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ALTERNATIVE INVENTORY CONTROL METHODS

FOR USE IN MANAGING MEDICAL SUPPLY INVENTORY

THESIS

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Abstract

The purpose of this ~~study~~ was to examine the characteristics of demand for medical supplies in Air Force medical treatment facilities in an effort to improve inventory control. One method proposed to improve system performance was use of a more sophisticated forecasting technique than the 12 month moving average currently used in forecasting demand for economic order quantity computations. This would better match supply to demand.

The research also examined whether: (1) major workload measures were highly correlated to medical supply usage; (2) there were demand patterns for major stock classes which were common to all facilities; and (3) whether differences in medical treatment facilities affected inventory performance measures to the extent that a service-wide model should not be used.

Workload and medical supply demand data were collected from 13 facilities and analyzed. When workload and supply expenditure data were tested for correlation, the findings indicated little or no relationship. Plotting the data from each facility revealed that both a trend and seasonality were common. It was also shown that grouping the data according to facility category; clinics, hospitals, and regional hospitals/medical centers, reduced the within group variance

of the data. The demand data were found to fit primarily exponential and poisson distributions.

In studying alternative forecasting techniques, a strong explanatory model based upon multiple regression analysis was not found. Three other forecasting techniques; exponential smoothing, a linear trend model incorporating seasonal indexing, and a Winter's exponential smoothing model, were tested using computer simulation to produce simulated "actual" demands against the 15 medical supplies in the sample. The simulation technique was employed to substitute for the insufficient amount of actual demand data available. The simulation showed that both the linear trend and Winter's models would produce smaller forecasting errors than the 12 month moving average.

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I. Introduction

General Issue

The United States Air Force Medical Service has invested years of study and millions of dollars in developing a new on-line computer based system to assist in the management of medical supply inventory. The system has been tested and is at the mid-point of implementation in Air Force medical treatment facilities (MTFs). These mini-computer systems should be installed and operating in nearly all of the 121 MTFs in the Air Force by the end of fiscal year 1989. With the conversion to an on-line system, senior medical logisticians believe that current inventory control procedures and ordering guidelines should be reviewed to determine if modification would improve system performance and efficiency (15)(13).

Background

The Air Force maintains medical supply accounts at 121 medical treatment facilities (MTFs) around the world. The number of items carried and the total amount of inventory varies greatly with the size of the facility; from the smallest clinic, to the 1000 bed USAF Medical Center at Lackland AFB, Texas.

In 1987 the Air Force began the process of installing a new on-line computer-based inventory control system in all hospital and clinic medical supply accounts. This system, referred to as MEDLOG, replaces a batch process punched-card inventory transaction system (13). The on-line computer system was badly needed to assist in the management of inventories of thousands of items. For example, the medical logistics function at USAF Medical Center Wright-Patterson AFB carries master inventory records on over 16,000 medical supply items, approximately 9,000 of which are actively ordered and consumed during the year (27). Even at smaller MTFs, the large number of items held in inventory relates to a substantial investment.

In civilian hospitals, it has been estimated that 20% to 40% of total costs are inventory related (24:74). If it can be assumed that the percentage is similar in Air Force MTFs, any actions that can reduce inventory levels without degrading service levels could result in substantial cost savings.

The Air Force manages medical supply inventory with a modified fixed order quantity model. The order quantity and safety level for an item are determined by computing its annual demand (in dollars) and assigning a corresponding "requirement code." The requirement code is then translated into a given order quantity and safety level (in weeks of supply) (9:Chap 8,34). Ordering costs and holding costs are not considered directly in determining order quantities and safety levels for individual medical supply items (27).

MEDLOG's main purpose was to streamline inventory record up-dating and provide real-time inventory information, rather than make major changes to the system. The underlying inventory model remained relatively unchanged. With the old system, the forecast demand figure for each medical supply item was used in the quarterly revision of the order quantity and safety stock levels (27). The new system re-computes that demand forecast each time the reorder point is reached on an item, or every three months for those items for which there has been no consumption during the quarter (27). Both the old and the new systems compute the forecast using the 12 month moving average (15). Both systems maintain only a 12 month demand history on each medical supply item.

Senior medical logistics personnel (13) acknowledged that a forecasting method better than the simple 12 month moving average might be applied to reduce inventory levels in Air Force hospitals. While the 12 month moving average technique does provide some estimate of future demand, it significantly "smooths," or reduces recognition of the month to month variability in demand. The variation in demand, coupled with the age of supply demand data from the old system, however, made more sophisticated methods difficult to apply. For instance, demand on many medical items is known to fluctuate with the month or time of year, yet the variability in demand was not recognized by the system until as much as three months after it occurred (27).

With the much improved data collection capability of the MEDLOG on-line computer system, successful application of a different forecasting method is more promising. There are numerous forecasting methods available that are capable of compensating for seasonal factors in time series demands (25:115).

Although double exponential smoothing was tried as an alternate forecasting technique in 1981, it was considered unsuitable due the variability in demand for medical supplies and its inherent time lag in responding to the actual dynamic demand pattern (13). It occasionally produced forecasts that were out of cycle, or in the opposite direction of the actual change in demand. One response to that deficiency would be to use a different forecasting technique--one which is both accurate and more reactive to the varying demand pattern.

Both the new on-line computer system and the old system, where still in use, maintain only 12 month demand histories. Since more data are needed to analyze long term trend and recurring patterns for forecasting, an alternative source of data is needed. A logical assumption, thought not yet shown, is that medical supply usage is related to certain MTF workload measurements. It seems likely that as workload varies from season to season, that the quantities of medical supplies consumed would also vary.

A final point in the background necessary to the understanding of the demand for medical supplies in Air Force medical treatment facilities regards the medical supply account. The medical supply account at each MTF is a "revolving stock fund." It functions as a self-sustaining supply organization which services the medical facility by "selling" its supplies to the cost centers within the facility having funds available for their purchase. A cost center is a workcenter with clearly defined unit of output, to which operating costs are assigned. Cost centers include administrative offices and other ancillary non-medical functions, as well as the patient care cost centers. For the purposes of medical supplies, however, the clinical services cost centers such as primary care, pediatrics, surgery suit, the nursing care units, laboratory, and radiology are obviously more important than ancillary functions due to the higher levels of medical supply usage.

The medical logistics function (the Medical-Dental Stock Fund) corresponds to the "central stores" function within a civilian medical facility and the medical supplies in inventory represent the facility's "official inventory" (22:7). Official inventory is strictly within the control of the Medical Logistics function.

When supplies are ordered by a cost center, the medical logistics function charges their cost to the cost center. Once delivered, the medical supplies become the second type of inventory found in MTFs, "unofficial inventory," which in a practical sense is no longer under the control of Medical Logistics.

Air Force MTFs are in transition in the manner in which cost centers order medical supplies. The modified system is similar to the periodic automatic replenishment systems (PAR) found in the civilian sector (25:44). Under the Air Force system, stock levels are estimated for commonly used supplies for each cost center. The medical supply personnel are then responsible for periodically reviewing each cost center's supply cabinet, ordering and replenishing supplies as necessary, thereby greatly reducing the duties of the cost center's supply custodian. Another objective of the new system is to improve central control over medical supplies and reduce abnormalities in ordering, such as the tendency by some cost centers to over stock (27).

Specific Problem

The fixed order quantity model which the Air Force uses for medical supply inventory control was last modified in 1981. In that model, medical supply demand is forecast using a 12 month moving average. The demand figure is then used to determine the order quantity and stock safety level. A detailed study has not been accomplished to determine whether inventory levels can be reduced, without degrading customer service levels, by using a more sophisticated forecasting method to predict demand.

Research Questions

1. Are there MTF workload measurements that exhibit a high correlation to medical supply usage that can be used to satisfy the problem of the limited amount of medical supply demand history available?

2. Are there demand patterns for medical supplies by major stock class that are common to all Air Force MTFs?

3. Would application of a forecasting technique more advanced that the twelve month moving average now in use better track actual demand?

4. Does the range in size and services offered by Air Force MTFs affect inventory performance measures to the extent that a service-wide inventory control forecasting model should not be used?

Justification for the Research

MEDLOG provides inventory information in a much more timely manner than was previously possible. Now that these data are available, research should be undertaken to determine if adjustments to the inventory system used to manage medical supplies could improve operations. One potential benefit would allow reduced inventory levels to be maintained through better matching of supply and demand. Another would be more responsive service to the cost centers. The study of forecasting methods for predicting medical supply demand for inclusion in the EOQ computations is an area that may offer such benefits. This would occur by adjusting medical supply inventory levels in anticipation of increased/decreased demand. Rather than maintaining an inventory level all year which is sufficient to meet peak requirements which might occur, for instance, in March and April, a lower level could normally be maintained and increased prior to the forecast increase in demand during the spring.

Scope and Limitations of the Research

This research will be restricted in four areas. First, both MEDLOG and the old batch processing system retain only 12 months of item demand history. There is no other source from which to obtain more than 12 months of this data. Since actual demand is thought to be seasonal over a twelve month period, the preferred method of evaluating a forecast against "hold out" data for the same demand history is not possible. However, three years of historical data on various workload measurements are available. In order to have a base of data greater than 12 months, workload data may be tested instead of supply demand data.

Second, only routinely used medical supplies are considered in this study. War Reserve Materiel (WRM) will not be included, as different inventory control policies govern this category of medical supplies.

Third, to keep the statistical analyses required in this thesis to a manageable level, a limited number of medical supply items were selected for study of their demand histories. Experienced medical logistics personnel at USAF

Medical Center Wright-Patterson assisted in the research by recommending fifteen stock numbers (Table I, below) thought to be representative of a wide range of stock classes.

Table I. Sample Medical Supply Items

Stock Number	Nomenclature	Cost	Unit Issue
4720-00-141-9080	Tubing, Non-metal 3-16ID3-32	.15	FT
6505-00-083-6541	Dex Sod-chl Inj 1000ml	9.49	BX
6505-00-926-8985	Dex Hydrob-Guaife Syr 4oz.	.45	BT
6505-01-201-3458	Acetaminophen Sol 4fl oz.	.35	BT
6510-00-582-7992	Bandage Gauze 4.5in x 4yd	7.21	PG
6510-00-782-2698	Sponge Sur Gauze 4x4in 200s	3.49	PG
6510-00-926-8883	Adhesive Tape Surgical 2in x 10yd	4.97	PG
6515-00-720-7277	Cath/Ndl Un Disp 23GA	.31	SE
6515-00-926-2089	Razor Surg Prep Str SM	.46	EA
6515-01-125-6606	Syr & Ndle Insulin 27GA 100s	5.97	PG
6520-00-982-9377	Cup Polish Den Hdnpc 36s	2.55	PG
6525-01-205-6752	Film, Rad 24 x 30cm 100s	69.60	PG
6530-00-112-0162	Btl Safety Cap 11 DR 72s	10.51	PG
6530-00-890-0176	Patient Utility Kit Plast	.63	EA
6640-00-074-4191	Slide Micro Plain Frost 72	1.92	PG

Fourth, although a substantial portion of MTF medical supplies may be found in individual cost centers as unofficial inventory, the subject of this research is the official inventory maintained by the MTF's medical logistics function.

Structure of this Thesis

The remainder of this thesis will seek to answer the research questions posed above. Chapter II, Literature Review, summarizes the literature concerning economic order quantity (EOQ) models employed in hospital medical supply inventory control and forecasting techniques which might be utilized in determining the demand figure required for that model. Chapter III, Methodology, presents the approach taken in gathering and analyzing the data to answer the research questions. Chapter IV, Analysis, offers the results of the statistical analysis conducted on the medical supply demand data. The results of the simulation of demands against medical supplies based upon different forecasting techniques are also presented. In Chapter V, conclusions and recommendations are offered for improvements in managing medical supply inventories.

II. Literature Review

This chapter is divided into two major subjects. The first part reviews economic order quantity models (EOQ) frequently employed by civilian hospitals in the control of medical supplies. The second part reviews the various forecasting methods which might be appropriate for predicting future demand for medical supplies.

Inventory Models and the Demand for Medical Supplies

With regard to EOQ inventory control models, the management of other resources such as medical equipment and non-medical supplies are applicable to those methods, but were not considered in this research. Furthermore, in a paper of this length it was not possible to fully discuss all the aspects of all inventory methods. Therefore, attention was focused upon fixed order quantity models (the type used by the Air Force Medical Service).

Fixed Reorder Quantity Models of Inventory Control

The classic Wilson economic order quantity (EOQ) model is a fixed order quantity model widely used for hospital inventory control. It is also the basis behind the Air Force Medical Service system (27). It can best be applied when demand can be said to be independent, certain, and occurs at a constant rate. The simple EOQ model is effective in determining the quantity to order while minimizing the costs to order and hold inventory. Using the model, however, requires that a number of assumptions be made. The average demand should be deterministic, continuous, occur at a constant rate, and not change over time. Replenishment lead time should be constant. Items must be considered independently. Finally, there can be no advantages to joint review or replenishment, or they are excluded (4:319).

The Wilson EOQ model is given by the equation:

$$EOQ = \sqrt{\frac{2DC_o}{C_h}}$$

where

C_o = ordering cost per order,

C_h = cost to hold one unit of the item for one year,

D = annual demand for the item.

<u>Application of EOQ Models to Hospitals</u>. Ammer states that there are three common types of inventory control systems found in hospitals (1:118): no control, order point, and periodic control. The "no control" systems are found in very small facilities where one person has overall responsibility and daily control over inventory. Order point controls involve EOQ models and other fixed order quantity systems. More sophisticated health care institutions may have computer systems which print out, by vendor, items at reorder point (1:121). Periodic controls are quite common since many hospitals have sole supplier relationships, or chose to purchase from a small number of medical supply companies. In these cases the medical supply company sales representatives

may make weekly visits to assist in determining needs and take orders.

EOQ models are the most common methods of inventory control found in hospitals. To assist in management of their inventory systems there are at least twelve major computer software inventory management systems commercially available to hospitals (25:44).

<u>Weaknesses of the Use of EOQ Models by Hospitals</u>. There are difficulties, however, in satisfying the assumptions noted above which are necessary for use of the simple EOQ models in hospital environments. A major concern is that the demand for medical supplies may not be constant or continuous. One solution might be to consider the treated patient as the final product. By doing this, demand for medical supplies can be thought of as dependent and an alternative inventory control technique such as material requirements planning (MRP) might be applied (24:74).

An indication of the variability of total medical supply demand in two very dissimilar Air Force hospitals is reflected by the graph, Figure 1. The USAF Medical Center at Wright-Patterson is a 240 bed medical center offering a wide range of both inpatient and outpatient services to a population composed of 27% active duty military members; 31% dependents of active duty; and 42% retired, dependents of retired, miscellaneous (19). USAF Hospital Misawa is a 20 bed Air Force hospital located in a remote area of Japan. It offers limited inpatient and outpatient medical services to a population of approximately 55% active duty, and 45% dependents of active duty (18).

Another weakness of the use of EOQ models by either civilian or military hospitals is that both health care systems exhibit erratic demand.

> The variability of utilization within the year is an unavoidable and significant fact of life for virtually all providers of health care. Emergency room and immediate care programs (urgicenters, walk-in clinics, etc.) experience substantial variations in demand from hour to hour every day. Day-of-the-week fluctuation patterns characterize admissions to hospitals as well as emergency care demand, with particularly serious trauma more common on week-end and payday evenings. Seasonal fluctuations in demand may relate to cold and flu increases in the winter, ski injuries or drownings in resort areas by season. Hunting seasons may produce dramatic increases in poison ivy cases, gunshot wounds, or other injuries.
>
> To the extent that such fluctuations may be consistent, and linked to known factors in the environment, they may be predictable. To the extent that they can be accurately forecast, they can enable appropriate management and short-term planning decisions. [16:189]

The EOQ model further assumes that the costs to order and to hold inventory can be computed, or at least approximated. This is another concern with using EOQ models. Both the large number of items stocked in hospitals (over 9,000 at USAF Medical Center Wright-Patterson) (27) and accounting measures employed make calculating both holding costs and ordering costs extremely difficult. Only gross estimates are possible. Errors in the cost parameters C_o and C_h, however, are dampened when converted to changes in EOQ (26:115), thereby allowing estimates. It must be understood, however, that with cost estimates, attaining an absolute minimization of the total variable cost is unlikely. Ammer

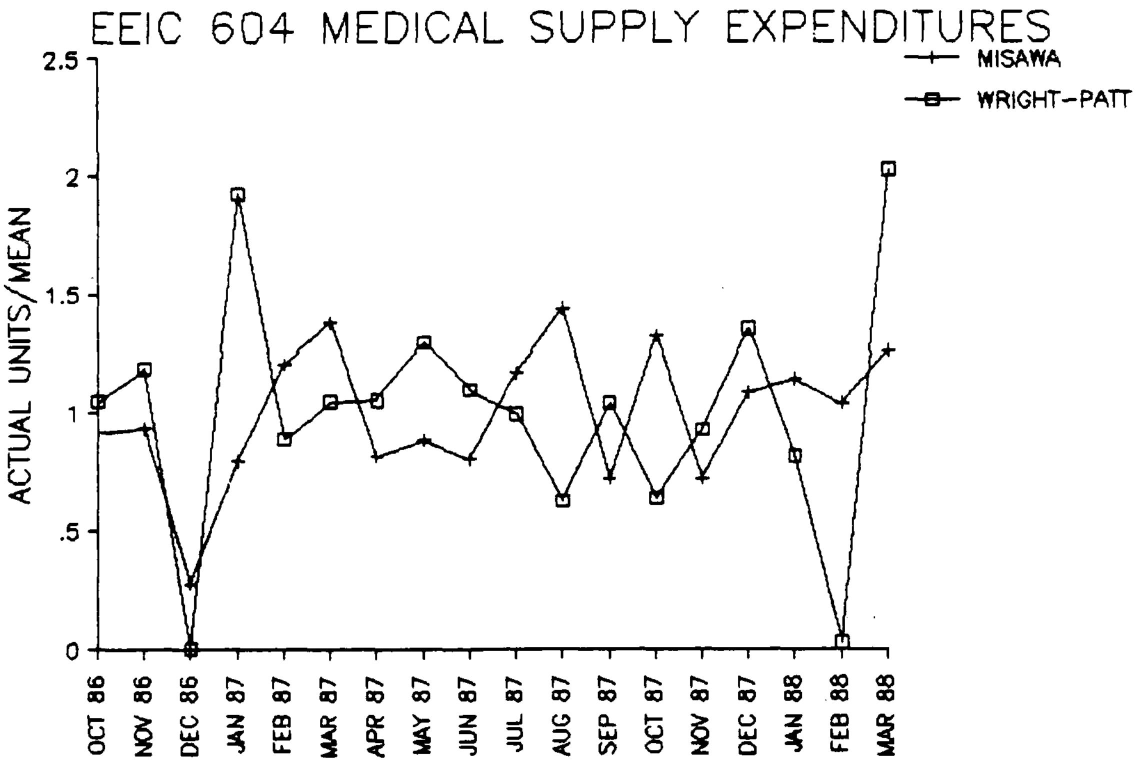

Figure 1. Comparison of Medical Supply Usage of Two Air Force Hospitals (Source 18, 19)

states that determining actual ordering and holding costs in hospital settings is difficult and has been found to vary widely among facilities. One of the most detailed attempts to determine actual carrying costs was done at an Iowa hospital about 15 years ago. That hospital computed its total holding cost to be 32.1% of the value of inventory (1:124). Other hospitals have used different figures.

There are a number of variations upon the fixed order quantity (EOQ) and fixed order interval inventory control models that are employed by medical treatment facilities. Regardless of the system chosen, many civilian medical treatment facilities institute their preferred system by trial and error. This often results in inventory inefficiencies and a large amount of waste due to expiration of medical supplies with limited shelf lives (1:121). Ammer further pointed out that obsolescence and shrinkage losses in health care institutions tend to be much higher than for manufacturing companies (1:125). This underscores the necessity to have a workable, effective inventory control system which maintains the lowest inventory levels practical while still supporting the target medical supply fill rate.

Showalter (24:71) pointed out that since the great majority of hospitals use some form of EOQ inventory control system, they replenish stock based upon past demand. This is reactionary in nature and normally does not consider the timing of future demand. The replenishment system purchases for that demand, whether it was expected to occur next week or six months later. The greater the time interval between when the item is restocked and when it is consumed, the greater the carrying cost. Furthermore, if the future demand is very volatile or erratic in quantity and timing, the reorder point must be higher in order to allow a larger safety stock to protect against out of stock conditions (24:71). This condition begs for the use of forecasting methods.

Determining the demand figure for inclusion in EOQ computations is an important step in ultimately determining order quantities. A common approach is to simply take an average for the preceding year. As noted above, this fails to consider the possible erratic nature of the demand, seasonality, and long-term trends. Where demand is computed monthly and future demand is not expected to be the same as historical demand, some type of forecasting is required. It follows that the better the forecast of future demand, the better inventory levels can be controlled. Improved control can translate into savings in inventory holding and ordering costs. Unless the organization is willing to maintain excessive safety stock or incur frequent stockouts, some demand forecasting is necessary.

Fluctuating demand patterns and uncertainty in lead time will always make safety stocks appropriate. This is especially true for health care organizations, where the importance of patient care would dictate some level of safety stock of critical medical supplies.

The demand for medical supplies can be forecast directly, or indirectly by forecasting the demand for health care services (utilization). Utilization in both civilian and military hospitals may be forecast with some degree of certainty. Health service utilization rates for specific diagnostic conditions are available from many sources. Inpatient rates by diagnosis and patient demographics are particularly well documented since the implementation of the diagnostic related groups (DRG) prospective payment system in the early 1980s (23:17). Forecasting the demand for services in the Air Force setting is simplified since the beneficiary population is very clearly defined, and there is less "shopping around" between providers of medical care. In other words, even though dependents of active duty military members and retired military members and their dependents can elect to seek care outside the military MTF, it is at some cost to them--in contrast to free care at the military facility.

<u>The Role of Forecasting in Medical Supply Inventory Control</u>

There are many different forecasting models that could be used in medical supply inventory control. In selecting a forecasting method, it is first necessary to define the inputs available to the process, the output desired, and the constraints and environmental factors affecting the process (26:37). In a business situation, inputs include such items as the demand history and marketing research available, knowledge of special situations which may have affected the historical data, and the availability of opinions of knowledgeable personnel. Outputs of the process include the timing of expected demand, broken down by such segments as product, customer, and region. Constraints include such things as management policies, available resources, market conditions, and technology (26:37).

Classifications of Forecasting Techniques

Various authors offer different classification schemes to categorize the variety of forecasting techniques available. One simple classification technique was presented by Cleary (8:6). His model, modified to include informal forecasting (20:79), is shown in Figure 2, below. Though not mathematically based, informal, "seat-of-the-pants" forecasting is common and cannot be ignored (20:79).

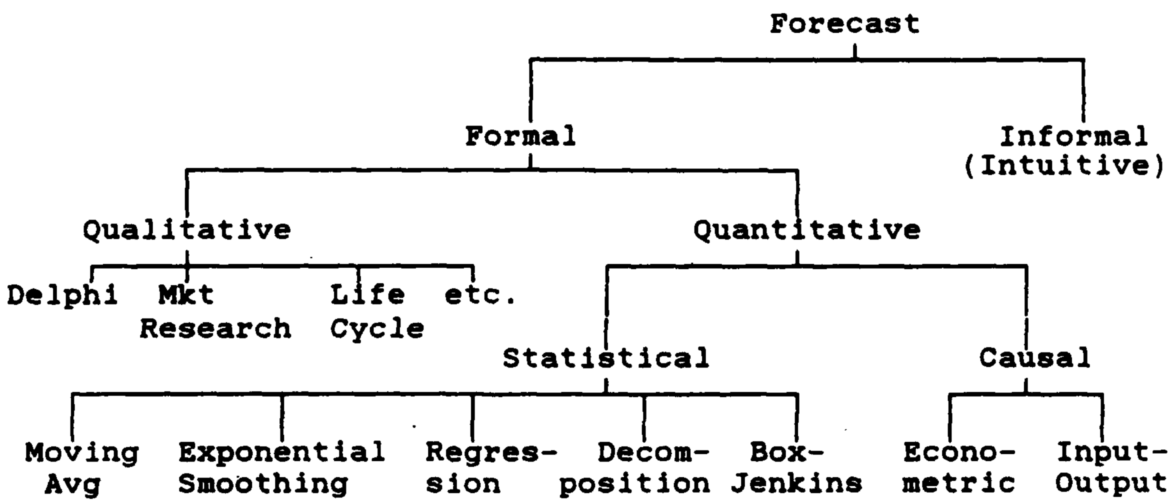

Figure 2. A Classification of Forecasting Methods
Source (8:6)

There are many different classification models. Some writers, such as Cleary and Levenbach (8:13) and Georgoff and Murdick (12:121-122) prefer to include the Box-Jenkins forecasting technique under the category of statistical (otherwise known as auto-projection or time series), while others such as Meredith (20:79) include it under the category of causal or deterministic. A review of the literature revealed that there is no universally accepted system of classification of the various forecasting models. The diagram presented above was included to facilitate a discussion of some of the more popular forecasting methods.

<u>Qualitative Forecasting Techniques</u>. Qualitative techniques are usually employed in cases where there is a lack of data, such as in the case of a new product in the market (5:49). They include forecasts based on judgment and experience. The Delphi technique, which uses expert opinion, falls into this category. Qualitative techniques are also appropriate for long-range forecasts, "especially where external factors (e.g., the 1974 OPEC oil crisis) may play a significant role" (20:79).

<u>Quantitative Techniques</u>. Quantitative, or mathematical based forecasting techniques, require sufficient quantities of accurate data for their application. Most forecasts are involved with data occurring in a "time series." Cleary defined a time series as

> ...a set of chronologically ordered points of raw data; an example would be revenue received, by month, for several years. An assumption often made in a time series analysis is that the factors that caused demand in the past will persist into the future. [8:6]

The demand for goods and services over time can also be thought of as a time series. The demand for medical supplies is such an example.

Time series can be broken down into the four components of trend, seasonality, cycle, and random variation (20:84). Trend is the tendency of the data to grow or decline over time. An example would be business sales that display a gradual month to month increase. Seasonality refers to recurring patterns in the data corresponding to time. An example would be the increased sales during the Christmas season, or the increase in clothing sales every August for "back-to-school." Cycles refer to long-term patterns which repeat every two or more years, usually corresponding to changes in the economy (20:86). Random variation, sometimes referred to as "noise," is the random occurrence component which is incapable of being forecast.

Quantitative models can be further categorized into two major classes: the statistical (auto-projection or filtering techniques), and causal techniques (8:6).

Causal Deterministic Models. The causal models include econometric, Input-Output forecasting techniques, and others (20:79). Causal models are based upon explicit relationships between the dependent variable to be forecast and other variables that cause change in the dependent variable (8:6).

Causal models assume that changes in inputs will result in predictable changes in the forecast output--that the value of the variable of interest is a function of one or more other independent variables (28:40). Wheelwright and Makridakis observed that time series data could be considered within this definition in the narrow sense, but the label is usually reserved for models with variables other than time. The main disadvantages with causal models are that they are generally complex and require information (future values) on other variables (inputs) before the output can be forecast. They also have a much larger data requirement than most other forecasting techniques (28:40).

MacStravic advocated using causal rather than statistical forecasting methods in forecasting health care utilization. Even recognizing that causal techniques require information on at least one other independent variable as a basis for the forecast, he argued that they produce more accurate and less risky forecasts than do statistical methods (16:18). He faulted the statistical methods for relying solely on past patterns in the data to predict future utilization while ignoring the factors which caused those changes (16:39).

> Depending on the technique, [statistical] forecasting can lead to estimates of enormous change in utilization, especially where small numbers are involved, yet incorporate no reason for such changes. [16:18]

He also noted that causal techniques may be employed for short, medium, or long-range forecasting while statistical techniques should only be used for short term forecasting because "changes in dynamics are not only possible but likely in intermediate and long time frames" (16:17). This would not be a limitation for forecasting medical supplies, since only the short term is considered.

Applying causal forecasting techniques to predict future health care utilization would be a far less complicated procedure than attempting to forecast demand for medical supplies. There are only 400+ diagnostic related groups (DRGs) which cover all significant injuries and illness for which utilization can be forecast. For the DRGs, there are three major factors (categories of independent variables) known to affect utilization. They include people factors (demographics, psychographic, behavior), provider factors (access, insurance, psychographic), and environmental factors (economy, type of reimbursement, regulation)(16:111). To forecast medical supply usage, however, independent variables would have to be considered for the thousands of commonly used items, unless it can be shown that stock classes or groups of related items behave in a similar manner.

Statistical/Auto-projection Models. Statistical, or auto-projection models include the various moving-average forecasting methods to statistical regression models, and autoregressive integrated moving average models (commonly referred to as the Box-Jenkins class of models).

Very simple statistical forecasting techniques are often referred to as naive forecasts and are frequently used as a basis for comparison of more sophisticated methods (28:51). They include the averaging of the periods (e.g., the 12 month cumulative average), moving averages, basing the next period's forecast on the last period actual data, and a forecast equal to the last period plus or minus some percent to account for trend.

Most of the more sophisticated forecasting techniques--more complex than the average of the periods or simple moving average--were developed after the mid 1950s (28:27). Exponential smoothing models, more complex forms of moving average models, were among the earliest examples. Decomposition models were also developed during this time period. These models separately account for trend, seasonality, cycle, and random noise (28:27). In the 1960s, the availability of computers allowed the more statistically complex methods of regression models to become popular. Finally, in the 1970s, Box and Jenkins developed a complex statistically based forecasting procedure "that was sufficiently general to handle virtually all empirically observed time-series data patterns" (28:27).

The basic assumption of all statistical models is that existing patterns observed in the data will continue into the future. For this reason, these models are best suited to short term forecasts. Furthermore, these models are unable to predict turning points, or when the rate of growth in a trend will change significantly (5:50).

Moving average models are among the simplest statistical models. Advantages are that they are easy to understand, easy to calculate, and have intuitive appeal. On the other hand, there are disadvantages to be considered. The more periods that are considered, the more the data are smoothed. The forecast will always lag the actual data on which it was based. These methods require maintaining a larger amount of data than the exponential smoothing techniques (28:55). For instance, a 12 month moving average model requires that 12 months of data be maintained, whereas an exponential smoothing model, to be discussed below, only requires the most recent observation and forecast and weighting value for the most recent observation.

Moving average models are of the form (20:89):

$$F_{t+1} = \frac{\Sigma X_i}{n}$$

where

F = forecast,

t = current time period,

i = from 1 to n periods,

n = an arbitrarily selected number of periods, normally selected based upon the expected seasonality of the data (20:89).

There are other variations of the moving average models, such as the weighted moving average, which places specific weights on previous time periods corresponding to their relative effect on the future.

To compensate for the systematic error that occurs when applying moving average techniques to data exhibiting a trend, linear moving average (or double moving average) methods were developed (17:56). With these methods, the first moving average is calculated, then the double moving average is taken on the first calculation. The difference, or error, between the single moving average and the double moving average is the trend. By adding this difference to the single moving average, the forecast is brought up to the level of the actual data (17:56).

Exponential smoothing models are a major category of forecasting techniques which address the two major limitations inherent in moving average techniques, namely, the large database requirement and the equal weight placed on each time period regardless of its distance from the present (17:48). Exponential smoothing models place more weight on recent data and considerably reduce the amount of historical data which must be maintained (17:48). Since the 1960s, "the concept of exponential smoothing has grown and become a practical method, with wide application, mainly in forecasting inventories" (17:80). The exponential smoothing models are variations of the moving average model of the form (20:91):

$$F_{t+1} = \alpha X_t + (1-\alpha)F_t$$

where

F = forecast,

α = a smoothing constant with a weight between 0 and 1,

X = actual value,

t = current time period.

The basic notion in using the smoothing techniques is that there is an underlying pattern plus random fluctuation in the historical data. The goal is to distinguish between the pattern and the randomness by smoothing (or eliminating) the extreme values. Exponential smoothing models are, however, easy for the user to understand and compute. Another advantage is the ability to adjust the α value according to the circumstances of the situation, i.e., whether more weight should be given to recent data or historical data. The exponential smoothing models, like moving average models, are inexpensive to apply and effective with horizontal patterns, but are not effective with trends and seasonality (28:55). In such cases, the forecast always lags the actual data for both the trend and season. Furthermore, depending upon the length of the season, the lag in the forecast may approach counter-cyclical movements. That is, the forecast may rise when the actual data values are falling.

An exponential smoothing technique similar to the linear moving average technique discussed above is known as Brown's One-Parameter Linear Exponential Smoothing. Applying the same principles, the double exponential smoothed values are calculated. These results are added to the single exponential smoothed values to correct for the trend (17:61).

Holt's linear smoothing is another variation of an exponential smoothing model and is effective for time series exhibiting a linear trend. It is similar to Brown's, but rather than double smoothing, it smooths the trend values directly (17:64). It is also more flexible, since the trend can be smoothed by a different value than the α applied to the original data. It uses two smoothing constants and three equations in the forecast (17:64):

$$S_t = \alpha X_t + (1 - \alpha)(S_{t-1} + T_{t-1})$$

$$T_t = \beta(S_t - S_{t-1}) + (1 - \beta)T_{t-1}$$

$$F_{t+1} = S_t + T_t i$$

where

S is the single exponential smoothed value of the series,

β is a smoothing constant with a weight between 0 and 1,

T is a smoothed value of the trend,

i is the number of periods into the future,

t is the current period, t-1 is last period.

The first equation updates the smoothed value directly for the trend of the last period, bringing it up to the approximate level of the current value and compensating for the lag. The second equation then updates the trend, the difference between the two prior smoothed values.

> Since there is some randomness remaining, it is eliminated by smoothing with β the trend in the last period ($S_t - S_{t-1}$), and adding that to the previous estimate of the trend multiplied by $(1 - \beta)$. [17:65]

The last equation computes the forecast by adding the trend times the number of periods into the horizon to be forecast to the base value (17:66).

Winter's Linear and Seasonal Exponential Smoothing model is similar to Holt's model except that it adds an additional equation to deal with seasonality. Each of the equations smooths one of the components of the time series; randomness, trend, and seasonality (17:72). As with all smoothing constants employed in the exponential smoothing models, the constants take on values between 0 and 1. The three equations are as follows (17:72):

$$S_t = \alpha\frac{X}{I_{t-L}} + (1 - \alpha)(S_{t-1} + T_{t-1})$$

$$T_t = \beta(S_t - S_{t-1}) + (1 - \beta)T_{t-1}$$

$$I_t = \tau\frac{X_t}{S_t} + (1 - \tau)I_{t-L}$$

where

L is the length of the seasonality,

τ is a smoothing constant with a weight between 0 and 1,

I is the smoothed value of the seasonal factor,

and Y is a smoothing constant with a weight between 0 and 1.

The forecast equation is the same as in the Holt model with the addition of the seasonal index factor:

$$F_{t+1} = (S_t + T_t i)I_{t-L+1}$$

Autoregressive integrated moving-average (ARIMA) models are another type of statistical or auto-projection models. They are more commonly referred to as Box-Jenkins forecasting models, after professors G. E. P. Box and G. M. Jenkins (8:222). Box-Jenkins methodology refers to a family of forecasting models rather than to one single model and can be categorized into three basic classes--autoregressive models, moving average models, and mixed autoregressive-moving average models (3:20).

The Box-Jenkins models employ a variety of statistical and mathematical techniques to "extract pertinent information from time series data, establish relationships among relevant factors, and extrapolate past behavior into the future" (14:9). These more advanced statistical or filtering techniques are applied to time series and "focus entirely on patterns, pattern changes, and disturbances caused by random influences" (8:6). The Box-Jenkins group of models is purely statistically based and does not explicitly assume that a time series is represented by the composition of separate components (i.e., trend, seasonality, cycle, and error)(8:7). They instead seek to identify and account for autoregressive and moving average factors affecting a time series. Several studies even concluded that the Box-Jenkins methods were as accurate as the much more complex econometric approaches (28:27).

Briefly, the autoregressive component refers to the property that the value of X_t in a series "is directly proportional to the previous value X_{t-1} plus some random error" (14:50). X_t may in fact be related to other values than just the one prior. The moving-average parameters, in contrast,

> ...relate what happens in period t only to the random errors that occurred in past time periods... as opposed to being related to the actual series values X_{t-1}, X_{t-2},... [14:51]

To successfully apply the Box-Jenkins forecasting method, most experts recommend that a minimum of 40 periods of data, and preferably 50 periods be used (14:30). While there are strong proponents of the Box-Jenkins approach to forecasting, it has not been widely applied to inventory control (26:69). The reasons cited are that the procedure is difficult to understand and to master, and the data must often be transformed to make it suitable for use. Finally, it is more costly than exponential smoothing methods (26:70).

> The thing to keep in mind with any form of time series analysis is that like all projection techniques, it relies on the proper identification of past patterns and their persistence into the future. More complicated forms of analysis can succeed in identifying more complex patterns. No form of time series analysis can even guess as to the probable persistence of the patterns, however. An understanding of why patterns have occurred, together with reasoned confidence in their persistence, should be reached before any form of projection forecasting is used. [16:80-81].

The Forecasting Process

Hoff stated that the development of a forecast should follow a systematic, six step process which includes (14:39):

1. Defining the forecasting problem.
2. Collecting and preparing the data.
3. Selecting and applying a forecasting method.
4. Reviewing and adjusting the preliminary forecasts.
5. Tracking the forecast accuracy.
6. Updating the forecasts and the forecasting system.

The first step requires that the forecaster have an understanding of the problem and the purpose of the forecast.

The second step involves gathering the data and ensuring that it represents what data are needed in order to make a forecast. Consideration must be given to adjusting or "cleaning" the data as necessary. This involves eliminating or adjusting for one-time or unusual events. Examples would be the effects of business closure due to severe weather or the effects of the occurrence of Easter in March or April on department store monthly sales.

Step three involves selecting the forecasting technique most appropriate for the data available, the forecasting problem, and the situation or environment that exists. Selecting a forecasting technique is covered in more detail below.

Step four involves combining the historical data, the forecast technique, and management experience and judgment to produce a forecast model. The model must be applied and the results of the preliminary forecast examined to determine if they are reasonable and consistent with the assumptions made (14:39).

Steps five and six involve comparing the output of the model to the actual future data to determine effectiveness of the model and whether adjustments are required. This is an iterative process that recognizes that forecasting models usually require refinement as time passes (14:39).

Selection of a Forecasting Technique

In selecting a forecasting technique, the purpose of the forecast and the nature of the forecasting environment must be considered. The following six factors to consider in picking a forecasting method were given by Chambers et al.:

1. The context of the forecast.
2. The relevance and availability of historical data.
3. The degree of accuracy desired.
4. The time period to be forecast.
5. The cost/benefit (or value) of the forecast to the company.
6. The time available for making the analysis. [5:45]

Two other factors which Wheelwright and Makridakis add are the availability of computer resources and software, and the simplicity and ease of application (28:34).

Context. The first factor, the context of the forecast, refers to the characteristics of the situation. The purpose of the forecast and the number of items for which forecasts are needed are important characteristics. For example, certain techniques require large amounts of data. A highly accurate technique which at first might seem attractive, would be unsuitable if it requires more data than are available to perform correctly.

Data. The second step necessary in the selection of the appropriate forecasting technique is to analyze the nature of the data. Cleary noted that the characteristics of the data being considered should play a crucial role in the selection of the forecasting methods (8:12). Such characteristics include peculiarities in the data, (i.e. discontinuities or abnormal values that may have been affected by unusual or one-time events); whether the data are constant/smooth or irregular; and whether trend, seasonal, and cyclical patterns are present (8:12).

Accuracy. After the appropriate data have been gathered, the requisite accuracy of the forecast must be decided upon. If a lesser degree of accuracy is required, then less complex, less time consuming and costly methods may be appropriate. To achieve greater accuracy, generally more data and more complex methods must be employed. This may necessitate extensive use of expensive computer time. Accuracy alone should not be the only factor in selecting a particular forecasting method, but should be weighed along with other considerations such as cost and ease of application. Also, it may be advisable to sacrifice some accuracy in favor of a forecasting technique that can signal turning points or provide other useful information (12:119).

There are numerous formulae to apply in measuring forecasting accuracy--the "goodness of fit" or how well the model reproduces the data that are already known (28:43). There are two categories of measures of accuracy, the descriptive and the relative accuracy measures. The mean error (ME), mean absolute deviation (MAD), mean squared error (MSE), root mean square error (RMSE), and standard deviation of errors (SDE) are the more common descriptive accuracy measures. The relative accuracy measures include the percentage error (PE), the mean percentage error (MPE), and the mean absolute percentage error (MAPE) (28:47). The formulae for these measures of forecasting accuracy can be found in most forecasting and statistics texts and are included as Appendix A.

When comparing different forecasting models, the measure of accuracy employed may determine which of the models appears to be the best. In other words, different forecasting models may be rated in a different order by different measures of accuracy. An important fact to remember is that the method used to evaluate the forecasting method may dictate the method to be used for the forecast (6).

Wheelwright and Makridakis reported on the accuracy of statistical forecasting methods (exponential smoothing, decomposition, Box-Jenkins) versus causal methods (econometrics). Although their review of the literature revealed inconsistencies, they concluded that "explanatory models do not provide significantly more accurate forecasts than time-series methods, even though the former are much more complex and expensive than the latter" (28:264). They also reported that the accuracy of causal methods degraded considerably for forecasts beyond three periods into the future.

The accuracy of the many different forecasting techniques was compared in competition (later known as the M-Competition) in which experts in each of the main time series forecasting methods prepared forecasts for up to 1001 actual time series (28:265). Twenty-four methods were compared based upon their mean absolute percentage error (MAPE) for forecasts covering ten different time horizons from 1 to 18 months. The results indicated that "increasing the complexity and statistical sophistication [did] not automatically mean an improvement in forecasting accuracy" (28:265). Simplicity was found to be a positive factor. In addition, combining forecasts obtained by various methods was found to work well (28:272).

Wheelwright and Makridakis presented graphs that compared forecasting accuracy with perceived complexity in grading different forecasting techniques for appropriateness (28:274). The complexity index was based upon the judgment of the authors. As the graph, Figure 3, shows, there is a tradeoff required between higher accuracy and greater complexity. The Parzen and Lewandowski forecasting techniques referred to in the chart are two other methods the authors discuss in their text. Though highly accurate, they are complex and are infrequently applied.

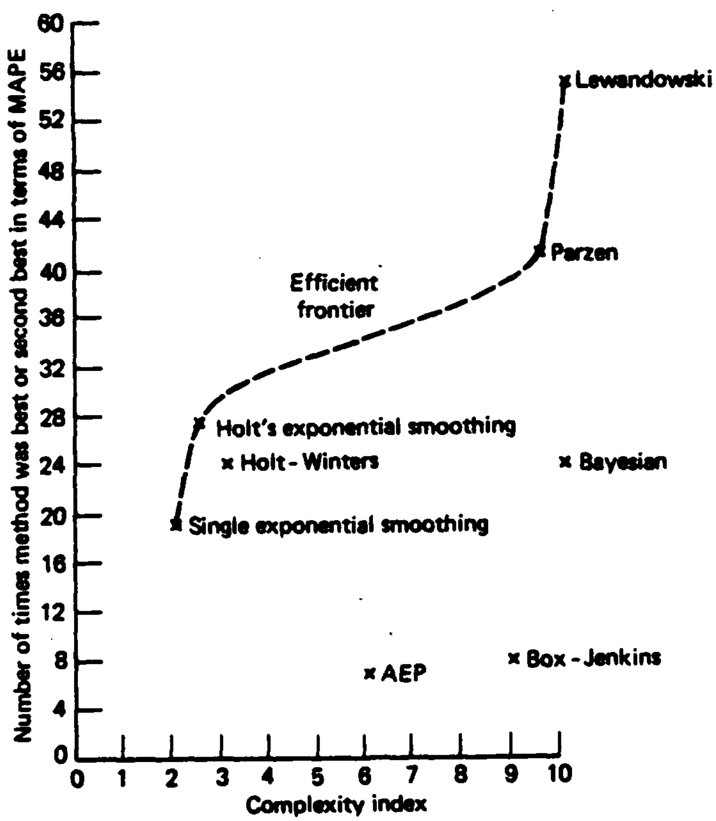

Figure 3. Efficient Frontier for Time-Series Forecasting Methods

Source (28:273)

Time Period. Often a relevant factor in determining the acceptable accuracy is the time span of the forecast. Different models provide different degrees of accuracy for different time horizons. The degree of accuracy is important, since forecasting techniques that offer greater accuracy are generally more time consuming and costly to employ.

The period to be forecast may be important if considering the life cycle of a product, known advances in technology, or changes in the general economy. Wheelwright and Makridakis categorize forecasts as immediate, short term, medium term, and long term. Immediate term (less than one month) would be used in considering scheduling production and in factoring weather conditions. Short term (one to three months) includes such things as the demand for materials and product demand. Medium term (three months to two years) would be used for such things as considering labor strikes or transportation facilities. Long term (two years or longer) would be appropriate for considering total sales and expansion of warehouses (28:22).

Cost/benefit. The cost/benefit analysis is another factor for consideration in the selection process. Chambers warned against the tendency of the forecaster to use a more sophisticated forecasting method in lieu of a simpler method which would produce acceptable accuracy. He referred to this as a "gold plated" result which is of "potentially greater accuracy but that requires nonexistent information or information that is costly to obtain" (5:46).

Time Available for the Forecast. The time available to make the forecast is often a deciding factor in which forecasting technique to employ. Application of some forecasting techniques require large amounts of historical data, and the data must be prepared, or adjusted to remove outliers, account for uncharacteristic one-time events in the data. Such actions may require much more time than is available to develop the forecast. If only a short time is available, the forecaster may have to forego a more accurate forecasting method because of its complexity and the time required to apply it.

The Availability of Computer Resources. Due to the complexity of some of the forecasting techniques and the quantities of data which must be manipulated, computer support may be essential to apply certain models. For example, the computations necessary to employ the Box-Jenkins forecasting models are too complex and time consuming to perform without the use of a computer program (14:29). In the Winter's Exponential Smoothing model, the smoothing values to use for α, β and τ which will minimize the forecasting error must be determined by trial and error. The iterative process of incrementally changing the values in the direction of change that reduces the MSE requires the use of a computer (28:75). These are but two of the many cases of models that require computer resources for model application.

Simplicity and Ease of Application. In some respects this factor relates to both the cost versus benefit to be derived using a specific forecasting model and the availability of computer resources. Another consideration, however, involves the "understandability" of the model. It is important to note that studies have shown (28:34)(11:93)(23:6) that managers will distrust and tend not to use forecasting methods that they do not understand.

Armstrong is a strong advocate of using the simplest forecasting method which produces an acceptable result. In addition, they are cheaper, easier to apply, and often produce more accurate forecast than more complex models (23:6). Nevertheless, there is the tendency to invest in complex models.

> The rain dance has something for everyone. The dancer gets paid; the client gets to watch a good dance; the decision maker gets to shift the problem on to someone else in a socially acceptable way. (Who can blame him?) He hired the best dancer in the business. The major shortcoming of the rain dance is that it focuses the problem on something outside of us. The problem is due to the odds or to the environment--not to us. This attitude is more comfortable, but it is seldom valid in forecasting. Most problems in forecasting come from ourselves. For example: (1) we like to adjust to suit our biases, (2) we put too much faith in judgmental methods, (3) we fail to consider the relationship between the forecasting method and the situation, and (4) we confuse measurement models with forecasting models. [2:399]

Alternate forecasting techniques to that presently used might produce better management of medical supplies. The "best" method is not known, although several factors suggest improvement is possible over the 12 month moving average currently used in conjunction with the EOQ model.

The methodology used in this research to evaluate the various forecasting techniques to manage medical supply inventories follows in Chapter III.

III. Methodology

This thesis utilized a combination of methods to solve the research problem. First, the literature on inventory control and forecasting was reviewed, with the focus on the health care industry. Air Force Manual 67-1, Volume 5, Air Force Medical Materiel Management System - General; and Air Force Manual 167-230, Medical Materiel Management System On-Line (MMMS-OL) were reviewed to gain an understanding of the medical supply inventory control system and MEDLOG. Medical logistics personnel at the USAF Medical Center Wright-Patterson and senior medical logistics personnel at the Air Force Medical Logistics Office at Frederick, Maryland were also interviewed for information regarding the operation of the current Air Force system.

From a review of the literature, three forecasting techniques were selected which might offer an improvement over the 12 month moving average currently employed to forecast medical supply demand. Next, workload and medical supply demand history data were requested from a sample of Air Force medical treatment facilities (MTFs). The data were analyzed for an understanding of the system. Finally, simulation was used to test the relative effectiveness of the selected alternative forecasting models against the current method used to forecast the demand figure for use in the EOQ formula. The following pages elaborate upon these steps of the methodology.

Data Collection

A sample of Air Force MTFs representative of the size distribution of all MTFs in the Air Force was selected. The MTF sample was gathered employing a proportionate stratified selection plan (10:306) designed to choose facilities based upon the following categories: clinics, hospitals, and regional hospitals/medical centers. The first category accounts for 32% of the total Air Force MTFs, the second: 49%, and the third: 19%. Three were needed from the first, four from the second, and two from the last category. In order to obtain this sample of nine, requests were made of 18 MTFs selected from the approximately 40 MTFs with MEDLOG installed and operating for three or more months. These facilities were randomly selected, with the exception of Wright-Patterson, which was chosen for convenience in gathering data.

The above MTF classification system used by the Air Force was employed in selecting the study sample since it was known from experience that workload and supply usage varies between different sizes of facilities. Although not known before the research, it was suspected that the data within each MTF category would vary less than the variation found in the sample of all facilities combined. This assumption was statistically tested and shown to be accurate. Details of this test are discussed later in Chapter IV.

The MTF classifications are generally set up according to services offered, size (number of inpatient beds), and workload, though there are other factors involved. Clinics only provide outpatient (ambulatory care) services, whereas hospitals and regional hospitals/medical centers also provide inpatient services. Regional hospitals and medical centers will usually have greater workload than hospitals, which in turn have higher workload statistics than clinics. It must be noted, however, that some Air Force clinics experience higher workload (monthly outpatient visits) than some small Air Force hospitals.

The next step was to request data from the MTFs in the sample group. The requested data included actual total medical expenditures (accounting code EEIC 604), the number of outpatient visits (OPV) per month, number of admissions (ADM) per month where applicable, and the number of occupied bed days (OBD) per month where applicable, for fiscal years 1985 through 1987. Clinics do not admit patients and therefore do not have data for admissions and occupied bed days.

Since one objective of collecting the data was to show a statistical relationship between workload and the demand for medical supplies, broad workload measures were also selected. The broadest and most frequently used measures of workload tracked by Air Force MTFs include OPVs, admissions, OBDs, and average daily patient load. All these measures apply to more than one workcenter, even in small facilities.

Examples of other common workload measurements include births, dental clinical treatment visits, X-Ray films exposed, and laboratory procedures. Although it is logical to assume that there might be a relationship between these more specific workload measurements and usage of certain supply items or stock classes, this research sought to disclose relationships with broader application, i.e., pertaining to most workcenters. The data received from the MTFs appears in Appendix B.

Tests for Correlation

To answer research question 1, which asked whether there was a high degree of correlation between workload and demand, regression analyses were performed on the data from each MTF. Correlations between the workload measures and actual total medical supply expenditures were computed. For clinics, this involved performing correlation analyses on the total medical supply expenditures (accounting code EEIC 604) and outpatient workload data to show the degree of relationship (Pearson product-moment coefficient "r"). For hospitals, analyses were conducted between the OPV, ADM, OBD, month data and EEIC 604 data.

Next, the same analyses were separately conducted for each of the 15 medical supply items and for each of the 13 MTFs to determine the degree of correlation between individual supply item demand and workload.

To explore the possibility of an explanatory (causal) forecasting model which would use workload measure(s) to predict item demand, the SAS statistical computer program RS-REG procedure was used. RS-REG tested for possible quadratic or cross-product effects of the independent variables (workload) on the behavior of the dependent variable (item demand). This tested not only for linear models (i.e., Dependent Variable = $\beta_0 + \beta_1 X_1$), but also for complete second order models with two or three independent variables and interaction (i.e., Dependent Variable = $\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + \beta_4 X_1^2 + \beta_5 X_2^2$). If the procedure pointed to a model in which changes in the independent variables accounted for a large percentage of the variation in item demand (large r^2, coefficient of determination), then the model was further investigated using the SAS procedures: REG, for regression analysis; and STEPWISE, for model parameter selection.

Probability Distributions of the Demand Data

A SLAM II simulation program, discussed in greater detail below, was used to generate the demand data against which to test the various forecasting techniques. To simulate demands that were representative of the size and variation of the empirical data gathered, the statistical characteristics of the data had to be determined. Analysis of variance (ANOVA) procedures would be the common procedure to use in such a case to test whether all the samples were drawn from a common population or whether there were statistically significant differences in the means due to facility classification. This would have answered research question 2. ANOVA, however, requires the assumption that the population probability distributions are normal.

The histograms of the data were then inspected to determine which standard distributions they might fit. Finally, the Chi-Square goodness of fit test was performed on the data and the suspected standard distribution. Histograms of the monthly quantities ordered of each item revealed that the sample distributions were distinctly non-normal. Therefore, the coefficient of variation was computed.

The coefficient of variation is a unitless measure of the amount of variation in the data, and is useful in comparing the variation between two or more sets of data (21:37). It is computed by dividing the sample standard deviation by the sample mean. Using this measure, the amount of variation within the data was compared for all MTFs taken together as a single group; for the MTFs grouped according to size: clinic, hospital, regional hospital/medical center; and for MTFs grouped according to OPV workload.

Tests for the Presence of Seasonality

The time series data were then tested for the presence of seasonality. The 12 months of data for the individual items were plotted by MTF size group for a visual inspection of possible seasonality, and to answer the research question as to whether demand patterns for major stock classes were common to all Air Force MTFs.

Next, the 36 months of EEIC 604 total medical supply expenditure data and the workload data were examined for a common pattern. The time series were converted into a standard base by computing the mean of the series and then dividing each data point by the mean. Only a visual inspection was possible to draw conclusions about the similarity of the plots to determine if there was a medical supply usage pattern common among Air Force MTFs. Since the original data (raw workload and dollar expenditures) differed greatly in magnitude, the time series clearly did not come from the same populations. There was, therefore, no statistical test that could be applied to the time series plots of the nine MTFs to quantify their degree of fit (7).

Computing Seasonality Indices

Seasonality indices were computed as described by Meredith (20:101). This was done by first fitting the least squares regression line to the 12 months of actual demand history for each of the 15 medical supply items. The regression equation was then applied to determine the computed monthly trend value. Next, the actual monthly value was divided by the computed value of the trend to arrive at an index.

Had a strong correlation been found between workload and usage, workload data would have been used to provide a more robust basis for the index. Computing seasonal indices from more than 12 months of medical supply demand data would also have produced more accurate results since each month's index could have been averaged across the years. The correlation was too low, however, and only 12 months of data were retained in the supply system. An alternative method was necessary.

The shortcomings of trying to compute annual seasonality from only 12 months of data were recognized. The 12 months of supply data, being all that were available, also forced creation of a different method of comparing forecasts. The traditional method of testing forecasting accuracy is to compare the forecast against actual "hold out" data from the same time series. In this case, not enough data were available. As an alternate method, simulation was used to test the various forecasting techniques.

As can be seen from the procedures outlined above, the seasonal indices used in the simulation were somewhat inaccurate. This was due to the fact that the indices computed as being strictly seasonal actually also contained random noise. However, for purposes of simulation, all that was needed was to inject a seasonal pattern. The seasonal indices used for the test, although likely included random error of unknown magnitude, were at a minimum derived from the actual data.

Selection of Forecasting Techniques to be Tested

From the literature, appropriate forecasting techniques were identified for use with the Air Force Medical Service inventory control system. Moving average models, various exponential smoothing models, and the Box-Jenkins category of time series models were considered.

The Box-Jenkins time series models were not selected for testing for two reasons. First, their operation is complex and difficult to understand; and second, they require a minimum of 40 periods of data, with 50 or more recommended. As discussed in Chapter II, model simplicity and "understandability" have been found to be a major factor in model acceptance and effective use. Box-Jenkins models rank low in both simplicity and understandability. See Figure 3 in Chapter II. Furthermore, only 12 months of data were available for actual medical supply demand, and generally only 36 months of workload data were available.

Causal models were not considered, since preliminary analysis failed to establish a common relationship between the broad workload measures and supply usage. In addition, causal models are more complex, costly to administer, and require forecasting levels of the independent variable(s) prior to forecasting the dependent variable, as noted in Chapter II. The failure to find strong correlation between workload measurements and supply usage will be discussed in greater detail in Chapter IV.

A number of common forecasting models were initially considered for testing: three month moving average, simple exponential smoothing, Holt's Two Parameter Exponential Smoothing, Winter's Exponential Smoothing, a linear regression model incorporating seasonal indexing, and Box Jenkins. Three models were ultimately chosen for testing based upon their ability to handle trends and seasonality, ability to recognize pattern changes, their data requirements, and their ease of application and simplicity (the ability of the materiel manager to understand the forecasting model's operation). Based upon the research discussed in Chapter II, the following rating system was employed.

Table II

Ratings of the Forecasting Methods Considered

Model	Simplicity	Data Points Req'd	Ability To Handle Trends	Ability To Handle Seasonality	Responsive To Change
3 Mo Moving Average	Excellent	3	Poor	No	Poor
Exponential Smoothing	Excellent	2	Fair	Poor	Fair
Holt	Good	2	Good	Poor	Good
Winters	Fair	2	Good	Good	Good
Linear Regression w/Seasonal Indexing	Good	12	Good	Good	Poor
Box-Jenkins	Poor	40-50	Good	Good	Fair

The techniques selected were simple exponential smoothing, a linear trend model incorporating seasonal indexing, Winter's three parameter exponential smoothing model.

To determine appropriate values for the Winter's exponential smoothing constants α, β, and τ, the computer program Forecast Master was used. This commercially available program runs on a personal computer and produces forecasts employing a variety of methods. In this case it was only used to perform the iterative process of selecting appropriate values for the smoothing constants required by the Winter's model. The actual demand data for each supply item and MTF combination (15 items x 3 MTF categories) were entered into Forecast Master and the three values for the smoothing constants computed, producing the 45 equations necessary for the research test. Alternatively, the constants could have been assigned values in much the same manner as the single smoothing constant is selected in simple exponential smoothing--by examining the plot of the data and judging how much weight should be given to the more recent data versus historical data.

<u>Applying the Forecasting Techniques and Measuring Accuracy</u>

The three models were tested, along with the presently employed 12 month moving average model in the computer simulation of monthly demand for each of the medical supply items. The program was written using SLAM II simulation language and Fortran subroutines. An annotated listing of the SLAM II program appears as Appendix C.

The purpose of using simulation in this research was to generate realistic "actual" demand data against which to test the forecasts for each technique. As noted previously, the preferred method to test the different forecasts would have been to prepare forecasting equations based upon the first 24 months of the 36 months collected. Forecasts would then be made for the remaining 12 months and compared against the actual 12 months "hold out" data to determine accuracy. In this case there was insufficient data to perform such an analysis, hence the use of simulation.

To generate realistic data on which to prepare forecasts, the nature of the real demand data had to be understood. The mean, standard deviation, and coefficient of variation were computed on the actual demand history of each of the 15 medical supply items. As described above, the data were grouped by MTF category and histograms drawn to determine their distributions. This was important since using a normal probability distribution in the simulation might have led to erroneous results if the data in fact exhibited a different distribution.

Briefly, 39 simulations were run; one for each of the combinations of supply item and MTF category having data. Each run tested the four forecasting techniques. This was done to simulate actual demand based upon the frequency distributions found to apply to the data, the statistics derived from the data, and the trend and seasonal components extracted by the least squares regression. Each technique was simulated for 48 months with 25 repetitions of each four year period, each time using a different random number seed. Running each simulation 25 times and taking the averages increased the level of confidence for the findings.

To ensure model validity, the SLAM II simulation program was written in an incremental process. That is, the skeleton program was written with enhancements added incrementally and tested. For example, the program was first written with subroutines for only two months. The procedure to produce a simulated actual demand figure based upon a given starting value and trend and drawing from a given standard distribution was added. The SLAM II MONTR TRACE statement was used to produce an output which traced each step taken by the program and printed the values of the attributes and variables at each step. The same steps were performed manually to ensure that the computations performed by the simulation program were correct, that its program branching occurred as planned, and that the logic employed was correct.

This testing of model validity was repeated with the addition of each new function or subroutine, e.g., computing the moving average, exponential smoothing, linear trend, and Winter's exponential smoothing forecasts; and computing the various measures of forecasting accuracy.

Each forecasting model forecast two periods in the future (F_{t+2}) to make the simulation more closely reflect the real world operations of a medical supply function. To allow time for ordering and shipping, the forecast would have to be available at least 30 days in advance for the supplies to be received prior to being needed.

The four forecasting model predictions were compared against the "actual" demand generated by the simulation. The differences were computed and used to rate the forecasting techniques based upon three measures of forecasting accuracy.

In Chapter II it was noted that there are two categories of measures of forecasting accuracy: descriptive and relative. As measures of forecast accuracy, two descriptive measures, the mean absolute deviation (MAD) and the mean squared error (MSE) were chosen. The mean absolute percentage error (MAPE) was chosen as a relative accuracy measure. The selection of specific measures was arbitrary since all of the various measures of accuracy reviewed in Chapter II are widely accepted. It was appropriate to use more than one measure, rather than deciding on a single method as the "best" indicator of accuracy. This is due to the fact that different measures will sometimes produce different relative ratings depending upon the manner in which they weight the differences between the forecast and the actual data.

To compute the MSE, MAD, and MAPE for each supply item and MTF category combination, the mean values for each measure (average of the 48 months) for each of the 25 runs were averaged.

The overall results of the accuracy of the forecasting techniques were summarized and the Friedman test of a randomized block design performed. This was done to determine if results indicated a statistically significant difference in the accuracy of the four forecasting methods.

In addition to measuring accuracy of the four forecasting techniques, a subroutine was added to the simulation program to determine whether the monthly forecast was above or below the simulated actual demand. Each of the 48 monthly forecasts was tested in this manner to produce a count that was used as a subjective valuation of each of the forecasting techniques. If, for example, two techniques had approximately the same measurements of accuracy, but one tended to produce forecasts over the actual amount while the other tended to forecast below the actual, the former technique was better. In the case of medical supplies, carrying a slightly larger inventory than necessary is better than experiencing out of stock conditions.

The figures reflecting the number of times over/under the actual demand also conveyed other information about the particular forecasting method and the demand data against which it was applied. This will be discussed in greater detail when the actual results of the analyses are presented in the next chapter.

The testing of the different models for different MTF categories answered the research question regarding whether the range in size and services of MTFs would preclude application of a service-wide model.

The methodology described in this chapter has been lengthy and complex. Multiple measures were required and several techniques had to be employed to ensure that unbiased tests could be performed on the four forecasting techniques.

The extensive method was necessary, as has been stated, due to the limited amount of data available. The following chapter will review the findings of the analyses described above.

IV. Analysis

Overview

This chapter is divided into four sections corresponding to the methodology of the research discussed in the preceding chapter. The first section presents the results of the correlation between workload and the total expenditures for medical supplies (accounting code EEIC 604). The correlations between the workload measures and the actual unit demand are also given. Both the very limited quantity of data and the nature of the distributions contributed problems to the analyses. Those problems are discussed.

The second section looks at the characteristics of the distributions of the 12 months of actual demand data for the 15 medical supply items in the sample. Sample histograms of the distributions are presented, and the reasons behind the data occurring in particular distributions are explored.

The next section discusses the occurrence of seasonality and trend in the demand data. Those components of the time series were extracted and quantified for later application in both the simulation and forecasting techniques. The trend factors and seasonal indices prepared for use in the simulation are summarized.

The final section presents the simulation results and summarizes the forecasting accuracy of the currently used 12 month moving average forecast and the three alternative forecast techniques applied. Tables are included which summarize the effectiveness of the alternative forecasting techniques, with additional data included in the appendices.

As mentioned in the previous chapter, workload and medical supply expenditure and demand data were requested from 18 medical treatment facilities under a proportionate stratified selection plan. The workload and expenditure data were requested from the facilities' Medical Resource Management Offices, and the demand data from the Medical Logistics Offices. Seventeen of the eighteen MTFs responded with the demand data. Fifteen of the eighteen submitted workload and expenditure data. The demand data were provided in the form of a standard MEDLOG computer report giving the 12 months of history maintained. The workload and expenditure data, however, were not maintained in a standard format at the facilities. Some MTFs were unable to submit more than 18 months of data, while others sent 36 months. EEIC 604 medical supply expenditure data were a frequent problem. Many MTFs could only supply 12 to 24 months of data. Others were able to provide only quarterly, rather than monthly data. The data are provided in Appendix B for reference.

Data from nine facilities were used in the studies of correlation between workload and medical supply expenditures, as will be discussed below. Data from 13 MTFs were used in analyses of correlation between workload and demand.

Statistical Relationships Between Workload and Supply Data

Workload - EEIC 604 Expenditure Correlation

As with all time series data, a useful first step is to plot the data. This was done with the workload and supply expenditure data. The data were first standardized and graphs, such as the one below, were made for each medical treatment facility for each variable.

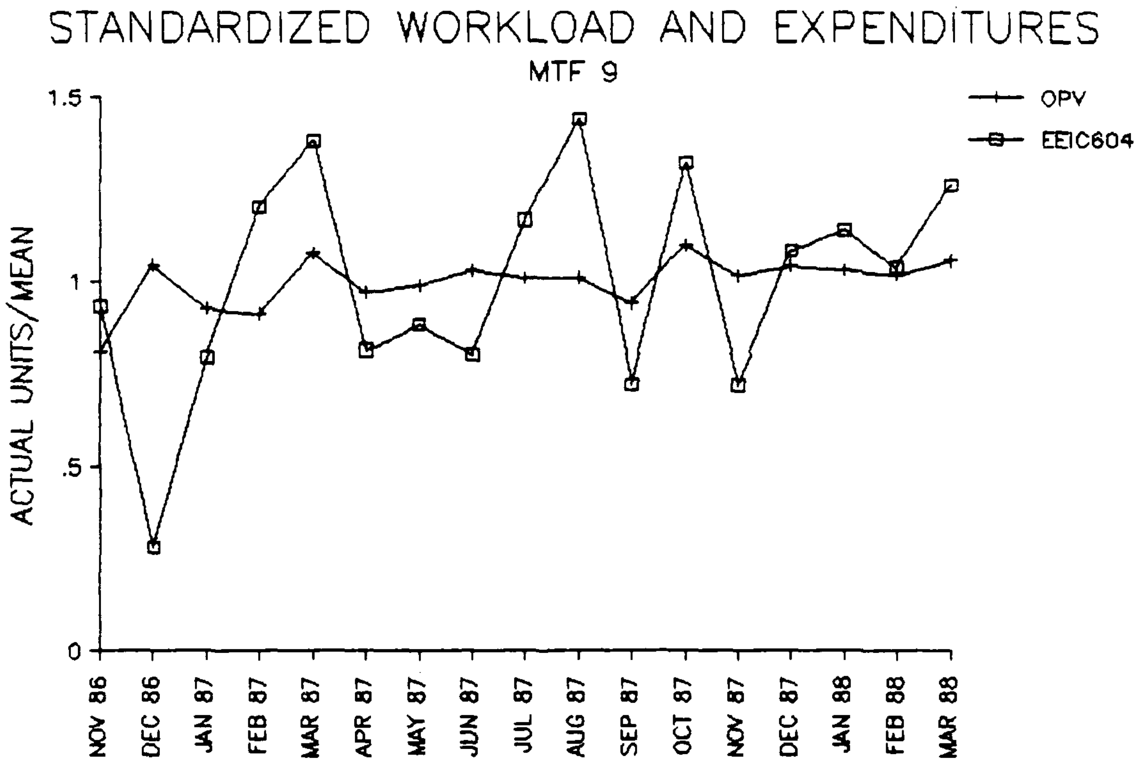

Figure 4. Standardized Workload and Expenditures

Visual inspection of the graphs indicated the strong possibility of trends and seasonality in both workload and expenditures, but a relationship between the two was not clearly evident.

The same workload measures for different MTFs were standardized and plotted together to allow identification of facility-wide common patterns. This was also done for EEIC 604 expenditures. Figures 5 and 6 are examples of the graphs.

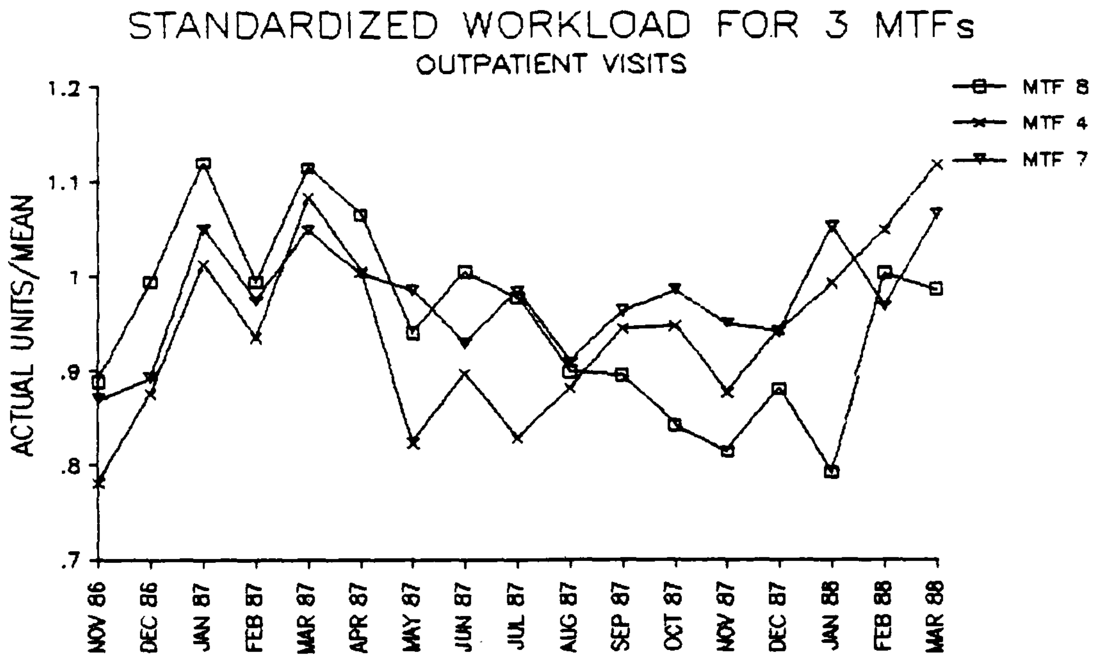

Figure 5. Standardized Workload for 3 MTFs

Although some MTFs exhibited similar patterns in plots of their workload and EEIC 604 expenditures, the majority either exhibited poor fit or no apparent fit at all. As noted in the methodology chapter, there is no method that will give a statistic representing the closeness of fit between two or more such time series patterns. Therefore, any conclusion that the workload or expenditure data followed

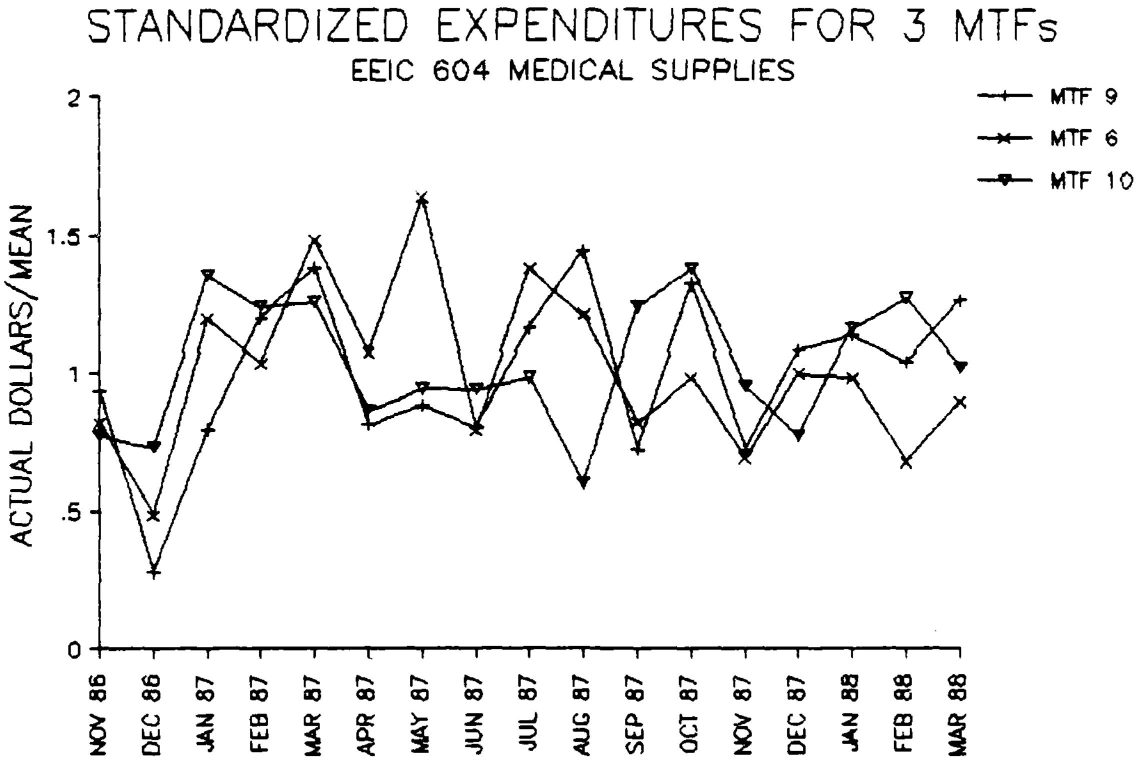

Figure 6. Standardized Expenditures for 3 MTFs

common seasonal patterns was largely subjective. The graphs did indicate, however, that there was a common underlying seasonal pattern that was followed in approximately half of the MTFs. For instance, in nearly all cases, both the workload and EEIC 604 data dipped during November and December and showed high levels in January and March.

The monthly EEIC 604 expenditures and the workload measurements of outpatient visits (OPV), admissions (ADM), and occupied bed days (OBD) were tested for correlation. That analysis resulted in a finding of only weak correlations in some cases, with only two meeting the arbitrarily set criteria of a correlation of r^2 of .50 or greater at a t probability of .05 or less. Table III summarizes those findings.

Table III.

Significant Correlations Between Medical Supply Expenditures and Workload Data
(Significant: $r^2 > .50$ at $t < .05$)

	Workload Measure		
Facility	OPV	ADM	OBD
MTF 1 (Clinic)	.50	N/A	N/A
MTF 2 (Clinic)	-	N/A	N/A
MTF 3 (Clinic)	*	*	*
MTF 4 (Clinic)	*	*	*
MTF 5 (Hospital)	-	N/A	N/A
MTF 6 (Hospital)	-	-	-
MTF 7 (Hospital)	*	*	*
MTF 8 (Hospital)	-	-	-
MTF 9 (Hospital)	-	-	.54
MTF 10 (Regional Hosp)	-	-	-
MTF 11 (Regional Hosp)	-	-	-
MTF 12 (Regional Hosp)	-	-	-
MTF 13 (Medical Center)	-	-	-

Notes: * = Insufficient data supplied by MTF
- = No significant correlation

The dollar expenditures for medical supplies (EEIC 604) were not adjusted for inflation before use in correlation analysis. The quantity of data supplied was in most cases between 24 to 36 months, so the difference was assumed to be minimal.

The original purpose of the analysis was to show a strong correlation between workload and expenditures so that an explanatory forecasting model might be developed. Failing to find such a relationship at a broad level (aggregate spending for medical supplies), the 12 months of demand history for the sample of 15 medical supply items were examined.

Statistical Relationship Between Workload and Demand

The workload data were extracted from the workload reports sent by the Medical Resource Management Offices from each MTF. The individual medical supply demand data were extracted from the Special Stock Status Reports submitted by the Medical Logistics Offices at each MTF. The twelve months of data for the applicable workload factors and the fifteen supply items were combined. The data can be found in Appendix D.

The demand data for the medical supply items within each stock class were plotted on the same graph to determine if there were common demand patterns for stock classes. Examples are given below in Figures 7 and 8. Although some similarity was noted, the commonality was not strong overall. Furthermore, plots of items not of the same stock class, but for the same MTF, tended to show a similar degree of agreement in the shape of the demand pattern. This finding suggested that demand patterns were MTF unique.

Next, the demand data for each item were aggregated; in total, by MTF classification (clinic, hospital, regional hospitals and medical centers), and by outpatient workload. This was done to test the variation of the data within grouping schemes and to test whether the data came from the same population (had the same sample mean). As discussed in Chapter III, some clinics experienced higher workload than some

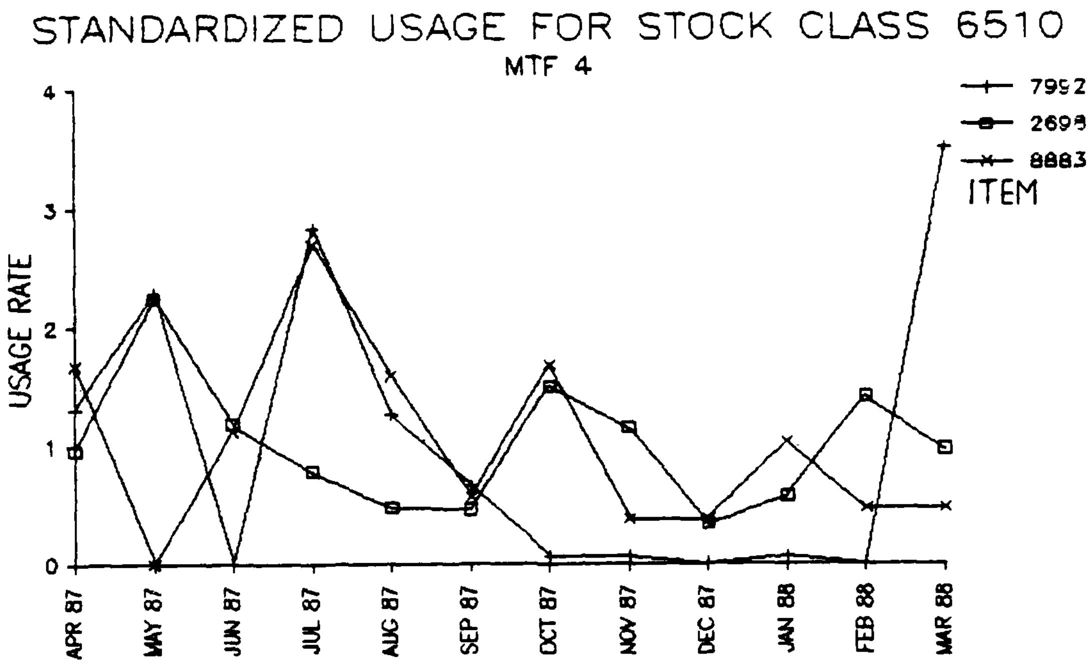

Figure 7. Standardized Usage for Stock Class 6510 (MTF 4)

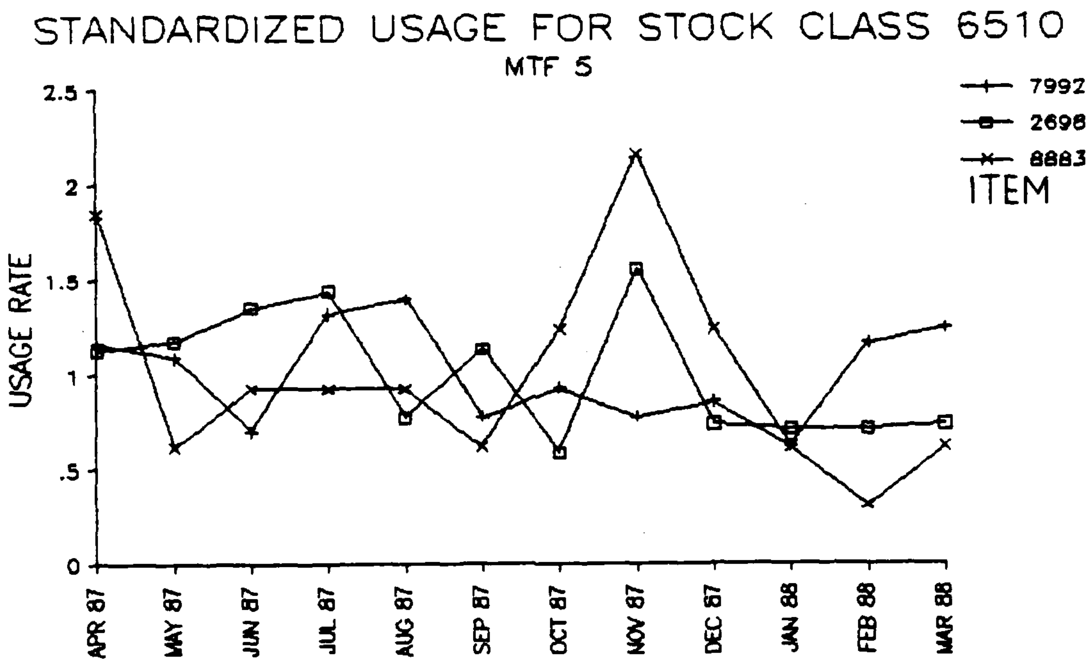

Figure 8. Standardized Usage for Stock Class 6510 (MTF 5)

hospitals, which was the reason for also testing the grouping of the data based upon MTF workload.

The coefficients of variation, a measure useful for comparing the variation of different groups of data, were computed. Table IV, below, shows the results of the three groupings.

Table IV

Covariance of Various Data Groupings

Grouping Scheme	Medical Supply Item (last four digits) -9080	-6541	-8985	-3458	-7992	-2698	-8883	-7277	-2089	-6606	-9377	-6752	-0162	-1786	-4191
Grouping Scheme I															
All MTFs Combined	2.14	2.37	1.80	1.05	1.83	.88	2.30	2.20	1.35	1.78	1.17	*	.96	.92	1.12
Grouping Scheme II By MTF Category															
Clinics	1.11	2.29	.82	1.15	1.40	.07	1.46	1.44	1.43	1.26	.97	*	1.15	*	1.46
Hospitals	1.14	2.05	.87	.65	1.43	.60	1.05	.95	1.31	*	.90	*	1.05	.60	.61
Regional Hosp/ Med Ctrs	1.42	1.55	1.37	.68	1.01	.56	1.48	1.27	1.03	1.79	1.11	*	.61	.51	.46
	----	----			----	----			----					----	----
Grouping Scheme III By Workload															
			----	----			----	----		----	----		----		
Low	.88	1.52	.87	.94	1.49	.68	.93	1.37	2.29	1.03	.86	*	.69	.56	1.77
Medium	1.39	3.01	.75	.73	1.42	.58	.95	.90	1.95	1.15	.82	*	.73	.64	.51
High	1.42	1.55	1.37	.68	1.01	.56	1.48	1.27	1.03	1.79	1.11	*	.61	.51	.46

* = Insufficient data - some facilities did not order this item
--- Indicates lower overall group covariance, better grouping (comparing only scheme II and III)

To determine the relative strengths of the grouping methods, individual MTF category covariances within each scheme were compared against the single covariance figure for scheme I. As an example, the covariance for demand for medical supply item 9080 for all MTFs grouped together was 2.14 (from Table IV). Compared to scheme II and scheme III, lumping all MTF data together resulted in greater within group variance. It is obvious then, that segmenting the data reduced variance.

To compare scheme II against scheme III, the figures for the former (1.11, 1.14, and 1.42) were summed for a total of 3.67. That figure was meaningless in itself, but was used for comparison against 3.69, the corresponding figure from scheme III. For item 9080, scheme II was judged the better.

As the table indicates, the variation of the data in almost all cases was less when grouped either by MTF category (grouping scheme II) or based upon MTF workload (grouping scheme III) than when aggregated for all the facilities (grouping scheme I). The results of grouping by MTF category and workload grouping schemes were similar.

In 7 of the cases, the MTF category grouping appeared to be better, and in 7 of the cases, the workload grouping appeared to have the least variability in the data. Grouping according to workload, however, is a more complicated procedure requiring definition of the ranges of workload for particular groupings and deciding upon which workload measurement to base the grouping. Basing groups upon different workload measures (i.e., OPV, ADM, or OBD) would likely result in different group membership in some cases. For simplicity, the MTF category grouping scheme was used throughout the analyses.

To determine if the data grouped by MTF category had different means, and therefore should be grouped, the Friedman F_r test for a randomized block design was applied to the data. This nonparametric test was chosen instead of the more common parametric since the assumption that the data came from normal probability distributions was violated. This test rejected the null hypothesis that the distributions were the same, supporting the blocking (grouping) design.

The demand data for each sample medical supply item was grouped according to MTF category, the means and standard deviations computed, and the distributions plotted on histograms, such as those below.

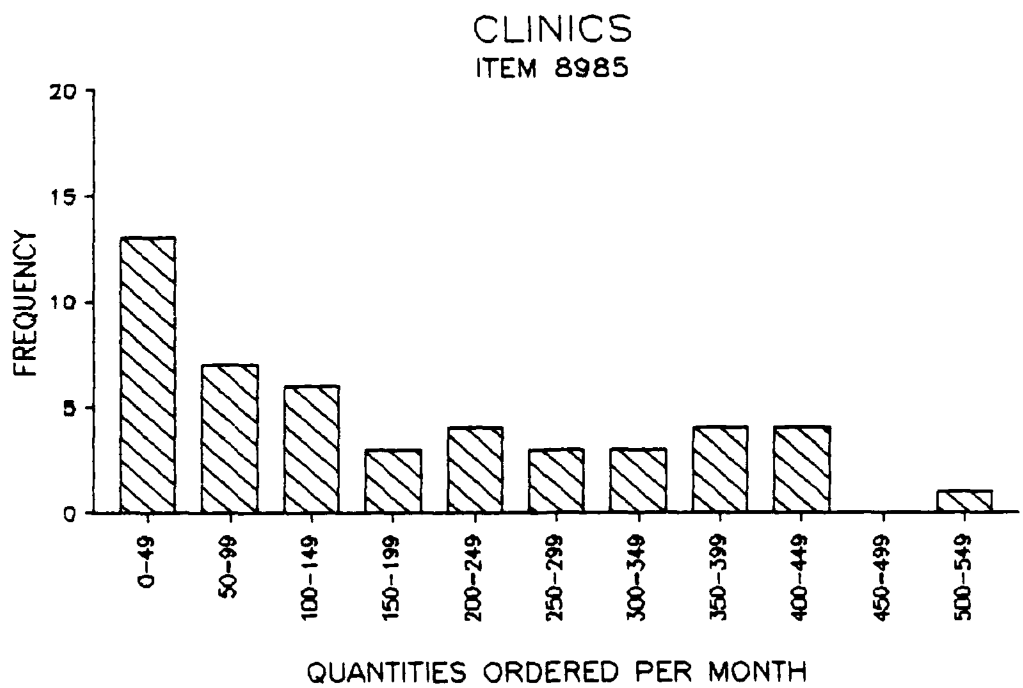

Figure 9. Frequency of Occurrence of
Monthly Order Quantities (Item 8985 - Clinics)

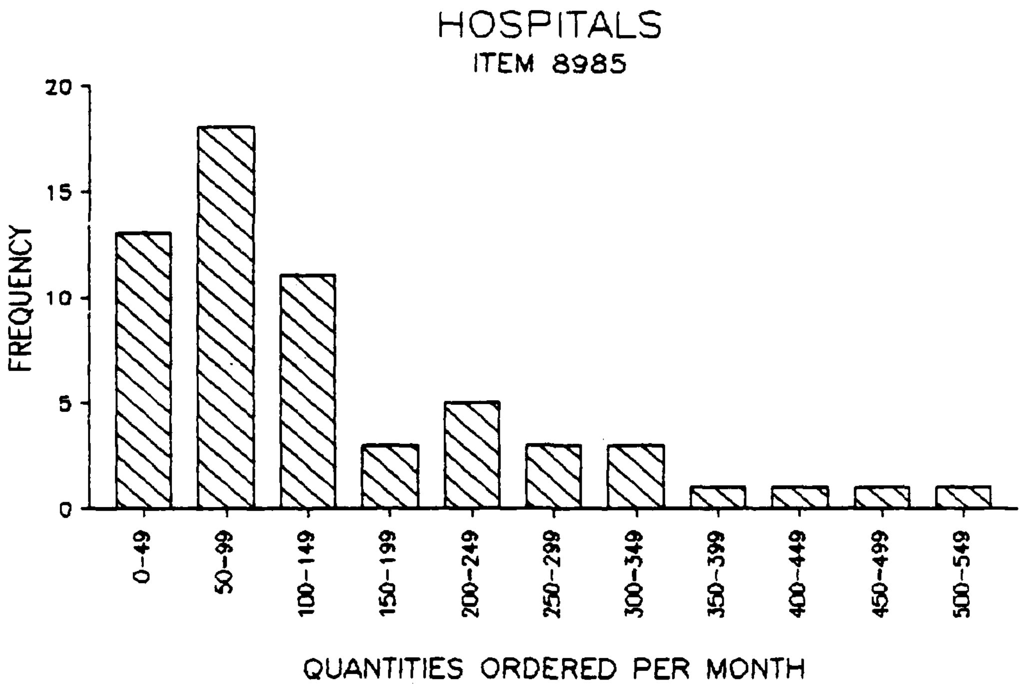

Figure 10. Frequency of Occurrence of Monthly Order Quantities (Item 8985 - Hospitals)

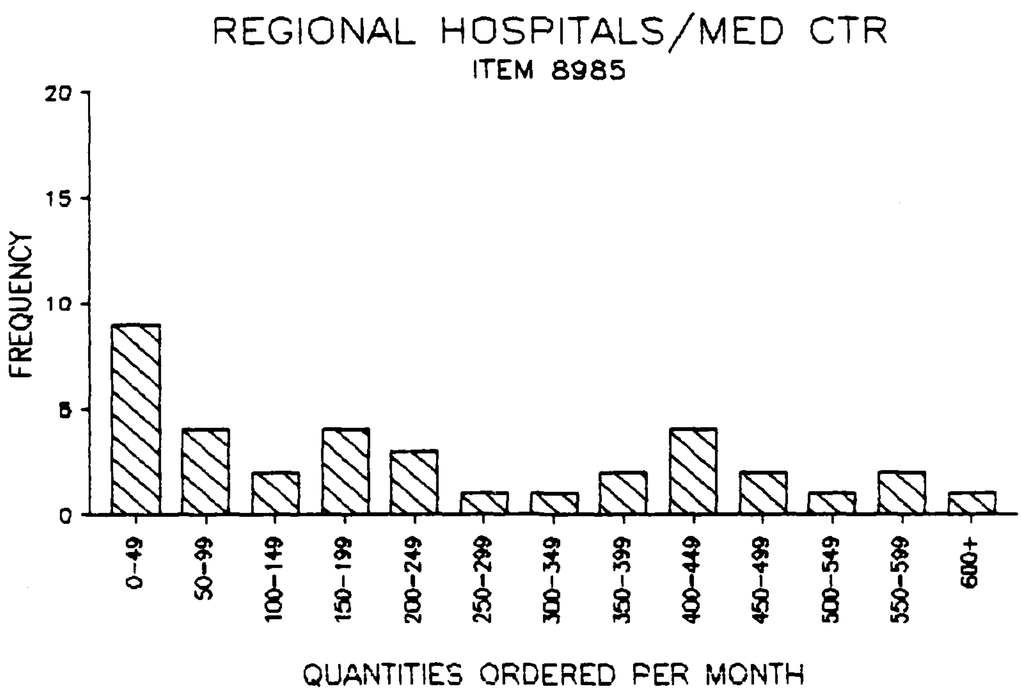

Figure 11. Frequency of Occurrence of Monthly Order Quantities (Item 8985 - Regional Hospitals/Med Center)

The resulting 45 histograms were tested for goodness-of-fit against the normal, poisson, exponential, and uniform standard distributions. The results of the tests for the 15 items and 13 MTFs are presented below.

Table V.

Distributions of the 12 Months of
Actual Medical Supply Demand Data, by MTF Category

Data Grouping	Exponential	Poisson	Normal	Uniform	No Fit	No Data
Clinics	10	2	0	0	1	2
Hospital	5	6	0	0	2	2
Regional Hosp/ Med Center	3	4	1	1	6	0

Logic concerning the operations of the various sizes of facilities supports the finding that clinics most often exhibited exponential distributions and hospitals poisson distributions. With small facilities, the demand for medical supplies, especially those ordered in lot sizes, is less than for larger facilities. The data indicated that most often small numbers or zero quantities were ordered per month. The frequency of the data is therefore greatest near zero, and the distribution is truncated at zero (negative orders are not possible).

A similar finding held true for hospitals. The mean quantity ordered per month was greater than for clinics, but the distribution of the data was truncated at zero and the data skewed to the right. Hence, the poisson distribution was appropriate for modeling hospital demand.

For the larger facilities there was much less commonality in distributions. This was due to the much greater covariance noted (see Table IV, previously presented) and the small number of facilities in the sample that fit into that size category.

The distributions and statistics derived from the data groupings needed to be identified for application during the simulation. Once the underlying distributions were determined, the data were examined for relationships between workload and the individual item demands.

As the distributions of the demand data were most often other than normal, the usual parametric test for correlation was not appropriate. Spearman's Rank Correlation Coefficient, a nonparametric statistical test of correlation, was employed to test for a relationship between workload and supply demand. Spearman's rank correlation coefficients, r_s, can range from -1 to +1, with the extreme values indicating perfect correlation, and zero indicating a total lack of correlation. The Prob>$|r_s|$ column in the table below indicates the likelihood of computing the r_s coefficient even when there is no correlation.

Spearman's Rank Correlation test was conducted on data for 13 MTF-supply item combinations chosen at random. The results are given below.

Table VI.

Spearman's Rank Correlation Coefficients Showing Relationships Between Workload and Supply Demand

	OPV		ADM		OBD	
MTF/Item	r_s	Prob>|r_s|	r_s	Prob>|r_s|	r_s	Prob>|r_s|
5/8985	.13	.75	*	*	.57	.11
8/7277	.50	.09	*	*	.56	.06
3/8985	.05	.80	*	*	*	*
2/4191	.24	.46	*	*	*	*
12/2698	.38	.22	.25	.43	.34	.28
8/3458	-.01	.97	*	*	-.27	.40
4/7992	.12	.71	*	*	*	*
11/8985	-.19	.62	*	*	.25	.54
13/6541	.10	.76	.13	.69	-.29	.37
2/2698	-.09	.79	*	*	*	*
11/6606	-.06	.87	*	*	-.21	.59
4/9377	-.15	.63	*	*	*	*
10/9080	-.01	.97	-.11	.74	-.22	.49

* Data not provided
Note: Correlation coefficients with associated probabilities >.05 are considered to be insignificant.

As the table shows, none of the tests showed a significant correlation. A t-test was conducted on the findings for the null hypothesis that the mean of the sample statistics for the sample of 195 item/MTF combinations was equal to 0.50 and an alternate hypothesis that the mean was less than 0.50. At a 95% confidence level, the null hypothesis was rejected, indicating that there was insufficient evidence to conclude that the mean of the population of 195 combinations was 0.50 or greater.

Unfortunately, the limited amount of data available (12 data points) probably affected the analyses. Had a greater number been available, it is possible that some significant correlations might have been revealed. Nevertheless, demand

and workload were insufficiently correlated to support using workload to predict supply demand.

Spearman's Rank Correlation tested only for a relationship between two variables. The SAS statistical computer program RS-REG procedure was used to test for possible quadratic or cross-product effects of the independent variables (workload) on the behavior of the dependent variable (demand). The RS-REG procedure was conducted on 11 of the 195 demand/MTF combinations chosen at random, and the SAS Stepwise screening procedure run against the most promising model parameters identified by RS-REG. Of the 11 tests performed, only 3 resulted in models with adjusted $R^2 > .60$ and significant F values, as summarized in Table VII, below.

Table VII.

Summary of Results of Multiple Regression Model Fitting

MTF/Item	Model Parameters	Adj R^2	F Value	Prob>F	Met Criteria
1/9377	OPV, OPV^2	.55	7.87	0.011	
3/7992	MO, MO^2	.68	9.54	0.013	Yes
5/6541	OBD, OPV*OBD	.11	0.59	0.584	
13/4191	OPV, OBD, MO, OPV^2, OPV*OBD	.49	0.22	0.958	
4/0162	OPV, OPV^2, OPV*MO, MO^2	.72	8.23	0.009	Yes
4/9080	OPV, MO, OPV*MO, OPV^2, MO^2	.32	2.04	0.205	
6/8883	OPV	.27	5.15	0.047	
7/1786	OPV, OBD, OPV*MO, MO^2	.75	9.41	0.006	Yes
9/8883	OPV, OBD, MO, OPV*OBD, OBD^2	.24	1.21	0.531	
10/8985	OPV*OBD	.19	3.64	0.085	
11/2089	OPV, OBD^2	.58	1.84	0.597	

As the table shows, the final models were generally complex and some of the parameters beyond interpretation. In regression model building, simplicity in the final model is important. With the use of complex models and independent variables that are not understood, there is the danger that the variable relationships important to the model could change without being noticed by the user. Also, an independent variable found in nearly all the models was MO, the time component, which is better handled by a time series forecasting model. For these reasons, and the fact that only 3 of 11 models proved useful, the multiple regression models were not further investigated. Although a few predicted relatively well, their predictive values were much too low to be acceptable basing estimates of Air Force wide inventory management.

The analysis of the statistical relationships between workload and demand was aimed at developing explanatory models useful in forecasting future demand. Had such a relationship been found, the 36 months of workload data available could have been used as a basis for testing the alternative forecasting techniques. Since such a relationship was not found, other methods had to be employed to test alternative forecasting techniques for use in approximating demand in the EOQ computations. To this end, a simulation technique employing SLAM II simulation language was decided upon to generate demand data based upon observed patterns of the actual demand, as discussed in Chapter III.

Seasonality and Trends in the Demand Data

As noted previously and shown in the graphs of the 36 months of workload and medical supply (EEIC 604) expenditure data, both seasonality and trend components were usually present in the time series. The same appeared to be true of the 12 months actual supply demand data. It made sense that if workload for an individual MTF exhibited a trend and seasonality, that supply demand might also contain those components, even if not strongly correlated to workload.

Trend was frequently evident when the 12 months of demand data were plotted. Monthly data also exhibited peaks and valleys throughout the 12 months, which for later simulation purposes was assumed to indicate seasonal influences. However, it is important to remember that with only 12 months of data, the presence of seasons recurring at 12 month intervals could not be proven.

For purposes of this research, to isolate the trend and compute seasonal indices, least squares lines were computed on the 12 months of demand data for each of the 15 supply items. The actual value for each month was then divided by the corresponding value from the least squares regression to arrive at a seasonal index for later use in simulation. Samples of the plotted data and least squares lines are shown below. Again, the limited amount of data adversely affected the analysis since what was called a seasonal component in a given month could have been purely random. To correctly judge the presence of seasonality, at least two, and preferably three or more seasons (12 month periods in this case) needed to be analyzed.

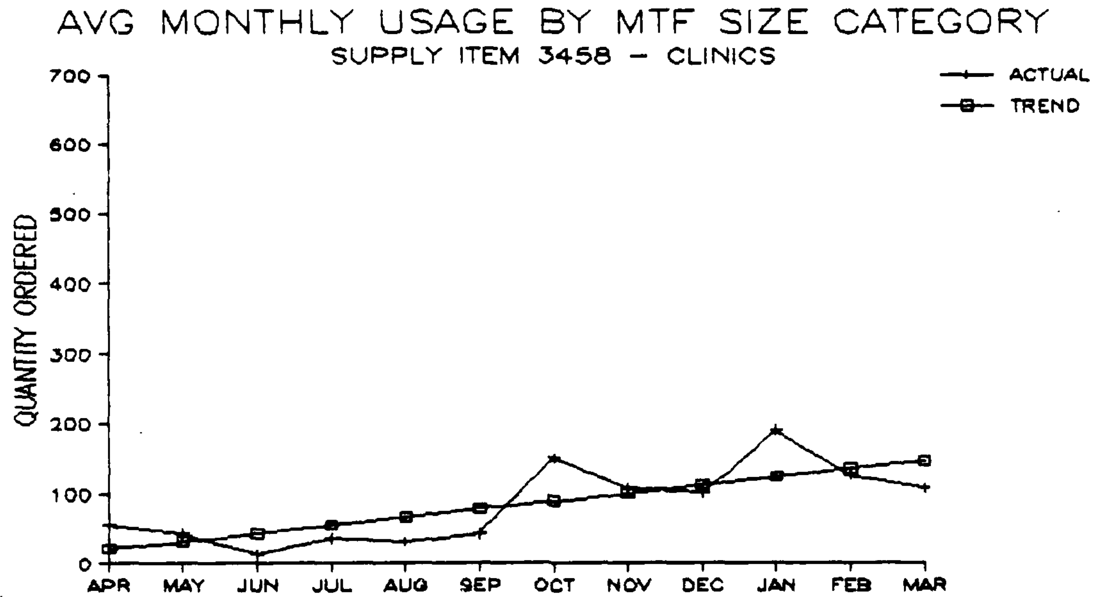

Figure 12. Average Quantity of Item 3458 Ordered Monthly by Clinics

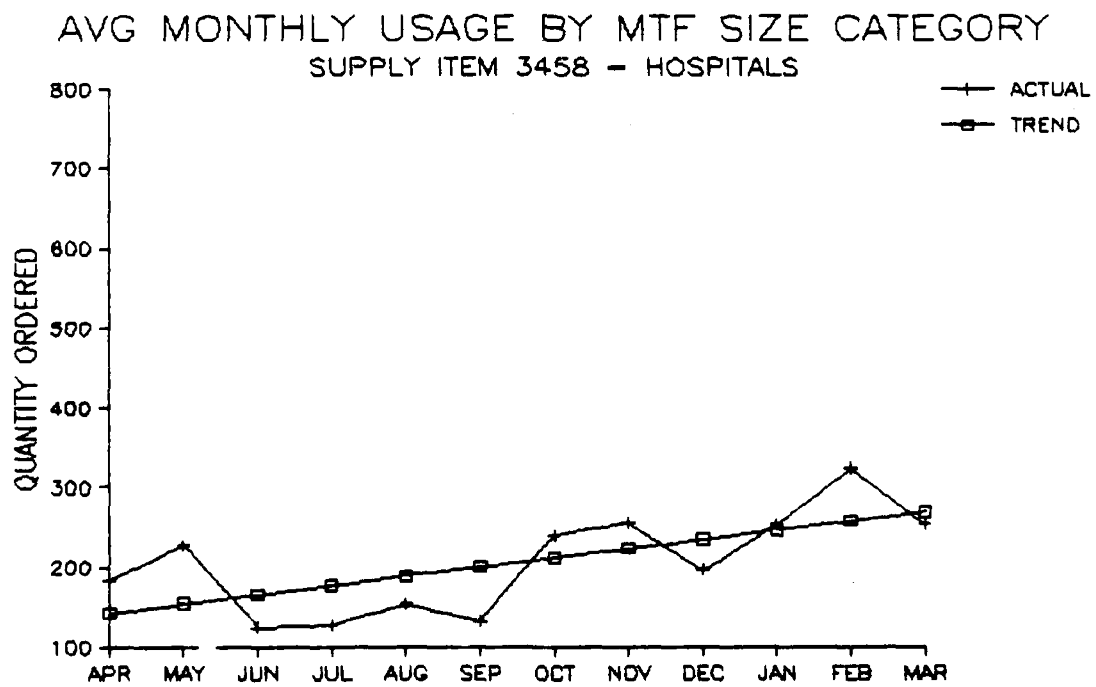

Figure 13. Average Quantity of Item 3458 Ordered Monthly by Hospitals

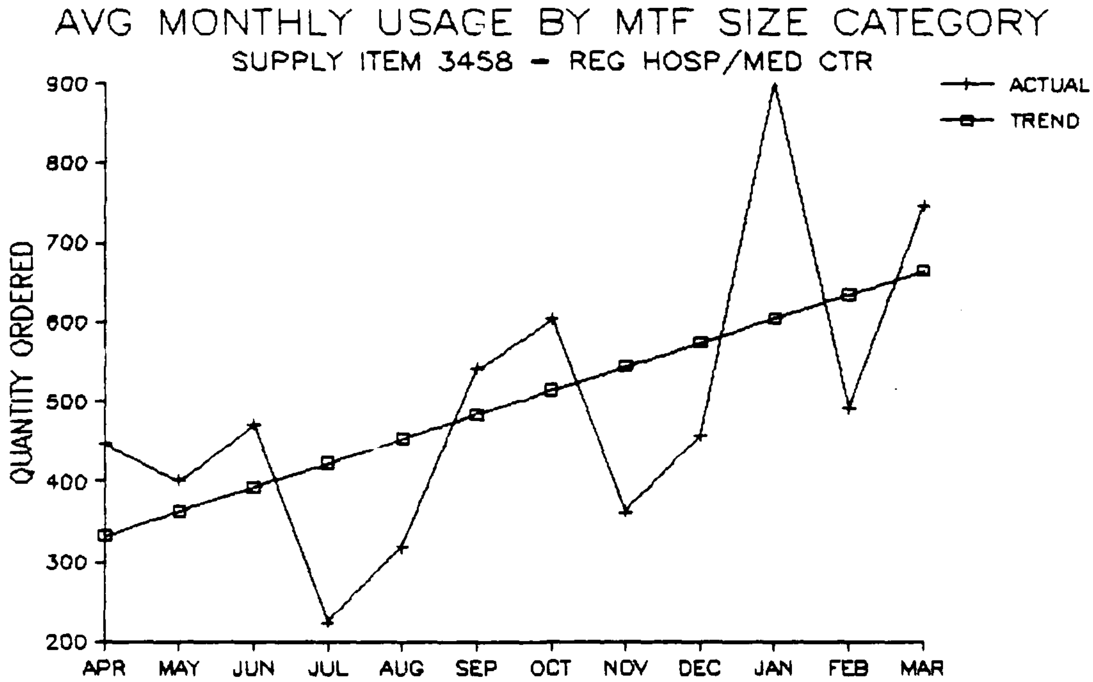

Figure 14. Average Quantity of Item 3458 Ordered Monthly by Regional Hospitals/Medical Center

<u>Applying the Forecasting Techniques and Measuring Accuracy</u>

The currently used 12 month moving average forecasting technique, a simple exponential smoothing model, a linear trend model with seasonal indexing, and a Winter's exponential smoothing model were tested in a simulation program written in SLAM II simulation language as discussed in Chapter III, Methodology. Each month the four forecasting model predictions were compared against the "actual" demand generated by the simulation. The differences were computed and used to rate the forecasting techniques based upon three measures of forecasting accuracy: MSE, MAD, and MAPE. In addition, the number of times the forecast value was greater than the actual or less than the actual demand were averaged.

The MSE, MAD, and MAPE values for the 25 repetitions of the simulation were averaged to arrive at one figure for each measure for each supply item/MTF category combination. Model performance was then ranked from one to four. An extract of a typical finding for one MTF category for one supply item is given below. The remaining findings are included in Appendix E.

It must be noted that comparing MSE, and MAD raw values for individual tests is inappropriate since they vary depending upon the level of demand. For instance, an attempt to compare the MSE of 2,539 for the 12 month moving average in Table VIII to the MSE of 6,915 for the 12 month moving average in Table IX is inappropriate since the levels of the actual demand (the bases) used in computing errors were different.

Table VIII.

Results of Simulation
Measures of Accuracy for Supply Item 0162
MTF Category: Regional Hospitals/Med Center

	Accuracy Measures				
Model	MSE/ (RANK)	MAD/ (RANK)	MAPE/ (RANK)	Nbr Over Actual	Nbr Under Actual
12 MO MOV AVG	2,539 (3)	39.7 (3)	202.4 (3)	23	25
EXPON SMOOTHING	3,208 (4)	44.2 (4)	265.3 (4)	23	25
TREND W/ SEASONAL INDEX	1,019 (1)	23.2 (1)	57.3 (1)	30	18
WINTERS	1,302 (2)	26.3 (2)	84.8 (2)	26	22

Note: The accuracy measures are the average of 25 runs of 48 months each.

Table IX.

Results of Simulation
Measures of Accuracy for Supply Item 3458
MTF Category: Hospitals

Model	MSE/ (RANK)	MAD/ (RANK)	MAPE/ (RANK)	Nbr Over Actual	Nbr Under Actual
	Accuracy Measures				
12 MO MOV AVG	69,156 (3)	179.0 (3)	39.7 (1)	18	30
EXPON SMOOTHING	77,825 (4)	200.5 (4)	51.2 (3)	20	28
TREND W/ SEASONAL INDEX	30,406 (1)	140.9 (1)	45.7 (2)	37	11
WINTERS	50,977 (2)	151.6 (2)	56.9 (4)	28	20

Note: The accuracy measures are the average of 25 runs of 48 months each.

Data on the number of times that the four models produced forecasts that were above and below the actual demand were also collected. This measure could be used as an additional evaluator of the various techniques. Generally, it would be expected that a good forecasting technique would produce approximately equal numbers of forecasts above and below the actual demand. Examination of the results, however, indicated a weakness inherent in both the 12 month moving average and the exponential smoothing forecasting models.

Plotting the demand data for 45 time series (15 supply items x 3 MTF categories) showed that an upward or downward trend was commonly found in the data. As discussed in Chapter II, moving average models react slowly to change.

This is also true, to a lesser extent, for the simple exponential smoothing technique. Another factor affecting the model's lag in reacting to change came from the fact that in this simulation all the forecasting models were programmed to compute forecasts for the month two periods into the future. Examination of the exponential smoothing formula reveals that the forecast for two periods into the future is the same the forecast for one period into the future. Both of these factors caused the exponential smoothing technique to react slowly the upward or downward trend in the actual data.

Because of the above mentioned characteristics of the 12 month moving average and the exponential smoothing techniques, when there was a trend in the data, both techniques tended to produce forecasts which were above or below the actual demand. For instance, if the trend were downward, the two forecasting techniques tended to produce forecasts above the actual demand. Furthermore, the steeper the trend, the greater was the tendency.

For the linear trend model, "over/under" computations showed that if the trend value used in the model was slightly different than the actual trend, as time progressed that forecasting technique produced a larger and larger proportion of its forecasts above or below the actual demand.

The Winter's model did not suffer from any of the aforementioned weaknesses since it is adaptive--it continually re-evaluated the trend value.

A final note on the over/under measure. This measure is of lesser value than the other accuracy measures for determining which forecasting technique to use. While the over/under measure helps in understanding what is going on within the test, the measures do not mean that the forecasting technique is unacceptable. The traditional accuracy measures are much better suited for assisting in that determination.

The ranking of each forecasting technique over all the simulations was computed by adding the individual simulation rankings and dividing by the number of simulations. Division by the number of simulations was necessary as six of the possible 45 supply item/MTF category combinations had data from only one MTF or none at all. This was possible because not all MTFs ordered all of the supply items in the sample.

The numbers in the table below indicate the average of the sums of the three forecast accuracy measures. For example, to arrive at the overall figure for the accuracy of the 12 month moving average model for the clinic MTF category in Table X, the following computations were performed. The forecast accuracy measure rankings (MSE, MAD, and MAPE) were totaled for each simulation to arrive at a figure from three (each of the three measures ranked number one) to twelve (each of the three measures ranked number four). Next the ranking sums from all the simulations were added. In the case of clinics, there were 12 item demand simulations.

Finally, the total was divided by 12 to arrive at an average which could be compared against the two other MTF categories.

Table X.

Overall Forecasting Model Performance

Average of Rankings of Individual Simulation Runs By MTF Category

Model	Clinics	Hospitals	Regional Hosp/ Med Centers
12 Mo Moving Avg	7.7	8.7	8.4
Exponential Smoothing	9.7	9.0	10.6
Linear Trend w/ Seasonal Indexing	5.1	4.3	3.7
Winter's Exponential Smoothing	7.6	8.0	7.3

Note: Lower number indicates higher performance relative to other models.

To test whether the probability distributions for the four treatments (forecasting methods) summarized in the table were different, the Friedman F_r test for a randomized block design was conducted. The rejection region at a 95% confidence level was 7.814. The F_r statistic was computed to be 9.0, leading to the conclusion that there was a statistically significant difference in the distributions of the four methods.

Another finding of the analysis which warranted discussion was the performance of the Winter's exponential smoothing forecasting technique. While it performed well overall, examination of the summary of simulation results found in

Appendix E will reveal that Winter's occasionally produced forecasts that were significantly in error. By comparing plots of the Winter's forecasts and the actual demand and studying the trace report from the simulation (discussed in the preceding chapter), it was found that the poor measurements of accuracy were usually due to one or two monthly forecasts which were grossly in error.

It occurred as follows. Before a simulation could be run, starting values for the seasonal indices had to be entered. In some cases the index computed for a particular month was very high (or low). The Winter's model would consider the trend and the large seasonal index and predict a very high (or low) demand on the next occurrence of that month. If the sample drawn from the standard distribution used in the simulation to represent the actual demand was near the opposite possible extreme, then the forecasting error was very large. The Winter's model, did, however, note its mistake and adjust the seasonal index for that month for the forecast to occur 12 months in the future.

The next chapter will apply the findings of the statistical analyses and the simulation to answer the research questions posed in Chapter I.

V. Conclusions and Recommendations

Overview

Medical Supply inventory represents a substantial investment of Air Force funds. The current method of determining economic order quantities in the management of inventory uses a demand figure based upon a 12 month moving average. This simple forecasting technique is easy to apply but may result in maintaining a higher average level of inventory to support demand which has been shown to fluctuate. The objective of this research was to study the methods used to compute the demand figure which is used in determining inventory order quantities and safety levels. This also necessitated examining the relationships between workload, supply usage, and MTF size. Those objectives were met by answering the research questions below.

This chapter is divided into two major sections. The first summarizes the findings of the analyses presented in Chapter IV to answer the research questions. The second section makes conclusions about the research in general and offers recommendations for improving the inventory control system of the USAF Medical Service.

Answers to the Research Questions

Research Question One

Are there MTF workload measurements that exhibit a high correlation to medical supply usage that can be used to satisfy the problem of the limited amount of medical supply demand history available?

The research showed that there was little correlation, between either workload and total medical supply expenditures (EEIC 604) or workload and the demand for the individual supply items in the sample. Statistical analyses showed a significant relations between the two in only a few cases of the sample tested. A significant relationship was defined as one in which 50% or more of the variation of the supply variable was explained by differences in the workload variable. In other words, an $r^2 \geq 0.5$ was sought. A simple t-test conducted on the results of the tests for correlation showed at a confidence level of 95% that the mean r^2 for the population was lower than 0.5. This indicated that significant correlations did not exist. Therefore, workload measurements should not be used to predict supply demand.

Research Question Two

Are there demand patterns for medical supplies by major stock class that are common to all Air Force MTFs?

To answer this question, the demand data for single items from multiple MTFs were standardized and plotted together. Disregarding upward or downward trends, some common patterns could be visually discerned from the graphs; examples were given in the preceding chapter as Figures 7 and 8. At best, however, the fit was only strong for certain months. Most combinations graphed failed to exhibit fit among MTFs as prevalent as the one presented in Figure 6. The existence of a clear demand pattern common to all MTFs could not be shown. Nor did plotting demands for items of the same stock class indicate a strong similarity of patterns between facilities. The strongest common pattern was found only to exist between different items within the same stock class for the same facility (see Figure 8 in the previous chapter). No common demand patterns were found to exist for all Air Force MTFs studied.

Research Question Three

Would application of a forecasting technique more advanced than the 12 month moving average now in use better track actual demand?

The extensive amount of simulation performed indicated that use of a more sophisticated forecasting technique would lead to better inventory control by more closely matching supply to demand. The actual 12 month demand data used in the research in most cases showed wide variability in the sizes of orders placed. If a forecasting technique could be applied which, based upon past historical demand patterns recognized in the data, could predict future peaks and valleys in demand, then the average inventory level could be reduced without significantly affecting the service levels provided.

The results of the simulation indicated that a simple linear trend model incorporating seasonal indexing, or the Winter's Exponential Smoothing model could produce a lower forecasting error than the 12 month moving average currently used. In 31 of 39 simulations the linear trend model produced the best results or tied for first place. In 7 of the 39 simulations the Winter's model produced the best results or tied for first place. Seventeen times Winter's came in in second place, or tied for that position. This clearly reflected the ability of the two models to predict the seasonal component in the time series. Neither the moving average model, nor simple exponential smoothing take seasonal effects in the data into direct consideration.

It was observed that in the actual 12 month demand history for most items, demand fluctuated greatly throughout the year. The 12 month moving average produced greatly attenuated, or smoothed forecasts which were reflected by the forecasting errors reported that were usually higher than those of the linear trend model or Winter's exponential smoothing model. Furthermore, in cases where the simulation used data that had a significant upward or downward trend, the 12 month moving average showed even higher forecasting error. This was because it was very slow to reflect to change. By its definition, the 12 month moving average model averages the evenly weighted preceding 12 months to arrive at a forecast.

Since the data were known to fluctuate greatly, it is understandable that exponential smoothing fared poorly. Although that model recognized change, it responded with a lag. The lag was further exacerbated because that model (and the other 3 models) was forced in the simulation to forecast two periods into the future. This was necessary to more realistically simulate the need in real life operations to order 30 days in advance to allow for order and shipping lead time.

A major difference between the linear trend model and the Winter's model is that Winter's is self-adapting, while the linear trend model can only change after intervention by the user. Referring to the equations for the Winter's model presented in Chapter II, it can be seen that at each new period the model re-computes the level, trend, and seasonal index. Winter's would automatically react to a change in direction of the long term trend, while the linear trend model with seasonal indexing would not.

There are a number of weaknesses that must be addressed when developing conclusions from the simulation process. First, although the simulated "actual" demands were based upon statistics derived from real demand histories, some of the real world stochastic nature of demand was not captured. A distribution was used to randomly draw simulated demand from a characteristic range of values, but the trend and seasonal patterns were fixed in time and degree. In other words, the direction or slope of the trend did not change in the simulation, nor did the occurrences of seasons change. The seasons could not shift to earlier or later months, but were fixed in time within the simulation.

Second, the linear trend model incorporating seasonal indexing was given an unfair advantage in the simulation. This was due to using the same trend and seasonality indices in the forecasting model that were used to simulate the actual demands. The guesswork and estimation of trend and seasonal factors which would occur in real life in the model building process were lost.

Overall, recognizing the limitations of the simulation program, both the linear trend model with seasonal indexing and the Winter's Exponential Smoothing model performed better than the currently used 12 month moving average. Better matching of supply to demand through better forecasting techniques would allow maintaining lower inventory levels while still protecting against stockouts.

Research Question Four

Does the range and size of services offered by Air Force MTFs affect inventory performance measures to the extent that a service-wide inventory control forecasting model should not be used?

Analysis of the data showed that the variance in demand was greater for all MTFs in the sample taken together than it was for MTFs grouped by the classification categories; clinics, hospitals, and regional hospitals/medical centers; or grouped together by workload range. This was shown by computing the covariance, which measured variance within the groupings.

The histograms of the frequency of medical supply order size also showed that the different MTF categories most often followed different demand distributions. Recall that clinic demand tended to follow the exponential distribution, and hospitals and regional hospitals/medical centers tended to follow either the exponential or poisson distribution. Among regional hospitals/medical centers there was much less congruity in the demand data. The variation in order size was greater, and the histograms frequently failed to fit any common standard distribution. Often the histograms were bi-modal, or multi-modal. That is, they showed that there were more than one statistical mode for the data as a group, indicating the individuality of the group members.

While the data variability and demand distributions did change according to MTF category, the performance of the forecasting models tested did not. Although different model parameters were necessary for each group, and would be necessary if applied to individual facilities, there was no indication that certain models performed better or worse for different MTF categories. Segregating facilities together by MTF category was useful, but the same forecasting model could be employed equally well on any category.

Recommendations for Implementation

The Winter's exponential smoothing forecast technique should be tested on a limited scale in actual use in forecasting medical supply demand. It was shown to be a better forecasting technique than either the currently used 12 month moving average or the simple exponential smoothing forecasting technique in model simulation. Use of the Winter's technique would allow a reduction in the overall average inventory investment by more closely matching inventory levels to anticipated demand. Safety levels might also be reduced, since the 12 month moving average model requires higher levels be maintained to cover its greater forecasting error.

The Winter's forecasting technique should be tested on a sample of medical supply items at a few MTFs as a test only after three years of actual demand history have been collected and analyzed and confirm the presence of predictable seasonal fluctuations.

It is further recommended that the smoothing constants for level, trend, and especially trend, be restricted to a maximum value of 0.40. With highly erratic data, restricting the smoothing constants from taking on higher values could reduce tracking performance but would also lessen the possibility of a very large error occurring in any single month, as explained above.

With implementation of a Winter's forecasting model, increased management review of demand forecasts would be necessary to allow management to override extreme forecasts. This could be integrated into the forecasting system as a management by exception procedure.

The linear trend model incorporating seasonal indexing should also be considered for limited real-world testing. Though this model is not self-adapting, it is simple and proved highly accurate in simulation. For this model to function well, management oversight would be necessary to ensure that the trend parameter used by the model remained accurate. At a facility that carried 9,000 medical supply items in its inventory, this would require monitoring 9,000 equations.

Finally, it is recommended that no attempt be made to implement new forecasting techniques in all MTFs in a global manner. While the use of the same forecasting technique is appropriate for all MTF categories, one model, with fixed level, trend, and seasonal smoothing constants should not be applied to all facilities and products. The same type of model, e.g. Winter's exponential smoothing, can be used, but the parameters need to be specific to each MTF. The data indicated that there were no demand patterns common to all MTFs in the sample.

Recommendations for Further Study

Throughout this research, problems of insufficient data hampered the analysis. Great difficulty was experienced in trying to extract meaningful data, explore relationships, and draw conclusions on only 12 months of actual demand data. Findings of low correlation between workload measures or no correlation at all may have been affected by the limited amount of data available to test. There were even weaknesses within that data, since it was not possible to know whether the monthly figure represented a single order or a total of multiple orders placed during the month.

To improve upon the study of forecasting techniques for predicting medical supply demand, it is recommended that a number of carefully chosen facilities be selected to maintain demand data for a sample of medical supply items for at least 36 months. There were clearly recurring patterns in the workload data. What is needed now is to determine the extent of recurring patterns in supply demand. With three years of data, seasonal fluctuations and their magnitude can be determined.

As noted throughout this research, the lack of sufficient data forced many assumptions to be made and limited the research in a number of areas. With more complete data, the conclusions presented above could be strengthened and analysis conducted in more depth.

Lastly, in reviewing the literature on inventory control systems employed in the health care industry, some studies were found where material requirements planning, MRP, had been applied to hospitals. Briefly, MRP takes a deterministic approach to determining future supply needs. This is done by considering the demand for supplies as dependent demand based upon some higher level final product--in this case, a treated patient. Since the size of the beneficiary population for a military MTF is more easily and accurately estimated than for civilian counterparts, it may be possible to accurately derive dependent demand figures. MRP has only recently been applied to service industries, but was judged successful in the few hospital applications studied.

Appendix A: FORECAST ACCURACY MEASURES

ME: Mean Error $$\frac{1}{n}\sum_{i=1}^{n}(X_t - F_t)$$

MAD: Mean Absolute Error $$\frac{1}{n}\sum_{i=1}^{n}\left|(X_t - F_t)\right|$$

MSE: Mean Squared Error $$\frac{1}{n}\Sigma(X_t - F_t)$$

PE: Percentage Error $$\frac{(X_t - F_t)}{X_t} * 100$$

MPE: Mean Percentage Error $$\frac{1}{n}\Sigma\left[\frac{(X_t - F_t)}{X_t} * 100\right]$$

MAPE: Mean Absolute % Error $$\frac{1}{n}\Sigma\left|\left[\frac{(X_t - F_t)}{X_t} * 100\right]\right|$$

LEGEND: X = Actual
F = Forecast
t = time period

Source (28:46)

APPENDIX B: WORKLOAD AND MEDICAL SUPPLY EXPENDITURE DATA

	MTF #1 (CLINIC)		MTR #2 (CLINIC)		MTF #3 (CLINIC)	
COUNT =	42.00		42.00	13.00	39.00	
MEAN =	2292.81		4353.76	179.30	9927.44	
STD DEV =	372.49		557.78	32.83	780.74	
	OPV	EEIC604	OPV	EEIC604	OPV	EEIC604
OCT 84	2219.00		4953.00		9570.00	
NOV 84	1958.00		4090.00		10360.00	
DEC 84	1732.00		3250.00	153.70	8730.00	
JAN 85	2178.00		4815.00		11870.00	
FEB 85	2123.00		3973.00		10320.00	
MAR 85	2325.00		4163.00	153.30	10720.00	
APR 85	2480.00		4347.00		10210.00	
MAY 85	2451.00		4322.00		9660.00	
JUN 85	2143.00		3353.00	151.90	8060.00	
JUL 85	1815.00		3757.00		9550.00	
AUG 85	1799.00		3629.00		10490.00	
SEP 85	1718.00		3622.00	160.10	9110.00	
OCT 85	1992.00		3978.00		9850.00	
NOV 85	1610.00		3615.00		8350.00	
DEC 85	1703.00		3458.00	185.40	9620.00	
JAN 86	1833.00		4489.00		10210.00	
FEB 86	1728.00		4276.00		10800.00	
MAR 86	1897.00		4167.00	164.40	10530.00	
APR 86	1934.00		4390.00		10970.00	
MAY 86	2417.00		4080.00		9580.00	
JUN 86	2178.00		3852.00	242.70	8570.00	
JUL 86	2403.00		4076.00		9760.00	
AUG 86	2432.00		3962.00		9500.00	
SEP 86	2561.00		4217.00	216.80	9880.00	
OCT 86	2714.00		4743.00		10550.00	
NOV 86	2400.00		4038.00		8890.00	
DEC 86	2086.00		3648.00	155.80	10340.00	
JAN 87	2726.00		4744.00		10260.00	
FEB 87	2463.00		4896.00		9300.00	
MAR 87	2554.00		5139.00	195.10	10890.00	
APR 87	2883.00		4931.00		11270.00	
MAY 87	2514.00		4473.00		10370.00	
JUN 87	2903.00		5027.00	150.00	9980.00	
JUL 87	2798.00		5057.00		10360.00	
AUG 87	2666.00		4709.00		9540.00	
SEP 87	2580.00		5159.00	241.40	9840.00	
OCT 87	2552.00		5164.00		9870.00	
NOV 87	2312.00		4477.00		9450.00	
DEC 87	2168.00		4408.00	160.30	9990.00	
JAN 88	2631.00		5002.00			
FEB 88	2782.00		5037.00			
MAR 88	2937.00		5372.00			

	MTF #4 (CLINIC)		MTF #5 (HOSPITAL)			
COUNT =	42.00	4.00	27.00	13.00	39.00	4.00
MEAN =	10499.24	1038.73	9379.74	508.23	545.44	1187.40
STD DEV =	1002.32	304.71	894.91	59.71	99.48	638.97
	OPV	EEIC604	OPV	ADM	OBD	EEIC604
OCT 84	11144.00				551.00	
NOV 84	10265.00				545.00	
DEC 84	9606.00			462.00	540.00	
JAN 85	10797.00				599.00	
FEB 85	10882.00				573.00	
MAR 85	11277.00			549.00	736.00	
APR 85	11921.00				627.00	
MAY 85	11469.00				647.00	
JUN 85	10010.00			550.00	583.00	
JUL 85	10706.00				520.00	
AUG 85	11784.00				622.00	
SEP 85	10747.00	1191.51		563.00	635.00	
OCT 85	11649.00		9905.00		501.00	
NOV 85	10585.00		9753.00		517.00	
DEC 85	10419.00		10286.00	503.00	566.00	
JAN 86	12518.00		10285.00		654.00	
FEB 86	11221.00		10524.00		765.00	
MAR 86	11419.00		10015.00	644.00	736.00	
APR 86	12202.00		11398.00		680.00	
MAY 86	11929.00		10281.00		673.00	
JUN 86	9819.00		9555.00	554.00	507.00	
JUL 86	10422.00		9424.00		502.00	
AUG 86	10271.00		8535.00		566.00	
SEP 86	9720.00	1186.83	8932.00	507.00	514.00	1793.90
OCT 86	10408.00		9097.00		600.00	
NOV 86	8191.00		8428.00		509.00	
DEC 86	9180.00		8825.00	452.00	394.00	485.40
JAN 87	10615.00		10296.00		531.00	
FEB 87	9809.00		9470.00		459.00	
MAR 87	11357.00		10285.00	472.00	537.00	
APR 87	10549.00		10271.00		487.00	
MAY 87	8642.00		9069.00		485.00	
JUN 87	9410.00		8831.00	491.00	449.00	
JUL 87	8690.00		8119.00		374.00	
AUG 87	9245.00		8415.00		350.00	
SEP 87	9913.00	1263.02	9086.00	441.00	456.00	1854.80
OCT 87	9936.00		8084.00		485.00	
NOV 87	9201.00		7993.00		416.00	
DEC 87	9891.00		8091.00	419.00	381.00	615.50
JAN 88	10413.00					
FEB 88	11007.00					
MAR 88	11729.00	513.56				

MTF #6 (HOSPITAL)

COUNT =	42.00	42.00	42.00	18.00
MEAN =	6671.12	78.52	289.81	7833.33
STD DEV =	608.82	29.63	103.32	2244.50

	OPV	ADM	OBD	EEIC604
OCT 84	6639.00	119.00	481.00	
NOV 84	6705.00	118.00	375.00	
DEC 84	5466.00	75.00	288.00	
JAN 85	7308.00	127.00	428.00	
FEB 85	6612.00	113.00	392.00	
MAR 85	7569.00	112.00	335.00	
APR 85	6913.00	110.00	338.00	
MAY 85	6931.00	101.00	400.00	
JUN 85	6179.00	100.00	418.00	
JUL 85	6037.00	119.00	407.00	
AUG 85	6048.00	100.00	319.00	
SEP 85	5718.00	92.00	454.00	
OCT 85	6908.00	44.00	134.00	
NOV 85	5928.00	39.00	144.00	
DEC 85	5904.00	39.00	125.00	
JAN 86	7561.00	53.00	177.00	
FEB 86	6773.00	64.00	269.00	
MAR 86	7500.00	55.00	256.00	
APR 86	7582.00	94.00	384.00	
MAY 86	7124.00	97.00	371.00	
JUN 86	6942.00	81.00	291.00	
JUL 86	7143.00	86.00	284.00	
AUG 86	6928.00	89.00	292.00	
SEP 86	7564.00	108.00	373.00	
OCT 86	7215.00	93.00	326.00	6700.00
NOV 86	6352.00	80.00	308.00	6400.00
DEC 86	6831.00	89.00	333.00	3800.00
JAN 87	7035.00	97.00	378.00	9400.00
FEB 87	6697.00	99.00	407.00	8100.00
MAR 87	7827.00	94.00	322.00	11600.00
APR 87	7549.00	86.00	290.00	8400.00
MAY 87	6850.00	99.00	345.00	12800.00
JUN 87	6708.00	17.00	204.00	6200.00
JUL 87	6364.00	63.00	220.00	10800.00
AUG 87	6112.00	79.00	286.00	9500.00
SEP 87	6370.00	32.00	142.00	6400.00
OCT 87	6175.00	42.00	182.00	7700.00
NOV 87	5668.00	33.00	125.00	5400.00
DEC 87	5892.00	35.00	113.00	7800.00
JAN 88	5898.00	47.00	175.00	7700.00
FEB 88	6146.00	40.00	134.00	5300.00
MAR 88	6516.00	38.00	147.00	7000.00

MTF #7 (HOSPITAL)

COUNT	=	42.00	42.00	42.00
MEAN	=	5978.43	99.55	317.00
STD DEV	=	430.22	16.92	76.23

	OPV	ADM	OBD	EEIC604
OCT 84	5829.00	120.00	427.00	
NOV 84	5793.00	108.00	426.00	
DEC 84	5203.00	105.00	328.00	
JAN 85	6542.00	124.00	472.00	
FEB 85	5691.00	97.00	432.00	
MAR 85	5867.00	92.00	364.00	
APR 85	6626.00	110.00	434.00	
MAY 85	6292.00	109.00	343.00	
JUN 85	5353.00	111.00	338.00	
JUL 85	6169.00	105.00	382.00	
AUG 85	6633.00	97.00	313.00	
SEP 85	6177.00	103.00	347.00	
OCT 85	6426.00	106.00	343.00	
NOV 85	5573.00	87.00	344.00	
DEC 85	5306.00	87.00	285.00	
JAN 86	6831.00	101.00	420.00	
FEB 86	6475.00	104.00	394.00	
MAR 86	6456.00	116.00	415.00	
APR 86	6642.00	110.00	360.00	
MAY 86	5953.00	104.00	337.00	
JUN 86	5749.00	113.00	380.00	
JUL 86	6616.00	101.00	290.00	
AUG 86	5822.00	107.00	324.00	
SEP 86	5851.00	140.00	322.00	
OCT 86	6192.00	114.00	301.00	
NOV 86	5199.00	76.00	180.00	
DEC 86	5333.00	85.00	216.00	
JAN 87	6274.00	73.00	210.00	
FEB 87	5818.00	102.00	304.00	
MAR 87	6270.00	102.00	238.00	
APR 87	5995.00	110.00	330.00	
MAY 87	5886.00	99.00	269.00	
JUN 87	5551.00	109.00	248.00	
JUL 87	5882.00	124.00	344.00	
AUG 87	5432.00	104.00	292.00	
SEP 87	5754.00	47.00	183.00	
OCT 87	5891.00	83.00	253.00	
NOV 87	5676.00	79.00	228.00	
DEC 87	5622.00	76.00	182.00	
JAN 88	6290.00	91.00	281.00	
FEB 88	5785.00	72.00	217.00	
MAR 88	6369.00	78.00	218.00	

MTF #8 (HOSPITAL)

COUNT	=	42.00	42.00	42.00	42.00
MEAN	=	13345.74	167.07	561.98	192.12
STD DEV	=	1315.65	41.12	162.83	63.88

	OPV	ADM	OBD	EEIC604
OCT 84	15322.00	248.00	980.00	160.10
NOV 84	14090.00	162.00	634.00	112.70
DEC 84	12719.00	153.00	525.00	217.30
JAN 85	16207.00	209.00	652.00	187.10
FEB 85	13301.00	186.00	648.00	155.90
MAR 85	15776.00	223.00	807.00	179.90
APR 85	16049.00	204.00	603.00	177.30
MAY 85	15288.00	207.00	756.00	180.50
JUN 85	13156.00	162.00	591.00	191.20
JUL 85	13253.00	166.00	627.00	191.20
AUG 85	13823.00	185.00	674.00	203.20
SEP 85	13230.00	169.00	629.00	256.90
OCT 85	14769.00	175.00	617.00	151.40
NOV 85	12287.00	145.00	453.00	185.60
DEC 85	12839.00	152.00	486.00	233.90
JAN 86	14293.00	159.00	519.00	123.80
FEB 86	13568.00	120.00	416.00	184.10
MAR 86	13159.00	169.00	557.00	156.10
APR 86	14043.00	158.00	524.00	147.00
MAY 86	12108.00	137.00	386.00	170.00
JUN 86	12878.00	149.00	435.00	166.10
JUL 86	13271.00	151.00	448.00	186.30
AUG 86	11877.00	149.00	502.00	141.50
SEP 86	13152.00	167.00	557.00	318.40
OCT 86	13813.00	192.00	684.00	254.40
NOV 86	11852.00	174.00	626.00	275.00
DEC 86	13255.00	185.00	658.00	137.30
JAN 87	14945.00	223.00	719.00	185.60
FEB 87	13254.00	200.00	782.00	109.30
MAR 87	14871.00	234.00	745.00	245.80
APR 87	14200.00	173.00	605.00	218.30
MAY 87	12537.00	185.00	632.00	192.80
JUN 87	13403.00	242.00	768.00	194.60
JUL 87	13047.00	192.00	612.00	362.60
AUG 87	11987.00	156.00	475.00	40.60
SEP 87	11952.00	77.00	273.00	378.80
OCT 87	11235.00	93.00	244.00	139.80
NOV 87	10864.00	85.00	206.00	154.80
DEC 87	11745.00	76.00	228.00	176.30
JAN 88	10565.00	92.00	319.00	184.90
FEB 88	13387.00	172.00	538.00	287.10
MAR 88	13151.00	161.00	463.00	153.70

MTF #9 (HOSPITAL)

COUNT =	42.00	42.00	42.00	18.00
MEAN =	6920.90	104.10	305.38	68.08
STD DEV =	1144.35	15.86	48.76	20.78

	OPV	ADM	OBD	EEIC604
OCT 84	5754.00	111.00	270.00	
NOV 84	5087.00	85.00	279.00	
DEC 84	4632.00	73.00	211.00	
JAN 85	5676.00	105.00	313.00	
FEB 85	5431.00	89.00	260.00	
MAR 85	5844.00	87.00	304.00	
APR 85	6076.00	86.00	273.00	
MAY 85	5971.00	76.00	260.00	
JUN 85	5162.00	90.00	309.00	
JUL 85	5447.00	71.00	220.00	
AUG 85	5999.00	121.00	390.60	
SEP 85	6466.00	115.00	384.00	
OCT 85	6917.00	102.00	310.00	
NOV 85	5389.00	87.00	252.00	
DEC 85	6173.00	110.00	288.30	
JAN 86	6560.00	123.00	375.10	
FEB 86	6095.00	100.00	302.40	
MAR 86	6872.00	100.00	313.10	
APR 86	7540.00	113.00	312.00	
MAY 86	6979.00	79.00	217.00	
JUN 86	6612.00	118.00	309.00	
JUL 86	6590.00	91.00	263.50	
AUG 86	6339.00	102.00	279.00	
SEP 86	6626.00	122.00	345.00	
OCT 86	7480.00	118.00	362.70	107.50
NOV 86	6526.00	85.00	249.00	61.50
DEC 86	8419.00	108.00	240.00	18.50
JAN 87	7469.00	121.00	362.70	52.30
FEB 87	7356.00	106.00	302.40	79.10
MAR 87	8682.00	114.00	322.40	90.90
APR 87	7819.00	97.00	252.00	53.60
MAY 87	7991.00	119.00	316.20	58.20
JUN 87	8306.00	125.00	354.00	52.70
JUL 87	8141.00	108.00	356.50	76.70
AUG 87	8149.00	99.00	316.20	94.70
SEP 87	7574.00	116.00	330.00	47.50
OCT 87	8872.00	138.00	378.20	87.10
NOV 87	8187.00	96.00	243.00	47.40
DEC 87	8416.00	115.00	328.60	71.30
JAN 88	8322.00	121.00	387.50	75.00
FEB 88	8211.00	112.00	322.00	68.40
MAR 88	8521.00	118.00	362.70	83.10

MTF #10 (REGIONAL HOSPITAL)

COUNT =	42.00	42.00	42.00	3.00
MEAN =	24132.43	484.74	2383.62	6933.93
STD DEV =	1728.27	50.19	242.33	618.11

	OPV	ADM	OBD	EEIC604
OCT 84	25094.00	520.00	2716.00	
NOV 84	24620.00	497.00	2680.00	
DEC 84	21510.00	446.00	2535.00	
JAN 85	24989.00	572.00	2897.00	
FEB 85	23461.00	496.00	2578.00	
MAR 85	24700.00	512.00	2764.00	
APR 85	26357.00	530.00	2779.00	
MAY 85	22366.00	459.00	2153.00	
JUN 85	21480.00	484.00	2240.00	
JUL 85	23606.00	484.00	2353.00	
AUG 85	23907.00	495.00	2518.00	
SEP 85	22577.00	522.00	2670.00	6102.10
OCT 85	25685.00	513.00	2574.00	
NOV 85	22690.00	466.00	2435.00	
DEC 85	21343.00	495.00	2240.00	
JAN 86	25222.00	528.00	2600.00	
FEB 86	23290.00	461.00	2234.00	
MAR 86	25233.00	533.00	2474.00	
APR 86	26296.00	490.00	2343.00	
MAY 86	23878.00	487.00	2400.00	
JUN 86	21849.00	472.00	2201.00	
JUL 86	23971.00	482.00	2178.00	
AUG 86	24352.00	496.00	2536.00	
SEP 86	23577.00	486.00	2374.00	7117.20
OCT 86	25953.00	451.00	2323.00	
NOV 86	20950.00	333.00	1767.00	
DEC 86	23134.00	420.00	2227.00	
JAN 87	25612.00	461.00	2324.00	
FEB 87	23539.00	427.00	2140.00	
MAR 87	26377.00	354.00	1811.00	
APR 87	25211.00	444.00	2116.00	
MAY 87	23423.00	493.00	2404.00	
JUN 87	23146.00	483.00	2153.00	
JUL 87	23364.00	449.00	2223.00	
AUG 87	22128.00	431.00	2016.00	
SEP 87	23315.00	485.00	2359.00	7582.50
OCT 87	24987.00	520.00	2434.00	
NOV 87	25074.00	531.00	2447.00	
DEC 87	25784.00	470.00	2200.00	
JAN 88	22928.00	490.00	2508.00	
FEB 88	27293.00	580.00	2599.00	
MAR 88	29291.00	611.00	2589.00	

MTF #11 (REGIONAL HOSPITAL)

		OPV	ADM	OBD	EEIC604
COUNT	=	24.00	.00	24.00	22.00
MEAN	=	22845.83		1555.79	506.10
STD DEV	=	2457.64		308.69	261.86

	OPV	ADM	OBD	EEIC604
OCT 84				
NOV 84				
DEC 84				
JAN 85				
FEB 85				
MAR 85				
APR 85				
MAY 85				
JUN 85				
JUL 85				
AUG 85				
SEP 85				
OCT 85	23400.00		2167.00	
NOV 85	20500.00		1809.00	
DEC 85	19100.00		831.00	868.90
JAN 86	22000.00		822.00	
FEB 86	21400.00		1274.00	
MAR 86	22300.00		1934.00	1124.50
APR 86	21800.00		1536.00	
MAY 86	22700.00		1401.00	
JUN 86	19400.00		1350.00	906.40
JUL 86	31100.00		1665.00	
AUG 86	21800.00		1423.00	
SEP 86	19800.00		1377.00	1168.10
OCT 86	23300.00		1562.00	473.50
NOV 86	21200.00		1500.00	214.80
DEC 86	21700.00		1603.00	363.80
JAN 87	24300.00		1854.00	394.00
FEB 87	23500.00		1770.00	333.70
MAR 87	25500.00		1956.00	461.80
APR 87	26000.00		1518.00	378.60
MAY 87	24800.00		1482.00	378.60
JUN 87	23900.00		1512.00	277.40
JUL 87	23900.00		1649.00	463.70
AUG 87	22900.00		1460.00	476.00
SEP 87	22000.00		1884.00	264.30
OCT 87				379.00
NOV 87				638.00
DEC 87				363.00
JAN 88				388.30
FEB 88				328.90
MAR 88				488.80

MTF #12 (REGIONAL HOSPITAL)

COUNT =	42.00	42.00	42.00	42.00
MEAN =	20053.26	334.62	1396.52	507.14
STD DEV =	1948.05	44.32	182.08	126.45

	OPV	ADM	OBD	EEIC604
OCT 84	19796.00	369.00	1466.00	435.90
NOV 84	18484.00	336.00	1426.00	538.90
DEC 84	16096.00	283.00	1300.00	140.80
JAN 85	20403.00	375.00	1551.00	515.50
FEB 85	18182.00	323.00	1442.00	435.20
MAR 85	18475.00	200.00	781.00	439.90
APR 85	18878.00	205.00	862.00	398.30
MAY 85	19007.00	324.00	1048.00	528.50
JUN 85	16374.00	297.00	1275.00	351.70
JUL 85	17241.00	376.00	1526.00	396.90
AUG 85	18498.00	353.00	1598.00	417.00
SEP 85	17295.00	416.00	1395.00	551.80
OCT 85	21459.00	416.00	1717.00	313.20
NOV 85	20186.00	341.00	1612.00	698.20
DEC 85	22546.00	320.00	1470.00	378.40
JAN 86	24504.00	340.00	1391.00	482.30
FEB 86	21572.00	288.00	1346.00	625.90
MAR 86	22457.00	354.00	1567.00	383.40
APR 86	21632.00	359.00	1486.00	627.90
MAY 86	21489.00	386.00	1670.00	651.90
JUN 86	20148.00	323.00	1440.00	340.10
JUL 86	20423.00	312.00	1224.00	324.80
AUG 86	19869.00	287.00	1318.00	550.00
SEP 86	21468.00	354.00	1434.00	478.20
OCT 86	21719.00	327.00	1407.00	526.90
NOV 86	18019.00	304.00	1413.00	467.20
DEC 86	20000.00	285.00	1355.00	560.40
JAN 87	21537.00	322.00	1425.00	519.60
FEB 87	20237.00	334.00	1437.00	670.10
MAR 87	22353.00	343.00	1436.00	469.40
APR 87	19940.00	292.00	1210.00	534.50
MAY 87	18048.00	339.00	1247.00	630.20
JUN 87	20112.00	331.00	1342.00	505.80
JUL 87	18944.00	338.00	1466.00	610.60
AUG 87	17837.00	335.00	1410.00	472.50
SEP 87	20371.00	355.00	1460.00	575.10
OCT 87	19949.00	361.00	1696.00	754.10
NOV 87	18575.00	359.00	1433.00	438.20
DEC 87	19679.00	332.00	1291.00	574.00
JAN 88	20648.00	375.00	1426.00	797.70
FEB 88	23059.00	402.00	1477.00	533.40
MAR 88	24728.00	383.00	1378.00	655.30

MTF #13 (MEDICAL CENTER)

COUNT	=	24.00	24.00	24.00	18.00
MEAN	=	1710.46	725.00	5714.96	938.66
STD DEV	=	140.19	50.23	410.48	465.48

	OPV	ADM	OBD	EEIC604
OCT 84				
NOV 84				
DEC 84				
JAN 85				
FEB 85				
MAR 85				
APR 85				
MAY 85				
JUN 85				
JUL 85				
AUG 85				
SEP 85				
OCT 85	32186.00	760.00	5699.00	
NOV 85	38060.00	740.00	5232.00	
DEC 85	29546.00	736.00	5065.00	
JAN 86	35046.00	838.00	6067.00	
FEB 86	36102.00	717.00	5656.00	
MAR 86	37752.00	746.00	5752.00	
APR 86	34650.00	725.00	5808.00	
MAY 86	36718.00	691.00	5802.00	
JUN 86	37664.00	699.00	5495.00	
JUL 86	34540.00	720.00	5795.00	
AUG 86	38742.00	767.00	6330.00	
SEP 86	37664.00	781.00	6099.00	
OCT 86	39023.00	803.00	6309.00	986.20
NOV 86	33288.00	727.00	5651.00	1111.50
DEC 86	36769.00	654.00	5105.00	5.10
JAN 87	37653.00	727.00	6029.00	1805.70
FEB 87	37957.00	682.00	5809.00	835.80
MAR 87	41993.00	787.00	6530.00	981.90
APR 87	41052.00	741.00	5906.00	987.80
MAY 87	35918.00	650.00	5671.00	1215.90
JUN 87	38237.00	665.00	4993.00	1029.00
JUL 87	35077.00	723.00	5517.00	932.50
AUG 87	36905.00	707.00	5860.00	588.50
SEP 87	37225.00	614.00	4979.00	976.20
OCT 87	37258.00	725.00	5474.00	599.40
NOV 87	34664.00	653.00	4983.00	867.20
DEC 87	35767.00	593.00	4288.00	1274.50
JAN 88	36394.00	709.00	5138.00	767.10
FEB 88	39038.00	714.00	5240.00	28.50
MAR 88	41430.00	710.00	5295.00	1903.00

Appendix C: SLAM II Simulation Program and Fortran Subroutine

```
GEN,HILL,DEMAND CLINIC 9080,6/18/88,25,N,N,,N,,72;
LIMITS,1,36,12;
EQUIV/XX(1),COUNTER/
      XX(2),SINDX1/
      XX(3),SINDX2/
      XX(4),SINDX3/
      XX(5),SINDX4/
      XX(6),SINDX5/
      XX(7),SINDX6/
      XX(8),SINDX7/
      XX(9),SINDX8/
      XX(10),SINDX9;
EQUIV/XX(11),SINDX10/
      XX(12),SINDX11/
      XX(13),SINDX12/
      XX(14),MO/
      XX(15),D1/
      XX(16),D2;
EQUIV/XX(17),D3/
      XX(18),D4/
      XX(19),D5/
      XX(20),D6/
      XX(21),D7/
      XX(22),D8/
      XX(23),D9/
      XX(24),D10/
      XX(25),D11/
      XX(26),D12/
      XX(29),PRE_ACT/XX(30),ACTUAL/
      XX(31),MOVAVG;
EQUIV/XX(32),XSMTH1/
      XX(33),XSMTH2/
      XX(34),XSMTH3/
      XX(35),XSMTH4/
      XX(36),XSMTH5/
      XX(37),XSMTH6/
      XX(38),XSMTH7/
      XX(39),XSMTH8/
      XX(40),XSMTH9/
      XX(41),XSMTH10/
      XX(42),XSMTH11/
      XX(43),XSMTH12/
      XX(44),STRND;
EQUIV/XX(45),ALPHA/
      XX(46),BETA0/XX(47),BETA1/
      XX(48),XSMTH/
      XX(49),SINDX/
      XX(50),WALPHA/
      XX(51),WBETA/
      XX(52),WGAMMA/
      XX(53),WSEAS1/
      XX(54),WSEAS2/
      XX(55),WSEAS3/
```

```
      XX(56),WSEAS4/
      XX(57),WSEAS5;
EQUIV/XX(58),WSEAS6/
      XX(59),WSEAS7/
      XX(60),WSEAS8/
      XX(61),WSEAS9/
      XX(62),WSEAS10/
      XX(63),WSEAS11/
      XX(64),WSEAS12/
      XX(65),WTRND1/
      XX(66),WTRND2/
      XX(67),WTRND3/
      XX(68),WTRND4/
      XX(69),WTRND5/
      XX(70),WTRND6/
      XX(71),WTRND7;
EQUIV/XX(72),WTRND8/
      XX(73),WTRND9/
      XX(74),WTRND10/
      XX(75),WTRND11/
      XX(76),WTRND12/
      XX(77),WINDX1/
      XX(78),WINDX2/
      XX(79),WINDX3/
      XX(80),WINDX4/
      XX(81),WINDX5;
EQUIV/XX(82),WINDX6/
      XX(83),WINDX7/
      XX(84),WINDX8/
      XX(85),WINDX9/
      XX(86),WINDX10/
      XX(87),WINDX11/
      XX(88),WINDX12;
EQUIV/XX(89),WINTER/
      ATRIB(1),SQERRMA/
      ATRIB(2),SQERRX/
      ATRIB(3),SQERRT/
      ATRIB(4),ABSDEVMA/
      ATRIB(5),ABSDEVX/
      ATRIB(6),ABSDEVT/
      ATRIB(7),ABSPERMA/
      ATRIB(8),ABSPERX/
      ATRIB(9),ABSPERT;
EQUIV/ATRIB(10),SQERRW/
      ATRIB(11),ABSDEVW/
      ATRIB(12),ABSPERW/
;
```

```
;
; ASSIGN INITIAL VALUES OF COUNTER, SEAS INDICES, MO, DEMANDS
;
INTLC,XX(1)=0;
;                      SEASONAL INDICES - SINDX
INTLC,XX(2)=0.0,XX(3)=3.0,XX(4)=0.0,XX(5)=1.8,XX(6)=0.9,
      XX(7)=1.6,XX(8)=0.0,XX(9)=0.8,XX(10)=0.7,XX(11)=0.0,
INTLC,XX(12)=1.3,XX(13)=1.9;
;
;                      WINTERS' STARTING INDICES SAME AS ABOVE
INTLC,XX(77)=0.0,XX(78)=3.0,XX(79)=0.0,XX(80)=1.8,XX(81)=0.9,
      XX(82)=1.6,XX(83)=0.0,XX(84)=0.8,XX(85)=0.7,XX(86)=0.0;
INTLC,XX(87)=1.3,XX(88)=1.9;
;
INTLC,XX(14)=0;
;                      MONTHLY DEMANDS ACTUAL OLD FIGURES
INTLC,XX(15)=0.0,XX(16)=74.0,XX(17)=0.0,XX(18)=50.0,
      XX(19)=25.0,XX(20)=50.0,XX(21)=0.0,XX(22)=25.5;
      XX(23)=25.5,XX(24)=0.0,XX(25)=50.0,XX(26)=74.0;
;
INTLC,XX(42)=50.0,XX(43)=74.0;
;
INTLC,XX(45)=0.3;        LEAVE UNTOUCHED
;
;    XX(46)=BO STRND, (47)=STRND SLOPE
INTLC,XX(46)=21.46,XX(47)=1.49,
      XX(50)=0.066,XX(51)=0.140,XX(52)=0.416;
;
;                      XX(53)=XX(46)
INTLC,XX(53)=21.46,XX(63)=50,XX(64)=51.50,XX(75)=1.49,
      XX(76)=1.49;
;
INTLC,XX(90)=0,XX(91)=0,XX(92)=0,XX(93)=0,XX(94)=0,XX(95)=0,
      XX(96)=0,XX(97)=0,XX(98)=0,XX(99)=0,XX(100)=0;
INTLC,XX(27)=0,XX(28)=0;
;
NETWORK;
      CREATE,,0;
;
;          INITIAL VALUES FOR ATRIBUTES
;
      ASSIGN,ATRIB(24)=74.0,ATRIB(25)=50.0;
;
;          UPDATE COUNTER, MONTH
;
CNTR  GOON,1;
      ASSIGN,COUNTER=COUNTER+1,MO=MO+1,XX(100)=XX(100)+1.49;
```

```
        GOON,1;
           ACT,1,COUNTER.EQ.49,FNSH;    RUN SIMULATION 48 TIMES
           ACT,0,MO.LT.13,ROUT;         CYCLE MONTH FROM 1 TO 12
           ACT,0,MO.EQ.13,RSET;

RSET    ASSIGN,MO=1;
;
ROUT    GOON,1;                         ROUTE TO CORRECT MONTH
           ACT,0,MO.EQ.1,MO1;
           ACT,0,MO.EQ.2,MO2;
           ACT,0,MO.EQ.3,MO3;
           ACT,0,MO.EQ.4,MO4;
           ACT,0,MO.EQ.5,MO5;
           ACT,0,MO.EQ.6,MO6;
           ACT,0,MO.EQ.7,MO7;
           ACT,0,MO.EQ.8,MO8;
           ACT,0,MO.EQ.9,MO9;
           ACT,0,MO.EQ.10,M10;
           ACT,0,MO.EQ.11,M11;
           ACT,0,MO.EQ.12,M12;
;
MO1     ASSIGN,SINDX=SINDX1; ALLOWS USING SAME FORTRAN EQUATION
        ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
        ASSIGN,ACTUAL=PRE_ACT*SINDX;    ACT DEMAND
        ASSIGN,ATRIB(13)=ACTUAL;        HOLD ACTUAL TO LAG 2 MOS
           ACT,0,COUNTER.EQ.1,MM1;
           ACT,0,COUNTER.GT.1,V1;
MM1     ASSIGN,MOVAVG=USERF(77);     STARTUP MOVING AVG PROCESS
           ACT,,,CTMA;
V1      GOON;
        ASSIGN,D11=ATRIB(23);        UPDATE LAGGED MO DATA
        ASSIGN,MOVAVG=USERF(1);      FORTRAN COMPUTES MOVING AVG
           ACT,,,CTMA;               GOTO COUNTER SUBROUTINE
X1      ASSIGN,XSMTH1=USERF(2);      FORTRAN COMPUTES EX SMOOTHING
        ASSIGN,XSMTH=XSMTH1;         FOR GENERIC USE CMPTING ERROR
           ACT,,,CTXS;
T1      ASSIGN,STRND=USERF(3);       FORTRAN COMPUTES SEAS TREND
           ACT,,,CTST;
W1      ASSIGN,WINTER=USERF(14);     FORTRAN COMPUTES WINTERS
           ACT,,,CTW;
WS1     ASSIGN,WSEAS1=USERF(15);
        ASSIGN,WTRND1=USERF(16);
        ASSIGN,WINDX1=USERF(17);
S1      ASSIGN,SQERRMA=USERF(4);     FORTRAN CMPTS SQ ERR MOV AVG
        ASSIGN,SQERRX=USERF(5);      FORTRAN CMPTS SQ ERR EX SMTH
        ASSIGN,SQERRT=USERF(6);      FORTRAN CMPTS SQ ERR SEASTRND
        ASSIGN,SQERRW=USERF(18);     FORTRAN CMPTS SQ ERR WINTERS
A1      ASSIGN,ABSDEVMA=USERF(7);    CMPTS ABSOLUTE DEVIATION ERR
        ASSIGN,ABSDEVX=USERF(8);             "
        ASSIGN,ABSDEVT=USERF(9);             "
        ASSIGN,ABSDEVW=USERF(19);            "
        ASSIGN,ABSPERMA=USERF(10);CMPTS ABSOLUTE % ERROR
        ASSIGN,ABSPERX=USERF(11);            "
        ASSIGN,ABSPERT=USERF(12);            "
        ASSIGN,ABSPERW=USERF(20);            "
```

```
        GOON,1;
           ACT,,,COL;
;
;                   MONTH TWO PROCESSES
;
MO2     ASSIGN,SINDX=SINDX2;
        ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
        ASSIGN,ACTUAL=PRE_ACT*SINDX;
        ASSIGN,ATRIB(14)=ACTUAL;
        ASSIGN,D12=ATRIB(24);
V2      ASSIGN,MOVAVG=USERF(1);
           ACT,,,CTMA;
X2      ASSIGN,XSMTH2=USERF(13);
        ASSIGN,XSMTH=XSMTH2;
           ACT,,,CTXS;
T2      ASSIGN,STRND=USERF(3);
           ACT,,,CTST;
W2      ASSIGN,WINTER=USERF(21);
           ACT,,,CTW;
WS2     ASSIGN,WSEAS2=USERF(32);
        ASSIGN,WTRND2=USERF(43);
        ASSIGN,WINDX2=USERF(54);
S2      ASSIGN,SQERRMA=USERF(4);
        ASSIGN,SQERRX=USERF(5);
        ASSIGN,SQERRT=USERF(6);
        ASSIGN,SQERRW=USERF(18);
A2      ASSIGN,ABSDEVMA=USERF(7);
        ASSIGN,ABSDEVX=USERF(8);
        ASSIGN,ABSDEVT=USERF(9);
        ASSIGN,ABSDEVW=USERF(19);
        ASSIGN,ABSPERMA=USERF(10);
        ASSIGN,ABSPERX=USERF(11);
        ASSIGN,ABSPERT=USERF(12);
        ASSIGN,ABSPERW=USERF(20);

        GOON,1;
           ACT,,,COL;
;
;
;                   MONTH THREE PROCESSES
;
MO3     ASSIGN,SINDX=SINDX3;
        ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
        ASSIGN,ACTUAL=PRE_ACT*SINDX;
        ASSIGN,ATRIB(15)=ACTUAL;
        ASSIGN,D1=ATRIB(13);
V3      ASSIGN,MOVAVG=USERF(1);
           ACT,,,CTMA;
X3      ASSIGN,XSMTH3=USERF(65);
        ASSIGN,XSMTH=XSMTH3;
           ACT,,,CTXS;B
T3      ASSIGN,STRND=USERF(3);
           ACT,,,CTST;
W3      ASSIGN,WINTER=USERF(22);
           ACT,,,CTW;
```

```
WS3    ASSIGN,WSEAS3=USERF(33);
       ASSIGN,WTRND3=USERF(44);
       ASSIGN,WINDX3=USERF(55);
S3     ASSIGN,SQERRMA=USERF(4);
       ASSIGN,SQERRX=USERF(5);
       ASSIGN,SQERRT=USERF(6);
       ASSIGN,SQERRW=USERF(18);
A3     ASSIGN,ABSDEVMA=USERF(7);
       ASSIGN,ABSDEVX=USERF(8);
       ASSIGN,ABSDEVT=USERF(9);
       ASSIGN,ABSDEVW=USERF(19);
       ASSIGN,ABSPERMA=USERF(10);
       ASSIGN,ABSPERX=USERF(11);
       ASSIGN,ABSPERT=USERF(12);
       ASSIGN,ABSPERW=USERF(20);

       GOON,1;
          ACT,,,COL;
;
;
;                MONTH FOUR PROCESSES
;
MO4    ASSIGN,SINDX=SINDX4;
       ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
       ASSIGN,ACTUAL=PRE_ACT*SINDX;
       ASSIGN,ATRIB(16)=ACTUAL;
       ASSIGN,D2=ATRIB(14);
V4     ASSIGN,MOVAVG=USERF(1);
          ACT,,,CTMA;
X4     ASSIGN,XSMTH4=USERF(66);
       ASSIGN,XSMTH=XSMTH4;
          ACT,,,CTXS;
T4     ASSIGN,STRND=USERF(3);
          ACT,,,CTST;
W4     ASSIGN,WINTER=USERF(23);
          ACT,,,CTW;
WS4    ASSIGN,WSEAS4=USERF(34);
       ASSIGN,WTRND4=USERF(45);
       ASSIGN,WINDX4=USERF(56);
S4     ASSIGN,SQERRMA=USERF(4);
       ASSIGN,SQERRX=USERF(5);
       ASSIGN,SQERRT=USERF(6);
       ASSIGN,SQERRW=USERF(18);
A4     ASSIGN,ABSDEVMA=USERF(7);
       ASSIGN,ABSDEVX=USERF(8);
       ASSIGN,ABSDEVT=USERF(9);
       ASSIGN,ABSDEVW=USERF(19);
       ASSIGN,ABSPERMA=USERF(10);
       ASSIGN,ABSPERX=USERF(11);
       ASSIGN,ABSPERT=USERF(12);
       ASSIGN,ABSPERW=USERF(20);

       GOON,1;
          ACT,,,COL;
;
;
```

```
;
;                  MONTH FIVE PROCESSES
;
MO5    ASSIGN,SINDX=SINDX5;
       ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
       ASSIGN,ACTUAL=PRE_ACT*SINDX;
       ASSIGN,ATRIB(17)=ACTUAL;
       ASSIGN,D3=ATRIB(15);
V5     ASSIGN,MOVAVG=USERF(1);
          ACT,,,CTMA;
X5     ASSIGN,XSMTH5=USERF(67);
       ASSIGN,XSMTH=XSMTH5;
          ACT,,,CTXS;
T5     ASSIGN,STRND=USERF(3);
          ACT,,,CTST;
W5     ASSIGN,WINTER=USERF(24);
          ACT,,,CTW;
WS5    ASSIGN,WSEAS5=USERF(35);
       ASSIGN,WTRND5=USERF(46);
       ASSIGN,WINDX5=USERF(57);
S5     ASSIGN,SQERRMA=USERF(4);
       ASSIGN,SQERRX=USERF(5);
       ASSIGN,SQERRT=USERF(6);
       ASSIGN,SQERRW=USERF(18);
A5     ASSIGN,ABSDEVMA=USERF(7);
       ASSIGN,ABSDEVX=USERF(8);
       ASSIGN,ABSDEVT=USERF(9);
       ASSIGN,ABSDEVW=USERF(19);
       ASSIGN,ABSPERMA=USERF(10);
       ASSIGN,ABSPERX=USERF(11);
       ASSIGN,ABSPERT=USERF(12);
       ASSIGN,ABSPERW=USERF(20);

       GOON,1;
          ACT,,,COL;
;
;
;                  MONTH SIX PROCESSES
;
MO6    ASSIGN,SINDX=SINDX6;
       ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
       ASSIGN,ACTUAL=PRE_ACT*SINDX;
       ASSIGN,ATRIB(18)=ACTUAL;
       ASSIGN,D4=ATRIB(16);
V6     ASSIGN,MOVAVG=USERF(1);
          ACT,,,CTMA;
X6     ASSIGN,XSMTH6=USERF(68);
       ASSIGN,XSMTH=XSMTH6;
          ACT,,,CTXS;
T6     ASSIGN,STRND=USERF(3);
          ACT,,,CTST;
W6     ASSIGN,WINTER=USERF(25);
          ACT,,,CTW;
```

```
S6      ASSIGN,SQERRMA=USERF(4);
        ASSIGN,SQERRX=USERF(5);
        ASSIGN,SQERRT=USERF(6);
        ASSIGN,SQERRW=USERF(18);
A6      ASSIGN,ABSDEVMA=USERF(7);
        ASSIGN,ABSDEVX=USERF(8);
        ASSIGN,ABSDEVT=USERF(9);
        ASSIGN,ABSDEVW=USERF(19);
        ASSIGN,ABSPERMA=USERF(10);
        ASSIGN,ABSPERX=USERF(11);
        ASSIGN,ABSPERT=USERF(12);
        ASSIGN,ABSPERW=USERF(20);

        GOON,1;
           ACT,,,COL;
;
;
;                MONTH SEVEN PROCESSES
;
MO7     ASSIGN,SINDX=SINDX7;
        ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
        ASSIGN,ACTUAL=PRE_ACT*SINDX;
        ASSIGN,ATRIB(19)=ACTUAL;
        ASSIGN,D5=ATRIB(17);
V7      ASSIGN,MOVAVG=USERF(1);
           ACT,,,CTMA;
X7      ASSIGN,XSMTH7=USERF(69);
        ASSIGN,XSMTH=XSMTH7;
           ACT,,,CTXS;
T7      ASSIGN,STRND=USERF(3);
           ACT,,,CTST;
W7      ASSIGN,WINTER=USERF(26);
           ACT,,,CTW;
WS7     ASSIGN,WSEAS7=USERF(37);
        ASSIGN,WTRND7=USERF(48);
        ASSIGN,WINDX7=USERF(59);
S7      ASSIGN,SQERRMA=USERF(4);
        ASSIGN,SQERRX=USERF(5);
        ASSIGN,SQERRT=USERF(6);
        ASSIGN,SQERRW=USERF(18);
A7      ASSIGN,ABSDEVMA=USERF(7);
        ASSIGN,ABSDEVX=USERF(8);
        ASSIGN,ABSDEVT=USERF(9);
        ASSIGN,ABSDEVW=USERF(19);
        ASSIGN,ABSPERMA=USERF(10);
        ASSIGN,ABSPERX=USERF(11);
        ASSIGN,ABSPERT=USERF(12);
        ASSIGN,ABSPERW=USERF(20);

        GOON,1;
           ACT,,,COL;
;
```

```
;                 MONTH EIGHT PROCESSES
;
MO8    ASSIGN,SINDX=SINDX8;
       ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
       ASSIGN,ACTUAL=PRE_ACT*SINDX;
       ASSIGN,ATRIB(20)=ACTUAL;
       ASSIGN,D6=ATRIB(18);
V8     ASSIGN,MOVAVG=USERF(1);
          ACT,,,CTMA;
X8     ASSIGN,XSMTH8=USERF(70);
       ASSIGN,XSMTH=XSMTH8;
          ACT,,,CTXS;
T8     ASSIGN,STRND=USERF(3);
          ACT,,,CTST;
W8     ASSIGN,WINTER=USERF(27);
          ACT,,,CTW;
WS8    ASSIGN,WSEAS8=USERF(38);
       ASSIGN,WTRND8=USERF(49);
       ASSIGN,WINDX8=USERF(60);
S8     ASSIGN,SQERRMA=USERF(4);
       ASSIGN,SQERRX=USERF(5);
       ASSIGN,SQERRT=USERF(6);
       ASSIGN,SQERRW=USERF(18);
A8     ASSIGN,ABSDEVMA=USERF(7);
       ASSIGN,ABSDEVX=USERF(8);
       ASSIGN,ABSDEVT=USERF(9);
       ASSIGN,ABSDEVW=USERF(19);
       ASSIGN,ABSPERMA=USERF(10);
       ASSIGN,ABSPERX=USERF(11);
       ASSIGN,ABSPERT=USERF(12);
       ASSIGN,ABSPERW=USERF(20);

       GOON,1;
          ACT,,,COL;
;
;
;                 MONTH NINE PROCESSES
;
MO9    ASSIGN,SINDX=SINDX9;
       ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
       ASSIGN,ACTUAL=PRE_ACT*SINDX;
       ASSIGN,ATRIB(21)=ACTUAL;
       ASSIGN,D7=ATRIB(19);
V9     ASSIGN,MOVAVG=USERF(1);
          ACT,,,CTMA;
X9     ASSIGN,XSMTH9=USERF(71);
       ASSIGN,XSMTH=XSMTH9;
          ACT,,,CTXS;
T9     ASSIGN,STRND=USERF(3);
          ACT,,,CTST;
W9     ASSIGN,WINTER=USERF(28);
          ACT,,,CTW;
WS9    ASSIGN,WSEAS9=USERF(39);
       ASSIGN,WTRND9=USERF(50);
       ASSIGN,WINDX9=USERF(61);
```

```
S9      ASSIGN,SQERRMA=USERF(4);
        ASSIGN,SQERRX=USERF(5);
        ASSIGN,SQERRT=USERF(6);
        ASSIGN,SQERRW=USERF(18);
A9      ASSIGN,ABSDEVMA=USERF(7);
        ASSIGN,ABSDEVX=USERF(8);
        ASSIGN,ABSDEVT=USERF(9);
        ASSIGN,ABSDEVW=USERF(19);
        ASSIGN,ABSPERMA=USERF(10);
        ASSIGN,ABSPERX=USERF(11);
        ASSIGN,ABSPERT=USERF(12);
        ASSIGN,ABSPERW=USERF(20);

        GOON,1;
           ACT,,,COL;
;
;
;                 MONTH TEN PROCESSES
;
M10     ASSIGN,SINDX=SINDX10;
        ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
        ASSIGN,ACTUAL=PRE_ACT*SINDX;
        ASSIGN,ATRIB(22)=ACTUAL;
        ASSIGN,D8=ATRIB(20);
V10     ASSIGN,MOVAVG=USERF(1);
           ACT,,,CTMA;
X10     ASSIGN,XSMTH10=USERF(72);
        ASSIGN,XSMTH=XSMTH10;
           ACT,,,CTXS;
T10     ASSIGN,STRND=USERF(3);
           ACT,,,CTST;
W10     ASSIGN,WINTER=USERF(29);
           ACT,,,CTW;
WS10    ASSIGN,WSEAS10=USERF(40);
        ASSIGN,WTRND10=USERF(51);
        ASSIGN,WINDX10=USERF(62);
S10     ASSIGN,SQERRMA=USERF(4);
        ASSIGN,SQERRX=USERF(5);
        ASSIGN,SQERRT=USERF(6);
        ASSIGN,SQERRW=USERF(18);
A10     ASSIGN,ABSDEVMA=USERF(7);
        ASSIGN,ABSDEVX=USERF(8);
        ASSIGN,ABSDEVT=USERF(9);
        ASSIGN,ABSDEVW=USERF(19);
        ASSIGN,ABSPERMA=USERF(10);
        ASSIGN,ABSPERX=USERF(11);
        ASSIGN,ABSPERT=USERF(12);
        ASSIGN,ABSPERW=USERF(20);

        GOON,1;
           ACT,,,COL;
;
;
```

```
;                    MONTH ELEVEN PROCESSES
;
M11     ASSIGN,SINDX=SINDX11;
        ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
        ASSIGN,ACTUAL=PRE_ACT*SINDX;
        ASSIGN,ATRIB(23)=ACTUAL;
        ASSIGN,D9=ATRIB(21);
V11     ASSIGN,MOVAVG=USERF(1);
           ACT,,,CTMA;
X11     ASSIGN,XSMTH11=USERF(73);
        ASSIGN,XSMTH=XSMTH11;
           ACT,,,CTXS;
T11     ASSIGN,STRND=USERF(3);
           ACT,,,CTST;
W11     ASSIGN,WINTER=USERF(30);
           ACT,,,CTW;
WS11    ASSIGN,WSEAS11=USERF(41);
        ASSIGN,WTRND11=USERF(52);
        ASSIGN,WINDX11=USERF(63);
S11     ASSIGN,SQERRMA=USERF(4);
        ASSIGN,SQERRX=USERF(5);
        ASSIGN,SQERRT=USERF(6);
        ASSIGN,SQERRW=USERF(18);
A11     ASSIGN,ABSDEVMA=USERF(7);
        ASSIGN,ABSDEVX=USERF(8);
        ASSIGN,ABSDEVT=USERF(9);
        ASSIGN,ABSDEVW=USERF(19);
        ASSIGN,ABSPERMA=USERF(10);
        ASSIGN,ABSPERX=USERF(11);
        ASSIGN,ABSPERT=USERF(12);
        ASSIGN,ABSPERW=USERF(20);

        GOON,1;
           ACT,,,COL;
;
;
;                    MONTH TWELVE PROCESSES
;
M12     ASSIGN,SINDX=SINDX12;
        ASSIGN,PRE_ACT=EXPON(31.2)+XX(100);
        ASSIGN,ACTUAL=PRE_ACT*SINDX;
        ASSIGN,ATRIB(24)=ACTUAL;
        ASSIGN,D10=ATRIB(22);
V12     ASSIGN,MOVAVG=USERF(1);
           ACT,,,CTMA;
X12     ASSIGN,XSMTH12=USERF(74);
        ASSIGN,XSMTH=XSMTH12;
           ACT,,,CTXS;
T12     ASSIGN,STRND=USERF(3);
           ACT,,,CTST;
W12     ASSIGN,WINTER=USERF(31);
           ACT,,,CTW;
WS12    ASSIGN,WSEAS12=USERF(42);
        ASSIGN,WTRND12=USERF(53);
        ASSIGN,WINDX12=USERF(64);
```

```
S12    ASSIGN,SQERRMA=USERF(4);
       ASSIGN,SQERRX=USERF(5);
       ASSIGN,SQERRT=USERF(6);
       ASSIGN,SQERRW=USERF(18);
A12    ASSIGN,ABSDEVMA=USERF(7);
       ASSIGN,ABSDEVX=USERF(8);
       ASSIGN,ABSDEVT=USERF(9);
       ASSIGN,ABSDEVW=USERF(19);
       ASSIGN,ABSPERMA=USERF(10);
       ASSIGN,ABSPERX=USERF(11);
       ASSIGN,ABSPERT=USERF(12);
       ASSIGN,ABSPERW=USERF(20);

       GOON,1;
          ACT,,,COL;
;
;                COLLECT FORECASTS, ERRORS
;
COL    COLCT,ACTUAL,ACTUAL DEMAND;
       COLCT,MOVAVG,MOV AVG FCST;
       COLCT,XSMTH,EX SMOOTH FCST;
       COLCT,STRND,SEAS TRND FCST;
       COLCT,WINTER,WINTERS EX SM;
       COLCT,SQERRMA,SQ ERROR MOV AVG;
       COLCT,SQERRX,SQ ERR EX SMOOTH;
       COLCT,SQERRT,SQ ERR SEAS TRND;
       COLCT,SQERRW,SQ ERR WINTERS;
       COLCT,ABSDEVMA,ABS DEV MOV AVG;
       COLCT,ABSDEVX,ABSDEV EX SMOOTH;
       COLCT,ABSDEVT,ABSDEV SEAS TRND;
       COLCT,ABSDEVW,ABSDEV WINTERS;
       COLCT,ABSPERMA,ABS % ERR MA;
       COLCT,ABSPERX,ABS % ERR EX SM;
       COLCT,ABSPERT,ABS % ERR S TRND;
       COLCT,ABSPERW,ABS % ERR WINTER;
       COLCT,XX(90),DIFF MOVAVG;
       COLCT,XX(94),POS MOVAVG;
       COLCT,XX(95),NEG MOVAVG;
       COLCT,XX(91),DIFF EX SM;
       COLCT,XX(96),POS EX SM;
       COLCT,XX(97),NEG EX SM;
       COLCT,XX(92),DIFF SEASTRND;
       COLCT,XX(98),POS SEASTRND;
       COLCT,XX(99),NEG SEASTRND;
       COLCT,XX(93),DIFF WINTER;
       COLCT,XX(27),POS WINTER;
       COLCT,XX(28),NEG WINTER;
LOOP   GOON,1;
          ACT,,,CNTR;
;
```

```
;             UPDATE INTEGER COUNT OF OVER AND UNDER FORECASTS
;
CTMA   ASSIGN,XX(90)=MOVAVG-ACTUAL;    COUNTER FOR MOV AVG FCST
          ACT,0,XX(90).LT.0,NMA;
          ACT,0,XX(90).GE.0,PMA;
PMA    GOON,1;
       ASSIGN,XX(94)=XX(94)+1;         UPDATE POS MOV AVG COUNT
          ACT,,,CMA;
NMA    ASSIGN,XX(95)=XX(95)+1;         UPDATE NEG MOV AVG COUNT
CMA    GOON;
          ACT,0,MO.EQ.1,X1;            RETURN TO MONTH ROUTINE
          ACT,0,MO.EQ.2,X2;
          ACT,0,MO.EQ.3,X3;
          ACT,0,MO.EQ.4,X4;
          ACT,0,MO.EQ.5,X5;
          ACT,0,MO.EQ.6,X6;
          ACT,0,MO.EQ.7,X7;
          ACT,0,MO.EQ.8,X8;
          ACT,0,MO.EQ.9,X9;
          ACT,0,MO.EQ.10,X10;
          ACT,0,MO.EQ.11,X11;
          ACT,0,MO.EQ.12,X12;
;
CTXS   ASSIGN,XX(91)=XSMTH-ACTUAL;
          ACT,0,XX(91).LT.0,NXS;
          ACT,0,XX(91).GE.0,PXS;
PXS    GOON,1;
       ASSIGN,XX(96)=XX(96)+1;   UPDATE POS EX SMOOTHING COUNT
          ACT,,,CNX;
NXS    ASSIGN,XX(97)=XX(97)+1;   UPDATE NEG EX SMOOTHING COUNT
CNX    GOON;
          ACT,0,MO.EQ.1,T1;            RETURN TO MONTH ROUTINE
          ACT,0,MO.EQ.2,T2;
          ACT,0,MO.EQ.3,T3;
          ACT,0,MO.EQ.4,T4;
          ACT,0,MO.EQ.5,T5;
          ACT,0,MO.EQ.6,T6;
          ACT,0,MO.EQ.7,T7;
          ACT,0,MO.EQ.8,T8;
          ACT,0,MO.EQ.9,T9;
          ACT,0,MO.EQ.10,T10;
          ACT,0,MO.EQ.11,T11;
          ACT,0,MO.EQ.12,T12;
;
CTST   ASSIGN,XX(92)=STRND-ACTUAL;
          ACT,0,XX(92).LT.0,NST;
          ACT,0,XX(92).GE.0,PST;
PST    GOON;
       ASSIGN,XX(98)=XX(98)+1;      UPDATE POS SEAS TRND COUNT
          ACT,,,CNST;
NST    ASSIGN,XX(99)=XX(99)+1;      UPDATE NEG SEAS TRND COUNT
```

```
CNST    GOON;
           ACT,0,MO.EQ.1,W1;              RETURN TO MONTH ROUTINE
           ACT,0,MO.EQ.2,W2;
           ACT,0,MO.EQ.3,W3;
           ACT,0,MO.EQ.4,W4;
           ACT,0,MO.EQ.5,W5;
           ACT,0,MO.EQ.6,W6;
           ACT,0,MO.EQ.7,W7;
           ACT,0,MO.EQ.8,W8;
           ACT,0,MO.EQ.9,W9;
           ACT,0,MO.EQ.10,W10;
           ACT,0,MO.EQ.11,W11;
           ACT,0,MO.EQ.12,W12;
;
CTW     ASSIGN,XX(93)=WINTER-ACTUAL;
           ACT,0,XX(93).LT.0,NW;
           ACT,0,XX(93).GE.0,PW;
PW      GOON;
        ASSIGN,XX(27)=XX(27)+1;        UPDATE POS WINTER COUNT
           ACT,,,CNW;
NW      ASSIGN,XX(28)=XX(28)+1;        UPDATE NEG WINTER COUNT
CNW     GOON;
           ACT,0,MO.EQ.1,WS1;             RETURN TO MONTH ROUTINE
           ACT,0,MO.EQ.2,WS2;
           ACT,0,MO.EQ.3,WS3;
           ACT,0,MO.EQ.4,WS4;
           ACT,0,MO.EQ.5,WS5;
           ACT,0,MO.EQ.6,WS6;
           ACT,0,MO.EQ.7,WS7;
           ACT,0,MO.EQ.8,WS8;
           ACT,0,MO.EQ.9,WS9;
           ACT,0,MO.EQ.10,WS10;
           ACT,0,MO.EQ.11,WS11;
           ACT,0,MO.EQ.12,WS12;
;
FNSH    GOON,1;
        TERM;
        END;

INIT,0,1200;
;MONTR,TRACE(COL),0,24,XX(30),XX(31),XX(48),XX(44),XX(89);
FIN;
```

```
      PROGRAM MAIN
      DIMENSION NSET(15000)
      INCLUDE 'PARAM.INC'
      COMMON/SCOM1/ATRIB(MATRB),DD(MEQT),DDL(MEQT),DTNOW,II,
     1MFA,MSTOP,NCLNR,NCRDR,NPRNT,NNRUN,NNSET,NTAPE,SS(MEQT),
     2SSL(MEQT),TNEXT,TNOW,XX(MMXXV)
      COMMON QSET(15000)
      EQUIVALENCE (NSET(1),QSET(1))
      NNSET=15000
      NCRDR=5
      NPRNT=6
      NTAPE=7
      NPLOT=2
      CALL SLAM
      STOP
      END
C
      FUNCTION USERF(I)
      INCLUDE 'PARAM.INC'
      COMMON/SCOM1/ATRIB(MATRB),DD(MEQT),DDL(MEQT),DTNOW,II,
     1MFA,MSTOP,NCLNR,NCRDR,NPRNT,NNRUN,NNSET,NTAPE,SS(MEQT),
     2SSL(MEQT),TNEXT, TNOW, XX(MMXXV)
      GO TO (1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,
     121,22,23,24,25,26,27,28,29,30,31,32,33,34,35,36,37,38,39,
     240,41,42,43,44,45,46,47,48,49,50,51,52,53,54,55,56,57,58,59,
     360,61,62,63,64,65,66,67,68,69,70,71,72,73,74,75,76,77),I
1     P=XX(15)+XX(16)+XX(17)+XX(18)+XX(19)+XX(20)+XX(21)+XX(22)
      USERF=(P+XX(23)+XX(24)+XX(25)+XX(26))/12
      RETURN
2     USERF=(XX(45)*XX(25))+(1-XX(45))*XX(42)
      RETURN
3     USERF=(XX(46)+(XX(47)*(XX(1)+12)))*XX(49)
      RETURN
4     USERF=(XX(30)-XX(31))**2
      RETURN
5     USERF=(XX(30)-XX(48))**2
      RETURN
6     USERF=(XX(30)-XX(44))**2
      RETURN
7     USERF=ABS(XX(30)-XX(31))
      RETURN
8     USERF=ABS(XX(30)-XX(48))
      RETURN
9     USERF=ABS(XX(30)-XX(44))
      RETURN
10    USERF=(ABS((XX(30)-XX(31))/XX(30)))*100
      RETURN
11    USERF=(ABS((XX(30)-XX(48))/XX(30)))*100
      RETURN
12    USERF=(ABS((XX(30)-XX(44))/XX(30)))*100
      RETURN
```

```
13    USERF=(XX(45)*XX(26))+(1-XX(45))*XX(43)
      RETURN
14    USERF=(XX(63)+2*XX(75))*XX(77)
      RETURN
15    USERF=((XX(50)*XX(30))/XX(77))+(1-XX(50))*(XX(64)+XX(76))
      RETURN
16    USERF=XX(51)*(XX(53)-XX(64))+(1-XX(51))*XX(76)
      RETURN
17    USERF=XX(52)*(XX(30)/XX(53))+(1-XX(52))*XX(77)
      RETURN
18    USERF=(XX(30)-XX(89))**2
      RETURN
19    USERF=ABS(XX(30)-XX(89))
      RETURN
20    USERF=(ABS((XX(30)-XX(89))/XX(30)))*100
      RETURN
21    USERF=(XX(64)+2*XX(76))*XX(78)
      RETURN
22    USERF=(XX(53)+2*XX(65))*XX(79)
      RETURN
23    USERF=(XX(54)+2*XX(66))*XX(80)
      RETURN
24    USERF=(XX(55)+2*XX(67))*XX(81)
      RETURN
25    USERF=(XX(56)+2*XX(68))*XX(82)
      RETURN
26    USERF=(XX(57)+2*XX(69))*XX(83)
      RETURN
27    USERF=(XX(58)+2*XX(70))*XX(84)
      RETURN
28    USERF=(XX(59)+2*XX(71))*XX(85)
      RETURN
29    USERF=(XX(60)+2*XX(72))*XX(86)
      RETURN
30    USERF=(XX(61)+2*XX(73))*XX(87)
      RETURN
31    USERF=(XX(62)+2*XX(74))*XX(88)
      RETURN
32    USERF=((XX(50)*XX(30))/XX(78))+(1-XX(50))*(XX(53)+XX(65))
      RETURN
33    USERF=((XX(50)*XX(30))/XX(79))+(1-XX(50))*(XX(54)+XX(66))
      RETURN
34    USERF=((XX(50)*XX(30))/XX(80))+(1-XX(50))*(XX(55)+XX(67))
      RETURN
35    USERF=((XX(50)*XX(30))/XX(81))+(1-XX(50))*(XX(56)+XX(68))
      RETURN
36    USERF=((XX(50)*XX(30))/XX(82))+(1-XX(50))*(XX(57)+XX(69))
      RETURN
37    USERF=((XX(50)*XX(30))/XX(83))+(1-XX(50))*(XX(58)+XX(70))
      RETURN
38    USERF=((XX(50)*XX(30))/XX(84))+(1-XX(50))*(XX(59)+XX(71))
      RETURN
39    USERF=((XX(50)*XX(30))/XX(85))+(1-XX(50))*(XX(60)+XX(72))
      RETURN
```

```
40    USERF=((XX(50)*XX(30))/XX(86))+(1-XX(50))*(XX(61)+XX(73))
      RETURN
41    USERF=((XX(50)*XX(30))/XX(87))+(1-XX(50))*(XX(62)+XX(74))
      RETURN
42    USERF=((XX(50)*XX(30))/XX(88))+(1-XX(50))*(XX(63)+XX(75))
      RETURN
43    USERF=XX(51)*(XX(54)-XX(53))+(1-XX(51))*XX(65)
      RETURN
44    USERF=XX(51)*(XX(55)-XX(54))+(1-XX(51))*XX(66)
      RETURN
45    USERF=XX(51)*(XX(56)-XX(55))+(1-XX(51))*XX(67)
      RETURN
46    USERF=XX(51)*(XX(57)-XX(56))+(1-XX(51))*XX(68)
      RETURN
47    USERF=XX(51)*(XX(58)-XX(57))+(1-XX(51))*XX(69)
      RETURN
48    USERF=XX(51)*(XX(59)-XX(58))+(1-XX(51))*XX(70)
      RETURN
49    USERF=XX(51)*(XX(60)-XX(59))+(1-XX(51))*XX(71)
      RETURN
50    USERF=XX(51)*(XX(61)-XX(60))+(1-XX(51))*XX(72)
      RETURN
51    USERF=XX(51)*(XX(62)-XX(61))+(1-XX(51))*XX(73)
      RETURN
52    USERF=XX(51)*(XX(63)-XX(62))+(1-XX(51))*XX(74)
      RETURN
53    USERF=XX(51)*(XX(64)-XX(63))+(1-XX(51))*XX(75)
      RETURN
54    USERF=XX(52)*(XX(30)/XX(54))+(1-XX(52))*XX(78)
      RETURN
55    USERF=XX(52)*(XX(30)/XX(55))+(1-XX(52))*XX(79)
      RETURN
56    USERF=XX(52)*(XX(30)/XX(56))+(1-XX(52))*XX(80)
      RETURN
57    USERF=XX(52)*(XX(30)/XX(57))+(1-XX(52))*XX(81)
      RETURN
58    USERF=XX(52)*(XX(30)/XX(58))+(1-XX(52))*XX(82)
      RETURN
59    USERF=XX(52)*(XX(30)/XX(59))+(1-XX(52))*XX(83)
      RETURN
60    USERF=XX(52)*(XX(30)/XX(60))+(1-XX(52))*XX(84)
      RETURN
61    USERF=XX(52)*(XX(30)/XX(61))+(1-XX(52))*XX(85)
      RETURN
62    USERF=XX(52)*(XX(30)/XX(62))+(1-XX(52))*XX(86)
      RETURN
63    USERF=XX(52)*(XX(30)/XX(63))+(1-XX(52))*XX(87)
      RETURN
64    USERF=XX(52)*(XX(30)/XX(64))+(1-XX(52))*XX(88)
      RETURN
65    USERF=(XX(45)*XX(15))+(1-XX(45))*XX(32)
      RETURN
66    USERF=(XX(45)*XX(16))+(1-XX(45))*XX(33)
      RETURN
```

```
67    USERF=(XX(45)*XX(17))+(1-XX(45))*XX(34)
      RETURN
68    USERF=(XX(45)*XX(18))+(1-XX(45))*XX(35)
      RETURN
69    USERF=(XX(45)*XX(19))+(1-XX(45))*XX(36)
      RETURN
70    USERF=(XX(45)*XX(20))+(1-XX(45))*XX(37)
      RETURN
71    USERF=(XX(45)*XX(21))+(1-XX(45))*XX(38)
      RETURN
72    USERF=(XX(45)*XX(22))+(1-XX(45))*XX(39)
      RETURN
73    USERF=(XX(45)*XX(23))+(1-XX(45))*XX(40)
      RETURN
74    USERF=(XX(45)*XX(24))+(1-XX(45))*XX(41)
      RETURN
75    USERF=(XX(45)*XX(26))+(1-XX(45))*XX(43)
      RETURN
76    USERF=(XX(45)*XX(26))+(1-XX(45))*XX(43)
      RETURN
77    R=XX(15)+XX(16)+XX(17)+XX(18)+XX(19)+XX(20)+XX(21)+XX(22)
      USERF=(R+XX(23)+XX(24)+XX(25)+ATRIB(25))/12
      RETURN
      END
```

Appendix D: Twelve Months Supply Demand and Workload Data

MTF #1 (CLINIC)

12	COUNT =	12	12	12	12	12	12	12	12	12	12
2643.83	MEAN =	28.00	14.00	7.75	166.83	3.00	1.83	58.08	4.17	4.75	61.08
227.25	STD DEV=	25.14	9.86	4.38	40.27	5.39	4.12	41.73	3.18	4.17	70.90
OPV	MO	8985	3458	7992	2698	8883	7277	2089	9377	0162	4191
2883	1	36	0	2	187	0	0	43	8	8	219
2514	2	24	24	9	204	0	0	50	4	14	0
2903	3	0	24	13	180	1	0	22	8	0	49
2798	4	84	0	3	183	1	0	69	8	0	41
2666	5	24	18	9	174	2	0	33	0	0	0
2580	6	24	0	8	181	20	12	17	4	8	212
2552	7	48	29	13	159	0	0	105	0	5	21
2312	8	48	25	2	76	6	0	165	2	7	33
2168	9	48	12	10	101	0	0	24	2	0	24
2631	10	0	12	10	207	1	0	20	0	6	44
2782	11	0	12	1	139	2	0	68	7	6	42
2937	12	0	12	13	211	3	10	81	7	3	48

MTF #2 (CLINIC)

12	COUNT =	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00	12.00
4901.333	MEAN =	214.17	96.00	37.42	.75	1.67	1.00	16.67	6.08	11.67
298.6434	STD DEV=	111.40	128.17	17.28	.83	5.53	2.24	17.19	4.73	10.53
OPV	MO	8985	3458	2698	8883	7277	2089	6606	9377	4191
4931	1	108	0	30	3	0	6	0	16	3
4473	2	240	0	18	0	0	0	0	8	4
5027	3	194	0	27	1	20	0	66	5	8
5057	4	96	0	28	0	0	0	20	8	14
4709	5	144	0	47	0	0	0	20	8	10
5159	6	96	0	16	1	0	0	10	0	10
5164	7	348	360	75	1	0	0	28	4	44
4477	8	216	86	47	1	0	0	13	0	6
4408	9	408	132	36	1	0	0	14	8	12
5002	10	411	358	52	0	0	6	21	0	17
5037	11	189	138	55	1	0	0	4	12	7
5372	12	120	78	18	0	0	0	4	4	5

MTF #3 (CLINIC)

OPV	MO	9080	6541	8985	3458	7992	2698	8883	7277	2089	6606	9377	0162	4191
9	COUNT =	12	12	12	12	12	12	12	12	12	12	12	12	12
10074.44	MEAN =	33.33	2.92	198.08	64.75	22.67	50.08	2.25	6.67	19.83	6.33	8.67	12.08	19.50
514.9565	STD DEV=	37.16	6.68	99.11	37.02	23.61	24.78	1.74	6.03	29.73	7.30	5.41	5.98	11.56
11270	1	0	0	216	72	0	47	2	8	10	16	4	19	29
10370	2	50	0	222	72	0	57	2	8	0	4	12	18	4
9980	3	0	0	156	0	48	71	0	22	10	10	13	7	15
10360	4	50	0	72	72	0	39	3	6	30	0	5	17	34
9540	5	0	0	48	0	24	51	2	6	0	24	12	2	6
9840	6	100	24	144	36	84	36	4	5	22	6	12	0	26
9870	7	0	0	250	81	24	67	6	15	61	10	20	18	15
9450	8	51	0	272	144	12	33	2	0	5	0	0	10	46
9990	9	0	0	309	72	12	45	2	4	0	5	8	14	13
	10	0	0	56	72	24	6	0	4	0	0	4	14	15
	11	50	6	368	84	6	112	4	0	0	0	3	13	16
	12	99	5	264	72	38	37	0	2	100	0	11	13	15

MTF #4 (CLINIC)

OPV	MO	9080	8985	3458	7992	2698	8883	7277	9377	0162	4191
12	COUNT =	12	12	12	12	12	12	12	12	12	12
9885.5	MEAN =	29.00	286.00	161.00	36.75	120.58	10.83	38.25	18.75	21.42	20.75
887.8097	STD DEV=	31.64	175.40	88.38	44.08	62.87	7.98	13.99	12.18	12.96	7.80
10549	1	0	360	144	48	115	18	39	19	48	19
8642	2	98	144	72	84	270	0	34	42	24	23
9410	3	0	72	24	0	142	12	66	10	29	31
8690	4	50	144	72	104	94	29	26	2	1	31
9245	5	50	48	108	46	57	17	53	20	0	13
9913	6	0	96	132	24	55	6	21	25	7	29
9936	7	0	336	132	2	181	18	32	20	20	22
9201	8	0	408	180	2	138	4	40	34	25	5
9891	9	51	648	192	0	40	4	24	0	21	13
10413	10	0	360	324	2	69	11	25	8	32	28
11007	11	50	432	276	0	170	5	39	30	27	17
11729	12	49	384	276	129	116	6	60	15	23	18

MTF 5 (HOSPITAL)

9	9		12	12	12	12	12	12	12	12	12	12	12
8662.11	431.44		100.08	1.92	69.17	323.83	12.92	133.67	3.25	61.33	13.33	26.00	30.00
701.30	49.94		99.84	1.32	42.19	104.41	3.20	42.44	1.69	54.58	10.84	18.10	13.08

LAST FOUR DIGITS OF MEDICAL SUPPLY ITEM

OPV	OBD	MO	9080	6541	8985	3458	7992	2698	8883	7277	9377	0162	4191
10271	487	1	51	2	120	432	15	150	6	140	30	32	35
9069	485	2	0	4	24	264	14	157	2	140	10	24	42
8831	449	3	100	0	72	300	9	180	3	139	18	42	30
8119	374	4	101	1	24	132	17	192	3	19	10	5	34
8415	350	5	147	1	12	162	18	103	3	102	12	0	16
9086	456	6	0	2	72	240	10	151	2	80	0	3	51
8084	485	7	300	3	74	440	12	78	4	27	4	66	41
7993	416	8	102	3	48	456	10	207	7	62	6	27	37
8091	381	9	0	4	96	328	11	98	4	0	0	21	16
		10	300	0	144	400	8	95	2	25	22	44	9
		11	50	2	24	318	15	95	1	0	12	20	38
		12	50	1	120	414	16	98	2	2	36	28	11

MTF #6 (HOSPITAL)

COUNT	12	12	12	12	12	12	12	12	12	12	12
MEAN	87.08	7.67	99.00	135	44.67	111	24.33	10.00	6.00	46.33	13.92
STD DEV	49.52	7.91	49.75	54.77	35.53	52.34	9.50	9.83	3.83	30.83	6.86

LAST FOUR DIGITS OF MEDICAL SUPPLY ITEM

OPV	ADM	OBD	MO	9080	6541	8985	3458	7992	2698	8883	7277	9377	1786	4191
7549	86	290	1	50	6	48	90	69	169	34	0	12	59	17
6850	99	345	2	100	12	168	221	54	134	31	3	8	78	24
6708	17	204	3	150	6	48	61	134	172	31	0	8	99	14
6364	63	220	4	51	0	204	108	49	204	25	28	12	31	18
6112	79	286	5	100	18	24	180	56	108	20	0	0	80	15
6370	32	142	6	99	25	72	48	12	40	13	9	4	0	13
6175	42	182	7	100	11	84	204	34	52	26	1	8	53	12
5668	33	125	8	0	13	108	126	0	84	0	20	4	24	1
5892	35	113	9	50	0	96	126	59	123	34	25	8	36	15
5898	47	175	10	50	1	96	168	15	130	22	10	4	72	16
6146	40	134	11	100	0	144	192	54	38	24	18	4	0	22
6516	38	147	12	195	0	96	96	0	72	32	6	0	24	0

MTF #7 (HOSPITAL)

12	12	12	COUNT	12	12	12	12	12	12	12	12	12	12	12	12
5844.4	89.3	253.8	MEAN	58.3	1.0	100.0	135.3	3.4	112.6	3.9	27.4	9.2	5.5	41.3	12.2
265.7	20.2	49.9	S DEV	72.9	1.2	62.4	50.7	1.6	88.4	2.9	23.0	7.7	2.7	15.2	5.8
				LAST FOUR DIGITS OF MEDICAL SUPPLY ITEM											
OPV	ADM	OBD	MO	9080	6541	8985	3458	7992	2698	8883	7277	9377	0162	1786	4191
5995	110	330	1	50	0	120	72	1	300	3	15	8	5	31	13
5886	99	269	2	100	1	72	168	4	183	3	68	0	6	48	10
5551	109	248	3	249	0	24	84	3	116	0	20	10	0	24	4
5882	124	344	4	0	0	36	180	3	224	9	5	16	11	44	23
5432	104	292	5	0	3	24	90	7	200	10	8	20	2	15	9
5754	47	183	6	100	0	84	108	5	92	6	75	12	5	70	18
5891	83	253	7	0	1	144	144	5	18	1	35	0	8	48	9
5676	79	228	8	100	1	144	96	2	46	3	21	19	5	48	15
5622	76	182	9	0	1	72	130	3	40	1	30	0	4	36	5
6290	91	281	10	100	4	168	264	2	36	4	0	0	6	48	13
5785	72	217	11	0	1	240	144	4	61	4	10	19	7	24	20
6369	78	218	12	0	0	72	144	2	35	3	42	6	7	60	6

MTF #8 (HOSPITAL)

12	12	12	COUNT =	12	12	12	12	12	12	12	12	12	12	12	12
12339.4	142.0	446.9	MEAN =	129.9	1.3	281.2	312.3	11.5	74.0	9.6	69.3	36.2	15.3	33.9	
1082.5	52.8	180.9	STD DEV=	166.1	1.2	154.0	139.6	5.5	24.5	5.2	31.5	39.2	9.1	15.7	
				LAST FOUR DIGITS OF MEDICAL SUPPLY ITEM											
OPV	ADM	OBD	MO	9080	6541	8985	3458	7992	2698	8883	7277	2089	9377	4191	
14200	173	605	1	3	0	310	216	12	69	9	100	100	8	46	
12537	185	632	2	52	0	120	408	22	91	17	114	50	18	43	
13403	242	768	3	1	0	120	108	13	70	11	60	0	21	21	
13047	192	612	4	391	3	96	180	10	96	12	72	0	15	66	
11987	156	475	5	9	0	220	288	18	72	20	93	0	28	30	
11952	77	273	6	503	2	216	240	18	114	14	60	0	28	51	
11235	93	244	7	0	2	264	336	14	55	7	36	0	0	32	
10864	85	206	8	50	3	336	324	6	69	5	20	0	24	33	
11745	76	228	9	150	0	312	396	5	35	7	90	50	18	38	
10565	92	319	10	0	2	432	180	5	32	2	40	76	12	27	
13387	172	538	11	300	1	684	648	6	78	4	114	100	0	10	
13151	161	463	12	100	2	264	424	9	107	7	32	58	12	10	

MTF #9 (HOSPITAL)

12	12	12	COUNT =	12	12	12	12	12	12	12	12	12	12	12	12
8209.1	113.7	328.9	MEAN =	70.9	1.3	174.0	122.0	4.8	58.5	4.3	35.3	16.0	10.5	31.8	21.0
318.0	11.8	42.9	STD DEV=	58.8	1.2	133.9	103.0	3.5	19.5	2.3	23.1	24.1	12.2	20.3	6.9

LAST FOUR DIGITS OF MEDICAL SUPPLY ITEM

OPV	ADM	OBD	MO	9080	6541	8985	3458	7992	2698	8883	7277	2089	9377	1786	4191
7819	97	252	1	149	0	96	108	2	93	5	80	0	40	20	33
7991	119	316	2	149	1	96	72	1	89	3	4	71	25	12	20
8306	125	354	3	149	0	72	72	6	59	8	15	0	24	78	24
8141	108	357	4	51	0	48	36	7	54	6	53	29	5	24	24
8149	99	315	5	0	2	48	48	2	36	3	5	41	0	35	8
7574	116	330	6	50	2	72	24	3	18	1	5	0	10	41	23
8872	138	378	7	1	4	192	72	14	60	2	32	0	0	32	21
8187	96	243	8	51	2	263	276	7	54	4	40	0	0	0	14
8416	115	329	9	51	1	121	0	5	52	5	41	0	10	33	31
8322	121	388	10	150	0	216	252	5	58	9	40	1	4	20	20
8211	112	322	11	0	2	384	315	1	56	3	46	0	0	25	22
8521	118	363	12	50	1	480	189	4	73	2	51	50	8	62	12

MTF #10 (REGIONAL HOSPITAL)

12	12	12	COUNT =	12	12	12	12	12	12	12	12	12	12	12	12	12
24662.0	498.9	2337.3	MEAN =	254	149	131	746	39	261	35	209	35	14	10	279	118
1977.9	51.7	183.8	STD DEV=	254	55	71	461	12	64	16	86	42	9	33	86	30

LAST FOUR DIGITS OF MEDICAL SUPPLY ITEM

OPV	ADM	OBD	MO	9080	6541	8985	3458	7992	2698	8883	7277	2089	9377	0162	1786	4191
25211	444	2116	1	296	168	144	360	53	351	38	85	0	0	0	255	83
23423	493	2404	2	704	168	72	960	56	130	20	384	50	28	0	323	120
23146	483	2153	3	50	192	72	744	31	304	23	248	0	16	0	205	88
23364	449	2223	4	171	240	120	144	31	280	75	201	0	12	0	186	167
22128	431	2016	5	650	132	0	384	60	238	58	132	50	12	0	232	65
23315	485	2359	6	100	84	48	1156	18	236	21	140	0	16	0	271	113
24987	520	2434	7	675	180	192	696	37	241	25	210	50	10	0	337	131
25074	531	2447	8	150	27	192	660	37	336	38	102	10	4	0	242	148
25784	470	2200	9	50	109	199	432	36	264	38	258	10	16	0	215	128
22928	490	2508	10	0	126	192	1944	32	182	17	324	30	8	0	227	111
27293	580	2599	11	100	208	240	468	28	223	40	168	150	14	0	334	97
29291	611	2589	12	100	152	96	1008	46	347	29	250	70	34	120	516	164

MTF #11 (REGIONAL HOSPITAL)

OPV	OBD	MO	9080	6541	8985	3458	7992	2698	8883	7277	2089	6606	9377	0162	1786	4191
9	9	COUNT =	12	12	12	12	12	12	12	12	12	12	12	12	12	12
23377.8	1647.6	MEAN =	155	3	237	524	25	270	17	106	104	23	31	38	240	117
1403.0	203.4	STD DEV=	104	3	197	275	12	41	5	78	120	18	23	18	48	32

LAST FOUR DIGITS OF MEDICAL SUPPLY ITEM

OPV	OBD	MO	9080	6541	8985	3458	7992	2698	8883	7277	2089	6606	9377	0162	1786	4191
26000	1518	1	150	0	396	794	30	311	20	181	10	64	75	42	198	179
24800	1482	2	50	0	96	108	28	278	15	80	50	0	52	31	250	55
23900	1512	3	400	8	0	576	62	251	10	22	100	20	4	36	226	110
23900	1649	4	50	0	0	216	16	256	14	0	50	14	32	31	161	136
22900	1460	5	150	2	0	312	24	273	11	140	250	22	32	0	251	120
22000	1884	6	12	6	0	372	24	252	11	128	50	36	0	12	228	93
23600	2111	7	200	8	404	541	26	257	18	104	50	0	32	41	226	140
21400	1589	8	250	1	500	576	23	252	20	14	0	20	18	36	264	122
21900	1623	9	50	4	216	426	19	220	28	80	150	15	32	42	180	89
		10	150	1	336	726	16	254	22	266	440	6	32	60	348	151
		11	200	2	408	454	18	389	18	54	50	30	64	48	288	81
		12	200	8	483	1186	18	248	18	202	50	46	0	72	264	128

MTF #12 (REGIONAL HOSPITAL)

OPV	ADM	OBD	MO	9080	6541	8985	3458	7992	2698	8883	7277	2089	6606	9377	0162	1786	4191
12	12	12	COUNT =	12	12	12	12	12	12	12	12	12	12	12	12	12	12
20158	350	1403	MEAN =	75	5	1985	334	25	171	12	35	66	1	8	34	164	98
1909	28	122	STD DEV=	68	3	990	204	6	75	3	37	55	1	7	23	28	36

LAST FOUR DIGITS OF MEDICAL SUPPLY ITEM

OPV	ADM	OBD	MO	9080	6541	8985	3458	7992	2698	8883	7277	2089	6606	9377	0162	1786	4191
19940	292	1210	1	0	7	2896	204	23	253	8	8	153	0	9	40	132	133
18048	339	1247	2	169	5	726	180	22	102	14	86	50	0	16	36	168	164
20112	331	1342	3	182	1	720	228	14	93	14	32	139	3	16	0	121	108
18944	338	1466	4	150	4	1440	228	28	250	8	57	0	0	19	48	198	113
17837	335	1410	5	0	5	2244	216	17	76	11	32	102	0	0	0	112	51
20371	355	1460	6	3	5	20	444	32	125	14	81	48	0	0	0	180	72
19949	361	1696	7	50	11	2776	648	37	309	18	109	114	0	10	59	164	92
18575	359	1433	8	0	2	1728	0	25	103	11	0	0	0	12	22	145	78
19679	332	1291	9	50	4	2728	252	24	142	6	0	0	0	0	33	191	66
20648	375	1426	10	50	4	2689	672	24	245	13	18	85	0	4	66	180	98
23059	402	1477	11	150	9	3000	324	27	214	16	0	0	0	5	38	195	149
24728	383	1378	12	100	4	2848	612	30	145	11	0	100	3	0	64	183	46

MTF #13 (MEDICAL CENTER)

12	12	12	COUNT =	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
37414	684	5279	MEAN =	1683	16	343	392	123	460	139	813	131	38	29	38	58	513	195
2082	45	432	STD DEV=	733	10	222	174	67	225	108	390	73	54	32	19	29	121	78

LAST FOUR DIGITS OF MEDICAL SUPPLY ITEM

OPV	ADM	OBD	MO	9080	6541	8985	3458	7992	2698	8883	7277	2089	6606	9377	6752	0162	1786	4191
41052	741	5906	1	2001	20	436	432	171	367	71	1444	199	10	32	37	113	504	248
35918	650	5671	2	1700	0	264	357	158	571	145	804	91	12	36	65	40	432	176
38237	665	4993	3	200	0	0	336	181	343	162	600	250	20	80	25	84	564	108
35077	723	5517	4	793	2	240	312	77	563	62	304	48	18	20	45	50	384	234
36905	707	5860	5	1800	15	0	360	112	521	92	1080	80	35	0	35	17	516	208
37225	614	4979	6	2400	19	660	192	255	876	137	1090	102	0	0	60	26	636	203
37258	725	5474	7	2500	15	48	528	36	130	60	680	20	40	0	0	50	324	60
34664	653	4983	8	1450	30	480	216	185	532	160	940	113	40	0	70	30	636	187
35767	593	4288	9	2800	19	585	720	147	819	299	840	80	70	92	20	100	732	151
36394	709	5138	10	1120	23	396	350	51	131	410	654	220	206	28	25	52	396	143
39038	714	5240	11	2231	25	576	720	60	319	21	1320	130	4	65	40	44	411	228
41430	710	5295	12	1200	20	432	180	48	343	48	0	235	0	0	39	84	624	388

Appendix E: Results of Simulations

SIMULATION RESULTS - ITEM 8985

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	85,870.0	3	203.6	3	54.4	3	27	21
EXPON SMOOTH	94,710.0	4	217.4	4	60.3	4	22	26
LINEAR TREND	34,500.0	1	155.3	1	52.1	2	22	26
WINTERS	57,940.0	2	165.9	2	51.2	1	26	22

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	69,156.0	4	179.0	3	39.7	1	18	30
EXPON SMOOTH	77,825.0	3	200.5	4	51.2	3	20	28
LINEAR TREND	30,406.0	1	140.9	1	45.7	2	37	11
WINTERS	50,977.0	2	156.6	2	56.9	4	28	20

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	1,090,100.0	3	770.1	3	73.7	3	19	29
EXPON SMOOTH	1,128,100.0	4	823.1	4	86.7	4	19	29
LINEAR TREND	398,200.0	1	479.3	1	53.2	1	35	13
WINTERS	1,040,900.0	2	659.9	2	60.3	2	28	20

SIMULATION RESULTS - ITEM 6752

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AVG								
EXPON SMOOTH								
			INSUFFICIENT DATA					
LINEAR TREND								
WINTERS								

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AVG								
EXPON SMOOTH								
			INSUFFICIENT DATA					
LINEAR TREND								
WINTERS								

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	629.5	2	20.0	2	369.6	3	31	17
EXPON SMOOTH	661.8	3	20.3	3	386.3	4	30	18
LINEAR TREND	526.9	1	17.5	1	218.6	1	20	28
WINTERS	1,444.3	4	21.5	4	300.8	2	27	21

SIMULATION RESULTS - ITEM 4191

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	364.1	2	14.5	3	531.0	4	40	8
EXPON SMOOTH	370.2	3	14.2	2	480.3	3	37	11
LINEAR TREND	145.7	1	8.9	1	257.6	2	3	45
WINTERS	4,100.7	4	22.4	4	171.8	1	21	27

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	124.4	3	17.5	3	271.8	4	42	6
EXPON SMOOTH	112.8	2	8.7	2	227.1	1	38	10
LINEAR TREND	70.2	1	6.8	1	262.9	3	5	43
WINTERS	458,378.3	4	41.9	4	239.1	2	27	21

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	1,067.4	3	25.3	3	15.8	3	24	24
EXPON SMOOTH	1,154.2	4	27.4	4	17.7	4	28	20
LINEAR TREND	180.3	1	10.2	1	7.3	1	31	17
WINTERS	459.8	2	17.1	2	11.7	2	21	27

SIMULATION RESULTS - ITEM 1786

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AVG								
EXPON SMOOTH				INSUFFICIENT DATA				
LINEAR TREND								
WINTERS								

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	118.1	3	9.3	3	200.8	3	39	9
EXPON SMOOTH	135.3	4	9.5	4	344.6	4	36	12
LINEAR TREND	82.0	1	7.3	1	137.6	1	10	38
WINTERS	107.1	2	8.4	2	142.6	2	23	25

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	6,238.3	3	62.8	4	12.7	4	10	38
EXPON SMOOTH	6,258.3	4	61.1	3	12.3	3	15	33
LINEAR TREND	2,021.7	2	41.1	2	9.1	2	36	12
WINTERS	1,363.3	1	28.6	1	6.6	1	22	26

SIMULATION RESULTS - ITEM 9080

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	4,384.4	3	42.1	4	53.1	1	23	25
EXPON SMOOTH	4,396.3	4	41.2	3	65.8	3	24	24
LINEAR TREND	2,275.0	1	33.7	1	64.8	2	35	13
WINTERS	3,321.7	2	37.7	2	74.0	4	26	22

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	3,694.0	3	47.3	3	272.9	4	27	21
EXPON SMOOTH	3,978.0	4	49.5	4	251.7	3	27	21
LINEAR TREND	2,835.0	1	42.3	1	213.0	1	23	25
WINTERS	3,643.0	2	44.0	2	244.2	2	24	24

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	372,300.0	2	492.8	2	430.4	3	25	23
EXPON SMOOTH	421,700.0	3	507.7	3	472.4	4	25	23
LINEAR TREND	326,600.0	1	428.1	1	427.3	1	24	24
WINTERS	625,700.0	4	571.0	4	430.0	2	24	24

SIMULATION RESULTS - ITEM 6541

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AVG								
EXPON SMOOTH			INSUFFICIENT DATA					
LINEAR TREND								
WINTERS								

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	8.3	2	2.0	2	554.4	4	32	16
EXPON SMOOTH	9.7	3	2.1	3	534.6	2	30	18
LINEAR TREND	7.5	1	1.4	1	317.0	1	27	21
WINTERS	52.8	4	3.0	4	549.8	3	29	19

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	2,339.3	4	32.0	3	1050	3	30	18
EXPON SMOOTH	2,315.0	3	33.8	4	1226	4	31	17
LINEAR TREND	2,096.7	1	29.6	1	775.3	2	29	19
WINTERS	2,197.2	2	31.3	2	673.6	1	30	18

SIMULATION RESULTS - ITEM 3458

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	71,295.0	3	178.8	3	61.0	3	22	26
EXPON SMOOTH	86,530.0	4	205.9	4	80.6	4	25	23
LINEAR TREND	16,007.0	1	80.7	1	43.1	2	41	7
WINTERS	30,040.0	2	90.3	2	28.7	1	26	22

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	20,380.0	3	105.3	3	21.0	2	17	31
EXPON SMOOTH	21,922.0	4	119.6	4	26.5	4	21	21
LINEAR TREND	8,710.0	2	89.3	2	22.5	3	48	0
WINTERS	4,360.0	1	43.6	1	13.1	1	23	25

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	330.0	3	440.5	3	52.3	1	19	29
EXPON SMOOTH	386.4	4	473.6	4	57.2	3	21	27
LINEAR TREND	185.9	1	320.0	1	60.0	4	34	14
WINTERS	237.6	2	362.9	2	55.2	2	25	23

SIMULATION RESULTS - ITEM 7992

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	639.6	2	17.9	2	2648	4	32	16
EXPON SMOOTH	823.5	3	19.2	3.5	1470	2	30	18
LINEAR TREND	614.5	1	14.6	1	802	1	28	20
WINTERS	885.4	4	19.2	3.5	1707	3	28	20

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	500.5	3	16.9	3	266.9	2	36	12
EXPON SMOOTH	406.6	2	15.4	2	227.2	1	35	13
LINEAR TREND	317.1	1	11.8	1	322.0	3	20	28
WINTERS	2,136.6	4	24.2	4	334.5	4	27	21

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	3,128.2	3	46.3	3	184.7	3	29	19
EXPON SMOOTH	3,877.0	4	47.2	4	210.0	4	28	20
LINEAR TREND	1,541.9	1	23.2	1	84.5	1	25	23
WINTERS	2,612.5	2	33.0	2	101.3	2	24	24

SIMULATION RESULTS - ITEM 2698

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	9,364.0	3	70.6	3	1283	4	31	17
EXPON SMOOTH	11,402.0	4	77.4	4	1001	3	30	18
LINEAR TREND	9,114.0	1	65.0	1	995	2	27	21
WINTERS	9,209.9	2	68.1	2	991	1	30	18

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	4,412.8	3	57.0	3	310.0	4	42	6
EXPON SMOOTH	3,667.3	2	51.0	2	227.0	2	43	5
LINEAR TREND	2,123.2	1	45.0	1	262.5	3	31	17
WINTERS	33,319.0	4	61.0	4	126.8	1	30	18

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	33,640.0	2	146.6	2	303.4	3	27	21
EXPON SMOOTH	36,933.0	3	155.5	3	296.3	2	26	22
LINEAR TREND	29,066.0	1	134.5	1	263.4	1	24	24
WINTERS	57,313.0	4	190.9	4	463.6	4	27	21

SIMULATION RESULTS - ITEM 8883

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	24.4	2	3.6	2	9,326.0	4	33	15
EXPON SMOOTH	25.0	3	3.7	3	7,364.0	3	31	17
LINEAR TREND	21.2	1	3.2	1	1,067.0	1	26	22
WINTERS	559.0	4	10.7	4	1,082.0	2	29	19

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	19.3	4	3.6	3	223.4	2	37	11
EXPON SMOOTH	19.2	3	3.8	4	269.3	3	34	14
LINEAR TREND	14.7	1	3.0	1	276.9	4	15	33
WINTERS	18.1	2	3.4	2	222.0	1	26	22

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	3,439.3	4	33.0	3	1,255.0	3	30	18
EXPON SMOOTH	3,418.1	3	34.1	4	1,334.0	4	31	17
LINEAR TREND	3,088.2	1	30.6	1	800.0	2	28	20
WINTERS	3,296.6	2	31.5	2	758.4	1	30	18

SIMULATION RESULTS - ITEM 7277

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	156.9	1	6.6	1	447.1	2	32	16
EXPON SMOOTH	172.5	2	8.9	3	754.4	4	31	17
LINEAR TREND	196.5	3	7.9	2	297.6	1	28	20
WINTERS	35,753.0	4	25.1	4	748.5	3	28	20

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	798.7	2	24.6	3	370.4	4	35	13
EXPON SMOOTH	819.4	3	23.8	2	286.4	3	35	13
LINEAR TREND	355.7	1	17.8	1	145.0	2	10	38
WINTERS	3,348.3	4	28.0	4	105.5	1	25	23

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	54,081.8	2	185.2	2	568.5	3	29	19
EXPON SMOOTH	57,560.0	3	192.1	3	553.6	2	28	20
LINEAR TREND	47,090.0	1	167.0	1	354.0	1	22	26
WINTERS	530,660.0	4	347.5	4	1,074.4	4	24	24

SIMULATION RESULTS - ITEM 2089

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	3,213.3	3	43.9	2	37.3	1	24	24
EXPON SMOOTH	4,045.0	4	46.9	3	103.8	4	26	22
LINEAR TREND	956.0	1	213.5	4	50.0	3	37	11
WINTERS	1,238.5	2	22.5	1	44.9	2	27	21

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AVG								
EXPON SMOOTH								
LINEAR TREND			INSUFFICIENT DATA					
WINTERS								

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	17,700.0	3	102.7	3	261.7	4	26	22
EXPON SMOOTH	20,200.0	4	106.7	4	195.2	3	27	21
LINEAR TREND	10,125.0	1	72.4	1	72.4	1	27	21
WINTERS	14,200.0	2	85.8	2	85.8	2	25	23

SIMULATION RESULTS - ITEM 6606

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	482.1	2	15.8	2	586.0	2	33	15
EXPON SMOOTH	521.7	3	16.0	3	699.6	3	30	18
LINEAR TREND	276.9	1	8.4	1	703.5	4	18	30
WINTERS	3,258.2	4	107.2	4	492.3	1	28	20

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AVG								
EXPON SMOOTH								
LINEAR TREND								
WINTERS								

INSUFFICIENT DATA

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	4,215.0	3	33.8	3	73.9	3	26	22
EXPON SMOOTH	5,080.0	4	38.2	4	81.8	4	25	23
LINEAR TREND	1,965.8	1	20.6	2	52.6	2	37	11
WINTERS	2,563.4	2	19.4	1	36.8	1	28	20

SIMULATION RESULTS - ITEM 9377

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	25,282.0	2	123.4	2	46.6	3	9	39
EXPON SMOOTH	28,880.0	3	126.9	3	40.6	2	13	35
LINEAR TREND	135,556.0	4	297.2	4	98.1	4	0	48
WINTERS	4,522.0	1	52.9	1	30.5	1	4	44

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	173.6	2	10.1	2	203.3	2	34	14
EXPON SMOOTH	186.4	3	10.2	3	217.6	3	33	15
LINEAR TREND	151.0	1	7.1	1	146.8	1	22	26
WINTERS	22,724.3	4	50.2	4	600.5	4	28	20

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	844.4	2	20.9	2	3,388.2	1	29	19
EXPON SMOOTH	2,138.0	3	21.9	3	5,056.3	3	27	21
LINEAR TREND	749.0	1	19.4	1	4,336.0	2	21	27
WINTERS	940,298.0	4	195.4	4	9,587.8	4	26	22

SIMULATION RESULTS - ITEM 0162

MTF GROUP: CLINICS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	23.5	2	3.9	2	802.8	4	33	15
EXPON SMOOTH	27.5	3	4.2	3	696.9	3	31	17
LINEAR TREND	19.5	1	3.2	1	268.2	1	35	13
WINTERS	139.1	4	7.0	4	425.9	2	23	25

MTF GROUP: HOSPITALS

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	483.1	3	13.7	3	203.0	3	26	22
EXPON SMOOTH	929.5	4	14.9	4	225.1	4	26	22
LINEAR TREND	322.8	1	11.2	2	68.9	1	34	14
WINTERS	357.8	2	10.7	1	69.1	2	28	20

MTF GROUP: REGIONAL HOSPITALS/MED CENTER

FORECASTING METHOD	MSE	RANK	MAD	RANK	MAPE	RANK	# TIMES ABOVE ACTUAL	# TIMES BELOW ACTUAL
12 MO MOV AV	2,539.2	3	39.7	3	202.4	3	23	25
EXPON SMOOTH	3,208.0	4	44.2	4	265.3	4	23	25
LINEAR TREND	1,018.8	1	23.2	1	57.3	1	30	18
WINTERS	1,302.2	2	26.3	2	84.8	2	26	22

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VITA

Captain W. John Hill was born on [redacted] He graduated from [redacted] High School in [redacted] 1969. From 1969 to 1971 he attended Sophia University in Tokyo, Japan.

He joined the Air Force in 1971, and served four years as a Ground Radio Repairman. In June 1975 he graduated magna cum laude from California State University, Sacramento with a B.S. in Business Administration. After graduation, he was employed by a large department store chain as assistant store manager.

In 1980, Captain Hill entered California State University, Stanislaus. Upon graduating in 1981 with an M.B.A., he entered the Air Force as a Second Lieutenant Medical Service Corps officer. His first assignment was at USAF Hospital George from 1982 to 1984, first as Commander, Medical Squadron Section; and later as Director, Patient Affairs.

In 1984 he was transferred to USAF Hospital Misawa at Misawa Air Base, Japan, where he was assigned as Director, Resource Management. While at Misawa he was selected Pacific Air Forces Medical Resource Management Officer of the Year 1986, and Pacific Air Forces Company Grade Medical Service Corps Officer of the Year, 1986 - 1987.

In May 1987 he entered the School of Systems and Logistics, Air Force Institute of Technology.

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Thesis Advisor: Larry W. Emmelhainz, Major, USAF
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The purpose of this study was to examine the characteristics of demand for medical supplies in Air Force medical treatment facilities in an effort to improve inventory control. One method proposed to improve system performance was use of a more sophisticated forecasting technique than the 12 month moving average currently used in forecasting demand for economic order quantity computations. This would better match supply to demand. (Continued on reverse)

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Block 19. ABSTRACT

The research also examined whether: (1) major workload measures were highly correlated to medical supply usage, (2) there were demand patterns for major stock classes which were common to all facilities, and (3) whether differences in medical treatment facilities affected inventory performance measures to the extent that a service-wide model should not be used.

Workload and medical supply demand data were collected from 13 facilities and analyzed. When workload and supply expenditure data were tested for correlation, the findings indicated little or no relationship. Plotting the data from each facility revealed that both a trend and seasonality were common. It was also shown that grouping the data according to facility category; clinics, hospitals, and regional hospitals/medical centers, reduced the within group variance of the data. The demand data were found to fit primarily exponential and poisson distributions.

In studying alternative forecasting techniques, a strong explanatory model based upon multiple regression analysis was not found. Three other forecasting techniques; exponential smoothing, a linear trend model incorporating seasonal indexing, and a Winter's exponential smoothing model, were tested using computer simulation to produce simulated "actual" demands against the 15 medical supplies in the sample. The simulation technique was employed to substitute for the insufficient amount of actual demand data available. The simulation showed that both the linear trend and Winter's models would produce smaller forecasting errors than the 12 month moving average.

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