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THE IMPACT OF A LEARN-FORGET-LEARN (LFL) CURVE AND LEARNING CUR--ETC(U)

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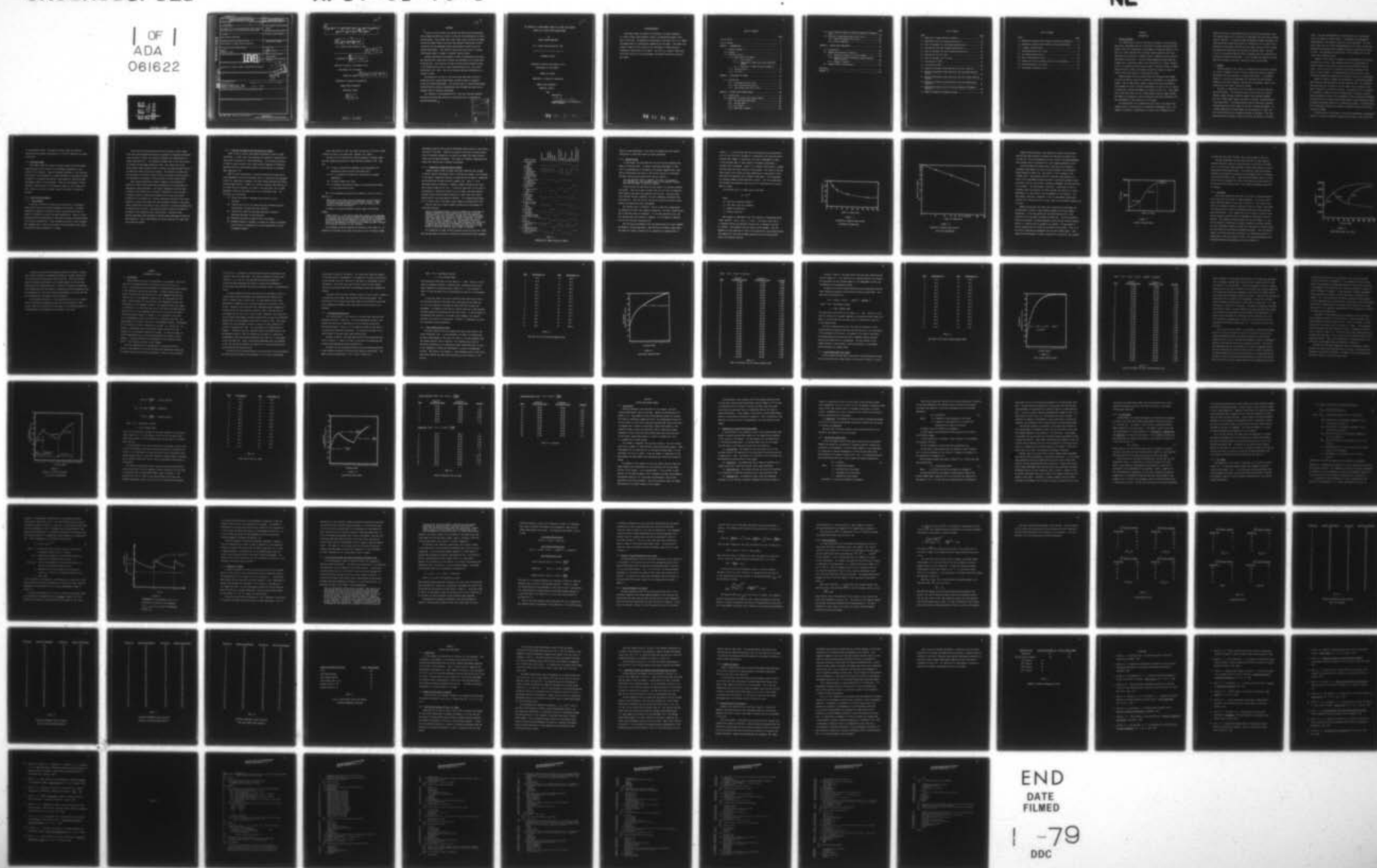

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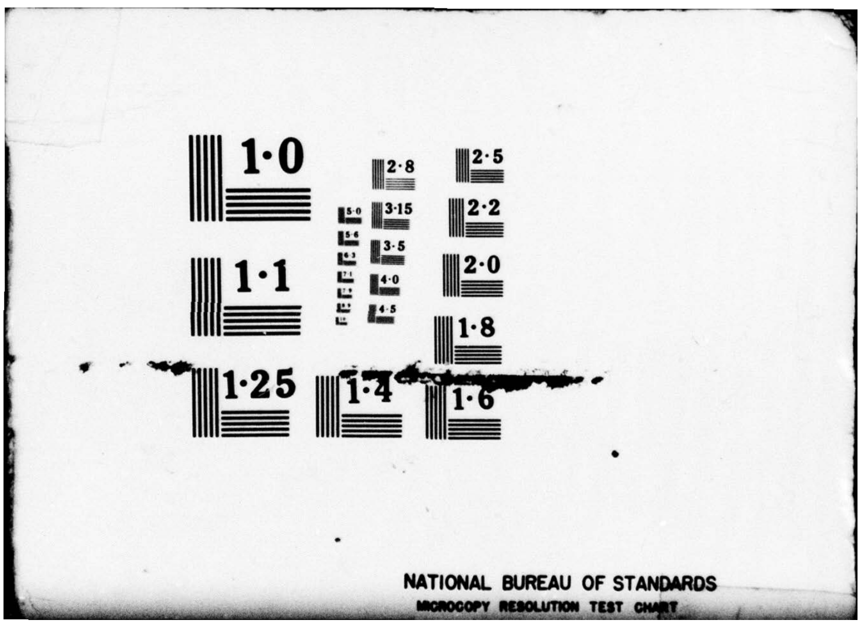
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THE IMPACT OF A LEARN-FORGET-LEARN (LFL) CURVE AND LEARNING CURVES ON A SYSTEM EFFECTIVENESS MODEL

by

10 DWIGHT EDWARD BEAUCHAMP

B.S., Kansas State University, 1972

12 97 p.

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AN ABSTRACT OF A MASTER'S THESIS

submitted in partial fulfillment of the

requirements for the degree

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ABSTRACT

In only the last 25 years has operator reliability been incorporated with hardware reliability to obtain a value for the effectiveness of a man-machine system. Very seldom, and in most cases, never, do any of the human reliability models address the effect that operator learning has on human reliability and the subsequent impact that operator reliability has on system effectiveness. This research studied the sensitivity of a system effectiveness model to changes in operator learning levels.

Learning data which was expressed in terms of performance versus time, was obtained from a paper which analyzed the performance of an actual manufacturing task. This data was utilized to develop three different curves - a log pseudo-learning curve, a cubic pseudo-learning curve, and a Learn-Forget-Learn (LFL) curve. Each curve expressed operator performance as a function of time.

The expressions for each of the three curves were then utilized in conjunction with a system effectiveness simulation model to formulate values for system effectiveness. The various values of system effectiveness obtained from the simulation demonstrated that the model was sensitive to changing levels of operator performance.

This research is unique because this is the first time that operator learning curves have been utilized in conjunction with a simulation of system effectiveness.

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Approved by:

Frank A. Tillman
Major Professor

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CHAPTER 1

INTRODUCTION

1.1 Problem Statement

In a 1960 survey of nine Air Force missile systems, it was found that human error contributed from 20 to 53 percent to system unreliability (26). Another study (24) investigated a large number of production defects at the plant of a prime contractor for the Atomic Energy Commission and it was determined that 82 percent of defects found by inspectors could be directly attributed to human error. The above figures demonstrate that human performance has a significant impact on the reliability of a system. Because of this, a concentrated effort has been made in the past 25 years to combine human reliability values with hardware reliability figures to obtain an overall reliability index for the man-machine system.

Numerous human reliability models have been formulated that attempt to assign reliability values to an operator's performance in a man-machine system. Some of these models attempt to demonstrate that relationships exist between the level of operator performance and factors such as: amount of supervision, working environment, willingness to work, etc. Very seldom, and in most cases never, do any of these human reliability models address the impact of an operator's rate of learning on the human performance level and subsequently on the reliability of the system.

The problem that will be addressed by this study is the impact that changing rates of learning have on an operator's performance level. This change in an operator's performance for various time increments will be found by utilizing a Learn-Forget-Learn (LFL) curve and two learning curves. The learning curves and LFL curve will be developed using data from a previous study of learning. A simulation model, developed by another researcher (16), which quantifies System Effectiveness (or reliability) will be used in conjunction with the results from the two curve types (learning & LFL) to study the impact that learning has on the system reliability index. The sensitivity of the system reliability index to changing rates of learning will be calculated, analyzed and discussed. It will be shown that operator learning does have an effect on the total reliability value of the system.

1.2 Purpose

The main purpose of this study is to demonstrate that operator learning for various increments of time will have a significant impact on operator performance and also, therefore, on System Effectiveness. The secondary purpose is to outline the requirement for additional and more thorough research in the area of operator learning and its subsequent impact on the reliability of the overall man-machine system.

The study is organized so as to lend support to the main theme that was outlined above. The literature survey, which follows this section, reviews a number of human reliability models that have been proposed. Only two of these models address the aspect of operator learning/training to any great detail. The remaining models make no reference to operator training/learning and their impact on the level of human performance. An in depth comparison of various models will be presented in a table that will outline the positive and negative aspects of the models. The literature survey also contains a review of articles that pertain to learning curves. The uses and methodology of learning curves will be presented along with examples of typical curves. The graphical and mathematical representation of the learning curves will also be discussed. The literature survey also will outline the methodology of LFL curves, but only one reference was discovered which attempted to explain and discuss this type of curve. The techniques and conclusions of this reference will be outlined in the literature survey.

Chapter 2 of this report is devoted to the development of two learning curves and an LFL curve. Data obtained from one of the references on learning curves will be used as a basis to plot two different learning curves. The LFL curve will be plotted using the data presented in the lone LFL curve reference. The characteristics of each curve will be explained and mathematical expressions for the three curves will be developed.

Chapter 3 presents a summary and explanation of a System Effectiveness model which has been developed by another researcher (16). The "personnel" term associated with the equation for this model will be analyzed in more detail, especially in relation to learning. The effects on this "personnel" or, preferably, "operator" term for changing rates of learning, obtained from the respective curves, will be analyzed in terms of operator performance. The sensitivity of the System Effectiveness model to these fluctuating levels of operator performance then will be studied and discussed. Conclusions then will be formulated concerning the impact of operator learning on the System Effectiveness model.

The last section of the study will outline the requirement for additional research in the area of operator learning and its effect on the reliability of a man-machine system. The question of what impact does operator learning have on operator performance is of critical importance to system reliability.

1.3 Literature Survey

This study's three main areas of interest (human reliability models, learning curves and LFL curves) will be addressed separately in this survey of the literature. There are abundant references in the literature which pertain to the prediction of human performance in man-machine systems. A summary of a representative and well known method for predicting human performance, THERP, will be presented. There are also numerous articles devoted to learning curves, but references related to Learn-Forget-Learn (LFL) curves are very few in number, almost to the point of being non-existant.

1.3.1 Human Reliability Models

1.3.1.1 Early Studies

In the past, reliability figures were calculated for a man-machine system based solely on the machine component of the system. The human component was assumed to be totally reliable and no provisions were included in the models to account for human unreliability. Later on it was determined that the human aspects of man-machine systems contributed greatly to the system unreliability, in some instances even more so than the equipment component [27]. After this discovery, much more emphasis was placed on predicting human performance in a system.

One of the earliest man-machine reliability studies in which human error rates were estimated and related to estimates of equipment malfunction rates was done in 1952 by an electronics engineer and a mathematician at Sandia Corporation (27). The treatment of human error in this 1952 study of an aircraft nuclear weapon system was crude. Only those errors which would directly reduce system reliability without any other equipment failure or human error being involved were studied. The estimates of human error were included in the overall system reliability equation and were treated in the same manner as estimates of failures rates for other system factors.

Later studies became more refined in regards to the quantitative methods utilized for evaluating human performance and its relationship to man-machine system performance. One report recommended a) making rough estimates of the probability of successful completion of each sub-task in a system and then b) combining the probabilities to obtain the overall reliability of the system (32). Another researcher pointed out that it was necessary to treat those rough error rate estimates, mentioned in the above study, differentially according to their importance to system performance (23). He defined task criticality in quantitative terms related to the effect of unsuccessful task completion upon system success. Eventually, more sophisticated models were developed to predict human performance reliability more accurately. One of these methods was called Technique for Human Error Rate Prediction (THERP).

1.3.1.2 Technique for Human Error Rate Prediction (THERP).

THERP is one of the best known methods developed to quantify human performance. In 1961, Swain (28) developed this method for evaluating the human error contribution to system degradation. The following discussion of THERP is almost entirely from a paper entitled "Methods of Predicting Human Reliability in Man-Machine Systems" by David Meister of the Bunker-Ramo Corporation (17).

THERP has been used primarily to provide quantitative predictions of system degradation resulting from human errors in association with equipment reliability, operational procedures, and other system characteristics which influence human behavior. THERP is an iterative procedure that consists of five steps which are repeated, not always in the same order, until system degradation resulting from human error is at an acceptable level. The five steps are listed below.

"(1) Define the system or subsystem failure which is to be evaluated.

(2) Identify and list all the human operations performed and their relationships to system tasks and functions.

(3) Predict error rates for each human operation or group of operations pertinent to the evaluation.

(4) Determine the effect on human errors on the system.

(5) Recommend changes as necessary to reduce the system or subsystem failure rate as a consequence of the estimated effects on the recommended changes."

Swain (29) points out that "the steps are typical of the usual system reliability study if one substitutes 'hardware' for 'human'."

The goals of this technique are listed by Meister in another report entitled "Comparative Analysis of Human Reliability Models" (18). They are:

"(1) To derive 'quantitative estimates of the degradation to a man-machine system resulting from human error.'

(2) Or, 'to evaluate the human error contribution to systems degradation.'

(3) To predict human error rates.

(4) To determine those design changes to the system necessitated by the system failure rate."

One of the assumptions associated with THERP, as listed in (18) by Meister, is:

> "THERP takes into account various psychological and physiological stresses, training, motivation and situational factors. These are called Performance Shaping Factors (PSF) and they are very subjective in their application."

In regard to the above assumption, Meister makes the following comment:

> "These factors, i.e. PSF, must be taken into account in the gathering of error rate data and the error estimates derived should be modified in accordance with the presumed effect of these factors on performance. One difficulty that arises, however, in accounting for these molar factors on performance is the difficulty of recognizing their influence and estimating the extent of that influence."

This statement by Meister embodies the purpose of this study, i.e. to recognize the influence and estimate the extent of that influence on human performance caused by the so-called Performance Shaping Factors, specifically, the factor of learning. THERP has no specific provisions to handle varying levels of operator learning nor to predict the impact that these learning levels have on human performance. This study will hopefully demonstrate the effect that learning has on operator performance.

1.3.1.3 Comparison of Human Reliability Models

Numerous human reliability models have been formulated that attempt to predict operator performance levels in man-machine systems. Davis Meister, in the report, "Comparative Analysis of Human Reliability Models," summarized and characterized 18 human reliability models (18). Table 1.1 is an abbreviated version of Meister's "Summary of Model Characteristics" which can be found on page 414 of (18). It should be noted that for the table's sub-category of "Selection/Training" only two models, the Human Operator Simulator (HOS) and the Personnel Reliability Index, meet the criteria established for that sub-category by Meister. For a complete description of all criteria used in the table, consult pages 413 through 425 of (18).

Meister makes the following remarks concerning the sub-category of "Selection/Training":

> "Most of the methods possess little or no capability in the areas of manpower selection and training despite the fact that claims for these capabilities are often made. We feel that to be sensitive to training, a model must indicate what capabilities should be trained, rather than merely that additional training is required. On that basis only a few of the models, i.e., the personnel reliability technique of Siegel and Wherry's HOS, seem to possess this sensitivity. It may be that the majority of the models available do not include parameters which are sensitive to the factor of training or it may be that a distinctly different type of model is required.

This comparison of human reliability models points out that very little work has been done in the area of training and learning with their attendant

Descriptive Categories	Air Data Store	THERP	TEPPS	Pickrel/McDonald	Askren/Regulinski	Berry/Wulff	Throughput	DEI	Personnel Perf. Metric	Digital Simulation	TACDEN	Boolean Approach	HOS	ORACLE	Personnel Subsystem	ERUPT	Maintainability Prediction	Personnel Reliability
1. General Classification																		
Simulation										X	X	X	X	X	X			
Analytic	X	X	X	X	X	X	X	X	X							X	X	X
2. Model Uses																		
A. Prediction	X	X	X	X	X	X	X			X	X		X		X	X	X	X
B. Evaluation	X	X	X	X	X	X	X		X	X	X		X		X			X
C. Design Comparison	X	X	X	X	X		X	X		X	X		X	X	X			
D. Design Analysis										X	X	X	X	X	X			
E. Selection/Training													X					X
F. Personnel Standards			X															
3. Model Scope																		
A. All Tasks/All Systems		X		X	X	X	X			X	X	X	X	X	X			
B. System-Limited								X	X									
C. Discrete Tasks Only	X		X															
D. Maintenance Only																X	X	X
4. Input Data Source																		
A. All		X		X						X	X			X	X			
B. Experimental/Empirical only	X				X	X	X		X			X	X				X	
C. Subjective Only			X															X
D. Other								X								X		
5. Input Data Detail																		
A. Very Detailed	X	X		X	X	X	X		X	X	X	X	X	X	X	X	X	
B. More Molar		X	X												X			X
C. Not Applicable								X										
6. Behavioral Unit Employed																		
A. Subtask or S-R Unit	X	X		X	X				X	X	X	X	X	X	X		X	
B. Task		X	X	X	X										X			
C. Function																X		X
D. Not Applicable						X	X	X										
7. Analytic Method																		
A. Task Analysis	X	X	X	X		X	X			X	X	X	X	X	X		X	
B. Other Methods																X		X
C. Task Analysis Not Needed					X			X	X									
8. Use of Combinatorial Statistics																		
A. Yes	X	X	X	X	X										X	X	X	X
B. No						X	X	X	X	X	X	X	X	X				
9. Output Metric																		
A. Prob. Successful Perf.	X	X	X	X	X	X				X	X				X			X
B. Response Time	X	X	X	X						X	X		X	X	X		X	
C. Other							X	X	X			X		X		X		
10. Validation/Application Data																		
A. Formal Validation Tests	X							X		X	X						X	X
B. Partial Data Available		X	X											X				
C. None Available				X	X	X	X		X			X	X		X	X		

Table 1.1

COMPARISON OF HUMAN RELIABILITY MODELS

impact on human performance. This study will demonstrate that operator learning has a significant effect on human performance.

1.3.2 Learning Curves

In 1936 Wright (33) published the first article that formulated the theory of learning curves. He noted a continuous improvement in labor cost in the manufacture of airplanes as the workers repeated their tasks. From his observations and study in the aircraft industry, he developed the basic learning curve theorem which can be stated as:

> "For any operation which is repeated, the time of the operation will decrease by a fixed fraction, known as the reduction fraction, each time the number of operations doubles."

Learning curves are applicable to many aspects of production planning and control. They can be used to predict the cost per unit of production, offer quantity discounts, and establish selling price. Learning curves also influence delivery schedules, set labor standards, and measure shop efficiency (2). They can also be utilized for establishing costs of manufacture and determining labor requirements.

The learning curve is actually a line on a graph which demonstrates the reduction of time in any repetitive operation. Two facts concerning the use of learning curves are important: (1) The time required to do a job will decrease each time the job is repeated. (2) The amount of decrease will be less with each successive unit.

The curve may be presented on any type graph paper but is more commonly portrayed on log-log graph paper. When plotted on arithmetic graph paper, the shape of a typical learning will be exponential as demonstrated in

Figure 1.1. It can be noted that the curve possesses the characteristics of an initial rapid fall followed by a flattening of the curve and after a relative small number of repetitions, the rate of improvement is small. If log-log graph paper is used instead of arithmetic graph paper, a straight line is presented. Figure 1.2 is identical with Figure 1.1 except that the points have been plotted on log-log paper. The nature of log-log scales permits the inclusion of many repetitions or long periods of time which would be impossible with arithmetic graph paper. On log-log paper, the distance between doubled quantities is equal. This fact coupled with the learning curve theorem is why the plot of a learning curve on log-log paper is linear.

The learning curve is a power curve of the form:

$$t_n = t_1 n^{-m}$$

where:

t_n = the time of operation number n

t_1 = the time of the first operation

n = number of repetitions

m = slope of the curve

When reduced to logarithmic form, this equation is represented by the linear equation: $\log t_n = \log t_1 - m \log n$. The slope of the line, m, is frequently called the reduction fraction and it represents the rate of learning. The reduction fraction usually varies between .7 and .95 depending on the proportion of labor in the task which is man-controlled (8). The complexity of the task and human motivation are also factors which affect the reduction fraction.

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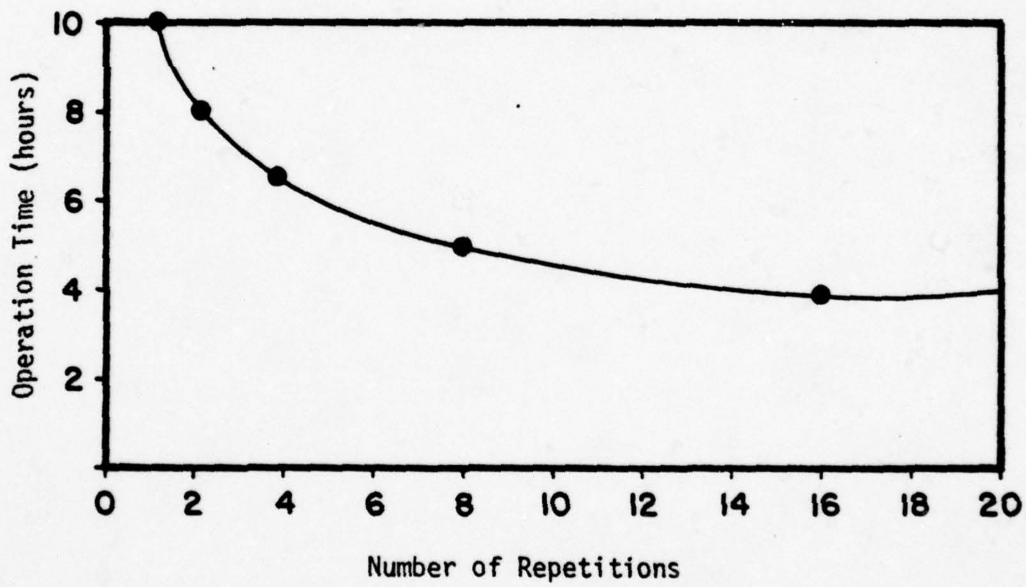

FIGURE 1.1

EXPONENTIAL LEARNING CURVE PLOTTED

ON CARTESIAN COORDINATES

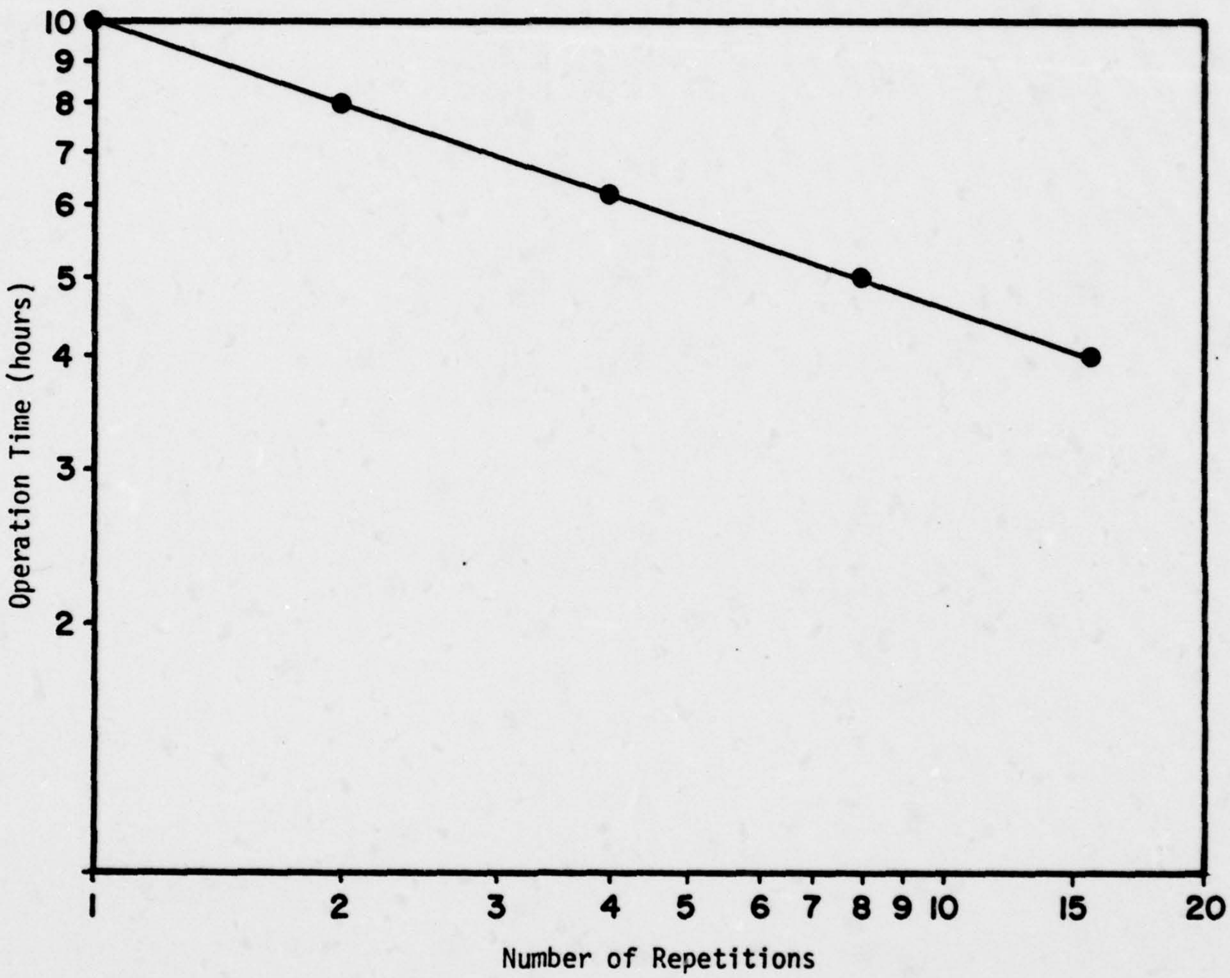

FIGURE 1.2

EXPONENTIAL LEARNING CURVE PLOTTED

ON LOG-LOG COORDINATES

Numerous other equations, more complex and involved than the above equation have been developed to express the learning curve theory (31), (5) and (15). One of the equations fits an S-curve to learning phenomenon while another gives an expression for a more complex exponential curve.

Carlson and Rowe (6) advocate that a learning curve, plotted on arithmetic graph paper, will have an S-shape instead of the exponential shape proposed by Wright (33). See Figure 1.3 for an example of the S-shaped curve. They maintain that the "incipient" phase generally involves little improvement because the worker is getting accustomed to the shop setup, tooling, instructions, workplace arrangement, and the conditions of the process. The second phase, "learning," is where most of the improvement takes place because this phase includes the reduction in errors, development of a work pattern, and rearrangement of the workplace. The third phase, "maturity," represents a limit to improvement because some learning still takes place but at a much slower rate and becomes asymptotic to the limit.

Numerous discussions have taken place concerning the advantages and disadvantages of Wright's simple equation compared to the more complex expressions. It has been pointed out that deficiencies exist in the practical use of the power form model of Wright (5). Two of these deficiencies are the model's ultimate asymptote of zero and the infinite learning period i.e. learning rate is assumed to be constant. The advantages of Wright's equation are its simplicity and ease of calculations. Also, it is more easily understood by management than the more complex models. Even though the disadvantages of Wright's equation are significant, the consensus

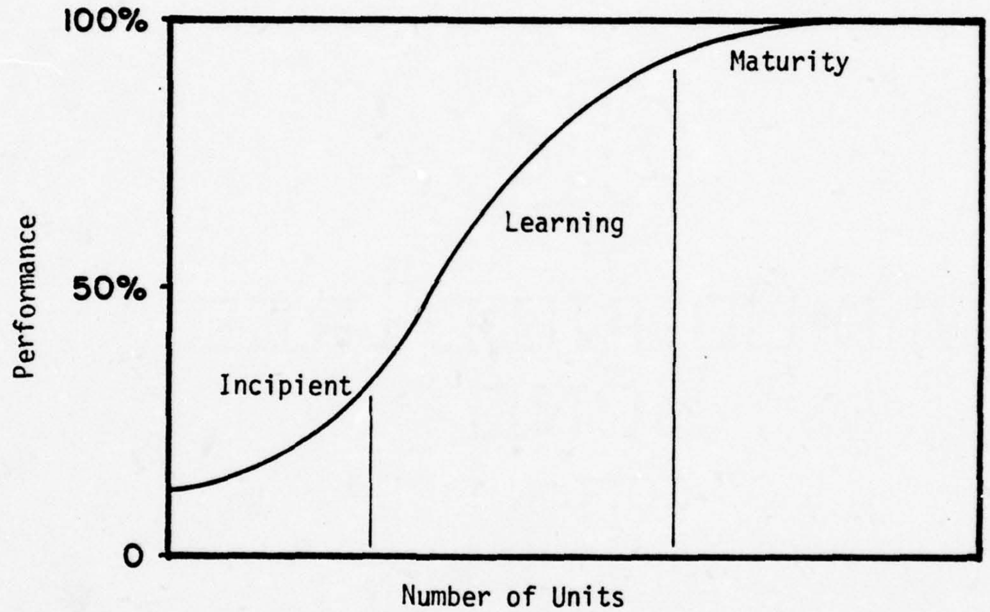

FIGURE 1.3

S-SHAPED LEARNING CURVE

has been that the simple straight line on log-log paper is best (11).

Corlett and Morcombe (8) state that there are not many industrial studies reported of the use of learning curves in the field of training, but it is in training, where learning is taking place continually, that it should have the most applications. This study will apply two different learning curve equations to ascertain the performance level of an operator over various periods of time. These various performance levels will then be utilized in an equation for System Effectiveness, and the sensitivity of the System Effectiveness index to the changing performance levels will be studied.

1.3.3 LFL Curves

Very little research has been done in the area of Learn-Forget-Learn (LFL) curves and their impact on human performance. LFL curves usually have a saw-tooth shape as can be seen in Figure 1.4. This shape is the result of an operator learning a particular task for a certain time period and then having that learning interrupted by some event which takes him away from the task. In all probability, he will forget a portion of what he had originally learned, and his performance on the original task will decline. This sequence of events account for the curve shape, i.e., the initial learning is depicted as a gradual increase in the curve followed by a more pronounced increase, but when the interruption of learning occurs, the curve drops off and operator performance decreases. When the operator returns to the task after the interruption, his performance starts to increase again as the curve begins to climb. The learning/forgetting curve explained above has been proposed by Carlson and Rowe (6).

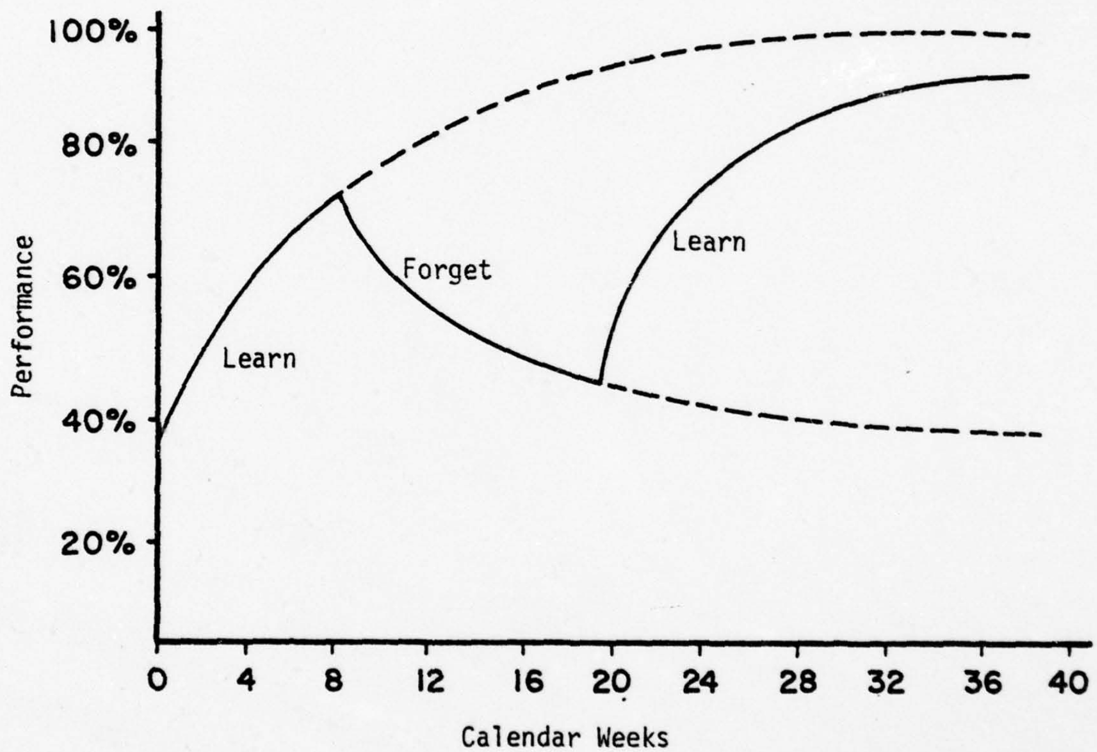

FIGURE 1.4

LEARN-FORGET-LEARN (LFL) CURVE

It should be noted that the forgetting portion of Figure 1.4 shows a rapid initial decrease in performance followed by a gradual leveling off as a function of the interruption interval period. Also, the rate and amount of forgetting decreases as an increased number of units are completed before an interruption occurs. These two attributes of forgetting curves demonstrate that the amount of forgetting and the corresponding level of performance are a function of both the performance at the time the task was interrupted and the length of the interruption.

From the above discussion, it can be deduced that an LFL is a combination of learning and forgetting curves over various periods of time. The LFL curve will be explained in more detail in the following chapter to include graphical and mathematical derivations of the curve.

CHAPTER 2

DEVELOPMENT OF CURVES

2.1 Introduction

Three different curves will be developed in this chapter. Two of the curves will be pseudo-learning curves while the third will be a LFL curve. The learning curves are referred to as pseudo-learning curves because of the coordinates used to plot the curves. A normal learning curve is usually plotted using "Cumulative Units" as the independent variable and "Time per Unit" as the dependent variable, but, for the purposes of this paper, "Calendar Weeks" will be utilized as the independent variable and "Performance" as the dependent variable. The reasoning behind this change in coordinates is to insure that the units of the results obtained from the learning curves will be compatible with the units utilized in the System Effectiveness model because, in Chapter 3, it is required to have time as the independent variable, and reliability is expressed over time. For the purposes of this paper, the units of the dependent variable, "Performance", will be defined in terms of probability of success, i.e. reliability. For example, a performance value of 35 percent implies 35 hits out of 100 attempts for an infantryman shooting at a target. It could also imply 35 correct observations out of 100 total observations for a radar or sonar operator. The above definition of performance will be explained in more detail in the following sections of this chapter.

The first learning curve is expressed by a log equation which is similar to the equation of the first learning curve proposed by Wright (33). The second learning curve has been formulated in terms of a cubic equation.

The LFL curve is expressed by three different equations depending on the section of the curve under study. Data used to develop the three curves, (Tables 2.1, 2.3, and 2.5), was obtained from Carlson and Rowe (6). Carlson and Rowe accumulated this data by studying the performance of 60 individuals who performed the same skilled manual tasks in a manufacturing plant.

The data presented by Carlson and Rowe (6) was expressed in terms of calendar weeks versus performance where performance was defined as the ratio of standard time to actual time. For the purposes of this study, performance is redefined so as to express probability of success or reliability. Because of this new definition, performance means probability of success and not the usual measure of quantity output, thus the value of performance must be less than or equal to 100%. Because of this constraint on the values of performance, the data obtained from (6) had to be normalized because some of the performance values were in excess of 100%. This transformation of the performance variable is required so that probability of success is expressed over time. This requirement will become evident in Chapter 3. Therefore, the basic hypothesis behind the redefinition of the performance variable is that the probability of success is a one-to-one transformation with the observed performance data, that is, it was assumed to have the same form. Hence, the observed performance data, as presented in (6), was utilized to generate the probability of success data which was used to develop the learning curves.

The data for the log pseudo-learning curve and the LFL curve was obtained by normalizing the original data presented in (6) so that no performance values were in excess of 100 percent. All values were normalized because of the definition of "Performance" i.e. probability of success (reliability) can not exceed a value of 1.00 which is the same as a performance value of 100 percent. The original data was utilized to plot the cubic pseudo-learning curve because there were no performance values which exceeded 100 percent.

The results from the three different curves will be utilized in Chapter 3 in conjunction with a model that formulates System Effectiveness. The sensitivity of this System Effectiveness model to the different curve types and to changing performance values associated with the curves will be analyzed.

2.1.1 Log Pseudo-Learning Curve

This learning curve is very similar to the log-linear learning curve developed by Wright in 1936 (33). The curve developed by Wright is the simplest and most easily understood of all the learning curves which have been developed. Figure 1.1 is an example of Wright's curve when it is plotted using Cartesian coordinates. Its simplicity and ease of calculation make it the most widely used learning curve.

The data in Table 2.1 has been used to plot the log pseudo-learning curve of Figure 2.1. Again, this data is the result of normalizing the original data presented by Carlson and Rowe (6).

The model for the log pseudo-learning curve was developed using the linear regression program of the Statistical Analysis System (SAS). The model has the following form: $P(t) = 31.534 + 19.549 \log t$

30

where: P(t) = Performance, percent

t = Time, calendar weeks

The correlation coefficient for this model is r = .997. Table 2.2 is the table of residuals (residual = observed value - predicted value) of the model compared to the observed values (Table 2.1). It can be noted in Table 2.2 that the model gives an extraordinarily good fit to the observed data.

In practical terms, this type of learning curve would result from a work situation where the individual works continuously on the same job, i.e. he is not detailed or assigned to tasks other than his main job assignment. An example of this type of situation would be a radar operator who does nothing else except monitor the radar screen. If the individual is interrupted while working at his primary job assignment, this type of learning curve would not be applicable. Section 2.1.3 addresses this type of interrupted learning experience.

2.1.2 Cubic Pseudo-Learning Curve

The cubic learning curve was proposed some years after Wright's log-linear formulation (33). It was developed in an effort to eliminate the two major disadvantages of the log-linear form i.e. the zero asymptote and the assumed constant rate of learning. This learning curve plots on Cartesian coordinates as an S-shaped curve when "Cumulative Units" is used as the independent variable and "Performance" is used as the dependent variable. See Figure 1.3 of Chapter 1. Many references exist in the literature which address the theory and formulation of cubic curves (1), (6) and (7).

Week	Performance (%)	Week	Performance (%)
1	34.4	16	85.0
2	47.0	17	86.4
3	53.6	18	87.6
4	58.3	19	88.9
5	62.1	20	90.1
6	65.4	21	91.2
7	68.3	22	92.3
8	70.8	23	93.4
9	73.0	24	94.4
10	75.1	25	95.4
11	77.0	26	96.4
12	78.8	27	97.3
13	80.5	28	98.2
14	82.0	29	99.1
15	83.5	30	100.0

TABLE 2.1

DATA USED TO PLOT LOG PSEUDO-LEARNING CURVE

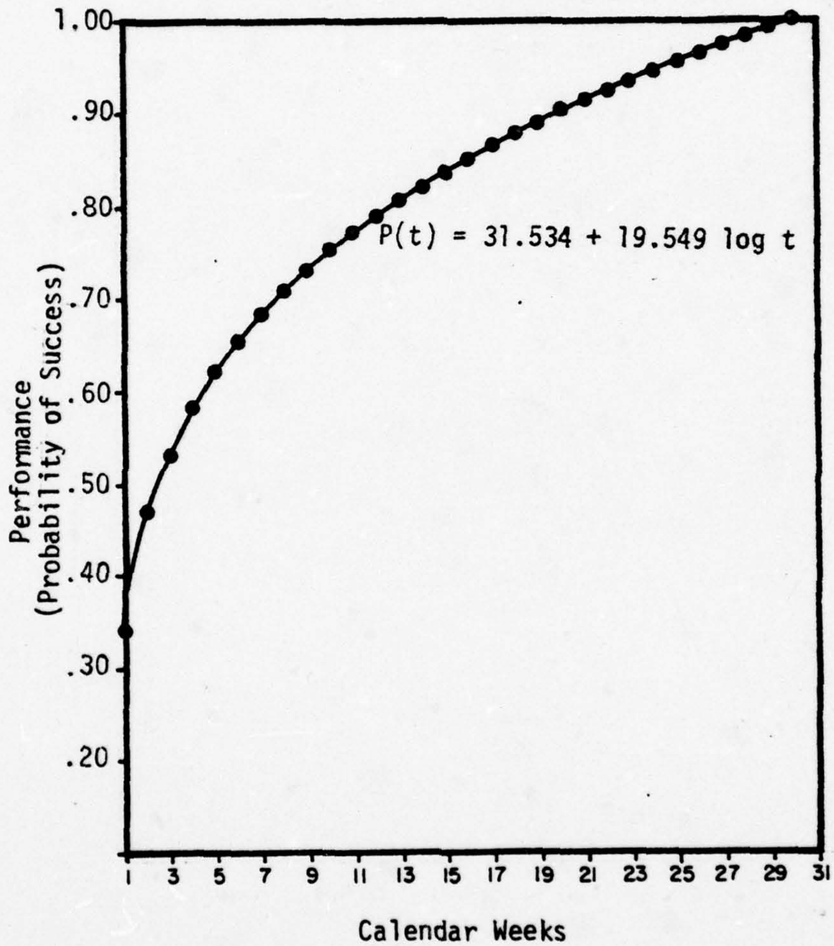

FIGURE 2.1

LOG-PSEUDO LEARNING CURVE

Model: $P(t) = 31.534 + 19.549 \log t$

Week	Observed Performance Value	Predicted Performance Value	Residual
1	34.400	31.534	2.866
2	47.000	45.084	1.916
3	53.600	53.011	0.589
4	58.300	58.634	-0.334
5	62.100	62.997	-0.897
6	65.400	66.561	-1.161
7	68.300	69.574	-1.274
8	70.800	72.185	-1.385
9	73.000	74.487	-1.487
10	75.100	76.547	-1.447
11	77.000	78.410	-1.410
12	78.800	80.111	-1.311
13	80.500	81.676	-1.176
14	82.000	83.124	-1.124
15	83.500	84.473	-0.973
16	85.000	85.735	-0.735
17	86.400	86.920	-0.520
18	87.600	88.037	-0.437
19	88.900	89.094	-0.194
20	90.100	90.097	0.003
21	91.200	91.051	0.149
22	92.300	91.960	0.340
23	93.400	92.829	0.571
24	94.400	93.661	0.739
25	95.400	94.459	0.941
26	96.400	95.226	1.174
27	97.300	95.964	1.336
28	98.200	96.675	1.525
29	99.100	97.361	1.739
30	100.000	98.023	1.977

TABLE 2.2

TABLE OF RESIDUALS FOR LOG PSEUDO-LEARNING CURVE

The data in Table 2.3 has been used to plot the cubic pseudo-learning curve of Figure 2.2. It is referred to as a pseudo-learning curve because the coordinates are now "Calendar Weeks" as the independent variable and "Performance" as the dependent variable.

The model for the cubic pseudo-learning curve was developed using the linear regression program of the Statistical Analysis System (SAS). The model has the following form:

$$P(t) = 10.622 + 12.615\ t - .59465\ t^2 + .0091986\ t^3$$

where: $P(t)$ = Performance, percent

t = Time, calendar weeks

The correlation coefficient for this model is $r = .997$. Table 2.4 is the table of residuals of the model compared to the observed values (Table 2.3). Again, it can be noted that the model gives an extraordinarily good fit to the observed data.

The cubic pseudo-learning curve also would be obtained in a work situation where the operator performs only one task and is not interrupted in his performance of that task. An example of this type of continuous and uninterrupted job position would be a telephone operator who does nothing else except work at a switchboard. The next section of this chapter explains a job situation in which the operator is interrupted while performing his primary duties.

2.1.3 Learn-Forget-Learn (LFL) Curve

Little research has been done in the area of Learn-Forget-Learn curves. An LFL curve, which has a shape similar to the curve in Figure 1.4, occurs

Week	Performance (%)	Week	Performance (%)
1	17.7	16	96.3
2	32.6	17	97.1
3	44.8	18	97.8
4	54.7	19	98.4
5	62.8	20	98.8
6	69.4	21	99.1
7	74.8	22	99.4
8	79.3	23	99.6
9	83.0	24	99.7
10	86.1	25	99.8
11	88.7	26	99.8
12	90.8	27	99.8
13	92.6	28	99.7
14	94.0	29	99.6
15	95.3	30	99.5

TABLE 2.3

DATA USED TO PLOT CUBIC PSEUDO-LEARNING CURVE

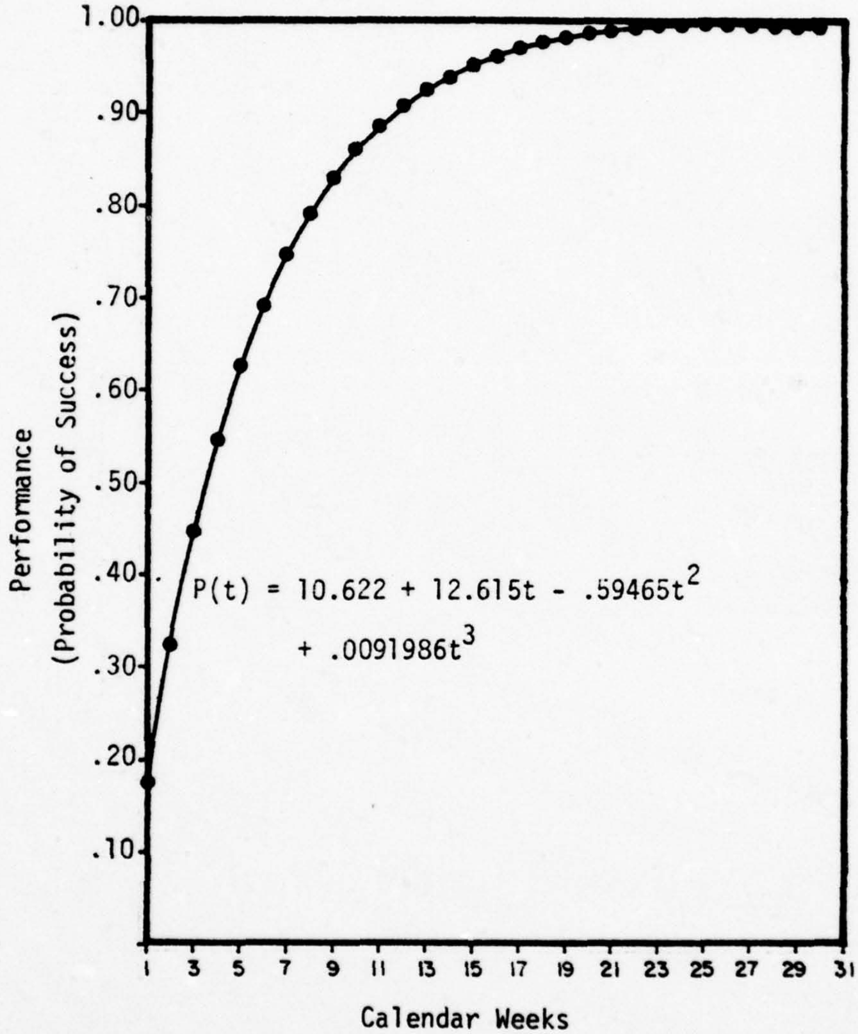

FIGURE 2.2

CUBIC PSEUDO-LEARNING CURVE

Model: $P(t) = 10.622 + 12.615t - .59465t^2 + .0091986t^3$

Week	Observed Performance Value	Predicted Performance Value	Residual
1	17.700	22.651	-4.951
2	32.600	33.546	-0.946
3	44.800	43.362	1.438
4	54.700	52.155	2.545
5	62.800	59.979	2.821
6	69.400	66.889	2.511
7	74.800	72.941	1.859
8	79.300	78.191	1.109
9	83.000	82.692	0.308
10	86.100	86.501	-0.401
11	88.700	89.673	-0.973
12	90.800	92.263	-1.463
13	92.600	94.325	-1.725
14	94.000	95.916	-1.916
15	95.300	97.090	-1.790
16	96.300	97.902	-1.602
17	97.100	98.409	-1.309
18	97.800	98.664	-0.864
19	98.400	98.724	-0.324
20	98.800	98.643	0.157
21	99.100	98.476	0.624
22	99.400	98.279	1.121
23	99.600	98.107	1.493
24	99.700	98.016	1.684
25	99.800	98.059	1.741
26	99.800	98.293	1.507
27	99.800	98.773	1.027
28	99.700	99.553	0.147
29	99.600	100.690	-1.090
30	99.500	102.238	-2.738

TABLE 2.4

TABLE OF RESIDUALS FOR CUBIC PSEUDO-LEARNING CURVE when an operator is interrupted while working at his primary job assignment and is assigned to another task, and then, after a certain period of time, he returns to his primary duties. The curve portrayed in Figure 1.4 depicts these events as the initial learning on the primary task, then the forgetting that takes place during the interruption, and finally the resumed learning of the task after the operator returns to the job. Instead of the interruption taking the form of a change in job assignments, it could also indicate a period of absence that the worker is away from his primary job, i.e. a weekend break or a vacation for the worker. The amount of forgetting that takes place during a break in the work depends on how much the worker has learned up to the point of interruption and the length of the interruption (13). Another study concerned with interrupted learning theorizes that a non-work interruption (weekend break or vacation) is not the same as a work interruption (performing another task) (9). This theory still has to be verified.

The LFL curve also can depicit an individual's increasing performance during his initial training for a job (first section of curve), his decreasing performance caused by forgetting since the initial training (second section of curve), and then the subsequent increase in performance caused by retraining for the job (third section of curve). The various work phenomena which can be explained by LFL curves are numerous and can be easily understood by using this type of curve. A practical example of a situation where an LFL curve could be applied is an infantryman who received his initial training on the use and firing of an anti-tank missile. After the initial or basic training period, which included actual firings of the missile, the soldier is assigned to a unit in which the actual firing of the missile is impossible. In all probability he will forget some of the procedures and techniques required to fire the missile during his assignment to this particular unit, and his performance in regards to missile firings will decrease. In this particular instance, performance can be construed as accuracy in hitting the target i.e. probability of success. He is then retrained on the missile system by being assigned to a firing range where he can perform actual firings again, and his performance level should increase because of the experience he received on the range. See Figure 2.3 for a graphical representation of the infantryman's training cycle which was explained above.

The example of interrupted learning presented by Carlson and Rowe (6) has an operator performing a certain task for a seven week period, then being assigned to perform another task for a period of 12 weeks, and then returning to the original task for a period of 11 weeks. The performance data that portrays the above sequence of events is presented in Table 2.5 and is plotted in Figure 2.4. This data has again been normalized from the original data presented in (6) to insure that the performance values do not exceed 100 percent. Again, this normalization is required because of the definition of performance which was explained in section 2.1.

The model for the Learn-Forget-Learn curve was developed by finding equations for each of the three sections of the curve. Each equation was formulated using analytical methods. The model, which was developed using the data of Table 2.5, has the following form:

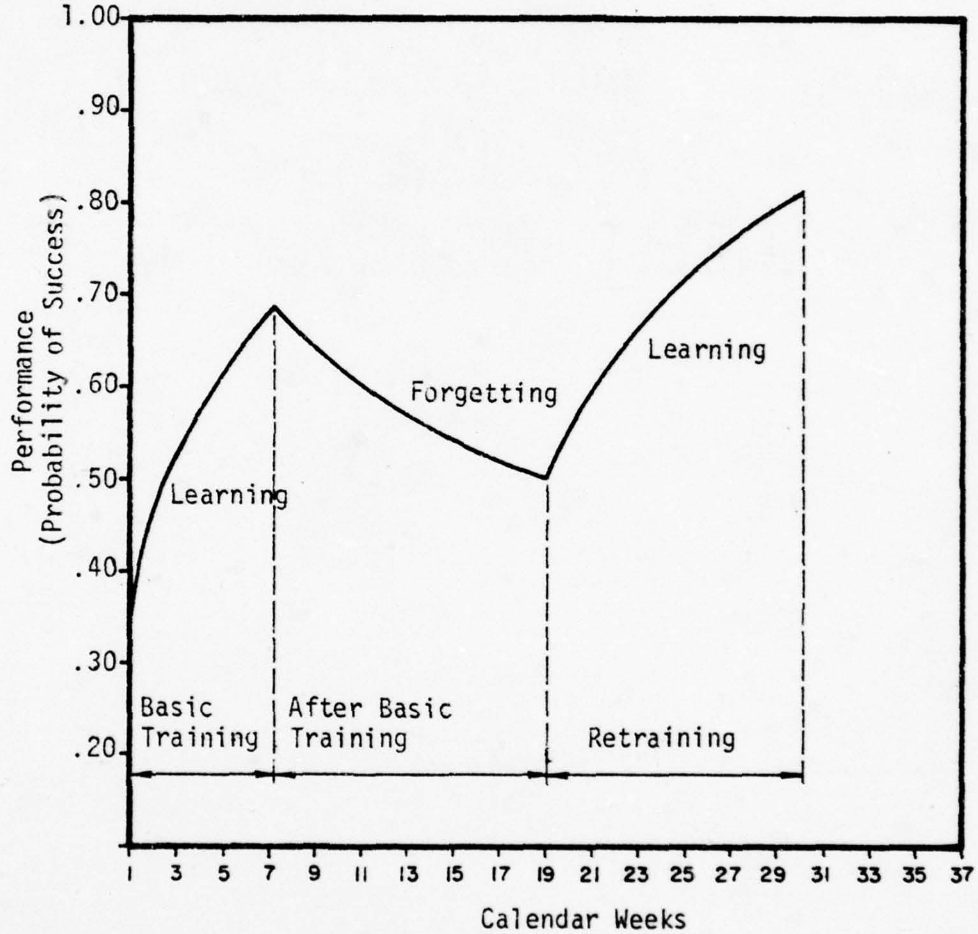

FIGURE 2.3

EXAMPLE LFL CURVE OF TRAINING

CYCLE FOR AN INFANTRYMAN

$$P(t) = \begin{cases} 821.63 - \dfrac{787.23}{t^{.02}}, & \text{Initial Learning} \\[2ex] -15.690 + \dfrac{133.98}{t^{.24}}, & \text{Forgetting} \\[2ex] 108.47 - \dfrac{7480}{t^{1.65}}, & \text{Resumed Learning} \end{cases}$$

where: $P(t)$ = Performance, percent

t = Time, calendar weeks

Table 2.6 is the table of residuals of the model compared to the observed values (Table 2.5). It can be noted in Table 2.6 that the model gives a better than average fit to the observed data, and the pattern of residuals bears this out.

As was mentioned in the earlier sections of the chapter, the LFL curve can be utilized when an individual operator experiences an interruption in his work. The interruption can take the form of a work interruption (performing another task) or a non-work interruption (weekend break or vacation), and it should be stated that the LFL curve is applicable to both types of interruption.

The results obtained from the LFL curve and the two pseudo-learning curves (log and cubic) of this chapter's earlier sections will be utilized in conjunction with a System Effectiveness model in Chapter 3. The sensitivity of the SE model to the three different curve types and changing performance values of each curve will be analyzed and discussed.

Week	Performance %	Week	Performance (%)
1	34.4	16	53.1
2	47.0	17	52.1
3	53.6	18	51.2
4	58.3	19	50.3
5	62.1	20	56.0
6	65.4	21	60.2
7	68.3	22	63.8
8	66.5	23	66.8
9	64.6	24	69.6
10	62.0	25	71.9
11	60.0	26	74.0
12	58.2	27	76.0
13	56.7	28	77.9
14	55.4	29	79.6
15	54.1	30	81.2

TABLE 2.5

DATA USED TO PLOT LFL CURVE

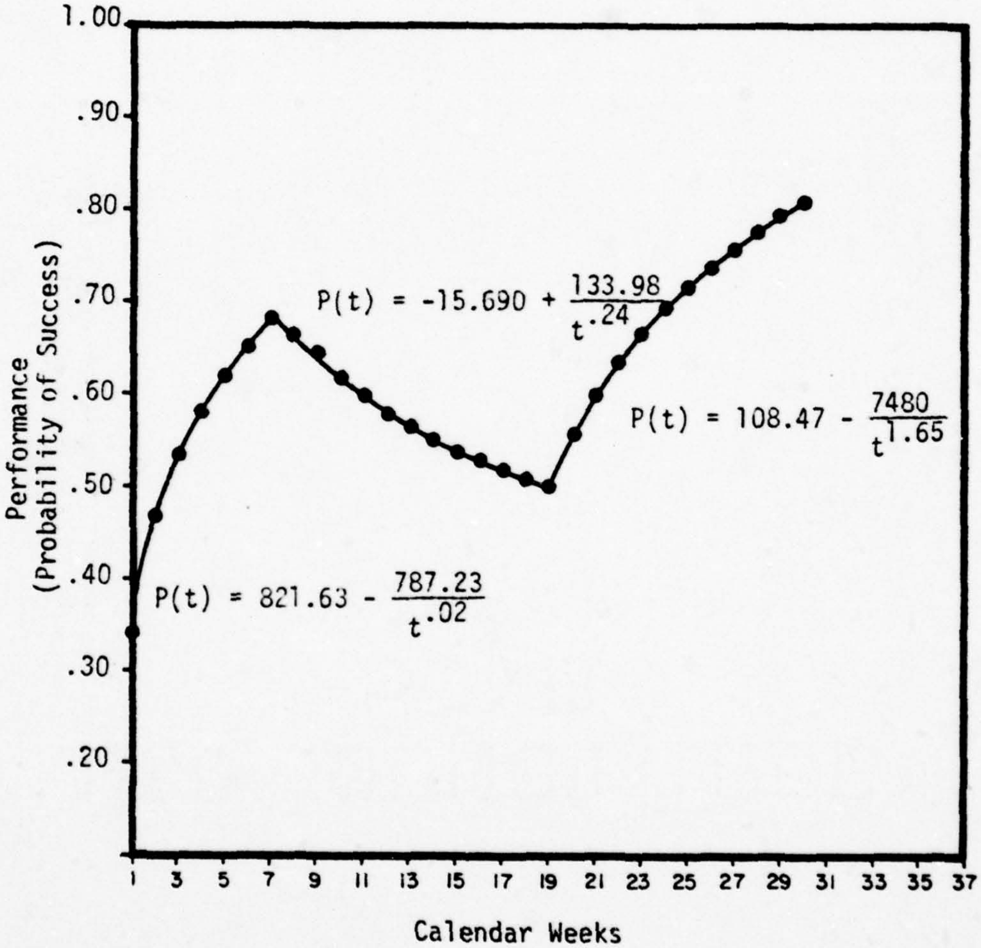

FIGURE 2.4

LEARN-FORGET-LEARN CURVE

<u>Initial Learning</u>, Model: $P(t) = 821.63 - \frac{787.23}{t^{.0225}}$

Week	Observed Performance Value	Predicted Performance Value	Residual
1	34.40	34.40	0
2	47.00	46.58	0.42
3	53.60	53.62	-0.02
4	58.30	58.58	-0.28
5	62.10	62.40	-0.30
6	65.40	65.51	-0.11
7	68.30	68.12	0.18

<u>Forgetting</u>, Model: $P(t) = -15.690 + \frac{133.98}{t^{.24}}$

7	68.30	68.30	0
8	66.50	65.60	0.90
9	64.60	63.40	1.20
10	62.00	61.40	0.60
11	60.00	59.70	0.30
12	58.20	58.10	0.10
13	56.70	56.70	0
14	55.40	55.40	0
15	54.10	54.30	-0.20
16	53.10	53.20	-0.10
17	52.10	52.20	-0.10
18	51.20	51.30	-0.10
19	50.40	50.40	0

TABLE 2.6

TABLE OF RESIDUALS FOR LFL CURVE

Resumed Learning, Model: $P(t) = 108.47 - \frac{7480}{t^{1.65}}$

Week	Observed Performance Value	Predicted Performance Value	Residual
19	50.40	50.40	0
20	56.00	55.10	0.90
21	60.20	59.20	1.00
22	63.80	62.90	0.90
23	66.80	66.10	0.70
24	69.60	69.00	0.60
25	71.90	71.60	0.30
26	74.00	73.90	0.10
27	76.00	76.00	0
28	77.90	77.80	0.10
29	79.60	79.60	0
30	81.20	81.10	0.10

TABLE 2.6 continued

CHAPTER 3

SYSTEM EFFECTIVENESS MODELS

3.1 Introduction

Before proceeding to the discussions of this chapter, the term, "System Effectiveness" should be defined. Gephart and Balachandran (10) define it as: "The probability that the man-machine system will successfully meet an operational demand and fulfill the predetermined mission objectives within a given mission time when operated under stated conditions." In language that is easier to understand, System Effectiveness is "the probability that a system can successfully meet an operational demand throughout a given time period when operated under specified conditions." In most cases, System Effectiveness is stated in probabilistic form, i.e. probability of system success.

This chapter is organized into two major sections. The first section consists of a summary of three different System Effectiveness models. These three models will be identified as (1) The Modified WSEIAC Model, (2) The Navy Model, and (3) Lie's Model. After the summary, a comparison will be made between the three models with differences and similarities being discussed.

The summary of Lie's model will be in more detail than the other two models because Lie's formulation will form the basis for the next major section of this chapter. Lie's proposed model, is very similar in some aspects, to the other two models, but it addresses two areas (environmental and operator impact on SE) which were not mentioned or only briefly explained in the first two models. The area of operator impact on System Effectiveness is of major interest in this chapter.

The performance values obtained from the two pseudo-learning curves (log and cubic) and the Learn-Forget-Learn curve of Chapter 2 will be used in conjunction with Lie's model to analyze the effect that the various curve forms and associated levels of performance have on the value of System Effectiveness. These changes in the values of System Effectiveness then will be analyzed and discussed in Chapter 4. Also, an analysis of the behavior of the LFL curve will be undertaken in the last section of this chapter.

3.2 Comparison of System Effectiveness Models

As was mentioned in the preceding section, three proposed models that attempt to quantify System Effectiveness will be summarized and compared in this section of the chapter. The three models will be referred to as (1) The Modified WSEIAC Model, (2) The Navy Model, and (3) Lie's Model. The terms used in the discussion and analysis are defined as:

(1) Availability - The probability that the system is in an "up" and ready state at the beginning of the mission when the mission occurs at a random point in time. Availability is a function of the reliability and maintainability characteristics of the system.

(2) Reliability - The probability that an item will perform its intended function for a specified interval under stated conditions.

(3) Maintainability - The probability that an item will be retained in or restored to a specified condition within a given period of time.

(4) Dependability - The probability that, given the system was available, it will continue to operate throughout the mission either (1)

without a system-level failure (a failure that causes the entire system to be inoperable), or (2) if it fails, it will be restored to operation within some critical time interval which, if exceeded, would result in mission failure. Dependability is also a function of the reliability and maintainability characteristics of the system.

(5) Capability - The probability that the system's designed performance will allow it to meet mission demands successfully assuming that the system is available and dependable.

Now that some of the more important terms have been defined, we can proceed to the summaries of the three models.

3.2.1 The Modified WSEIAC Model

In 1963, the Weapon System Effectiveness Industry Advisory Committee (WSEIAC) was formed for the purpose of "providing technical guidance and assistance to the Commander, Air Force Systems Command, in the development of a technique to appraise management of current and predicted System Effectiveness at all phases of system life." (10). The committee theorized that System Effectiveness was a joint probability measure expressed as:

$$SE = (A)(D)(C) \tag{1}$$

where:
- SE = System Effectiveness
- A = Availability of the system
- D = Dependability of the system
- C = Capability of the system

and where A, D, and C are probability statements.

They further stated that availability (A) may be obtained as a function of the state readiness of the system and the utilization of the system. This meant that equation (1) was then transformed to be the following expression:

$$SE = (V)(W)(D)(C) \tag{2}$$

where: V = a measure of state readiness of the system.

W = a measure of the probability of utilizing the system given the state of the system.

and where V and W are probability statements.

In 1969, Gephart and Balachandran modified equation (2) by making the following changes:

(1) They relabelled V to become S (state readiness), and relabelled W to become U (utility).

(2) They relabeled D as RE-RE (Reliability-Repairability).

(3) And lastly, they proposed that the capability term of equation (2), C, could be expressed as the product of "adequacy of personnel", A, and "capability of hardware", CH.

With the above changes being made to equation (2), it would then take the following form:

$$SE = (S)(U)(RE\text{-}RE)(A)(CH) \tag{3}$$

where S, U, RE-RE, A, and CH are probability statements.

The major modification that Gephart and Balachandran made to the original WSEIAC model, equation (2), was to partition the capability of the system, C, into: (a) that which was contributed by the hardware of the system, and (b) that which was attributable to the human factor (operator). By partitioning the capability of the system, they realized that the performance of the operator has a definite impact on System Effectiveness. In earlier studies, operator performance was assumed to have a constant value of 100 per cent i.e., the operator was totally reliable. In actuality, an operator's performance is very seldom totally reliable and therefore, this assumption led to miscalculations of System Effectiveness.

They defined "adequacy of personnel" as the conditional probability that the personnel will perform at their level of proficiency, given that the hardware component of the system is in a given state. They assumed in the model that the variable which describes operator performance follows a normal distribution. They further stated that the parameters of this distribution can be obtained from the training programs or proficiency evaluations of a sample from the relevant population of subjects. These parameters then can be used in the Systems Effectiveness simulation.

However, they did not detail how to obtain useable human performance data from the training programs or proficiency evaluations. In other words, they presented no analytical method which could be used to extract data from the training programs/proficiency evaluations. Without being able to extract human performance data from the sources they mentioned, the human performance portion of their Capability term is useless. Because of this, no operator performance data was utilized in the example problem they presented in their paper. Therefore, in essence, Gephart and Balachandran outlined the requirement for including an operator performance term in the calculation of System Effectiveness, but did not explain how to obtain operator performance data which could then be utilized in the System Effectiveness simulation.

3.2.2 The Navy Model

The Navy Model for System Effectiveness was obtained from a proposed revision of the "Navy System Effectiveness Manual" which was written by D. T. Hanifan (14). This model is very similar to the Modified WSEIAC Model presented in the last section. In the manual, Hanifan states that "the effectiveness of a system depends on its availability, dependability, and capability in relation to the mission." This statement expresses the same formulation for System Effectiveness as was presented by equation (1) of the last section, i.e.:

$$SE = (A)(D)(C) \tag{1}$$

Hanifan goes on to state that the three terms of the model are mutually exclusive, and great care should be exercised in modeling to guarantee that the same data are not included in more than one term of the model.

As was the case for the Modified WSEIAC Model, Hanifan says that the "Capability" term, C, of equation (1) can be partitioned into a term which is contributed by the hardware of the system and a term which is attributable to the performance of the operator. Usually, Capability is less than theoretical computations or test results because the human performance part of the Capability term may have been overestimated or even assumed to be 1.0 (which is the assumption when the human performance term is effectively left out). Hanifan says that because of the above assumption, "the effectiveness modeler must usually modify the system performance numbers obtained from hardware designers in order to obtain a more accurate estimate of total system Capability." Because of the difficulty in obtaining suitable human performance data, estimates for this data must frequently be substituted for empirically-obtained data. He says some of the human performance parameters can be estimated from experimental data or operational records, but many are at present known only qualitatively and their effects must be estimated on the basis of judgement. Too often the tendency is to leave the human performance data completely out of the model.

As in the last section, the author notes the importance of including an operator performance term in the formulation of System Effectiveness, but gives no concrete method for obtaining data which can be used in the operator performance term. In addition to not presenting any concrete method for obtaining this data, he does not present a method for estimating the data that would be required to formulate the human performance term. He discusses the importance of human performance, but that's all.

3.2.3 Lie's Model

The formulation of this model is contained in Lie's doctorial dissertation (16). Lie developed numerous models that attempted to quantify Mission Effectiveness (ME). To be consistent with the terminology used in the preceding two models, we note that System Effectiveness is Mission Effectiveness, hence Lie's term of Mission Effectiveness will be labelled System Effectiveness.

Lie's general formulation of System Effectiveness is:

$$(SE)_{ij} = A^h_{ij} \cdot A^o_{ij} \cdot R^h_{ij} \cdot R^o_{ij} \cdot E_{ij} \cdot P_{ij} \tag{4}$$

where: $(SE)_{ij}$ = System Effectiveness of unit i for mission j

A^h_{ij} = Availability of the hardware component of unit i at the start of mission j

A^o_{ij} = Availability of the operator component of unit i at the start of mission j

R^h_{ij} = Mission reliability of the hardware component of unit i for mission j

R^o_{ij} = Mission reliability of the operator of unit i for mission j

E_{ij} = Performance of unit i during mission j for a given status of the environment

P_{ij} = Performance of the operator of unit i during mission j

and where all the terms of equation (4) are probability statements.

Equation (4) is comparable to equation (1) of the preceding sections except for one major deviation - the "Capability" portion of the model represented by equation (1) is now expressed by a term for environmental impact on SE and a term that deals with operator performance and its effect on SE.

Lie states that "the performance of a unit is dependent upon the status of the environment", i.e. a better performance of the unit is expected in a good weather condition than in a bad weather condition (cold winter, stormy night, etc.). Lie classified the status of the environment as excellent, good, fair, poor, etc. He also expressed the idea that the performance of a unit is dependent upon the performance of the operator, and performance is a function of the quality of the operator and the retraining period. He assumed that the performance of the operator of unit i can be expressed by the following functional form:

$$y_i = (y_1)_i + (y_2)_i \, e^{-\beta_i t} \tag{5}$$

where: y_i = Probability of the mission success as a function of the operator effect of unit i at time t

$(y_1)_i$ = Steady-state probability of the mission success as a function of the operator effect of unit i

$(y_1)_i + (y_2)_i$ = Initial peak probability of the mission success as a function of the operator effect of unit i

β_i = Decreasing rate of the probability of the mission success as a function of the operator effect of unit i

t = time, hours

If the retraining of the operator is performed every T_i time units, and if every retraining brings the performance up to the initial level, then the performance of the operator of unit i may be represented as shown in Figure 3.1.

Lie states that equation (5) is one of a variety of functional forms for the operator performance that can be <u>assumed</u>. Equation (5) is an expression for operator performance and could be termed an "LFL" curve.

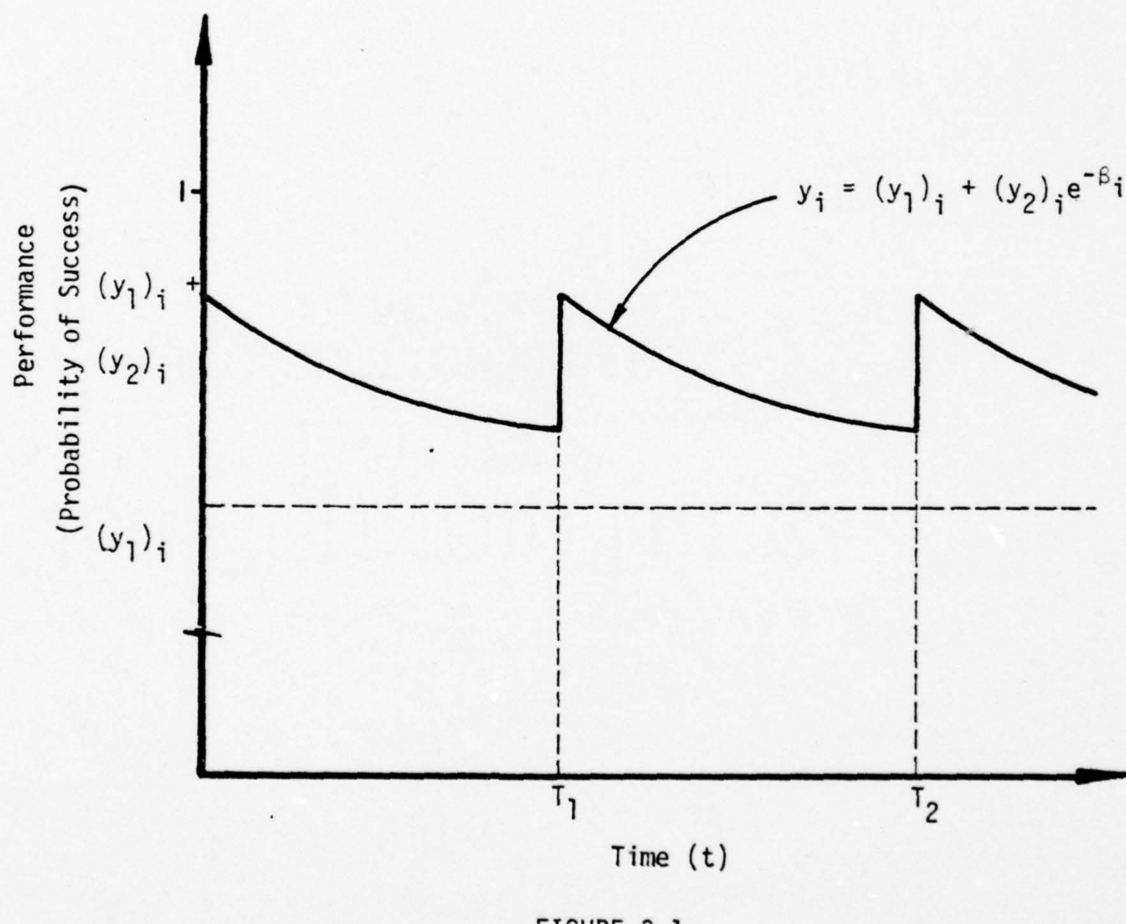

FIGURE 3.1

PERFORMANCE OF THE OPERATOR OF UNIT i AS A FUNCTION OF THE QUALITY OF THE OPERATOR ($(y_1)_i$, $(y_2)_i$, and β_i) AND THE RETRAINING PERIOD (T_i).

Lie assigned arbitrary values to the parameters of equation (5) when the expression was utilized in his simulation of the model. He provided no explanation as to why he used the particular equation he did, equation (5), or why he chose the particular values for the parameters that he did. He did not mention how values for the parameters could be obtained from training programs, proficiency evaluations, etc.

Using the equations for operator performance developed in Chapter 2 from the learning and LFL curves in place of equation (5), the simulation program for System Effectiveness (the simulation program for SE is listed in Appendix A) which Lie developed was run to determine what effect the various curve forms would have on the overall System Effectiveness. The results of the various simulation runs will be outlined in section 3.3. with subsequent conclusions made in Chapter 4.

3.2.4 Comparison of Models

It should be evident from the three preceding sections that the three models are very similar in most aspects with the only differences being in the interpretation of the "Capability" term of equation (1). The Modified WSEIAC Model and the Navy Model are almost identical in their formulation of System Effectiveness while the model of Lie's differs in the make-up of the "Capability" term. Lie also developed his model for Mission Effectiveness while the other two were formulated in terms of System Effectiveness, but both terms (SE and ME) employ the same concepts.

The one fact that should be brought out in this comparison is that none of the models provided any definitive data on human performance. Also, no guidance at all was provided in regards to obtaining analytical expressions that could be used to quantify human performance. Lie did the most work in this area, but he was deficient in the explanation of the equation he used, and he did not list possible sources of human performance data. As far as the operator performance term in each of the models, there was much discussion about what should be done in this area, but no one gave any direction that could be followed when trying to quantify human performance levels. This paper will give insight into the collecting of human performance data,development of analytical expressions for the performance, and their subsequent use in effectiveness simulation models.

3.3 Lie's Simulation Model with Modified Operator Performance Term

Lie (16) developed a number of simulation models that attempted to quantify System Effectiveness. The models varied according to the constraints and assumptions that were applied to the various systems. The particular simulation model that will be utilized in this section was developed for a system which was required to carry out various types of missions. In this particular model, each mission type is characterized by the maximum allowable time that determines the success of a given mission type. Lie described the logic of this model in the following way:

> "For a given type of a mission to be successful, the system is required to be available at the start of a mission, and the system must complete its mission within the maximum allowable duration of time that this given mission type specifies without any failure during this period. If the system cannot accomplish a mission within the specified duration of time, the mission is terminated at this point and is considered to be failed even though the system is still operable. Failures of the system are induced by both the hardware itself and the operator. Furthermore, the effects of the environment and the operator are reflected in the mission duration.

In other words, poor environmental conditions and poor operator performance are assumed to make the actual mission duration longer than the mission duration under ideal conditions. Thereby, adverse effects of the environment and the operator tend to reduce the probability of mission success, i.e. System Effectiveness."

Hopefully, this short synopsis of the system will help explain the simulation model for this particular system. Again, a printout of the simulation program used in this section is listed in Appendix A.

The section of the simulation program which was of major interest in this paper dealt with the operator performance term, OP(I,J), and its formulation. In the simulation program (Appendix A), cards number 177 through 206 calculated the operator performance for unit i and mission j, OP(I,J), and printed the various values of OP(I,J) in the output. Equation (5) of section 3.2.3 was used by Lie to express the operator performance of unit i and mission j in the simulation program. He assumed the following values for the parameters of equation (5):

$$y_1 = .8, y_2 = .2, \beta = .0014, T = 2160 \text{ hours}$$

where y_1, y_2, and β are probability values.

When the above values were used in equation (5), and a total of 50 missions were simulated for a single unit, the operator performance for each of the 50 missions was calculated to be the values in Table 3.3. Using the values of Table 3.3, the overall System Effectiveness for the unit turned out to be .52 after all the calculations of the simulation were completed.

The equations for operator performance, which were developed in Chapter 2 from the three different curves, were substituted into Lie's simulation program in place of his expression for OP(I,J) to determine what values of operator performance, and subsequently, what value of System Effectiveness would result. The equations from Chapter 2 are as follows:

Log Pseudo-Learning Curve

$$OP(I,J) = 31.534 + 19.549 \log t$$

Cubic Pseudo-Learning Curve

$$OP(I,J) = 10.622 + 12.615\ t - 0.59465\ t^2 + 0.0091986\ t^3$$

Learn-Forget-Learn Curve

Initial Learning, $OP(I,J) = 821.63 - \dfrac{787.23}{t^{.02}}$

Forgetting, $OP(I,J) = -15.690 + \dfrac{133.98}{t^{.24}}$

Resumed Learning, $OP(I,J) = 108.47 - \dfrac{7480}{t^{1.65}}$

Note that "t" in the above equations was replaced by "CTMS(I,J)" when the equations were utilized in the simulation program. "CTMS(I,J)" stands for the mission start time expressed in clock time for unit i and mission j. This transformation was made because the simulation program operates on a clock time basis, and "CTMS(I,J)" is Lie's clock time term which is equivalent to "t".

Each of the three equations were substituted into Lie's program with each equation being run separately in the simulation. The resulting values of operator performance for the 50 missions obtained from the Log Pseudo-Learning curve, Cubic Pseudo-Learning curve, and Learn-Forget-Learn curve are listed in Tables 3.4, 3.5, and 3.6 respectively. The subsequent values for overall System Effectiveness after the three equations from Chapter 2 and Lie's equation were utilized are tabulated in Table 3.7. The values of OP(I,J) = .50 and 1.0 were also used in the simulation to obtain a range for the System Effectiveness values. The resulting SE values for these two constant operator performance terms are also listed in Table 3.7.

3.4 Analysis of Learn-Forget-Learn (LFL) Curve

The mean performance value for the Learn-Forget-Learn curve, Figure 2.4, is calculated in this section along with the corresponding mean value of System Effectiveness which results when the performance mean is utilized in Lie's simulation program. Also, in this section, the average operator performance is calculated for sample missions taken from the total of 50 missions. The values of the above mean performance figures and their resulting System Effectiveness indexes will be compared and discussed in Chapter 4.

3.4.1 Mean Performance of LFL Curve

The mean performance value for the Learn-Forget-Learn curve is calculated by integrating the three separate segments of the curve over the time periods that they cover and then dividing the sum of the integration results by the total time period for which the curve is effective. The LFL curve is portrayed in Figure 2.4 with the equation for each of the three sections of the curve listed above the portion of the curve to which it applies. The integration which yields the area below the LFL curve is as follows:

$$\int_{1}^{7}(821.63 - \frac{787.23}{t^{.02}})dt + \int_{7}^{19}(-15,690 + \frac{133.98}{t^{.24}})dt + \int_{19}^{30}(108.47 - \frac{7480}{t^{1.65}})dt$$

From the above integration, the total area below the curve is found to be:

$$339.18 + 690.41 + 757.13 = 1786.72 \text{ weeks}$$

When this total area is divided by the total time interval for which the curve is effective, the mean operator performance, $\overline{O.P.}$, will result:

$$\overline{O.P.} = \frac{1786.12}{29} = 61.6\%$$

By using the predicted performance values, P_i, from the table of residuals for the LFL curve, Table 2.6, in conjunction with the value of $\bar{P}$, the standard deviation that pertains to the mean performance, $s_{\overline{O.P.}}$, can be calculated as follows:

$$s_{\overline{O.P.}} = \left(\frac{\sum_{i=1}^{30} (P_i - \bar{P})^2}{n-1}\right)^{1/2} = \left(\frac{3197.99}{30-1}\right)^{1/2} = 10.50\%$$

The values of $\overline{O.P.}$ and $s_{\overline{O.P.}}$ will be utilized in Chapter 4 for comparing various values obtained from the LFL curve. Before proceeding to the next section, it should be noted that the value of $\bar{P}$ obtained above is only valid for a large number of missions, and it should not be utilized when estimating the performance for a single mission or a small sample of missions. The reasoning behind this statement will be demonstrated in Chapter 4.

When the value of $\overline{O.P.}$ is substituted into Lie's simulation program, the System Effectiveness turns out to be .38.

3.4.2 Mission Sampling

To study the sensitivity of the operator performance at a point in time versus the overall performance value, four samples (n=4), each of size five, of missions out of the total of 50 simulated mission were taken. The four samples were taken from around the 10^{th}, 20^{th}, 3 , and 40^{th} mission intervals. As was mentioned earlier, each sample will consist of five observations. For example, the sample for the 10^{th} mission interval is comprised of five observations, i.e. readings from mission numbers 8, 9, 10, 11, and 12. From the computer output of Lie's simulation which was run using the equations for the LFL curve, operator performance values (O.P.) for each individual mission are obtained. The average operator performance for each of the four samples is then calculated as depicted in Table 3.1.

When each of the $\overline{O.P.}_i$ (i = 10,20,30,40) are averaged together, the resulting value, the grand mean ($\overline{\overline{O.P.}}$) of the four samples, turns out to be:

$$\overline{\overline{O.P.}} = 60\%$$

Note that the value of 60% obtained in this section is very close to the value of 62% obtained in section 3.4.1. This result is only logical because the two mean values were obtained from the same population. The small difference in their values is the result of the two different methods utilized to calculate the means.

By using the values of $\overline{O.P.}_i$ (i=10,20,30,40) in conjunction with the value of $\overline{\overline{O.P.}}$, the standard deviation that pertains to the mean performance calculated in this section is found as follows:

$$s = \left(\frac{\sum_{i=1}^{4} \left(\overline{O.P.}_i - \overline{\overline{O.P.}} \right)^2}{n-1} \right)^{1/2} = \left(\frac{162}{4-1} \right)^{1/2} = 7.35\%$$

The values of $\overline{\overline{O.P.}}$ and s which were calculated in this section will be utilized in Chapter 4 for comparing various values obtained from the LFL curve.

For each of the four mission intervals sampled, the average System Effectiveness (SE) for each interval can be calculated by using the computer output of Lie's simulation. It should be noted that System Effectiveness can only have values of 0 or 1, i.e. the mission either fails or it is successful. The calculations for average System Effectiveness are depicted in Table 3.2.

When each of the $\overline{SE}_i$ (i=10,20,30,40) are averaged together, the resulting value, $\overline{\overline{SE}}$, turns out to be:

$$\overline{\overline{SE}} = .40$$

Note that the average value for System Effectiveness obtained in this section, .40, and for the entire period found in the preceding section, .38, are very close, as well they should be, because they were obtained from the same population of values. The small difference in their values results from the two different methods utilized to calculate the averages.

One final item should be mentioned in this section. Since the results of this section were calculated by using the output from Lie's simulation and since the form/content of the output was not listed here, Lie's dissertation (16) can be consulted for further explanation.

10^{th} Mission Interval

Mission No.	O.P.
8	61
9	61
10	59
11	58
12	57

$\overline{O.P.}_{10}=59$

20^{th} Mission Interval

Mission No.	O.P.
18	55
19	54
20	54
21	53
22	52

$\overline{O.P.}_{20}=54$

30^{th} Mission Interval

Mission No.	O.P.
28	50
29	52
30	56
31	58
32	60

$\overline{O.P.}_{30}=55$

40^{th} Mission Interval

Mission No.	O.P.
38	67
39	69
40	70
41	71
42	72

$\overline{O.P.}_{40}=70$

TABLE 3.1

CALCULATIONS OF $\overline{O.P.}_i$

10^{th} Mission Interval

Mission No.	SE
8	0
9	0
10	1
11	0
12	0

$\overline{SE}_{10}=.20$

20^{th} Mission Interval

Mission No.	SE
18	1
19	1
20	0
21	1
22	0

$\overline{SE}_{20}=.60$

30^{th} Mission Interval

Mission No.	SE
28	0
29	0
30	0
31	0
32	0

$\overline{SE}_{30}=0$

40^{th} Mission Interval

Mission No.	SE
38	1
39	0
40	1
41	1
42	1

$\overline{SE}_{40}=.80$

TABLE 3.2

CALCULATIONS OF $\overline{SE}_i$

Mission No.	Operator Performance	Mission No.	Operator Performance
1	.99	26	.95
2	.99	27	.95
3	.98	28	.95
4	.98	29	.94
5	.97	30	.94
6	.97	31	.94
7	.97	32	.94
8	.97	33	.94
9	.97	34	.94
10	.97	35	.94
11	.96	36	.94
12	.96	37	.94
13	.96	38	.94
14	.96	39	.93
15	.96	40	.93
16	.96	41	.93
17	.96	42	.93
18	.96	43	.93
19	.96	44	.93
20	.95	45	.93
21	.95	46	.93
22	.95	47	.93
23	.95	48	.93
24	.95	49	.93
25	.95	50	.92

TABLE 3.3

OPERATOR PERFORMANCE VALUES RESULTING

FROM LIE'S EQUATION

Mission No.	Operator Performance	Mission No.	Operator Performance
1	.45	26	.88
2	.59	27	.89
3	.67	28	.89
4	.72	29	.89
5	.74	30	.90
6	.74	31	.91
7	.76	32	.91
8	.77	33	.91
9	.77	34	.92
10	.79	35	.92
11	.80	36	.92
12	.81	37	.93
13	.82	38	.93
14	.82	39	.94
15	.82	40	.94
16	.83	41	.94
17	.83	42	.95
18	.83	43	.95
19	.84	44	.95
20	.85	45	.95
21	.86	46	.96
22	.87	47	.96
23	.87	48	.96
24	.87	49	.96
25	.88	50	.98

TABLE 3.4

OPERATOR PERFORMANCE VALUES RESULTING

FROM LOG PSEUDO-LEARNING EQUATION

Mission No.	Operator Performance	Mission No.	Operator Performance
1	.34	26	.99
2	.52	27	.99
3	.67	28	.99
4	.78	29	.99
5	.81	30	.99
6	.82	31	.99
7	.85	32	.98
8	.87	33	.98
9	.88	34	.98
10	.91	35	.98
11	.92	36	.98
12	.94	37	.98
13	.94	38	.98
14	.95	39	.98
15	.95	40	.98
16	.95	41	.98
17	.96	42	.98
18	.96	43	.98
19	.97	44	.98
20	.98	45	.98
21	.98	46	.99
22	.98	47	.99
23	.98	48	.99
24	.99	49	.99
25	.99	50	1.00

TABLE 3.5

OPERATOR PERFORMANCE VALUES RESULTING

FROM CUBIC PSEUDO-LEARNING EQUATION

Mission No.	Operator Performance	Mission No.	Operator Performance
1	.47	26	.51
2	.59	27	.51
3	.66	28	.50
4	.66	29	.52
5	.64	30	.56
6	.64	31	.58
7	.62	32	.60
8	.61	33	.61
9	.61	34	.62
10	.59	35	.63
11	.58	36	.65
12	.57	37	.66
13	.57	38	.67
14	.56	39	.69
15	.56	40	.70
16	.56	41	.71
17	.55	42	.72
18	.55	43	.73
19	.54	44	.73
20	.54	45	.74
21	.53	46	.75
22	.52	47	.75
23	.52	48	.77
24	.52	49	.77
25	.52	50	.81

TABLE 3.6

OPERATOR PERFORMANCE VALUES RESULTING

FROM LEARN-FORGET-LEARN EQUATION

Operator Performance Equation	System Effectiveness
Lie's	.52
Log Pseudo-Learning	.56
Cubic Pseudo-Learing	.58
Learn-Forget-Learn (LFL)	.42
Constant value of .50	.32
Constant value of 1.0	.70

TABLE 3.7

SYSTEM EFFECTIVENESS VALUES FOR VARIOUS

OPERATOR PERFORMANCE EQUATIONS

CHAPTER 4

RESULTS AND CONCLUSIONS

4.1 Introduction

In this chapter, the conclusions of this work will be discussed. Also contained in this chapter is a discussion of the sensitivity of Lie's System Effectiveness model when the various operator performance equations are utilized in the simulation. There is also an analysis comparing the mean operator performance for a small number of missions in the same region of the LFL curve with the mean performance value for the entire cycle of the LFL curve. The last section of this chapter will outline the requirement for possible future investigations in the area of training/learning and their impact on operator performance and the subsequent effect of operator performance on the effectiveness of a system.

4.2 Summary and Discussion of Results

In this section, the findings of Chapter 3 are summarized and analyzed. The sections of Chapter 3 which are of interest here are: 3.3, 3.4.1, and 3.4.2.

4.2.1 Sensitivity Analysis of Lie's SE Model

Referring back to Table 3.7 which lists values of System Effectiveness for the various expressions of operator performance, it can be seen that the values for System Effectiveness definitely depend upon which equation for operator performance is utilized in the simulation program. In other words, System Effectiveness is a function of operator performance when the expression for operator performance is used in conjunction with the simulation.

The resultant System Effectiveness values for the Log Pseudo-Learning and Cubic Pseudo-Learning curves (.56 vs .58) are relatively close together as would be expected by comparing the shapes of the two curves in Figures 2.1 and 2.2. They both represent increasing performance functions with the only difference being that the Cubic curve reaches the asymptote of 1.0 faster than the Log curve. This explains why the System Effectiveness value of the Cubic curve (.58) is slightly larger than that of the Log curve (.56).

The System Effectiveness index corresponding to the Learn-Forget-Learn (LFL) curve (SE = .42) is significantly less than the SE values of the Log and Cubic curves (.56 and .58). The reasoning behind this difference in values can again be explained by comparing the shapes of the three curves (Figures 2.1, 2.2, and 2.4). The LFL curve portrays an increasing-decreasing-increasing function of performance while the other two curves are strictly increasing functions of performance. Because the LFL curve has a decreasing performance section, this explains the smaller value of System Effectiveness for this particular curve.

Lie's expression for operator performance, $y = y_1 + y_2e^{-\beta t}$, that he utilized in the simulation yielded a System Effectiveness value of .52. Even though this expression is a decreasing function of performance between retraining periods, it still produces a relatively high index of System Effectiveness. This is because the curve starts at a performance value close to 100 per cent and decreases from there to a operator performance value of 92 per cent which is large compared to the performance values of the Log and Cubic curves.

When the constant values of .50 and 1.0 for operator performance are utilized in the simulation, they produced a range of System Effectiveness values from .32 to .70. It should be noted that the other four values for System Effectiveness fall between the values of .32 and .70.

From the above discussion, it is clear that System Effectiveness is very sensitive to the various equations that express operator performance.

4.2.2 Comparison of Mean Performance Values Obtained from LFL Curve

The mean operator performance values calculated in sections 3.4.1 and 3.4.2 are summarized in Table 4.1. Note that the grand mean calculated from the means of the four samples is approximately the same as the mean calculated by the integration method. As was mentioned in section 3.4.2, this result is not surprising because the sample population of values were utilized to calculate the two means. The same logic applies to the fact that the two System Effectiveness values are approximately the same.

The most important result obtained from the method of mission interval samples is that the means of the individual samples are, in most cases, significantly different than the overall mean value; that is, .55, .54, .57, and .70 are significantly different than .60. This implies that the overall mean can be used to estimate the average System Effectiveness if a large number of missions are to be considered, but if the average System Effectiveness for a small interval of missions is required, the overall mean performance value can not be utilized. When a small interval of missions is to be studied, the average operator performance has to be obtained by consulting the portion of the LFL curve which applies to the mission interval under study. The average operator performance value obtained from the applicable portion of the LFL curve then can be utilized to calculate the average System Effectiveness for the specific interval of missions under consideration.

4.2.3 Summary of Results

Table 3.7 demonstrated that the System Effectiveness model developed by Lie (16) is sensitive to changing operator performance expressions which are utilized in the simulation.

It also was shown that the overall mean performance value of the LFL curve can be utilized to estimate an average System Effectiveness value when a large number of missions are to be considered. But it was also demonstrated that the LFL curve's mean performance value could not be used to obtain an average System Effectiveness value if only a small sample of missions was to be studied. In this type of situation, the average performance had to be obtained directly from the LFL curve.

4.3 Proposed Future Investigations

Because of the absence of any significant research in the area of operator training/learning and their subsequent effect on operator performance, the field is open to any number of studies that can be developed in this area.

First and foremost, a consistent and reliable source for operator performance data should be identified. Without operator performance data, the plotting of training/learning curves would be impossible, and if the curves can not be obtained, there can be no analytic expression for operator performance developed. Gephart and Balachandran (10) suggested that human performance data could be obtained from the training programs or proficiency evaluations of the operators whose performance was of interest. This suggestion appears to be logical and should warrant further research in the areas of training programs and proficiency evaluations to ascertain if they would constitute a good source for operator performance data. Surely, there are other sources of operator performance data which can be identified and utilized, and, if at all possible, the data should be expressable in terms of operator performance versus time. The utilization of these specific units (performance vs. time) would facilitate the inclusion of the operator performance expression into all the System Effectiveness simulation models.

Lie's simulation model is rather generalized in its formulation. The development of models which are more specific in their formulation and which can be applied in detail to a particular system is also proposed as a possible future investigation.

Also, in Lie's simulation it was assumed that the probability of mission success due to environmental conditions was a constant in each environmental condition. Furthermore, the probability of mission success due to the operator was assumed to be independent of the environmental conditions. In actuality, the performance of an operator is almost certain to be affected by the environmental conditions in which the operator has to perform. In other words, an operator is likely to perform at a higher level in good weather conditions (moderate temperatures, low humidity, etc.) than in bad weather conditions (high or low temperatures, mud, snow, etc.). The dependence of operator performance on the environmental conditions, or the conditional probability of operator performance given a certain environment, is an area that needs to be researched.

Once a source of operator performance is identified, then analytical expressions for operator performance can be formulated. Research should be conducted in the area of applying these operator performance expressions to the various other Systems Effectiveness models which were described in references (10) and (14). The sensitivity of these models to various expressions for operator performance should also be studied.

Method Utilized	Average Performance (%)	System Effectiveness
Integration	62	.38
Mission Interval Samples	60	.40
10^{th} Interval	59	
20^{th} Interval	54	
30^{th} Interval	55	
40^{th} Interval	70	

TABLE 4.1

SUMMARY OF OPERATOR PERFORMANCE VALUES

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APPENDIX A

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$JOB            L,PAGES=100
C**** COMPUTER SIMULATION MODEL FOR THE EVALUATION OF MISSION EFFECTIVENESS ****
C...                ***** REQUIRED INFORMATION *****
C...
C...  REMARK 1
C...
C     USERS ARE REQUIRED TO SUPPLY THE FOLLOWING DATA
C        MC=NUMBER OF UNIT(LIMITED UP TO 10)
C        MM=NUMBER OF MISSION(LIMITED UP TO 200)
C...
C...  REMARK 2
C...
C     EIGHT PROBABILITY DISTRIBUTIONS FOR THE FOLLOWING RANDOM VARIABLES
C     (K=1,2,3,4,5,6,11,12) ARE REQUIRED.
C        K=1 : TIME INTERVAL BETWEEN MISSION STARTS
C        K=2 : MISSION DURATION
C        K=3 : TIME INTERVAL BETWEEN FAILURE INDUCED BY HARDWARE
C        K=4 : DOWNTIME(HARDWARE INDUCED)
C        K=5 : TIME INTERVAL BETWEEN FAILURE INDUCED BY OPERATOR
C        K=6 : DOWNTIME(OPERATOR INDUCED)
C        K=11: ENVIRONMENTAL CONDITION AND SYSTEM PERFORMANCE UNDER GIVEN
C              CONDITION
C        K=12: MISSION TYPE
C     EACH DISTRIBUTION IS REQUIRED TO BE DEFINED IN THE FOLLOWING FORMAT.
C           ________________
C           XK(I)     CFK(I)
C           _______   _______
C           XK(1)     CFK(1)
C           XK(2)     CFK(2)
C             .          .
C             .          .
C             .          .
C           XK(NIK)   CFK(NIK)
C           ________________
C     WHERE, XK(I) IS THE NUMERICAL VALUE THAT RANDOM VARIABLES CAN TAKE,
C            CFK(I) IS THE CUMULATIVE FREQUENCY, AND
C            NIK IS LIMITED UP TO 10.
C...
C...  REMARK 3
C...
C     FOR EACH UNIT(I=1,2, ... ,MC), THE FOLLOWING OPERATOR PERFORMANCE
C     INDICES ARE RECUIRED.
C        Y1(I)=STEADY-STATE PERFORMANCE
C        Y2(I)=(INITIAL PERFORMANCE)-Y1(I)
C        B(I)=DECREASING RATE OF PERFORMANCE
C        TP(I)=RETRAINING PERIOD
C...
C...                ***** INPUT DATA FORMAT *****
C...
C     FOR THE INPUT DATA FORMAT AND ORDER,
C     REFER TO THE READ STATEMENTS AND THE CORRESPONDING FORMAT
C     STATEMENTS IN THE FIRST PART OF THE MAIN PROGRAM.
C...
C...  MAIN PROGRAM
C...
      DIMENSION TBMS(10,200),CTMS(10,200),D(10,200),CTMF(10,200),
     1          TBHF(10,200),CTHFS(10,200),RTH(10,200),CTHRF(10,200),
     2CTHRF1(10),TYPE(10,200),DEU(10,200),KH1(10),JH(10),JC(10)
      DIMENSION ENVMT(10,200),OP(10,200),Y1(10),Y2(10),B(10),TP(10),
     1AH(10,200),RH(10,200),RHA(10,200),EM(10,200),EMC(10),EMS(200)
```

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```
      DIMENSION X1(10),X2(10),X3(10),X4(10),X5(10),
     1X6(10),X11(10),X12(10)
      DIMENSION CF1(10),CF2(10),CF3(10),CF4(10),CF5(10),
     1CF6(10),CF11(10),CF12(10)
C...
C...  READ INPUT DATA
C...
      READ(5,700)MC,MM
  700 FORMAT(2I4)
      READ(5,710)NI1,NI2,NI3,NI4,NI5,NI6,NI11,NI12
  710 FORMAT(8I4)
  750 FORMAT(10F8.3)
      READ(5,750)(X1(I),I=1,NI1)
      READ(5,750)(CF1(I),I=1,NI1)
      READ(5,750)(X2(I),I=1,NI2)
      READ(5,750)(CF2(I),I=1,NI2)
      READ(5,750)(X3(I),I=1,NI3)
      READ(5,750)(CF3(I),I=1,NI3)
      READ(5,750)(X4(I),I=1,NI4)
      READ(5,750)(CF4(I),I=1,NI4)
      READ(5,750)(X5(I),I=1,NI5)
      READ(5,750)(CF5(I),I=1,NI5)
      READ(5,750)(X6(I),I=1,NI6)
      READ(5,750)(CF6(I),I=1,NI6)
      READ(5,750)(X11(I),I=1,NI11)
      READ(5,750)(CF11(I),I=1,NI11)
      READ(5,750)(X12(I),I=1,NI12)
      READ(5,750)(CF12(I),I=1,NI12)
      READ(5,750)(Y1(I),I=1,MC)
      READ(5,750)(Y2(I),I=1,MC)
      READ(5,750)(B(I),I=1,MC)
      READ(5,750)(TP(I),I=1,MC)
C...
C...  GENERATE TIME INTERVAL BETWEEN MISSION STARTS
C...
      IX1=11
      DO 10 I=1,MC
      IX1=IX1+10
      DO 10 J=1,MM
      CALL RANDU(IX1,IY1,YFL1)
      CALL DISTN(X1,CF1,YFL1,RN1,NI1)
      TBMS(I,J)=RN1
      IX1=IY1
   10 CONTINUE
      WRITE(6,500)
  500 FORMAT('1','TABLE A. TIME INTERVAL BETWEEN MISSION STARTS'/)
      WRITE(6,502)(I,I=1,MC)
  502 FORMAT(' ',15X,'UNIT'/' ','MISSION',10I12)
      DO 505 J=1,MM
  505 WRITE(6,501) J,(TBMS(I,J),I=1,MC)
  501 FORMAT(' ',I7,10F12.2)
C...
C...  COMPUTE ACTUAL MISSION STARTING TIMES(CLOCK TIMES)
C...
      DO 20 I=1,MC
      CTMSIN=0.
      DO 20 J=1,MM
      CTMS(I,J)=CTMSIN+TBMS(I,J)
      CTMSIN=CTMS(I,J)
   20 CONTINUE
```

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```
      WRITE(6,510)
  510 FORMAT('1','TABLE B. ACTUAL MISSION STARTING TIMES(CLOCK TIMES)'/)
      WRITE(6,502)(I,I=1,MC)
      DO 515 J=1,MM
  515 WRITE(6,501) J,(CTMS(I,J),I=1,MC)
C...
C...  GENERATE IDEAL MISSION DURATIONS
C...
      IX2=21
      DO 30 I=1,MC
      IX2=IX2+20
      DO 30 J=1,MM
      CALL RANDU(IX2,IY2,YFL2)
      CALL DISTN(X2,CF2,YFL2,RN2,N12)
      D(I,J)=RN2
      IX2=IY2
   30 CONTINUE
      WRITE(6,520)
  520 FORMAT('1','TABLE C. IDEAL MISSION DURATIONS'/)
      WRITE(6,502)(I,I=1,MC)
      DO 525 J=1,MM
  525 WRITE(6,501) J,(D(I,J),I=1,MC)
C...
C...  COMPUTE IDEAL  MISSION FINISHING TIMES(CLOCK TIMES)
C...
      DO 40 I=1,MC
      DO 40 J=1,MM
      CTMF(I,J)=CTMS(I,J)+D(I,J)
   40 CONTINUE
      WRITE(6,530)
  530 FORMAT('1','TABLE D.  IDEAL MISSION FINISHING TIMES(CLOCK TIMES)'/
     1)
      WRITE(6,502)(I,I=1,MC)
      DO 535 J=1,MM
  535 WRITE(6,501) J,(CTMF(I,J),I=1,MC)
C...
C...  GENERATE MISSION TYPES
C...
      IX12=121
      DO 1110 I=1,MC
      IX12=IX12+100
      DO 1110 J=1,MM
      CALL RANDU(IX12,IY12,YFL12)
      CALL DISTN(X12,CF12,YFL12,RN12,N12)
      TYPE(I,J)=RN12
      IX12=IY12
 1110 CONTINUE
      WRITE(6,1300)
 1300 FORMAT('1','TABLE E. MISSION TYPES'/)
      WRITE(6,502)(I,I=1,MC)
      DO 1310 J=1,MM
 1310 WRITE(6,501) J,(TYPE(I,J),I=1,MC)
C...
C...  GENERATE TIME INTERVAL BETWEEN FAILURES AND DURATION OF REPAIR
C...  COMPUTE ACTUAL FAILURE STARTING TIMES AND ACTUAL REPAIR FINISHING
C...  TIMES(CLOCK TIMES)
C...
CC... FOR THE FAILURE INDUCED BY HARDWARES
C...
      WRITE(6,539)
```

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```
  539 FORMAT('1','THE FOLLOWING TABLES SHOW '/' ','TIME INTERVAL BETWEEN
     1 FAILURES(TBHF),'/' ','ACTUAL FAILURE STARTING TIMES(CTHFS),'/' ',
     2'DURATION OF REPAIR(RTH),'/' ','AND ACTUAL REPAIR FINISHING TIMES(
     3CTHRF)'/' ','FOR THE FAILURE INDUCED BY HARDWARES')
      IX3=31
      IX4=41
      DO 540 I=1,MC
      WRITE(6,541)I,I
  541 FORMAT('1','TABLE F.',I2,'.HARDWARE INDUCED',I3//' ','FAILURE AND'
     1/' ','REPAIR INDEX',8X,'TBHF',7X,'CTHFS',9X,'RTH',7X,'CTHRF')
      CTHFSZ=0.
      RTHZ=0.
      IX3=IX3+100
      IX4=IX4+100
      J=1
  545 CALL REFAIL(IX3,IX4,IY3,IY4,X3,CF3,NI3,X4,CF4,NI4,
     1TBHFD,RTHD,CTHFSD,CTHRFD,CTHFSZ,RTHZ)
      TBHF(I,J)=TBHFD
      CTHFS(I,J)=CTHFSD
      RTH(I,J)=RTHD
      CTHRF(I,J)=CTHRFD
      JH(I)=J
      WRITE(6,542)J,TBHF(I,J),CTHFS(I,J),RTH(I,J),CTHRF(I,J)
      CTHFSZ=CTHFS(I,J)
      RTHZ=RTH(I,J)
      IF(CTHFSZ.GE.CTMF(I,MM)) GO TO 540
      J=J+1
      IX3=IY3
      IX4=IY4
      GO TO 545
  540 CONTINUE
  542 FORMAT(' ',I12,4F12.2)
C...
CC... FOR THE FAILURE INDUCED BY OPERATORS
C...
      WRITE(6,550)
  550 FORMAT('1','THE FOLLOWING TABLES SHOW'/' ','TIME INTERVAL BETWEEN
     1FAILURES(TBOF),'/' ','ACTUAL FAILURE STARTING TIMES(CTOFS),'/' ','
     2DURATION OF REPAIR(RTO),'/' ','AND ACTUAL REPAIR FINISHING TIMES(C
     3TORF)'/' ','FOR THE FAILURE INDUCED BY OPERATORS')
      IX5=51
      IX6=61
      DO 551 I=1,MC
      WRITE(6,552)I,I
  552 FORMAT('1','TABLE G.',I2,'.OPERATOR INDUCED',I3//' ','FAILURE AND'
     1/' ','REPAIR INDEX',8X,'TBOF',7X,'CTOFS',9X,'RTO',7X,'CTORF')
      CTOFSZ=0.
      RTOZ=0.
      IX5=IX5+100
      IX6=IX6+100
      J=1+JH(I)
  555 CALL REFAIL(IX5,IX6,IY5,IY6,X5,CF5,NI5,X6,CF6,NI6,
     1TBOFD,RTOD,CTOFSD,CTORFD,CTOFSZ,RTOZ)
      TBHF(I,J)=TBOFD
      CTHFS(I,J)=CTOFSD
      RTH(I,J)=RTOD
      CTHRF(I,J)=CTORFD
      JO(I)=J
      WRITE(6,542)J,TBHF(I,J),CTHFS(I,J),RTH(I,J),CTHRF(I,J)
      CTOFSZ=CTHFS(I,J)
```

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```
      RTO2=RTH(I,J)
      IF(CTOFSZ.GE.CTMF(I,MM)) GO TO 551
      J=J+1
      IX5=IY5
      IX6=IY6
      GO TO 555
  551 CONTINUE
C...
C...  REARRANGE FAILURE STARTING TIMES AND
C...  REPAIR FINISHING TIMES IN ASCENDING ORDER
C...
      DO 1000 I=1,MC
      KA=JO(I)-1
      DO 1000 II=1,KA
      JA=JO(I)-1
      DO 1000 K=1,JA
      IF(CTHFS(I,K+1).GE.CTHFS(I,K)) GO TO 1001
      TEMP=CTHFS(I,K)
      CTHFS(I,K)=CTHFS(I,K+1)
      CTHFS(I,K+1)=TEMP
 1001 IF(CTHRF(I,K+1).GE.CTHRF(I,K)) GO TO 1000
      TEMP1=CTHRF(I,K)
      CTHRF(I,K)=CTHRF(I,K+1)
      CTHRF(I,K+1)=TEMP1
 1000 CONTINUE
C...
C...  PERFORMANCE OF UNIT IN DIFFERENT ENVIRONMENT
C...
   90 IX11=111
      DO 100 I=1,MC
      IX11=IX11+100
      DO 100 J=1,MM
      CALL RANDU(IX11,IY11,YFL11)
      CALL DISTN(X11,CF11,YFL11,RN11,NI11)
      ENVMT(I,J)=RN11
      IX11=IY11
  100 CONTINUE
      WRITE(6,580)
  580 FORMAT('1','TABLE H. PERFORMANCE OF UNIT FOR GIVEN ENVIRONMENT'/)
      WRITE(6,502)(I,I=1,MC)
      DO 586 J=1,MM
  586 WRITE(6,501) J,(ENVMT(I,J),I=1,MC)
C...
C...  OPERATOR PERFORMANCE DURING MISSION
C...
      DO 300 I=1,MC
      TPI=0.
      TPF=TP(I)
      DO 300 J=1,MM
      IF(CTMF(I,J).LE.TPF) GO TO 310
      CSP2=CTMS(I,J)-TPI
      CFP2=CTMF(I,J)-TPF
      TPT=TPF-TPI
      DP(I,J)=Y1(I)+(Y1(I)/TPT+Y2(I)/B(I))*(1.+EXP(-B(I)*CSP2)-
     1EXP(-B(I)*CFP2)-EXP(-B(I)*TPT)))/D(I,J)
      TPI=TPF
      TPF=TPI+TP(I)
      GO TO 300
  310 CSP=CTMS(I,J)-TPI
      CFP=CTMF(I,J)-TPI
```

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```
      OP(I,J)=Y1(I)+Y2(I)/(B(I)*D(I,J))*(EXP(-B(I)*CSP)-EXP(-B(I)*CFP))
  300 CONTINUE
      WRITE(6,620)
  620 FORMAT('1','TABLE I.  OPERATOR PERFORMANCE DURING MISSION'/)
      WRITE(6,591)(I,I=1,MC)
  591 FORMAT(' ',11X,'OPERATOR'/' ','MISSION',10I12)
      DO 625 J=1,MM
  625 WRITE(6,501) J,(OP(I,J),I=1,MC)
C...
C...  COMPUTE EXPECTED MISSION DURATIONS
C...
      DO 1100 I=1,MC
      DO 1100 J=1,MM
 1100 DEO(I,J)=D(I,J)/(ENVMT(I,J)*OP(I,J))
      WRITE(6,1500)
 1500 FORMAT('1','TABLE J. EXPECTED MISSION DURATIONS'/)
      WRITE(6,502)(I,I=1,MC)
      DO 1550 J=1,MM
 1550 WRITE(6,501) J,(DEO(I,J),I=1,MC)
C...
C...  COMPUTE EXPECTED MISSION FINISHING TIMES
C...
      DO 1200 I=1,MC
      DO 1200 J=1,MM
      IF(DEO(I,J).LE.TYPE(I,J)) GO TO 1210
      CTMF(I,J)=CTMS(I,J)+TYPE(I,J)
      GO TO 1200
 1210 CTMF(I,J)=CTMS(I,J)+DEO(I,J)
 1200 CONTINUE
      WRITE(6,1600)
 1600 FORMAT('1','TABLE K. EXPECTED MISSION FINISHING TIMES'/)
      WRITE(6,502)(I,I=1,MC)
      DO 1650 J=1,MM
 1650 WRITE(6,501) J,(CTMF(I,J),I=1,MC)
C...
C...  COMPUTE MISSION RELIABILITY AND AVAILABILITY
C...
CC... INITIALIZATION
C...
      DO 110 I=1,MC
      CTHRF1(I)=0.
      KH1(I)=1
  110 CONTINUE
C...
      DO 200 J=1,MM
      DO 200 K=1,MC
 1976 IF(CTMS(K,J).LE.CTHRF(K,KH1(K))) GO TO 210
      CTHRF1(K)=CTHRF(K,KH1(K))
      KH1(K)=KH1(K)+1
      GO TO 1976
  210 IF((CTMS(K,J).GE.CTHRF1(K)).AND.(CTMS(K,J).LT.
     1CTHFS(K,KH1(K)))) GO TO 220
      AH(K,J)=0.
      RH(K,J)=0.
      RHA(K,J)=0.
      GO TO 200
  220 AH(K,J)=1.
      IF((CTMF(K,J).GT.CTHRF1(K)).AND.(CTMF(K,J).LE.
     1CTHFS(K,KH1(K)))) GO TO 230
  240 RH(K,J)=0.
```

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```
          RHA(K,J)=CTHFS(K,KHI(K))-CTMS(K,J)
          GO TO 200
      230 IF(DEO(K,J).LE.TYPE(K,J)) GO TO 1120
          RH(K,J)=0.
          RHA(K,J)=TYPE(K,J)
          GO TO 200
     1120 RH(K,J)=1.
          RHA(K,J)=DEC(K,J)
      200 CONTINUE
          WRITE(6,585)
      585 FORMAT('1','TABLE L. AVALABILITY OF EACH UNIT'/)
          WRITE(6,581)(I,I=1,MC)
      581 FORMAT(' ',15X,'UNIT     '/' ','MISSION',10I12)
          DO 583 J=1,MM
      583 WRITE(6,501) J,(AH(I,J),I=1,MC)
          WRITE(6,600)
      600 FORMAT('1','TABLE M.  MISSION RELIABILITY OF UNIT     '/' ',10X,'NO
         1TE:IMPLICATION OF (A)  '/' ',15X,'A IS THE DURATION OF MISSION PER
         2IOD CARRIED OUT BY UNIT'/)
          WRITE(6,581)(I,I=1,MC)
          DO 605 J=1,MM
      605 WRITE(6,602) J,(RH(I,J),RHA(I,J),I=1,MC)
      602 FORMAT(' ',I7,10(F3.0,'(',F7.2,')'))
C...
C...  COMPUTE MISSION EFFECTIVENESS
C...
          DO 400 I=1,MC
          SUMCI=0.
          DO 410 J=1,MM
          EM(I,J)=AH(I,J)*RH(I,J)
          SUMCI=SUMCI+EM(I,J)
      410 CONTINUE
          EMC(I)=SUMCI/MM
      400 CONTINUE
          WRITE(6,630)
      630 FORMAT('1','TABLE N.  MISSION EFFECTIVENESS OF EACH UNIT FOR EACH
         1MISSION'/)
          WRITE(6,502)(I,I=1,MC)
          DO 635 J=1,MM
      635 WRITE(6,501) J,(EM(I,J),I=1,MC)
          WRITE(6,650)(I,I=1,MC)
      650 FORMAT('1','TABLE O.  OVERALL MISSION EFFECTIVENESS OF UNIT (ME(I)
         1)'//' ',7X,10I12)
          WRITE(6,651)(EMC(I),I=1,MC)
      651 FORMAT(' ',7X,10F12.2)
          WRITE(6,5000)
     5000 FORMAT('1')
          STOP
          END
C...
C...  GENERATE RANDOM NUMBERS
C...

          SUBROUTINE RANDU(IX,IY,YFL)
          IY=IX*65539
          IF(IY)5,6,6
        5 IY=IY+2147483647+1
        6 YFL=IY
          YFL=YFL*.4656613E-9
          RETURN
```

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```
          END
    C...
    C...  FIT RANDOM NUMBERS INTO DISTRIBUTION
    C...

          SUBROUTINE DISTN(X,CF,RV,RN,NI)
          DIMENSION X(NI),CF(NI)
          RV=100.*RV
          IF(RV.LE.CF(1)) GO TO 20
          I=2
       40 J=I-1
          IF((RV.GT.CF(J)).AND.(RV.LE.CF(I))) GO TO 30
          I=I+1
          GO TO 40
       20 RN=X(1)
          GO TO 100
       30 RN=X(I)
      100 RETURN
          END
    C...
    C...  GENERATE TIME INTERVAL BETWEEN FAILURES AND DURATION OF REPAIR FOR
    C...  HARDWARE AND OPERATOR INDUCED FAILURES.
    C...  COMPUTE ACTUAL FAILURE STARTING TIMES AND ACTUAL REPAIR FINISHING
    C...  TIMES(CLOCK TIMES)
    C...

          SUBROUTINE REFAIL(IXS1,IXS2,IYS1,IYS2,XS1,CFS1,NIS1,XS2,CFS2,NIS2,
         1TBSF,RTS,CTSFS,CTSRF,CTSFSI,RTSIN)
          DIMENSION XS1(NIS1),CFS1(NIS1),XS2(NIS2),CFS2(NIS2)
          CALL RANDU(IXS1,IYS1,YFLS1)
          CALL DISTN(XS1,CFS1,YFLS1,RNS1,NIS1)
          TBSF=RNS1
          CALL RANDU(IXS2,IYS2,YFLS2)
          CALL DISTN(XS2,CFS2,YFLS2,RNS2,NIS2)
          RTS=RNS2
          CTSFS=CTSFSI+TBSF+RTSIN
          CTSRF=CTSFS+RTS
          RETURN
          END

    $ENTRY
```