AFIT/GIM/LAL/95S-1

AN EVALUATION OF THE APPROPRIATENESS OF THE

DEFENSE LOGISTICS AGENCY'S REQUIREMENTS MODEL

THESIS

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Abstract

This thesis discusses the appropriateness of the Defense Logistics Agency's (DLA) requirements model in managing consumable support for Air Force specific items. Currently, DLA uses a lot sizing technique referred to as the classic Economic Order Quantity, (EOQ) model. One of the key assumptions of this model is that demand is constant and continuous. Yet with Air Force bases using a lot sizing technique to place their demands for consumable items to DLA, it is apparent that the demand pattern that DLA faces, at least for Air Force specific items, is not constant and continuous. This study looks at the impact of violations of the constant and continuous demand assumption on DLA's ability to support its customers. The findings of this study highlight the fact that the EOQ model does not perform well under the lumpy demand patterns that DLA faces. In addition, the Silver-Meal algorithm was used as a comparison to see if other inventory models could better handle this lumpy demand pattern. The Silver-Meal model required less inventory on hand and at a lower total variable cost than the EOQ model DLA is currently using.

AN EVALUATION OF THE APPROPRIATENESS OF THE DEFENSE LOGISTICS AGENCY REQUIREMENTS MODEL

I. Background and Problem Presentation

Introduction

The Defense Logistics Agency, commonly referred to as DLA, was established to provide standardized item management and economical supply support to the Department of Defense. As such, it has grown to be the largest wholesaler of consumable items in the Department of Defense (DOD). For the Air Force logistics community , this has come to mean that Air Force capabilities and operational readiness have become tied directly to understanding DLA support programs. (Robinson, 1993 : xvii)

With the Air Force sending over 2 million requisitions yearly for consumable items to DLA in support of over 360 weapon systems, any impact on DLA's ability to provide consumable support is of major importance to DLA and the Air Force (Robinson, 1993 : 76). DLA has and continues to use a specific requirements model to provide support on consumable items. There are certain key assumptions made in using this requirements model. In practice, some of these assumptions are violated. The impact of the violation of these key assumptions has not been fully investigated. The purpose of this study is to analyze the impact of violations of a key assumption of DLA's requirements model.

The Requirements Model

In an interview with Captain William Long on June 21, 1994, Mr. N. Balwally, a member of the Operations Research Analysis and Projects Division, Defense Electronics Supply Center, stated that the requirements model currently used by DLA is a hybrid of Wilson's Economic Order Quantity (EOQ) model with an additional variable safety stock (Long, 1994: 2). Both the Wilson and the DLA EOQ models attempt to minimize total variable costs by finding the point where holding costs and ordering costs balance.

In order to use these models, certain assumptions must be made. These assumptions, as they apply to both models, are listed in Table 1.

Table 1-1. Assumptions of Wilson s Classic Economic Order Quantity Model

1. The demand rate is known, constant, and continuous
2. The lead time is known and constant
3. The entire lot size is added to inventory at the same time
4. No stockouts are permitted; since demand and lead time are known, stockouts can be avoided
5. The cost structure is fixed; order/setup costs are the same regardless of the lot size, holding cost is a linear function based on average inventory, and unit purchase cost is constant
6. There is sufficient space, capacity, and capital to procure the desired quantity
7. The item is a single product; it does not interact with any other inventory items (there are know joint orders)

(Tersine, 1994: 95)

These assumptions are required to develop the model, but are not realistic in normal business operations. "In reality, we find few cases where a deterministic EOQ model can be used because we cannot satisfy all of the assumptions of the deterministic model" (Hood, 1987: 20). Although the hybrid models used by DLA and other companies have been built to adjust to the dynamic environment of the real world, these models still rely on the general assumptions listed in Table 1. This leads to the issue of what effect does violations of the assumptions have on the model's ability to minimize overall variable cost and inventory levels.

Figure 1-1 shows the EOQ model when all assumptions have been met. As one can see, additional supplies are ordered at a precise time to ensure that just as inventory on hand drops to zero the new supplies arrive. In addition, no requests for supplies go unfilled. Figure 1-2 illustrates what can happen when demand rate and lead time assumptions are violated. From the figure, one can see that these violations can cause negative stock levels, commonly called backorders. These backorders represent unfilled requests. While many of the assumptions are subject to violation, the emphasis of this research will be the effect of non-constant and non-continuous demand patterns on DLA's model and its ability to serve its customers.

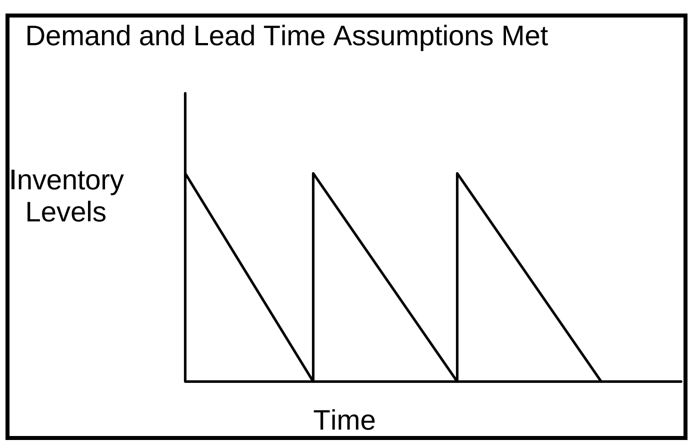

Figure 1-1. Assumptions met (Tersine, 1994: 93).

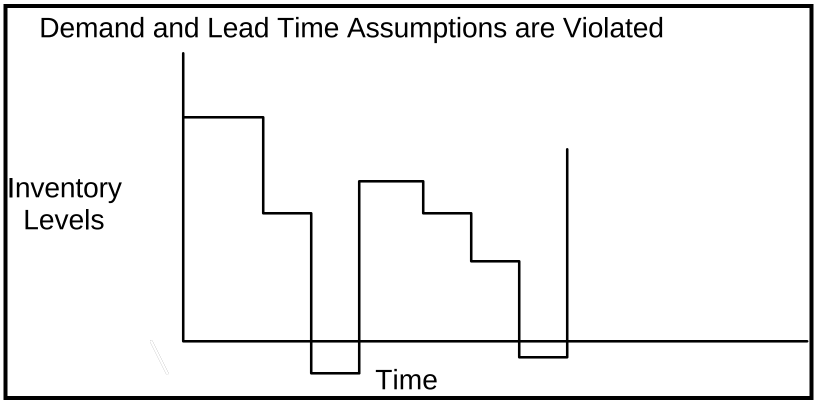

Figure 1-2. Assumptions not met (Tersine, 1994: 207).

Given the somewhat unrealistic expectations of the EOQ model, one might wonder why anyone would use this model in practice. One of the key features of the EOQ model is its robustness. By this it is meant that the model can handle errors in the input variables, holding cost, ordering cost, and demand rate, without significant changes in the total variable cost (TVC) or the economic ordering quantity. According to Prichard and Eagle, “Not only is the error in the TVC relatively insensitive to errors in individual parameters, but it is affected only by the ratio of input error ratios, which may be less than the individual error ratios” (Prichard and Eagle, 1965: 87-89).

The consumable requisitioning system for DLA and its customers is a multi-echelon system. From an Air Force perspective, the first echelon is the base or retail level which represents DLA's customers. DLA represents the second level, providing consumable items to the bases. The third level is composed of DLA's vendors supplying consumable items to DLA (Long, 1994 : 5).

From base level, consumable item demand is not constant or continuous. "Air Force demand patterns tend to be lumpy and erratic" (Blazer, 1986 : 1). At base level, each base operates under an EOQ type model that emphasizes economic lot ordering to balance ordering and holding costs (Hood, 1987 : 22). Customer demands at base level, regardless of the demand pattern, are consolidated into EOQ lot sizes and then sent to DLA. This use of the EOQ model at the first level ensures that demands placed against DLA are not constant or continuous, but lumpy from the lot size orders. This causes DLA to face a demand pattern similar Figure 1-2 while their EOQ model assumes that demands are like Figure 1-1. This disconnect can lead to stockouts or unnecessary stock being carried by DLA depending on the type of lumpy demand pattern.

It is the effect of this lumpy demand placed against DLA's requirements model that is the subject of this study. A significant negative impact on the model would ultimately degrade customer support and call into question the appropriateness of the model under these conditions. A prior thesis attempted to analyze this impact of demand rate and lead time assumption violations on DLA's model. Unfortunately, the study, while providing a practical observation that lumpy demand appears to effect the model, was unable to establish any statistical significance because of problems with data manipulation (Long, 1994 : 69).

Research Objectives

The purpose of this research is to analyze the impact of demand rate assumption violations on DLA's requirements model to support Air Force consumable demands. The specific objectives are:

1. Evaluate and change, if necessary, the performance measures of total variable cost and inventory levels at DLA as established in the prior thesis performed by Captains Long and Engberson.
2. Gather and adjust data collected from the Defense Electronics Supply Center (DESC) to provide a database to evaluate the effect of lumpy demand on the model.
3. Perform a simulation of DLA's model using the database to determine the impact of lumpy demand on the model.
4. Statistically, determine if violations of the constant and continuous demand assumption have any impact on DLA’s requirements model in terms of total cost and average inventory on hand.
5. Based on the first four steps, determine if DLA’s model is the best model available under “lumpy” demand conditions. The model will be evaluated in terms of total cost and average inventory on hand.

In order to achieve the stated research objectives, specific research questions have been established. These are:

1. How does lumpy demand affect the total variable cost portion of DLA's requirements model?
2. How does lumpy demand affect DLA's requirements model with regard to inventory levels maintained at DLA?
3. Can a different approach provide improvement over the existing DLA model?

Answers to these questions will provide a picture of the total impact of lumpy demand on DLA's model, customer support, and ultimately, the appropriateness of the model under these conditions.

Methodology

The primary tool used in this research will be simulation. A model will be created that replicates the primary functions of DLA's requirements model. The simulation model will be manipulated using constant and continuous demand patterns to establish baselines for variable cost and inventory levels. The second run of the model will be with the real world requirements data collected from DESC , which is lumpy in nature, and a comparison of the variable cost and inventory levels generated from each run will be made. Statistical analysis will be used to quantify the significance of the differences in the runs and ultimately establish whether the current DLA requirements model is appropriate for the non-constant demands DLA faces.

Scope and Limitations

The scope of this research is on the impact of lumpy demand for consumable items from Air Force bases placed against DLA's requirements model. The analysis will concentrate on the effect over time of this lumpy demand. Therefore, data from DLA on past Air Force demand patterns will be used to evaluate the effect of this lumpy demand.

In regard to this data, there are limiting factors. Because of budgetary and time constraints, the data was collected from DESC as a representative sampling of DLA's overall consumable national stock numbers. In addition, the data was collected by DESC analysts. It is their belief that this data sampling is representative of the demand pattern that the Air Force places on DLA.

Organization of Thesis

Chapter I has introduced the idea of lumpy demand and its effect on the Standard EOQ model. In addition, the chapter established that DLA, which uses a hybrid of the standard EOQ model, theoretically faces lumpy demand patterns. The impact of this lumpy demand on DLA's model and its ability to support consumable requirements is the emphasis of the remainder of this thesis.

Chapter II will focus on inventory theory and the theoretical effects of "lumpy" demand on the EOQ model. In addition, Air Force consumable management philosophy and prior Air Force studies on demand patterns will be discussed. Finally, the chapter will describe DLA's requirements model in greater detail and compare it to the classical EOQ model.

In Chapter III, the methodology of the research will be discussed. The use of simulation to answer the research questions posed in Chapter I will be justified. In addition, the simulation model used to replicate DLA's requirements model will be presented. Applicable variables , factors and levels of treatments, and simulation steps taken will also be discussed. Finally, the proposed data analysis methodology will be presented.

Chapter IV presents the data output from the simulation model, the analysis of the data, and the results of the tests conducted on the data. Hypotheses about the data will be rejected or not rejected based on the output data. This discussion will lay the foundation for the conclusions and recommendations in Chapter V.

Chapter V will present the conclusions from the data provided in Chapter IV. The adequacy of DLA's requirements model will be determined and based on this determination, recommendations about the model as well as future research considerations will be provided.

II. Literature Review

In order to understand the relationship between lumpy demand and DLA's requirements model, it is important to first understand the concepts of inventory and the EOQ model. The purpose of this chapter is to provide a basic understanding of these concepts and then apply them directly to the issue of lumpy demand and the DLA requirements model. The chapter begins with a review of inventory, to include the definition of inventory, reasons for holding inventory, and the costs associated with holding inventory. Next, the classic EOQ model will be analyzed and its basic assumptions will be discussed.

Using these concepts, the review will then focus on DLA and the requirements model. A brief review of DLA's mission and role will be provided and then a breakdown of the requirements model will follow. After discussing DLA and its requirements model, the review will focus on defining lumpy demand and examining the environment that DLA operates within. Relevant research in this area will then be presented and discussed in relation to DLA and its requirements model and operating environment.

Inventory

The American Production and Inventory Control Society (APICS) define inventory as "those stocks or items used to support production, supporting activities, and customer service." (APICS, 1992: 23) Inventory is further categorized based on its utility or purpose and divided into the following categories, "working stock, safety stock, anticipation stock, pipeline stock, decoupling stock and psychic stock" (Tersine, 1994: 7). A closer look at each of these categories is required to fully understand why inventory is acquired and maintained.

Working stock, also referred to as cycle stock or lot size stock, is inventory that is purchased and held in anticipation of a need. Lot sizes allow purchasing to achieve quantity discounts, as well as to minimize holding and ordering costs. These items are commonly referred to as supplies or raw materials (Tersine, 1994:7-8).

Safety stock "is inventory held in reserve to protect against uncertainties of supply and demand" (Tersine, 1994: 8). Safety stock also protects against stockouts during the replenishment cycle or lead time, which is "the delay between placing an order for materials and receiving the materials" (Knowles, 1989: 724). Other factors influencing the amount of safety stock are, the number of backorders allowed during one order cycle, the cost to hold versus the cost to back order, or financial limitations within the organization.

Anticipation stock is "inventory built up to cope with peak seasonal demand, erratic requirements, or deficiencies in production capacity" (Tersine, 1994: 8). These are foreseen requirements that would typically exceed current stock levels and could be negotiated for and purchased prior to the requirement.

Pipeline stock is inventory in transit that is ordered at a predetermined time permitting continuation of the operation during lead time. The APICS definition of pipeline stock is "inventory to fill the transportation network and distribution system including the flow through intermediate stocking points"

(APICS, 1992: 35). Furthermore, “the flow time through the pipeline has a major effect on the amount of inventory required in the pipeline” (APICS, 1992: 35).

Decoupling stock is inventory held to allow multiple production or manufacturing operations to operate independently. Psychic stock refers to the items on display in retail stores. Neither decoupling stock nor psychic stock have a significant role in the environment DLA operates in, although decoupling stock stock is used in Air Force depot level repair.

Purpose of Inventory

“Inventories are kept so that products are available when they are needed or available for sale when customers want to buy them” (Knowles, 1989:722). Not for profit organizations, like the Air Force, would not typically purchase inventory for resale at a profit, but rather to have assets available when organizations and individuals request it. The functional factors of inventory, time, discontinuity, uncertainty, and economy, further stratify the need or purpose of inventory (Tersine, 1994: 6).

The time factor involves “the long process of production and distribution required before goods reach the final consumer” (Tersine, 1994: 6). Here inventory is held to cover the time necessary to develop and bring the product to the point of sale. Time factor examples include the time to prepare and execute the purchase schedule, the actual production time of the asset, and the transit time from vendor to customer.

Inventory held for the discontinuity factor absorbs the differences in vendor production capacity and customer demand, thus allowing an uninterrupted inventory flow. The uncertainty factor concerns unforeseen events that modify the original plans of the organization such as errors in demand estimates, variable production yields, and shipping delays. The economy factor includes efforts to achieve economies of scale and to take advantage of cost-reducing alternatives (Tersine, 1994: 7).

Inventory Costs

Historically inventory only represented a small amount of an organizations' total investment. "It was better (and cheaper) to have the material than not to have it" (Harding, 1990: 255). However, "as manufacturers became more efficient, more automated; labor costs declined and material cost grew" (Harding, 1990: 255). Now "purchased materials account for 60-70% of the cost to manufacture on a national average" (Harding, 1990: 255). This means that overall inventory costs have increased dramatically and therefore necessitate effective management control.

In order to better manage and control inventory, materiel managers must know the specific costs incurred with inventory. In fact there are four primary costs associated with inventory: purchase cost, order/setup cost, holding cost, and stockout cost. "The purchase cost of an item is the unit purchase price if it is obtained from an external source, or the unit production cost if it is produced internally" (Tersine, 1994: 13). Order and setup costs include any cost associated with placing an order, mostly administrative time, or physically reconfiguring a production operation or processes. Order and setup costs are “usually assumed to vary directly with the number of order or setups placed and not at all with the size of the order” (Tersine, 1994: 14).

Holding costs, or carrying costs, are comprised of the costs associated with purchasing and maintaining inventory. Many costs are considered in holding inventories and typically include but are not limited to, cost of capital, obsolescence, shrinkage, taxes, and manpower. Cost of capital or opportunity cost reflect the lost profit if the organization had invested the money in the next best alternative to inventory. Obsolescence is the risk incurred that inventory will lose value while being held. Shrinkage indicates the amount of inventory lost to damage, pilferage or misconduct. Some states consider inventory taxable property subject to annual collection. During the time inventory is in storage, there is a cost associated with the manpower or material handling equipment used to manage it. All of these costs vary directly with the amount of inventory held (Tersine, 1994:14).

The stockout cost is “the economic consequence of an external or an internal shortage” (Tersine, 1994: 14). In the retail market, no revenue is gained when goods are unavailable for purchase. Military organizations do not necessarily incur revenue losses due to stock outs but do incur additional expenses for back ordering or expediting, shipping, and processing of assets not available in stock, loss of productive time in maintenance, and aircraft downtime.

Managing inventory expenses is one of the primary functions of an inventory manager. As organizations become increasingly concerned with financial efficiency, the costs associated with inventory become increasingly critical.

> The aim of inventory control is to maintain inventories at such a level that the goals and objectives of the organization are achieved. Poor control of inventory can create a negative cash flow, tie up large amounts of capital, limit the expansion of an organization through lack of capital, and reduce the return on investment by broadening the investment base. (Tersine, 1994: 20)

To manage the inventory costs appropriately, the total annual costs for the inventory must be calculated, which is the sum of the purchase cost, order cost, and holding cost. The formula for total annual cost is:

$$TC(Q) = PR + \frac{CR}{Q} + \frac{HQ}{2} \tag{1}$$

where

R = annual demand in units,

P = purchase cost of an item,

C = ordering cost per order,

H = PF = holding cost per unit this year,

Q = lot size or order quantity in units,

F = annual holding cost as a fraction of unit cost,

TC(Q) = total annual costs for the inventory. (Tersine: 92)

There is an optimum level of investment in inventory where having too much can impair finances just as much as having too little; too much inventory may result in unnecessary holding costs, and too little inventory can result in disrupted operations (Tersine, 1994: 21). Therefore it is imperative to minimize total costs which occurs when holding costs equal ordering costs. Figure 2-1 graphically indicates that total costs are minimized at the point where holding costs equal ordering costs.

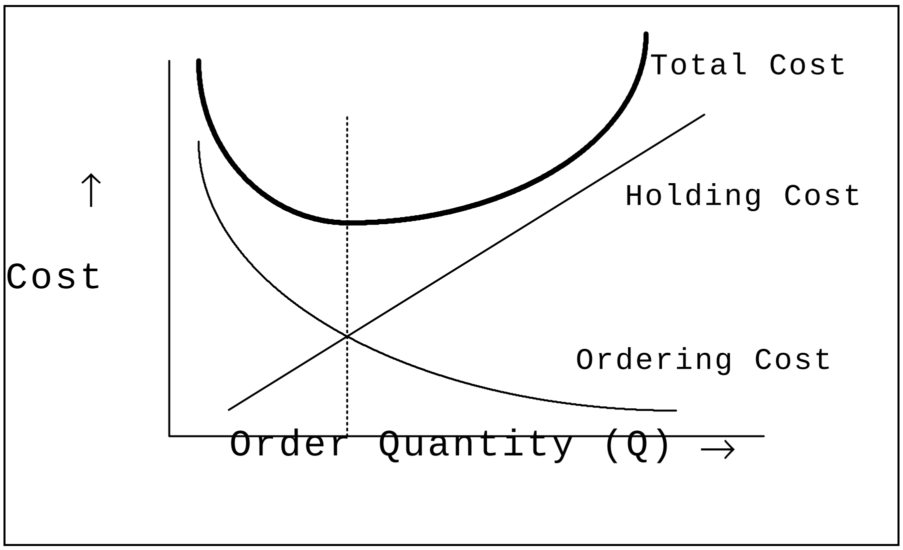

Figure 2-1. Cost Curve (Tersine: 94)

Economic Order Quantity. Organizations must find a way to minimize these inventory costs as well as satisfy customer demands. The economic order quantity (EOQ) inventory model determines how much to order by determining the amount that will minimize total ordering and holding costs (Coyle, 1994: 560). In other words “the order size that minimizes the total variable inventory cost is known as the economic order quantity” (Tersine, 1994: 92).

The formula for the classical EOQ model is:

$$Q^* = \sqrt{\frac{2RC}{H}} \tag{2}$$

where

Q* = Economic Order Quantity

R = Annual Demands

C = Cost to order

H = Holding cost

and,

H = PF

P = Price

F = Holding cost factor.

As stated in chapter I, the classical EOQ model is based on several key assumptions. Based on these assumptions, Tersine highlights how the EOQ model reacts to varying costs and unit prices.

> The EOQ results in an item with a high unit cost being ordered frequently in small quantities (the saving in inventory investment pays for the extra orders); an item with a low unit cost is ordered in large quantities (the inventory investment is small and the repeated expense of orders can be avoided). If the order cost is zero, orders are placed to satisfy each demand as it occurs, which results in no holding cost. If the holding cost H is zero, an order (only one) is placed for an amount that will satisfy the lifetime demand for the item. (Tersine: 94)

The EOQ model serves as the basis for DLA's requirements model, as will be shown in the following section.

The Defense Logistics Agency

In August 1961, Secretary Robert S. MacNamara established the Defense Supply Agency as an attempt to capitalize on the benefits of centralized logistical support for common DOD items, while still providing the responsiveness that the Services had come to rely on from their internal supply systems. At first, the Services were skeptical of the ability of DSA to provide the specific support they required. There was a belief that each Services individual needs would be overcome by the requirement to support a large customer base as a whole. Over time, this belief was replaced by a growing dependence on DSA for logistical support. DSA had quickly proven its ability to save the DOD operating funds. In its first year of existence, DSA saved the DOD over $31 million while providing better support than the inter-service systems it replaced. During the following years, its role and mission expanded until the name, Defense Supply Agency, no longer reflected the scope of its responsibilities. In 1977, the DSA became the Defense Logistics Agency to reflect its growth from a supply manager to an agency handling the complete logistical functions for numerous commodities (Robinson, 1994: 5).

Today, DLA's responsibilities can best be summed up by its mission statement. Its primary mission is:

> To function as an integral element of the DOD logistics system and to provide effective an efficient logistics support to DOD components as well as federal agencies, foreign governments, or international organizations as assigned in peace or war. Our vision at DLA is to continually improve the combat readiness of America's fighting forces by providing soldiers, sailors, airmen, and

marines the best value in services when and where needed. (DLA, 1991:2-1)

In order to provide the logistics support required by the DOD and other agencies, DLA is organized into six divisions. The focus of this paper is on the six supply centers operated by DLA and how they manage their inventory. Exhibit 1 shows these supply centers and their location.

Table 2-1. DLA Supply Centers

Supply Center	Location
Construction	Columbus, Ohio
Personnel Support	Philadelphia, Pennsylvania
Industrial	Philadelphia, Pennsylvania
Fuel	Alexandria, Virginia
Electronics	Dayton, Ohio
General	Richmond, Virginia

(Robinson, 1994: 7)

When the statistics for these centers are combined, DLA, as a whole, stocks over three million items worth over $10 billion, requiring 96.4 million feet of storage space. In addition, during 1991, these centers processed over 29 million requisitions while maintaining an eighty-six percent stockage effectiveness rating (Robinson, 1994: 6). Based on this data, one can see how crucial inventory management is to DLA in supporting its customers.

The DLA Model

The DLA model used to manage inventory levels is very similar to the classic EOQ model with some minor modifications. One such modification is the use of quarterly forecasted demand instead of annual demand. Instead of using the annual demand, as the classic model does, DLA relies on the quarterly forecasted demand times 4. This is then inserted into the equation as the annual demand. DLA's model appears as follows: (Balwally, 1994: Interview and notes)

$$EOQ_{DLA} = \sqrt{\frac{2(4QFD)C}{hP}} \qquad (3)$$

where

EOQ_{DLA} = Economic Order Quantity for DLA

QFD = Quarterly Forecasted Demand

C = Ordering Costs

h = Holding Rate

P = Standard Price Per Item

In addition, DLA factors out all the constants in the equation to reduce computation time. For DLA, these constants are the ordering costs, the holding rate, and the constant (2) used in the equation. (T) is then set equal to these constants. This formula is as follows: (Balwally, 1994: Interview and notes)

$$T = 2\sqrt{\frac{2C}{h}} \qquad (4)$$

where

T = Constant Factor for DLA requirements model

C = Ordering Costs

h = Holding Costs

The DLA model is expressed as :

$$EOQ = T\sqrt{\frac{QFD}{p}} = \frac{T}{2p}\sqrt{AD\$} \quad (5)$$

where

EOQ = Economic Order Quantity

T = DLA's Constant Factor

QFD = Quarterly Forecasted Demand

P = Standard Price per Item

AD$ = Annual Predicted demand in dollars (AD$ = {4(QFD)p})

In order to determine the quarterly forecasted demand, QFD, DLA relies on a double exponential smoothing formula. The formula and its subparts are listed below: (Balwally, 1994: Interview and notes)

$$2F_t - F'_t = QFD \quad (6)$$

and,

$$F_t = \alpha A_t + (1-\alpha)F_{t-1} \quad (7)$$

$$F'_t = \alpha(F_t - F'_{t-1}) + F'_{t-1} \quad (8)$$

where

F_t = Single forecast smoothing value

α = Smoothing constant

A_t = Actual period demand

F_{t-1} = Single forecasted smoothing value , one period in the past

F'_t = Double forecast smoothing value

F'_{t-1} = Double forecast smoothing value, one month in the past

It should be noted that DLA is in the process of switching from this current double exponential smoothing formula to the Statistical Demand Forecasting model acquired from the U.S. Navy. This new model will allow each activity in DLA, such as DESC, to determine its own forecasting method from the moving average to the double exponential smoothing formula depending on which is a better predictor of future demand.

DLA also adds a variable safety level to the EOQ model. The appropriate level is determined quarterly using a constrained optimization model which attempts to minimize holding and ordering costs, given a target number of backorders (Balwally, 1994: Interview and notes). Initially, DLA applies a Selective Management Category Code (SMCC) to its items to differentiate between high dollar and frequency items and low dollar and low frequency items. Exhibit 2 shows the SMCC categories.

Table 2-2. SMCC Categories

HIGH DOLLAR	A	C	E
LOW DOLLAR	B	D	F
	HIGH FREQUENCY	MEDIUM FREQUENCY	LOW FREQUENCY

(Bilikam, 1994)

Using simulation, DLA determines a multiplication factor , called essentiality, that will maximize availability through safety level application in the most economical way. Based on the simulation, categories A and B receive an essentiality factor of 6, category C receive an essentiality factor of 2, and the other categories receive no essentiality factor. This factor, in basic terms, highlights the importance of having sufficient safety stock on hand to avoid a stock out. This factor is then used in the calculation of the variable safety stock level (Bilikam, 1994: Interview and notes).

DLA uses a modified Lagrange Method to determine its variable safety stock. The equation is as follows:

$$\text{VSL} = \text{k} \times 1.25 \times \text{MADPLT} \tag{9}$$

where

$$\text{k} = -.7071 \times \text{LOG(e)}\chi, \tag{10}$$

$$\chi = \left[\frac{UP \times R \times ARS}{X \times Z} \times \frac{2.56 \times \text{b}}{SYS.CON}\right] \tag{11}$$

MADPLT (smoothed mean absolute deviation per lead time) = (a $\times$ bT) $\times$ smoothing factor and,

T = Lead time in months or quarters (per item)

a = .63 (months) or .55 (quarters)

b = .41 (months) or .49 (quarters)

Smoothing factor = .1 (months) or .2 (quarters)

UP = unit price (per item)

R = $\frac{procurement - cycle(units)}{MADPLT}$ (per item)

Z = Essentiality factor discussed above (per item)

X = 1-e $^{-1.1R}$ (per item)

ARS = average requisition size (per item)

b = Backorder target (all items) currently set at approximately 37,000

SYS.CON = sum of MADPLT $\times$ Unit Price (all items) currently set at approximately $130 million

In addition, DLA overlays a “readiness” safety level on top of the variable safety level for items with weapons applications and deficient safety levels. This additional safety level is to reduce the probability that a weapon system will be grounded for lack of a DLA managed consumable part. This may seem excessive at first, but as of 1994, only 4,000 items required this readiness safety level in addition to the variable safety level. The equation for this safety level is the same as for the variable level except for the following changes: (Bilikam, 1994: Interview and notes)

$$\chi = \frac{2.2627 \times R \times (1 - SA)}{X} \qquad (12)$$

where

SA = availability parameter (set at 90%)

Lumpy Demand

As we have seen, the DLA requirements model is very similar to the classic EOQ model and therefore relies on the same basic underlying assumptions. One of these key assumptions is constant and continuous demand. Our interest is in the impact of violations of this assumption on the DLA model. For the purpose of this paper, non-constant nor continuous demand is referred to as "lumpy" demand. Tersine, in his text, identifies lumpy demand as "time variations in demand occurring over a finite time horizon." He further states that there are situations where lumpy demand is so pronounced that the constant demand assumption is called into question. (Tersine, 1994: 178)

Given this fact, Silver and Peterson have established a ratio to determine exactly the point where lumpy demand patterns significantly violate the constant demand assumption (Silver, 1985: 238). This measure is called the variability coefficient and is denoted by *VC*. Its formula is as follows:

$$VC = \frac{\text{Variance of demand per period}}{\text{Square of average demand per period}} \tag{13}$$

If $VC < 0.2$, then Silver and Peterson state that the EOQ assumption of constant and continuous demand is still valid. If on the other hand, $VC \geq 0.2$, they suggest that the constant demand assumption has been significantly violated and that other models should be considered (Silver, 1985: 238). Yet, one must question whether the amount of items displaying lumpy demand patterns warrants concerns over its impact, on the whole.

According to Delurgio and Bhame, in a presentation to attendees of the 1991 International American Production and Inventory Control Conference, " It is not uncommon to find 50 to 60 percent of a firm's items and nearly as high an investment, are in low, lumpy demand items." They also highlight the fact that a significant amount of lumpiness in demand is caused by lot sizing and timing in a network or multi-level system (Delurgio, 1991: 589-590). Using Delurgio's logic, one could argue that because the relationship between Air Force bases and DLA is a multi-level network with the bases using lot sizing methods to place requirements for consumable items against DLA, the system itself would cause lumpiness in demand. Two USAF studies in this area found just that.

In 1974, the Air Force Academy performed a study of the Air Force's EOQ model. As a side note, they highlighted the fact that 64% of the consumable items they sampled, exhibited other than normal demand patterns (Shields, 1990: 19-21). Again in 1985, Blazer verified that demand patterns tended to be lumpy in nature. Given that the Air Force EOQ model expects a variance of demand to mean demand ratio of 3, Blazer discovered, at the five bases he analyzed, this ratio varied from a low of 14.2 to a high of 29.5, illustrating the lumpiness of the demand patterns (Blazer, 1985: 11-12).

Related Studies

Captains William Long and Douglas Engberson attempted to determine the effects of violations of the constant demand assumption on DLA's requirements model. Using simulation, they replicated DLA's requirements model and collected data on 540 stock numbers managed by DESC. This data consisted of holding costs, ordering costs, standard unit price, and quarterly demand data for the last 16 quarters. Based on the data and the simulation model, Long and Engberson set up a complete $3 \times 3 \times 3$ factorial experimental design as follows (Long and Engberson, 1994: 44):

Input Factors	Levels
Ordering*	1. All activities order frequently (1 order per month) 2. Half the activities order frequently, Half infrequently) 3. All activities order infrequently (1 order every 6 months)

* the simulation model had four activities placing orders against DLA

Annual Demand (in units)	1. High (determined to be 3750 units based on data) 2. Medium (determined to be 481 units based on the data) 3. Low (determined to be 70 units based on the data)
Lead time (in months)	1. High (determined to be 14.4 months based on the data) 2. Medium (determined to be 7 months based on the data) 3. Low (determined to be 3.27 months based on the data)

The three response variables were established as total variable cost, average on hand inventory, and pre-replenishment inventory. These three response variables were used to determine the impact of lumpy demand on the costs associated with inventory for DLA, as well as the ability of DLA to support customer requests. If lumpy demand causes total variable costs to go up or customer support to go down, the appropriateness of DLA's requirements model is called into question (Long and Engberson, 1994: 46).

Long and Engberson intended to use the analysis of variance (ANOVA) statistical method to evaluate the output of the simulation model to determine the impact of lumpy demand. However, the variances between treatment means were not equal and this violation of the ANOVA assumptions forced them to consider non-parametric statistical methods. Because of the lack of independence between simulation runs, non-parametric methods could not be used either. Practical observation of the output data was used to made conclusions on the impact of lumpy demand. Based on their observations, Long and Engberson determined that lumpy demand caused average on hand inventory to fluctuate widely between periods. In addition, almost all pre-replenishment inventory levels were negative, implying lumpy demand would require higher levels of safety stock than under constant demand. They also determined that lead times and annual demand, when combined with lumpy demand, have an impact on the on hand balances and overall customer support. This led Long and Engberson to recommend further studies in this area to quantify the impact of lumpy demand on DLA's requirements model (Long and Engberson, 1994: 69-77). This study has served as the foundation for our current research.

This chapter provided background information needed to understand the importance and relevance of this research. Reasons for holding inventory as well as the costs associated with inventory were described. In addition, the components of the classical EOQ model and the DLA requirements model were outlined. Finally, the concept of lumpy demand was presented and past relevant research was discussed. The following chapter will discuss the proposed methodology to analyze the impact of lumpy demand on DLA's model.

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III. Methodology

This chapter will discuss the methodology chosen to answer the research questions posed in Chapter I. In order to ensure all aspects of the research are discussed, this chapter will be organized according to the seven steps Cooper and Emory have established as essential to successful experiments (Cooper and Emory, 1995: 353).

Conducting An Experiment

The method chosen for this research is experimentation. Experimentation is defined as “a study involving the intervention by the researcher beyond that required for measurement” (Cooper and Emory, 1994: 351). The researcher attempts to manipulate the independent variables and then record the effect of the manipulation on the dependent variables. There are four distinct advantages of experimentation. The first advantage is the researcher’s ability to manipulate the independent variable to determine the effect on the dependent variable. The second advantage is that the effect of extraneous variables can be removed from the experiment. The third advantage is that cost and convenience of the experiment is superior to other methods. The fourth advantage is the ability to replicate an experiment to verify results (Cooper and Emory, 1994: 352).

To make experimentation a success, a researcher must complete a series of activities in a logical manner in order to ensure the experiment’s success. According to Cooper and Emory, there are seven specific activities that a researcher must follow in order to guard against defects in the experiment and its results. Those seven activities are listed below: (Cooper and Emory, 1995: 353-370)

1. Select relevant variables
2. Specify the level(s) of the treatments
3. Control the experimental environment
4. Choose the experimental design
5. Select and assign the subjects
6. Pilot test, revise, and test
7. Analyze the data

The remainder of this chapter will focus on applying each of these activities to this study to establish a concrete foundation to determine the results and subsequent conclusions.

Selecting Relevant Variables

The focus of research is to answer a question that is not readily answerable based on current knowledge. As such, the research question establishes what relevant variables will be required for the experiment. For this research, the question , as stated in Chapter I, is “What is the impact of violations of the constant demand assumption on DLA’s requirements model?”. More specifically, the experiment must answer the following three questions:

1. How does lumpy demand affect the total variable cost portion of DLA’s requirements model?
2. How does lumpy demand affect DLA’s requirements model in regard to inventory levels maintained at DLA?
3. Is there a better model that could be used instead of the current requirements model used by DLA?

The answers to these questions will provide a picture of the total impact of lumpy demand on DLA's model and ultimately, the appropriateness of the model under these conditions. In order to establish and measure the impact of lumpy demand, the relevant performance measures for the experiment must be identified. Two performance measures were established as relevant and important. They are total variable cost and average on-hand inventory at DLA.

Total variable cost is an important measure in evaluating the EOQ model. The EOQ model attempts to balance ordering and holding costs to minimize total variable costs. Therefore, if the total variable cost under lumpy demand was significantly different than under constant and continuous demand, the impact of lumpy demand on the model would be demonstrated as being significant.

Another important performance measure is average on hand inventory. It provides a gauge of how much inventory the model requires to satisfy demand. If it can be shown that the average on hand inventory under lumpy demand is significantly different than under constant and continuous demand, given the overall annual demand is the same under both conditions, one could argue that the lumpy demand has an observable impact on the model.

Factors and Levels of Treatment

Factors and levels of treatments for this research were determined based on knowledge of the EOQ model, the documented research of Long and Engberson, and the characteristics of the data sample collected from the Defense Electronics Supply Center. Before discussing each of these factors and its appropriate levels, it is important to describe the data collection procedures used to develop the characteristics for these factors.

In order to determine the DLA specific characteristics for these factors, a sample of 525 national stock numbers was collected by DESC personnel for this research. According to Mr. Balwally and Mr. Bilikam, operations analysts at DESC, this sample is representative of the demand patterns that all of DLA's EOQ managed items face. The data collected included the national stock number for each unit, the past sixteen quarters of demand data, the calculated quarterly forecasted demand, the lead time, and the nomenclature. This data was then used to determine the characteristics or levels for the factors for this research. Appendix A provides an example of the data that was collected.

Using the collected data, factors and levels of treatment were established. Long and Engberson, in their experiment on the effect of lumpy demand on DLA's requirements model, used demand patterns, annual demand, and total lead time as their factors. Initially, this study began on the assumption that Long and Engberson's three factors and levels would be used to replicate their experiment. These factors and levels are listed in Table 3-1. However, preliminary analysis of the DLA data made it apparent that these factors and levels would not be appropriate for this study.

The first factor established by Long and Engberson was demand pattern. They used three levels to represent constant and continuous demand, lumpy demand, and a mixture of the two. For the purpose of this research, it was decided that demand is either constant and continuous or lumpy in nature.

Although demand patterns may vary between these two patterns during a given time period, the objective of this research is to determine the impact of lumpy demand on DLA's model. Therefore, levels of demand pattern will be either constant and continuous or lumpy. Using Silver and Peterson's definition of lumpy demand provided in Chapter II, lumpy demand patterns will be such that the variance of demand divided by the mean demand squared will be greater than 0.20 (Silver, 1985: 238). Based on the sample data, 95.38% of items DLA manages exhibit lumpy demand patterns. On the other hand, constant and continuous demand will be such that the variance to mean squared ratio is less than 0.20. Appendix I illustrates these calculations on a sample of a few items to give the reader a better understanding of what would be considered lumpy and what would be considered constant and continuous.

A second factor used by Long and Engberson in determining the impact of lumpy demand was the annual demand placed on DLA. This annual demand is in units. They hypothesized that in order to determine the appropriateness of DLA's model under lumpy demand, one must account for the different annual demands that are placed against DLA and its impact on the model. There is the possibility that the model will react differently under lumpy demand with varying levels of annual demand. In order to evaluate these possibilities, categories of annual demand had to be established. Long and Engberson, in their study, established three levels of annual demand. Those levels were low, medium, and high. The values for each category were determined using the data sample they collected from DESC. Based on their data analysis, the average low annual demand was set at 70 units. Medium demand was set at 481, and high annual demand was set at 3750 (Long and Engberson, 1994). However, when the sample data was analyzed, there were no specific data points that could be extracted that were representative of the sample.

Table 3-1. Long s Experimental Factors and Levels

Factors	Levels	Value Activity 1&2	Activity 3&4
Demand Pattern	Low	2.1%	2.1%
(% of annual demand)	Mixture	0.7%	4.1%
	High	12.5%	12.5%
Annual Demand	Low	70	
(units)	Medium	481	
	High	3750	
Lead Time	Low	3.267	
(months)	Medium	7.0	
	High	14.4	

Appendix B, a graph of the quarterly demand pattern from the collected sample, illustrates the problem encountered in extracting specific data points. Because the graph appears to represent a exponential distribution with a long tail of large but infrequent orders, there were no natural breaks in the data to categorize it into levels of demand. *SAS/STAT* Release 6.03, a statistical software package, was then used to analyze the data and locate any clusters of data points which could be used as levels. The results of the cluster analysis indicated that there were no clusters in the data collected. Therefore, the observed data pattern was validated with Mr. Michael Pouy, headquarters DLA. He agreed that the demand pattern DLA faces fits the exponential distribution with a long sparsely populated tail. Based on this information and the inability of the cluster analysis to find natural levels in the data, annual demand was eliminated as a factor and allowed to fluctuate according to a exponential distribution with the parameters extracted from the collected data to reflect the actual demand pattern.

The third factor Long and Engberson chose for this experiment was lead time. Long and Engberson determined that lead time could be divided into three categories: low, medium, and high. Based on the data, low lead time averaged 3.267 months, medium lead time averaged 7.0 months, and long lead time averaged 14.4 months. As with the annual demand, this study's analysis of the data provided different results. Using the data collected from DESC, an attempt was made to determine natural levels of lead times. This analysis uncovered a distribution of lead times that appeared to fit an exponential distribution with a long sparsely populated tail similar to the annual demand distribution discussed above.

Therefore, *SAS/STAT* Release 6.03 was used to analyze the data and locate any clusters of data points which could be used as levels. According to SAS output results, there were no clusters in the data collected. Again, DLA was contacted to determine if they had specific categories of lead times to indicate short and long lead times. If specific numbers could be assigned to these categories, they could then serve as DLA determined breaks in the data. Unfortunately, it was discovered that there is no such categorization of lead times at DLA. After further examination of the data and based on the preliminary data, it was determined that lead time was not a factor in this experiment. Failure to categorize the lead times was not the reason for its elimination. Lead time was not a factor for two reasons. First, lead time only impacts the EOQ model in the safety stock and reorder point calculations. From the beginning, safety stock was eliminated from this experiment because it could hide the real impact of lumpy demand on DLA's requirements model. After all, the purpose of safety stock is to protect the organization from fluctuations in demand. The reorder point then, without safety stock, is simply the mean demand during lead time. This leads to the second point. This research does not use customer service levels as a performance measure; therefore, changing the reorder point by varying lead times does not provide any insight into the impact of lumpy demands being placed against DLA's requirements model and could actually confound the results if it were allowed to vary. For these reasons, it was decided to hold the lead time for DLA from its suppliers constant throughout the experiment at 100 days. This figure was determined based on the data collected from DESC. Appendix J provides a graph of the leadtimes from the collected data.

Experimental Environment

The control of the environment refers to the ability of the researcher to minimize his impact on the environment and the impact of all extraneous variables to the experiment. Simulation, the methodolgy chosen for this research, inherently reduces the impact of both of these problems on the experiment. An in-depth analysis of exactly how simulation aids in the control of the experimental environment will be discussed as part of the next section.

Experimental Design

The method chosen for this research is simulation. Simulation , as defined by Pritsker, is "the process of designing a mathematical-logical model of a real system and experimenting with this model on a computer" (Pritsker, 1986: 6). There are several advantages of studying a system in this manner. First, the system can be tested and manipulated before incurring the cost of actually building the system. Secondly, the system can be studied without bringing the existing system off-line. Finally, one avoids the potential of damaging or destroying the existing system through testing procedures (Pritsker, 1986: 6). The last two advantages are relevant to this study. Because the DLA requirements model is continually being used to determine requirements and manage transactions, it would be impractical to bring this system off-line for our experiment. In addition, the potential costs associated with any down time in the system prohibit direct manipulation of the DLA requirements model.

The use of simulation for inventory related issues is not new. Andrew Clark, in his article, "The Use of Simulation to Evaluate a Multiechelon, Dynamic Inventory Model," highlights examples where simulation is the only real method available to solve complex inventory issues (Clark, 1993: 429-444). In addition, Choi, Malstrom, and Tsai, used simulation to evaluate several lot sizing methods within multilevel inventory systems, to include the EOQ model. This analysis of the lotsizing methods was performed to establish a ranking of the effectiveness of the lot-sizing methods (Choi, Malstrom, and Tsai, 1988: 4-10).

Pritsker has developed ten basic steps for successful simulation. Table 3-2 lists these ten steps and then subsequent discussion will focus on applying those steps to the current research experiment.

Table 3-2. Steps For Successful Simulation

1. **Problem Formulation.** The definition of the problem being studied to include a statement of the objectives of the study.
2. **Model Building.** The conversion of the system under study to a mathematical-logical representation.
3. **Data Acquisition.** The identification, specification, and collection of appropriate data.
4. **Model Translation.** The preparation of the model for computer processing.
5. **Verification.** Establishing that the model works as intended.
6. **Validation.** Establishing that the model replicates the real system.
7. **Strategic and Tactical Planning.** The process of establishing the conditions for using the model.
8. **Experimentation.** The execution of the model to obtain the required output.
9. **Analysis of Results.** the analysis of the output to draw inferences and make recommendations.
10. **Implementation and Documentation.** The process of implementing decisions based on the results of the model and documenting the model and its use.

(Pritsker, 1986: 1-10)

Problem Formulation. The problem this research attempts to resolve is the appropriateness of DLA's requirements model under lumpy demand patterns. The research questions are stated in Chapter I and earlier in this chapter.

Model Building. Simulation models will be created using Pritsker's SLAM II software (Version 4.4) on the Digital Equipment Corporation's VAX 6420 mainframe computer. These models will then be compiled and linked using DEC VAX FORTRAN Compiler (Version 6.1). The purpose of these models is to replicate the DLA requirements model under lumpy demand so that the researchers can statistically determine the impact of lumpy demand. A total of four models will be built using *SLAMSYS* (Version 4.0).

Each of the four models will reflect will represent different assumptions of the demand pattern DLA faces. The first model is referred to as the Normal, Constant and Continuous model and reflects all the assumptions of the EOQ model that DLA uses for their requirements computations. As such, demand is generated from the bases and sent to DLA on a deterministic schedule. This implies that each bases orders the same quantity during a set period. The second model is called the Normal Demand model. It is similar to the previous model except it relaxes the assumption of constant and continuous demand to allow the amount of an item ordered by the bases to vary according to a normal distribution. Most inventory text books use this assumption of a normal distribution of demand when applying the EOQ model to real situations. This assumption is generally true for a majority of the consumable items (Tersine, 1994: 212).

The third model is called the Lumpy demand model. This model incorporates DLA's requirements model like the previous models, except demand from the bases is allowed to fluctuate. The demand faced by DLA comes from a exponential distribution, as reflected in the sample from DESC, and the timing of the demand comes from a normal distribution. This model is reflective of the current conditions that DLA operates in. The fourth model is the same as the Lumpy demand model except the EOQ model that DLA uses is replaced with the Silver-Meal model which is designed to more effectively handle lumpy demand. Table 3-3 summarizes the comparisons of the models.

Table 3-3. Comparison of Models

Model	Timing of demands from bases	Quantity of each order	Requirements Model used
Normal, Constant and Continuous	Orders placed every month	8 units per order	DLA's EOQ model
Normal Demand	Orders placed every month	Normal distribution with mean of 8 and standard deviation of 1	DLA's EOQ model
Lumpy Demand	Triangular distribution with a mean of 90 days, a max of 150, and a min of 30 days	Exponential distribution with mean of 89.36543	DLA's EOQ model
Silver-Meal	Triangular distribution with a mean of 90 days, a max of 150, and a min of 30 days	Exponential distribution with mean of 89.36543	Silver-Meal model

Data Acquisition. As mentioned earlier in this chapter, data was collected from DESC to establish the parameters for the independent variables in the model. Table 3-3 outlines the values chosen for the variables. These values will be incorporated into the simulation model. As discussed in Chapter II, DLA uses a Lagrangean method to determine its variable safety stock. For the purpose of this experiment, the variable safety stock will not be included in the simulation model. It was determined that safety stock might mask the impact of lumpy demand on the model. Long and Engberson, in their experiment, eliminated safety stock from their experiment for the same reason.

Model Translation. Appendix C provides a detailed discussion of the simulation model to include the program logic.

Verification. The verification of the models was completed in two steps. In the first step, the authors went step by step through the code to ensure that it worked as it was designed to. Also, the authors relied on the *SLAMSYS* (Version 4.4) syntax check and the DEC VAX FORTRAN Compiler (Version 6.1) to aid in validating the program code and fortran code. Secondly, a pilot test of five runs for each model was accomplished. Results of the runs were analyzed to determine if the models were working properly. This process was repeated until the models were working properly.

Validation. The models were validated by inventory instructors at the Air Force Institute of Technology (AFIT) and personnel at DLA. First, personnel at DESC were interviewed to determine any specific DLA policies that needed to be reflected in the model (Balwally, 1994: Interview). Next, the issues raised by the DESC personnel were discussed with the inventory instructors at AFIT. Each model was analyzed to ensure it reflected DLA’s inventory system, applicable DLA policies, and the assumptions implied by each model’s environment.

Strategic and Tactical Planning. Before each model can be run to collect the required data, three very important questions must be answered. They concern initial starting conditions, how long the model should be run for each run, and how many samples or runs need to be made to ensure that the collected data is reflective of its population. All of these questions will be answered next.

First, the initial starting conditions for each model had to be determined. The models called for customers to begin placing demands to DLA as soon as the model started. This means that unless the model began with some inventory at DLA, it would backorder immediately. Secondly, until after the first quarter, there is no forecasted demand to use in determining order quantities. Therefore, the initial amount of inventory on hand was set at a rough-cut EOQ amount. Also, the forecasted demand was set at this same amount. Appendix C provides specific details on these initial conditions. These predetermined starting conditions allow the model to start at a more steady state but do not impact the collected data from the model, as we will see next.

The second question raised earlier concerned the length of time the models should be run. One of the assumptions of simulation models is that the output reflects the system in steady state. Yet, with many models there is a warm up period, also called the transient period, where the model is moving toward steady state but the model output is still affected by the initial starting conditions. If this transient period were included in the output of the model it might bias the results because it doesn't reflect the true steady state of the system. Therefore, modelers must attempt to determine where the transient period ends so that the observations during the transient period can be deleted (Law and Kelton, 1991: 545).

One method to estimate the beginning of steady state is to use a pilot run from each model and apply a moving average to the periodic output on the measured variable. When the graphed moving averages are analyzed, steady state begins as the moving average curve levels off (Law and Kelton, 1991: 545-551). This was the method used to determine the end of the transient phase for this experiment. Appendix D provides the graphs of average inventory and total variable cost over time. The longest transient phase lasted 55 years or 19,800 days (days are used in the simulation, but the output is per year). In order to ensure that the model was in steady state, all statistical arrays were cleared at 20,000 days. The model was then allowed to run for an additional 20,000 time units for data collection purposes. Therefore, the overall lenght of each run was set at 40,000 days or 111 years.

The third question raised earlier concerned the number of runs required of each model to ensure meaningful output data. In order to determine the correct sample size necessary for the experiment, a sample of five runs was produced from each model. The models were lumpy demand with the EOQ, normal demand with the EOQ, and lumpy demand with the Silver and Meal model. The constant and continuous model is deterministic and therefore does not require a sample size calculation. The standard deviation of the five runs was calculated and used as part of the calculation of sample size.

Next, a level for α and β level were determined. The α level is the probability of a type one error or stated otherwise, the probability of rejecting the null hypothesis when it is true. The α for this experiment was set at 0.05. The β

level is the probability of a type two error. This occurs when you accept the null hypothesis when it is false. Based on discussions with AFIT statistics instuctors, β was set at 0.05. Finally, a value for ϕ must be established. ϕ reflects the amount of the acceptable difference between the true mean and the observed mean divided by the standard deviation of the sample. The acceptable difference was set at 20 units to keep the sample size manageable while maintaining acceptable levels for α and β. These parameters were then used to determine the sample size required from Table A11, page 632 of *Statistical Design and Analysis of Experiments with Applications to Engineering and Science* by Mason, Gunst, and Hess. Based on the chart, the highest required runs was 24. Therefore the number of runs was set at 30. Appendix E provides the computations associated with this process.

Experimentation. Appendix C provides a detailed explanation of how the models were run. A discussion of the logical flow of each model to include the specific functions of the various subparts is given. In addition, the simulation code and Fortran subroutines for each model are provided.

Analysis of Results. The analysis of results will be discussed in detail in a subsequent section titled "Analyze the Data." Specifically, the analysis will be divided into two parts. Part one will be a check for normality of the output data. Based on the results of this test, parametric or nonparametric procedures will be used to determine if the hypotheses will be rejected.

Implementation and Documentation. Appendix C provides all documentation on each model and its code. Any recommendations for implementation will be discussed in detail in Chapter V of this thesis.

Select and Assign the Subjects

The focus of this portion of the experiment is on ensuring that the subjects are representative of the population. The subjects for this simulation are the demand patterns created during the simulation process. The question to be answered is whether they are representative of the population demand patterns that DLA faces. The demand patterns created in the simulation are derived from the sample collected by DESC personnel. The goal of the DESC personnel during this collection of data was to collect a representative sample of the demand patterns DLA faces. Therefore, it is assumed that the demand patterns created in the simulation are reflective of the population of demand patterns DLA faces.

Testing Data

This section refers to the verification and validation process. A pilot test of our simulation model will be conducted to ensure the model accurately represents the DLA consumable item environment. The Long and Engberson study concluded that verification and validation involved the coordination and review of AFIT instructors and experts from DESC. We have chosen the same method of verification and validation. A pilot test of five runs will be used for this process.

Analyze the Data

The analysis of the data will involve a two step process. The first step will be to test the output of the models to check for normality. This requirement must be met in order to use parametric measures for statistical analysis. Assuming that the data meets this requirement, then a two sample t-test with equal or unequal variances will be used to determine if there is a statistical difference between the models. The decision on whether to use a t test with equal or unequal variances will depend on how close the variances of the models' output is to one another. If the output from each model does not meet the test of normality, then a nonparametric measure , such as the Wilcoxon Rank Sum test, will be used to compare the models. Table 3-4 reflects the expected analysis of results.

Table 3-4. Expected Analysis of Results

Model Comparison	Hypothesis	Test
Lumpy Demand vs Constant and Continuous	$\mu_L = \mu_{CC}$ for Avg Inv and TVC	Because the C&C output is deterministic, it will not be normally distributed. Therefore, a 95% Confidence will be built around μ_L and μ_{CC} will be checked to see if it falls within this range
Lumpy Demand vs Normal Demand	$\mu_L = \mu_N$ for Avg Inv and TVC	Two sample t-test with unequal variances
Lumpy Demand vs Silver-Meal	$\mu_L = \mu_{SM}$ for Avg Inv and TVC	Two sample t-test with unequal variances

This chapter examined the methodology chosen to answer the research questions posed in Chapter I. Simulation was chosen and justified as the best method available to provide answers to these questions. A description of the experimental design was given to include the response variables, dependent variables, and factors and levels of treatments. In addition, the proposed method of statistical analysis was discussed. Chapter IV will now discuss the actual execution of the experiment and the subsequent analysis of the results. Chapter V will then provide conclusions and recommendations based on the results discussed in Chapter IV.

IV. Data Analysis

This chapter discusses the simulation output data and explains the statistical techniques used to analyze the data. First, the proposed statistical analysis techniques will be presented. Next, the assumptions of these techniques and the validation that the experiment met these assumptions will be discussed. Finally, the output data will be analyzed and comparisons between models will be made.

Proposed Statistical Analysis

In Chapter III, the proposed statistical analysis technique was the two-sample t-test with unequal variances. The assumption that accompanies that test is that the two populations from which the samples were collected are normally distributed (Montgomery, 1991: 30). In order to confirm the assumption of normality, the output from each model was tested using the Wilkes-Shapiro test. This test was performed using *Statistics*, Version 4.0. Using a sample size of 30 and an alpha of 0.05, the critical value for the test was determined from Table A11, page 632, of *Statistical Design and Analysis of Experiments with Applications to Engineering and Science* by Mason, Gunst, and Hess. Based on the critical value from the chart and the calculated values from the samples, all the samples, except the Constant and Continuous model, exceeded the critical value and therefore, can be assumed to be normally distributed. Appendix F contains the scores of each of the samples and the critical value from Table A11.

The Constant and Continuous model is a deterministic model and cannot meet the assumption of normality. By deterministic, it is meant that the results are the same for every run of the model. Therefore, in order to compare any of the other models to it, one must build a confidence interval around the mean of the output that is being compared to the results of the Constant and Continuous model. The hypothesis being tested is that the mean of the sample is equal to the answer derived from the Constant and Continuous model. If the Constant and Continuous model's result is not within this confidence interval, then the hypothesis of equal means is rejected. This requires that the sample being compared to the Constant and Continuous model come from a population that is normally distributed. As mentioned earlier, all of the other models passed the test for normality. Therefore, this assumption has been met.

Output Data Analysis

Data was collected from the simulation models for the response variables, average on-hand inventory and total variable cost. This data was then used to make comparisons between models. The following discussion is organized by variable and then by model comparison.

Average On-Hand Inventory. Average on-hand inventory represents the average amount of inventory maintained at DLA. Table 4-1 highlights the mean value for average on-hand inventory for each model.

Table 4-1. Average On-Hand Inventory Values

Model	Average On-Hand Inventory	Standard Deviation
Constant and Continuous	80.5	0
Lumpy Demand	106.36	3.911
Normal Demand	86.093	0.883
Silver-Meal Model	52.47	9.35

The first test conducted was a comparison between the Constant and Continuous model and the Lumpy Demand model. The Constant and Continuous model represents the ordering process for DLA when all of the EOQ assumptions are met. For that reason, it is a deterministic model where demand is held constant at one order per month with the same number of units ordered each time. The Lumpy Demand model represents more of the real conditions that DLA faces in its ordering process. The amount ordered from each base and the timing of those orders is allowed to vary creating lumpy demand patterns at DLA. The test is to determine if the value from the Constant and Continuous model lies within a 95% confidence interval around the Lumpy demand model's mean output. The test can be written as,

$$H_o : \mu_A = \mu_B$$

$$H_A : \mu_A \neq \mu_B$$

where

μ_A = the mean average on-hand inventory under lumpy demand

μ_B = the constant value from the Constant and Continuous model

H_o = the null hypothesis being tested

H_A = the alternative hypothesis, if the null hypothesis is rejected

Based on this information, Table 4-2 reflects the results of the test.

Table 4-2. Test of Hypothesis C&C vs. Lumpy

	Lumpy demand with the EOQ	**Constant and Continuous Demand**
Variable	Average Inventory	Average Inventory
Mean Value	106.36	**80.5**
Upper 95% C.I.	**107.82**	
Lower 95% C.I.	**104.89**	

As one can see from the table, the constant and continuous value does not lie in the 95% confidence interval. Therefore, the hypothesis that the two means are equal is rejected and it is concluded that a lumpy demand condition causes higher average inventory to be maintained if the EOQ model used by DLA is implemented.

The next step is to compare the Lumpy Demand model to the Normal model. The Normal model is very similar to the Constant and Continuous model except that the amount bases order is allowed to fluctuate about the mean according to a normal distribution. This is often discussed in inventory texts, such as Tersine's *Principles of Inventory and Materials Management*, when demand patterns resemble practical situations (Tersine, 1994: 212). The test can be written as,

$$H_o : \mu_A = \mu_B$$

$$H_A : \mu_A \neq \mu_B$$

where,

μ_A = the mean average on-hand inventory under lumpy demand

μ_B = the mean average on-hand inventory under normal demand

The test for comparison is a two-tailed t-test with unequal variances. Table 4-3 reflects the results of the test. As one can see, the probability of getting these values and still having the two true means equal is 0.0315×10^{-22}. Therefore, the null hypothesis that the means are equal is rejected. Here the conclusion reached is that lumpy demand requires higher average on-hand inventory levels than under normal demand conditions.

Table 4-3. Test of Hypothesis, Lumpy vs. Normal

Average On-Hand Inventory	Lumpy Demand Model	Normal Demand Model
Mean	106.36	86.09
Standard Deviation	3.91	0.883
Degrees of Freedom	32	
t stat	27.68	
t-critical value	1.69	
α	0.05	
observed p value	0.00	

Based on these two tests, it is apparent that lumpy demand causes higher inventory levels with the EOQ model. The next issue to examine is if any other model could do a better job of handling lumpy demand patterns. In this study, the lumpy demand EOQ model will be compared to the Silver-Meal model. The only difference between the two models is that the Silver-Meal model uses a heuristic in place of the DLA's requirements model. The Silver-Meal heuristic is a variation of the EOQ model and is designed to handle lumpy demand patterns better than the EOQ model (Peterson and Silver, 1979: 317). The test can be written as,

$$H_o : \mu_A = \mu_B$$

$$H_A : \mu_A \neq \mu_B$$

where

μ_A = the mean average on-hand inventory under lumpy demand

μ_B = the mean average on-hand inventory under lumpy demand with the Silver-Meal heuristic

The test for comparison is again a two-tailed t-test with unequal variances. Table 4-4 shows the results of this test. As one can see, the probability of getting these values and still having the two true means equal is $0.0225\text{x}10^{-22}$. Therefore, one would reject the null hypothesis that the means are equal and conclude that lumpy demand with the EOQ model requires higher average on-hand inventory levels than under lumpy demand with the Silver-Meal model. However, one must consider the fact that the Silver-Meal model produces a high standard deviation about the mean.

Table 4-4. Test of Hypothesis, Lumpy vs. Silver-Meal

Average On-Hand Inventory	Lumpy Demand Model	Silver-Meal Model
Mean	106.36	52.47
Standard Deviation	3.91	9.35
Degrees of Freedom	39	
t stat	29.12	
t-critical value	1.69	
α	0.05	
observed p value	0.00	

Total Variable Cost. Total variable cost reflects the variable portion of the inventory costs at DLA. The analysis in this section will be similar to that in the last section except that the response variable, total variable cost, will be evaluated. Table 4.5 highlights the mean value and standard deviation for total variable costs for each model.

Table 4-5. Total Variable Cost Values

Model	Average On-Hand Inventory	Standard Deviation
Constant and Continuous	221	0
Lumpy Demand	283.53	9.43
Normal Demand	234.66	2.21
Silver-Meal Model	193.96	24.28

First, a comparison between the Constant and Continuous model and the Lumpy demand model is required. Again, the Constant and Continuous model is deterministic because it represents the ordering process for DLA when all of the EOQ assumptions are met. The Lumpy Demand model represents more of the real conditions that DLA faces in its ordering process. The amount ordered from each base and the timing of those orders is allowed to vary creating lumpy demand patterns at DLA. The test is to determine if the total variable cost from the Constant and Continuous model falls within a 95% confidence interval around the Lumpy demand model's mean total variable cost. The test can be written as,

$$H_o : \mu_A = \mu_B$$

$$H_A : \mu_A \neq \mu_B$$

where

μ_A = the mean total variable cost under lumpy demand

μ_B = the constant value from the Constant and Continuous model

Table 4-6 shows the results of the test.

Table 4-6. Test of Hypothesis C&C vs. Lumpy

	Lumpy demand with the EOQ	**Constant and Continuous Demand**
Variable	Total Variable Cost	Total Variable Cost
Mean Value	283.53	**221**
Upper 95% C.I.	**287.05**	
Lower 95% C.I.	**280.01**	

As one can see from the table, the constant and continuous mean value is less than the lower 95% bound and consequently does not lie within the 95% confidence interval. Therefore, the null hypothesis that the two means are equal is rejected and the conclusion reached is that lumpy demand conditions cause higher total variable costs to be incurred at DLA if the present model is used.

The next step is to compare the lumpy demand model to the normal model. Here, the amount bases order is allowed to fluctuate according to a normal distribution, which is an assumption made in most inventory text books when describing continuous demand patterns and also when calculating safety stock levels (Tersine, 1994:212). The test can be written as,

$$H_o : \mu_A = \mu_B$$

$$H_A : \mu_A \neq \mu_B$$

where,

μ_A = the mean total variable cost under lumpy demand

μ_B = the mean total variable cost under normal demand

The test for comparison is a two-tailed t-test with unequal variances. Table 4-7 shows the results of the test. As one can see, the probability of getting these values and still having the two true means equal is 0.03412×10^{-22}. Therefore, one would reject the null hypothesis that the means are equal and conclude that lumpy demand causes higher total variable costs than under normal demand.

Table 4-7. Test of Hypothesis, Lumpy vs. Normal

Average On-Hand Inventory	Lumpy Demand Model	Normal Demand Model
Mean	283.53	234.66
Standard Deviation	9.43	2.22
Degrees of Freedom	32	
t stat	27.61	
t-critical value	1.69	
α	0.05	
observed p value	0.00	

As for the inventory criterion, the EOQ model under lumpy demand will now be compared to the Silver-Meal model to determine if there are other models that will handle lumpy demand conditions better than the EOQ model. For the same reasons when testing average on hand inventory, the test to determine if the Silver-Meal model handles lumpy demand patterns better than the EOQ model regarding total variable cost can be written,

$$H_o : \mu_A = \mu_B$$

$$H_A : \mu_A \neq \mu_B$$

where

μ_A = the mean total variable cost under lumpy demand

μ_B = the mean total variable cost under lumpy demand with the Silver-Meal heuristic

The test for comparison is a two-tailed t-test with unequal variances. Table 4-8 illustrates the results of the test. The table indicates the probability of getting these values and still having the two true means equal is $0.0362\text{x}10^{-22}$. Therefore, one would reject the null hypothesis that the means are equal and conclude that lumpy demand with the EOQ model causes higher total variable costs than under lumpy demand with the Silver-Meal model. It is also important to note that the Silver-Meal model results have a large standard deviation, indicating a large variation in the sample results. Over the long run, the test shows that this model has a lower total variable cost.

Table 4-8. Test of Hypothesis, Lumpy vs. Silver-Meal

Average On-Hand Inventory	**Lumpy Demand Model**	**Normal Demand Model**
Mean	283.53	193.96
Standard Deviation	9.43	24.28
Degrees of Freedom	38	
t stat	18.83	
t-critical value	1.68	
α	0.05	
observed p value	0.00	

In this chapter, simulation output data for each model was presented and comparisons between the models was accomplished. The tests used for comparisons were discussed along with their applicable assumptions. Tests of those assumptions were performed and discussed. Finally, comparisons between models for each performance measure were made and the results were discussed. Appendix G provides the results for each run for every model and a detailed analysis of the comparisons. Now that the experiment has been accomplished and the results presented, what should be done to counter act lumpy demand conditions? Chapter V provides an explanation of the conclusions from this research, some implications for DLA, and recommendations for future research.

V. Conclusions, Implications and Recommendations

Based on the results of the experiment provided in Chapter IV, this chapter provides implications about the appropriateness of the Defense Logistics Agency's requirements model under lumpy demand conditions. From these conclusions, management implications are drawn that DLA should consider given the lumpy nature of the demand pattern they face. In addition, several recommendations for future research are provided.

Conclusions

This section answers the research questions posed in Chapter I. The first question to be answered is:

> *How does lumpy demand effect DLA's requirements model in regard to inventory levels maintained at DLA*?

The results presented in Chapter IV and in Appendix G provide several findings with regard to average on-hand inventory. First, it is apparent that relaxing the assumption of constant and continuous demand causes higher inventory levels to be maintained at DLA. As one moves from the Constant and Continuous model to the Normal model and finally, to the Lumpy model, total average on-hand inventory increases dramatically. It is apparent that lumpy demand conditions cause the EOQ model to maintain a higher amount of inventory even when the annual demand does not change. From this, one can see that the requirements model used by DLA is not robust enough to handle lumpy demand patterns.

The second research question is:

How does lumpy demand affect the total variable cost portion of DLA's requirements model?

Based on the results of the experiment, it was discovered that lumpy demand impacts total variable cost in a similar way as the average on hand inventory level. First, relaxing the assumption of constant and continuous demand causes higher total variable costs to be incurred. As one moves from the constant and continuous model to the normal model and finally, to the lumpy model, total variable costs increase dramatically as demand patterns approach the DLA environment. Therefore, it is apparent that the requirements model used by DLA is not robust enough to handle lumpy demand patterns. As mentioned earlier in Chapters III and IV, this lumpy demand pattern is exactly what DLA faces from Air Forces bases.

The third research question is:

Can a different approach provide improvement over the existing DLA model?

Given these conditions, a case could be made that DLA’s requirements model handles lumpy demand as well as any other model available. In order to test that assertion, the Silver-Meal heuristic model was analyzed under the same lumpy environment as the requirements model had undergone. The Silver-Meal heuristic model was chosen for several reasons, its simplicity, its similarity to the EOQ model, and its ability to handle lumpy demand patterns. Based on the results in Chapter IV, it is apparent that the Silver-Meal model is able to provide lower average inventory levels and ultimately, lower total variable costs than the current EOQ model , given lumpy demand conditions. This also illustrates that there are other models in existence that do a much better job of handling lumpy demand patterns than the EOQ model.

Implications

The conclusions have several implications for DLA and other organizations operating in a multi-echelon environment. DLA inherently operates in a lumpy environment. The two echelon system with EOQ models operating at both levels will generate lumpy demand at the second echelon because of the EOQ ordering scheme at the first level. This research has shown that lumpy demand adversely affects the average inventory and total variable cost when an EOQ type requirements model is used at the second echelon. The test of the Silver-Meal model illustrates that there are other models available better suited for the lumpy demand conditions DLA faces. Given these results, DLA should explore using another lot-sizing technique that would be more suited to handling lumpy demand patterns.

Another consideration is forecasting methods and safety stock. This study replicated the current forecasting technique being employed by DLA. However, forecasting only affects the accuracy of demand estimates, as such it would not change the demand pattern. This leaves a discussion of safety stock. Again, no safety stock was utilized in this experiment; however, DLA does carry safety stock, as do the bases. These stocks are used to maintain a certain customer service level. Again, these additional levels of safety stock were not used in this experiment because they would compound the effects of the variables evaluated. As such, the effect on the models of varying service levels was not evaluated.

Recommendations for Future Research

There are several recommendations for future research that were identified throughout this research.

1. Other inventory management models should be tested to determine the appropriate model for DLA given their lumpy demand patterns. For example, the Distribution Requirements Planning model appears to be well suited for DLA and its environment. Due to the data sample distributions and assumptions of the statistical analysis tools a similar experiment to this one is recommended to evaluate these alternative models. A simulation of the model and operating environment could also be used to compare the models in a lumpy demand environment. This research has shown that the EOQ model is adversely affected by lumpy demand, therefore determining the optimal model to use under these conditions would be of significance to DLA and the Air Force.
2. Another area of interest for research would be to quantify the overall effects of lumpy demand on the Air Force. One approach would be to actually observe base level ordering requirements and monitor them through the requisition process. Variables to consider would be the ordering costs for the bases and DLA as well as the impact of delivery delays at base level if stock outages occur. Another possible variable would be the interaction with other services that are users of common items. An alternative approach to analyzing the requisitioning of consumable items would be to apply the findings of this study to a wartime scenario and track the consumable requisition through the established supply channels as identified in Operations Plans for that particular theater. A research goal could be to identify the best system for Air Force units to follow in the deployed environment.
3. Another possible research avenue would be to test and determine the a better forecasting method for the EOQ model given the lumpy demand patterns DLA faces. The research should consider the time period being forecasted for as well as the forecasting method. The current method, Double Exponential Smoothing, used by DLA was employed in this experiment. However, there are other time series and explanatory quantitative methods available that might produce better results. Examples of these methods are Naive methods, other Smoothing methods, and Monitoring approaches that could be

effectively implemented in the DLA requirements model (Makridakis and Wheelwright, 1989: 14).

This study has discussed the appropriateness of the Defense Logistics Agency's requirements model in managing consumable support for Air Force peculiar items. Chapter I outlined the research problem and identified the operating environment in which the EOQ model is used. Chapter II provided a thorough literature review of relevant topics as well as recent research that dealt with lumpy demand. Chapter III presented the actual experiment methodology used in this research as well as verification and validation of the simulation models used in this experiment. Chapter IV presented the results of the experiments and discussed the statistical elements used to analyze the data. Chapter V concluded the research by answering the research questions posed in chapter one and raising additional questions worthy of further research. Overall, this research has conclusively shown that lumpy demand adversely impacts both average on hand inventory and total variable cost. Based on the sample data collected for this study, it is obvious that DLA faces lumpy demand patterns from its customers, at least for Air Force specific items. Yet, DLA uses a EOQ model which assumes that the demand patterns are constant and continuous. This study has shown that the EOQ model does not handle lumpy demand well and that there are other models available that can do a better job of managing inventory levels in a lumpy demand environment.

Appendix A. Sample Data

Sample data set, quarterly demand data periods 1-7.

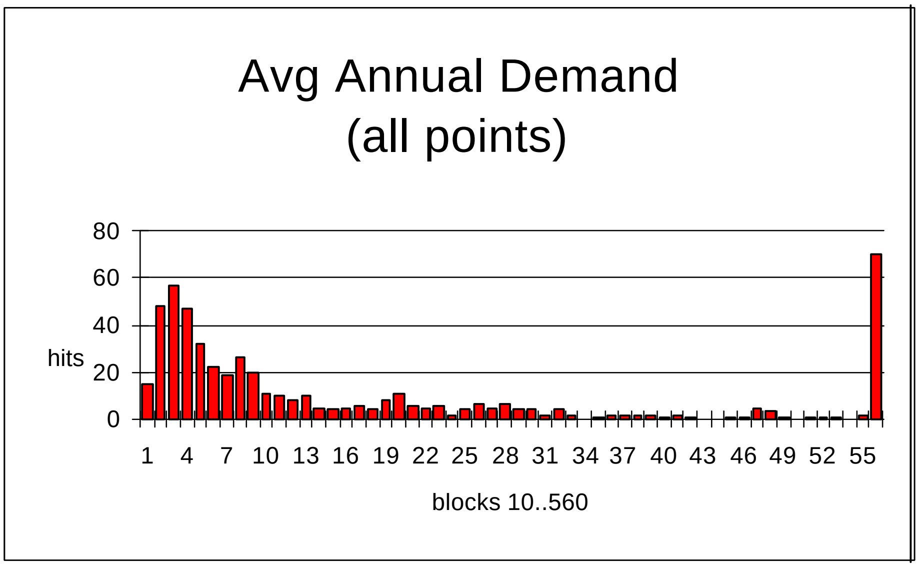
Table A-1. Sample Data

NSN	Q1	Q2	Q3	Q4	Q5	Q6	Q7
1260010735896	16	7	42	16	6	45	15
1440005727648	542	577	965	928	442	251	429
5805001408643	480	316	215	249	460	200	328
5805010773349	54	261	15	48	11	35	73
5805011775421	4927	10325	7680	6377	4299	8745	6414
5815006517030	691	289	352	475	52	13	23
5815009781363	1592	1855	2031	1474	1083	2464	1137
5895004375925	4	5	5	3	0	3	3
5895011706715	4	1	5	3	2	0	5
5905000037717	83	104	47	62	4	379	466
5905000069064	1	5	2	0	0	1	0
5905000514631	27	14	6	42	8	25	7
5905001048353	352	510	215	275	610	375	145
5905001114840	56	170	280	300	60	163	310
5905001193503	1838	3105	1208	2234	3055	3305	1937
5905001383431	2	2	3	6	1	0	101
5905001405657	76	114	164	78	72	638	536

NSN	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16
1260010735896	14	13	0	15	38	26	25	1
1440005727648	340	215	283	145	120	134	518	216
5805001408643	210	225	183	286	140	274	137	87
5805010773349	37	71	1	11	136	15	28	30
5805011775421	4690	10813	3450	4209	6144	19916	6679	8332
5815006517030	1	25	55	20	15	5	13	5
5815009781363	1801	1460	616	808	995	1550	476	265
5895004375925	2	0	21	77	7	20	13	98
5895011706715	3	5	3	3	2	17	18	2
5905000037717	17	32	1	7	147	538	266	30
5905000069064	0	0	0	0	31	1	0	1
5905000514631	6	2	12	2	3	5	4	0
5905001048353	25	547	493	95	276	390	143	555
5905001114840	125	39	53	70	150	230	230	60
5905001193503	1464	775	1321	1110	1330	1170	930	1605
5905001383431	0	20	2	0	4	20	21	0
5905001405657	60	15	145	54	30	123	0	199
5905001424523	155	21	13	27	15	20	2	17
5905001514666	0	0	0	5	0	13	10	0

NSN	ALT	PLT	QFD	S1	S2	VSL	Nomenclature
1260010735896	83	125	19	245	303	43	COVER FIRE CONTROL
1440005727648	98	362	257	2415	2264	1139	FLAG ASSEMBLY
5805001408643	85	325	207	681	675	787	TELEPHONE TERMINAL
5805010773349	150	227	29	386	484	0	TELEPHONE CIRCUIT T
5805011775421	78	332	4305	15839	17325	9596	TELEPHONE SET
5815006517030	72	129	13	169	207	29	HOLDER NUMBER TAPE
5815009781363	150	260	513	7566	9999	2311	PLATEN PRINTER
5895004375925	88	44	33	330	330	0	PANEL INDICATOR
5895011706715	139	207	8	97	115	0	KEYER
5905000037717	48	166	210	2006	1912	494	RESISTOR FIXED FILM
5905000069064	63	119	2	39	63	4	RESISTOR FIXED WIRE
5905000514631	30	184	1	46	80	2	RESISTOR FIXED COMP
5905001048353	33	109	336	3386	3408	524	RESISTOR FIXED COMP
5905001114840	39	118	190	1900	1900	328	RESISTOR FIXED COMP
5905001193503	58	68	1179	13891	15989	1111	RESISTOR FIXED COMP
5905001383431	55	145	9	100	113	20	RESISTOR FIXED FILM
5905001405657	69	206	69	1310	1926	208	RESISTOR FIXED FILM
5905001424523	92	89	13	121	112	26	RESISTOR VARIABLE W
5905001514666	69	118	4	44	46	8	RESISTOR FIXED FILM

Appendix B. Graph of Sample Demand Pattern



The annual demand chart above represents a histogram (number of demands or hits of a particular demand value) of the average annual demand for all the items in the sample data. Each block on the x-axis has a width of 10 observations. The chart only goes up through items with 560 demands, however there are many more items with one and two demands stretching out to the 7,000 range. These values could not be considered outliers because of the even spread of demands beyond 560.

Appendix C. Model Description and Code

This appendix identifies the simulation models used in this experiment. The first model listed is the Normal model and will be used as the benchmark for the other models. Except for the Silver & Meal model, all of the models use the EOQ method of inventory management. The SLAM II code is provided for the first model, the subsequent models will have only the differences highlighted and described. The Silver & Meal model will be the final model discussed in this appendix.

PART 1—NORMAL MODEL: The Normal model is the basis for all of the other models in this project. It consists of four networks. The first network represents demands being placed against DLA by the four bases (create nodes labeled BAS1, BAS2, BAS3, BAS4) and the subsequent stock issue or the backordering of the bases requirement. The time between creations of entities in this model is 30 days. This is one source of variation used in the overall experiment that is changed from model to model. After the create nodes, the entities fifth attribute is assigned the number of units requisitioned for this particular order. The number of units ordered is based on a random number generated from a normal distribution with mean of 8 and standard deviation of 1. A different random number seed is used for each random number draw. The resource paper is used to reflect inventory on the shelf at DLA. Paper is initially set at the expected EOQ value so that the model doesn't instantly start backordering at time unit 1. While there is inventory on the shelf entities will capture a paper resource and terminate without relinquishing the resource. Otherwise entities wait for replenishment at an await node (labeled BO). Counters are used to track on hand inventory as well as the number of backorders. Remember, safety stock was intentionally left out of the model to measure the true effects of the different demand patterns. Consequently this model allows partial shipments to the bases to fill requisitions.

The second network represents the daily releveling process the DLA computer system executes to see if an order should be placed. At a create node labeled REPL, one entity is created at each time unit and tests the on hand inventory plus the pipeline inventory against the reorder point. If a requisition is required the cumulative order counter is incremented and an order for the current EOQ is placed. This entity delays for the lead time then increments the on hand inventory counter and alters the resource by adding the EOQ. The alter allows backordered requisitions from the bases to be processed and filled. If no requisition is required then a snapshot of on hand inventory is captured to be used later in the model. Entities along both paths are routed through collect nodes to generate statistical data.

The third network in this system calculates a new EOQ on a quarterly basis. Only one entity is generated and cycles through this network continuously as long as the model is running. Here the double exponential smoothing values are calculated and the quarterly forecast demand is also derived in several steps. Next, user written FORTRAN functions are invoked to complete the calculation of a reorder point and EOQ values. Now the entity loops back to start the process over again but only after a 91 day delay.

The fourth network calculates the annual average on hand inventory and total variable cost (TVC). Again the calculations must be made in several steps due to restrictions with SLAM. The fifth network is used to calculate the monthly average on hand inventory levels. This is accomplished by calling a third user written FORTRAN function.

Throughout this system statistical data is collected on several variables in addition to the TVC and average on hand inventory. These values were used in the validation and verification process. Leaving these collect nodes in the program should not significantly affect the system performance of the model. Global variables are also used in conjunction with the system generated resource information as a means to double check the results of each simulation run.

The actual SLAM code from the DEC VAX/VMS system is listed below. The monitor clear statements at the end of the model are necessary to clear the statistical arrays after the transient period has elapsed for each run. Comments are provided throughout the model.

```
GEN,BTR,NORMAL MODEL,19/6/1995,30,Y,Y,Y/Y,Y,Y/1,72;
LIMITS,2,5,4000;
INITIALIZE,,40000,Y;
INTLC,XX(2)=48,XX(15)=25,XX(6)=100,XX(3)=147,XX(1)=200;
NETWORK;
      RESOURCE/1,PAPER(200),1,2;
;
BAS1  CREATE,30,,1,,1;                          frequency of orders—base 1
      ACTIVITY;
B1AD  ASSIGN,ATRIB(5)=RNORM(8,1,1),1;  determine number of units ordered
      ACTIVITY;
DDR   UNBATCH,5,1;               generate 1 entity for each unit ordered
      ACTIVITY;
QTR   ASSIGN,XX(5)=XX(5)+1,1;                   increment quarterly demand
      ACTIVITY/1,,NNRSC(PAPER).GT.0.;         fill requisition from shelf?
      ACTIVITY/2,,,BACK;                      none on hand then back order
INV   ASSIGN,XX(1)=XX(1)-1,1;                decrement on hand inv counter
      ACTIVITY;
GETI  AWAIT(2),PAPER,,1;                                    issue property
      ACTIVITY;
END   TERMINATE;              entity dies without releasing the resource
BACK  ASSIGN,XX(4)=XX(4)+1,1;                         increment backorders
      ACTIVITY;
BO    AWAIT(1),PAPER,,1;      backorders waiting for stock replenishment
      ACTIVITY,,,END;
;
BAS2  CREATE,30,,1,,1;                          frequency of orders—base 2
      ACTIVITY;
B2AD  ASSIGN,ATRIB(5)=RNORM(8,1,2),1;  determine number of units ordered
      ACTIVITY,,,DDR;                                        goto unbatch
;
BAS3  CREATE,30,,1,,1;                          frequency of orders—base 3
      ACTIVITY;
B3AD  ASSIGN,ATRIB(5)=RNORM(8,1,3),1;  determine number of units ordered
      ACTIVITY,,,DDR;                                        goto unbatch
;
BAS4  CREATE,30,,1,,1;                          frequency of orders—base 4
      ACTIVITY;
B4AD  ASSIGN,ATRIB(5)=RNORM(8,1,4),1;  determine number of units ordered
      ACTIVITY,,,DDR;                                        goto unbatch
;
; replenishment cycle—daily releveling
;
REPL  CREATE,1,,1,,1;
; o/h inv + pipeline less than reorder point?
      ACTIVITY/3,,XX(1)+XX(9).LE.XX(3);
      ACTIVITY,,,ZAAB;
CUM   ASSIGN,XX(21)=XX(21)+1,1;                 cumlative number of orders
      ACTIVITY;
EOQ   ASSIGN,ATRIB(2)=XX(2),XX(9)=XX(9)+ATRIB(2),1;         place order
      ACTIVITY/5,XX(6);                  wait lead time for order arrival
PREI  COLCT,XX(1),PRE REPLIN INV;
      ACTIVITY;
PREB  COLCT,XX(4),PRE REPLEN BO;
      ACTIVITY,,,REN;       goto increment inv with new shipment arrival
ZAAB  ASSIGN,XX(22)=XX(22)+XX(1),1;                 increment inv on hand
      ACTIVITY;
INFO  COLCT,XX(1),AVG INV,20/200/200;
      ACTIVITY,,,END;
;
```

```
REN   ALTER,PAPER,ATRIB(2),1;       increase resource to new on hand inv
      ACTIVITY,,,NEWI;
; reset onhand inv counter, clear backorders, decrement pipeline qty
NEWI  ASSIGN,XX(1)=XX(1)+ATRIB(2)-XX(4),XX(4)=0,
      XX(9)=XX(9)-ATRIB(2),1;
      ACTIVITY,,,INFO;
;
;  quarterly calculation of new eoq and variables
;
      CREATE,,,1,1,1;
      ACTIVITY,91;                                         delay one quarter
DATA  COLCT,XX(5),QTRLY DMD;          colect statistics on quarterly dmd
      ACTIVITY;
; calculations of double exponential smoothing values
QFRCS ASSIGN,XX(16)=0.1*XX(5),XX(17)=0.9*XX(12),
      XX(12)=XX(16)+XX(17),XX(18)=XX(12)-XX(13),XX(19)=0.1*XX(18),
      XX(13)=XX(19)+XX(13),XX(20)=2*XX(12),XX(14)=XX(20)-XX(13),1;
      ACTIVITY;
      ASSIGN,XX(3)=USERF(1),XX(7)=USERF(2),1;     new reorder pt and eoq
      ACTIVITY;
      ASSIGN,XX(2)=XX(7)+XX(3),XX(10)=20485+XX(5),XX(11)=1456+TNOW,
      XX(8)=XX(10)/XX(11),XX(5)=0,1;
      ACTIVITY;
AVGE  COLCT,XX(2),AVG EOQ,,1;
      ACTIVITY,91,,DATA;                 delay another quarter goto data
;
; calcualte annual average on hand inv and tvc
;
YEAR  CREATE,364,364,,,1;
      ACTIVITY;
      ASSIGN,XX(25)=365-XX(21),XX(23)=XX(22)/XX(25),
      XX(24)=XX(21)*5.2+XX(23)*2.5,XX(21)=0,XX(22)=0;
      ACTIVITY;
CTVC  COLCT,XX(24),TVC,,1;                total variable cost statistics
      ACTIVITY;
DONE  TERMINATE;
;
;  calculate monthly average on hand inv
;
MO    CREATE,30,30,,,1;
      ACTIVITY;
      ASSIGN,XX(31)=USERF(3);
      ACTIVITY;
EMO   TERMINATE;
;
      END;
;
;  clear statistical arrays every 20000 time units
;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
```

```
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
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SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
SIM;
MONTR,CLEAR,20000;
;
FIN;
```

PART 2—FORTRAN Code: The FORTRAN code presented in this section was used in conjunction with each SLAM system. Portions of the program main and user-f function are canned statements necessary with this particular system. USERF(IFN) is a function defined by SLAM that can be modified to allow user written functions that are typically easier in FORTRAN than in traditional SLAM code. Comments separate the primary sections written for this experiment. The first, referred to as USERF(1) in SLAM, simply calculates the reorder point. The second section calculates the EOQ value. While the third section adjusts the monthly average inventory value from a negative number to a value of 0. This function returns a value generated in the FORTRAN code or since global variables are used the function returns an arbitrary value of 1.

The FORTRAN code follows.

```
      PROGRAM MAIN
      DIMENSION NSET(50000)
      PARAMETER  (MEQT=100,  MSCND=25,  MENTR=25, MRSC=75,  MARR=50,
     1 MGAT=25,   MHIST=50,  MCELS=500, MCLCT=50, MSTAT=50, MEQV=100,
     2 MATRB=100, MFILS=100, MPLOT=10,  MVARP=10, MSTRM=10,
     3 MACT=100,  MNODE=500, MITYP=50,  MMXXV=100)
      PARAMETER (MVARP1=MVARP+1)
      COMMON/SCOM1/ATRIB(MATRB), DD(MEQT), DDL(MEQT), DTNOW, II, MFA,
     1 MSTOP, NCLNR, NCRDR, NPRNT, NNRUN, NNSET, NTAPE, SS(MEQT),
     2 SSL(MEQT), TNEXT, TNOW, XX(MMXXV)
      COMMON QSET(50000)
      EQUIVALENCE (NSET(1),QSET(1))
      NNSET=50000
      NCRDR=5
      NPRNT=6
      NTAPE=7
      CALL SLAM
      STOP
      END
C
C
      FUNCTION USERF(IFN)
      PARAMETER  (MEQT=100,  MSCND=25,  MENTR=25, MRSC=75,  MARR=50,
     1 MGAT=25,   MHIST=50,  MCELS=500, MCLCT=50, MSTAT=50, MEQV=100,
     2 MATRB=100, MFILS=100, MPLOT=10,  MVARP=10, MSTRM=10,
     3 MACT=100,  MNODE=500, MITYP=50,  MMXXV=100)
      PARAMETER (MVARP1=MVARP+1)
      COMMON/SCOM1/ATRIB(MATRB), DD(MEQT), DDL(MEQT), DTNOW, II, MFA,
```

```
     1 MSTOP, NCLNR, NCRDR, NPRNT, NNRUN, NNSET, NTAPE, SS(MEQT),
     2 SSL(MEQT), TNEXT, TNOW, XX(MMXXV)
C  branch based on ifn, determined in calling program
      GOTO (10,20,30),IFN
C
C  Calculate INTEGER values for reorder point
C
10    I=XX(8)*XX(6)
      USERF=I
      GOTO 40
C
C  calculate integer values for eoq
C
20    J=20.396*(SQRT(XX(14)/XX(15)))
      USERF=J
      GOTO 40
C
C  adjust monthly average inventory on hand for calculation of tvc
C
30    IF (XX(23).LE.0.) THEN
        XX(23)=0
        GOTO 39
      ENDIF
39    USERF=1
40    RETURN
      END
```

PART 3—OTHER MODELS: This section lists the components of the two other models, Lumpy and Constant and Continuous, that differ from the Normal model previously discussed. Each section will discuss the differences as well as provide the code that is specific to the model of discussion.

The first model to discuss is the Constant And Continuous model. The primary differences between this model and the Normal model is that the number requisitioned from each base is set to 8. In the Normal model this was randomly generated from a normal distribution. The node labels in the code listed below coincide with the those in the Normal model.

```
GEN,BTR,CONST AND CONT MODEL,19/6/1995,30,Y,Y,Y/Y,Y,Y/1,72;
B1AD  ASSIGN,ATRIB(5)=8,1;
      ACTIVITY;
B2AD  ASSIGN,ATRIB(5)=8,1;
      ACTIVITY,,,DDR;
B3AD  ASSIGN,ATRIB(5)=8,1;
      ACTIVITY,,,DDR;
B4AD  ASSIGN,ATRIB(5)=8,1;
      ACTIVITY,,,DDR;
```

The Lumpy model differentiates slightly more than the Normal model. Here the time between orders is also generated from a random number generator as well as the number of units ordered in each requisition. The time between creations is determined by a triangular distribution with mean of 90, low of 30 and high of 150. The number of units ordered is generated randomly form an exponential distribution. The triangular distribution is used because no data was available on the frequency of requisitions to DLA. The exponential distribution however was derived from the sample data collected from DESC as well as recommended by DLA analysts. Again, the code listed below coincides with the Normal model.

```
GEN,BTR,LUMPY MODEL,19/6/1995,30,Y,Y,Y/Y,Y,Y/1,72;
BAS1  CREATE,TRIAG(30,90,150,1),,1,,1;
      ACTIVITY;
B1AD  ASSIGN,ATRIB(4)=EXPON(89.3654,5),ATRIB(5)=ATRIB(4)/4,1;
      ACTIVITY,,ATRIB(5).LT.1.0,ABD1;
      ACTIVITY;
ABD1  ASSIGN,ATRIB(5)=1,1;
      ACTIVITY,,,DDR;
BAS2  CREATE,TRIAG(30,90,150,2),,1,,1;
      ACTIVITY;
B2AD  ASSIGN,ATRIB(4)=EXPON(89.36543,6),ATRIB(5)=ATRIB(4)/4,1;
      ACTIVITY,,ATRIB(5).LT.1.0,ABD1;
      ACTIVITY,,,DDR;
;
BAS3  CREATE,TRIAG(30,90,150,3),,1,,1;
      ACTIVITY;
B3AD  ASSIGN,ATRIB(4)=EXPON(89.36543,7),ATRIB(5)=ATRIB(4)/4,1;
      ACTIVITY,,ATRIB(5).LT.1.0,ABD1;
      ACTIVITY,,,DDR;
;
BAS4  CREATE,TRIAG(30,90,150,4),,1,,1;
      ACTIVITY;
B4AD  ASSIGN,ATRIB(4)=EXPON(89.36543,8),ATRIB(5)=ATRIB(4)/4,1;
      ACTIVITY,,ATRIB(5).LT.1.0,ABD1;
      ACTIVITY,,,DDR;
```

The Silver and Meal inventory method was suggested to be modeled to demonstrate that there are other models that operate in a reorder point system similar to the EOQ model that might be better than the EOQ under certain conditions. The lumpy model was modified to accommodate the Silver and Meal inventory method. This modified model is listed below. Some comments are provided throughout the code to help follow the logic, however we recommend readers reference Appendix H for a further explanation of this method.

```
GEN,BTR,SILVER MEAL MODEL,19/6/1995,30,Y,Y,Y/Y,Y,Y/1,72;
LIMITS,2,5,4000;
INITIALIZE,,40000,Y;
INTLC,XX(2)=48,XX(15)=25,XX(6)=100,XX(3)=147,XX(1)=200;
NETWORK;
      RESOURCE/1,PAPER(200),1,2;
;
; generate demands from 4 bases to DLA, issue or back order requirements
;
BAS1  CREATE,TRIAG(30,90,150,1),,1,,1;        frequency of orders—base 1
      ACTIVITY;
;           number of units ordered
B1AD  ASSIGN,ATRIB(4)=EXPON(89.3654,5),ATRIB(5)=ATRIB(4)/4,1;
      ACTIVITY,,ATRIB(5).LT.1.0,ABD1;
      ACTIVITY;
```

```
ABD1  ASSIGN,ATRIB(5)=1,1;       set number of demands to 1 if necessary
      ACTIVITY,,,DDR;
DDR   UNBATCH,5,1;               generate 1 entity for each unit ordered
      ACTIVITY;
QTR   ASSIGN,XX(5)=XX(5)+1,1;                 increment quarterly demand
      ACTIVITY/1,,NNRSC(PAPER).GT.0.;       fill requisition from shelf?
      ACTIVITY/2,,,BACK;                    none on hand then back order
INV   ASSIGN,XX(1)=XX(1)-1,1;              decrement on hand inv counter
      ACTIVITY;
GETI  AWAIT(2),PAPER,,1;                                  issue property
      ACTIVITY;
END   TERMINATE;              entity dies without releasing the resource
BACK  ASSIGN,XX(4)=XX(4)+1,1;                       increment backorders
      ACTIVITY;
BO    AWAIT(1),PAPER,,1;      backorders waiting for stock replenishment
      ACTIVITY,,,END;
;
BAS2  CREATE,TRIAG(30,90,150,2),,1,,1;        frequency of orders—base 2
      ACTIVITY;
;           number of units ordered
B2AD  ASSIGN,ATRIB(4)=EXPON(89.36543,6),ATRIB(5)=ATRIB(4)/4,1;
      ACTIVITY,,ATRIB(5).LT.1.0,ABD1;
      ACTIVITY,,,DDR;                                       goto unbatch
;
BAS3  CREATE,TRIAG(30,90,150,3),,1,,1;        frequency of orders—base 3
      ACTIVITY;
;  number of units ordered
B3AD  ASSIGN,ATRIB(4)=EXPON(89.36543,7),ATRIB(5)=ATRIB(4)/4,1;
      ACTIVITY,,ATRIB(5).LT.1.0,ABD1;
      ACTIVITY,,,DDR;                                       goto unbatch
;
BAS4  CREATE,TRIAG(30,90,150,4),,1,,1;
      ACTIVITY;
;  number of units ordered
B4AD  ASSIGN,ATRIB(4)=EXPON(89.36543,8),ATRIB(5)=ATRIB(4)/4,1;
      ACTIVITY,,ATRIB(5).LT.1.0,ABD1;
      ACTIVITY,,,DDR;                                       goto unbatch
;
; releveling process,
;
REPL  CREATE,1,,1,,1;
      ACTIVITY;
      ASSIGN,XX(30)=XX(30)+XX(1);            cumlative on hand inventory
      ACTIVITY,,,INF1;
;CUM   ASSIGN,XX(21)=XX(21)+1,1;       cumlative number of orders placed
;      ACTIVITY;
;EOQ   ASSIGN,ATRIB(2)=XX(2),XX(9)=XX(9)+ATRIB(2),1;        requisition
;      ACTIVITY/5,XX(6);                  wait lead time for order arrival
;PREI  COLCT,XX(1),PRE REPLIN INV;
;      ACTIVITY;
;PREB  COLCT,XX(4),PRE REPLEN BO;
;      ACTIVITY,,,REN;      goto increment inv with new shipment arrival
INF1  ASSIGN,XX(22)=XX(22)+XX(1),1;                increment inv on hand
INFO  COLCT,XX(1),AVG INV,20/200/200;
      ACTIVITY,,,END;
;
;REN   ALTER,PAPER,ATRIB(2),1;      increase resource to new on hand inv
;      ACTIVITY,,,NEWI;
NEWI  ASSIGN,XX(1)=XX(1)+ATRIB(2)-XX(4),XX(4)=0,1;
      ACTIVITY,,,END;
```

```
;
; quarterly update of Silver-Meal variables
;
SMM   CREATE,91,,1,,1;
      ACTIVITY;
QT1   ASSIGN,ATRIB(2)=XX(26),XX(21)=XX(21)+1,2;
      ACTIVITY,XX(6),,REN1;
      ACTIVITY,30,,QT2;
REN1  ALTER,PAPER,ATRIB(2),1;
      ACTIVITY,,,NEWI;
QT2   ASSIGN,ATRIB(2)=XX(27),XX(21)=XX(21)+1,2;
      ACTIVITY,XX(6),ATRIB(2).GT.0,REN1;
      ACTIVITY,30,,QT3;
QT3   ASSIGN,ATRIB(2)=XX(28),XX(21)=XX(21)+1,2;
      ACTIVITY,XX(6),ATRIB(2).GT.0,REN1;
      ACTIVITY,,,END;
;
      CREATE,,,1,1,1;
      ACTIVITY,91;
DATA  COLCT,XX(5),QTRLY DMD;
      ACTIVITY;
QFRCS ASSIGN,XX(16)=0.1*XX(5),XX(17)=0.9*XX(12),
      XX(12)=XX(16)+XX(17),XX(18)=XX(12)-XX(13),XX(19)=0.1*XX(18),
      XX(13)=XX(19)+XX(13),XX(20)=2*XX(12),XX(14)=XX(20)-XX(13),
      XX(5)=0,1;
      ACTIVITY;
      ASSIGN,XX(3)=USERF(3),1;
      ACTIVITY,91,,DATA;
;
; calcualte annual average on hand inv and tvc
;
YEAR  CREATE,364,364,,,1;
      ACTIVITY;
      ASSIGN,XX(23)=XX(22)/365,XX(50)=USERF(4),
      XX(24)=XX(21)*5.2+XX(23)*2.5,
      XX(21)=0,XX(22)=0;
      ACTIVITY;
CTVC  COLCT,XX(24),TVC,,1;                total variable cost statistics
      ACTIVITY;
DONE  TERMINATE;
;
      END;
;
;  clear statistical arrays every 20000 time units
;
MONTR,CLEAR,20000;
SIM;
; to run 30 times, need 30 monitor clear statements
FIN;
```

Silver-Meal FORTRAN code:

```
      PROGRAM MAIN
      DIMENSION NSET(50000)
      PARAMETER  (MEQT=100,  MSCND=25,  MENTR=25, MRSC=75,  MARR=50,
     1 MGAT=25,   MHIST=50,  MCELS=500, MCLCT=50, MSTAT=50, MEQV=100,
     2 MATRB=100, MFILS=100, MPLOT=10,  MVARP=10, MSTRM=10,
     3 MACT=100,  MNODE=500, MITYP=50,  MMXXV=100)
      PARAMETER (MVARP1=MVARP+1)
```

```
      COMMON/SCOM1/ATRIB(MATRB), DD(MEQT), DDL(MEQT), DTNOW, II, MFA,
     1 MSTOP, NCLNR, NCRDR, NPRNT, NNRUN, NNSET, NTAPE, SS(MEQT),
     2 SSL(MEQT), TNEXT, TNOW, XX(MMXXV)
      COMMON QSET(50000)
      EQUIVALENCE (NSET(1),QSET(1))
      NNSET=50000
      NCRDR=5
      NPRNT=6
      NTAPE=7
      CALL SLAM
      STOP
      END
C
C
      FUNCTION USERF(IFN)
      PARAMETER  (MEQT=100,  MSCND=25,  MENTR=25, MRSC=75,  MARR=50,
     1 MGAT=25,   MHIST=50,  MCELS=500, MCLCT=50, MSTAT=50, MEQV=100,
     2 MATRB=100, MFILS=100, MPLOT=10,  MVARP=10, MSTRM=10,
     3 MACT=100,  MNODE=500, MITYP=50,  MMXXV=100)
      PARAMETER (MVARP1=MVARP+1)
      COMMON/SCOM1/ATRIB(MATRB), DD(MEQT), DDL(MEQT), DTNOW, II, MFA,
     1 MSTOP, NCLNR, NCRDR, NPRNT, NNRUN, NNSET, NTAPE, SS(MEQT),
     2 SSL(MEQT), TNEXT, TNOW, XX(MMXXV)
      GOTO (10,20,30,40),IFN
C
C     Calculate INTEGER values for reorder point and EOQ
C
10    I=XX(8)*XX(6)
      USERF=I
      GOTO 50
20    J=20.396*(SQRT(XX(14)/XX(15)))
      USERF=J
      GOTO 50
C
C  calculate monthly average inventory on hand
C
30    SMT1=5.20
      SMT2=(smt1+(XX(14)/3)*0.208)/2
      IF (SMT2.GT.SMT1) THEN
        XX(26)=XX(14)/3
        XX(27)=XX(14)/3
        XX(28)=XX(14)/3
        GOTO 39
      ENDIF
      SMT3=(SMT1+(XX(14)/3)*0.208)+(((2*XX(14))/3)*0.208)/3
      IF (SMT3.GT.SMT2) THEN
        XX(26)=(2*XX(14))/3
        XX(27)=0.0
        XX(28)=XX(14)/3
        GOTO 39
      ENDIF
      IF (SMT3.LE.SMT2) THEN
        XX(26)=XX(14)
        XX(27)=0.0
        XX(28)=0.0
        GOTO 39
      ENDIF
C999   FORMAT(F12.2,',',F12.2)
39    USERF=1
C      GOTO 50
```

```
40    IF (XX(23).LE.0.) THEN
        XX(23)=0
        GOTO 49
      ENDIF
49    USERF=1
50    RETURN
      END
```

PART 4—VARIABLE DEFINITIONS: The following tables reflect the values and definitions of the variables used in the simulation models.

Table C-1. Global Definitions

Variable - Equivalence	Definition
XX(1) - OHINV	On hand inventory
XX(2) - EOQORD	EOQ ordered
XX(3) - REORDRPT	Re-order point
XX(4) - BORDR	Backorders awaiting stock replenishment
XX(5) - QTRLYDMD	Quarterly Demand
XX(6) - LT	Lead Time
XX(7) - CALCEOQ	Calculated EOQ; from USERF(2)
XX(8) - DDR	Cumulative Daily Demand Rate
XX(9) - PINV	Pipeline Inventory (inventory on order)
XX(10) - CUMDMD	Cumulative Demand
XX(11) - CUMDAYS	Cumulative Days
XX(12) - SSMOOTH	Single Forecast Smoothing Value
XX(13) - DSMOOTHBK	Double Forecast Smoothing Value - 1 period back
XX(14) - DSMOOTH	Double Forecast Smoothing Value
XX(15) - UP	Unit Price
XX(16)	Part of Single Forecast Smoothing Value
XX(17)	Part of Single Forecast Smoothing Value
XX(18)	Part of Double Forecast Smoothing Value - 1 period back
XX(19)	Part of Double Forecast Smoothing Value - 1 period back
XX(20)	Part of Double Forecast Smoothing Value
XX(21)	Orders placed counter
XX(22)	Cumlative on hand inventory
XX(23)	Avg annual on hand inventory
XX(24)	Total Variable Cost
XX(25)	Number of days inventory taken
XX(26)	Order quantity month 1 of current quarter. Silver-Meal model
XX(27)	Order quantity month 2 of current quarter. Silver-Meal model
XX(28)	Order quantity month 3 of current quarter. Silver-Meal model
XX(30)	Cumlative on hand inventory. Silver-Meal model

Table C-2. Entity Attributes

Attribute #	Definition
1	Time of Creation
2	The EOQ ordered for a particular daily check; from XX(2)
3	vacant
4	Annual demand
5	Actual number of demands, given ATRIB(4)=1,2,3

Table C-3. Files

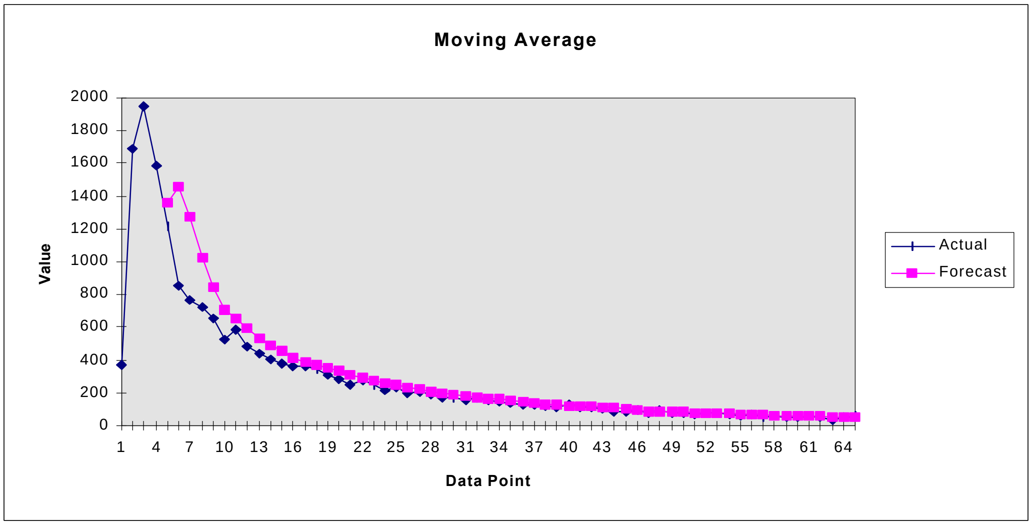
File	Definition
1	Entities/Backorders awaiting stock replenishment
2	Entities/Demands receiving on hand stock

Table C-4. Resources

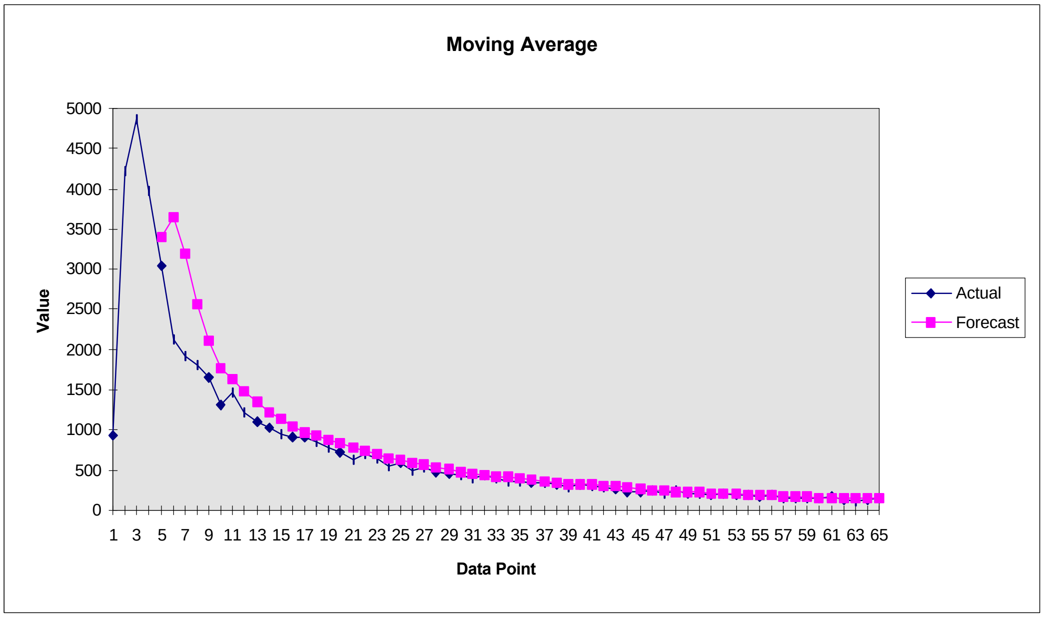
File	Definition
Paper	Inventory on hand or backorders awaiting stock relenishment

Appendix D. Transient Period Determination

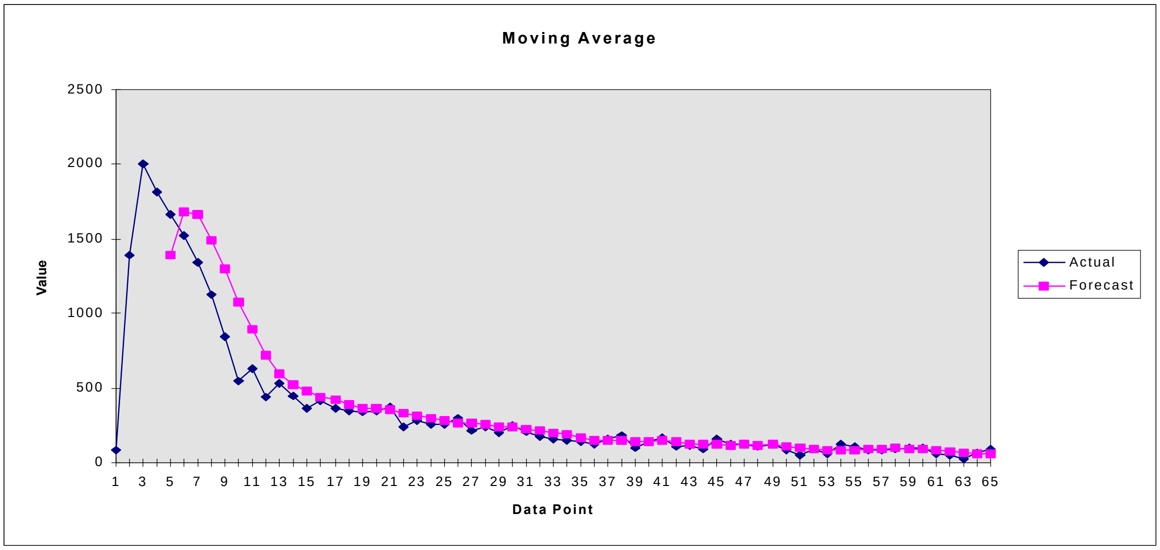
NORMAL AVG INV



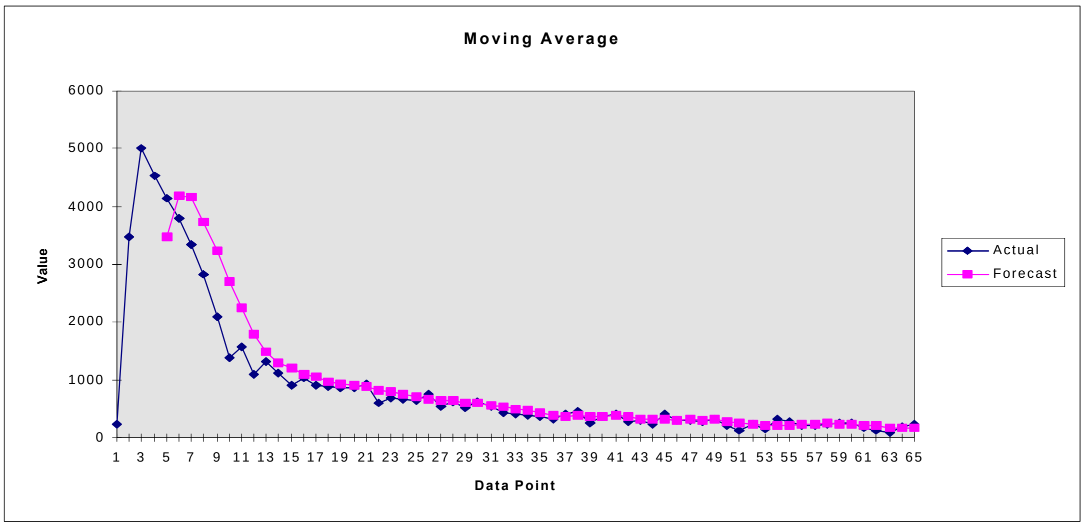
NORMAL TVC



LUMPY AVG INV



LUMPY TVC



Appendix E. Sample Size Determination

In order to determine the correct sample size necessary for the experiment, a sample of five runs was taken for each variable, average on-hand inventory and total variable cost, from the model's output. The models were Lumpy demand with the EOQ, Normal demand with the EOQ, and Lumpy demand with the Silver and Meal model. The constant and continuous model is deterministic and therefore does not require a sample size calculation. The standard deviation of the five runs was calculated and used as part of the calculation of sample size.

Next, a level for α and β level were determined. The α level is the probability of a type one error or stated otherwise, the probability of rejecting the null hypothesis when it is true. The α for this experiment was set at 0.05. The β level is the probability of a type two error. This occurs when you accept the null hypothesis when it is false. For this experiment, β was set at 0.05. Finally, a value for ϕ must be established. ϕ reflects the amount of the acceptable difference between the true mean and the observed mean divided by the standard deviation of the sample. The acceptable difference was set at 20 units to keep the sample size manageable while maintaining acceptable levels for α and β. These parameters were then used to determine the sample size required from Table A11, page 632 of *Statistical Design and Analysis of Experiments with Applications to Engineering and Science* by Mason, Gunst, and Hess. The table below reflects the sample values and the applicable run requirements.

Table E-1. Required Runs

	Lumpy with the Model	**Demand EOQ**	*Normal with the Model*	*Demand EOQ*	Lumpy with the Meal	Demand Silver-Model
	Avg Inv	TVC	Avg Inv	TVC	Avg Inv	TVC
Run 1	104	277	85.3	232	50	186
Run 2	113	297	87	238	61.7	213
Run 3	109	290	86.3	233	64.2	232
Run 4	99.8	266	85.2	237	45.4	163
Run 5	108	289	86.8	235	60.5	214
std dev	5.039	12.276	0.835	2.55	8.181	27.116
ϕ	1.98	1.629	11.976	3.90	1.22	0.738
Sample Size	6	6	6	6	10	24

Based on the required sample sizes, at least 24 runs per model were required. To ensure that we had more than the required runs, we chose to have 30 runs per model.

Appendix F. Test for Normality

One of the key assumptions of the two sample t test with unequal variances is the normality of the data samples. In order to ensure this assumption is met, each model's results were tested using the Wilkes-Shapiro test for normality in the *Statistix* version 4.0 software program. The critical value to meet the condition of normality was determined using Table A11, page 632 of *Statistical Design and Analysis of Experiments with Applications to Engineering and Science* by Mason, Gunst, and Hess. Based on the sample size of thirty and an α of 0.05, the critical value is equal to 0.90. In order to claim normality of data for each model's results, its Wilkes-Shapiro score must exceed this 0.90 threshold. Below is the results of these tests.

Table F-1. Test for Normality

	Wilkes-Shapiro Score	Required Score
Lumpy Demand/EOQ Model		
Average Inventory	0.9692	0.9000
Total Variable Cost	0.9842	0.9000
Normal Demand/EOQ Model		
Average Inventory	0.9819	0.9000
Total Variable Cost	0.9702	0.9000
Lumpy Demand/Silver Meal Model		
Average Inventory	0.9800	0.9000
Total Variable Cost	0.9878	0.9000

As one can see from the table, all the experimental results met the test of normality and therefore, the t test is an acceptable test in this instance. As a side note, the Constant and Continuous model does not meet the requirements of normality because it is a deterministic model. Therefore, other nonparametric measures will be used to compare it with other models.

Appendix G. Test Results

Bold headings reflect that model's runs

Constant & Continuous = Constant and Continuous demand with the EOQ model
Normal Demand = A normally distributed demand with the EOQ model
Silver-Meal = Lumpy demand with the Silver-Meal model
Lumpy Demand = Lumpy demand with the EOQ model

LUMPY DEMAND		Constant & Continuous		NORMAL DEMAND		Silver-Meal / Lumpy Demand	
AVG INV	TVC	AVG INV	TVC	AVG INV	TVC	AVG INV	TVC
104.000	277.000	80.5	221	85.3	232.	50	186
113.000	297.000			87.0	238.	61.7	213
109.000	290.000			86.3	233.	64.2	232
99.800	266.000			85.2	233.	45.4	163
108.000	289.000			86.8	237.	60.5	214
107.000	283.000			86.4	235.	53.4	196
110.000	287.000			84.9	232.	54.3	199
111.000	299.000			87.2	238.	48.2	196
102.000	275.000			84.5	232.	37.3	160
105.000	279.000			85.7	234.	56.2	201
106.000	286.000			85.9	234.	50.3	194
101.000	271.000			86.0	235.	35.1	162
113.000	296.000			86.5	236.	62.8	224
113.000	301.000			86.6	235.	71.6	248
102.000	276.000			84.6	231.	45.8	178
102.000	274.000			85.3	233.	42.7	169
107.000	286.000			86.9	236.	52.4	195
101.000	268.000			87.4	237.	50.1	182
106.000	284.000			86.8	235.	65.8	225
108.000	287.000			85.2	232.	46.8	170
108.000	290.000			84.6	231.	56.2	209
110.000	291.000			86.7	236.	63.4	217
103.000	278.000			85.7	233.	48.9	185
112.000	297.000			86.7	237.	58.8	204
106.000	284.000			87.0	238.	56.1	193
104.000	273.000			86.1	235.	48.8	185
108.000	287.000			87.9	239.	47.8	184
105.000	280.000			85.8	235.	47.8	181
101.000	271.000			85.8	234.	30.9	136
106.000	284.000			86.0	234.	60.8	218
mean	mean	mean	mean	mean	mean	mean	mean
106.360	283.533	80.5	221	86.093	234.667	52.470	193.967
stdev	stdev	stdev	stdev	stdev	stdev	stdev	stdev
3.911	9.435	0	0	0.883	2.218	9.350	24.2806

t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances		
Lumpy demand & EOQ vs Normal demand & EOQ			Lumpy demand & EOQ vs Lumpy demand & Silver-Meal		
Avg Inv	*Variable 1*	*Variable 2*	*Avg Inv*	*Variable 1*	*Variable 2*
Mean	106.36	86.093333	Mean	106.36	52.47
Variance	15.29489	0.7792643	Variance	15.294	87.429
Observations	30	30	Observations	30	30
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	32		df	39	
t Stat	27.6871846		t Stat	29.12279	
P(T<=t) one-tail	3.1521E-24		P(T<=t) one-tail	2.25E-28	
t Critical one-tail	1.69388841		t Critical one-tail	1.684875	
P(T<=t) two-tail	6.3041E-24		P(T<=t) two-tail	4.5E-28	
t Critical two-tail	2.03693162		t Critical two-tail	2.022689	

t-Test: Two-Sample Assuming Unequal Variances			t-Test: Two-Sample Assuming Unequal Variances		
Lumpy demand & EOQ vs Normal demand & EOQ			Lumpy demand & EOQ vs Lumpy demand & Silver-Meal		
TVC	*Variable 1*	*Variable 2*	*TVC*	*Variable 1*	*Variable 2*
Mean	283.5333	234.66666	Mean	283.5333	193.9667
Variance	89.01609	4.9195402	Variance	89.01609	589.5506
Observations	30	30	Observations	30	30
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	32		df	38	
t Stat	27.6158339		t Stat	18.83262	
P(T<=t) one-tail	3.4124E-24		P(T<=t) one-tail	3.62E-21	
t Critical one-tail	1.69388841		t Critical one-tail	1.685953	
P(T<=t) two-tail	6.8247E-24		P(T<=t) two-tail	7.24E-21	
t Critical two-tail	2.03693162		t Critical two-tail	2.024394	

Because the Constant and Continuous model is deterministic, it does not meet the requirement of normality to use the two-sample t test as with the other models. Therefore, in order to compare the output of this model to the Lumpy demand with the EOQ model, we built a 95% confidence interval around the means of Average Inventory and Total Variable Cost under the Lumpy demand with the EOQ model. We then tested the hypothesis that the mean generated from the deterministic model lies within the confidence interval we established. If this is true, then one cannot reject the hypothesis that the two means are equal. If the deterministic mean lies outside the confidence interval, then we would fail to accept the hypothesis that the means from the two models are equal.

The table below reflects the results of this test. The test results were determined using *Statistics* version 4.1.

Table G-1. Confidence Intervals

	Lumpy demand with the EOQ	Constant and Continuous Demand	Lumpy demand with the EOQ	Constant and Continuous Demand
Variable	*Average Inventory*	*Average Inventory*	*Total Variable cost*	*Total Variable cost*
Mean Value	106.36	**80.5**	283.53	**221**
Upper 95% C.I.	**107.82**		**287.05**	
Lower 95% C.I.	**104.89**		**280.01**	

Appendix H. Silver-Meal Model Description

The Silver-Meal model used in this research is a heuristic variation of the EOQ model design to handle significantly variable demand patterns. The heuristic selects the replenishment quantity so as to minimize the total relevant costs per unit of time for the duration of replenishment period. Total relevant costs per time period are define by the following equation:

$$\frac{\text{(setup cost)} + \text{Total carrying costs to the end of period T}}{\text{T}}$$

For this equation, the ratio is calculated for increasing time periods until the total relevant costs of (T+1) exceed the costs of T . "Total carrying costs to the end of the period" reflects the carrying costs for the inventory held up to T periods. When (T+1) costs exceed the costs of T, then a order is placed for the demand for the T period(s). The ordered quantity is simply the sum of the demands during T period(s). In numerous test examples, this method has performed extremely well when compared to other inventory models and rules (Peterson and Silver, 1979: 317-320).

Appendix I. Lumpy Demand Application

This appendix provides a simple illustration of how Silver and Peterson's definition of Lumpy demand is applied to a data set. The three data sets listed below are fictitious but represent three different demand patterns. Pattern one is more constant and continuous in nature. Pattern two reflects a upward trend in the data and pattern three represents more of a lumpy demand pattern.

Table I-1. Demand Patterns

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7	Period 8
Pattern 1	100	120	100	110	100	110	90	100
Pattern 2	80	85	90	95	100	105	110	115
Pattern 3	80	0	30	110	27	0	0	120

Silver and Peterson have established a ratio to determine exactly the point where lumpy demand patterns significantly violate the constant demand assumption (Silver, 1985: 238). This measure is called the variability coefficient and is denoted by *VC*. Its formula is as follows:

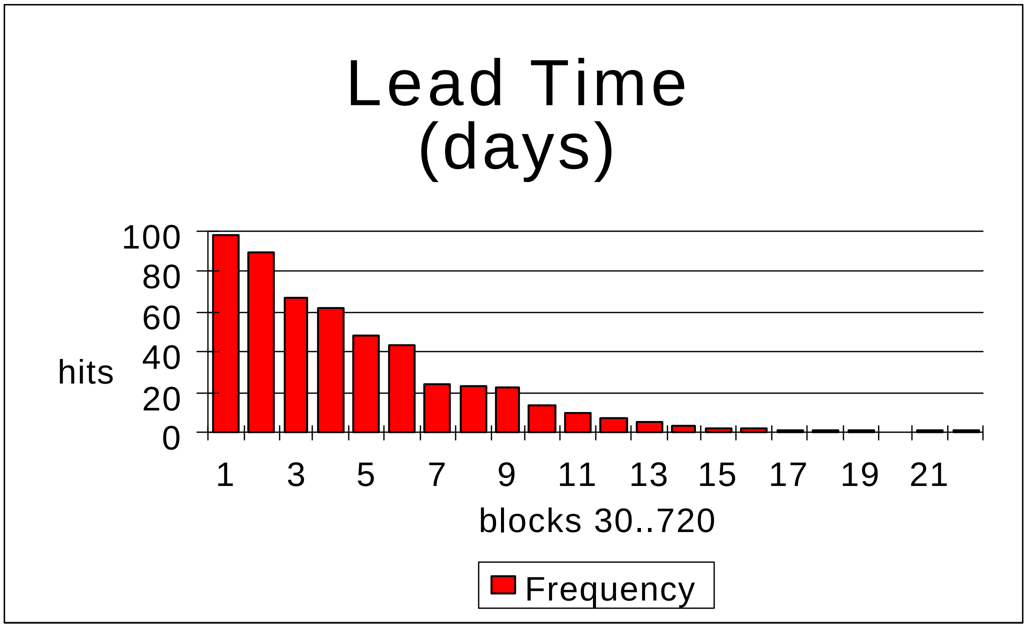
$$VC = \frac{\text{Variance of demand per period}}{\text{Square of average demand per period}}$$

If $VC < 0.2$, then Silver and Peterson state that the EOQ's assumption of constant and continuous demand is still valid. If on the other hand, $VC \geq 0.2$, they suggest that the constant demand assumption has been significantly violated and that other models should be considered (Silver, 1985: 238). Based on the data for this example, it is apparent that patterns do not have to be absolutely constant and continuous for the EOQ model to treat them as constant and continuous. Pattern two demonstrates that the EOQ model can even handle some trend in the data and still keep the assumption of constant and continuous demand. Yet, pattern three clearly illustrates that demand patterns exhibiting lumpy or high variance do not meet Silver and Peterson’s definition of constant and continuous demand. It is with these types of lumpy demand patterns that the EOQ’s assumption of constant and continuous demand is no longer valid.

Table I-2. Silver and Meal s Heuristic Results

	Mean of Data	Mean (squared)	Variance	Lumpy Score
Pattern 1	103.75	10764.063	83.929	0.008
Pattern 2	97.50	9506.25	150.0	0.016
Pattern 3	45.875	2104.51	2,527.554	1.20

Appendix J. Graph of Lead Time Pattern



The lead time chart above represents a histogram (number of demands or hits of a particular demand value) of the average lead time for all the items in the sample data. Each block on the x-axis has a width of 30 observations. For the first block 98 items have a lead time of less than thirty days. All of the data points are represented in this graph.

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Berry Vita

Captain Harry A. Berry is from Salt Lake City, Utah. He graduated from the University of Utah in 1984 with a Bachelor of Science degree in Finance and again in 1986 with a Master's degree in Business Administration. After receiving his commission into the United States Air Force in 1987 through the Officers Training School, Captain Berry was assigned to the 27th Supply Squadron at Cannon AFB, New Mexico.

During his tour at Cannon AFB, Captain Berry served as the Chief, AGS Parts Store in support of the F-111D and subsequently, Chief, Materiel Management Branch. In 1989, he was assigned to the 15th Supply Squadron at Hickam AFB, Hawaii. During his tour in Hawaii, Captain Berry filled a variety of positions within the squadron. These positions included Chief, Operations Support Branch, Chief, Materiel Management Branch, and Chief, Management and Systems Flight.

In 1994, Captain Berry entered the Air Force Institute of Technology at Wright-Patterson AFB, Ohio, and graduated in 1995 with a Masters degree in Logistics Management. He was subsequently assigned to the Logistics Management Agency, Maxwell AFB, Alabama.

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In 1992, he was assigned to Shaw AFB, South Carolina, where he served nearly two years on the US Central Command Air Forces (USCENTAF) Staff as the Supply, Management and Systems Branch Chief. Capt Tatge was selected into the Air Force Institute of Technology at Wright-Patterson AFB, Ohio in May 1994 and graduated with a Masters degree in Logistics Management in September 1995. He was subsequently assigned to the Logistics Management Agency, Maxwell AFB, Gunter Annex, Alabama.

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