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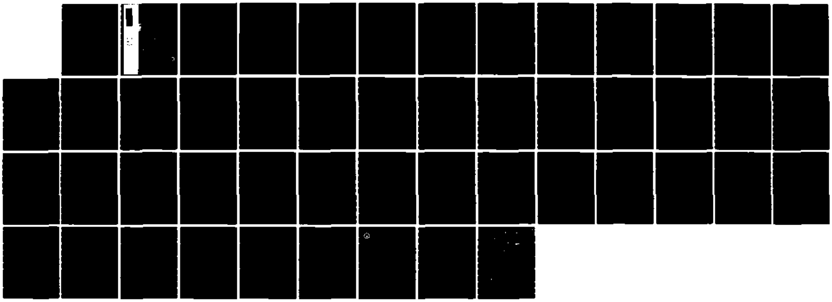

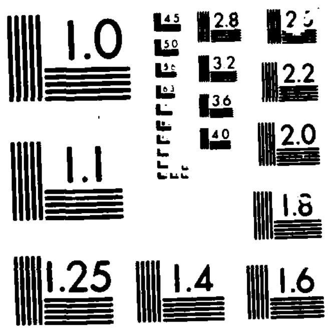

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AD-A166 451

DEPARTMENT OF DEFENSE

DEFENSE LOGISTICS AGENCY

REPORT ON ANALYSIS OF THE PROGRAM ORIENTED ITEM SYSTEM FOR FORECASTING CLOTHING ITEMS

Cameron Station,
Alexandria, Virginia 22304 6100

January 1985

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Report on Analysis of the Program Oriented Item System
for Forecasting Clothing Items

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FOREWORD

The Defense Personnel Support Center (DPSC) uses a unique system, known as the Program Oriented Item (POI) system, to forecast demand for certain clothing items. This report describes the results of a study designed to examine the extent and causes of forecast error in the POI system.

The report compares the forecasted demand for POI items to actual demand for those items and summarizes the degree of forecast error. The report goes on to examine several areas which might contribute to forecast inaccuracy, including the effects of item seasonality on demand, and the accuracy of the Services' troop strength projections. The report presents the results of data analyses and provides conclusions and recommendations in each of these areas.

This study has been beneficial in identifying potential causes of forecast error in the POI system. We believe the findings of this study can be used by DPSC management to examine specific areas of the POI system for possible changes and improvements.

ROGER C. ROY
Assistant Director,
Policy and Plans

ACKNOWLEDGMENTS

This study could not have been completed without the cooperation of the staff of the Clothing and Textiles Directorate at the Defense Personnel Support Center (DPSC) in Philadelphia, Pennsylvania. We would especially like to thank all of the item managers who discussed their concerns with the POI system. We would also like to thank Ms. Jean Farney of the Management Support Office at DPSC for her invaluable assistance in providing information throughout the course of this project.

Captain Douglas Popken was the associate analyst on this project from its inception through July of 1984. Captain Dale Kem, Captain Ronald Kirchoff, and Ms. Janet Rider, all of DLA Operations Research and Economic Analysis Office, contributed substantially to the data analysis and interpretation.

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I. BACKGROUND

The Clothing and Textile Directorate of DPSC uses a unique procedure, known as the Program Oriented Item (POI) system, to forecast demand for certain clothing items. Some questions have arisen as to whether this is the best method to use, and how the current system could be improved.

In July of 1983, DLA's Supply Management Division (DLA-OS) requested that the DLA Operations Research and Economic Analysis Office examine the POI system's operation for possible areas of modification. All facets of the system were to be examined to determine the extent and causes of forecast error.

II. SCOPE

Initially, several sources of information were consulted in order to determine areas of the POI system which might be causing problems. Through examination of previous research which had been done as well as conversations with knowledgeable individuals, several areas were identified for study. They were as follows:

A. Compare forecasted demand for POI items to actual demand for those items.

B. Determine the influence of seasonality and trend on demand for POI items.

C. Determine whether service customers are ordering according to operating levels, as assumed by the POI system.

D. Compare Service forecasts of troop strength and induction levels to actual strength and induction levels.

The purpose of the first area of study was to determine the actual degree of error in the POI forecast. This was accomplished by comparing forecasted demand to actual demand for some specified time period using certain statistical measures to determine the relative accuracy of the forecasts.

The purpose of the second area was to address one of the frequently heard criticisms of the POI system, namely, it fails to take into account seasonality or trends in demand. Both of these factors would result in fluctuations or changes in demand patterns, from one time period to the next, which may not be predicted by the POI forecasts. Again, in order to determine the existence of seasonality or trend in POI items, it was necessary to examine actual historic demand for these items.

The third area dealt with the concept of the operating level. This level represents the amount of stock, expressed in months, that the customer will order at one time. As designed, the POI system adjusts its requirements calculations to take into consideration the operating level.

Therefore, if customers are not ordering according to the levels assumed by the system, then requirements may be incorrect. This step of the analysis was conducted by computing average times between requisitions for service customers, and comparing them to the POI system operating levels.

Finally, the fourth area was to examine the Services' troop strength projections which the POI system uses to compute forecasts. These projections are of future levels of troop end strengths as well as of numbers of new recruits. The accuracy of these Service forecasts is thus an important issue, since the forecasts to a large degree drive the rest of the system. A comparison of forecasted and actual troop strengths over some common time period will allow for an assessment of the accuracy of the Service projections.

These four are served as the basis for this investigation. While other aspects of the system exist which could be examined, these four areas seemed to offer the most potential for uncovering possible areas of improvement in the POI system.

An additional focus of the investigation was monetary clothing allowance items, also referred to as "bag" items. These are the clothing items which comprise the initial issue bag of new recruits. They are important due to the seriousness of potential out-of-stock conditions. Since not all items which receive a POI forecast are bag items, this subgroup was examined in separate analyses where appropriate.

III. ANALYSIS

A. *Comparison of Forecasted and Actual Demand*

1. Approach

The first step in determining forecast accuracy was to obtain both actual and forecasted monthly demand over some common time interval. Forecasted demand was obtained from the program requirements trailers of the Supply Control File, which store the computed POI forecasts. Supply Control Files from September 1982, September 1983, and the first three quarters of Fiscal Year (FY) 1984 were available. Using these files, 33 months of forecasted POI demand were obtained, from October 1981 through June 1984.

Items in the Supply Control Files were screened on three criteria at this point in the analysis. First, only those items or National Stock Numbers (NSNs) with entries in their program requirements trailers were included in the analysis. Next, Method of Computation Codes (MCC) were examined to determine NSNs appropriate for POI forecasting. Those NSNs with codes indicating program-oriented (MCCs A, B, J, K, L, M, N, and P), as opposed to demand-oriented, forecasting, were included in the analysis. Finally, any NSNs coded as new items were eliminated from the analysis, since the forecasts for these items are not computed by the usual POI methods. A total of 4,563 NSNs met the above criteria and appeared in at least one of the Supply Control Files.

Actual demand was obtained from the DLA Inventory Data Bank (DIDB) requisition history files. As stated before, five requisition history files were used: FY82 and FY83, and the first three quarters of FY84. A total of 3,162,378 requisitions for the 4,563 POI NSNs were gathered for the 33-month time period under examination. Monthly demand was obtained by summing the demand quantities for all requisitions by each of the 33 months.

The NSNs identified as having POI forecasts were combined into their respective Procurement Grouping Codes (PGCs). In Clothing and Textiles, the PGC is a code which identifies a generic end item, while NSNs represent the various sizes of the sized generic items. For example, a PGC may be a particular dress shoe with each NSN in the PGC being a different size of that shoe. Since POI forecasts and DPSC item management are done on a PGC basis, forecast accuracy was examined by PGC. The 4,563 NSNs identified as having POI forecasts comprised 300 distinct PGCs.

In order to identify "bag" items, a tape file of monetary clothing allowance items was obtained from DPSC. These NSNs were then matched against the NSNs which had POI forecasts. This process resulted in the identification of 3,081 NSNs, belonging to 172 PGCs, as initial issue items.

2. Results

a. <u>All items</u>. For the 300 PGCs examined, a total of 182 (61%) were, on the average, overforecast for the 33-month time period, while the remaining 118 (39%) were underforecast. In order to assess the degree of error in the forecasts, a modified Mean Absolute Percentage Error (MAPE) statistic was computed.

The standard MAPE is based on the formula for percentage error (PE):

$$PE_t = (X_t - F_t) / X_t$$

where X_t = actual demand for month t

and F_t = forecasted demand for month t

An underforecast is represented by a positive PE value, while an overforecast would have a negative PE.

The MAPE is obtained by taking the absolute value of the PE and computing the average across all time periods:

$$MAPE = \Sigma_1^N |PE_i| / N$$

The modified MAPE used here computes an absolute percent error by summing the absolute values of the forecast errors (actual demand - forecasted demand) then dividing this quantity by the sum of the actual demand:

$$\text{MAPE(mod)} = \Sigma_1^{33} |X_t - F_t| \ / \ \Sigma_1^{33} X_t$$

This modified MAPE tends to place less weight on extreme forecast errors for a particular time period than the standard MAPE does. In addition, the value of the standard MAPE is more strongly influenced by overforecasts than by underforecasts. The reason for this is that the largest PE which can be obtained for an underforecast is 100%, while overforecast values can be infinitely large. The modified MAPE used here does not demonstrate this property, since its computation depends on the pattern of over and underforecasts across all time periods. Note that a MAPE(mod) value of 0 would indicate exact forecasts (i.e., no forecast error).

The modified MAPE values for the 300 PGCs are summarized in Table I. As the table shows, about 6% of the PGCs had MAPEs of less than 25%. At the other extreme, almost one third of the PGCs had MAPEs greater than 100%.

TABLE I

Distribution of Modified MAPE Values for all PGCs

MAPE	Number	Percent	Cumulative Percent
0 - .24	18	6.1%	6.1%
.25 - .49	84	28.3%	34.3%
.50 - .74	64	21.5%	55.9%
.75 - .99	37	12.5%	68.3%
> 1.00	97	31.6%	100.0%

The median MAPE(mod) for the entire group of PGCs was 64%. Based on these figures, then, there would appear to be a considerable degree of error associated with the forecasts for these PGCs.

Of the 97 PGCs which had forecast errors in excess of 100%, a total of 17 (5.6%) had extremely large forecast errors (defined as a MAPE(mod) of 1000% or greater). Examination of these individual PGCs showed that in each case, these groups had extremely low demand relative to forecast values. In many cases, there was no demand for 9-12 of the 33 months examined, despite constant large forecast values over the same time period. In addition, demand for these PGCs was extremely variable, compared with relatively consistent forecast quantities over the 33-month period. It may be, then, that such erratic demand could not be accurately predicted by any forecasting method. In any case, it is clear that these extreme overforecasts have a major impact on the summary statistics reported above.

In assessing the accuracy of the POI forecasting method, it would be useful to have some alternative method against which to compare the above-described statistics. One such method, known as the naive forecast, uses the previous month's actual demand to predict the current month's demand. A MAPE can be computed for this naive forecast method, and the two MAPEs can then be compared. If the POI forecasting method fails to produce more accurate results than the naive method, we would question the need for a formal forecasting method at all.

A statistic which allows for direct comparison between a forecasting method's MAPE and the MAPE of the naive forecast is Theil's U statistic[1]. Values for U of less than one indicate that the formal forecasting method is superior to the naive forecasting method. In addition to this U statistic, the MAPE(mod) statistic discussed earlier was also used to compare the two forecasting methods.

Based on the values of Theil's U statistic, the POI forecasting method was superior to the naive method for slightly over half (56%) of the 300 PGCs. Comparison of the modified MAPEs for the two methods showed that the POI method was superior for less than half (48%) of the PGCs. As would be expected, those PGCs for which the POI forecast was superior tended to have greater variability in actual demand than PGCs for which the naive forecast produced a smaller MAPE. Thus when forecast accuracy is judged strictly by the criterion of the MAPE, it appears that demand for half the PGCs could be forecast more accurately using each previous time period's actual demand. This approach would not be feasible in the current context, of course, since POI forecasts must be produced over a much longer time period than the one month being examined here.

To summarize, the results of the comparison of forecast and actual demand for the 300 PGCs examined shows that there was a substantial degree of forecast error over the time period under consideration. More PGCs were overforecasted than were underforecast. Comparison with the results of a naive forecasting method showed that for about one-half of the generic items, the naive method was just as good, if not better than, the POI forecast method.

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[1]S. Makridakis, S. C. Wheelwright, & V. E. McGee, <u>Forecasting: Methods and Applications</u>, 2nd Ed. (N. Y.: John Wiley, 1983), pp. 50-52.

b. "Bag" items. The analysis described above was also carried out for the 172 PGCs which were identified as "bag PGCs". For these PGCs, a total of 51 (29.7%) were underforecast, while the remaining 121 (70.3%) were overforecast. Thus bag items were slightly more likely to be overforecast than was generally the case for all PGCs. The values for the modified MAPEs are summarized in Table II.

TABLE II

Distribution of Modified MAPE Values for Bag PGCs

MAPE	No.	Percent of PGCs	Cumulative Percent
0 - .24	13	7.7%	7.7%
.25 - .49	57	33.7%	41.4%
.50 - .74	41	24.3%	65.7%
.75 - .99	19	11.2%	76.9%
> 1.00	42	23.1%	100.0%

The median MAPE(mod) value for the bag PGCs was 55%. Comparison of Tables I and II shows that modified MAPEs tended to be smaller for bag items than they were for all PGCs. Despite this fact, the degree of forecast error for bag items must still be considered quite high.

Comparisons were also made between the POI forecast error and the errors resulting from the naive forecast for bag items only. Examination of the U statistic showed that the POI forecast produced the smaller MAPE for 99 (58%) of the bag items, while the naive forecast was superior for the remaining 73 PGCs. Using the modified MAPEs as the criterion, the POI forecast performed better than the naive forecast for 92 (53%) of the PGCs. These figures are quite similar to those produced for all PGCs. Overall, bag PGCs were forecast with slightly more accuracy than the total group of PGCs.

c. Sized vs. non-sized items. PGCs are comprised of both sized and non-sized items. Forecasts for individual NSNs in sized PGCs are derived from overall PGC forecasts by taking a percentage (based on past demand) of the total forecast. For non-sized items, the entire PGC forecast is applied to the corresponding NSN.

A comparison of the modified MAPE values for sized and non-sized PGCs, overall and for bag items, is shown in Table III.

TABLE III

MAPE(mod) for Sized and Non-sized PGCs

	All Items		Bag Items	
	Sized	Non-sized	Sized	Non-sized
	(N=223)	(N=77)	(N=147)	(N=25)
Mean	1960.2%	134.6%	2656.8%	149.5%
SD	24358.9	307.0	29914.2	388.6
Median	64.4	62.7	53.7	59.9

As Table III shows, there is a considerably greater range of forecast errors in sized items as compared to non-sized items. This is indicated by the large standard deviations (SD) shown in the table, and is the cause for the much larger mean MAPE(mod) values for sized items. Comparison of the median error rates, however, shows that the difference between sized and non-sized items is not as great as the mean values suggest. For all items, the median MAPE(mod) values are very similar. For bag items only, more forecast error exists for non-sized items than for sized items. In both cases, the extreme forecast errors are associated with the sized PGCs.

Non-sized PGCs were underforecasted more often than sized items. A total of 48% of non-sized items were underforecasted, while only 36% of sized items were underforecasted. For bag items only, however, 31% of sized PGCs were underforecasted, while 24% of non-sized PGCs were underforecasted.

3. Discussion

The results of the analyses presented above showed that over the time period examined, a considerable amount of error exists in the POI forecasts. Half of the items had greater than 64% forecast errors, as determined by the modified MAPE used in the analysis. In over half the cases, simply using last month's actual demand would have produced a more accurate forecast than the one produced by the POI system.

The size of these forecast errors must be interpreted with some caution. The analyses described above attempted to re-create a large amount of historic data. Although the most accurate data available were used for the analysis, this does not guarantee that the forecast and actual demand values were exactly those used at the time. As an example, the forecasts were obtained from files which represented snapshots of a single point in time. Since the forecasts are updated quarterly, and since quarterly files were not available, it was not possible to obtain the actual forecast values used by DPSC at that time. Considerations such as these, while inherent in the type of analysis conducted here, suggest that the actual error values reported here not be taken too literally.

Given the above warning, however, it should be noted that the error statistics presented in this analysis are not dissimilar from those reported for other commodities. A recent study of forecast accuracy for over two million electronics items reported a mean absolute percent error (MAPE) of 144%, a MAPE for overforecast items of 247%, and 5% of all items with MAPEs greater than 500%[2]. Thus the errors reported here appear to be comparable to those which have been found for other commodities.

Part of the explanation for these large forecast errors relates to the nature of the demand. Many PGCs displayed erratic demand pattterns, including multiple months of zero demand. In some cases, these demand patterns raised suspicions that the PGCs being examined had been phased out, or were new items introduced during the 33-month time period (despite the attempt to screen out the latter). In any case, the forecasts did not usually reflect the erratic nature of the demand for these items, leading to large forecast errors.

To summarize, the results presented in this section show large errors associated with the POI forecasts. Several possible explanations for this were suggested, including problems in re-creating accurately the historical data used in the analyses. Regardless of the explanation, it seems clear that there is substantial room for improvement in forecasting POI items. The remaining sections of this report will explore areas which might be improved.

B. Analysis of Seasonality and Trend in Demand for POI Items

1. Approach

As noted at the outset of this report, one of the criticisms of the POI forecasting system is its failure to take seasonality or trend of demand into account when computing its requirements. The purpose of this section is: (a) to determine the extent to which the historic demand by PGC in fact demonstrates trend and/or seasonality, and (b) to examine alternate forecasting techniques for items which do exhibit trend or seasonality. Before examining these issues, the POI system's forecasting procedures will be briefly reviewed.

Initial issue requirements are based directly on the Service projections of new recruit numbers as discussed in Section D of this report. Trend in new recruit input would occur if the number of new recruits was consistently increasing or decreasing over the time period under

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[2] "Interim Report on DESC Demand Forecasting Study", DESC-LO Technical Report No. 84-02, October 1984.

consideration. Seasonality in new recruit input would occur if the number of recruits increased or decreased at certain times in every year. As an example, new recruits may be higher in May and June, after school years are completed, than they are the rest of the year. The POI requirements will take into account seasonality and trend for initial issue demand only to the extent that these are taken into account by the service projections.

Replenishment requirements in the POI system are computed based on past actual demand. Trend in past actual demand would occur if sales for particular items had been increasing or decreasing steadily over the time period under consideration. This might occur, for example, if a particular item was increasing in popularity. Seasonality in the replenishment demand would occur if sales were greater during certain times of the year than others; for example, more pairs of gloves were purchased in January and February than in June and July.

The POI system calculates replenishment requirements by applying a replacement percentage to the Services' forecasted end strengths. The replacement percentage is derived by taking the last four quarters of demand for an item and dividing this by the total actual troop end strength for those four quarters. These rates are recomputed each quarter, with the data from the recently ended quarter included, and the data from the oldest past quarter dropped from the four-quarter total. This quarterly recomputation of the replacement rate would take into consideration trend in replenishment demand by including the most recent quarter of data and dropping out the oldest quarter. If the demand were increasing or decreasing rapidly, however, the quarterly calculations would probably not keep pace with the changes. Seasonal variations are not taken into account by the POI system, since all demand data for the past year are averaged together. (Note that these replacement rates are automatically calculated by the POI system. Item managers can place their own replacement rates into the system, and these will be used instead of the rates calculated automatically by the POI system.)

The 33 months of historic demand data described in Section III.A.1 of this report was examined in order to determine the existence of trend and/or seasonality in the data. It should be noted that 33 months is not a long enough time period over which to accurately assess either trend or seasonality in a data series. As an example, if there were a 12-month season for an item (that is, sales peak every December), 33 months would provide only two cycles over which to observe the seasonal effect. This shortcoming of the data should be kept in mind throughout the discussion in this section.

Preliminary examination of the 33 months of data for the 300 PGCs showed that the actual demand recorded for the time period under consideration was extremely erratic. In some cases, demand which was in the thousands of units would suddenly drop to near zero for the remainder of the time periods. In other cases, demand would fluctuate wildly from month to month over the 33-month time period.

Adding to the erratic nature of the demand data was the existence of zero demand in some months. Of the 300 PGCs, 84 (28%) had at least one month in which there were no demands recorded against the NSNs in that PGC. Of these, 45 PGCs had 10 or more months of zero demand. In some cases, the months with zero demand occurred consecutively, suggesting the possibility of item phaseouts or new item start-ups. In any case, the existence of zero-demand time periods contributes to the "lumpiness" of the data, making forecasting more difficult. These large swings in demand must be kept in mind throughout this section of the report. Assuming the accuracy of the demand data used for the analysis, it would be very difficult, if not impossible, for any forecasting technique to successfully predict such demand patterns.

The analyses reported in this section apply simple alternative forecasting techniques to the data, when appropriate, and compare the forecast errors produced by these methods to the errors produced by the POI forecasts. The purpose of this comparison is not to demonstrate the inferiority of the POI method as a forecasting technique, nor is this meant to suggest that these other methods could or should be implemented as an alternative to the POI system. Rather, the purpose is to examine methods which are simple to employ and which are more appropriate for forecasting the specific patterns identified in the data series. If such methods prove to be as good as the current system, then this would serve as confirmation of the patterns identified in the demand data. The problem of how to forecast for large numbers of items which have varying demand patterns is not addressed by these analyses.

2. Results

a. Identification of random demand patterns. Despite the cautions previously noted, the analysis presented here attempted to identify those PGCs which exhibited seasonal or trend patterns in the 33-month series available for each PGC. Since 300 generic items are too many to attempt to forecast individually, the analysis began by screening out those PGCs which showed no obvious demand patterns. This was accomplished by examining the autocorrelation functions (ACF) for the series. The ACF is a measure of the relationship (correlation) of the time series with itself, lagged by some number of time periods. For example, the autocorrelation for the first lag measures the relationship between the demand at each time period and the demand at the time period preceeding it. The autocorrelation at the second lag measures the relationship between demand values two periods apart. In general, the autocorrelation at the k^{th} lag measures the relationship between observations k periods apart. Large ACFs indicate the existence of a pattern in the series.

For the initial screening, the ACFs for the first 12 lags were examined. The standard error (SE) for each ACF was computed, and, under the assumption of normality, a 95% confidence interval was identified for each ACF (1.96 multiplied by the SE). If the ACFs for all of the first 12 lags fell within this confidence interval, it was assumed that no pattern existed in the data. In such cases, the data series was considered to be random.

The results of the above-described process showed that of the 300 PGCs examined, 183 (61%) had no ACFs outside of the confidence intervals, and therefore were judged to have random demand patterns (see Appendix A for an example of a PGC which displays a random demand pattern). Further analysis revealed no significant relationship between demand patterns (random vs. non-random) and type of item (bag item vs. non-bag item), size (sized vs. non-sized PGCs), or whether or not the PGC had any zero demand months.

The findings presented above suggest that for almost two-thirds of the POI PGCs, the available demand data are essentially unpredictable by the use of a formal, time series forecasting method. In fact, the finding of random demand patterns indicates that adequate forecasts could be obtained by simply using the mean of the series to forecast all future values of the series. An analysis was conducted to determine how the forecast derived by taking the mean of the series would compare with the POI forecast.

This portion of the analysis was limited to the 183 PGCs which showed random demand patterns. The first 12 months of actual demand was used to initialize the forecasts for each PGC. Thus the forecast for Month 13 was the mean of the demand for the first 12 months, the forecast for Month 14 was the mean for the first 13 months, and so on. The forecast errors were then compared for Months 13 through 33 using the mean squared error (MSE) statistic. This statistic was chosen because it places greater emphasis on extreme forecast errors. Such extreme errors would more likely to occur using the mean as the forecast, since sudden changes in demand can not be accurately predicted by this method. The MSE for the mean-based forecasts was then compared with the MSE computed for the POI forecasts.

The results of this analysis showed that using the mean of the past actual demand as the forecast resulted in a lower MSE than the POI forecast for 130 (71%) of the 183 random PGCs. The improvements in forecast error ranged from a low of 0.1% to a high of 100%. The average percentage decrease in the MSE was 39%. These results indicate that for fully 43% (130 of 300) of the generic items, more accurate forecasts (using the MSE criterion) could have been obtained using the average of the past demand values, rather than the POI method, as the forecast for subsequent months.

To summarize to this point, the analysis began by attempting to differentiate between those PGCs whose past demand showed some systematic pattern, and those for which past demand appeared to be random. A total of 183 items were identified as having random demand patterns. For this group, the mean of the past demand values was used as the forecast for subsequent months. The results of this procedure demonstrated that for 130 of the 183 PGCs, the more simplistic forecasting procedure resulted in lower forecast errors than the POI system.

b. Identification of trends in demand. The next step in the analysis was to identify those items, out of the 117 that did show some pattern in their demand data, which exhibited trend over the time period under consideration. Once again, examination of the autocorrelation functions proved to be a useful screening device. A time series with a relatively constant mean (i.e., one without trend) is said to be stationary. ACFs for a stationary time series drop to near zero after the second or third time lag, while ACFs for a non-stationary series remain significantly different from zero for several time periods. In order to identify items with potential trend, the first several ACFs were examined. Any item which showed at least the first three ACFs significantly different from zero (i.e., outside of the 95% confidence interval) was flagged as containing trend. In addition, any item which showed this type of pattern whose ACFs were nearly significant were also flagged as showing trend.

The above procedure resulted in the identification of 27 PGCs which appeared to have trend in them (see Appendix B for an example). Plots of the demand data and the ACFs were then examined for each of the 27 generic items (see Appendix C for further information on these items). None of the 27 PGCs exhibited what might be termed a "pure" trend; that is, consistently increasing or decreasing demand across the entire 33-month period. In fact, many of the items showed patterns which might not be called trend at all. Ten of the 27 PGCs began with very low demand for the first 12-15 months, then showed sudden increases in the level of demand, with fluctuations from high to low, over the rest of the series. For most of these items, the initial low demand was actually zero demand. Five PGCs had zero demand for the first 12-15 time periods, while three others showed zero demand for many of the first few observations (for example, zero demand for five of the first seven months). One item had zero demand for 25 of the first 26 months in the series.

Of the 17 PGCs which did not show the "step" function in demand described above, three showed the opposite effect; that is, high initial demand followed by a sudden drop-off in demand for the remainder of the series. In all three cases, the drop-off occurred between time periods 13 and 15.

The remaining PGCs in the series could be described as showing shifts in the level of demand, rather than smooth trends across the 33 months. Demand might fluctuate at a relatively high level for the first 15-20 months of the series, then drop to a lower level, and fluctuate at the lower level for the remainder of the series. In other cases, trends were obvious for a portion of the series, but not all of the series. Demand might increase rather steadily for the first 12 months of the series, then decrease to some lower point around which fluctuations might occur. This latter pattern accounted for most of the remaining PGCs which exhibited trend. A simple moving average (MA) technique was applied to the data for these 27 PGCs in order to compare an alternative forecasting method to the

POI method. For each PGC, 11 different MA models were compared, each using a different number of months to compute the moving average. Averaging periods ranging from 2 to 12 months were examined for each series. The MA model producing the smallest MSE was used as the final model to be compared to the POI method.

The results of this analysis showed that for all 27 PGCs, the simple moving average produced a lower MSE than the POI forecast. On the average, the moving average method produced MSEs which were 74% lower than those produced by the POI forecast. The percentage of MSE reductions ranged from 22% to 100% (see Appendix D for further detail). The actual moving average period which produced the optimal MSE varied depending on the PGC. The 2-month moving average produced the lowest MSE for 11 of the 27 PGCs.

The results presented above suggest that a simple alternative to forecasting items with trend produces lower MSEs than the POI forecasting method. The next section will examine seasonality in all items, including the 27 items exhibiting trend, and apply another alternative forecasting method.

c. Identification of seasonality in demand. The next step in the analysis was to examine the 117 PGCs which showed some pattern in their demand to determine whether seasonality exists in the demand data. For purposes of this analysis, seasonality is defined as any pattern that repeats itself over fixed intervals of time. In some cases, these patterns may correspond to seasons of the year; for example, demand for gloves may be higher in January than in July. This type of situation would generate a 12-month seasonal demand pattern. Other patterns may exist, however, which do not correspond to any identifiable cycle or season. Thus, the term "seasonality" is being used here in a very general sense.

The most straightforward method for determining seasonality in a time series is to visually examine the plot of the raw data. Peaks in demand at regular intervals can often be seen from such a visual inspection. In addition, the ACFs may be examined; any ACF beyond the first two or three lags which is significantly larger than zero is an indication of some regular pattern in demand.

The above-described procedure was used in this analysis to identify seasonal patterns in PGC demand. Plots of the raw data, along with ACF values and ACF plots, were examined for all 117 PGCs. Two analysts examined each plot to determine whether seasonal patterns were evident and, if so, to determine the length of the seasonal period. In the vast majority of cases, making this determination presented little difficulty since the patterns, when they existed at all, showed up clearly in both the plots and the ACF values. In one case, where the length of the season was questionable, two alternative seasonal lengths were utilized in further analyses (see Appendix E for an example of a seasonal demand pattern).

The results of the review process described above revealed 32 PGCs which had clearly defined seasonal patterns. These PGCs, along with their nomenclature and the length of the seasonal period identified for each, are provided in Appendix F. The most common seasonal period observed was a quarterly one, that is, demand spikes every three months. This pattern was seen for eight of the 32 seasonal PGCs. A 12-month seasonal pattern was observed for seven PGCs. Five of this latter group were cold weather items, such as gloves and boots, which showed demand peaks in December and January. The other two items, a woman's skirt and shirt, showed demand peaks in the spring and summer months.

Other demand patterns are also shown in Appendix F; for example, four-month, five-month, and so on. These do not appear to be seasonal patterns in the sense that they relate to the time of year. Once again, it should be noted that the 33 data points available for this analysis do not allow for a great deal of confidence in drawing conclusions about seasonality.

As noted previously, the POI system does not account for seasonality in demand in its forecasts. It is of interest to determine whether the forecast of those items identified as having seasonality in demand could be improved by using a technique which takes seasonality into account. The technique used in this analysis was Winters' Trend and Seasonal Smoothing Method[3].

Winters proposed an exponential smoothing method which uses three smoothing equations to develop the forecast for each period: one for stationarity, one for seasonality, and one for trend. Thus, Winter's method is applicable to demand data which contains trend, seasonality, or both.

Winters' model uses three different smoothing parameters: alpha (for overall smoothing), beta (for seasonal smoothing), and gamma (for trend smoothing). The analysis reported here determined the optimal values for these three parameters for each PGC empirically. For each PGC, the values of each parameter were varied, one at a time, from .00 to .50 in .05 increments. In effect, then, 1,331 models were tested for each PGC, each with a different combination of values for alpha, beta, and gamma (11 x 11 x 11 = 1,331). MSEs were calculated for the forecasts resulting from each of the 1,331 models. The model producing the lowest MSE was then compared to the MSE resulting from the POI forecast. Initialization of the seasonal and trend factors was accomplished using the procedures discussed in Makridakis, Wheelwright and McGee[4]. Each of the 32

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[3] P. R. Winters, "Forecasting Sales by Exponentially Weighted Moving Average," Management Science, 1960, Vol. 6, pp. 324-342.

[4] S. Makridakis, S. C. Wheelwright, & V. E. McGee, Forecasting: Methods and Applications, 2nd Ed. (N.Y.: John Wiley, 1983), p. 108.

PGCs was examined using the seasonal length identified in the analysis discussed above.

The results of this analysis showed that the Winters model produced forecasts with lower MSEs for 26 of the 32 PGCs. The percentage reductions in MSE using the Winters model ranged from 3% to 100%; the mean MSE reduction was 59% (see Appendix G for more detailed information). To summarize, an examination of the raw data and ACF plots for all 117 PGCs which had some pattern in their demand data revealed 32 PGCs which demonstrated seasonal patterns. Winters' exponential smoothing model was run against these PGCs, and forecast errors from the model were compared with the POI forecast errors. The results showed that the Winters model produced lower MSEs for 26 of the 32 PGCs. It would thus appear possible to isolate PGCs with seasonal demand and forecast these more accurately with a model which allows for seasonality than with the POI system.

3. Discussion

The purpose of this phase of the analysis was to determine the degree to which seasonality and trend were in fact present in the historic demand for POI items. The analysis was undertaken due to the fact that the POI system, by combining four quarters of past demand in its calculations of replenishment rates, fails to take either of these factors into account. It would therefore appear that any forecasting method which allows for trend and seasonal components in the data would produce superior forecasts for items which did in fact display these characteristics.

Using autocorrelation functions computed on the demand data as a screening device, along with visual inspections of data plots, it was possible to isolate PGCs which showed historical demand which was seasonal (32 PGCs), exhibited trend (27 PGCs), or was essentially random (183 PGCs). The remainder of the generic items (58 PGCs) showed patterns in their demand data, but these were not judged to be either trend or seasonal patterns (nor were they judged to be combinations of these two patterns).

For each of the first three PGC categories, an alternative forecasting method, chosen for its applicability to the pattern of the historical demand data, was applied. The mean of the past demand was used to forecast PGCs with random demand patterns, a moving average was used to forecast PGCs exhibiting trend, and Winters' exponential smoothing model, with separate smoothing parameters for seasonal and trend components, was used to forecast PGCs with seasonality in historic demand. These alternative techniques produced forecasts with lower mean squared errors than the POI method for 71% of the random PGCs, 100% of the PGCs with trend, and 81% of the PGCs exhibiting seasonality in demand.

For the fourth category, that is, PGCs which exhibited some demand pattern which was not trend or seasonal, no alternate forecasting techniques were tested. Using a time series analysis approach, it may have been possible to identify an underlying autoregressive or moving average model (or a model which combined the two) to be used for forecasting. However, this was not attempted as part of the analysis.

The first important observation in the analysis presented in this section was that 61% of the 300 POI PGCs were judged to show random historic demand patterns. As noted previously, this was in part due to zero demands for many of the items over a relatively large portion of the time periods examined. Regardless of the reason, this finding suggests that a formal forecasting method based on examination of historic demand only will not produce accurate forecasts. This being the case, it could be argued that the POI forecasting technique might be most appropriate for these PGCs. Further analysis showed, however, that 71% of these PGCs could be forecast more accurately using the mean of the past data rather than the POI system.

The point here is that the majority of POI PGCs defy attempts to forecast demand through formal forecasting methods which rely on historical demand as their bases. If the demand for these items is in fact random, then virtually any method of this kind is likely to do poorly in forecasting their demand. Given this, it might be useful to examine in greater detail the explanations for these erratic demand patterns, with an eye toward forecasting techniques which are more appropriate for the circumstances which give rise to these patterns. Alternatively, one could question the wisdom of employing complex forecasting techniques to items which may be forecast with equal success using more simplistic and less costly techniques.

The findings with regard to trend and seasonality suggest that these may also present problems for the POI system. Over half of the items which had some pattern had trend or seasonal demand patterns, and in the vast majority of cases, relatively simple alternate techniques produced forecasts with less error than did the POI system. It should be noted, however, that in many cases the trend observed could be attributed to either zero demand for some period of time, or to a relatively sudden shift in the level of demand, rather than a slow acceleration or deceleration in demand. Similarly, no attempt was made to justify the seasonal periods identified for many of the PGCs in the analysis, since to do so would require greater familiarity with the items.

Once again, it is necessary to repeat the warning that the analyses of trend and seasonality presented here are based on a relatively small number of data points, and must therefore be interpreted with caution. In addition, the conclusions presented here are based on the assumption that the historical patterns observed are enduring ones; that is, that items which showed seasonal variations in the past will continue to do so in the future. This is always a danger in this type of analysis, especially in the analysis of trend. Since any analysis of active items can view only a portion of the historic demand series, it is possible that what appears to be a trend now will reverse itself in successive time periods.

The methods used in this analysis may have served to underestimate the degree to which the demand for POI items exhibits trend and seasonality. Initial issue demand and replenishment demand should not be affected by seasonal and trend influences in the same manner. For example, retail sales for clothing items should be more influenced the seasonal variations of nature, while initial issue demand should be more influenced by seasonal variations in new enlistments. The latter fluctuations should be accounted for by the POI system in changes in the service strength forecasts, while the affects on replenishment demand are not factored into the system.

The above observations suggest that separate analyses of the two types of demand might demonstrate differences in the degree of seasonality and trend observed. If this were in fact the case, this would further suggest the utility of forecasting replenishment demand using all of the historical demand data available. In this way, a forecast might be generated which was more sensitive to trend and seasonal variations in generic item demand.

Finally, it should be noted that the type of analysis presented in this section is extremely complex and time-consuming. These characteristics are, in fact, typical of the type of time series approach to forecasting which was used here. Although the simple alternative forecasting techniques applied in this section can be applied easily, the process of identification and maintenance of the forecasting models is much more complex. Therefore, the techniques used in the analyses presented here are not being endorsed as substitutes for the POI system. The issue of the feasibility of the implementation of methods such as these presents a major stumbling block in developing a "new improved" forecasting system for POI items.

C. Comparison of Actual vs. Assumed Operating Levels

1. Approach

One of the concepts used in the POI forecast is the operating level. Every Program Identification Code (PIC) has an operating level associated with it (for a description of PICs, see Section D.1). The operating level is given in months and represents the amount of stock to be ordered by each DLA customer. It also represents the average time between orders. For example, if the operating level was one month, this would mean that one month of stock would be ordered at a time, and that the average time between orders will be one month. At the time this analysis was conducted, all PICs used by DPSC had operating levels of one month.

For purposes of this analysis, it would not have been practical to examine the operating levels actually used by every POI customer. The analysis was, therefore, limited to the recruit induction centers (RICs) and the military clothing sales stores (MCSSs), representing approximately 400 customers. For each customer, an "implied" operating level was computed for the NSNs ordered. The implied operating level was defined as the average time between orders for that item by a customer.

A customer usually does not order all items every month, especially items with low demand rates. This irregularity may be due to demand fluctuations, the need to order in full unit pack quantities, or possible item phase-outs. To minimize the effect of such situations, a minimum demand cut-off was introduced. Only those NSN-customer combinations which constituted at least 0.5% of total system demand for that NSN were included in the analysis.

A total of 27 months of requisition data (October 1981 through December 1983) was available for analysis. For all combinations meeting the 0.5% criterion, an average time between requisitions was calculated, and this became the implied operating level. These implied operating levels were then averaged over all NSNs ordered by each customer.

2. Results

The results of the analysis showed that the vast majority of implied operating levels were between 1.0 and 3.0 months. However, a few customers existed whose operating levels fell well out of this range. Careful examination was made of those extreme values where the average operating level for a customer was as low as .2 months or as high as 10 months. It was found that these extreme values were the result of only one or two NSNs providing a particular customer with an unusually high or low average. In all cases, these few NSNs had a total system demand which was quite low (10 units or less over 27 months). This would allow even a single order of one unit by a customer to meet the .5% demand cutoff. Thus although the implied operating levels for these NSN-customer combinations deviated substantially from the one month level assumed by the POI system, their impact on the overall forecast accuracy would be minimal due to the small size of the actual demand.

The above observation also applied for all of the observed implied operating levels. That is, for all NSNs in general, the higher the NSN's system demand, the closer the implied operating level was to one month. In no case was there a customer with a large implied operating level that was related to a high-demand NSN.

3. Discussion

The results of the above-described analysis suggest that differences between the one-month operating levels assumed by the POI system and the actual time between orders do not have a significant impact on the forecasts. In the cases where the implied operating levels were substantially different from one-month, the system-wide demand was so small that the impact of the deviation would be minimal.

It should be noted here that another factor in the POI system is often discussed in conjunction with the operating level. The "pipeline factor" is the time interval between the initiation of a requisition by a customer and the receipt of the item by the customer. The pipeline factor is used by the POI system to "back up" the forecast so that the Service demand is translated into DLA requirements. For example, suppose the system computes 1,000 as the forecasted requirements for a particular PGC for the month of June. Since this demand will occur in June, customers (for example, recruit centers) will need to requisition the item prior to this time, to ensure it is available in June. This time difference is the pipeline factor. If the pipeline factor is 60 days, then the POI system will compute its April requirements at 1,000, rather than its June requirements. Thus the pipeline, like the operating level, is used to convert forecasted demand into DLA requirements. Pipelines, like operating levels, are associated with PICs. Thus the POI system makes the assumption that customers will requisition items prior to when they actually need the item, and that the length of this time interval will vary depending on the service and type of demand for the item (for example, Army female reserve versus Air Force male reserve).

The present study did not examine the validity of the pipelines used by the POI system. Such an analysis would require data on the length of time between the receipt of a requisition by DPSC, and the receipt of the item by the customer. This type of data was not readily available for purposes of this analysis.

At the time the data for this study was being collected, the pipelines being used by DPSC ranged from 2 weeks to 3.5 months. Although no formal analysis of the accuracy of these values was conducted, Air Force and Navy Military Clothing Sales Store (MCSS) personnel were questioned regarding their knowledge of the pipelines. Personnel in both services' MCSSs indicated that it rarely takes more than 30-45 days between the time they send a requisition to DPSC and the time the merchandise is received. Sales store personnel had no knowledge of the existence of a pipeline, and showed no awareness of the POI system's assumption of differing ordering times for different subcategories of demand (i.e., PGCs) for the same item.

It would appear from these observations that the validity of the pipeline factors may be questionable. If their values were in fact incorrect, then it is possible for the forecasts to get "out of sync". That is, demand forecasted for June is incorrectly "pipelined" back 60 days to April, but customers order 30 days in advance, in May. Thus the forecast lags behind the actual demand. Based on the informal analysis presented here, an administrative review of the assumptions and actual values associated with the pipeline factors might prove useful in improving the accuracy of the POI forecasts.

D. Comparison of Forecasted and Actual Troop Strengths

1. Approach

The Services provide DPSC with troop strength levels on a regular basis. Specifically, they send DD Form 1967, Personnel End Strengths and Gains, to DLA three times a year. This form provides for monthly reporting of forecasted and actual demand for various categories of military personnel. The form is divided into two main sections, dealing with monthly end strengths and monthly gains. The former is used by DPSC for computing replenishment demand, while the latter is used for determining initial issue demand. Each of these major categories is, in turn, subdivided into various types of personnel: for example, officers versus enlisted, male versus female, and active duty versus reserve. Some, but not all of these subcategories are used by DPSC in determining their requirements.

Before discussing the data to be analyzed here, it is necessary to explain briefly the method used by DPSC to convert Service-provided forecasted and actual troop strengths to DLA requirements[5].

The POI forecast relates generic end items (PGCs) to troop strength data through a Program Identification Code (PIC). The PIC is a 5-digit alphanumeric code which uniquely identifies each specific subcategory of military personnel in each service. The first three digits of the PIC identify, respectively, the Service (A for Army, F for Air Force, etc.), duty (regular service or ROTC), and sex (male or female). The last two digits of the PIC further subdivide these basic categories.

Within each Service, PICs are divided into the two major categories of initial issue or replenishment. There are only three possible replenishment PICs for each Service: male, female, and total. The number of initial issue PICs varies by service. At the time this study was conducted, DPSC was using a total of 40 initial issue PICs, plus the 15 replenishment PICs described above (three PICs for each of five services).

PICs and PGCs are matched up in an internal DPSC file known as the Program Data Reference File (PDRF). In the PDRF, each PIC will have a number of PGCs associated with it, depending on how many different service elements use the item. For each of the PICs, forecasted troop strengths are entered into the PDRF by the Management Support Office at DPSC. These forecasted troop strengths are then translated into DPSC demand requirements. These demand requirements are then summed for all of the PICs associated with a given PGC, thus producing the demand for each generic end item.

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[5]For more detailed information, see DLAM 4140.2, Vol 2, Part 1, Ch 25.

The process of translating troop strengths to DPSC requirements differs according to whether the PICs involved are initial issue PICs or replenishment PICs. For each service, only one replenishment PIC is associated with a PGC (male, female, or total); there may, however, be multiple initial issue PICs per PGC (for example, the same item used by Air Force enlisted males, male officer candidates, and male reserves). To determine initial issue requirements, DPSC obtains from the services a list of the number of generic end item (PGC) issued to each new troop (for example, two neckties, three handkerchiefs, six undershirts, etc.). This number is then multiplied by the monthly troop strengths associated with all of the initial issue PICs for that PGC. The result is a requirements prediction, by month, for initial issue demand for each generic end item.

For replenishment PICs, requirements are based on the ratio of past demand to past total troop strength. Actual demand for the past year is obtained for each NSN from the Supply Control File. These demands are summed for each of the NSNs in a given PGC. This total is then divided by the actual troop strength for the PIC. The result is a fraction which represents the proportion of troops projected to require replenishment of the end item. This proportion is then multiplied by the projected end strengths for the PIC in order to obtain forecasted replenishment requirements for that PGC.

Ultimately, initial issue and replenishment requirements for all PICs for a given PGC are added together, resulting in the final set of monthly forecasts for each PGC. As this description shows, the Service projections of future end strengths and new recruit inputs are crucial to the POI forecasting process. It was therefore decided to examine the historical performance of these troop strength forecasts.

Copies of DD Form 1967 are sent from the Services to DLA's Supply Operations Division (DLA-OS), who in turn forwards copies to DPSC. For the purposes of this study, an attempt was made to gather all DD Form 1967s received by DLA over the 36-month period from October 1980 through September 1983. Although all of the forms available to DLA were obtained from DLA-OS, several gaps existed in the data for the different Services over the 36-month period. This was apparently due to the fact that not all of the Services send in their projections three times a year as DLA requests. In some instances, data were missing for all PICs for a given time period, say six months. In other cases, data might be missing selectively; for example, one PIC might be missing data in one month only. The situation was particularly severe for the Coast Guard. Only 23 months of forecasted and actual troop strength data could be obtained for the Coast Guard.

The analysis reported here used all of the available data from each Service. Both forecasted and actual troop strengths were coded for computer analysis from the DD Form 1967s supplied by the Services to DLA-OS. The accuracy of the forecasts was assessed using the same types of statistics discussed in the previous section of this report.

It should be noted that DPSC does not use as a separate PIC every subcategory reported by the Services on DD Form 1967. The analysis presented here will examine only those subcategories of troops which are actually used in PICs established by DPSC. In addition to regular service demand, DPSC also fulfills ROTC demand for POI items. Projections of troop strengths for ROTC are reported by the Services on a separate form (DD Form 1968). No systematic effort was made to obtain these forms from DLA-OS; therefore, the analysis reported here will exclude ROTC PICs.

2. Results

a. Replenishment PICs. As noted previously, three replenishment PICs exist for each Service: male, female and aggregate. Aggregate monthly end strengths are predicted directly by the Services on DD Form 1967, and these figures are used for the aggregate PIC for each Service. Figures for the male and female replenishment PICs are obtained by adding the projections for officers and enlisted personnel of each sex. This same procedure was carried out for purposes of this analysis.

The 15 replenishment PICs, along with several summary measures of the accuracy of the Service projections, are presented in Table IV. The table shows, for each Service and PIC, the average forecast and the average actual troop strength for the period under study (the number of months of data actually used for each Service is shown below the Service in column 1 of the table). Four error statistics are also presented: the mean error, the mean percentage error, the mean absolute error, and the mean absolute percentage error. The mean error is the average of the errors over the time period, where an error is defined as the actual troop strength minus the forecast. The percentage error is the error divided by the actual troop strength for a given time period; the average of these is the mean percentage error. Negative values for the ME and the MPE indicate over-forecasts of troop strengths; that is, those cases in which forecasted troop strength exceeded actual troop strength. The MAE and the MAPE use the absolute values of the error and the percentage error, and therefore measure the total deviation of forecasts from actual troop strength, regardless of the direction of the difference.

Also presented in the table are the largest underforecast values, and the percentage errors represented by these values. Underforecasts are of particular concern since they may ultimately result in out-of-stock conditions, due to demand exceeding the POI forecast.

In Table IV, the male and female PICs represent the sum of the forecasts and actuals for both officers and enlisted personnel. The "aggregate" PIC represents the total for all regular military personnel. Note that the male and female PICs' numbers will not sum to the "aggregate" number, due to the fact that the aggregate contains other PICs which are not used by DPSC.

Examination of the MPE and MAPE values shown in Table IV indicates that the Service forecasts for end strengths appear to be quite accurate overall. MAPE values range from a low of 0.25% (Air Force males) to a high of 16.5% (Coast Guard females). With the exception of this latter value, all MAPEs were under 4%. The MAEs show that in absolute terms, however, these relatively small percentage errors translate into deviations of several thousand per month (on the average). Examination of the most extreme ME and MPE values observed in a single month shows that male end strengths were underforecasted by approximately 13,000, 17,000 and 36,000 by the Army, Navy and Marine Corps, respectively. Although the corresponding PEs are not terribly large (except for the Marine Corps), they still indicate that in any one month, DLA's forecasted requirements may fall short of actual demand by a considerable amount (although not by the amounts given above, since replenishment troop strength figures are multiplied by the replenishment rate in order to obtain the forecasted requirements).

Examination of the mean errors in Table IV shows that in the vast majority of cases, troop strengths for replenishment PICs tended to be underforecasted. Of the 15 PICs in the table, 11 were underforecasted. In fact, three of the four PICs which were overforecasted by the services were for female troops.

Comparison of the figures for the various Services in Table IV shows that the Air Force was able to forecast troop end strengths with a greater degree of accuracy than the other Services. The Coast Guard showed the greatest degree of inaccuracy, largely due to their inability to forecast female end strengths (also recall that only 23 months of data are being used for the Coast Guard). In fact, all of the Services had more inaccuracy in the forecasts for females than in either the male or total forecasts (comparing the MAPEs of these PICs). For the Army, Air Force and Coast Guard, this inaccuracy took the form of overforecasting female end strength levels. It should also be noted that in each of these instances, the PICs with the greatest forecast errors are those with the fewest numbers of troops to begin with (that is, females).

To summarize, troop strengths for replenishment PICs appear to be forecasted with a reasonable decree of accuracy, with the possible exception of Coast Guard females. In any given month, however, the Services may underforecasted replenishment strengths by several thousands of troops. In addition, it appears that the Services forecast smaller replenishment PICs with less accuracy than they do larger PICs. In absolute terms, however, the impact of this greater inaccuracy is diminished by the fact that fewer troops are in these PICs to begin with.

TABLE IV

Accuracy of Forecasts for Replenishment PICs

Service	PIC	Mean Forecast	Mean Actual	ME	MPE (%)	MAE	MAPE (%)	E(max)	PE(max) (%)
Army (N=29)	Male	698,842	701,048	3,479.3	0.49	5,100.0	0.73	12,800	1.83
	Female	74,214	73,317	-824.1	-1.17	1,265.5	1.75	1,100	1.44
	Aggregate	777,258	778,583	2,641.4	0.34	4,151.7	0.53	11,900	1.54
Navy (N=36)	Male	497,349	502,522	5,172.5	1.02	6,407.9	1.27	16,984	3.33
	Female	41,386	41,736	350.0	0.73	754.5	1.78	1,760	4.09
	Aggregate	543,235	549,029	5,793.6	1.04	6966.0	1.26	18,957	3.36
Marine Corps (N=36)	Male	180,909	184,184	3,274.6	1.76	3,437.4	1.85	36,582	19.37
	Female	7,708	7,971	263.3	3.38	266.1	3.42	495	6.34
	Aggregate	189,528	192,154	2,626.4	1.37	2751.8	1.43	4,978	2.62
Coast Guard (N=23)	Male	36,418	36,702	347.6	0.87	1,214.5	3.31	2,627	6.85
	Female	1,898	1,696	-134.6	-9.13	268.0	16.54	327	17.29
	Aggregate	39,195	38,935	-139.0	-0.39	772.9	1.99	1,430	3.59
Air Force (N=31)	Male	497,338	510,945	420.1	0.09	1,287.8	0.25	4,649	0.93
	Female	64,785	63,938	-388.4	-0.63	618.2	0.98	414	0.65
	Aggregate	566,385	579,410	57.7	0.01	785.4	0.14	1,507	0.27

Note. ME = Mean Error; MAE = Mean Absolute Error;
MPE = Mean Percent Error; MAPE = Mean Absolute Percent Error;
E(max) = largest underforecast error; PE(max) = largest percentage underforecast error.

b. <u>Initial Issue PICs</u>. DPSC uses a total of 22 initial issue PICs to forecast this portion of the POI requirements. Different PICs are used by different Services, and the number of PICs varies from one Service to the next. Only these 22 PICs will be used in this analysis. The comparison of the forecast errors for the initial issue PICs is shown in Table V.

Examination of the data presented in Table V shows that the Services' forecasts for initial issue PICs have considerably greater error than those for replenishment PICs. The MAPE values for the initial issue PICs ranged from a low of 6.4% (Air Force male enlisted) to a high of 225% (Coast Guard female enlisted). This range is much higher than the one observed for the replenishment PICs. Since new recruit levels are much lower than end strengths, however, the absolute magnitude of the errors for the initial issue PICs is not as great as for the replenishment PICs. In addition, underforecasts do not predominate as they did for the replenishment PICs. Of the 22 PICs in Table V, 15 were overforecasted, while only 7 were underforecasted (on the average, and across all time periods examined).

Examination of the largest underforecasted values shows that the initial issue forecasts can be considerably lower than the actual new recruit input for any particular month. PICs which show the most extreme underforecasted errors include Army male enlisted and male reserve, Navy male enlisted and male reserve, and Marine Corps male reserve. Again, one possible ramification of these underforecasts by the Services is the situation where DLA forecasted requirements are exceeded by demand for initial issue items in some given month.

Further inspection of Table V shows that, as was true of replenishment PICs, greater error is associated with PICs which have smaller numbers of troops. For the initial issue PICs, these include females in the smaller Services like the Coast Guard, and Navy and Air Force officer candidates.

To summarize, new recruit input is forecasted with considerably less accuracy than end strengths. Greater variation [illegible] in forecast accuracy for initial issue PICs than for replenishment PICs. New recruit levels are more often overforecasted than underforecasted, and the most serious underforecasts are much smaller in absolute magnitude than those observed for replenishment PICs. As was the case for replenishment PICs, the more specific the Services had to get, in terms of the size of the troop strength categories they were trying to forecast, the more inaccurate their forecasts became.

TABLE V

Accuracy of Forecasts for Initial Issue PICs

Service	PIC	Mean Forecast	Mean Actual	ME	MPE (%)	MAE	MAPE (%)	E(max)	PE(max) (%)
Army	Male Enl	10,397	9,928	-582.8	-8.11	1,548.3	16.53	3,400	30.49
	Female Enl	1,681	1,655	-131.0	-9.31	296.5	18.49	700	43.75
	Male Res	3,231	3,538	341.4	3.50	913.8	21.41	6,400	72.72
Navy	Male Enl	5,140	4,848	-292.1	-8.32	588.5	12.56	1,705	22.14
	Male OC	292	386	93.5	-4.08	154.8	55.69	700	85.05
	Female Enl	791	718	-73.1	-13.96	98.2	16.68	199	20.95
	Male Res	1,587	1,640	53.4	-5.62	362.5	18.02	3,104	70.13
	Female Res	30	95	64.9	7.71	65.7	11.25	819	97.38
Marine Corps	Male Enl	3,226	3,119	-106.1	-4.21	225.1	7.51	334	9.77
	Female Enl	202	182	-19.7	-15.57	47.1	28.82	103	53.09
	Male Res	632	716	83.6	3.55	140.7	14.36	1,238	51.41
Coast Guard	Male Enl	444	410	-46.3	-22.13	144.7	42.19	300	44.00
	Female Enl	46	36	-17.3	-190.50	35.8	224.90	54	72.97
	Male Res	128	100	64.9	7.71	65.7	11.25	39	31.17
	Female Res	14	11	-4.0	-46.17	5.9	62.38	6	40.00
Air Force	Male Enl	5,094	4,941	43.5	0.67	316.3	6.38	703	12.70
	Male OC	266	183	-74.1	-77.75	116.0	92.68	282	76.87
	Female Enl	914	819	-44.7	-4.80	95.8	11.61	227	34.76
	Female OC	30	12	-15.8	-206.54	17.6	213.01	25	89.29
	Male Res	157	172	16.3	4.54	34.0	19.74	113	42.64
	Female Res	107	98	-3.3	-11.6	26.1	28.36	74	43.23
	Natl Guard	384	334	-51.5	-22.86	107.8	36.30	210	38.89

Note. Enl = Enlisted; Res = Reserve; OC = Officer Candidate; ME = Mean Error; MPE = Mean Percent Error; MAE = Mean Absolute Error; MAPE = Mean Absolute Percent Error; E(max) = largest underforecast error; PE(max) = largest underforecast percent error.

3. Discussion

The analysis above suggests two different sets of findings regarding the accuracy of the Services' forecasts of new recruit input and end strength levels. The former showed larger errors when expressed in relative terms, smaller errors in absolute numbers, and a predominance of overforecasts, while end strengths showed the opposite pattern. Examination of the maximum underforecast for a given month showed that for both initial issue and replenishment PICs, considerable underforecasting occurred for selected months over the time period under consideration. This would result in a shortage in DLA's requirements calculations for that month. For example, in a single month, the Army underforecasted its male strength by 12,800. If the replacement rate had been .10 for this item for this example, the DLA requirements for this PIC would have been 1,280 units short. Several consecutive months of underforecasts of this type could eventually result in a stockout condition.

The results of this analysis also showed that for both initial issue and replenishment, the Services are less accurate for PICs which are smaller in terms of number of troops than for larger PICs. When extreme errors occured, they were more likely to correspond to PICs with small numbers of troops. However, these errors have a relatively small impact, because the actual strengths are so small to begin with.

This observation regarding smaller PICs leads to the question of why it is necessary to break out the forecasts to this level of detail. In fact, the forecasts for the individual PICs are eventually combined into a single forecast for each PGC. Since the Services seem to have greater difficulty in forecasting these smaller breakdowns, and since these forecasts are combined anyway, it seems reasonable to ask the Services to forecast at more aggregate levels initially. One way to accomplish this would be to change the initial issue PIC structure so that it matches the replenishment PICs; that is, male, female and aggregate PICs for each Service. Potentially, forecasting accuracy would increase with less PICs, with no apparent loss of information to DPSC.

E. <u>Other Considerations Relative to POI Forecasting</u>

The POI system is a large and complex one, and many facets of the system exist which were not directly addressed by this study. Some of these factors may be contributing to the large forecast errors observed in the analysis.

The use of pipeline factors was discussed briefly in the section on operating levels. The application of an incorrect pipeline factor could lead to forecasts which were "out of sync" with actual demand. That is, by assuming an incorrect length of time between customer requisitions and receipt of items, the POI system could calculate the correct forecast, but apply it to the wrong time period.

Interviews with personnel at DPSC and at Navy and Air Force retail sales stores failed to find any conceptual support for the use of the pipeline factor. It is not at all clear why different PICs should be associated with different pipeline times, as opposed to factors such as the distance from the customer to the closest DLA stockage point, the mode of transportation, the priority of the requisition, and so on. It would therefore seem appropriate for DPSC to review the entire concept of the pipeline factor, or at least to ensure that the factors currently in use are accurate.

Another factor which has not been examined in this study is the size tariffs used by the POI system. The size tariff is the method by which the system breaks down the forecasted demand for a generic item (PGC) into forecasts for the individual sizes (NSNs) which comprise the PGC. This process involves collecting the previous four quarters of demand by NSN, and dividing the demand for each NSN by the total demand for the PGC. The resulting fraction is that portion of the generic item demand which is applicable to that size of the item.

If size tariff values were incorrect, this could result in requirements being overforecasted for some NSNs and underforecasted for others, even if the overall requirements for the PGC were correct. In addition, any trends in changes of tariff values (for example, changes over the years in the physical makeup of new recruits) would not be accounted for by the current method of computing the tariffs. The analyses presented here did not directly examine the accuracy of the size tariff values. The study did show substantial errors in the forecasts of the generic items, suggesting that sizes are not the only problem with the POI forecasts.

The process described above for the computation of size tariffs is similar to the manner in which mechanical replacement rate values for the PGC are computed. In both cases, however, the system allows the item manager to insert manual values (for either replacement rates or size tariffs) into the calculations. Each manual value is entered along with an effective date, that is, the date on which the manual value is to be used by the system in computing its requirements. Any manual value present for a PGC or an NSN is always used by the system in lieu of its own calculated replacement rate or size tariff values.

The use of manual values provides the item manager with a mechanism by which to alter the POI forecasts to take external information into account. For example, information about trend or seasonality in an item could be incorporated into the forecast through the judicious use of manual replacement rate values.

In discussions with item managers at DPSC, it appears that manual values are seldom, if ever, utilized. More often than not, these manual values appear to be used as a quick method for correcting system mistakes in forecast computations. Cursory examination of the manual values actually present in the Program Data Requirements File (as of June of 1983) revealed several manual replacement rate values with effective dates well over a year old. The age of these values suggests that a more careful review of the use of manual replacement rate values might be in order. If used appropriately, it would appear that these values offer a useful method for incorporating the forecasts for items with unique requirements into the overall POI system.

Judging from the comments of DPSC personnel, new items also represent a potential problem area for the POI system. New items must be handled differently from established items, since demand histories are not available for calculating replenishment rates. Instead, Service forecasts of anticipated demand for these items is used to determine DLA requirements. Thus the accuracy of the forecasts for these items depends on the accuracy of the data provided by the Services.

Another area of potential problems with the POI system was suggested in conversations with DPSC personnel. Various levels of personnel expressed their concerns about having to function without a good means of obtaining important information. Probably the most serious lack of information relates to the failure of the system to systematically capture and report past demand data. At any point in time, item managers seem to be unaware of the discrepancies that currently exist between the forecasts and the actual demand. There appears to be no way that anyone knows if the demand for an item is in the process of changing (for example, showing an increasing or decreasing trend).

The above observations suggest the utility of implementing a tracking signal which would warn the item manager of deviations between the POI forecasts and the actual demand, and/or changing demand patterns. Such a signal could be tied to changes in demand, to changes in forecasts, or to discrepancies between forecasts and actual demand. In this way, the item manager would be made aware of impending difficulties prior to their actually causing problems. Other external information was suggested in interviews which could be beneficial to the forecasting process. This would include impending uniform changes, changes in the allowance factors for initial issue items, and anticipated demand surges. As examples of the latter, retail demand may increase when reserve units have access to sales stores, usually in the summer months. Similarly, ship movements can cause demand surges at the Navy sales stores. In many cases, the Services may know in advance of similar circumstances which will affect demand. Formal communication channels for this type of information should be developed where they do not currently exist. Finally, there are many issues which do not necessarily relate to the POI system itself, but which may lead to problems in inventory management. The list of such issues would include: the need to order whole unit packs for sizes which show small demand, the problems associated forecasting and handling returns for items being phased out, the problems associated with manufacturers' delays in delivering items on schedule, the appropriate type and size of the safety level for POI items, and the problems associated with the phased delivery schedules used by DPSC on many of its contracts. These are the types of issues being addressed by the Clothing and Textiles Task Force as a by-product of its concern with the quality of C&T items.

IV. CONCLUSIONS AND RECOMMENDATIONS

This study addressed itself to four specific areas of concern with demand forecasting in the POI system. They are (1) the comparison of historic POI forecasts to actual demand, (2) the determination of the extent of seasonality and trend in the historic demand for POI items, (3) an examination of the actual operating levels used by POI customers, and (4) the comparison of projected and actual Service troop strengths. Conclusions and recommendations for each of these areas are presented.

(1) Conclusion: The analysis of the POI forecasts showed that considerable discrepancy exists between forecast and actual demand. In fact, the median or halfway point of the mean absolute percent error for all PGCs was 64%. A cursory analysis of the data showed that, for the most part, the demand data appeared to be quite erratic and unpredictable. This being the case, over half of all PGCs would have been forecasted with less error if each previous month's demand was used as the forecast for the next month.

Recommendation: In order to reduce the size of this error, a detailed examination of historic demand patterns is necessary to isolate the demand patterns and identify causal factors. One pattern requiring special attention is the one involving very low and/or zero demand for many time periods. If such a pattern was deemed to be typical of demand for a single PGC or a group of PGCs, then forecasting techniques which can handle this type of "lumpy" demand would need to be identified.

The problem of low or zero demand noted above suggests that some of the generic items examined may have been either new items replacing others or items being phased out (despite an attempt to exclude the former from the analyses). If this were the case, it would help to provide an explanation for the patterns observed in the demand data. If these were in fact discovered to be circumstances leading to erratic demand patterns, then these types of items could be addressed separately for forecasting purposes.

Until a detailed examination of demand patterns is performed, comparisons of the POI forecasts to those produced by alternate forecasting methods should be viewed with caution. Such comparisons, citing the superiority of one method over another, may be spurious as they are based on the data on hand and may not be true for future data.

(2) Conclusion: Although seasonal and trend patterns were identified for some PGCs, the majority did not show such patterns. Specifically, of the 300 PGCs studied, 32 were seasonal, 27 exhibited trend, 183 were essentially random, and 58 showed pattern not judged as trend or seasonal.

Given the erratic nature of the demand, it is perhaps not surprising that an attempt to identify consistent patterns in historic demand would prove fruitless for the majority of POI PGCs. However, some POI items do appear to demonstrate these patterns; and the POI system, due to its procedure for computing replenishment factors, fails to account for such patterns in demand (the exponential smoothing method used for other DLA items suffers from the same limitation). This suggests that an alternative method, such as the Winters procedure used in the analyses presented here, would produce superior forecasts for these items.

The 59 PGCs having trend or seasonal patterns represent just under 20% of all POI PGCs examined. Given this fact, it seems reasonable to conclude that seasonality and trend do not present widespread problems for the POI system (depending on one's perspective, 1 out of every 5 generic items may or may not meet the definition for "widespread". Other considerations here might include the number of NSNs represented by these 59 PGCs, and the demand quantity or dollar value of these items).

Recommendation: Some POI items could be forecasted more accurately by the use of techniques more appropriate for handling trend and seasonality. The use of a more specialized technique would undoubtedly produce more accurate forecasts for these items. It is not possible, however, to avoid first identifying those items which would be likely to benefit from this more specialized (and probably more complex) forecasting method, and then applying this method only to those items. To apply such a method "across the board" to all POI PGCs would represent a waste of effort and resources.

Identifying trend and seasonality is a time-consuming and subjective process. Demand data must constantly be monitored to ensure that past patterns, once identified, have not disappeared from more recent data. However, external sources of information exist which can aid tremendously in this process. For example, the Navy currently works closely with DPSC in identifying anticipated changes in retail sales due to trend or seasonality in its items. This type of information can be used in conjunction with the examination of historic demand data to generate forecasts which account for trend and seasonal patterns in demand.

(3) Conclusion. Analysis of the operating levels used by the POI system to compute DLA requirements failed to find any significant deviations from the one month level assumed by the POI system.

Recommendation: Operating levels may be dismissed as an issue in judging the accuracy of the POI system.

(4) Conclusion: A comparison of the forecast and actual troop strengths, used by the POI system to forecast replenishment demand, showed that the Service forecasts were reasonably accurate, especially when compared to the POI forecast errors discussed above. Projections of monthly end strengths, were quite accurate when errors were examined as a percentage of actual end strength. It should be noted, however, that end strengths for the Services are large enough so that even small percentage errors represent actual deviations in the thousands.

Service projections of new recruits were not as accurate as end strength forecasts. An explanation for this finding was suggested by the fact that the Services project new recruit input for many more subcategories of troops (i.e., PICs) than they do for end strengths. Attempts to forecast these subcategories, which have fewer troops to begin with, seem to be generally unsucessful. Moreover, since the POI system combines all of the requirements computed from the various PICs, it appears that greater precision might be gained by having the Services provide projections for fewer categories encompassing larger numbers of troops.

Recommendation: DLA continue to work with the Services to ensure the best possible information on troop strengths. Any forecasting system which relies on external data such as Service troop strength projections can only be as accurate as the data it receives. Improving the Service forecasts, especially for new recruit input, would improve the POI forecasts as well. Improving the former, however, is largely out of the control of DLA.

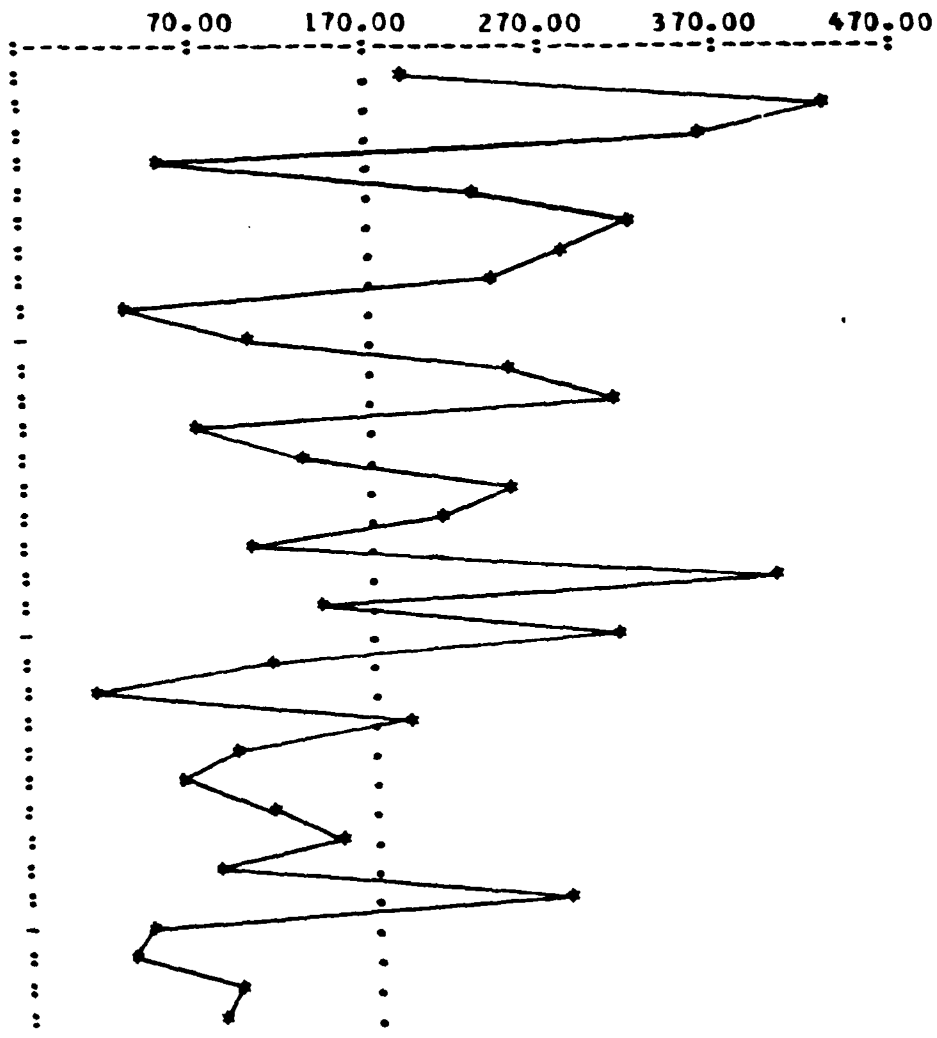
The actual reporting process is another factor that must be considered. It was observed that the Services have, over the last three years, sent in troop strength projections late, incomplete, and, occasionally, not at all. This is not to place blame for POI forecast inaccuracies on the Services, but rather to point out that these types of problems are inherent in a system which relies on external data. A forecasting system based strictly on data obtained internally (historic demand, for example) will have a different set of problems generated by its procedures. Therefore, a tradeoff must be made between the increase in forecast accuracy and the decrease in control associated with the use of external data.

Nothing in the analyses which produced the above suggests that the entire POI system be replaced by some other forecasting technique. Any of the issues discussed here could, and should, be handled within the structure of the current system.

Appendix A
Example of a Random Demand Pattern

GRAPHIC DISPLAY OF SERIES FOR VARIABLE IDMD
DATA - *
MEAN - .

OBS	DATA
1	192.000
2	435.000
3	359.000
4	49.0000
5	234.000
6	317.000
7	284.000
8	238.000
9	28.0000
10	97.0000
11	250.000
12	310.000
13	69.0000
14	133.000
15	252.000
16	211.000
17	104.000
18	398.000
19	139.000
20	313.000
21	111.000
22	8.00000
23	188.000
24	88.0000
25	57.0000
26	106.000
27	146.000
28	82.0000
29	285.000
30	37.0000
31	27.0000
32	91.0000
33	85.0000



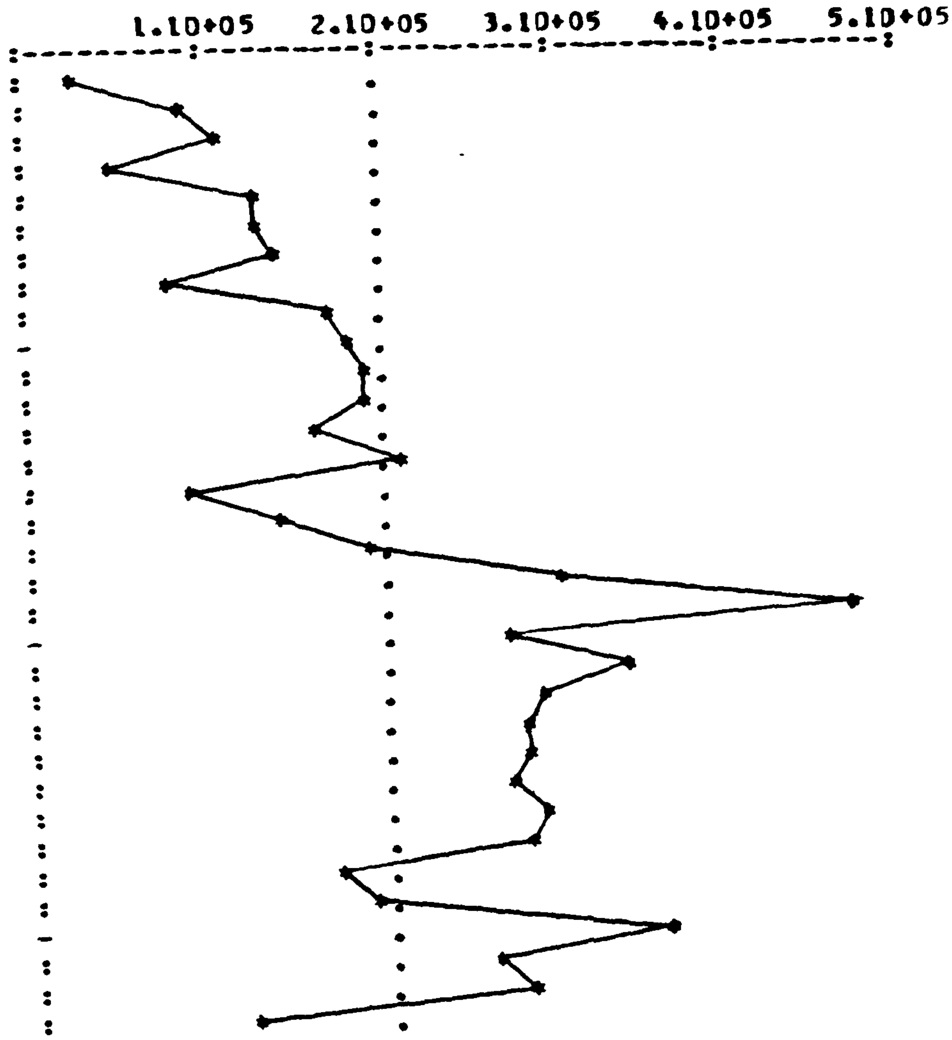
MEAN VALUE OF THE PROCESS
0.173420+03

STANDARD DEVIATION OF THE PROCESS
0.115470+03

Appendix B
Example of a Demand Pattern with Trend

GRAPHIC DISPLAY OF SERIES FOR VARIABLE IDMD
DATA - *
MEAN - .

OBS.	DATA
1	35419.0
2	100021.
3	121595.
4	55819.0
5	136185.
6	135808.
7	145015.
8	92778.0
9	178259.
10	187258.
11	203361.
12	195382.
13	171331.
14	221467.
15	96490.0
16	153193.
17	199171.
18	314331.
19	478148.
20	276432.
21	353419.
22	302941.
23	292766.
24	289073.
25	281313.
26	304862.
27	285908.
28	179096.
29	195153.
30	365254.
31	274192.
32	286060.
33	129079.



MEAN VALUE OF THE PROCESS
0.21323D+06

STANDARD DEVIATION OF THE PROCESS
0.97462D+05

APPENDIX C

PGCs With Trend in Demand

PGC	Nomenclature	Trend Direction	Peak Month
00143	Trousers, Men's	up/down	10-82
00179	Coat, All-Weather	up	10-82
00292	Coat, Camouflage	down	10-81
00833	Belt, Individual Equ	up/down	3-82
01278 *	Coat, Woman's	up/down	5-82
01298 *	Shirt, Woman's	down	4-82
01304	Skirt, Woman's	down	8-82
01307 *	Skirt, Woman's	up/down	5-82
01312 *	Slacks, Women's	down	12-81
01317	Tunic, Woman's	down	3-82
01470	Boots, Safety	down	5-82
01507 *	Shoes, Basketball	up/down	8-82
01666 *	Jumper, Man's	up/down	10-82
01667 *	Trousers, Men's	up/down	10-82
01694 *	Cap, Camouflage	up/down	6-82
01713 *	Socks, Men's	up	4-83
01741 *	Shirt, Woman's	up	10-83
01753 *	Cap, Garrison	up	5-83
01765 *	Coat, Man's	up	10-83
01770 *	Undershirt, Man's	up/down	6-83
01771	Drawers, Men's	up	7-83
01776 *	Trousers, Men's	up	10-83
01781 *	Beret, Woman's	up	9-83
01783 *	Neck Tab WM Sht F/S	up	10-83
01827	Trousers, Men's	up	3-84
10344	Canteen, Water	up	5-83
17630 *	Neck Tab WM Sht Blk	up	10-83

* Denotes monetary clothing allowance (bag) item.

APPENDIX D

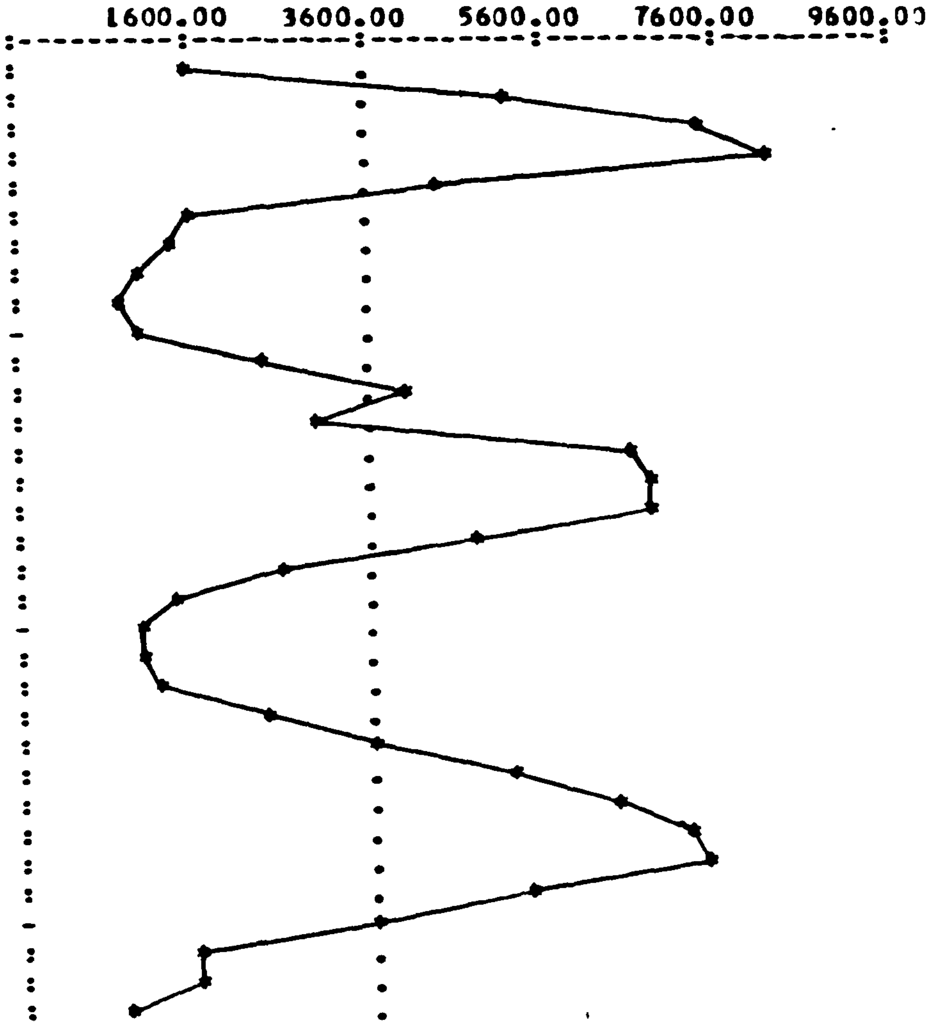
Comparison of Moving Average (MA) and POI Forecasts for Items with Trend

PGC	POI MSE	MA MSE	Percent Difference	MA Length
00143	30,913	22,631	26.8%	3
00179	92,201	44,179	52.6%	2
00292	573,598,464	7,181,581	98.7%	10
00833	265,712,144	73,002,096	72.5%	2
01278	12,277,715	1,150,221	90.6%	10
01298	83,758,736	5,829,728	93.0%	9
01304	30,928,144	2,250,497	92.7%	6
01307	13,237,314	1,162,463	91.5%	10
01312	5,260,625	268,928	94.9%	4
01317	6,898,407	1,843,952	73.3%	6
01470	628,389,632	201,526,640	67.9%	8
01507	145,652,384	23,373,152	83.9%	3
01666	71,794,544	42,398,512	40.9%	2
01667	68,279,200	52,916,656	22.5%	2
01694	4,720,521,220	3,343,079,940	29.2%	2
01713	39,355,592,700	6,199,443,460	84.2%	2
01741	184,688,768	31,491,408	82.9%	2
01753	3,069,837	731,688	76.2%	4
01765	1,726,080,770	20,024,256	98.8%	2
01770	35,335,204,900	10,971,594,800	68.9%	2
01771	7,346,200,580	2,794,383,100	62.0%	2
01776	438,969,856	299,009,280	31.9%	2
01781	95,516,912	70,798	100.0%	6
01783	4,066,746,880	11,473,467	99.7%	3
01827	105,221,472	1,340,248	98.7%	3
10344	535,783,680	234,396,416	56.2%	4
17630	4,210,358,020	6,153,120	99.8%	3

Appendix E
Example of a Seasonal demand Pattern
(12-Month Season)

GRAPHIC DISPLAY OF SERIES FOR VARIABLE IDMD
DATA - *
MEAN - .

OBS	DATA
1	1514.00
2	5253.00
3	7344.00
4	8117.00
5	4305.00
6	1503.00
7	1439.00
8	961.000
9	868.000
10	1000.00
11	2467.00
12	3957.00
13	2964.00
14	6634.00
15	6843.00
16	6741.00
17	4851.00
18	2524.00
19	1468.00
20	972.000
21	917.000
22	1115.00
23	2307.00
24	3581.00
25	5126.00
26	6420.00
27	7285.00
28	7377.00
29	5362.00
30	3666.00
31	1615.00
32	1648.00
33	900.000



MEAN VALUE OF THE PROCESS
0.36074D+04

STANDARD DEVIATION OF THE PROCESS
0.23942D+04

APPENDIX F

PGCs With Seasonal Patterns

Season Length	PGC	Nomenclature
3 mo.	00007	Coat, Men's
	00021	Trousers, Men's
	00292	Coat, Camouflage
	00794	Body Armor, Fragment
	01507 *	Shoes, Basketball
	01646 *	Cap, Hot Weather
	01758 *	Shirt, Utility
	01964 *	Overcoat, Men's
4 mo.	00110 *	Cap, Garrison
	01649 *	Shirt, Utility
5 mo.	00066 *	Coat, All-Weather
	00279 *	Frame, Service Cap
	00309 *	Trousers, Utility
	01757 *	Shirt, Utility
	01776 *	Trousers, Men's
6 mo.	00301 *	Shirt, Utility
	01647 *	Coat, Women's
	10316	Bag, Laundry
7 mo.	01667 *	Trousers, Men's
	01745 *	Slacks, Women's
8 mo.	10550	Shower Pail, Collaps
9 mo.	01783 *	Neck Tab WM Sht F/S
10 mo.	01469	Boots, Flyers'
	10516	Pocket, Ammunition
12 mo.	00049	Glove, Inserts, Cold
	00172	Gloves, Men's
	00179	Coat, All Weather
	01338 *	Shirt, Woman's
	01474	Boots, Cold Weather
	01478	Boots, Extreme Cold
	01635 *	Skirt, Woman's
15 mo.	01628	Overshoes, Men's

* Denotes monetary clothing allowance (bag) item.

APPENDIX G

Comparison of Winters' Model and POI Forecasts for Seasonal PGCs

Season Length	PGC	POI MSE	Winters MSE	Percent Difference
3 mo.	00007	115,825,443	263,901	99.8
	00021	116,364,739	755,075	99.3
	00292	561,558,345	2,487,393	99.6
	00794	3,380,724	1,243,173	63.2
	01507	147,752,899	16,232,466	89.0
	01646	1,413,496,311	58,818,848	95.8
	01758	7,724,167	1,287,572	83.3
	01964	9,239,369	3,999,244	56.7
4 mo.	00110	3,488,340	2,177,762	37.6
	01649	6,187,068	6,016,450	2.7
5 mo.	00066	27,240,543	6,230,025	77.1
	00279	144,601	85,595	40.8
	00309	494,137,108	439,169,280	11.1
	01757	201,546	16,166,833	*
	01776	521,443,862	152,899,728	70.7
6 mo.	00301	408,688,662	201,392,944	50.7
	01647	1,623,918	964,916	40.6
	10316	3,956,975	2,912,576	26.4
7 mo.	01667	72,900,936	63,934,224	12.3
	01745	74,392,364	19,894,460,400	*
8 mo.	10550	165,618	1,153,735	*
9 mo.	01783	3,314,812,544	10,320,423	99.7
10 mo.	01469	151,241	411,165	*
	10516	140,239	498,734	*
12 mo.	00049	5,782,074	1,009,357	82.5
	00172	540,649	16,706	*
	00179	93,679	51,411	45.1
	01338	3,957,611	1,961,064	50.4
	01474	171,220,190	75,433,248	55.9
	01478	9,645,859	6,428,086	33.3
	01635	25,770,177	14,945,253	42.0
15 mo.	01628	531,770,207	169,044,256	68.2

* Indicates POI forecast superior to Winters' model.

APPENDIX H

DEFENSE LOGISTICS AGENCY
HEADQUARTERS, DEFENSE PERSONNEL SUPPORT CENTER
2800 SOUTH 20TH STREET
PHILADELPHIA, PENNSYLVANIA 19101

IN REPLY REFER TO DPSC-TM (J. Farny/(AV)444-3174/amr)

FEB 14 1985

SUBJECT: Analysis of Program Oriented Item System (POIS) for Forecasting Clothing Items

TO: DLA-O

1. Reference: "Analysis of the Program Oriented Item System for Forecasting Clothing Items" prepared by Dr. Stan Orchowsky, DALO-DORO, dated 25 January 85.

2. The Program Oriented Item System of forecasting for clothing items was originally designed to respond quickly and accurately to fluctuations in troop end strengths and recruit input. The accuracy of this system is dependent on the maintenance of accurate data such as allowances, timely and accurate projections of troop strengths and recruit input, relationships between clothing items and the various service programs which use the items, pipeline factors, and operating levels. The analysis of the program oriented items system prepared by Dr. Stan Orchowsky, DALO-DORO, has indicated several areas which might benefit from further examination.

a. First, demand patterns for POIS items should be examined to identify groups of items which might benefit from specialized forecasting techniques. Concur in the need for special forecasting for such items as new and phase-out items for which adjusted replenishment rates and size tariffs are utilized. For items for which demand surges or decreases are anticipated quarterly adjustments to the replenishment rates are programmed.

b. Second, items which exhibit seasonality should be forecast using different procedures than the standard POIS forecast. Concur in the need for seasonal forecasting techique for affected items. Current SAMMS system does not accommodate seasonality. When seasonality is result of recruit input variation with the time of the year, the POIS system can forecast this seasonality if the service submits a seasonal requirement.

c. Third, troop strength projections and the number of service programs for which initial issue forecasts are generated should be reexamined with an emphasis on improving accuracy and reducing the number of programs. Concur in the need for more accurate troop projections. The use of the program identification codes (PIC) currently in POIS is determined by the use of various items by different service groups. Items used by one initial issue group may not be used by another or may have different allowances. To roll up all initial issue requirements under one PIC is to assume that all initial issue groups are users and have the same allowance. Therefore, do not agree on the suggestion of reducing the number of separate PIC's.

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3. A brief examination of the items used in the study revealed that new and phase-out items were included and may have affected the comparison of forecast and demand.

4. The POIS forecasting performs with accuracy similar to the methods of forecasting used by other commodities. The study has found no single method of forecasting that performs more accurately for all of the items within POIS. We should proceed with extreme caution before making any minor changes to the techniques now used which in the end could result in decreased overall reliability.

FOR THE COMMANDER:

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