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Improving Marine Corps Enlisted Personnel Loss Forecasting

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James P. Boyle
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13. ABSTRACT (Maximum 200 words) This report describes the development of a model to forecast End of Active Service (EAS) and non-End of Active Service (non-EAS) losses. A validation study was conducted comparing the forecasts generated by the current method and forecasts generated by the method described in this report with actual FY87 losses. The Linear Exponential Smoothing method outperformed the current method in producing 1-year ahead forecasts at the pay grade and year of service level of detail. Further research will explore other model specifications including multivariate and econometric techniques.				
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FOREWORD

This report describes the method used in the prototype Enlisted Rate Generator to produce forecasts of End of Active Service (EAS) and non-End of Active Service (non-EAS) loss rates. The Enlisted Rate Generator is one of the components of the Enlisted Planning System (EPS). This work was conducted under program element 0603732M (Marine Corps Advanced Manpower Training Systems), work unit number C0073-D (Human Resources Management and Forecasting), sponsored by the Deputy Chief of Staff for Manpower and Reserve Affairs (MIS).

JOE SILVERMAN
Director
Manpower Systems Department

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SUMMARY

This report describes the development of a model to forecast End of Active Service (EAS) and non-End of Active Service (non-EAS) loss rates at the pay grade and year of service level of detail. Loss rate series were constructed using inventory and loss data extracted from the Enlisted Personnel Database for the period FY81 through FY86. Several univariate time-series techniques were applied to each series. The techniques were ranked according to how accurately they forecasted losses over history. The winning technique, the technique which was found to be the most accurate, was used to forecast FY87 EAS and non-EAS losses.

The FY87 forecasts of EAS and non-EAS losses were compared with forecasts of FY87 losses generated by the current Enlisted Plans Section, MPP-20, method and with actual FY87 losses. Validation was performed separately for each loss type. For EAS losses, the forecasts generated by the winning technique were more accurate than the forecasts generated by the current MPP-20 technique in three of the four pay grades (E3, E4, and E6) in which over 90 percent of total EAS losses occur. Comparable results were obtained for non-EAS losses. The forecasts generated by the current method are less accurate in three of the four pay grades (E1, E3, and E4) in which most non-EAS losses occur. The current MPP-20 method is considerably more accurate in the second largest pay grade, E2.

The prototype Enlisted Rate Generator will use the winning technique, Linear Exponential Smoothing. The rate generator, a component of the new Enlisted Planning System (EPS), produces forecasts of EAS and non-EAS loss rates by pay grade and year of service. These rates are used by the prototype Inventory Projection Model (IPM) to produce forecasts of EAS and non-EAS losses. A subsequent version of the IPM will require loss rate forecasts at the occupational field level of detail in addition to pay grade and year of service. Further research will explore other model specifications including econometric and multivariate techniques using occupational field, pay grade, and year of service data.

CONTENTS

	Page
INTRODUCTION	1
Problem	1
Objective	1
USMC Enlisted Personnel Losses	2
APPROACH	4
Techniques Examined	7
The Forecasting Competition	10
Generating FY87 Loss Forecasts	10
RESULTS	11
CONCLUSIONS AND FUTURE PLANS	13

INTRODUCTION

Problem

Marine Corps enlisted force managers depend on accurate forecasts of personnel inventories to develop and execute a set of personnel plans. Because of the vacancy-driven nature of the personnel system, accurate inventory projections hinge on accurate forecasts of annual personnel losses. The current Marine Corps loss forecasting method has two serious shortcomings: it generates inaccurate forecasts, and the forecasts are not at the level of detail needed to produce accurate and defensible plans. These shortcomings have force management consequences. For example, in FY87 an overforecast of nearly 700 attrition losses from pay grade E-1 led to a large, unplanned reduction in recruit accessions to avoid violating end strength and budget constraints.

Objective

This report describes research intended to: (1) improve United States Marine Corps (USMC) enlisted loss forecasting accuracy at the pay grade level, while (2) providing a forecasting method capable of operating at the pay grade and year of service (YOS) level of detail. The research consisted of a forecasting "competition" among a set of univariate time series methods and the current Marine Corps loss forecasting technique. Each method was used to predict All-Marine (ALMAR) End-of-Active-Service (EAS) and non-EAS (attrition) loss rates by individual pay grades and YOS, 1 year ahead.¹ The validation identified a "winner," a technique that, on average, was more accurate at the pay grade level than the others. The report summarizes the improvements in accuracy realized by using the new technique.

The winning technique has been incorporated into the prototype Enlisted Rate Generator. As a component of the new Enlisted Planning System (EPS), the rate generator produces forecasts of EAS and non-EAS loss rates by pay grade and YOS.² These rates are used by the prototype Inventory Projection Model (IPM) to produce EAS and non-EAS loss forecasts.

¹Loss rate is defined as the proportion of a begin fiscal year inventory cell (e.g., pay grade E-4, YOS 4), which leaves during the fiscal year. The rate, when applied to the begin inventory population, yields losses from the population.

²EPS is a collection of models currently under development. When completed, it will be used to forecast the behavior of the enlisted force and produce a variety of manpower plans (e.g., Promotion Plan, Accession Plan).

Methods other than univariate time series can be used to forecast loss behavior. Demographic and compensation related information can be incorporated into econometric forecasting models. These models allow the effect(s) of changes in policy on loss behavior to be estimated.³ Combining forecasts generated by multiple models can be used to produce a single forecast of loss behavior.⁴ Alternatively, multivariate time series methods can be used to forecast losses. The methods described above and their appropriateness for forecasting Marine Corps enlisted personnel losses will be investigated under a separate research effort.

USMC Enlisted Personnel Losses

Enlisted personnel losses are divided into two types: EAS and non-EAS losses. Marines who reach the end of their service contract (i.e., End of Active Service (EAS) date) and do not reenlist or extend are considered EAS losses.⁵ In contrast, when a Marine departs the service for administrative or disciplinary reasons, it is considered a non-EAS loss. Separation Designator Numbers (SDNs) identify the reason an individual has left the Marine Corps. For example, completion of required service is represented by SDN MBK1 and is included in the group of SDNs that make up the EAS loss category. Similarly, fraudulent entry into the Marine Corps, represented by SDN JDA1, is included in the group of SDNs that make up non-EAS losses. Figure 1 shows the size of non-EAS and EAS losses for FY81-FY87.

A begin fiscal year inventory can be divided into two distinct groups: the population "at risk" and the population "not at risk." The "at risk" group includes all Marines who will reach EAS sometime during the fiscal year, as well as those Marines whose EAS dates have already expired and Marines who are being retained beyond their EAS for the "convenience of the government." The remainder of the begin inventory makes up the population "not at

³See Carter, G. M., Michael P. Murray, R. Yilmaz Arguden, Marygail K. Brauner, Allan F. Abrahamse, Harvey Greenberg, and Deborah K. Skoller (1981). Middle term loss prediction models for the Air Force's enlisted force management system. RAND/R-3482-AF for a discussion of a variety of econometric models used to forecast Air Force enlisted personnel losses.

⁴Alternative ways of combining forecasts are discussed in Russel, T. D., and E. E. Adam, Jr. (1987). An Empirical Evaluation of Alternative Forecasting Combinations. Management Science. 33(10).

⁵Some early release and early out programs permit Marines to leave prior to EAS. However, the loss is still considered an EAS loss.

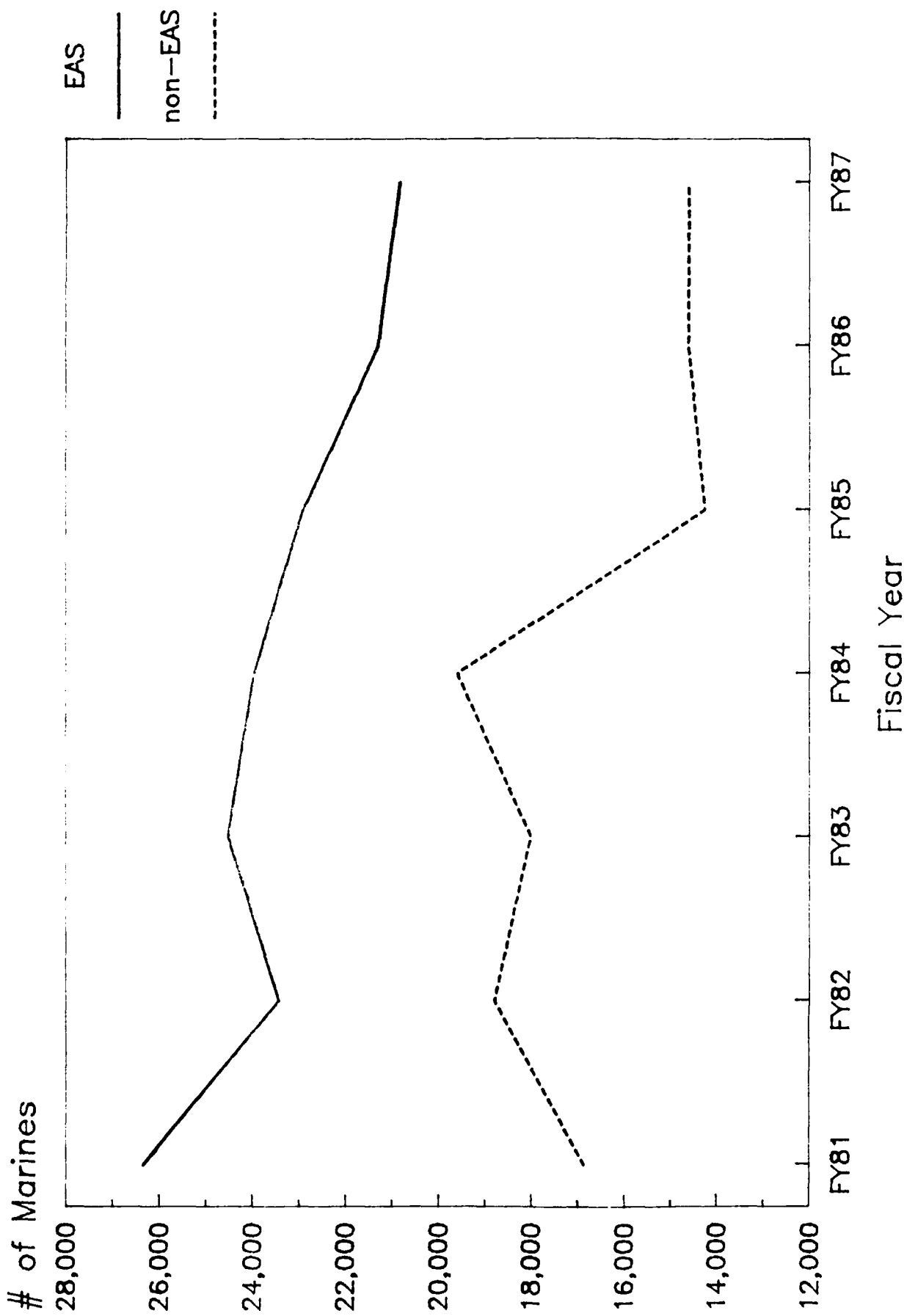


Figure 1. EAS and Non-EAS Losses, FY81-FY87.

risk." Marines in this group have EAS dates beyond the end of the fiscal year. The majority of EAS losses derive from that portion of the inventory said to be "at risk."⁶ For example, 87 percent of all FY87 EAS losses came from the population at risk.

As shown in Figure 2, the proportion of the begin fiscal year inventory in the population "at risk" has been declining from over 25 percent at the beginning of FY81 to 18 percent at the beginning of FY87. At least two explanations account for this phenomena. First, the mean length of enlistment for non-prior service gains has grown from 3.6 years in FY81 to 4.5 years in FY87. Second, the increasing frequency of early reenlistments has reduced the number of Marines in the population at risk.

APPROACH

Figure 3 outlines the process used to generate historical EAS and non-EAS loss rates. Begin fiscal year inventories by pay grade and YOS were extracted from the Enlisted Personnel Data Base for FY81-FY86. These inventories were then divided into population at risk and population not at risk using the criteria described above. EAS and non-EAS losses for FY81-FY86 were also extracted from the data base and arrayed by pay grade and YOS. Each loss type was further subdivided into losses from the population at risk and losses from the population not at risk.⁷ These inventory and loss data were used to generate EAS and non-EAS loss rates defined as the number of losses from a population type, pay grade, and YOS cell (e.g., EAS losses from the population at risk, E-4, YOS 4) divided by the begin fiscal year inventory in that cell (e.g., population at risk, E-4, YOS 4).

Several univariate time series techniques were applied to each loss rate series.⁸ In a univariate method, the forecasted rate for a cell depends only on historical rates for that cell. No effort

⁶Most EAS losses from the population not at risk are retirement losses. Other EAS losses from this population include some early releases and Officer Candidate Class (OCC) graduates.

⁷Logically, all Marines are "at-risk" to be a non-EAS loss. To maintain consistency across both loss types, non-EAS losses from the population at risk and the population not at risk were forecasted separately. Again, the EAS date was used to identify the at risk and not at risk populations.

⁸There are a total of 1,116 series, one for each rate type (EAS and non-EAS), population (at risk and not at risk), pay grade, and YOS (i.e., $2 \times 2 \times 9 \times 31 = 1,116$ series).

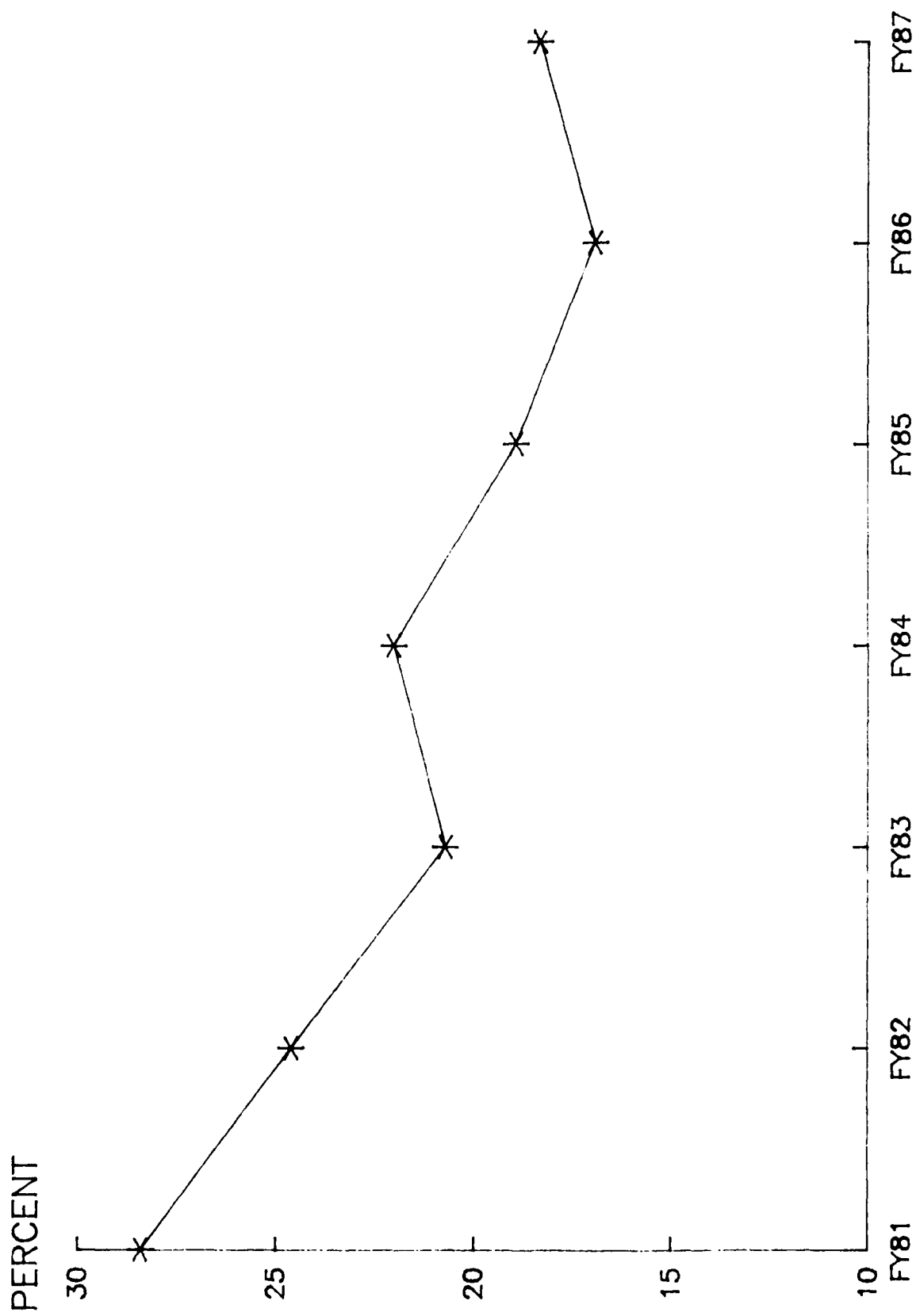


Figure 2. Percent of Begin Inventory in Population at Risk.

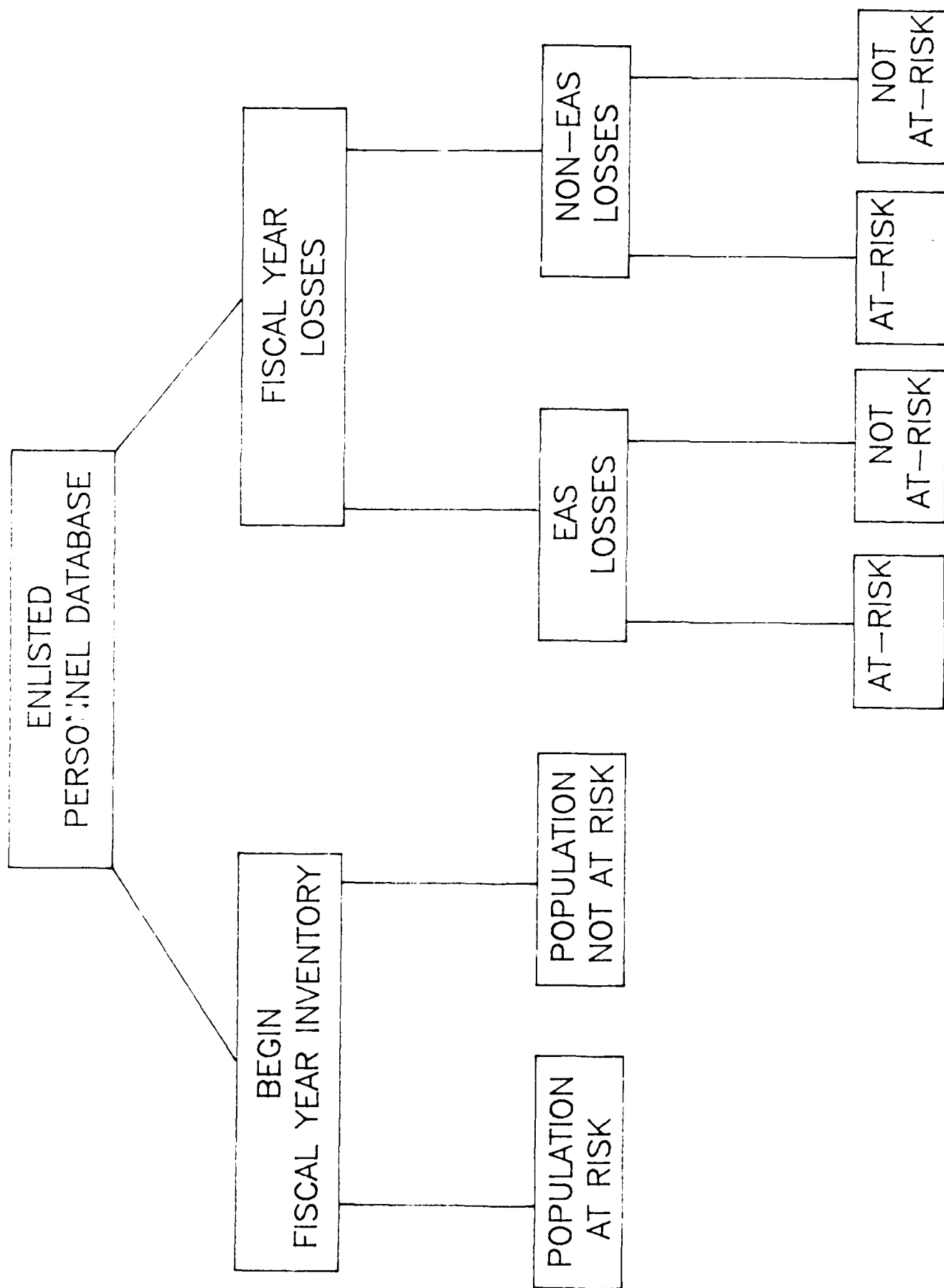


Figure 3. EAS and Non-EAS Loss Rate Generation Process

was made to allow rates from the other cells to influence a forecast as in multivariate time series methods. The techniques were ranked according to how accurately they forecasted losses over history. The most accurate technique was then selected to generate FY87 loss forecasts. These forecasts were then compared to FY87 loss forecasts made by the current USMC method.⁹ The results quantify the improvements in forecast accuracy that could have been realized in FY87 by using the winning technique. Since MPP-20 could supply only FY87 forecasts, comparisons of accuracy were based on this 1 year.

Techniques Examined

Examination of a number of loss rate series revealed several patterns in the data. Some series appeared to fluctuate about a constant value, while others exhibited either increasing or decreasing trends. This diversity demanded a collection of forecasting techniques capable of modeling a variety of loss rate behavior. Because only six observations per series were available (FY81-FY86), methods requiring many observations to estimate model parameters (e.g., Box-Jenkins models) could not be employed. These considerations led to the selection of the four techniques described below. With the exception of the naive technique, several model specifications were examined under each technique.

1. Naive: The naive technique forecasts the next year's rate with the current year's rate. The forecasting equation is

$$F_{t+1} = R_t \quad (1)$$

where R_t is the loss rate for year t and F_{t+1} is the forecasted rate for year $t+1$. The naive technique can give reasonable forecasts if rates are similar from year to year.

2. Weighted Averages: Forecasts representing weighted averages of historical rates also give reasonable results for stable time series. In contrast to the naive technique, a weighted average technique allows older historical rates to contribute to the forecast. Three weighted average models (WA1 through WA3) were tried. The first model, WA1, weights historical loss rates by their respective begin year inventories. The forecasting equation is

⁹The current USMC method for forecasting losses uses the naive technique to forecast EAS and non-EAS loss rates. Both rates are forecasted at the pay grade and month level of detail. Other dimensions vary by type of loss. For example, non-EAS loss rates are produced at the mental category and education level of detail. EAS loss rates are produced at the occupational field and YOS level of detail.

$$F_{t+1} = \frac{I_t}{\sum_{i=1}^n I_{t-i+1}} R_t + \dots + \frac{I_{t-n+1}}{\sum_{i=1}^n I_{t-i+1}} R_{t-n+1} \quad (2)$$

$$= \frac{L_t + \dots + L_{t-n+1}}{I_t + \dots + I_{t-n+1}}$$

where the R's are past loss rates, the I's are past begin year inventories, the L's are historical losses, and F_{t+1} is the forecast for year $t+1$. In (2), the value n represents the total number of years of data available. This model is appropriate for a binomial model which hypothesizes that losses are generated by a probability of leaving which is constant over time.¹⁰

The second weighted average model, WA2, weights all past year's rates equally. The forecasting equation is

$$F_{t+1} = \frac{R_t + R_{t-1} + \dots + R_{t-n+1}}{n} \quad (3)$$

All past rates contribute equally to the forecast.

Finally, a third weighted average model, WA3, weighting recent rates more heavily than rates in the more distant past, was used. The forecasting equation is given by

$$F_{t+1} = \frac{n}{\sum_{i=1}^n i} R_t + \frac{n-1}{\sum_{i=1}^n i} R_{t-1} + \dots + \frac{1}{\sum_{i=1}^n i} R_{t-n+1} \quad (4)$$

In all of the above weighted average forecasts, n represents the total number of years of data available. All three models use FY81 through FY86 rates to forecast the FY87 rate.

3. Simple Exponential Smoothing: Simple exponential smoothing models are weighted average models in which the weights

¹⁰See Grissmer, D. W. (1985). The accuracy of simple enlisted forecasts, RAND Corp/N-2078-MIL for a discussion of the binomial model as applied to enlisted personnel loss rates.

decline exponentially into the infinite past.¹¹ This relationship can be represented algebraically as:

$$F_{t+1} = \alpha R_t + (1-\alpha)F_t \quad (5)$$

where α is a "smoothing parameter" lying between 0 and 1. Note that the forecast for the next period, F_{t+1} , is a compromise between the current rate, R_t , and the forecast for the current period, F_t . When $\alpha = 0$, the model ignores the current rate, and the forecast is constant from year to year. At the other extreme, when $\alpha = 1$, the model completely ignores the current forecast and immediately adapts to the new level of the series. Note that $\alpha = 1$ corresponds to the naive forecast. Three models (ES1 through ES3), corresponding to the values $\alpha = .2, .5$, and $.8$, were chosen to represent the exponential smoothing technique.

It should be noted that to initiate the process in (5), an initial forecast must be supplied. Any convenient value can be chosen. For example, often the simple average of the available data is used. This convention was followed in applying all exponential smoothing models described in this report.

4. Linear Exponential Smoothing: The linear exponential smoothing technique is an extension of the exponential smoothing technique. The forecasting equations are

$$S_t = \alpha R_t + (1-\alpha)F_t \quad (6a)$$

$$T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1} \quad (6b)$$

$$F_{t+1} = S_t + T_t \quad (6c)$$

Two smoothing parameters, α and β , assume values between 0 and 1. Equation (6a) supplies a new level, S_t , as a weighted average of the new observation and the previous forecast. Equation (6b) updates a trend, T_t , in a similar manner. The new forecast, F_{t+1} , given by equation (6c), is the sum of the new level and new trend. Linear exponential smoothing models can adapt to both changing level and changing trend in a time series. Three models (LES1 through LES3) were chosen to test the linear exponential smoothing technique. The associated α -values were equal to those used for the exponential smoothing case (i.e., $\alpha = .2, .5$, and $.8$, with $\beta = .5$ in all three cases).

As in the exponential smoothing models, start-up values are needed to begin the process. An initial level and initial trend

¹¹A presentation of exponential smoothing models and their equivalent forms can be found in Makridakis, S., Wheelwright, S., & McGee, V. (1983). Forecasting methods and applications (2nd ed.). John Wiley and Sons.

can be chosen in a number of ways. Frequent choices for these start-up values are obtained by performing a simple linear regression of the available data against time and setting them equal to the intercept and slope, respectively, of the fitted regression line. All linear exponential smoothing models considered were initialized in this way.

The Forecasting Competition

Each of the 10 models was used to generate annual 1 year ahead loss rate forecasts for each rate type, pay grade, and YOS for FY82-FY86. The rate forecasts were then applied to their corresponding begin year inventories to yield a forecast of losses. Next, the losses were summed across YOS to produce a forecast of pay grade losses by type. Then, these pay grade level forecasts were compared to actual losses for each year. Finally, the accuracy of each method was summarized by computing the mean absolute deviation (MAD) over the 5 year period. The model with the smallest MAD was considered best. The technique associated with the best model was the winning technique.

Table 1 records the results of the 36 (4 rate types x 9 pay grades) forecasting competitions. Note that the linear exponential smoothing technique won in 17 of the 36 competitions--almost 50 percent of the time. The other techniques won less often, with the naive technique the overall loser--winning only 2 of 36 competitions. Furthermore, the 17 rate type-pay grade combinations where the linear exponential smoothing technique prevailed accounted for, on average, over 56 percent of the total historical losses.

Generating FY87 Loss Forecasts

Because the linear exponential smoothing technique was the winning technique from Table 1, all rate series were forecasted with a linear exponential smoothing model.¹² Since there are an infinity of possible linear exponential smoothing models (corresponding to all possible pairs α and β), a decision had to be made to restrict the number of pairs considered. Somewhat arbitrarily, nine models corresponding to the pairs $(\alpha, \beta) = .2, .5, .8$ were chosen to represent the class of linear exponential smoothing models. For each series, the MAD was computed for each of the nine pairs. The pair yielding the smallest MAD was used to generate the FY87 rate forecast. The loss forecast was then obtained by applying the forecasted rate to the FY87 beginning inventory. In this way, EAS and non-EAS losses from both the at

¹²Many of the loss rate series were consistently zero over the sample period. The forecast for these series was automatically set to zero, and it was not necessary to apply the linear exponential smoothing technique.

risk and not at risk populations were forecasted by pay grade and YOS.

Table 1
Results of Forecasting Competitions

Technique	Wins	Percent of Total Losses	Winning Percentage
Naive	2	1.72	6
Weighted Average: (all models)	2	.58	6
WA1	1	.01	
WA2	1	.57	
WA3	0	.00	
Exponential Smoothing: (all models)	15	41.47	41
ES1	14	40.73	
ES2	1	.74	
ES3	0	.00	
Linear Exponential Smoothing: (all models)	17	56.23	47
LES1	16	54.90	
LES2	1	1.33	
LES3	0	.00	

It should be pointed out that the above procedure is repeated when forecasts are to be updated (i.e., when new data becomes available). Specifically, given the FY81 through FY87 rates for a particular series, the minimizing pair (α , β) (possibly different than before) generates the FY88 forecast for that series.

RESULTS

Forecasted EAS losses were summed across the at risk and not at risk populations and across all YOS cells to produce the total pay grade EAS loss forecasts. Table 2 lists these FY87 forecasts along with the actual EAS losses. The forecast errors are also reported, as are the errors as percentages of the actual losses. The last column gives the percentage error associated with MPP-20's forecasts. Note that MPP-20's percentage errors are larger in seven of the nine pay grades. Furthermore, the MPP-20 forecast of losses for E-4, the pay grade with the largest number of losses, is less accurate, and the MPP-20 forecast is less accurate in three

of the four pay grades (E-3, E-4, E-5, E-6) accounting for over 90 percent of the total EAS losses.

Table 2

FY87 EAS Loss Forecasts by Pay Grade

Pay grade	Losses (L)	Forecasts (F)	Error (F-L)	%Error $((F-L)/L) \times 100$	MPP-20 %Error
E-1	166	209	43	25.90	7.59
E-2	572	450	-122	-21.33	47.13
E-3	5744	5782	38	.66	27.33
E-4	8849	7779	-1070	-12.09	-17.70
E-5	3058	2951	-107	-3.50	2.63
E-6	922	852	-70	-7.59	30.45
E-7	375	354	-20	-5.60	194.34
E-8	575	590	15	2.61	1966.67
E-9	284	282	-2	-.70	100.00

Table 3 provides a similar report on FY87 non-EAS losses. The results are comparable to those from Table 2, but less dramatic. The MPP-20 forecast is less accurate in six rather than seven of the nine pay grades. Moreover, although the MPP-20 forecast is again less accurate in three of the four largest pay grades (E-1, E-2, E-3, E-4), it is only slightly less accurate in the largest pay grade, E-1, and considerably more accurate in the second largest pay grade, E-2.

Table 3

FY87 Non-EAS Loss Forecasts by Pay Grade

Pay grade	Losses (L)	Forecasts (F)	Error (F-L)	%Error $((F-L)/L) \times 100$	MPP-20 %Error
E-1	5443	5942	499	9.17	10.95
E-2	3593	4182	589	16.39	-0.32
E-3	3103	2992	-111	-3.58	-19.51
E-4	977	939	-38	-3.89	-23.63
E-5	534	546	12	2.25	33.24
E-6	231	297	66	28.57	-39.12
E-7	61	58	-3	-4.92	-45.03
E-8	7	11	4	57.14	-27.12
E-9	2	12	10	500.00	23.40

Recall that the accuracies reported in Tables 2 and 3 were the result of using the best LES model in a restricted class of nine LES models. Note that these accuracies likely would have improved

if a broader class of LES models had been considered, or if the winning technique were used for each rate type x pay grade combination, as reported in Table 1. The objective of this research however, was to identify one technique that could on average outperform MPP-20's incumbent loss forecasting technique across pay grades and loss types. (The Marine Corps' desire to rapidly implement the Enlisted Rate Generator in EPS precluded the extensive, custom computer programming required to implement cell-by-cell winning techniques.)

CONCLUSIONS AND FUTURE PLANS

The initial prototype Enlisted Rate Generator will employ the linear exponential smoothing technique. Based on the available data, this technique outperformed the current MPP-20 method for generating 1-year ahead forecasts at the pay grade and YOS level of detail. Further research is underway, which will expand the techniques considered to include multivariate methods and econometric model specifications. Also, various ways of combining forecasts generated by multiple techniques will be explored.

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