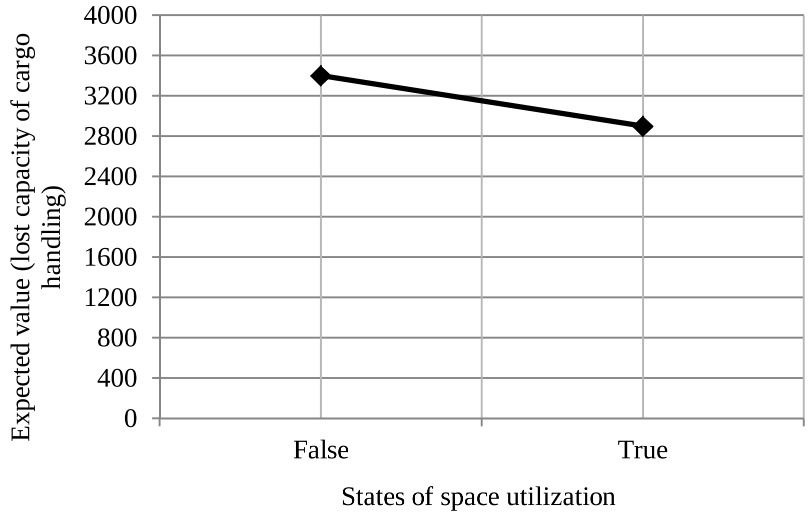


Figure 3.11 Sensitivity analysis of lost capacity of cargo handling with respect to six contributors to the port's absorptive capacity

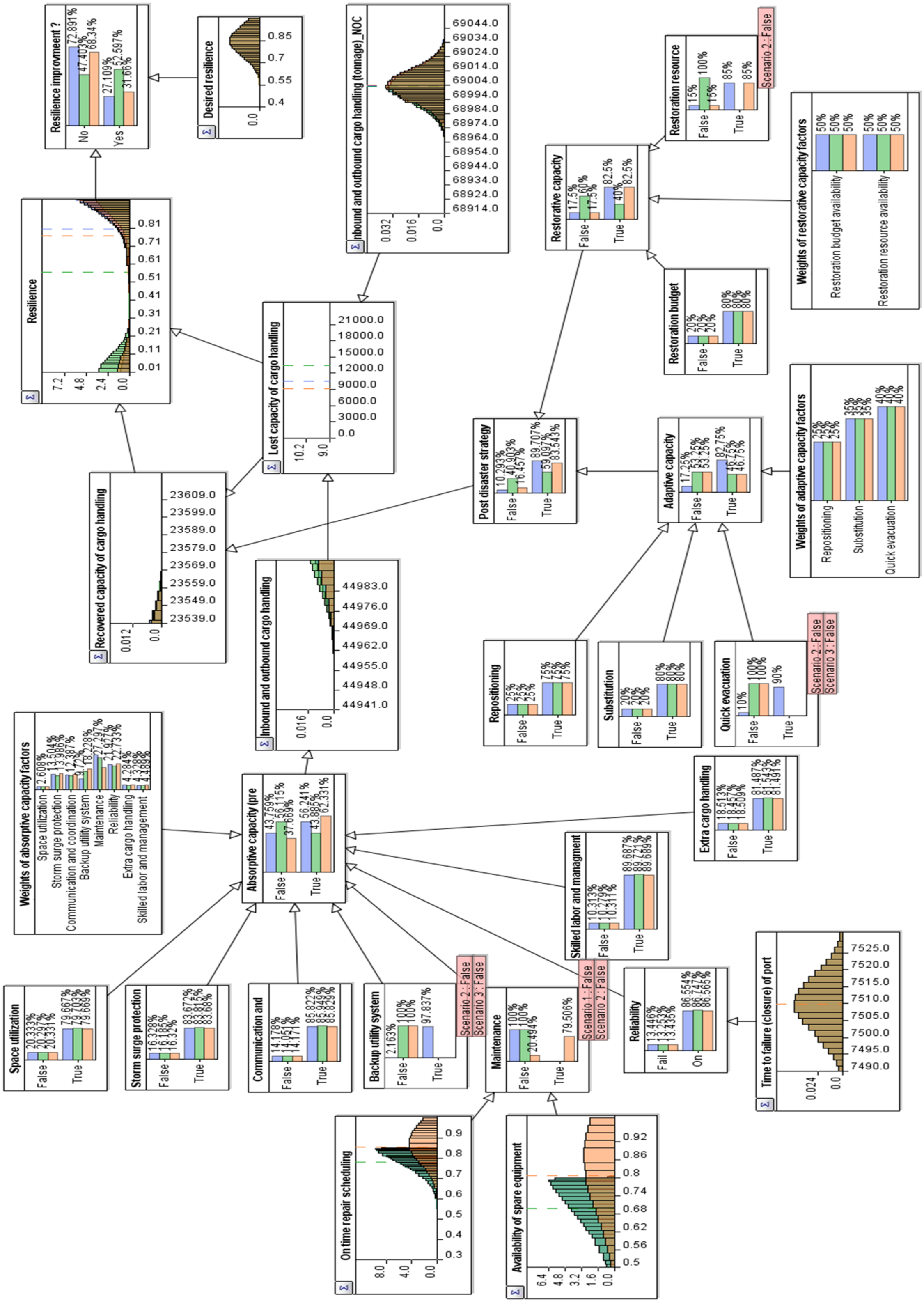


Figure 3.12 Forward propagation analysis for scenarios 1, 3, and 4

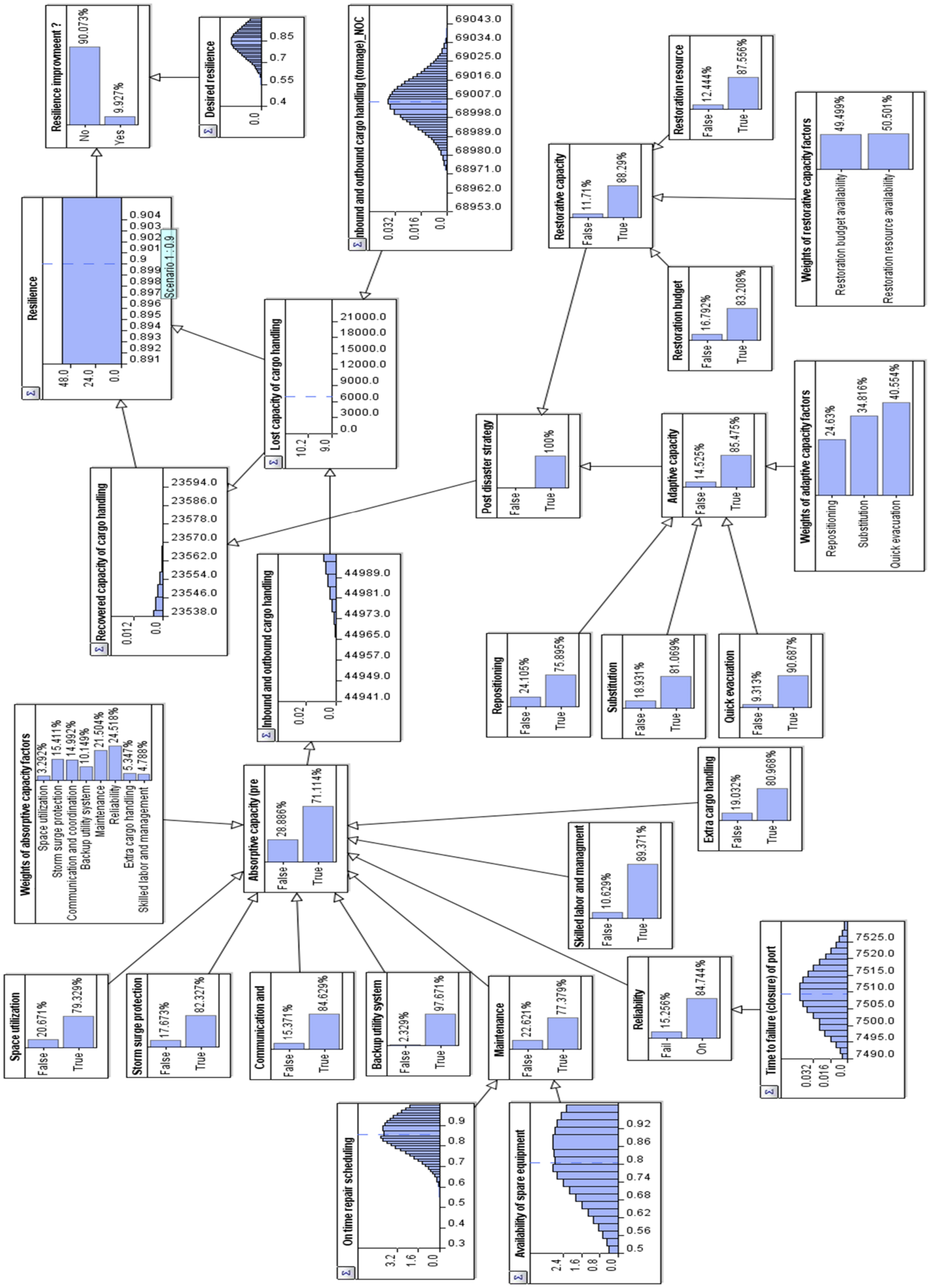


Figure 3.13 Backward scenario when the expected resilience is set to 90%

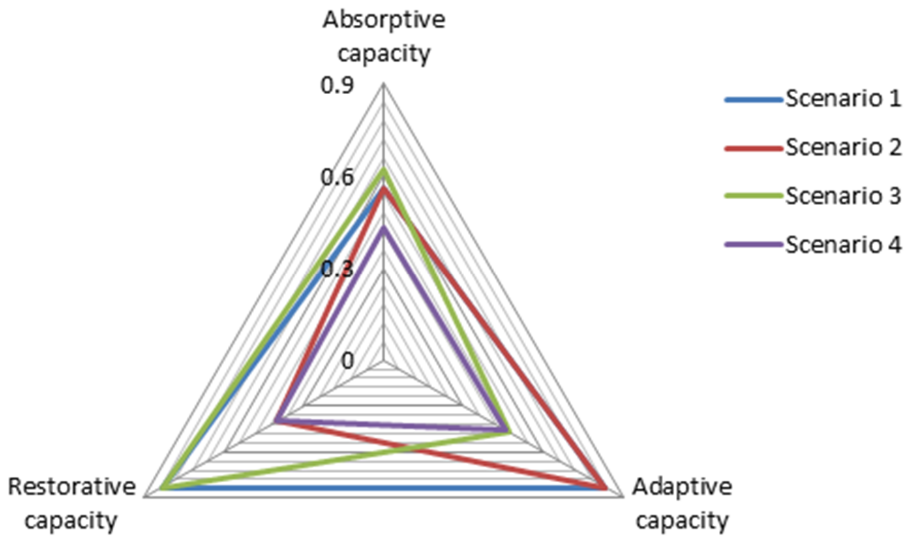


Figure 3.14 Radar chart for comparison absorptive, adaptive, and restorative capacities of four scenarios

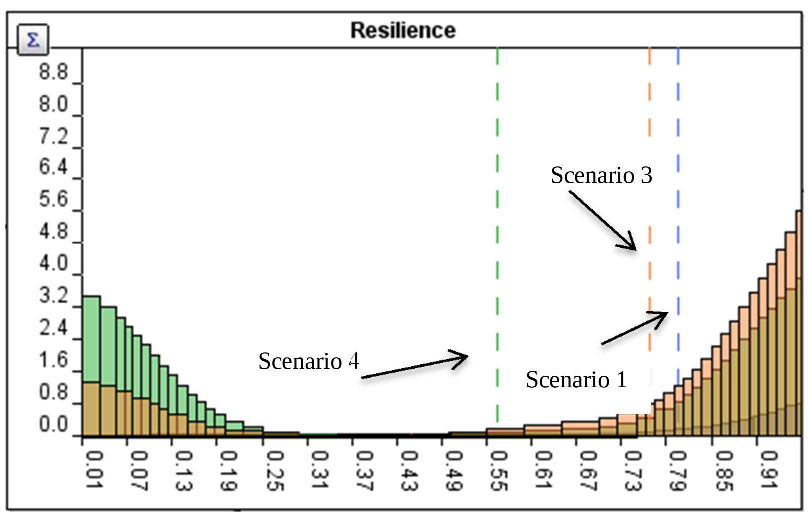


Figure 3.15 The comparison of resilience among scenarios 1, 3, and 4

CHAPTER

4

A BAYESIAN NETWORK MODEL FOR RESILIENCE-BASED SUPPLIER SELECTION[§]

ABSTRACT

Supplier selection is an important strategic decision in the context of supply chain management. Existing literature on the subject of supplier selection is focused on evaluating primary (e.g., cost, quality, lead time) and green (e.g., CO_2 emission, environmental practices) criteria. However, the concept of supplier resilience has recently emerged due to advent of competitive and global supply chains (and the operational and disruptive risks to which they are exposed). Several resilience-based supplier selection criteria are developed with respect to absorptive, adaptive, and restorative capacities. This paper further proposes a Bayesian network (BN), a paradigm that effectively models the causal relationships among variables but that has not been used in the context of supplier evaluation and selection, to quantify the appropriateness of suppliers across primary, green, and resilience criteria. Some benefits of the BN paradigm, including an ability to handle expert evidence and to perform sensitivity and

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propagation analyses, are demonstrated with an initial illustrative example of three suppliers.

Keywords: Resilience, Supplier selection, Bayesian Network

4.1 Introduction and Motivations

According to recent estimates (Beli 2010), the average U.S. manufacturer spends roughly half its revenue to purchase goods and services. As such, the choice of suppliers poses an important consideration for manufacturers as they have a large financial stake in how suppliers perform. And such a decision is made all along the supply chain, with ramifications to all members of the supply chain.

The supplier selection problem is a challenging multi-criteria decision problem that involves tangible and intangible factors (Ho et al. 2010). Gonzalez and Quesada (2004) highlighted the important role of suppliers in meeting the goals of a larger supply chain, particularly in achieving high quality products and customer satisfaction. The supplier selection problem aims to select the best supplier among a set of potential suppliers to satisfy certain requirements while subject to their limitations. Traditionally, supplier selection problems account for primary criteria including quality, cost, service level, and lead time, among others (Dickson 1966).

Given the recent (and perhaps more frequent) occurrence of large-scale disruptions in the form of natural disasters (e.g., earthquakes, tsunamis, floods) and man-made events (e.g., labor strikes, human errors, transportation mishaps), supplier selection criteria should also include the concept of supplier resilience. Resilience is often thought of as the ability of a system or organization to withstand the effects of a disruption and to recover to a desired level of performance in a timely manner.

The earthquake and tsunami that struck in Japan in March 2011 caused significant disruptions throughout the supply chains of many industries, leading to massive economic losses (MacKenzie et al. 2012). One significantly impacted industry was automobile manufacturing. Many of Toyota's part suppliers were unable to deliver parts at their expected volume and suffered from significant delays. General Motors was forced to halt the production of its vehicles due to the shortage of raw materials from Japanese suppliers (Huffington Post 2015). Nissan suffered greatly because of its high level of dependency on raw material suppliers in the earthquake zone that supplied about 12% of its engines (BBC News 2011), forcing Nissan to shut down production at its Sunderland, UK plant for several days (Massey 2011).

The adverse impacts of natural disasters on the suppliers of automotive parts are significant due to the size and complex nature of the automotive supply chain. A car consists of 20,000 parts on average, and if any one of those parts is unavailable, the finished product cannot be shipped. Many of the car's components, such as engines and transmissions, are supplied by Japanese companies located in regions affected by natural disasters (Business Theory 2011). Hence, segregation of suppliers geographically from disaster-prone areas could help suppliers to efficiently mitigate the effects of disruptions. For example, Toyota asked their suppliers to either spread production to multiple locations or hold extra inventory buffers as a mitigation strategy to withstand disruptions (Supply Chain Digest 2012). Nissan also asked the same of its suppliers, suggesting the importance of supplier segregation and extra buffer inventory to enhance the resilience of auto manufacturing suppliers. Electronics supply chains are also very similar to the automotive part supply chains where products such as desktop

PC, laptops, smart phones consist of hundreds of components that are commonly supplied by Japan (Monczka et al. 2014).

More recently, Hurricane Sandy struck New York and New Jersey, among other east coast U.S. states, in October 2012, causing the stoppage of normal daily operations of ports and resulting in massive economic losses. For example, the commercial trucking industry was halted due to the effects of the hurricane with losses of approximately $140 million per day (U.S. Department of Commerce 2013). This highlights the idea that designing robust protection strategies is not sufficient to withstand against disruptive events, especially large-scale natural disasters.

These recent events suggest that supply chain disruptions are inevitable and their adverse impacts to revenue and productivity can be significant. In general, risks associated with supply chains can be classified into two categories: *operational* and *disruption* (Tang 2006a). Operational risks refer to the inherent "every day" events that occur within a supply chain, including uncertainty in customer demand, transportation cost, and supply uncertainty due to operational problems such as power outages and technical equipment failures. Disruption risks refer to the major event-driven disruptions, including natural disasters, human-made accidents, or malevolent attacks. Disruption risks tend to be lower in likelihood but higher in adverse consequences compared to operational risks. Resilient suppliers are those that can withstand and recover from multiple sources of risk.

This work aims to develop a new decision approach for supplier selection based on Bayesian network theory, a power tool for handling risk and uncertainty in decision making with the capability of modeling both qualitative and quantitative variables

(Fenton and Neil 2013). Bayesian networks have been used for decision making in a variety of applications such as software development projects (Perkusich et al. 2015), data classification (Arizmendi et al. 2014), safety management (Hanninen et al. 2014), customer service management (Song et al. 2013), and traffic accidents (Hanninen 2014), among others. However, there appears to be no use of Bayesian networks for aiding the supplier selection process. We propose a Bayesian network formulation for supplier selection, accounting for operational (e.g., customer demand) and disruption (e.g., natural disaster) risks and their effect on resilient suppliers.

4.2 Literature Review

This work accounts for supplier selection criteria from three perspectives, defined here as *primary criteria*, *green criteria*, and *resilience criteria*. This section highlights literature dealing with primary and green criteria, as well as respective supplier selection problem formulations. A summary of recent literature on supplier selection and related methodologies is represented in Table 4.1.

4.2.1 Primary Criteria for Supplier Selection

Primary criteria are comprised of the common criteria used for decades in supplier selection, including cost, quality, lead time, and service level, among others. For example, Dickson (1966) introduced 23 supplier selection criteria still found in literature today. Kotula et al. (2015) investigated the supplier assessment criteria from multiple stakeholder perspectives specific to industry and country. They found that for the construction industry, quality, supplier relationship management, and profit were the important factors for evaluating suppliers, while for the electronics industry, quality, a sourcing strategy aligned with corporate goals, and supply flexibility were the most important ones.

Many supplier selection problems have been addressed with multi-criteria decision analysis tools that compare discrete supplier alternatives, including TOPSIS (Wang et al. 2009), VIKOR (You et al. 2015), ELECTRE (Sevkli 2010), and data envelopment analysis (DEA) (Toloo and Nalchigar 2011). Generally, these approaches provide a ranked order of alternatives (i.e., suppliers) given a set of weighted criteria, where weights are elicited through the analytic hierarchy process (AHP) or a similar approach. Fazlollahtabar et al. (2011) integrated AHP and TOPSIS for evaluate suppliers based on cost, quality, service, delivery, and innovation. You et al. (2015) applied the VIKOR method with interval 2-tuple linguistic information considering four criteria: technical capability, delivery performance, quality, and price. Liu and Zhang (2011) applied the ELECTRE III method for supplier selection considering technology available, service, management capability, and enterprise environment. Viswanadham and Samvedi (2013) considered lead time, cost, and quality performance with a fuzzy version of AHP and fuzzy TOPSIS. Hague et al. (2015) apply an interval-value TOPSIS approach with importance measure-driven weights to select suppliers based primarily on part reliability and maintainability. Memon et al. (2015) applied a combination of grey system theory and uncertainty theory for evaluating supplier criteria of quality, delivery capability, logistics service, and risk factors. Pitchipoo et al. (2015) also applied a grey decision model for supplier assessment and selection in the process industry where cost, delivery, capacity and warranty of potential suppliers were evaluated. Yucenur et al. (2011) considered quality, cost, and risk with AHP and analytical network process (ANP) approaches under a fuzzy environment. Saghiri and Barnes (2016) addressed the relationship between supplier flexibility and postponement as a strategy for managing demand under uncertainty through an empirical analysis.

Mathematical programming formulations have also been developed for the supplier selection problem. Jadidi et al. (2014) proposed a goal programing approach for multiobjective joint supplier selection and order allocation. Ustun and Demitras (2008) integrated ANP and multi-objective mixed integer linear programming for selection of suppliers with consideration of finance, quality, delivery, customer relationships, service, and risk. Sawik (2010) introduced a mixed integer programming formulation to consider supplier finance, quality, delivery, management, and organization. Karimi and Rezaeinia (2014) introduced a multi-segment goal programming approach accounting for four primary criteria including warranty, price, delivery, and service satisfaction. Mohammaditabar et al. (2016) developed a game theoretic analysis for capacity-constrained supplier selection to analyze selected suppliers and agreed-upon prices in decentralized supply chains. Other recent work related to primary criteria for supplier selection includes those by Rezaei and Davoodi (2011), Zhang and Zhang (2011), and Zhang et al. (2016).

4.2.2 Green Criteria for Supplier Selection

The threat of increased greenhouse gas emissions has led some governments to impose stricter regulations and standards. These requirements, as well as environmental consciousness on the part of industry decision makers, have led to green considerations in doing business, including supplier selection. There has been a recent increase in supplier selection work that addresses both primary and green criteria.

Lee et al. (2009) extended a fuzzy AHP approach for green supplier selection with five primary criteria (quality, finance, organization, technology capability, and service) and four green criteria (total product life cycle cost, green image, pollution control, and environmental management). Hashemi et al. (2015) proposed an a grey relation analysis and ANP for green supplier selection, accounting for primary criteria of cost, quality, and technology and green criteria of pollution production, resource consumption, and management commitments. Huang and Keskar (2007) applied AHP with carbon footprint considerations, along with finance, delivery, service, and organizational performance. Zhang et al. (2013) developed a nonlinear multi-objective optimization model for green supplier selection that accounted for prolusion emitted by gasoline consumption during transportation, cost, delivery rate, transportation time, and service level, solved with a Pareto genetic algorithm. Akman (2015) integrated fuzzy *c*-means and VIKOR methods to evaluate green suppliers based on green design, pollution prevention, green image, green capability, and environmental management. Kumar and Jain (2010) developed a DEA model considering carbon footprint monitoring. Mahdiloo et al. (2015) also applied DEA considering technical and environmental criteria, referred to as an eco-efficiency measurement. Theiben and Spinler (2014) evaluated the efficiency of green suppliers based on their CO_2 emission level using ANP. Tsui and Wen (2014) proposed a hybrid multi-criteria decision making approach by integrating AHP, ELECTRE III, and the linear assignment method to prioritize suppliers considering safety and health, air pollution, recovery, and strategic fit. Kuo et al. (2014) developed a carbon footprint inventory route model based on the vehicle routing problem. More literature related to green criteria in supplier selection can be found in Nielsen et al. (2014), Palak et al. (2014), and Banaeian et al. (2015).

4.3 Development of Resilience Supplier Selection Criteria

The ability to withstand, adapt to, and recover from a disruption is generally referred to as *resilience*, a definition with which many would largely agree (Haimes 2009, Aven 2011, Barker et al. 2016). Resilience is a concept that is increasingly gaining traction in government, industry, academia, and popular science (Park et al. 2013, Zolli and Healy 2013, Hosseini et al. 2016).

Resilient supply chain practices have been a well-studied topic for the last decade or so. Particularly in a supply chain context, Sheffi (2005) defined the resilience of a firm within a supply chain as its inherent ability to maintain or recover its steady state behavior, thereby allowing it to continue normal operations after a disruptive event. Rice and Caniatio (2003) highlighted that supply chain resilience in the upstream level could be enhanced with the multiple-sourcing of suppliers, sourcing strategies to allow switching of suppliers, and commitment to contracts for material supply. Christopher and Peck (2004) emphasized that developing visibility to a better view of upstream inventories and supply conditions would positively contributes to the resilience of supply chain context, while Tang (2006b) pointed out the importance of flexible supply base (sourcing).

However, in contrast to the extensive work to explore the role of primary and green criteria in the supplier selection problem, accounting for the concept of resilience in supplier selection is relatively new and with no consensus on factors contributing to the resilient characteristics of suppliers. Rajesh and Ravi (2015) proposed a grey relational analysis method for selecting suppliers considering vulnerability, collaboration, risk awareness, supply chain continuity management for selection of resilience suppliers. Torabi et al. (2015) developed a two-stage stochastic programming model to solve a resilient supplier selection and allocation problem under operational and disruption risks. They account for four resilience-building strategies including supplier's business continuity plans, extra inventory maintained by the supplier, fortification of suppliers, and contracting with backup suppliers. Sawik (2013) investigated the problem of resilient supply portfolio, including the pre-positioning of emergency inventory as a primary strategy to mitigate the effects of a disruption, using a mixed integer programming model using concepts from value-at-risk and conditional value-at-risk. Sawik (2016) proposed a risk-averse optimization model in the presence of a supply chain disruption with two different service levels measures: the expected worst-case demand fulfilment rate and the expected worst-case order fulfillment rate with consideration that suppliers are geographically dispersed. The findings suggest that the worst-case order fulfillment results in a higher service performance than the worst-case demand fulfilment. Haldar et al. (2014) proposed a fuzzy group decision making approach for resilient supplier selection where the importance degrees of supplier attributes are expressed in terms of linguistic variables.

Vugrin et al. (2011) defined the resilience capacity of a system as a function of the absorptive, adaptive, and restorative capacities of the system, clearly identifying pre-disruption and post-disruption planning. We make use of this concept of *resilience capacity* and its three dimensions to explore the factors contributing to a resilient supplier in the supplier selection problem.

Absorptive capacity is the extent to which a system (or a supplier in the context of this study) is able to absorb shocks from disruptive events, implying proactive planning for resilience or the development of pre-disaster strategies that can be considered as a first line of defense. Absorptive capacity can be viewed as being endogenous to the system (Vugrin et al. 2011). It is similar to the concept of inherent resilience described by Rose (2009) as the "ordinary ability to deal with crises." Features of absorptive capacity in the context of supplier selection are proposed here.

Geographical segregation: Segregation or separation of a supplier geographically from natural disasters can reduce the likelihood of adverse impacts on the supplier if the disaster occurs. Alluded to previously in the discussion of automakers after the Japanese earthquake and tsunami, Nissan and Toyota requested that their part suppliers establish facilities that are geographically separated from disaster prone areas. Note that not only should the location of suppliers be segregated from natural disasters but also the location of suppliers in a multi-sourcing supply chain network (Vugrin et al. 2011).

Surplus inventory: Although maintaining more on-hand inventory may increase holding costs, it can also enhance the ability of the supplier to absorb a disruptive event. Note that pre-positioned inventory levels are restricted by space availability. Torabi et al. [2015] discussed that pre-positioning extra inventory can enhance the resilience of a supplier. Turnquist and Vugrin (2013) developed a stochastic model for design of resilience in infrastructure distribution networks, and they treat extra inventory as a feature of absorptive capacity in a distribution center. Little (2005) suggests that New York City's recovery following the terrorist attacks of September 11, 2001, would have been hampered had more organizations taken an inventory reduction (e.g., just-in-time) philosophy.

Backup supplier contracting: A disrupted supplier may contract with a backup supplier to fulfill manufacturer orders. Such a contract is assumed to be in place prior to a disruption. Contracting with a backup supplier can be viewed as a form of redundancy, a common absorptive capacity enhancement philosophy in my infrastructure systems (Vugrin et al. 2011).

Physical protection: Physical protection and facility safety can reduce the initial impact of disruptive consequences. Physical protection refers to the security of supplier's facility from disruptive events that could cause serious losses or damage to a supplier's facility. To protect from attacks, this could include security cameras, or for natural disasters, a form of physical protection is system hardening. Hosseini and Barker (2016) define physical protection strategies for inland waterway port infrastructure as a form of absorptive capacity.

Adaptive capacity is the extent to which a supplier can adapt itself after a disruption to minimize adverse consequences on the performance of system. Adaptive capacity is considered to be a second line of defense against disruption as a part of a temporary post-disaster strategy.

Rerouting: Redundant transportation usually allows supplier to use nonstandard, but more expensive, rerouting options if the original transportation mode is disrupted. A recent example of rerouting through a different transportation mode occurred when a drought on the Mississippi River caused a considerable portion of the waterway to be unusable by barges (National Geographic News 2013). Shipping companies were forced to lighten their load or switch to railway or highway modes suitable for long distance bulk transportation.

Restorative capacity is the extent to which a supplier is able to recover permanently from disruption. Restorative capacity differs from adaptive capacity in that restorative strategies are longer term in nature. Restorative capacity can be thought of the last line of defense against disruption. In cases where the impact of extreme event is significant, the supplier's facility site may be disrupted partially or entirely. The supplier's facility site or equipment needs to be repaired to fully recover to its normal operating conditions in a permanent way. Hosseini and Barker (2016) highlighted the restoration budget and technical resource restoration as the main factors of restorative capacity of long-term recovery for inland waterway port infrastructure.

Restoration budget: Monetary capital is typically required for a supplier to restore its productivity. Therefore, restoration could be hampered by a lack of budget resources.

Technical resource restoration: The capability of a supplier to restore its damaged equipment and facilities is dependent on the availability of equipment resources (e.g., repair vehicles) and human resources (e.g., repair crews).

4.4 Background of Bayesian Networks

Bayesian networks (BNs), structured based on Bayes' theorem for calculating conditional probabilities, are power tools for handling risk assessment and decision making under uncertainty (Fenton and Neil 2013). BNs have been widely used as a decision support tool in a diverse set of application domains such as risk analysis (Song et al. 2013, Khanzad 2015), safety management (Hanninen et al. 2014, Wu et al. 2015), and reliability engineering (Cai et al. 2012, Liu et al. 2015), among others, including some initial work in modeling infrastructure resilience (Hosseini and Barker 2016). BNs are popular method of modeling uncertain and complex domains (Uusitalo 2007) and are capable of integrating different sources of information such as observed data and expert judgment. As BN models focus on the relationship between information and uncertainty with action, the consequences of various management decisions can be studied through BNs (Uusitalo 2007). Unlike black-box models (e.g., neural networks and certain other statistical learning approaches), there are no hidden variables in the BN model. Further, BNs can handle both types of qualitative and qualitative variables. More details about advantages of BNs can be found in Uusitalo (2007) and especially (Fenton and Neil 2013) for risk applications.

BNs graphically describe networks of causes and effects using a set of variables (nodes) and a set of causal relationships (edges) that exist among the variables. The causal relationship between variables can be expressed in terms of conditional probabilities. BNs are capable of encoding both qualitative (low/medium/high), Boolean (yes/no, true/false), or continuous variables. Data describing these variables can come from historical data, expert knowledge, or a combination of the two.

From a mathematical standpoint, BNs are acyclic graphs with a set of variables (nodes), represented by $V = \{X_1, X_2, \dots, X_n\}$, and a set of edges whose structure determines interdependencies among variables. An outgoing edge from X_i to X_j indicates a relationship that value of variable X_j is dependent of the value of X_i. Further, if there is an outgoing edge from X_i to X_j, then X_i is the *parent node* of X_j, and X_j is a *child node* of X_i.Three classes of nodes exist in BN: (i) nodes without a child node are called *leaf nodes*, (ii) nodes without a parent node are called *root nodes*, and (iii) nodes with parent and child nodes are called *intermediate nodes*. For example, in Figure 4.1, nodes X_1 and X_2 are root nodes, X_3 and X_4 are intermediate nodes, and X_5 is a leaf node.

The causal relationship among variables of a BN can be measured through conditional probability distributions. The full joint probability distributions of the BN given in Figure 4.1 can be expressed in Equation 4.1, which can be thought of as a representation of the topology of the BN and dependencies among variables. In the example above, two priori probabilities, $P(X_1)$ and $P(X_2)$, and three conditional probabilities,$P(X_3|X_1)$, $P(X_4|X_2, X_3)$, and $P(X_5|X_4)$, must be defined. Each variable (node) is associated with a node probability table, or NPT, which lists the probability of the occurrence of a realization of a variable given the values of other variables. NPTs contain probability information that underpins the structural relationship in a model.

$$P(X_1, X_2, X_3, X_4, X_5) = P(X_1)P(X_2)P(X_3|X_1)P(X_4|X_2, X_3)P(X_5|X_4) \tag{4.1}$$

The joint probability distribution can be used for calculating the probability of an individual variable in a BN. Suppose that we are interested in calculating X_3, then $P(X_3)$ can be written with Equation 4.2 using marginalization.

$$P(X_3) = \sum_{X_1, X_2, X_4, X_5} P(X_1)P(X_2)P(X_3|X_1)P(X_4|X_2, X_3)P(X_5|X_4) \tag{4.2}$$

Marginalization is a distributive operation over combinations of local joint probabilities, meaning that we can marginalize the global joint probability by marginalizing local NPTs (Fenton 2013). In the example given in Figure 4.1, the marginalization of $P(X_3)$ consists of factors in Equation 4.3. More details about the technical aspects of marginalization, among other topics related to Bayesian networks, can be found in Fenton (2013).

$$P(X_3) = \left(\sum_{X_1} P(X_1)P(X_3|X_1)\left(\sum_{X_4}\left(\sum_{X_2} P(X_4|X_2,X_3)P(X_2)\left(\sum_{X_5} P(X_5|X_4)\right)\right)\right)\right) \tag{4.3}$$

Note that Equation 4.1 to 4.3 hold true when all the variables in the BN are binary (e.g., True/False). In fact, the theory of BN discussed above can be expressed in terms of binary variables, but in many real case studies such as the one studied in this paper, different type of variables, including continuous and fixed variables, must be taken into account.

4.5 Proposed BN for Supplier Evaluation and Selection

BNs provide flexibility to construct the causal structure based on expert judgment, an important trait when evaluating the performance of suppliers as a function of some available data but also expert knowledge about supplier behavior and the conditional dependencies among variables related to supplier performance. The proposed BN in this study is used for evaluating the performance of candidate suppliers in terms of primary, green, and resilience criteria to eventually guide the selection of the best supplier. The primary steps of model development include: (i) identification of model variables that contribute to the supplier selection problem, and then (ii) building the causal model structure based of conditional dependencies among those variables. The proposed general framework for supplier selection is illustrated in Figure 4.2. As shown, the target variable is *Supplier evaluation*, which is conditioned on primary, green, and resilience criteria variables (derived from Sections 2 and 3), as well as a *Weighting factor* that captures the importance of each criterion.

The supplier selection model, the complete BN for which is depicted in Figure 4.8, was built using the AgenaRisk BN tool (AgenaRisk 2005). AgenaRisk supports standard discrete, labelled, and continuous state variables approximated using dynamic discretization (Fenton et al. 2010). There are four types of variables used in the proposed BN model:

1. Boolean variables (BVs) have a binary response whose two states of True and False are used to represent positive and negative outcomes, respectively.
2. Continuous variables (CVs) capture uncertainty associated with a variable that can take on continuous realizations via a probability distribution.
3. Fixed variables (FVs) represent a variable whose value is constant.
4. Labelled variables (LVs) can have a number of discrete states.

These variables are explained subsequently in the context of a particular supplier, referred to as Supplier 1. The parameters of the variables will change from supplier to supplier for the ultimate purpose of assessing each supplier to allow for their comparison.

4.5.1 Modeling Primary Criteria

The primary criterion, defined by a Boolean variable for which a probability measures whether criterion is met (True) or not (False), is measured as a collection of *Delivery robustness*, *Quality of products*, *Service*, and *Total costs* variables. The relationships among these variables and depicted in Figure 4.5.

4.5.1.1 Delivery Robustness

The ability of the supplier to meet the predefined delivery schedule is an often-used criterion for supplier selection (Mwikali and Kavale 2012). The supplier must be able to respond to the customer order with short lead time. Lead time is defined with a truncated normal distribution (TNORM) as shown by Equation 4.4 and depicted in Figure 4.3. Assume Supplier 1 has an expected lead time for delivery of raw materials of sixteen days with a variance of 1.5 day. The shortest and longest lead time are 1 day, denoted by LB (lower bound) and 12 days, denoted by UB (upper bound), respectively. These data can be obtained through empirical observation over a specified time period. The *Delivery robustness* variable is conditioned on response rate and lead time as represented in Figure 4.3.

$$\text{Lead time} \sim \text{TNORM}\ (\mu{=}16\text{ day}, \sigma^2{=}1.5\text{ day}, \text{LB}{=}1, \text{UB}{=}12) \qquad (4.4)$$

Note that TNORM is an extension of the normal distribution in which occurrences are bounded to values that lie within a specified range (Burkardt 2014). TNORM is an appropriate distribution to use when the data are normally distributed on a finite range. TNORM can be presented by four parameters: mean, average, lower bound, and upper bound respectively.

The response rate, or the ratio of satisfied ordered items of product to ordered items of product (Rezaei and Davoodi 2011), is also modeled with a truncated normal distribution shown in Equation 4.5. For Supplier 1, the mean response is 94%.

$$\text{Response rate} \sim \text{TNORM}\ (\mu{=}0.94, \sigma^2{=}0.01, \text{LB}{=}0.87, \text{UB}{=}1) \qquad (4.5)$$

A Boolean expression is used to calculate the probability of successful *Delivery robustness*, as represented in Table 4.2. The Boolean expression defines the probability of *Delivery robustness* being True when the lead time is less than 10 days and response rate is at least 90%. Maximum allowable and minimum acceptable response rates (10% and 90%, respectively) are values determined by the manufacturer who receives the raw materials. Note that the probability of *Delivery robustness* being true reduces if the lead time threshold is shorter and the response rate threshold approaches 1. A schematic representation for modeling of delivery robustness variable is illustrated in Figure 4.4. Note that the prior probability of response rate and lead time can be obtained by fitting appropriate distribution to the historical data, or in the cases which a little data are available, expert judgements can be incorporated (Constantinou et al. 2016).

4.5.1.2 Quality of products

The quality of delivered raw materials or products has been an important factor in the selection of suppliers in many studies (Fazlollahtabar et al. 2011, Chai and Ngai 2015, Chan and Chan 2010). The likelihood that items from a supplier are of sufficient quality, as measured by True or False states, is conditioned on the probability of the product being faulty during inspection by the manufacturer. The NPTs of these two variables are described in Table 4.3 for the illustrative Supplier 1.

4.5.1.3 Service

A supplier's service level is defined as all those activities provided by the supplier to enhance or augment the product and have value for the buyer, thus increasing customer satisfaction and better relationship between supplier and manufacturer (Donaldson 1994) and is a commonly used criterion in supplier selection (Mwikali and Kavale 2012). Fazlollahtabar et al. (2011) considered after-sales service and technical support as attributes of service level for the selection of best supplier, and these characteristics are also used in this study. The NPTs for the *Service* variable and its prior nodes (technical service and after-sale service) are represented in Tables 4.4 through 6 for Supplier 1.

4.5.1.4 Total Costs

Supplier costs are perhaps the most common criterion in the supplier selection problem (Ho et al. 2010, Lee et al. 2009, Fazlollahtabar et al. 2011). The total costs of a supplier are represented here as the sum of order cost, total transportation cost, purchase cost, and tardiness penalty cost. The NPT for total cost variable is represented in Table 4.7. The NPT suggests that the Boolean variable for cost is acceptable below some budget value, which is $127,000 for this illustrative example.

From Figure 4.5, the probability of total costs of the first supplier being True (satisfactory) is about 56% while the probability of about 44% is False (unsatisfactory). The components of total cost of the supplier are: (i) *Order cost*, a constant in Figure 4.5, set at $45 for Supplier 1 in this example, (ii) *Purchase cost*, the multiplication of the purchase cost per item and the number of purchased items, where the purchased cost per item is a constant set to $125 in this example and the number of items purchased from the supplier is dependent on customer demand and capacity of supplier whose NPTs are shown in Table 4.8, (iii) *Tardiness penalty cost*, a penalty for delayed delivery that is assigned if the actual order completion time is beyond its expected due time as calculated in the NPT is found in Table 4.9, and (iv) *Total transportation cost*, calculated as the sum of fixed and variable transportation costs.

4.5.1.5 Primary Criteria for variable

The posterior probability of the primary criteria variable being either True or False depends on the probability of its prior variables: delivery robustness, quality of products, service, and total cost. One way to model the NPT for the primary criteria node is similar to that of the service variable, represented in Table 4.6. However, the

NPT for the service variable requires only eight entries since it is conditioned on only two variables, but as the primary criteria variable has five Boolean variables (and thus $2^5 = 32$ entries), its calculation can be tedious and error prone. Moreover, many of those 32 entries may be unnecessary as the effects of the parent nodes on the child node may be essentially independent. The NPT for technical support variables is represented in Table 4.5.

An alternative, perhaps more effective approach, is called the NoisyOR function. NoisyOR has been well established as a standard means of encoding expertise in large NPTs (Huang and Henrion 1996). Suppose there are *n* causal factors, $X_1, \dots, X_n$ of a condition, *Y*, with a probability value for *Y* being true when one and only one X_i is true, and all causes other than X_i are false. The NoisyOR function is defined in Equation 4.6, where for each *i*, $v_i = P(Y = \text{true} | X_i = \text{true}, X_j = \text{false}, \text{for each } j \neq i)$ is the probability of the conditional being true if and only if that causal factor is true (Fenton and Neil 2013).

$$\text{NoisyOR}(X_1, v_1, X_2, v_2, \dots, X_n, v_n, l) \tag{4.6}$$

Term *l* is referred to as the *leak probability* representing the probability that *Y* will be true when all of its causal factors are false, as shown in Equation 4.7.

$$l = P(Y = \text{true} | X_1 = \text{false}, X_2 = \text{false}, \dots, X_n = \text{false}) \tag{4.7}$$

In general, the conditional probability of *Y* obtained with NoisyOR function can be represented with Equation 4.8.

$$P(Y = \text{true} | X_1, X_2, \dots, X_n) = 1 - \prod_{i=1}^{n} [(1 - P(Y = \text{true} | X_i = \text{true})(1 - P(l))] \tag{4.8}$$

The NoisyOR function is used here to calculate the conditional probability of the primary criteria as defined in Equation 4.9, which suggests that the likelihood of Supplier 1 successfully achieving the primary criteria is 0.15 if only the desired service level of the supplier is met, while this probability changes to 0.30, 0.40, and 0.25 when total cost, quality of products, and delivery and response, are individually not met, respectively. Finally, the values associated with the leak will be 0.05. In general leak probability is a non-zero probability for the effect to be triggered even if all the causes are false (Antonucci 2011), generally used to reflect when another factor not considered causes the trigger. In this case, there is a 5% likelihood that primary criteria being met while delivery robustness, quality, service, and total costs are all false. There might be other factors that contribute to the primary criteria (e.g., ease of communication with supplier, supplier’s profile, performance history of supplier) that are not included among the four defined primary criteria. Note that when more primary criteria factors are considered, the leak probability reduces. These parameters could realistically be obtained through decision maker experience, perhaps combined with historical data.

NoisyOR (total cost, 0.3, quality of products, 0.4, service, 0.15,
delivery and response, 0.25, 0.05) (4.9)

4.5.2 Modeling Green Criteria

The use of green supplier selection criteria has grown in the recent literature (e.g., Hashemi et al. 2015, Dobos and Vorosmarty 2014, You et al. 2015, Scott et al. 2015, Lee et al. 2009, Akman, 2015, Tsui and Wen 2014). As environmental awareness increases, manufacturers today are more interested in purchasing goods and services from suppliers with environmental responsibility (Lee et al. 2009). Different green factors including product life cycle, green image, CO_2 emission and environment management, reusability among others have been used to evaluate green suppliers. Among aforementioned factors, CO_2 emission is among the more common factors (Lee et al. 2009, Dobos and Vorosmarty 2014). In this study, the green performance of supplier is assessed based on the amount of CO_2 emitted by that supplier. The NPTs of green criteria are found in Table 4.10, and a depiction of the portion of the BN is represented in Figure 4.6. The total amount of CO_2 emitted by the supplier depends on the distance between customer and supplier (km), as well as CO_2 emission (g/km). Note that the level of CO_2 emission depends on the type of transportation mode used for the shipment of commodities. Note that in this paper, the focus of the green criteria is given to CO_2 emission only, as it contributes to over 95% of greenhouse gas emissions (Marufuzzaman et al. 2014). Carbon capacity is one of the carbon regulatory mechanisms that limit carbon emissions produced by transportation activities in the supply chain, and the aim of the carbon capacity constraint is to diminish carbon emission produced by supplier companies.

4.5.3 Modeling Resilience Criteria

Discussed previously, the idea of resilience in the supplier selection problem is relatively new and becoming more important due to the vulnerabilities of an increasingly global supply chain. The contributors to the supplier resilience, identified in Section 3, are modeled using the Bayesian network illustrated in Figure 4.7. The NPTs of the resilience criteria and its contributors are listed in Table 4.11.

4.5.4 Modeling the Supplier Evaluation Variable

The ultimate target node is the *Supplier evaluation* variable provides a probability statement about whether the supplier should be selected, conditioned on the primary, green, and resilience criteria nodes, as well as the weighting factor. The weighting factor is a labelled variable with three states that captures weights of three criteria. Initially, it is assumed that the weight of each factor is equally distributed, 33.33%. As illustrated in Figure 4.8, the probability of selecting Supplier 1 (the *Supplier evaluation* variable being True) is 66.8%, with the probability that Supplier 1 not being selected of 33.2% (the False state). BN models were similarly developed for Suppliers 2 and 3, whose BNs were developed similarly to that of Supplier 1 and are provided in the Appendix. The resulting probability of selection of Suppliers 2 and 3 are 59.6% and 53.5% as depicted in Figures 4.17 and 4.18 respectively.

4.6 Results and Analysis

The results of the illustrative example built around Supplier 1, as discussed in the previous sections, are provided here.

4.6.1 Sensitivity Analysis

A useful method to investigate the validity of an expert-built model is to perform sensitivity analysis to get a sense of how the model's output is affected by uncertainty in input parameters. *Resilience criteria* is set as the target node, and the impacts of its causal factors are measured in terms of conditional probability. The sensitivity analysis of resilience factors is represented in Figures 4.9 and 4.10, which represent the probability of resilience of Supplier 1 being "True" and "False" respectively given a set of its contributors respectively.

From a purely visual inspection, the length of the bars in the tornado graphs can be thought of as the measure of the impact of that variable on the resilience criteria. Figure 4.9 illustrates the impacts of six Boolean variables including *Technical resources*, *Budget resources*, *Segregation*, *Backup supplier*, *Surplus inventory*, and *Physical protection* when the resilience criteria is True. Figure 4.10 shows the impacts of the six variables when the resilience criteria is False. It is clear that technical resources and physical protection have the greatest and lowest impact on the resilience of supplier, respectively. The formal interpretation is that the probability of resilience of Supplier 1 given the results of technical resources goes from 69.6% (when technical resource is Fail) to 87.6% (when technical resource is True), as shown in Figure 4.9. The impact of physical protection on the resilience of Supplier 1 is limited to narrow range, from 83.1% to 84.2%. This suggests enhancing the availability of technical resources is more impactful than any other factor in improving the resilience of Supplier 1. A sensitivity analysis was also performed for the *Supplier evaluation* node with respect to some key factors including *Restorative capacity*, *Quality of products*, *Cost*, *Delivery robustness*, *Absorptive capacity*, *Service*, and *Adaptive capacity*. The probability of supplier selection being True and False is 66.8% and 33.2%, respectively, as illustrated in the tornado graphs in Figures 4.11 and 4.12. From these figures, it can be concluded that the probability selecting Supplier 1 is more sensitive to the changes in the states of restorative capacity and least sensitive to changes in adaptive capacity.

4.6.2 Weighting Factor Analysis

Discussed previously, the weights of each of the three supplier selection criteria (primary, green, and resilience) are assumed to be equally distributed of 33% in the baseline BN. Figure 4.13 shows that *P*(selection of the Supplier 1 | resilience, green, primary, weight of each criteria = 33%) = 66.8%, while this probability for Suppliers 2 and 3 are 59.6% and 53.5%, respectively. Hence, the first supplier is selected as the most appropriate when primary, green, and resilience criteria are aggregated and considered to be equally important. In the second scenario illustrated in Figure 4.14, emphasis is placed on the supplier's resilience, which receives a 50% weight relative to primary and green criteria, both equally set to 25%. The results of this scenario shows that the probability of selection of Supplier 1 increases from 66.8% to 71.1% and still remains as the highest ranked supplier, while the probability of selection for Suppliers 2 and 3 increase from 59.6% to 64.7% and 53.5% to 59.4%, respectively. The BN models for Suppliers 2 and 3 are illustrated in Figures 4.17 and 4.18.

4.6.3 Inference Process Analysis

The inference process in Bayesian networks generally requires obtaining the posterior probabilities for a set of variables $X_I \subset v$ given evidence *e*. This probability is shown in Equation 4.10. This is typically referred to as *propagation analysis*. Forward propagation analysis aims to propagate the impact of observing one or set of variables and measure its impact on the target node. Such "what-if" analyses can be performed in a backward fashion, where a value can be entered in a target node, and information is propagated to update the distributions of all remaining unknown variables. Note that forward propagation is a type of reasoning from cause to effect, while backward propagation describes effect-to-cause.

$$P(X_i|e) \quad \forall X_i \in X_I \tag{4.10}$$

4.6.3.1 Forward Propagation Analysis

A number of observations can be entered in the BN, and forward propagation can be used to update the marginal probabilities of any unobserved variables, primarily a target node. If, for example, sufficient evidence suggests that surplus inventory is unavailable (in its False state), forward propagation can be used to determine the impact on the supplier's resilience and ultimately its overall evaluation. To perform a forward propagation analysis, four factors including *Surplus inventory*, *Rerouting*, *Quality*, and *Technical resources* were chosen, and four scenarios were defined for the supplier with the highest overall evaluation (Supplier 1). Scenario 1 contains False states for *Rerouting* and *Technical resources*, Scenario 2 contains False states for *Surplus inventory* and *Quality*, Scenario 3 contains False states for *Quality* and *Technical resources*, and Scenario 4 includes False states in all four variables, as shown in Table 4.12. The change in the probability selecting Supplier 1 for each of the scenarios, including the baseline, is desired. For example, in the probability of interest in Scenario 1 is P(selection of supplier 1 | Rerouting = False, Technical resources = False). The junction tree algorithm [Jensen 1996] is used for the purpose of propagation analysis, where the joint probability for the model from the BN's conditional probability structure is calculated in a computationally efficient manner. As illustrated in Figure 4.15, the probability of selecting Supplier 1 under scenarios 1, 2, 3, and 4 is reduced to 62.1%, 61.3%, 56.9%, and 56.4% respectively, relative to the baseline of 66.8%. Different suppliers could also be compared under these four scenarios.

4.6.3.2 Backward Propagation Analysis

Backward propagation analysis is a unique capability of Bayesian networks, increasing the scope of what-if scenarios especially giving insight to less competitive suppliers on how the components of their performance criteria (primary, green, resilience) can be improved to reach an overall evaluation level.

To demonstrate back propagation analysis, the overall supplier evaluation for Supplier 1 was increased from 66.8% to 100% (that is, the probability of *Supplier evaluation* equating to True being 100%), and the distributions of the remaining variables were updated using the junction tree algorithm [Jensen 1996]. As a result, the probability of primary, green, and resilience criteria must be improved to 68.09%, 72.32%, and 90.72% respectively as highlighted in green in Figure 4.16.

4.7 Concluding Remarks

This work proposes a novel Bayesian network model for evaluating and selecting the best supplier across criteria falling into *primary* (or traditional), *green*, and *resilience* categories. The concept of resilience in the supplier evaluation and selection process has become more important due to the emergence of global supply chains and the (seemingly more frequent) events that can disrupt them. The BN model quantifies resilience in terms of absorptive, adaptive, and restorative capacities. This initial implementation was illustrated with a simple example of the comparison of three suppliers with realistic parameters, and the sensitivity analysis capabilities of the BN paradigm were explored. The capability of BN approach was compared with other existing approaches and presented in Table 4.13.

4.7.1 Benefits of BN Formulation

The major methodological benefits of the BN model proposed here include the following.

- *Flexibility of variable types*: In contrast to mathematical modeling approaches such as a mixed integer programming based approach, the proposed BN captures both tangible and intangible factors that contribute to the selection of a resilient supplier. Different types of variables including Boolean, continuous, constant, and labeled extend the flexibility of this modeling approach. Further, different sources of data ranging from historical observations to expert evidence can be incorporated in the BN framework.
- *Inference analysis:* Different what-if scenarios can be analyzed, providing insights to the decision maker as to how the probability of the selection of a supplier varies under different scenarios. By performing inference analysis, a decision maker can evaluate the performance of a supplier, or compare multiple suppliers, under extreme conditions. Inference analysis can be performed on both subjective beliefs and objective data. Bayesian networks are capable of performing both cause-to-effect analysis, or *forward propagation analysis,* and effect-to-cause analysis, or *backward propagation analysis*. Such backward propagation analysis is not proposed by other approaches.
- *Accounting for uncertainty*: The uncertainty associated with the modeling of system variables can be captured using BNs models. In this paper, two types of uncertainty have been captured: operational uncertainty (e.g., demand uncertainty) and disruption uncertainty (e.g., natural disasters).
- *Accounting for multiple sources of risk*: Two types of risks are often associated with the supplier selection problem: operational risks (e.g.,

demand uncertainty and variation on the variable transportation costs) and disruption risks (e.g., the occurrence of disruptive events). The BN model developed in this study addresses these two types of risks.

4.7.2 Limitations of the BN Formulation

The methodological limitations can be summarized as follows.

- *Necessary use of subjectivity:* Relying on expert judgment in cases where data are sparse or not available implies inevitable subjectivity and possible bias (Constantinou et al. 2015). This can be partially addressed by using multiple experts.
- *Complexity:* Developing causal expert-driven Bayesian networks requires significant development, as they are usually complex due to a large number of variables that capture causality. Although Bayesian networks are conceptually easier than regression and rule-based predictors, they are generally not very simple to build.

4.7.3 Future Work

The future research directions of this study are as follows.

- Further green criteria beyond CO_2 emission could be accounted for, including environmentally friendly product design, packing, and warehousing, among others.
- More detail could be given to the important decision of how suppliers choose transportation modes. Qualitative and quantitative factors involved in the selection of the best transportation mode include total cost of

transportation (fixed cost + variable cost), reliability of transportation mode, transport time, and air emission, among others.

- Bayesian networks can be used to study the resilience of various infrastructure sectors, from physical infrastructure networks (e.g., energy, telecommunications) to service networks (e.g., emergency services, humanitarian relief). The interaction among physical and service networks, as well as community networks that require the services of both, is a growing concern in the face of more frequent large-scale disruptions (Barker et al. 2016).

Table 4.1 Recent literature on supplier selection and analysis methodologies

Literature	Selection factor																														Methodology
	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y	z	ra	scc	fl	rd	
Fazlollahtabar et al. (2011)	✓	✓	✓	✓	✓																										Multi-objective nonlinear + AHP+ TOPSIS
Lee et al. (2009)		✓	✓			✓	✓	✓									✓	✓	✓												Fuzzy AHP
You et al. (2015)	✓	✓		✓				✓																							VIKOR
Mahdiloo et al. (2015)								✓	✓																						DEA
Karimi and Rezaeian (2014)	✓		✓	✓						✓																					Multi-stage goal programming
Liu and Zhang (2011)			✓					✓			✓	✓																			ELECTRE III
Viswanadham et al. (2013)	✓	✓											✓																		AHP and Fuzzy TOPSIS
Memon et al. (2015)		✓	✓	✓										✓																	Grey theory
Yuncenur et al. (2011)	✓	✓												✓																	AHP and ANP
Ustun and Demitras (2008)		✓	✓	✓		✓								✓	✓																ANP and multi-objective mixed integer prog.
Sawik (2010)		✓		✓		✓	✓				✓																				Mixed integer programming
Pitchipoo al. (2015)	✓			✓						✓						✓															Grey theory
Hashemi et al. (2015)	✓	✓						✓	✓							✓				✓											Grey relation analysis and ANP
Huang and Keskar (2007)			✓	✓		✓	✓				✓					✓															AHP
Zhang et al. (2013)	✓		✓	✓									✓			✓															Nonlinear multi-objective
Akman (2015)									✓							✓		✓			✓	✓									Fuzzy c-means and VIKOR
Kumar and Jain (2010)																✓															DEA
Theiben and Spinler (2014)																✓															ANP
Tsui and Wen (2014)																✓			✓				✓								AHP, ELECTRE III and linear assignment
Rajesh and ravi (2015)	✓	✓						✓	✓															✓	✓	✓	✓	✓	✓	✓	Grey relational analysis

Table 4.2 Boolean expression used to calculate the NPT of delivery robustness

Variable name	NPT	Meaning
Delivery and response	IF (Lead time <17 && response rate >0.9, "True", "False")	If lead time is less than 10 days and response rate is greater than 90%, then delivery and response is being met (True), *otherwise* not being met (False)

Table 4.3 NPTs of the variables describing the quality of products and probability of the product being faulty

Variable names	NPT	Meaning
Probability of product being faulty	Beta(α=0.8, β=30, UB=0, LB=1)	The probability of a product being shipped by the supplier to the manufacturer follows a beta distribution.
Quality of products	IF (prob. of product being faulty <7%, "True", "False")	If the probability of a product being faulty is less than 7%, then the quality of the product is acceptable (True state), otherwise not (False state)

Table 4.4 NPT of the variable describing after-sale service

False	0.1
True	0.9

Table 4.5 NPT of the variable describing technical service

False	0.15
True	0.85

Table 4.6 NPT of the variable describing after-sale service

After sale service	False		True	
Technical service	False	True	False	True
False	1.0	0.4	0.45	0.0
True	0.0	0.6	0.55	1.0

Table 4.7 NPT of the variable describing total cost

Variable name	NPT	Meaning
Total cost	IF (order cost + total transportation cost + purchased cost + tardiness cost < 127,000, "True", "False")	If the sum of supplier costs is less than the budget limitation of the buyer (manufacturer), then the cost of the supplier is in a True state (satisfactory), otherwise is in a False state (unsatisfactory).

Table 4.8 NPTs of the variables describing customer demand, capacity of supplier, and purchased items

Variable names	NPT	Meaning
Customer demand	TNORM (μ=1000, σ^2=20, LB=980, UB=1020)	The customer demand follows a truncated normal distribution with an average of 1000, variance of 20, and lower minimum and maximum of 980 and 1020 respectively.
Capacity of supplier	Constant value (1000)	The capacity of Supplier 1 is 1000.
Purchased items	Min (customer demand, capacity of supplier)	The number of purchased items is determined by taking the minimum values between customer demand and supplier's capacity.

Table 4.9 NPTs of the variable describing tardiness penalty cost and its parents

Variable names	NPT	Meaning
Tardiness penalty cost	Tardy penalty × Tardiness	Tardiness penalty cost is calculated as product of tardy penalty by tardiness.
Tardiness	Max (0, completion time – due date)	Tardiness occurs when the order competition time is greater than order due date.
Completion time	TNORM (μ=18, σ^2=1.5, LB=15, UB=24)	The average order completion time on average is the 18th day of the month with variance of 1.5 days. The earliest completion time is not earlier than the 15th, and the latest not beyond the 24th.
Due date	Constant value (20)	The order due date is the 20th day of the month.

Table 4.10 NPTs of the variable describing CO2 emission

Variable names	NPT	Meaning
CO_2 emission (g/km)	Triangular distribution (25, 120, 150)	Amount of emitted CO_2 depends on many factors such as mode of transportation. The first supplier uses roadways for the shipping of products. The CO_2 emitted by truck may varies depending on the age of truck, slope of roads, among others. It is assumed that the emitted CO_2 by truck follows a triangular distribution [Kahn Ribeiro et al. 2007] with minimum, most likely, and maximum estimates of 25, 120, and 150 g/km, respectively.
Distance between supplier and customer (manufacturer)	Constant (1450)	The distance between the supplier's location and manufacturer's location is a constant 1450 kilometers.
Total emitted CO_2	Distance × CO_2 emission	Total emitted CO_2 is calculated as the product of distance between supplier and manufacturer and the amount of CO_2 (gram) per kilometer.
Green criteria	If (total emitted CO_2 <170000, "True", "False")	If the total emitted CO_2 is less than some carbon capacity limitation (170,000), then green criteria is met (True state), otherwise not (False state).

Table 4.11 NPTs of resilience criteria and its contributors

Variable names	NPT	Meaning
Prob. of tornado	TNORM (0.025, 0.001, 0, 0.04)	Assume that a tornado is a common natural disaster in the area of Supplier 1.
Prob. of flood	TNORM (0.02, 0.002, 0, 0.025)	Assume that flooding is a common natural disaster in the area of Supplier 1.
Segregation	If (pro. of tornado && prob. of flood <0.03, “True”, “False”)	Conditional logic is used to determine the probability that the supplier is geographically separated from disaster prone areas.
Surplus inventory	True =90%, False=10%	90% of the time the first supplier keeps surplus inventory, while 10% of times the supplier fails to do that.
Backup supplier availability	TNORM (0.96, 0.005, 0.75, 1)	The backup supplier contract with the first supplier is available 96% of the time with standard deviation of 0.5%.
Backup supplier	If (backup supplier >0.95, “True”, “False”)	Conditional logic is used to determine the probability that backup supplier is being True of False.
Physical protection	True=85%, False=15%	The chance of physical protection of building and equipment against disruption is 85%.
Rerouting	True=90%, False=10%	The probability of rerouting and using alternative transportation mode in the presence of disruption being True is 90%.
Adaptive capacity	Rerouting: False / True False: 1.0 / 0.02 True: 0.0 / 0.98	The posterior probability of adaptive capacity is conditioned on rerouting variable.
Technical resources	True=80%, False=20%	The chance of availability of technical resource in the presence of disruptive

Table 4.12 Forward propagation scenarios

	Surplus inventory	Rerouting	Quality	Technical resources
Scenario 1	None	False	None	False
Scenario 2	False	None	False	None
Scenario 3	None	None	False	False
Scenario 4	False	False	False	False

Table 4.13 Factors impacting on primary supplier selection

a	cost
b	quality
c	service
d	delivery
e	innovation
f	finance
g	organization
h	technology capability
i	environmental management
j	Warranty
k	managing ability
l	Enterprise environment
m	lead time
n	risk factor
o	relationship
p	capacity
q	product life cycle cost
r	green image
s	pollution control
t	resource consumption
u	green capability
v	green design
w	recovery and strategy fit
x	safety
y	vulnerability
z	collaboration
ra	risk awareness
scc	supply chain continuity

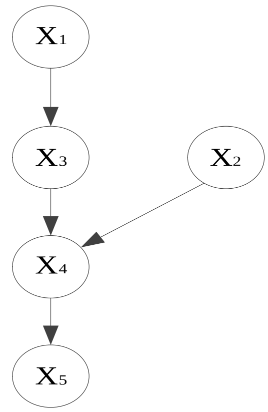


Figure 4.1 An example BN with five variables (nodes)

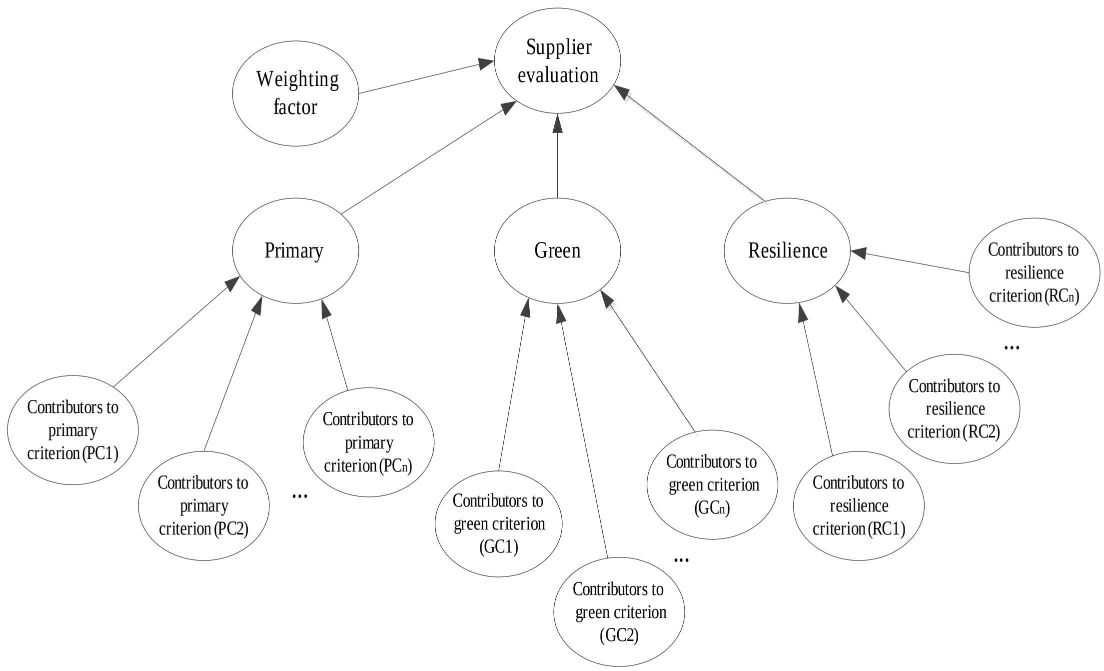


Figure 4.2 General BN framework evaluating the selection of a supplier

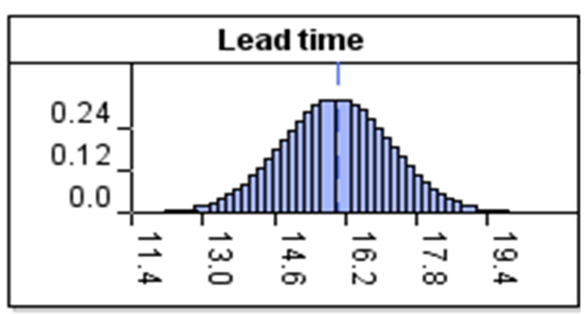
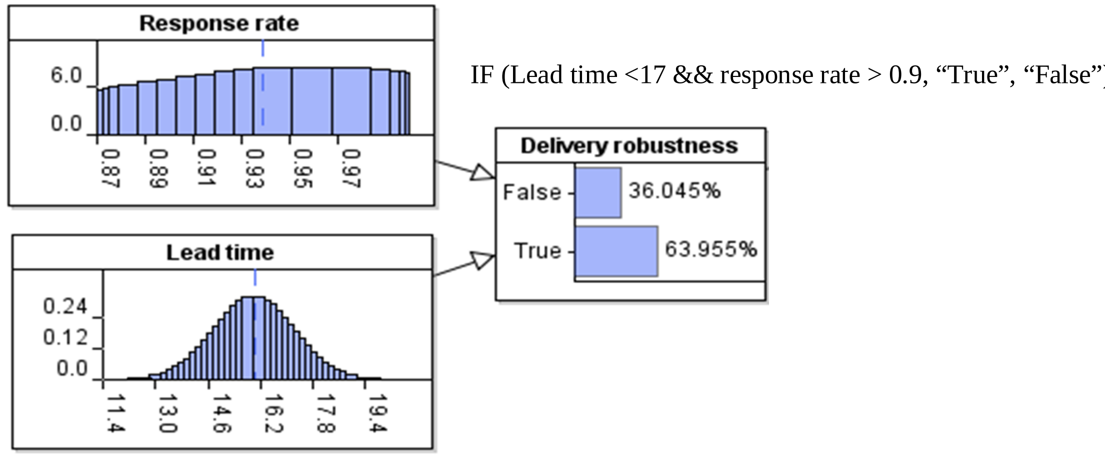


Figure 4.3 Lead time of supplier 1

Response rate ~ TNORM (μ=0.94, σ^2=0.01, LB=0.87, UB=1)



Lead time ~ TNORM (μ=16 day, σ^2=1.5 day, LB=1, UB=12)

Figure 4.4 The modeling procedure for the variable describing delivery robustness

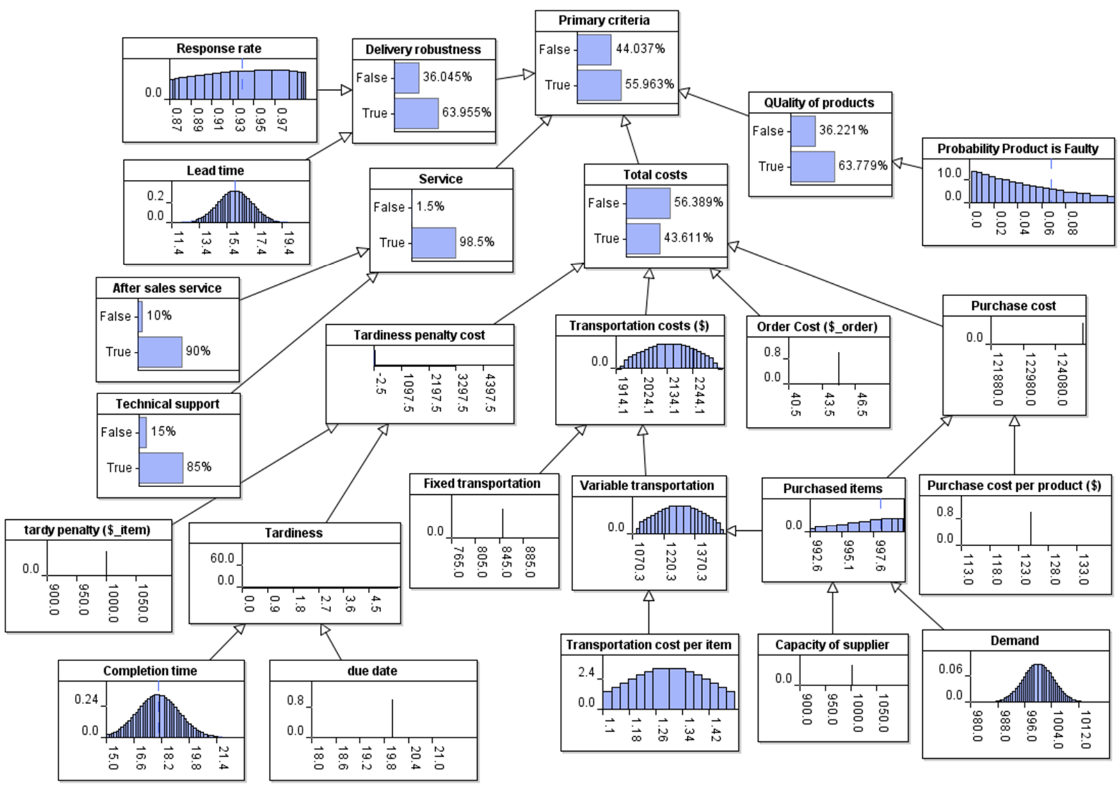


Figure 4.5 Graphical representation of the BN model for primary criteria

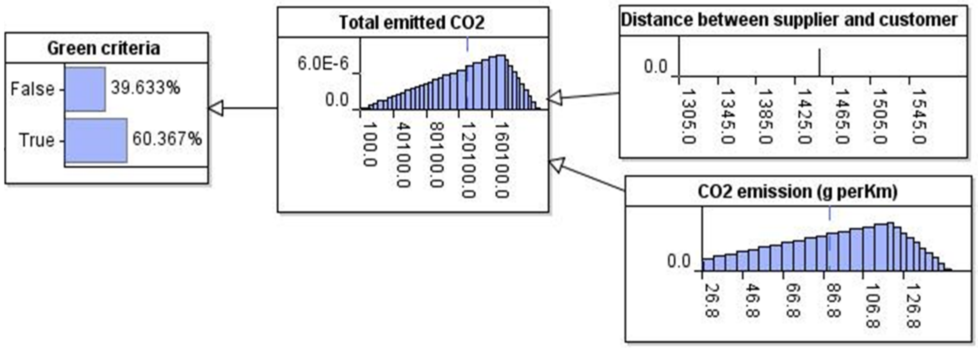


Figure 4.6 Graphical depiction of the BN model for green criteria

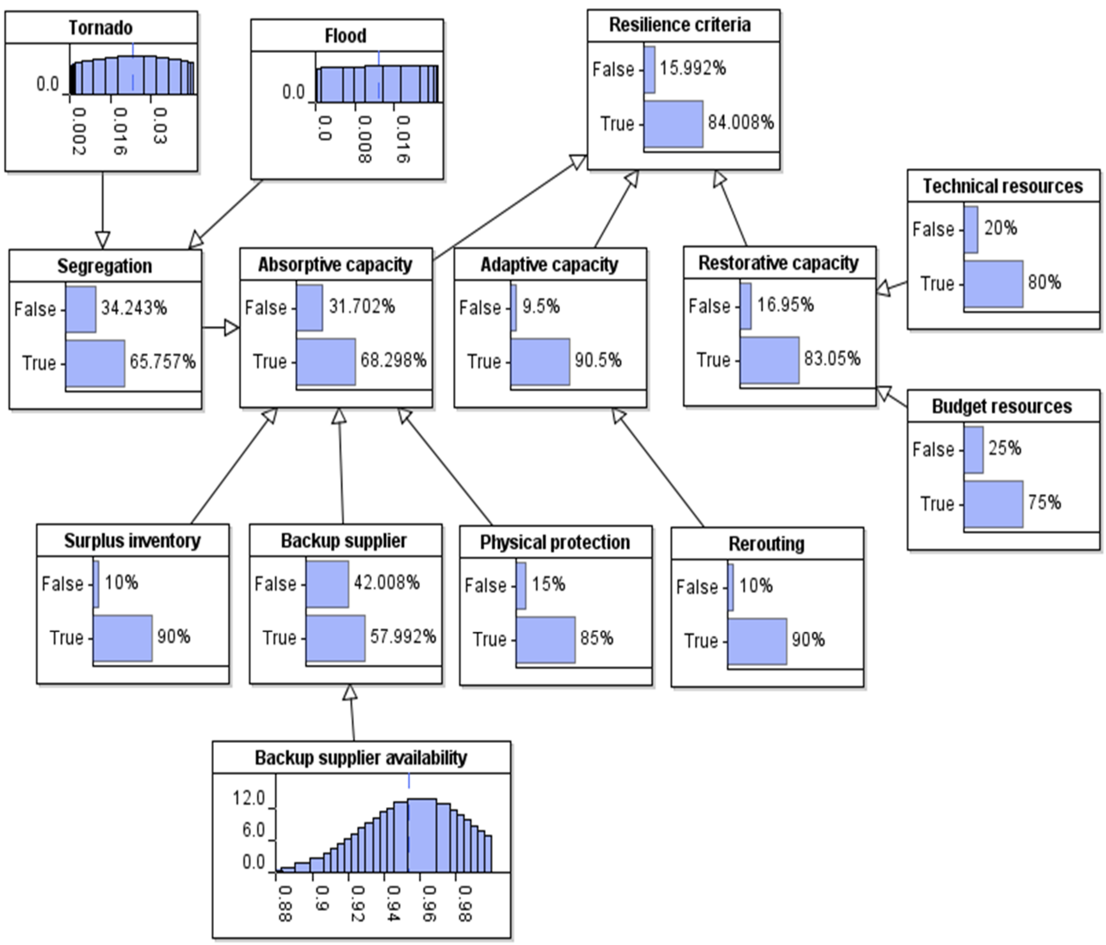


Figure 4.7 Graphical depiction of the BN model for resilience criteria

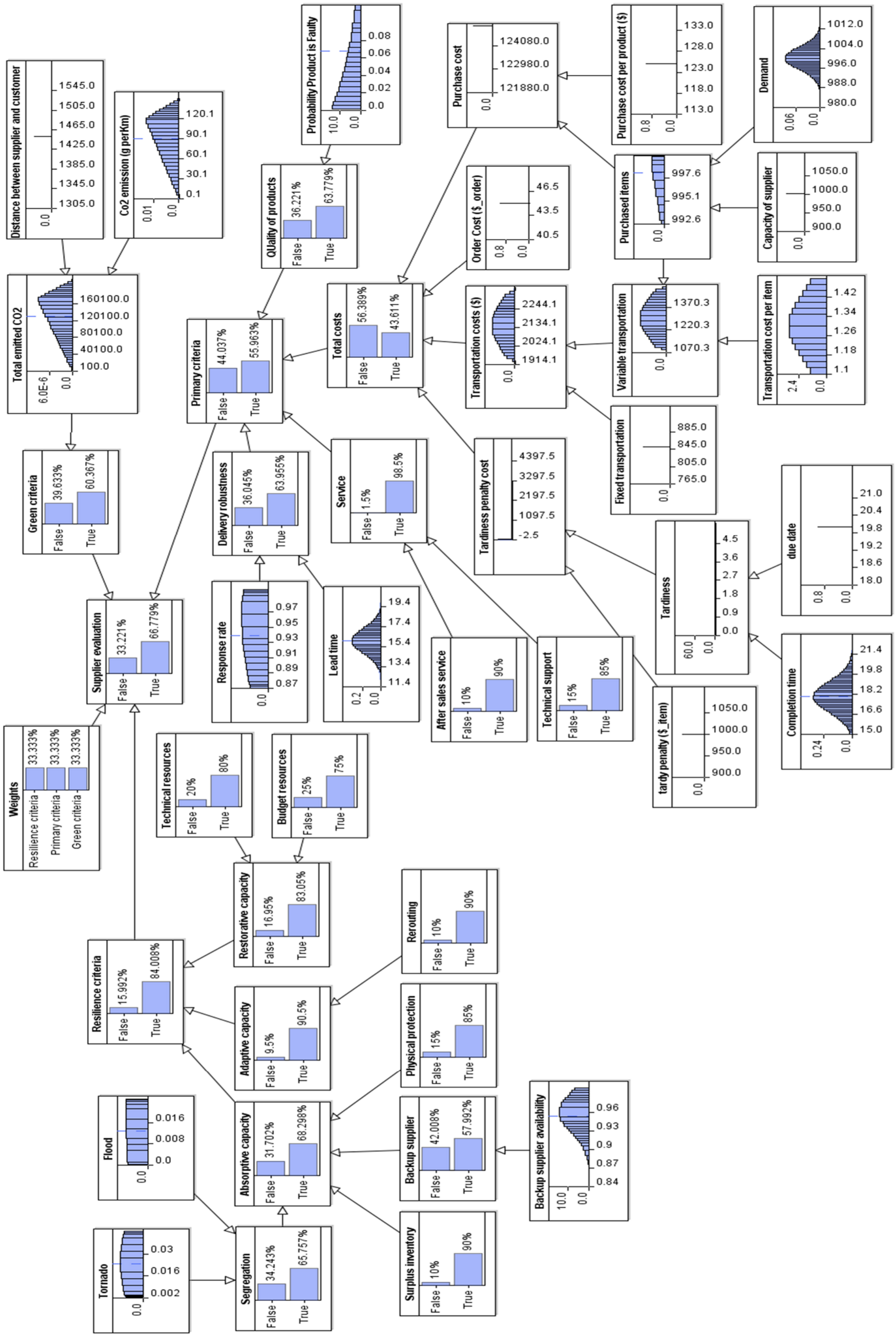


Figure 4.8 The BN model to evaluate Supplier 1

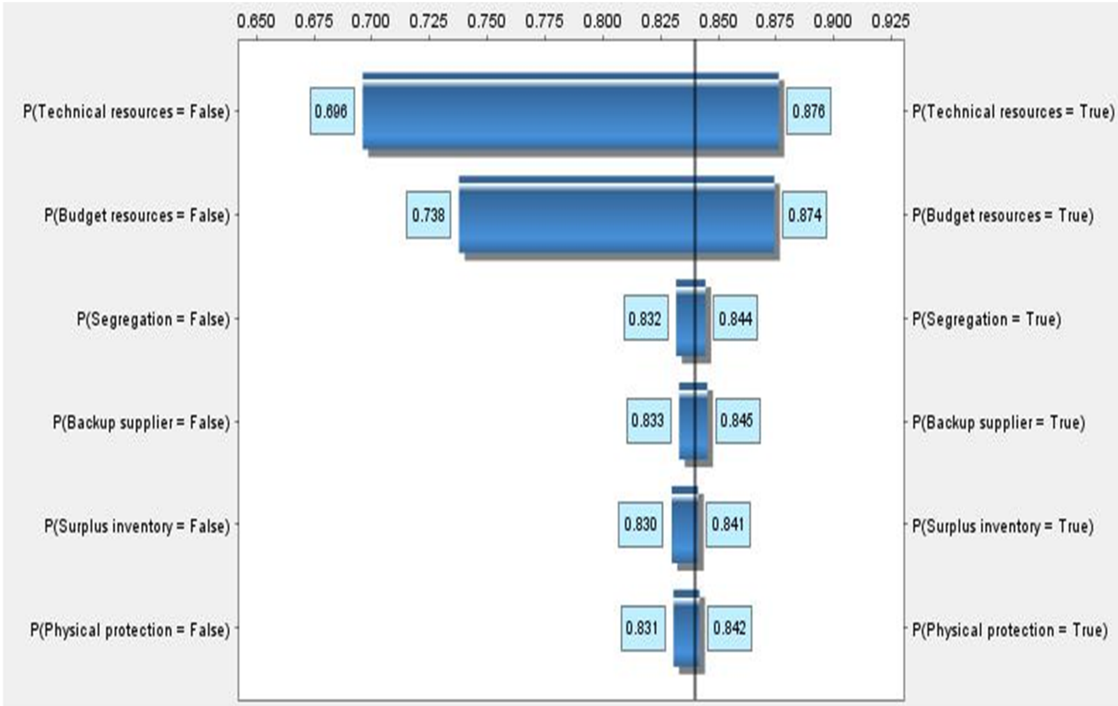


Figure 4.9 Tornado graph to analyze the sensitivity analysis of Supplier 1's resilience: P(Resilience criteria = True)=84%

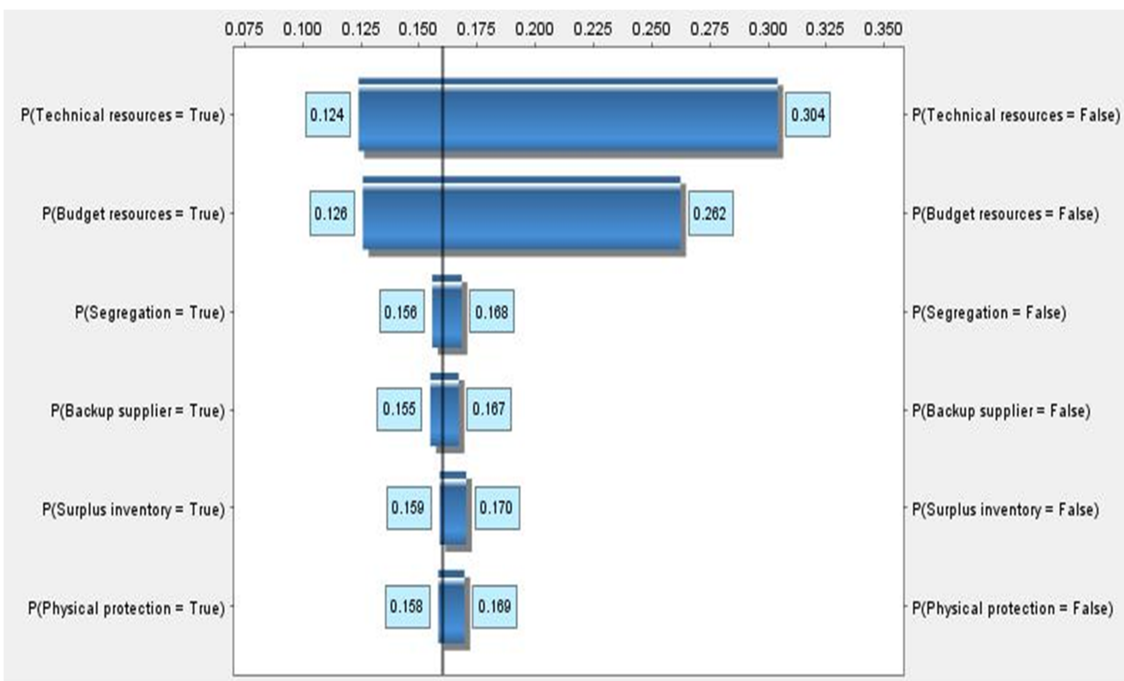


Figure 4.10 Tornado graph to analyze the sensitivity of Supplier 1's resilience: *P*(Resilience criteria = False) = 16%

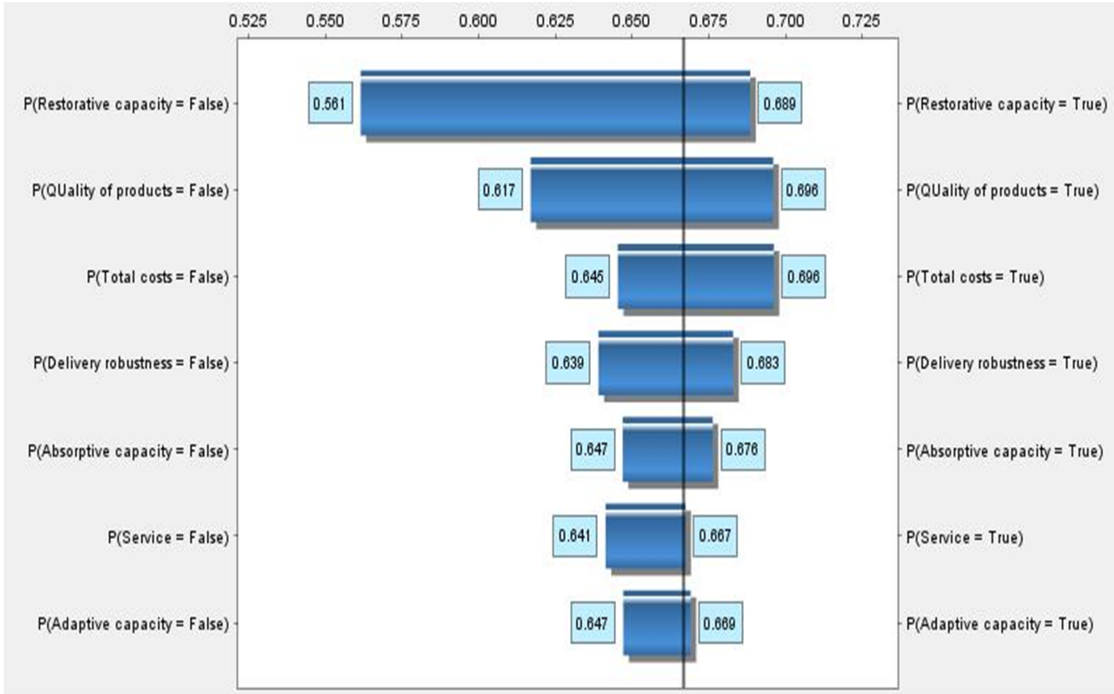


Figure 4.11 Tornado graph to analyze the sensitivity of Supplier 1's evaluation across primary, green, and resilience criteria: *P*(supplier evaluation = True) = 66.8%

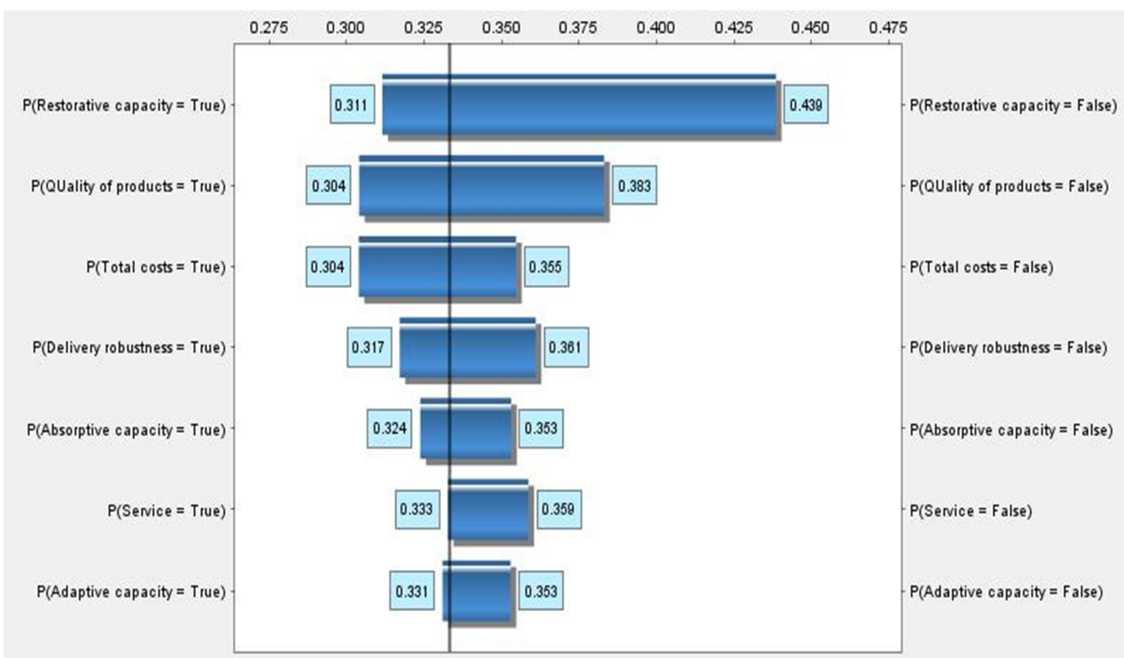


Figure 4.12 Tornado graph to analyze the sensitivity of Supplier 1's evaluation across primary, green, and resilience criteria: *P*(supplier evaluation = False) = 33.2%

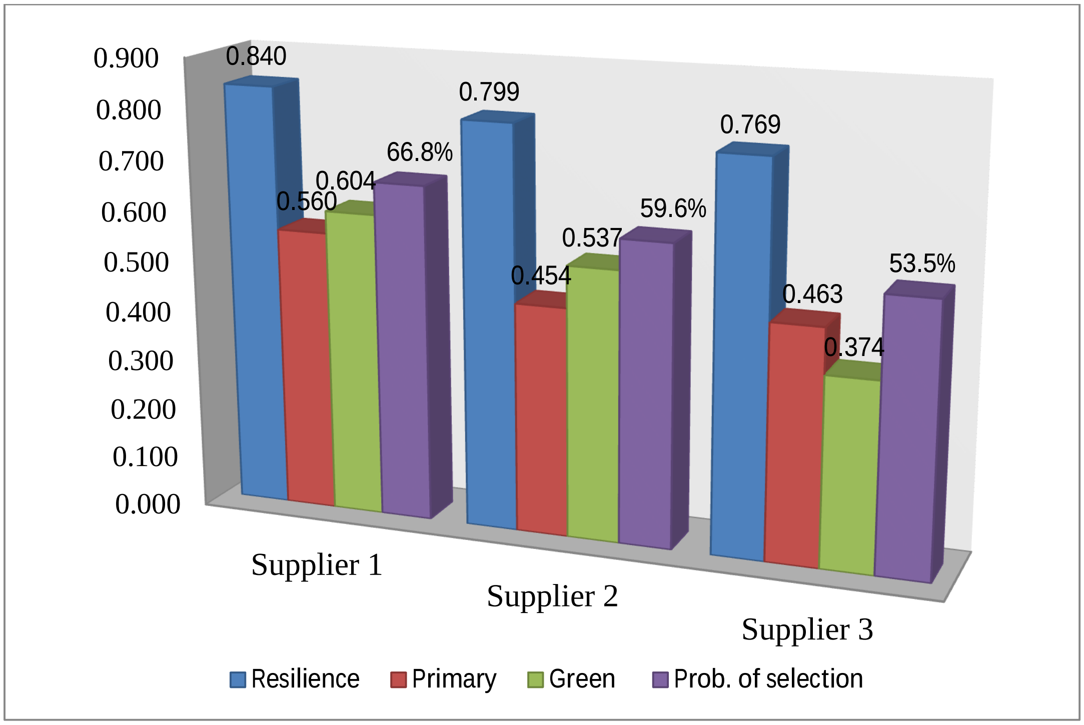


Figure 4.13 The impact of the weights of the three criteria when all are equally distributed

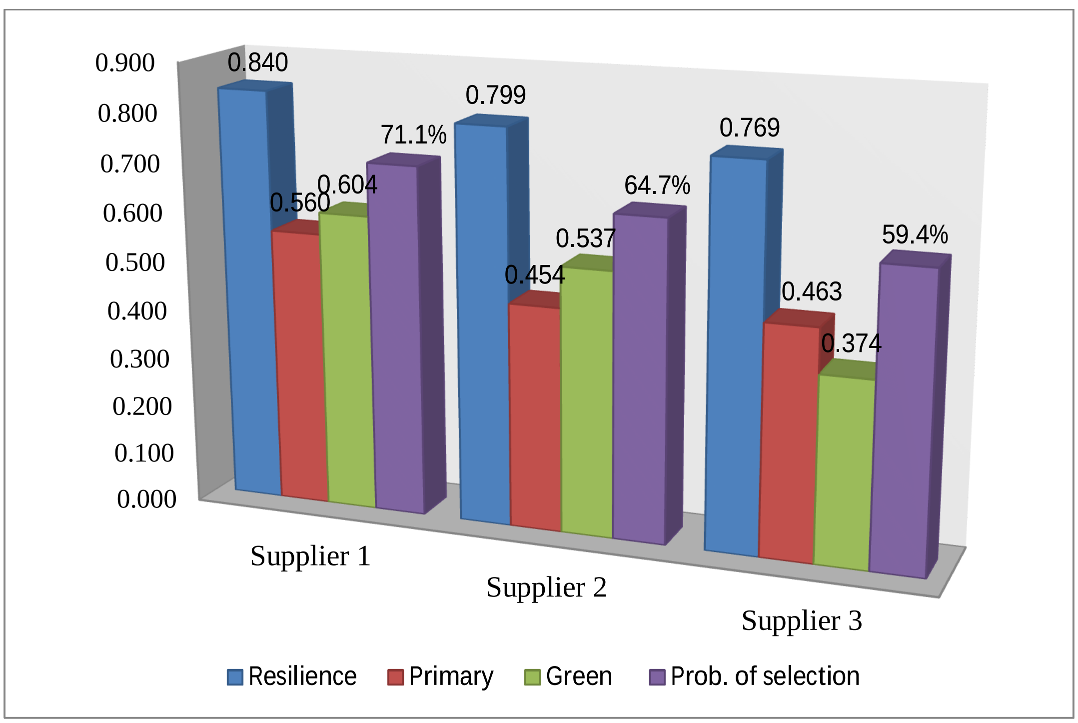


Figure 4.14 The impact of the weights of the three criteria when resilience is weighted twice as much as primary and green criteria

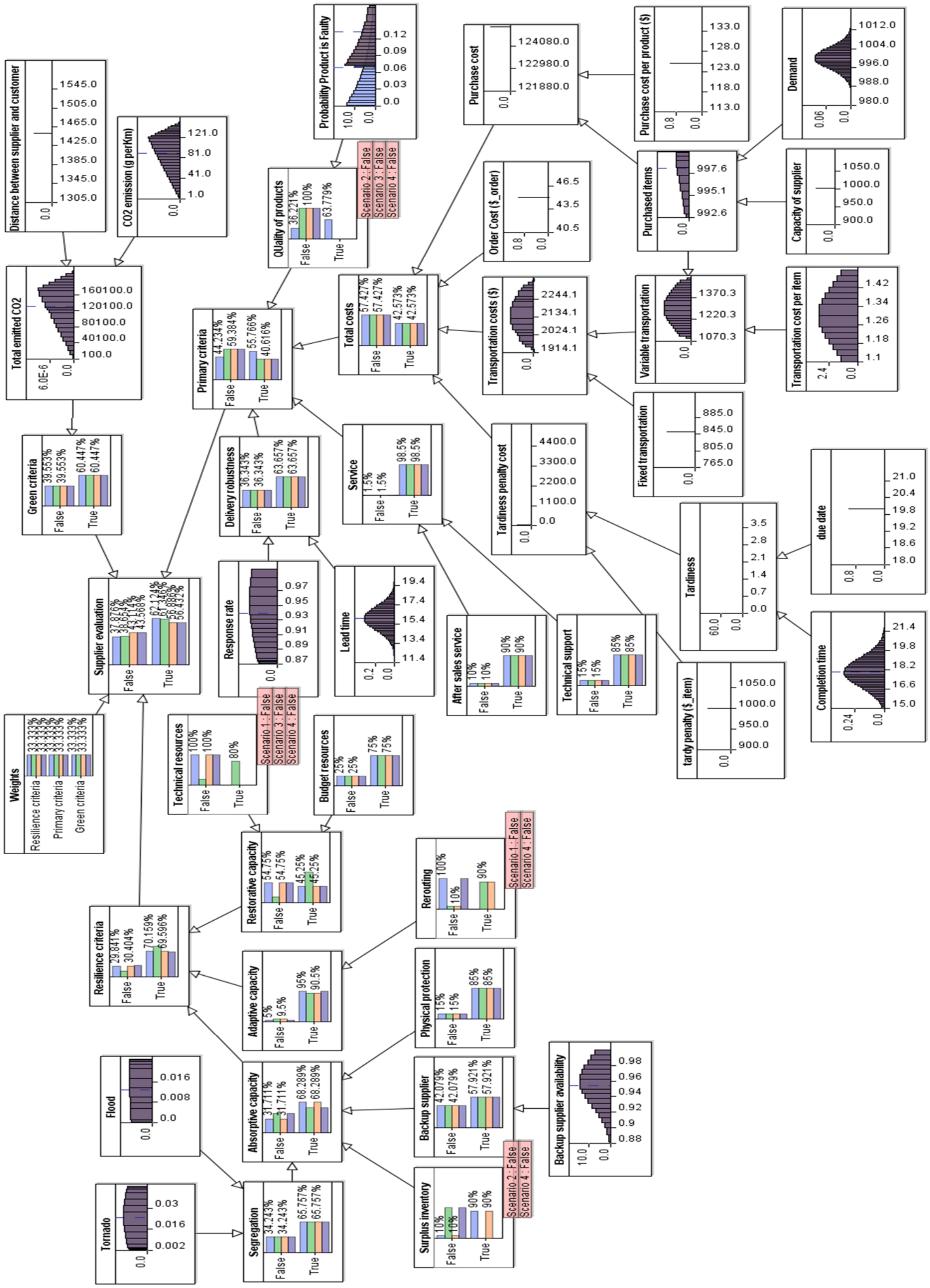


Figure 4.15 Four scenarios of forward propagation analysis

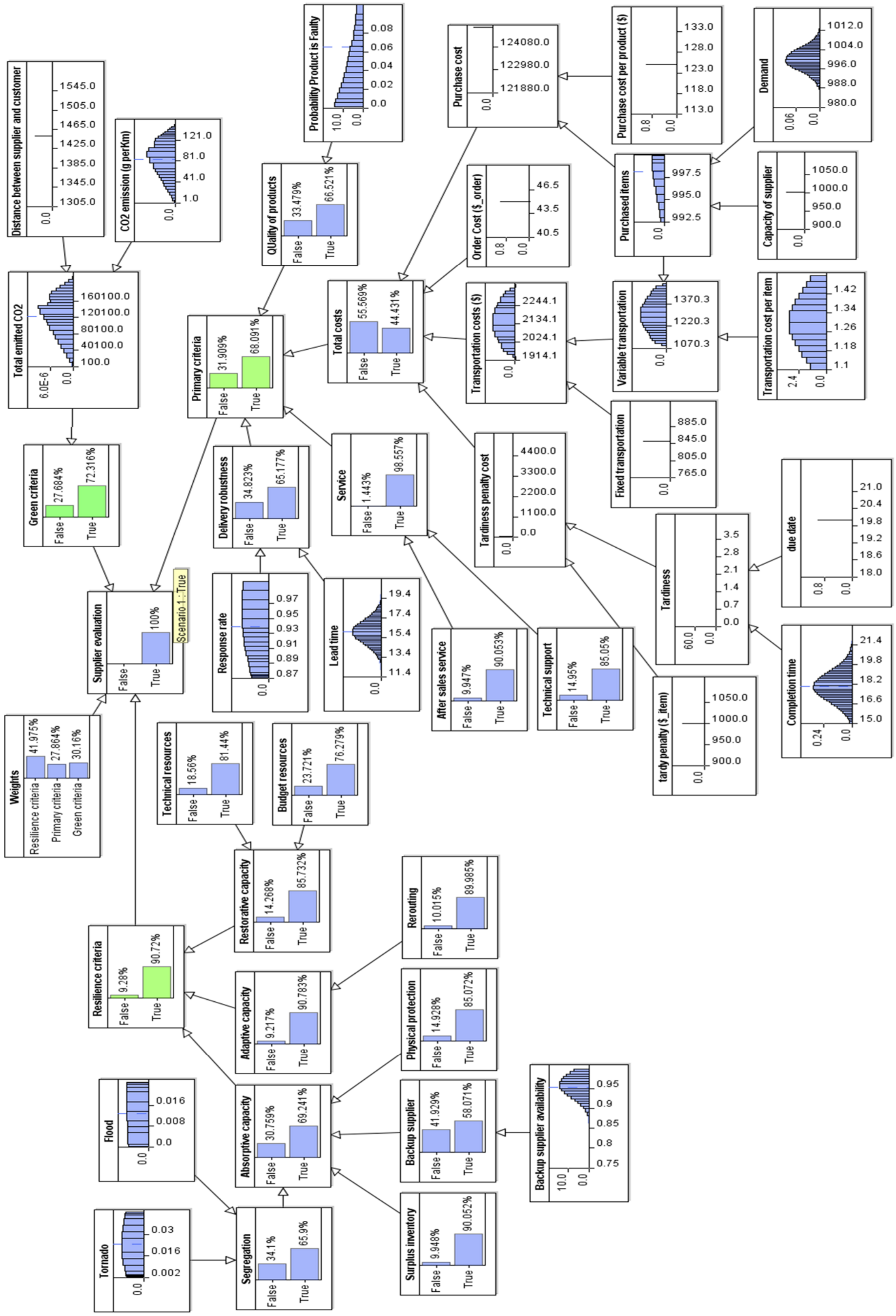


Figure 4.16 Backward propagation analysis

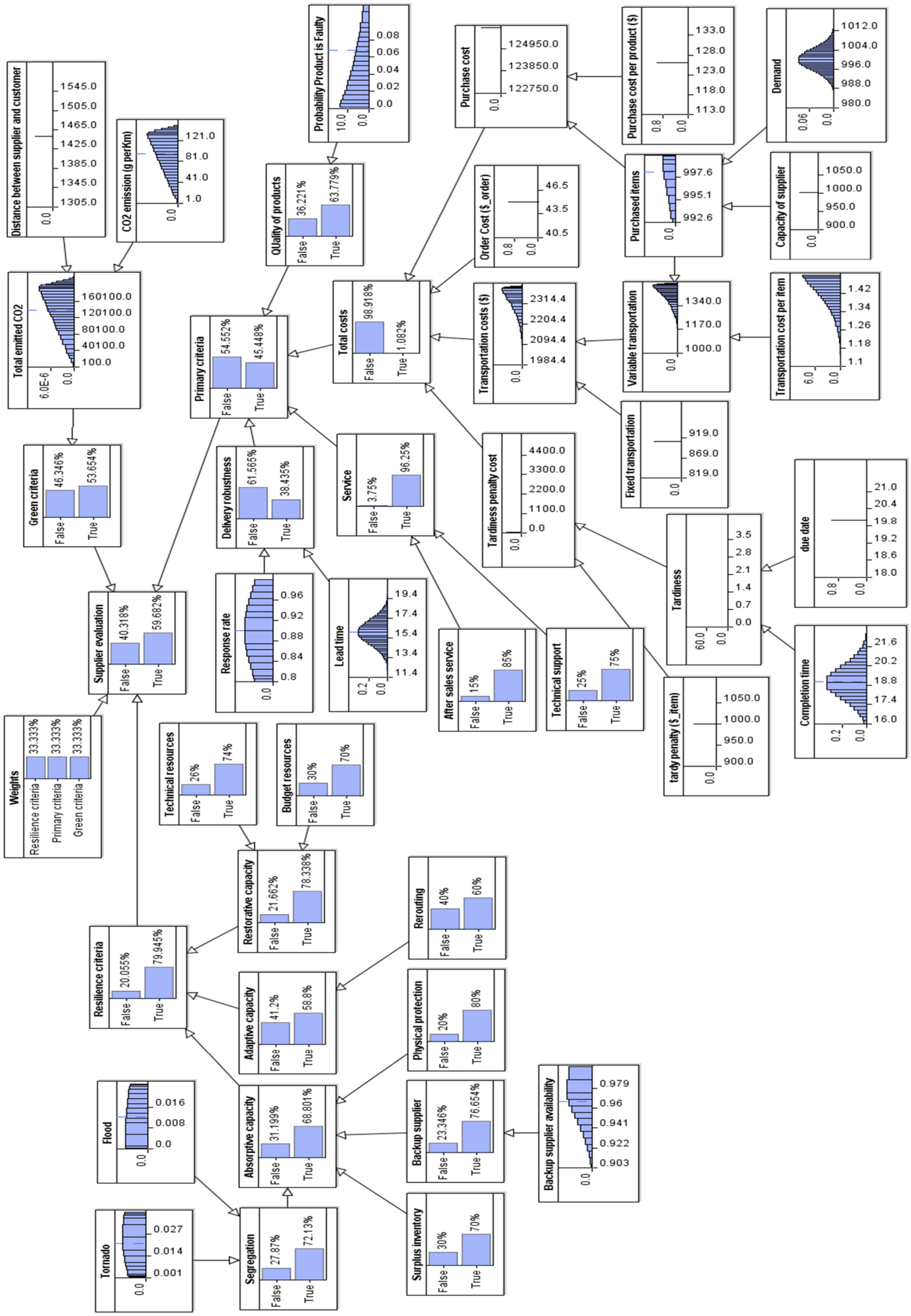


Figure 4.17 BN model for Supplier 2

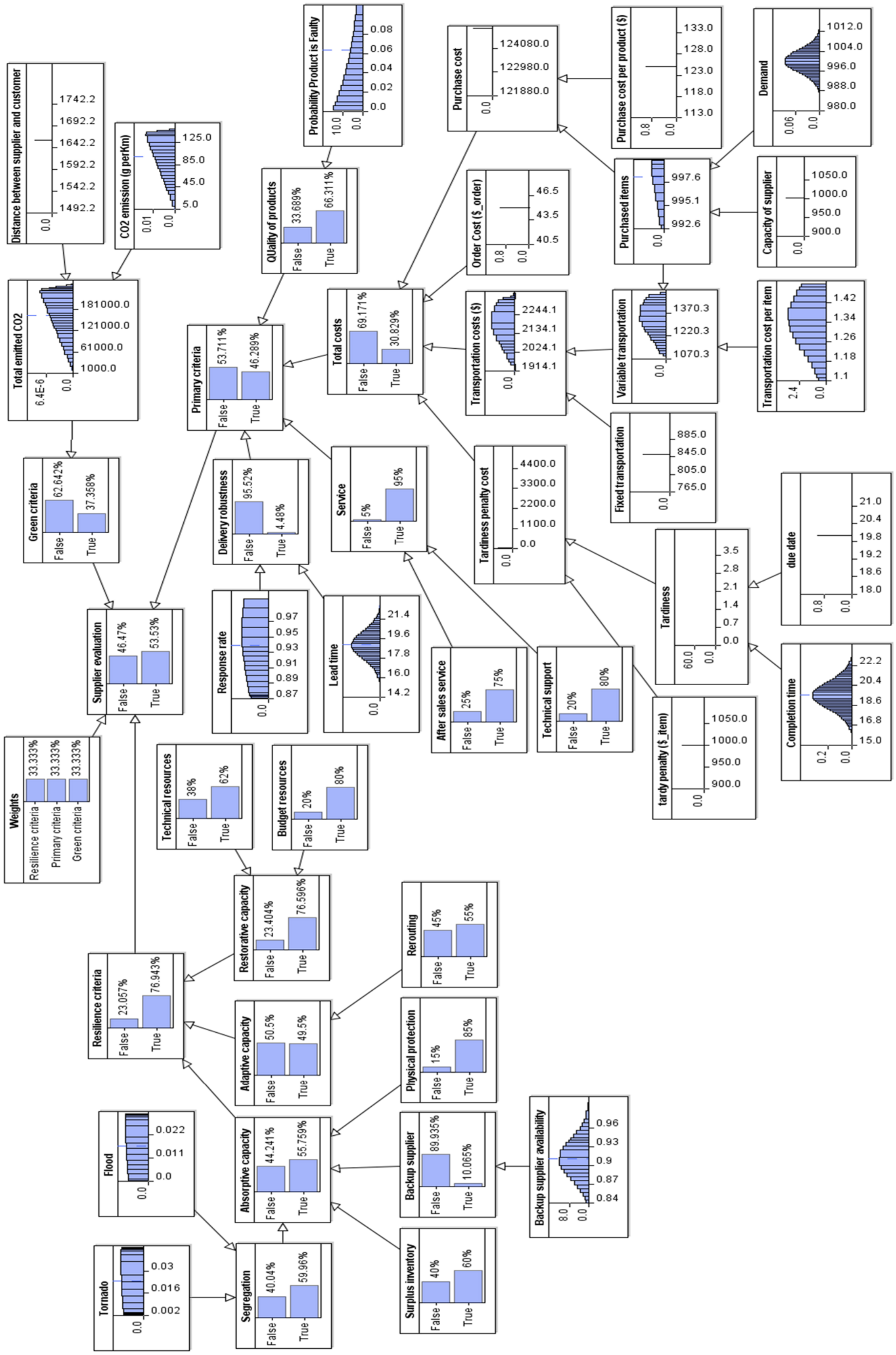


Figure 4.18 BN model for Supplier 3

CHAPTER

5

RESILIENCE ASSESSMENT OF SUPPLIER ALTERNATIVE IN SUPPLY CHAIN

ABSTRACT

This chapter presents a stochastic optimization model for evaluating and selecting the best resilience supplier for a supply chain system. The supplier selection is a key problem in the context of supply chain system which has significant impact on the quality and reliability of supply chain. Supplier selection is a multi-criteria decision making problem that includes tangible and intangible factors. The primary and green supplier selection has been studied extensively by researchers; however the resilient supplier selection has not been explored well yet in compared with primary and green supplier selection. This study presents a stochastic optimization model for resilient supplier selection problem.

Keywords: resilience, supply chain, resilience capacity

5.1 Introduction

With the advent of competitive supply chains, the role of supply chain management is becoming increasingly important. Due to this reason, the competition between individuals firms has been shifted to the competition between supply chain systems (Fazlollahtabar et al. 2011). The relationship between supplier and manufacturing has significant impact on the success of supply chain system. The quality of finished product is highly depends on the quality of raw material supplied by the supplier. The shortage on supplying raw materials can downgrade the performance of entire supply chain. Manufacturing companies must work with different suppliers to ensure the continuity of their activities. In the manufacturing industries, the raw materials can amount up to 70% of the product cost (Fazlollahtabar et al. 2011). Under this circumstance, procuring department can play a crucial role in cost reduction, and supplier selection is one of the most functions of procuring department (Ghodsypour and O'Brien 1998).

The aim of supplier selection problem is to evaluate and select the best supplier among a set of supplier alternatives. Different tangible and intangible factors involve with supplier selection problem such as primary factors (e.g., quality, cost, lead time, response rate, etc.). More recent type of supplier selection is called green supplier selection that focuses on green related criteria of supplier such as CO_2 emission, green packing, green transportation mode, etc. Recently, resilient supplier selection has received a great deal of attentions by researchers. Supplier's resilience refers to the ability of supplier to withstand against variety of disruptions and also must quickly recover in the cases that perturbations of disruption cannot be absorbed.

The resilience of supplier can be viewed as ability of supplier to absorb shocks from disruption and recover from disruption if the severity of disruption cannot be absorbed. One of the factors that contribute to the supplier resilience is reliability. Of course, manufacturers would like to collaborate with reliable suppliers. Reliable suppliers are those with less failure rate. Hence, supplier's reliability is an important factor for evaluating suppliers.

5.2 Mathematical modeling

This subsection presents an optimization model for resilient supplier selection. As discussed earlier, supplier reliability is an important issue in the context of supplier selection and has a probabilistic nature. Hence, it is necessary to incorporate the supplier reliability in the mathematical mode. There are two important assumptions for modeling supplier reliability.

- The breakdown time for each supplier follows an exponential distribution with a known failure rate.
- The breakdown cost for each supplier is known and constant.

5.2.1 Reliability modeling

Considering z_i is a binary decision variable indicating that whether a supplier is selected or not and x_i is a decision variable indicating that the number of products that can be assigned to the supplier *i*, and y_i as the number of breakdowns occurring for *i*th supplier in a specified time period *T*, then the total breakdown cost of not supplying raw material can be calculated as follows:

$$\sum_{i=1}^{n} z_i\, y_i B \tag{5.1}$$

where *B* is breakdown unit cost. The difficulty with the above formula is that y_i has stochastic nature. One way to deal with this stochastic nature of formulation is to use of chance constraint programming approach. As discussed earlier, it is known that the time between suppliers failures are following exponential distribution. Hence, the number of breakdowns for each supplier can follow a Poisson distribution. Considering the proposed notation, the probability of N_i failures in the ith supplier can be calculated as follows:

$$\Pr(y_i = N_i) = \frac{(\lambda_i T)^{N_i} \exp(-\lambda_i T_i)}{N!} \tag{5.2}$$

According to the chance constraint programming approach, the stochastic variable y_i in equation above is replaced by N_i as a new deterministic variable, and the following CCP is added to the model to ensure that the number of supplier breakdown in a given time period T does not exceeds N_i in at least α of time.

$$\Pr(y_i \leq N_i) \geq \alpha \tag{5.3}$$

Considering the Equation 5.2, then the Equation 5.3 can be rewritten as follows:

$$\sum_{s=0}^{N_i} \frac{(\lambda_i T)^s \exp(-\lambda_i T)}{s!} \geq \alpha \tag{5.4}$$

The supplier reliability formulation can be then summarized as follows:

$$\text{Total breakdown cost of suppliers} = \sum_{i=1}^{n} z_i \, N_i B \tag{5.5}$$

$$\sum_{s=0}^{N_i} \frac{(\lambda_i T)^s \exp(-\lambda_i T)}{s!} \geq \alpha \qquad \forall i$$

$$N_i \quad \text{is integer} \ \ \forall i$$

Note that $z_i N_i$ is nonlinear term which makes the problem difficult. To handle this difficulty, the following variable is introduced:

$$w_i = z_i N_i \tag{5.6}$$

In the equation above z_i is binary indicating whether supplier i is assigned to the customer or not and N_i is the number of times that supplier i fails to supply raw materials and is an integer variable. Therefore, a new constraint is introduced.

$$w_i \geq N_i - (1 - z_i)M \tag{5.7}$$

5.2.2 Disruption risk modeling

Different approaches can be used to model the disruption cost poses to the supplier for not supplying the raw materials. Here, a conditional value at risk (CVaR) is used to model the disruption costs of supplier's failure. CVaR has been extensively used to calculate the disruption loss in the context of financial management. The concept of CVaR is originated from value at risk (VaR). VaR is calculated based on probability distribution of loss for a given system and focuses on high frequency and low-consequence conventional risk incidents for a specified time horizon. CVaR is sued to quantify the expected loss exceeding VaR limit. Accoring to (Deborah Kidd 2012) "*CVaR is superior to VaR because CVaR quantifies tail risk and has been shown to be sub additive*". To represent how CVaR mathematically can be modeled, consider $f(x, y)$ as the losses of a portfolio depending on decision vector x, and y, where x represents a set of decision units to be selected and y represents stochastic variable that indicates uncertainty. According to (Rockafellar and Uryasev 2002), the definition of CVaR can be represented as follows:

$$\mathrm{CVaR}_\delta(x) = E[f(x, y) | f(x, y) \geq VaR_\delta] \tag{5.8}$$

$$= \frac{1}{1-\delta} \int_{f(x,y) \geq VaR_\delta} f(x, y) \times p(y) dy$$

Due to exist of δ-function distribution, the CVaR model represented above cannot be easily solved. Instead, Rockafeller (2000) defined an alternative way with use of auxiliary function as follows:

$$F_\delta(x,\phi) = \phi + \frac{1}{1-\delta}\int [f(x,y) - \phi]^{+} p(y)dy \tag{5.9}$$

Rockafellar (2000) demonstrated that the minimizing $\mathrm{CVaR}_\delta(x)$ is equivalent to minimizing $F_\delta(x,\phi)$

$$Min\ \mathrm{CVaR}_\delta(x) = Min\ F_\delta(x,\phi) \tag{5.10}$$

Rockafellar (2000) introduced a dummy variable T that can be replaced with the minimum of $F_\delta(x,\phi)$ as follows:

$$\mathrm{Min}\ F_\delta(x,\phi) = \phi + \frac{1}{1-\delta}\int T \times p(y)dy \tag{5.11}$$

$$T \geq f(x,y) - \phi; \quad T \geq 0$$

The disruption risks poses to the supplier can be modeled using definition of CVaR. The basic elements for modeling the disruption risk of supplier are to measure the probability of disruption and also amount of disruption poses to the supplier. Let ρ to be the shortage loss that customer experience due to the supplier disruption and p_i is the probability of disruption associated with supplier i, then the total expected disruption of suppliers loss under scenario s is

$$L_s = \sum_{i=1}^{n} z_i \rho x_i - \phi \tag{5.12}$$

where x_i is the number of items (products) allocated to supplier i. So the disruption risks of supplier selection problem can be then modeled as follows:

$$\text{Min } F_\delta(x,\phi) = \phi + \frac{1}{(1-\delta)}\sum \pi_s T$$

$$T \geq \sum_{i=1}^{n} z_i \rho x_i - \phi\,; \quad T \geq 0 \tag{5.13}$$

where π_s is the probability of disruption scenario *s*. There are two other important constraints that are taken into account; demand constraint and supplier's capacity constraint. The demand constraint is modeled as follows:

$$p\left(\sum_{i=1}^{n} x_i \geq D\right) \geq \alpha \tag{5.14}$$

The chance constraint above ensures that the customer's demands is met with confidence level of α%. The chance constraint above can be rewritten as follows with the assumption that customer's demand follows normal distribution:

$$\sum_{i=1}^{n} x_i \geq \mu + \Phi^{-1}(\alpha)\delta \tag{5.15}$$

where

$$\Phi(x) = \frac{1}{\delta\sqrt{2\pi}} \int_{-\infty}^{x} e^{-\left(\frac{x-\mu}{2\delta}\right)^2} = \alpha \tag{5.16}$$

The capacity constraint of each supplier is modeled as follows:

$$x_i \leq z_i Q_i \qquad \forall i \in I \tag{5.17}$$

where Q_i is the capacity of supplier *i*. A weighted goal programming approach is used to model the objective functions.

$$z = w_1\left(\sum_{i=1}^{n} z_i o_i + c_i x_i\right) + w_2\left(\phi + \frac{1}{(1-\delta)}\sum \pi_s T\right) \tag{5.18}$$

where the first term in objective function is sum of order cost and purchase cost and second terms is the disruption cost of suppliers. w_1 and w_2 are weights of these two objective functions respectively.

5.3 Experimental results

As discussed earlier, the main decisions for solving supplier selection is to find optimal suppliers and optimal size of order to each one. The data required to solve this problem is summarized below:

n, number of supplier is 15 (*i*=1,…,15), each supplier can be either fail of operating. Hence, there are 2^{15} disruption scenarios.

p_i, probability of disruption associated with supplier i, $p_i \in$ Uniform[0.002, 0.03]

o_i, Order cost of supplier i, $o_i \in$ Unifrom [300, 800]

c_j, purchase cost from supplier i, $c_i \in$ Uniform [40,100]

D, demand is assumed to be normally distributed with an average of 1500 and variance of 25

Q_i, Capacity of supplier i, $Q_i \in$ Uniform [50, 150]

Note that confidence level is assumed to be 95% and w_1 and w_2 are set to be 0.6 and 0.4 respectively in the test problems. The results of selecting supplier for different demands are graphically represented in Table 5.1.

5.4 Final remarks

The resilience supplier selection has become an important problem in the context of supply chain systems due to the global and competitive features of supply chain systems. This chapter introduced a weighted goal programming model for resilient supplier selection problem. The reliability of supplier and supplier disruption risk due to disruptive events are taken into the model. The supplier disruption risk is modeled using conditional value at risk (CVaR) technique. To handle the stochastic nature of demand, a chance constraint model is represented. The future work can be extended by introducing different transportation modes by suppliers. Extra inventory capacity can be also modeled as pre-disaster strategy to enhance the resilience of supplier.

Table 5.1 Supplier selection and allocated order quantity

Demand	Supplier (order quantity)	
D1	S4 (600)	S11 (1400)
D2	S1(1300)	S9(800)
D3	S6(2000)	S15(1600)
D4	S6(2200)	S12(1700)
D5	S8(1800)	S12(1850)
D6	S9(2200)	S15(1750)
D7	S10(3070)	S15(1700)
D8	S14(2550)	S10(3050)
D9	S14(2685)	S10(3155)
D10	S14(2970)	S10(3260)

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