A DESIGN-ORIENTED PREDICTION MODEL FOR LEARNING RATES OF INDIVIDUAL MECHANICAL ASSEMBLY TASKS

By

LEON MELVIN DELIONBACK

Bachelor of Science
Duke University
Durham, North Carolina
1950

Master of Science
University of Tennessee
Knoxville, Tennessee
1955

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
May, 1972

A DESIGN-ORIENTED PREDICTION MODEL FOR
LEARNING RATES OF INDIVIDUAL
MECHANICAL ASSEMBLY TASKS

Thesis Approved:

James E. Shamblin
Thesis Adviser

Earl J. Ferguson

M Palmer Terrell

James A. Jackson

D. Durham
Dean of the Graduate College

PREFACE

Recent trends in industry have brought two very significant effects to the center of attention by management, namely: (a) A continued increase in technological progress has resulted in over-all systems which are extremely complex and correspondingly more expensive (examples would be the Boeing 747 or the Nautilus class submarine); (b) There is an increased emphasis by practically all political and social groups on resource allocations to social problems and activities to alleviate or restore the polluted environment. Both of the above conditions have increased the pressure on cost and price analysts to provide more accurate estimates and forecasts. The price per unit has increased, while the number of units per production run has decreased.

Based on the above background information, the prime objective of this study has been to develop a method to predict the learnability of mechanical systems based on actual design parameters of mechanical assemblies. If we assume this approach is feasible, then a quantitative design-oriented prediction model can be specified to forecast learnability of mechanical assembly tasks. Thus, learning allowances for a new design may be prepared, based directly on the unique features of this design, rather than having to rely on historical averages. A series of exploratory tests positively supported the feasibility of this concept. Based on the initial success of these tests, a further series of controlled experiments were run, which further substantiated the effectiveness of this method and permitted the formulation of a prediction model based on the measured sensitivity of design parameters.

More experience and additional tests would be required to further increase confidence in these described techniques. However, an illustrative sample mechanical design assembly analyzed by the prediction model, indicated an apparent error of less than one percent, when compared with results from a series of test runs that were used to generate a learning curve.

Based on the nature of stated industrial problems, the results outlined above were deemed gratifying since the objectives of the research were substantially fulfilled. The author knows of no reason why the methodologies presented in this report cannot be applied immediately to real world problems. The figure of merit and decision making procedures described herein could also be adapted to a wide range of real problems where quantitative measures are needed.

My graduate study at Oklahoma State University was made possible by the support from the National Aeronautics and Space Administration and the Marshall Space Flight Center. I am extremely appreciative for this support and for the unswerving cooperation of Mr. Clyde M. Hightower of the Training Office in Huntsville, Alabama.

There were many individuals who made invaluable contributions to the success of my graduate study and research program. Dr. James E. Shamblin deserves my particular gratitude for his invaluable advice and encouragement, and a special note of appreciation for suggesting the research subject for this dissertation. I also feel a deep debt of appreciation to the late Professor Wilson J. Bentley who was Chairman of my Doctoral Committee. His advice, friendliness, and consideration were always available and cannot easily be forgotten. Dr. Earl J. Ferguson deserves my deep appreciation for his advice, help, and warm encouragement throughout my association with Oklahoma State University. The other members of my graduate committee, Dr. M. Palmer Terrell and Dr. James F. Jackson, also have given their valuable advice and encouragement. Their never-ending search for excellence in the classroom has provided both challenge and inspiration to the graduate students at Oklahoma State University.

I would also like to acknowledge my sincere appreciation to my wife, Clara, who typed the rough draft of my dissertation, and who always provided encouragement and understanding when it was needed. I am also grateful to Miss Velda Davis for her many valuable suggestions and for her excellence in typing the final copy of this dissertation.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Figure | Page

CHAPTER I

INTRODUCTION

Statement of Problem and Hypothesis

Background

Research activities that are both directly and indirectly linked with learning theory have been actively pursued for many years by representatives of several scientific disciplines. Since the majority of the researchers have been psychologists, it is not unusual that most of the resulting studies emphasized observations of the test subjects, which included such animals as dogs, birds, and mice. The results of this research have provided a valuable storehouse of data which continue to be useful.

Engineers have also contributed to the field of learning research. Using different experimental techniques than those of the psychologists and placing different demands on test subjects, the engineers have placed major emphasis on the results of the tests or, more specifically, the learning progress (learning curves). The experimental activities conducted by engineers have been concerned with attempts to forecast, control, or reduce costs and other resource outlays. In previous studies, Baloff (1) reported a procedure to predict learning rates based on performance by groups; Hancock (2) predicted learning rates by use of job start-up parameters, such as type of work, age and sex of the operator, operator skill, and breaks in production cycle; Nelson (3) proposed forecasting learning progress by means of rate differences between slow and fast learners. Regretfully, no examples of research studies were uncovered which were devoted to scaling the possible effects of design complexity on learning progress.

Statement of Problem

Recent trends in American industry have shown a continuous increase in resource requirements for certain production units (e.g., Boeing 747, Air Force C-5A, or NASA Space Shuttle). While the design complexity has been increasing for these production units, the demand in terms of required delivery of production units has decreased. Part of the increase in costs can be attributed to inflation, while part is due to a growth in design complexity. Naturally, there has been increased emphasis in both business and government on more accurate cost estimates. There is, therefore, an increased need to more accurately forecast learning rates in preparation of cost proposals and budgets. One approach would be to base learning-rate estimates on the design complexity of the unique hardware design under consideration. It is felt that approaches of this type will permit more accurate learning-rate forecasts than previous estimating techniques which relied heavily on industrial learning-rate averages and other generalized parameters.

Hypothesis

Based on consideration of the above cited information, it is hypothesized: By use of systems analysis and a series of controlled experiments, perturbations in design configuration can be used to gauge learning rate sensitivity for a minimum set of design-oriented factors. This set will be selected from such factors as the number of parts, the number of sub-assemblies, the number of fasteners, or the required skill level. (See list of Mechanical Assembly Skill Levels in Appendix A.) Based on these factors, prediction models of individual learning progress can be determined for simple mechanical assembly tasks. All tests will be controlled to minimize potential deviations in either the task, test subject, or physical environment. All improvements in output will be assumed to result primarily from individual operator learning as measured by replications of a mechanical assembly task. Outputs from such prediction models will take the form of log-linear learning curve slopes, or the equivalent learnability estimates for each unique hardware design considered.

Learnability Concept

Most of the previous engineering-oriented studies in learning research have reported learning progress functions as approximations of exponential-type functions. The ordinate term is usually expressed as some function of Y, which represents either the time to complete a specific unit or the average process time for "X" units. The abscissa is denoted by X and represents either the total number of units produced or the serial number of a specific unit. For example, if X = 20, this would represent either a total of all units produced (cumulative), or the twentieth unit. Expression of these functional terms in equation format is as follows:

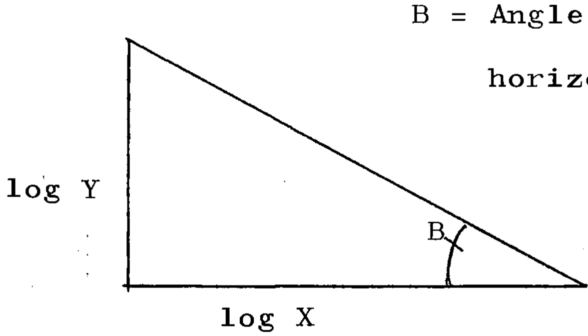
$$Y = a \cdot X^{-b} \tag{1-1}$$

where a = constant, and will represent the Y axis intercept for the condition of X = 1. Equation (1-1) can be rewritten in logarithmic form as shown:

$$\log Y = \log a - b \log X \tag{1-2}$$

where b = an exponent representing a constant reduction in time (Y) per unit (X), or the mathematical slope. Another way of expressing the mathematical learning curve slope is in trigonometric terms for the log-linear learning curve plot as shown below:

B = Angle of learning curve with horizontal axis.



Since tangent of angle equals ratio of opposite to adjacent sides, the tangent of angle B would b

$$\text{Tan B} = \frac{\log Y}{\log X} = [b]. \tag{1-3}$$

If function is montonically decreasing, b is negative. Customarily, log-linear learning curve trends are expressed in terms of learning progress in percent or, more commonly, as "learning curve slope in percent". Since this term for slope is different from the notation for slope as defined above, confusion could result unless there is a clear understanding of the difference.

In order to assure no misinterpretation, the term "m" is assigned to the slope of the log-linear learning curve trace as illustrated in Figure 1. To further clarify, the slope (m) may be defined numerically as the ratio of one ordinate value (and a corresponding abscissa) to a succeeding ordinate value (and an abscissa value which is double the first abscissa). To specify "m" in percent, this ratio must be multiplied by 100, although "m" expressed as a fractional ratio should be assumed for all forms below.

So learning slope in % $= \frac{Y_2}{Y_1} \times 100$ (1-4)

or

$$m = \frac{Y_2}{Y_1} = \frac{a(2\ X_1)^{-b}}{a(X_1)^{-b}}; \tag{1-5}$$

then, simplifying and cancelling gives ...

$$m = 2^{-b} \tag{1-6}$$

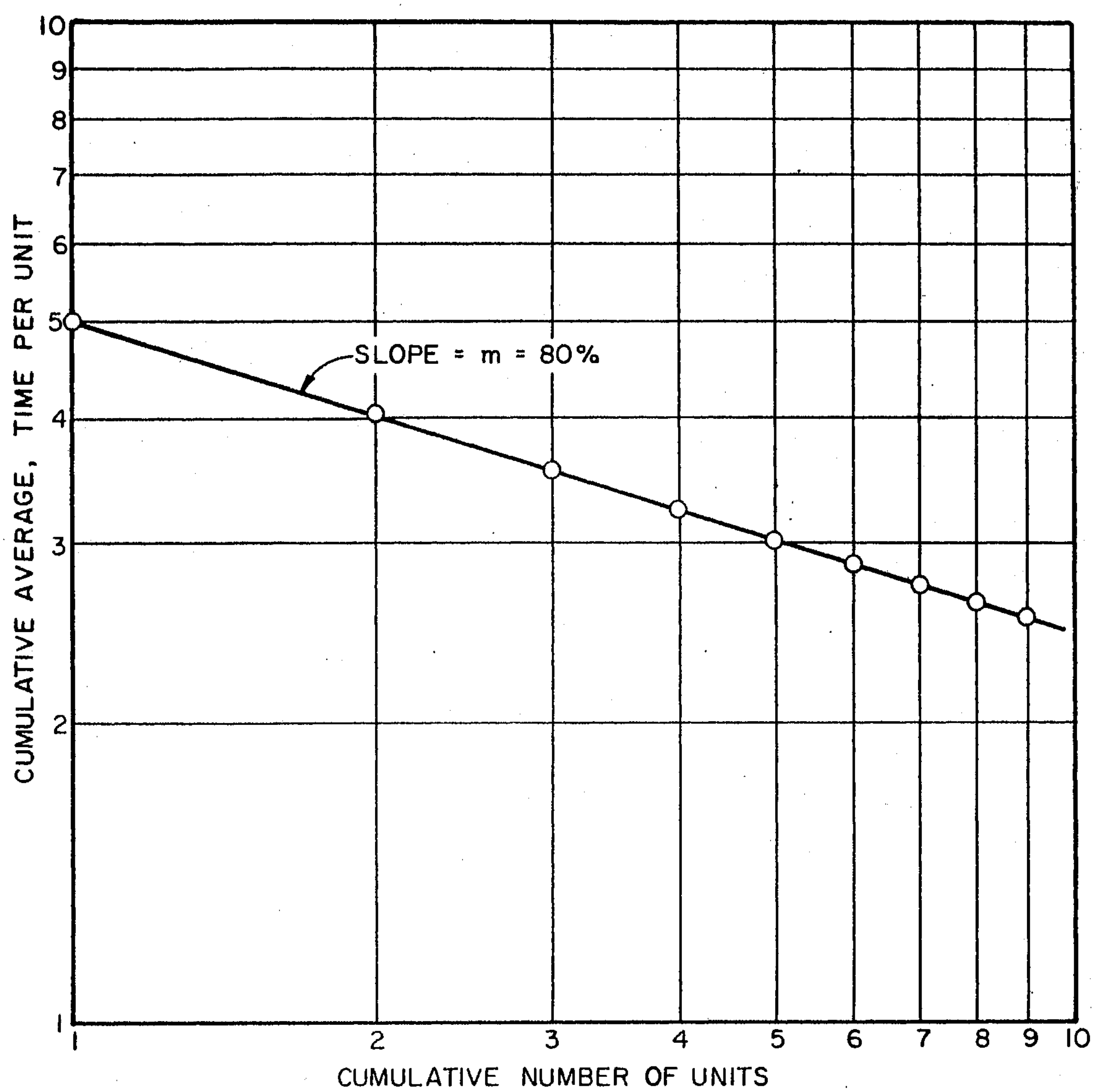


Figure 1. Typical Log-Linear Learning Curve Plot

or $$m = 1/2^b$$

so $$\log m = 0 - b \log 2$$

$$\therefore \log m = -.30103\, b$$

or $$b = -3.32 \log m. \tag{1-7}$$

If Equation (1-2) is plotted on log-log coordinates, it will yield a monotonically decreasing straight line which intersects the Y axis at point X = 1 (see Figure 1). This ordinate intercept may represent the time for unit number one, and is the same value regardless of whether a cumulative-type or a unit-type learning function is used to represent the learning progress trace. Since this relation is linear in logarithmic terms, the slope of the straight line plot is a constant (b in 1-1, 1-2), but it is commonly referred to in terms of percent slope or "m". This percent slope notation is used in industrial as well as government circles to represent rate of learning. The Department of Defense has published a document entitled "Report on Improvement Curve Experience", which lists in tabular form the percent slopes for improvement curves plus a designation as to whether slope is based on "unit" or "cumulative" theory for a large number of NASA, Navy, Army, or Air Force projects (4). In addition, many other sources of historical learning curve slope information are available, e.g., see Dahlhaus (5), Large (6), or Hartmeyer (7). In these and other references, it is the practice to refer to a plot of learning or improvement information on log-log coordinates as the log-linear learning curve, or simply as the log-linear plot. It follows that two terms must be known in order to specify learning accurately:

a) Slope (either b or m).

b) Curve Theory (either unit or cumulative).

Need for New Term

Frequent problems in communication have come up because of the use of "percent slope" to refer to a change in the rate of learning progress. This happens because it has been conventional to use the term "percent slope" (m) of the learning or improvement curve to specify rate of progress on a particular task. If a task is more difficult, the slope (m) increases; if a task is easier, slope (m) decreases. Thus, a task which indicates virtually no learning progress may approach an "m" value of 100%. A learning curve plot for a slope of 100% would be parallel with the X axis on a log-log set of coordinates. This is often confusing to laymen because an increase in percent slope of a learning curve means a lower rate of learning progress is being made. To minimize such problems, it was decided to provide a new term which responds algebraically the same as a corresponding increase or decrease in learning progress. This term is designated as LEARNABILITY (L), and it is defined as follows.

Learnability Definition

Learnability (L) is a measure of the relative ease or difficulty that a designated task(s) may be learned by qualified individuals or groups of individuals. Such tasks may include steps which are purely mental, manual, or combinations of types of activities.

In order to provide a link between previously compiled learning data and this new definition, the term learnability (L) is also defined as approximately equal to the reciprocal of the log-linear learning curve slope or,

$$L \cong 1/m. \tag{1-8}$$

As a typical task becomes easier to perform (or learn), the learnability estimate (L) will increase in value, and, if the task becomes more difficult, the estimate will decrease. The normal range for such learnability estimates will vary between 1.0 for no learning progress to a value of around 1.7 for a rapid rate of learning progress. In this new context, the higher the learnability estimate number, the greater the degree of learning progress can be expected. To illustrate an application of this new term, an example is outlined below.

Learnability Example

The XYZ Furnace Company has designed a new model furnace which it hopes to market in order to become more competitive in the industry. The new design has approximately the same thermal performance as the old furnace design, but design changes have reduced the number of fasteners from 42 to 20 per assembly; the number of sub-assemblies from 10 to 5; and the total of parts from 130 to 44. For the purpose of discussion, the old design is referred to as design A, and the new design as design B. The old design has exhibited a learnability of approximately 1.18 (m = 85%). The new design indicates a learnability of approximately 1.33 (m = 76%). As a reflection of the reductions in values for several design parameters which are sensitive to learning, the learnability value for design B increased significantly. Learning curves for both design A and design B have been plotted on Figure 2. It should be noted that there is not only a difference in percent slope, but also a decrease in the first unit time for design B. This and other effectiveness parameters must be considered if the analyst is to make an over-all progress or improvement comparison between the two designs. On the other hand, the intent in this study will be to focus attention on those differences in learning performance brought about by variations or changes in the design configuration. Other measures of over-all performance (e.g., material cost) could either add to or subtract from any gains from increased learnability. Learnability, thus, becomes one of a list of performance sensitive parameters which must be reviewed prior to making the final decision to incorporate a design change.

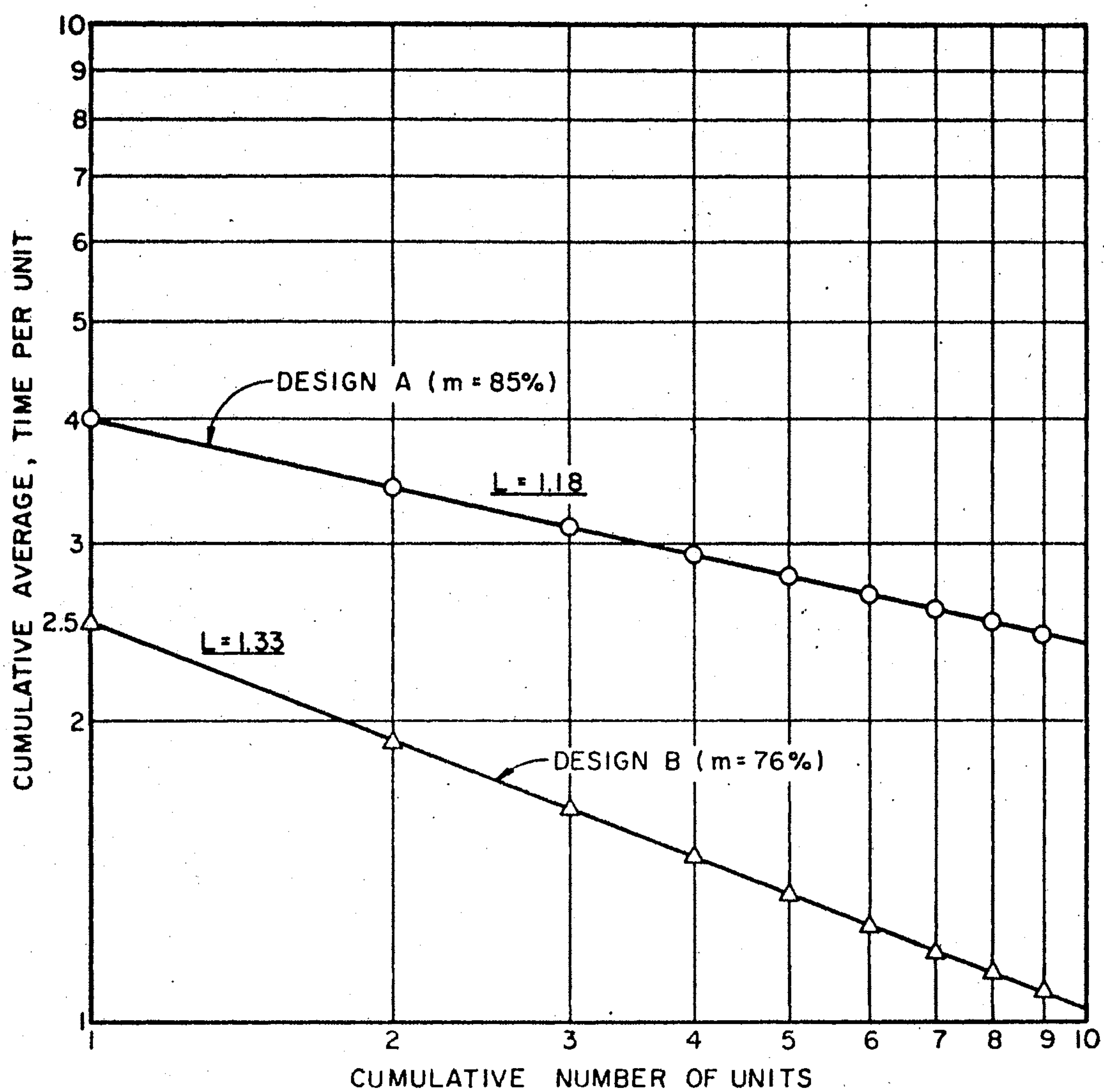


Figure 2. XYZ Learning Curves for Design A Versus Design B

Relationship of Learnability and Systems Engineering Parameters

In order to achieve maximum usefulness in relation to existing technology and/or systems engineering terms, the "Learnability Concept" as developed in the previous section must be clearly stated here and must be understood with respect to those previously established terms. The learnability term is defined particularly such that it would be compatible with a category of system engineering terms called "specialty parameters". Other similar parameters in this grouping include: reliability, maintainability, producibility, etc. As may be observed, all of these terms may be thought of as general technical characteristics of an over-all system to provide more information and engineering confidence in the relative adequacy of the entire system. Learnability has a definite relationship to several of the systems engineering specialty parameters (see MIL-STD-499 USAF, 8). The unique roles played by learnability with respect to these parameters will be cited below. In addition, Figure 3 illustrates schematically the relationship of learnability to other systems specialty parameters.

Learnability and producibility are considered to have a special mutual relationship. For example, if a certain mechanical assembly were to be rated on producibility, the analyst would need to have some measure of the ease or difficulty required to assemble the parts or sub-assemblies. Learnability could be one of the sub-parameters utilized in

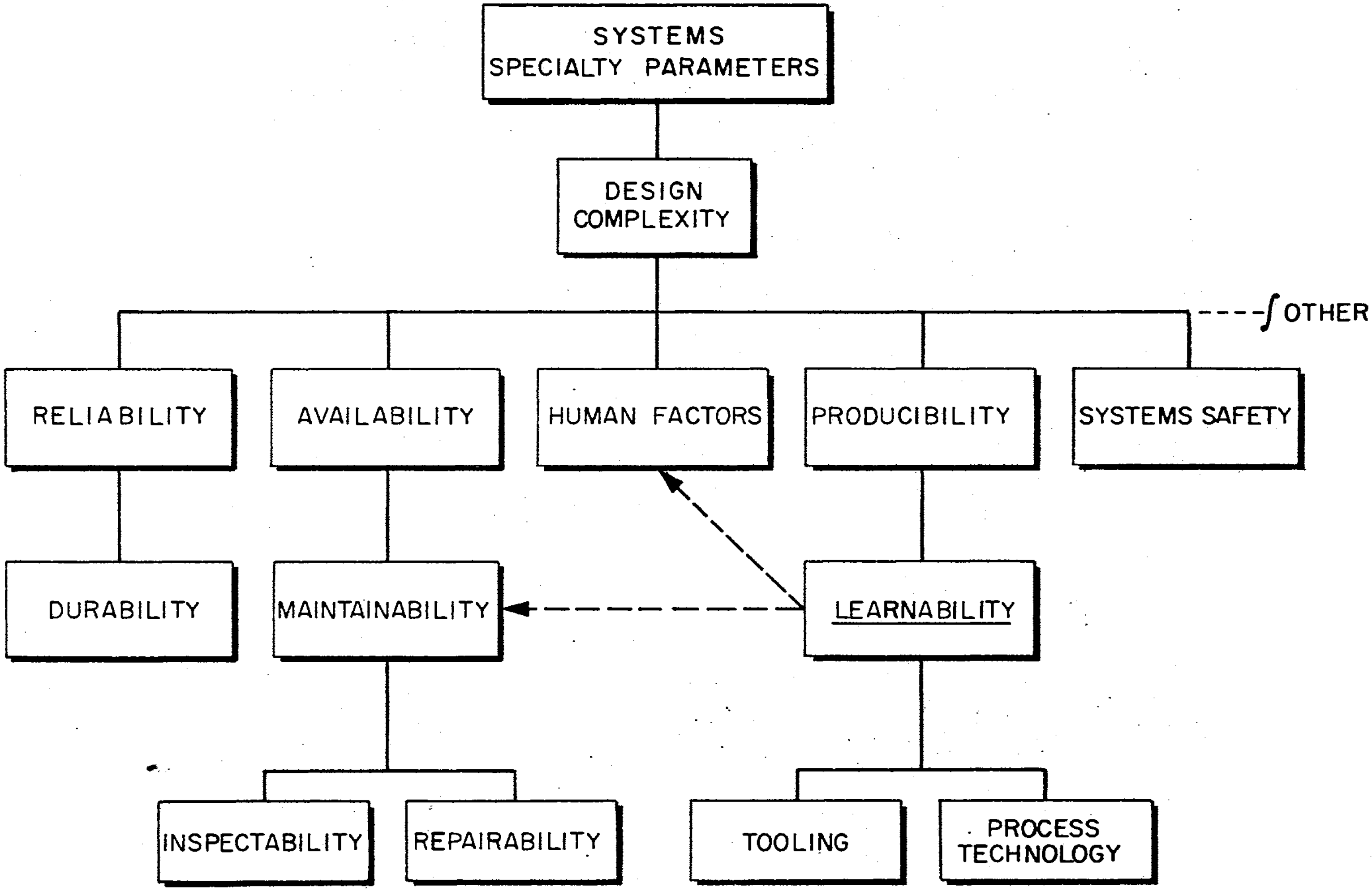


Figure 3. Relationship of Learnability to System Specialty Parameters

estimating the over-all producibility. Learnability would also have significance in any "Maintainability" analysis of a technical system, since, generally speaking, the simpler a mechanical assembly is to assemble/disassemble, the easier it is to maintain. In a similar vein, the simpler an assembly task can be made, the easier it is to control quality and to provide quality and reliability assurances.

Complexity and Learnability

Although references to the term "complexity" may be found in a wide range of sources, the depth of penetration in treatment is generally very shallow. Ellis and Ludwig (9), in their book Systems Philosophy, have devoted one chapter to the subject. As is the case with the term "system", complexity commands a broad interest by various physical and human scientific disciplines, including psychology, training/education, engineering design, industrial engineering/management, reliability, systems safety, etc. A total listing would be almost endless, as would be any attempt to pursue a study of the entire spectrum of involvement. Therefore, in keeping with the purpose of this study, an attempt will be made to clarify the special or unique role played by complexity as it relates to the learnability concept previously described. In this application, "design complexity" is the particular part of complexity which appears to be most important to this investigation. Other system parameters which are succinctly related to design complexity are such systems aspects as flexibility, operability, producibility, and maintainability. Ellis and Ludwig (9) have reported that a general increase in complexity shows an exponential increase in the probability of failure. They also report an apparent engineering paradox which results when components or sub-systems are added to a prime system to increase reliability through redundant "share-the-load" or "stand-by" capabilities. (Usually, reliability decreases with increasing design complexity.) The addition of "self-checking" and in some cases "self-healing" components/sub-systems also are intended to increase reliability, even though such additions add to a general growth in complexity. Other side effects brought about by a general increase in complexity are the increased requirements for the test and checkout of parts, components, and sub-systems. In the case of certain super systems (e.g., Apollo Program), there will be a need to provide additional design, documentation, and, in some cases, test and checkout efforts to develop interface (or between systems) requirements. Such activities tend to increase over-all complexity and program costs. (See article by Harris (10)).

Micro Complexity Analysis

The above information was developed primarily from an over-all or total-systems point of view. Based on the limits of manageability, and also from the standpoint of a logical starting place, attempts to quantify complexity data are constrained to the micro or individual worker level. The approach at this level is to run controlled experiments using a single operator performing mechanical assembly tasks. Experimental data points keyed to certain design-oriented factors of the mechanical assembly tasks can be used to scale complexity and to measure rates of learning progress over time, i.e., learnability. These micro level gauges of complexity might eventually be integrated or otherwise expanded to provide some measures of macro or over-all system complexity. In general, it has been found that learnability will tend to decrease as complexity increases. In other words, a subject (or operator) will find any task more difficult to learn as its complexity is increased. The task taxonomy must be scrutinized carefully in order to ascertain which factors, aspects, or other characteristics make the activities more or less difficult to accomplish. As shown graphically in Figure 4, there are three prime factors involved in this analysis: a) the subject, b) the job taxonomy, and c) the design features or characteristics. As shown in the diagram, each of these prime factors have unique sub-factors which must be considered in any learnability analysis. In a controlled experiment of this type, changes in task complexity will be minimized for any one test as will be changes in operator-oriented variables. Learnability values are determined

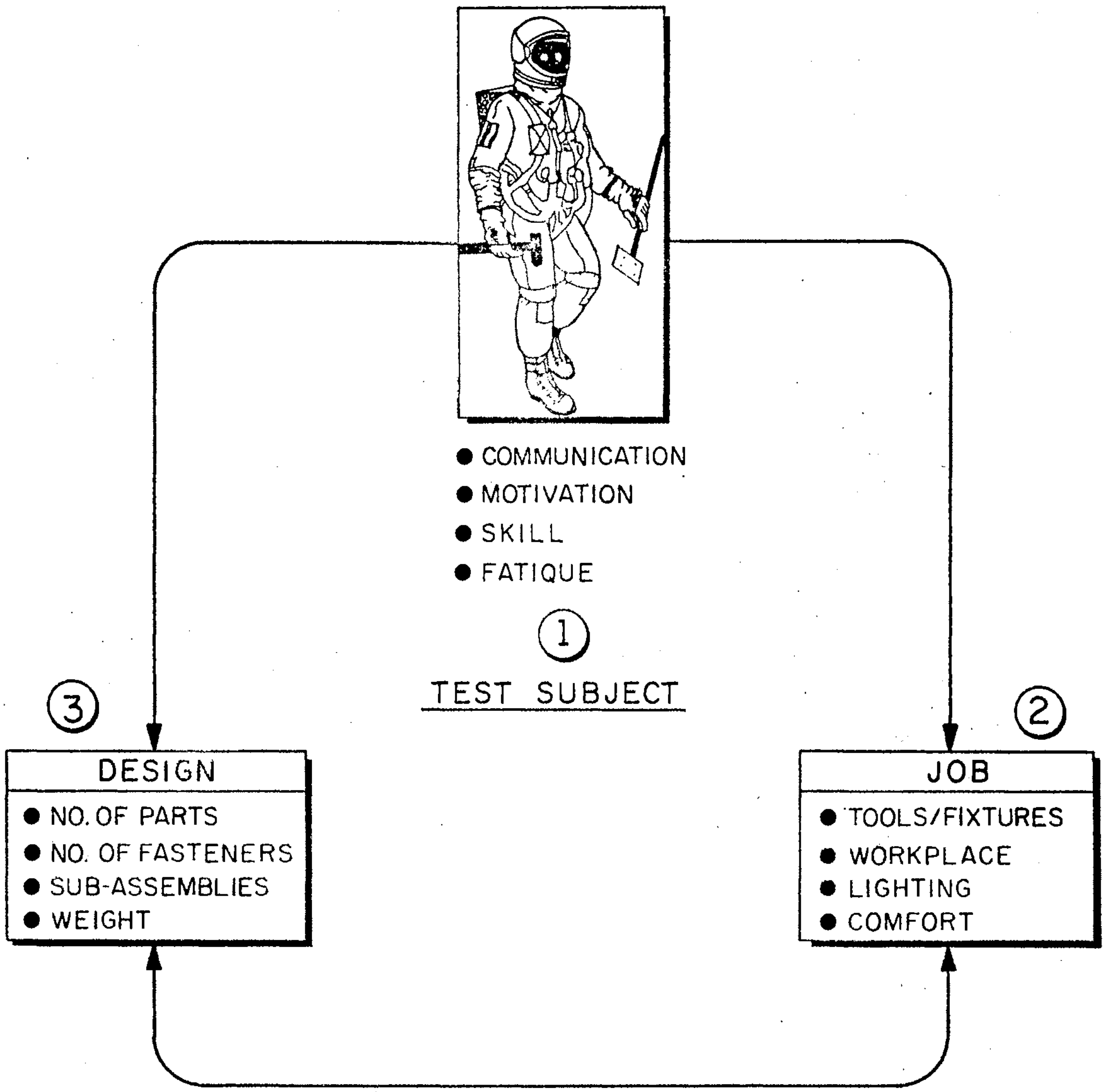


Figure 4. Man-in-the-Loop Flow Diagram Showing Three Prime Factors

as indicated by the cyclic output of a test subject/operator over time. A plot such values has commonly been referred to as a "Learning Curve".

Design Impact on Learnability

Design complexity will play a major role in any analysis of design effects on learnability. This effect or impact is also a major consideration when attempting a learnability review of a mechanical assembly task. As outlined previously, such mechanical design features as the number of parts, the number of sub-assemblies, or the number of fasteners will directly affect the inherent or relative difficulty experienced by an operator in completing a task of this type. A listing of other mechanical system design-oriented features which directly affect learnability are pressure relief valves, shaft seals, ball bearings, and gasket closures. These parts tend to critically affect operation of some assemblies and must be assembled with utmost care and precision to assure proper performance of the total system. This tends to increase skill requirements, and learnability would, therefore, decrease with the increased use of this type of part in a system.

Goldman and Slattery (11) have reported that in the case of electronic modules, an optimum design complexity range exists for electronic modules in terms of number of transistor parts per module. This analysis was based on the policy assumption that the electronic module being considered was designed for discard, as opposed to being repaired when a malfunction occurred. The optimum occurred at around 30 transistors per module but with a constant decrease in cost effectiveness after this point was passed. At present, there is insufficient information available to permit any valid comparisons (using this approach) with respect to mechanical components, sub-systems, or systems.

To control a potential growth in number of parts and other undesirable trends, an organized attempt for "simplification of design" would be an alternative. Fewer parts and, in particular, fewer moving/closure parts would not only tend to make a system more reliable but would also tend to reduce costs and increase learnability.

Special Tools/Equipment Required by Design

Sometimes when certain unique design features are established or introduced into the design configuration, there will automatically be established a need for special tools or equipment and, at the same time, special skills/ processes to meet these technical requirements. Typical examples would be an assembly fixture required to meet close tolerances on assembly dimensions; or the need for a special reaming tool to meet a very small allowable parallelism tolerance; or design specifications calling for specific torque values for threaded studs, which might require special "torque wrench" as well as special skill. In all of these examples, there is an increase in complexity and a corresponding tendency toward a decrease in learnability. This is generally true of any deviation from the norm in usage of standard tools, equipment, fixtures, processes, or modes of operation.

Engineering Materials Versus Learnability

It appears logical to assume that costs will go up and learnability value will go down as more sophisticated materials and/or processes are specified in design criteria. Again, this is primarily related to an increase in skills required to complete the various fabrication and assembly tasks. A recent report published by the Aerospace Corp. (12) lists complexity factors with respect to choices of several exotic alloys, including coated tantalum, coated columbium, Rene 41, etc. Since such materials normally require more time and care to process, complexity will increase as will the skill requirements for production workers.

In summary, it has been stated that learnability may be affected by one or more of the several types of design features related to mechanical assemblies, such as the number of moving parts, the number of closure parts (shaft seals, gaskets, etc.), the number and type of different materials used, the number of parts, the number of sub-assemblies, the number of fasteners, the number of heat treatments, the need for special coatings or surfaces, or the need for special tools/equipment.

Design Effect on Mechanical Assembly Learning

Previous sections have discussed complexity and how complexity affects learnability, or how certain design features will tend to increase complexity and, thus, decrease learnability as a task becomes more difficult to perform. Such effects are perhaps more transparent insofar as mechanical assembly tasks are concerned, since it can readily be seen, for example, that a metal shelving unit with ten shelves will be more difficult to learn to assemble than a three-shelf unit. Also, the ten-shelf unit will automatically have a much larger number of fasteners and other related parts. These aspects are all design-oriented features, and they will usually have an effect on the time required to complete mechanical assemblies. Suppose a design change in a mechanical assembly replaces a machine screw fastener with a self-tapping sheet metal screw. As before, the total number of parts would decrease and learnability increase. The operator would have a simpler job to perform, since he would have fewer parts to handle and install. By use of creative design, a designer might be able to completely eliminate all fasteners from this unit by redesigning the shelving posts such that they would accept the shelves with a simple plug-in type connection.

Even greater savings could then be effected through further reductions in parts, lower standard times, and increased learnability.

Material Selection Impact on Mechanical Assembly

In some cases, the choice of aluminum instead of steel could have a significant effect upon the ability of an assembler to handle either component parts or a complete assembly (e.g., aluminum lawn furniture). Also, in some instances it may be possible to substitute a single part for several smaller parts by use of a metal die casting, or a moulded plastic. Other possible design innovations might involve use of epoxy cements to bond together component parts in lieu of traditional screw or bolt fasteners. Gains in learnability might result by reductions in required skill, weight, and number of component parts.

If the designer plans his design not only for ease of manipulation by the assembler, but also for easy access with standard tools and fixtures, there could be an additional increase in learnability for a mechanical assembly.

Closing Remarks

This chapter has endeavored to introduce the Learnability Concept, and demonstrate how it fits with other previously established system engineering parameters. Descriptive information has also been presented for the key term "Complexity", and the unique role it plays, for example, in attempts to quantify learnability. Narrative has also been submitted concerning other related aspects which tend to affect learning in performance of a mechanical assembly task. Chapter II will utilize information from Chapter I as a foundation for a more complete description of critical parameters/aspects involved with learning theory, and a taxonomy of relevant learning theory terms. The goal will be to build a bridge of understanding between the large contribution to applied learning theory by the behavioral scientists (psychologists, sociologists, etc.) and the industrial/systems engineers. Hopefully, these discussions will furnish a necessary background of learning theory fundamentals, and at the same time provide the basis for a learnability prediction model.

CHAPTER II

LEARNING THEORY AND APPLICATIONS

Learning Theory Overview

Problems of Classification

Although the main body of learning theory is centered in the field of psychology, interest by academicians and laymen is clearly evident in such other disciplines as management, sociology, and engineering. Since different points of emphasis and paradigms of investigation are practiced by each group outside of psychology, the problem of choosing rigorously correct categories is magnified. Another facet of the classification problem is the sheer size of the sub-field called Learning Theory. Were it not already classified as a sub-set of the much larger discipline of psychology, it could easily qualify as an independent discipline. Although a portrayal of the entire scope of learning theory is beyond the scope of this study, an effort will be made to present an abbreviated summary of the primary categories with emphasis on the "Perceptual-Motor Skill Learning" category. This category includes the particular experimental investigations which were utilized in this study. Actually, the category is a sub-category of

"Learned Skills", the other sub-category being "Language Skills". A tree diagram, which depits the logical representation of some categories of human learning and/or performance, is included as Figure 5. This schematic representation, in conjunction with the descriptive definitions given below, is intended to provide a capsule understanding of learning theory, as developed and portrayed by the psychology discipline. These descriptions are felt to be necessary for a more complete understanding of the stated problem(s), in spite of an almost universal convention by psychology researchers to focus observations on the test subject's reaction and performance (see Figure 4, p. 17). The praxis of this study has been to consider all aspects of a mechanical assembly task/job. In some references, research in perceptual-motor skill learning is referred to as training research (12). Much of the research activities in training have been sponsored by various military agencies, particularly the Air Force relative to flight crew tasks (e.g., pilot, navigator, bombardier, gunner, etc.). More recently, with the advent of larger and more complex aircraft, this type of activity has been given increased emphasis by commercial airlines and the Federal Aviation Administration (FAA). Also, the National Aeronautics and Space Administration (NASA), chiefly at the Houston Manned Spacecraft Center, has been engaged in highly detailed training exercises utilizing very complex training aids and simulators. The degree of success by both commercial carriers and NASA in

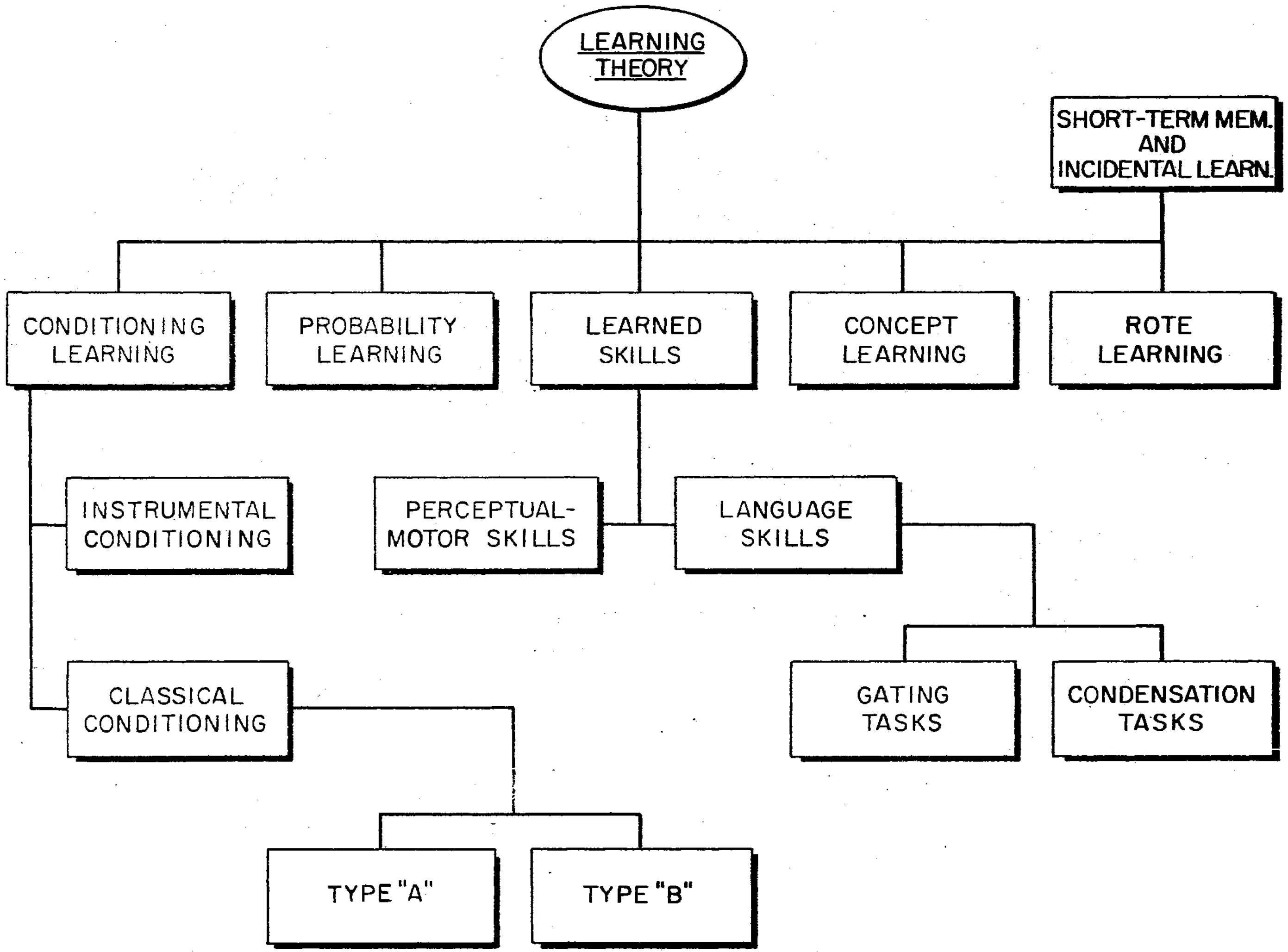


Figure 5. Categories of Learning Theory

space and flight operations would appear to justify the need for this type of research activity.

The work that follows has been structured to present a compendium of learning theory as it relates to the stated hypothesis in Chapter I. The order of the various categories presented is not intended to indicate any degree of importance, although as previously stated, the section on "Learned Skills" embraces the sub-set (Perceptual-Motor Skills) which was studied in the experimental parts of this research.

Conditioning

Conditioning, as a learning theory sub-discipline, probably had its beginning in the 1920's with the research conducted by the Russian scientist, I. P. Pavlov (13). As is the custom in many Russian experimental studies, Pavlov utilized dogs as test subjects. The conditioning training given to the dogs consisted essentially of audio signals (bell ringing) each time hungry dogs were fed. Eventually, the dogs salivated in anticipation of food each time a bell was rung, even though in some instances there was no reward of food. This type of conditioning has become known as "Classical Conditioning". It has two sub-classes -- type "A" conditioning, as in the dog experiment outlined above, and Pavlovian type "B" conditioning, after another Pavlov dog experiment in which the animals exhibited both nausea and salivary secretions with a mere touch by the experimenter (after first being conditioned by several injections of morphine). The primary difference between type A and type B is the kind of motivation present in each case. The test subject in type A is positively motivated with the possible reward of food. In type B, the motivation is negative, since it is based on the fear which the animal experiences after repetitive injections of morphine by the experimenter.

The other main class of conditioned learning is known as "Instrumental Conditioning". This type of conditioning may be illustrated by the tests reported by B. F. Skinner (14). White rats were conditioned to press a small lever in their cage, which would automatically drop a food pellet in a cup as the reward. There are eight sub-categories of instrumental conditioning, and approximately one-half of these sub-categories depend on rewards for motivation reinforcement, while the other one-half depend on some form of punishment (15). The thread of commonality running through all forms of instrumental conditioning is the use of some device or mechanism in the actual conditioning process. For example, in Skinner's rat experiments, it was a clicking lever in a soundproof box; in Sheffield's and Temmer's experiments (16), it was the electrically charged floor. In some cases, the cue/signal is audio; in others, it is visual (color-coded, etc.). Alternatively, it may be in the form of punishing-type cues, such as electric shock, excessive heating, or cooling. The organism, whether human or animal, learns from cues that either motivate the subject positively by reward or negatively by some form of punishment.

Rote Learning

This category of learning has been called "Verbal Learning", which can be considered a synonym for it. As contrasted with conditioning or skill-type learning, rote learning, by individuals, has to do with individual learners whose learning may be the memorization of words or groups of letters (e.g., VXK). Sometimes single letters, such as those commonly used in psychological journals, are memorized (for example, S = test subject, E = experimenter). Learning of this type is strictly mental and does not normally have physical cues. As illustrated in the examples given above, the use of an acronym may serve to reinforce memorization in rote learning. Further examples are such terms as "ID" to represent Index of Difficulty or "RT" for Reaction Time.

Probability Learning

This sub-group of learning theory encompasses a large group of activities that include a significant proportion of the quantitative and applied mathematical/statistical analysis of experimental learning data. A classical example would be an investigation in which the test subject is given a series of experimenter-defined sets of alternatives. After making a choice, the subject receives a signal from the experimenter indicating whether or not his responses were correct. Also typical for this type of experiment design, each response has some fixed probability of being reinforced (noted as being correct by the experimenter), and this probability is independent of the test subject's present or past choices. To be more specific, a test subject may be asked to predict which of two alternative events will occur (e.g., light on or light off). After each trial, either one or the other of the two events does take place (17). However, there is virtually no limit to the number and variety of tests or experiment designs that could be devised to probe the unknowns of this sub-field. In some studies, the subject is motivated by either a reward or a punishment, depending on a proper selection of alternatives (18). Results have shown a tendency toward "repetition responding". From the standpoint of such responses, a correct response by a test subject tends to be repeated, whereas an incorrect response tends to be changed. Since such trends are not necessarily congruent with the expected likelihood of occurrence for each of the alternatives, this type of response tends to bias the recorded data.

Short-Term Memory and Incidental Learning

Although these two learning sub-categories are grouped together, there are some unique differences. For example, a distinguishing feature of incidental learning is that a limit is placed on the number of presentations of material to a single or, at most, a few replications. On the other hand, short-term memorization is primarily concerned with a subject's ability to immediately reproduce the materials to which he has been exposed. Short-term memorization is also concerned with serial organization and the process of forgetting.

Typical examples of short-term memory being used in learning applications are:

(a) Copying Morse code signals behind real-time; transmission has been used by radio operators to copy a signal speed which would be virtually impossible to copy continuously in real-time. Morse code speeds in excess of 30 groups/minute* have been copied on a real-time basis by using this technique.

(b) In essence, the same approach has been used by secretaries in copying shorthand characters behind the real-time dictation speed for correspondence (19).

In both of these cases, serial organization within a short-term memory trace is important, so characters will be transposed from short-term memory to a written manuscript in the correct sequence.

---

*Morse code groups consist of alpha-numeric characters copied in groups of five characters per group by a transcriber. These groups are sometimes referred to as "words" in the radio-operator discipline.

Concept Learning

Although this sub-class of learning does not appear difficult to characterize on the surface, clear and concise definitions do not appear to be readily available. Three suggested identifying properties of "concepts" are: (a) associations, (b) cues or stimuli, and (c) responses. The "Learning Curve Concept" could be used as an illustration. This approach should stimulate associations with other types of curves and even other concepts such as the law of diminishing returns, a situation which might be graphically illustrated by a plot of human performance data over a period of time.

Concept learning is, therefore, something more than a neat package of information which can be transmitted or received in a discrete manner. It has to do with acquiring by learning some distinguishing features or criteria of one "thing", which can set it apart from other "things". Concept learning may also be a general idea, or property, that can be assigned to two or more individual items.

Learned Skills

As previously noted, this category of learning theory includes two principle sub-categories: (1) perceptual-motor skills and (2) language skills. Both categories include rather extensive ranges of information, which must be included in classes of activities that people perform every day. There is little doubt that humans participate in both sub-categories, the only uncertainty being in the relative proportions of Type I (perceptual-motor skills) versus Type 2 (language skills). Some jobs require a preponderance of manual/physical actions, such as agricultural harvesting, ditch digging, or professional football. Other tasks require a primarily "mental" or "thinking" set of activities, such as would be performed by an accountant, scientist, or chess player. Even so, no single job would normally require only mental, or strictly manual operations; logically, it would contain instead a combination of the two.

The Type 1, or perceptual-motor skill, sub-category as noted above includes those tasks which are primarily manual or physical. There are many factors which affect the learning performance of a human in this context. Some of the more sensitive variables are:

(a) Complexity of task (number of separate steps or processes required to complete task), including design complexity.

(b) Time interval required to complete cycle.

(c) Individual/natural skill or compatibility of operator.

(d) Bias-type constraints placed on test subject due to environmental and/or job design aspects.

(e) Motivation of operator, including knowledge of results, rewards (whether positive or negative), etc.

(f) Pressure to reduce cycle time, whether self-imposed by the operator or by supervision.

(g) Number of practice cycles or replications of a perceptual-motor task.

(h) Similarity of the task to other tasks previously performed by the operator.

Each of the above factors may influence the accuracy of human performance measurements, if they are not controlled or adequately considered prior to measurement. For example, if an Air Force bombardier uses a bomb-sight device which is out of calibration, his performance will surely reflect this type of bias. Another example is the negative motivation of an operator who receives no feedback on the accuracy or speed of a task he is performing. By proper understanding and consideration of each such factor, it should be possible to increase the accuracy of measurements for perceptual-motor skill tests. This objective was established as a ground-rule for controlled experiments in perceptual-motor skill learning, which will be described in subsequent chapters. Task complexity or, more specifically, "design complexity" was utilized as an independent variable. Readings at several levels of design complexity were taken for a single test subject, while other variables were either controlled or held constant.

The Type 2, or language skills, sub-category, has been used to include all those varieties of learned skills which require thinking or mental effort. Such skills include mathematics, logic, science, and other related disciplines normally used in problem solving. Also included is the normal day-to-day use of language in conversation, reading, and writing. Although speed of learning is a factor in this sub-category, success may be more important in the solution of problems. Typical in language-type skills is an activity that has been called "information reduction".

Information reduction involves the normal summarization and abstraction of information such that it is in manageable proportions. Attendees to management staff meetings frequently communicate with other parts of the organization by writing what is called "Highlights of the Meeting". These highlights represent a condensation of the information covered in the staff meeting. Highlights from meetings may also represent the output from a gating-type sort of meeting topics into either relevant or trivial information by the meeting secretary. The meeting highlights will normally include only relevant information, trivial topics will simply be overlooked or deleted by the meeting chairman.

The human mind is continually required to process raw information by means of "gating tasks" (sorting books as cloth bound or paper bound, allowing other features to be ignored), "condensation tasks" (classifying digits as odd or even, retaining only part of the information received from the numbers), or both. In general, the more dimensions/parameters which a test subject has to either ignore or classify, the slower he learns (20). This observation is related to experiment observations in subsequent chapters. When perceptual-motor tasks increase in complexity, progress of learning is slower (assuming other variables do not vary). It has been argued that the larger the number of factors or sub-parameters requiring consideration in a decision-making exercise, the greater will be the expected number of errors (21).

Industrial Applications of Learning Theory

Training Production Workers

With the advent of automation, there has been increased emphasis on micro-level planning of production activities for workers. At the same time, there has also been a trend toward positions which are less complex and are shorter in cycle time. Such tasks are basically simpler and demand less skill from the workers. For this reason, the training activities have become restricted to brief pre-job orientation and training sessions just in the specific activities which the employees will be required to perform. There are many reasons why the individual jobs have been structured as described above, but, primarily, the justifications have been that the total job or process is machine-paced. In other words, the speed or rate of output is tied to the speed of a production line. With this approach, the operators' movements must be coupled with or integrated with the speed of machines. This tends to subordinate the roles played by individual workers with a corresponding decline in the emphasis on workmanship and craftsmanship. Many such workers are simply trained on the job with no formal training period. In some cases, no training is needed since many of the jobs are so simple in skill requirements and number of steps. Although it may seem paradoxical, measurable learning progress is very difficult to ascertain when a task is broken into sub-tasks that are minimum in number of steps and cycle time. Crossman (22) reported on a study of such tasks as cigar-making by individual operators who used cigar machines instead of employing the older technique of hand-rolling cigars. Results indicated that a large number of replications were required in order to demonstrate a traditional learning curve response; also, a rather long time was required (over one year) to register the expected response. It was noteworthy that as the improvement in cycle time was gradually recorded, a leveling-off trend developed as the cycle time of the operator-plus-machine-time approached the cycle time of the machine alone. This result is, of course, as one would expect for an operation which is machine-paced. The study of long-term learning progress for subjects, who use machines to complete their tasks, is outside of the objectives of this study. It represents an important but quite different sub-category in the over-all field of learning theory.

Another aspect of training production workers which is closely related to the technique of breaking down tasks is the strategy of specialization of workers according to individual talents or previously acquired skills. This method tends to support automation and assembly line production techniques. The training periods for individual workers are reduced, and the time required to reach over-all production goals is shortened. Based on pre-employment interviews and tests, workers are normally placed in specific jobs which require skills and aptitudes in which they excell. In some states, such tests are administered by the state employment agency as a service to individuals as well as a means to encourage new plant locations or expansions.

In a plant tour of the Prestolite Corporation* in Decatur, Alabama, it was learned that all prospective employees are given a battery of pre-employment tests which are prepared and administered by the State. This battery of tests includes tests for: (a) intelligence/general ability, (b) verbal aptitude, (c) numerical aptitude, (d) spatial aptitude, (e) form perception, (f) clerical perception, (g) motor coordination, (h) finger dexterity, and (i) manual dexterity. Indications were that a high degree of success had been realized in the placement of employees at the Prestolite plant based on these tests. The only recognized

*The Decatur works of the Prestolite Corporation is engaged primarily in the fabrication and assembly of ignition systems for internal combustion engines. This includes such ignition components as breaker-points, distributors, spark plugs, and voltage regulators.

problem was the tendency of some employees to become bored or restless on job assignments which were well below the individual's performance ability (in the punch press department, for example). The apparently successful corrective action was to assign workers to this location with relatively lower qualifications (e.g., high school dropouts). There was a significant reduction in turnover for these jobs and an improvement in morale. The output from this department was also judged to be completely satisfactory after the change in placement policy.

Hartmeyer (23) in his book has hypothesized: "Only the non-repetitive portion of the job cycle warrants a learning allowance". Presumably, this means that most workers will naturally go through a series of "false starts", redundant, or otherwise superfluous motions during the first few replications of a motor-task. Since these non-mandatory motions are presumably not a part of an officially planned procedure or programmed step, they are classified as "non-repetitive" as well as non-essential. At least a portion, if not all, of the progress made during a learning phase of an on-the-job training exercise would be the gradual elimination of all unnecessary motions. As noted above, high-volume production tasks usually involve jobs which have such a small number of steps, that learning progress may not be detected by normal measurement techniques. There may be no non-essential motions if the job is simple enough; the only apparent learning effects for such a task would be primarily improvements in speed and/or dexterity, after long-term observations. As noted in Crossman above, high-volume production tasks improve at a slower rate, but over a longer time span. Short-term observations may not indicate any learning progress at all, since the rate is so minimal.

Training Military, Air Lines, and Space Personnel in Transportation Equipment Operations

The greatly increased demand for skilled and semi-skilled workers during World War II provided an impetus for a large number of studies on applied learning theory and training research. This series of studies continued well into the 1960's, and only recently appears to have subsided, the slowdown being more or less the result of general cutbacks in federally sponsored studies.

It was during World War II that the use of highly planned training programs came into general use by the military establishment. Special schools were set up to train individuals as well as teams in skills of the motor and/or verbal learning categories. The U. S. Army (including what is now the Air Force) set up separate schools to train individuals in the special skills they would require to become pilots, bombardiers, navigators, gunners, radio-operator/mechanics, engine mechanics, armorers, and so forth. In order to determine individual qualifications for such skills, a battery of tests was set up by learning theory specialists. Several centers (such as the one set up by the Army at Nashville, Tennessee, to test flight crew candidates) were located throughout the continental United States at convenient locations. Tests given flight crews probed perceptual-motor, language, and personality qualifications of the candidate flying cadets. In addition, each candidate was subjected to extremely detailed physical examinations. The students who remained after this lengthy screening process were presumed qualified in one or more of the classification categories. The subsequent activities involved highly programmed training sessions which, in the case of flight crew trainees, were split approximately on a 50-50 basis between verbal and motor skill learning. Classes were arranged such that each morning or afternoon was devoted to either verbal or motor skills. In some cases, students would be scheduled for one week with morning classes in physics, math, and other verbal learning courses. The afternoons would then be utilized for marching, physical training, etc. By alternating between morning and afternoon sessions, it was possible to reduce for students at least some of the potential boredom of the material, which, in the case of verbal learning activities, was related to the necessity of considerable overlearning. As a flight crew candidate progressed through training from beginning levels to advanced training schools, a large portion of the basic verbal learning courses were repeated often at each station in the training cycle. As a result, American flight crews were among the most proficient in the entire world. Overlearning is still utilized by the U. S. Air Force, but to a somewhat reduced degree. Its value, however, has clearly been proven as a means to reduce risks of performance errors by flight crews, as well as ground personnel.

Training Military, Air Lines, and Space Personnel Using Simulators

Another training strategy which received extended trial and use during World War II was the use of training simulators along with other types of training aids to accelerate or improve learning of complex tasks. Such devices varied from such simple devices as headphones and telegraphic keys installed on tables to train Air Force personnel in Morse code to the complex training devices called "Link Trainers", which trained flying students in instrument flying techniques. The link trainer approach has survived to the present time and is being actively utilized by commerical air lines to train pilots to fly the latest commercial jet passenger aircraft such as the Boeing 747. Naturally, improvements and refinements have been made in this technique. One such improvement is the addition of a viewing screen of the closed circuit television type, which presents the trainee with an almost perfect pictorial view of a simulated horizon during landing, take-off, and other critical maneuvers. This and other similar improvements in the design of simulators has enabled training organizations to significantly improve the quality and reliability of such training activities. Consequently, the number of hours required to qualify pilots in actual flight conditions has been reduced as well. This represents a savings in training costs since actual flight time in 747 type equipment is extremely expensive. The military establishment, including the Army, Navy, and Air Force, continue to utilize simulators for unmanned as well as man-machine systems training. Cost-effectiveness as well as increased safety assurance are the justifications. There exists a similar situation in the space administration, for which a very limited number of launch windows and space vehicles are available. The cost of failure in these cases is so astronomical that virtually no opportunity to reduce risks by training is ignored. Elaborate training procedures and mock-ups have been devised for the astronauts. In addition, electrical system "breadboards" have been designed and assembled to simulate the complex electrical systems of the total launch vehicle. With these elaborate simulation devices, it is possible to train operations personnel as well as flight personnel in detailed procedures. It is also possible to probe effects of design changes with less risk to the lives of personnel and less chance of possible damage to equipment. Over-learning is utilized extensively to minimize the risk of forgetting key information at a moment of maximum stress.

Closely related to these procedures is the type of activity called "system checkout". In this type of activity man-machine relationships are developed in which huge complex systems, such as the Apollo launch vehicle, are functionally inspected electrically and, to a limited degree, mechanically. By this method, many otherwise unknown defects and malfunctions have been located in various components and sub-systems of the assembly. Normal practice is to repeat the system checkout two or more times and to correct all discrepancies which are found. Ground personnel learn from practice replications of these ground check-outs, and manufacturing personnel naturally improve the quality of workmanship with each succeeding vehicle. The result is a learning curve output which contains parameters related to several improvements embedded in a single response. Such functions may also contain maturation and/or design innovations in tooling and/or process aspects of manufacturing. These interactions have prompted some researchers to refer to such functions as "Progress Functions", in deference to the fact that not all of the improvement can be truly classified as learning (24).

It can be summarized that simulators and other devices may be utilized for training maintenance, operations, flight, and quality control personnel and that these devices can also be used beneficially in development engineering and the investigation of potential systems safety hazards.

Application of Learning Theory to Human Engineering Problems

Often, it is neither possible nor feasible to measure directly the performance of man-machine combinations. It is also virtually impossible to forecast the performance of functions involving man-machine activities. From this point of view, Meister (25), in his recent book, has stated:

> From a pragmatic standpoint (i.e., the cost of training and its relative lack of effectiveness) we must assign a relatively high priority to any research that attacks the relationship between training and system design in concrete terms.

One possible way to control human engineering design is to observe replicated human performance under stress in the operation of some machine. For example, suppose a test subject driving an auto was given a series of random emergency stops. If these tests were repeated with different emergency-brake designs on the auto, it might be possible to determine which of the designs constituted the best human-engineered emergency brake designs. The best human-engineered brake design would be the one which indicated the most rapid learning progress (steepest slope of log-log plot of stopping time versus number of trials). It would, of course, be preferable to eliminate or hold constant as many other sources of error or variability as possible in the running of such tests. General Motors has recently announced a research program in human engineering which involves a small digital device to prevent intoxicated drivers from being able to turn on the car ignition.

Involved here is the learning theory that most persons are not able to utilize short-term memory when intoxicated. Even when given a random number to reproduce on a push-button type keyboard three separate times, the likelihood is heavily biased that the subject will not be able to recall the correct series of numerical characters if he is intoxicated. In this proposed safety interlock device, the switch for the auto ignition cannot be turned on if the correct random number is not fed into the keyboard by the driver. This type of device could also screen out other potentially hazardous drivers having, for example symptoms of certain drug side-effects such as blurred vision, temporary memory lapse, temporary loss of motor-dexterity (coordination), etc. In certain instances where the driver has neither drugs nor alcohol in his system, he still may not be physically able to drive safely if he cannot complete this simple task.

Another recent application of learning theory to human engineering problems was a series of simulator experiments which were run to optimize the shape of the control stick handle for the lunar rover (moon car). Handle configurations were varied starting with the conventional-type "Joyce" stick handle common to certain pursuit-type military planes, and also some private aircraft. The selected optimum configuration, however, was what has been called a "T" handle, except that the horizontal portion of the handle was canted (or rotated) slightly to the right in the horizontal plane. This configuration apparently was more natural and comfortable to the test subject. In addition, learning progress for this configuration was maximum as measured in terms of number of corrections required by the test subject when traversing a standard, simulated lunar surface mission path in the simulator.

Language Training: Memorization Learning Tasks, e.g., Foreign Languages or Computer Based Languages

This category of learning theory applications includes the type of learning in which individuals primarily utilize sight and sound senses and, to a much lesser degree, the perceptual-motor approaches. Some examples have already been cited above in the section under short-term memorization. One of the examples, Morse code, is a good illustration of a non-spoken language. Computer programming languages, such as Fortran IV or COBOL, are also of the non-spoken variety. These basic languages can all be learned more efficiently by the application of known rules of learning theory. At least to some extent, the learning requirements and/or objectives will determine the emphasis on particular aspects of learning, as will be cited below under the individual discussions of factors which affect learning:

(a) Motivation, which, in many cases, will affect rate of learning progress as well as forgetting. The two main sub-categories are intrinsic (self-inspired drive), and extrinsic (status, rewards, penalties, rivalry/competition, feedback, knowledge of results or progress, etc.).

(b) Personnel placement cognizant of known physical handicaps/attributes and mental or skill aptitudes in order to match requirements of particular jobs and individual qualifications.

(c) The physical environment of the learning situation, including temperature, sound, light, color, space, or other physical parameters which have been known to affect learning by individuals.

(d) Learning techniques/methods. Examples include the whole-to-part method, the whole-versus-part method (which depends on the type of learning and fractional ratio of motor to memory), the mediating method (involving the giving of increased attention to harder parts of the learning task), the recitation method (which tends to reinforce the memory process), the regulation of learning periods (giving consideration to productive span-of-attention) and over-learning (to counteract forgetting and to prepare for the demands of delayed recall (26)).

Forecasting Demand for Resources With Learning Theory Principles

Recently, policy trends of the Department of Defense (DOD) have been in the direction of greater use of learning theory in the preparation of estimates and in Requests for Quotation (RFQ) criteria (27). Most contracts for military weapon systems require the contractor to include in his quotation an estimated cost of the first article to be delivered and a learning-curve slope estimate expressed in percent (whether "unit" or "cumulative" type learning-curve formats, must also be stated). As previously noted, the improvement over time with the serial production of military systems is considered to be a composite of several factors. Included in the total performance improvement would be such factors as: (a) reduction in material costs due to quantity buying practices, (b) improvement in management and/or administrative techniques over time, (c) reduction in costs due to tooling and/or manufacturing process improvements over time, (d) reduction in product complexity and material costs, so that cheaper materials are used or design changes that reduce manufacturing time or handling charges are implemented, and (e) traditional learning by manufacturing fabricators or assemblers, who may improve both the quantity and quality of manufactured products over time. Hartmeyer (28) has proposed two factors which involve a learning allowance based on the size of a production run and an allowance based on relative "newness" or "complexity" of the product. He also states that, if all non-recurring costs are included for consideration when preparing a forecast for a new program progress function, a curve slope which is approximately 5% steeper will result.

If it is possible to estimate the slope of the progress function accurately, then it will provide information vitally needed in the detailed preparation of resource allocation plans. Such plans would include manpower hiring and releasing, as well as purchase and delivery of needed raw materials or "buy" items, in a time-phased relationship. In the case of a contractor preparing a quotation for a military weapon system, the ability to forecast accurately the expected costs is an extremely valuable tool. It also provides an effective control to use in project management after a contract has been awarded.

Although limited to the electronics industry so far as data is concerned, Hartmeyer (28) presents a methodology for estimating material discount curves based on predicted decrements in unit cost as the quantity of units purchased increases. These applications generate surprisingly accurate approximations of exponential decreasing functions (relative cost values versus quantity of units). The curves, which appear linear when plotted on log-log coordinates, have been entitled "Material Discount Curves". Undoubtedly, there is a close relationship between the learning/improvement functions for a manufacturer and his ability and/or willingness to quote lower prices for larger quantity orders. This procedure could prove valuable to cost estimators in preparing bids. In a similar manner, it could be equally useful to a program cost analyst who is evaluating a cost proposal from a contractor/bidder.

Taxonomy of Learning Terms

Introduction

The context of this section should be interpreted to include not only the descriptions, which are related to pure learning theory considerations, but also to the complete range of applied learning theory. As noted in Chapter I, there have been misinterpretations involving the use of the term "learning-curve slope". Consequently, there appears to be a strong likelihood that some confusion in the applied learning theory field will continue, if for no other reason than the wide diversity of disciplines which are involved. In some cases, shop foremen and even production workers or inspectors can be directly involved. It is easy to understand how such issues could create problems in day-to-day communications between management and workers. For similar reasons, this could easily generate a dispute during contract negotiations with bargaining units, unless terms are both defined and agreed to by all involved parties. It is with these thoughts in mind that the following descriptions are presented:

(a) Job/Task design (JD)

(b) Job/Task environment (JE)

(c) Short-term memory (STM)

(d) Long-term memory (LTM)

(e) Perceptual-motor function (PM)

(f) Decision-making and problem solving

(g) Operator/Test Subject/Worker (S)

(h) Evaluator/Experimenter (E)

(i) Reinforcement/Cues (R,C)

(j) Overlearning (OL)

(k) Conditioning and Training (CG,TR)

(l) Learning curve (LC)

(m) Slope in percent (θ)

(n) Learnability/Trainability (LY,TY)

(o) Progress/Improvement functions

(p) Other.

Discussion

The above listing of terms is intended to supply a relevant set of categories which represent both parametric learning variables and other vital aspects in learnability analysis and learning theory. In some cases, learning terms which are closely related to each other are listed together. No claim is made that the set of items presented is exhaustive, although within the context cited, these terms have performed satisfactorily during both the literature search and experimental investigations parts of the learning research. Some of these terms have been defined in Chapter I or in previous sections of this chapter. Those terms which have not been previously described may be found in Appendix D, Glossary of Learning and Related Systems Engineering Terms. As may be observed above, abbreviations or acronyms are given for several of the terms. Many of the articles, papers, and books written on learning theory by the psychology discipline make frequent use of such acronyms in all parts of their manuscripts. A typical communication problem develops, however, in the use of acronyms which have not been duly defined, at least once, in the text in which they appear. Persons having legitimate interest in such documents sometimes have doubts as to the true or intended meaning of the acronyms. There are, even so, certain advantages to the use of these abbreviations. Sometimes, it is easier to memorize such terms than it might be if they were written out in complete phrases; also, the use of acronyms tends to relieve the tautologous appearance of a paper in which certain terms must be repeated over and over to insure a rigorous interpretation of written descriptions. Recognizing the inter-disciplinary scope of this work, the policy has been to avoid the general use of acronyms or other esoteric terms wherever possible. As cited above, a glossary of terms is included in the Appendix to minimize potential communication problems.

CHAPTER III

FORMULATION AND ANALYSIS OF LEARNABILITY PREDICTION METHODOLOGY

Interactions Between Prime Factors in the Learnability Loop

Introduction

In Chapter I, Figure 4 (page 17) depicts schematically the three prime factors in a learnability loop; namely, the Test Subject, the Job, and the Design. The purpose of Chapter III will be to define the role of each of these factors and to determine, where feasible, any impact or interaction each of these aspects might have on the performance of the over-all learnability loop. To accomplish this classification of role and impact, one might consider the learnability loop as a "system" in which each prime factor is either a component or a subsystem of the over-all system. As with other system elements, these components and/or subsystems interact with each other in a special way which may affect not only the performance of each elemental part but also the performance of the whole system. As described above, the multiplicity of interactions, reactions, and effects tends to justify the term "complex system".

Circumspectly, optimum performances can be achieved only by proper control and by the individual specification of each factor, with proper attention given to interaction with other factors in the functioning of the entire system (learnability loop). The following information sets forth, for intrinsic as well as extrinsic consideration, all aspects which might naturally affect the outcome of the analysis. It should be possible, as the result of this presentation, to accurately specify a system with proper recognition given to the physical and operational constraints that are involved in such specifications.

Specifications/Criteria for Prime Factors

If the performance of the prime factors is to be optimized, the structure of these elements cannot be left to chance. Each of the factors must be viewed both independently and as an element in the learnability loop. Consequently, if optimum performance is the goal, specifications/criteria for the job/task in question, the human organism, and the product design must be accurately defined. After each prime factor is considered separately, the standard approach will be to make necessary adjustments or changes to ensure that all parts are compatible with each other and that they perform efficiently as elements of the over-all system.

As may be observed in Figure 4 (page 17), specifications/criteria for the "human organism" consist of skill level required, communication, motivation (incentives, feedback, etc.), endurance or fatigue criteria, etc. Essentially everything having either a direct or indirect affect on the ability of an operator to perform an assigned task should be considered. Although an operator cannot be molded or shaped in the same manner as a hardware design, it is possible to select from a group of job candidates those who most closely meet the established criteria. Sometimes a "job specification" is used to assist in the selection process. This document is intended to provide the specification/criteria needed for a learnability analysis.

A "job specification" should not be confused with the specification or criteria for the "Job" prime factor in the learnability loop (29). The prior term "job specification" is primarily "people" oriented, whereas the "Job" term in the loop is oriented to the equipment, tools, working conditions, or other comfort parameters, all of which are involved in the "how" and/or effectiveness of completing a task. These aspects are inanimate and, although they enhance or support the human organism, specifications/criteria are developed separately. Specifications for a job or task must also be closely coordinated with the design of the product for which the job sub-factors provide support. To complete mechanical assembly tasks such production tooling as assembly fixtures and drill-jigs are often utilized to increase production rates and/or maintain quality control.

In addition, such hand tools as screwdrivers, hammers, mallets, wrenches, pliers, punches, rivet tools and clamps are frequently used. Such equipment as tables, benches, ladders, special light fixtures or power supplies are also needed frequently for assembly operations. Special environment-conditioning equipment such as air conditioning and heating units, humidifiers, and dehumidifiers may be necessary in the maintenance of product quality, and to create an environment conducive to better operator performance. Such conditioning equipment may be needed only for quality control, or it may be strictly used for "comfort" air conditioning. If all of the job variables are considered as a package, the structuring process may be thought of as a "job design" (30), the second prime factor, in a context similar to the design of a hardware device.

The third prime factor in the learnability loop is, of course, the "product design". Customarily, the product design is considered as "given" and not treated as an element which may be changed by choice. However, if certain design features or criteria are found to impede normal progress, to require excessive time for assembly, or to create a potential safety hazard, changes to the basic product design may be generated to eliminate or minimize the problem. Numerous examples might be given to illustrate real situations in which this type of problem exists:

(a) A hole in a sheet metal part is slightly undersize, requiring excessive screwdriver torque by the operator to insert a sheet metal screw. (Hole size is increased.)*

(b) Excessive burrs and sharp edges on metal parts which must be handled by the operator cause frequent cuts to fingers and hands. (Add a deburring operation to drawing specification.)

(c) Metal parts which receive excessive cold working during their forming process require excessive drill-bit pressure to drill holes, causing a high rate of tool breakage and undue operator fatigue. (Anneal metal parts after deepdraw operation.)

As may be observed in the above examples, a change in any one of the prime factors of the learnability loop could easily affect one or both of the other two. The operator should be assigned a task which is compatible with his qualifications and for which he has been adequately motivated. If a change in the product design places demands on the operator in excess of his current qualifications, he might have to be retrained or replaced. On the other hand, a design change might reduce operator qualification requirements, thus permitting the use of a lower skilled worker or even the use of a worker with lower physical capabilities.

---

*Phrases inside parentheses indicate type of remedial action taken to correct the problem.

To illustrate the interdependence of design changes with other aspects of a particular task, consider a change in design which imposed a demand for greater precision of assembly. This increase in precision could affect both operator performance and one or more of the job sub-factors, such as tools, workplace, or lighting. A reduction in lighting levels, for example, could affect performance of the operator by reducing his ability to meet quality specifications. If planned changes to the product design are introduced as independent variables, in order to gauge learning progress, any variation in the other prime factors must be minimized. The accuracy of progress data will be in question, and there may be an element of unexplained error if these factors are not closely controlled.

Recognition of Factors Sensitive to Learning Progress

Introduction

With due consideration of the stated research objectives, there exists a recognized analytical need to determine which factors are sensitive to learning progress. In the determination of these factors, the first logical step is to select from those factors under study a set which could be used to effectively measure the rate of learning progress. Moreover, the dictates of manageability further limit the scope of interest to only the design-oriented parameters for mechanical assemblies. The combined effects of this set of parameters can be used to measure the "design complexity" of a particular mechanical assembly design. The design complexity can subsequently be used to estimate the "Learnability" quotient for a particular assembly.

Principle Design-Oriented Factors

Intuitively, certain design features might be nominated as candidates for learnability analysis. One approach would be simply to count the number of parts required to complete each assembly. This is based on the knowledge that, as the number of parts increases in a given type of mechanical assembly, more time is required to process these parts. If each part has a unique or specific location in the assembly (as opposed to a random selection and location), indications are that learning progress will be affected by the number of component parts in the assembly (31). If there is a mechanical assembly in which parts have no specific or unique location, then the design-oriented learning progress would be minimal or nonexistent. An example of this latter situation is the assembly of a wall made up of bricks, all of which are virtually identical in color, shape, and size. Learning progress in the assembly of such masonry may indeed occur in the long run, but it will be reflected primarily in improvements in manual dexterity or physical speed by the operators and not in design features of the assembly.

Controlled experiments to probe "number of parts" and other parameters of learning progress have been performed. Analyses of data derived from these experiments and summaries of progress will be presented in subsequent chapters. The cited design feature (number of parts) provides an ideal candidate parameter for study, since the number of parts is normally counted anyway by production planners, stores personnel, and cost estimators.

The number of sub-assemblies or subsystems may also provide a means to gauge learning progress. The assumption made here is that mechanical assemblies will, in general, be more complex and that learning progress will be slower as the number of sub-assemblies increases. An experimental investigation and an analysis of this candidate learning progress factor will also be included in subsequent chapters and will illustrate the connection between aspects that make an assembly more complex and its potential sensitivity for learning or learnability.

Another design feature, related to the "number of parts", is the number of fasteners. Of course, this candidate factor is included in the number of parts count. Quite frequently, perceptual-motor skill requirements for mechanical assemblies are directly tied to the type and number of fasteners, and variety of fastener categories. Some fasteners require careful installation to avoid sub-standard quality of workmanship. This might lead to the rejection of a complete assembly due to faulty installations (consider the example of a cylinder-head on an internal combustion engine). Consequently, some fastener designs require installation by highly-skilled operators, and may have a significant influence on learning progress. This factor has been investigated in the experimental sections of this work, and an analysis of its effect on learnability is detailed in subsequent chapters.

"Skill-level" has been discussed previously as it relates to other sensitive design-oriented parameters. Clearly, the designer of a mechanical assembly can regulate the degree of skill required by virtue of the nature of certain design specifications. Relevant design specifications often include such aspects as machined-surface finish specifications, dimensional tolerances, heat-treating requirements, surface treatment specifications (anodize, alodine, phosphate, etc.). Because these parameters can vary over such a wide range, their impact on learning progress is a distinct possibility. Normally, the higher the degree or level of skill required to perform a certain task, the longer it takes an operator to become proficient (or to be trained).

Several possible learning-sensitive factors have been reviewed in this section. Experimental investigations to establish their degree of validity in gauging the learnability of certain mechanical assemblies are described in subsequent chapters. One of the objectives thus far has been to discover, where possible, those parameters which can be measured by discrete dimensions (the number of parts, for example). Variables of this type are felt to be more reliable and easier to use in practical applications.

Any attempt to predict learnability of a unique design must be carefully planned to be certain that all aspects of the learnability loop are given proper emphasis and consideration. If this is not done, paradoxical situations can easily arise. This type of problem in learnability analysis is treated in the next section.

Learning Progress Paradox

Proper understanding as well as an effective application of learning/improvement theory is a necessary condition for successful results. Otherwise, situations may arise which appear to be contradictory. The two following examples are representative illustrations of the complex and seemingly contradictory relationships.

An operator may perform a series of mechanical assembly tasks at an initially accelerated pace (e.g., 120% of the normal or standard speed, see Figure 6). As a result, the first unit cycle time will be lower than would otherwise be the case, and the second cycle time may also be depressed below its expected value. In effect, the entire learning curve will progress downward over time, although at a somewhat shallower slope than standard. Without proper understanding of learning/improvement theory, this outcome may mislead an analyst to conclude that progress is less than expected for the conditions of the task (operator, tools,

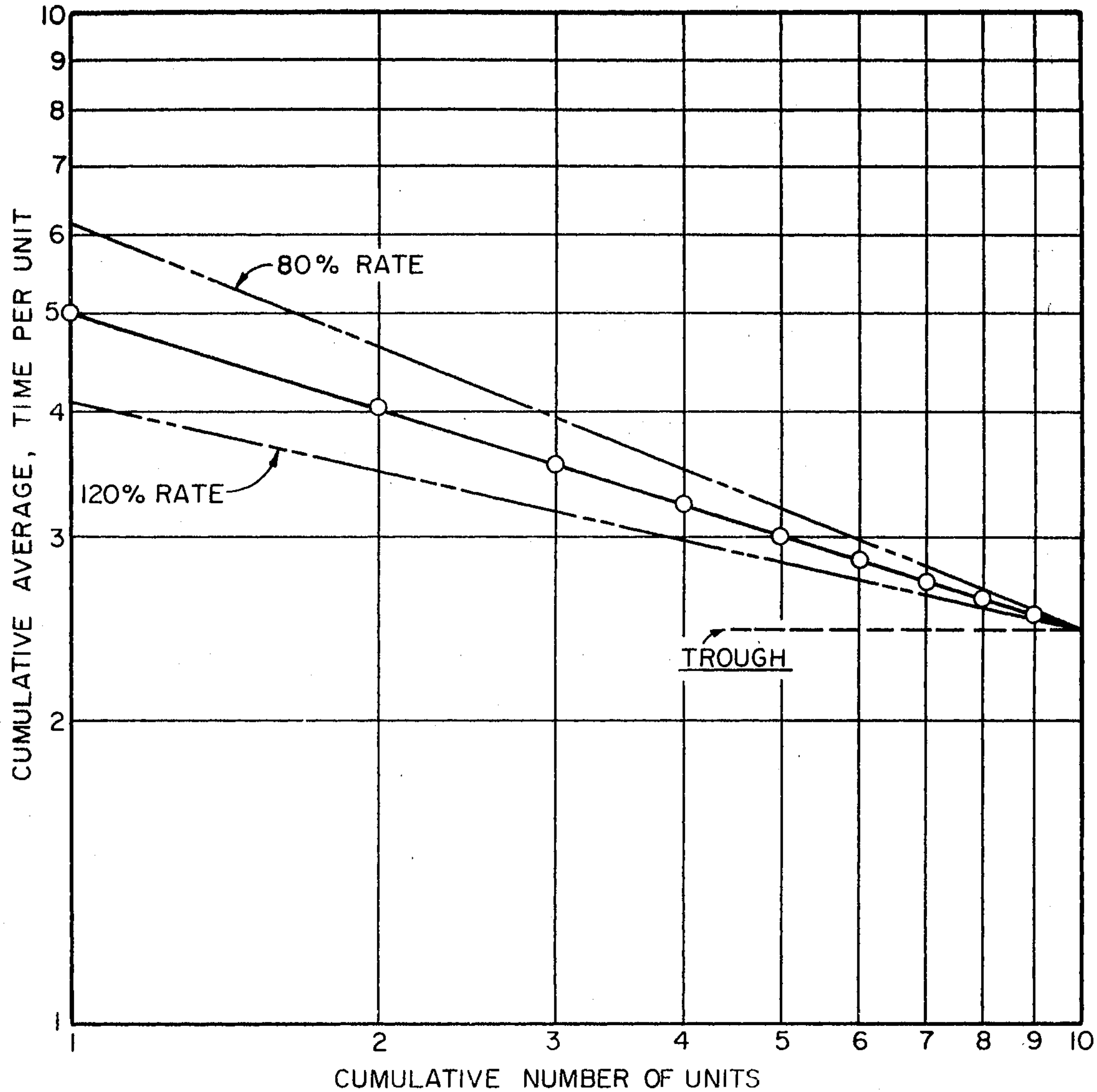


Figure 6. Effect of Operator Performance Rate Variance on Typical Learning Curve

environment, sub-assemblies/parts, etc.). In other words, although the operator's performance clearly exceeds the job requirements, his apparent learning progress is deficient, as indicated by the reduced slope of the learning curve. This may be due, in part, to the existence of a certain "incompressible trough" in the curve, which serves as a lower boundary constraint.

Conversely, if the same operator begins a similar mechanical assembly task at a slower pace (e.g., 80% of the expected speed), then a rate of progress may be attained which seems to exceed the anticipated level, and the slope of the learning curve will be steeper. As in the first example, the decrease in cycle time, with successive replications, is constrained on the lower side by the same incompressible trough or boundary (Figure 6). In the second example, however, the slower-than-normal pace results in a first unit cycle time which is higher than expected, suggesting there is considerable room for improvement, but this could also be a misleading conclusion, when viewed in relation to the complexity of the task or design. If the slope is depressed as in the case of the above-normal pace, the apparent complexity will be greater, and conversely, a simpler task is suggested for the opposite condition, where the learning curve slope is steeper. Such conditions require a careful analysis of all job-oriented parameters, including the possible use of predetermined time standards (MTM), or some other method to estimate a standard time to complete the task. The results could then be compared with the actual observed times, and a more accurate rating of the job pace would be possible.

<u>Sub-Task Learning Paradox</u>

Another paradoxical condition occurs when a task is broken down into a group of sub-elements. In instances where the size of the production run justifies it, single operators placed on each sub-task can be expected to produce an over-all reduction in the learning curve slope or, in other words, a slower apparent rate of progress. This productivity enhancing technique can be checked by comparing actual data with the standard times. In this situation, the potential learning for sub-tasks may have been reduced to the vanishing point, since each sub-task will require only a fractional part of the required learning for the whole job. The over-all effect is such that the initial unit time cycles will be depressed, generally below the time for a single operator doing the entire job, and the learning curve slope for the whole job will be less steep. This might create the misleading impression that the task is more difficult. The net effect in this instance is very similar to that where a single operator performs at a pace greater than 100%. Actually, such comparisons are not admissible for the thesis problem, since they compare the performance of a <u>single operator</u> in the first situation with a <u>team of operators</u>, each of whom does only a portion of the over-all task. Since learning requirements are minimized in this example, so is the training problem, and, for this reason, the majority of such operators are simply trained on the job.

Measurement/Quantification of Learnability Prediction Methodology

Recognition of Constraints and Establishment of Ground Rules for Learnability Predictions

To assure the widest range of applicability, as well as repeatability for the experimental data, it is well to recognize the inherent as well as the necessary constraints for this type of problem. As mentioned above, the limitations of manageability forced a certain set of limits insofar as the scope of interest is concerned. Another constraint was the limiting of consideration to mechanical assemblies. Because of the number and variety of organizations which engage in this type of work, the range of consideration was still rather broad. Both the physical size and design complexity of mechanical assemblies can vary from something as small as a lady's wrist watch to a huge self-propelled earth moving machine.

Since this second constraint did not narrow the focus of attention significantly, it was desirable, in the study conducted, to limit observations to tasks performed by a single operator. In order to ensure adequate motivation of test subjects, an incentive arrangement was provided in each set of experimental runs. Cooperation was rated good to excellent in all cases, even though, in one situation, incentives for some trade school students did not involve monetary rewards. Nevertheless, an incentive of one form or another was found to be a very desirable, if not required, adjunct of learning research.

Because it was generally not convenient to make learning observations of task-cycles lasting longer than around one hour, tasks which exceeded this time constraint were ruled out for study purposes, thereby eliminating observations of long-term trends or very long cycle-times. This does not necessarily mean, however, that data taken in the actual study would not be useful in the analysis of long-term trend data.

Another rather obvious study constraint involved limiting consideration of learning progress to single-operator tasks which do not involve machines. (Consideration of machine-assisted single-operator tasks would have constituted a unique task-category with different expected results from the various operators.)

Operators were instructed to work at a normal or average pace.* As a part of the observation, operators who

---

*A normal/average pace is defined as simply a rate of performance or output which a qualified operator can maintain for a full day's work, without excessive fatigue.

were used as test subjects were required to perform on a skill level at least equal to the minimum acceptable performance levels for a particular task.

In order to assure that apparent gains in performance were primarily due to learning by the test subject, no methods and/or tool improvements were allowed during the observed data runs. In a similar vein, no unplanned work stoppages were charged to the cycle times for observed task replications. All tasks were performed in accordance with established procedures, and times required to brief operators concerning procedural matters were changed to the first unit cycle time. However, in subsequent replications, additional time required to brief test subjects (concerning procedural problems) was charged to the particular cycle in which the question arose.

In all of the ground rules and constraints, the objective was to structure the data format such that it would be as free from "built-in" inaccuracies as possible. These planning and control approaches produced data which appears to reinforce the appropriateness of their application. Examples are provided in the next two chapters.

Procedures for Learnability Measurement

Although prior methods and procedures for measuring learning progress have existed for some time, little or no effort has been made to measure learnability, either of a specific task or of a unique design configuration requiring assembly. What is required is a means to utilize design features/parameters in the establishment of learning progress trends. The design parametric values are utilized as the independent variables in experimental learning progress runs. For such data, a family of learning curves can be plotted. Each determined design configuration will produce a unique learning curve. Ideally, it would be desirable to change only one design parameter at a time and to make an experimental learning progress run for each condition. If more than one independent design parameter is changed in each run, there may be a potential problem with interactions. Conversely, only artificially contrived designs exhibit the characteristic of only one design parameter change at a time.

One approach used in the study was to use artificially contrived designs to establish the approximate sensitivities of certain parameters in the measurement of learning progress. Later tests were run on existing commercial product designs to verify the earlier findings. By these procedures, it was possible to establish trends in learning sensitivity (learnability) versus several design parameter values. Each experimental run produces one unique learning curve, and, if plotted on log-log graph paper, it may yield a monotonically decreasing, log-linear plot (Figure 1, page 6). As defined in Chapter I, each log-linear plot will represent one "Learnability" value, computed as the reciprocal of the slope of the log-linear plot. In this way, each learnability value is joined directly with the learning progress information. This technique produces learnability values that will logically decrease as the design becomes more complex and increase if the design configuration is simplified (Appendix B).

Data Conditioning and Structuring Information for Prediction Effectiveness

As previously described in this thesis, some learning curve analysts prefer to utilize the cumulative average times per unit, while others prefer to plot the actual unit times for each cycle replication versus the serial number of units (first, second, third, etc.). There seems to be no conclusive evidence to support a contention that either method is superior. However, the cumulative average mode does tend to smooth the data point trend lines. As a result, there is less apparent variation in learning curve plots, and the estimation of a log-linear slope is easier. It was for these reasons that the cumulative average method of data conditioning was selected for the experimental research parts of this thesis. Also, it was necessary to plot learning data such that all time values were in the same units -- in this case, "minutes".

After learning curves had been developed for a variety of design complexities, it was necessary to determine the trend lines based on these design configurations and the corresponding learning curve slopes in percent (or learnability values). In order for these trend curves to be useful in making learnability predictions, it was desirable that all trend lines increase or decrease in the same direction monotonically.

Since various mechanical assemblies require widely varying motor-skill requirements, it is desirable that a set of prediction data be established for each skill category, with the selection of any particular category of learnability data being made after a review of the engineering design and criteria for a given mechanical assembly.

Delineation of Learning-Sensitive Design Parameters for Mechanical Assemblies

Previously, several factors were discussed which might show promise in measuring learning progress. Included in this group were: number of parts, number of fasteners, number of sub-assemblies or subsystems, ratio of fasteners to non-fastener parts, ratio of fastener parts to total parts, and ratio of fasteners to number of sub-assemblies. Each of these parameters has an inherent characteristic which permits the analyst to count and record the number of units of each item, or, by making a simple arithmetic calculation, to derive quantified values. This information can usually be obtained by a review of design drawings and related parts lists or by a physical audit of component parts and sub-assemblies. In general, as the quantities of such parameters increase, so does the complexity, so far as assembling the parts, components, sub-assemblies, etc., into a complete working assembly is concerned. There are exceptions, however, which illustrate that such design parameters may sometimes fail as indicator/indices of complexity and difficulty. For example, a railroad track may increase in length, number of parts, number of sub-assemblies/subsystems without any significant increase in complexity or difficulty of assembly. Of course, the longer the railroad, the longer the time that will be required to complete assembly of the parts, but learnability in this example would not be significantly different. The salient feature of this mechanical design (railroad track) which rules out application of total number of parts as a learning sensitive parameter is the fact that the design has highly repetitive design features (cross-ties, rails, and spikes) which are duplicated over and over. To minimize the inclusion of such meaningless features, an additional ground-rule seems appropriate: If an engineering design has a highly repetitive design feature, then the total number of parts may not be useful in making a learnability analysis. The specific set of design-oriented factors must be carefully selected such that they are compatible with the type or category of design configuration being considered. For some types of hardware, design complexity might be gauged by design features different from those previously named. To illustrate, very large assemblies such as ships might be correlated with displacement or total weight. Passenger aircraft might utilize either speed or number of passengers to estimate complexity and learnability. Almost any design aspect that can be counted or measured (number of joints, thrust) could be utilized to quantitatively predict complexity and learnability. Another aspect of this analysis could be a tabulation not only of sub-assemblies, but also a count of the number of different types of sub-assemblies or different types of processes needed to complete an assembly. Examples might be a speed reducing gear box or an electric power-conditioner requiring heat treating and electron-beam welding. Thus, assemblies which comprise a large variety of generically different subsystems and/or require a large variety of different processes or procedures to complete the task are generally more complex, and learning progress is correspondingly slower.

Approaches for selection of design-oriented parameters to use in measuring learnability are similar, regardless of the type of design. The parameters selected for the mechanical assemblies used in the experimental runs for this study were taken from a list given in an earlier section of this chapter. As will be demonstrated in Chapter V, the actual selection can be made in a manner that is not tightly bound. So long as the parameters are reproducible and exhibit adequate sensitivity, the actual choice can be more or less arbitrary -- both with reference to the particular parameters selected and to the number of parameters being employed in the model.

Use of Learning-Sensitive Mechanical Assembly Parameters to Formulate Prediction Model

Categorization of Data Collection by Skill Level

In Chapter I, a schedule of mechanical assembly skill levels was introduced as Appendix A. This schedule defines four categories of skills. The level designations have been set up such that Level I includes skill requirements for the simplest mechanical assembly tasks. As the numerical designations increase, the skill demands also increase until the highest skill requirements for ultra-precision assemblies are displayed in the Level IV category.

Since each category will involve different categories of mechanical assembly designs, it is reasonable to expect different operators and job design categories for each. Consequently, meaningful data collection for these unique sets of conditions should be taken at the particular level being studied. As more data is generated, a storehouse of information is gradually built up. This data bank could be unique to a special industry or a product design, depending on the intended application and the degree of precision desired. The larger the number of samples included in the data population, the higher will be the reliability of the results.

To summarize, all experimental data should be classified in accord with the schedule of skill levels in Appendix A.

Application of Decision Theory Concepts to Formulate Prediction Model

Quite often in decision theory problems, it is necessary to classify, define, or otherwise determine the unique superlatives of one or more alternative solutions. These information packages are then compared with a set of standard criteria or perhaps a bench mark, sometimes referred to as a "baseline" solution. This baseline solution is ordinarily a solution to the problem which has been generally acknowledged as satisfactory or feasible, but not necessarily optimum. At any rate, a score or performance rating may be generated for a baseline solution, with similar scores or ratings being assigned to each of the projected alternative solutions. In some cases, only technical criteria and superlatives are used to generate a performance rating; in other situations, economic criteria (such as profit or return on investment) are used, and sometimes a combination of both types of information is utilized to formulate a score.

In this learnability application, very similar techniques will be employed to analyze and then rate various mechanical assembly design configurations. These performance ratings, or scores, are based on a sum of the individual key parameter scores for the mechanical assembly designs being evaluated. Certain key parameters which indicate a significant sensitivity to learnability will be utilized to build a table of learnability values. Once a table of learnability values has been established, it should be possible to evaluate any unique mechanical assembly design* using the same key parameters that were used to assemble the learnability table data. In normal industrial applications, there should be no problem in following this convention, since radical changes in design are the exception rather than the rule. If radical changes should occur, a new table might be necessary, and a substitute course of action involving the use of the trend curve for a single parameter could be used until a new complete table of learnability data could be assembled.

In the above descriptions, a methodology has been outlined which makes use of parametric design features from a set of mechanical assembly designs. Learnability data is collected experimentally at several levels for each of the designated design parameters (features). With this information, the next step is to establish a family of trend curves which include all of the design microvariables (parameters),

---

*Any design being evaluated by table data must fit within the range of constraints and application rules for the table.

and in which all of the curves are monotonic in the same direction and represent a plot of learnability versus the particular parameter. Thus, if properly selected, each of the trend curves for the design microvariables provide a limited means to predict learnability. An alternative mode of identification would be to designate these plots as a set of micro trend curves for learnability. However, in the quest for optimality, a single prediction or forecast is desired which embraces all of the microvariable trend values for learnability. This single value, which can be referred to as a "macrovariable", represents all of the individual microvariables in a context which is similar to the principles of the law of large numbers (32). Each of the learnability values for the microvariables might be considered as individual or micro figures of merit, and the summation of these values comprise a macro figure of merit, or an over-all learnability Figure of Merit (FOM). A more detailed description of structuring this over-all FOM is given in the next section.

Utilizing Time-Series Analysis Concepts to Structure Learnability Figure of Merit

In a typical time series analysis, a trend line is plotted over time, with the time series numbers as the ordinate values. These time series numbers are made up of several component values, each of which represents some effect on the over-all time series number. In one generally accepted model, the time series number is generated as a product of the effects of the component parameters.* Thus, the individual effects are embedded in a single number, which in this case may be referred to as FOM (33). With respect to this work, a similar approach may be used to generate learnability FOM values. The learnability FOM values may be computed by taking reference points from each of the component trend curves and multiplying each of these numbers by each other number. As a result, there is a single function which represents all of the family of trend curves. Since there are several levels of skills, a separate set of learnability FOM values is required for each category for which learnability forecasts are needed. These sets of data may take the form of a trend curve or a table of FOM numbers versus learnability values.

Preliminary Outline of a Design-Oriented Learnability Prediction Model

The learnability concept has been presented in an earlier section. In addition, the approach is to use parameters sensitive to learning progress to generate FOM scores. Since these parameter/factors are design-oriented by selection, the over-all FOM can be expected to be design-oriented

*Time series number = $T \times S \times C \times I$, where T = trend factor, S = seasonal factor, C = cyclical, and I = irregular component.

as well. This macrovariable can then be used to tabulate an over-all trend of learnability versus the composite FOM values. When different designs are reviewed, and relevant FOM scores are computed -- the values can be compared with previously established FOM values in order to predict learnability for the new designs. This method will be outlined below in sequential order:

(1) Review criteria, parts lists, and drawings for mechanical assembly design.

(2) After review, tabulate such design information as the number of parts, the number of fastener parts, the number of sub-assemblies, etc.

(3) Based on the list of key factors which were used to construct the learnability table, compute a learnability FOM score, using the multiplicative time series format. For example:

$$Q = P_a^{w_1} \cdot P_b^{w_2} \ldots P_N^{w_k} \tag{3-1}$$

where

Q = Figure of Merit Score.

P = Parametric design factors which explain variation in learnability for various design configurations.

w = Weighting coefficients to indicate

relative importance to the learning process.*

For ease of computation, the above relation can be rewritten as

$$\text{Log } Q = w_1 \text{ Log } P_a + w_2 \text{ Log } P_b \ldots \qquad (3\text{-}2)$$

and, for a system which includes several design related factors,

$$\text{Log } Q = \Sigma(w_1 \text{ Log } P_a \ldots w_k \text{ Log } P_N). \qquad (3\text{-}3)$$

(4) After computing the FOM score with the above forms, select the corresponding learnability value from the table.

In order to further clarify the steps in such a learnability analysis, a flow diagram (Figure 7) has been prepared to present an over-all summary of the analysis process. The next chapter will include a comprehensive review of a series of exploratory experiments which were used to determine and measure some of the design parameters sensitive to learning progress.

---

*If there is no background information to justify the assignment of weights to the various factors, a value of one (1) will be assigned to each factor.

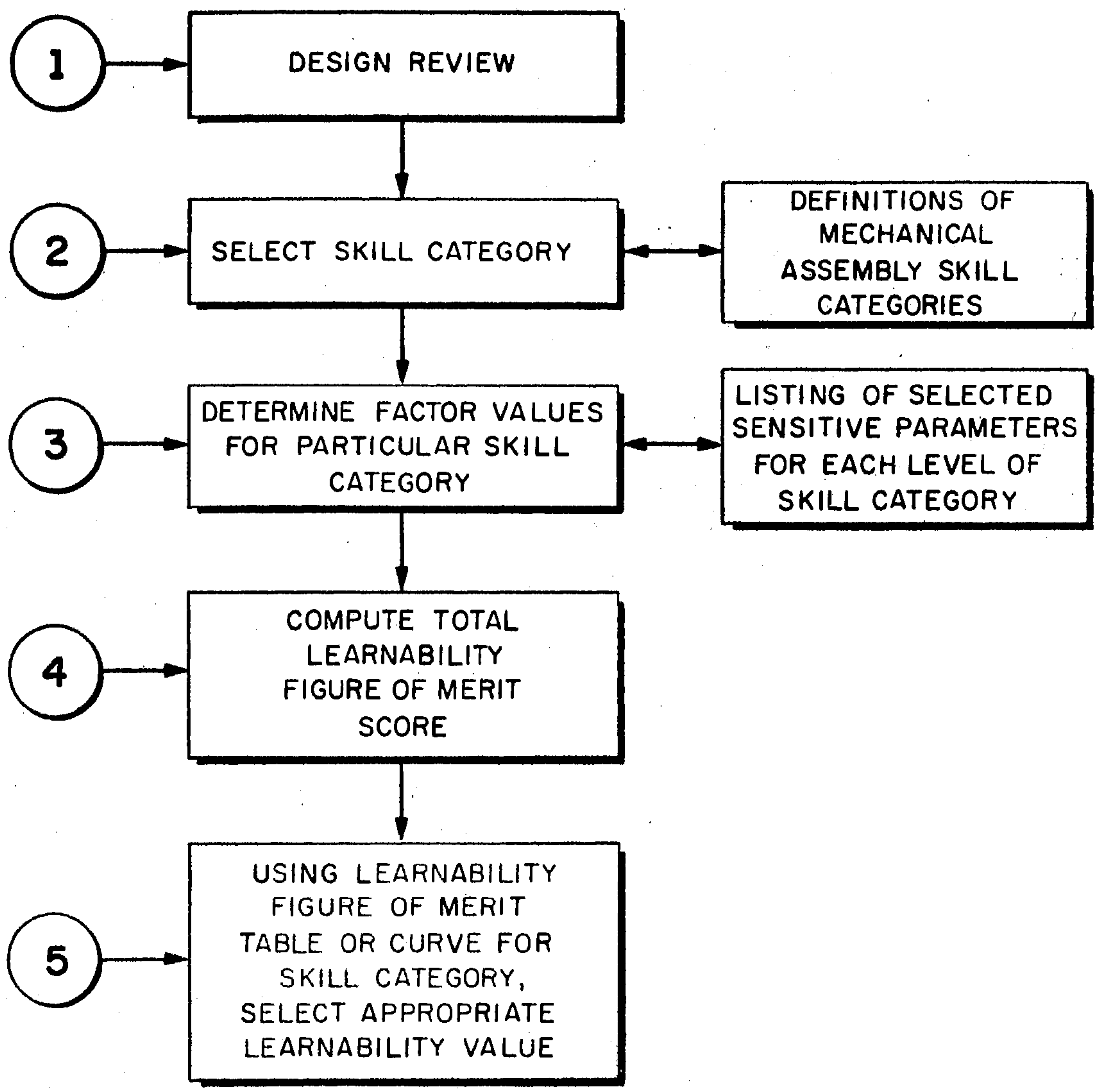


Figure 7. Learnability Analysis Flow Diagram

CHAPTER IV

EXPLORATORY EXPERIMENTS TO PROBE UTILITY OF PROPOSED LEARNABILITY-SENSITIVE FACTORS

Test Philosophy

Previous learning or progress tests have focused attention primarily on either the type of work (task) or on the human operator (age, sex, experience, etc.) (34). As previously discussed and pictured schematically in Figure 5 (page 26), a perceptual-motor task which involves mechanical assembly has three basic operational aspects: the job, the human organism, and the product design. The approach in this study has been to hold constant the job and human aspects of the experiments. Planned changes were introduced in the product design element. Product design factors, such as total number of parts, number of fastener parts, or number of sub-assemblies were varied within a range of practicability. In this context, the product design configuration is an independent additive "macrovariable", which represents the combination of two or more microvariables (parts, fasteners, sub-assemblies, etc.), any one of which could exert influence on the learnability of the subject assembly. Since flexibility in making planned changes to the product design configuration was of prime importance, it was decided to use "Tinker Toys" to build laboratory type product designs. This type of assembly design also represents the simplest, most basic mode of mechanical assembly, i.e., "plug-in/pull out", requiring a minimum level of dexterity, coordination, and other indicators of mechanical assembly skill. This elementary approach would permit learnability testing to start with very simple tasks and then progress step by step upward to more complex tasks requiring higher levels of skill. Thus, it would be possible to observe variability in skill requirements as the complexity of a task is increased. The "Tinker Toy" approach would also provide a means to gauge learning progress over time for unique product design configurations and provide a method for forecasting changes in learnability based on perturbations in design factors.

Plans were made to extend the scope of the exploratory tests to include "Erector Set" parts, if the initial tests based on tinker toy parts showed promise. This extension was, in fact, carried out.

Test Plans

Preplanning Activities

Since the first series of tests were to be based on the use of tinker toy parts, a test subject who met all of the minimum requirements was selected, but the subject (a college student) was not trained in any particular skill. To enhance motivation for the tests, a rate of pay which was slightly higher than the going rate for such work was agreed upon with the student. In addition, the test subject was provided with the usual "coffee break" and rest breaks. The work place was well lighted and air conditioned. Everything that could be reasonably done to exclude environmental interactions was done. All of these preparations were made with the intention of making the acquired data as free from bias as possible.

Detail Test Plans

In order to have a range of design complexities to use in gauging learnability variation between different designs, a group of six designs was chosen from the tinker toy set from which parts were supplied. For purposes of identification, these designs were titled a, b, c, d, e, and f. Using a uniform approach to assemble each design, a series of from six to ten runs were made on each design, and time studies of each run were taken.

Data Reduction Plans

After completion of experimental runs, all time values were tabulated in whole and decimal fractions of minutes. Cumulative average times (also in minutes) were computed for each run and each design. These cumulative average time values were used to plot learning curves on double-logarithmic graph paper. After plotting, log-linear learning curves were drawn for each design, and a slope value in percent was determined for each curve.

A complexity analysis was made for each design to obtain such information as the total number of parts or the number of possible sub-assemblies for each different configuration. Finally, in order to test the potential of these tests as a means to gauge learnability, trend curve plots were made of the learning curve slope (in percent) versus the number of parts and the number of sub-assemblies.

Based on promise shown in initial tests on tinker toy designs, a series of tests was planned for two product designs using "Erector Set" parts. The first two erector set designs were titled g and h. Since erector set designs required fasteners to complete mechanical assemblies, it was possible to collect data from tasks which required a higher level of skill (Level II). It was also possible to collect data for possible learning sensitive factors based on the increase in design complexity by the addition of fasteners. The two new parameters which showed promise were the number of fasteners and the ratio of fasteners to the total number of parts.

Prior to starting any of the test runs outlined above, test subjects were given the following type of verbal instructions:

(1) Time keeping on assembly runs starts at the

time of first discussions between test conductor and test subject.

(2) All parts must be in cardboard boxes prior to the start of any run.

(3) Final step by the test subject for any assembly will be to verify that the completed assembly complies with the design requirements.

(4) If any unplanned event interrupts a test run, time keeping should stop until normal activities can commence again.

(5) Test subject must signal the test conductor as soon as a test run has been completed.

Summary of Results

Discussion

In general, all of the test plans outlined above were found to be completely satisfactory. Test data were used to plot a series of learning curves which indicated a gradually increasing complexity as the number of component parts increased. The erector set assemblies also exhibited a similar sensitivity trend for increasing complexity. Learnability decreased as the number of parts and the number of sub-assemblies increased. A series of trend curves were plotted to indicate learning sensitivity of various design configurations to changes in design parametric values. Results were promising in all examples cited above. Trend curve performance in all of these samples was approximately in line with predictions.

Table I, included below, summarizes the experimental data taken on the six tinker toy configurations and the two erector set designs. Also included is a series of learning curves (one for each design). Finally, a series of trend curves are presented to demonstrate graphically the variations in learnability brought about by design changes. An analysis of these results may be found in the next section.

Analysis of Findings and Presentation of Conclusions

A perusal of the set of learning curves for the six design trials with tinker toy parts and for the two configurations made from erector set parts will indicate that significant progress was recorded on each plot. The curves also show almost perfect log-linear traces on the log-log paper.

As may be noted in Table I, the assembly designs started with a unit which had only thirteen parts and required less than a minute to assemble. The learning curve for unit "a" indicated a slope of approximately 70%, which is in line with expectations for such a simple assembly. Each of the other five tinker toy assemblies was carefully chosen so each successive design would be slightly more complex than its predecessor and, presumably, more difficult to learn. As indicated in Table I, a definite trend in the

TABLE I

EXPLORATORY TESTS OF LEARNING PROGRESS FOR DIFFERENT DESIGN CONFIGURATIONS

Design Type	Skill Level	**Slope In Percent	No. of Parts	No. of Sub-Assmb.	*Cycle Time in Minutes	Remarks
a	I	70	13	1	0.5	Tinker Toy Design
b	I	73	30	3	2.0	"
c	I	75	38	4	3.0	"
d	I	77	108	5	10.1	"
e	I	79	96	6	8.0	"
f	I	83	93	7	11.6	"
g	II	72	68	3	12.4	Erector Set Design
h	II	85	200	8	42.6	"

*These times represent the minimum cycle times recorded for each type of design.

**Slope values were determined by graphical measurements on learning curve plots.

predicted direction between design complexity and learnability was indicated. The trend curves display learning curve slope in percent versus number of sub-assemblies in one example and total of parts for the other example (see Figures 16 and 17). The data in Table I, as well as the trend curves, reinforced the notion that learnability does correlate with design complexity.

Conclusions

(1) Although both the tinker toy parts and the erector set parts proved beneficial as laboratory devices to probe the learnability principle, the erector set designs appeared to simulate more closely the design complexity of industrial mechanical assemblies.

(2) Based on the promising results that were registered with the erector set contrived designs, it was decided that erector set designs would be used for any future laboratory tests requiring such designs.

(3) Future learnability tests should involve some actual industrial designs, where possible, to verify sensitivity of learnability to variations in the design complexity of mechanical assemblies.

(4) In order to minimize random variations in replications of mechanical assembly tasks,

written procedures should be developed for each new task.

Revisions to Methodology and Planning for Extension of Learnability Testing

Discussion

Valuable experience was gained through the use of the contrived designs using tinker toy and erector set parts. With this approach, it was possible to make a large number of experimental runs in a limited time span. Changes in design configuration were, of course, very easy to implement. As can be seen in the resulting learning curves in Figures 8 through 15, each separate design clearly demonstrated learning progress functions that were approximately exponential. Indications were, however, that the erector set parts provide closer simulation of industrial-type mechanical assemblies. It was primarily for this reason that a decision was made to utilize erector set parts for future laboratory tests requiring a contrived design.

In addition to the information cited above, the exploratory tests (see Figures 16 and 17) also indicated that learnability sensitivity might be gauged by such design complexity factors as (1) number of parts, (2) number of sub-assemblies, or (3) number of fasteners. Since these observations are based on a very limited number of cases,

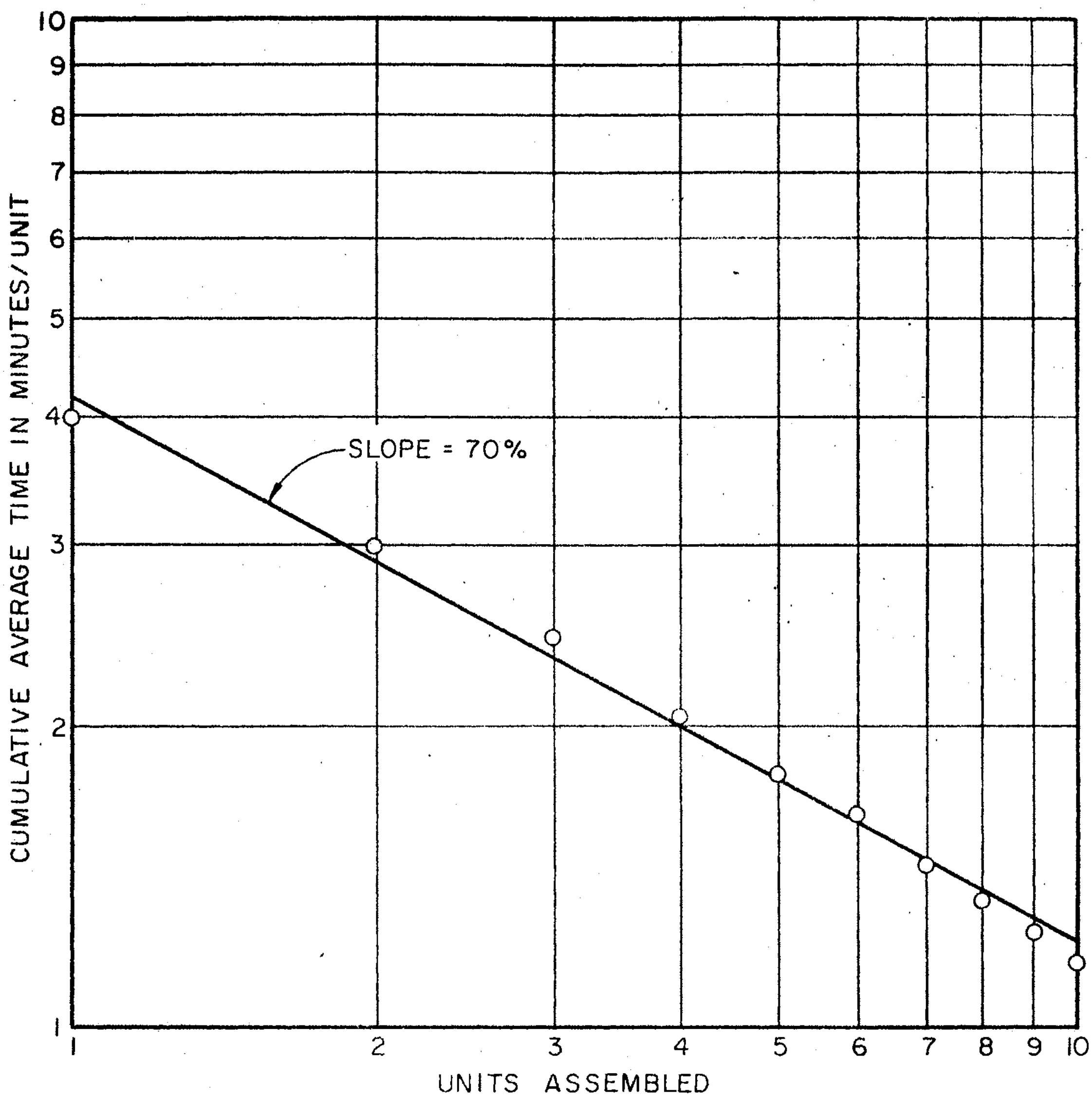


Figure 8. Learning Curve Design Configuration a

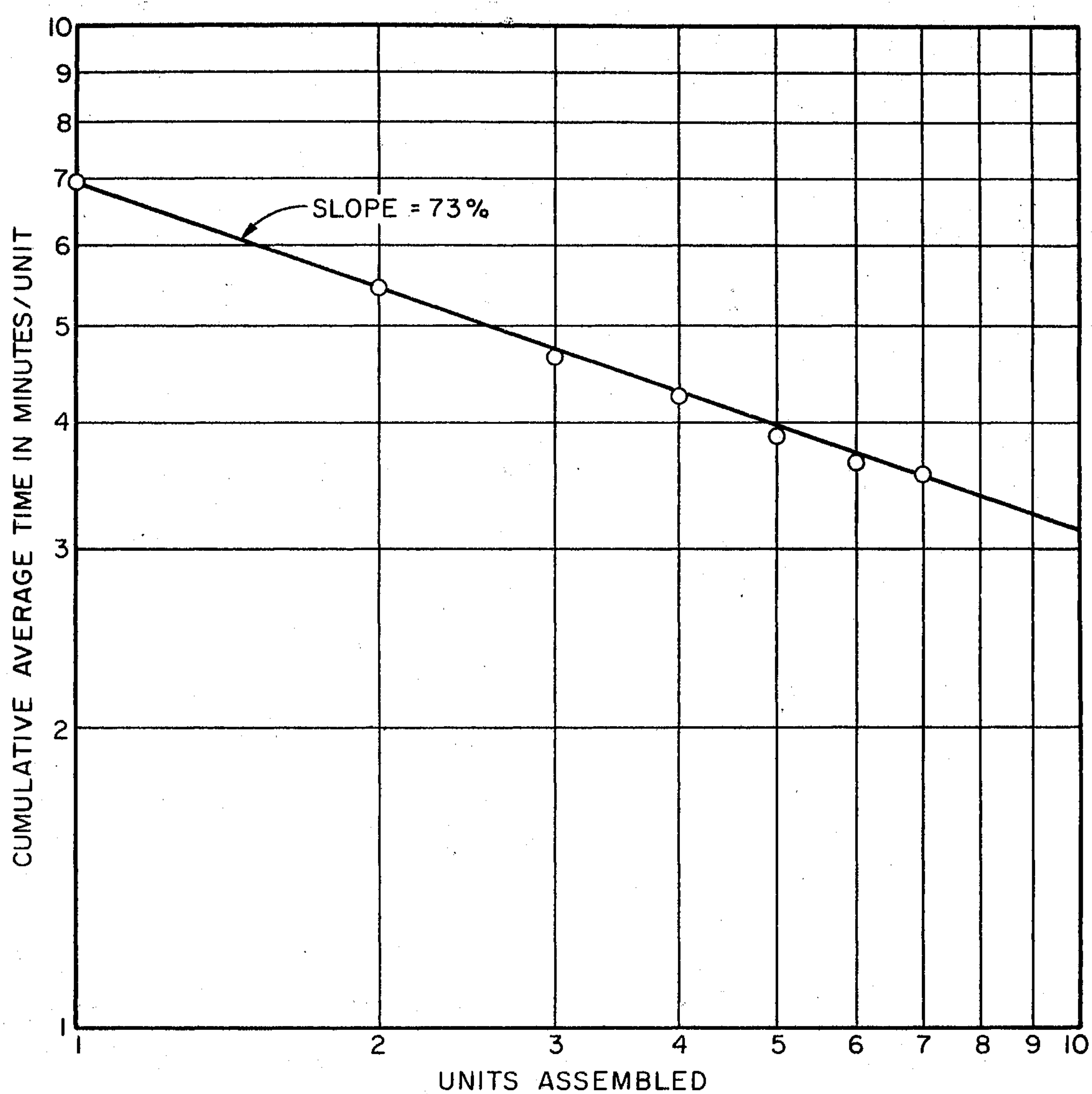


Figure 9. Learning Curve Design Configuration b

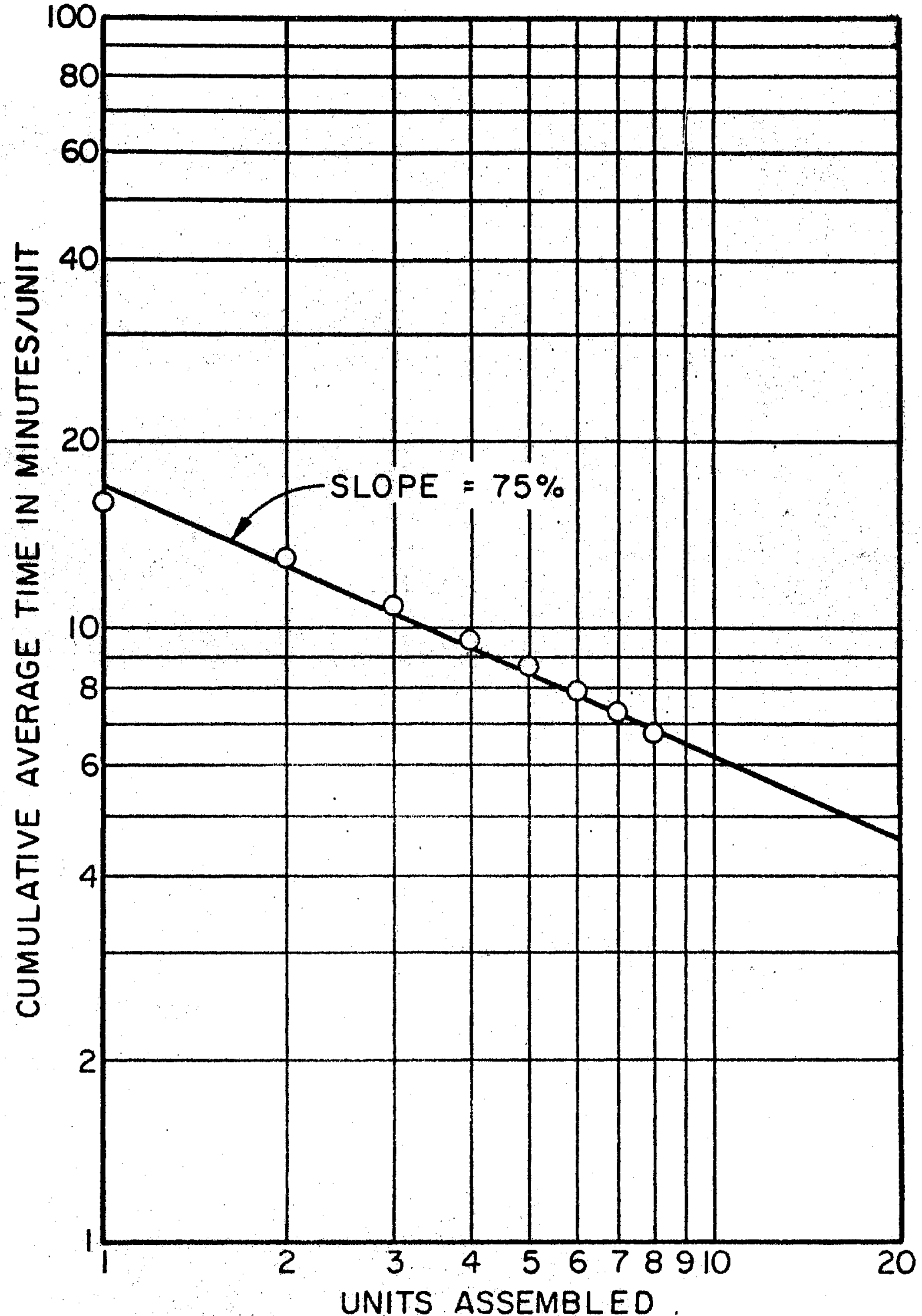


Figure 10. Learning Curve Design Configuration c

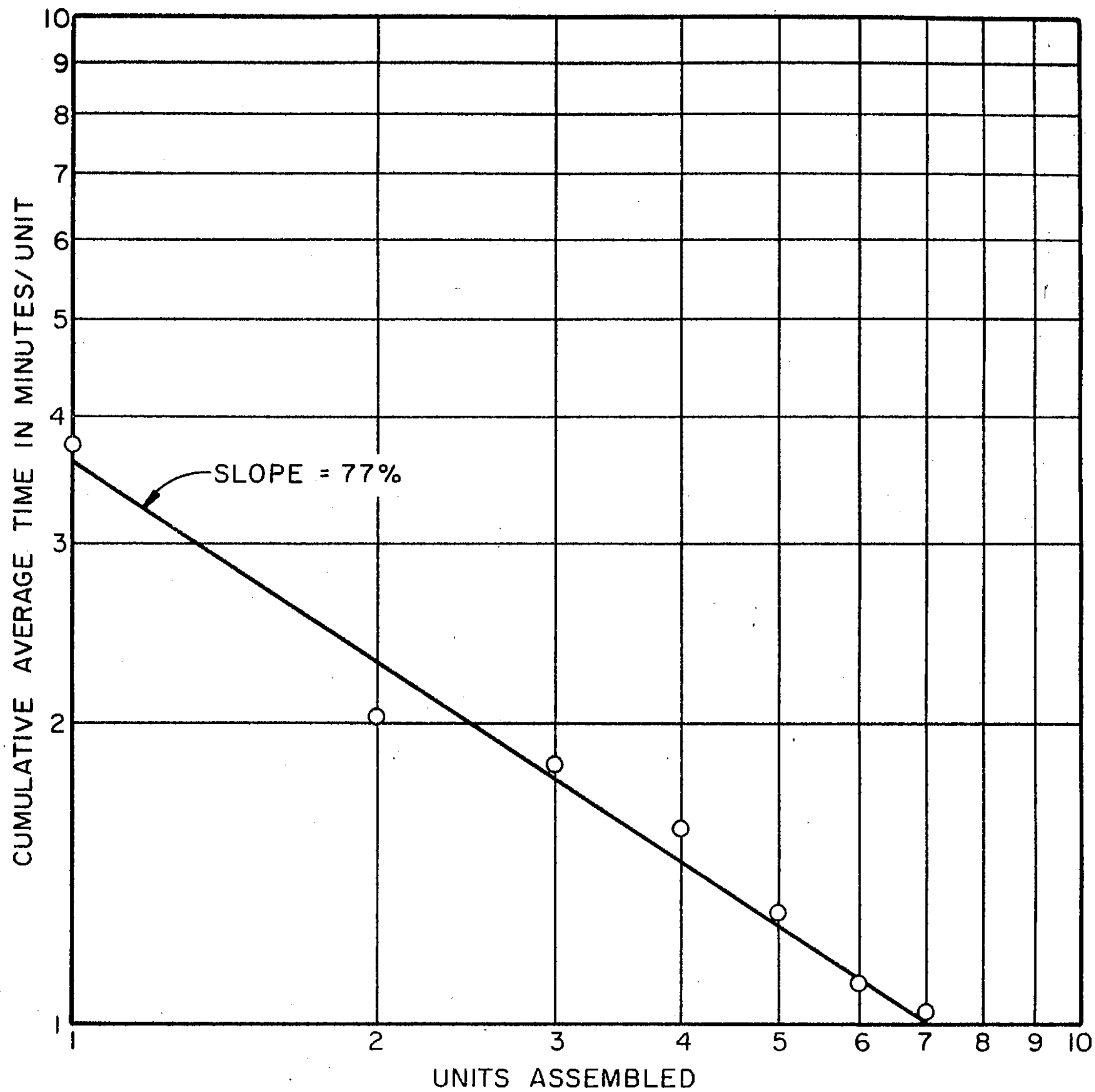


Figure 11. Learning Curve Design Configuration d

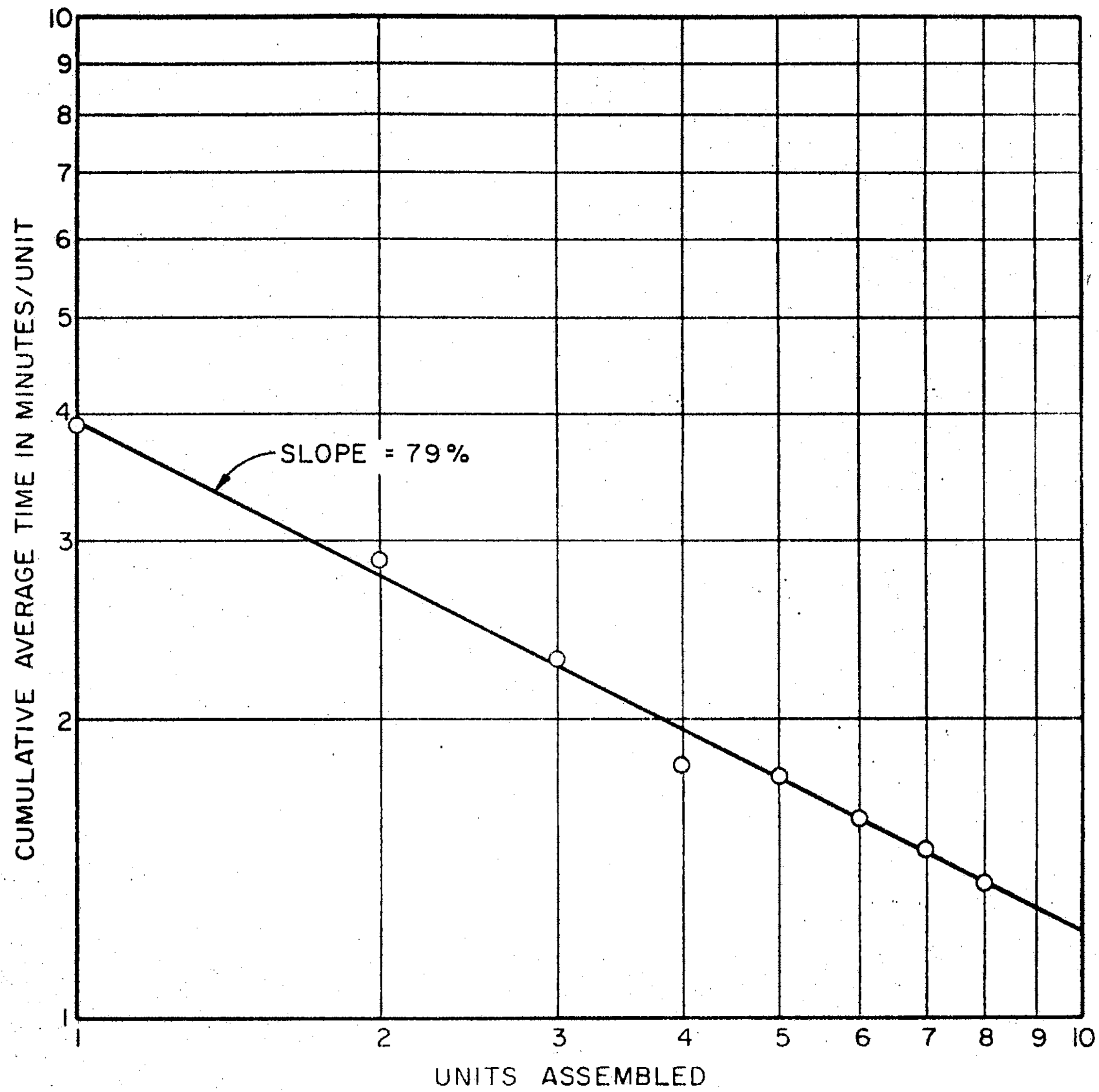


Figure 12. Learning Curve Design Configuration e

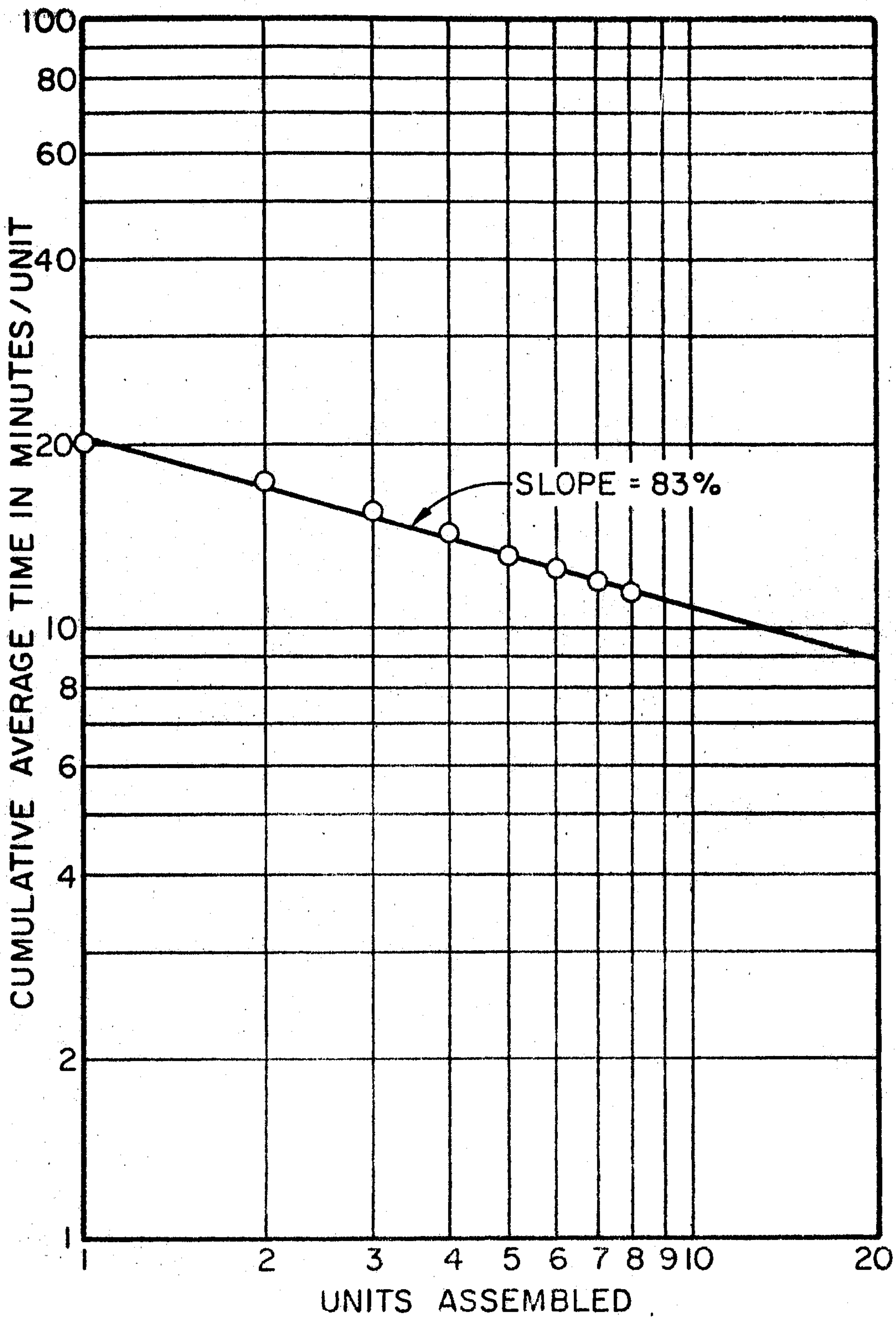


Figure 13. Learning Curve Design Configuration f

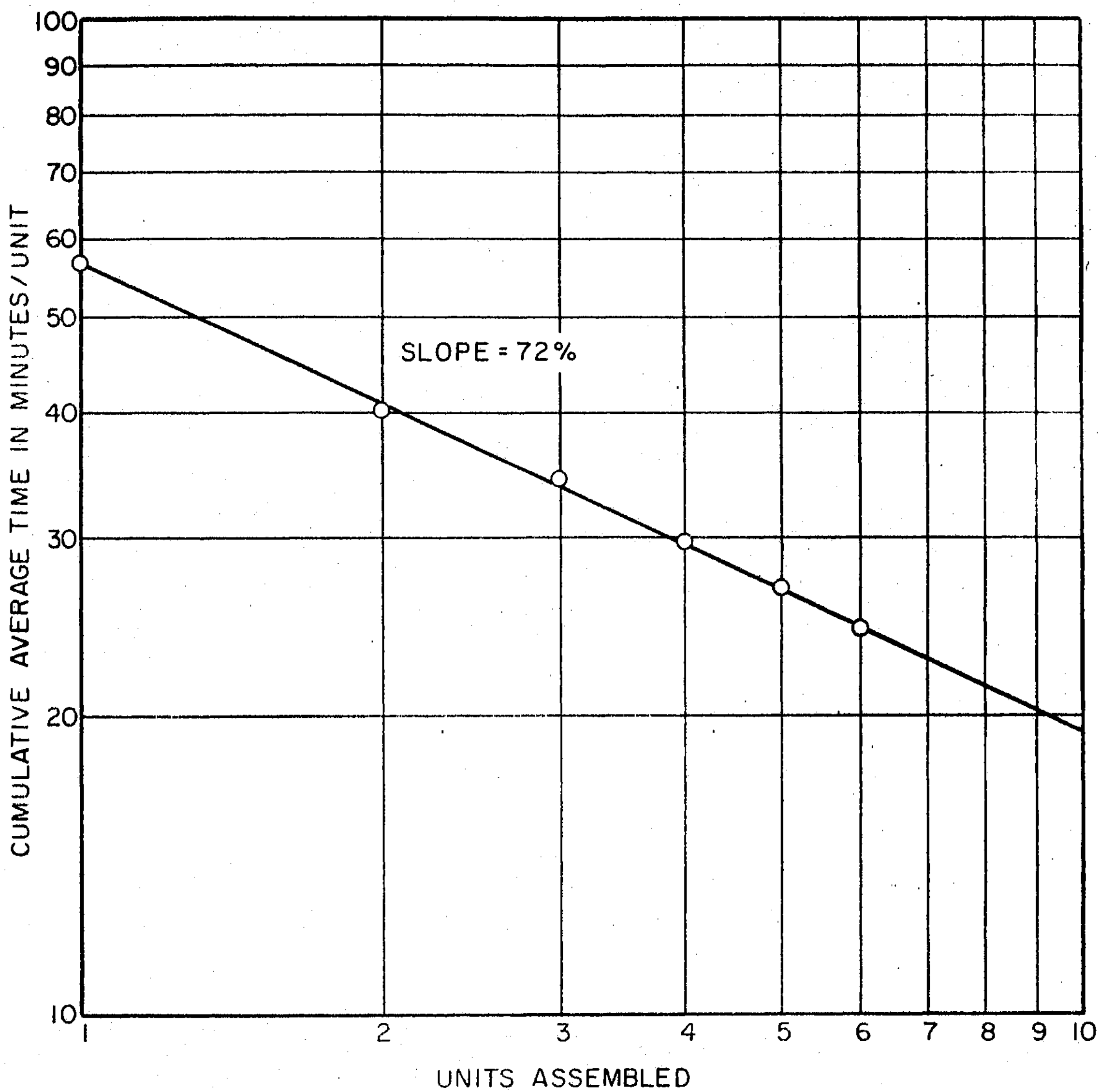


Figure 14. Learning Curve Design Configuration g

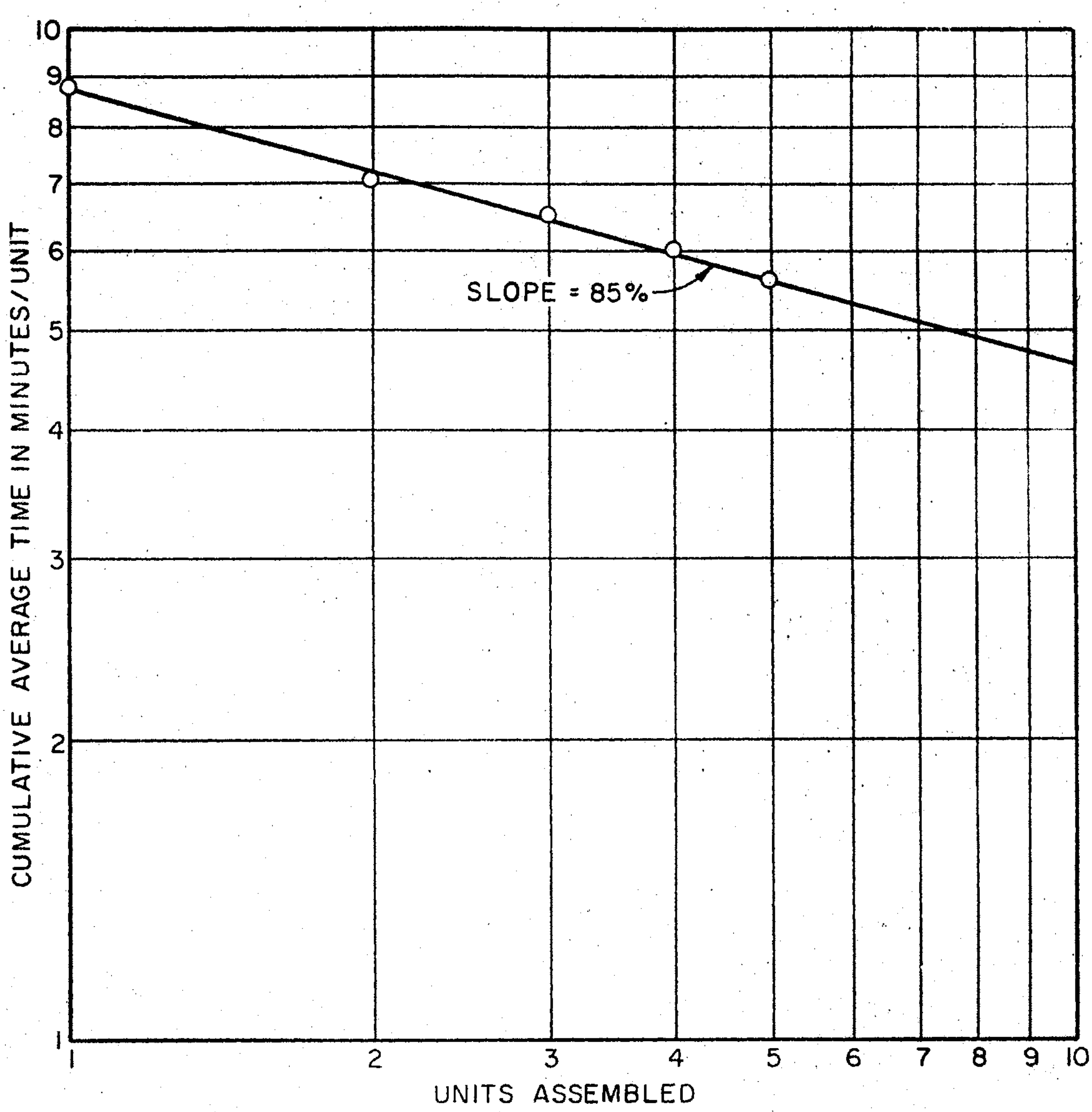


Figure 15. Learning Curve Design Configuration h

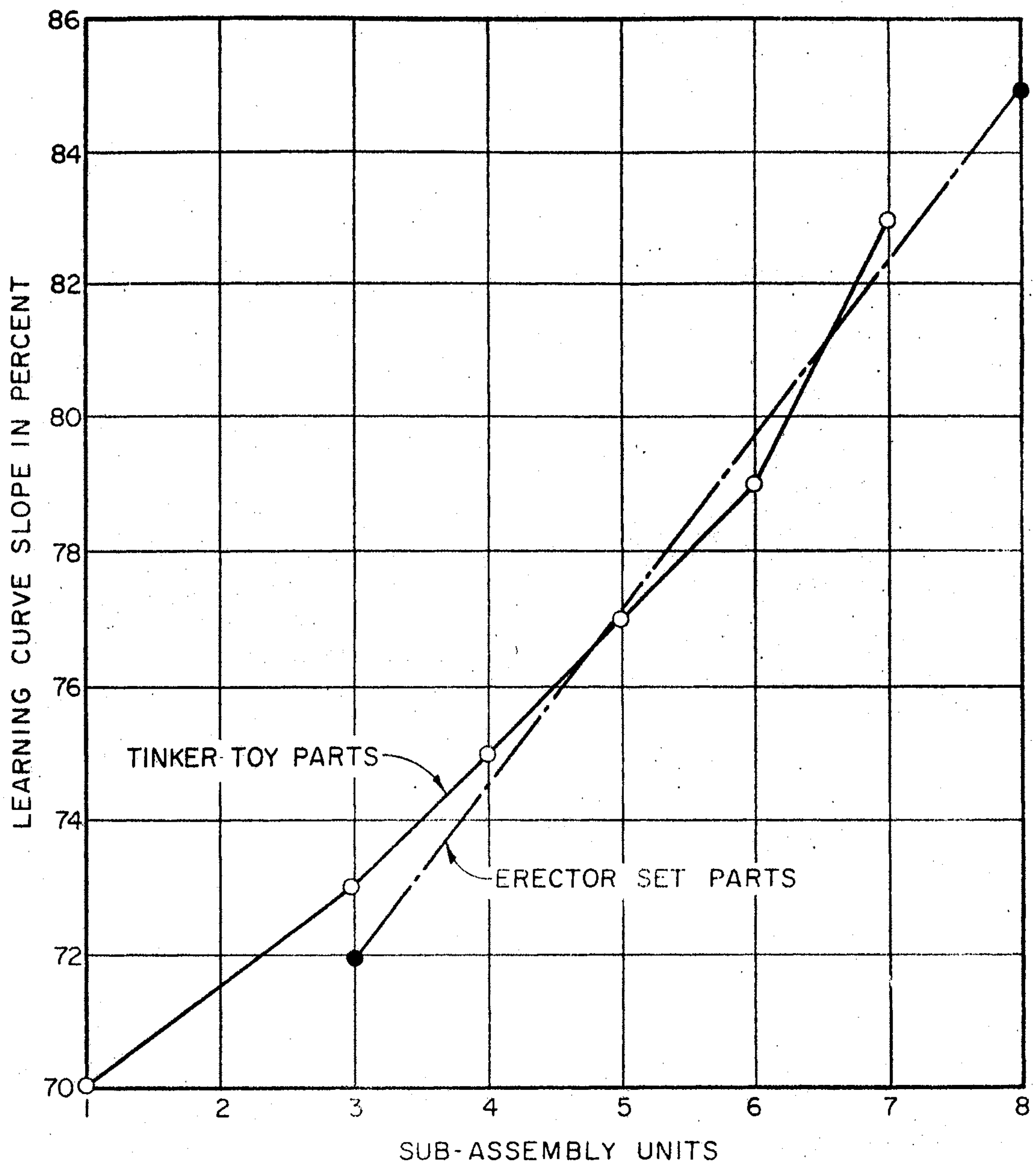


Figure 16. Learnability/Sub-Assembly Trend Chart

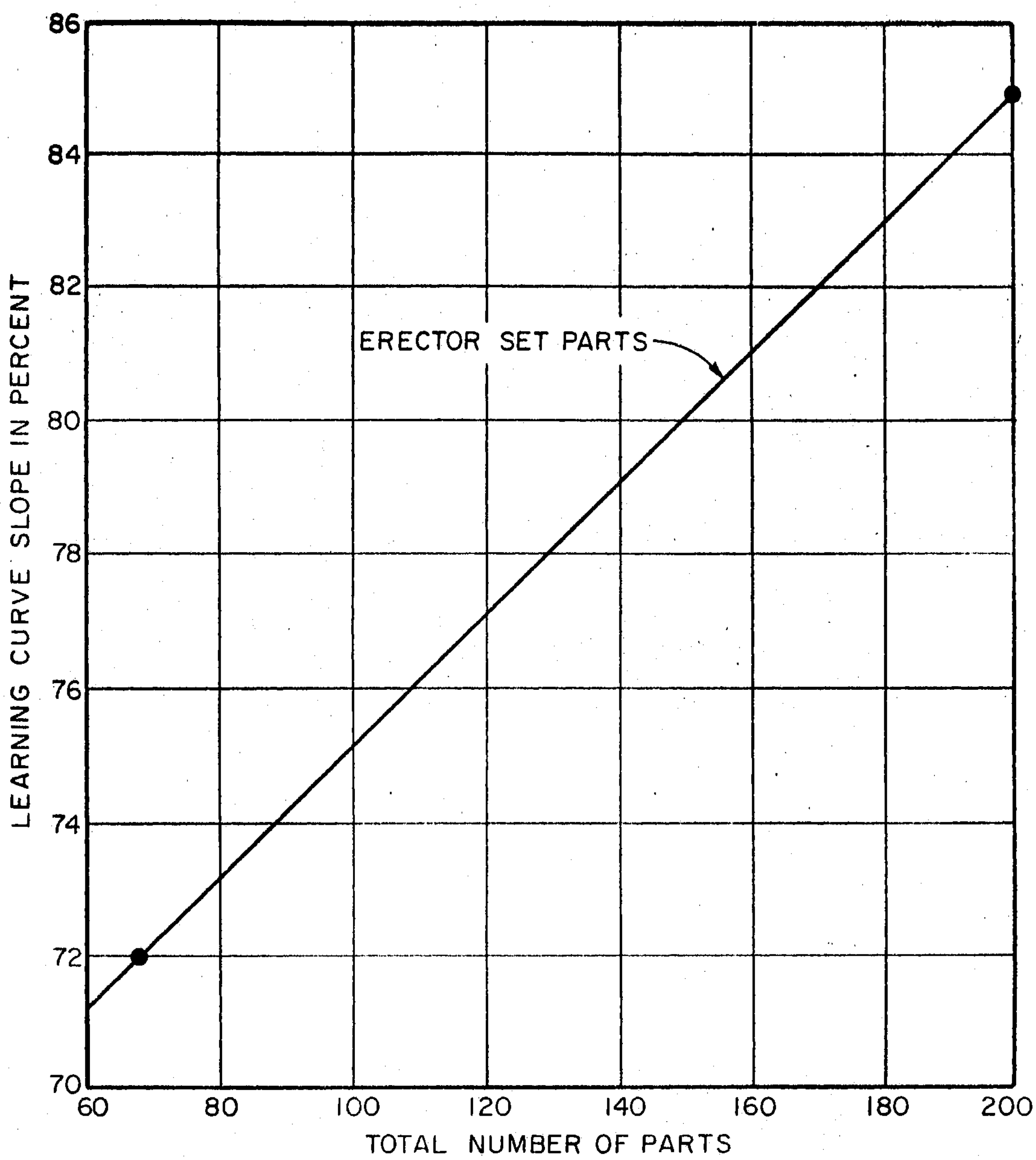


Figure 17. Learnability/Total Number of Parts Trend Chart

further testing will be necessary to extend the scope and depth of the experimental program.

A new series of experimental learnability tests were run to expand the data base with learning progress tests on mechanical assemblies. Where possible, these tests utilized actual industrial mechanical assembly designs. The major over-all purpose of the study was to accumulate sufficient experimental data to show that the proposed learnability prediction model could be demonstrated. A secondary purpose of the extended tests was to verify the selection and sensitivity of the proposed learnability sensitive design factors in mechanical assembly tasks.

The next chapter will review specific objectives in the test extensions and describe analyses and results of the extended runs. Also included will be a discussion of the trial application of the proposed model to a sample problem.

CHAPTER V

EXTENSION OF LEARNABILITY TESTING AND FORMULATION OF A DESIGN-ORIENTED PREDICTION MODEL

Objectives in Test Extension

Simulation Aspects of Extended Tests

In the previous chapter, it was noted that some of the extended runs did not provide a close simulation of the planned category of mechanical assemblies. This was not of serious consequence, since closeness of simulation was not a major objective of the exploratory tests. However, accuracy of simulation was deemed to be very important for data which was to be used in an operational prediction model. For this reason, the selections of design configurations for these tests were made to simulate as closely as possible industrial-type mechanical assembly tasks. A second objective was to determine the relative usefulness in learnability testing of contrived laboratory-type mechanical assembly designs (assembled from erector set parts). If such contrived designs can be substituted in some cases for actual industrial design configurations, there is a clear advantage in flexibility. The prime consideration in the use of simulation testing for mechanical assembly learnability analysis becomes one of the accuracy of simulation of design complexity.

Verification of Proposed Design Factors

In addition to foregoing discussions relative to extensions of learnability testing, there is a need to expand the depth and quantity of experimental tests in order to more clearly establish confidence in the proposed design factors and to identify any new parameters which might be useful in forecasting learnability. Factors which are both reproducible and reliable are naturally more desirable in a prediction model. Also, factors which are common to the largest variety of configurations or, in other words, common to the largest number of different assembly designs will be more desirable for model application. An additional objective to be considered in Chapter V will be to demonstrate the usefulness of contrived designs in verifying the simulation of design complexity. In working toward this objective, the capability to closely simulate industrial-type design configurations with contrived designs will greatly enhance the flexibility of the proposed methodology.

Frequently, certain sub-tasks or procedural steps have become critical aspects in the successful accomplishment of a manual task which is composed of multiple steps. Some sub-tasks consume an unusually long time and/or account for a disproportionate number of defects due either to a need for further methods development or to the high degree of skill required to accomplish a particular job element. If the techniques of learnability analysis are extended to include separate analyses of certain sub-elements, valuable contributions to the art of "methods engineering" can be made. Often, in industrial situations, time and other resource expenditures become excessive due to an isolated incongruous step in a task. A learnability analysis of all sub-tasks could be used to locate those elements which need special attention to reduce surfeited direct labor costs.

Expansion of Data Base for Model

Tests which were run in the exploratory phase of the study were not intended to have sufficient depth or breadth to support the proposed learnability analysis prediction model. Since the analysis methodology was constrained to only mechanical assemblies, it became necessary to plan further experimental runs for this unique type of design configuration. Further, it was desirable that these extended tests be as typical and representative as possible of real industrial tasks within the constraints which have been adopted for this work. Finally, beyond all the established qualitative constraints, the discrete quantity of data was expanded for such obvious reasons as reliability, flexibility of applications, etc.

Verification of Test Subject Variability

Most of the experimental runs were made intentionally with a single test subject. There is, therefore, a natural concern relative to whether or not the operator-to-operator variations are significant. It is recognized that there will always be a small amount of variation between any two operators or test subjects, but the aspect for this study which is of prime interest is a possible variation in learning rates between two otherwise qualified operators. If there is a significant difference, it will be demonstrated by variability in the slopes of the learning curves. The hypothesis that requires verification states: "there is no significant operator-to-operator difference in learnability for completion of identical manual tasks". Of course, the additional implied assumption is that the other parameters of the learnability loop are also closely controlled. Subsequent sections of Chapter V will describe how effectively the above points have been validated by the controlled learnability tests.

Description of Extended Testing and Summary of Results

Foreword

The order of presentation of extended experiments results do not necessarily represent the chronological sequence in which the tests were run. The first category presented includes all of the test activity on the metal shelving, even though all of these tests were not run at the same time. This category was found to provide an excellent source of data, and, so far as could be determined, the results were reliable and accurate. Consideration of the data taken from a series of runs on a commercial gas heater assembly was intended to provide diversification and a real example of a commercial product being produced in an industrial manufacturing environment. The inclusion of observed data taken of the wrist watch assembly tasks was also intended to provide further diversification of types of mechanical assemblies. Thus, collected data came from a broad range of mechanical assemblies, some of which were almost too large for a single operator to handle, while the lady's wrist watch assembly, the opposite extreme of the large assemblies, required optical magnification for the assembler to see the miniature parts well enough to put them together. This represents a considerable range of size, as well as precision in the assembly of individual parts.

A final category of extended testing involves the use of erector set parts, and a contrived design to make learnability test runs. Flexibility of technique makes this approach to data accumulation attractive. As the detail descriptions below will indicate, this method continues to show promise; correlation with test data taken from commercial type mechanical assemblies is very good.

Extended Tests Using Metal Shelving Assemblies

The metal shelving assemblies were selected as suitable test configurations because of their inherent flexibility as test hardware. Moreover, after several runs had been completed, it became obvious that learnability data taken with this type of hardware was both reproducible and predictable within the context of the proposed model. Although the research information is grouped together here, not all of these tests were run at the same time. The period of observations was spread over a period of approximately eighteen months, and, although most of the tests involved primarily one test subject, a second test subject was used on one series of runs to test for operator-to-operator variability. Each group of tests which were run on metal shelving assemblies will be described below. The appropriate tables of data, and/or analyses of results will be included with each sub-set of results, including the learning curves and trend charts. Over-all significance of these test results or other comments relative to support of the prediction model will be included in the analyses and discussions for the sub-section, "Summary and Evaluation of Test Results".

Learnability Testing With Four-Shelf Assemblies. In the consideration of a stated test objective to obtain learning progress test data from mechanical assemblies which closely simulate industrial-type hardware, a four-shelf metal shelving unit was selected (Figure 18). This particular unit utilized self-tapping sheet-metal screws as fasteners. The assembly also included metal posts which had been predrilled to accept the sheet-metal screws (see Table II). Table II includes a simple list of procedural steps which were used to guide the test subject. Prior to the assembly of the first unit, the test subject was given a copy of this information to read and was also given an opportunity to ask questions prior to starting the assembly activities. This approach was adopted as the standard policy for all subsequent experimental runs and was proven to be highly satisfactory. In each instance, the time required for the operator to review written information sheets and for the test conductor to answer questions was charged to the time for the first unit. The same policy was followed for any problems which required consultation between test subject and the test conductor while the assembly activities were in progress. In each case, the time required to answer questions was charged to the particular cycle during which the problem arose. This approach not only appeared logical, but it was also found to be practical when the points for the various learning runs were plotted for the learning curves. For example, the points for the learning curve plot on double-logarithmic paper formed a very good log-linear trace, as can be seen in the learning curve of Figure 19. These facts tended to establish confidence in the policies and methodology which had been employed in this initial

Figure 18. Illustration of Four-Shelf Shelving Unit

TABLE II

FOUR-SHELF CONFIGURATION DATA AND METHODS ANALYSIS

Parts		Number
1.	Shelves	4
2.	Post Sections	8
3.	Post Section Joiners	4
4.	Plastic Shims	4
5.	Plastic Caps	4
6.	Plastic Feet	4
7.	Sheet-Metal Screws	16
8.	Corner Braces	16
	Total Parts	60

Tools Required: Screwdriver, Punch, Pliers, File.

Assembly Operations:

1. Get ready (count parts, align tools, etc.)
2. Assemble four posts using sections, joiners with plastic shims, plastic feet and caps.
3. Install top shelf to four metal posts.
4. Install bottom shelf.
5. Install shelf number two.
6. Install shelf number three.
7. Final checkout and adjustments, check screws for tightness, and entire assembly for squareness.

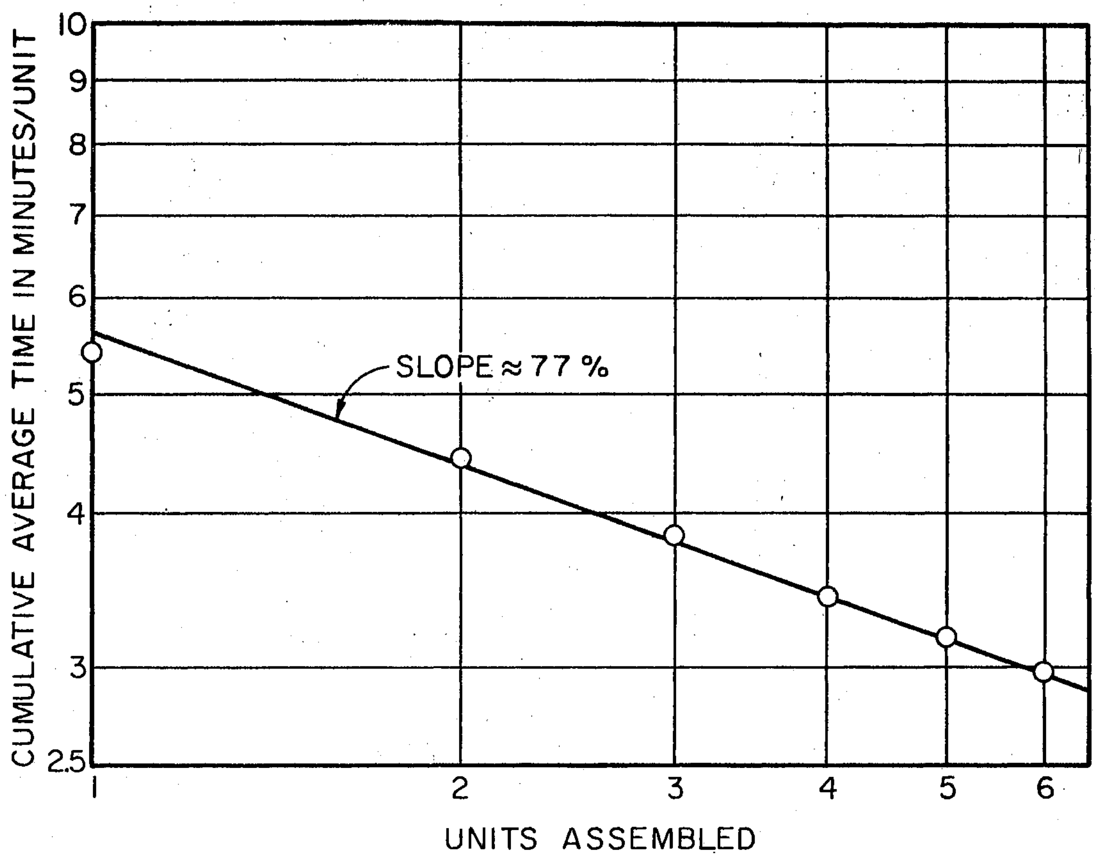


Figure 19. Learning Curve for Four-Shelf Shelving Unit

group of tests. Also, the inherent flexibility of design innovation was found to be very desirable, as was the ease with which the assemblies could be disassembled and reused in subsequent assembly runs. By merely relocating the positioning of the shelves and, at the same time, adding or deleting one or more shelves from the assembly configuration, it was possible to generate several different design configurations within the same generic type of mechanical assembly. This made possible the simple perturbation of one or more of the design-oriented learning-sensitive parameters previously discussed in Chapters II and III.

Use of a Ten-Shelf Shelving Unit to Extend Metal Shelving Learning Tests. Based on the definite promise which was indicated by the first series of learning tests using metal shelving assemblies, a further group of tests were programmed with a similar unit containing ten shelves (see Figure 20). This unit was found to represent nearly the maximum in over-all size which could be handled during assembly operations by a single operator. Except for its large size, this assembly was similar in construction to the assembly used in the first series of tests on four-shelf assemblies. The same type of self-tapping sheet metal screws were specified, and the vertical posts were predrilled to accept the sheet-metal screws. The purpose in going from a four-shelf assembly to a ten-shelf unit of the same general type was to probe the effect on design complexity resulting rom a significant increase in number of

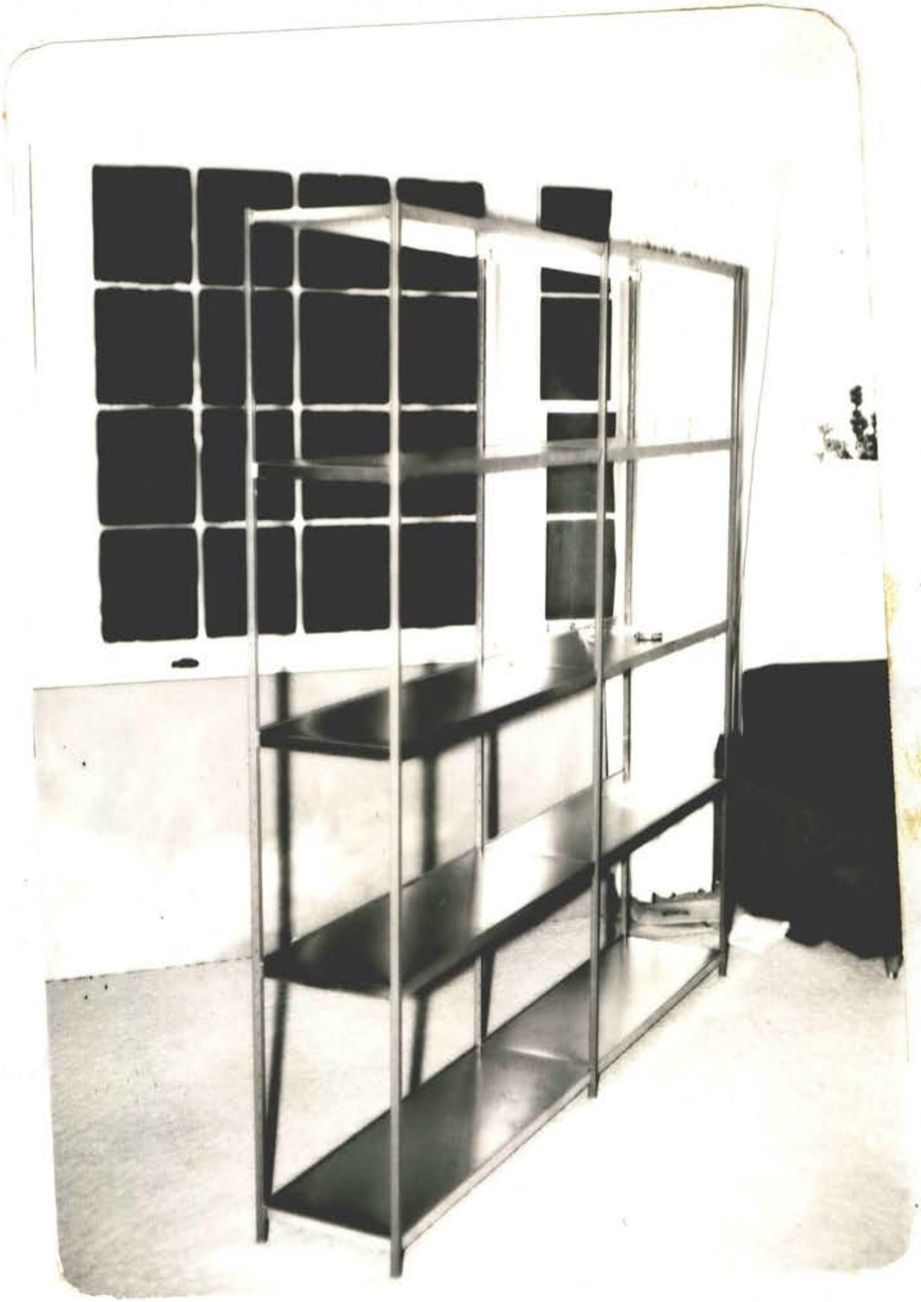


Figure 20. Illustration of Ten-Shelf Shelving Unit

parts. Of course, in this example, there is a corresponding increase in the number of sub-assemblies and in the number of fasteners. Each of these design-oriented factors could influence the over-all learnability of the mechanical assembly task. For this case, a change in the number of shelves will automatically change the numerical count of the number of fasteners and the total number of parts parameter. For this reason, the apparent change in learnability for the ten-shelf configuration from the four-shelf unit will represent a composite of the individual effects for the three single parameters. The results from a series of learning progress runs were plotted, as before, on the double-logarithmic paper to obtain a log-linear learning curve trace (Figure 21). Results from these runs continued to show promising contrast with test results from the first series of runs on shelving.

Sub-Task Learnability Analysis on Shelving Assemblies. As a means to probe the role played by the various sub-tasks in the determination of learning progress for an over-all assembly analysis, a series of sub-task learning curves were plotted for sub-tasks in both the initial four-shelf assembly unit and the ten-shelf metal shelving unit described above. In both of these cited examples, the results were considered very encouraging. An evaluation of this application of learning theory will be made later in this chapter. Two typical examples of sub-task curves have been included as Figures 22 and 23.

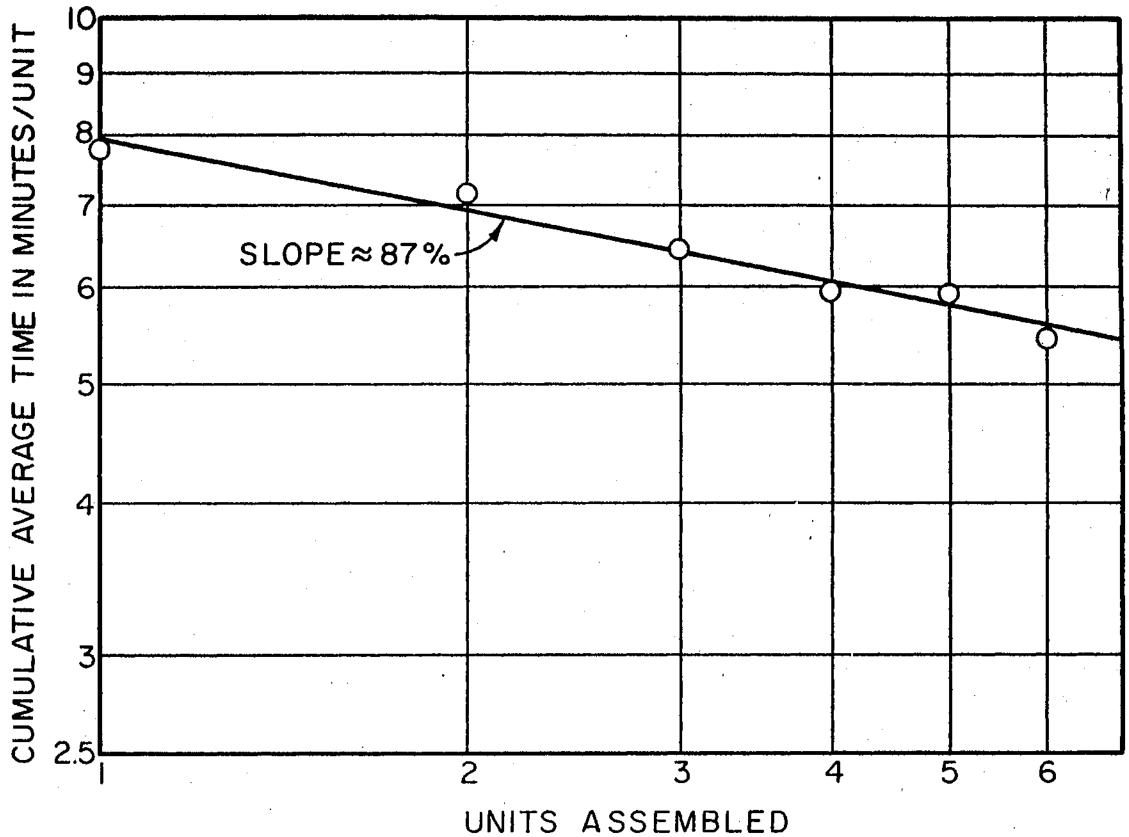


Figure 21. Learning Curve for Ten-Shelf Shelving Unit

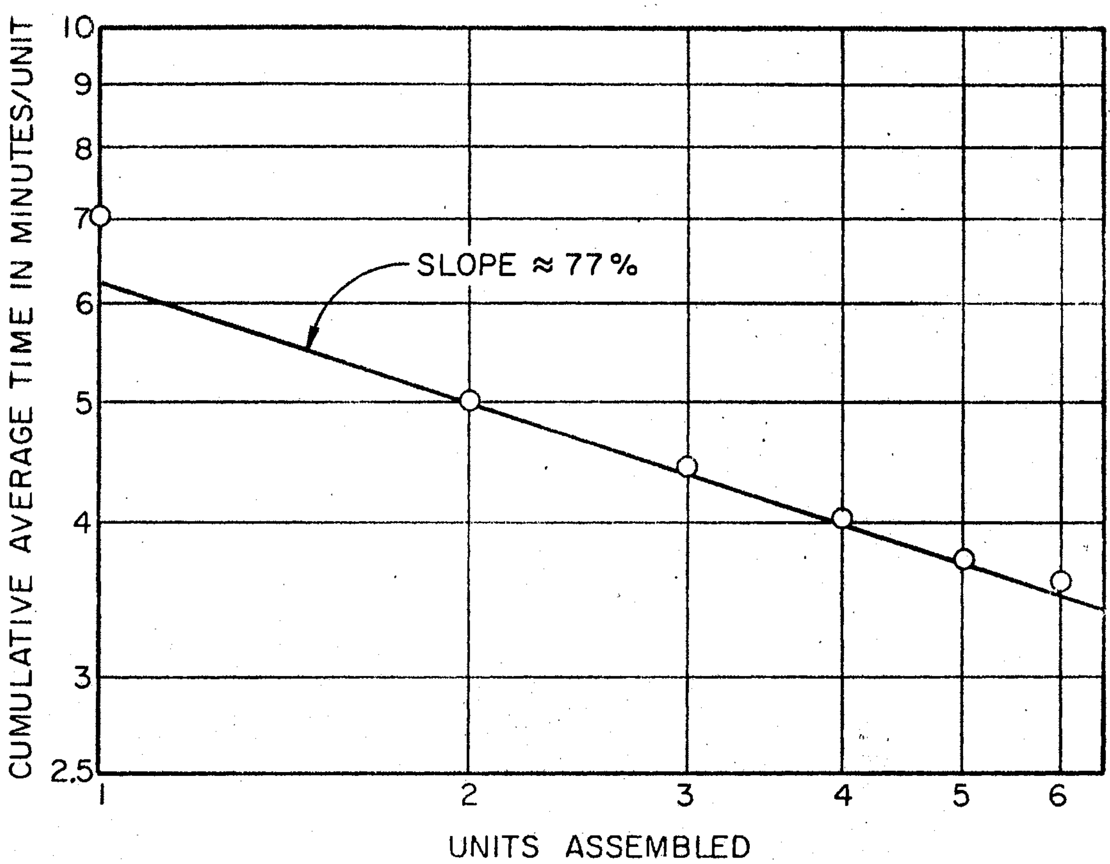


Figure 22. Learning Curve for Element #5 for Four-Shelf Unit

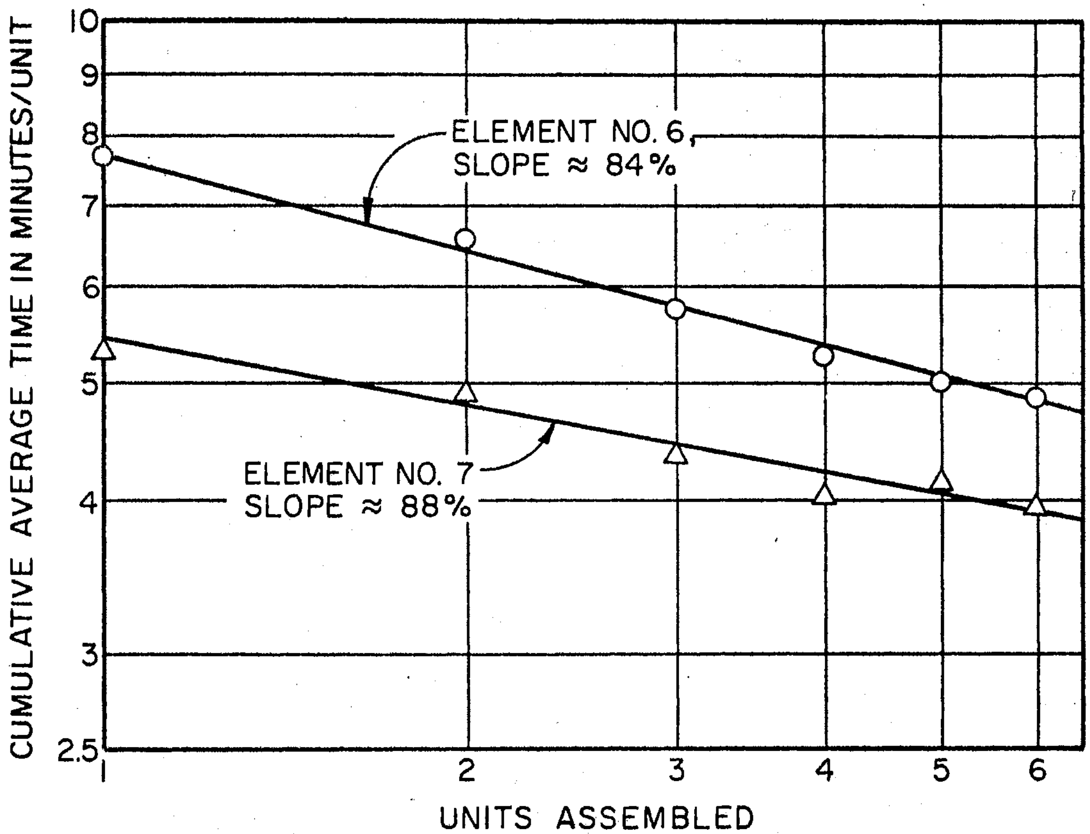


Figure 23. Learning Curve for Element #6 for Ten-Shelf Unit

<u>Final Extension of Metal Shelving Tests Using a Three-Shelf Assembly Design</u>. This series of learning progress tests were run on a shelving design which was different from the other previous designs. The prime generic difference was in the type of fastener used to assemble the metal parts. This unit had only three shelves, and "machine screws" were specified instead of sheet-metal self-tapping screws. In addition, the machine screws required "machine nuts" to complete the assembly. This meant a corresponding increase in the number of required parts per unit (as compared with a unit using the sheet-metal screws). As before, a series of learning progress tests were used to probe the learnability of this design. The results have been plotted as a log-linear learning curve, as may be seen in Figure 24. Table III includes information tabulated relative to the design configuration and related parameters. In Figure 24, data is plotted from two individual test subjects, so an analysis may be made of any potential operator-to-operator variation. An evaluation of these results will be made in a subsequent section of this chapter. These tests were useful in the analysis of learning data. No significant differences in performance were noted for the two test subjects who had basically the same qualifications and performed identical tasks. A more detailed analysis of any potential differences in work performance between the two test subjects will be included below.

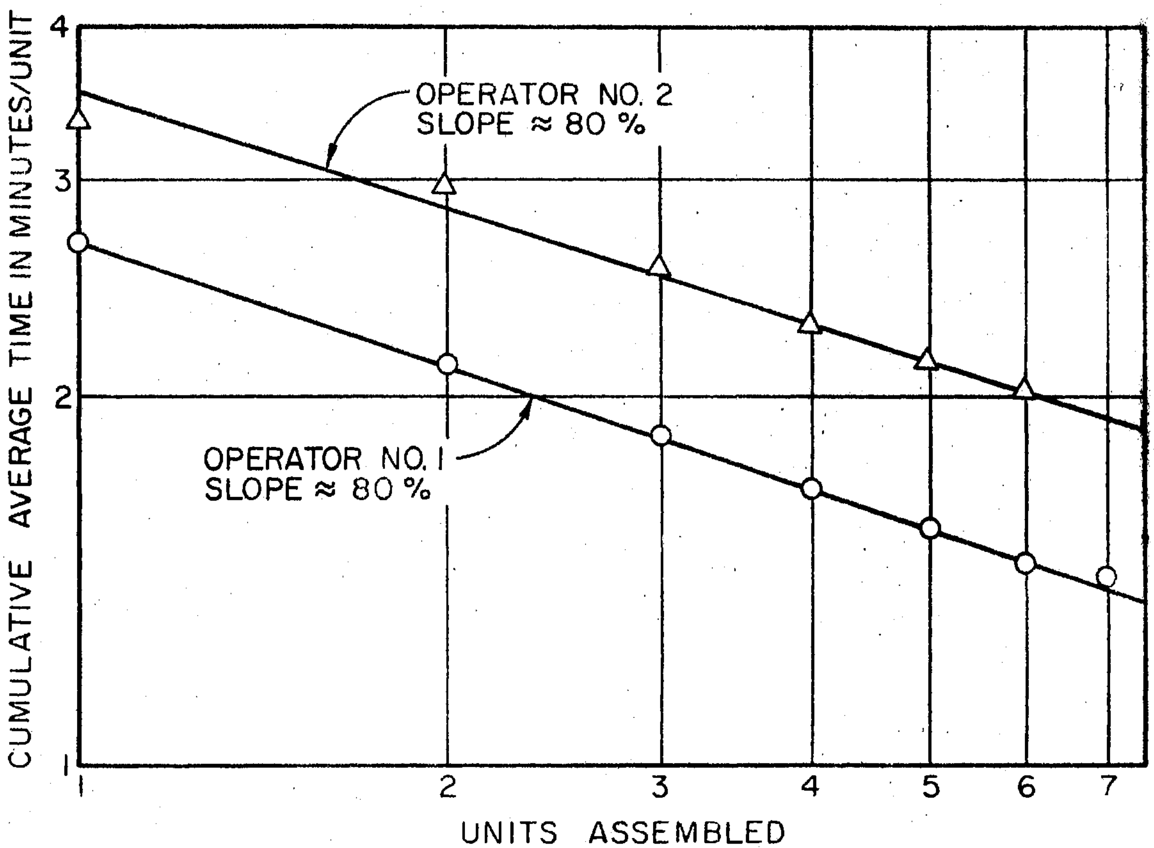


Figure 24. Learning Curve for Three-Shelf Shelving Unit

TABLE III

THREE-SHELF SHELVING UNIT CONFIGURATION DATA

Parts	Number
1. Shelves	3
2. Braces	4
3. Plastic Feet	4
4. Posts	4
5. Bolts	31
6. Nuts	31
Total Parts	77

1. P_a - Total number of parts (77).
2. P_b - Total number of sub-assemblies (6).
3. P_e - Number of fasteners (31).
4. P_f - Number of non-fastener parts (46).

Learnability Test of a Gas Heater Assembly

This investigation represents a series of experimental learnability tests on a typical commercial product manufactured in a typical industrial environment. The assembly consisted primarily of sheet metal stampings, machine burner parts, sheet-metal screws and other metal fasteners, along with certain ceramic flame-distributors and asbestos insulation. The assembly is a floor-mounted gas space heater usually intended to heat one room in a private home or cabin not equipped with a central heating system. A summary of pertinent information relative to the gas heater assembly is displayed in Table IV.

TABLE IV

GAS HEATER CONFIGURATION DATA

(Heater Model 1540, Martin Stove & Stamping Co.)*

Description	Number
1. Non-Fastener Parts	75
2. Fasteners	36
3. Sub-Assemblies	10
4. Total Number of Parts**	111

*Location: Huntsville, Alabama.

**Item 4 is the total of items 1 and 2.

The learning progress data has been plotted on a double-logarithmic learning curve format as before, and it may be viewed in Figure 25. The closeness of the data points to a perfect log-linear trace indicates that the experimental runs have continued to show correlation with predicted results. The test subject for these runs was selected from a group of average industrial production workers who worked in assembly activities for the industrial firm. As in previous tests, six runs were found to be adequate to establish a definite trend in learning progress. Details of the test results are presented near the end of this chapter.

Learnability Tests of Wrist Watch Assemblies

The addition of the wrist watch assembly tests to the previous set of learnability tests added several dimensions to the previous experimental data. In the first place, previous tests had been primarily concerned with the assembly of hardware which was relatively non-precision. Also, the parts were generally large enough in over-all size to be classified as either "small" or "average" in size. However, most of the assemblies of wrist watch parts were made with the aid of a "loupe" or other magnifying device. Such devices were needed because the sizes of the parts were so small they could not be seen easily with the naked eye. The tools and various handling devices also had to be miniaturized such that the parts could be assembled/disassembled

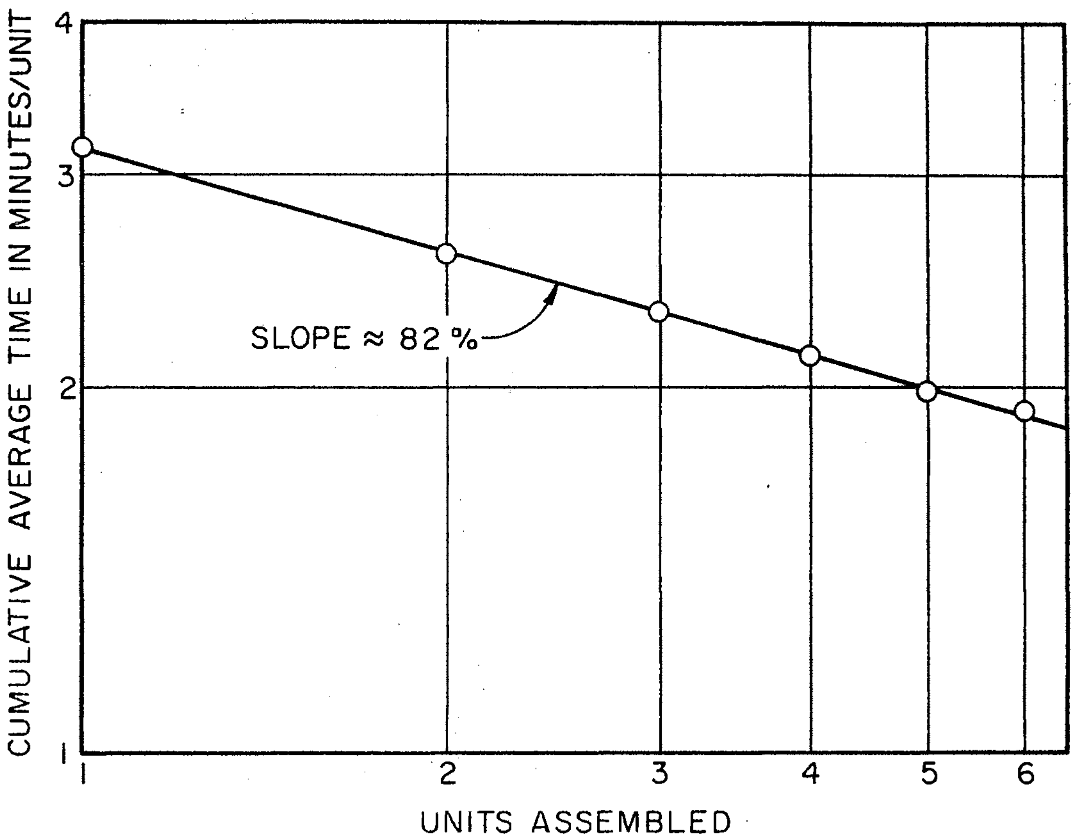


Figure 25. Learning Curve for Gas Heater Assembly

readily. It was also very important for the work place to be well lighted and otherwise comfortable for the operator. Thus, the "job" aspects of the learnability loop were made more critical by the unique design features of the category of mechanical assemblies under consideration. Initially, the thought had been that the highest level of skill category would be required for the assembly of these precision watch parts (Level IV). Later, as more experience and familiarity was gained with this type of hardware, it was concluded that this type of assembly actually required a Level III skill (see Appendix A). Of course, there are always some individuals who cannot master the watch assembly type of motor skills due either to vision or to manual dexterity handicaps. The test subjects used for these experimental runs were selected from a group of operator-students who had already been screened for potential qualification deficiencies.

With due consideration given to the several novel aspects of assembly activities using watch parts, a series of learnability tests were run. Two assembly design configuration were used, one being a self-winding man's wrist watch and the other being a manual-wind lady's wrist watch. Table V shows a summary of the parts and sub-assemblies for both watch types. Observations were made of two individual test subjects, both performing identical tasks. These dual runs were made, as before, to test the potential operator-to-operator variability aspects of learning

TABLE V

CONFIGURATION DATA FOR WRIST WATCH ASSEMBLIES

Description	Number
A. Watch No. 1*: 17-Jewel, Self-Winding, Man's Watch	
1. Total Number of Component Parts	85
2. Total Number of Screw-Fasteners	31
3. Total Number of Sub-Assemblies**	8
a) Setting Mechanism b) Winding Mechanism c) Power Unit (Main Spring) d) Train-of-Wheels e) Escapement f) Self-Winding Mechanism g) Dial-Train Mechanism h) Power Indicator (Running Time)	
B. Watch No. 2*: 17-Jewel, Manual-Wind, Lady's Watch	
1. Total Number of Component Parts	43
2. Total Number of Screw-Fasteners	16
3. Total Number of Sub-Assemblies	6
a) Setting Mechanism b) Winding Mechanism c) Power Unit (Main Spring) d) Train-of-Wheels e) Escapement f) Dial-Train Mechanism	

*Both watches No. 1 and No. 2 have cases which could constitute another sub-assembly. Since the assembly procedure did not include replacing watch movement in its case, this item was not included in the parts lists shown above.

**In the watchmaker trade, sub-assemblies are referred to as units.

progress. As may be observed in Figures 26 and 27, a close agreement in learning progress was indicated for both test subjects, and the indicated difference in learnability between the two types of wrist watches correlated well with predicted results. Again, the results from this series of test runs continued to show excellent promise in support of the proposed prediction model.

Further Use of Contrived Design Configurations in Learnability Testing

A need was recognized for a technique which would permit contrived designs to be used in making laboratory-type learnability tests and analyses. Since exploratory tests demonstrated the utility of erector set parts, it was decided to generate a contrived design using these parts and to employ learning tests to further probe the usefulness of this approach. The resulting design from erector set parts was named "utility van truck". The results from a series of six learning progress runs have been plotted on the standard double-logarithmic paper (Figure 28). Figure 28 indicates that the learning curve has formed an almost perfect log-linear trace. As will be discussed in detail in the last section of Chapter V, this configuration was used as a sample problem to test the proposed prediction model. Results were again positive as a validation of the prediction methodology.

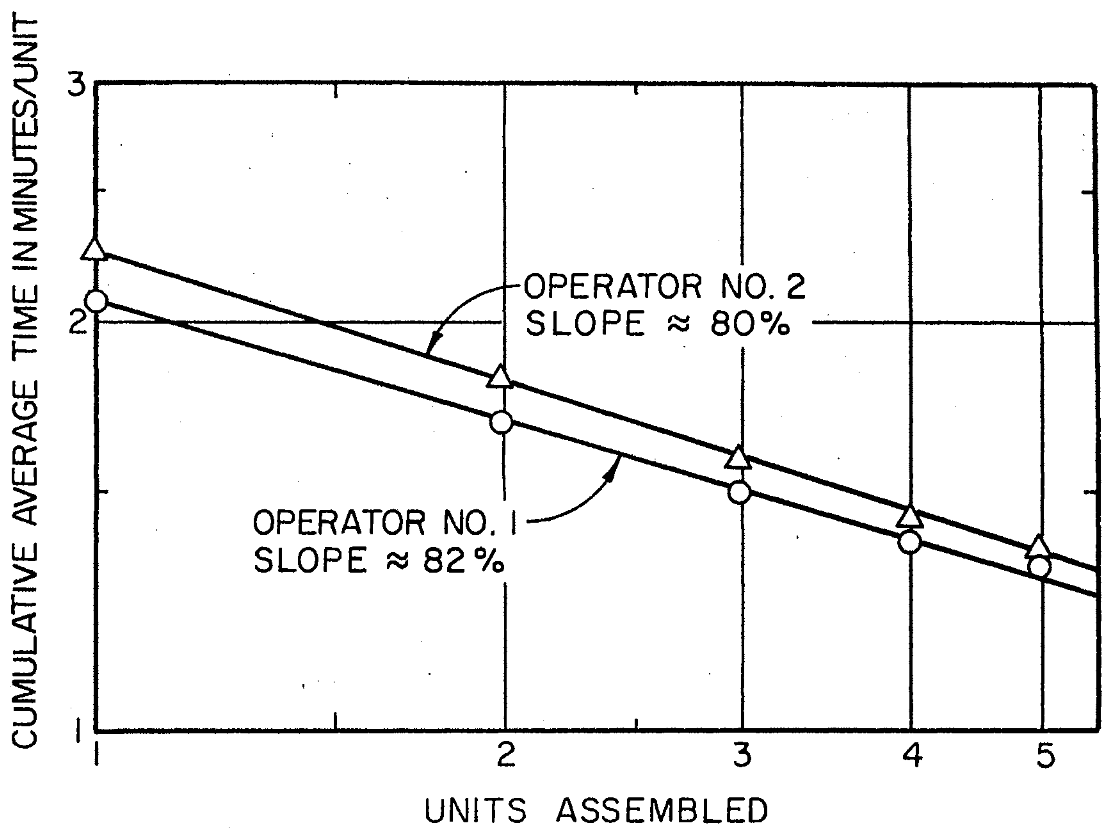


Figure 26. Learning Curves for Man's Wrist Watch

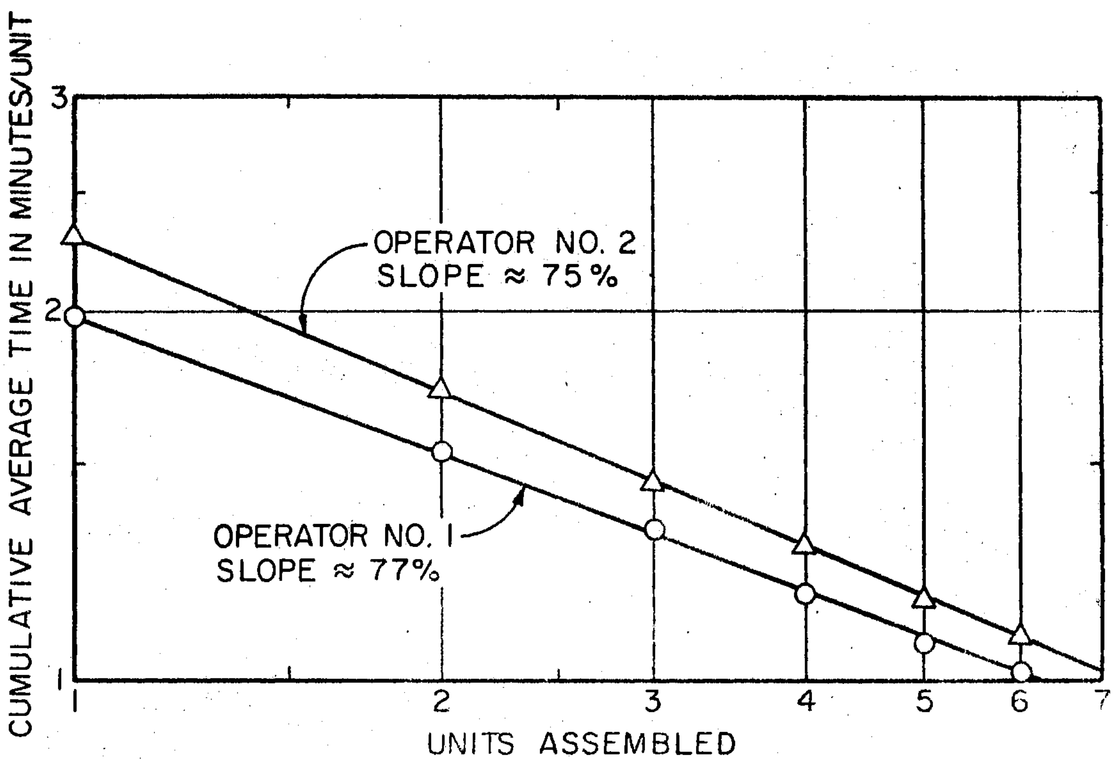


Figure 27. Learning Curves for Lady's Wrist Watch

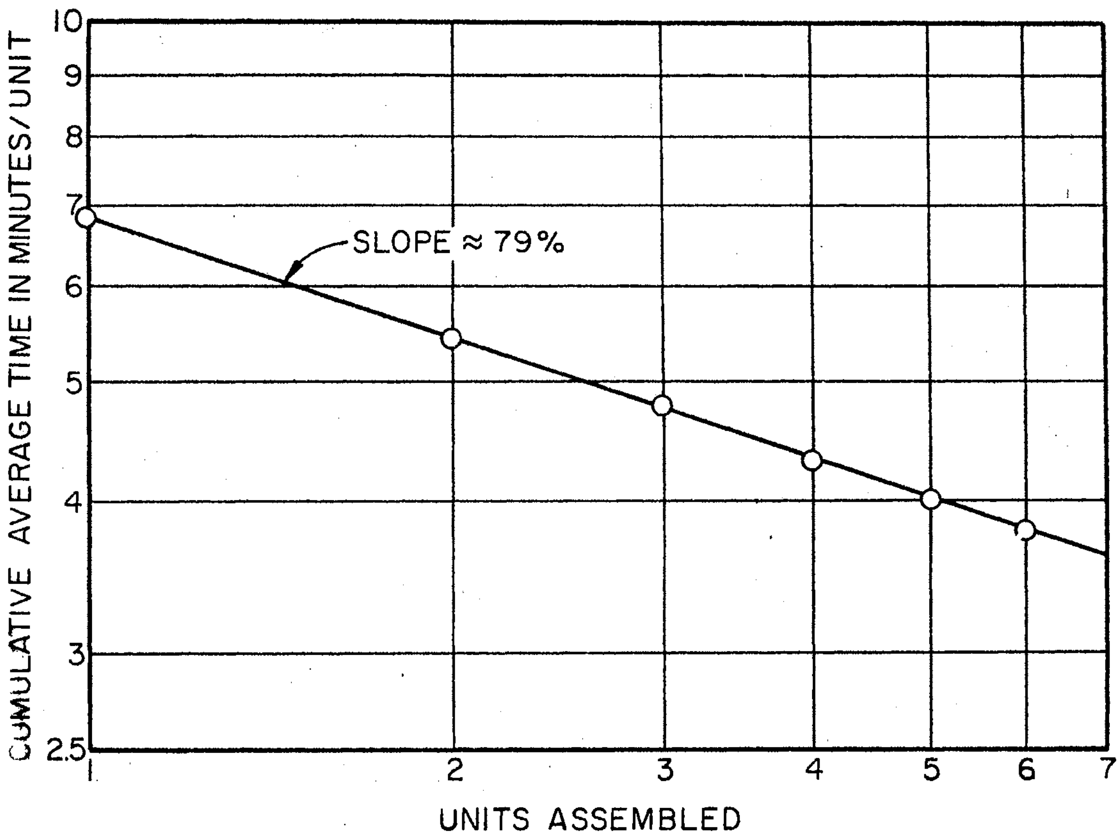


Figure 28. Learning Curve for Utility Van Truck

Summary and Evaluation of Test Results

Summary. In the previous sections of Chapter V, several different test extensions have been outlined. The objectives for these extensions naturally included the goal to increase the over-all quantity of data to support the proposed model. During the course of these tests, it was also possible to increase the level of understanding in the application of design-oriented parameters to predict learnability for a specific mechanical assembly design. Based on the rather wide variety of types of mechanical assemblies employed in the experimental runs, the aspect of generality of application was enhanced. One disappointment, however, was the difficulty in obtaining industrial-type data from private industrial firms. Some firms offered cooperation but simply were not engaged in the type of operations which would support this research work. Others took the position that this type of information was sensitive from a competitive position point of view. One of the most beneficial sources of information was a technical school (Calhoun State Technical School*), where the information obtained was excellent and the cooperation of academic officials outstanding. In two separate sets of experimental runs (three-shelf assembly, wrist watch assemblies) it was possible to probe the operator-to-operator potential source of

*Location: Decatur, Alabama.

variability in the learnability evaluations. In both sets of experimental results, the differences in performance between two qualified operators doing identical tasks was deemed insignificant. This judgment was based principally on comparisons between rates of learning progress or learnability values as determined from the learning curves of the experimental runs.

Evaluation of Test Results for Mechanical Assemblies. The first set of test results for a typical industrial-type design configuration was demonstrated by the four-shelf assembly. These results have been plotted in the learning curve of Figure 18 (page 110). As previously explained, this learning curve is based on a cumulative data reduction principle, since this approach tends to effect an element of smoothing to the data values, making it easier to fit a curve to the plotted points. Since the parts used in this assembly were the output of "high-volume production", it was not surprising that some difficulties were experienced in fitting the parts together. In accord with a previously stated ground rule, the time required to correct ill-fitting parts was not charged to the cycle time in which the problem surfaced. An example of such problems was the occurrence of excessive burrs on sheet-metal corner braces for the shelves. It was necessary to remove these burrs with a file in order to permit a properly fitted joint. Another minor problem resulted from the undersize holes in the sheet-metal posts for the shelves. This condition required excessive torque by the operator to set the self-tapping sheet-metal screws. An additional drilling operation was required on some of the holes to make a small increase in the diameter of the holes. When this type of operation was required, the time-study watch was stopped, and the time required to correct the problem was not charged to the cycle time. This same approach was used for all of the subsequent runs, and the policy of not charging parts correction time to the cycle time was established as one of the experimental ground rules for this study. The slope of the learning curve for the four-shelf assembly was approximately 77%. This value corresponds very well with an expected learnability value for an assembly of this type with a total of 60 parts and five sub-assemblies. These and other design-oriented data may be seen displayed in Table VI, "Trend Curve Parametric Data". From these data values, a series of learnability trend curves have been plotted based on a set of selected learning sensitive design-oriented parameters. These trend curves appear as follows: Figure 29 for P_e or "Total Number of Fasteners", Figure 30 for P_f or "Non-Fastener Parts", Figure 31 for P_b or "Number of Sub-Assemblies", Figure 32 for P_a or "Total Number of Parts". Individually, and also collectively, these trend curves have provided the basis for the "Learnability Figure of Merit", which is the key element in the prediction model. The learning sensitive parameters utilized in Figures 29-32 were selected from a larger set of

TABLE VI

TREND CURVE PARAMETRIC DATA

Description of Test	Curve Slope	Total No. Fasteners P_e	Non-Fasteners Parts P_f	No. of Sub Assemb. P_b	Total No. of Parts P_a
#1540 Martin Stove Gas Heater	82%	36	75	10	111
*Calhoun-Tech Benrus Lady's Watch	76%	16	27	6	43
*Calhoun-Tech Benrus Man's Watch	81%	31	54	9	85
3-Shelf Shelving Unit	80%	31	46	6	77
4-Shelf Shelving Unit	77%	20	40	5	60
10-Shelf Shelving Unit	87%	46	80	11	126

*Average of runs by 2 operators.

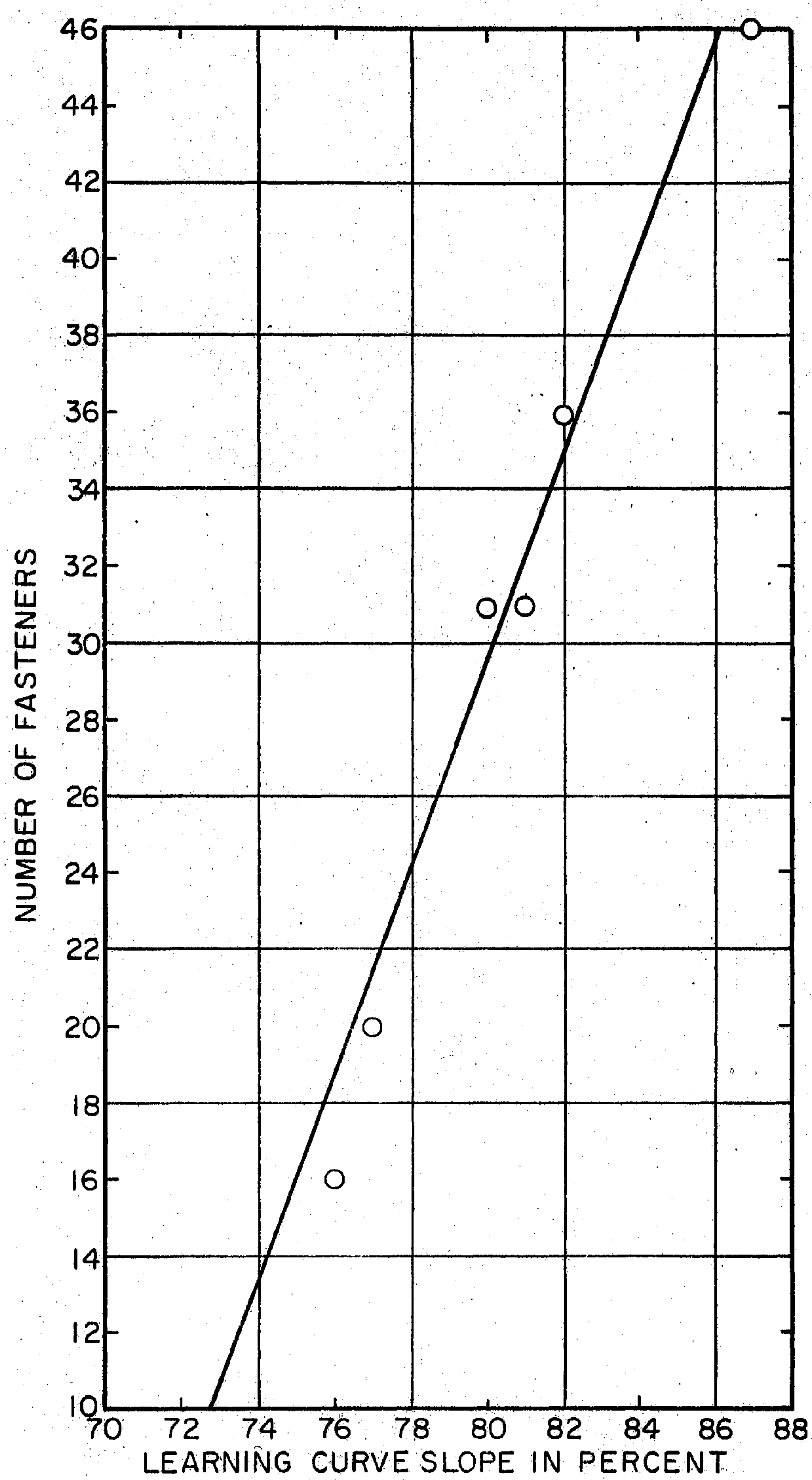


Figure 29. Trend Curve for Total Number of Fasteners, P_e

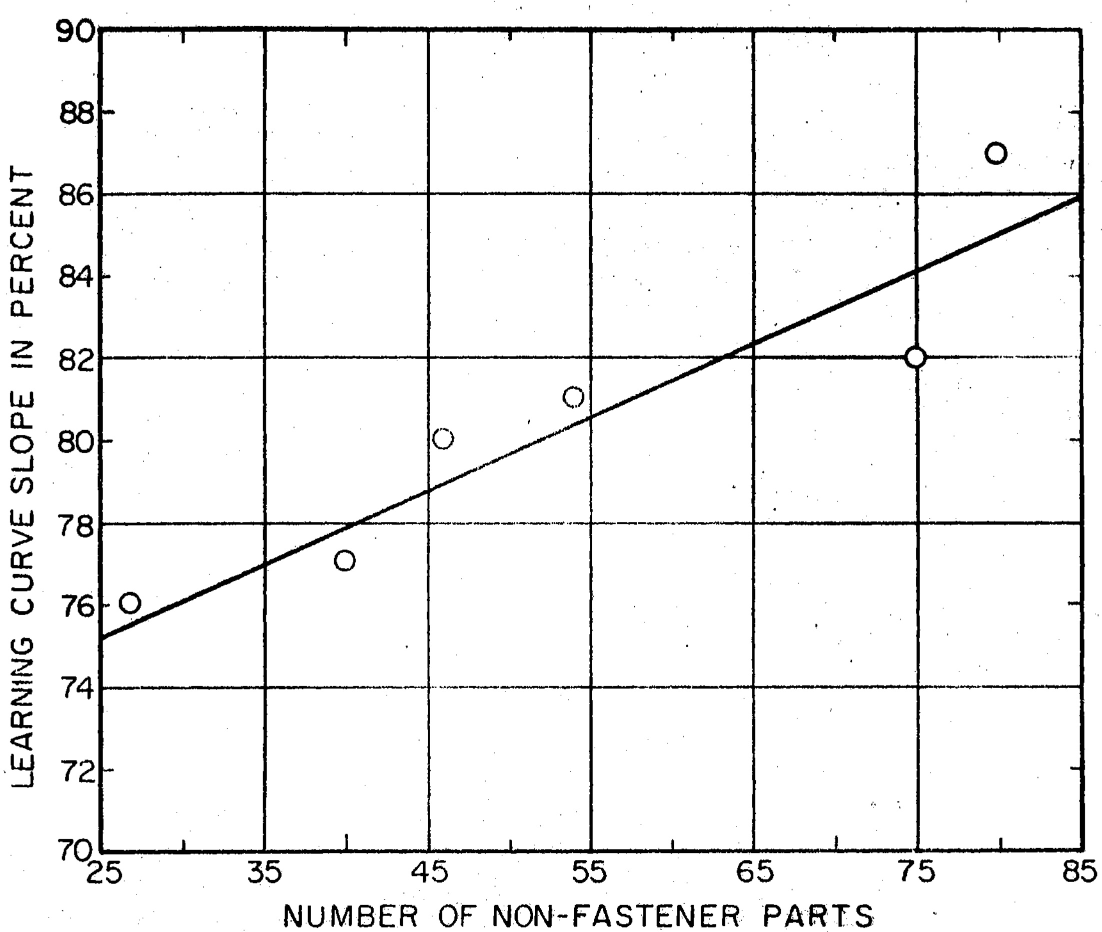


Figure 30. Trend Curve for Non-Fastener Parts Count, P_f

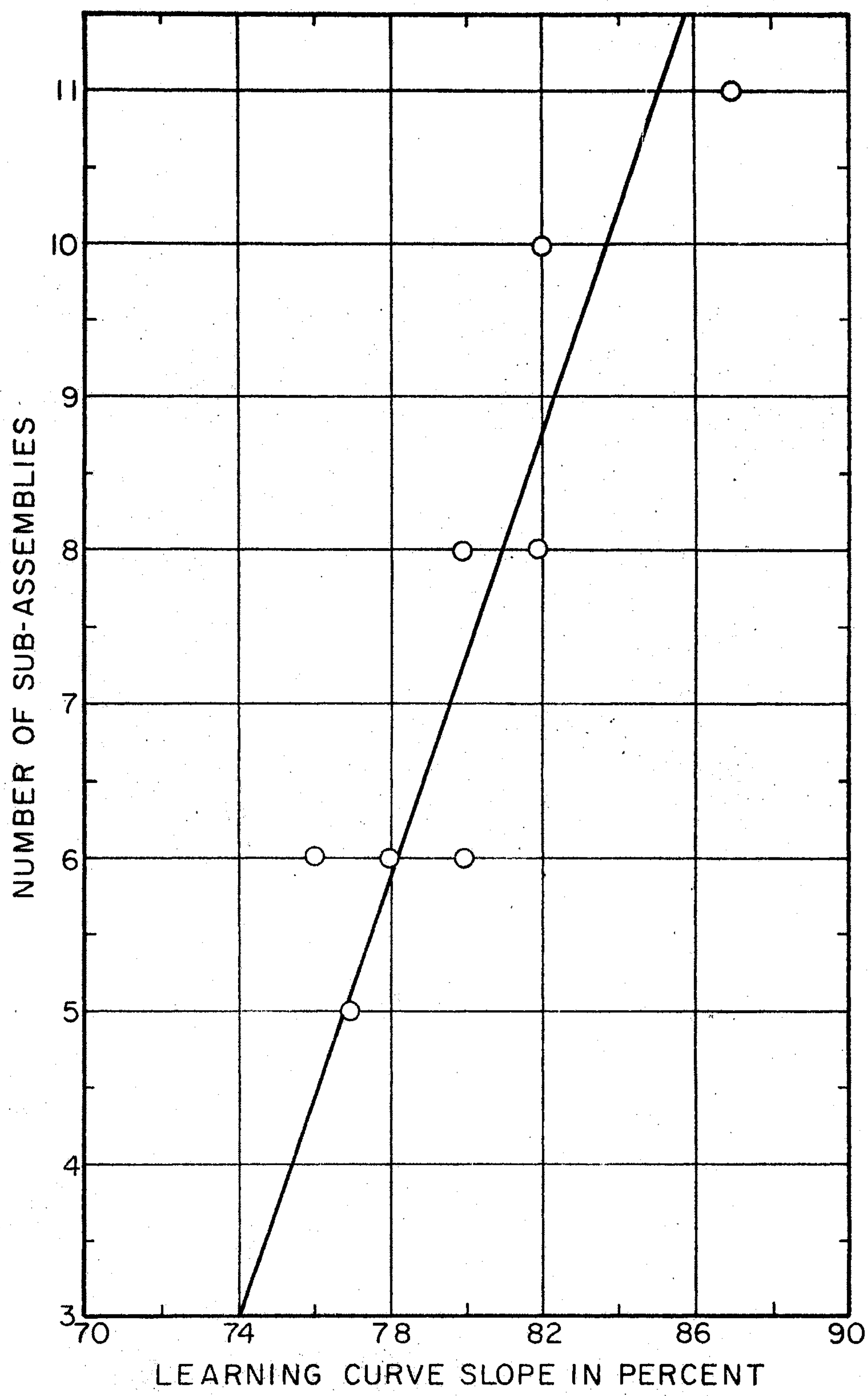


Figure 31. Trend Curve for Number of Sub-Assemblies, P_b

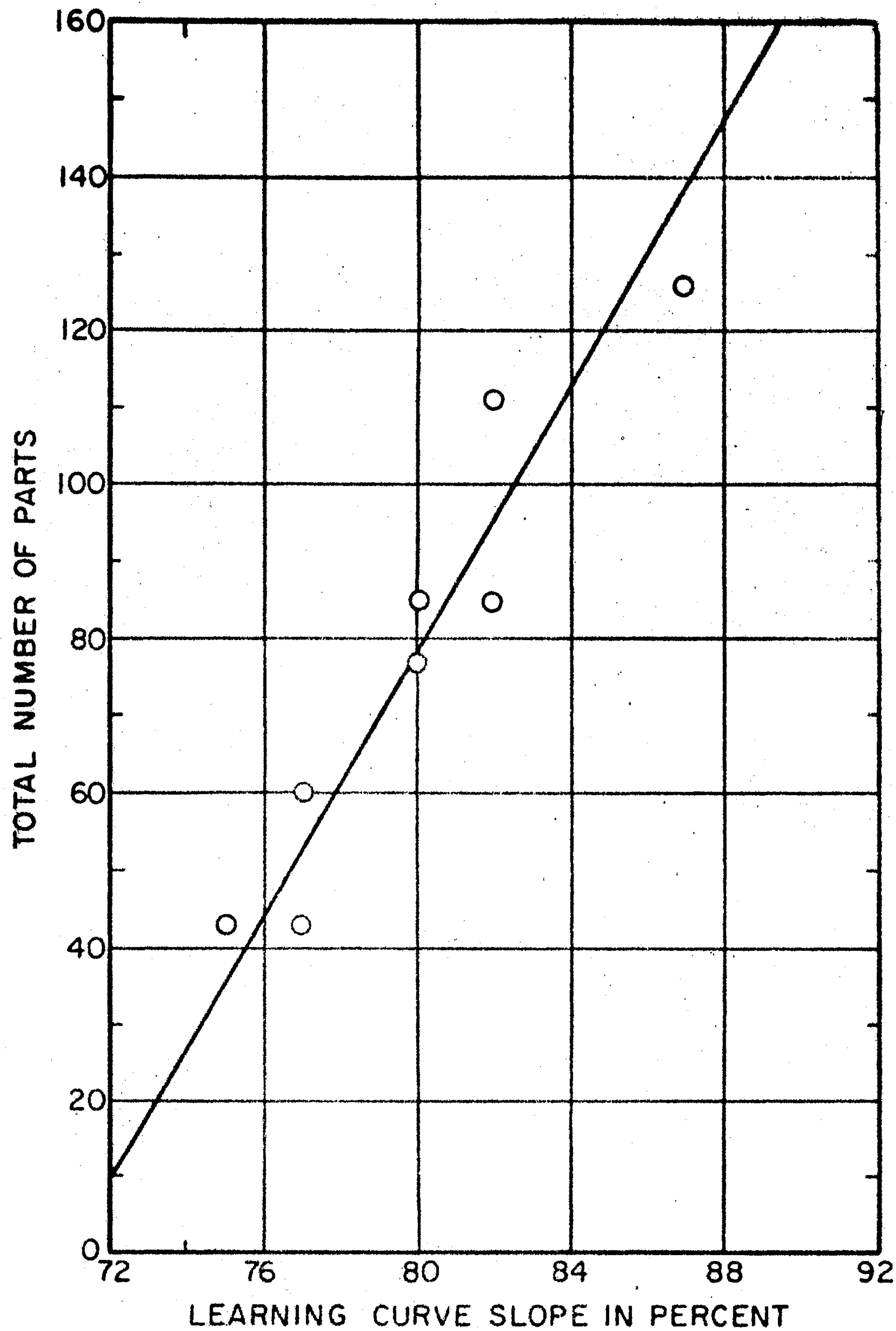


Figure 32. Trend Curve for Total Number of Parts, P_a

factors as outlined in Chapter III. The ones selected were found to be more effective as predictors of changes in learnability resulting from planned or discrete changes in design features for the mechanical assemblies being studied. Further extensions of the research started in this effort could possibly yield a more efficient set of parameters, as well as some different factors to use in a forecast of learnability. Further discussions concerning this and other recommendations for future research and potential applications have been made in Chapter VI.

Development of Figure of Merit (FOM) and the Characteristic Learnability FOM Curve. As explained in Chapter III, the selected learning sensitive factors, as depicted in the trend curves, have provided an information source essential to the development of the prediction model. Also, the use of a "time series" approach makes it possible to establish a predictable trend in learning performance. The FOM values and the "time series" numbers may be considered as synonymous within the context of this work. The development of the FOM values was accomplished by the following procedural steps:

(a) Make cuts through each of the trend curves being utilized at programmed intervals of learning slope (72, 75, 78, etc.).

(b) Form a matrix of values from the above cuts such that the steps in slope percent are on the vertical axis of the matrix, and the parametric values obtained by the cuts are the cell-entries on the matrix. The column headings represent the nomenclature for the various learning sensitive factors such as P_a, P_b, etc.

(c) In order to facilitate mathematical processing of the data, take logarithms of each cell entry and enter them in each of the cell spaces (logarithms to the base 10 are used although this choice is arbitrary). An illustration of such data is displayed in Table VII, entitled "Learnability Parameters Trend Curve Data".

(d) As may be seen in the cited table, the FOM value for a particular cut or slope value may be found in the total column. Compute these values by the time series multiplicative method of multiplying each of the chosen parametric values (for a particular cut) times each other, or $P_a \times P_b \times P_e \times P_f$. To simplify this operation, $Q = \text{Anti-log } (\log P_a + \log P_b + \log P_e + \log P_f)$.

(e) As the final step in this procedure, use the values in the total column in the trend curve data matrix (Table VII) to plot the FOM characteristic curve (Figure 33).

TABLE VII

LEARNABILITY PARAMETERS TREND CURVE DATA

$\frac{m}{L}$	$\frac{P_a}{(\text{Log } P_a)}$	$\frac{P_b}{(\text{Log } P_b)}$	$\frac{P_e}{(\text{Log } P_e)}$	$\frac{P_f}{(\text{Log } P_f)}$	Totals Q (Log Q)
72 1.39	10.0 (1.00000)	1.5 (0.17609)	8.0 (0.90309)	8.0 (0.90309)	960 (2.98227)
75 1.33	35.0 (1.54407)	3.7 (0.56820)	16.0 (1.20412)	24.0 (1.38021)	49,730 (4.69660)
78 1.28	61.0 (1.78533)	5.86 (0.76790)	24.3 (1.38561)	40.7 (1.60959)	353,530 (5.54843)
81 1.24	87.0 (1.93952)	8.05 (0.90580)	32.3 (1.50920)	57.5 (1.75967)	1,300,700 (6.11419)
84 1.19	113.0 (2.05308)	10.2 (1.00860)	40.3 (1.60531)	74.5 (1.87216)	3,460,500 (6.53914)
87 1.15	139.0 (2.14301)	12.4 (1.09342)	48.6 (1.68664)	91.1 (1.95952)	7,631,200 (6.88259)
90 1.11	163.0 (2.21219)	14.4 (1.15836)	56.6 (1.75282)	107.5 (2.03140)	14,810,000 (7.15477)

1. All logarithms are to base 10.

2. $Q = P_a \times P_b \times P_e \times P_f$ (all with weights assumed equal to one).

3. Above values were taken from samples of trend curve cuts taken at each of the 7 slope values.

4. m = slope of learning curve.

5. L = Learnability or 1/m.

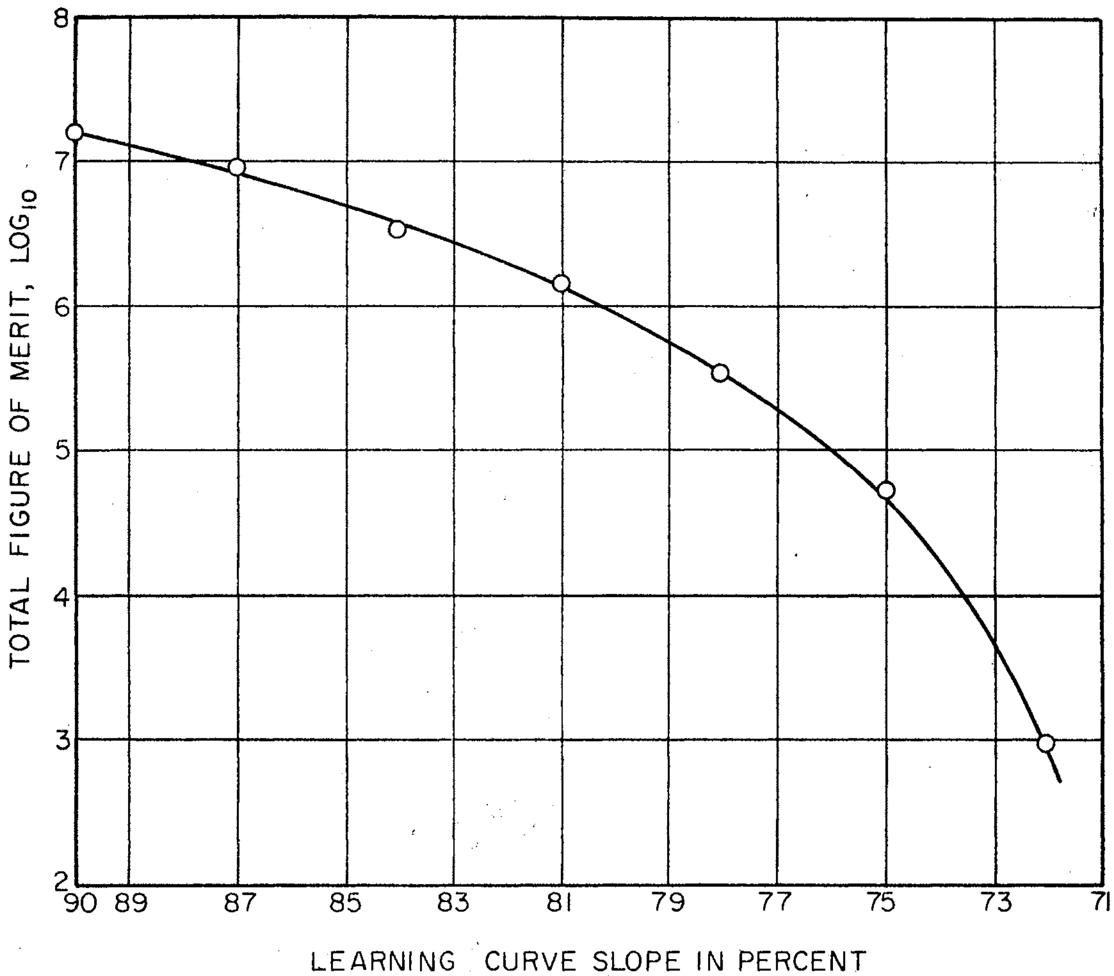


Figure 33. Figure of Merit, Characteristic Curve

If the analyst prefers to work with a table in making a learnability analysis, it is possible to make a series of cuts at uniform increments on the characteristic curve illustrated by Figure 33. An example of a table built by this method is Table VIII, "Learnability Figure of Merit Table". The analyst may, therefore, choose either format of data presentation when making a learnability prediction analysis. The sample application to an illustrative example in the last section of Chapter V illustrates both of these methods, but the choice is felt to be strictly a matter of personal preference. As may be observed in the item "d" above, no weighting or preference values were assigned to the parameter entries since there was no basis for placing more emphasis on one parameter than on any other. For this reason, all of these values may be assumed to have the implied weight of "one", which, of course, vanishes from the above mathematical notations. If further test extensions should reveal the existence of actual or implied weights in the trend data, these weight values can easily be incorporated in the FOM computation forms (see Chapter III).

Revisions to Prediction Model Format

Subsequent to the initial formulation of a prediction model, several additional test extensions have been accomplished. There have been no startling revelations based on the information obtained through these experimental investigations. However, based on an analysis of the data, it has

TABLE VIII

LEARNABILITY FIGURE OF MERIT TABLE

Slope % m	1/m or L	Q, Figure of Merit Scores	
		Log_{10}	Anti-Log x 10^3
72	1.389	2.98	.96
73	1.370	3.62	4.17
74	1.351	4.18	15.14
75	1.333	4.69	49.70
76	1.316	5.00	100.00
77	1.299	5.23	169.90
78	1.282	5.54	354.00
79	1.266	5.78	603.00
80	1.250	5.96	913.00
81	1.235	6.11	1,300.00
82	1.220	6.33	2,140.00
83	1.205	6.45	2,820.00
84	1.190	6.54	3,460.00
85	1.176	6.65	4,470.00
86	1.163	6.84	6,919.00
87	1.149	6.88	7,631.00
88	1.136	7.02	10,470.00
89	1.124	7.09	12,310.00
90	1.111	7.15	14,810.00

been possible to screen a list of potential candidate factors which are learnability sensitive after programmed changes in design configuration have been introduced. One such candidate factor (which was deleted) was the "ratio of number of fasteners to total number of parts". The attempt to form a trend curve with this parameter failed, as can be seen in the Figure 34 scatter diagram. As is evident from the random distribution of points in Figure 34, there was virtually no indication of predictable variability based on this factor. In addition, all of the points included on this scatter diagram were taken from actual industrial or industrial-type mechanical assembly observations. By contrast, the set of design-oriented parameters exhbited in Figures 29-32 (pages 135-138) were judged to be reasonable predictors of learning progress. Each of these factors exhibited predictable changes in learnability as programmed changes to a design configuration were made. In other words, these factors did support the proposed prediction model as originally described, and they are herewith nominated as the preferred set of learnability factors for this work. The applicability and/or flexibility of the revised model must, quite logically, be subject to appropriate ground rules and constraints. These will be discussed in more detail in the next section.

Another aspect of the experiment analysis which could influence application of the model is the "skill level" factor. Initially, it was felt that rigor would require a

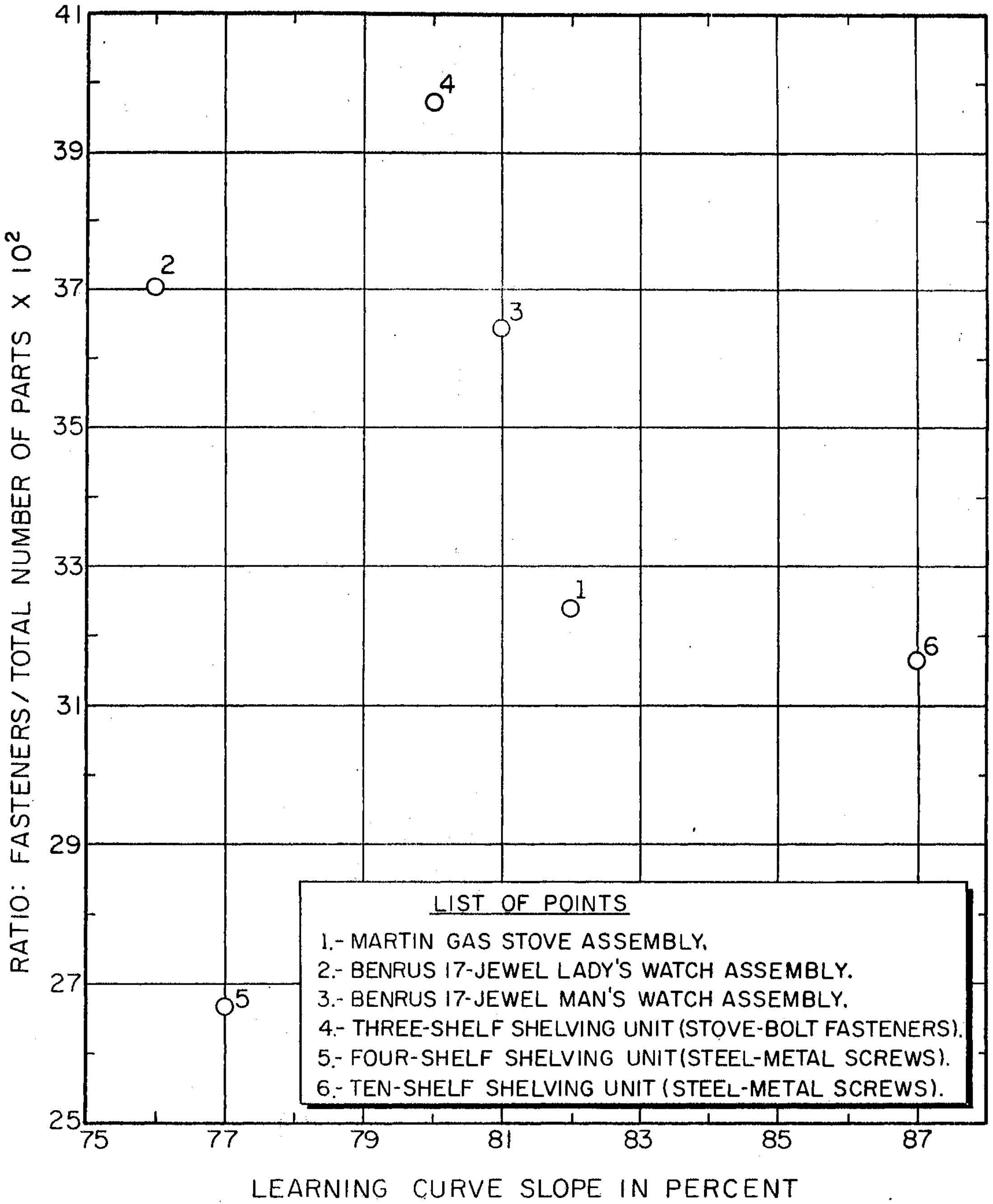


Figure 34. Scatter Diagram

learnability characteristic curve or table for each skill level itemized in Appendix A. Later, it was realized that Levels II and III could be combined, so far as application of the model is concerned, although this combination represents a rather broad band of operator expertise. What is particularly relevant in this situation is the capability of the operator to meet the skill demands of the particular job assignment. Routine screening of candidate operators will normally satisfy this requirement. For the technical school watchmaker students, normal student entrance testing eliminates practically all candidate trainees who are not qualified to meet the skill demands for this type of work. No deficiencies in skill were observed during any of the experimental runs documented in this research. The test subjects were screened by standard procedures which gave no indication of selection bias. For each series of experimental runs, a planned effort was made to provide some small but significant increase in motivation to each separate test subject. A review of these results indicated that all test subjects observed in this work were positively motivated. This judgment was based on such quantitative aspects as the steady improvements indicated by the several learning curves and by the reproducibility of replicated task assignments.

Based on the above discussion, suggested revisions to the previously proposed prediction model format are as follows:

(a) The learnability "factor set" for the body of test data engendered here shall include such factors as P_e, number of fasteners per unit; P_f, the non-fastener parts count per unit; P_b, the number of subassemblies per unit; and P_a, the total number of parts per unit.

(b) Predictions or forecasts of learnability based on evaluations of pertinent design criteria and requirements will be made considering skill Levels II and III as a single category. For example, Figure 33 may be used for preparation of estimates on tasks requiring either Level II or Level III skills.*

So far as can be determined, neither of the above revisions make the model less useful or affect its accuracy.

Discussion of Ground Rules and Constraints in Application of Prediction Model

One of the minor modifications to the prediction model as initially proposed was a suggested change in the ground rule that a separate set of learnability data be developed for each level of skill. This revision simply combines

*The assumption is made that all operators have been screened in accord with the skill requirements for each task observed.

Levels II and III for purposes of model application based on experience gained from the several test extensions described above. In effect, this makes application of the prediction model to a wider variety of mechanical assemblies less critical and, presumably, simpler. Based on these and other previously noted considerations, a modified set of ground rules and constraints are outlined below:

(1) Model shall be applied to mechanical assemblies only.

(2) Model shall be applicable to single operator activities only.

(3) Model data (see Table VII) may be applied to any task requiring Level II or Level III skills as described in Appendix A (operators are assumed to be qualified).

(4) Derived learnability values should always be considered as a "best estimate" and not absolute.

(5) Model format and data may be considered as substantially typical, based on a limited data population. Its use, however, should be complemented or replaced when discrete historical information is available for a specific design.

(6) Limit applications to mechanical assemblies which have between 30-140 total parts.

Trial Application of Model to a Sample Problem

Foreword

One reason for using the contrived design as a sample application of the prediction model was the desire by the test conductor to maintain very close control of the experimental runs, at least in the outset. The test subject for these runs was the same operator who performed the majority of the earlier shelving and erector set runs. All of the normal conventions of time study practice were used. In addition, the set of ground rules and constraints outlined in the previous section were observed. Also, the same conventions for starting/stopping, interruptions, and other unplanned events were followed for this final set of experimental runs. This contrived design, which was assembled from erector set parts, is illustrated by Figure 35.

Details of Experimental Runs and Data Analysis

Again, as on previous test runs, six replications of the assembly cycle were sufficient to establish a definite trend in learning progress. Data from these six test runs was plotted on the usual double-logarithmic paper, as shown in Figure 28 (page 130). Agreement with a perfect log-linear trace was very close, and most of the points fell directly on a straight line. These results tended to

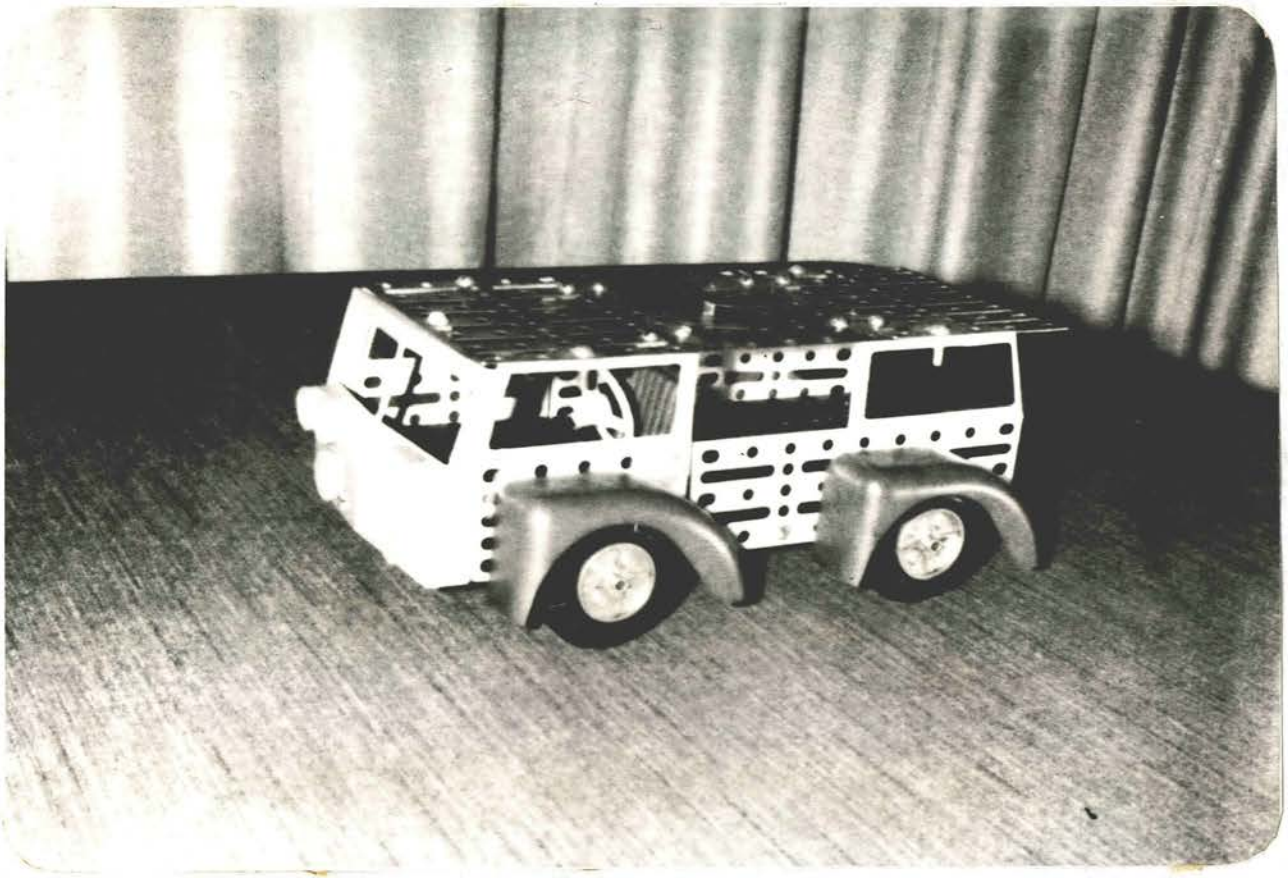


Figure 35. Illustration of Utility Van Truck
(Contrived Design

reinforce the suitability and reliability of the various procedures, conventions, and techniques practiced throughout the entire study.

Learnability Analysis by Model

Some analysts may prefer to utilize an "MTM" type table, as opposed to a characteristic curve such as Figure 33 (page 142). It is possible to create such a table of learnability values simply by taking cuts across the curve. To illustrate both approaches to the learnability analysis, Table VIII has been created from the Figure 33 characteristic curve. Also, the design configuration in question, the "Utility Van Truck", has been reviewed in detail, and a list of parts is displayed in Table IX. Using all of this information, a learnability analysis has been completed for this sample problem, and the results are summarized in Table X. Both approaches to the determination of the learnability estimate are illustrated by the analysis, and both of these numerical predictions were found to agree very closely with a learnability value which was determined directly from the learning curve of Figure 28 (page 130). Figure 36 has been included to illustrate how the characteristic curve can be used to obtain a learnability estimate, if the over-all learnability FOM for a particular design configuration is known. The apparent error of prediction for this sample

TABLE IX

PARTS LIST FOR UTILITY VAN TRUCK

Description		Number
1.	Axels	2
2.	Cab Front	1
3.	Chassis Parts	2
4.	Door Panels	4
5.	Finders	4
6.	Front Bumper Pads	2
7.	Head Lights	4
8.	Nuts	27
9.	Screws	27
10.	Seat Assembly	1
11.	Side Panels	2
12.	Steering Column	1
13.	Steering Wheel	1
14.	Straight Brackets	4
15.	Tail Lights	2
16.	Tires	4
17.	Top Plates	3
18.	Wheel Hubs	4
	Total	89

TABLE X

LEARNABILITY FIGURE OF MERIT ANALYSIS*

Design Name: Utility Van Truck**	
1. P_a, Total number of Parts = 89, $\log_{10}$	1.94,939
2. P_b, Number of Sub-Assemblies = 6, $\log_{10}$	0.77,815
3. P_e, Number of Fasteners/Unit = 27, $\log_{10}$	1.48,059
4. P_f, Number of Non-Fastener Parts/Unit = 35, $\log_{10}$	1.54,407
Total Log_{10}	5.75,220
Anti-Log_{10}	565.2×10^3
5. Learnability Prediction Estimate from Table VIII	78.9%
6. Learnability Prediction Estimate from Figure 36	79%
7. Learnability Graphically Determined from Figure 28	79%
Apparent Error (Difference over Measured)	<1%

*Factor weights assumed equal to one (1) for this problem.

**Utility Van Truck was contrived design, and was assembled from erector set parts.

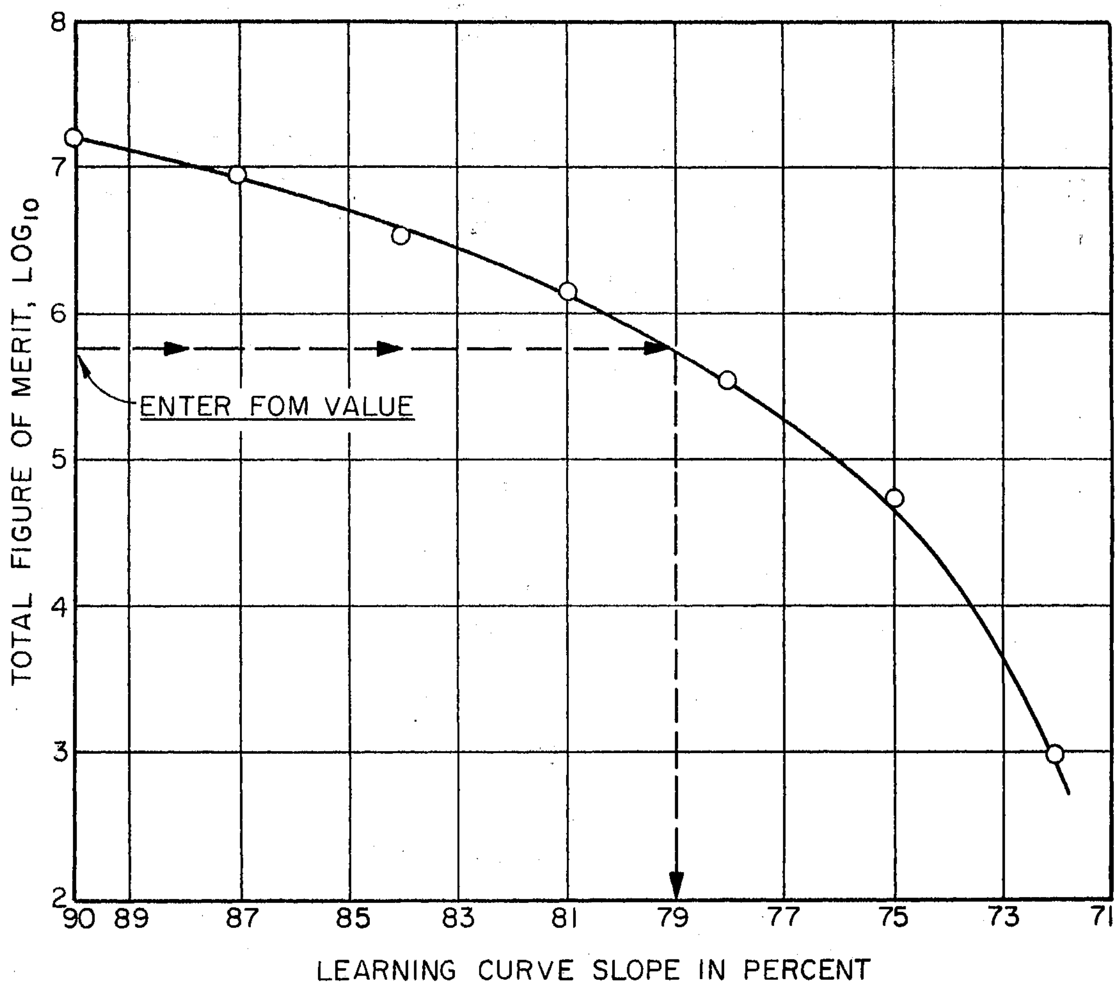


Figure 36. Learnability Solution Using Characteristic Curve

problem is very small. Further comments relative to this trial application of the model and the results obtained will be made in Chapter VI.

CHAPTER VI

SUMMARY AND CONCLUSIONS

Summary of Research Activities

During the early phase of this research work, the activities were concentrated primarily on a search of engineering publications for information on learning theory. This source of information, unfortunately, did not provide either the quantity or the level of information which would support the objectives of this study. Most of the engineering sources appeared to view learning theory primarily from the viewpoint of a shop foreman or production manager. Indeed, most of the society papers appeared to be concentrating on the "learning curve" as the principal item requiring consideration for research in learning theory. This was further complicated by the multiplicity of terms which were sometimes used to convey the same thought but did not actually qualify as synonyms. Some of the alternative terms which appear frequently are: (a) progress functions, (b) improvement functions, (c) complexity functions, (d) memory functions, (e) training transfer, (f) motor learning, (g) maturation, and others. This listing includes several examples, although it cannot be considered exhaustive.

Other terms could be added to the list, but this would not eliminate the problem of using non-equal terms interchangeably. One attempt to minimize this problem was to include a glossary of learning and related systems engineering in the appendixes (see Appendix D).

During the course of the literature search, several excellent sources of information on learning theory were found which did supply satisfactory and sufficient information in support of the selected research topic. Typical of such research categories were: Learning Theory, Experimental Psychology, Human Factors, Ergonomics, Educational Psychology, Physiology, Human Performance, Space Biology, Training and Training Research, Systems Engineering, Perceptual-Motor Learning, Simulation, Mathematical Learning Theory, Technological Forecasting, Decision Theory, Time-Series Analysis, Psychological Statistics, Multiple Regression Analysis, Product Design, Factor Analysis, Trend Analysis, Operations Research, Prediction Models, Large Number Theory, Project Management, Cost Estimation, Job/Personnel Analysis, and Econometrics. Again, this listing is not exhaustive, since there is hardly any activity involving the human organism that does not in a small or large way involve "learning". Based on these information sources, however, both theoretical concepts and practical applications of learning theory and its related peripheral disciplines were investigated in support of the stated objective to develop "prediction models" which could be used operationally to prepare learning forecasts of certain mechanical assembly designs.

Although literature research continued throughout the entire study, the main thrust of the second phase of the program was to plan and execute a series of exploratory tests to gauge the sensitivity of a set of design-oriented factors as a means to predict rates of learning for unique mechanical assembly tasks. A preliminary model format and prediction methodology was developed, and it is described in Chapter III. The exploratory tests have been documented in Chapter IV. The analysis of these runs was sufficiently successful to plan a series of test extensions. The objectives of these extended tests were twofold: first, to introduce more variety in mechanical assembly design and to further enhance confidence in the methodology by substantially increasing the number of separate tests, and, second, to obtain as much industrial-type data as possible. This would also increase confidence in the utility of the model for applications to mechanical assembly tasks in industry. Industrial data proved to be very difficult to obtain, since many managers felt it was detrimental to their competitive position to release such information. To a large extent, this problem was overcome by using student test subjects and by making time studies under laboratory-type conditions. Thus, by one means or another, a considerable number of test extensions were completed on industrial or industrial-type hardware. The results of these extended tests have been documented in Chapter V. The quality and reproducibility of these data tended to support the research hypothesis and to further reinforce confidence in the proposed prediction model. Modifications to the model based on the broader and larger volume of data were essentially trivial. Actually, a set of design-oriented parameters was selected (four were chosen from a larger group). The minor revisions to the prediction model were displayed in Chapter V.

To further illustrate the flexibility of test runs on contrived designs, a sample illustrative problem was presented in the final section of Chapter V. This sample problem also served to exercise the revised prediction model and to demonstrate how it would perform when applied to a real problem. As a check against any possible inaccuracy of the model, a series of six learning progress runs (replications) were made on the contrived design, the "Utility Van Truck" assembled from erector set parts. The learnability analysis shown in Table X (page 154) indicates that the apparent error of prediction in forecasting the learnability of this mechanical assembly was less than one percent.

Conclusions

As described in the problem statement, previous learning theory methodologies have not provided a means to predict learning progress which can be correlated with design-oriented parameters of a mechanical assembly task. There is another related problem -- the learning theory disciplinarians have not provided a clear, concise understanding of the interacting factors of such learning problems. The descriptive materials provided in Chapters I and III represent an attempt to fill this void. For example, the "Learnability" concept, and the closely related descriptions of the "Learnability Loop" depicted schematically in Figure 5 (page 26), provide this needed clarification.

Another facet of the above problems was the need for a bridge of understanding between practitioners of learning theory in the social sciences and those in the engineering discipline. Through a vigorous multidisciplinary search of the literature, the beginning of such a bridge is displayed in Chapter II.

A proposed prediction model is presented in Chapter III. It is constructed with due consideration to learned contributions from all those working in the area of learning theory and is not based solely on engineering generated methodologies. This model also adds to the desired bridge of understanding between engineering and the social sciences.

In the hypothesis, it was stated that a "minimum set of design-oriented parameters" could be employed in a prediction model to forecast the potential learning progress of a single person mechanical assembly task. Based on the descriptive materials in Chapters III and V, this goal has been fulfilled and validated by the experimental verification tests outlined in Chapters IV and V. The application of the model to a sample problem, as detailed in Chapter V, further validates the adequacy of the prediction model. Although a greater volume of data would undoubtedly add statistical depth to the accuracy and reliability of the model, it appears that the prior assumptions made in the hypothesis have been substantially fulfilled by the prediction model as presented. It may also be concluded by a review of the data generated to support the prediction model, that it is feasible to develop methodologies to quantitatively measure "design complexity".

Recommendations for Further Research

Extension of Prediction Model Applications

The variety and depth of data utilized in the prediction model was limited because of the unavailability of data from industrial sources and the usual manageability problems that are normal when trying to build a general use model in a limited time span. An industrial firm, however, which specializes in manufacturing a particular type of assembly could easily accumulate its own data bank of information tailored to fit a given line of products. This approach would be strongly recommended for an industrial firm if there is a need to prepare forecasts of learning progress for industrial products.

There is also a potential need to extend the prediction model to include multi-operator tasks, tasks other than assembly tasks (e.g., inspection tasks), and tasks in which machines are sharing the production work load with the operator (e.g., machine operators). This list is not exhaustive since the approach might be beneficially applied to non-manual tasks such as clerical, or even to certain tasks in the medical sciences. As stated above, the data could be selected in each application to fit the type of product or service being considered. The model approach for a large variety of applications would not change, only the supporting data would vary depending on the degree of skill or type of skill required. The set of prediction parameters would be selected to match the product.

Expansion and Qualification of Complexity

Frequent references have been found in the literature which make brief qualitative discussions of the term "Complexity". It has a broad base of interest including experimental psychology, engineering, training, simulation, and other disciplines. The problem is that very little published work has been devoted to the quantification of complexity even though the interest is intense and widespread. A companion problem is that little has been done to define the necessary sub-parameters for complexity. One minor exception is a study of the interactions of complexity with the performance of an inspection task by

Harris (35). In this work, the term "Equipment Complexity" was employed in the problem to predict learnability for the inspection activities.

A general study to define the many aspects of complexity is recommended as a highly desirable future area of research. After definition, a second phase of such a study would be to investigate methods to quantify complexity. Applications would be useful in engineering, physical sciences, economics, and social sciences.

Extension of Figure of Merit Criteria Developed in Model to Generalized Decision Model

The approach developed in this work to evaluate the over-all Figure of Merit is based on a characteristic independent variable with a set of key sub-factors that could be used to develop a general decision model to use in making trade studies of large complex systems. This technique could be useful for any decision problem where one approach is compared with a known standard or with an alternative approach. A sample application of this methodology would be to evaluate alternative modes of solution for ecology problems involving air pollution. Almost any problem which can identify a set of functional trend parameters could be serviced by this approach.

Further Mathematical or Statistical Investigations

These functions are related to the time series multiplicative trend functions which are used in economic forecasting, since they are formed by similar embedding operations of several sub-factor values. A study of the mathematical boundary constraints, limits, maxima/minima, optimality, or the relationship of such artifical functions to the theory of "large numbers" would be highly beneficial to a better understanding of these functions. A statistical solution to the problem of fitting a curve to a set of learning trend data is illustrated by a modified "Doolittle" solution in Appendix C. This approach utilized the logarithms of the data to simplify the regression of the information. An alternative and much simpler solution is also given which utilizes the sum of the sub-factor logarithms to effect a single factor regression. Both approaches were applied to the exploratory data described in Chapter IV and indicated completely satisfactory results for the illustrative examples. Further study of the application of multifactor analysis techniques to the class of problems and functions typical of the learning theory disciplines is also recommended. Such studies would increase the needed understanding of this very large and important field.

BIBLIOGRAPHY

(1) Baloff, Nicholas. "Estimating the Parameters of the Startup Model--An Empirical Approach." The Journal of Industrial Engineering (April, 1967), pp. 248-253.

(2) Hancock, W. M. "Prediction of Learning Rates for Manual Opns." The Journal of Industrial Engineering (January, 1967), p. 42.

(3) Nelson, J. B. "A Procedure for Developing Prediction Models for the Reduction of Restraining Costs on Manual Repetitive Tasks." (Master's Thesis, Purdue University, August, 1965.)

(4) Report on Improvement Curve Experience. Department of Defense, Defense Contract Audit Agency, DCAAP 7641.14, Rev. 1, April, 1970.

(5) Dahlhaus, F. J. "Learning Curve Methodology for Cost Analysts." Defense Documentation Center, Cameron Station, Alexandria, Virginia, October, 1967.

(6) Large, J. P. An Introduction to Equipment Cost Estimating. Santa Monica, California: The Rand Corp., 1968.

(7) Hartmeyer, Fred C. Electronics Industry Cost Estimating Data. New York: The Ronald Press Co., 1964.

(8) System Engineering Management. MIL-STD-499 (USAF), Military Standard, July 17, 1969, pp. 15, 20, 21.

(9) Ellis, David O., and Fred J. Ludwig. Systems Philosophy. Englewood Cliffs, N. J.: Prentice-Hall, Inc., 1962.

(10) Goldman, A. S., and T. B. Slattery. Maintainability: A Major Element of System Effectiveness. New York: John Wiley & Sons, Inc., 1964.

(11) STS Cost Methodology. Systems Cost Office, The Aerospace Corp., California, August 31, 1970.

(12) Fitts, P. M. "Skill Training." Training Research and Education. Pittsburgh: University of Pittsburgh Press, 1962.

(13) Pavlov, I. P. Conditioned Reflexes. London: Oxford University Press, 1927

(14) Skinner, B. F. The Behavior of Organisms: An Experimental Analysis. New York: Appleton-Century, 1938.

(15) Grant, D. A. "Conditioning." Categories of Human Learning. New York: Academic Press, 1964.

(16) Sheffield, F. D., and H. W. Temmer. "Relative Resistance to Extinction of Escape Training and Avoidance Training." Journal of Experimental Psychology, Vol. 40 (1950), pp. 287-298.

(17) Humphreys, L. G. "Acquisition and Extinction of Verbal Expectations in a Situation analogous to Conditioning." Journal of Experimental Psychology, Vol. 25 (1939), pp. 294-301.

(18) Woods, P. J. "The Effects of Motivation and Probability of Reward on Two-Choice Learning." Journal of Experimental Psychology, Vol. 57 (1959), pp. 380-385.

(19) Poulton, E. C. "Copying Behind During Dictation." Quarterly Journal of Experimental Psychology, Vol. 10 (1958), pp. 48-55.

(20) Fitts, P. J., and M. I. Posner. Human Performance. California: Brooks/Cole Publishing Co., 1967.

(21) Edwards, W., H. Lindman, and L. Phillips. "Emerging Technologies for Making Decisions." New Directions in Psychology. New York: Holt, Rinehart, and Winston, 1965.

(22) Crossman, E. R. F. W. "A Theory of Acquisition of Speed-Skill." Ergonomics, Vol. 2 (1959), pp. 153-166.

(23) Hartmeyer, Fred C. Electronics Industry Cost Estimating Data. New York: The Ronald Press Co., 1964, p. 248.

(24) Walker, Jack Rudolph. "Theory and Applications of the Manufacturing Progress Function." (Unpublished Ph. D. Dissertation, Oklahoma State University, Stillwater, August, 1964.)

(25) Meister, David. *Human Factors: Theory and Practice*. New York: Wiley-Interscience, 1971, pp. 95-147.

(26) Smith, Samuel. *Educational Psychology*. New York: Barnes & Noble, 1963, pp. 61-77.

(27) *Report on Improvement Curve Experience*. Department of Defense, Defense Contract Audit Agency, DCAAP 7641.14, Rev. 1, April, 1970.

(28) Hartmeyer, Fred C. *Electronics Industry Cost Estimating Data*. New York: The Ronald Press Co., 1964, pp. 245-256.

(29) Otis, Jay L., and Richard H. Leukart. *Job Evaluation*, 2nd ed. Englewood Cliffs, N. J.: Prentice-Hall, Inc., 1963.

(30) Nadler, Gerald. *Work Design: A Systems Concept*. Homewood, Ill.: Richard D. Irwin, Inc., 1970.

(31) Hartmeyer, Fred C. *Electronics Industry Cost Estimating Data*. New York: The Ronald Press Co., 1964, p. 248.

(32) Jantsch, Erich. *Technology Forecasting in Perspective*. Paris, France: Organization for Economic Cooperation and Development, 1967, p. 163.

(33) Ayres, Robert U. *Technological Forecasting and Long-Range Planning*. New York: McGraw-Hill Book Co., 1969.

(34) Annett, J., C. W. Golby, and H. Kay. "The Measurement of Elements in an Assembly Task: The Information Output of the Human Motor System." *Quarterly Journal of Experimental Psychology*, Vol. 10 (1958), pp. 1-11.

(35) Harris, Douglas. "Effect of Equipment Complexity on Inspection Performance." *Journal of Applied Psychology*, Vol. 50 (1966), pp. 236-237.

APPENDIX A

MECHANICAL ASSEMBLY SKILL LEVELS

Level I

Operator must demonstrate the ability to follow written instructions and to interpret isometric type diagrams or schematics. He must demonstrate sufficient motor dexterity for plug-in/plug-out type connectors, for example, tinker toy assemblies, electronic tubes, electrical fuses, or electronic plug-in circuit boards.

Level II

Operator must meet requirements of Level I and demonstrate ability to assemble piece parts which have threaded connections, such as screws, bolts, nuts, washers, utilizing such tools as wrenches, screw drivers, pliers, and allen wrenches. Motor dexterity requirements are higher than Level I since ability to align threaded connections and judge applied torques is mandatory.

Level III

Operator must meet requirements for skill Levels I and II and be proficient in reading blueprints, making necessary on-the-spot minor adjustments and/or alterations to mating parts to make sure that they fit together properly or perform within specified requirements and criteria. This category might occasionally require the use of such precision measuring tools as micrometers, vernier calipers, depth gauges, or thread gauges. Operator might also need to use such hand tools as drills, reamers, thread taps and dies, files, or deburring tools in order to complete an acceptable mechanical assembly.

Level IV

Operator must meet all previous skill requirements and have the ability to utilize measurement and alignment tools requiring the highest degree of precision. For example, such instruments as a precision optical level may be utilized in locating assembly parts. In general, component parts may be either ultra precision parts, or require precision alignment during their installation. Maximum care and dexterity is required to handle such parts, many of which could be ruined by careless or awkward handling. Products requiring this level of skill would be precision instruments or special camera on optical assemblies intended for space application. Operator must be able to comprehend the intended use of the assembly and to evaluate the correctness of his own workmanship.

APPENDIX B

LEARNABILITY VERSUS PERCENT SLOPE

CONVERSION TABLE

TABLE XI

LEARNABILITY VERSUS PERCENT SLOPE CONVERSION TABLE
(m = Learning Curve Slope in %)

% m	0	1	2	3	4	5	6	7	8	9
50	2.00	1.996	1.992	1.988	1.984	1.980	1.976	1.972	1.969	1.965
51	1.96	1.957	1.953	1.949	1.946	1.942	1.938	1.934	1.931	1.927
52	1.92	1.919	1.916	1.912	1.908	1.905	1.901	1.898	1.894	1.890
53	1.89	1.883	1.880	1.876	1.873	1.869	1.866	1.862	1.859	1.855
54	1.85	1.848	1.845	1.842	1.838	1.835	1.832	1.828	1.825	1.822
55	1.82	1.815	1.812	1.808	1.805	1.802	1.799	1.795	1.792	1.789
56	1.79	1.783	1.779	1.776	1.773	1.770	1.768	1.764	1.761	1.758
57	1.75	1.751	1.748	1.745	1.742	1.739	1.736	1.733	1.730	1.727
58	1.72	1.721	1.718	1.715	1.712	1.709	1.707	1.704	1.701	1.698
59	1.70	1.692	1.689	1.686	1.684	1.681	1.678	1.675	1.672	1.670
60	1.67	1.664	1.661	1.658	1.656	1.653	1.650	1.648	1.645	1.642
61	1.64	1.637	1.634	1.631	1.629	1.626	1.623	1.621	1.618	1.616
62	1.61	1.610	1.608	1.605	1.603	1.600	1.597	1.595	1.592	1.590
63	1.59	1.585	1.582	1.580	1.577	1.575	1.572	1.570	1.567	1.565
64	1.56	1.560	1.558	1.555	1.553	1.550	1.548	1.546	1.543	1.541
65	1.54	1.536	1.534	1.531	1.529	1.527	1.524	1.522	1.520	1.518
66	1.52	1.513	1.511	1.508	1.506	1.504	1.502	1.500	1.497	1.495
67	1.49	1.490	1.488	1.486	1.484	1.482	1.479	1.477	1.475	1.473
68	1.47	1.468	1.466	1.464	1.462	1.460	1.458	1.456	1.454	1.451
69	1.45	1.447	1.445	1.443	1.441	1.439	1.438	1.435	1.433	1.431
70	1.43	1.427	1.425	1.423	1.421	1.418	1.416	1.414	1.412	1.410

TABLE XI (Continued)

% m	0	1	2	3	4	5	6	7	8	9
71	1.41	1.407	1.405	1.403	1.401	1.399	1.397	1.395	1.393	1.391
72	1.39	1.387	1.385	1.383	1.381	1.379	1.377	1.376	1.374	1.372
73	1.37	1.368	1.366	1.364	1.362	1.361	1.359	1.357	1.355	1.353
74	1.35	1.350	1.348	1.346	1.344	1.342	1.341	1.339	1.337	1.335
75	1.33	1.332	1.330	1.328	1.326	1.325	1.323	1.321	1.319	1.318
76	1.32	1.314	1.312	1.311	1.309	1.307	1.306	1.304	1.302	1.300
77	1.30	1.297	1.295	1.294	1.292	1.290	1.289	1.287	1.285	1.284
78	1.28	1.280	1.279	1.277	1.276	1.274	1.272	1.271	1.269	1.267
79	1.27	1.264	1.263	1.261	1.260	1.258	1.256	1.255	1.253	1.252
80	1.25	1.248	1.247	1.245	1.244	1.242	1.241	1.239	1.238	1.236
81	1.24	1.233	1.232	1.230	1.229	1.227	1.226	1.224	1.223	1.221
82	1.22	1.218	1.217	1.215	1.214	1.212	1.211	1.210	1.208	1.206
83	1.21	1.203	1.202	1.201	1.199	1.198	1.196	1.195	1.193	1.192
84	1.19	1.189	1.188	1.186	1.185	1.183	1.182	1.181	1.180	1.178
85	1.18	1.175	1.175	1.172	1.171	1.170	1.168	1.167	1.166	1.164
86	1.16	1.161	1.160	1.159	1.157	1.156	1.155	1.153	1.152	1.151
87	1.15	1.148	1.147	1.146	1.144	1.143	1.142	1.140	1.139	1.138
88	1.14	1.135	1.134	1.133	1.131	1.130	1.129	1.127	1.126	1.125
89	1.12	1.122	1.121	1.120	1.119	1.117	1.116	1.115	1.114	1.112
90	1.11	1.110	1.109	1.107	1.106	1.105	1.104	1.103	1.101	1.100
91	1.10	1.098	1.097	1.095	1.094	1.093	1.092	1.091	1.090	1.090
92	1.09	1.086	1.085	1.083	1.082	1.081	1.080	1.079	1.078	1.076
93	1.08	1.074	1.073	1.072	1.071	1.070	1.068	1.067	1.066	1.065
94	1.06	1.063	1.062	1.061	1.059	1.058	1.057	1.056	1.055	1.054
95	1.05	1.052	1.050	1.049	1.048	1.047	1.046	1.045	1.044	1.043

TABLE XI (Continued)

% m	0	1	2	3	4	5	6	7	8	9
96	1.04	1.041	1.040	1.038	1.037	1.036	1.035	1.034	1.033	1.032
97	1.03	1.030	1.029	1.028	1.027	1.026	1.025	1.024	1.023	1.022
98	1.02	1.019	1.018	1.017	1.016	1.015	1.014	1.013	1.012	1.011
99	1.01	1.009	1.008	1.007	1.006	1.005	1.004	1.003	1.002	1.001
100	1.000									

APPENDIX C

SOLUTION FOR LEARNABILITY FOM REGRESSION, SKILL LEVEL I

Pt. No.	X_1 Log P_a	X_2 Log P_b	X_3 Log P_c	Q Log Tot.	"L" or 1/m	m %
1	1.3424	0.3137	1.0682	2.7253	1.39 / 1.402*	72 / 71.30*
2	1.6721	0.5401	1.3324	3.5486	1.33 / 1.317*	75 / 75.92*
3	1.8751	0.7033	1.4928	4.0712	1.28 / 1.264*	78 / 79.09*
4	2.0043	0.8195	1.6075	4.4313	1.24 / 1.225*	81 / 81.62*
5	2.1038	0.9063	1.6990	4.7091	1.19 / 1.2012*	84 / 83.25*
6	2.1847	0.9823	1.7767	4.9437	1.15 / 1.171*	87 / 85.42*

*Calculated Values

1. Math Model → $\underline{Y = a + B \log X_1 + B_2 \text{ Log } X_2 + B_3 \text{ Log } X_3}$

2. To convert to format for "Doolittle" solution, the following matrices are formed from above information:
(Note: Column of X_2's multiplied by 10 to code)

$$Y^* = \begin{bmatrix} 7.2 \\ 7.5 \\ 7.8 \\ 8.1 \\ 8.4 \\ 8.7 \end{bmatrix} \qquad X^* = \begin{array}{cccc} X_0 & X_1 & X_2 & X_3 \\ \hline 1.0 & 1.3424 & 3.137 & 1.0682 \\ 1.0 & 1.6721 & 5.401 & 1.3324 \\ 1.0 & 1.8751 & 7.033 & 1.4928 \\ 1.0 & 2.0043 & 8.195 & 1.6075 \\ 1.0 & 2.1038 & 9.063 & 1.6990 \\ 1.0 & 2.1847 & 9.823 & 1.7767 \end{array}$$

3. Transpose as follows:

X'^{*} =

1.0	1.0	1.0	1.0	1.0	1.0
1.3424	1.6721	1.8751	2.0043	2.1038	2.1847
3.137	5.401	7.033	8.195	9.063	9.823
1.0682	1.3324	1.4928	1.6075	1.6990	1.7767

4. Now, to get $X'X$, rank will be 4 X 4:

$X'^{*}X^{*}$ =

6.0	11.1824	42.622	8.9766
11.1824	21.3301	83.382	17.161
42.622	59.790	334.262	67.0726
8.9766	17.161	67.0726	13.5297

Matrix Line of Symmetry

5. Now, to get $X'Y$, rank will be 4 X 1:

$X'^{*}Y^{*}$ =

47.7
89.746
345.92
72.078

Lines	X'X				X'Y
	0	1	2	3	g
(0) a	6.0	11.1824	42.622	8.9766	47.70
(1) a	X	21.3301	83.382	17.161	89.746
(2) a	X	X	334.262	67.0726	345.920
(3) a	X	X	X	13.5297	72.078
(4) A_0	6.0	11.1824	42.622	8.9766	47.70
(5) B_0	1.0	1.8637	7.120	1.4961	7.95
(6) A_1	X	0.48946	3.640	0.431	0.8459
(7) B_1	X	1.0	7.4368	0.8806	1.7282
(8) A_2	X	X	3.723448	0.100516	0.784452
(9) B_2	X	X	1.0	0.026995	0.210678
(10) A_3	X	X	X	0.282442	0.784452
(11) B_3	X	X	X	1.0	2.777395

$B_3 = 2.7774$

$B_2 + .026995\ (2.777395) = 0.210678$

$B_2 = 0.135702$

$B_1 + (7.4368)(.135702) + (.8806)\ (2.7774) = 1.7282$

$B_1 = 1.7282 - 1.0092 - 2.44586209$

$B_1 = 1.726862$

$B_0 - (1.8637)\ (1.726862) + (7.12)\ (.135702) + (1.4961)\ (2.7774) = 7.95$

$B_0 = 6.0468938$

$Y/10^* = 6.0469 - 1.7269 \text{ Log } X_1 + 1.357 \text{ Log } X_2 + 2.7774 \text{ Log } X_3$

or

$Y = 60.469 - 17.269 \text{ Log } X_1 + 13.57 \text{ Log } X_2 + 27.77 \text{ Log } X_3$

Abbreviated Solution for Skill Level I

X* =

1.0	5.5476
1.0	8.4055
1.0	10.4000
1.0	11.8068
1.0	12.8658
1.0	13.7844

Y* =

7.2
7.5
7.8
8.1
8.4
8.7

X'* =

1.0	1.0	1.0	1.0	1.0	1.0
5.5476	8.4055	10.40	11.8068	12.8658	13.7844

X'*X* =

6.0	62.81
62.81	704.53

X'Y* =

47.70
507.736

	X'X			X'Y
	Rows	0	1	g
a_{ij}	(0)	6.0	62.81	47.79
	(1)		704.53	507.736
A_{0j}	(2)	6.0	62.81	47.70
	(3)	1.0	10.468	7.95
A_{1j}	(4)		47.03492	8.3965
	(5)		1.0	0.17852

NOTE: $Y_c^* = Y_c/10$

Math Model:

$Y_c^* = B_0 + B_1 \text{ Log } X$

or

$Y_c = 60.81 + 1.7852 \text{ Log } X^*$

Example

$Y_{75} = 60.81 + 1.7852\ (8.4055)$

$= 60.81 + 15$

$Y_{75} = 75.81$

$B_1 = .17852$

$B_0 = 10.468\ b_1 = 7.95$

$B_0 = 7.95 - (10.468)\ (.17852)$

$B_0 = 6.081253$

APPENDIX D

GLOSSARY OF LEARNING AND RELATED SYSTEMS ENGINEERING TERMS

Introduction

The terms which are described here have been screened for relevancy to the subject areas covered in this research. Those terms which have been defined elsewhere in this work will be referenced to the section of the thesis in which they appear, and will not be repeated here. Definitions will, in general, be brief and will employ style patterns which are indigenous to the field of engineering, although it is recognized that other professional disciplines may have a natural interest in the subject matter. Where appropriate acronyms are listed in parenthesis after the term.

Terms

1. Complexity Function (CF) - This term refers to approximate relations emperically relating complexity to some other parameter, such as cost or reliability. In general, such functions depict reliability decreasing, and cost increasing as the complexity of a system or design increases.

2. Conditioning (CG) - See definitions in section with same name in Chapter II of text.

3. Cues (C) - This term is used frequently in experimental psychology documents to refer to a signal from a test conductor to a test subject (may be animal or human). Some cues are audio, others are visual (lights, color code, etc.). In other cases cue may be combined with some form of motivation such as click/food pellet, or punishment cue such as electric shock, or unpleasant noise.

4. Design Complexity (DC) - This form of complexity has to do with features or parameters of an engineering design which contribute to its complexity. Examples of such features which tend to increase the measure of design complexity are such aspects as total number of parts, number of fasteners, or number of sub-assemblies. Others might be the number of different steps or processes required to fabricate, assemble, and inspect.

5. Evaluator/Experimentor (E) - This term simply means the person who is making the analysis or performing the experiment.

6. Factor - This term can be considered a synonym of parameter as far as this research is concerned (see Parameter definition below).

7. Figure of Merit (FOM) - This term can be considered a numerical performance rating which is a measure of the relative performance of a system or design. Term is usually dimensionless or is considered so in its applications to decision theory.

8. Improvement Function (IF) - This term is often used to describe the performance aspects of a system or design over time which tend to improve. Since both learning and other changes in a system performance may be included it cannot be considered as a synonym for "learning curve", but may be interchanged with the term "Progress Function" which is listed below.

9. Job Specification (JS) - This term refers to the qualifications, performance/experience requirements, skill, and/or education that a prospective candidate must have in order to qualify for a particular job. Usually there is a corresponding job/position description which defines the duties, functions, and responsibilities which a candidate would be expected to perform.

10. Job/Task Design (JD) - This term refers to the total activity of planning and specifying all of the necessary steps, tools, equipment, environmental requirements, and/or any other performance criteria required for a qualified operator to perform.

11. Job/Task Environment (JE) - All of the atmospheric or comfort requirements which are necessary for a worker to successfully perform his job. Included would be lighting, heating, cooling, ventilation, safety and health needs, and, in some cases, acoustical or structural dynamics attenuation.

12. Learnability (L) - This term has been defined in detail in the section by the same name in Chapter I.

13. Learnability Loop (LL) - This concept has been defined in Chapter I, and is depicted schematically in the flow diagram of Figure 4.

14. Learning Curve (LC) - A learning curve is a graphical plot on either cartesian coordinates or on double logarithmic paper, which represents the rate of learning progress by humans, usually in performance of some

task or group of tasks. In the engineering discipline, this plot is usually made with time as the ordinate parameter, and number of units complete or simply number of units as the abscissa. In general, these curves will approximate an exponential shaped function, if the progress is normal. This function should be separated from progress and improvement functions by the fact that only human learning progress is to be included in a learning curve...not tooling, design, or other gains in performance which may be a part of progress or improvement functions. Figure 1 illustrates a typical learning curve plotted on double-log paper.

15. Log-Linear - This term is often used to describe learning curves which are plotted on double-logarithmic paper. In general, such curves will appear as straight lines. This greatly simplifies computation of the slope, and will, of course, make these curves easier to plot.

16. Long-Term Memory (LTM) - This term refers to the retention of information by an organism which is available for recall at a point in time which may vary from a few days to several years. (See short-term memory below for contrast.)

17. Material Discount Curves (LTM) - This term refers to curves which are used to project the decrease in the cost of material and many purchased items, as the quantity of the item purchased is increased. Sometimes tables are used to reflect this information, and also double logarithmic paper is used since this function will frequently have a shape similar to a learning curve and will appear linear on double-log paper.

18. Maturation - This term refers to the sub-set of improvement or progress factors which relate to the segment of progress by individuals or other organisms that results from a time-related maturing or "growing-up" process. Maturation is not considered a normal part of learning progress.

19. Model - A model is an approximation of reality which is frequently used to forecast or predict performance approximations of real world situations. Models may be physical or analytical within this context. Analytical models are sometimes referred to as math models, or as algorithms which consist of a necessary and sufficient set of terms, values, and formuli needed to compute or predict an output value based on a known input or set of input values and recognized constraints or limitations.

20. Monotonic Function - This term is used to designate a mathematical function, either theoretical or empirical, which has single maximum and minimum points. If the function is an increasing function, it would be referred to as a monotonic increasing function and conversely a monotonic decreasing function. Learning curves are normally monotonic decreasing functions over time.

21. Motor Learning - Refers to the category of human learning that is primarily manual or physical. The preponderance of learning by practicing athletes is motor learning and, to a lesser degree, the verbal or mental type learning.

22. Motor Skill - This is the skill that is acquired by a transfer of training on the motor learning described above.

23. MTM - This is an acronym commonly used to refer to a type of time study values that are determined by reference to standard tables, as opposed to making actual time studies of a job or task. The specific words are Methods Time Measurement or MTM.

24. Operator - Within the context of this research, the terms operator, test subject, and worker are all interchangeable...the person who is performing the job or task.

25. Operator Performance Rate (OPR) - This term refers to a performance rating given a worker by an observer which is relative to a standard time or standard output rate for a particular job or task. If the person is performing at a speed which is, for example, 20% above normal, his rating would be 120%. Conversely, if the individual is performing at a speed which is 20% below normal, he would be given a rating of 80% (see Figure 6).

26. Overlearning (OL) - Refers to condition frequently referred to in psychological documents which implies that an organism (animal or man) may be trained repetitively beyond the point that an acceptable performance has been reached. In the case of the military, this technique can be used effectively to reduce the risk that an individual may forget a correct procedure or strategy under extreme pressure of battle. Overlearning is also obviously important as a safety assurance strategy, and as a means to minimize unintentional demage to machines by operators.

27. Parameter - For purposes of this study, the terms factor, design feature, or parameter may be used

interchangeably. A parameter is a term which is used to measure or gauge some feature or physical characteristic of a system or design. This measurement is usually defined in some unit which is officially accepted, such as weight in grams or volume in cubic feet, etc.

28. Perceptual-Motor Function (PM) - This term refers to terminology used in the experimental psychology discipline to describe an activity which is primarily accomplished by physical effort as opposed to verbal or mental activities.

29. Producibility (P) - This systems specialty parameter refers to the inherent capability or characteristics which enable a system to be manufactured, inspected, and/or checked out.

30. Progress Functions (PF) - This term refers to the class of functions, which although related to learning curves, cannot be interchanged since a progress function should include all improvements, maturations, learning, or other advances in technology or management which would tend to reduce resource requirements over time.

31. Reinforcement - This term frequently appears in psychological journals and is used to infer that anything which tends to help a person to recall from memory or to accelerate the learning process, is considered a reinforcement. Sometimes reinforcements may be considered as positive or negative depending on the purpose or objective. One form of reinforcement would be to repeat a rule to a group of army recruits to assure a transfer to memory. A memorized poem may be repeated over several times by a student to reinforce the memorization of this passage.

32. Short-Term Memory (STM) - The part of an individual's recall capability which enables him to immediately recall from memory materials to which he had only a brief exposure. Serialization is an important feature of this aspect (see the section on Short-Term Memory in Chapter II).

33. Slope in Percent (m) - See section entitled Learnability Concept in Chapter I.

34. Sub-Task - A sub-task refers to a separate part of a job or task, in other words, one of several procedural steps required to complete an activity.

35. System - A system is a planned, integrated assembly or grouping of hardware, software, and/or human elements

which function as a unit to produce some specific or unique desired effect or result. A subsystem is subordinate to a system, but must meet the same definition criteria.

36. System Specialty Parameters (SSP) - Expressions of system performance variables or characteristics concerned with the over-all technical effectiveness of an integrated system. System specialty parameters are used in system modeling, system trade studies, technical performance measurements, and assessments. Typical examples of specialty parameters are reliability, availability, maintainability, safety, survivability, etc.

37. Systems Engineering (SE) - The discipline in which engineering principles are used to plan, group, design, integrate, coordinate, specify, analyze or otherwise bring together all of the elements or component parts of a system such that each element operates in unison with all other elements of the system to produce a predictable and desired effect or output when operating in a specified environment.

38. Test Conductor (TC) - A test conductor is a researcher who supervises an experimental test run or performs the test himself.

39. Test Subject (S) - A familiar term in experimental psychology used to describe the organism (human or animal) who is a part of the experiment. In some experiments, the test subject would be the prime interest of the research, but in this work the test subject is merely playing a supporting role.

40. Time Series - This well-known statistical analysis technique employs an artificial parameter (called time series) which is created from selected sub-factors additively or by a multiplicative process. This macro-variable when plotted over time produces a trend line which is one basis for forecasts or predictions of future performance.

41. Training Transfer - This is a term used frequently in psychology anals to refer to the part of a trained skill that is actually learned by the trainee.

42. Weighting Coefficients - These values are usually expressed in fractional parts and are used to transfer the desired emphasis to alternative performance ratings or estimates of value. The sum of such weights must always equal 1; if whole numbers are preferred the sum must equal 10. If there is no particular emphasis desired by the decision maker, then each alternative will receive an implied weight of one.

2

VITA

Leon Melvin Delionback

Candidate for the Degree of

Doctor of Philosophy

Thesis: A DESIGN-ORIENTED PREDICTION MODEL FOR LEARNING RATES OF INDIVIDUAL MECHANICAL ASSEMBLY TASKS

Major Field: Engineering

Biographical:

Personal Data: Born in Durham, North Carolina, April 5, 1924, the son of Mr. and Mrs. M. L. Delionback.

Education: Graduated from Durham High School, Durham, North Carolina, in June, 1942; received the Bachelor of Science degree in Mechanical Engineering from Duke University in 1950; received the Master of Science degree in Engineering from University of Tennessee in 1955; enrolled in the doctoral program at Oklahoma State University in 1966; completed requirements for the Doctor of Philosophy degree, with a major in Industrial Engineering and Management, at Oklahoma State University in May, 1972.

Professional Experience: Development Engineer, Carbide Nuclear Corporation, 1951-53; Project Engineer, Goodyear Atomic Corporation, 1953-55; Senior Engineer, The Martin Company, 1955-57; Development Engineer, Combustion Engineering Corporation, 1958-60; Aerosapce Engineer, National Aeronautics and Space Administration, Marshall Space Flight Center, 1961-present.

Honor Society: Alpha Pi Mu.

Technical Socities: American Society of Mechanical Engineers, American Institute of Industrial Engineers, American Society of Professional Engineers, Registered Professional Engineer, Tennessee.