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REQUISITIONING OBJECTIVE AND ORDER SHIP TIME STUDY.(U)
MAY 78 R H DAVIS, D P HERRON DAAG39-77-C-0095

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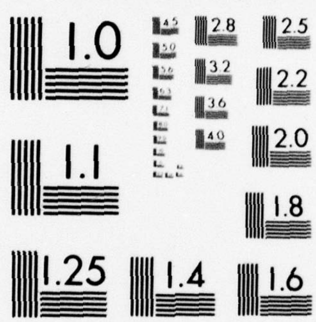
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REQUISITIONING OBJECTIVE AND ORDER SHIP TIME STUDY.

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TABLE OF CONTENTS

TABLE OF CONTENTS (continued)

TABLE OF CONTENTS (continued)

LIST OF TABLES

I. INTRODUCTION AND BACKGROUND

ABSTRACT

A. Introduction

This is the final report of a one-year project (Contract No. DAAG39-77-C-0095 Department of the Army, Harry Diamond Laboratories), undertaken in June 1977, to develop improved forecasting procedures for Order Ship Times (OSTs) and updating procedures for inventory control requisitioning objectives (ROs) for direct support units (DSUs) of the Army's Direct Support Unit Standard Supply System (DS4). The study has consisted of a review of the current status and practices relating to these two aspects of inventory control, the development of alternative candidate procedures for OST forecasting and RO updating, the evaluation of these alternatives utilizing actual OST and demand data from sample DSUs, and the development of recommendations for OST forecasting and RO updating. The
report presents the summary and conclusions in Chapter II, a 2
3 detailed discussion of the methodology used in the study in
Chapter III, the detailed results for sample DSUs in Chapters
4 IV and V, the analysis of results in Chapter VI, implementation 6
5 considerations in Chapter VII, and the detailed analysis of 7
RO-updating procedures in Chapter VIII. Appendices giving technical results and detailed data are also included. 8

ABSTRACT

B. OSTs In The Army Logistics Systems

This section briefly discusses the concept of the Order Ship Time (OST), the importance of obtaining accurate forecasts of the OST when requisitioning replenishments for the DSUs of the Direct Support System, currently prescribed techniques for estimating OSTs, and recent studies on improved OST forecasting techniques and the benefits expected from such improvements.

1. Order Ship Time Defined

The Order Ship Time (OST) is the actual time elapsing in days between the initiation date of stock replenishment action for a specific activity and the date of recording of the receipt by that activity of the material on the requisitioner's inventory records. [1] The U.S. Army DARCOM Logistic Control Activity in San Francisco maintains a computerized tracking system for Army supply and transportation actions called the Logistics Intelligence File (LIF). Each segment of the OST for a requisition is recorded in this file. From this information, monthly Direct Support System Performance Evaluations are issued. These show the average pipeline segment processing time for all segments of the OST for re-supplying Army activities throughout the world. Breakdowns are given by requisition priority classes and by surface and air replenishment.

2. Importance of Accurate OST Forecasts

The timing of replenishment requisitions depends on the estimated OST for the particular path the requisition must follow. The requisition must be placed early enough so that during the time required

[1] DOA AR 710-2, C 4, Inventory Management, Paragraph 3-28-b, May, 1977.

for its processing and the replenishment quantity to arrive, there will be sufficient inventory still at the requisitioning point to prevent excessive stockouts. The inventory level at which a requisition should be placed is the Reorder Point (ROP), given by:

$$\text{ROP} = \text{Average Demand During OST} + \text{Safety Stock}$$

The Safety Stock may be decomposed into a Safety Factor and the Standard Deviation of demand during the forecasted OST:

$$\text{Safety Stock} = (\text{Safety Factor}) \times \begin{pmatrix} \text{Standard Deviation of} \\ \text{Demand in Forecast OST} \end{pmatrix} \qquad (1)$$

Safety Stock is required because the actual OSTs vary unpredictably around the forecasted value. If the ROP were set equal to only the average demand during the OST, stockout conditions would be expected on about half the requisitions, which is too frequent. Hence a Safety Stock margin is added to the expected demand during the OST.

From Eq. (1), a Safety Stock based on a poor forecast of the OST will result in an actual Safety Factor considerably different from the desired Safety Factor, and hence a Demand Satisfaction percentage considerably different from the desired level.

Accurate forecasts of OSTs are necessary not only to control Demand Satisfaction at the desired level, but also to achieve this level at a low inventory investment. This may be seen from the following relations:

$$\begin{aligned} \text{Average Inventory Level} &= 0.5 \text{ Order Quantity} + \text{Safety Stock} \\ &= 0.5 \text{ Order Quantity} + \begin{pmatrix} \text{Safety} \\ \text{Factor} \end{pmatrix} \times \begin{pmatrix} \text{Standard} \\ \text{Deviation} \end{pmatrix} \end{aligned}$$

or

$$\text{Safety Factor} = \frac{\text{Average Inventory Level} - 0.5 \text{ Order Quantity}}{\text{Standard Deviation}} \qquad (2)$$

The Standard Deviation depends on how accurately the OST and the demand rate during the OST can be forecasted. An accurate forecasting technique for OSTs will reduce the Standard Deviation, thus achieving a given Safety Factor and Demand Satisfaction level at a lower required inventory investment.

3. Forecasting Methods for OSTs

With hundreds of OST forecasts required almost continuously by Army units such as DSUs, it is inevitable that a detailed and sophisticated forecasting technique cannot be used in each case. Instead, a technique based on past OST history, modified by any new intelligence that can practicably be incorporated into the forecast, must be used.

Prescribed techniques for estimating OSTs have been as follows:

a. In the first edition of the Army Inventory Management Manual (AR 710-2, October, 1971), OSTs for each material category in the Authorized Stock List (ASL) were calculated as the average elapsed time of the most recent six replenishment transactions for a representative 5 percent of ASL items.

b. In the latest version (Change 4, May, 1977) of AR 710-2, Direct Support Units calculate OSTs quarterly as a random sample of 10 percent of all requisitions for ASL items completed during the quarter (excluding high priority requisitions and those affected by delays), without regard to materiel category.

c. The currently proposed method of forecasting OSTs in the Direct Support Unit Standard Supply System (DS4) is to use individual item OSTs, based on the arithmetic average of the most recent six replenishments, excluding high priority requisitions. The DSS Standard OST, applicable to the DSU's geographical location, may be used until sufficient OSTs can be compiled and the average OST computed for an item.

The average OST recorded will be automatically compared to the OST of each shipment of like items received. Those OSTs beyond an allowable percent of variation will be identified as candidates for exclusion in the OST computations.

Shortcomings of the above techniques have been recognized, and several studies have been conducted on alternative forecasting techniques for OSTs. Recently the Logistics Control Activity at the Presidio analyzed the frequency distribution of OSTs and concluded that use of an average OST value was undesirable because of the undue influence of outliers. [2] Instead, it was recommended that for DSS inventory management, the median OST value rather than the average value be used, and that thereby overstockage at the DSU would be minimized in the long run.

The DRC Inventory Research Office in Philadelphia has completed a study on the forecasting of OSTs for CONUS depots and found that OST forecasts by groups of items were more accurate than for individual items, although in some cases a weighted average of the group and individual item OST forecast was desirable. [3]

Further investigation of using individual item OSTs versus group OSTs has been carried out in the comprehensive RIMSTOP studies [4]. It was found that there was little difference in results between the two methods of forecasting OSTs. However, the specific question of how to improve the forecast of individual item OSTs was not addressed.

The above summary of prescriptions and studies of OST estimation makes clear the need for this present study on specific comparisons of OST forecasting techniques and the effect of forecasting accuracy on inventory system performance.

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[2] U.S. Army DARCOM Logistic Control Activity, DSS Distribution Analysis Study Program, FY77.

[3] Kruse, W. K., Forecasting Order & Ship Time for CONUS Depots, DRC Inventory Research Office Report No. 238 (Phase 1)), June 1977.

[4] Joint DoD Retail Inventory Management and Stockage Policy (RIMSTOP) Working Group Report, Vol. III, Part 2, Pages IV-22 to IV-28, Sept.1976.

II SUMMARY AND CONCLUSIONS

The two basic objectives of the present study were 1) to develop improved OST forecasting techniques and 2) to develop improved ROP and RO updating procedures. The first phase of the effort was concentrated on developing the OST forecasting techniques, then the question of ROP/RO updating was analyzed. In this way, it was possible to consider a specific OST-forecasting model when carrying out this latter analysis.

A. OST-Forecast Models

A number of alternative candidate OST-forecast models were developed for evaluation during the study. These included the mean (OSTN), median (OSTM), and mode (OSTMO) of a sample of historical OST observations, the mean of the OST observations occurring in a specified past time period (OSTT), the mean of the (variable) number of OST observations necessary to produce a specific forecast accuracy of the OST mean (OSTNE), adaptive single exponential smoothing (OSTES), adaptive double exponential smoothing (OSTDES), and least-squares regression (trend) line (OSTR). Also, periodic update versions of OSTN and OSTES were developed (OSTNP and OSTESP). These models are specified in greater detail in Section III.A.

B. OST Data Base

In order to evaluate the candidate OST-forecast models, two sample DSUs were selected. These were both Divisional DSUs, one in CONUS and one in Europe:

CONUS Divisional DSU:	704th Maintenance Bn.
EUROPE " "	703rd Maintenance Bn.

These two large DSUs have a wide variety of types of items and materiel classes, adequate to provide a good basis for evaluation of the alternative forecasting models. The selecting of the European DSU made it possible to evaluate the performance of the models on ALOC-requisition data, a unique feature for overseas DSUs.

The basic OST data were obtained from the US DARCOM LCA Logistic Intelligence File, both active and retired. This resulted in about a one-year period of OST-data from about mid 1976 to mid 1977. For each sample DSU, requisitions were grouped by item (NSN) and those items selected that had at least 6 computable (completed) requisitions. Only ASL routine priority requisitions were selected, and CONUS requisitions having OSTs greater than 100 days and European requisitions having OSTs greater than 150 days were eliminated. This provided a comprehensive data base of OSTs for both the domestic and overseas DSUs.

C. OST Item Groups

It was found that the principal factor for the classification of OSTs into homogeneous groups was the cognizant National Inventory Control Point for supplying the items. This is indicated in the LIF by the Routing Indicator Code (RIC). The OST characteristics showed considerable variation for the various RICs. Some RICs however, showed no statistically significant differences among themselves. A "clustering" technique was developed to collect such RICs into homogeneous RIC-groups which then formed the OST item-groups for use in generating OST forecasts for items within the group. This procedure is discussed in more detail in Section III.D.

D. Item/Group OST-Forecasting Classification

The formation of OST item-groups does not necessarily mean that all items within the group should be forecasted by using only group OSTs. It was found that within an item-group some items had statistically significant different OST characteristics than those of the whole group. These items could be better forecasted by using only their own historical OSTs or some kind of combination of the group and item OST forecasts. Based on the number of OST observations in the data base for the item-group, their mean and standard deviation and these same quantities for an individual item, it was possible to develop an expression for the expected item OST as a probability weighting of the group and item mean OSTs. This was compared to other weighting schemes proposed in the past and with a scheme developed in this study for classifying an item as either group-forecast or item-forecast.

As a result of this analysis (see Section III.D) it was concluded that item/group-forecast classification was essentially equivalent to the "expected-value" procedure, whereas the other weighting scheme resulted in significant deviations from this procedure. It was concluded that the item/group-forecast classification procedure provides a simple and effective means of determining whether to utilize an item or group forecast for a particular item.

E. Forecast Error Evaluation of OST-Forecasting Models

A first screening of the candidate OST-forecasting models was based on measures of total error of the OST forecasts. This measure was the root-mean-square forecast error, RMSE. This measure does not take into account explicitly the effect of forecast error on the performance of the inventory control system in which these forecasts are used, but is a strictly statistical measure that would be expected to be larger for generally poor forecasting procedures and smaller for better procedures. In order to evaluate OST-forecast model performance as indicated by this measure the models were applied by means of a simulator/evaluator to random samples of OSTs selected from the principal RIC-groups of the 2 sample DSUs. Based on the RMSE values obtained in these simulations, it was concluded that for both DSUs the five models (not in priority sequence):

OSTN
OSTM
OSTT
OSTNE
OSTES

were the most promising for further evaluation with respect to inventory effects of OST forecast error. These analyses are discussed in greater detail in Section III.E below.

F. Evaluation of Inventory Effects of OST-Forecast Error

To evaluate the inventory effects of OST-forecast error it was necessary to select item samples for each DSU and determine the individual item and overall sample inventory effects of the five above (screened) candidate OST-forecast models. These effects depended on the forecast error statistics for the alternative models and the item parameters (inventory holding cost rate, fixed requisition order cost, and safety stock coverage period).

Inventory effects of the alternative OST-forecast models were measured in two ways: 1) comparison of the resulting average inventory requirement and demand satisfaction rate with those resulting from a perfect OST-forecast, and 2) comparison of a single measure, a normalized increase in inventory requirement over that for a perfect forecast. The technique used in this study for obtaining this normalized single performance measure of the inventory effect of a particular model was to adjust the value of the safety stock coverage period until the demand satisfaction rate for the model was equal to that for a perfect forecast, then determine the required increase in inventory necessary to accomplish this. This was done for individual items of the samples and for the sample as a whole, for each sample DSU (see Section IV.D and V.D).

It was found that composite ranking for individual items in the samples and for the samples as a whole, were consistent with each other and for both DSUs. This ranking was:

	OST-Forecasting Model	
Rank	CONUS DSU	EUROPEAN DSU
1	OSTES	OSTES
2	OSTNE	OSTN
3	OSTN	OSTT
4	OSTT	OSTM
5	OSTM	OSTNE

Only OSTNE shows a significantly different sequencing. Although it was possible to rank the OST-forecast models, the differences of inventory effects among the models was not found to be very great, of the order of 1% to 2% of the perfect forecast inventory requirement. This meant that implementation aspects of introducing the models into the DS4 system are important in the final selection of a recommended model.

G. Improved OST-Forecast Error Measure

In the present study a two-staged evaluation procedure was used. The candidate OST-forecast models were first screened by using general statistical measure of forecast error from actual OSTs (RMSE) and from OST mean (RMSE'). Another such statistical measure of error frequency used is the Mean Absolute Deviation (MAD) which was calculated in the present study but not found to be a consistent or useful measure. Then the screened models were subjected to a more refined analysis based on inventory effects. It would be very desirable to have a general statistical measure of OST forecast error that would correlate closely with the ultimate resulting inventory performance.

It was found (see Section VII) that the effect of forecast error on inventory performance may be decomposed into the effect of forecast bias (mean forecast error) and standard deviation (or statistical variance) of forecast error. The effect of forecast bias was found to be very slight since its effects can be almost completely eliminated by a compensating adjustment of the safety stock coverage period. The inventory effect performance of the models correlated almost perfectly, for both individual items and the entire item samples with the standard deviation (or variance) of OST forecast error.

Thus it was concluded that the use of the statistical variance as a measure of OST-forecast error provides a reliable indicator of the inventory effects performance of an OST-forecasting procedure. This makes possible a much simpler evaluation of alternative such procedures, based on the relatively simple forecast error evaluation techniques used in the initial screening of models in the present study.

H. Implementation Considerations

As indicated in Section F above, the final selection of a recommended OST forecasting model depends on the relative ease with which they may be implemented and utilized in the DSS system. It was found (see Section VII.A-E) that all models except OSTES would require relatively large (and sometimes variable) OST data base storage requirements. The model

OSTES, on the other hand, in addition to showing the (slightly) best overall performance requires a data base of only 3 elements for carrying out the OST forecasting procedures. Thus it is concluded that the OSTES OST-forecast model is clearly to be recommended among the alternatives considered in the present study.

I. Reorder Point/Requisitioning Objective Updating

It was found (see Section VIII) that the primary inventory effects of alternative updating procedures relate to the reorder point (ROP) rather than to the requisitioning objective (RO). Current Army policy is to update both ROP and RO at the time a requisition for an item is placed - that is, when the inventory position of the items falls to the ROP calculated at the time of the previous requisition. This value of the ROP may be quite different from the most appropriate value, the one recalculated for the present requisition. This means that this requisition is placed when the inventory position is too high or too low, both cases having undesirable inventory or service effects. The RO calculated at this time is the appropriate value to use in determining the requisition order quantity and there is no necessity to update the RO itself during the interim between requisitions, as is more necessary for the ROP as discussed above.

The formula for updating the ROP is very simple and in a computerized system there is essentially no cost, time, or effort in updating this value at the time either the demand forecast or OST forecast (the two forecasts on which the ROP and RO depend) is updated. Consequently, it is recommended that the ROP be updated whenever the demand or OST forecasts are updated, and the RO be updated at the time a requisition is triggered by the ROP. In this way, the requisition will be triggered at the most appropriate inventory level, and the RO is recalculated only when it is necessary for determining the requisition order quantity. However, with essentially no additional effort the RO could be updated at the same time as the ROP so that both of these control levels could be maintained at their most appropriate current values at all times, as might be desirable if the ROP and RO are included on any inventory control reports or listings that may be generated in the system.

J. Summary of Recommendations

1. Utilize RIC-Groups based on OST data in the US DARCOM LCA/LIF to define OST item groups.

2. Apply the item/group-forecast criteria developed in this study to classify items as item-forecast or group-forecast.

3. Utilize the OSTES OST-forecasting model for generating item and item-group OST forecasts.

4. Update ROP whenever the demand or OST forecasts are updated, and update the RO whenever a requisition is triggered, or simultaneously with the ROP update-whichever is most desirable from an implementation standpoint.

5. Utilize the statistical standard deviation (or variance) of OST-forecast error as a measure of the inventory effects performance in any further evaluations of OST-forecasting models.

III. DETAILED METHODOLOGY

A. Forecast Models

Ten basic alternative OST forecasting procedures (models) were developed for application to any time series of OST observations:

OSTN: The average of the last N OST observations

OSTM: The median of the last N observations

OSTMO: The mode of last N observations

OSTT: The average of the OST observations occurring in the past time period T. This procedure includes both upper and lower limits on the number of observations to use in computing the OST forecast. These are determined by specifying lower and upper limits, respectively, on the error with which the mean OST is estimated by the model. These errors, together with the statistics of forecast errors generated by successive forecasts, are used to calculate the upper and lower limits on the number of required OST observations. If the number of observations falling in the previous time period T lies between these limits then this number of OSTs is taken to compute the average. Otherwise the upper or lower limit number of OST observations is taken.

OSTNE: The average of the number of past OST observations necessary to give a specified error (eg., 5% or 10%) in the forecast of the OST mean.

OSTES: Simple exponential smoothing of successive OST observations, with the smoothing constant automatically calculated to give a specified error in the forecast of the OST mean.

OSTDES: Adaptive double exponential smoothing of successive OST observations with the smoothing constant taken(within specified limits) equal to the tracking signal, and corrected by a specified fraction of the trend and lag correction.

OSTR: The one-step-ahead OST value based on a linear least squares regression of the last specified number (N) of OST observations.

In order to investigate the effect on forecast accuracy of updating the OST forecast periodically rather than for each OST occurrence, the following two models were also developed:

OSTNP: For each period of specified duration (eg., weekly, monthly, etc.), the average of the last N OST observations. This is similar to OSTN except for periodic rather than ad hoc updating.

OSTESP: For each period of specified duration, the adaptive exponentially smoothed value of all OST observations occurring in the preceding period.

The above OST forecasting models are described in detail in the following technical memoranda submitted during the project:

"OST Forecasting and Evaluation Models", R.H. Davis, 8/18/77

"OST - MODE Forecasting Model", R. H. Davis, 10/17/77

"Least-squares Trend Line OST-Forecasting Model", R.H. Davis, 10/28/77

These memoranda contain listings of the FORTRAN computer programs developed to evaluate the models. Updated listings are given in Appendix H.

B. OST Data Base

The basic source of the OST data used in the present study was the (active and retired) U.S.Army DARCOM Logistics Control Activity's Logistics Intelligence File. These files give a computer-record image of the origin, intermediate status, and completion of each requisition for stock replenishment by units (DSUs) of the Army's Direct Support System (DSS). The data elements included in these records are given in Appendix A.

All such records for 2 sample DSUs:

CONUS -

704th Maintenance Bn. DODAAC A5110F

EUROPE -

703rd Maintenance Bn. DODAAC AK4912/WK4GE4

were provided by LCA on magnetic tapes generated from the current active and retired LIFs. These tapes were copied and converted to (SRI's) CDC - 6400 machine readable form for further processing. During this conversion the requisition records for each sample DSU were sorted by origination date sequence within NSN sequence. OSTs for each completed requisition were then calculated as the difference between the master inventory record post date MIRP for the first record segment (first receipt of material by the DSU) and the requisition origination date (RQNDT). Next, only those items (NSNs) on the Authorized Stock List (ASL) having at least 6 computable requisitions, and requisitions having routine priority (9-15) were selected to provide the data base of requisitions to be utilized in the study. For each such item the mean (aveage) and standard deviation of the OSTs for all requisitions for that item were calculated, as well as these same statistics over all requisitions for all items for the DSU. Histograms for the set of all requisitions for the DSU were also developed. In addition to the OST statistics for each item, the average daily demand rate (units/day) for each item was calculated by dividing the total quantity requisitioned for the item by the difference beween the earliest and latest requisition date. This demand rate was extended by the unit price (UP) in the record to give a $-demand value for each item. This value is an important item parameter in selection of an item sample for the purpose of determining the inventory effects of OST forecast errors.

C. Item Groups

Typically, items in the data base have relatively few completed requisitions. The time spanned by the data base was about a year, so that the number of requisitions per item ranged between 6 (the lower limit considered) and 15 or 20, more usually between about 8 and 12. This indicates that the number of requisitions of an item occurring in a relevant historical time period constitutes a relatively small statistical sample for forecasting future OSTs. Consequently, it is of interest and importance to determine groupings of items into homogeneous item-groups having essentially the same OST characteristics, in order to provide a better data base for forecasting individual item OSTs.

Data elements in the LIF that might be expected to be related to the selected OSTs for a particular DSU are:

Routing Identifier Code	(RIC)
ALOC Indicators	(ALOC)
Shipping Depot	(DEPOT)
Mode of Shipment	(MODE)

Another factor that might be expected to be significantly related to an item's OST characteristics (suggested by Dr. W. Karl Kruse of the U.S. Army Logistics Management Center) is the likelihood of a DSU requisition for the item encountering a backorder condition at the wholesale supply level. Army ICPs set item availability levels according to a formula that involves the unit price of the item and the average requisition quantity submitted to the ICP for the item. A DSU can estimate this quantity based on its own requisitions for the item. Since DSU requisition quantities are based on an EOQ calculation, it can be shown that the combination of unit price and requisitioning quantity occurring in the availability formula reduces to a dependence on the unit price <u>times</u> the DSU demand rate for the item - that is, the \$-demand value for the item. An analysis was made of the relationship of item OSTs and this item parameter value to determine if it might be a fruitful item characteristic to use for item classification. It was concluded that this is not the case.* This result is perhaps not surprising

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*A more detailed description of this analysis is given in the memorandum "The Use of Demand Value as an OST Item Group Criterion," R. H. Davis, 3 March, 1978.

since backorders occur on only a small fraction of an item's requisitions and when they do occur the incremental time added to the OSTs is only the final portion of depot's OST from its source of supply.

Returning to the item classification factors listed above, the RIC indicates the cognizant DOD National Inventory Control Point to which the item is assigned and through which the item's replenishment requisitions are processed. The ALOC indicator signals those requisitions that are to be routinely shipped by air from CONUS depots to overseas DSUs. DEPOT indicates the identity of the depot from which a full or partial shipment of a requisition quantity is shipped. MODE indicates the primary mode of shipment from the depot to the DSU. By sorting on MODE within DEPOT within RIC within ALOC for a particular DSU, and developing OST statistics at each level of aggregation, it was determined that differences in OSTs for different MODEs and DEPOTs were statistically insignificant. However, such differences for differing RICs and ALOCs (applicable to only overseas DSUs) were significant. Nearly all overseas Class IX Repair Parts items were phased onto the ALOC system at about mid-period in the LIF OST data. Since this is the situation of interest in the future, only ALOC requisitions were considered for the overseas DSU.

For each RIC the requisition statistics (number, mean, and standard deviation) for each sample DSU were computed. Utilizing these statistics, the RICs for a given DSU were grouped into RIC-groups, among which there were no statistically significant difference in OSTs. These RIC-groups then formed the basic item-groups for forecasting OST. The basic criteria for "clustering" RICs into RIC-groups were that they have OST means whose practical or statistical differences are insignificant. Symbolically, letting

N_1 = the number of OST observations (requisitions) for a RIC

$\bar{X}_1$ = the mean OST for that RIC

σ_1 = the standard deviation of OSTs for that RIC

and N_2, $\bar{X}_2$, σ_2 be the corresponding quantities for another RIC, the differences in the OSTs for two RICs were considered to be insignificant if

$$\left| \bar{X}_1 - \bar{X}_2 \right| \leq 2.5 \text{ days}$$

or

$$\frac{\left| \bar{X}_1 - \bar{X}_2 \right|}{\sigma} \leq 1.65$$

where

$$\sigma = \sqrt{(\sigma_1^2 / N_1) + (\sigma_2^2 / N_2)}$$

The clustering procedure was as follows:

1. Select the RIC having the largest number of OST observations (N)
2. Apply the cluster criteria to this RIC and each of the other RICs, and group those RICs satisfying the criteria into a single RIC group
3. Eliminate these RICs from further consideration and repeat steps 1, 2, and 3 until all RICs for the DSU are grouped.

D. Item/Group Classification

The grouping of items into RIC groups is for the purpose of generating OST forecasts for those items within the groups that have an insufficient number of observations to yield a statistically significantly different mean than that of the RIC group. For such items the group forecast can provide a much more timely and adaptive indication of an item's current and future OST than a forecast based on only the item's historical OST observations. This is particularly true for slower-moving items that have low order frequencies (e.g. once or twice per year). If only item-forecasts are utilized, such items would have their forecasts updated correspondingly infrequently. On the other hand, the group forecast, based on much more frequently occurring OST observations, provides much more timely and adaptive forecasts(for those items having essentially the same OST characteristics as the group) during the possibly lengthy interim between OST occurrences and updates of an individual item's forecast. For example, if an item at an overseas DSU has a replenishment requisition placed and delivered <u>before</u> converting to ALOC status and the next requisition is placed <u>after</u> this transition, the item OST forecast for the second requisition would be based entirely on pre-ALOC OST observations, which could lead to a substantial error in the timing of this requisition, through the erroneous ROP, as well as in the order quantity, through the erroneous RO. On the other hand, group forecasts would have been made frequently during the transition of items from non-ALOC to ALOC status and would have adapted continuously to the changing OST values, thus providing a more accurate OST forecast for the second requisition for the item. This is true as long as the OST characteristics for the item are insignificantly different from the group. Consequently, whenever warranted it is desirable to utilize group rather than item OST forecasts. However, if the OST observations for an item give a mean that is significantly different from the group mean, then forecasts based on the item OSTs would be more accurate than those based on the group. Consequently, items could be classified as "group-forecast" or "item-forecast" depending on whether the group and item means are significantly different. Or, alternatively, an appropriately weighted mean of the group and item forecasts could be taken as the item forecast. A natural weighting would be the respective probabilities that the item and group means calculated from the OST observations are or are not based on samples from the same OST population.

Letting

N_o = the number of OST observations used to calculate the group mean

$\bar{X}_o$ = the group mean

σ_o = the standard deviation of the group OST observations

N_1 = the number of OSTs used to calculate the item mean OST

$\bar{X}_1$ = the item mean OST

σ_1 = the standard deviation of the item OST observations

Then the probability that the two sample means are based on the same OST population is given by

$$P = 2 \cdot N(>|t|)$$

where t is the standardized normal deviate of the observed difference between the item and group OST means and $N(>x)$ is the probability that the standardized normal deviate exceeds x. That is,

$$t = (\bar{X}_1 - \bar{X}_o)/\sigma$$

where

$$\sigma = \sqrt{(\sigma_o^2/N_o) + (\sigma_1^2/N_1)} \quad *$$

The expected value of the item OST mean would then be

$$\bar{X} = P \cdot \bar{X}_o + (1-P) \cdot \bar{X}_1$$

* This expression neglects the effect of removing the item from the group on the residual group's statistics, a valid assumption since N_o is generally large compared to N_1 .

These same mixing factors, P and (1-P), can then be used to combine item and group forecasts. Thus if it is likely (i.e., P is large) that the item and group OST are samples from the same population, the expected OST forecast is near the group forecast, and approaches the item forecast as P becomes small.

Other wieghting factors may be used. In particular, W. Karl Kruse has reported* the use of a weighting function of the form:

$$W = 1/(1+N_1/m)$$

where

$$N_1 = \text{the number of item OST observations}$$

and

$$m = \text{an empirically determined parameter}$$

The weighted average forecast is then given by:

$$\bar{X} = W \cdot \bar{X}_o + (1-W) \cdot \bar{X}_1$$

In that study the most appropriate value of m depended on the degree of truncation of the OST value used in determining the forecasts, varying from 7 for no truncation to 3 for one standard deviation truncation. The above weighting expression takes into account only the number, N_1, of item OST observations, whereas it can be seen above that not only this value but other item sample statistics, as well as group statistics, should also, in principle, be considered. However, since the number (N_o) of group observations is generally quite large compared to N_1, the group OST mean can probably be well approximated by a fixed value ($\bar{X}_o$) with no uncertainty. The above weighting expression, W, does not explicitly consider the variability of item OSTs indicated by the item OST sample. However, it is somewhat simpler than the "expected value" weighting scheme described previously.

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* "Forecasting Order and Ship Time for CONUS Depots", June, 1977, DRC Inventory Research Office, U.S. Army Logistics Management Center.

In order to evaluate the "item classification" and "empirical weighting" procedures versus the "expected value" procedure, sample calculations were performed for a range of values of deviations of item means from group means. Since the degree of OST truncation used in the present study was intermediate between the extremes used in the Kruse study the value m = 5, was used. Also, typical values of 30 days for the group mean ($\bar{X}_o$), .50 for the item standard-deviation-to-mean ratio, and 6 for the number (N) of item OST observations, have been used. The item was classified as item-forecast if the mixing factor P is less than 0.5, and group-forecast otherwise. The results are given in Table III-1.

It is seen that the deviations of the empirically weighted OST mean from the expected OST mean become quite large for relatively large deviations of the item OST mean from the group mean. On the other hand, corresponding deviations of the classified item OST means are not more than 2.5 days, being less for large deviations of item from group means. Consequently, it is concluded that the use of either the expected or classified item forecasts constitutes a satisfactory procedure for combining item and group OST forecasts. However, the classification scheme would be simpler to use in practice since the expected-value technique requires the use of both the item forecast and its item-group forecast, as well as a calculation of the probability weighting factor for each forecast. For the item/group classification procedure, the classification could be updated periodically (say, annually) and during the interim only the item or group forecast is used.

TABLE III-1

ITEM/GROUP-FORECAST ALTERNATIVES

Item OST Mean	Group/Item Mixing Factor (P)	Expected Item OST	Group/Item Weighting Factor (W)	Weighted Item OST	Item/Group Classi-fication	Classified Item OST
20 days	.01	20.1 days	.45	24.6 (4.5) *	Item	20 (-.1)
25	.33	26.7		27.3 (.6)	Item	25 (-1.7)
28	.74	29.5		28.9 (-.6)	Group	30 (.5)
30	1.00	30.0		30.0 (0)	Group	30 (0)
32	.77	30.5		31.1 (.6)	Group	30 (-.5)
35	.49	32.5		32.7 (.2)	Item	35 (2.5)
40	.22	37.8		35.5 (-2.3)	Item	40 (2.2)
50	.05	49.0		40.9 (-8.1)	Item	50 (1.0)
60	.01	59.6		46.4 (-13.2)	Item	60 (.4)

* Figures in parentheses are deviations from the Expected Item OST

E. OST-Forecast Error Evaluation

A simulation-evaluation computer program was developed (described in the first of the memoranda indicated above) for accepting input OST-time-series data of OST originations and completions, applying the forecasting models to these data, and calculating measures of forecast performance throughout the simulations. This forecast evaluator was used to calibrate the parameters of the various models, and to determine a first-screening of the models based on forecast accuracy alone. This evaluation does not take into account the inventory effects resulting from the use of OST forecasts in controlling item inventories at the DSUs, but assumes that there is a sufficient correlation between forecast error and these inventory effects that a first screening of OST models can be carried out by means of a forecast error evaluation alone.

When the OST-forecast models are applied to a time series of OST observations and the successive OST forecasts are compared with the actual OST observations, a series of forecast errors are generated. The fundamental measure of forecast error for calculating the overall performance of a model in any such simulation was the root-mean-square-error (RMSE). This is defined as the square root of the average squared error occurring during the simulation. This is a commonly used measure of fit of one time series (the OST forecasts) to another series (the OST observations) that has theoretical justification for certain types of error distributions (Normal). When the values of the RMSE for two models (or two sets of parameter values for the same model) are significantly different, the one having the smaller RMSE was judged to be superior. In the case where there is an insignificant difference in the RMSE values, another measure (RMSE') estimating the deviations of the OST forecasts from the OST mean was used to evaluate the relative performance of the models. The rationale for this procedure is that, in principle, it is desired to forecast the individual OST observations, as closely as possible, and the RMSE is a measure that indicates this. If the OST forecasts are perfect, all forecast errors are zero and the resulting RMSE will be zero. On the other hand, if the inherent variability of the OST observations is large (as tends to be the case for the data utilized in the present study, and presumably in general) and the OST forecasting models are of the smoothing type such as the average, median, or mode of some number of observations or exponential smoothing, then a "good" forecasting procedure is one that estimates the true OST mean as closely as possible. For forecasts of this type the RMSE value results primarily from the large inherent OST variability, and therefore relatively small differences in RMSE values may be obscured by this variability. Consequently, when this is the case, the estimated error, RMSE', of the forecast from true OST mean is used as secondary indicator of forecast performance. A more detailed discussion of this subject is given in the memo "OST-Forecasting Evaluation Measures", R.H. Davis, 9/20/77.

F. Inventory Effect Evaluation

Since the purpose of forecasting item OSTs for a DSU is for use in formulas controlling the timing and quantitites of requisitions for replenishment of stock at the DSU, the ultimate criteria for evaluating OST forecasting procedures should depend on this effect on the performance of the inventory control system. A calculation of these effects can be obtained by combining the statistics of the OST forecast errors for the various models, with the inventory control rules and individual item parameters, and calculating the resulting inventory levels and not-in-stock (NIS)* rates for a cross-section sample of items for a DSU. The rationale and details of this procedure are given in the technical memorandum "Analytic OST-Forecasting Inventory Control Evaluator", R. H. Davis, 9/13/77, as amended in Appendix C. the basic input parameters required for this analysis are:

System parameters -

- h = inventory holding cost rate (% per year)
- A = the fixed order (requisition) cost ($)
- S = the safety stock coverage period (days)

Item parameters -

- c = item unit cost (price) ($)
- $\bar{D}$ = item demand rate (units/day, month, year)
- $\bar{s}$ = average item demand quantity (units)
- σ_s = standard deviation of demand quantity (units)
- $\bar{L}$ = item OST mean

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* This measure of inventory system service-level is the complement of the demand satisfaction rate: NIS=1-Demand Satisfaction rate.

OST-forecast parameters -

$\bar{E}$ = OST forecast bias (average forecast error)

σ_E = standard deviation of OST forecast error from actual OST

$\sigma_{E'}$ = standard deviation of OST forecast from mean OST

From these parameters, the resulting expected inventory levels, $\bar{I}$, and NIS rates were calculated for each sample item and each OST forecasting model, and also the expected sample inventory value and value-averaged sample NIS rate were computed for the sample of items for each OST forecasting model.

As a basis for comparison, the corresponding inventory performance measures were also determined for the perfect OST forecast (that is, $\bar{E} = \sigma_E = \sigma_{E'} = 0$). The error parameters for each OST forecasting model then yield incremental deviations in inventory levels and NIS rates from those of the perfect OST forecast. However, since, in general, <u>both</u> the inventory level and NIS rate for an OST forecasting model are different from those for the perfect forecast, and other models, it is difficult to interpret the relative quality of inventory performance resulting from the various models. For example, if the inventory level for the model is higher than that for another model, but the NIS rate is lower, then the question arises as to whether or not the reduction in NIS rate more than compensates for the inventory increase. The technique used in the present study for normalizing the performance measure for all models was to artificially adjust the safety stock parameter, S, used in setting the item inventory levels (reorder point and requisitioning objective), so that the NIS rate for each model is the same as that for the perfect forecast. Then the corresponding increases in inventory above those for the perfect forecast constitute a single performance measure that can be used to indicate the relative inventory effects of each of the models evaluated.

G. Summary of OST-Forecasting Methodology

In summary, the methodology followed in evaluating OST forecasting models for each sample DSU was:

1. Process the LCA/LIF data to obtain, for all ASL items having six or more computable OSTs, all requisitions of routine priority.

2. Sort requisitions by item (NSN) within RIC and calculate item OST statistics ($N,\bar{X},\sigma_X$) and demand rates, as well as RIC OST statistics (N, $\bar{X},\sigma_X$ over all RIC requisitions).

3. Collect RIC requisitions into RIC groups of requisitions by means of a cluster analysis procedure, and calculate the RIC-group OST statistics.

4. Generate time series of OST originations and completions for each RIC-group and each item within the group.

5. Select the major RIC-group and a sample of typical items from this group.

6. Classify sample items into item-forecast or group-forecast.

7. Evaluate OST forecasting models for group-forecast items by applying the OST-forecast simulator/evaluator computer program to the RIC-group time series of OSTs.

8. Evaluate OST forecasting models for item forecast items by simulating using the item time series of OSTs.

9. Screen out the less promising models based on the results of steps 7 and 8.

10. Evaluate the remaining models by means of the inventory effects evaluator applied to a cross-sectional item sample, using the OST-forecast error statistics obtained in steps 7 and 8.

H. Reorder Point/Requisitioning Objective Updating

Current Army policy is to update the reorder point(ROP) and requisitioning objective (RO) whenever the inventory position of an item falls to or below the current reorder point. The consequences of this policy may be compared to maintaining current ROP and ROs and analyzed under different assumptions concerning increasing or decreasing demand rates and OSTs. This analysis is described in more detail in Section VIII.

IV. RESULTS FOR THE 704TH MAINTENANCE BN. (CONUS)

A. RIC-Groups

For the CONUS DSU (704th Maintenance Bn) the RIC statistics were:

RIC	N	$\bar{X}$ (days)	σ_X (days)
AKZ	2056	40.6	18.4
AP5	4	57.3	19.4
A12	121	34.8	12.9
A35	102	46.8	14.5
B14	455	36.5	14.8
B16	91	45.7	21.9
B17	1	71.6	-
FFZ	29	40.0	16.1
FHZ	5	34.2	7.9
FLZ	19	38.4	12.0
MPB	4	48.2	11.3
N35	6	37.0	5.6
S9C	635	38.3	16.5
S9E	327	37.4	14.2
S9G	413	44.8	15.4
S9I	752	37.9	14.1
S9T	3	25.7	9.5

Applying the cluster procedure to these data yields the RIC-groups:

Group I: AKZ, FFZ, FLZ, N35, S9C, S9E, S9I
(N = 3824, $\bar{X}$ = 39.4 days, σ_X = 17.0 days)

Group II: B14, A12, FHZ
(N = 581, $\bar{X}$ = 36.1 days, σ_X = 14.4 days)

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* The cognizant agencies corresponding to these RICs are given in Appendix B.

Group III: A35, B16, MPB, S9G

($N = 610$, $\bar{X} = 45.3$, $\sigma_X = 16.4$)

Group IV: AP5, B17

($N = 5$, $\bar{X} = 60.0$, $\sigma_X = 17.9$)

Group V: S9T

($N = 3$, $\bar{X} = 25.7$, $\sigma_X = 9.5$)

The major RIC-group for this DSU is seen to be Group I. This group had 3824 OST observations with an average OST of 39.4 days and a standard deviation of 17.0 days. The overall performance of the OST forecasting models on all "group-forecast" items within this RIC group can be determined by applying the models to the OST time series for this group. The use of all 3824 observations (an average of about 11 per day) would constitute a far more fine-grained simulation than is required to determine the relative merit of the forecasting models, and would entail time-consuming and costly data preparation and computer running time. Consequently, in order to utilize the project resources in a more cost effective manner, the RIC group OST time series was randomly sampled to obtain OST series spanning the same time period with fewer observations having essentially the same statistical characteristics.

B. Model Parameter Determination

Each of the OST forecasting models has one or more parameters that must be specified before numerical applications can be made to any OST time series. For the purpose of determining these parameter settings for each model, a random sample of 120 OST observations was selected from the set of all OST observations for the RIC-group. The statistics of this sample were $\bar{X} = 40.4$ days and $\sigma_X = 17.3$ days versus $\bar{X} = 39.4$ days and $\sigma_X = 17.0$ days for the entire RIC group. The sample was considered to be an adequate representation of the RIC group for the purposes of calibrating the parameters of the models.

The results of applying the OST forecasting models to this OST time series for various model paramter values by means of the OST forecast error simulator/evaluator program, are shown in Table IV-1. For some models an estimate of the standard error of the RMSE and RMSE' measurements have been calculated and are indicated following their respective values in Table IV-1.

For the model OSTN (average of last N) it is seen that the RMSE performance measure is not significantly different for N=6 and N=12; however, the RMSE' measure shows a significant improvement over N=12, and the RMSE' indicates a statistically significant but very small such improvement. Consequently, the parameter value adopted for OSTN was N=24.

The results for OSTM (median of last N) are similar and the parameter value taken for this model was N=24.

For OSTMO (mode of last N) the RMSE shows a generally deteriorating performance as N increases, with a barely significant slight improvement for N=24 over N=12. The RMSE' measure indicates a continually decreasing performance as N increase. Therefore, the parameter chosen for this model was the lowest value tested, N=6. This result is in contrast to that for OSTM (median). Both the median and mode are biased low, but the mode more so than the median. For small OST samples the bias is not as great as for larger samples. Consequently, as the sample size increases the increasing bias competes with the decreasing variance of the error to yield the total error measures RMSE and RMSE'. Apparently the increasing bias predominates for the mode, but not for the median whose performance continues to improve for larger OST samples.

For OSTT(average of OSTs in last time period T) the RMSE does not show a significant difference for the different T values. The RMSE' indicates a significant increase in performance for T=180 days over T=90 days, but no further significant improvement for T=360. Consequently, the value of T taken for this model was 180 days. In the case of this model, the fact that a sample rather than the entire RIC group of OSTs was used must be taken into account. The number of sample OSTs occurring in a time period T

TABLE IV-1

PERFORMANCE OF OST-FORECAST MODELS FOR ALTERNATIVE MODEL PARAMETER VALUES

OST-Forecast Model	Principal Parameter Value	RMSE	RMSE'
OSTN	N = 6	18.90 ± .13	7.32 ± .05
	N = 12	19.04 ± .12	5.74 ± .01
	N = 24	17.40 ± .12	5.58 ± .04
OSTM	N = 6	18.35	7.12 ± .04
	N = 12	18.67	5.31 ± .04
	N = 24	16.64	3.57 ± .04
OSTMO	N = 6	18.65 ± .11	8.04 ± .05
	N = 12	20.13 ± .14	9.26 ± .09
	N = 24	19.70 ± .13	9.62 ± .06
OSTT	T = 90 days	18.71	3.35 ± .05
	T = 180 "	18.83	2.67 ± .10
	T = 360 "	18.70	2.68 ± .14
OSTNE	e = .05	18.74	2.71 ± .14
	e = .10	18.68	4.69 ± .06
	e = .20	19.04	7.43 ± .71
OSTES	T_X = 90 days	17.77	3.61 ± .06
	T_X = 180 "	17.81	2.45 ± .05
	T_X = 360 "	17.86	2.13 ± .02
OSTDES	F = 1.0	20.99	8.92 ± .63
	F = 0.7	20.28	8.53 ± .62
	F = 0.5	19.88	8.29 ± .62
OSTR	N = 6	20.35 ± .11	8.80 ± .05
	N = 12	19.07 ± .12	7.86 ± .04
	N = 24	17.53 ± .15	5.66 ± .04
OSTNP	UDI = 7 days	18.33 (vs 18.73)*	5.41 (vs 5.75)*
	UDI =15 "	18.85	5.81
	UDI =30 "	18.86	6.39
OSTESP	UDI = 7 days	17.48 (vs.17.81)*	2.32 (vs. 2.58)*
	UDI =15 "	17.63	2.32
	UDI =30 "	17.55	2.43

* For the corresponding non-periodic models.

is only about 120/3824 as many RIC-group OSTs as would occur in this time period. To translate time periods for OSTT from the sample OST time series to any other it is necessary to normalize the period by the ratio of the OST occurrence rates for the two series. Since the total time spanned by the sample and RIC-group OST series are the same, the appropriate ratio is that given above for the numbers of observations in the two series. This means that the corresponding parameter values for the complete RIC-group OST series would be about T=3, 6,12 days compared to the value T=90, 180, 360 days for the sample. So the use of T=180 for the sample series would correspond to a T of about one week for the entire RIC group.

For the OSTNE (average of last N necessary to produce a specified error, e, in the forecast of the OST mean) the RMSE shows very little difference for the various e values; however, the RMSE' shows a pronounced deterioration in performance of the forecast as e increases. Consequently, an error of e=.05 was selected as the parameter to use for this model.

The model OSTES (adaptive exponential smoothing) has several parameters:

T_X = the time period over which an expected number of OST occurrences is calculated. Short periods give more dynamically responsive OST forecasts.

T_Δ = the time period over which an expected OST inter-arrival interval is calculated. Short periods give more responsive estimates of this inter-arrival interval.

e_{min} = the desired minimum error of the forecast of OST mean:

e_{max} = the desired maximum error of the forecast of OST mean

The value chosen for T_X depends upon the time period over which it is desired to detect changes in the OST mean. The value e_{min} has the effect of shortening T_X (that is, making the forecast more responsive) in case the error of the OST-mean forecast using T_X would be smaller than desired.

e_{max} has the opposite effect in case the error using T_X would be greater than desired. The values chosen for e_{min} and e_{max} were .05 and .20.

The value of T_Δ depends on the time period over which it is desired to detect changes in mean OST arrival rate, which depends on the change in demand rates of the items in the RIC group. Typically the demand processes are more dynamic than the OST process, so that an appropriate value for T_Δ tends to be smaller than that for T_X. For the alternative values of T_X chosen (90,180, 360 days) the corresponding values of T_Δ were 90, 90, 180 days.

The RMSE is not significantly different for the alternatives, whereas the RMSE' shows a significant improvement for 180 days over 90 days and only a slight further improvement for 360 days. Since in order to maintain forecast responsiveness it is desirable to make T_X no longer than actually required, the value of T_X=180 (and T_Δ=90 days) was selected for the OSTES model.

The parameters of the OSTDES (adaptive double exponential smoothing) are the upper and lower limits on the smoothing constant, as calculated from the tracking signal, and the fraction, F, of the trend and lag correction utilized by the procedure. Typical values for the smoothing constant limits have been 0.1 and 0.3 in previous applications, and these were assumed in the present case. Neither the RMSE or RMSE' indicate very significant differences for the alternative values of F (1,0, 0.7, 0.5); however, there is a slight indication of improvement as F decreases. The value of F=0.7 was selected for this model.

For OSTR (least squares regression, or trend, line based on the last N OST observations) both the RMSE and RMSE' indicate significant improvement as N increases from 6 to 24. The value N=24 was used for further evaluation of this model.

The remaining two models OSTNP and OSTESP are periodic-update versions of OSTN and OSTES. As such, the question for these models is not the best parameter value (update interval, UDI) but the extent of the effect on the quality of the forecast as the update interval is increased. For each of these two models, alternative update intervals of 7,14 and 30 days were used. For OSTNP the value N=12 was used and for OSTESP the values T_X = 180 days, T_Δ = 90 day, e_{min} = .05, e_{max} = .20 were used. The performance of the periodic update models are to be compared with the <u>ad hoc</u> update models having the same parameter values.

The RMSE and RMSE' values for these latter models are indicated in parentheses for these two periodic update models, in Table IV-1.

For OSTNP the RMSE indicates an insignificant change in forecast performance resulting from updating intervals from 7 to 30 days. The RMSE' shows a very slightly deteriorating effect as UDI increases from 7 to 15 days, and a more pronounced increase in error for 30 days. Also, for UDI = 7 days, evidently the increased smoothing effect of the periodic updating increased the quality of the forecast sufficiently to more than compensate for any deteriorating effect, so that the resultant performance was slightly better than that for ad hoc updating. This is indicated by both the RMSE and RMSE' measures.

For OSTESP neither the RMSE or RMSE' shows any significant change for UDI ranging from 7 to 30 days.

Moreover, as in the case of OSTNP for UDI = 7, for OSTESP both RMSE and RMSE' indicate a slightly improved performance for all UDIs from 7 - 30 days over the corresponding ad hoc forecasts.

These results indicate that there is very little effect on the quality of OST forecasts resulting from the utilization of update intervals of 30 days or less.

C. Evaluation of OST-Forecast Models

The alternative OST-forecasting models were evaluated on the basis of their error performance for both RIC-group and individual item OST time series data. The group data were obtained as a 202-observation random sample of the 3824 RIC-group I OST observations. Using this OST time series as the basis for both generating the forecasts and the time series of OSTs being forecasted yields the composite performance of each model on all items within the group that are classified as "group-forecast" items. When the group OST time series is used to generate the forecasts and an individual "group-forecast" item's OST time series is used as the forecasted OSTs, a model's performance refers to that particular "group-forecast" item. For an "item-forecast" item a time series of OSTs for that item is used for both the generation of the OST forecasts and as the forecasted OST time series.

1. RIC-Group Data

The results of using the RIC-group sample OST series for generating the forecasts and as the forecasted series are shown in Table IV-2, it can be seen that both RMSE and RMSE' indicate that three of the models have significantly poorer performance than the others (indicated by boxed values), among which there is little difference in indicated performance. Thus RIC-group evaluation yields the models

OSTN

OSTM

OSTT

OSTNE

OSTES

as those most promising for further evaluation, and eliminates OSTMO (mode), OSTDES (double exponential smoothing), and OSTR (least squares trend line) from further consideration.

2. Item Data

In order to evaluate the performance of the OST-forecasting models on individual items, three items having differing OST statistics were selected from RIC-group I. They were:

	NSN	N	$\bar{X}$	σ_X	Over the time period
1.	2540 007146156	8	40.1 days	12.2 days	307 days
2.	2530 006784131	9	31.9	7.7	287
3.	2540 001345093	10	63.8	18.3	314

It is seen that for individual items there are far too few OST observations for an adequate simulation/evaluation of the OST-forecasting models. Consequently, an approximately 5-year OST-time series was generated for each item from their respective OST statistics. For this purpose a shifted log-Normal probability distribution was used. Both the simplicity of generating random OST sequences according to this distribution and the adequacy with which it was possible to fit the RIC and RIC group OST histograms with the distribution led to its use for this purpose. A shift of 10 days was found to result in a good fit of the log-Normal to the actual OST data.

TABLE IV-2

ERROR PERFORMANCE EVALUATION OF OST-FORECASTING MODELS

DSU: 704th Maintenance Bn. (CONUS)

RIC-Group I

202-OST Sample

OST-Forecasting Model	RMSE	RMSE'
OSTN	$\boxed{14.92 \pm .03}$	$\boxed{3.91 \pm .05}$
OSTM	$\boxed{15.02}$	$\boxed{2.97 \pm .02}$
OSTMO	16.92	6.94± .08
OSTT	$\boxed{14.92}$	$\boxed{3.66 \pm .04}$
OSTNE	$\boxed{14.77}$	$\boxed{3.68 \pm .05}$
OSTES	$\boxed{14.62}$	$\boxed{4.09 \pm .05}$
OSTDES	16.72	5.45± .17
OSTR	15.91± .03	4.28± .07

In this way it was possible to obtain quite representative OST time series for the three test items, over a sufficient time period to simulate/evaluate the relative performance of the various OST-forecasting models. The three sets of time series used are given in Appendix D. The results of applying the OST forecast models to the time series for these three items are given in Table IV-3. It can be seen that the performance of the models on these item OST time series is consistent with that using the RIC-group time series above.

Model	Number of Items for Which Model was Among the Best Four
OSTN	3
OSTM	2
OSTT	3
OSTES	3
OSTR	1

It was not possible to obtain a valid indication of the performance of the model OSTNE (average of the last N OSTs necessary to give an error of forecast of OST mean of 5%). The numbers of observations required for the successive forecasts during the simulation of the model were always greater than the number of OST observations available.

Consequently, based on the error performance of the alternative OST-forecasting models on both RIC-group and individual item OST time series, it was concluded that the five models:

OSTN
OSTM
OSTT
OSTNE
OSTES

appear most promising for more definitive evaluation with respect to the inventory effects of OST forecast errors.

TABLE IV-3

PERFORMANCE OF OST-FORECASTING MODELS FOR INDIVIDUAL ITEMS

DSU: 704th Maintenance Bn. (CONUS)
RIC- Group I

5-year Simulated OST Time Series

Item No.:	1	2	3
NSN :	2540-7146156	2530-6784131	2540-1345093
$\overline{X}$:	42 days	30 days	64 days
σ_X :	15 days	7 days	20 days

OST-Forecasting Model	RMSE	RMSE'	RMSE	RMSE'	RMSE	RMSE'
OSTN	13.1± 1.0	3.1± .4	7.6± .2	2.5± .1	18.0± .6	6.0± .7
OSTM	13.5	3.2± .4	8.0	3.5± .2	17.2	4.2± .4
OSTMO	15.4± 1.0	7.8± .7	10.8± .4	6.4± .4	20.5± .8	8.8± .7
OSTT	13.6	3.6± .4	7.6	2.6± .1	17.8	7.0± .6
OSTNE *	-	-	-	-		-
OSTES	13.6	3.8± .5	7.5	1.9± .2	18.6	6.0± .8
OSTDES	16.2	5.0± .9	8.4	1.8± .3	25.1	11.8± 1.5
OSTR	13.8	4.8± .6	7.6± .2	2.0± .3	20.3± .7	7.8± 1.0

Four Best Models	1	2	3
	OSTN	OSTN	OSTN
	OSTM	OSTT	OSTM
	OSTT	OSTES	OSTT
	OSTES	OSTR	OSTES

* 5-year time series too short to establish steady state simulation conditions for this model, because of large initialization effects.

3. Effects of Using Item Forecasts versus Group Forecasts

The effects of utilizing item forecasts for item-forecast items can be seen by comparing the performance of RIC-group forecasts when applied to the item OST time series to those given in Table IV-3 for the individual item forecasts. These effects are similar for the various models. For the OSTN model this comparison is given in Table IV-4. Item No. 1 is a "group-forecast" item and one would not expect much difference between using item or group forecasts. Both the RMSE and RMSE' performance measures indicate that this is the case. Item No. 2 is an "item-forecast" item having an OST mean ($\bar{X}$ = 30 days) considerably smaller than the group OST mean ($\bar{X}$ = 38.5 days). Both performance measures indicate a substantial deterioration in the quality of the group forecast compared to that of the item forecast. Item No. 3 is also an item-forecast item with OST mean considerably larger than the group mean. The performance of the group-forecast for this item is seen to be much poorer than that of the item forecast. These results illustrate the importance of utilizing item forecasts whenever items have OST characteristics with statistically significant difference from those of the RIC-group to which they belong.

TABLE IV-4

EFFECTS OF GROUP AND ITEM FORECASTS

DSU: 704th Maintenance Bn. (CONUS)

OSTN Forecast Model

RIC-Group I

$N = 202$ OST Observations

$\overline{X} = 38.5$ days

$\sigma_X = 15.1$ days

Item Number	Item OST Mean	Type Forecast	RMSE	RMSE'
1	42 days	Item	13.1	3.1
		Group	14.6	2.9
2	30 days	Item	7.6	2.5
		Group	14.3	10.2
3	64 days	Item	18.0	6.0
		Group	32.5	24.1

D. Evaluation Of The Inventory Effects of OST-Forecasting Models

The OST-forecasting models having the most promising performance with respect to forecast error were further evaluated with respect to their inventory effects performance. These models were OSTN, OSTM, OSTT, OSTNE, and OSTES. As discussed above, the technique employed to develop a single performance measure for each model was to determine the inventory requirement above that for a perfect forecast, necessary to give the same not-in-stock (NIS) rate as that for the perfect forecast.

1. Item Sample

To evaluate inventory effects of the alternative OST-forecasting models it is necessary to select a cross section of individual items and determine the inventory effects for each item. For each model these effects depend on the OST-forecasting error characterisitcs and the various item parameters (demand, price, etc.) of the item sample. Such a cross sectional sample was selected for this DSU from the RIC-group I set of items. The items were selected to reflect a wide range of price, demand, and $-demand values. They consisted of 10 group-forecast items and the two item-forecast items (items No. 2 and No. 3) considered above. These items together with their parameter values are given in Table IV-5. The forecast error characteristics for the candidate models are given in Table IV-6. These were obtained from the simulation/evaluation computer runs performed in the evaluation of the OST forecasting models based on forecast error, as discussed above.

2. Inventory Effects Evaluation

These data provided the input to the inventory effects evaluator program which then calculated the expected inventory level and NIS rate for each item, and the expected inventory value and $-demand-weighted NIS rate for the entire sample of items. These results are given in Table IV-7. As discussed in general above, based on these two measures there is some difficulty in determining the relative quality of the performance of the various models for the sample items, and for the sample as a whole. For example,

TABLE IV-5

CROSS-SECTIONAL SAMPLE OF ITEMS FOR EVALUATING INVENTORY EFFECTS OF OST-FORECASTING MODELS

DSU: 704th Maintenance Bn. (CONUS)

RIC-Group I

Sample Item Number	NSN	Item/Group Classification	Unit Price	Demand Rate	$-Demand Rate	Average of User Requisition Quantity	Standard Deviation of User Requisition Quantity
1	2520-6799657	Group	$ 96.74	380/yr	$36,723/yr	1.9 units	3.9 units
2	2540-7146156	"	37.00	288	10,669	2.1	3.1
3	2530-7364672	"	2.90	285	826	2.8	3.5
4	2520-5728715	"	34.53	33	1,134	1.0	0.3
5	2520-6799247	"	12.40	110	1,358	1.3	1.9
6	2540-0473926	"	11.32	22	248	1.0	0.3
7	2540-0644603	"	0.33	18	6	1.0	0
8	2520-2535824	"	6.60	7	48	1.0	0
9	2520-6799246	"	8.28	33	272	1.1	1.1
10	2520-7372019	"	4.28	11	47	1.2	1.1
11	2530-6784131	Item	107.00	26	2,734	1.2	1.2
12	2540-1345093	Item	8.50	73	621	1.9	4.0

* Obtained from DSU Demand History Report (Class IX Repair Parts-Common)

TABLE IV-6

FORECAST ERROR PARAMETERS FOR OST-FORECASTING MODELS

DSU: 704th Maintenance Bn. (CONUS)

RIC-GROUP I (12-item cross sectional sample)

OST Forecast Model	Group Forecast Items			Item No.11			Item No. 12		
	$\overline{E}$	σ_E	$\sigma_{E'}$	$\overline{E}$	σ_E	$\sigma_{E'}$	$\overline{E}$	σ_E	$\sigma_{E'}$
OSTN	2.82	14.7	2.93	-1.9	7.3	1.5	4.2	17.5	3.5
OSTM	0.22	15.0	2.94	-2.9	7.4	1.5	-2.5	17.0	3.3
OSTT	3.30	14.6	1.86	-1.8	7.4	1.7	5.1	17.0	3.3
OSTNE	3.31	14.4	1.86	-1.1	8.5	1.6	4.1	17.0	3.0
OSTES	3.78	14.1	1.93	-0.9	7.5	1.6	3.7	18.3	3.3
PERFECT	0	0	0	0	0	0	0	0	0

NOTE: $\overline{E}$ = Average forecast error

σ_E = Standard deviation of forecast error

$\sigma_{E'}$ = Estimated standard deviation of error of forecast of OST mean.

TABLE IV-7

INVENTORY AND SERVICE-LEVEL EFFECTS OF OST-FORECASTING MODELS

DSU: 704th Maintenance Bn. (CONUS)

RIC-Group I

Cross-sectional Sample of Items

	OST-FORECASTING MODEL											
Item No.	OSTN		OSTM		OSTT		OSTNE		OSTES		PERFECT	
	$\overline{I}$	NIS	$\overline{I}$	NIS	$\overline{I}$	NIS	$\overline{I}$	NIS	$\overline{I}$	NIS	$\overline{I}$	NIS
1	27.3	.30	25.5	.32	27.6	.29	27.6	.29	27.9	.28	23.4	.30
2	28.9	.25	27.5	.28	29.2	.24	29.2	.24	29.4	.23	26.0	.24
3	77.7	.10	75.9	.12	78.0	.10	78.0	.10	78.3	.10	75.2	.09
4	7.8	.14	7.6	.15	7.9	.13	7.9	.13	7.9	.13	7.5	.12
5	24.2	.15	23.6	.17	24.4	.15	24.4	.15	24.5	.15	23.2	.14
6	10.5	.08	10.3	.09	10.5	.08	10.5	.08	10.5	.07	10.3	.08
7	53.3	.01	53.2	.01	53.3	.01	53.3	.01	53.4	.01	53.2	.01
8	7.7	.06	7.6	.06	7.7	.06	7.7	.06	7.7	.06	7.6	.06
9	15.1	.10	14.8	.11	15.1	.09	15.1	.09	15.1	.09	14.8	.09
10	11.7	.07	11.6	.07	11.7	.07	11.7	.07	11.7	.07	11.6	.07
11	4.1	.27	4.1	.28	4.1	.27	4.2	.27	4.2	.27	4.2	.26
12	24.5	.23	23.5	.26	24.6	.23	24.5	.23	24.4	.24	23.7	.24
Sample	$5,522	.27	5,256	.30	5,567	.27	5,566	.27	5,607	.26	5,001	.27

for Item No. 1 OSTM has the lowest average inventory level, $\bar{I}$, but also the highest NIS rate, and OSTES has the lowest NIS rate but the highest average inventory level. For the sample as a whole, a similar result is true. As indicated above, the technique utilized in the present study for resolving this ambiguity is to adjust the inventory control rules by means of the safety stock coverage period until the NIS rate for a given model and a given sample item is the same as that for the PERFECT forecast. When this was done the results are as shown in Table IV-8. As can be seen the % increase in inventory over that for the perfect forecast ranges from less than 0.1% (for Item No. 11) to about 15% (for Item No. 1). The differences in the standardized inventory requirements for the various models are generally quite small for each item. For the entire sample the increase over perfect forecast inventory requirements ranges from 9.8% (for OSTES) to 10.9% (for OSTM). However, it is possible to develop a consistent ranking of the OST-forecasting models from these data. By assigning for each sample item a rank number from 1 to 5 for each of the five candidate models, it is possible to develop a composite ranking number over all sample items for each model. This result is shown in Table IV-9. The composite ranking yields the following corresponding ranking of the models:

Rank	Model	Composite Rank
1	OSTES	2.04
2	OSTNE	2.58
3	OSTN	3.04
4	OSTT	3.83
5	OSTM	3.83

Another type of overall ranking can be obtained by considering the sample performance results given in Table IV-8. This ranking is:

TABLE IV-8

INVENTORY EFFECTS OF OST-FORECASTING MODELS

DSU: 704th Maintenance Bn. (CONUS)

RIC-Group I

Cross-Sectional Sample of Items

$\bar{I}$ = Average Inventory Required to Give the Same NIS Rate as the Perfect Forecast

	$\bar{I}$					$\bar{I}$	NIS
ITEM NO.	OSTN	OSTM	OSTT	OSTNE	OSTES	PERFECT	
1	27.0(15.2%)*	27.1(15.8%)	27.0(15.3%)	26.8(14.7%)	26.7(14.3%)	23.4	.30
2	29.5(13.3)	29.6(13.9)	29.4(13.3)	29.4(13.0)	29.2(12.4)	26.0	.24
3	79.6(5.9)	79.7(6.0)	79.1(5.2)	79.3(5.5)	79.2(5.3)	75.2	.09
4	8.0(6.5)	7.9(5.7)	8.0(6.9)	8.0(6.8)	8.0(6.0)	7.5	.12
5	24.6(6.2)	24.7(6.3)	24.7(6.3)	24.6(6.1)	24.5(5.8)	23.2	.14
6	10.5(2.1)	10.5(1.9)	10.6(2.5)	10.5(2.4)	10.5(1.8)	10.3	.08
7	53.4(0.4)	53.4(0.4)	53.3(0.2)	53.3(0.2)	53.4(0.3)	53.2	.01
8	7.7(1.3)	7.7(1.3)	7.7(1.3)	7.7(1.3)	7.7(1.3)	7.6	.06
9	15.1(2.0)	15.1(2.3)	15.1(2.1)	15.1(2.0)	15.0(1.6)	14.8	.09
10	11.7(0.9)	11.7(0.8)	11.7(0.9)	11.7(0.9)	11.7(0.9)	11.6	.07
11	4.2(0)	4.3(1.7)	4.2(0)	4.2(0)	4.2(0)	4.2	.26
12	24.0(1.3)	24.1(1.8)	24.3(2.3)	24.0(1.3)	24.1(1.9)	23.7	.24
SAMPLE	$5,528(10.5)	$5,548(10.9)	$5,521(10.4)	$5,511(10.2)	$5,489(9.8)	$5,001	.27

* % increase over PERFECT forecast inventory requirement

TABLE IV-9

INVENTORY EFFECTS PERFORMANCE RANKING FOR OST-FORECASTING MODELS

DSU: 704th Maintenance Bn.(CONUS)

RIC-GROUP I

CROSS-SECTIONAL ITEM SAMPLE

ITEM NO.	OSTN	OSTM	OSTT	OSTNE	OSTES
	PERFORMANCE RANK				
1	3	5	4	2	1
2	3.5	5	3.5	2	1
3	4	5	1	3	2
4	3	1	5	4	2
5	3	4.5	4.5	2	1
6	3	2	5	4	1
7	4.5	4.5	1.5	1.5	3
8	3	3	3	3	3
9	2.5	5	4	2.5	1
10	3	3	3	3	3
11	2.5	5	2.5	2.5	2.5
12	1.5	3	5	1.5	4
Composite	3.04	3.83	3.50	2.58	2.04

Rank	Model	% Inventory Increase Over Perfect Forecast
1	OSTES	9.8% (0)
2	OSTNE	10.2 (+0.4)
3	OSTT	10.4 (+0.6)
4	OSTN	10.5 (+0.7)
5	OSTM	10.9 (+1.1)

This is essentially the same as the above composite ranking, with only the rankings 3 and 4 (OSTN and OSTT) being reversed.

Although it is possible to develop such rankings for the relative performance of the models, the difference in inventory requirement from the highest (OSTES) to the lowest (OSTM) performance models is only about 1% of the perfect forecast inventory requirement. This suggests that implementation considerations will play an important role in the final selection of the most appropriate model. These factors will be considered below, following the analysis of performance of the OST forecasting models when applied to the European DSU.

V. RESULTS FOR THE DSU: 703RD MAINTENANCE BN. (EUROPE)

A. RIC-Groups

The basic data provided by the LCA/LIF for this DSU were read, converted and processed to yield the individual RIC OST statistics for both ALOC and non-ALOC requisitions. These results are shown in Table V-1. In general, for RICs having significant numbers of non-ALOC and ALOC requisitions, the average OSTs ($\bar{X}$) for ALOC requisitions are seen to be from about 20 to 35 days less than those for non-ALOC requisitions. Since the transition from non-ALOC to ALOC occurring during the time span of the LIF data is now essentially complete and ALOC is the condition of interest in the future, the further analysis pertains to only ALOC requisitions. Applying the cluster analysis procedure to the RIC statistics for ALOC requisitions yields the following RIC-groups:

		N	$\bar{X}$	σ_X
RIC-Group I:	AKZ, B14, GNO, S9C	820	38.3.	23.3
RIC-Group II:	S9I	185	32.4	15.2
" " III:	S9G	107	41.5	14.0
" " IV:	S9E	60	47.3	19.8
" " V:	A35, B16, MPB	56	63.2	34.0
" " VI:	A12	24	27.0	9.1

B. RIC-Group Sample

The major RIC Group is seen to be RIC Group I. Consequently, a 205 random sample of OSTs was selected from this RIC-Group to utilize for the simulation/evaluation of the OST-forecasting models with respect to forecast error. This OST time series is given in Appendix F. The OST statistics for this sample versus those for the entire RIC-Group are:

	N	$\bar{X}$	σ_X
OST Sample	205	37.8 ± 1.7	24.6
RIC-Group I	820	38.3 ± 0.8	23.3

The indicated $\pm$ quantities are the standard error of measurement of the mean OST for a sample size of N and population standard deviation σ_X. These statistics indicate that the sample is a good representation of the RIC-Group.

TABLE V-1

RIC OST-STATISTICS

DSU: 703rd Maintenance Bn. (EUROPE)

	NON-ALOC			ALOC		
RIC	N	$\overline{X}$	σ_X	N	$\overline{X}$	σ_X
AKZ	1249	59.7 days	25.4 days	613	38.5 days	24.5 days
A12	14	60.9	33.8	24	27.0	9.1
A35	24	66.9	14.1	10	59.0	24.7
B14	92	70.4	30.5	61	37.6	18.8
B16	52	60.7	26.9	45	62.4	34.3
DDD	4	57.3	2.5			
FHZ	1	73.0				
GNO	46	56.3	12.5	2	39.0	1.4
MPB				1	141.0	
S9C	85	66.8	24.9	144	37.5	19.4
S9E	32	62.8	22.8	60	47.3	19.8
S9G	75	76.5	25.0	107	41.5	14.0
S9I	116	55.9	14.0	185	32.4	15.2
S9T	13	45.6	10.2			

C. Evaluation Of OST-Forecasting Models With Respect To Forecast Error

As in the case of the CONUS DSU, the error performance of the forecasting models were evaluated by applying them to the principal RIC Group time series by means of the OST-forecasting simulator/evaluator program. These simulations represent the composite performance of the various models for all group-forecast items in the RIC Group. As such they constitute a comprehensive basis for performance evaluation of the models with respect to forecast error.

1. Parameter Value Adjustments

As a result of experience gained with the OST forecasting models in the CONUS DSU analysis, some adjustments were made in the parameter values of the models. The principal such adjustment was for the model OSTES (adaptive exponential smoothing). It was found that for the values of the time-period response parameters (T_X=180 days, T_Δ=90 days) and the error-limit parameters (e_{max}=0.20, e_{min}=0.05) used, the performance of the model was determined primarily by the value of e_{min}, and that when the effect of the time-period response parameters was nullified by setting $e_{max}=e_{min}=.05$, the performance of this model was insignificantly altered. It was also found that for the ALOC RIC-Group I OST time series for this DSU, the value $e_{min}=e_{max}=0.03$ gave a slight but statistically significant improvement in forecast error performance. This value was used in the evaluation. This is one of the modes in which the OSTES model was designed to be used. It results in a much simpler model to apply since only the single parameter $e_{max}=e_{min}$ must be specified. The model then automatically adapts to any particular OST time series to meet the specified error value. Consequently, this version of the OSTES model was used in the present evaluation.

It was also found that the poor performance of the model OSTDES (adaptive double exponential smoothing) was due to the use of the tracking signal for determining the value of the smoothing constant to use in the procedure. The smoothing constant limits, α_{min} and α_{max} , used in the procedure to constrain the calculated value may be used to eliminate the adaptive feature of this model by setting $\alpha_{min} = \alpha_{max}$. In an effort to improve the performance of this model, these two parameter values were set at 0.05.

Another parameter adjustment that was made was in the model OSTT (average of observations occurring in the last time period T). As discussed earlier, it is necessary to adjust the time period T for this model to take into account the differing rates at which OSTS occur for different RIC-group or individual item OST time series. In the present case the total number of OSTS (205) is essentially the same as that (202) for the CONUS DSU, however, the time span for ALOC requisitions in the present case is only about one-half that for the former DSU. Consequently, the corresponding value of the parameter T in this model was taken to be T = 90 days.

As in the case of OSTES, it was found that for OSTNE the use of a value of 0.03 rather than 0.05 for the specified error parameter resulted in a slight but statistically significant improvement in forecast error performance. Consequently, this value was used for this model.

For OSTN it was found that the use of N = 48 rather than N = 24 resulted in some improvement in forecast error performance, so this parameter value was used for this model in the evaluation.

2. Evaluation Results

The results of applying the OST-forecasting models to the sampled RIC-Group I OST time series are given in Table V-2. It is seen that the same models have poor forecast error performance as in the case above for the CONUS DSU; namely, OSTMO, OSTEDES, and OSTR. Thus the candidate models for further evaluation with respect to inventory effects are, as before:

OSTN
OSTM
OSTT
OSTNE
OSTES

The error statistics for these models generated by the simulation runs are given in Table V-3. These are the forecast error parameters to be used in evaluating the inventory effect of the models on the group-forecast items of the RIC-Group.

TABLE V-2

EVALUATION OF OST-FORECASTING MODELS WITH RESPECT TO FORECAST ERROR

DSU: 703rd Maintenance Bn. (EUROPE)

RIC-Group I (ALOC)

205-OST SAMPLE

OST-Forecasting Model	RMSE	RMSE'
OSTN	12.64± .13 days	3.60± .16 days
OSTM	12.53	3.05± .07
OSTMO	14.30± .02	5.93± .06
OSTT	12.56	3.12± .17
OSTNE	14.20	3.92± .17
OSTES	13.83	6.78± .11
OSTDES	15.26	6.60± .20
OSTR	18.83± .45	7.15± .33

TABLE V-3

FORECAST ERROR PARAMETERS FOR OST-FORECAST MODELS

DSU: 703rd Maintenance Bn. (EUROPE)

RIC-Group I (ALOC)

205-OST SAMPLE

OST Forecast Models	$\bar{E}$	σ_E	$\sigma_{E'}$
OSTN	3.15 days	12.24 days	1.71 days
OSTM	-1.39	12.46	2.44
OSTT	2.90	12.22	2.27
OSTNE	4.12	13.69	1.12
OSTES	7.05	11.90	1.20
PERFECT	0	0	0

D. Evaluation Of OST-Forecasting Models With Respect To Inventory Effects

1. Cross-Sectional Sample of Items

In order to further evaluate the most promising OST-forecasting models with respect to inventory effects it was necessary to select a cross-sectional sample of items for the DSU. Such a sample was chosen from the principal RIC Group (I) for this DSU. The item parameters for this sample are shown in Table V-4. Unit prices range from \$2 to \$43, demand rates from \$11/year to \$1490/year and \$185/year to \$3500/year. The parameter values given in Table V-4, together with the forecast error parameters given in Table V-3, constitute the input data required for the inventory effects evaluation of the OST-forecasting models by means of the analytic inventory control evaluator program.

2. Evaluation Results

The results of this evaluation are given in Table V-5. The performance measures given in this table are the expected inventory level ($\bar{I}$) and the not-in-stock rate (NIS) for each sample item and the entire sample, resulting from the specified forecast error statistics and sample item parameters. As in the case of the CONUS DSU, there is some difficulty in determining the relative quality of performance of the different models based on these two measures. This is because it is desirable to have both low inventories ($\bar{I}$) and low not-in-stock rate (NIS) yet these quantities are reciprocally related so that lower inventory tends to be associated with a higher NIS rate. For example, for Item 11 OSTM is more favorable than OSTN with respect to $\bar{I}$ (246 versus 262) but it also has a higher NIS rate (0.10 versus 0.07). So the question arises as to whether the increase in NIS rate more or less than compensates for the decrease in inventory. As indicated in the case of the CONUS DSU, this ambiguity is resolved in the present study by artificially adjusting the specified safety stock coverage period (15 days for the European DSU) until the NIS rate is the same as that for the perfect forecast, then the increase in required inventory over that for the perfect forecast is taken as the single performance measure for evaluating the various OST-forecast models. The results of performing this procedure for the sample items and

TABLE V-4

CROSS-SECTIONAL SAMPLE OF ITEMS FOR EVALUATING INVENTORY EFFECTS OF OST-FORECASTING MODELS

DSU: 703rd Maintenance Bn. (EUROPE)

RIC-Group I (ALOC)

Sample Item Number	NSN	Unit Price	Demand Rate	$ Demand Rate	Average User Requisition Quantity *	Standard Deviation of User Requisition Quantity *
1	2510-1769146	$ 42.48	11.0/yr	$465/yr	1.1	1.3
2	2510-4025184	18.49	43.8	810	2.0	1.6
3	2530-6799181	3.83	295.7	1,132	1.2	1.7
4	2540-0401120	37.36	76.7	2,864	1.9	2.0
5	2540-0646587	5.88	602.3	3,541	1.1	1.4
6	2540-4605815	5.88	51.1	300	1.2	1.7
7	2540-8396641	39.13	32.9	1,285	1.0	0
8	2590-6068504	3.14	390.6	1,226	1.1	1.2
9	2910-9309367	13.86	167.9	2,327	1.7	2.0
10	2920-1130693	10.14	18.3	185	1.1	1.4
11	5330-6783239	2.19	1,489.2	3,261	2.4	8.0
12	2510-7328306	13.83	29.2	404	1.0	0

* Obtained from the DSU Demand History Report (Class IX Repair Parts-Common)

TABLE V-5

INVENTORY AND SERVICE LEVEL EFFECTS OF OST-FORECASTING MODELS

DSU: 703rd Maintenance Bn. (EUROPE)

RIC-Group I: OST-Forecast Error Statistics

Cross-Sectional Item Sample

ITEM NUMBER		OST-FORECAST MODEL OSTN	OSTM	OSTT	OSTNE	OSTES	PERFECT
1	$\bar{I}$ =	4.3 units	4.2	4.3	4.4	4.4	4.3
	NIS =	0.18	0.19	0.18	0.17	0.16	0.18
2	$\bar{I}$ =	13.4	12.9	13.3	13.5	13.8	13.0
	NIS =	0.11	0.13	0.11	0.11	0.09	0.11
3	$\bar{I}$ =	77.4	73.9	77.2	78.2	80.5	74.7
	NIS -	0.03	0.05	0.03	0.03	0.02	0.02
4	$\bar{I}$ =	14.5	13.7	14.4	14.7	15.2	13.8
	NIS =	0.14	0.17	0.14	0.14	0.11	0.14
5	$\bar{I}$ =	23.7	23.1	23.6	23.8	24.2	23.2
	NIS =	0.06	0.08	0.06	0.06	0.05	0.06
6	$\bar{I}$ =	102.2	95.1	101.8	103.9	108.5	96.8
	NIS =	0.03	0.05	0.03	0.03	0.01	0.004
7	$\bar{I}$ =	8.2	7.9	8.2	8.3	8.6	7.9
	NIS =	0.08	0.10	0.08	0.08	0.06	0.07
8	$\bar{I}$ =	98.9	94.2	98.6	100.0	103.0	95.4
	NIS =	0.02	0.03	0.02	0.02	0.01	0.004
9	$\bar{I}$ =	33.5	31.6	33.4	33.9	35.1	31.9
	NIS =	0.07	0.10	0.07	0.07	0.05	0.06
10	$\bar{I}$ =	10.6	10.4	10.6	10.6	10.8	10.4
	NIS =	0.09	0.10	0.09	0.09	0.08	0.10
11	$\bar{I}$ =	262.4	245.6	261.4	266.5	277.2	248.4
	NIS =	0.07	0.10	0.07	0.07	0.05	0.05
12	$\bar{I}$ =	11.8	11.5	11.8	11.9	12.1	11.6
	NIS =	0.04	0.06	0.04	0.04	0.03	0.04
SAMPLE	$\bar{I}$	\$3,951	\$3,750	\$3,940	\$3,999	\$4,129	\$3,790
	NIS =	0.07	0.10	0.07	0.07	0.05	0.06

for the entire sample are given in Table V-6. The table also gives the % increase in inventory requirements over that for the perfect forecast for each model for each sample item. These increases are seen to be generally higher for the higher demand (or $\bar{I}$) items. For example, for Item 2, having a perfect forecast inventory requirement of 13 units, these increases range from about 2 to 3% for the different models. On the other hand, for Item 6, having an inventory requirement of 97 units, the increases range from about 26 to 32%. This indicates that the major effect of forecast error tends to occur for high inventory items, which account for a large share of the total inventory held by a DSU.

a. RIC-Group Ranking of OST-Forecast Models

For the entire cross-sectional sample of items, the increase in inventory value over the perfect forecast value ranges between 6.7 and 8.8% for the candidate models.

The ranking of the models based on the entire sample is:

Rank	OST-Forecast Model	% Inventory Increase Over Perfect Forecast
1	OSTES	6.73% (0)
2	OSTN	7.31 (+.58)
3	OSTT	7.36 (+.63)
4	OSTM	7.66 (+.93)
5	OSTNE	8.81 (+2.08)

b. Individual Item Ranking of OST-Forecast Models

It is possible to obtain a composite ranking over the individual items of the sample by ranking the models for each item and computing an average rank. This result is shown in Table V-7. The composite ranking is:

Rank	OST-Forecast Model	Composite Rank
1	OSTES	1.17
2.5	OSTN	2.50
2.5	OSTT	2.50
4	OSTM	3.83
5	OSTNE	5.00

TABLE V-6

INVENTORY EFFECTS OF OST-FORECASTING MODELS

DSU: 703rd Maintenance Bn. (EUROPE)

RIC-Group I (ALOC)

Cross-Sectional Sample of Items

$\bar{I}$ = Average Inventory Required to Give the Same NIS Rate as the Perfect Forecast

OST-FORECASTING MODEL

ITEM NUMBER	$\bar{I}$ OSTN	OSTM	OSTT	OSTNE	OSTES	$\bar{I}$ PERFECT	NIS
1	4.300 (0.0%) *	4.304 (0.1%)	4.300 (0.%)	4.311 (0.25%)	4.300 (0%)	4.30	.18
2	13.33 (2.56)	13.31 (2.38)	13.27 (2.05)	13.40 (3.09)	13.25 (1.91)	13.00	.11
3	81.9 (9.60)	82.0 (9.70)	81.7 (9.37)	82.9 (10.92)	81.6 (9.20)	74.70	.02
4	14.43 (4.58)	14.49 (4.97)	14.39 (4.25)	14.57 (5.56)	14.39 (4.27)	13.80	.14
5	23.65 (1.94)	23.62 (1.81	23.59 (1.67)	23.71 (2.19)	23.58 (1.65)	23.20	.06
6	123.32 (27.40)	124.45 (28.57)	123.57 (27.65)	127.52 (31.73)	121.94 (25.97)	96.80	.04
7	8.30 (5.10)	8.36 (5.82)	8.31 (5.15)	8.38 (6.03)	8.28 (4.77)	7.90	.07
8	109.61 (14.89)	110.42 (15.75)	109.85 (15.14)	112.73 (18.17)	108.92 (14.18)	95.40	.004
9	34.45 (8.00)	34.57 (8.36)	34.48 (8.09)	34.97 (9.63	34.20 (7.21)	31.90	.06
10	10.51 (1.02)	10.53 (1.24)	10.52 (1.18)	10.53 (1.29)	10.48 0.76)	10.40	.10
11	274.26 (10.41)	275.52 (10.92)	274.42 (10.47)	279.45 (12.50)	272.27 (9.61)	248.40	.05
12	11.90 (2.61)	11.98 (3.31)	11.93 (2.82)	12.00 (3.48)	11.90 (2.59)	11.60	.04
SAMPLE	\$4,067 (7.31)	\$4,080 (7.66)	\$4,069 (7.36)	\$4,124 8.81)	\$4,045 (6.73)	\$3,790	.06

* % increase over PERFECT forecast inventory requirement.

TABLE V-7

INDIVIDUAL ITEM AND COMPOSITE RANKING OF OST-FORECASTING

MODELS WITH RESPECT TO INVENTORY EFFECTS

DSU: 703rd Maintenance Bn. (EUROPE)

RIC-Group I (ALOC)

Cross-Sectional Item Sample

PERFORMANCE RANKING

Item Number	OST-FORECASTING MODEL				
	OSTN	OSTM	OSTT	OSTNE	OSTES
1	2	4	2	5	2
2	4	3	2	5	1
3	3	4	2	5	1
4	3	4	1	5	2
5	4	3	2	5	1
6	2	4	3	5	1
7	2	4	3	5	1
8	2	4	3	5	1
9	2	4	3	5	1
10	2	4	3	5	1
11	2	4	3	5	1
12	2	4	3	5	1
COMPOSITE	2.50	3.83	2.50	5.00	1.17

c. Overall Evaluation

Thus it is seen that the rankings of the OST-forecast models with respect to inventory effects, for the sample as a whole and for the individual items of the sample, are essentially the same for this DSU-being OSTES, OSTN, OSTT, OSTM, OSTNE. These are the same top-5-models indicated by the results for the CONUS DSU, and, except for OSTNE, the same ranking as previously.

Again, as in the case of the CONUS DSU, the differences between the performances of the OST forecast models is not great, ranging to a maximum of about 2% perfect-forecast inventory levels, from OSTES (6.7% increase) to OSTNE (8.8% increase). Consequently, the decision as to the most appropriate model to use will depend strongly on implementation considerations, to be discussed below.

VI. IMPROVED OST-FORECASTING ERROR MEASURE

A. Decompositon of Inventory Effects

The OST-forecast errors are reflected by three basic error statistics:

$\bar{E}$ = the average error of the forecast from actual OSTs

= the average error of the forecast from true OST mean

σ_E = the standard deviation of the forecast error from actual OSTs

$\sigma_{E'}$ = the standard deviation of the forecast error from the OST mean

The inventory and service level effects of OST forecast errors may be decomposed into the two separate effects:

1) An effect due to deviations (E') of the forecast from the OST mean (summarized by $\bar{E}$ and $\sigma_{E'}$)
2) An effect due to the deviations of the forecast from actual OSTs (summarized by $\bar{E}$ and $\sigma_{\bar{E}}$)

The first effect results from the use of the OST-forecast in the calculation of the reorder point for an item. Letting

ROP = the reorder point

$\bar{D}$ = the forecasted demand rate

$\bar{L}$ = the true OST mean

S = the safety stock coverage period

$\hat{X}$ = the forecasted OST

then

$$
\begin{aligned}
ROP &= \bar{D} \,.\, (\hat{X} + S) \\
&= \bar{D} \,.\, (\bar{L} + S + \hat{X} - \bar{L}) \\
&= \bar{D} \,.\, (\bar{L} + S + E')
\end{aligned}
$$

This shows explicitly how the OST forecast errors, E', from true OST mean affect the inventory control rules. The component of average inventory associated with the reorder point is

$$(ROP - \bar{D} \cdot \bar{L}) = \bar{D}\ (S + E')$$

showing the effect of E' on inventory levels resulting from the OST-forecast.

The second of the above effects results from the random number of units of an item demanded during the actual OST. The random distribution of this number determines the number of units backordered during the OST, being zero if the number is less than the reorder point and this number minus the reorder point if the number is greater than the reorder point. The mean of this distribution is given by $\bar{D} \cdot \bar{L}$ and its standard deviation by*

$$\sigma = \sqrt{\bar{L}\ \sigma_D^{\ 2} + (\bar{D}\ \sigma_E)^2}$$

where

σ_D = the standard deviation of the number of units demanded per unit time (e.g. per month).

Thus the service-level effect is determined by the OST-forecast error parameter.

B. Relative Importance of Component Effects

It is these two effects due to $(\bar{E}, \sigma_{E'})$ and to σ_E that are taken into account in the calculation of the inventory and service-level effects upon items in the inventory-effect evaluator program. It was found that by far the major effect was due to σ_E through its influence in the above formula for σ. The effect of $\sigma_{E'}$ was found to be almost completely negligible due to compensating inventory and service-level effects as the forecast error varies above and below $\bar{E}$. Thus the effect due to $(\bar{E}, \sigma_{E'})$ was essentially that which would result from $\bar{E}$ alone (i.e., for $\sigma_{E'} = 0$). This means that the above inventory effect due to E' was essentially

$$\bar{D} \cdot (S + E') \doteq \bar{D} \cdot (S + \bar{E})$$

The technique used to reduce the performance of the OST-forecasting models to a single measure was to adjust the value of S until the service-level measure (NIS rate) was equal to that for the perfect forecast. The effect of $\bar{E}$ was largely eliminated by this adjustment process. Thus with the effects of both $\bar{E}$ and $\sigma_{E'}$ almost completely eliminated, the inventory and service-level effects resulting from OST-forecast error were found to be due principally to the error parameter σ_E. From this it may be concluded

---

*See Appendix C.

that this measure of forecast error, rather than

$$RMSE = \sqrt{\sigma_E^2 + \bar{E}^2}$$

or

$$RMSE' = \sqrt{\sigma_{E'}^2 + \bar{E}^2}$$

would be a more appropriate indicator of the inventory effects of OST-forecast error.

The weak effect of $\sigma_{E'}$ for the European DSU is shown in Table VI-1. It can be seen that for all sample items the average required inventories and corresponding service-levels are almost identical for $\sigma_{E'} = 0$ as for the values used in the above evaluations.

C. Most Important Error Parameter

That the single forecast error parameter σ_E is a reliable indicator for the quality of performance of an OST-forecasting model is illustrated by the ranking of models that is given by σ_E for the European DSU (see Table V-3):

Entire-Sample Ranking	Composite Individual Item Ranking	σ_E-Ranking	(σ_E)
OSTES	OSTES	OSTES	(11.90)
OSTN	(OSTN	OSTT	(12.22)
OSTT	OSTT)	OSTN	(12.24)
OSTM	OSTM	OSTM	(12.46)
OSTNE	OSTNE	OSTNE	(13.69)

It is seen that there is essentially perfect correlation between the previous ranking and that based on σ_E. Similarly, for the CONUS DSU, the comparative rankings are:

Entire-Sample Ranking	Composite Individual Item Ranking	σ_E-Ranking	(σ_E)
OSTES	OSTES	OSTES	(14.1)
OSTNE	OSTNE	OSTNE	(14.4)
OSTT	OSTN	OSTT	(14.6)
OSTN	OSTT	OSTN	(14.7)
OSTM	OSTM	OSTM	(15.0)

Again the correlation between the previous inventory effect ranking and that given by σ_E (for the RIC-Group) is essentialy perfect.

TABLE VI-1

EFFECT OF $\sigma_{E'}$ ON OST-FORECASTING PERFORMANCE

DSU: 703rd Maintenance Bn. (EUROPE)

RIC-Group I

Cross-Sectional Sample of Items

Model: OSTN
S = 15 days

Item Number	Average Inventory Requirement		NIS-Rate	
	$\sigma_{E'} \neq 0$	$\sigma_{E'} = 0$	$\sigma_{E'} \neq 0$	$\sigma_{E'} = 0$
1	4.341	4.341	.1774	.1774
2	13.366	13.365	.1076	.1074
3	77.397	77.393	.0285	.0281
4	14.467	14.465	.1397	.1394
5	23.672	23.672	.0634	.0633
6	102.237	102.228	.0276	.0270
7	8.240	8.239	.0760	.0756
8	98.903	98.899	.0188	.0184
9	33.464	33.460	.0721	.0717
10	10.577	10.577	.0914	.0913
11	262.364	262.328	.0704	.0698
12	11.831	11.830	.0407	.0406

These results give a strong indication that for the purpose of assessing the inventory control effects of OST-forecast error, the <u>standard deviation</u> of the forecast error is a much more indicative measure of the inventory effects of forecast error than is the RMSE, used in the initial evaluation of OST-forecasting models in this study. This measure eliminates the forecast bias (<u>average</u> forecast error) from consideration and reflects only the <u>variance</u> of the forecast error about this bias.

VII. IMPLEMENTATION CONSIDERATIONS FOR OST-FORECASTING MODELS

The above results indicate that although it is possible to obtain a clear ranking of the OST-forecasting models, the differences in performance among the models is not great, on the order of 1 to 2% saving in total inventory investment value. The model that performed uniformly best for both DSUs used in the study and for both group-forecast and item-forecast items, was OSTES-the adaptive exponential smoothing model. However, if there are significant difficulties in applying this model in actual practice, compared to any other of four screend OST-forecast models (OSTN, OSTM, OSTT, OSTNE), then it might well be that one of these other models should be selected as the best overall choice of OST-forecast model. Consequently, it is necessary to consider the implementation aspects of the candidate models.

A. OSTN Model

The relative performance among the OST-forecast models can be indicated by the equivalent % inventory increase over that required for the OSTES model - the one having the least % inventory increase over perfect-forecast. For OSTN this inventory increase is about 0.7% for the CONUS DSU and 0.6% for the European DSU (see Table IV-8 and Table V-6, respectively, for the entire sample results). The required number of OST observations for this model is in the range from about 24 to 48. This contrasts with the number 6 for the current system (which utilizes the OSTN model with N = 6). Thus the use of the OSTN model would require a substantial expansion of the fixed-size OST data base for storing historical OST observations. Also there would be a considerable problem of initialization or build-up of the data base for item-forecast items to that required for this model. Slower moving items would require several years of OST data. Even items ordered monthly would require 2 to 4 years of data. In addition, to the unavailability or incompleteness of such data, there would be the question of the relevance of OST data in the considerably distant past. These factors pose serious problems for the implementation of this model that mitigate against its selection.

B. <u>OSTM Model</u>

This model would require about 1% more inventory than OSTES (1.1% for the CONUS DSU and 0.9% for the European DSU). It would require a fixed-size data base of about 25 OST observations, and thus would tend to have implementation objections similar to those discussed above for OSTN.

C. <u>OSTT Model</u>

This model would require about 0.6% increase in inventory (for both the CONUS and European DSUs) over that required for OSTES. Since the number of OST observations required by this model is the number falling in a specified time period, the OST data base is variable, so that allowance must be made for some maximum number of observations. For the CONUS DSU the number of OST observations required in the simulation for this model ranged from 26 to 69. For the European DSU the number of required observations ranged from 23 to 57. Consequently, implementation of this model would require a quite large allocation for storage of the requisite number of OSTs. In addition, the large maximum number of required observations would raise initialization, build-up, and relevance problems similar to those discussed above for OSTN and OSTM. Consequently, the difficulties associated with the implementation of this model are compounded by not only these latter problems, but also the question of the provision of maximum storage space for OST observations.

D. <u>OSTNE Model</u>

The performance of this model was somewhat variable for the two DSUs, varying from a requirement of 0.4% increase of inventory over OSTES for the CONUS DSU to one of 2% increase for the European DSU. This model also, like OSTT, requires a variable number of OST observations for calculating the OST forecast - this number being that required to give a specified error of the forecast of the OST mean. For the CONUS DSU simulation this number ranged from 23 to 67 observations and for the European DSU from 37 to 73 observations. Consequently, the same observations apply to this model as for the above variable size OST data base requirement for OSTT.

E. OSTES Model

This model performed uniformly (slightly) best for both DSUs. It requires no actual historical OST observations, but only the summarization of all past observations by means of the single quantity, the most recent forecast value. This value is then used, together with the next OST observation to generate the next OST forecast. In order to perform the automatic calculation of the smoothing constant used in the model, it is necessary to utilize not only the most recent value of the OST forecast, but also the standard deviation (σ_E) of the forecast error. For the simulation in the present study, the values of σ_E were calculated from the beginning of the simulation. In actual practice this could be accomplished more simply and in a more adaptive manner by obtaining this value by smoothing. It is shown in Appendix G how to accomplish this. It requires the maintenance of the two error measures $\bar{E}$ and σ_E.

Thus the data base for each item or item-group consists, for this model, of only the three elements: the current OST forecast ($\hat{X}$), the current OST forecast bias, $\bar{E}$, and the current standard deviation (σ_E) of the forecast error.

Another factor simplifying the application of OSTES is the finding in this study that the use of the response time-period parameters of the model T_X and T_Δ, contributed very little to the quality of the forecasts over that resulting from nullifying the effect of these parameters by setting $e_{min} = e_{max} = e$ the specified error of the forecast of OST mean. This simplifies the OSTES model considerably, requiring only the single parameter e for application. The appropriate values of the smoothing constant, α, are then automatically calculated from item to item, group to group, and over time for individual items or groups by the adaptive procedure incorporated into the OSTES model. This feature answers the objection sometimes expressed against exponential smoothing techniques;namely how is one to specify and maintain the appropriate values of the smoothing constants for many thousands of items over long periods of time? In the OSTES model it is required to specify only the desired standard error, e, of the forecast of the OST mean. This is policy-type criterion that can be specified quite generally for broad classes of items - or all items. Then the OSTES procedure automatically adjusts to the error statistics for different items, groups, and times.

This simplified modification of the original OSTES previously reported in the memorandum "OST-Forecasting and Evaluating Models", 18 August, 1977, is given in Appendix G.

Hence it is concluded on the basis of both the performance of the OSTES model and the simplicity of its implementation, that (of the OST-forecast models evaluated in this study) the OSTES model is clearly to be recommended.

VIII. UPDATING OF THE REQUISITIONING OBJECTIVE

The basic purpose for which demand and OST forecasts are made is for use in calculating the item inventory control decision levels (reorder point ROP and requisitioning objective RO). These control levels are given by

$$ROP = \bar{D}\,(\hat{X} + S)$$

$$RO = ROP + Q$$

where

$\bar{D}$ = the forecasted item demand rate

$\hat{X}$ = the forecasted item OST

S = the safety-stock coverage period

$Q = 4.75\sqrt{\bar{D}/c}$

c = the item cost (price)

In principle, the best values of ROP and RO result from using the best available values of the demand and OST forecast, $\bar{D}$ and $\hat{X}$. The best estimates for these forecast values at any time are those most recently calculated. Thus the best values of ROP and RO result from updating their values whenever either $\bar{D}$ of $\hat{X}$ are updated. This is particularly true for ROP which controls the timing of replenishment requisitions. If the demand rate or OSTs change but ROP is not updated, then requisitions will not be triggered in accordance with current conditions. This will result in excess inventories in case triggering is too early (i.e. if demand and/or OST are decreasing) and excess stock shortages if triggering is too late (i.e. demand and/or OST are increasing).

Present ROP/RO updating policy is to update both ROP and RO whenever a requisition is triggered - that is, whenever the inventory position of an item falls to or below the <u>previously updated</u> ROP, calculated at the time of the preceding requisition. The updating of the RO at this time does indeed appropriately adjust the requisition quantity to reflect current conditions. However, this procedure does not allow any such compensating adjustment in the <u>timing</u> of the requisition if the requisition is triggered, based on the ROP calculated at the previous requisition update, too early or too late relative to the currently updated ROP. Then the requisition is still placed at the present time and the detrimental consequences of this mistiming will result. To illustrate this effect, consider an item whose demand and OST forecasts at the time of the last requisition were

$$\overline{D} = 10 \text{ units/month}$$
$$\hat{X} = 35 \text{ days}$$

Suppose also that the safety stock period is

$$S = 5 \text{ days}$$

The ROP calculated at the time of the previous update would be

$$ROP = 10(35 + 5)/30 = 13 \text{ units}$$

This value of ROP is then used until the next requisition is triggered.

Suppose that when this occurs the current forecasts are

$$\overline{D} = 12 \text{ units/month}$$
$$\hat{X} = 37 \text{ days}$$

so that the updated ROP at this time is

$$ROP = 13(42)/30 = 18 \text{ units.}$$

Thus the requisition which was triggered at an inventory position of 13 should have been triggered at a level of 18. With the current demand rate of 13/month, this translates into a postponement of about 12 days in placing the requisition. This is, in effect, equivalent to adding 12 days to the OST for the current requisition. The result would be a substantial increase in the likelihood and number of expected shortages. The fact that an updated RO is calculated at this time would in no way mitigate the consequences of the delayed placing of the requisition. If the current values of the demand and OST forecast are less than those at the time of the last requisition, say

$$\overline{D} = 8 \text{ units/month}$$
$$\hat{X} = 32 \text{ days}$$

then the currently updated values of the ROP would be

$$ROP = 8\ (37)30 = 10 \text{ units.}$$

The requisition would then have been triggered when the inventory was 3 units higher (or 11 days earlier) than necessary. If the unit price of the item is \$2, then

$$Q = 4.75\ \sqrt{8/2} = 9.5 \text{ units}$$

This compares with $Q = 10.6$ for the previous value of Q. Thus the inventory is 3 units too high due to use of the previous ROP, but the Q is reduced by only about 1 unit and the corresponding average inventory reduction is only 1/2 this amount, consequently, an excess inventory of about 2.5 units would occur in this case.

These examples illustrate the potential importance of updating the ROP during the interim between requisitions. Although it is not necessary to update the RO until a requisition is triggered, there is essentially no increase in cost, time, or effort in a computerized system to calculating the current economic order quantity Q from the above formula and adding to the ROP to obtain the updated RO. A similar comment applies to the updating of the ROP itself. At the time of an updating of the demand or OST forecast it is very simple to recalculate the corresponding updated ROP and RO. Thus it is possible to simply maintain updated values of both of these fundamental inventory control levels and obtain the most effective performance possible from the demand and OST forecasts. This updating procedure would occur monthly for demand forecasts since these are updated monthly. For item-forecast items the updating would occur on the occasion of each new OST observation (requisition completion), at which time the OST forecast is updated. For OST group-forecast items the rate of group OST observations is much higher than for individual items. OST group forecasts would not generally be updated for each OST observation. As discussed in section IV. B above, there is no significant deterioration at intervals of up to 30 days. The OST-group update intervals will depend upon the group requisition rates and available file storage space. These factors would have to be taken into account in any implementation of the recommended OST-forecast model, OSTES.

APPENDIX A

US DARCOM LCA/LIF DATA ELEMENTS

For each LIF record (requisition) the following selected data elements are defined:

Basic (leader) record field

CODE	DESCRIPTION
DIC	Document Identifier Code
RIC	Routing Identifier Code
NSN	National Stock Number
UI	Unit of Issue
QTY	Requisition Quantity
DODAAC	Identification of Requisitioner
RQNDT	Requisition Date
D	Demand Code
PRI	Issue Priority
UP	Unit Price
ALOC	ALOC Indicator

Segment record field

MIRP	Master Inventory Record Post Date
DEPOT	Shipping Depot
BOI	Backorder Indicator
MODE	Mode of Shipment
SEGQTY	Segment Shipped Quantity

APPENDIX B

DEFINITIONS OF ROUTING INDICATOR CODES (RIC)

RIC	COGNIZANT AGENCY
AKZ	U.S. Army Tank Automotive Readiness Command (TARCOM)
AP5	U.S. Army Support Center
A12	U.S. Army Transport Support Command (TROSCOM) (TROSCOM)
A35	U.S. Army General Military and Parts Center (GMPC)
B14	U.S. Army Armaments Command (ARRCOM)
B16	U.S. Army Electronics Command (ECOM)
B17	U.S. Army Aviation System Command (AVSCOM)
FFZ	Sacramento Air Materiel Area
FHZ	Oklahoma City Air Materiel Area
FLZ	Warner Robbins Air Materiel Area
MPB	Marine Corps Supply Activity
N35	Navy Ship Parts Control Center
S9C	Defense Construction Supply Center
S9E	Defense Electronics Supply Center
S9G	Defense General Supply Center
S9I	Defense Industrial Supply Center
S9T	Defense Personnel Support Center
GNO	GSA Federal Supply Service

APPENDIX C

MODIFICATIONS OF THE ANALYTIC OST-FORECASTING INVENTORY CONTROL EVALUATOR

In the memorandum "Analytic OST-Forecasting Inventory Control Evaluator", R.H. Davis, 13 September 1977, were derived the formulas for calculating the inventory and service-level effects of OST forecast errors for individual items The formulas used for the average number of backorders, BO, and the not-in-stock rate, NIS, were the usual formulas that apply when shortages and backorders are not too large. However, it was found, especially for the CONUS DSU that has a quite low safety stock average period (5 days), that this assumption was not satisfied and therefore the formulas were modified to give more accurate results. The original expression for $\overline{BO}$ was

$$\overline{BO}_o = D \cdot \overline{BO}_o / Q$$

where

$$\overline{BO}_o = (\sigma^2/2D) \cdot G(t)$$

$$G\ (t) = 0.5e^{-(at^2 + bt)}$$

$$a = .362805$$

$$b = 1.513$$

$$t = (\ ROP - \mu)/\sigma$$

In the exact formula for $\overline{BO}_o$, G (t) is replaced by

$$G\ (t) - G\ (\ t + q\ )$$

where

$$q = Q/\ \sigma$$

Consequently, this change was introduced into the evaluator.

Similarly, in the exact expression for the NIS, E (t) is replaced by E (t) - E (t + q).

The expression used by approximating E(t) was for the form

$$E\ (\ t\ ) = B\ e^{-(\ a'\ t^2 + b'\ t\ )}$$

This formula and the one given above for $G(t)$ are good individual approximations to their respective functions, however, there is a theoretical relationship that exists between $G(t)$ and $E(t)$:

$$E(t) = -0.5\ (dG/dt)$$

It is important when evaluating small differences in performance of alternative OST-forecast models, as was the case in the present study, that this relation be satisfied. Otherwise anomalous results can occur - for example, non-optimal safety stocks can yield lower total cost than optimal safety stocks. Consequently, the formula used for $E(t)$ was that given by the above relationship:

$$E(t) = (2at + b)G(t)/2\ .$$

A listing of a FORTRAN computer program for the modified analytic inventory control evaluator (ICEVAL) is given on the next page.

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```
      PROGRAM ICEVAL(INPUT,OUTPUT,TAPE4)
      DIMENSION DEL(4),P(4),BO(4),FI(4),TC(4),W(4)
      REAL K,L
      READ(4,10)WW,H,A,SS
      PRINT 10,WW,H,A,SS
      READ(4,20) N
   10 FORMAT(10F7.2)
   20 FORMAT(I4)
      K-SQRT(2.*WW)
      W(2)-1.-2.*WW
      W(3)-WW
      W(4)-WW
      DATA SCDI,STCI,SCFII,SCBOI,SCDPI,STCI,SCFII,SCBOI,SCPDI/9*0./
      DO 30 I-1,N
      PRINT 20,I
      READ(4,10)C,D,S,SIGS,RHO,L,SIGL,EB,SIGEB
      PRINT 10,C,D,S,SIGS,RHO,L,SIGL,EB,SIGEB
      DEL(2)-EB
      DEL(3)-EB+SIGEB/K
      DEL(4)-EB-SIGEB/K
      DEL(1)-0.
      AA-(L*L+SIGL*SIGL)*RHO/L/365.
      B-1.+AA/2.
      CC-1.+2.*AA
      FMU-D*L*B
      SIG-SQRT(FMU*S*(1.+(SIGS/S)**2)+CC*(D*SIGL)**2)
      Q-SQRT(2.*A*D*365./(H*C))
      QP-Q/SIG
      DO 40 J=1,4
      DELT-DEL(J)
      R-(L+SS+DELT)*D
      T=(R-FMU)/SIG
      IF(T.LT.-1.)T=-1.
      G-EXP((-.363*T-1.513)*T)/2.
      E-(.726*T+1.513)*G/2.
      T-T+QP
      IF(T.LT.-1.)T--1.
      G1-EXP((-.363*T-1.513)*T)/2.
      E1-(.726*T+1.513)*G1/2.
      G-G-G1
      BO(J)-SIG*G/(2.*QP)
      FI(J)-BO(J)+SIG*(T+QP/2.)
      P(J)-(E-E1)/QP
      IF(J.EQ.1)X=1./P(J)-1.
   40 TC(J)-H*C*(FI(J)+X*BO(J))
```

```
      TCI=0.
      BOI=0.
      FII=0.
      PI=0.
      DO 35 J=2,4
      WJ=W(J)
      TCI=TCI+WJ*TC(J)
      BOI=BOI+WJ*BO(J)
      FII=FII+WJ*FI(J)
   35 PI=PI+WJ*P(J)
      DELTC=TCI-TC(1)
      PRINT   5,FI(1),BO(1),TC(1),P(1)
      PRINT   5,FII,BOI,TCI,PI,DELTC
      SCDI=SCDI+C*D
      STC1=STC1+TC(1)
      SCFI1=SCFI1+C*FI(1)
      SCBO1=SCBO1+C*BO(1)
      SCDP1=SCDP1+C*D*P(1)
      STCI=STCI+TCI
      SCFII=SCFII+C*FII
      SCBOI=SCBOI+C*BOI
      SCDPI=SCDPI+C*D*PI
   30 CONTINUE
      PP1=SCDP1/SCDI
      PPI=SCDPI/SCDI
      DELTC=STCI-STC1
      PRINT 20,N
      PRINT   5,SCFI1,SCBO1,STC1,PP1
      PRINT   5,SCFII,SCBOI,STCI,PPI,DELTC
    5 FORMAT(3F8.1,F8.4,F8.2)
      END
```

APPENDIX D

SYNTHETIC 5-YEAR OST TIME SERIES FOR THREE TEST ITEMS

DSU: 704th Maintenance Bn.

RIC-Group I

	1	2	3
Item No :	1	2	3
NSN:	7146156	6784131	1345093
$\bar{X}$ =	40.1 days	31.9 days	63.8 days
$_X$ =	12.2 "	7.7 "	18.3 "

Origination Time	OST	Origination Time	OST	Origination Time	OST
Day 2417*	36 days	2419	36	2408	80
2434	44	2425	25	2412	43
2444	27	2429	23	2412	69
2444	51	2445	33	2413	59
2457	38	2450	22	2426	52
2464	30	2458	25	2426	91
2465	35	2460	46	2443	79
2476	57	2462	31	2444	70
2491	45	2464	35	2464	44
2495	49	2472	19	2472	51
2513	31	2479	24	2473	60
2516	63	2495	40	2476	77
2521	57	2504	29	2495	36
2528	32	2507	26	2495	78
2534	64	2510	39	2512	44
2536	51	2515	18	2527	50
2541	35	2533	33	2535	41
2545	25	2539	22	2538	107
2562	41	2540	27	2540	73
2565	60	2542	35	2563	63
2584	36	2547	24	2564	51
2588	35	2548	31	2569	63

APPENDIX D (Continued)

2597	22	2550	42	2587	57
2620	31	2553	22	2594	96
2621	18	2566	22	2600	107
2621	51	2569	32	2604	129
2625	47	2571	30	2609	56
2632	44	2606	21	2610	50
2643	40	2615	47	2617	45
2663	29	2616	24	2640	40
2687	53	2621	28	2644	77
2687	76	2626	23	2673	44
2688	27	2645	21	2677	60
2699	23	2650	30	2685	67
2709	28	2656	36	2696	44
2715	30	2660	22	2696	68
2724	36	2670	39	2701	54
2735	28	2700	35	2704	52
2742	41	2700	40	2708	72
2754	52	2704	45	2708	99
2765	43	2705	34	2709	90
2774	42	2708	32	2711	69
2787	38	2712	29	2714	42
2794	68	2712	37	2719	60
2806	83	2716	32	2731	63
		2716	39	2736	60
		2730	28	2765	40
		2730	30	2769	46
		2732	37	2779	57
		2741	28	2780	96
				2790	60
	N = 45 days		50		51
	$\bar{X}$ = 42 days		30 days		64 days
	σ_X = 15 days		7 days		20 days

* Days are from a 1 Jan. 1970 origin: Note that time scale has been compressed by a factor of about 5. This is for the purpose of using the item OST series as the forecasted series together with the (sampled) RIC-Group I OST time series for generating the forecasts. Thus the item and group OST series cover the same time period.

APPENDIX E

202-OST SAMPLE TIME SERIES

DSU: 704th Maintenance Bn.(CONUS)

RIC-Group I

Requisition Dates *

```
2373.002415.002416.002416.002416.002420.002423.002426.002426.002427.00
2429.002430.002430.002430.002430.002433.002433.002434.002435.002435.00
2436.002437.002441.002442.002444.002444.002447.002447.002448.002448.00
2449.002451.002451.002451.002451.002454.002458.002458.002458.002458.00
2461.002461.002462.002468.002468.002468.002470.002470.002471.002472.00
2472.002472.002476.002476.002476.002480.002480.002483.002483.002484.00
2484.002486.002486.002486.002491.002492.002498.002501.002506.002508.00
2512.002514.002515.002515.002523.002526.002527.002528.002529.002532.00
2536.002536.002542.002546.002546.002553.002560.002561.002565.002565.00
2566.002566.002566.002566.002569.002573.002573.002573.002575.002576.00
2580.002580.002581.002583.002588.002592.002592.002593.002594.002595.00
2596.002596.002597.002600.002601.002607.002607.002608.002608.002608.00
2613.002613.002613.002613.002613.002616.002620.002620.002621.002621.00
2624.002628.002630.002630.002632.002635.002637.002638.002641.002641.00
2641.002642.002644.002644.002644.002644.002645.002648.002648.002649.00
2650.002652.002655.002657.002659.002661.002664.002664.002669.002669.00
2670.002671.002672.002676.002676.002677.002677.002678.002678.002680.00
2684.002685.002686.002688.002690.002692.002697.002698.002702.002711.00
2711.002711.002713.002714.002715.002715.002718.002721.002722.002726.00
2728.002732.002734.002735.002735.002735.002735.002735.002735.002736.00
2741.002748.00
```

OSTs (Days)

43.00	27.00	26.00	26.00	45.00	22.00	19.00	22.00	92.00	35.00
33.00	24.00	32.00	53.00	88.00	21.00	50.00	57.00	35.00	83.00
27.00	24.00	50.00	49.00	19.00	32.00	23.00	44.00	23.00	38.00
35.00	29.00	33.00	40.00	78.00	44.00	22.00	22.00	26.00	71.00
40.00	67.00	85.00	30.00	40.00	93.00	43.00	91.00	55.00	34.00
54.00	57.00	30.00	50.00	70.00	26.00	62.00	25.00	32.00	22.00
56.00	29.00	50.00	61.00	23.00	26.00	20.00	27.00	30.00	31.00
33.00	31.00	27.00	54.00	42.00	32.00	42.00	44.00	51.00	41.00
29.00	57.00	30.00	42.00	55.00	42.00	28.00	40.00	30.00	63.00
29.00	29.00	50.00	75.00	67.00	22.00	28.00	59.00	45.00	65.00
33.00	43.00	26.00	49.00	49.00	31.00	63.00	39.00	44.00	43.00
27.00	42.00	35.00	41.00	40.00	23.00	34.00	29.00	33.00	59.00
25.00	28.00	28.00	28.00	82.00	29.00	24.00	49.00	24.00	29.00
25.00	21.00	20.00	70.00	68.00	29.00	32.00	64.00	23.00	43.00
61.00	34.00	25.00	32.00	32.00	47.00	31.00	28.00	28.00	20.00
47.00	24.00	21.00	21.00	29.00	26.00	20.00	34.00	18.00	59.00
56.00	31.00	39.00	26.00	35.00	25.00	49.00	29.00	86.00	27.00
27.00	40.00	35.00	63.00	51.00	31.00	35.00	64.00	54.00	30.00
32.00	59.00	30.00	27.00	36.00	36.00	25.00	27.00	21.00	37.00
28.00	24.00	29.00	21.00	28.00	29.00	33.00	34.00	36.00	28.00
30.00	23.00								

* Number of days from 1 January 1970

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APPENDIX F

205-OST SAMPLE TIME SERIES

DSU: 703rd Maintenance Bn. (EUROPE)

ALOC Requisitions

RIC-Group I

Requisition Origination Times *

2560.002563.002568.002573.002575.002579.002580.002583.002590.002590.00
2590.002591.002593.002595.002595.002596.002596.002596.002597.002597.00
2597.002598.002600.002602.002604.002605.002610.002611.002614.002615.00
2617.002618.002618.002618.002618.002618.002622.002622.002623.002624.00
2625.002626.002626.002626.002629.002629.002629.002629.002630.002630.00
2630.002630.002630.002631.002631.002632.002632.002632.002632.002635.00
2635.002635.002635.002635.002635.002637.002638.002638.002638.002638.00
2638.002638.002640.002640.002640.002640.002642.002642.002642.002643.00
2643.002644.002644.002644.002644.002644.002645.002645.002646.002646.00
2649.002649.002650.002650.002651.002651.002653.002653.002653.002653.00
2654.002654.002656.002656.002656.002658.002658.002658.002658.002658.00
2658.002658.002658.002659.002659.002659.002659.002659.002660.002660.00
2660.002660.002660.002664.002664.002664.002664.002664.002664.002665.00
2665.002665.002665.002665.002666.002666.002666.002667.002667.002667.00
2668.002668.002671.002671.002671.002671.002671.002672.002672.002673.00
2675.002675.002677.002677.002677.002677.002677.002677.002678.002678.00
2678.002679.002679.002680.002680.002681.002681.002682.002682.002684.00
2684.002685.002685.002686.002687.002687.002687.002687.002688.002689.00
2691.002691.002691.002691.002692.002692.002693.002693.002693.002694.00
2694.002694.002695.002695.002698.002699.002721.002722.002729.002729.00
2734.002737.002737.002737.002737.00

Requisition OSTs (Days)

24.00	60.00	111.00	37.00	35.00	35.00	87.00	27.00	75.00	92.00
145.00	96.00	19.00	22.00	113.00	19.00	27.00	116.00	18.00	17.00
34.00	25.00	124.00	56.00	54.00	60.00	78.00	54.00	18.00	94.00
63.00	38.00	42.00	46.00	47.00	53.00	23.00	60.00	42.00	34.00
28.00	34.00	39.00	39.00	31.00	36.00	49.00	74.00	30.00	49.00
50.00	50.00	113.00	29.00	62.00	26.00	26.00	33.00	110.00	21.00
23.00	24.00	30.00	35.00	74.00	45.00	27.00	28.00	30.00	37.00
49.00	57.00	25.00	26.00	26.00	40.00	23.00	38.00	107.00	32.00
71.00	27.00	36.00	37.00	43.00	69.00	34.00	42.00	25.00	32.00
17.00	21.00	20.00	23.00	19.00	20.00	24.00	25.00	29.00	39.00
28.00	49.00	25.00	25.00	30.00	22.00	23.00	23.00	23.00	27.00
30.00	35.00	41.00	21.00	22.00	23.00	26.00	44.00	20.00	21.00
21.00	26.00	61.00	24.00	24.00	29.00	29.00	36.00	79.00	22.00
23.00	28.00	28.00	38.00	20.00	26.00	27.00	19.00	25.00	45.00
24.00	44.00	21.00	23.00	28.00	41.00	43.00	20.00	22.00	19.00
18.00	39.00	18.00	22.00	26.00	32.00	42.00	47.00	17.00	25.00
46.00	28.00	40.00	27.00	39.00	22.00	43.00	30.00	60.00	23.00
35.00	28.00	48.00	26.00	25.00	25.00	39.00	62.00	33.00	28.00
28.00	28.00	30.00	36.00	25.00	50.00	26.00	28.00	50.00	25.00
27.00	48.00	26.00	40.00	45.00	25.00	42.00	34.00	20.00	32.00
27.00	18.00	18.00	18.00	21.00					

* Days from 1 January 1970

APPENDIX G

SIMPLIFIED MODIFICATION OF THE OSTES MODEL

In the memorandum "OST Forecasting and Evaluation Models", 18 August, 1977, pp. 17-20, the original OSTES forecasting model was described. It involved two response time-period parameters:

T_X = the effective OST sampling interval

T_Δ = the effective demand-rate sampling interval

These two parameters exert the primary control over the automatic adaptive calculation of the smoothing constant, α , in the procedure. Two additional parameters that exert secondary, and overriding, control over the α calculation are e_{min} and e_{max} the minimum and maximum desired % error in the forecast of the OST mean. One of the simplified modes in which the OSTES model can be used is to nullify the effect of the two response parameters T_X and T_Δ and to utilize the single parameter

$$e_{min} = e_{max} = e$$

to control the adaptive calculation of the smoothing constant, α .

The adapative formula for α is:

$$\alpha = 2. (e . \hat{X})^2/\sigma_E^2$$

where

$\hat{X}$ = the current OST forecast

σ_X^2 = the current variance of OST forecast error

The updated OST forecast is then given by:

$$\hat{X} = \alpha \cdot X + (1 - \alpha) \cdot \hat{X}$$

where

X = the current OST observation

This procedure is very simple, but it depends on mantaining a current value of the forecast error parameter σ_E . This quantity is related but not identical with the RMSE measure of forecast error. This relationship is given by

$$RMSE^2 = \sigma_E^2 + \bar{E}$$

where $\bar{E}$ = the current value of the bias of the OST forecast (average error of forecast)

So an updated value of σ_E^2 can be calculated from

$$\sigma_E^2 = RMSE^2 - \bar{E}^2$$

where $RMSE^2$ and $\bar{E}$ are updated values of these error measures. During the OST-forecast simulations in the present study the error measures (RMSE, $\bar{E}$, σ_E) were calculated directly from the time series of forecast errors generated by the simulation. In practice the values could be simply updated by exponential smoothing. Using a smoothing constant corresponding to about 20 past OST observations, these updating formulas would be

$$\bar{E} = 0.1 (\hat{X} - X) + 0.9 \bar{E}$$

$$RMSE^2 = 0.1 (\hat{X} - X)^2 + 0.9 RMSE^2$$

where quantitites on the right-hand side are current values and those on the left are updated values. Then the updated value of σ_E^2 is

$$\sigma_E^2 = RMSE^2 - \bar{E}^2 .$$

The simplified procedure is then

1. Specify the forecast error parameter, e .
2. Specify current values of

$\hat{X}$ = the OST forecast

X = the OST observed value

$\bar{E}$ = the OST forecast bias

σ_E^2 = the variance of OST forecast error

3. Calculate

$$\alpha = (2e^2)\ \hat{X}^2 / \sigma_E^2$$

$$RMSE^2 = \sigma_E^2 + \bar{E}^2$$

$$\bar{E} = 0.1\ (\hat{X} - X) + 0.9\ \bar{E}$$

$$\sigma_E^2 = 0.1\ (\hat{X} - X)^2 - 0.9\ RMSE^2 - \bar{E}^2$$

$$\hat{X} = \alpha X + (1 - \alpha)\ \hat{X}$$

4. Save $\hat{X}$, $\bar{E}$, σ_E^2 for next forecast.

APPENDIX H

LISTING OF OST-FORECAST ERROR SIMULATOR/EVALUATOR COMPUTER PROGRAM (FORTRAN)

```
STATS     TRACE                                   CDC 6700 FTN V3.0-355F OPT
      PROGRAM STATS (INPUT,TAPE1,TAPE2,OUTPUT,TAPE6=OUTPUT)
      DIMENSION IA(8)
      READ (2,1) IA
1     FORMAT (8A10)
       READ(1,1111) INDXX
1111  FORMAT (I1)
      WRITE (6,123) INDXX
123    FORMAT (*  NUMBER OF DATA SETS *,I2)
      DO 999 INDX=1,INDXX
      PRINT 6,IA
6     FORMAT (1H1,8A10)
      PRINT 7
7     FORMAT (*  PROGRAM OSTN *)
      CALL OSTN
      PRINT 8
8     FORMAT (1H1,* PROGRAM OSTM*,/)
      CALL OSTM
      PRINT 9
9     FORMAT (1H1,* PROGRAM OSTT*,/)
      CALL OSTT
      PRINT 10
10    FORMAT (1H1,*PROGRAM OSTNE *,//)
      CALL OSTNE
      PRINT 11
11    FORMAT (1H1,* PROGRAM OSTES*,/)
      CALL OSTES
      PRINT 12
12    FORMAT (1H1,* PROGRAM OSTDES*,/)
      CALL OSTDES
      PRINT 13
13    FORMAT (1H1,* PROGRAM OSTNP*,/)
      CALL OSTNP
      PRINT 14
14    FORMAT (1H1,* PROGRAM OSTESP*,/)
      CALL OSTESP
20     PRINT 21
21     FORMAT (1H1,* PROGRAM OSTR.  LEAST SQUARES TRENDLINE.*,/)
       CALL OSTR
       PRINT 22
22     FORMAT (1H1,* PROGRAM OSTMO.  MODE SEARCH.*,/)
       CALL OSTMO
999    CONTINUE
      STOP
      END
```

```
      SUBROUTINE CSTN
      COMMON /B/ N1,T(2000),X(2000),TS(2000),XS(2000)
      REAL M
      READ(1,10)N,I0,I1,NN,N1
10    FORMAT(5I3,7F7.2)
      PRINT 10,N,I0,I1,NN,N1
      READ(2,20)(T(I),I=1,N)
      READ(2,20)(X(I),I=1,N)
      READ(2,20)(TS(I),I=1,N1)
      READ(2,20)(XS(I),I=1,N1)
20    FORMAT(10F7.2)
      M=0.
      SE=0.
      SE2=0.
      SAE=0.
      TI0=T(I0)
      SRMSEB=0.
      SRMSE=0.
      SSRMSE=0.
      SSSRMSE=0.
      K=0
5     K=K+1
      TSK=TS(K)
      IF(TSK.LT.TI0)GO TO 5
      DO 30 I=I0,I1
      K=K-1
      S=0.
      NNN=0
      DO 25 J=1,I
      IJ=I-J+1
      NNN=NNN+1
      S=S+X(IJ)
      IF(NNN.EQ.NN)GO TO 27
25    CONTINUE
27    XX=S/NNN
      IP1=I+1
      TIP1=T(IP1)
24    K=K+1
      IF(K.GT.N1)GO TO 70
      TSK=TS(K)
      IF(TSK.GE.TIP1)GO TO 30
      M=M+1.
      E=XX-XS(K)
      SE=SE+E
      SE2=SE2+E*E
      SAE=SAE+ABS(E)
      EB=SE/M
      AEB=SAE/M
      IF(M.GT.1.)GO TO 50
      SIGE=0.
      GO TO 60
50    A=(SE2-(SE*SE/M))/(M-1.)
      SIGE=SQRT(A)
60    SIGEB=SIGE/SQRT(FLOAT(NNN+1))
      RMSE=SQRT(SIGE*SIGE+EB*EB)
      SSSRMSE=SQRT(.2*(RMSE-SSRMSE)**2/9+.8*SSSRMSE*SSSRMSE)
      SSRMSE=.2*RMSE+.8*SSRMSE
      RMSEB=SQRT(SIGEB*SIGEB+EB*EB)
      DELT=RMSEB-SRMSEB
      SRMSE=SQRT(.2*DELT*DELT/9+.8*SRMSE*SRMSE)
      SRMSEB=.2*RMSEB+.8*SRMSEB
      PRINT 20,XX,EB,SIGE,SIGEB,AEB,RMSE,SSRMSE,SSSRMSE,RMSEB,SRMSEB
      PRINT 20,SRMSE
      GO TO 24
30    CONTINUE
70    CONTINUE
      RETURN
      END
```

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```
      SUBROUTINE OSTM
      COMMON /B/ N1,T(2000),X(2000),TS(2000),XS(2000)
      REAL M
      READ(1,10)N,I0,I1,NN,N1
   10 FORMAT(5I3,7F7.2)
      PRINT 10,N,I0,I1,NN,N1
C     READ(1,20)(T(I),I=1,N)
C     READ(1,20)(X(I),I=1,N)
C     READ(1,20)(TS(I),I=1,N)
C     READ(1,20)(XS(I),I=1,N)
   20 FORMAT(10F7.2)
      M=0.
      SE=0.
      SE2=0.
      SAE=0.
      TI0=T(I0)
      SRMSEB=0.
      SRMSE=0.
      K=0
    5 K=K+1
      IF(TS(K).LT.TI0)GO TO 5
       DO 30 I=I0,I1
      K=K-1
      DO 32 J=1,NN
      IJ=I-J+1
      Y=X(IJ)
      MM=0
      MMM=0
      DO 34 JJ=1,NN
      L=I-JJ+1
      XL=X(L)
      IF(XL.LT.Y)MM=MM+2
      IF(XL.LE.Y)MMM=MMM+2
      IF(MM.GT.NN)GO TO 32
   34 CONTINUE
      IF((MM.LE.NN).AND.(MMM.GT.NN))GO TO 36
   32 CONTINUE
   36 XX=Y
      PRINT 20,XX
      IP1=I+1
      TIP1=T(IP1)
   24 K=K+1
      IF(K.GT.N1)GO TO 70
      IF(TS(K).GE.TIP1)GO TO 30
       M=M+1.
       E=XX-XS(K)
       SE=SE+E
       SE2=SE2+E*E
       SAE=SAE+ABS(E)
       EB=SE/M
       AEB=SAE/M
       IF(M.GT.1.)GO TO 50
       SIGE=0.
       GO TO 60
   50  A=(SE2-(SE*SE/M))/(M-1.)
       SIGE=SQRT(A)
   60  SIGEB=SIGE/SQRT(FLOAT(NN+1))
       RMSE=SQRT(SIGE*SIGE+EB*EB)
       RMSEB=SQRT(SIGEB*SIGEB+EB*EB)
       DELT=RMSEB-SRMSEB
       SRMSE=SQRT(.2*DELT*DELT/9+.8*SRMSE*SRMSE)
       SRMSEB=.2*RMSEB+.8*SRMSEB
       PRINT 20,XX,EB,SIGE,SIGEB,AEB,RMSE,RMSEB,SRMSEB,SRMSE
      GO TO 24
   30  CONTINUE
   70 CONTINUE
      RETURN
       END
```

```
      [illegible]
      DIMENSION Z(2000),Y(2000)
      COMMON /B/ N1,T(2000),X(2000),TS(2000),XS(2000)
      REAL M
      READ(1,10)N,I0,I1,NN,N1
10    FORMAT(5I5,7F7.2)
      PRINT 10,N,I0,I1,NN,N1
C     READ(1,20)(T(I),I=1,N)
C     READ(1,20)(X(I),I=1,N)
C     READ(1,20)(TS(I),I=1,N)
C     READ(1,20)(XS(I),I=1,N)
20    FORMAT(10F7.2)
      M=0.
      SE=0.
      SE2=0.
      SAE=0.
      SRMSEB=0.
      SSRMSE=0.
      SSSRMSE=0.
      SRMSE=0.
      TI0=T(I0)
      K=0
    5 K=K+1
      TSK=TS(K)
      IF(TSK.LT.TI0)GO TO 5
      DO 30 I=I0,I1
      K=K-1
      DO 15 L=1,NN
      L2=L+I-NN
      Y(L)=X(L2)
   15 CONTINUE
      CALL SORTAG(Y,1,NN,Z)
      L0=1
      L1=NN
      FN=FLOAT(NN)
      B=Y(L0)
      C=Y(L1)
35    IF((C-B).LT.1.)GO TO 65
      A=(B+C)/2.
      DO 40 L=L0,L1
      IF(Y(L).GT.A)GO TO 45
   40 CONTINUE
   45 FL=FLOAT(L-L0)
      IF(Y(L).LT.A)FL=FL+1.
      IF(FL.LE.FN/2.)GO TO 55
      C=A
      IF(Y(L).GT.A)L1=L-1
      FN=FL
      GO TO 35
   55 IF(FL.EQ.FN/2.) GO TO 65
      B=A
      L0=L
      FN=FN-FL
      GO TO 35
65    XX=(B+C)/2.

      IP1=I+1
      TIP1=T(IP1)
24    K=K+1
      IF(K.GT.N1)GO TO 70
      TSK=TS(K)
      IF(TSK.GE.TIP1)GO TO 30
      M=M+1.
      E=XX-XS(K)
      SE=SE+E
      SE2=SE2+E*E
      SAE=SAE+ABS(E)
      EB=SE/M
      AEB=SAE/M
      IF(M.GT.1.)GO TO 50
      SIGE=0.
      GO TO 60
50    A=(SE2-(SE*SE/M))/(M-1.)
      SIGE=SQRT(A)
60    SIGEB=SIGE/SQRT(FLOAT(NN+1))
      RMSE=SQRT(SIGE*SIGE+EB*EB)
     SSSRMSE=SQRT(.2*(RMSE-SSRMSE)**2/9+.8*SSSRMSE*SSSRMSE)
     SSRMSE=.2*RMSE+.8*SSRMSE
      RMSEB=SQRT(SIGEB*SIGEB+EB*EB)
      DELT=RMSEB-SRMSEB
      SRMSE=SQRT(.2*DELT*DELT/9+.8*SRMSE*SRMSE)
      SRMSEB=.2*RMSEB+.8*SRMSEB
      PRINT 20,XX,EB,SIGE,SIGEB,AEB,RMSE,SSRMSE,SSSRMSE,RMSEB,SRMSEB
     PRINT 20,SRMSE
     GO TO 24
   30 CONTINUE
   70 CONTINUE
      RETURN
      [illegible]
```

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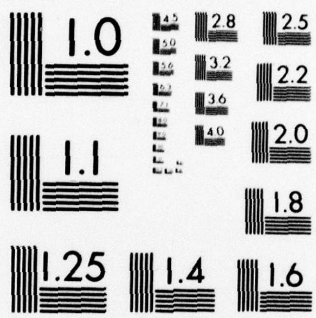

MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

```
      SUBROUTINE OSTT
      COMMON /B/ N1,T(2000),X(2000),TS(2000),XS(2000)
      REAL M
      READ(1,10)N,I0,I1,N1,TT,EMX,EMN
 10   FORMAT(4I3,3F7.2)
      PRINT 10,N,I0,I1,N1,TT,EMX,EMN
C     READ(1,20)(T(I),I=1,N)
C     READ(1,20)(X(I),I=1,N)
C     READ(1,20)(TS(I),I=1,N)
C     READ(1,20)(XS(I),I=1,N)
 20   FORMAT(10F7.2)
      M=0.
      SE=0.
      SE2=0.
      SAE=0.
     TI0=T(I0)
     SRMDEB=0.
     SRMSE=0.
     K=0
  5  K=K+1
     IF(TS(K).LT.TI0)GO TO 5
      DO 30 I=I0,I1
     K=K-1
     NN=0
     S=0.
     NU=1000
     TI=T(I)
     TP=TI-TT
     IF(M.LE.1.)GO  TO 32
     NL=INT((SIGE/XX/EMX)**2+.5)-1
     IF(NL.LE.0)NL=1
     NU=INT((SIGE/XX/EMN)**2+.5)-1
     IF(NU.LE.0)NU=1
     PRINT 10,NL,NU
 32  DO 25 J=1,I
     IJ=I-J+1
     TIJ=T(IJ)
     IF(M.GT.1.)GO TO 21
     IF(TIJ.GT.TP)GO TO 23
     GO TO 45
 21  IF(NN.EQ.NU)GO TO 45
     IF((TIJ.LT.TP).AND.(NN.GE.NL))GO TO 45
 23  NN=NN+1
     S=S+X(IJ)
 25  CONTINUE
 45   XX=S/NN
     PRINT 10,NN
     PRINT 20,XX
     IP1=I+1
     TIP1=T(IP1)
 24  K=K+1
     IF(K.GT.N1)GO TO 70
     IF(TS(K).GE.TIP1)GO TO 30
      M=M+1.
      E=XX-XS(K)
      SE=SE+E
      SE2=SE2+E*E
      SAE=SAE+ABS(E)
      EB=SE/M
      AEB=SAE/M
      IF(M.GT.1.)GO TO 50
      SIGE=0.
      GO TO 60
 50   A=(SE2-(SE*SE/M))/(M-1.)
      SIGE=SQRT(A)
 60   SIGEB=SIGE/SQRT(FLOAT(NN))
      RMSE=SQRT(SIGE*SIGE+EB*EB)
      RMSEB=SQRT(SIGEB*SIGEB+EB*EB)
      DELT=RMSEB-SRMSEB
      SRMSE=SQRT(.2*DELT*DELT/9+.8*SRMSE*SRMSE)
      SRMSEB=.2*RMSEB+.8*SRMSEB
      FNN=FLOAT(NN)
      PRINT 20,XX,FNN,EB,SIGE,SIGEB,AEB,RMSE,RMSEB,SRMSEB,SRMSE
      GO TO 24
 30   CONTINUE
 70  CONTINUE
     RETURN
      END
```

```
      SUBROUTINE OSTNE
      COMMON /B/ N1.T(2000).X(2000).TS(2000).XS(2000)
      REAL M
      READ(1.10)N.I0.I1.N1.EE
 10   FORMAT(4I3.7F7.2)
      PRINT 10.N.I0.I1.N1.EE
C     READ(1.20)(T(I).I=1.N)
C     READ(1.20)(X(I).I=1.N)
C     READ(1.20)(TS(I).I=1.N)
C     READ(1.20)(XS(I).I=1.N)
 20   FORMAT(10F7.2)
      M=0.
      SE=0.
      SE2=0.
      SAE=0.
      TI0=T(I0)
      SRMSEB=0.
      SRMSE=0.
      K=0
  5   K=K+1
      TSK=TS(K)
      IF(TSK.LT.TI0)GO TO 5
      DO 30 I=I0.I1
      IF(M.GT.1.)NN=INT((SIGE/XX/EE)**2+.5)-1
      IF(NN.LE.0)NN=1
      PRINT 10.NN
      K=K-1
      S=0.
      NNN=0
      I11=I-1
      DO 25 J=1.I
      IJ=I-J+1
      NNN=NNN+1
      S=S+X(IJ)
      IF(NNN.EQ.NN)GO TO 27
 25   CONTINUE
 27   XX=S/NNN
      PRINT 20.XX
      IP1=I+1
      TIP1=T(IP1)
 24   K=K+1
      IF(K.GT.N1)GO TO 70
      TSK=TS(K)
      IF(TSK.GE.TIP1)GO TO 30
      M=M+1.
      E=XX-XS(K)
      SE=SE+E
      SE2=SE2+E*E
      SAE=SAE+ABS(E)
      EB=SE/M
      AEB=SAE/M
      IF(M.GT.1.)GO TO 50
      SIGE=0.
      GO TO 60
 50   A=(SE2-(SE*SE/M))/(M-1.)
      SIGE=SQRT(A)
 60   SIGEB=SIGE/SQRT(FLOAT(NNN))
      RMSE=SQRT(SIGE*SIGE+EB*EB)
      RMSEB=SQRT(SIGEB*SIGEB+EB*EB)
      DELT=RMSEB-SRMSEB
      SRMSE=SQRT(.2*DELT*DELT/9+.8*SRMSE*SRMSE)
      SRMSEB=.2*RMSEB+.8*SRMSEB
      PRINT 20.XX.EB.SIGE.SIGEB.AEB.RMSE.RMSEB.SRMSEB.SRMSE
      GO TO 24
 30   CONTINUE
 70   CONTINUE
      RETURN
      END
```

```
      SUBROUTINE OSTES
      COMMON /B/ N1,T(2000),X(2000),TS(2000),XS(2000)
      REAL M
      READ(1,10)N,I0,I1,N1,TDEL,TX,DEL0,XX0,EMX,EMN
   10 FORMAT(4I3,8F7.2)
      PRINT 10,N,I0,I1,N1,TDEL,TX,DEL0,XX0,EMX,EMN
C     READ(1,20)(T(I),I=1,N)
C     READ(1,20)(X(I),I=1,N)
C     READ(1,20)(TS(I),I=1,N)
C     READ(1,20)(XS(I),I=1,N)
   20 FORMAT(10F7.2)
      M=0.
      SE=0.
      SE2=0.
      SAE=0.
     DEL=DEL0
     XX=XX0
     TI0=T(I0)
     SRMSEB=0.
     SRMSE=0.
     K=0
    5 K=K+1
     IF(TS(K).LT.TI0)GO TO 5
      DO 30 I=I0,I1
     K=K-1
     IF(M.LE.1.)GO TO 35
     FNL=(SIGE/XX/EMX)**2-1
     IF(FNL.LT.1)FNL=2
     FNU=(SIGE/XX/EMN)**2-1
     IF(FNU.LT.1)FNU=2
     PRINT 20,FNL,FNU
   35 I11=I-1
     FN1=TDEL/DEL
     IF(M.LE.1.)GO TO 37
     IF(FN1.LT.FNL)FN1=FNL
     IF(FN1.GT.FNU)FN1=FNU
   37 ADEL=2./(FN1+1.)
     DEL=ADEL*(T(I)-T(I11)-DEL)+DEL
     FN2=TX/DEL
     IF(M.LE.1.)GO TO 39
     IF(FN2.LT.FNL)FN2=FNL
     IF(FN2.GT.FNU)FN2=FNU
   39 AX=2./(FN2+1.)
     XX=AX*(X(I)-XX)+XX
     PRINT 20,FN1,ADEL,FN2,AX,XX
     IP1=I+1
     TIP1=T(IP1)
   24 K=K+1
     IF(K.GT.N1)GO TO 70
     IF(TS(K).GT.TIP1)GO TO 30
      M=M+1.
      E=XX-XS(K)
      SE=SE+E
      SE2=SE2+E*E
      SAE=SAE+ABS(E)
      EB=SE/M
      AEB=SAE/M
      IF(M.GT.1.)GO TO 50
      SIGE=0.
      GO TO 60
   50 A=(SE2-(SE*SE/M))/(M-1.)
      SIGE=SQRT(A)
   60 SIGEB=SIGE/SQRT(FN2)
      RMSE=SQRT(SIGE*SIGE+EB*EB)
      RMSEB=SQRT(SIGEB*SIGEB+EB*EB)
      DELT=RMSEB-SRMSEB
      SRMSE=SQRT(.2*DELT*DELT/9+.8*SRMSE*SRMSE)
      SRMSEB=.2*RMSEB+.8*SRMSEB
      PRINT 20,XX,EB,SIGE,SIGEB,AEB,RMSE,RMSEB,SRMSEB,SRMSE
      GO TO 24
   30 CONTINUE
   70 CONTINUE
     RETURN
      END
```

```
      SUBROUTINE OSTDES
      COMMON /B/ N1,T(2000),X(2000),TS(2000),XS(2000)
      REAL M
      READ(1,10)N,I0,I1,N1,SX0,SSX0,EBB0,AEB0,A0,A1,F
   10 FORMAT(4I3,7F7.3)
      PRINT 10,N,I0,I1,N1,SX0,SSX0,EBB0,AEB0,A0,A1,F
C      READ(1,20)(T(I),I=1,N)
C      READ(1,20)(X(I),I=1,N)
C      READ(1,20)(TS(I),I=1,N)
C      READ(1,20)(XS(I),I=1,N)
   20 FORMAT(10F7.2)
       M=0.
       SE=0.
       SE2=0.
       SAE=0.
      TI0=T(I0)
      SRMSEB=0.
       SRMSE=0.
      K=0
    5 K=K+1
      IF(TS(K).LT.TI0)GO TO 5
      KK=0
       DO 30 I=I0,I1
      K=K-1
      IF(M.GT.0.)GO TO 37
      SX=SX0
      SSX=SSX0
      EBB=EBB0
      AEB=AEB0
   31 TSS=ABS(EBB/AEB)
      IF(TSS.LT.A0)GO TO 32
      IF(TSS.GT.A1)GO TO 34
      ALF=TSS
      GO TO 36
   32 ALF=A0
      GO TO 36
   34 ALF=A1
   36 IF(KK.GT.0)GO TO 38
      KK=1
   37 EBB=ALF*(SX-X(I))+(1.-ALF)*EBB
      AEB=ALF*ABS(SX-X(I))+(1.-ALF)*AEB
      GO TO 31
   38 SX=ALF*(X(I)-SX)+SX
      SSXL=SSX
      SSX=ALF*(SX-SSX)+SSX
      XX=SX+F*(SX-SSXL)
      PRINT 20,M,ALF,TSS,XX
      IP1=I+1
      TIP1=T(IP1)
   24 K=K+1
      IF(K.GT.N1)GO TO 70
      IF(TS(K).GE.TIP1)GO TO 30
       M=M+1.
       E=XX-XS(K)
       SE=SE+E
       SE2=SE2+E*E
       SAE=SAE+ABS(E)
       EB=SE/M
       AEBB=SAE/M
       IF(M.GT.1.)GO TO 50
       SIGE=0.
       GO TO 60
   50  A=(SE2-(SE*SE/M))/(M-1.)
       SIGE=SQRT(A)
   60  SIGEB=SIGE/SQRT((2./ALF)-!.)
       RMSE=SQRT(SIGE*SIGE+EB*EB)
       RMSEB=SQRT(SIGEB*SIGEB+EB*EB)
       DELT=RMSEB-SRMSEB
       SRMSE=SQRT(.2*DELT*DELT/9+.8*SRMSE*SRMSE)
       SRMSEB=.2*RMSEB+.8*SRMSEB
       PRINT 20,XX,EB,SIGE,SIGEB,AEBB,RMSE,RMSEB,SRMSEB,SRMSE
       GO TO 24
   30  CONTINUE
   70  CONTINUE
      RETURN
       END
       /
```

```
      SUBROUTINE OSTR
      COMMON /B/ N1,T(2000),X(2000),TS(2000),XS(2000)
      REAL M
      READ(1,10)N,I0,I1,NN,N1
   10 FORMAT(5I3,7F7.2)
      PRINT 10,N,I0,I1,NN,N1
C     READ(1,20)(T(I),I=1,N)
C     READ(1,20)(X(I),I=1,N)
C     READ(1,20)(TS(I),I=1,N)
C     READ(1,20)(XS(I),I=1,N)
   20 FORMAT(10F7.2)
      M=0.
      SE=0.
      SE2=0.
      SAE=0.
      TI0=T(I0)
      SRMSEB=0.
      SRMSE=0.
      SSRMSE=0.
      SSSRMSE=0.
      K=0
    5 K=K+1
      TSK=TS(K)
      IF(TSK.LT.TI0)GO TO 5
      DO 30 I=I0,I1
      K=K-1
      A=0.
      B=0.
      D=0.
      E=0.
      F=0.
      DO 40 J=1,NN
      IJ=I-J+1
      XIJ=X(IJ)
      W=1.
      A=A+W*IJ*IJ
      B=B+W*IJ
      D=D+W
      E=E+W*XIJ*IJ
   40 F=F+W*XIJ
      DEN=A*D-B*B
      AA=(D*E-B*F)/DEN
      BB=(A*F-B*E)/DEN
      XX=AA*(I+1)+BB
      IP1=I+1
      TIP1=T(IP1)
   24 K=K+1
      IF(K.GT.N1)GO TO 70
      TSK=TS(K)
      IF(TSK.GE.TIP1)GO TO 30
      M=M+1.
      E=XX-XS(K)
      SE=SE+E
      SE2=SE2+E*E
      SAE=SAE+ABS(E)
      EB=SE/M
      AEB=SAE/M
      IF(M.GT.1.)GO TO 50
      SIGE=0.
      GO TO 60
   50 AAA=(SE2-(SE*SE/M))/(M-1.)
      SIGE=SQRT(AAA)
   60 SIGEB=SIGE/SQRT(FLOAT(NN+1))
      RMSE=SQRT(SIGE*SIGE+EB*EB)
      SSSRMSE=SQRT(.2*(RMSE-SSRMSE)**2/9+.8*SSSRMSE*SSSRMSE)
      SSRMSE=.2*RMSE+.8*SSRMSE
      RMSEB=SQRT(SIGEB*SIGEB+EB*EB)
      DELT=RMSEB-SRMSEB
      SRMSE=SQRT(.2*DELT*DELT/9+.8*SRMSE*SRMSE)
      SRMSEB=.2*RMSEB+.8*SRMSEB
      PRINT 20,XX,EB,SIGE,SIGEB,AEB,RMSE,SSRMSE,SSSRMSE,RMSEB,SRMSEB
      PRINT 20,SRMSE
      GO TO 24
   30 CONTINUE
   70 CONTINUE
      RETURN
      END
```

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```
      SUBROUTINE CSTNP
      COMMON /B/ N1,T(2000),X(2000),TS(2000),XS(2000)
      REAL M
      READ(1,10)N,NN,NUD,N1,UDT,UDI
   10 FORMAT(4I3,7F7.2)
      PRINT 10,N,NN,NUD,N1,UDT,UDI
C      READ(1,20)(T(I),I=1,N)
C      READ(1,20)(X(I),I=1,N)
C      READ(1,20)(TS(I),I=1,N)
C      READ(1,20)(XS(I),I=1,N)
   20 FORMAT(10F7.2)
      M=0.
      SE=0.
      SE2=0.
      SAE=0.
     TT=UDT+NUD*UDI
     K=0
     KK=0
     UT=UDT
    7 K=K+1
     TSK=TS(K)
     IF(TSK.LT.UT)GO TO 7
     K=K-1
    5 KK=KK+1
     IF(KK.GT.N)GO TO 70
     TKK=T(KK)
     IF(TKK.LE.UT)GO TO 5
     KK1=KK-1
     NNN=0
     S=0.
     DO 15 J=1,KK1
     KKJ=KK-J
     NNN=NNN+1
     S=S+X(KKJ)
     IF(J.EQ.NN)GO TO 17
   15 CONTINUE
   17 XX=S/NNN
     PRINT 10,NNN,K,KK1,XX
     UT=UT+UDI
     IF(UT.GT.TT)GO TO 70
   24 K=K+1
     IF(K.GT.N1)GO TO 70
     TSK=TS(K)
     IF(TSK.LE.UT)GO TO 35
     K=K-1
     GO TO 5
   35 M=M+1.
      E=XX-XS(K)
      SE=SE+E
      SE2=SE2+E*E
      SAE=SAE+ABS(E)
      EB=SE/M
      AEB=SAE/M
      IF(M.GT.1.)GO TO 50
      SIGE=0.
      GO TO 60
   50 A=(SE2-(SE*SE/M))/(M-1.)
      SIGE=SQRT(A)
   60 SIGEB=SIGE/SQRT(FLOAT(NNN))
      RMSE=SQRT(SIGE*SIGE+EB*EB)
      RMSEB=SQRT(SIGEB*SIGEB+EB*EB)
      RE=RMSE/XX
      REB=RMSEB/XX
      PRINT 20,M,XX,EB,SIGE,SIGEB,AEB,RMSE,RMSEB,RE,REB
     GO TO 24
   30 CONTINUE
   70 CONTINUE
     RETURN
      END
```

```
      SUBROUTINE CSTESP
      COMMON /B/ N1,T(2000),X(2000),TS(2000),XS(2000)
      REAL M
      READ(1,10)N,NUD,N1,TDEL,TX,DELO,XXO,EMX,EMN,UDT,UDI
 10   FORMAT(3I3,8F7.2)
      PRINT 10,N,NUD,N1,TDEL,TX,DELO,XXO,EMX,EMN,UDT,UDI
C      READ(1,20)(T(I),I=1,N)
C      READ(1,20)(X(I),I=1,N)
C      READ(1,20)(TS(I),I=1,N)
C      READ(1,20)(XS(I),I=1,N)
 20   FORMAT(10F7.2)
      M=0.
      SE=0.
      SE2=0.
      SAE=0.
     TT=UDT+NUD*UDI
     K=0
     KK=0
     UT=UDT
 7   K=K+1
     TSK=TS(K)
     IF(TSK.LT.UT)GO TO 7
     K=K-1
 5   KK=KK+1
     TKK=T(KK)
     IF(TKK.LE.UT)GO TO 5
     KK1=KK-1
     DEL=DELO
     XX=XXO
     XXX=XXO
     FN2=TX/DEL
 13  UT=UT+UDI
     IF(UT.GT.TT)GO TO 70
 24  K=K+1
     IF(K.GT.N1)GO TO 70
     IF(TS(K).LE.UT)GO TO 35
     K=K-1
 16  IF(T(KK).GT.UT)GO TO 14
     IF(M.LT.1.)GO TO 17
     FNL=(SIGE/XX/EMX)**2-1
     IF(FNL.LT.1.)FNL=2.
     FNU=(SIGE/XX/EMN)**2-1
     IF(FNU.LT.1.)FNU=2.
     PRINT 20,FNL,FNU
 17  FN1=TDEL/DEL
     IF(M.LE.1.)GO TO 37
     IF(FN1.LT.FNL)FN1=FNL
     IF(FN1.GT.FNU)FN1=FNU
 37  ADEL=2./(FN1+1.)
     DEL=ADEL*(T(KK)-T(KK1)-DEL)+DEL
     FN2=TX/DEL
     IF(M.LE.1.)GO TO 39
     IF(FN2.LT.FNL)FN2=FNL
     IF(FN2.GT.FNU)FN2=FNU
 39  AX=2./(FN2+1.)
     XXX=AX*(X(KK)-XXX)+XXX
     PRINT 20,FN1,ADEL,FN2,AX,XXX
     KK=KK+1
     KK1=KK1+1
     GO TO 16
 14  XX=XXX
     GO TO 13
 35   M=M+1.
      E=XX-XS(K)
      SE=SE+E
      SE2=SE2+E*E
      SAE=SAE+ABS(E)
      EB=SE/M
      AEB=SAE/M
      IF(M.GT.1.)GO TO 50
      SIGE=0.
      GO TO 65
 50   A=(SE2-(SE*SE/M))/(M-1.)
      SIGE=SQRT(A)
 60   SIGEB=SIGE/SQRT(FN2)
      RMSE=SQRT(SIGE*SIGE+EB*EB)
      RMSEB=SQRT(SIGEB*SIGEB+EB*EB)
      RE=RMSE/XX
      REB=RMSEB/XX
 65   PRINT 20,M,XX,EB,SIGE,SIGEB,AEB,RMSE,RMSEB,RE,REB
     GO TO 24
 30   CONTINUE
 70  CONTINUE
     RETURN
      END
```

```
      SUBROUTINE SORTAG(A,II,JJ,TAG)
C     SORTS ARRAY A INTO INCREASING ORDER FROM A(II) TO A(JJ)
C     ARRAY TAG IS PERMUTED THE SAME AS ARRAY A
C     ORDERING IS BY INTEGER SUBTRACTION, THUS FLOATING POINT
C       NUMBERS MUST BE IN NORMALIZED FORM.
C     ARRAYS IU(K) AND IL(K) PERMIT SORTING UP TO 2**(K+1)-1 ELEMENTS
C     CDC 6400 TIME IS 3.26 SEC. FOR 10000 RANDOM ITEMS,
C       AND OTHERWISE PROPORTIONAL TO N*LOG(N)
C         R. SINGLETON, SEPTEMBER 1968
      DIMENSION A(1),IU(16),IL(16),TAG(1)
      INTEGER A,T,TT
      M=1
      I=II
      J=JJ
    5 IF(I .GE. J) GO TO 70
   10 K=I
      IJ=(J+I)/2
      T=A(IJ)
      IF(A(I) .LE. T) GO TO 20
      A(IJ)=A(I)
      A(I)=T
      T=A(IJ)
      TG=TAG(IJ)
      TAG(IJ)=TAG(I)
      TAG(I)=TG
   20 L=J
      IF(A(J) .GE. T) GO TO 40
      A(IJ)=A(J)
      A(J)=T
      T=A(IJ)
      TG=TAG(IJ)
      TAG(IJ)=TAG(J)
      TAG(J)=TG
      IF(A(I) .LE. T) GO TO 40
      A(IJ)=A(I)
      A(I)=T
      T=A(IJ)
      TG=TAG(IJ)
      TAG(IJ)=TAG(I)
      TAG(I)=TG
      GO TO 40
   30 A(L)=A(K)
      A(K)=TT
      TG=TAG(L)
      TAG(L)=TAG(K)
      TAG(K)=TG
   40 L=L-1
      IF(A(L) .GT. T) GO TO 40
      TT=A(L)
   50 K=K+1
      IF(A(K) .LT. T) GO TO 50
      IF(K .LE. L) GO TO 30
      IF(L-I .LE. J-K) GO TO 60
      IL(M)=I
      IU(M)=L
      I=K
      M=M+1
      GO TO 80
   60 IL(M)=K
      IU(M)=J
      J=L
      M=M+1
      GO TO 80
   70 M=M-1
      IF(M .EQ. 0) RETURN
      I=IL(M)
      J=IU(M)
   80 IF(J-I .GE. 11) GO TO 10
      IF(I .EQ. II) GO TO 5
      I=I-1
   90 I=I+1
      IF(I .EQ. J) GO TO 70
      T=A(I+1)
      IF(A(I) .LE. T) GO TO 90
      TG=TAG(I+1)
      K=I
  100 A(K+1)=A(K)
      TAG(K+1)=TAG(K)
      K=K-1
      IF(T .LT. A(K)) GO TO 100
      A(K+1)=T
      TAG(K+1)=TG
      GO TO 90
      END
```