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20. ABSTRACT (*Continue on reverse side if necessary and identify by block number*)

Several time-series-based forecasting techniques were used to project Navy unrestricted line officer loss rates, by grade and length of service category. An autoregressive minimum absolute error regression model was selected as the overall best technique, producing a substantial increase in forecasting accuracy over previously used techniques.

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DEVELOPMENT AND ANALYSIS OF LOSS RATE FORECASTING TECHNIQUES FOR THE NAVY'S UNRESTRICTED LINE (URL) OFFICERS

NAVY PERSONNEL RESEARCH
AND
DEVELOPMENT CENTER
San Diego, California 92152

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DEVELOPMENT AND ANALYSIS OF LOSS RATE FORECASTING TECHNIQUES FOR THE NAVY'S UNRESTRICTED LINE (URL) OFFICERS

Edward S. Bres
Murray W. Rowe

Reviewed by
J. Silverman

Approved by
James J. Regan
Technical Director

Navy Personnel Research and Development Center
San Diego, California 92152

FOREWORD

This research and development effort was conducted in response to Navy Decision Coordinating Paper, Personnel Supply Systems (NDCP-Z0107-PN) under subproject PN.12, Officer Management Systems, and the sponsorship of the Deputy Chief of Naval Operations (OP-01). The objective of the subproject is to develop a set of user-oriented, computer-based models and techniques to assist in the development of a Navy officer force that meets its manpower requirements. This report describes improved techniques for forecasting loss rates for the Navy's unrestricted line (URL) officer community. The results of this work are now being used by OP-130, Officer Programs Implementation Branch, on a regular basis.

Acknowledgments are due to LCDR D. Parker and LT D. Burns, OP-130, for assistance in data collection and analysis.

DONALD F. PARKER
Commanding Officer

SUMMARY

Problem

The Navy uses estimates of unrestricted line (URL) officer losses (by type and grade) to plan promotions and accessions. Without accurate estimates, these plans could yield an officer force that does not meet authorized strengths.

Objective

The purpose of this effort was to compare the accuracy of an existing URL loss rate forecasting method with that of other techniques and to recommend an improved technique for estimating losses in each grade/length of service category.

Approach

A number of estimating techniques were tested to forecast loss rates for the total URL. These techniques used historical loss rate data (FY 1969-1977) by grade, years of commissioned service (YCS), and promotion status. Estimates generated for each technique were compared and the "best" techniques chosen on the basis of their relative forecasting accuracy over time.

Findings

1. Autoregressive time series methods produced generally more accurate estimates than simple or weighted moving averages when judged with a minimum mean absolute error (MAE) criterion.

2. Minimum absolute deviation (MAD) regression produced better autoregressive time series estimates than ordinary least squares (OLS) regression.

3. The best autoregressive technique, a 3-year MAD approach, reduced the forecast error of the previous technique over all grade/length of service combinations by 65 percent.

4. The autoregressive, 3-year MAD forecasting technique produces substantially more accurate loss rate estimates than the existing OP-130 method.

Conclusions

Although other techniques may produce better estimates in isolated cases, the autoregressive, 3-year MAD technique can conveniently be used in all cases with little loss of accuracy.

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INTRODUCTION

Problem

Within the Navy's officer personnel system, the expected number of vacancies at a particular grade (rank) determines the number of officers that will be (1) promoted to that grade and all lower grades, (2) gained from a variety of commissioning sources, and (3) transferred from a reserve to a regular commissioned status (a process called augmentation). Vacancies occur when the number of officers in a particular grade falls below the authorized strength for that grade. Vacancies are created when officers are promoted to the next grade or when officers leave the Navy (e.g., retire, resign, die, or leave through a variety of administrative actions). Without an accurate estimate of losses within each grade, plans for subsequent promotion, accession, and augmentation actions are likely to fall short of or exceed authorized strength.

Background

The Officer Program Implementation Branch of the Deputy Chief of Naval Operations (Manpower) (OP-130) operates the Projected Officer Personnel Inventory (POPI) model, in part, to project unrestricted line officer (URL) personnel inventories based on predicted loss behavior. These projections are used to help derived promotion, augmentation, and accession plans.

Losses are forecast for each URL grade, years of commissioned service (YCS),[1] and promotion status (PS)[2] "cell" by applying, for each cell, an estimated loss rate to the inventory at the beginning of the planning period. The rate indicates the proportion of officers from an inventory that can be expected to be lost during the period.

Loss rate forecasts are needed not only for the URL, but also for individual specialty areas within the URL (e.g., surface, submarine) and for the restricted line (RL) and Staff Corps. Forecasted rates are used in POPI, an accession planning model, a steady-state inventory projection model, and in studying the inventory structure of various speciality groups under a variety of scenarios.

The loss rate forecasts formerly used in these models and studies were generated from weighted averages of historical loss rates. After several years of using this method, OP-130 felt that an improved method was needed for estimating losses for all grade, YCS, and PS cells.

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[1]Years of commissioned service are computed from an officer's relative year group. The <u>year group</u> is the fiscal year of first commissioning. An officer's <u>relative year group</u> is then the number of years between the current fiscal year and that first commissioning. Hence, <u>relative year group</u> serves as a measure of length of (commissioned) service.

[2]<u>Promotion status</u> refers to whether or not an officer has failed to be selected for promotion to the next higher grade. Loss behavior tends to be significantly different for a LCDR or CDR who has failed selection to CDR or CAPT, respectively, than for one who has not failed ("due course"). As a result, historical loss trends and forecasts for "due course" and "failed selection" officers must be studied separately.

Objective

The purpose of this effort was to compare the accuracy of the existing URL loss rate forecasting method with that of other techniques and to recommend a "best" technique for each grade/YCS cell.[3]

[3]Henceforth, grade will refer to rank as well as to promotion status.

APPROACH

A number of techniques were tested in an attempt to forecast reasonably accurate loss rates for the total URL. Loss rates were forecasted and evaluated by grade (Ensign through Captain), years of commissioned service (YCS) (measured by relative year group), and promotion status. Table 1 displays the eight grades for which estimates were made and their relevant YCS. Each of the techniques employed assume that projected loss rates for a cell depend only on past rates for that cell. No attempt was made to relate loss rates to exogenous variables (e.g., private sector employment behavior) or individual officer attributes (e.g., education levels).

Table 1

Grades/Years of Commissioned Service (YCS) for Which Loss Rate Estimates Were Produced

Grade	YCS
Ensign (ENS)	0-1
Lieutenant JG (LTJG)	1-5
Lieutenant (LT)	3-11
Lieutenant Commander (LCDR)	8-15
Lieutenant Commander-Failed for Selection to Commander (LCDRF)	14-20
Commander (CDR)	14-21
Commander-Failed for Selection to Captain (CDRF)	20-26
Captain (CAPT)	20-29

Note. These YCS "zones" tend to represent length of service typical for "due course" and "fail select" officers. "Early select" officers are not broken out in this analysis.

After loss rate estimates were generated by each technique, they were compared and the "best" techniques chosen on the basis of their forecasting accuracy over time.

Nine years of historical loss rate data (FY69 through FY77, excluding FY7T) were used in the computations. These data were taken from the Attrition Data Base (ADB) maintained by OP-01. In the ADB, loss rates are generated each fiscal year by dividing the total number of losses in a grade/YCS cell by the beginning inventory in the cell. Losses in the ADB are defined in Table 2.

Techniques Examined

A plot of the nine annual observations for each grade/YCS cell indicated initially that several techniques or models might explain loss rate behavior. Some of the series displayed seemingly constant trends, others appeared to have increasing or decreasing linear trends, while still others suggested exponentially increasing or decreasing behavior over at least part of the observed period. This examination led to the test of the techniques described below:

Table 2

Losses by Type and BUPERS Loss Code

Type of Loss	BUPERS Loss Code
Retirement	891-898
Released from Active Duty (RAD)	890
Resignation	701-705, 810-811, 889, 912
Death	870
Discharge	801-807, 899, 903, 905
Community Change[a]	997

[a]Signifies change from one "community" to another (e.g., from URL to RL, from aviation to surface warfare) depending on how "communities" are defined.

1. "Naive" or Previous Year (PY): The simplest of all forecasting techniques is to suggest that next year's loss rate will be the same as this year's rate. This naive approach is described by

$$\hat{X}_{t+1} = X_t \tag{1}$$

where X_t is the loss rate for year t, and $\hat{X}_{t+1}$ is the estimated loss rate for year t + 1. It should be noted, however, that the naive model is reliable only if the data displays a rather constant trend.

2. Simple (Unweighted) Moving Averages (SM): A second approach was to take a simple or unweighted moving average of some specified number of past year's loss rates as a forecast for the current year. The forecast is then

$$\hat{X}_{t+1} = \frac{\sum_{i=1}^{n} X_{t-i+1}}{n} . \tag{2}$$

In order to smooth the data (i.e., to remove any extreme outliers), this method was modified as follows: The rates used for each estimate were compared to the mean of those rates--any data point falling outside of plus or minus (±) one standard deviation from that mean was removed from the moving average.

Five variations of this method were tried, using from 3 to 7 years of data to estimate the following year's rate. Although the SM approach gives relatively accurate estimates (i.e., the estimates minimize the sum of squared error from historical data), these estimates are not responsive to recent data. As the number of observations used (n) increases, the stability of the estimate increases, but the estimate will take n years to respond fully to an abrupt change in data. Since a dynamic process is being modelled, it may be more appropriate to use larger weights for recent data than those used for older data.[4] This consideration leads to the next method.

3. Weighted Moving Averages (WM): Intuitively, loss behavior for a grade/YCS cell should resemble the recent past more than the distant past, but the older observations may still have some influence. A weighted moving average with larger weights on recent data will reflect this emphasis. The prior OP-130 method of loss rate forecasting used a weighted moving average of this type:[5]

$$\hat{X}_{t+1} = \sum_{i=1}^{n} \frac{X_{t-i+1} \cdot (n-i+1)}{\sum_{i=1}^{n} i} \tag{3}$$

This method was also modified to exclude "outliers" in a fashion similar to the SM method.

As with the previous method, five versions of the SM method were tried, using from 3 to 7 years of data to estimate the next year's data.

Both the SM and WM methods are computationally convenient but they lack a methodology for selecting an appropriate weighting structure. For this reason, two additional types of weighting models that attempt to choose the appropriate weights were employed. These were exponential smoothing and autoregressive time-series models.

4. Exponential Smoothing (ES): The exponential smoothing (ES) model is a weighted moving average model, but with a set of weights that declines exponentially. The forecast for a loss rate one period ahead using the ES method is

$$\begin{aligned} \hat{X}_{t+1} &= (1-\alpha)X_t + (1-\alpha)\alpha X_{t-1} \\ &\quad + (1-\alpha)\alpha^2 X_{t-2} + \dots \end{aligned} \tag{4}$$

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[4] Brown, R. G. Smoothing, forecasting, and prediction. Englewood Cliffs, NJ: Prentice-Hall, Inc., 1963.

[5] The OP-130 method uses all historical data available to compute its loss rate estimate. For example, to estimate the FY78 rate, it would use FY69-FY77 rates. Under this scheme, the FY77 rate would have nine times the weight or importance of the FY69 rate. To obtain more than one estimate for validation purposes, however, the OP-130 method was represented by the model using only 7 years of historical data.

where α is a fraction between 0 and 1. The weighting pattern may be adjusted by selecting different values of α. When α is small, the weight given to the current observation is large and successive weights decline rapidly. On the other hand, if α is large, little weight is given to the current observation and subsequent weights decay slowly.

In practice, the form of the ES model in equation (4) is not suitable because computation of the forecasts requires an infinite number of previous observations. The following expression is used to compute the ES estimate for year t + 1 as function of the loss rate for year t and the prior ES estimate for year t:[6]

$$\hat{X}_{t+1} = (1-\alpha)X_t + \alpha\hat{X}_t \ . \tag{5}$$

This model was run for each grade/YCS cell using values of α from 0.0 to 1.0 in increments of 0.1. The "best" ES model for each cell (the "best" value of α) was selected on the basis of minimum forecast error (see section below on Selecting the "Best" Forecasting Technique).

5. Autoregressive Time Series (ARTS): In an ARTS model, the loss rate estimate is still a function of past observations, but the weights given to past observations are computed to minimize some function of forecasting error, rather than being selected a priori by the analyst. The form of the estimate is

$$\hat{X}_{t+1} = \hat{\emptyset}_1 + \hat{\emptyset}_2 X_t + \ldots + \hat{\emptyset}_{n+2} X_{t-n} \tag{6}$$

where the $\hat{\emptyset}_i$ are the parameter estimates determined from the regression.

Two regression approaches were used to estimate the parameters in (6). The first approach was the ordinary least squares (OLS) regression. This method finds the parameter estimates that minimize the sum of the squared errors between the loss rate estimates and observed values

$$\sum_{i=t-n}^{t} (X_i - \hat{X}_i)^2 \ . \tag{7}$$

Although computational requirements for OLS regression are more than those for previous methods, they are not excessive. Given certain assumptions about the loss rate distributions, the method also supplies estimates with desirable statistical properties. There are several reasons to look beyond OLS in our case, however. First, OLS estimates are sensitive to disturbance by outlier data--any data points that differ markedly from the rest of the historical data. Second, the criterion used to select a "best" forecasting

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[6]Nelson, C. R. Applied time series analysis for managerial forecasting. San Francisco: Holden-Day, Inc. 1973.

method will be minimum mean absolute forecast error--it's more important to come as close as possible each year than coming as close as possible in the "worst" year. There is another regression method that directly minimizes mean absolute forecast error and that is less sensitive to outliers--minimum absolute deviation (MAD) regression, a special case of constrained regression.[7] This method minimizes the sum of the absolute values of errors between loss rate estimates and historical rates

$$\sum_{i=t-n}^{t} |\hat{X}_i - X_i| \; . \tag{8}$$

MAD estimates can be computed using a linear programming (LP) software package, as was done here. Computational requirements are larger than for previous methods--a linear program must be solved for each loss rate estimate--but efficient use of an LP package or a special-purpose program limits computational requirements to an acceptable level.

The OLS and MAD regression approaches were tried with an ARTS model using 1, 2, and 3 years of historical data to forecast a second, third, and fourth year respectively. (Use of more than 3 years would be statistically unacceptable as it would reduce the number of degrees of freedom, already small, to only one.)

6. Time Trend (T): While few of the loss rate series examined appeared to follow a secular or time trend, the method of relating loss rates to a nonstationary, linear, time trend rather than past loss rates was tried. This involved regressing loss rates against relative time (1,2,...9) as indicated by

$$\hat{X}_{t+1} = \hat{a} + \hat{B}t \; . \tag{9}$$

Selecting the "Best" Forecasting Technique

Results for each loss rate estimating technique were calculated for each grade/YCS cell using the 9 years of historical data available. A technique was judged superior to another if it had a lower mean absolute error (MAE). The MAE was computed by summing the absolute deviations of a technique's estimated values from the corresponding actual loss rates over time and dividing by the number of years forecast. (The number of years forecast differed across techniques as some methods require more data than others to produce a forecast.)

Table 3 summarizes the techniques described above and indicates the number of estimates made for validation purposes for each period.

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[7] Charnes, A., & Cooper, W. W. Management models and industrial applications of linear programming, Vol. I & II. New York: John Wiley and Sons, Inc., 1961.

Table 3

Loss Rate Techniques Examined and Number of Validation Estimates Made with Each

Technique	Abbreviation	Number of Estimates
Naive or Previous Year	PY	8
Simple Moving Average (3 years)	SM3	6
Simple Moving Average (4 years)	SM4	5
Simple Moving Average (5 years)	SM5	4
Simple Moving Average (6 years)	SM6	3
Simple Moving Average (7 years)	SM7	2
Weighted Moving Average (3 years)	WM3	6
Weighted Moving Average (4 years)	WM4	5
Weighted Moving Average (5 years)	WM5	4
Weighted Moving Average (6 years)	WM6	3
Weighted Moving Average[a] (7 years)	WM7	2
Exponential Smoothing	ES	8
Autoregressive Time Series-OLS (1 year)	ARTS1-OLS	8
Autoregressive Time Series-OLS (2 years)	ARTS2-OLS	7
Autoregressive Time Series-OLS (3 years)	ARTS3-OLS	6
Autoregressive Time Series-MAD (1 year)	ARTS1-MAD	8
Autoregressive Time Series-MAD (2 years)	ARTS1-MAD	7
Autoregressive Time Series-MAD (3 years)	ARTS3-MAD	6
Time Trend	T	9

[a]The weighted moving average using 7 years of data represents the OP-130 technique.

RESULTS

The Navy Officer Corps is divided into three broad groups or "communities." The unrestricted line officers (URL), the restricted line and staff corps officers (RL/SC), and limited duty officers (LDO). As the largest of the three communities with nearly 60 percent of the active officer force, the URL is comprised of four general warfare specialities: surface, submarine, aviation (pilot and flight officer), and special warfare.

Loss rate techniques were evaluated for the total URL by grade and YCS cell. The best technique in each cell--that which has the smallest mean absolute error (BEST MAE)--is listed in Table 4. Analysis of the results addresses three questions: What are the best forecasting techniques? How accurate are they? How much of an improvement in forecast accuracy do the new techniques provide?

Table 4 is summarized in Table 5, which displays the distribution of BEST MAEs by grade. It indicates that the ARTS3-MAD technique has the minimum MAE in 38 of 56 (68%) grade/YCS cells. Alternatively, the previous technique, WM7, produces the best results in only 6 cells (10.7%). Finally, of the 13 techniques examined, three (ARTS2-MAD, ARTS3-MAD, and WM7) accounted for nearly 90 percent of the lowest MAEs.

Table 4

Best Loss Rate Forecasting Techniques (Minimum MAE) by Grade/YCS for Total URL

Grade	YCS	Technique	Mean Absolute Error
CAPT	20	ARTS3-MAD	.0042
	21	ARTS3-MAD	.0052
	22	ARTS3-MAD	.0192
	23	ARTS3-MAD	.0082
	24	WM7	.0110
	25	ARTS3-MAD	.0106
	26	WM7	.0218
	27	ARTS3-MAD	.0190
	28	ARTS3-MAD	.0032
	29	WM3	.0509
CDR	14	WM7	.0000
	15	ARTS3-MAD	.0024
	16	ARTS3-MAD	.0031
	17	ARTS3-MAD	.0022
	18	ARTS3-MAD	.0035
	19	ARTS3-MAD	.0114
	20	ARTS3-MAD	.0125
	21	SM7	.0029
CDRF	20	WM7	.0084
	21	ARTS3-MAD	.0084
	22	ARTS3-MAD	.0154
	23	ARTS2-MAD	.0189
	24	ARTS3-MAD	.0014
	25	SM6	.0143
	26	ARTS3-MAD	.1735
LCDR	8	ARTS3-MAD	.0103
	9	ARTS3-MAD	.0017
	10	ARTS3-MAD	.0009
	11	ARTS2-MAD	.0007
	12	ARTS3-MAD	.0032
	13	ARTS3-MAD	.0020
	14	ARTS3-MAD	.0017
	15	SM7	.0046
LCDRF	14	ARTS3-MAD	.0071
	15	WM5	.0081
	16	ARTS3-MAD	.0057
	17	ARTS3-MAD	.0169
	18	WM6	.0159
	19	WM7	.0280
	20	ARTS3-MAD	.1091
LT	3	ARTS3-MAD	.0726
	4	ARTS3-MAD	.0141
	5	ARTS3-MAD	.0111
	6	ARTS2-MAD	.0109
	7	ARTS3-MAD	.0049
	8	ARTS3-MAD	.0358
	9	ARTS2-MAD	.0604
	10	ARTS3-MAD	.1224
	11	ARTS3-MAD	.0580
LTJG	1	ARTS2-MAD	.1293
	2	ARTS3-MAD	.0180
	3	WM7	.0343
	4	ARTS3-MAD	.0322
	5	ARTS3-MAD	.1442
ENS	0	ARTS3-MAD	.0043
	1	ARTS3-MAD	.0016

Table 5

Distribution of Best Techniques (Minimum MAE) Over YCS by Grade

GRADE	PY	SM3	SM4	SM5	SM6	SM7	WM3	WM4	WM5	WM6	WM7	T	ES	ARTS1-MAD	ARTS2-MAD	ARTS3-MAD	TOTAL
CAPT	--	--	--	--	--	--	1	--	--	--	2	-	--	--	--	7	10
CDR	--	--	--	--	--	1	--	--	--	--	1	-	--	--	--	6	8
CDRF	--	--	--	--	1	--	--	--	--	--	1	-	--	--	1	4	7
LCDR	--	--	--	--	--	1	--	--	--	--	--	-	--	--	1	6	8
LCDRF	--	--	--	--	--	--	--	--	1	1	1	-	--	--	1	3	7
LT	--	--	--	--	--	--	--	--	--	--	--	-	--	--	2	7	9
LTJG	--	--	--	--	--	--	--	--	--	--	1	-	--	--	1	3	5
ENS	--	--	--	--	--	--	--	--	--	--	--	-	--	--	--	2	2
TOTAL	0	0	0	0	1	2	1	0	1	1	6	0	0	0	6	38	56
PERCENT OF TOTAL	(0.0)	(0.0)	(0.0)	(0.0)	(1.8)	(3.6)	(1.8)	(0.0)	(1.8)	(1.8)	(10.7)	(0.0)	(0.0)	(0.0)	(10.7)	(67.9)	(100.0)

To assess the accuracy of the best forecasting techniques, the grade/YCS cells were grouped by size of the minimum MAEs achieved. The groupings were:

Group	MAE Range
0	0.0000--0.0100
1	0.0101--0.0200
2	0.0201--0.0300
3	0.0301 and greater

A MAE of 0.0100 (Group 0) suggests that, "on the average," the loss rate estimate will lie in a range of ± 0.0100 around the actual loss rate value. For example, if the actual loss rate were 0.0200, the estimate is likely to be somewhere between 0.2100 and 0.1900. Hence, these "ranges" of MAE provide a sense of relative confidence in loss rate forecasts.

As Table 6 shows, in nearly half of the cells forecasted, the minimum MAE value fell in Group 0 (less than 0.0100). More important, roughly three-quarters of the cells had a MAE of 0.0200 or less.

Several of the least accurate forecasts (MAE greater than 0.0300) were found in YCS cells that represent the "flow" or promotion points during an officer's career. These flow points change frequently due to the effect of specific promotion plans. These changes can result in erratic cell sizes over time and, in turn, highly variable loss rates. As an example of this problem, see LT 3, LT 8-11, and LTJG 4-5 in Table 4. Other relatively inaccurate estimates were produced in junior grade (LT and below) cells where the number of losses varied widely relative to strength as a result of policy changes designed to adjust the force to meet future needs. As an example, in ENS 1, a changing release from active duty (RAD) policy caused loss rates to vary from .0230 to .1250 in a 4-year period (FY72-75).

To reduce complexity and data processing costs in inventory projection models, it is desirable to minimize the number of loss rate forecasting techniques used. Ideally, the same technique would be used for all forecasts. Since ARTS3-MAD was the best technique in 38 of 56 cells, an examination was made to determine if ARTS3-MAD might be an acceptable "second best" estimator in the other 18 cells as well. This involved computing weighted averages of the BEST and the ARTS3-MAD MAEs. To indicate relative importance of each error, the weight assigned to a cell's MAE was its FY77 begin strength. This produced average BEST and ARTS3-MAD MAEs of .0135 and .0166, respectively. This 23 percent increase in average MAE (from .0135 to .0166) suggests the extent of the forecast accuracy sacrificed by reducing data processing costs. The ARTS3-MAD MAE of .0166, however, indicates that ARTS3-MAD is still a rather accurate forecasting method. OP-130 has, in fact, elected to minimize data processing costs and assure increased accuracy by using ARTS3-MAD as its sole loss rate forecasting technique.

Finally, while the ARTS3-MAD method was found, in most cases, to be a better loss rate estimator than the previous method (WM7), it is still important to determine how much of an improvement the new technique realized. Weighted averages of the MAEs produced by the two techniques in each cell gave an average error of .0166 for ARTS3-MAD and .0469 for WM7. This implies that the change from the old to the new technique resulted in an average reduction in forecast error of nearly 65 percent. To illustrate this improvement, the new technique reduces mean error for projected LT losses by 418 people out of a mean loss of 2000 people each year. This improvement will allow more accurate accession plans, as well as a better estimate of the promotion base for LCDRs.

Table 6

Relative Accuracy of Best URL Loss Forecasts by Grade
(Distribution of Techniques by MAE Groupings)

MAE GROUP (Range)	Number of Best Forecasts by Grade								Total	
	CAPT	CDR	CDRF	LCDR	LCDRF	LT	LTJG	ENS	N	Percent
0 (0.0000-0.0100)	4	6	3	7	3	1	0	2	26	46.4
1 (0.0101-0.0200)	4	2	3	1	2	3	1	0	16	28.6
2 (0.0201-0.0300)	1	0	0	0	1	0	0	0	2	3.6
3 (0.0301 and greater)	1	0	1	0	1	5	4	0	12	21.4
Total	10	8	7	8	7	9	5	2	56	100.0

CONCLUSIONS

1. The 3-year autoregressive time series model (ARTS3-MAD) produces substantially more accurate loss rate estimates than the existing OP-130 method.

2. Although other techniques may produce better estimates in isolated cases, the ARTS3-MAD technique can conveniently be used in all grade/length of service cases while still increasing accuracy relative to the OP-130 method.

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Analysis Division, Directorate of Personnel Plans, Headquarters, U. S. Air Force, Washington
Personnel Research and Measurement Division, Assistant for Plans, Programs, and Analysis, Air Force Manpower Personnel Center, Randolph Air Force Base
Systems Development and Support Division, Directorate of Personnel Data Systems, Air Force Manpower Personnel Center, Randolph Air Force Base
Personnel Research Division, Air Force Human Resources Laboratory (AFSC), Brooks Air Force Base
Occupational and Manpower Research Division, Air Force Human Resources Laboratory (AFSC), Brooks Air Force Base
Technical Library, Air Force Human Resources Laboratory (AFSC), Brooks Air Force Base
Program Manager, Life Sciences Directorate, Air Force Office of Scientific Research (AFSC)
Army Research Institute for the Behavioral and Social Sciences (Reference Service)
Defense Documentation Center (12)