A COMPARATIVE STUDY OF DEMAND FORECASTING TECHNIQUES FOR MILITARY HELICOPTER SPARE PARTS*

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ABSTRACT

This paper deals with techniques applicable to predicting spare parts demand for military helicopters. The military helicopter is a distinct weapons system, whose unique configuration may preclude the direct application of forecasting techniques which have proved successful for other weapon systems. Furthermore, although the military helicopter has become extremely important tactically in modern warfare, it has received scant attention in terms of research concerning its supply support.

Specifically, this paper summarizes research done to measure and compare the forecasting accuracy of six mathematical models, as they were applied to three prominent military helicopters. In addition, the paper describes attempts that were made to define, where possible, the conditions under which a specific forecasting technique might be applicable. In general, it is shown that the most accurate set of helicopter spare parts demand forecasts are produced by a second order polynomial exponential smoothing model. This model is observed to have most accurately described the highly volatile, and upward-trended demand time series which were the subject of the study.

INTRODUCTION

An efficient method for determining the demand for military equipment spare parts is critical to the design of an effective and economical logistics system. Demand forecasts are of importance to the logistics system manager in provisioning, budgeting, procurement, repair scheduling, determining distribution and stockage policies, and in other decision areas. Obviously, the operating cost of the logistics system and its number of supply failures is significantly affected by the accuracy with which demand is predicted. Because forecasts of demand cannot be perfect, the logistics system manager is confronted with making decisions under conditions of demand uncertainty. Any technique or procedure which reduces this uncertainty increases the probability of improvement in the aggregate logistic decision process. It is upon this phase of logistics management—the forecasting of spare parts demand—that this study has been conducted.

This particular study was concerned with the analysis, design, and testing of statistical forecasting systems applicable to spare parts demand for United States Army helicopters. The data used in the study applied to those helicopters under the control of the United States Army Aviation Systems Command (AVSCOM), St. Louis, Missouri.

Research concerning time series forecasting for military equipment spare parts has been extensive. One significant portion of this previous research has been concerned with the cost savings resulting from improved demand prediction [13, 14, 16, 34–38]. Another important research topic has

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been that of spare parts demand prediction for fixed wing aircraft and missles [3, 6, 7, 10, 18, 32, 33]. Research concerning spare parts demand prediction for rotary winged aircraft (helicopters) has been extremely limited; primary concern has been in statistically analyzing failure data [5, 31, 39].

It should be emphasized that the unique configuration of a rotary winged aircraft may well preclude the direct application of forecasting techniques which have proved successful for other weapon systems. In essence, this question was one of the major considerations of this study. The importance of the helicopter as distinct from fixed wing aircraft in Army aviation should also be emphasized. During the period of this study, almost 80 percent of the aircraft being supported by AVSCOM were helicopters [40]. This proportion could be expected to increase as the Army continues to emphasize increased air mobility in ground combat. Finally, it may also be expected that the increased reliance on helicopters for combat operations will increase the complexity of demand prediction, because past experience has indicated that helicopters require more logistical support than do fixed wing aircraft [41].

REVIEW OF PREVIOUS DEMAND PREDICTION RESEARCH

The major emphasis of previous research concerning military spares demand prediction has been on isolating a "preferred" technique for demand prediction. The demand forecasting techniques previously explored can be summarized into eight general categories, as follows:

1. *Regression Techniques.* Regression techniques are well developed and have been widely applied to time series forecasting. Applications of such techniques to military spares demand prediction have usually involved an attempt at developing a relationship between spares demand (dependent variable) and various activity measures (independent variables), such as flying hours, calendar time, number of sorties flown, and engine operating hours [3, 11, 19].

2. *Issue Interval Techniques.* Use of an issue interval technique is based upon the assumption of a constant demand rate over time, so that the relationship between past and future demand populations is a function only of total program activity in each period. The total demand for a given part during an experience period is divided by the total activity of the aircraft during the experience period to give an average forecast rate. The forecast for a future period is then obtained by multiplying the average forecast rate by the planned activity for the future period [1–3].

3. *Service Life Techniques.* Use of service life techniques require estimates of the service life characteristics of the part, derived from historical data. Future spares demands are then assumed to be affected by both the planned future activity for the weapons system, and by the service life characteristic of the part [2, 20, 23, 24].

4. *Exponential Smoothing Techniques.* Use of exponential smoothing techniques does not require the assumption of dependence of demand for a part on the level of activity of the weapons system. Instead, forecasted future demand is based solely on the exponentially weighted previous demand data [3, 4].

5. *Bayesian Techniques.* Use of a Bayesian technique involves combining a priori information (for example, the initial estimate of demand provided by an engineer familiar with the technical characteristics of the part) and data derived from subsequent events (early demand experience), to predict future demand. As operational experience grows there is a gradual shift, by means of Bayesian revision, from the initial estimate of the demand rate to the actual demand rate being experienced [5, 25, 26].

6. *Conditional Probability Techniques.* Use of these techniques require the empirical development of formulae for predicting the probability that a demand of Y units of an item will occur in a specified future time period, given that X units have been demanded in a past period. Conditional probabilities employing a number of probability distributions have been developed [43].

7. *Distribution Fitting Techniques.* These techniques are applicable when it is possible statistically to fit past demand data to particular probability distributions. Distribution fitting techniques have often been used in situations requiring relatively inexpensive predictions [6, 12, 22, 28].

8. *Spectral Analysis Techniques.* Spectral analysis, an outgrowth of the theory of stationary time series, attempts to decompose demand into its three basic components: trend, cyclical, and random. The significance of each of these components in the demand process is then evaluated, and the power spectrum of the underlying demand generating process is identified and used to predict future demand [3, 17].

It should be noted that these eight techniques represent a broad spectrum in terms of mathematical sophistication, ranging from the naive issue interval technique to the complex spectral analysis technique. Unfortunately, very little research concerning the comparative effectiveness of alternative forecasting techniques has been undertaken. In essence, only one major study of such a comparative nature has been made, that being a study by Astrachan, Brown, and Houghten [2]. However, even this study considered only two major types of forecasting techniques, issue interval and service life. In summary, previous military spares demand prediction research has centered almost exclusively on the development of a single preferred forecasting technique.

OBJECTIVES OF THE PRESENT STUDY

The major objectives of the present study were markedly different from those of previous studies. The first objective was to appraise critically the predictive accuracy of a number of demand prediction techniques, as they were applied to a common sample of military helicopter spare parts. The second objective of the study was to determine if there were isolatable conditions, or characteristics of helicopters and/or their associated parts which caused certain forecasting techniques to predict more accurately. The third objective was to appraise critically the forecasting technique employed by AVSCOM (issue interval technique) during the time period covered by the study. The evaluations made in the study were essentially comparative rather than absolute, and were made for a weapons system which had previously received little attention.

DATA USED IN THE STUDY

During the period of this study, AVSCOM provided spare parts support for 13 helicopter systems, 3 of which were chosen for analysis based on the following factors:

1. High helicopter density, that is, a large number of helicopters deployed to field.
2. High helicopter usage, that is, those helicopters being flown a large number of hours each month.
3. Availability of data, that is, those helicopters for which accurate demand and activity data could be obtained.

The helicopters considered as a result of the three previous factors were:

1. *The Bell UH–1D "Iroquois."* The UH–1D is a single engine, single main rotor helicopter used as the standard utility-tactical helicopter of the U.S. Army [21].
2. *The Hiller OH–23D "Raven."* The OH–23D is a single engine, single main rotor helicopter used for observation, reconnaissance, training, and medical evacuation [21].
3. *The Boeing CH–47A "Chinook."* The CH–47A is a twin turbine, tandem rotor helicopter used to transport troops, cargo, and weapons within a combat area [21].

Part samples for each of these three helicopter systems were next selected, with the samples being confined to critical item parts in the "High-Value" or "Super High-Value" categories.* At the time of this study, there were approximately 15 critical item spare parts on the OH–23D, 25 critical item spare parts on the UH–1D, and 35 critical item spare parts on the CH–47A. A simple random sampling procedure was employed in general; however, this procedure was modified in some instances so that parts common to all three helicopter systems could be included. This was done so that certain relationships between helicopter systems could be examined. The sampling procedure resulted in samples whose parts exhibited widely varying demand characteristics. For example, the samples included inexpensive parts with very high demand rates, and expensive parts with very low demand rates. The helicopter systems and the associated parts for which demand histories were collected are shown in Table 1.

The demand data for the parts shown in Table 1 were obtained from the AVSCOM Demand Data History File. Only recurring demands, which could be expected to occur routinely as a result of helicopter activity, were considered in this study. Thus, initial support requirements, mobilization requirements, and non-recurring base requirements were eliminated from consideration. The CH–47A helicopter and the UH–ID helicopters were both used in the United States and in Vietnam. Consequently, two demand time series were collected for each of the parts in the sample for these two helicopters. In addition to demand data, helicopter activity data, in terms of flying hours and number of helicopters deployed, were collected for the same time periods for which demand histories were accumulated. In general, about 60 months of demand and activity data were available.

FORECASTING TECHNIQUES TESTED

Six forecasting methods were considered in the study, they have been designated as Prediction Techniques 1 through 6. These six techniques were selected from the eight general categories of

*Critical item spare parts were defined as those parts that were essential to the operation of the helicopter. The "High-Value" or "Super-High Value" categories included parts whose yearly issues were in excess of $25,000.

TABLE 1. *Helicopter Systems and Parts Sampled*

Parts in sample	Helicopter systems		
	UH–1D	OH–23D	CH–47A[a]
Driveshaft	X	X	X
Engine	X	X	X
Fuel Control	X	X	X
Gear Box	X	X	....
Main Rotor Blade	X	X	X (Forward)
Main Rotor Blade	....	....	X (After)
Main Rotor Hub	X	X	X (After)
Scissors	X	X	....
Swashplate	X	X	X (Forward)
Swashplate	....	....	X (After)
Tail Rotor Blade	X	X	....
Transmission	X	X	X (Forward)
Transmission	....	....	X (After)
Total Number of Parts Sampled	10	10	10

[a] The CH–47A helicopter is powered by tandem engines. Thus, a number of its parts occur in pairs, that is, a forward and an after component corresponding to the forward and after power unit.

demand prediction techniques which were reviewed in an earlier section of the paper. A categorization of the forecasting techniques used in this study is as follows:

Category	*Forecasting Technique(s)*
Issue Interval	Prediction Technique #1
Regression	Prediction Technique #2
Exponential Smoothing	Prediction Techniques #3, #4, #5, and #6

Each prediction technique employed in this study will be briefly described at this point in the paper.

Prediction Technique #1: Issue Interval*

The total number of demands during the experience period is divided by the number of flying hours for the experience period to give an average demand rate. The rate thus obtained is multiplied by the planned number of flying hours for the prediction period to obtain the predicted number of demands for the prediction period:

$$\hat{d}_{t+i} = (D/F)\hat{f}_{t+i}, \tag{1}$$

where $\hat{d}_{t+i}$ = predicted number of demands for the $t+i$ future period;
D = observed number of demands during the experience period;
F = observed flying hours during the experience period; and
$\hat{f}_{t+i}$ = predicted flying hours for the $t+i$ future period.

Prediction Technique #2: Moving Regression

Multiple regression relationships were derived for the initial experience period, with number of demands as the dependent variable. The independent variables considered were the actual flying hours over time, helicopter density over time, and various transformations of these two variables. From 18 to 36 monthly observations were employed in the regression fitting process. Both linear and curvilinear regression equations were considered.

The "best fitting" regression equations were then used to make forecasts over the prediction period.† After each forecasting cycle, the parameters of the regression equation were revised, and forecasts for the next cycle were made. The moving regression procedure thus attempted to track the demand process over time.

Prediction Technique #3: General Exponential Smoothing

A general exponential smoothing model, employing a linear trend and a multiplicative seasonal, and based on the work of Peter R. Winters was used for forecasting [42]. The forecasting equations for the model were given by

$$\hat{d}_t = Ad_t/S_{t-L} + (1-A)(\hat{d}_{t-1} + T_{t-1}) \tag{2}$$

*The issue interval technique was the basic demand forecasting technique employed by AVSCOM during the course of this study.

†Best fitting regression equations were generally determined by maximizing the coefficient of multiple determination. However, the significance of the net regression coefficients was also tested, and non-significant independent variables were eliminated from the multiple regression equation.

(3) $$\hat{d}_{t+i}=(\hat{d}_t+iT_t)S_{t-L+1} \qquad i=1, 2, \ldots, L,$$

where

d_t = actual demand during the t^{th} period;

$\hat{d}_t$ = forecasted demand during the t^{th} period;

$\hat{d}_{t+i}$ = forecasted demand during the $t+i$ future period;

S_{t-L} = the multiplicative seasonal effect;

T_{t-L} = the current estimate of the linear trend effect;

L = the number of months in a cycle period, the periodicity of the seasonal effect; and

A = the exponential smoothing coefficient, $0 \leq A \leq 1.0$.

Initial estimates of demand rate, the seasonal effect in the demand rate, and the trend effect in the demand rate were made using the 18 to 36 months of data in the initial experience period. Forecasts were then made over the forecasting horizon, and the trend and seasonal factors were revised using the following relationships:

(4) $$S_t=Bd_t/\hat{d}_t+(1-B)S_{t-L}$$

and

(5) $$T_t=C(\hat{d}_t-\hat{d}_{t-1})+(1-C)T_{t-1},$$

where

B = The seasonal effect coefficient, $0 \leq B \leq 1.0$; and

C = The trend effect coefficient, $0 \leq C \leq 1.0$.

These forecasts were a function of the set of coefficients, A, B, and C. Determination of the set of coefficients which produced the most accurate demand forecast was accomplished by a three-dimensional grid search procedure. A grid of values, composed of all combinations of A, B, and C from 0.0 to 0.7 in increments of 0.1 was employed. The set of A, B, and C which was found to produce the forecast having the smallest forecasting error, was selected as being optimum.

Prediction Techniques #4: Single Exponential Smoothing

A simple algebraic model was used to describe the stochastic process underlying the demand time series. Forecasts for future time periods were obtained by the relationship:

(6) $$\hat{d}_{t+i}=\hat{a}_t,$$

where $\hat{d}_{t+i}$ = an estimate of demand in time period $t+i$ made in time period t; and

$\hat{a}_t$ = the simple average demand during the time periods from 0 to t.

Prediction Technique #5: Double Exponential Smoothing

A first degree polynomial model was used to describe demand over time, assuming that there was a significant linear trend to demand. Forecasts for future periods were obtained by the relationships:

$$\hat{d}_{t+i} = \hat{a}_t + \hat{b}_t i, \tag{7}$$

where $\hat{b}_t$ = the linear trend during the time period 0 to t, and $\hat{a}_t$ is the same as previously defined.

Prediction Technique #6: Triple Exponential Smoothing

A second degree polynomial model was used to describe demand over time, assuming that there was trend in demand which was changing as a quadratic function of time. Forecasts for future periods were obtained by the relationships:

$$\hat{d}_{t+i} = \hat{a}_t + \hat{b}_t i + 1/2\hat{c}_t i^2,$$

where $\hat{c}_t$ = the rate of change of trend during time period 0 to t, and $\hat{a}_t$ and $\hat{b}_t$ are the same as previously defined.

Brown and Meyer have rigorously proved that it is possible to estimate the $(n+1)$ coefficients in an n^{th} order polynomial exponential smoothing model by a linear combination of the first $(n+1)$ orders of exponential smoothing [9]. Brown has applied the results of this proof to the derivation of equations for the coefficients $\hat{a}_t$, $\hat{b}_t$, and $\hat{c}_t$ [13]. His procedure is recursive, and requires only the specification of a smoothing coefficient A, and an estimate of the demand rate, $\hat{d}_t$. The estimate of the demand rate was once again made using the 18 to 36 months of data in the initial experience period. The smoothing coefficient, A, was then defined and forecasts were made over the forecasting horizon. These forecasts were a function of the value of the smoothing coefficient, A. Determination of the value of A which produced the most accurate demand forecast was accomplished by a one-dimensional grid search procedure. A grid of values for A, composed of all values from 0.00 to 0.50 in increments of 0.05, was employed. The value of A which was found to produce the forecast having the smallest forecasting error, was selected as being optimum. This procedure was utilized for each of the latter three exponential smoothing models.

METHODOLOGY USED IN THE STUDY

The methodology used in the study encompassed three major steps. First, a period of time known as the *initial experience period* was established. The duration of the initial experience period was determined as a function of the total length of the time series being analyzed, with a longer time series resulting in a longer initial experience period. Thus, from 18 to 36 months of data were available for the initial experience period, with the variation being dependent upon the length of the time series being analyzed. During the initial experience period, demand and activity data were collected, and initial parameters for the various forecasting models were derived.

Second, a forecast *cycle period* in months was established. The length of the cycle period was determined as a function of two factors:

1. The duration of the difference between the total length of time series and the length of the experience period. This period of time, in months, was defined as the *forecast horizon.*

2. The actual replenishment lead time used at AVSCOM. During this study, the replenishment lead time was in the range of 6 to 12 months. In essence, the cycle period was selected as being either

6 or 12 months in length, with the shorter cycle period corresponding to the shorter forecast horizon, and vice versa.

Third, a forecast was made for the first cycle period using the initialization parameters established with data from the initial experience period. At the end of this cycle period, a new set of model parameters was computed based on a new experience period which included the most recent cycle period, and, in general, excluded data from the early part of the previous experience period. Then a new forecast for the next cycle period was made, and the previous parameter revision process was repeated. This procedure continued over the entire forecasting horizon.

MEASUREMENT OF FORECASTING ERROR

Upon completion of the forecasting procedure, forecasting errors were computed for the series of L month cycle period forecasts. The forecast error, $e_{t,L}$, for an L month cycle was given by:

(9) $$e_{t,L}=\sum_{i=1}^{L}(\hat{d}_{t+i}-d_{t+i}) \qquad t=1, 2, \ldots, n-L+1$$

where

$\hat{d}_{t+i}$ = forecasted demand in month $t+i$;

d_{t+i} = actual demand in month $t+i$;

L = number of months in a cycle period (6 or 12); and

n = number of months in the forecasting horizon.

Since forecasts were made in L month cycles over the forecasting horizon of n months, there were $k=n-L+1$ such summations. Each summation produced a total forecasting error for one cycle. The standard deviation, δ_L, for k such L month cycles was given by

(10) $$\delta_L=\sqrt{\sum_{t=1}^{k}\frac{(e_{t,L})^2}{k-1}}.$$

Finally, the coefficient of variation, CV_L, over the forecasting horizon was given by

(11) $$CV_L=\frac{\delta_L}{\sum_{i=1}^{L}d_{t+i}/k} \quad t=1, 2, \ldots, n-L+1.$$

The coefficient of variation over the forecasting horizon was used as the primary measure of forecast accuracy.

Bias was measured by computing the relative cycle error, RE_L, given by

(12) $$RE_L=\frac{\sum_{i=1}^{L}(\hat{d}_{t+i}-d_{t+i})}{\sum_{i=1}^{L}(d_{t+i})} \quad t=1, 2, \ldots, n-L+1.$$

The measurement of relative bias over the forecasting horizon was used to compare the underprediction and overprediction resulting from the application of the various forecasting techniques. Underpredictions were inherently considered to be more undesirable than overpredictions, since they prevented the helicopter from accomplishing its mission.

TEST RESULTS

The coefficient of variation and relative errors for each of the three helicopters and for each of their associated parts sample are shown in Tables A–1 through A–5 in the appendix. In order to summarize these extensive results, mean coefficients of variation and mean relative errors were computed for each helicopter and type of demand. This summary is presented in Table 2.

TABLE 2. *Summary of Test Results*

Helicopter system	Type of demand	Techniques					
		1	2	3	4	5	6
		A. Mean Coefficients of Variation					
OH–23D	Non-Vietnam	0.47	0.77	0.49	0.49	0.47	0.42
CH–47A	Non-Vietnam	1.86	0.61	0.69	0.46	0.43	0.38
	Vietnam	0.39	1.14	0.44	0.38	0.34	0.30
UH–1D	Non-Vietnam	1.26	0.76	0.59	0.42	0.36	0.28
	Vietnam	0.30	0.38	0.26	0.26	0.26	0.25
		B. Mean Relative Errors					
OH–23D	Non-Vietnam	−0.17	−0.64	−0.56	+0.01	+0.04	+0.05
CH–47A	Non-Vietnam	+1.57	+0.28	+0.15	−0.06	−0.05	−0.04
	Vietnam	+0.12	+0.42	+0.06	+0.17	+0.16	+0.15
UH–1D	Non-Vietnam	+1.12	+0.09	−0.02	−0.02	−0.01	+0.00
	Vietnam	−0.10	−0.22	−0.01	−0.01	−0.03	−0.02

An appraisal of the forecasting accuracy results presented in Table 2 clearly indicated the general superiority of the triple exponential smoothing technique. The lowest mean coefficient of variation was produced by the triple exponential smoothing technique for each of the five "helicopter" and "type of demand" categories. Similarly, the lowest mean relative error was produced by the triple exponential smoothing technique for two of the five "helicopter" and "type of demand" categories and was only slightly larger for the remaining three demand categories.

A comparison of the test results for a number of different parts sample classifications was next made. The following classifications were employed:

1. Helicopter mission.
2. Technical property of the parts.
3. Theater of operations.
4. Statistical property of the parts.

Mean coefficients of variation were next computed for each of the six forecasting techniques within the framework of the various parts sample classifications. A summary of the test results made in this manner is presented in Table 3. These results again strongly indicated the marked superiority of the triple exponential smoothing technique. In all categories, the smallest mean coefficient of variation was produced by triple exponential smoothing.

A final series of tests was made to compare the statistical significance of the differences between

TABLE 3. *Comparison of Test Results by Parts Sample Classifications*

(Mean Coefficients of Variation)

Classifications	Techniques					
	1	2	3	4	5	6
Helicopter Missions:						
Training	0.47	0.77	0.49	0.49	0.47	0.42
Combat—Transport	1.12	0.87	0.56	0.42	0.39	0.34
Combat—Assault	0.78	0.57	0.43	0.34	0.31	0.27
Technical Property:						
Vulnerable and/or Exposed	0.41	0.63	0.31	0.28	0.24	0.21
Power Transmission	0.63	0.65	0.39	0.34	0.31	0.29
Mandatory Replacement	0.52	0.31	0.31	0.27	0.25	0.24
Theater of Operations:						
Non-Vietnam	1.55	0.68	0.64	0.51	0.43	0.33
Vietnam	0.35	0.76	0.35	0.30	0.28	0.27
Statistical Property:[a]						
Low-Mean Dem./Month (0.00–5.00)	0.61	0.67	0.39	0.34	0.27	0.25
Medium-Mean Dem./Month (5.01–25.00)	0.63	0.73	0.36	0.33	0.30	0.29
High-Mean Dem./Month (25.01+)	0.46	0.55	0.35	0.34	0.28	0.24
Low-Coeff. of Dispersion (0.00–0.90)	0.55	0.53	0.38	0.33	0.30	0.27
High-Coeff. of Dispersion (0.91+)	0.55	0.78	0.34	0.33	0.32	0.25

[a] Class intervals for each of the statistical properties are shown in parentheses.

the mean coefficients of variation produced by the various forecasting techniques. The two sample t-test was employed, with the significance level for the difference between each pair of coefficients of variation being computed. The significance level was interpreted as the probability of a difference in sample means being as large as that observed, purely due to random effects. A high level of significance indicated that such a difference could be attributed to chance, while a low level of significance indicated that the observed difference was not due to chance alone. A summary of the test results made in this manner is presented in Table 4.*

The results shown in Table 4 reinforced, once again, the contention of superiority of triple exponentional smoothing. For 21 of the 25 comparisons made, there was less than a 40 percent chance that the difference in mean coefficients of variation produced by triple exponential smoothing and any of

*For sake of brevity, only comparisons involving the triple exponential smoothing model are presented here. More comprehensive results may be found in Markland [27].

TABLE 4. *Significance Levels for Differences Between Mean Coefficients of Variation*[a]

Helicopter System	Type of Demand	Techniques				
		1 vs 6	2 vs 6	3 vs 6	4 vs 6	5 vs 6
OH–23D....	Non-Vietnam....	0.40	0.16	0.36	0.40	0.31
CH–47A....	Non-Vietnam....	0.03	0.23	0.15	0.33	0.37
	Vietnam....	0.30	0.03	0.25	0.40	0.43
UH–1D	Non-Vietnam....	0.04	0.06	0.10	0.14	0.17
	Vietnam....	0.36	0.22	0.95	0.95	0.95

[a] Each significance level was computed by a two sample t-test with 18 degrees of freedom.

the other techniques would have occurred purely due to chance. Thus, there was a very strong indication that triple exponential smoothing produced forecasts which were significantly better than those produced by any of the other forecasting techniques in a statistical sense.

DISCUSSION OF RESULTS

The objectives of this study, as stated earlier, were three-fold. The initial objective was to compare the predictive accuracy of a number of demand prediction techniques, as they were applied to a common sample of military helicopter spare parts. The findings of this study strongly indicated the superiority of the triple exponential smoothing technique among the six techniques tested.

The second objective of the study was to determine if there were isolatable conditions, or characteristics of helicopters and/or their associated parts which caused certain forecasting techniques to predict more accurately. The results of testing were largely inconclusive in this area, as the triple exponential smoothing technique produced the most accurate sets of forecasts for virtually all of the part sample classifications.

The third objective of the study was to appraise critically the forecasting procedure utilized by AVSCOM during the time period covered by the study. Fruitful results were obtained in this regard, as it was conclusively shown that the issue interval technique produced relatively poor forecasting results when compared to the other methods tested. The result had obvious implications to the agency which participated in the investigation.

In conclusion, reasons for the superiority of the triple exponential smoothing technique can be suggested. The majority of the time series considered in the investigation had volatile demand patterns, with demand over time generally subject to a substantial upward trend. In addition, month to month fluctuations in demand were often pronounced. Now, the triple exponential smoothing model was explicitly formulated to consider demand processes having a changing, and hence nonlinear, trend in demand. In addition, the updating procedure used for the parameters of the triple exponential smoothing model allowed for rapid recognition of fundamental long-run changes in demand, as well as short-run fluctuations in demand which were of a more random nature. The general exponential smoothing model and the double exponential smoothing models considered only a linear trend. As a result, their parameter updating procedures reacted more slowly to fundamental long-run changes in demand, and tended to blur short-term changes in trend. The regression equation forecasting model implicity considered the presence of a trend in demand as a part of the derivation and revision of the regression equations used to make forecasts. However, these regression equations were derived for a time period which considerably lagged the time periods for which forecasts were being made (by an average of 3 to 6 months). Similarly, in the issue interval model, the forecasting parameter, the demand rate, was derived for a time period which lagged the time periods for which forecasts were being made by an average of 3 to 6 months. The results obtained by using triple exponential smoothing suggested that some of the most important trend effects were of a short duration, that is, 3 months or less. Essentially, the regression equation model and the issue interval model ignored these short-term trend effects in their parameter updating procedures. Since short-run trend effects were generally pronounced in the time series considered in this research, very inaccurate results were obtained from these two forecasting models.

CONCLUSION

In conclusion it must be stated that the present study is in no way definitive, but is rather a consideration of the general problem of military spares demand prediction for a unique and heretofore unexamined weapons system. For the government agency which was the subject of the research, the test results indicated that the triple exponential smoothing technique should replace the issue interval method, with a resultant increase in forecasting accuracy.

The general area of demand prediction for military equipment spares parts remains very fertile for continued study. Certainly, the important question of the cost of overestimation versus the cost of underestimation deserves increased attention. Similarly, moving regression equation forecasting, although unsuccessful in this study, offers promise if more sophisticated data for the independent variable can be derived (e.g., hours flown at high speed, combat hours, number of takeoffs and landings, etc.). Finally, the dynamic character of military equipment spare parts time series seems to suggest that an adaptive or error tracking forecasting procedure might improve forecasting accuracy.

Appendix

TABLE A–1. *Coefficients of Variation*
(OH–23D Parts Sample)

Part description	Techniques					
	1	2	3	4	5	6
Driveshaft	0.54	0.96	0.60	0.46	0.37	0.29
Engine	0.19	0.18	0.92	0.93	0.96	0.94
Fuel control	0.53	0.66	0.50	0.52	0.51	0.45
Gear box	0.34	0.53	0.35	0.37	0.29	0.23
Main rotor blade	0.35	0.39	0.19	0.20	0.27	0.29
Main rotor hub	0.75	1.25	0.74	0.76	0.68	0.52
Scissors	0.53	1.37	0.24	0.29	0.37	0.42
Swashplate	0.71	1.02	0.51	0.56	0.54	0.53
Tail rotor blade	0.42	0.91	0.43	0.32	0.29	0.18
Transmission	0.39	0.44	0.45	0.44	0.37	0.31

TABLE A–2. *Relative Errors*
(OH–23D Parts Sample)

Part description	Techniques					
	1	2	3	4	5	6
Driveshaft	−0.36	−0.88	−0.48	−0.32	−0.19	−0.11
Engine	+0.12	−0.15	+0.45	+0.21	+0.27	+0.22
Fuel control	−0.37	−0.50	−0.13	+0.40	+0.39	+0.36
Gear box	+0.18	−0.30	+0.13	−0.14	−0.09	−0.07
Main rotor blade	−0.28	−0.28	−0.02	+0.01	+0.05	+0.03
Main rotor hub	−0.21	−0.98	−0.16	+0.34	+0.28	+0.20
Scissors	−0.31	−1.27	−0.01	+0.06	+0.14	+0.18
Swashplate	−0.39	−1.22	−0.37	−0.10	−0.08	−0.09
Tail rotor blade	−0.33	−1.17	−0.03	−0.11	−0.09	−0.07
Transmission	+0.21	+0.35	+0.06	−0.29	−0.22	−0.18

TABLE A-3. *Coefficients of Variation*
(CH-47A Parts Sample)

Part description	Techniques 1	2	3	4	5	6
Non-Vietnam Demand Time Series						
Driveshaft	0.65	0.30	1.61	0.54	0.69	0.64
Engine	1.73	0.96	0.53	0.47	0.32	0.25
Fuel control	1.75	0.93	0.79	0.80	0.78	0.78
Main rotor bl.—aft	1.13	0.27	1.10	0.27	0.21	0.19
Main rotor bl.—fwd	0.68	0.22	0.36	0.35	0.31	0.28
Main rotor hub—aft	1.00	1.04	0.51	0.51	0.48	0.45
Swashplate—aft	5.13	0.27	0.54	0.52	0.47	0.39
Swashplate—fwd	2.89	0.25	0.77	0.47	0.39	0.26
Transmission—aft	2.45	1.33	0.48	0.46	0.42	0.37
Transmission—fwd	1.01	0.48	0.23	0.25	0.24	0.22
Vietnam Demand Time Series						
Driveshaft	0.87	1.21	0.55	0.39	0.27	0.19
Engine	0.23	0.52	0.15	0.16	0.12	0.10
Fuel control	0.22	0.75	0.94	0.73	0.62	0.41
Main rotor bl.—aft	0.34	1.07	0.15	0.20	0.32	0.38
Main rotor bl.—fwd	0.31	2.06	0.45	0.39	0.31	0.26
Main rotor hub—aft	0.39	1.26	0.40	0.40	0.39	0.36
Swashplate—aft	0.27	1.00	0.48	0.33	0.19	0.13
Swashplate—fwd	0.41	0.52	0.34	0.33	0.29	0.25
Transmission—aft	0.52	1.72	0.52	0.51	0.49	0.48
Transmission—fwd	0.34	1.31	0.41	0.40	0.40	0.39

TABLE A-4. *Relative Errors*
(CH-47A Parts Sample)

Part description	Techniques 1	2	3	4	5	6
Non-Vietnam Demand Time Series						
Driveshaft	+0.68	−0.27	+1.25	+0.11	+0.17	+0.13
Engine	+0.96	+0.65	−0.08	+0.12	+0.10	+0.06
Fuel control	+0.93	+0.55	−0.02	−0.20	−0.16	−0.16
Main rotor bl.—aft	+1.03	−0.23	+1.00	+0.09	+0.03	+0.00
Main rotor bl.—fwd	+0.45	+0.15	+0.06	+0.09	+0.07	+0.04
Main rotor hub—aft	+0.66	+0.52	−0.10	−0.24	−0.21	−0.17
Swashplate—aft	+4.63	−0.10	−0.24	−0.43	−0.37	−0.32
Swashplate—fwd	+3.33	−0.15	−0.60	−0.37	−0.32	−0.21
Transmission—aft	+2.15	+1.23	+0.12	+0.14	+0.11	+0.17
Transmission—fwd	+0.83	+0.42	+0.09	+0.11	+0.11	+0.10
Vietnam Demand Time Series						
Driveshaft	+0.48	+0.89	+0.46	+0.36	+0.27	+0.21
Engine	+0.02	+0.39	−0.06	+0.08	+0.05	+0.03
Fuel control	−0.18	+0.20	+0.16	+0.37	+0.31	+0.26
Main rotor bl.—aft	+0.18	+0.87	−0.01	+0.11	+0.17	−0.23
Main rotor bl.—fwd	+0.25	+1.08	+0.19	+0.19	+0.14	+0.11
Main rotor hub—aft	+0.15	+1.00	−0.17	+0.16	+0.15	+0.13
Swashplate—aft	+0.12	−0.94	+0.15	−0.12	−0.09	−0.06
Swashplate—fwd	+0.26	−0.47	−0.06	−0.04	−0.03	−0.01
Transmission—aft	−0.33	+0.82	−0.33	+0.43	+0.41	+0.40
Transmission—fwd	−0.20	+0.38	−0.20	+0.20	+0.20	+0.19

TABLE A–5. *Coefficients of Variation*
(UH–1D Parts Sample)

Part description	Techniques					
	1	2	3	4	5	6
Non-Vietnam Demand Time Series						
Driveshaft	1.52	0.44	0.25	0.25	0.24	0.23
Engine	3.77	1.09	0.77	0.51	0.32	0.15
Fuel control	0.45	0.42	1.37	0.38	0.37	0.35
Gear box	0.28	0.55	0.36	0.34	0.27	0.20
Main rotor blade	1.48	0.68	0.78	0.66	0.61	0.49
Main rotor hub	1.04	1.08	0.46	0.45	0.43	0.41
Scissors	0.76	1.04	0.65	0.51	0.43	0.26
Swashplate	1.04	0.59	0.56	0.42	0.37	0.31
Tail rotor blade	1.85	1.15	0.35	0.32	0.29	0.27
Transmission	0.36	0.57	0.37	0.31	0.27	0.12
Vietnam Demand Time Series						
Driveshaft	0.53	0.62	0.26	0.28	0.31	0.36
Engine	0.19	0.23	0.17	0.19	0.23	0.24
Fuel control	0.17	0.40	0.28	0.29	0.31	0.30
Gear box	0.27	0.24	0.18	0.16	0.17	0.17
Main rotor blade	0.44	0.51	0.19	0.16	0.15	0.13
Main rotor hub	0.41	0.35	0.35	0.31	0.24	0.17
Scissors	0.36	0.59	0.35	0.32	0.29	0.26
Swashplate	0.24	0.33	0.34	0.38	0.39	0.39
Tail rotor blade	0.13	0.26	0.29	0.30	0.31	0.33
Transmission	0.30	0.26	0.20	0.19	0.17	0.15

TABLE A–6. *Relative Errors*
(UH–1D Parts Sample)

Part description	Techniques					
	1	2	3	4	5	6
Non-Vietnam Demand Time Series						
Driveshaft	+1.36	−0.35	−0.04	−0.03	−0.02	−0.02
Engine	−3.62	+0.80	−0.08	−0.07	−0.06	−0.04
Fuel control	+0.31	+0.35	+0.80	−0.26	−0.24	−0.23
Gear box	+0.17	−0.52	−0.16	−0.12	−0.06	−0.02
Main rotor blade	+1.26	+0.26	+0.37	+0.14	+0.12	+0.06
Main rotor hub	+0.63	−0.93	−0.28	+0.20	+0.18	+0.16
Scissors	+0.63	+0.82	−0.33	−0.14	−0.09	−0.01
Swashplate	+0.66	+0.06	−0.30	+0.12	+0.10	+0.07
Tail rotor blade	+1.74	+0.81	+0.02	−0.06	−0.05	−0.03
Transmission	+0.77	−0.40	−0.15	+0.07	+0.04	+0.02
Vietnam Demand Time Series						
Driveshaft	+0.47	−0.37	+0.04	−0.06	−0.09	−0.10
Engine	−0.07	−0.18	−0.05	+0.01	+0.02	+0.00
Fuel control	+0.15	−0.36	+0.05	−0.04	−0.06	−0.05
Gear box	−0.25	−0.20	−0.06	−0.03	−0.05	−0.02
Main rotor blade	−0.40	−0.11	−0.10	+0.06	+0.06	+0.05
Main rotor hub	−0.36	−0.17	−0.01	+0.14	+0.09	+0.07
Scissors	−0.20	−0.46	+0.09	+0.03	+0.02	+0.01
Swashplate	−0.09	−0.10	−0.02	−0.12	−0.16	−0.15
Tail rotor blade	−0.04	−0.13	+0.02	−0.14	−0.17	−0.18
Transmission	−0.25	−0.16	−0.02	±0.10	+0.09	+0.07

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