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ANALYSIS OF THE EFFECTS OF FIXED COSTS
ON LEARNING CURVE CALCULATIONS

THESIS
Charles B. Shea, Captain, USAF
Kenneth P.N. Thomson, Captain, USAF

AFIT/GCA/LAS/94S-6

DEPARTMENT OF THE AIR FORCE

AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

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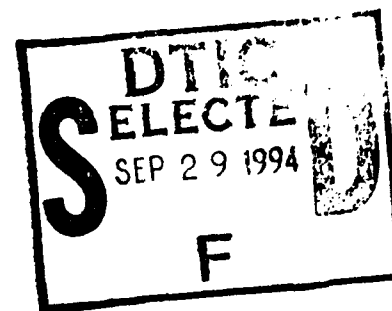Kenneth P.N. Thomson, Captain, USAF

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CALCULATIONS

THESIS

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of the Air Force Institute of Technology

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In Partial Fulfillment of the Requirements for the Degree of

Master of Science in Cost Analysis

Charles B. Shea, B.A.   Kenneth P. N. Thomson, B.S.

Captain, USAF   Captain, USAF

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<div style="text-align: right">Charles B. Shea and Kenneth P.N. Thomson</div>

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Abstract

The goal of this research effort was to analyze the effect of fixed costs on learning curve calculations. Specifically, the research effort focused on two general research areas. The first general area addressed the identification of current cost analysis practice with respect to handling of fixed costs in learning curve calculations. After identification of current practice, the standard unit learning curve model's (AX^b) ability to estimate total production run costs for a new production run when the slope was derived from both historical total cost lot data and historical variable cost lot data was examined. Historical lot cost data was simulated for both the total cost and variable cost cases under three slopes, three fixed cost percentages, and three lot sizing profiles.

The second general area addressed the predictive ability, measured in terms of the mean absolute deviation (MAD), of the AX^b model versus the SAF/FMC model ($F/Q + AX^b$) when fit to total cost lot data. The SAF/FMC model explicitly incorporates a fixed cost component while the AX^b model does not. Comparisons between models using different slopes, fixed cost percentages, and lot sizing profiles were addressed through ANOVA.

The results demonstrated three main points: 1) there are a wide variety of cost analysis practices with respect to treatment of fixed costs in learning curve calculations, 2) the AX^b model by itself was inadequate for production run total cost estimating, and 3) the SAF/FMC model was superior to the standard model under all conditions investigated when fitted to total cost lot data.

ANALYSIS OF THE EFFECTS OF FIXED COSTS ON LEARNING CURVE CALCULATIONS

I. <u>Introduction</u>

<u>General Issue</u>

The Department of Defense (DOD) uses forecasting to determine the future demand for resources. Cost estimating is a valuable area of forecasting and has the following characteristics as described by Nahmias. First, point estimates are usually wrong. Second, a good cost estimate is more than a point estimate. Since point estimates are wrong, a good cost estimate will include some method of including expected cost estimating error. Third, aggregate cost estimates are more accurate and have less variance. To illustrate, "from statistics, the variance of the average of a collection of independent identically distributed random variables is lower than the variance of each of the random variables; that is, the variance of the sample mean is smaller than the population variance." (24:50-51). Fourth, the longer the cost estimate horizon, the less likely the cost estimate will be accurate. Last, cost estimates should not be used to the exclusion of known information. Keeping in mind the characteristics of cost estimating, good cost estimates are invaluable to decision makers when planning their resource requirements.

Within DOD, cost estimating is a forecast of future costs based upon available historical data and on our best understanding of current and future trends. The type of cost estimating method to be used will depend on the amount of detail of program

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definition, level of detail required, availability of data, and time constraints. Three of the most common methods are analogy, grass roots, and parametric (2:Sec 3, 21).

The analogous or comparative method is based on the assumption that a new program can be represented by systems/components produced in the past. The analogous method uses actual costs of a similar program and adjusts these costs for complexity, technical, or physical differences to estimate the cost of the new system. Analogy estimates are most appropriate in the early phases of the acquisition process. These early phases represent the time period when actual cost data is insufficient for detailed analysis, but the system and technical definition are sufficient to draw an analogy to an existing system.

The second method is the grass roots or engineering build-up method. This estimate is conducted at the lowest levels of the work breakdown structure (WBS). "The underlying assumption of the grass roots methodology is that future costs for a system can be predicted with a great deal of accuracy from historical costs of that system." (2:Sec 3, 25). The grass roots method requires time, detailed engineering information, and design stabilization. The drawback of this method is the time and detailed information required. Grass roots is most appropriate in the later phases of the system acquisition process when the system and technical definition are well defined and sufficient actual cost data is available.

The third method is parametric estimation. This method can be used early in the acquisition process since it requires only limited program and technical definition. It uses mathematical and statistical techniques to relate relevant historical data to the system

being estimated. The results of using these techniques are the generation of one or more cost estimating relationships (CERs) or a cost model.

Besides needing only limited program and technical definition for development, CERs are usually simple and easy to use which reduces the time needed to perform cost estimates. A widely used CER is the learning curve (2:Sec 3, 22).

The learning curve is used extensively for estimating production and modification costs of major systems. To use the learning curve properly, DOD cost analysts must clearly understand both the learning curve construction and underlying assumptions. Improperly using the learning curve will likely lead to less accurate estimates and loss of credibility.

Specific Issue

Within DOD, USAF uses learning curves extensively for estimating production costs, specifically in acquisition of new weapon systems and major modifications of existing systems. These production costs can be categorized as recurring and non-recurring. Recurring costs are those "costs common to every production unit" (2:Appendix A, 62) and include costs such as direct materials and direct labor. Non-recurring costs are "elements of development and production cost that generally occur only once in the life cycle of a weapon/support system" (2:Appendix A, 50) and include costs such as tooling, prototyping, and setup. Recently, costs are more commonly divided into the categories of fixed and variable (these two definitions are provided in the definitions section on pg 9).

Basic learning curve theory, when applied to historical dollar costs, mandates the use of only constant dollar recurring (variable) costs in learning curve calculations; calculations which provide learning curve slopes and associated cost estimates for both current and future programs. Unfortunately, numerous USAF cost studies include both recurring and non-recurring historical costs in these calculations. This could lead to inaccuracies in cost estimates for both production and modification programs.

To estimate weapon system production or modification costs using learning curves, USAF cost analysts use the following steps: 1) define the new system, 2) identify comparable systems, 3) fit production lot data from the comparable systems to derive a set of learning curve slopes, 4) derive an expected slope for the new system, and 5) apply the derived slope in the cost estimate. If during these steps recurring and non-recurring, or variable and fixed, costs are not separated, the derived slope used for the estimation could be overstated (too steep) due to the inclusion of non-recurring costs. If the slope is too steep, the production or modification cost estimates for the system would be understated.

To illustrate these concepts, Figure 1 shows two unit formulation learning curves: one has a slope of 80% while the other has a slope of 75% (the steeper slope). Note the unit costs from the 75% curve are lower than those from the 80% curve.
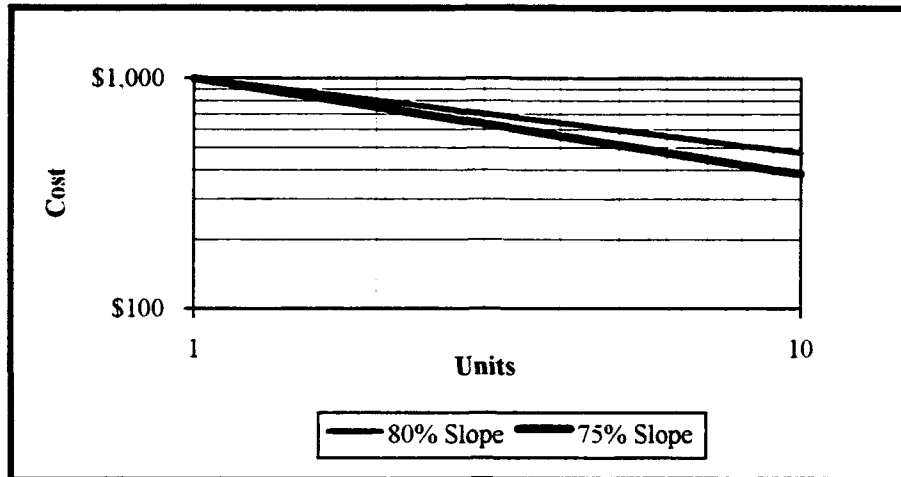
Figure 1 Unit Cost Plot Showing Unit Costs Under Different Slopes

This is but one example of the misapplication of learning curves. One of the main issues to be addressed in this thesis is whether the inclusion of non-recurring (fixed) costs in development and/or application of the standard unit formulation learning curve causes a significant error in production cost estimates.

The other major issue is: If inclusion of fixed costs in the development and/or application of the standard unit formulation causes a significant error in production cost estimates, will a learning curve formulation which includes a fixed cost component do a better job?

General Research Hypotheses

This thesis attempted to address two general research hypotheses:

1. Developing or applying slopes based on total cost data leads to total cost estimates which differ significantly from cost estimates derived using the theoretically correct method of recurring (variable) cost data for either slope development or slope application when computing total costs.

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2. When confronted with total cost and lot data, a standard learning curve model which includes a non-recurring (fixed) cost component is superior to the standard learning curve model in terms of mean absolute deviation.

Research Questions

To test the above hypotheses, the following specific research questions were developed. Each of the research questions related to a specific general hypothesis:

Research Questions for General Research Hypothesis #1.

1. With the standard learning curve model, do USAF cost studies calculate learning curve slopes correctly but apply them incorrectly when estimating total production run costs, i.e., do they use recurring costs only for calculating the slope but include fixed cost in the theoretical first unit cost when applying that slope?

2. With the standard learning curve model, do USAF cost studies develop learning curve slopes incorrectly but apply them correctly when estimating total production run costs, i.e., do they use total cost data for calculating the slope but include variable cost only in the theoretical first unit cost when applying that slope?

3. With the standard learning curve model, do USAF cost studies develop learning curve slopes incorrectly and apply them incorrectly when estimating total production run costs, i.e., do they use total cost data for slope development and include fixed cost in the theoretical first unit cost when applying that slope?

4. Do the correct slope development and incorrect slope applications lead to significant differences in total cost estimates for a fixed length production run when compared to the correct/correct combination?

5. Do the incorrect slope development and correct slope applications lead to significant differences in total cost estimates for a fixed length production run when compared to the correct/correct combination?

6. Do the incorrect slope development and incorrect slope applications lead to significant differences in total cost estimates for a fixed length production run when compared to the correct/correct combination?

Research Questions for General Research Hypothesis #2.

7. Is the SAF/FMC model, a model which includes a fixed cost component, superior to the standard learning curve model in terms of mean absolute deviation under all of the slope levels under consideration?

8. Is the SAF/FMC model superior to the standard learning curve model in terms of mean absolute deviation under all of the fixed cost percentage levels under consideration?

9. Is the SAF/FMC model superior to the standard learning curve model in terms of mean absolute deviation under the lot size profiles under consideration?

General Approach

In order to test our hypotheses, this study will take the following steps: a) conduct a comprehensive review of pertinent literature, b) conduct interviews with appropriate AFIT course instructors and cost analysts in selected system program offices at Wright-Patterson AFB, c) establish a methodology (under certain scope, assumptions, and limitations) to test our hypotheses, d) analyze the output data, and e) draw conclusions and recommend areas for further research.

Limitations and Assumptions of the Study

Limitations.

1. This study will address only the unit formulation of the learning curve.

2. Simulating one new production run from the derived slopes allows only assessment of the magnitude in standard deviations from a theoretical mean as a judgment of the significance of the underestimation or overestimation.

3. The ranges for the slope (75%, 85%, and 95%) were chosen in order to compare systems which would encounter a small learning effect (5%) with systems which would have a larger learning effect (25% and 15%). Also, this range is consistent with different systems within the Air Force which have shown learning from less than 5% to greater than 30%.

4. The ranges for the fixed cost burden (20%, 35%, and 50%) were chosen in order to determine the effects low, medium and high burden rates would have on cost estimates. According to a Balut, Frazier, and Bui study in 1991 (5:3), airframe manufacturers were averaging around 33% fixed costs with the percentage increasing. Also, Moses used a range of 15%, 33%, and 50% when studying the effects of fixed cost burden in his studies from 1990 to 1991 (22:12, 23:14). Our range was chosen based upon these two facts.

5. Only lot fixed costs such as setup, tooling, and ordering are captured in this study.

6. The use of a fixed effects model for the analysis of variance (ANOVA) makes inferential conclusions to other factor levels statistically improper.

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Assumptions.

1. The population follows the unit formulation of the learning curve theory.

2. The error term for the learning curve formulation, expressed in log space, is a random independent term with a mean of zero and a constant variance.

3. Fixed and non-recurring costs and variable and recurring costs are treated synonymously.

Definition of Terms

Variable/Recurring Costs: "costs common to every production unit" (2:Appendix A, 62)

Fixed/Non-recurring Costs: elements of production costs that generally occur only once
    per lot during a production run of a weapon/support system (2: Appendix A, 50).

Learning: The improvements (lower costs or less labor hours required) represented by the
    results not only of cumulative repetition of past practices, but of changes in:
    production designs; product mix; operating technology; facilities and equipment;
    management, planning, and control; materials quality; and labor capabilities and
    incentives (21:11).

Overview of Remaining Chapters

The remaining four chapters address all of the research questions. The next chapter, Chapter 2, is the literature review. Relevant literature was reviewed, the basics of the learning curve described, and models which treat fixed costs were reviewed. Chapter 3 outlines the methodology used to answer the research questions. It includes the techniques and tests used as well as the justification for the selected techniques and tests. Chapter 4 analyzes the results of the techniques and tests described in Chapter 3. Finally, Chapter 5 states the conclusions drawn from the analysis and states areas for future research.

II. Literature Review

Chapter Overview

The first section defines the learning curve theory, explores a brief history of learning curves, lists various learning curve formulations, examines the two common log-linear formulations, and selects the best formulation for this thesis effort. The second chapter section explores the fixed component of costs, its functional treatment, and methods to include a fixed component of costs in learning curve calculations.

Learning Curve Theory

Learning curve theory, in its most elementary expression, states that as the quantity of units produced increases, the cost per unit of production decreases in some regular pattern (15:9 Feb 94). According to Asher, "the theory of the progress curve in its most popular form states that as the total quantity of units produced doubles, the cost per unit declines by some constant percentage. The cost per unit may be either the average cost of a given number of units or the cost of a specific unit"(3:1). Using the average cost of a given number of units would represent the cumulative average formulation while using the cost of a specific unit would represent the unit formulation. The 'cost' described by Asher has traditionally been measured with labor hours or constant dollar costs. This thesis deals with constant dollar costs, but results could be generalized to labor hours as well.

Either of the popular formulations (cumulative average and unit) of learning curve theory discussed above demonstrate a decreasing exponential function plotted on

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arithmetic grids and a decreasing linear function plotted on logarithmic grids. For

illustrative purposes, Figures 2 and 3 show the unit formulation for a learning curve with a

first unit cost of $1,000 and a slope of 80%. The slope will be outlined and explained later

in another section.
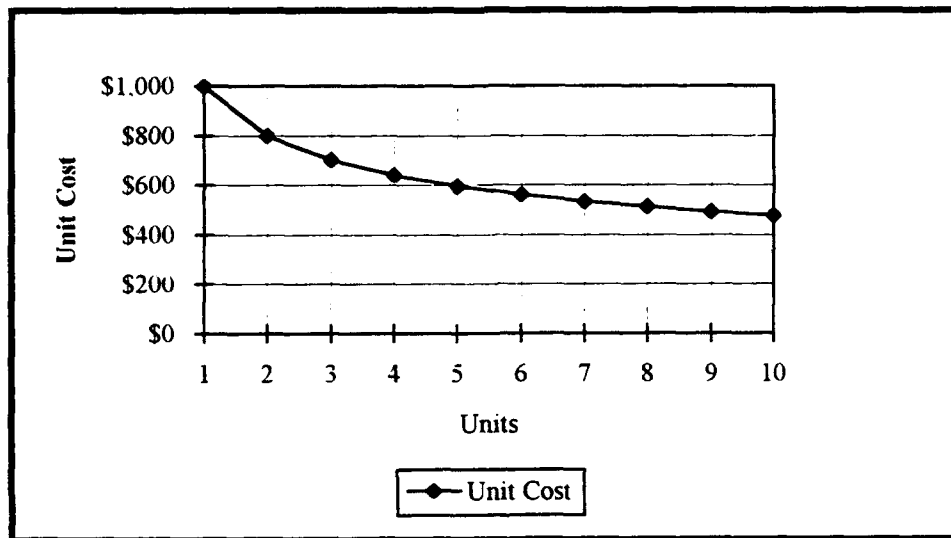
Figure 2 Unit Learning Curve Plotted on Arithmetic Grids
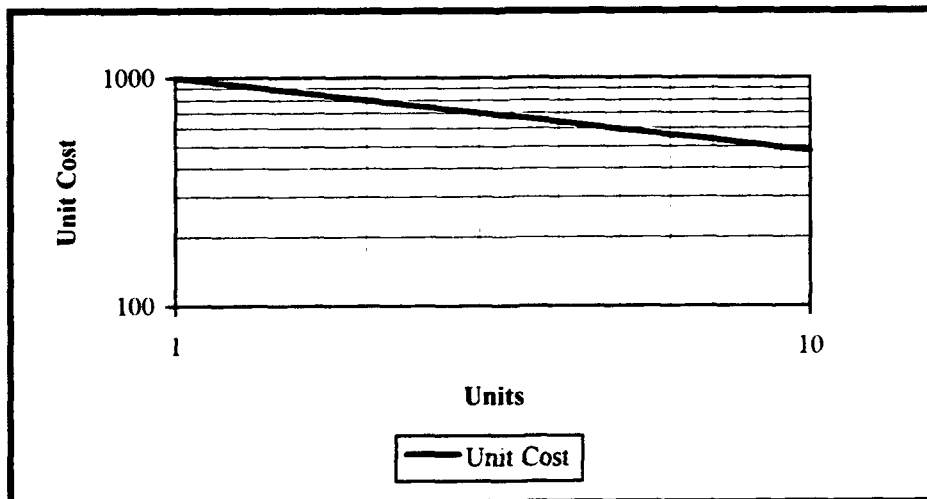
Figure 3 Unit Learning Curve Plotted on Logarithmic Grids

A number of different causes account for the decline in unit cost with increases in production. Some of those causes are as follows: 1) direct labor job familiarization resulting from repetition, 2) improvements in indirect (support) labor, 3) improvements in management, 4) advances in technology, 5) better designs and production methods, 6) reduced materials waste and scrap, 7) improvements in tooling, and 8) competition (3:3, 14:17, 26:38, 32:306-309). These causes merely comprise a representative sample of the many reasons unit costs decline with increasing production. Of the causes listed above, the first reason, direct labor job familiarization through repetition, has received the widest coverage in learning curve literature.

Given the multiple causes for unit cost reductions, the learning curve has taken on many different names which attempt to capture the essence of the differing causes. Some of those specific names include cost improvement curve, experience curve, and progress curve (32:303). Each of these names is used interchangeably with learning curve throughout the literature to describe the presence of the learning curve pattern. For consistency, the term learning curve will be used throughout this thesis.

History

The pioneering work in learning curves began in 1922 when T.P. Wright began researching the underlying concepts of learning curve theory. In February 1936, he formalized his research through publication of an article in the Journal of Aeronautical Sciences titled "Factors Affecting the Cost of Airplanes" (31:122). Wright identified several factors which affect airplane production cost: design, tooling and adaptability of the design to the tooling, engineering changes during production, size, weight, and the

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number of airplanes built. Wright asserted that the three recurring cost components, i.e., direct labor, materials, and overhead, vary with increases in production quantities (31:124-125).

With respect to direct labor, Wright concluded that average labor costs when compared to production quantity exhibited a decreasing exponential pattern (ratio relationship) that was linear when plotted on logarithmic grids (refer to Figures 2 and 3). He identified that decreasing exponential pattern as an "eighty percent curve" to which he attributed a specific meaning. Wright said the "eighty percent curve represents the factor by which the average labor cost in any quantity shall be multiplied in order to determine the average labor cost for a quantity of twice that number of airplanes" (31:124-125). In effect, Wright discovered a relationship between average labor costs and cumulative production. His research became widely known as the cumulative average formulation of learning curve theory. This specific formulation will be explained later in the formulations section.

During World War II, interest in the learning curve concept increased as defense production facilities struggled to plan manpower and financial requirements necessary for wartime production of ships and aircraft (32:303). In the early 1940s, J.R. Crawford, while working for the Lockheed Aircraft Corporation, published an undated booklet for Lockheed personnel titled Learning Curve, Ship Curve, Ratios, Related Data (3:21). In the booklet, Crawford presented an equation, based on his research, that showed a relationship between the direct labor hours per unit of production compared to the cumulative unit number of production. The mathematical function was a decreasing exponential function like Wright's; however, it had an entirely different meaning. While

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Wright focused on the average cost based on total units produced, Crawford focused on the unit cost of any unit in the production run. Crawford's research led to the formulation commonly known as the unit formulation of learning curve theory. This specific formulation will also be explained later in the formulations section.

After World War II, the USAF Air Material Command (AMC) conducted a comprehensive study and published the most famous data source for post World War II learning curve studies. That data source was titled <u>Source Book of World War II Basic Data: Airframe Industry, Volume 1</u> (3:38). This source contained a comprehensive collection of data for all aircraft manufacturers who produced military aircraft between 1940 and 1945.

Later the USAF contracted with the Stanford Research Institute to study and validate the unit learning curve formulation (1:Sec 1, 2). The study, led by J.R. Crawford, used all World War II airframe labor data and confirmed that direct labor hours declined by a constant percentage over successively doubled quantities of units produced. Many subsequent studies on learning curves have been published since these early studies of the 1930s and 40s to address underlying assumptions in the unit and cumulative average formulations, linearity of the learning curve, the effects of production rate, etc. Virtually all of these studies tie back to the original formulations proposed by Wright and Crawford.

Mathematical Expression of the Learning Curve

Numerous learning curve formulations have surfaced since the identification of the learning curve relationship in 1936. Some of the more prominent expressions include the log-linear (log-log) model, rate adjustment formulation, Stanford-B formulation, S curve

formulation, and plateau formulation. Each formulation has its own unique qualities and characteristics; however, the log-linear formulation is the most widely accepted in practice (32:304) and is the only formulation considered in this thesis.

Log-Linear Formulations

A log-linear expression simply describes the expected functional pattern of costs with increases in production; however, it does not define the underlying specific formulation under consideration. As mentioned in previous sections, two primary formulations using the log-linear expression exist today: the cumulative average formulation and the unit formulation.

Cumulative Average Formulation. The cumulative average formulation, also known as the Wright or Northrop construction, states that as the cumulative number of units produced doubles, the cumulative average cost per unit declines by a constant percentage (15:16 Feb 94). This can be expressed by the following function:

$$\overline{Y}_x = AX^b \tag{1}$$

where

$\overline{Y}_x$ = average cost of units 1 through X
A   = constant representing the theoretical cost of the first unit,
b   = learning curve exponent where $-1 \leq b \leq 0$

Unit Formulation. The unit formulation, also called the Boeing or Crawford construction, states that as the total quantity of units produced doubles, the cost per unit declines by a constant percentage (15:9 Feb 94). This can be expressed by the following function:

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$$Y_x = AX^b \qquad (2)$$

where

Y_x = the cost of unit X
A = constant representing the theoretical cost of the first unit,
b = learning curve exponent where $-1 \leq b \leq 0$

<u>Learning Curve Exponent.</u> The learning curve exponent, b, is related to the slope and rate of change of the learning curve (1:Sec 2, 2). The formula for calculation of the learning curve exponent is as follows:

$$B = \frac{\log(\text{slope expressed in decimal form})}{\log(2)} \qquad (3)$$

The slope of the learning curve is different from the normal mathematical definition of slope (i.e., rise/run or $\Delta Y/\Delta X$). Instead, the learning curve slope is related to the learning rate which is defined as the percentage of cost decrease between doubled quantities (14:17). For example, if unit 1 costs \$100 and unit 2 costs \$90, then (Cost of Unit 2) ÷ (Cost of Unit 1) = .90, so there is a 10% learning rate due to the 10% decline in cost between doubled quantities. The slope is nothing more than (1 - the learning rate), or in this case 1 - 10% = 90%. With this in mind, an alternative formula for computing b is as follows:

$$B = \frac{\log(1 - \text{learning rate in decimal form})}{\log(2)} \qquad (4)$$

<u>Comparison of the Two Formulations.</u> The two formulations functionally appear very similar; however, they are interpreted differently and also yield different results. The primary difference is the variable used on the vertical (Y) axis as the cost value. Let's

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define Y_x as the cost of unit X and $\overline{Y}_x$ as the average cost of X units. For the cumulative average formulation, the $\overline{Y}_x$ is believed to be appropriate, whereas the Y_x is used in the unit formulation (18:303). Both formulations model the fact that costs decrease by a constant percentage between doubled quantities (2:Sec 7, 10) which translate into linear functions when plotted on log-log grids; however, when both are calculated from the same data and plotted, both cannot be linear simultaneously (18:303). A mathematical table and graphs illustrate this point.

Suppose A = $1,000 and the Slope = 80%. The table that follows (Table 1) shows the calculated costs under both formulations:

Table 1 Comparison of Cumulative Average and Unit Formulations

Unit #	Cum Avg Formulation (80% Slope)		Unit Formulation (80% Slope)	
	Cum Avg Cost	Unit Cost	Cum Avg Cost	Unit Cost
1	$ 1,000	$ 1,000	$ 1,000	$ 1,000
2	$ 800	$ 600	$ 900	$ 800
3	$ 702	$ 506	$ 834	$ 702
4	$ 640	$ 454	$ 786	$ 640
5	$ 596	$ 418	$ 748	$ 596
6	$ 562	$ 392	$ 717	$ 562
7	$ 534	$ 371	$ 691	$ 534
8	$ 512	$ 355	$ 668	$ 512
9	$ 493	$ 341	$ 649	$ 493
10	$ 477	$ 329	$ 632	$ 477

Under the cumulative average formulation, note the cumulative average cost declines by a constant percentage between doubled quantities; however, when converted to incremental unit costs, the percent decline is non-constant. Under the unit formulation,

the reverse holds true, i.e., the unit formulation shows the constant percentage decline between doubled quantities while the cumulative average shows a non-constant percentage decline.

Figure 4 and Figure 5 illustrate these concepts graphically. Figure 4 plots the data from Table 1 shown under the cumulative average formulation while Figure 5 plots the data from Table 1 shown under the unit formulation. On Figure 4, note the cumulative average function is linear while the incremental unit cost is curvilinear. Figure 5 shows the reverse relationship where the unit formulation function is linear while the cumulative average function is curvilinear. Additionally, given the same slope and unit 1 cost, note the cumulative average function is always above the unit function except at unit 1 where they are equal. This relationship is often mistaken to imply that an estimate would be higher if the cumulative average formulation was selected over the unit formulation. If lot costs were computed from the information in Table 1, the cumulative average formulation lot costs would fall below the unit formulation lot costs. For example, if Lot #1 consisted of units 1-4, then total lot cost under the cumulative average formulation would be $2,560 whereas the total lot cost under the unit formulation would be $3,142. As a result, the cumulative average formulation lot costs are $582 less than the unit formulation lot costs.
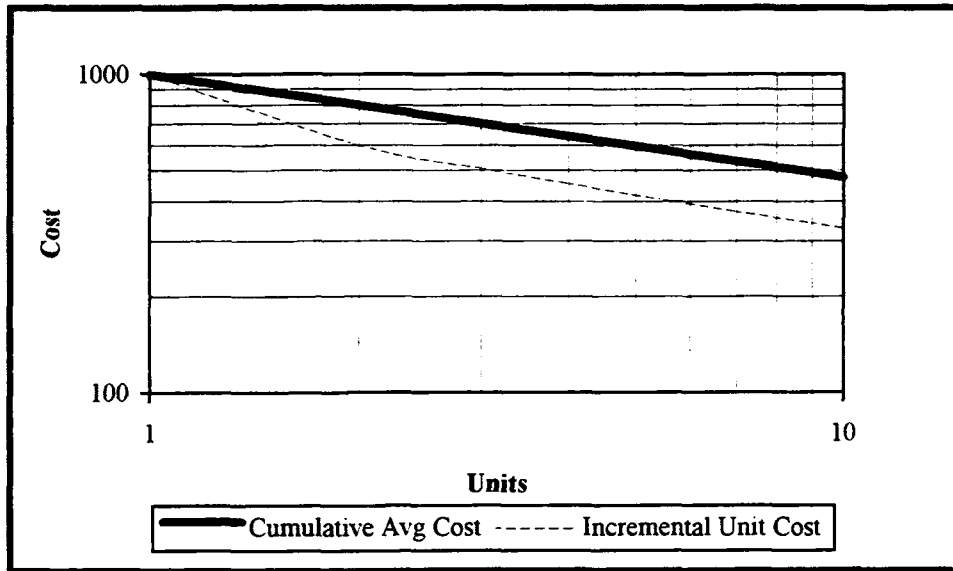
Figure 4 Cumulative Average Plot and Corresponding Incremental Unit Cost
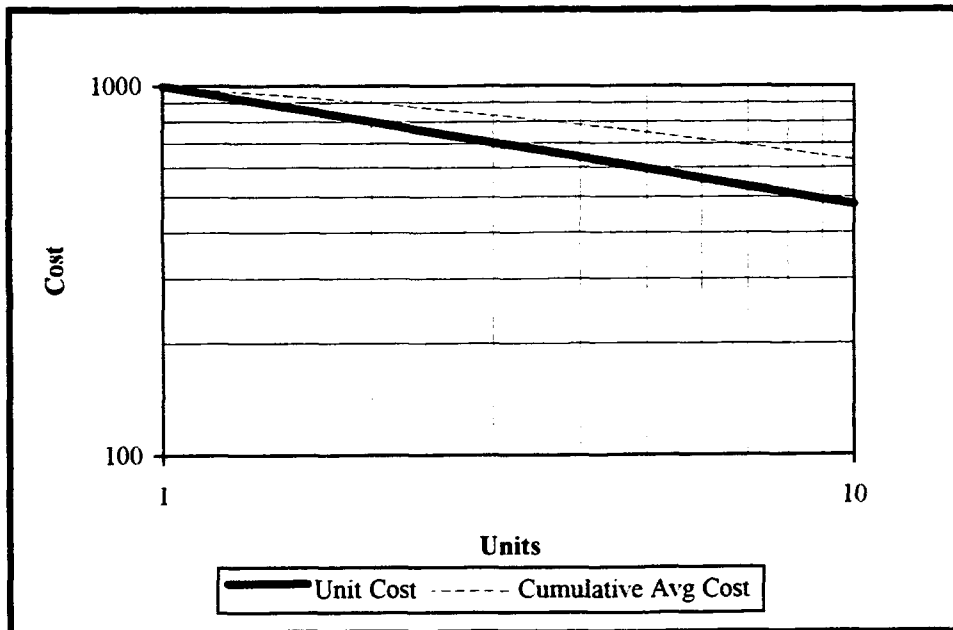
Figure 5 Unit Cost Plot and Corresponding Cumulative Average Cost

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Selected Formulation

Since most of the DOD and industrial applications today use the unit formulation (7:59, 13:8, 15:14 Feb 94, 26:38), this thesis effort will concentrate solely on the unit formulation.

Fixed Costs

Under the standard learning curve formulation (as discussed in the history of learning curves), only variable costs are used in calculation of the unit cost. This has one of two implied meanings: 1) all costs, including overhead, are variable or 2) fixed costs are not included in the computation of unit cost. The second implied meaning basically means variable and fixed costs are calculated separately then added for a total cost estimate.

A problem with the first implied meaning is not all overhead costs are variable in the short term or, in many instances like plant and equipment, in the intermediate term. According to Balut, Frazier, and Bui, "the assumption that all costs are variable is no longer acceptable. Almost one third of total cost is fixed and the proportion is increasing" (5:3). The first implied meaning appears to be the way fixed costs are considered, since learning has been defined in very broad terms to include areas beyond the reduction in costs due to the gaining of experience through repetition. This broad definition of learning includes savings due to improvements in facilities and equipment as well as better management, planning, and control. Facilities, equipment, and management are traditionally classified as fixed costs (11:35).

Treating fixed costs as variable costs causes greater uncertainties in the total cost estimates. Traditional learning curve theory states as the quantity produced doubles, the recurring (variable) cost decreases at a constant rate. In no literature reviewed has the behavior of fixed costs been said to exhibit this same behavioral pattern. Since the behavior of fixed costs differs from the behavior of variable costs, including fixed costs into traditional learning curve calculations would create uncertainty in the accuracy of the calculations.

One of the effects fixed costs would have on learning curve calculations is that as the quantity of a production lot increases, the fixed cost per unit decreases within the production lot. This happens since average fixed cost is determined by dividing the total fixed cost incurred by the quantity of the production lot. This effect has nothing to do with learning.

Distribution of Fixed and Variable Costs

A problem still exists with how one categorizes costs between fixed and variable costs and how to account for fixed costs within the learning curve formulation. Balut, Frazier, and Bui stated "...industry accounting systems do not provide visibility into fixed costs. This cost component is estimated, even by the accountants within the firm" (5:1).

They follow by providing a typical cost breakdown of a typical contractor:

> 39% -- Direct Materials (all variable)
> 16% -- Direct Labor (all variable)
> 45% -- Overhead (both fixed and variable) (5:2)

The question is how to break the 45% overhead cost into fixed and variable categories.

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Distribution of Fixed and Variable Overhead. According to Balut, Frazier, and Bui, two methods can be used to do this. The first method is the account classification method (ACM). ACM is best applied by contractors and requires a thorough understanding of the particular manufacturing operation and how the individual accounts mirror these activities. Typically, the government does not have the access, time, or expertise to use this method. Additionally, the contractors consider the results of the ACM method proprietary information (5:2).

The second method is through regression analysis. An equation is hypothesized to model the distribution of overhead costs into its fixed and variable components. This method is applied by both the government and contractors alike. The problem the government has is its inability to compare its regression results with either the contractor's ACM results or their regression results to validate the government's regression equation. Once again, the contractor's regression equations and results are usually classified as proprietary data and not made available to the government. This data restriction severely hampers government analysts from accurately breaking the overhead portion of total cost into its two components.

Another Balut article broke overhead costs into three categories: 1) variable to include employee benefits, payroll taxes, and other production-related indirect costs tied to the number of direct laborers; 2) fixed to include depreciation, amortization, insurance and other costs that do not vary with activity rate; and 3) semi-variable to include utilities (4:64). A prime example of how semi-variable costs present a problem is electricity. A certain amount of electricity is needed regardless of production, but as production increases -- electrical usage increases. The problem is: how is the electric bill allocated

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across the company? This problem can be overcome if changes in total overhead expenses are observed with respect to activity rate within the plant (overall plant production) rather than functionally (where the expenses actually occurred within the plant) (4:65).

Models for Treating Fixed Costs

The treatment of fixed costs in learning curve calculations has received more consideration recently. A possible reason for this attention is research has indicated the percentage of fixed costs to total costs has increased as industry moves towards automation. For airframe manufacturers, the fixed component of cost has risen from 19% two decades ago to 33% in 1991 (5:3).

Today, government analysts are concerned that as the military draws down and military weapon system production declines, the fixed overhead component of cost will continue to increase as a percentage of total costs (6:2 Sep 93). This view is comparable to that expressed by Gansler in a 1980 study of the defense industry. Gansler predicted that as defense spending decreased, weapon system overhead costs and total costs would increase. Further, Gansler contended that high levels of excess capacity drive up overhead costs (10:226).

Several methods have been hypothesized to include fixed costs in the learning curve models. The first group of methods (overhead cost models) uses the traditional unit formulation to estimate variable costs and a separate equation to estimate overhead costs. Total costs are determined by summing the variable and overhead costs.

The second group of methods (total cost models) includes both the overhead and variable cost components in a comprehensive model to estimate total cost.

<u>Overhead Cost Models.</u> 1) Kaplan proposed a basic linear model for distribution

of overhead costs based on a single cost driver, direct labor hours (DLH) (16:90). The

basic model was:

$$OH = b_0 + b_1*DLH \qquad (5)$$

where

        OH   = overhead
        b_0 = intercept (fixed cost)
        DLH = direct labor hours
        b_1 = parameter

Kaplan found one of the drawbacks to the basic model was it did not allow for

changes in fixed overhead costs found in many businesses. His solution for this problem

was inclusion of additional variables. One possible addition is a categorical variable for

jumps or shifts in fixed overhead costs during the estimation period due to increased

supervisory personnel, increased charges due to new machines, or expansion of the floor

space (16:91). A second possible addition is a time indexed variable to account for steady

increases in fixed overhead costs (16:92). The two adjusted models follow:

Basic model adjusted for a shift in fixed overhead costs.

$$OH = b_0 + b_1*DLH + b_2*JUMP \qquad (6)$$

where

        OH   = overhead
        b_0 = intercept (fixed cost)
        DLH   = direct labor hours
        JUMP = categorical variable(= 0 for no JUMP)
                                (= 1 for JUMP)
        b_1, b_2 = parameters

Basic model adjusted for a steady increase in fixed overhead costs.

$$OH = b_0 + b_1*DLH + b_2*TIME \qquad (7)$$

where

OH   = overhead
b_0 = intercept (fixed cost)
DLH   = direct labor hours
TIME   = time indexed variable (by month, quarter, year, etc.)
b_1, b_2 = parameters

The fixed overhead cost would be calculated in the following manner:

For the JUMP model

$$FOH = b_0 + b_2*JUMP \qquad (8)$$

For the time indexed model

$$FOH = b_0 + b_2*TIME \qquad (9)$$

2) Balut, Frazier, and Bui: Their study was an extension of Kaplan's model by making the model sensitive to the stock of capital facilities and equipment as well as direct labor. Also, it redefines the fixed component of overhead to include the capital measure and pools the cross-sectional and time series data to produce an industry wide model rather than a contractor specific model of overhead costs (5:8-9). Their model follows:

$$Y = a + b*K + c*DC + e \qquad (10)$$

where

Y   = plant-wide overhead
K   = net book value (used as proxy for value of capital)
DC   = direct costs
a   = intercept
b and c = parameters
e   = error term with mean zero and a constant variance (used to accommodate measurement error and the unsystematic effects of omitted variables)

From the above equation, the variable and fixed portions of overhead are defined as follows:

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$$\text{variable overhead} = c*DC \qquad (11)$$

$$\text{fixed overhead} = a + b*K \qquad (12)$$

$$\text{fraction of overhead that is fixed} = (a + b*K)/Y \qquad (13)$$

$$\text{fraction of total business that is fixed} = [(a + b*K)/Y]*[Y/\text{total business}] \qquad (14)$$

Both of the preceding models allow overhead costs to be estimated separately and then added to the estimated direct variable costs to estimate the total cost.

Total Cost Models. 3) Balut: He proposed a two step approach to cost estimating (4:65). First, use the learning curve which assumes fixed costs are 100% variable. Second, correct for the erroneous assumption that all costs are variable through use of a rate adjustment factor which accounts for the redistribution of fixed overhead across the new activity levels within the plant. That rate adjustment factor is (4:66):

$$F_i = [Qold_i/Qnew_i]^b*P*R + (1 - P*R) \qquad (15)$$

where

i = lot number
F_i = factor used to adjust estimate for lot i derived in step one
$Qold_i$ = quantity of aircraft in lot i in the basic service program
$Qnew_i$ = quantity of aircraft in lot i in the alternative program
b = parameter
P = fraction of price represented by overhead
R = fraction of overhead that is fixed in the short term

Lot quantity is used as a proxy for lot direct cost.

The unit cost equation would be as follows (4:70):

$$Y = A*X^b*F_i \qquad (16)$$

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where

Y = unit cost
A = first unit variable cost
X = midpoint of lot to be estimated
b = slope coefficient
F_i = as defined above

4) SAF/FMC: This method was briefed by SAF/FMC in 1993.

$$Y = F/Q + A*X^b + e \qquad (17)$$

where

Y = unit cost
F = fixed costs per lot
Q = quantity produced per lot
A = first unit variable cost
X = lot plot point (of each lot)
b = slope coefficient
e = error term with mean zero and a constant variance (used to accommodate measurement error and the unsystematic effects of omitted variables)

SAF/FMC used simulated data to test the accuracy of their model against the traditional learning curve model and the production rate learning curve model. The SAF/FMC study showed the learning curve model with a fixed cost component had a higher adjusted coefficient of determination (adjusted R-squared) and did a better job of predicting future lot costs (27:14,16-19).

5) Moses: In a 1990 article, Moses included a fixed cost component directly in his empirical model (21:16). His empirical model not only includes a production rate term, but adds a company-wide activity rate and an industry utilization rate. Instead of adding the fixed cost component as in the SAF/FMC model, he multiplied the term as follows:

$$Y = A*X^b*PR^d*CR^f*IR^g*e^{hFC} \qquad (18)$$

where

Y	= unit cost
A	= first unit variable cost
X	= lot midpoint
PR	= production rate
CR	= company-wide activity rate
IR	= industry utilization rate
FC	= fixed capacity cost (fixed cost burden -- measured by firm-wide property, plant, and equipment during production of the lot divided by the average property, plant, and equipment during the years of production on the program)
e	= constant (natural logarithm ≈ 2.7183)
b, d, f, g, h	= parameters

Moses found the significance of the fixed cost component to vary dependent on other factors. He tested his model at three fixed cost burden rates: 15%, 33%, and 50%. The fixed cost component was significant when the fixed cost burden was high (33% and 50% burden rates) and when future production was low or decreasing (22:24).

Model Summary/Selection

The results reported from SAF/FMC and Moses indicate that the inclusion of a fixed cost component is necessary for increasing the accuracy of learning curve calculations. Moses' finding that the fixed cost burden became significant at 33% with low or decreasing production levels was particularly interesting in light of the work of Balut, Frazier, and Bui and others who reported the fixed component of cost for airframe manufacturers is around 33%. Furthermore, the DOD is undergoing a drawdown and its contractors are experiencing lower production rates and lower future demand for weapon systems. This could drive up the fixed component of total costs.

Chapter Summary

This chapter defined learning curve theory, explored a brief history of learning curves, examined mathematical expressions of the learning curve, reviewed the two common log-linear formulations, and selected the more widely used log-linear formulation for this thesis effort. Additionally, this chapter explored the fixed component of cost, its functional treatment, models for treatment of fixed costs, and the model most relevant for further investigation.

III. Methodology

Chapter Overview

This chapter discusses the methodology to meet the research questions specified in Chapter 1. Specifically, this chapter explains the three areas of research: 1) interview process, 2) comparison of correct/incorrect parameter development and application when estimating total production run costs, and 3) a comparison of the cost prediction variability between the standard unit learning curve model (AX^b) and the SAF/FMC model $(F/Q + AX^b)$ when fitted to total cost lot data. Within each of these research areas, the general processes are outlined.

Interview Process

Personal interviews were conducted with cost analysts at Wright Patterson AFB to address the first three research questions specified in Chapter 1. The primary purpose of the personal interviews was to sample current cost estimating practice to verify that a hypothesized problem with learning curve slope parameter development or application indeed existed. The results of the personal interview process are included in Chapter 4.

Comparison of Correct/Incorrect Parameter Development and Application

Since the interview process yielded a wide variety of methods for using the standard unit learning curve model (AX^b) when estimating total production run costs, the question arose as to whether or not these different methods made a difference when compared to the correct development and correct application of the slope parameter when

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computing total production run costs. To address this question, the following process to

investigate Research Questions 4-6 from Chapter 1 was developed.

The four possible combinations of developing and applying the slope parameter,

summarized in Table 2,

Table 2 Combinations of Correct/Incorrect Slope Development & Application

Abbreviation for Combination	Slope Development	Slope Application to Cost Estimate
CC	Correct	Correct
CI	Correct	Incorrect
IC	Incorrect	Correct
II	Incorrect	Incorrect

were simulated in the following manner. First, the correct and incorrect slope coefficients

were developed. After the slope coefficients were developed, the correctly and incorrectly

developed slope coefficients had to be applied correctly and incorrectly. Correct and

incorrect application was based on application of the slope coefficient to theoretical first

unit (T1) values which contained variable and total costs, respectively.

The simulation process resulted in four different estimates for total cost for each

treatment, with each treatment being a unique combination of factors. The data simulation

process is explained in detail in following paragraphs.

Correct Slope Development. For correct slope development a number of steps

were taken as illustrated in Figure 6. Each of these steps will be explained in turn.

?= Wildcard for One Character

Simulate Production Run Data for 100
Production Runs per Slope with
Dispersion
Three Programs: NORMAL?.SAS
1

Three Outputs from
NORMAL*.SAS
Programs
(NORMAL?.DAT)
2

9 Lot Sizing Programs for 9
Combinations (3 Slopes, 3 Lot
Sizing Profiles)
(?LT?.SAS)
3

Output from Lot Sizing
Programs
(?LT?.DAT)
4

9 programs to fit the
Unit model by production
run to output from lot
sizing programs
(UNIT??.SAS)
6

Production run
numbering scheme to
segregate different
production runs
(PRDRUN.DAT)
5

Slope Coefficient Per Production Run
for Unit Model (100 slope
coefficients per program, 900 total
slope coefficients) written to
permanent data sets
(PARAMS.?U?)
7

2 Programs to take an average slope coefficient
for each combination (e.g., D1 Correct, D1
Incorrect, E1 Correct, E1 Incorrect) and write
them to two permanent data sets
(UNITC?.SAS)
8

Average Slope Coefficient For Each
Combination (9 average slope
coefficients per data set) written to
two permanent data sets
(PARAMS.TESTC?T)
9

t Test of Average, Correctly
Developed Slope Coefficients
from Population Mean
(Excel Spreadsheet)
10

Figure 6 Correct Slope Development Before Correct and Incorrect Application

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Production Run Data Simulation. In order to simulate production run data, specific factors and levels had to be selected . Those factors and levels selected are summarized in Table 3. Additionally, the number of production runs, number of units within the production run, number of lots within the production run, first unit cost, and level of dispersion had to be selected prior to data simulation.

Table 3 Simulation Factors and Levels

	Level 1	Level 2	Level 3
Slope	75% Slope	85% Slope	95% Slope
Lot Size Profile	Increasing	Equal	Decreasing

Variable Cost Data. The SAS system was used to simulate variable cost data (Steps 1 and 2 from Figure 6) for 100 production runs for three unit formulation learning curves (AX^b) with 75%, 85%, and 95% slopes; 480 units; first unit cost of $25,000; and a normally distributed random error.

This variable cost data simulation yielded three data files summarized in Table 4. A sample program is located in Appendix A (pg 92) with notes regarding modifications for each treatment.

Table 4 Three Variable Cost Simulation Programs and Output Data Files

Programs	Output Data File	Data File Description
NORMAL1.SAS	NORMAL1.DAT	75% Slope, 48000 Observations
NORMAL2.SAS	NORMAL2.DAT	85% Slope, 48000 Observations
NORMAL3.SAS	NORMAL3.DAT	95% Slope, 48000 Observations

The variable cost data was generated in the log-linear state and then transformed to unit space with a logarithmic transformation. The following formula was used to generate the data:

$$LNY = A + B*LNX + C*Z \qquad (19)$$

where

LNY = natural log(ln) of the unit variable cost
A   = ln($25,000) ≈ 10.12663 ($25,000 is the first unit variable cost)
LNX = natural log of the sequential unit number 1-480
B   = ln(slope in decimal form)/ln(2)
C   = standard deviation; a constant representing mean estimating error
Z   = RANNOR(seed)

The last term in Equation 19, C*Z, was used to introduce variability in the simulated data. A standard deviation of 0.20 was chosen for C. The SAS function for normal random error terms, RANNOR(seed), was used in consonance with C. The RANNOR(seed) generates a value from a normal distribution with a mean of zero and a standard deviation of one. The seed is nothing more than an arbitrary number to start the random number generation process (28:589).

Under the normal distribution, approximately 99.7% of the data should fall within 3 standard deviations of the mean (8:150), so the range of -3C to +3C should cover the vast majority of data. With a standard deviation of .20, the range would be from -.60 to +.60 in log space or .548 to 1.822 in unit space. Since the error term becomes a multiplicative error term in unit space, the first unit cost would range from ($25,000*.548) to ($25,000*1.822) or from $13,720 to $45,553. The actual range based on program runs

(Steps 1 and 2 from Figure 6) was from $13,286 to $41,010 with a mean first unit cost of $25,210.

Segregation of Production Run Data Into Lot Data. With the variable cost data generated from the tasks above, this data had to be broken out into lot data for each of the 100 production runs (Step 3 from Figure 6). Lot sizing programs were written to breakout this cost and unit data into lots for each production run (See Appendix A, pg 93).

Twelve lots were formed for each production run. This translated into 10,800 lot arrays. Each lot array contained six elements as follows:

Element 1 = the cumulative units for production run
Element 2 = the cumulative total variable cost for production run
Element 3 = the total lot cost (includes variable costs only)
Element 4 = the algebraic lot plot point
Element 5 = the lot average cost (includes variable costs only)
Element 6 = the lot size.

Lot Size Profiles. The units and their associated costs for each production run had to be grouped into 12 lots. This was accomplished using an increasing, equal, and decreasing lot size profile to coincide with the beginning, middle, and end stages of production, respectively (Step 3 from Figure 6).

The lot size was determined in the following manner:

$$\text{lot size} = C_i + (S_i * RANUNI(\text{seed})) \tag{20}$$

where

C_i = constant for lot i
S_i = scaling factor for lot i
RANUNI (seed) = a number from the uniform distribution between zero and one.

The scaling factor and constants were changed to allow for increasing and decreasing lot sizes where appropriate. To ensure cumulative units did not exceed 480, the decreasing lot size program used conditional statements for lots 10, 11, and 12. In contrast, the increasing lot size program was structured such that the cumulative units through lot 11 did not exceed 480. For the equal lot sizing program, the scaling factor and RANUNI terms were removed and C_i was set equal to 40, thus each of the 12 lots contained 40 units per lot. The lot size structure is included in Appendix A (pg 107, 108).

Lot Plot Point. Within each production run, the algebraic lot midpoint was computed for each of the lots and added to the cumulative number of units in the production run to determine the true lot plot points. This algebraic midpoint computation procedure provides greater accuracy than heuristic lot midpoints.

For example, the following procedure within the lot sizing program was used to determine the algebraic lot plot point for the tenth lot (30:36):

```
LOT[10,4] = 0;
Z = LOT[10,1] - LOT[9,1];
  DO I = 1 TO Z;
    DUM = LOT[10,4] + ((I + LOT[9,1])**B);
    LOT[10,4] = DUM;
  END;
LOT[10,4] = (LOT[10,4]/Z)**(1/B);
```

The above program started by initializing the array element (LOT[10,4]) for the lot plot point. Next, it computed the size of the tenth lot by subtracting the cumulative units through the ninth lot from the cumulative units through the tenth lot. Then the DO loop computed the summation of the sequential unit numbers raised to the power of B of the tenth lot. The last statement computed the X value using the previous calculations.

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Model Fitting. For each production run within a treatment, the standard unit learning curve model was fit using linear least-squares-best-fit (LSBF). Before the unit model could be fit, a production run data file to segregate the lot sizing output by production run (Step 5 from Figure 6) was created. This program (see Appendix A, pg 109) created a data file which assigned a unique, sequential production run number to each group of 12 lots and allowed analysis and model fitting by production run.

The linear LSBF technique was run on the SAS system using PROC REG with each data point receiving equal weight (Step 6 from Figure 6). Before fitting, the non-linear simulated data was converted to a linear form with the following logarithmic transformations:

$$y = \ln(Y) \tag{21}$$

$$x = \ln(X) \tag{22}$$

where

Y   = the average total cost of a production lot
X   = the algebraic lot plot point
ln(variable) = the natural logarithm function

The actual PROC REG statement required in SAS (29:Ch 28)was as follows:

    PROC REG;
      MODEL LNAVCUST = LNLPP;

Slope Determination. For correct slope development, the model fitting used only lot variable costs within each production run in order to compute the slope coefficient for each production run.

After model fitting, the mean of the 100 individual production run slope coefficients within a treatment was computed using the PROC MEANS statement in SAS

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(Step 8 from Figure 6). This mean slope coefficient, which was correctly developed since it used variable cost data only, was then used as the correctly estimated slope coefficient for estimating total cost for a new production run (Appendix A, pg 114).

   t Test for Slope Coefficient. With an average slope coefficient for each treatment, a t test was performed for each average slope coefficient (Step 10 from Figure 6). According to Ostle and Mensing (25:114), several factors require consideration when establishing a test procedure. Those factors are as follows:

1) The nature of the experiment that will produce the data must be defined.
2) The test statistic must be selected. In other words, the method of analyzing the data should be specified.
3) The nature of the critical region must be defined.
4) The size of the critical region (i.e., α) must be chosen.
5) The size of the sample must be determined.

In this case, the theoretical population was known, i.e., 75%, 85%, and 95% slope with no dispersion. Furthermore, when dispersion was included, it was known that the dispersion would be normally distributed since the simulation included a normal distribution random number generator, i.e., RANNOR(SEED).

In light of this, the nature of the experiment was simply a test of the sample mean of slope coefficients from a normal population being equal to the population mean. The two sided t test was selected for the test statistic. Since the sample mean could be higher or lower than the population mean, the test had to take into account reject regions on both sides of the population mean. The alpha value (α) was 0.05. The sample size (n) was 100. The experiment was developed as follows:

H: $\mu_0 = \mu_1$, where μ_0 is the population mean and μ_1 is the sample mean
A: $\mu_0 \neq \mu_1$

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Test Statistic: $t = \dfrac{u_1 - u_0}{\left(s / \sqrt{n}\right)}$ where s is the sample standard deviation

and n is the sample size

Decision Rule: If $|t| < t^*$ then cannot reject null hypothesis, else reject, where from the t tables $t^* = t_{(.975)(99)}$

The results are summarized in Chapter 4.

Incorrect Slope Development. For incorrect slope coefficient development, the steps taken were the same as for the correct slope development process with one major exception and limited minor exceptions.

The major exception was that the slope coefficients were developed from total cost lot data instead of variable cost lot data. This exception is illustrated as an addition of Steps 3 through 6 in Figure 7 below. These four steps were included to add fixed costs to the lot data before the lot data was fit using LSBF.

?= Wildcard for One Character

Simulate Production Run Data for 100 Production Runs per Slope with Dispersion
Three Programs: NORMAL?.SAS
1

Production Run Total Variable Cost Generation via LEARN Program (No Dispersion)
3

Three Outputs from NORMAL*.SAS Programs
(NORMAL?.DAT)
2

LEARN Program Total Variable Cost Output for 480 Unit Production Run Under 3 Slopes (3 Outputs)
4

27 Lot Sizing Programs for 27 Combinations (3 Slopes, 3 Fixed Cost %, 3 Lot Sizing Profiles)
(?LTGEN??.SAS)
7

Excel Spreadsheet To Compute Lot Fixed Costs for 9 Combinations (3 Slopes, 3 Fixed Cost %)
(LOTFC.XLS)
5

Output from Lot Sizing Programs
(?LTGEN??.DAT)
8

Excel Spreadsheet Output with Lot Fixed Costs for each of the 9 Combinations
6

27 programs to fit Unit Model by production run to output from lot sizing programs
(COMB???.SAS)
10

Production run numbering scheme to segregate different production runs
(PRDRUN.DAT)
9

Slope Coefficient Per Production Run for Unit Model (100 Slope Coefficients per program, 2700 total slope coefficients) written to permanent data sets
(PARAMS.?UNIT??)
11

2 Programs to take an average slope coefficient for each combination and write them to two permanent data sets
(UNITI?.SAS)
12

Average Slope Coefficient For Each Combination (9 average slope coefficients per data set) written to two permanent data sets
(PARAMS.TESTI?T)
13

t Test of Average, Incorrectly Developed Slope Coefficients from Population Mean
(Excel Spreadsheet)
14

Figure 7 Incorrect Slope Development Before Correct and Incorrect Application

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<u>Fixed Cost Data.</u> Using the LEARN program by Hutchison (12:Ch 4) (Step 3 from Figure 7, see output in Appendix A, pg 105), three unit formulation learning curves with 75%, 85%, and 95% slopes; 480 units; first unit cost of $25,000; and no error term were run in order to compute the production run total variable costs.

Under the assumption that these total variable costs represented 80%, 65%, and 50% of total costs, total fixed costs per production run were computed using an Excel spreadsheet (Steps 5 and 6 from Figure 7, see output in Appendix A, pg 104). For example,

    if
        Total Fixed Costs (TFC) = 20% of Total Costs (TC)
        Total Variable Costs (TVC) = 80% of TC
    then
        TC = TVC/.8
    by substitution,
        TFC = .2*(TVC/.8)
    simplifying the above equation,
        TFC = .25 * TVC

Some problems associated with computing fixed cost for production runs include a wide variety of accounting classification methods used by different firms as well as different classifications of fixed costs between those incurred on a per lot basis and those incurred on a per time basis such as rent or utilities. This analysis used a simplifying assumption that each lot has the same fixed cost, irrespective of lot size. The fixed costs modeled in this experiment include costs such as setup, tooling, and ordering costs. In light of this, the total computed fixed costs per production run on the Excel spreadsheet were divided by 12 to compute the fixed cost per lot.

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<u>Lot Total and Average Cost.</u> In the lot sizing programs, total cost per lot was determined by computing the variable cost of the lot and adding the fixed cost per lot. For example, the total lot cost for the tenth lot array was determined using the following procedure:

LOT[10,3] = LOT[10,2] - LOT[9,2] + LFC

where

LOT[10,3] = the array element for total lot cost of the tenth lot
LOT[10,2] = the array element for cumulative variable cost for the tenth lot
LOT[9,2] = the array element for cumulative variable cost for the ninth lot
LFC   = the lot fixed cost for the tenth lot.

LOT[10,3] was then divided by the lot size to compute the average lot cost (lot array element 5, LOT[10,5]) which was used by the model fitting programs.

<u>Slope Determination.</u> The mean slope coefficient was determined in the same manner as that for the correctly developed case. The t test for the mean of the sample being equal to the mean of the population was also applied to the incorrectly developed slope coefficients. These results are also included in Chapter 4. This mean slope coefficient, which was incorrectly developed since it used total cost lot data, was then used as the incorrectly estimated slope coefficient for estimating total cost for a new production run.

One problem initially occurred when it came to incorrectly calculating the slope in the case of decreasing lot sizes. In only three of the nine cases was the incorrectly calculated slope coefficient negative as one would expect. After examination of the data, it was determined that the reason for the positive slope coefficients was the inclusion of fixed cost data before fitting the models.

Simply stated, as lot size decreased, average fixed cost per unit in each successive

lot increased as one would expect since fixed cost per lot is fixed. This increase in fixed

cost outweighed the decrease in variable cost due to learning. This caused the lot average

total cost to have an increasing trend which resulted in a positive slope. Figure 8 shows a

graphical representation of this trend.
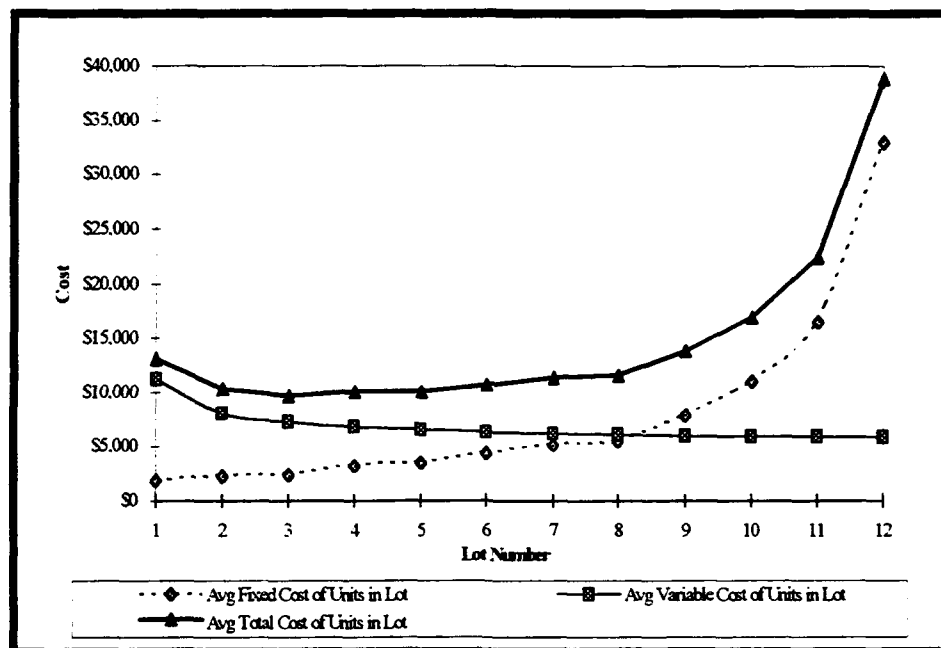
Figure 8 Graphical Example of Incorrect Slope Development Which Yields Positive Slope due to Increase in Average Fixed Cost Being Greater Than Decrease in Average Variable Costs (Example used 85% Slope, 35% Fixed Cost Percentage)

Correct Slope Application for Total Cost Estimates. For the correct slope

applications, both the correct and incorrect slope parameters from the slope development

stages above were used as shown in Figure 9. Correct slope application means that the

developed slope (whether correct or incorrect) was applied to a T1 that contained just

variable costs. If the developed slopes (whether correct or incorrect) were applied correctly, fixed costs would have to be added in after total variable costs were computed in order to compute total production run costs. This fixed cost addition was accomplished with a factor.

Since new systems rarely have the same T1 as previous systems, $40,000 was chosen as the T1 value for the new production. For an actual system, the T1 value would be calculated using a CER or other method.

Slope Correctly Developed
Slope Correctly Applied
(CC)

Slope Incorrectly Developed
Slope Correctly Applied
(IC)

Average Slope Coefficient For Each
Combination (9 average slope
coefficients per data set)
(PARAMS.TESTCCT)

1

Average Slope Coefficient For Each
Combination (27 average slope
coefficients per data set)
(PARAMS.TESTICT)

5

▼

One program to run each of the above
9 slopes down a 480 Unit Formulation
Curve with a T1 of $40,000 which
yields 9 production runs for
Total Variable Costs
(UNITCC.SAS)

2

▼

One program to run each of the above
27 slopes down a 480 Unit Formulation Curve
with a T1 of $40,000 which
yields 27 production runs for
Total Variable Costs
(UNITIC.SAS)

6

▼

One program to multiply each of the
above 9 production total variable cost
production runds by a factor to
incorporate fixed costs. Yields 27
unique total cost production runs
since there were 3 fixed cost factors
for each of the 9 production runs
(UNITCC.SAS)

3

▼

One program to multiply each of the
above 27 production total variable
cost production runs by a factor to
incorporate fixed costs.
Yields 27 unique total cost
production runs
(UNITIC.SAS)

7

▼

Permanent Data Set containing the
slope coefficient, total production
run costs, std deviation, and
standard error for each
combination (Total of 27
combinations)
(PARAMS.UNITCCT)

4

▼

Permanent Data Set containing the
slope coefficient, total production
run costs, std deviation, and
standard error for each
combination (Total of 27
combinations)
(PARAMS.UNITICT)

8

Figure 9 Correct Slope Application Combinations

For example, under the correct application, both correctly and incorrectly

developed slopes from above were applied to a unit formulation learning curve model with

a first unit variable cost of $40,000 and 480 units (Steps 2 and 6 from Figure 9). This

calculation yielded a total variable cost which was multiplied by a factor coinciding with

the fixed cost percentage (Steps 3 and 7 from Figure 9). The factors were 1.25 for 20% fixed cost, 1.5385 for 35%, and 2.00 for 50%.

Incorrect Slope Application for Total Cost Estimates. For the incorrect slope applications, both the correct and incorrect slope parameters from the slope development stages above were also used as shown in Figure 10 below. Incorrect slope application means that the developed slope (whether correct or incorrect) was applied to a first unit cost that contained both variable costs and fixed costs. If the developed slopes (whether correct or incorrect) were applied incorrectly, no adjustments would have to be made to account for fixed cost since the first unit cost is already adjusted to include fixed costs.

Slope Correctly Developed
Slope Incorrectly Applied
(CI)

| Average Slope Coefficient For Each Treatment (9 average slope coefficients per data set) (PARAMS.TESTCIT) | 1 |

▼

| One program to run each of the above 9 slopes down a 480 Unit Formulation Curve with three uniique T1s for each of the 9 slopes. Yields 27 unique Total Cost Production Runs (UNITCI.SAS) | 2 |

▼

| Permanent Data Set containing the slope coefficient, total production run costs, std deviation, and standard error of the estimate for each treatment (Total of 27 treatments) (PARAMS.UNITCIT) | 3 |

Slope Incorrectly Developed
Slope Incorrectly Applied
(II)

| Average Slope Coefficient For Each Treatment (27 average slope coefficients per data set) (PARAMS.TESTIIT) | 4 |

▼

| One program to run each of the above 27 slopes down a 480 Unit Formulation Curve with a unique T1 for each slope. Yields 27 unique Total Cost Production Runs. (UNITII.SAS) | 5 |

▼

| Permanent Data Set containing the slope coefficient, total production run costs, std deviation, and standard error of the estimate for each treatment (Total of 27 treatments) (PARAMS.UNITIIT) | 6 |

Figure 10 Incorrect Slope Application Combinations

To calculate the appropriate theoretical first unit cost, the lot fixed cost was

calculated in a similar manner as described above in the incorrect slope development

process; however, $40,000 was used as the first unit variable cost for the new production

run instead of $25,000. This process calculated the theoretical population total fixed costs

(see Appendix A, pg 127). For increasing and decreasing lot profiles, the mean of the 100

production run lot sizes was used to determine the lot size profile. Then the LEARN

program was used to fit the total cost data to determine the theoretical first unit cost for

the incorrectly applied treatments.

These adjusted first unit costs were used with the developed slopes (whether

correctly or incorrectly developed) to estimate total costs for a 480 unit production run

(Steps 2 and 5 from Figure 10).

Test on the Total Cost Estimates. Since only one new production run was

estimated with the developed slope coefficients, the tests available for the estimate were

limited. The test ran on the total cost estimate consisted of determining the magnitude of

the difference between the correctly developed and applied slope parameter with the

remaining three cases. The correct/correct case was used as the baseline because it is the

theoretically correct process.

In order to compare the correct/correct case with the other three cases, the total

cost estimates from the slope application process (described above) were entered into a

spreadsheet. Next a measure of dispersion needed to be calculated. This step called for

some assumptions. Since the slope coefficients were taken from the 100 simulated

production runs, the standard deviation of total cost for the 100 production runs was

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assumed to be an approximation of the standard deviation of the total cost for the new system.

This was calculated by using the total cost for the 100 production runs for the correctly applied unit formulation (Appendix A, pg 110). PROC MEANS in SAS was used to calculate the standard deviation of total cost for the 100 simulated production runs. Since the standard deviation was in dollars for a system with $25,000 theoretical first unit value, they had to be put into a format to be used for a system with a theoretical first unit value of $40,000. This was accomplished by converting the dollar value into a percent value. This was done because multiplicative models have a multiplicative error term instead of an additive error term. In other words, the error at any point will be a certain percentage away from the regression line in unit space, not a constant dollar amount away (see Figure 11 and Figure 12 for a graphical illustration of multiplicative and additive error terms).
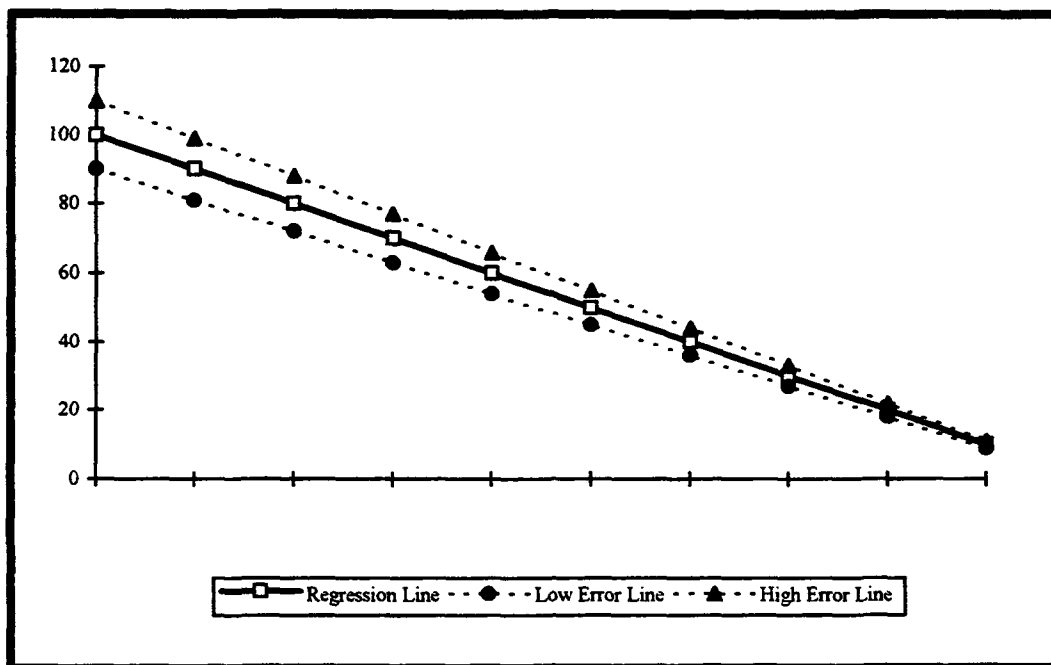
Figure 11 Illustration of Multiplicative Error Term
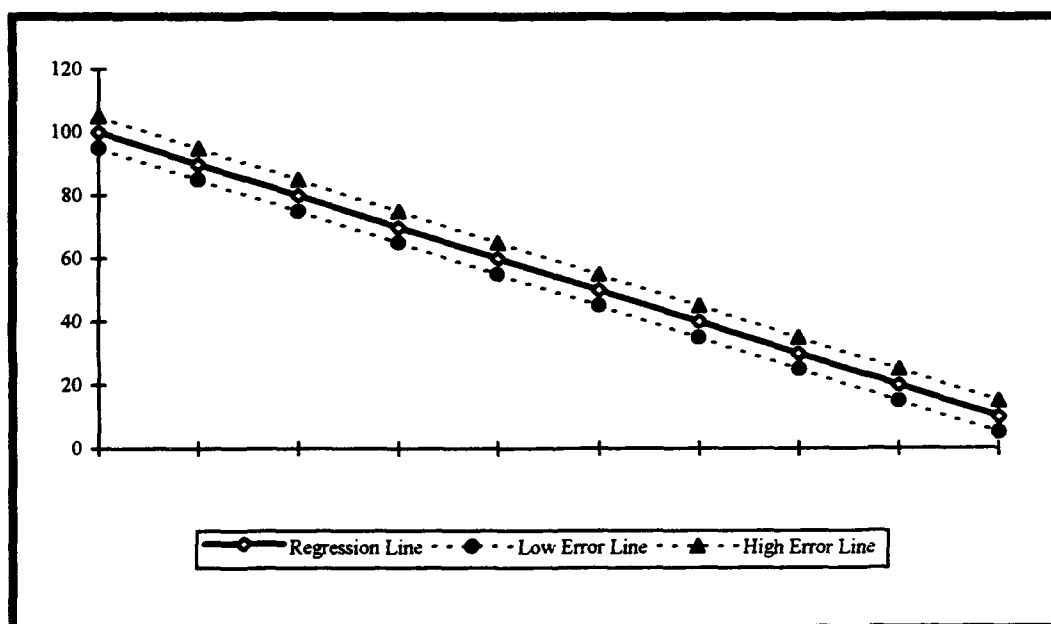
Figure 12 Illustration of Additive Error Term

As Figures 11 and 12 show, the deviation is greater at larger values for the multiplicative case when compared to the additive case. The opposite is true for smaller dollar values. At the mean (50), the deviation is the same. Under this assumption, the percent standard deviation was calculated by dividing the standard deviation by the mean of the total cost estimates. Now that the standard deviation was in a percent error format, this percentage was multiplied by the total cost estimate for the new production run to determine the dollar value of one standard deviation for the estimated total cost value. Once a dollar value of one standard deviation was determined, the fact that 99.7% of the values for a normal population fall within three standard deviations of the mean (8:150) was used to determine if any of the other estimates (correct/incorrect, incorrect/correct, and incorrect/incorrect) fell within three standard deviations of the correct/correct case. The results of this test are included in Chapter 4.

The tests of the total cost estimates concluded the research related to the second research area. The remainder of the chapter focuses on the third research area, i.e., a comparison of the cost prediction variability between the standard unit learning curve model (AX^b) and the SAF/FMC model ($F/Q + AX^b$) when fitted to total cost lot data.

Comparison Between Standard Unit Model and SAF/FMC Model

Since the standard unit learning curve model was insufficient when used with total cost lot data, an obvious question would be how it compares to a model that explicitly incorporates a fixed cost component. To address this question and Research Questions 7-9, two factorial experiments were designed and the results were analyzed.

Experimental Design. The design consisted of two balanced design, fixed effects factorial experiments. A factorial experiment is one where the researcher is interested in how two or more factors affect a measured response (20:529).

Table 5 lists the three factors (independent variables) and levels per factor for the first factorial experiment. In total, 18 treatments were considered in the first factorial experiment.

Table 5 First Factorial Experiment Factors (Independent Variables) and Levels Fixed Cost % Fixed at 35%

	Level 1	Level 2	Level 3
Model (Factor 1)	AX^b (Unit)	$F/Q + AX^b$ (SAF)	N/A
Lot Size Profile (Factor 2)	Increasing	Equal	Decreasing
Slope (Factor 3)	75% Slope	85% Slope	95% Slope

Table 6 lists the three factors (independent variables) and levels per factor for the second factorial experiment. In total, 18 treatments were considered in the second factorial experiment.

Table 6 Second Factorial Experiment Factors (Independent Variables) and Levels Slope Fixed at 85%

	Level 1	Level 2	Level 3
Model (Factor 1)	AX^b (Unit)	$F/Q + AX^b$ (SAF)	N/A
Lot Size Profile (Factor 2)	Increasing	Equal	Decreasing
Fixed Cost % (Factor 3)	20% Fixed Cost	35% Fixed Cost	50% Fixed Cost

The purpose of the factorial experiments was to examine how each model

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(Factor 1) performed under different lot sizing profiles, slopes, and fixed cost percentages. Performance, the dependent variable in the factorial design, was measured in terms of the Mean Absolute Deviation (MAD) for that treatment. Lower MADs were judged to be better than higher MADs since lower MADs are characteristic of a better fitting and better estimating model.

The rationale for two factorial experiments instead of one joint 3*3*3*3 factorial experiment was due to the dependency between the slope and calculated fixed costs in the data simulation. In the simulation, production run fixed costs are derived from production run total variable costs; however, production run total variable costs are a function of slope when a constant T1 across treatments is assumed. In light of this, the fixed cost is dependent upon the slope, thus the two are dependent. By dividing the experiment into two factorial experiments, this dependency between production run fixed costs and slope was minimized.

Factorial Design. The factorial design was chosen since it allows for a wide variety of conditions represented by the different factors and levels. Traditional experimentation using "one-at-a-time" changes in factor levels while holding all other factors and levels constant is extremely inefficient when there are many factors and levels under consideration. Furthermore, "one-at-a-time" experimentation does not allow for the assessment of joint factor effects (19:115). Since there are no a priori notions that interactions among the factors do not exist, the factorial design is appropriate since it provides for the investigation of those joint, interaction effects.

Balanced Design. The experiments included a balanced design since the number of MAD observations per treatment was equal, i.e., the sample sizes were equal. Specifically, each treatment had 100 MAD observations which coincided with the 100 production runs for that treatment.

Fixed Effects. The experiments were fixed effects experiments since the levels for each factor were explicitly selected in advance, i.e., the factor levels were not randomly, but intentionally selected from a population of factor levels. The fixed effects experiment, commonly referred to as a Model I experiment, only allows inferences for the specific factor levels selected (19:300). The important implication of the fixed effects experiment is that conclusions drawn cannot be generalized to factor levels which were not specifically included in the experiment.

Experimental Flows. Figure 13 illustrates the experimental flow for both factorial experiments.

?= Wildcard for One Character

| Simulate Production Run Data for 100 Production Runs with 85% Slope with Dispersion and new Seed Value One Program: NORM2.SAS **1** | One Output from NORM2.SAS Program (NORM2.DAT) **2** | 3 Lot Sizing Programs for 3 Combinations (85% Slope, 35% Fixed Cost %, 3 Lot Sizing Profiles) (LTGEN?2B.SAS) **3** |

| Output from 3 Lot Sizing Programs (LTGEN?2B.DAT) **4** | Output from 27 Lot Sizing Programs (?LTGEN??.DAT) **5** |

| 3 programs to fit two models (Unit and SAF) by production run to output from lot sizing programs (?2BCOMB.SAS) **7** | Production run numbering scheme to segregate different production runs (PRDRUN.DAT) **6** | 27 programs to fit two models (Unit and SAF) by production run to output from lot sizing programs (COMB???.SAS) **12** |

| Mean Absolute Deviation Per Production Run for Each Model (100 MADs per model, 200 MADs per program) written to permanent data sets (MAD.MAD?2B) **8** | Mean Absolute Deviation Per Production Run for Each Model (100 MADs per model, 200 MADs per program) written to permanent data sets (MAD.???MAD) **13** |

| 1 Program which combines 3 MAD permanent data sets from above with 6 independent permanent data sets containing an 85% Slope from previous data simulation into 1 permanent data set for use in PROC ANOVA program (COMBINSL.SAS) **9** | 1 Program which combines 9 MAD permanent data sets from above which have 35% Fixed Costs Only into 1 permanent data set for use in PROC ANOVA program (COMBINFC.SAS) **14** |

| Summary MAD Data Set (200 MADs per set X 9 sets = 1,800 MAD observations) (MAD.IN2) **10** | Summary MAD Data Set (200 MADs per set X 9 sets = 1,800 MAD observations) (MAD.IN1) **15** |

| PROC ANOVA program to examine main and interaction effects among model and other factors (PROCANSL.SAS) **11** | PROC ANOVA program to examine main and interaction effects among model and other factors (PROCANFC.SAS) **16** |

| PROC ANOVA output from PROCANSL.SAS. Output used to examine main, interaction, and factor level effects **17** | PROC ANOVA output from PROCANFC.SAS. Output used to examine main, interaction, and factor level effects **18** |

Figure 13 Total Cost Data Experiment Flow Chart

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Simulation of Production Run Data   To begin the second factorial experiment, production variable cost data was simulated for 100 production runs of 480 units each (Step 1 from Figure 13) This data was simulated with an 85% slope and standard deviation of 0 20 Production run variable cost data had already been accomplished for the first factorial experiment (Step 1 from Figure 6).

The second factorial simulation was exactly the same as that used in the NORMAL2.SAS program (refer to Step 1 from Figure 6) with the exception of the seed value A new seed value was used to make the simulated production runs from NORM2.SAS (Apr ʌ.ʾdix B, pg 128) independent from those simulated under NORMAL2.SAS ʌ ʌependence problem arose since the 85% slope was included in both factorial experiments, as a factor level in the first and as a fixed value in the second.

Fixed Cost Data Fixed cost data was added to the variable cost data from NORM2 SAS using the same procedure as Steps 3-6 from Figure 7 Only the 35% fixed cost data was added to the variable cost data since only 35% fixed costs were under consideration This resulted in 3 combinations of an 85% slope, 35% fixed cost percentage, and the three lot sizing profiles

Lot Total and Average Cost This procedure was the same procedure used in Step 7 from Figure 7 and explained under Figure 7

Model Fitting For each production run within a treatment, two learning curve models were fit (Steps 7 and 12 from Figure 13) The standard unit learning curve model was fit using linear LSBF By contrast, the SAF/FMC model was fit using a non-linear LSBF technique in SAS.

Linear LSBF for Standard Unit Model. The linear LSBF was run on the

SAS system using PROC REG in the same manner used in Figure 6

Nonlinear LSBF for SAF/FMC Model. The SAF/FMC model was a

nonlinear functional model with an additive error term which could not be transformed to

an intrinsically linear form; consequently, the model required a non-linear LSBF technique.

To fit the SAF/FMC model, PROC NLIN (nonlinear regression) in SAS was used (9:169).

The NLIN procedure was more complex than the linear LSBF procedure as it required a

complete specification of the model, declaration of parameter names, starting values for

the parameters, and bounds for the parameters (29:676). The SAS program to fit the

SAF/FMC model was as follows:

```
PROC NLIN;
*INITIAL GUESS VALUES FOR PARAMETERS;
        PARMS B=-.4 F=25000 A=25000;
        MODEL AVUNCST = F/LOTSZ + (A*LPP**B);
        BY PRDRUN;
        BOUNDS -1<=B<=0;
        BOUNDS 0<=F<=900000;
        BOUNDS 0<=A<=200000;
```

A sample program which includes the Unit and SAF/FMC fitting procedures is

located in Appendix A (pg 135) with notes regarding modifications for each of the

treatments.

Bias Adjustment Factor. The Unit fitting procedure did not incorporate a

bias adjustment factor to account for the intercept bias encountered when converting from

log space to unit space. The SAF/FMC fitting procedure did not require a bias

adjustment factor since the fitting was performed in unit space.

MAD. For the factorial experiments, MAD was used as the measured response (dependent variable) for each treatment (unique combination of factor levels). MAD is simply defined as an average of absolute errors (deviations) between predictions and actuals, i.e., the sum of absolute errors divided by the number of errors.

MAD was used as the dependent variable since it measures variability instead of bias (17:657). Additionally, it is less sensitive to large forecast errors than MSE since MSE squares each error (24:58).

COMBINSL.SAS (Appendix B, pg 139) combined the three MAD permanent data sets from Step 8 of Figure 13 with six MAD permanent data sets from Step 13 of Figure 13. The three MAD permanent data sets were based on treatments with an 85% slope, 35% fixed cost percentage, and three lot sizing profiles. The six MAD permanent data sets were based on treatments of 85% slope, all three fixed cost percentages, and the three lot sizing profiles. As previously explained, the rationale for combining MAD permanent data sets from different files was due to the 85% slope and 35% fixed cost overlap between the two factorial experiments.

COMBINFC.SAS (Appendix B, pg 138) combined nine selected MAD permanent data sets from Step 13 of Figure 13. The nine MAD permanent data sets were based on treatments with 35% fixed cost percentage, all three slopes, and all three lot sizing profiles.

The two programs described above yielded two MAD permanent data sets which contained 1,800 MAD observations per data set. These two data sets were now ready for input into the two ANOVA programs (Steps 10 and 15 from Figure 13).

ANOVA. To analyze the data contained in the two permanent MAD data sets, two ANOVA models were used. ANOVA models were used since they provide for the simultaneous investigation of the differences among the means of several populations (treatments) associated with multiple factors.

ANOVA was used to determine overall significance, main factor significance, interaction significance, and factor level effects.

ANOVA Program. To conduct the ANOVA analyses, two SAS programs were written (Steps 11 and 16 from Figure 13). These programs provided the significance of factor main effects, interaction effects, and allowed assessment of factor level effects on MAD through comparison of factor level means.

The first ANOVA program, PROCANSL.SAS (Appendix B, pg 140), looked strictly at an 85% slope, all three fixed cost percentage levels, all three lot sizing profiles, and both models. This program allowed analysis of interactions between model and fixed cost percentage as well as the interactions between model and lot sizing profile in terms of which model produced the lowest MAD under which conditions.

The second ANOVA program, PROCANFC.SAS (Appendix B, pg 147), looked strictly at a 35% fixed cost percentage, all three slopes, all three lot sizing profiles, and both models. This program allowed analysis of interactions between model and slope as well as the interactions between model and lot sizing profile in terms of which model produced the lowest MAD under which conditions.

ANOVA Analysis. The ANOVA output was analyzed by examining the overall significance, significance of the main effects, significance of the interaction effects,

and analysis of factor level means through graphical procedures and multiple comparison tests. The details for each of these assessments are included in Chapter 4.

Chapter Summary

This chapter has focused on the methodology to meet the research questions specified in Chapter 1. Specifically, this chapter explained three areas of research: 1) interview process, 2) comparison of correct/incorrect parameter development and application when estimating total production costs, and 3) a means to compare the cost prediction variability between the standard unit learning curve model (AX^b) and the SAF/FMC model ($F/Q + AX^b$) when fitted to total cost lot data. Within each of these research areas, the general processes were outlined. The following chapter will focus on the detailed analysis of the interview process, analysis of the of correct/incorrect parameter development and application simulation, and analysis of the ANOVA output.

IV. Analysis

Chapter Overview

This chapter addresses each of the research questions identified in Chapter 1. The first six research questions pertain to the first general research hypothesis which deals with the different uses and the accuracy of the standard unit learning curve model (AX^b) when estimating total costs for a production run. Specifically, personal interviews were conducted to assess current field practice, and then total cost estimates were computed based on simulated data to address the accuracy of the standard learning curve model when estimating total costs.

The remaining three research questions pertain to the second general research hypothesis which deals with the predictive accuracy of the standard unit learning curve model (AX^b) versus the SAF/FMC model ($F/Q + AX^b$) when fit to total cost lot data. Specifically, the conditions under which either model outperformed the other were examined.

Research Questions 1-3

Personal interviews were conducted to address the first three research questions, which were:

Research Question 1
With the standard unit learning curve model, do USAF cost studies calculate learning curve slopes correctly but apply them incorrectly when estimating total production run costs, i.e., do they use recurring costs only for calculating the slope but include fixed cost in the theoretical first unit cost when applying that slope?

Research Question 2
With the standard unit learning curve model, do USAF cost studies develop learning curve slopes incorrectly but apply them correctly when estimating total

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production run costs, i.e., do they use total cost data for calculating the slope but include variable cost only in the theoretical first unit cost when applying that slope?

Research Question 3

With the standard unit learning curve model, do USAF cost studies develop learning curve slopes incorrectly and apply them incorrectly when estimating total production run costs, i.e., do they use total cost data for slope development and include fixed cost in the theoretical first unit cost when applying that slope?

These three research questions represent three of the four possible combinations of correct/incorrect development of learning curve slope parameters and correct/incorrect application of those slope parameters to first unit values when estimating total costs for a fixed length production run. The one possible combination which is specifically excluded is the correct development and correct application combination.

To address these research questions, personal interviews with cost analysts at four system program offices at Wright-Patterson AFB and one AFIT instructor were conducted. The primary goal of the interviews was to survey current cost analysis practice with respect to learning curves. The secondary goal was to attempt to identify at least one case of field practice for each of the three categories identified in the research questions above.

Results from the interview process yielded at least one case for each of the three research questions identified above, i.e., at least one correct slope development and incorrect application (Research Question 1), at least one incorrect slope development and correct application (Research Question 2), and at least one incorrect slope development and incorrect slope application (Research Question 3). In fact, many interviewees reported knowledge of all three cases both within their current program office and at previous program offices. Data was not gathered to estimate the proportion of total

applications that diverge from the theoretically correct practice. In addition, anonymity was promised to those interviewed. In light of the primary and secondary goals established above, the first three research questions were met.

Given that current field practice deviates from the theoretically correct slope development and slope application process of estimating total costs, the next set of three research questions addressed whether or not these deviations cause a significant difference in total cost estimates when compared to the theoretically correct process.

Research Questions 4-6

Research Questions 4-6 deal with the correct slope coefficient development and incorrect slope coefficient application, incorrect slope coefficient development and correct slope coefficient application, and incorrect slope coefficient development and incorrect slope coefficient application. The actual research questions are addressed in the total cost estimates section of this chapter. Before addressing the correct and incorrect slope coefficient applications, the correct and incorrect slope coefficient development were analyzed.

Correct Slope Development. The correct slope development process followed the steps outlined in Figure 6 as described in Chapter 3. The results of this process are outlined in Table 7 below (For complete information including standard deviations, standard error of the estimates, and approximate p-values see Appendix A, pg 115).

Table 7 Analysis of Correctly Developed Slope Coefficients

Model	Estimated Slope Coefficient	Population Slope Coefficient	t Test Value	t*	Hypothesis Decision
D1A	-0.415318	-0.415037	-0.0233	+/-1.987	Cannot Reject
D1B	-0.415318	-0.415037	-0.0233	+/-1.987	Cannot Reject
D1C	-0.415318	-0.415037	-0.0233	+/-1.987	Cannot Reject
D2A	-0.245349	-0.234465	-0.8361	+/-1.987	Cannot Reject
D2B	-0.245349	-0.234465	-0.8361	+/-1.987	Cannot Reject
D2C	-0.245349	-0.234465	-0.8361	+/-1.987	Cannot Reject
D3A	-0.075426	-0.074001	-0.1102	+/-1.987	Cannot Reject
D3B	-0.075426	-0.074001	-0.1102	+/-1.987	Cannot Reject
D3C	-0.075426	-0.074001	-0.1102	+/-1.987	Cannot Reject
E1A	-0.437756	-0.415037	-2.0837	+/-1.987	Reject
E1B	-0.437756	-0.415037	-2.0837	+/-1.987	Reject
E1C	-0.437756	-0.415037	-2.0837	+/-1.987	Reject
E2A	-0.240869	-0.234465	-0.6068	+/-1.987	Cannot Reject
E2B	-0.240869	-0.234465	-0.6068	+/-1.987	Cannot Reject
E2C	-0.240869	-0.234465	-0.6068	+/-1.987	Cannot Reject
E3A	-0.073969	-0.074001	-0.0031	+/-1.987	Cannot Reject
E3B	-0.073969	-0.074001	-0.0031	+/-1.987	Cannot Reject
E3C	-0.073969	-0.074001	-0.0031	+/-1.987	Cannot Reject
I1A	-0.422261	-0.415037	-0.5866	+/-1.987	Cannot Reject
I1B	-0.422261	-0.415037	-0.5866	+/-1.987	Cannot Reject
I1C	-0.422261	-0.415037	-0.5866	+/-1.987	Cannot Reject
I2A	-0.236048	-0.234465	-0.1331	+/-1.987	Cannot Reject
I2B	-0.236048	-0.234465	-0.1331	+/-1.987	Cannot Reject
I2C	-0.236048	-0.234465	-0.1331	+/-1.987	Cannot Reject
I3A	-0.073291	-0.074001	0.0606	+/-1.987	Cannot Reject
I3B	-0.073291	-0.074001	0.0606	+/-1.987	Cannot Reject
I3C	-0.073291	-0.074001	0.0606	+/-1.987	Cannot Reject

As Table 7 shows, even when the slope is developed correctly, the derived slope is not always an accurate estimate of the true population slope. For the treatment with 75% slope and equal lot profile, the derived slope was significantly different from the population slope. This was with an $\alpha/2$ of 0.025 and 99 degrees of freedom.

In the instances described above, the derived slope coefficient was less than the population slope coefficient. This would equate to a steeper slope or a system with more learning. Using a steeper slope for estimates would lead to lower estimates as shown earlier in Chapter 1, Figure 1.

Incorrect Slope Development. The results of the incorrect slope development process as described in Figure 7 in Chapter 3 are summarized in Table 8 (For complete information including standard deviations, standard error of the estimates, and approximate p-values see Appendix A, pg 120).

Table 8 Analysis of Incorrectly Developed Slope Coefficients

Model	Estimated Slope Coefficient	Population Slope Coefficient	t Test Value	t*	Hypothesis Decision
D1A	-0.175813	-0.415037	12.8532	+/-1.987	Reject
D1B	-0.038092	-0.415037	16.3456	+/-1.987	Reject
D1C	*0.089137*	-0.415037	18.9042	+/-1.987	Reject
D2A	-0.036955	-0.234465	10.9279	+/-1.987	Reject
D2B	*0.082157*	-0.234465	13.7938	+/-1.987	Reject
D2C	*0.193083*	-0.234465	15.7511	+/-1.987	Reject
D3A	*0.093480*	-0.074001	9.2022	+/-1.987	Reject
D3B	*0.193105*	-0.074001	11.5735	+/-1.987	Reject
D3C	*0.287517*	-0.074001	13.0089	+/-1.987	Reject
E1A	-0.341567	-0.415037	8.2228	+/-1.987	Reject
E1B	-0.285903	-0.415037	16.4398	+/-1.987	Reject
E1C	-0.228114	-0.415037	28.0371	+/-1.987	Reject
E2A	-0.191735	-0.234465	4.9571	+/-1.987	Reject
E2B	-0.150181	-0.234465	10.2595	+/-1.987	Reject
E2C	-0.125422	-0.234465	18.2989	+/-1.987	Reject
E3A	-0.059363	-0.074001	1.7313	+/-1.987	Cannot Reject
E3B	-0.047035	-0.074001	3.9949	+/-1.987	Reject
E3C	-0.037840	-0.074001	6.6094	+/-1.987	Reject
I1A	-0.423340	-0.415037	-0.8043	+/-1.987	Cannot Reject
I1B	-0.430266	-0.415037	-1.4924	+/-1.987	Cannot Reject

Model	Estimated Slope Coefficient	Population Slope Coefficient	t Test Value	t*	Hypothesis Decision
I1C	-0.446366	-0.415037	-3.3643	+/-1.987	Reject
I2A	-0.287635	-0.234465	-5.2010	+/-1.987	Reject
I2B	-0.324256	-0.234465	-7.9913	+/-1.987	Reject
I2C	-0.358465	-0.234465	-9.7691	+/-1.987	Reject
I3A	-0.182044	-0.074001	-9.0953	+/-1.987	Reject
I3B	-0.246736	-0.074001	-12.5626	+/-1.987	Reject
I3C	-0.303469	-0.074001	-15.2806	+/-1.987	Reject

As Table 8 shows, three treatments: 1) equal lot profile, 95% slope, 20% fixed cost, 2) increasing lot profile, 75% slope, 20% fixed cost and 3) increasing lot profile, 75% slope, 35% fixed cost, resulted in a derived slope coefficient which was statistically the same as the population slope coefficient. In all other cases, the developed slope coefficient was significantly different from the population slope coefficient with the majority of p-values being 0.0001.

For decreasing and equal lot profiles, the derived slope was flatter than the population slope. This would lead to overestimations of variable costs. For the increasing lot profiles, the derived slope was steeper than the population slope. This would lead to underestimation of variable costs.

Once the tests of the developed slope coefficients was accomplished, the next step involved tests of the total cost estimates which were calculated using the developed slopes. The research questions will also be addressed in the total cost estimates section.

Total Cost Estimates. Before analyzing the results of the total cost estimates comparison, the effects of lot profile on the fixed costs incorporated into the T1 value, the

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effects of learning on the fixed costs incorporated into the T1 value, and the effects of the difference between correctly and incorrectly developed slopes need to be addressed.

The computation process for total cost estimates was described in Figures 8 and 9 from Chapter 3. For the incorrectly applied cases, this process called for adjusting the T1 value to include fixed costs. This process was expected to have the following results.

For treatments with a decreasing lot profile, the incorrect application cases would underestimate total cost due to the large first lot sizes lowering the amount of fixed costs added to the T1 value. For treatments with an equal lot profile, this effect should not be apparent. The treatments with an increasing lot profile would over estimate total cost due to the small first lot size increasing the amount of fixed costs added to the T1 value.

The second effect, the learning on fixed costs incorporated in the T1 value, had mixed effects in this thesis due to six incorrectly developed slope coefficients being positive. Incorporating fixed costs in the T1 value causes the learning effect to be applied to fixed costs as well as variable costs. This means fixed costs will increase or decrease (depending on the slope coefficient) at the same rate as variable costs. For negative slope coefficients, the fixed costs would decrease by the same proportion as variable costs leading to underestimation of total cost. For positive slope coefficients, fixed costs would increase by the same proportion as variable costs leading to overestimation of total cost.

The third effect, difference in slope coefficients, was discussed under the slope development analysis above. To recap, the estimate using a flatter slope will have a higher total cost estimate, all else being equal, and the estimate using a steeper slope will have a lower total cost estimate, all else being equal.

The results of the total cost estimate computation process are summarized in Tables 9, 10, 11, 12, and 13. The correct slope development/correct slope application case was used as the baseline to compare the total cost estimates (Tables 9 and 10). The correct/correct case was used as the baseline because it is the theoretically correct process to follow.

Correct/Correct Total Cost Estimates. The correct/correct case is summarized in two tables. The first table (Table 9) holds information regarding the total cost estimate and the standard deviation. The second table (Table 10) has confidence interval values for one, two, and three standard deviations (sigma). As discussed earlier, for normally distributed populations or samples, 99.7% of all values will fall within three standard deviations of the mean. These bounds were used to determine how closely the other three cases' (correct/incorrect, incorrect/correct, and incorrect/incorrect) total cost estimates were to the correct/correct case total cost estimates. In most instances, the total cost estimates for the three cases were not within three standard deviations of the correct/correct estimates.

Table 9 Correct/Correct Total Cost Estimates and Standard Deviations

Model	Slope Coefficient	Total Cost	Standard Deviation
D1A	-0.415318	$3,103,329	$19,066.3
D1B	-0.415318	$3,819,577	$19,066.3
D1C	-0.415318	$4,965,326	$19,066.3
D2A	-0.245349	$6,957,625	$40,150.8
D2B	-0.245349	$8,563,445	$40,150.8
D2C	-0.245349	$11,132,200	$40,150.8
D3A	-0.075426	$16,281,184	$87,098.5
D3B	-0.075426	$20,038,881	$87,098.5

Model	Slope Coefficient	Total Cost	Standard Deviation
D3C	-0.075426	$26,049,894	$87,098.5
E1A	-0.437756	$2,800,742	$19,066.3
E1B	-0.437756	$3,447,153	$19,066.3
E1C	-0.437756	$4,481,187	$19,066.3
E2A	-0.240869	$7,111,807	$40,150.8
E2B	-0.240869	$8,753,212	$40,150.8
E2C	-0.240869	$11,378,891	$40,150.8
E3A	-0.073969	$16,402,780	$87,098.5
E3B	-0.073969	$20,188,542	$87,098.5
E3C	-0.073969	$26,244,448	$87,098.5
I1A	-0.422261	$3,006,024	$19,066.3
I1B	-0.422261	$3,699,814	$19,066.3
I1C	-0.422261	$4,809,638	$19,066.3
I2A	-0.236048	$7,281,822	$40,150.8
I2B	-0.236048	$8,962,467	$40,150.8
I2C	-0.236048	$11,650,916	$40,150.8
I3A	-0.073291	$16,459,668	$87,098.5
I3B	-0.073291	$20,258,559	$87,098.5
I3C	-0.073291	$26,335,469	$87,098.5

Using the total cost estimates and the standard deviations, Table 10, below, was

constructed to show the one, two, and three standard deviation bounds.

Table 10 Standard Deviation Bound Values for Correct/Correct Total Cost Estimates

Lower Bound 1 Sigma	Upper Bound 1 Sigma	Lower Bound 2 Sigma	Upper Bound 2 Sigma	Lower Bound 3 Sigma	Upper Bound 3 Sigma
$3,084,262	$3,122,395	$3,065,196	$3,141,461	$3,046,130	$3,160,527
$3,800,511	$3,838,643	$3,781,444	$3,857,709	$3,762,378	$3,876,776
$4,946,259	$4,984,392	$4,927,193	$5,003,458	$4,908,127	$5,022,525
$6,917,474	$6,997,776	$6,877,323	$7,037,927	$6,837,173	$7,078,077
$8,523,294	$8,603,596	$8,483,143	$8,643,746	$8,442,992	$8,683,897
$11,092,049	$11,172,351	$11,051,898	$11,212,502	$11,011,748	$11,252,652

Lower Bound 1 Sigma	Upper Bound 1 Sigma	Lower Bound 2 Sigma	Upper Bound 2 Sigma	Lower Bound 3 Sigma	Upper Bound 3 Sigma
$16,194,085	$16,368,282	$16,106,987	$16,455,381	$16,019,888	$16,542,479
$19,951,783	$20,125,980	$19,864,684	$20,213,078	$19,777,586	$20,300,177
$25,962,796	$26,136,993	$25,875,697	$26,224,091	$25,788,599	$26,311,190
$2,781,675	$2,819,808	$2,762,609	$2,838,874	$2,743,543	$2,857,941
$3,428,087	$3,466,219	$3,409,020	$3,485,286	$3,389,954	$3,504,352
$4,462,120	$4,500,253	$4,443,054	$4,519,319	$4,423,988	$4,538,386
$7,071,656	$7,151,958	$7,031,505	$7,192,108	$6,991,354	$7,232,259
$8,713,061	$8,793,363	$8,672,910	$8,833,513	$8,632,759	$8,873,664
$11,338,740	$11,419,042	$11,298,539	$11,459,193	$11,258,439	$11,499,343
$16,315,682	$16,489,879	$16,228,583	$16,576,977	$16,141,485	$16,664,076
$20,101,443	$20,275,640	$20,014,345	$20,362,739	$19,927,246	$20,449,837
$26,157,350	$26,331,547	$26,070,251	$26,418,645	$25,983,153	$26,505,744
$2,986,958	$3,025,090	$2,967,891	$3,044,156	$2,948,825	$3,063,223
$3,680,748	$3,718,880	$3,661,682	$3,737,947	$3,642,615	$3,757,013
$4,790,572	$4,828,704	$4,771,506	$4,847,771	$4,752,439	$4,866,837
$7,241,671	$7,321,973	$7,201,521	$7,362,124	$7,161,370	$7,402,275
$8,922,316	$9,002,618	$8,882,165	$9,042,768	$8,842,014	$9,082,919
$11,610,765	$11,691,066	$11,570,614	$11,731,217	$11,530,463	$11,771,368
$16,372,569	$16,546,766	$16,285,471	$16,633,865	$16,198,372	$16,720,963
$20,171,461	$20,345,658	$20,084,362	$20,432,756	$19,997,264	$20,519,855
$26,248,370	$26,422,567	$26,161,272	$26,509,666	$26,074,173	$26,596,764

One reservation with using the correct/correct process as the baseline was that the correct development process did not always derive a slope that was statistically the same as the actual slope. Another reservation was, even though the correctly derived slope was statistically the same as the population slope, the slope was almost always steeper than the population slope with the three treatments characterized by an increasing lot profile and 95% slope being the only exceptions. As discussed earlier, steeper slopes lead to underestimation of variable costs.

The next three sections will discuss the correct/incorrect, incorrect/correct, and incorrect/incorrect cases and highlight the treatments where the total cost estimates were within three standard deviations of the correct/correct case.

Research Question 4
Do the correct slope development and incorrect slope applications lead to significant differences in total cost estimates for a fixed length production run when compared to the correct/correct combination?

Correct/Incorrect Total Cost Estimates. Table 11 summarizes the results of the total cost estimates and the comparison with the correct/correct total cost estimates. The correct/incorrect case had no total cost estimates that fell within three standard deviations of the correct/correct total cost estimates.

Table 11 Correct/Incorrect Total Cost Estimates and Comparison to
Correct/Correct Total Cost Estimates

Model	Slope	Total Cost	Confidence Interval Test Results	Direction of Estimate
D1A	-0.415318	$2,521,889	Not within 3 sigma	Under
D1B	-0.415318	$2,567,073	Not within 3 sigma	Under
D1C	-0.415318	$2,639,443	Not within 3 sigma	Under
D2A	-0.245349	$5,773,716	Not within 3 sigma	Under
D2B	-0.245349	$6,013,197	Not within 3 sigma	Under
D2C	-0.245349	$6,396,284	Not within 3 sigma	Under
D3A	-0.075426	$14,110.251	Not within 3 sigma	Under
D3B	-0.075426	$15,362,925	Not within 3 sigma	Under
D3C	-0.075426	$17,366,488	Not within 3 sigma	Under
E1A	-0.437756	$2,313,133	Not within 3 sigma	Under
E1B	-0.437756	$2,396,819	Not within 3 sigma	Under
E1C	-0.437756	$2,530,694	Not within 3 sigma	Under
E2A	-0.240869	$6,124,404	Not within 3 sigma	Under
E2B	-0.240869	$6,626,213	Not within 3 sigma	Under
E2C	-0.240869	$7,429,136	Not within 3 sigma	Under
E3A	-0.073969	$15,363,828	Not within 3 sigma	Under
E3B	-0.073969	$17,950,546	Not within 3 sigma	Under

Model	Slope	Total Cost	Confidence Interval Test Results	Direction of Estimate
E3C	-0.073969	$22,089,296	Not within 3 sigma	Under
I1A	-0.422261	$2,923,719	Not within 3 sigma	Under
I1B	-0.422261	$3,522,519	Not within 3 sigma	Under
I1C	-0.422261	$4,480,539	Not within 3 sigma	Under
I2A	-0.236048	$8,794,257	Not within 3 sigma	Over
I2B	-0.236048	$12,219,772	Not within 3 sigma	Over
I2C	-0.236048	$17,700,654	Not within 3 sigma	Over
I3A	-0.073291	$28,164,467	Not within 3 sigma	Over
I3B	-0.073291	$45,468,187	Not within 3 sigma	Over
I3C	-0.073291	$73,154,336	Not within 3 sigma	Over

Since the same slope parameter was used in both the correct/correct and correct/incorrect cases, the slope coefficients had no effect on the differences in the total cost estimates. The reason for the overestimation and underestimation of total cost was the process of adjusting the T1 value for incorporating fixed costs and the learning effect on fixed costs included in the T1 value.

For the treatments with a decreasing lot profile, the large first lot size effect and the learning effect led to underestimation of total cost when compared to the correct/correct case.

For the treatments with an equal lot profile, the learning effect caused the underestimation of total cost when compared to the correct/correct case.

The increasing lot profile treatments had mixed effects. The small first lot size would lead to overestimation of total cost while the learning effect would lead to underestimation of total cost. For the first three treatments, 75% slope (the steepest slope), the learning effect outweighed the small first lot size effect. For the other six

treatments, 85% and 95% slope (flatter slopes, less learning), the small first lot size effect was stronger.

Research Question 5
Do the incorrect slope development and correct slope applications lead to significant differences in total cost estimates for a fixed length production run when compared to the correct/correct combination?

Incorrect/Correct Total Cost Estimates. Table 12 lists the total cost estimates for this case and the results of the comparison with the correct/correct case. Since the fixed costs were treated the same in both cases, the differences in the total cost estimates can be fully explained by the differences in the slope coefficients.

Table 12 Incorrect/Correct Total Cost Estimates and Comparison to Correct/Correct Total Cost Estimates

Model	Slope	Total Cost	Confidence Interval Test Results	Direction of Estimate
D1A	-0.175813	$9,808,806	Not within 3 sigma	Over
D1B	-0.038092	$24,264,710	Not within 3 sigma	Over
D1C	*0.089137*	$61,164,070	Not within 3 sigma	Over
D2A	-0.036955	$19,830,308	Not within 3 sigma	Over
D2B	*0.082157*	$45,355,201	Not within 3 sigma	Over
D2C	*0.193083*	$106,117,215	Not within 3 sigma	Over
D3A	*0.093480*	$39,111,264	Not within 3 sigma	Over
D3B	*0.193105*	$81,640,313	Not within 3 sigma	Over
D3C	*0.287517*	$176,199,101	Not within 3 sigma	Over
E1A	-0.341567	$4,378,080	Not within 3 sigma	Over
E1B	-0.285903	$7,031,809	Not within 3 sigma	Over
E1C	-0.228114	$12,113,628	Not within 3 sigma	Over
E2A	-0.191735	$9,061,677	Not within 3 sigma	Over
E2B	-0.150181	$13,118,888	Not within 3 sigma	Over
E2C	-0.125422	$20,209,448	Not within 3 sigma	Over
E3A	-0.059363	$17,675,164	Not within 3 sigma	Over
E3B	-0.047035	$23,174,562	Not within 3 sigma	Over
E3C	-0.037840	$31,584,244	Not within 3 sigma	Over
I1A	-0.423340	$2,991,212	Within 1 sigma	Under

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Model	Slope	Total Cost	Confidence Interval Test Results	Direction of Estimate
I1B	-0.430266	$3,566,841	Not within 3 sigma	Under
I1C	-0.446366	$4,309,404	Not within 3 sigma	Under
I2A	-0.287635	$5,665,645	Not within 3 sigma	Under
I2B	-0.324256	$5,850,295	Not within 3 sigma	Under
I2C	-0.358465	$6,468,028	Not within 3 sigma	Under
I3A	-0.182044	$9,508,989	Not within 3 sigma	Under
I3B	-0.246736	$8,505,559	Not within 3 sigma	Under
I3C	-0.303469	$8,399,970	Not within 3 sigma	Under

For both the decreasing and equal lot profile treatments, the incorrectly developed slope coefficients were greater than the correctly developed slope coefficients. This led to the overestimation of total cost. This overestimation was compounded in six of the nine decreasing lot profile treatments where the incorrectly developed slope coefficients were positive.

For the increasing lot profile treatments, the incorrectly developed slope coefficients were less than the correctly developed slope coefficients. This led to underestimation of total costs. One case, increasing lot profile, 75% slope, 20% fixed cost burden, was within one standard deviation of the correct/correct total cost estimate. This occurred because the estimated slope coefficient was only 0.001079 less than the correctly developed slope coefficient. The difference between the slope coefficients in the other treatments was significant enough to cause the other total cost estimates to fall outside the three standard deviation bounds as shown in Figure 10.

Research Question 6
Do the incorrect slope development and incorrect slope applications lead to significant differences in total cost estimates for a fixed length production run when compared to the correct/correct combination?

Incorrect/Incorrect Total Cost Estimates. The results of this case are

summarized in Table 13. The over and underestimation of total costs followed the same

pattern as the previous case (incorrect/correct), but the amount of error differed.

**Table 13 Incorrect/Incorrect Total Cost Estimates and Comparison to
Correct/Correct Total Cost Estimates**

Model	Slope	Total Cost	Confidence Interval Test Results	Direction of Estimate
D1A	-0.175813	$7,971,028	Not within 3 sigma	Over
D1B	-0.038092	$16,307,904	Not within 3 sigma	Over
D1C	*0.089137*	$32,513,291	Not within 3 sigma	Over
D2A	-0.036955	$16,455,983	Not within 3 sigma	Over
D2B	*0.082157*	$31,848,136	Not within 3 sigma	Over
D2C	*0.193083*	$60,972,299	Not within 3 sigma	Over
D3A	*0.093480*	$33,896,168	Not within 3 sigma	Over
D3B	*0.193105*	$62,590,022	Not within 3 sigma	Over
D3C	*0.287517*	$117,465,333	Not within 3 sigma	Over
E1A	-0.341567	$3,615,856	Not within 3 sigma	Over
E1B	-0.285903	$4,889,244	Not within 3 sigma	Over
E1C	-0.228114	$6,841,020	Not within 3 sigma	Over
E2A	-0.191735	$7,803,554	Not within 3 sigma	Over
E2B	-0.150181	$9,931,045	Not within 3 sigma	Over
E2C	-0.125422	$13,194,496	Not within 3 sigma	Over
E3A	-0.059363	$16,555,619	Within 2 sigma	Over
E3B	-0.047035	$20,605,552	Not within 3 sigma	Over
E3C	-0.037840	$26,583,668	Not within 3 sigma	Over
I1A	-0.423340	$2,909,312	Not within 3 sigma	Under
I1B	-0.430266	$3,395,918	Not within 3 sigma	Under
I1C	-0.446366	$4,014,533	Not within 3 sigma	Under
I2A	-0.287635	$6,842,399	Not within 3 sigma	Under
I2B	-0.324256	$7,976,517	Not within 3 sigma	Under
I2C	-0.358465	$9,826,551	Not within 3 sigma	Under
I3A	-0.182044	$16,271,022	Within 3 sigma	Under
I3B	-0.246736	$19,089,824	Not within 3 sigma	Under
I3C	-0.303469	$23,333,331	Not within 3 sigma	Under

Although the pattern was the same between both the incorrectly developed slope coefficient cases, the causes of the over and underestimations differed. As discussed in the incorrect/correct section, the incorrectly developed slope coefficients lead to overestimation of total costs for treatments with decreasing or equal lot profiles and underestimation of total costs for treatments with increasing lot profiles. As discussed at the beginning of the total cost estimate section and the correct/incorrect case, the large first lot size for decreasing lot profile treatments would lead to underestimation of total costs while the small first lot size for increasing lot profile treatments would lead to overestimation of total costs. Also, the learning effect would cause overestimation of total cost for those treatments with a positive slope and underestimation of total cost for those treatments with negative slopes.

For decreasing lot profile treatments, the effects of the large first lot size are overwhelmed by the effects of the flatter slope estimates. For the six treatments with positive slopes, the learning effect adds to the overestimation. For the three treatments with negative slopes, the learning effect reduces the effect of the flatter slope; but, as with the first lot size effect, it cannot offset the effect of the flatter slope.

For the nine treatments with an equal lot profile, the overestimation of total cost due to a flatter slope outweighs the learning effect on fixed costs. The one treatment, 95% slope and 20% fixed cost burden, does have a total cost estimate within two standard deviations of the correct/correct total cost estimate. This is the one treatment where the learning effect almost offsets the effect of the flatter slope.

For the last nine treatments with an increasing lot profile, three different effects are occurring. The steeper slopes and the learning effect would lead to underestimation of total cost, while the small first lot size would lead to overestimation of total cost. The sum of these effects led to underestimation of total costs. These mixed effects led to one treatment's total cost estimate being within three standard deviations of the correct/correct total cost estimate. This treatment had an increasing lot profile with 95% slope and a 20% fixed cost burden.

For the three cases, correct/incorrect, incorrect/correct, and incorrect/incorrect, the majority of the total cost estimates were not within three standard deviation of the correct/correct total cost estimates. When the total cost estimate did fall within three standard deviations, it was a result of differing effects canceling each other out or the rare instance when the correctly developed slope coefficients were similar. Overall, using any process other than the correct/correct process led to inaccurate total cost estimates when compared to the correct/correct process.

Since the standard unit learning curve model was clearly inadequate when slopes were developed from total cost lot data, a logical question arose as to whether a model that explicitly incorporates a fixed cost component would be superior when an analyst was faced with just total cost lot data from which to derive a slope parameter. This issue was addressed in Research Questions 7-9 by comparing the cost prediction variability between the standard unit learning curve model (AX^b) and the SAF/FMC model ($F/Q + AX^b$) when fitted to total cost lot data.

<u>Research Questions 7-9</u>

As mentioned in Chapter 3, two factorial experiments were established and the results were analyzed through ANOVA. The complete SAS output from both ANOVA programs is included in Appendix B (pg 140-146, 147-153). Before examining the conditions under which either model was superior, the ANOVA F tests and P-values required review.

<u>F Tests.</u> The F statistics and F test P-values for the overall ANOVA, main effects, and interaction effects (two-way) are summarized in Tables 14 and 15 for both ANOVA analyses. Table 14 is for the first factorial experiment where the fixed cost percentage is fixed at 35% while Table 15 is for the second factorial experiment where the slope is fixed at 85%.

Table 14 Overall, Main, and Two Factor Interaction F Test Results
(35% Fixed Cost)

Factor(s)	F Stat	P-Value	Factor(s)	F Stat	P-Value
Overall ANOVA	1,024.30	<0.0001	Model * Lot Profile	1,751.75	<0.0001
Model	2,678.16	<0.0001	Model * Slope	466.53	<0.0001
Lot Profile	1,733.22	<0.0001	Lot Profile * Slope	288.89	<0.0001
Slope	789.58	<0.0001			

Table 15 Overall, Main, and Two Factor Interaction F Test Results (85% Slope)

Factor(s)	F Stat	P-Value	Factor(s)	F Stat	P-Value
Overall ANOVA	1,150.31	<0.0001	Model * Lot Profile	2,249.71	<0.0001
Model	3,213.79	<0.0001	Model * FC Percent	424.46	<0.0001
Lot Profile	2,194.46	<0.0001	Lot Profile * FC %	290.30	<0.0001
FC Percent	420.90	<0.0001			

All three-way interaction effects in both factorial experiments were assumed to be zero in accordance with traditional experimental practice (19:315). As a result, both ANOVA programs were written to restrict the analysis to a maximum of two-way interactions. By restricting the analysis to two-way interactions, any three-way interactions were pooled into the error term for each factorial experiment.

Overall F Test. Based on the overall ANOVA F test at $\alpha=0.05$, both ANOVA models are significant since the P-values are <0.0001. This means that the ANOVA models as a whole account for the behavior of MAD for each factorial experiment.

Main Effects F Test. All of the main effects are statistically significant at $\alpha=0.05$; however, the main effects have little meaning if higher order interactions (i.e., two-way interactions) are significant. Significant two-way interactions indicate the main effects alone are insufficient to model the response of MAD (19:308), i.e., joint factor effects occur. This follows from the hierarchy principle which states that both lower order interactions (e.g., two-way interactions) and main effects are unimportant in the presence of higher order interactions such as three-way and four-way interactions (19:323).

Two-Way Interaction F Test. In light of the discussion in the preceding paragraph, a test for two-way interactions was required. Tables 14 and 15 report the F tests for two-way interactions in addition to the overall ANOVA and main effects. Note these tables include only two-way interactions due to the pooling assumption described earlier.

For both factorial experiments, all two-way interactions were significant at $\alpha=0.05$ since all two-way interaction P-values were < 0.0001. This meant the effect on MAD was explained by only joint factor effects as opposed to single factor effects (i.e., main effects).

Tests for main effects and two-way interaction significance were a necessary first step in terms of deciding whether or not the changes in MAD across treatments could be modeled by single factors alone or joint factors. Unfortunately, these significance tests provide no insight into the numerical values of factor level means. Factor level means, in both tabular and graphical form, are of more practical use to the researcher, but only after establishing significance as done above.

Main Effects Factor Level Means. Assuming there are no significant interactions among the factors, the main effects factor level means for each factorial experiment can be tabulated, graphed, and analyzed. For both factorial experiments, this is a poor assumption since two-way interaction significance has already been established as discussed above. The main effects factor level means analysis is provided for illustrative purposes only since many researchers tend to ignore all interactions, regardless of significance.

Each ANOVA program was written to provide all of the factor level means for both main effects and two-way interactions. Table 16 and Figure 14 below represent the main effects factor level means for the first factorial experiment with fixed cost percentage fixed at 35%.

Table 16 Main Effects Factor Level Means (35% Fixed Cost)

	Model	Model MAD	Lot Profile	Lot Profile MAD	Slope	Slope MAD
Lvl 1	Unit	$1,707.49	Incr	$ 514.72	75%	$ 359.25
Lvl 2	SAF	$ 209.60	Equal	$ 210.25	85%	$ 782.01
Lvl 3			Decr	$2,150.66	95%	$1,734.37
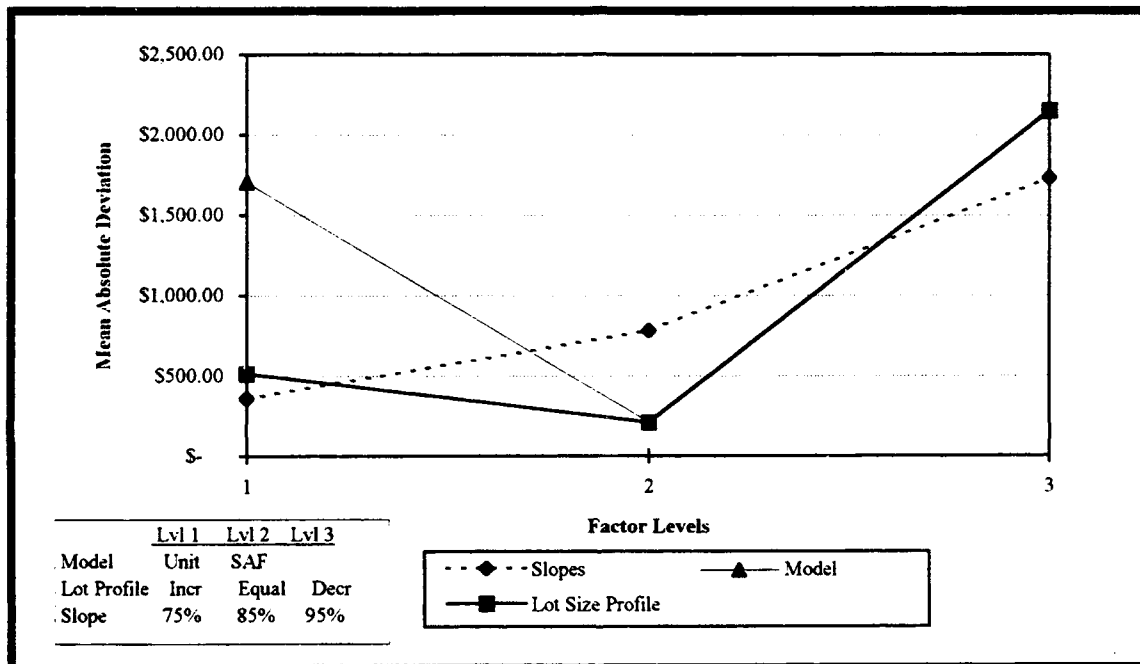
Figure 14 Main Effects (35% Fixed Costs)

Table 17 and Figure 15 below represent the main effects for the second factorial experiment with slope fixed at 85%.

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Table 17 Main Effects Factor Level Means (85% Slope)

	Model	Model MAD	Lot Profile	Lot Profile MAD	FC %	FC % MAD
Lvl 1	Unit	$1,495.56	Incr	$ 416.58	20%	$ 459.22
Lvl 2	SAF	$ 173.56	Equal	$ 169.49	35%	$ 765.31
Lvl 3			Decr	$1,917.61	50%	$1,279.14
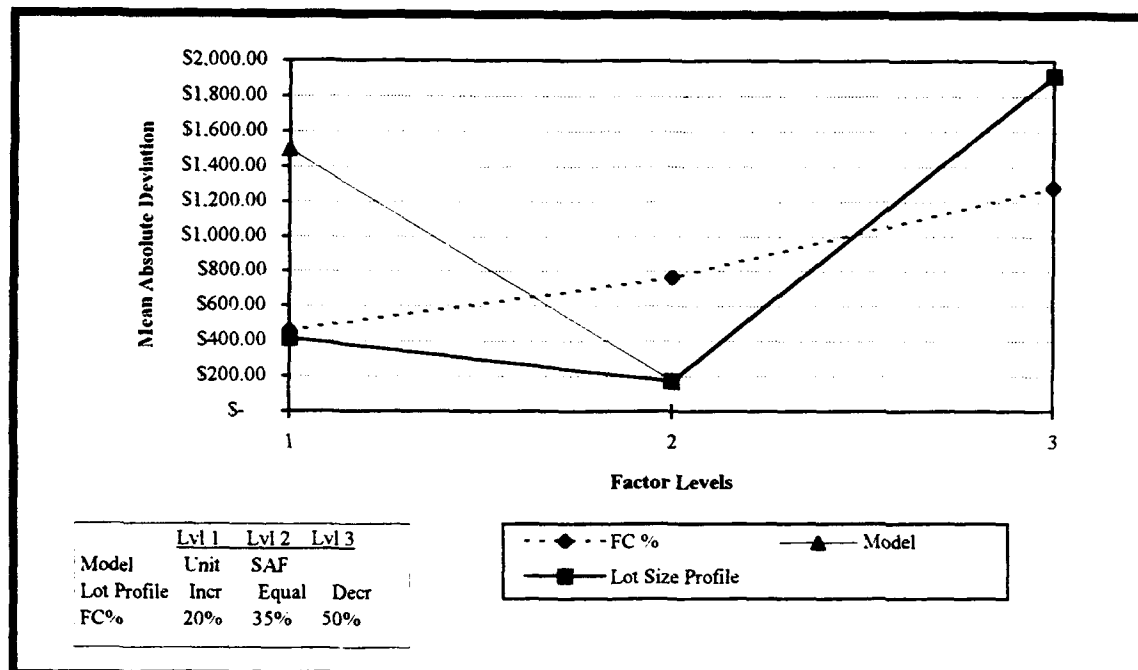
Figure 15 Main Effects (85% Slope)

Based on an examination of the tables and figures above, model and lot sizing

profile should have the highest F values of any single factors since they show the largest

MAD changes between factor levels and also the strongest deviation from a horizontal

line. A horizontal line indicates that the factor level effects on MAD for one factor have

the same MAD mean, i.e., no difference in their effect on MAD. Examination of Tables

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14 and 15 confirms that model and lot sizing profile have the highest F values for single

factors for both factorial experiments.

Two-Way Interaction Factor Level Means. To address Research Questions 7-9,

an examination of the joint factor level means was required since the research questions

specifically posed questions about model and other factors.

The two-way interaction factor level means are measured in terms of the

dependent variable, i.e., MAD. These means are also described as joint factor level means

since both factors interact to produce the specific MAD mean. For each of the Research

Questions 7-9, the joint factor level means will be examined in both tabular and graphical

form.

Research Question 7
Is the SAF/FMC model superior to the standard learning curve model under all of
the slope levels under consideration?

To answer this question, the output from the first ANOVA program for the first

factorial experiment was used. The joint factor level means were extracted and are

summarized in Table 18 below and graphed in Figure 16 below.

Table 18 Joint Factor Level Means for Model and Slope

	75%	85%	95%
Unit Model	$647.48	$1,395.34	$3,079.65
SAF/FMC Model	$ 71.02	$ 168.68	$ 389.10
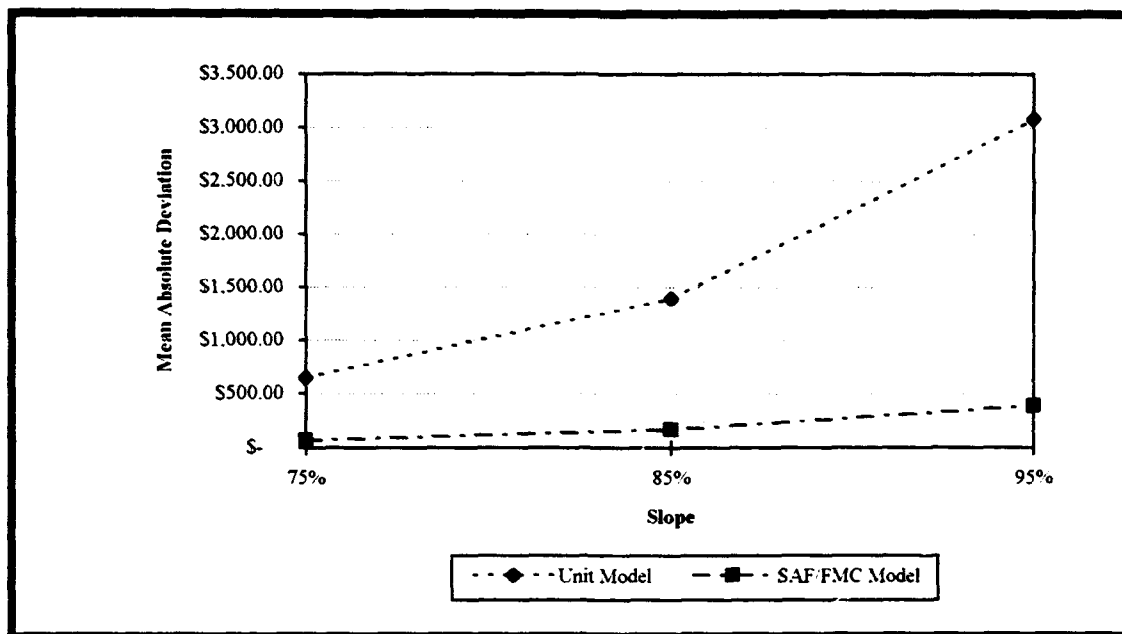
Figure 16 Interaction Effect Between Model and Slope

Based on Table 18 and Figure 16, the SAF/FMC model outperformed the Unit

model under all three slopes selected for the analysis since performance is measured in

terms of lowest MAD. As far as trends within the models, both models performed best

with a 75% slope, second best with a 85% slope, and worst with a 95% slope.

Research Question 8
Is the SAF/FMC model superior to the standard learning curve model under all of
the fixed cost percentage levels under consideration?

To answer this question, the output from the second ANOVA program for the

second factorial experiment was used. The joint factor level means were extracted and are

summarized in Table 19 below and graphed in Figure 17 below.

Table 19 Joint Factor Level Means for Model and Fixed Cost Percentage

	20% FC	35% FC	50% FC
Unit Model	$748.79	$1,348.12	$2,389.76
SAF/FMC Model	$169.66	$ 182.50	$ 168.53
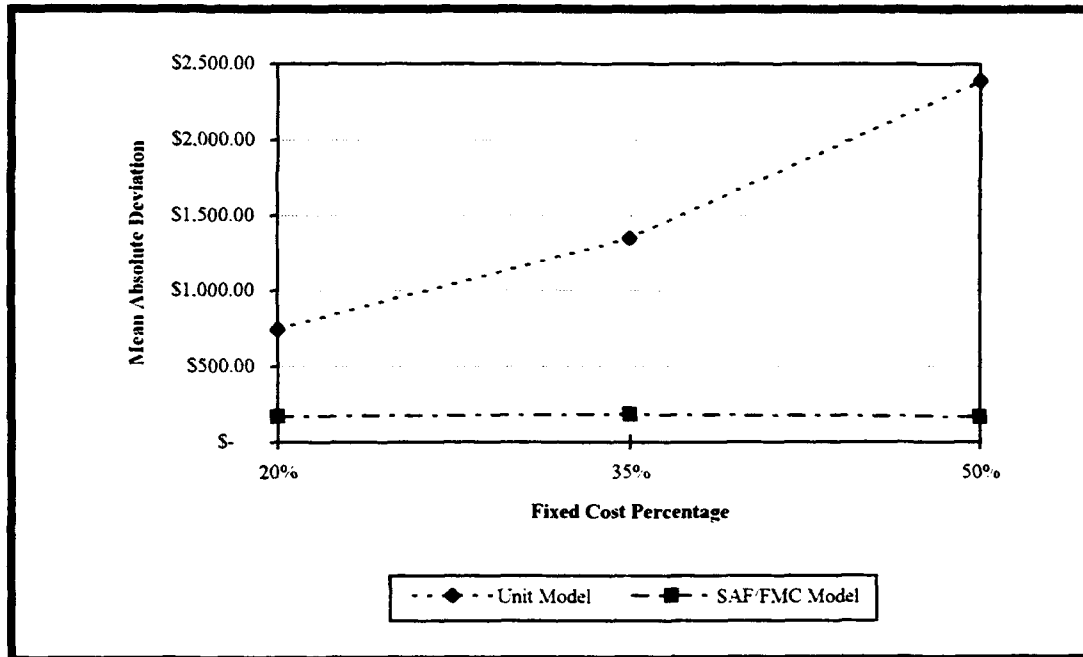
Figure 17 Interaction Effect Between Model and Fixed Cost Percentage

Based on Table 19 and Figure 17, the SAF/FMC model outperformed the Unit model under all three fixed cost percentages selected for the analysis. In terms of trends within the models, the SAF/FMC model performed best with 50% fixed costs while the Unit model performed best with 20% fixed costs. Second best results were also mixed as the SAF/FMC model performed second best with 20% fixed costs while the Unit model performed second best with 35% fixed costs.

Is the SAF/FMC model superior to the standard learning curve model under all of the lot size profiles under consideration?

To answer this question, the output from both ANOVA programs for both factorial experiments was used. The joint factor level means were extracted and are summarized in Tables 20 and 21 below and graphed in Figures 18 and 19 below.

Table 20 Joint Factor Level Means for Model and Lot Sizing Profile
(35% Fixed Costs)

	Increasing	Equal	Decreasing
Unit Model	$792.90	$227.91	$4,101.66
SAF/FMC Model	$236.55	$192.59	$ 199.66

Table 21 Joint Factor Level Means for Model and Lot Sizing Profile (85% Slope)

	Increasing	Equal	Decreasing
Unit Model	$621.35	$185.99	$3,679.33
SAF/FMC Model	$211.82	$152.98	$ 155.90
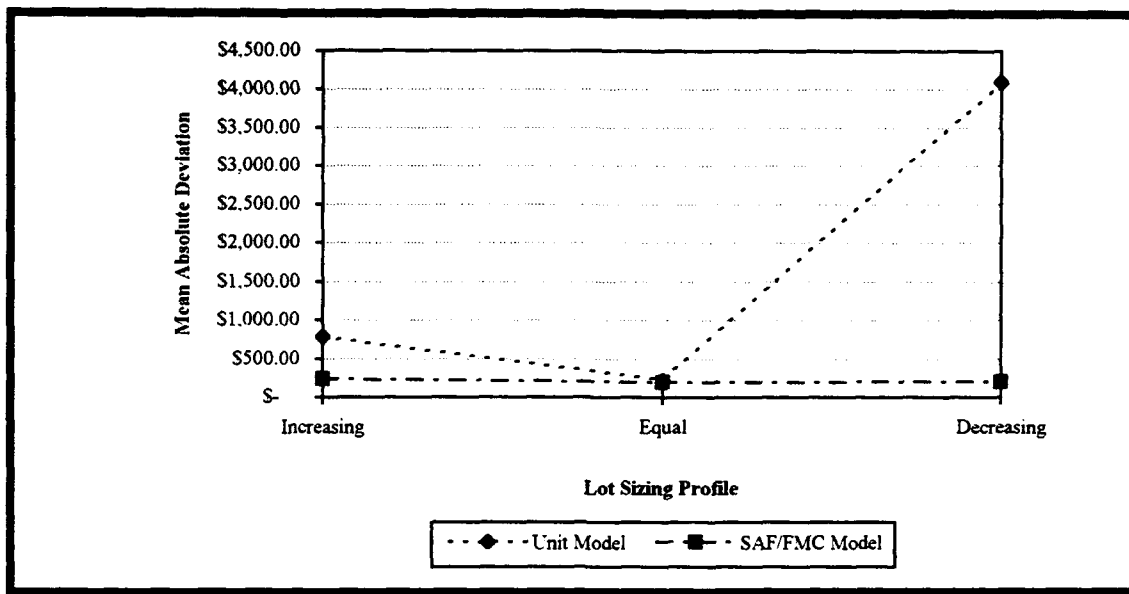
**Figure 18 Interaction Effect Between Model and Lot Sizing Profiles
(35% Fixed Costs)**
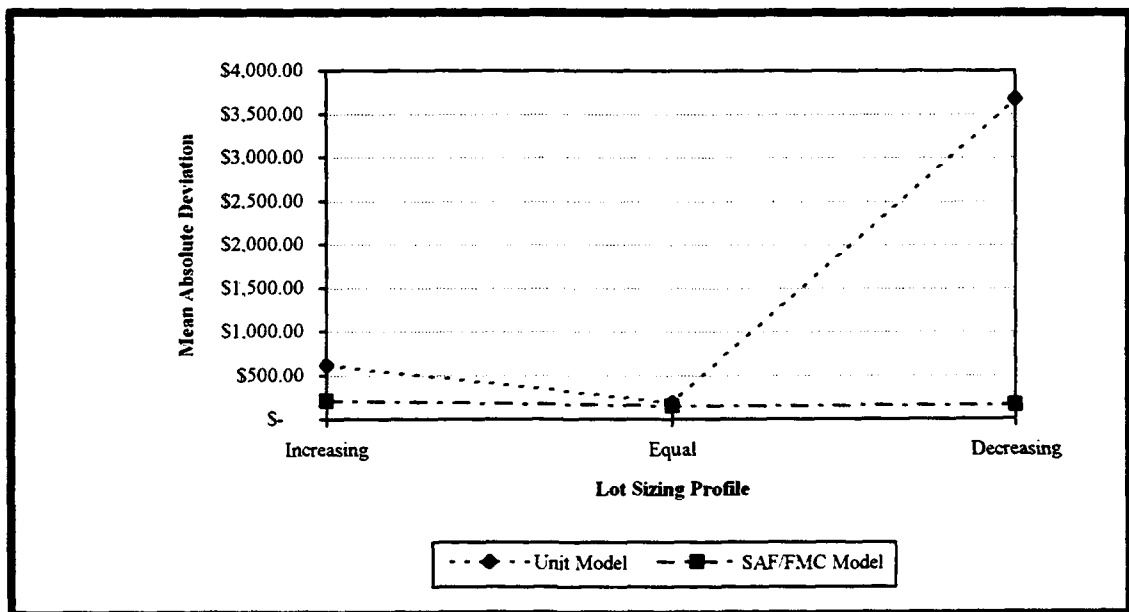
Figure 19 Interaction Effect Between Model and Lot Sizing Profiles (85% Slope)

Based on Tables 20 and 21 and Figures 18 and 19, the SAF/FMC model outperformed the Unit model under all three lot sizing profiles selected for the analysis. Both models performed best with an equal lot sizing profile (40 units per lot). In terms of trends within the model, the results for second best were mixed. The SAF/FMC model performed second best with a decreasing lot profile while the Unit model performed second best with an increasing lot profile.

Chapter Summary

This chapter addressed each of the nine research questions listed in Chapter 1. The first three research questions were addressed through personal interviews, the next three by development and application of slope parameters under various conditions, and the last three through factorial experiments and ANOVA. The next chapter will summarize findings from this chapter and suggest areas for further research.

V. Conclusions and Recommendations

Chapter Overview

This chapter summarizes the research findings for the nine research questions used to answer the two general hypotheses. Additionally, the chapter recommends areas for further learning curve research.

Summary of Findings

The first of the three research areas attempted to identify if a hypothesized problem with the development and application of the slope coefficient for the standard unit learning curve formulation (AX^b) indeed existed. A usage problem by definition is any deviation from the theoretically correct use of learning curves, i.e., development of slope coefficients based on variable (recurring) cost data only and application of the slope coefficients to T1 values which contain only variable cost data. Interviews with costs analysts at Wright-Patterson AFB and an AFIT instructor confirmed that problems do exist. There were numerous ways that the slope coefficients for standard unit learning curve formulation were being developed and applied. Part of the problem stemmed from the analyst's inability to gain insight into the segregation of historical data into its variable and fixed (non-recurring) cost components. Other problems stemmed from differing definitions of what constitutes a fixed cost and a variable cost. Another problem is that many CERs for production costs do not segregate fixed and variable costs.

Based on confirmation that hypothesized usage problems exist, the degree of inaccuracy was assessed through comparison of total cost estimates derived under various development and application combinations to the correct/correct slope development/application. For almost every treatment within the three cases (correct/incorrect, incorrect/correct, and incorrect/incorrect), the total cost estimate was significantly different from the total cost estimate calculated in the correct/correct case. The results show that when using the standard unit learning curve formulation, the analyst must ensure only variable costs are used for developing the slope coefficients and the slope coefficient is used to predict only variable costs. Another method for estimating the fixed portion of total costs should be used.

In light of the inaccuracy with the standard unit learning curve model when fit to total cost lot data, the SAF/FMC model ($F/Q + AX^b$) was investigated. Specifically, when fit to total cost lot data, the SAF/FMC model was compared to the AX^b model in terms of prediction variability (measured by MAD). As hypothesized in the second general research hypothesis from Chapter 1, the SAF/FMC model was superior (as measured by MAD) under all of the slopes, lot sizing profiles, and fixed cost percentages under consideration. This is logical in that the SAF/FMC model explicitly considers a fixed cost component whereas the AX^b model does not, thus, the prediction variability should be lower for the SAF/FMC model since it is a better fitting model.

<u>Areas for Further Research</u>

This research effort had numerous areas which warrant further research. Additionally, there are some other interesting research areas regarding learning curves and the mathematics of learning curve fitting that could be investigated.

First, investigation of a random effects design, instead of the fixed effects design used for the factorial experiments, would allow general statements regarding factor level trends. At present, the conclusions drawn from this research can only be applied to the specific factor levels chosen for investigation.

Second, a comparison of the $F/Q + AX^b$ model to the AX^b model when the former is fit to total cost lot data and the latter is fit to variable cost lot data would prove interesting as this represents more of an 'apples to apples' comparison than that used in this research.

Third, the use of historical production lot cost data, instead of simulated lot cost data used in this research, would serve to validate the research findings presented in this thesis.

Fourth, this study used the developed slope coefficients for only one new production run. In order to get a more definite finding of the inaccuracies involved with incorrectly developing and/or applying the slope coefficient, more new production runs need to be simulated. This would allow use of inferential statistics such as the t-test.

Fifth, a comprehensive study of the various learning curve models and their origin, underlying concepts, mathematical forms, and uses would prove interesting. This research would include, but not be limited to, the cumulative average model, the unit

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model, and production rate models. The conditions under which each is useful would also be examined. This would eliminate a great deal of confusion among DOD cost analysts with respect to which learning curve and which form should be used.

Last, non-linear fitting methodology and techniques require research. With many of the models, such as the SAF/FMC model, an iterative non-linear fitting technique must be used. Few analysts really understand the mathematics behind non-linear fitting nor are they aware of the different non-linear fitting options within statistical programs. A discussion as to which models require non-linear fitting, techniques for non-linear fitting, and when each technique should be used would prove useful to DOD cost analysts.

Appendix A: Sample Programs/Output for Correct/Incorrect Slope
Development and Application

The following programs were used for data simulation and analysis of correct/incorrect slope development and correct/incorrect slope application.

Program I: This is one of three programs created to insert variability into the unit data used in the fitting comparison between the Unit formulation and the SAF/FMC formulation. The other two programs were for the 85% and 95% learning curves. This program would be adjusted in the following way for the other two programs:

    1 = 75% slope
    2 = 85% slope
    3 = 95% slope

The bolded and underlined numbers would be changed to reflect the treatment under consideration.

```
* PROGRAM NAME:  NORMAL1.SAS;
;
*THIS PROGRAM SIMULATES A LEARNING CURVE WITH 25000 FIRST UNIT
COST, 75% SLOPE, CONSTANT STANDARD DEVIATION OF .2 AND A
RANDOM ERROR;
;
DATA ONE;
OPTIONS LINESIZE=72;
A = LOG (25000);
B = LOG (.75)/LOG (2);
C = .2;
DO J = 1 TO 100;
  TOTCOST = 0;
  DO I = 1 TO 480;
    LNX=LOG(I);
    Z = RANNOR (6969);
    LNY = A + (B * LNX) + (C*Z);
    COST = EXP (LNY);
    TOTCOST = TOTCOST + COST;
    FILE NORMAL1;
    PUT I COST TOTCOST;
  END;
END;
PROC PRINT;
```

Program II: This is one of nine programs used to separate the production run data created in NORMAL?.SAS into twelve lots. These nine programs were for variable cost only; therefore, fixed cost burden was not considered. The data file from this program was used as an input for UNITCC.SAS and UNITCI.SAS for correct slope developed. Using the following information, the other eight programs could be created:

> D = Decreasing lot profile
> E = Equal lot profile
> I = Increasing lot profile
> 1 = 75% slope
> 2 = 85% slope
> 3 = 95% slope

The bold and underlined letters and numbers would be changed to reflect the treatment under consideration.

```
*PROGRAM NAME: DLT1A;
;
*THIS PROGRAM IS FOR A DECREASING LOT SIZE PROFILE, WITH A 75%
SLOPE;
;
DATA TWO;
OPTIONS LINESIZE=72;
INFILE NORMAL1;
INPUT N1-N1440;
ARRAY NUM[1440] N1-N1440;
ARRAY COST[480] YY1-YY480;
ARRAY LOT[12,6] L1-L72;
ARRAY TOTCOST[480] TC1-TC480;
  DO I = 1 TO 480;
    COST[I] = NUM[I*3-1];
    TOTCOST[I] = NUM [I*3];
  END;
;
*THE FOLLOWING 12 ARRAYS ARE USED TO BREAK THE PRODUCTION RUN
DATA INTO LOTS. EACH ARRAY HAS THE FOLLOWING INFORMATION:
CUMULATIVE UNITS, CUMULATIVE TOTAL VARIABLE COST, TOTAL COST,
ALGEBRAIC LOT PLOT POINT, LOT AVERAGE COST, AND LOT SIZE;
;
LABEL1:
TEMP = 65 + (23 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
  LOT[1,1] = TEMP;
  LOT[1,2] = TOTCOST[TEMP];
```

```
        LOT[1,3] = TOTCOST[TEMP];
        LOT[1,4] = 0;
        B = LOG(.75)/LOG(2);
          DO I = 1 TO LOT[1,1];
            DUM = LOT[1,4] + (I**B);
            LOT[1,4] = DUM;
          END;
        LOT[1,4] = (LOT[1,4]/LOT[1,1])**(1/B);
        LOT[1,5] = LOT[1,3]/TEMP;
        LOT[1,6] = LOT[1,1];

      ;
      TEMP = 60 + (5 * RANUNI(0895));
      TEMP = ROUND(TEMP,1);
        LOT[2,1] = TEMP + LOT[1,1];
        LOT[2,2] = TOTCOST[LOT[2,1]];
        LOT[2,3] = LOT[2,2] - LOT[1,2];
        LOT[2,4] = 0;
          Z = LOT[2,1] - LOT[1,1];
          DO I = 1 TO Z;
            DUM = LOT[2,4] + ((I + LOT[1,1])**B);
            LOT[2,4] = DUM;
          END;
        LOT[2,4] = (LOT[2,4]/Z)**(1/B);
        LOT[2,5] = LOT[2,3]/TEMP;
        LOT[2,6] = LOT[2,1] - LOT[1,1];

      ;
      TEMP = 55 + (5 * RANUNI(0895));
      TEMP = ROUND(TEMP,1);
        LOT[3,1] = TEMP + LOT[2,1];
        LOT[3,2] = TOTCOST[LOT[3,1]];
        LOT[3,3] = LOT[3,2] - LOT[2,2];
        LOT[3,4] = 0;
        Z = LOT[3,1] - LOT[2,1];
          DO I = 1 TO Z;
            DUM = LOT[3,4] + ((I + LOT[2,1])**B);
            LOT[3,4] = DUM;
          END;
        LOT[3,4] = (LOT[3,4]/Z)**(1/B);
        LOT[3,5] = LOT[3,3]/TEMP;
        LOT[3,6] = LOT[3,1] - LOT[2,1];

      ;
      TEMP = 50 + (5 * RANUNI(0895));
      TEMP = ROUND(TEMP,1);
        LOT[4,1] = TEMP + LOT[3,1];
```

```
    LOT[4,2] = TOTCOST[LOT[4,1]];
    LOT[4,3] = LOT[4,2] - LOT[3,2];
    LOT[4,4] = 0;
    Z = LOT[4,1] - LOT[3,1];
      DO I = 1 TO Z;
        DUM = LOT[4,4] + ((I + LOT[3,1])**B);
        LOT[4,4] = DUM;
      END;
    LOT[4,4] = (LOT[4,4]/Z)**(1/B);
    LOT[4,5] = LOT[4,3]/TEMP;
    LOT[4,6] = LOT[4,1] - LOT[3,1];
;
TEMP = 45 + (5 * RANUNI (0895));
TEMP = ROUND(TEMP,1);
    LOT[5,1] = TEMP + LOT[4,1];
    LOT[5,2] = TOTCOST[LOT[5,1]];
    LOT[5,3] = LOT[5,2] - LOT[4,2];
    LOT[5,4] = 0;
    Z = LOT[5,1] - LOT[4,1];
      DO I = 1 TO Z;
        DUM = LOT[5,4] + ((I + LOT[4,1])**B);
        LOT[5,4] = DUM;
      END;
    LOT[5,4] = (LOT[5,4]/Z)**(1/B);
    LOT[5,5] = LOT[5,3]/TEMP;
    LOT[5,6] = LOT[5,1] - LOT[4,1];
;
TEMP = 40 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
    LOT[6,1] = TEMP + LOT[5,1];
    LOT[6,2] = TOTCOST[LOT[6,1]];
    LOT[6,3] = LOT[6,2] - LOT[5,2];
    LOT[6,4] = 0;
    Z = LOT[6,1] - LOT[5,1];
      DO I = 1 TO Z;
        DUM = LOT[6,4] + ((I + LOT[5,1])**B);
        LOT[6,4] = DUM;
      END;
    LOT[6,4] = (LOT[6,4]/Z)**(1/B);
    LOT[6,5] = LOT[6,3]/TEMP;
    LOT[6,6] = LOT[6,1] - LOT[5,1];
;
TEMP = 35 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
```

```
        LOT[7,1] = TEMP + LOT[6,1];
        LOT[7,2] = TOTCOST[LOT[7,1]];
        LOT[7,3] = LOT[7,2] - LOT[6,2];
        LOT[7,4] = 0;
        Z = LOT[7,1] - LOT[6,1];
          DO I = 1 TO Z;
            DUM = LOT[7,4] + ((I + LOT[6,1])**B);
            LOT[7,4] = DUM;
          END;
        LOT[7,4] = (LOT[7,4]/Z)**(1/B);
        LOT[7,5] = LOT[7,3]/TEMP;
        LOT[7,6] = Z;

      ;
      TEMP = 30 + (5 * RANUNI(0895));
      TEMP = ROUND(TEMP,1);
        LOT[8,1] = TEMP + LOT[7,1];
        LOT[8,2] = TOTCOST[LOT[8,1]];
        LOT[8,3] = LOT[8,2] - LOT[7,2];
        LOT[8,4] = 0;
        Z = LOT[8,1] - LOT[7,1];
          DO I = 1 TO Z;
            DUM = LOT[8,4] + ((I + LOT[7,1])**B);
            LOT[8,4] = DUM;
          END;
        LOT[8,4] = (LOT[8,4]/Z)**(1/B);
        LOT[8,5] = LOT[8,3]/TEMP;
        LOT[8,6] = Z;

      ;
      TEMP = 25 + (5 * RANUNI(0895));
      TEMP = ROUND(TEMP,1);
        LOT[9,1] = TEMP + LOT[8,1];
        LOT[9,2] = TOTCOST[LOT[9,1]];
        LOT[9,3] = LOT[9,2] - LOT[8,2];
        LOT[9,4] = 0;
        Z = LOT[9,1] - LOT[8,1];
          DO I = 1 TO Z;
            DUM = LOT[9,4] + ((I + LOT[8,1])**B);
            LOT[9,4] = DUM;
          END;
        LOT[9,4] = (LOT[9,4]/Z)**(1/B);
        LOT[9,5] = LOT[9,3]/TEMP;
        LOT[9,6] = Z;

      ;
      TEMP = 20 + (5 * RANUNI(0895));
```

```
TEMP = ROUND(TEMP,1);
  LOT[10,1] = TEMP + LOT[9,1];
  IF LOT[10,1] > 480 THEN GOTO LABEL1;
  LOT[10,2] = TOTCOST[LOT[10,1]];
  LOT[10,3] = LOT[10,2] - LOT[9,2];
  LOT[10,4] = 0;
  Z = LOT[10,1] - LOT[9,1];
    DO I = 1 TO Z;
      DUM = LOT[10,4] + ((I + LOT[9,1])**B);
      LOT[10,4] = DUM;
    END;
  LOT[10,4] = (LOT[10,4]/Z)**(1/B);
  LOT[10,5] = LOT[10,3]/TEMP;
  LOT[10,6] = Z;

;
TEMP = 10 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
  LOT[11,1] = TEMP + LOT[10,1];
  IF LOT[11,1] > 480 THEN GOTO LABEL1;
  LOT[11,2] = TOTCOST[LOT[11,1]];
  LOT[11,3] = LOT[11,2] - LOT[10,2];
  LOT[11,4] = 0;
  Z = LOT[11,1] - LOT[10,1];
    DO I = 1 TO Z;
      DUM = LOT[11,4] + ((I + LOT[10,1])**B);
      LOT[11,4] = DUM;
    END;
  LOT[11,4] = (LOT[11,4]/Z)**(1/B);
  LOT[11,5] = LOT[11,3]/TEMP;
  LOT[11,6] = Z;

;
TEMP = 480 - LOT[11,1];
IF TEMP < 5 OR TEMP > 10 THEN GOTO LABEL1;
  LOT[12,1] = TEMP + LOT[11,1];
  LOT[12,2] = TOTCOST[LOT[12,1]];
  LOT[12,3] = LOT[12,2] - LOT[11,2];
  LOT[12,4] = 0;
  Z = LOT[12,1] - LOT[11,1];
    DO I = 1 TO Z;
      DUM = LOT[12,4] + ((I + LOT[11,1])**B);
      LOT[12,4] = DUM;
    END;
  LOT[12,4] = (LOT[12,4]/Z)**(1/B);
  LOT[12,5] = LOT[12,3]/TEMP;
```

```
    LOT[12,6] = Z;
;
*THE FOLLOWING STATEMENTS OUTPUTS THE LOT DATA INTO A FILE TO
BE USED BY THE REGRESSION PROGRAMS;
;
FILE DLT1 A;
 DO I = 1 TO 12;
   PUT LOT[I,1] LOT[I,2] LOT[I,3] LOT[I,4] LOT[I,5] LOT[I,6];
 END;
```

Program III: This is one of 27 programs used to separate the production run data created in NORMAL?.SAS into twelve lots. These 27 programs were for total cost; therefore, fixed costs were added to each lot. The data file from this program was used as an input for UNITIC.SAS and UNITII.SAS for incorrect slope developed and the COMB???.SAS programs for fitting the Unit and SAF/FMC formulations. Using the following information, the other 28 programs could be created:

> D = Decreasing lot profile
> E = Equal lot profile
> I = Increasing lot profile
> 1 = 75% slope
> 2 = 85% slope
> 3 = 95% slope
> A = 20% fixed cost burden
> B = 35% fixed cost burden
> C = 50% fixed cost burden

The bold and underlined letters and numbers would be changed to reflect the treatment under consideration.

```
*PROGRAM NAME: DLTGEN1A;
;
*THIS PROGRAM IS FOR A DECREASING LOT SIZE PROFILE, WITH A 75%
SLOPE AND 20% FIXED COST BURDEN;
;
DATA TWO;
OPTIONS LINESIZE=72;
INFILE NORMAL1;
INPUT N1-N1440;
ARRAY NUM[1440] N1-N1440;
ARRAY COST[480] YY1-YY480;
ARRAY LOT[12,6] L1-L72;
ARRAY TOTCOST[480] TC1-TC480;
 DO I = 1 TO 480;
   COST[I] = NUM[I*3-1];
   TOTCOST[I] = NUM [I*3];
 END;
;
LFC = 32368; *LFC = LOT FIXED COST;
;
*THE FOLLOWING 12 ARRAYS ARE USED TO BREAK THE PRODUCTION RUN
DATA INTO LOTS. EACH ARRAY HAS THE FOLLOWING INFORMATION:
```

```
CUMULATIVE UNITS, CUMULATIVE TOTAL VARIABLE COST, TOTAL COST,
ALGEBRAIC LOT PLOT POINT, LOT AVERAGE COST, AND LOT SIZE;

;
LABEL1:
TEMP = 65 + (23 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
  LOT[1,1] = TEMP;
  LOT[1,2] = TOTCOST[TEMP];
  LOT[1,3] = TOTCOST[TEMP] + LFC;
  LOT[1,4] = 0;
  B = LOG(.75)/LOG(2);
    DO I = 1 TO LOT[1,1];
      DUM = LOT[1,4] + (I**B);
      LOT[1,4] = DUM;
    END;
  LOT[1,4] = (LOT[1,4]/LOT[1,1])**(1/B);
  LOT[1,5] = LOT[1,3]/TEMP;
  LOT[1,6] = LOT[1,1];

;
TEMP = 60 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
  LOT[2,1] = TEMP + LOT[1,1];
  LOT[2,2] = TOTCOST[LOT[2,1]];
  LOT[2,3] = LOT[2,2] - LOT[1,2] + LFC;
  LOT[2,4] = 0;
   Z = LOT[2,1] - LOT[1,1];
   DO I = 1 TO Z;
     DUM = LOT[2,4] + ((I + LOT[1,1])**B);
     LOT[2,4] = DUM;
   END;
  LOT[2,4] = (LOT[2,4]/Z)**(1/B);
  LOT[2,5] = LOT[2,3]/TEMP;
  LOT[2,6] = LOT[2,1] - LOT[1,1];

;
TEMP = 55 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
  LOT[3,1] = TEMP + LOT[2,1];
  LOT[3,2] = TOTCOST[LOT[3,1]];
  LOT[3,3] = LOT[3,2] - LOT[2,2] + LFC;
  LOT[3,4] = 0;
   Z = LOT[3,1] - LOT[2,1];
     DO I = 1 TO Z;
       DUM = LOT[3,4] + ((I + LOT[2,1])**B);
       LOT[3,4] = DUM;
```

```
      END;
   LOT[3,4] = (LOT[3,4]/Z)**(1/B);
   LOT[3,5] = LOT[3,3]/TEMP;
   LOT[3,6] = LOT[3,1] - LOT[2,1];
;
TEMP = 50 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
   LOT[4,1] = TEMP + LOT[3,1];
   LOT[4,2] = TOTCOST[LOT[4,1]];
   LOT[4,3] = LOT[4,2] - LOT[3,2] + LFC;
   LOT[4,4] = 0;
   Z = LOT[4,1] - LOT[3,1];
      DO I = 1 TO Z;
         DUM = LOT[4,4] + ((I + LOT[3,1])**B);
         LOT[4,4] = DUM;
      END;
   LOT[4,4] = (LOT[4,4]/Z)**(1/B);
   LOT[4,5] = LOT[4,3]/TEMP;
   LOT[4,6] = LOT[4,1] - LOT[3,1];
;
TEMP = 45 + (5 * RANUNI (0895));
TEMP = ROUND(TEMP,1);
   LOT[5,1] = TEMP + LOT[4,1];
   LOT[5,2] = TOTCOST[LOT[5,1]];
   LOT[5,3] = LOT[5,2] - LOT[4,2] + LFC;
   LOT[5,4] = 0;
   Z = LOT[5,1] - LOT[4,1];
      DO I = 1 TO Z;
         DUM = LOT[5,4] + ((I + LOT[4,1])**B);
         LOT[5,4] = DUM;
      END;
   LOT[5,4] = (LOT[5,4]/Z)**(1/B);
   LOT[5,5] = LOT[5,3]/TEMP;
   LOT[5,6] = LOT[5,1] - LOT[4,1];
;
TEMP = 40 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
   LOT[6,1] = TEMP + LOT[5,1];
   LOT[6,2] = TOTCOST[LOT[6,1]];
   LOT[6,3] = LOT[6,2] - LOT[5,2] + LFC;
   LOT[6,4] = 0;
   Z = LOT[6,1] - LOT[5,1];
      DO I = 1 TO Z;
         DUM = LOT[6,4] + ((I + LOT[5,1])**B);
```

```
          LOT[6,4] = DUM;
        END;
    LOT[6,4] = (LOT[6,4]/Z)**(1/B);
    LOT[6,5] = LOT[6,3]/TEMP;
    LOT[6,6] = LOT[6,1] - LOT[5,1];

  ;
TEMP = 35 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
    LOT[7,1] = TEMP + LOT[6,1];
    LOT[7,2] = TOTCOST[LOT[7,1]];
    LOT[7,3] = LOT[7,2] - LOT[6,2] + LFC;
    LOT[7,4] = 0;
    Z = LOT[7,1] - LOT[6,1];
        DO I = 1 TO Z;
          DUM = LOT[7,4] + ((I + LOT[6,1])**B);
          LOT[7,4] = DUM;
        END;
    LOT[7,4] = (LOT[7,4]/Z)**(1/B);
    LOT[7,5] = LOT[7,3]/TEMP;
    LOT[7,6] = Z;

  ;
TEMP = 30 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
    LOT[8,1] = TEMP + LOT[7,1];
    LOT[8,2] = TOTCOST[LOT[8,1]];
    LOT[8,3] = LOT[8,2] - LOT[7,2] + LFC;
    LOT[8,4] = 0;
    Z = LOT[8,1] - LOT[7,1];
        DO I = 1 TO Z;
          DUM = LOT[8,4] + ((I + LOT[7,1])**B);
          LOT[8,4] = DUM;
        END;
    LOT[8,4] = (LOT[8,4]/Z)**(1/B);
    LOT[8,5] = LOT[8,3]/TEMP;
    LOT[8,6] = Z;

  ;
TEMP = 25 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
    LOT[9,1] = TEMP + LOT[8,1];
    LOT[9,2] = TOTCOST[LOT[9,1]];
    LOT[9,3] = LOT[9,2] - LOT[8,2] + LFC;
    LOT[9,4] = 0;
    Z = LOT[9,1] - LOT[8,1];
        DO I = 1 TO Z;
```

```
          DUM = LOT[9,4] + ((I + LOT[8,1])**B);
          LOT[9,4] = DUM;
        END;
    LOT[9,4] = (LOT[9,4]/Z)**(1/B);
    LOT[9,5] = LOT[9,3]/TEMP;
    LOT[9,6] = Z;

;
TEMP = 20 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
    LOT[10,1] = TEMP + LOT[9,1];
      IF LOT[10,1] > 480 THEN GOTO LABEL1;
    LOT[10,2] = TOTCOST[LOT[10,1]];
    LOT[10,3] = LOT[10,2] - LOT[9,2] + LFC;
    LOT[10,4] = 0;
    Z = LOT[10,1] - LOT[9,1];
      DO I = 1 TO Z;
        DUM = LOT[10,4] + ((I + LOT[9,1])**B);
        LOT[10,4] = DUM;
      END;
    LOT[10,4] = (LOT[10,4]/Z)**(1/B);
    LOT[10,5] = LOT[10,3]/TEMP;
    LOT[10,6] = Z;

;
TEMP = 10 + (5 * RANUNI(0895));
TEMP = ROUND(TEMP,1);
    LOT[11,1] = TEMP + LOT[10,1];
      IF LOT[11,1] > 480 THEN GOTO LABEL1;
    LOT[11,2] = TOTCOST[LOT[11,1]];
    LOT[11,3] = LOT[11,2] - LOT[10,2] + LFC;
    LOT[11,4] = 0;
    Z = LOT[11,1] - LOT[10,1];
      DO I = 1 TO Z;
        DUM = LOT[11,4] + ((I + LOT[10,1])**B);
        LOT[11,4] = DUM;
      END;
    LOT[11,4] = (LOT[11,4]/Z)**(1/B);
    LOT[11,5] = LOT[11,3]/TEMP;
    LOT[11,6] = Z;

;
TEMP = 480 - LOT[11,1];
IF TEMP < 5 OR TEMP > 10 THEN GOTO LABEL1;
    LOT[12,1] = TEMP + LOT[11,1];
    LOT[12,2] = TOTCOST[LOT[12,1]];
    LOT[12,3] = LOT[12,2] - LOT[11,2] + LFC;
```

```
    LOT[12,4] = 0;
  Z = LOT[12,1] - LOT[11,1];
    DO I = 1 TO Z;
       DUM = LOT[12,4] + ((I + LOT[11,1])**B);
       LOT[12,4] = DUM;
    END;
  LOT[12,4] = (LOT[12,4]/Z)**(1/B);
  LOT[12,5] = LOT[12,3]/TEMP;
  LOT[12,6] = Z;

;
*THE FOLLOWING STATEMENTS OUTPUTS THE LOT DATA INTO A FILE TO
BE USED BY
THE REGRESSION PROGRAMS;

;
FILE DLTGEN1A;
  DO I = 1 TO 12;
    PUT LOT[I,1] LOT[I,2] LOT[I,3] LOT[I,4] LOT[I,5] LOT[I,6];
  END;
```

The following is the Excel Spreadsheet (LOTFC.XLS) was used to calculate the lot FC
for the above program. The TVC column was calculated using the LEARN Program
(output to follow).

T1 = $25,000

SLOPE	TVC	VC%	TC	FC%	TFC	LOT FC
0.75	1,553,665	0.80	1,942,081	0.20	388,416	32,368
0.75	1,553,665	0.65	2,390,254	0.35	836,589	69,716
0.75	1,553,665	0.50	3,107,330	0.50	1,553,665	129,472
0.85	3,669,279	0.80	4,586,599	0.20	917,320	76,443
0.85	3,669,279	0.65	5,645,045	0.35	1,975,766	164,647
0.85	3,669,279	0.50	7,338,558	0.50	3,669,279	305,773
0.95	8,200,051	0.80	10,250,064	0.20	2,050,013	170,834
0.95	8,200,051	0.65	12,615,463	0.35	4,415,412	367,951
0.95	8,200,051	0.50	16,400,102	0.50	8,200,051	683,338

This is the output from the LEARN program for a T1 of $25,000 and all three slopes:

Unit Curve Formulation

First unit (A)	=	****25000.00
Slope	=	75.0%
Slope coefficient (b)	=	-0.415037
Unit/lot	=	1 - 480
Cost of unit 480	=	*****1928.08
Average cost of unit 1 to 480	=	*****3236.80
Total cost through unit 480	=	**1553665.44
Total cost of lot (1 - 480)	=	**1553665.44
Average cost of units in lot	=	*****3236.80

Unit Curve Formulation

First unit (A)	=	****25000.00
Slope	=	85.0%
Slope coefficient (b)	=	-0.234465
Unit/lot	=	1 - 480
Cost of unit 480	=	*****5878.71
Average cost of unit 1 to 480	=	*****7644.33
Total cost through unit 480	=	**3669279.08
Total cost of lot (1 - 480)	=	**3669279.08
Average cost of units in lot	=	*****7644.33

Unit Curve Formulation

First unit (A)	=	****25000.00
Slope	=	95.0%
Slope coefficient (b)	=	-0.074001
Unit/lot	=	1 - 480
Cost of unit 480	=	****15831.67
Average cost of unit 1 to 480	=	****17083.44
Total cost through unit 480	=	**8200051.20
Total cost of lot (1 - 480)	=	**8200051.20
Average cost of units in lot	=	****17083.44

The following is an example of the output from the lot generating programs. This sample is from DLTGEN1A.SAS. It was copied from SAS into Excel so that headings could be added and the numbers would be aligned for easier reading.

Cum Unit #	Cum Lot Variable Cost	Lot Total Cost	Algebraic Lot Plot Point	Avg Lot Total Cost	Lot Size
79	$ 527,818.09	$ 560,186.09	24.5	$ 7,090.96	79
150	$ 772,120.88	$ 276,670.79	112.4	$ 3,896.77	71
211	$ 960,246.54	$ 220,493.65	179.8	$ 3,614.65	61
266	$ 1,101,170.94	$ 173,292.41	238.3	$ 3,150.77	55
319	$ 1,226,610.44	$ 157,807.50	292.4	$ 2,977.50	53
361	$ 1,323,871.11	$ 129,628.67	340.2	$ 3,086.40	42
394	$ 1,393,214.78	$ 101,711.67	377.8	$ 3,082.17	33
422	$ 1,454,437.60	$ 93,590.82	408.4	$ 3,342.53	28
444	$ 1,500,251.93	$ 78,182.33	433.4	$ 3,553.74	22
459	$ 1,530,833.24	$ 62,949.31	452.0	$ 4,196.62	15
472	$ 1,557,592.35	$ 59,127.11	466.0	$ 4,548.24	13
480	$ 1,574,080.08	$ 48,855.73	476.5	$ 6,106.97	8
79	$ 522,391.56	$ 554,759.56	24.5	$ 7,022.27	79
147	$ 773,170.27	$ 283,146.71	111.0	$ 4,163.92	68
212	$ 967,716.28	$ 226,914.02	178.6	$ 3,490.98	65
270	$ 1,123,465.45	$ 188,117.17	240.7	$ 3,243.40	58
316	$ 1,235,532.21	$ 144,434.75	293.1	$ 3,139.89	46
361	$ 1,336,987.75	$ 133,823.55	338.6	$ 2,973.86	45
396	$ 1,411,477.37	$ 106,857.61	378.8	$ 3,053.07	35
424	$ 1,471,863.17	$ 92,753.81	410.4	$ 3,312.64	28
448	$ 1,522,898.69	$ 83,403.52	436.4	$ 3,475.15	24
465	$ 1,555,195.27	$ 64,664.58	457.0	$ 3,803.80	17
477	$ 1,578,045.31	$ 55,218.03	471.5	$ 4,601.50	12
480	$ 1,584,676.60	$ 38,999.30	479.0	$ 12,999.77	3
80	$ 545,709.45	$ 578,077.45	24.8	$ 7,225.97	80
148	$ 789,688.55	$ 276,347.10	112.1	$ 4,063.93	68
209	$ 970,522.14	$ 213,201.58	177.8	$ 3,495.11	61
265	$ 1,123,665.18	$ 185,511.04	236.7	$ 3,312.70	56
310	$ 1,233,117.97	$ 141,820.79	287.6	$ 3,151.57	45
353	$ 1,333,467.20	$ 132,717.22	331.7	$ 3,086.45	43
391	$ 1,417,249.99	$ 116,150.80	372.3	$ 3,056.60	38
421	$ 1,478,667.25	$ 93,785.26	406.4	$ 3,126.18	30
444	$ 1,527,694.02	$ 81,394.77	432.9	$ 3,538.90	23
464	$ 1,566,158.25	$ 70,832.24	454.4	$ 3,541.61	20
475	$ 1,586,310.26	$ 52,520.00	470.0	$ 4,774.55	11
480	$ 1,595,804.50	$ 41,862.24	478.0	$ 8,372.45	5

The following two pages show the parameters of the decreasing and increasing lot sizing programs. The selected upper and lower bounds, the selected cumulative upper and lower bounds, the actual upper and lower bounds, the actual average lot size, and the actual cumulative lot size average.

DLTGEN**.SAS				
	Units	Unit	Cum	Cum
Lot #	Low Bnd	Upper Bnd	Low Bnd	Upper Bnd
1	65	88	65	88
2	60	65	125	153
3	55	60	180	213
4	50	55	230	268
5	45	50	275	318
6	40	45	315	363
7	35	40	350	403
8	30	35	380	438
9	25	30	405	468
10	20	25	425	493
11	10	15	435	508
12	480-CumX	480-CumX	435	508

Conditional Statements for DLTGEN.SAS:**

LOT 10: If the cumulative units through Lot 10>480, start over at Lot 1 and rerun the process.

LOT 11: If the cumulative units through Lot 10 > 480, start over at Lot 1 and rerun the process.

LOT 12: If the lotsize for Lot 12 <5 or >10, then start over at Lot 1 and rerun the process.

	Actual	Actual	Actual Avg	Actual Cum Lot
Lot #	Low Bnd	Upper Bnd	Lot Size	Size Avg
1	67	88	77.89	77.89
2	60	65	62.41	140.30
3	55	60	57.53	197.83
4	50	55	52.43	250.26
5	45	50	47.28	297.54
6	40	45	42.33	339.87
7	35	40	37.35	377.22
8	30	35	32.77	409.99
9	25	30	27.59	437.58
10	20	25	22.50	460.08
11	10	15	12.45	472.53
12	5	10	7.47	480.00

		ILTGEN**.SAS		
Lot #	Units Low Bnd	Unit Upper Bnd	Cum Low Bnd	Cum Upper Bnd
1	5	10	5	10
2	10	15	15	25
3	20	25	35	50
4	25	30	60	80
5	30	35	90	115
6	35	40	125	155
7	40	45	165	200
8	45	50	210	250
9	50	55	260	305
10	55	60	315	365
11	60	65	375	430
12	480-CumX	480-CumX	375	430

Lot #	Actual Low Bnd	Actual Upper Bnd	Actual Avg Lot Size	Actual Cum Lot Size Avg
1	5	10	7.76	7.76
2	10	15	12.62	20.38
3	20	25	22.59	42.97
4	25	30	27.43	70.40
5	30	35	32.42	102.82
6	35	40	37.68	140.50
7	40	45	42.22	182.72
8	45	50	47.34	230.06
9	50	55	52.55	282.61
10	55	60	57.53	340.14
11	60	65	62.64	402.78
12	65	88	77.22	480.00

Program IV: This file was created to allow for sorting the information used in later calculations to do those calculations by production run number.

```
*PROGRAM NAME: PRODRUN.SAS;
;
DATA ONE;
FILE PRODRUN;
DO I = 1 TO 100;
  DO J = 1 TO 12;
    PUT I;
  END;
END;
```

Program V: This is one of nine programs created to fit the lot profile data from the lot generating programs for variable cost only (?LT??.DAT). This would be return the correctly developed slope for later calculations. The other eight programs could be duplicated by using the following information:

D = Decreasing lot profile
E = Equal lot profile
I = Increasing lot profile
1 = 75% slope
2 = 85% slope
3 = 95% slope

The bold and underlined letters and numbers would be changed to reflect the treatment under consideration.

```
*PROGRAM NAME: UNITD1.SAS;
;
*THIS PROGRAM THE FITS THE STANDARD UNIT LEARNING CURVE TO A
DECREASING LOT PROFILE AND 75% SLOPE;
;
LIBNAME PARAMS '[KTHOMSON.THESIS]';
OPTIONS LINESIZE=72;
;
DATA THREE;
INFILE DLT1A;
   INPUT CUMX TOTY LOTCOST LPP AVUNCST LOTSZ;
INFILE PRODRUN;
   INPUT PRDRUN;
;
LNLPP = LOG(LPP);
LNAVUCST = LOG(AVUNCST);
;
PROC REG DATA=THREE OUTEST = PARAMS.DU1 NOPRINT;
 DU1:MODEL LNAVUCST = LNLPP;
 BY PRDRUN;
PROC PRINT;
```

Program VI: This program is an example of the 27 programs used to fit the Unit and SAF/FMC model to total cost lot data. The other 26 programs can be reproduced from this program by changing the variable and input file names using the following key.

      D = decreasing lot profile
      E = equal lot profile
      I = increasing lot profile
      1 = 75% slope
      2 = 85% slope
      3 = 95% slope
      A = 20% fixed cost burden
      B = 35% fixed cost burden
      C = 50% fixed cost burden

The bold and underlined characters would be changed depending on the treatment under consideration (i.e. the line INFILE DLTGEN1A would read INFILE ELTGEN3C for COMBE3C.SAS when fitting the treatment for equal lot profile, 95% slope, and 50% fixed cost burden)

```
*PROGRAM NAME: COMBD1A.SAS;
;
*THIS PROGRAM THE FITS THE STANDARD UNIT LEARNING CURVE AND
SAF/FMC MODEL TO AN DECREASING LOT PROFILE, 75% CURVE, WITH 20%
FIXED COSTS;
;
LIBNAME PARAMS '[KTHOMSON.THESIS]';
LIBNAME MAD '[KTHOMSON.THESIS]';
OPTIONS LINESIZE=72;
;
DATA THREE;
INFILE DLTGEN1A;
  INPUT CUMX TOTY LOTCOST LPP AVUNCST LOTSZ;
INFILE PRODRUN;
  INPUT PRDRUN;
;
LNLPP = LOG(LPP);
LNAVUCST = LOG(AVUNCST);
;
* NEXT TWO MODELS REGRESS NATURAL LOG OF AVG UNIT COST FOR
LOT (DEPENDENT VARIABLE) AGAINST NATURAL LOG OF ALGEBRAIC LOT
PLOT POINT (INDEPENDENT VARIABLE).  REGRESSION WILL PRODUCE AN
INTERCEPT AND A COEFFICIENT FOR THE ALGEBRAIC LOT PLOT POINT.
THE INTERCEPT, WHEN CONVERTED FROM LOG SPACE TO UNIT SPACE, IS
```

EQUIVALENT TO THE 1ST UNIT COST (A) WHEREAS THE COEFFICIENT FOR
THE NATURAL LOG OF THE ALGEBRAIC LOT PLOT POINT IS THE SLOPE
COEFFICIENT. TO COMPUTE THE SLOPE, ONE WOULD USE THE
FOLLOWING EQUATION: SLOPE = E**(COEFFICIENT * LOG(2));
;

```
PROC REG DATA=THREE OUTEST = PARAMS.DUNIT1A;
  DUNIT1A:MODEL LNAVUCST = LNLPP;
  BY PRDRUN;
  OUTPUT OUT=DUNIT1A P=PUC R=RESID;
  PROC PRINT;
;
```

* THE NEXT MODEL (SAF/FMC) USES NON LINEAR REGRESSION. PARTIAL
DERIVATIVES WITH RESPECT TO THE PARAMETERS HAVE NOT BEEN
SPECIFIED SINCE THE DUD (DOESN'T USE DERIVATIVES) METHOD IS BEING
USED;
;

```
PROC NLIN DATA=THREE OUTEST=PARAMS.DSAF1A;
*INITIAL GUESS VALUES FOR PARAMETERS;
  PARMS B=-.3 F=20000 A=25000;
  DSAF1A:MODEL AVUNCST = F/LOTSZ + (A*LPP**B);
  BY PRDRUN;
  BOUNDS -1<=B<=0;
  BOUNDS 0<=F<=900000;
  BOUNDS 0<=A<=200000;
  OUTPUT OUT=DSAF1A P=PUC R=RESIDLR;
```
*WRITES THE PREDICTED AVG COSTS (UNIT SPACE), RESIDUALS (UNIT
SPACE), AND ORIGINAL DATA SET TO A NEW DATA SET FOR FURTHER
ANALYSIS;
;

```
DATA UNITD1A;
  SET DUNIT1A;
  PUCDLR=EXP(PUC);
  AUCDLR=EXP(LNAVUCST);
  RESIDLR=AUCDLR-PUCDLR;
  ABRESID=ABS(RESIDLR);
  PROC PRINT;
;
DATA SAFD1A;
  SET DSAF1A;
  ABRESID=ABS(RESIDLR);
  PROC PRINT;
;
```
;
*THE FOLLOWING PROCEDURE IS FOR MAD CALCULATIONS FOR UNIT
MODEL;

```
;
PROC MEANS DATA=UNITD1A;
  VAR ABRESID;
  BY PRDRUN;
  OUTPUT OUT=MAD.MADUND1A N(ABRESID)=N MEAN(ABRESID)=MAD;

;
*THE FOLLOWING PROCEDURE IS FOR MAD CALCULATIONS FOR THE SAF
MODEL;

;
PROC MEANS DATA =SAFD1A;
  VAR ABRESID;
  BY PRDRUN;
  OUTPUT OUT=MAD.MADSAD1A N(ABRESID)=N MEAN(ABRESID)=MAD;

;
* THIS SECTION COMBINES THE PERMANENT PARAMETER DATA SETS
FROM EACH MODEL INTO ONE PERMANENT DATA SET;

;
DATA PARAMS.D1AFINAL;
  SET PARAMS.DSAF1A;
  IF _TYPE_='FINAL';
DATA PARAMS.D1APRM;
  SET PARAMS.DUNIT1A
    PARAMS.D1AFINAL;
  PROC PRINT;

;
* THIS SECTION COMBINES THE PERMANENT MAD DATA SETS FROM EACH
MODEL INTO ONE PERMANENT MAD DATA SET;

;
DATA MAD.D1AMAD;
  SET MAD.MADUND1A
    MAD.MADSAD1A;
PROC PRINT;
```

Program VII: This program is used to calculate the mean of the 100 correctly developed slope coefficients and correctly apply the mean slope in a new production run with fixed costs being added in afterwards by use of a factor.

```
* PROGRAM NAME:  UNITCC.SAS;
;
LIBNAME PARAMS '[KTHOMSON.THESIS]';
OPTIONS LINESIZE=72;
DATA ONE;
  SET PARAMS.DU1
     PARAMS.DU2
     PARAMS.DU3
     PARAMS.EU1
     PARAMS.EU2
     PARAMS.EU3
     PARAMS.IU1
     PARAMS.IU2
     PARAMS.IU3;
  PROC SORT;
   BY _MODEL_;
  PROC UNIVARIATE;
   VAR LNLPP;
   BY _MODEL_;
  PROC MEANS DATA=ONE;
   VAR LNLPP;
   BY _MODEL_;
   OUTPUT OUT = PARAMS.TESTCCT  MEAN(LNLPP) = SLPCOEFF
     STD(LNLPP) = STDDEV STDERR  (LNLPP) = ERROFEST;
  PROC PRINT;
DATA PARAMS.UNITCCT;
  SET PARAMS.TESTCCT;
  VARCOST=0;
  COST=0;
  X=0;
  T1=40000;
  DO I=1 TO 480;
   X=X+1;
   COST=T1*X**SLPCOEFF;
   VARCOST=VARCOST+COST;
  END;
  TOTCOSTA=VARCOST*1.25;
  TOTCOSTB=VARCOST*1.5385;
  TOTCOSTC=VARCOST*2.00;
PROC PRINT;
```

Hypothesis Test for Sample Slope Equals Population Slope
Data from UNITCC.SAS and UNITIC.SAS programs

| CORRECT SLOPE DEVELOPMENT | | | | | | | | Standard |
Model	Estimated Slpcoeff	Population Slpcoeff	t Test Value	t*	Hypothesis Decision	Approximate p-values	Standard Deviation	Error of the Estimate
DU1A	-0.415318	-0.415037	-0.0233	1.987	cannot reject	0.49	0.012056	0.0012056
DU1B	-0.415318	-0.415037	-0.0233	1.987	cannot reject	0.49	0.012056	0.0012056
DU1C	-0.415318	-0.415037	-0.0233	1.987	cannot reject	0.49	0.012056	0.0012056
DU2A	-0.245349	-0.234465	-0.8361	1.987	cannot reject	0.21	0.013017	0.0013017
DU2B	-0.245349	-0.234465	-0.8361	1.987	cannot reject	0.21	0.013017	0.0013017
DU2C	-0.245349	-0.234465	-0.8361	1.987	cannot reject	0.21	0.013017	0.0013017
DU3A	-0.075426	-0.074001	-0.1102	1.987	cannot reject	0.48	0.012933	0.0012933
DU3B	-0.075426	-0.074001	-0.1102	1.987	cannot reject	0.48	0.012933	0.0012933
DU3C	-0.075426	-0.074001	-0.1102	1.987	cannot reject	0.48	0.012933	0.0012933
EU1A	-0.437756	-0.415037	-2.0837	1.987	reject	0.004	0.010903	0.0010903
EU1B	-0.437756	-0.415037	-2.0837	1.987	reject	0.004	0.010903	0.0010903
EU1C	-0.437756	-0.415037	-2.0837	1.987	reject	0.004	0.010903	0.0010903
EU2A	-0.240869	-0.234465	-0.6068	1.987	cannot reject	0.3	0.010553	0.0010553
EU2B	-0.240869	-0.234465	-0.6068	1.987	cannot reject	0.3	0.010553	0.0010553
EU2C	-0.240869	-0.234465	-0.6068	1.987	cannot reject	0.3	0.010553	0.0010553
EU3A	-0.073969	-0.074001	0.0031	1.987	cannot reject	0.5	0.010447	0.0010447
EU3B	-0.073969	-0.074001	0.0031	1.987	cannot reject	0.5	0.010447	0.0010447
EU3C	-0.073969	-0.074001	0.0031	1.987	cannot reject	0.5	0.010447	0.0010447
IU1A	-0.422261	-0.415037	-0.5866	1.987	cannot reject	0.4	0.012314	0.0012314
IU1B	-0.422261	-0.415037	-0.5866	1.987	cannot reject	0.4	0.012314	0.0012314
IU1C	-0.422261	-0.415037	-0.5866	1.987	cannot reject	0.4	0.012314	0.0012314
IU2A	-0.236048	-0.234465	-0.1331	1.987	cannot reject	0.47	0.011885	0.0011885
IU2B	-0.236048	-0.234465	-0.1331	1.987	cannot reject	0.47	0.011885	0.0011885
IU2C	-0.236048	-0.234465	-0.1331	1.987	cannot reject	0.47	0.011885	0.0011885
IU3A	-0.073291	-0.074001	0.0606	1.987	cannot reject	0.49	0.011708	0.0011708
IU3B	-0.073291	-0.074001	0.0606	1.987	cannot reject	0.49	0.011708	0.0011708
IU3C	-0.073291	-0.074001	0.0606	1.987	cannot reject	0.49	0.011708	0.0011708

Program VIII: This program is used to calculate the mean of the 100 correctly developed slope coefficients and incorrectly apply the mean slope in a new production run with fixed costs included in the T1 value.

```
* PROGRAM NAME:  UNITCI.SAS;
LIBNAME PARAMS '[KTHOMSON.THESIS]';
OPTIONS LINESIZE=72;
DATA ONE;
 SET PARAMS.DU1
    PARAMS.DU2
    PARAMS.DU3
    PARAMS.EU1
    PARAMS.EU2
    PARAMS.EU3
    PARAMS.IU1
    PARAMS.IU2
    PARAMS.IU3;
 PROC SORT;
  BY _MODEL_;
 PROC UNIVARIATE;
  VAR LNLPP;
  BY _MODEL_;
 PROC MEANS DATA=ONE;
  VAR LNLPP;
  BY _MODEL_;
  OUTPUT OUT=PARAMS.TESTCIT  MEAN(LNLPP)=SLPCOEFF
    STD(LNLPP)=STDDEV  STDERR(LNLPP)=ERROFEST;
  PROC PRINT;
DATA PARAMS.UNITCIT;
 SET PARAMS.TESTCIT;
INFILE T1VALCI;
 INPUT T1A T1B T1C;
 TOTCOSTA=0;
 TOTCOSTB=0;
 TOTCOSTC=0;
 COSTA=0;
 COSTB=0;
 COSTC=0;
 XA=0;
 XB=0;
 XC=0;
 DO I=1 TO 480;
  XA=XA+1;
  COSTA=T1A*XA**SLPCOEFF;
```

```
   TOTCOSTA=TOTCOSTA+COSTA;
END;
DO J=1 TO 480;
 XB=XB+1;
 COSTB=T1B*XB**SLPCOEFF;
 TOTCOSTB=TOTCOSTB+COSTB;
END;
DO K=1 TO 480;
 XC=XC+1;
 COSTC=T1C*XC**SLPCOEFF;
 TOTCOSTC=TOTCOSTC+COSTC;
END;
PROC PRINT;
```

Program IX: This program is used to calculate the mean of the 100 incorrectly developed slope coefficients and correctly apply the mean slope in a new production run with fixed costs computed separately by use of a factor.

```
* PROGRAM NAME:  UNITIC.SAS;
;
LIBNAME PARAMS '[KTHOMSON.THESIS]';
OPTIONS LINESIZE=72;
DATA ONE;
  SET PARAMS.DUNIT1A
     PARAMS.DUNIT1B
     PARAMS.DUNIT1C
     PARAMS.EUNIT1A
     PARAMS.EUNIT1B
     PARAMS.EUNIT1C
     PARAMS.IUNIT1A
     PARAMS.IUNIT1B
     PARAMS.IUNIT1C
     PARAMS.DUNIT2A
     PARAMS.DUNIT2B
     PARAMS.DUNIT2C
     PARAMS.EUNIT2A
     PARAMS.EUNIT2B
     PARAMS.EUNIT2C
     PARAMS.IUNIT2A
     PARAMS.IUNIT2B
     PARAMS.IUNIT2C
     PARAMS.DUNIT3A
     PARAMS.DUNIT3B
     PARAMS.DUNIT3C
     PARAMS.EUNIT3A
     PARAMS.EUNIT3B
     PARAMS.EUNIT3C
     PARAMS.IUNIT3A
     PARAMS.IUNIT3B
     PARAMS.IUNIT3C;
 PROC SORT;
  BY _MODEL_;
 PROC UNIVARIATE;
  VAR LNLPP;
  BY _MODEL_;
 PROC MEANS DATA=ONE;
  VAR LNLPP;
  BY _MODEL_;
```

```
   OUTPUT OUT=PARAMS.TESTICT  MEAN(LNLPP)=SLPCOEFF
       STD(LNLPP)=STDDEV  STDERR(LNLPP)=ERROFEST;
   PROC PRINT;
DATA PARAMS.UNITICT;
 SET PARAMS.TESTICT;
 VARCOST=0;
 COST=0;
 X=0;
 T1=40000;
 DO I=1 TO 480;
  X=X+1;
  COST=T1*X**SLPCOEFF;
  VARCOST=VARCOST+COST;
 END;
 IF _MODEL_ = 'DUNIT1A' THEN
  TOTCOST = VARCOST*1.25;
 ELSE IF _MODEL_ = 'DUNIT2A' THEN
  TOTCOST = VARCOST*1.25;
 ELSE IF _MODEL_ = 'DUNIT3A' THEN
  TOTCOST = VARCOST*1.25;
 ELSE IF _MODEL_ = 'DUNIT1B' THEN
  TOTCOST = VARCOST*1.5385;
 ELSE IF _MODEL_ = 'DUNIT2B' THEN
  TOTCOST = VARCOST*1.5385;
 ELSE IF _MODEL_ = 'DUNIT3B' THEN
  TOTCOST = VARCOST*1.5385;
 ELSE IF _MODEL_ = 'EUNIT1A' THEN
  TOTCOST = VARCOST*1.25;
 ELSE IF _MODEL_ = 'EUNIT2A' THEN
  TOTCOST = VARCOST*1.25;
 ELSE IF _MODEL_ = 'EUNIT3A' THEN
  TOTCOST = VARCOST*1.25;
 ELSE IF _MODEL_ = 'EUNIT1B' THEN
  TOTCOST = VARCOST*1.5385;
 ELSE IF _MODEL_ = 'EUNIT2B' THEN
  TOTCOST = VARCOST*1.5385;
 ELSE IF _MODEL_ = 'EUNIT3B' THEN
  TOTCOST = VARCOST*1.5385;
 ELSE IF _MODEL_ = 'IUNIT1A' THEN
  TOTCOST = VARCOST*1.25;
 ELSE IF _MODEL_ = 'IUNIT2A' THEN
  TOTCOST = VARCOST*1.25;
 ELSE IF _MODEL_ = 'IUNIT3A' THEN
  TOTCOST = VARCOST*1.25;
```

```
ELSE IF _MODEL_ = 'IUNIT1B' THEN
  TOTCOST = VARCOST*1.5385;
ELSE IF _MODEL_ = 'IUNIT2B' THEN
  TOTCOST = VARCOST*1.5385;
ELSE IF _MODEL_ = 'IUNIT3B' THEN
  TOTCOST = VARCOST*1.5385;
ELSE TOTCOST = VARCOST*2;
PROC PRINT;
```

Hypothesis Test for Sample Slope Equals Population Slope
Data from UNITCC.SAS and UNITIC.SAS programs

INCORRECT SLOPE DEVELOPMENT								Standard
Model	Estimated Slpcoeff	Population Slpcoeff	t Test Value	t*	Hypothesis Decision	Approximate p-values	Standard Deviation	Error of the Estimate
DUNIT1A	-0.175813	-0.415037	12.8532	1.987	reject	0.0001	0.018612	0.0018612
DUNIT1B	-0.038092	-0.415037	16.3456	1.987	reject	0.0001	0.023061	0.0023061
DUNIT1C	0.089137	-0.415037	18.9042	1.987	reject	0.0001	0.026670	0.0026670
DUNIT2A	-0.036955	-0.234465	10.9279	1.987	reject	0.0001	0.018074	0.0018074
DUNIT2B	0.082157	-0.234465	13.7938	1.987	reject	0.0001	0.022954	0.0022954
DUNIT2C	0.193083	-0.234465	15.7511	1.987	reject	0.0001	0.027144	0.0027144
DUNIT3A	0.093480	-0.074001	9.2022	1.987	reject	0.0001	0.018200	0.0018200
DUNIT3B	0.193105	-0.074001	11.5735	1.987	reject	0.0001	0.023079	0.0023079
DUNIT3C	0.287517	-0.074001	13.0089	1.987	reject	0.0001	0.027790	0.0027790
EUNIT1A	-0.341567	-0.415037	8.2228	1.987	reject	0.0001	0.008935	0.0008935
EUNIT1B	-0.285903	-0.415037	16.4398	1.987	reject	0.0001	0.007855	0.0007855
EUNIT1C	-0.228114	-0.415037	28.0371	1.987	reject	0.0001	0.006667	0.0006667
EUNIT2A	-0.191735	-0.234465	4.9571	1.987	reject	0.0001	0.008620	0.0008620
EUNIT2B	-0.159181	-0.234465	10.2595	1.987	reject	0.0001	0.007338	0.0007338
EUNIT2C	-0.125422	-0.234465	18.2989	1.987	reject	0.0001	0.005959	0.0005959
EUNIT3A	-0.059363	-0.074001	1.7313	1.987	cannot reject	0.04	0.008455	0.0008455
EUNIT3B	-0.047035	-0.074001	3.9949	1.987	reject	0.0001	0.006750	0.0006750
EUNIT3C	-0.037840	-0.074001	6.6094	1.987	reject	0.0001	0.005471	0.0005471
IUNIT1A	-0.423340	-0.415037	-0.8043	1.987	cannot reject	0.21	0.010323	0.0010323
IUNIT1B	-0.430266	-0.415037	-1.4924	1.987	cannot reject	0.075	0.010204	0.0010204
IUNIT1C	-0.446366	-0.415037	-3.3643	1.987	reject	0.0005	0.009312	0.0009312
IUNIT2A	-0.287635	-0.234465	-5.2010	1.987	reject	0.0001	0.010223	0.0010223
IUNIT2B	-0.324256	-0.234465	-7.9913	1.987	reject	0.0001	0.011236	0.0011236
IUNIT2C	-0.358465	-0.234465	-9.7691	1.987	reject	0.0001	0.012693	0.0012693
IUNIT3A	-0.182044	-0.074001	-9.0953	1.987	reject	0.0001	0.011879	0.0011879
IUNIT3B	-0.246736	-0.074001	-12.5626	1.987	reject	0.0001	0.013750	0.0013750
IUNIT3C	-0.303469	-0.074001	-15.2806	1.987	reject	0.0001	0.015017	0.0015017

Program X: This program is used to calculate the mean of the 100 incorrectly developed slope coefficients and correctly apply the mean slope in a new production run with fixed costs computed separately by use of a factor.

```
* PROGRAM NAME: UNITIC.SAS;
;
LIBNAME PARAMS '[KTHOMSON.THESIS]';
OPTIONS LINESIZE=72;
DATA ONE;
 SET PARAMS.DUNIT1A
   PARAMS.DUNIT1B
   PARAMS.DUNIT1C
   PARAMS.EUNIT1A
   PARAMS.EUNIT1B
   PARAMS.EUNIT1C
   PARAMS.IUNIT1A
   PARAMS.IUNIT1B
   PARAMS.IUNIT1C
   PARAMS.DUNIT2A
   PARAMS.DUNIT2B
   PARAMS.DUNIT2C
   PARAMS.EUNIT2A
   PARAMS.EUNIT2B
   PARAMS.EUNIT2C
   PARAMS.IUNIT2A
   PARAMS.IUNIT2B
   PARAMS.IUNIT2C
   PARAMS.DUNIT3A
   PARAMS.DUNIT3B
   PARAMS.DUNIT3C
   PARAMS.EUNIT3A
   PARAMS.EUNIT3B
   PARAMS.EUNIT3C
   PARAMS.IUNIT3A
   PARAMS.IUNIT3B
   PARAMS.IUNIT3C;
 PROC SORT;
  BY _MODEL_;
 PROC UNIVARIATE;
  VAR LNLPP;
  BY _MODEL_;
 PROC MEANS DATA=ONE;
  VAR LNLPP;
  BY _MODEL_;
```

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```
      OUTPUT OUT=PARAMS.TESTICT  MEAN(LNLPP)=SLPCOEFF
         STD(LNLPP)=STDDEV  STDERR(LNLPP)=ERROFEST;
      PROC PRINT;
   DATA PARAMS.UNITICT;
    SET PARAMS.TESTICT;
    VARCOST=0;
    COST=0;
    X=0;
    T1=40000;
    DO I=1 TO 480;
     X=X+1;
     COST=T1*X**SLPCOEFF;
     VARCOST=VARCOST+COST;
    END;
    IF _MODEL_ = 'DUNIT1A' THEN
     TOTCOST = VARCOST*1.25;
    ELSE IF _MODEL_ = 'DUNIT2A' THEN
     TOTCOST = VARCOST*1.25;
    ELSE IF _MODEL_ = 'DUNIT3A' THEN
     TOTCOST = VARCOST*1.25;
    ELSE IF _MODEL_ = 'DUNIT1B' THEN
     TOTCOST = VARCOST*1.5385;
    ELSE IF _MODEL_ = 'DUNIT2B' THEN
     TOTCOST = VARCOST*1.5385;
    ELSE IF _MODEL_ = 'DUNIT3B' THEN
     TOTCOST = VARCOST*1.5385;
    ELSE IF _MODEL_ = 'EUNIT1A' THEN
     TOTCOST = VARCOST*1.25;
    ELSE IF _MODEL_ = 'EUNIT2A' THEN
     TOTCOST = VARCOST*1.25;
    ELSE IF _MODEL_ = 'EUNIT3A' THEN
     TOTCOST = VARCOST*1.25;
    ELSE IF _MODEL_ = 'EUNIT1B' THEN
     TOTCOST = VARCOST*1.5385;
    ELSE IF _MODEL_ = 'EUNIT2B' THEN
     TOTCOST = VARCOST*1.5385;
    ELSE IF _MODEL_ = 'EUNIT3B' THEN
     TOTCOST = VARCOST*1.5385;
    ELSE IF _MODEL_ = 'IUNIT1A' THEN
     TOTCOST = VARCOST*1.25;
    ELSE IF _MODEL_ = 'IUNIT2A' THEN
     TOTCOST = VARCOST*1.25;
    ELSE IF _MODEL_ = 'IUNIT3A' THEN
     TOTCOST = VARCOST*1.25;
```

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```
    ELSE IF _MODEL_ = 'IUNIT1B' THEN
      TOTCOST = VARCOST*1.5385;
    ELSE IF _MODEL_ = 'IUNIT2B' THEN
      TOTCOST = VARCOST*1.5385;
    ELSE IF _MODEL_ = 'IUNIT3B' THEN
      TOTCOST = VARCOST*1.5385;
    ELSE TOTCOST = VARCOST*2;
PROC PRINT;
```

Program XI: This program is used to calculate the mean of the 100 incorrectly developed slope coefficients and to incorrectly apply the mean slope in a new production run with fixed costs included in the T1 value.

```
* PROGRAM NAME:  UNITII.SAS;
;
LIBNAME PARAMS '[KTHOMSON.THESIS]';
OPTIONS LINESIZE=72;
DATA ONE;
  SET PARAMS.DUNIT1A
     PARAMS.DUNIT1B
     PARAMS.DUNIT1C
     PARAMS.EUNIT1A
     PARAMS.EUNIT1B
     PARAMS.EUNIT1C
     PARAMS.IUNIT1A
     PARAMS.IUNIT1B
     PARAMS.IUNIT1C
     PARAMS.DUNIT2A
     PARAMS.DUNIT2B
     PARAMS.DUNIT2C
     PARAMS.EUNIT2A
     PARAMS.EUNIT2B
     PARAMS.EUNIT2C
     PARAMS.IUNIT2A
     PARAMS.IUNIT2B
     PARAMS.IUNIT2C
     PARAMS.DUNIT3A
     PARAMS.DUNIT3B
     PARAMS.DUNIT3C
     PARAMS.EUNIT3A
     PARAMS.EUNIT3B
     PARAMS.EUNIT3C
     PARAMS.IUNIT3A
     PARAMS.IUNIT3B
     PARAMS.IUNIT3C;
  PROC SORT;
   BY _MODEL_;
  PROC UNIVARIATE;
   VAR LNLPP;
   BY _MODEL_;
  PROC MEANS DATA=ONE;
   VAR LNLPP;
```

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```
   BY _MODEL_;
   OUTPUT OUT=PARAMS.TESTIIT MEAN(LNLPP)=SLPCOEFF
     STD(LNLPP)=STDDEV STDERR(LNLPP)=ERROFEST;
   PROC PRINT;
DATA PARAMS.UNITIIT;
 SET PARAMS.TESTIIT;
 INFILE T1VALII;
  INPUT T1;
 TOTCOST=0;
 COST=0;
 X=0;
 DO I=1 TO 480;
  X=X+1;
  COST=T1*X**SLPCOEFF;
  TOTCOST=TOTCOST+COST;
 END;
PROC PRINT;
```

The following page has the another section of the Excel Spreadsheet (LOTFC.XLS) used
for calculation of the lot fixed costs with a T1 of $40,000 and the associated T1 values for
incorrect application of the learning curve coefficients. The TVC calculations from the
LEARN Program are on the following page.

T1 = $40,000

SLOPE	TVC	VC%	TC	FC%	TFC	LOT FC	T1 DFC	T1 EFC	T1 IFC	T1 DTC	T1 ETC	T1 ITC
0.75	2,485,865	0.80	3,107,331	0.20	621,466	51,789	632	1,295	8,631	40,632	41,295	48,631
0.75	2,485,865	0.65	3,824,407	0.35	1,338,543	111,545	1,360	2,789	18,591	41,360	42,789	58,591
0.75	2,485,865	0.50	4,971,729	0.50	2,485,865	207,155	2,526	5,179	34,526	42,526	45,179	74,526
0.85	5,870,847	0.80	7,338,558	0.20	1,467,712	122,309	1,492	3,058	20,385	41,492	43,058	60,385
0.85	5,870,847	0.65	9,032,072	0.35	3,161,225	263,435	3,213	6,586	43,906	43,213	46,586	83,906
0.85	5,870,847	0.50	11,741,693	0.50	5,870,847	489,237	5,966	12,231	81,540	45,966	52,231	121,540
0.95	13,120,082	0.80	16,400,102	0.20	3,280,020	273,335	3,333	6,833	45,556	43,333	46,833	85,556
0.95	13,120,082	0.65	20,184,741	0.35	7,064,659	588,722	7,180	14,718	98,120	47,180	54,718	138,120
0.95	13,120,082	0.50	26,240,164	0.50	13,120,082	1,093,340	13,333	27,334	182,223	53,333	67,334	222,223

This is the output from the LEARN program for a T1 of $40,000 and all three slopes:

Unit Curve Formulation

First unit (A)	=	****40000.00
Slope	=	75.0%
Slope coefficient (b)	=	-0.415037
Unit/lot	=	1 - 480
Cost of unit 480	=	*****3084.92
Average cost of unit 1 to 480	=	*****5178.88
Total cost through unit 480	=	**2485864.70
Total cost of lot (1 - 480)	=	**2485864.70
Average cost of units in lot	=	*****5178.88

Unit Curve Formulation

First unit (A)	=	****40000.00
Slope	=	85.0%
Slope coefficient (b)	=	-0.234465
Unit/lot	=	1 - 480
Cost of unit 480	=	*****9405.94
Average cost of unit 1 to 480	=	****12230.93
Total cost through unit 480	=	**5870846.52
Total cost of lot (1 - 480)	=	**5870846.52
Average cost of units in lot	=	****12230.93

Unit Curve Formulation

First unit (A)	=	****40000.00
Slope	=	95.0%
Slope coefficient (b)	=	-0.074001
Unit/lot	=	1 - 480
Cost of unit 480	=	****25330.66
Average cost of unit 1 to 480	=	****27333.50
Total cost through unit 480	=	*13120081.91
Total cost of lot (1 - 480)	=	*13120081.91
Average cost of units in lot	=	****27333.50

Appendix B: Sample Programs/Output for Analysis of Variance

The following programs were used for data simulation and analysis for comparison of the fitting capabilities of the Standard Unit Formulation and SAF/FMC Formulation of the learning curve. In addition to the programs below, the following programs from Appendix A were used: I, III, IV, and VI.

Program XII: This program was created to produce an independent data file for the three ???COMB.SAS files for fitting the Unit and SAF/FMC models. The seed for the RANNOR procedure was changed from the seed used in the NORMAL2.SAS RANNOR procedure.

```
*PROGRAM NAME: NORM2.SAS;
;
*THIS PROGRAM SIMULATES A LEARNING CURVE WITH FIRST UNIT VALUE
OF 25000 AND AN 85% SLOPE WITH A STANDARD DEVIATION OF .2 AND A
RANDOM ERROR;
;
DATA ONE;
OPTIONS LINESIZE=72;
A = LOG (25000);
B = LOG (.85)/LOG (2);
C = .2;
DO J = 1 TO 100;
  TOTCOST = 0;
   DO I = 1 TO 480;
    LNX=LOG(I);
    Z = RANNOR (1234);
    LNY = A + (B * LNX) + (C*Z);
    COST = EXP (LNY);
    TOTCOST = TOTCOST + COST;
    FILE NORM2;
    PUT I COST TOTCOST;
   END;
END;
PROC PRINT;
```

Program XIII: This is one of three programs used to separate the production run data created in NORM2.SAS into twelve lots. These three programs were for total cost; therefore, fixed cost were added to each lot. The data file from this program was used as an input for the ???COMB.SAS programs for fitting the unit and SAF/FMC formulations. Using the following information, the other two programs could be created:

        D = Decreasing lot profile
        E = Equal lot profile
        I = Increasing lot profile

The bold and underlined letters and numbers would be changed to reflect the treatment under consideration.

```
*PROGRAM NAME: LTGEND2B;
;
*THIS PROGRAM IS FOR A DECREASING LOT SIZE PROFILE, 85% SLOPE,
AND 35% FIXED COST BURDEN;
;
DATA TWO;
OPTIONS LINESIZE=72;
INFILE NORM2;
INPUT N1-N1440;
ARRAY NUM[1440] N1-N1440;
ARRAY COST[480] YY1-YY480;
ARRAY LOT[12,6] L1-L72;
ARRAY TOTCOST[480] TC1-TC480;
  DO I = 1 TO 480;
    COST[I] = NUM[I*3-1];
    TOTCOST[I] = NUM [I*3];
  END;
;
LFC = 164647;  *LFC = LOT FIXED COST;
;
*THE FOLLOWING STATEMENTS BREAKS THE PRODUCTION RUN DATA
INTO 12 ARRAYS EACH REPRESENTING A LOT. EACH ARRAY HAS SIX
ELEMENTS HOLDING THE FOLLOWING INFORMATION: CUMULATIVE
UNITS, CUMULATIVE VARIABLE COSTS, TOTAL COSTS, ALGEBRAIC LOT
PLOT POINT, LOT AVERAGE COSTS, AND LOT SIZE;
;
LABEL1:
TEMP = 65 + (23 * RANUNI(1110));
TEMP = ROUND(TEMP,1);
  LOT[1,1] = TEMP;
  LOT[1,2] = TOTCOST[TEMP];
```

```
      LOT[1,3] = TOTCOST[TEMP] + LFC;
      LOT[1,4] = 0;
      B = LOG(.85)/LOG(2);
        DO I = 1 TO LOT[1,1];
          DUM = LOT[1,4] + (I**B);
          LOT[1,4] = DUM;
        END;
      LOT[1,4] = (LOT[1,4]/LOT[1,1])**(1/B);
      LOT[1,5] = LOT[1,3]/TEMP;
      LOT[1,6] = LOT[1,1];

    ;
    TEMP = 60 + (5 * RANUNI(1110));
    TEMP = ROUND(TEMP,1);
      LOT[2,1] = TEMP + LOT[1,1];
      LOT[2,2] = TOTCOST[LOT[2,1]];
      LOT[2,3] = LOT[2,2] - LOT[1,2] + LFC;
      LOT[2,4] = 0;
        Z = LOT[2,1] - LOT[1,1];
        DO I = 1 TO Z;
          DUM = LOT[2,4] + ((I + LOT[1,1])**B);
          LOT[2,4] = DUM;
        END;
      LOT[2,4] = (LOT[2,4]/Z)**(1/B);
      LOT[2,5] = LOT[2,3]/TEMP;
      LOT[2,6] = LOT[2,1] - LOT[1,1];

    ;
    TEMP = 55 + (5 * RANUNI(1110));
    TEMP = ROUND(TEMP,1);
      LOT[3,1] = TEMP + LOT[2,1];
      LOT[3,2] = TOTCOST[LOT[3,1]];
      LOT[3,3] = LOT[3,2] - LOT[2,2] + LFC;
      LOT[3,4] = 0;
      Z = LOT[3,1] - LOT[2,1];
        DO I = 1 TO Z;
          DUM = LOT[3,4] + ((I + LOT[2,1])**B);
          LOT[3,4] = DUM;
        END;
      LOT[3,4] = (LOT[3,4]/Z)**(1/B);
      LOT[3,5] = LOT[3,3]/TEMP;
      LOT[3,6] = LOT[3,1] - LOT[2,1];

    ;
    TEMP = 50 + (5 * RANUNI(1110));
    TEMP = ROUND(TEMP,1);
      LOT[4,1] = TEMP + LOT[3,1];
```

```
    LOT[4,2] = TOTCOST[LOT[4,1]];
    LOT[4,3] = LOT[4,2] - LOT[3,2] + LFC;
    LOT[4,4] = 0;
    Z = LOT[4,1] - LOT[3,1];
      DO I = 1 TO Z;
        DUM = LOT[4,4] + ((I + LOT[3,1])**B);
        LOT[4,4] = DUM;
      END;
    LOT[4,4] = (LOT[4,4]/Z)**(1/B);
    LOT[4,5] = LOT[4,3]/TEMP;
    LOT[4,6] = LOT[4,1] - LOT[3,1];

;
TEMP = 45 + (5 * RANUNI (1110));
TEMP = ROUND(TEMP,1);
    LOT[5,1] = TEMP + LOT[4,1];
    LOT[5,2] = TOTCOST[LOT[5,1]];
    LOT[5,3] = LOT[5,2] - LOT[4,2] + LFC;
    LOT[5,4] = 0;
    Z = LOT[5,1] - LOT[4,1];
      DO I = 1 TO Z;
        DUM = LOT[5,4] + ((I + LOT[4,1])**B);
        LOT[5,4] = DUM;
      END;
    LOT[5,4] = (LOT[5,4]/Z)**(1/B);
    LOT[5,5] = LOT[5,3]/TEMP;
    LOT[5,6] = LOT[5,1] - LOT[4,1];

;
TEMP = 40 + (5 * RANUNI(1110));
TEMP = ROUND(TEMP,1);
    LOT[6,1] = TEMP + LOT[5,1];
    LOT[6,2] = TOTCOST[LOT[6,1]];
    LOT[6,3] = LOT[6,2] - LOT[5,2] + LFC;
    LOT[6,4] = 0;
    Z = LOT[6,1] - LOT[5,1];
      DO I = 1 TO Z;
        DUM = LOT[6,4] + ((I + LOT[5,1])**B);
        LOT[6,4] = DUM;
      END;
    LOT[6,4] = (LOT[6,4]/Z)**(1/B);
    LOT[6,5] = LOT[6,3]/TEMP;
    LOT[6,6] = LOT[6,1] - LOT[5,1];

;
TEMP = 35 + (5 * RANUNI(1110));
TEMP = ROUND(TEMP,1);
```

```
        LOT[7,1] = TEMP + LOT[6,1];
        LOT[7,2] = TOTCOST[LOT[7,1]];
        LOT[7,3] = LOT[7,2] - LOT[6,2] + LFC;
        LOT[7,4] = 0;
        Z = LOT[7,1] - LOT[6,1];
          DO I = 1 TO Z;
            DUM = LOT[7,4] + ((I + LOT[6,1])**B);
            LOT[7,4] = DUM;
          END;
        LOT[7,4] = (LOT[7,4]/Z)**(1/B);
        LOT[7,5] = LOT[7,3]/TEMP;
        LOT[7,6] = Z;

     ;
TEMP = 30 + (5 * RANUNI(1110));
TEMP = ROUND(TEMP,1);
        LOT[8,1] = TEMP + LOT[7,1];
        LOT[8,2] = TOTCOST[LOT[8,1]];
        LOT[8,3] = LOT[8,2] - LOT[7,2] + LFC;
        LOT[8,4] = 0;
        Z = LOT[8,1] - LOT[7,1];
          DO I = 1 TO Z;
            DUM = LOT[8,4] + ((I + LOT[7,1])**B);
            LOT[8,4] = DUM;
          END;
        LOT[8,4] = (LOT[8,4]/Z)**(1/B);
        LOT[8,5] = LOT[8,3]/TEMP;
        LOT[8,6] = Z;

     ;
TEMP = 25 + (5 * RANUNI(1110));
TEMP = ROUND(TEMP,1);
        LOT[9,1] = TEMP + LOT[8,1];
        LOT[9,2] = TOTCOST[LOT[9,1]];
        LOT[9,3] = LOT[9,2] - LOT[8,2] + LFC;
        LOT[9,4] = 0;
        Z = LOT[9,1] - LOT[8,1];
          DO I = 1 TO Z;
            DUM = LOT[9,4] + ((I + LOT[8,1])**B);
            LOT[9,4] = DUM;
          END;
        LOT[9,4] = (LOT[9,4]/Z)**(1/B);
        LOT[9,5] = LOT[9,3]/TEMP;
        LOT[9,6] = Z;

     ;
TEMP = 20 + (5 * RANUNI(1110));
```

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```
TEMP = ROUND(TEMP,1);
  LOT[10,1] = TEMP + LOT[9,1];
    IF LOT[10,1] > 480 THEN GOTO LABEL1;
  LOT[10,2] = TOTCOST[LOT[10,1]];
  LOT[10,3] = LOT[10,2] - LOT[9,2] + LFC;
  LOT[10,4] = 0;
  Z = LOT[10,1] - LOT[9,1];
    DO I = 1 TO Z;
      DUM = LOT[10,4] + ((I + LOT[9,1])**B);
      LOT[10,4] = DUM;
    END;
  LOT[10,4] = (LOT[10,4]/Z)**(1/B);
  LOT[10,5] = LOT[10,3]/TEMP;
  LOT[10,6] = Z;
;
TEMP = 10 + (5 * RANUNI(1110));
TEMP = ROUND(TEMP,1);
  LOT[11,1] = TEMP + LOT[10,1];
    IF LOT[11,1] > 480 THEN GOTO LABEL1;
  LOT[11,2] = TOTCOST[LOT[11,1]];
  LOT[11,3] = LOT[11,2] - LOT[10,2] + LFC;
  LOT[11,4] = 0;
  Z = LOT[11,1] - LOT[10,1];
    DO I = 1 TO Z;
      DUM = LOT[11,4] + ((I + LOT[10,1])**B);
      LOT[11,4] = DUM;
    END;
  LOT[11,4] = (LOT[11,4]/Z)**(1/B);
  LOT[11,5] = LOT[11,3]/TEMP;
  LOT[11,6] = Z;
;
TEMP = 480 - LOT[11,1];
IF TEMP < 5 OR TEMP > 10 THEN GOTO LABEL1;
  LOT[12,1] = TEMP + LOT[11,1];
  LOT[12,2] = TOTCOST[LOT[12,1]];
  LOT[12,3] = LOT[12,2] - LOT[11,2] + LFC;
  LOT[12,4] = 0;
  Z = LOT[12,1] - LOT[11,1];
    DO I = 1 TO Z;
      DUM = LOT[12,4] + ((I + LOT[11,1])**B);
      LOT[12,4] = DUM;
    END;
  LOT[12,4] = (LOT[12,4]/Z)**(1/B);
  LOT[12,5] = LOT[12,3]/TEMP;
```

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```
    LOT[12,6] = Z;
  ;
*THE FOLLOWING STATEMENTS PUTS THE LOT DATA INTO A FILE TO BE
USED BY THE
REGRESSION PROGRAMS;
  ;
FILE LTGEND2B;
  DO I = 1 TO 12;
    PUT LOT[I,1] LOT[I,2] LOT[I,3] LOT[I,4] LOT[I,5] LOT[I,6];
  END;
```

Program XIV: This program was created to reduce independence for the two ANOVA calculations. This is a sample of three programs written for the fitting of the two models with 35% fixed cost burden and 85% slope. The other 2 programs can be reproduced from this program by changing the variable and input file names using the following key.

D = decreasing lot profile
E = equal lot profile
I = increasing lot profile

The bold and underlined letter(s) would be changed depending on the treatment under consideration.

```
*PROGRAM NAME: D2BCOMB.SAS;

;

*THIS PROGRAM THE FITS THE STANDARD UNIT LEARNING CURVE AND
SAF/FMC MODEL TO AN DECREASING LOT PROFILE, 85% CURVE, WITH 35%
FIXED COSTS;

;

LIBNAME PARAMS '[KTHOMSON.THESIS]';
LIBNAME MAD '[KTHOMSON.THESIS]';
OPTIONS LINESIZE=72;

;

DATA THREE;
INFILE LTGEND2B;
  INPUT CUMX TOTY LOTCOST LPP AVUNCST LOTSZ;
INFILE PRODRUN;
  INPUT PRDRUN;

;

LNLPP = LOG(LPP);
LNAVUCST = LOG(AVUNCST);

;

* NEXT TWO MODELS REGRESS NATURAL LOG OF AVG UNIT COST FOR
LOT (DEPENDENT VARIABLE) AGAINST NATURAL LOG OF ALGEBRAIC LOT
PLOT POINT (INDEPENDENT VARIABLE). REGRESSION WILL PRODUCE AN
INTERCEPT AND A COEFFICIENT FOR THE ALGEBRAIC LOT PLOT POINT.
THE INTERCEPT, WHEN CONVERTED FROM LOG SPACE TO UNIT SPACE, IS
EQUIVALENT TO THE 1ST UNIT COST (A) WHEREAS THE COEFFICIENT FOR
THE NATURAL LOG OF THE ALGEBRAIC LOT PLOT POINT IS THE SLOPE
COEFFICIENT. TO COMPUTE THE SLOPE, ONE WOULD USE THE
FOLLOWING EQUATION: SLOPE = E**(COEFFICIENT * LOG(2));

;

PROC REG DATA=THREE OUTEST = PARAMS.DUN2B;
  DUN2B:MODEL LNAVUCST = LNLPP;
  BY PRDRUN;
```

```
   OUTPUT OUT=DUN2B P=PUC R=RESID;
   PROC PRINT;

 ;
 * THE NEXT MODEL (SAF/FMC) USES NON LINEAR REGRESSION. PARTIAL
 DERIVATIVES WITH RESPECT TO THE PARAMETERS HAVE NOT BEEN
 SPECIFIED SINCE THE DUD (DOESN'T USE DERIVATIVES) METHOD IS BEING
 USED;

 ;
 PROC NLIN DATA=THREE OUTEST=PARAMS.DS2B;
 *INITIAL GUESS VALUES FOR PARAMETERS;
  PARMS B=-.3 F=35000 A=25000;
  DS2B:MODEL AVUNCST = F/LOTSZ + (A*LPP**B);
  BY PRDRUN;
  BOUNDS -1<=B<=0;
  BOUNDS 0<=F<=900000;
  BOUNDS 0<=A<=200000;
  OUTPUT OUT=DS2B P=PUC R=RESIDLR;
 *WRITES THE PREDICTED AVG COSTS (UNIT SPACE), RESIDUALS (UNIT
 SPACE), AND ORIGINAL DATA SET TO A NEW DATA SET FOR FURTHER
 ANALYSIS;

 ;
 DATA UND2B;        *CREATES A NEW DATA SET USED FOR
 COMPUTATIONS;
  SET DUN2B;  *CALLS IN DATA SET CREATED ABOVE INTO NEW DATA SET;
  PUCDLR=EXP(PUC);
  AUCDLR=EXP(LNAVUCST);
  RESIDLR=AUCDLR-PUCDLR;
  ABRESID=ABS(RESIDLR);
  PROC PRINT;

 ;
 DATA SD2B;
  SET DS2B;
  ABRESID=ABS(RESIDLR);
  PROC PRINT;

 ;
 PROC MEANS DATA=UND2B;
  VAR ABRESID;
  BY PRDRUN;
  OUTPUT OUT=MAD.MUND2B N(ABRESID)=N MEAN(ABRESID)=MAD;

 ;
 PROC MEANS DATA = SD2B;
  VAR ABRESID;
  BY PRDRUN;
  OUTPUT OUT=MAD.MSAD2B N(ABRESID)=N MEAN(ABRESID)=MAD;
```

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```
;
* THIS SECTION COMBINES THE PERMANENT PARAMETER DATA SETS
FROM EACH MODEL INTO ONE PERMANENT DATA SET;
;
DATA PARAMS.FINALD2B;
  SET PARAMS.DS2B;
  IF _TYPE_='FINAL';
DATA PARAMS.PRMD2B;
  SET PARAMS.DUN2B
    PARAMS.FINALD2B;
  PROC PRINT;

;
* THIS SECTION COMBINES THE PERMANENT MAD DATA SETS FROM EACH
MODEL INTO ONE PERMANENT MAD DATA SET;
;
DATA MAD.MADD2B;
  SET MAD.MUND2B
    MAD.MSAD2B;
PROC PRINT;
```

Program XV: This program was created to combine the MAD files from nine of the
COMB???.SAS files for ANOVA calculations with fixed costs held constant at 35%.

```
*PROGRAM NAME:  COMBINEFC.SAS;
;
LIBNAME MAD '[KTHOMSON.THESIS]';
OPTIONS LINESIZE=72;
DATA MAD.IN1;
INFILE LABELSFC;
INPUT SLOPE$ LOTPRO$ FCPCNT$ MOD$;
SET MAD.D1BMAD
  MAD.E1BMAD
  MAD.I1BMAD
  MAD.D2BMAD
  MAD.E2BMAD
  MAD.I2BMAD
  MAD.D3BMAD
  MAD.E3BMAD
  MAD.I3BMAD;
PROC PRINT;
```

Program XVI: This program was created to combine the MAD files from six of the COMB???.SAS and three ???COMB.SAS for ANOVA calculations with slope held constant at 85%. The three ???COMB.SAS files were used instead of the COMB???.SAS for the same treatment to ensure this data set of MADs was independent of the COMBINFC.SAS MAD files. The three files had a fixed cost burden of 35%.

```
*PROGRAM NAME: COMBINSL.SAS;
;
LIBNAME MAD '[KTHOMSON.THESIS]';
OPTIONS LINESIZE=72;
DATA MAD.IN2;
INFILE LABELSSL;
INPUT SLOPE$ LOTPRO$ FCPCNT$ MOD$;
SET MAD.D2AMAD
  MAD.MADD2B
  MAD.D2CMAD
  MAD.E2AMAD
  MAD.MADE2B
  MAD.E2CMAD
  MAD.I2AMAD
  MAD.MADI2B
  MAD.I2CMAD;
PROC PRINT;
```

Program XVII: This program was used to analyze the main and two-way interaction effects between the Unit and SAF/FMC formulations, the three lot profiles, and the three fixed cost burden rates with the slope being held constant at 85%. The analysis was accomplished through ANOVA on the MAD for each treatment.

```
* FILENAME: PROCANSL.SAS;
;
LIBNAME MAD '[KTHOMSON.THESIS]';
DATA THREE;
SET MAD.IN2;
OPTIONS LINESIZE=72;
;
PROC ANOVA DATA=THREE;
  TITLE 'ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)';
*FACTORS UNDER CONSIDERATION;
  CLASSES SLOPE LOTPRO FCPCNT MOD;
*EXAMINE ALL MAIN AND TWO-WAY INTERACTION EFFECTS;
  MODEL MAD = SLOPE|LOTPRO|MOD@2;
  MEANS SLOPE|LOTPRO|MOD@2/REGWF REGWQ SCHEFFE;
```

The following is output from program XVII:

```
           ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)              1
                               23:40 Wednesday, July 27, 1994

                 Analysis of Variance Procedure
                   Class Level Information

          Class     Levels    Values

          SLOPE          1    85%SLOPE

          LOTPRO         3    DECREASE EQUAL INCREASE

          FCPCNT         3    20%FC 35%FC 50%FC

          MOD            2    SAF UNIT


          Number of observations in data set = 1800



           ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)              2
                               23:40 Wednesday, July 27, 1994
```

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Analysis of Variance Procedure

Dependent Variable: MAD

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	3.659E+09	2.815E+08	1150.31	0.0001
Error	1786	4.371E+08	2.447E+05		
Corrected Total	1799	4.096E+09			

	R-Square	C.V.	Root MSE	MAD Mean
	0.893310	59.27462	494.68	834.56

Source	DF	Anova SS	Mean Square	F Value	Pr > F
FCPCNT	2	2.060E+08	1.030E+08	420.90	0.0001
LOTPRO	2	1.074E+09	5.370E+08	2194.46	0.0001
LOTPRO*FCPCNT	4	2.842E+08	7.104E+07	290.30	0.0001
MOD	1	7.865E+08	7.865E+08	3213.79	0.0001
FCPCNT*MOD	2	2.077E+08	1.039E+08	424.46	0.0001
LOTPRO*MOD	2	1.101E+09	5.505E+08	2249.71	0.0001

ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)   3
                                23:40 Wednesday, July 27, 1994

Analysis of Variance Procedure

Ryan-Einot-Gabriel-Welsch Multiple F Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

Alpha= 0.05 df= 1786 MSE= 244710.7

Number of Means	2	3
Critical F	3.8466707	3.0007628

Means with the same letter are not significantly different.

REGWF Grouping	Mean	N	FCPCNT
A	1279.14	600	50%FC
B	765.31	600	35%FC
C	459.22	600	20%FC

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Analysis of Variance Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

Alpha= 0.05 df= 1786 MSE= 244710.7

Number of Means   2   3
Critical Range 56.015565 66.993245

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	FCPCNT
A	1279.14	600	50%FC
B	765.31	600	35%FC
C	459.22	600	20%FC

Analysis of Variance Procedure

Scheffe's test for variable: MAD

NOTE: This test controls the type I experimentwise error rate but
      generally has a higher type II error rate than REGWF for
      all pairwise comparisons

Alpha= 0.05 df= 1786 MSE= 244710.7
      Critical Value of F= 3.00076
Minimum Significant Difference= 69.968

Means with the same letter are not significantly different.

Scheffe Grouping	Mean	N	FCPCNT
A	1279.14	600	50%FC
B	765.31	600	35%FC
C	459.22	600	20%FC

Analysis of Variance Procedure

Ryan-Einot-Gabriel-Welsch Multiple F Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

Alpha= 0.05   df= 1786   MSE= 244710.7

Number of Means   2   3
Critical F   3.8466707 3.0007628

Means with the same letter are not significantly different.

REGWF Grouping	Mean	N	LOTPRO
A	1917.61	600	DECREASE
B	416.58	600	INCREASE
C	169.49	600	EQUAL

ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)   7
23:40 Wednesday, July 27, 1994

Analysis of Variance Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

Alpha= 0.05   df= 1786   MSE= 244710.7

Number of Means   2   3
Critical Range   56.015565 66.993245

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	LOTPRO
A	1917.61	600	DECREASE
B	416.58	600	INCREASE
C	169.49	600	EQUAL

ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)   8
23:40 Wednesday, July 27, 1994

Analysis of Variance Procedure

Scheffe's test for variable: MAD

NOTE: This test controls the type I experimentwise error rate but
       generally has a higher type II error rate than REGWF for
       all pairwise comparisons

Alpha= 0.05 df= 1786 MSE= 244710.7
Critical Value of F= 3.00076
Minimum Significant Difference= 69.968

Means with the same letter are not significantly different.

Scheffe Grouping		Mean	N	LOTPRO
A		1917.61	600	DECREASE
B		416.58	600	INCREASE
C		169.49	600	EQUAL

Level of LOTPRO	Level of FCPCNT	N	-------------MAD------------- Mean	SD
DECREASE	20%FC	200	937.16126	811.38663
DECREASE	35%FC	200	1711.83818	1598.80144
DECREASE	50%FC	200	3103.83399	3039.49906
EQUAL	20%FC	200	163.00909	45.33409
EQUAL	35%FC	200	172.01246	47.90825
EQUAL	50%FC	200	173.43797	51.98667
INCREASE	20%FC	200	277.50249	124.61460
INCREASE	35%FC	200	412.08605	253.08889
INCREASE	50%FC	200	560.16131	430.61474

ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)   9
                          23:40 Wednesday, July 27, 1994

Analysis of Variance Procedure

Ryan-Einot-Gabriel-Welsch Multiple F Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

Alpha= 0.05 df= 1786 MSE= 244710.7

Number of Means   2
Critical F   3.8466707

Means with the same letter are not significantly different.

REGWF Grouping		Mean	N	MOD
A		1495.56	900	UNIT

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ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)   10
23:40 Wednesday, July 27, 1994

Analysis of Variance Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

Alpha= 0.05   df= 1786   MSE= 244710.7

Number of Means   2
Critical Range   45.736517

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	MOD
A	1495.56	900	UNIT
B	173.56	900	SAF

ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)   11
23:40 Wednesday, July 27, 1994

Analysis of Variance Procedure

Scheffe's test for variable: MAD

NOTE: This test controls the type I experimentwise error rate but
generally has a higher type II error rate than REGWF for
all pairwise comparisons

Alpha= 0.05   df= 1786   MSE= 244710.7
Critical Value of F= 3.84667
Minimum Significant Difference= 45.736

Means with the same letter are not significantly different.

Scheffe Grouping	Mean	N	MOD
A	1495.56	900	UNIT
B	173.56	900	SAF

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Level of FCPCNT	Level of MOD	N	MAD Mean	SD
20%FC	SAF	300	169.66080	59.05640
20%FC	UNIT	300	748.78776	715.33023
35%FC	SAF	300	182.50388	71.89815
35%FC	UNIT	300	1348.12058	1405.99826
50%FC	SAF	300	168.52600	58.55962
50%FC	UNIT	300	2389.76285	2680.66553

Level of LOTPRO	Level of MOD	N	MAD Mean	SD
DECREASE	SAF	300	155.89527	44.09397
DECREASE	UNIT	300	3679.32702	1915.91076
EQUAL	SAF	300	152.97851	39.97157
EQUAL	UNIT	300	185.99451	50.91495
INCREASE	SAF	300	211.81690	80.36530
INCREASE	UNIT	300	621.34967	335.44433

Program XVIII: This program was used to analyze the main and two-way interaction effects between the Unit and SAF/FMC formulations, the three lot profiles, and the three slopes with the fixed cost burden being held constant at 35%. The analysis was accomplished through ANOVA on the MAD for each treatment.

```
* FILENAME:  PROCANFC.SAS;
;
LIBNAME MAD '[KTHOMSON.THESIS]';
DATA THREE;
SET MAD.IN1;
OPTIONS LINESIZE=72;
;
PROC ANOVA DATA=THREE;
  TITLE 'ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)';
*FACTORS UNDER CONSIDERATION;
  CLASSES SLOPE LOTPRO FCPCNT MOD;
*EXAMINE ALL MAIN AND TWO-WAY INTERACTION EFFECTS;
  MODEL MAD = SLOPE|LOTPRO|MOD@2;
  MEANS SLOPE|LOTPRO|MOD@2/REGWF REGWQ SCHEFFE;
```

The following is the output from Program XVIII:

```
ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)                1
                                        23:38 Wednesday, July 27, 1994

                   Analysis of Variance Procedure
                     Class Level Information

            Class     Levels     Values

            SLOPE        3       75%SLOPE 85%SLOPE 95%SLOPE

            LOTPRO       3       DECREASE EQUAL INCREASE

            FCPCNT       1       35%FC

            MOD          2       SAF UNIT


        Number of observations in data set = 1800




            ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)                2
                                        23:38 Wednesday, July 27, 1994

                   Analysis of Variance Procedure

Dependent Variable: MAD
```

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Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	5.020E+09	3.862E+08	1024.30	0.0001
Error	1786	6.733E+08	3.770E+05		
Corrected Total	1799	5.693E+09			

R-Square	C.V.	Root MSE	MAD Mean
0.881737	64.05549	614.00	958.54

Source	DF	Anova SS	Mean Square	F Value	Pr > F
SLOPE	2	5.953E+08	2.977E+08	789.58	0.0001
LOTPRO	2	1.307E+09	6.534E+08	1733.22	0.0001
SLOPE*LOTPRO	4	4.356E+08	1.089E+08	288.89	0.0001
MOD	1	1.010E+09	1.010E+09	2678.16	0.0001
SLOPE*MOD	2	3.518E+08	1.759E+08	466.53	0.0001
LOTPRO*MOD	2	1.321E+09	6.604E+08	1751.75	0.0001

Analysis of Variance Procedure

Ryan-Einot-Gabriel-Welsch Multiple F Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

Alpha= 0.05 df= 1786 MSE= 376996.6

Number of Means	2	3
Critical F	3.8466707	3.0007628

Means with the same letter are not significantly different.

REGWF Grouping	Mean	N	SLOPE
A	1734.37	600	95%SLOPE
B	782.01	600	85%SLOPE
C	359.25	600	75%SLOPE

Analysis of Variance Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

Alpha= 0.05   df= 1786   MSE= 376996.6

Number of Means   2   3
Critical Range   69.526586 83.152096

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	SLOPE
A	1734.37	600	95%SLOPE
B	782.01	600	85%SLOPE
C	359.25	600	75%SLOPE

ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)   5
                         23:38 Wednesday, July 27, 1994

Analysis of Variance Procedure

Scheffe's test for variable: MAD

NOTE: This test controls the type I experimentwise error rate but
      generally has a higher type II error rate than REGWF for
      all pairwise comparisons

Alpha= 0.05   df= 1786   MSE= 376996.6
      Critical Value of F= 3.00076
Minimum Significant Difference= 86.844

Means with the same letter are not significantly different.

Scheffe Grouping	Mean	N	SLOPE
A	1734.37	600	95%SLOPE
B	782.01	600	85%SLOPE
C	359.25	600	75%SLOPE

ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)   6
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Analysis of Variance Procedure

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Ryan-Einot-Gabriel-Welsch Multiple F Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

Alpha= 0.05   df= 1786   MSE= 376996.6

Number of Means   2   3
Critical F   3.8466707 3.0007628

Means with the same letter are not significantly different.

REGWF Grouping   Mean   N   LOTPRO

A   2150.66   600   DECREASE

B   514.72   600   INCREASE

C   210.25   600   EQUAL

ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)   7
                              23:38 Wednesday, July 27, 1994

Analysis of Variance Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

Alpha= 0.05   df= 1786   MSE= 376996.6

Number of Means   2   3
Critical Range   69.526586 83.152096

Means with the same letter are not significantly different.

REGWQ Grouping   Mean   N   LOTPRO

A   2150.66   600   DECREASE

B   514.72   600   INCREASE

C   210.25   600   EQUAL

ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)   8
                              23:38 Wednesday, July 27, 1994

Analysis of Variance Procedure

Scheffe's test for variable: MAD

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NOTE: This test controls the type I experimentwise error rate but
      generally has a higher type II error rate than REGWF for
      all pairwise comparisons

                 Alpha= 0.05 df= 1786 MSE= 376996.6
                     Critical Value of F= 3.00076
                 Minimum Significant Difference= 86.844

Means with the same letter are not significantly different.

            Scheffe Grouping   Mean   N LOTPRO

                        A   2150.66   600 DECREASE

                        B   514.72   600 INCREASE

                        C   210.25   600 EQUAL

| Level of | Level of | | ------------MAD------------ | |
SLOPE	LOTPRO	N	Mean	SD
75%SLOPE	DECREASE	200	815.37590	780.46615
75%SLOPE	EQUAL	200	88.41354	39.06454
75%SLOPE	INCREASE	200	173.95158	101.09395
85%SLOPE	DECREASE	200	1799.55136	1697.09014
85%SLOPE	EQUAL	200	166.74097	47.66152
85%SLOPE	INCREASE	200	379.74535	231.79613
95%SLOPE	DECREASE	200	3837.04919	3573.54278
95%SLOPE	EQUAL	200	375.60219	101.63555
95%SLOPE	INCREASE	200	990.47193	724.20598

         ANALYSIS OF MEAN ABSOLUTE DEVIATIONS (MAD)   9
                           23:38 Wednesday, July 27, 1994

                   Analysis of Variance Procedure

Ryan-Einot-Gabriel-Welsch Multiple F Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

                 Alpha= 0.05 df= 1786 MSE= 376996.6

                   Number of Means   2
                   Critical F   3.8466707

Means with the same letter are not significantly different.

            REGWF Grouping   Mean   N MOD

                        A   1707.49   900 UNIT

                        B   209.60   900 SAF

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Analysis of Variance Procedure

Ryan-Einot-Gabriel-Welsch Multiple Range Test for variable: MAD

NOTE: This test controls the type I experimentwise error rate.

Alpha= 0.05 df= 1786 MSE= 376996.6

Number of Means   2
Critical Range   56.76822

Means with the same letter are not significantly different.

REGWQ Grouping	Mean	N	MOD
A	1707.49	900	UNIT
B	209.60	900	SAF

Analysis of Variance Procedure

Scheffe's test for variable: MAD

NOTE: This test controls the type I experimentwise error rate but
      generally has a higher type II error rate than REGWF for
      all pairwise comparisons

Alpha= 0.05 df= 1786 MSE= 376996.6
     Critical Value of F= 3.84667
Minimum Significant Difference= 56.768

Means with the same letter are not significantly different.

Scheffe Grouping	Mean	N	MOD
A	1707.49	900	UNIT
B	209.60	900	SAF

Level of	Level of		--------------MAD--------------	
SLOPE	MOD	N	Mean	SD

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75%SLOPE	SAF	300	71.01825	35.89907
75%SLOPE	UNIT	300	647.47576	675.59149
85%SLOPE	SAF	300	168.68157	58.56982
85%SLOPE	UNIT	300	1395.34354	1499.95440
95%SLOPE	SAF	300	389.09583	110.63815
95%SLOPE	UNIT	300	3079.65304	3126.29987

Level of LOTPRO	Level of MOD	N	------------MAD------------	
			Mean	SD
DECREASE	SAF	300	199.65586	153.00837
DECREASE	UNIT	300	4101.66177	2517.37570
EQUAL	SAF	300	192.59293	146.34103
EQUAL	UNIT	300	227.91154	129.78832
INCREASE	SAF	300	236.54686	155.85339
INCREASE	UNIT	300	792.89904	673.28526

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Vita

Captain Charles B. Shea was born on 12 November 1966 in Charlotte, North Carolina. He graduated from North Mecklenburg Senior High School in Huntersville, North Carolina in 1985 and received a Bachelor of Arts in Business Administration/Finance from the University of North Carolina at Charlotte in 1989. He entered the Air Force in January 1990 as an AFROTC distinguished graduate and regular commissionee. Upon completion of Budget Officer School as a distinguished graduate in February 1990, he was assigned to K.I. Sawyer AFB, Michigan as the Base Budget Officer, where he was named Strategic Air Command Budget Officer of the Year for 1991. In May 1992, he was transferred to Kunsan AB, Korea as the Base Budget Officer where he served until entering the School of Logistics and Acquisition Management, Air Force Institute of Technology, in May 1993. Upon graduation in September 1994, he was assigned as a cost analyst to the C-17 System Program Office (SPO) at Wright-Patterson AFB, Ohio. He is married to the former Mary Margaret Levins.

Permanent Address: 1855-A J. Julian Lane
Charlotte, NC 28208

Vita

Captain Kenneth P. N. Thomson was born 8 November 1964 in Austin, Minnesota. He graduated from Stewartville High School in Stewartville, Minnesota, in 1983. He attended Iowa State University, College of Sciences and Humanities where he received a Bachelor of Science degree in Economics. He entered the Air Force in January 1989 as an AFROTC graduate with a reserve commission. Upon completion of Cost Analysis Officer School in March 1989, he was assigned to Incirlik, AB Turkey as Deputy Chief, Cost Branch. In October 1989, he was given the job of Chief, Cost Branch at Incirlik, AB Turkey. In August 1990, he was assigned to Hahn, AB Germany as the Chief, Cost Branch. In August 1991, he was transferred to Rhein-Main, AB Germany as the Deputy Chief, Financial Analysis Office. While at Rhein-Main, he also performed the duties of Deputy Accounting and Finance Officer. He served at Rhein-Main until April 1993 when he entered the School of Logistics and Acquisition Management, Air Force Institute of Technology, in May 1993. Upon graduation in September 1994, he was assigned as a cost analyst to Aeronautical Systems Center, Wright-Patterson AFB, Ohio.

Permanent Address: 719 Berg Boulevard
Stewartville, MN 55976

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13. ABSTRACT (Maximum 200 words)
The goal of this research was to analyze the effect of fixed costs on learning curve calculations. The research focused on two general research areas. The first area addressed the identification of current cost analysis practice for handling fixed costs in learning curve calculations. After identification of current practice, the unit learning curve model's (AX^b) ability to estimate total production run costs for a new production run when the slope was derived from both total cost and variable cost historical lot data was examined. Historical lot cost data was simulated for both the total cost and variable cost cases under three slopes, three fixed cost percentages, and three lot sizing profiles. The second area addressed the predictive ability, measured by mean absolute deviation (MAD), of the AX^b model versus the SAF/FMC model ($F/Q + AX^b$) when fit to total cost lot data. Comparisons between both models under different conditions were addressed through ANOVA. Three main findings: 1) there are a variety of practices when handling fixed costs in learning curve calculations, 2) the AX^b model by itself was inadequate for production run total cost estimating, and 3) the SAF/FMC model was superior to the AX^b model under all conditions.

14. SUBJECT TERMS
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