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An Analysis of the Navy's Selective Reenlistment Bonus (SRB) Management System and ROGER Model

15 March 2008

by

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Abstract

The Navy's Selective Reenlistment Bonus (SRB) Management System uses a model known as ROGER, which was developed as a Windows-based application in the mid-1990s to assist the Navy Enlisted Bonus manager in developing and analyzing SRB plans during the execution year. Substantial changes in the structure of the SRB program have led to increasing levels of predictive error in the model. Under-prediction of SRB Program costs by the model leads to over-execution of the SRB budget, and necessitates the reprogramming of funds from other enlisted programs.

The objective of this thesis is to assess the performance of the Navy's ROGER model, which is used to forecast the reenlistment behavior of sailors in Zones A, B, and C, and estimate the budget costs of the SRB Program. The thesis will assess the accuracy of the reenlistment-forecasting model and identify factors that lead to prediction errors. In addition, the thesis will analyze the role of ROGER in the SRB planning process, which involves Naval Personnel Command, Enlisted Community Management Branch (BUPERS-32), as well as the Office of the Chief of Naval Operations (OPNAV). Finally, the thesis will outline methods to improve the identification of the population of SRB-eligible sailors in all Zones and the predictive accuracy of the ROGER model.

Keywords: SRB, Reenlistment, ACOL, enlisted retention, ROGER

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We would also like to thank those military and civilian members on the OPNAV and BUPERS staffs who were willing to meet with us and give us information that was valuable throughout our process. Additionally, our appreciation goes to the Defense Acquisition Research Program, who accepted our thesis into their program, and provided travel funding and transcription/editing support.

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To Anna, Lily and Maggie this degree is meaningless without your love and support. Thank you for understanding when I could not be around.

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List of Abbreviations and Acronyms

ACOL	Annualized Cost of Leaving
AEF	Advanced Electronics Field
ALOR	Average Length of Reenlistment
ATF	Advanced Technical Field
BUPERS	Bureau of Naval Personnel
CNA	Center for Naval Analysis
CPI	Consumer Price Index
CPS	Current Population Survey
DCNO	Deputy Chief of Naval Operations
DMDC	Defense Manpower Data Center
DOD	Department of Defense
DRM	Dynamic Retention Model
EAOS	End of Active Obligated Service
ECM	Enlisted Community Manager
EMF	Enlisted Master File
EMR	Enlisted Master Record
EPA	Enlisted Program Authorizations
FY	Fiscal Year
GAO	Government Accounting Office
HEAOS	Hard End of Active Obligated Service
HM	Hospital Corpsman
ICT	Inventory Continuation Trackers
LOR	Length of Reenlistment
LOS	Length of Service
NAVADMIN	Naval Administrative Message
NEC	Naval Enlisted Classification
NF	Nuclear Field
NPC	Naval Personnel Command
OBLISERVE	Obligated Service

OMB	Office of Management and Budget
OLS	Ordinary Least Squares
OPNAV	Office of Chief of Naval Operations
OPTEMPO	Operational Tempo
OTT	OBLISERV to Train
PCS	Permanent Change of Station
PNEC	Primary Navy Enlisted Classification
POM	Program Objective Memorandum
PRD	Projected Rotation Date
RMC	Regular Military Compensation
SDAP	Special Duty Assignment Pay
SEAOS	Soft End of Active Obligated Service
SECNAV	Secretary of the Navy
SKIPPER	Skilled Inventory Personnel Projection for Enlisted Retention
SRB	Selective Reenlistment Bonus
SRBMS	Selective Reenlistment Bonus Management System
STAR	Selective Training and Reenlistment Program
YOS	Years of Service
4YO	4-Year Obligor
5YO	5-Year Obligor
6YO	6-Year Obligor

I. Introduction

A. Background

The Selective Reenlistment Bonus Management System (SRBMS), established in 1974 to replace the Regular Reenlistment Bonus system, is the Navy's "primary tool for addressing short-term [enlisted personnel] retention problems in critical military specialties (or skills)" (GAO, 2002, November, p. 1). The intent of the program is to facilitate retention of enlisted personnel in critical or undermanned occupational specialties, such as nuclear specialists and linguists. The reenlistment program is more cost-effective than alternatives such as across-the-board pay raises.

Initial guidance in a Department of Defense (DoD) Instruction and Directive of 1985 dictated that only critical specialties that affected readiness would be included in the program (GAO, 2002, November, p. 2). That Instruction was canceled in 1996 and was not replaced until 2004. Current guidance on the service-wide SRB program is provided in DoD Instruction 1304.29, December 2004, and DoD Directive 1304.21, January 2005.

The responsibility for the Navy's SRBMS falls under the Deputy Chief of Naval Operations (DCNO), Manpower, Personnel, Training and Education, (MTP&E), Code N1. As such, N1 views the Selective Reenlistment Bonus (SRB) as the Navy's primary force-shaping tool, vital in achieving enlisted retention requirements in ratings, Navy Enlisted Classifications (NECs), and skill areas.

1. History

Historically, at least since FY97, the Navy has, more often than not, failed to contain SRB costs within the congressionally appropriated amount. In most years, funds are reprogrammed from within the enlisted personnel budget in order to meet the increased costs of the SRB program (GAO, 2002, November). Figure 1 and

Table 1 show the requested and actual expenditures for the SRB program for fiscal years 1997 through 2007.

Figure 1. Navy's Selective Reenlistment Bonus Program's Requested and Actual Expenditures, Fiscal Years 1997-2007 (Navy budget justification books)

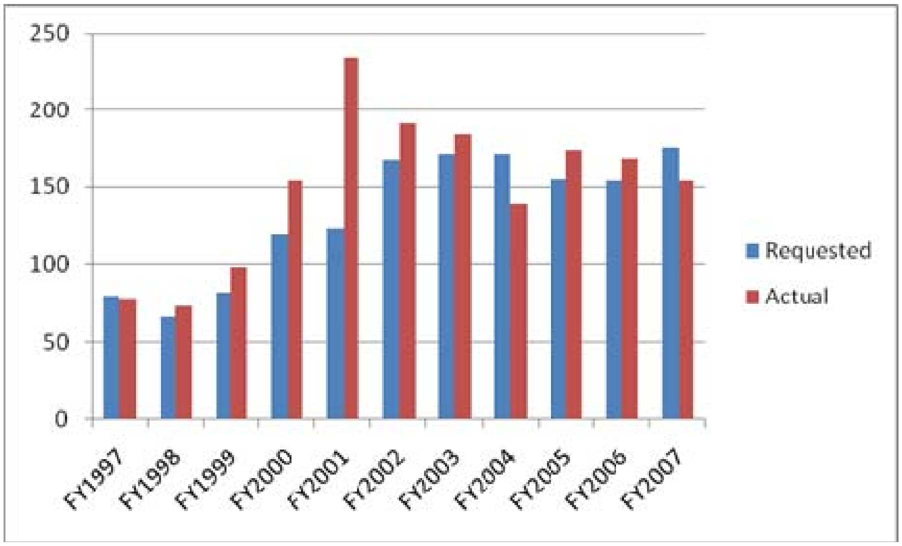

Table 1. Navy's Selective Reenlistment Bonus Program's Requested and Actual Expenditures, Fiscal Years 1997-2007 (Navy budget justification books)

		Initial SRB in Millions		
Year	Requested	Actual	diff	Missed
FY1997	80	78	2	2.56%
FY1998	66	73	-7	9.59%
FY1999	82	98	-16	16.33%
FY2000	120	154	-34	22.08%
FY2001	124	234	-110	47.01%
FY2002	168	191	-23	12.04%
FY2003	172	184	-12	6.52%
FY2004	172	139	33	23.74%
FY2005	155	174	-19	10.92%
FY2006	154	169	-15	8.88%
FY2007	176	*154	22	14.29%

*FY 2007 "actual" is an estimate as of Feb08

Not only has the number of specialties receiving SRBs increased over time, the number of SRB-takers has also increased. In FY97, the Navy offered SRBs to 204 of its 1,146 specialties (which included 107 ratings and 1,039 NECs) and had 11,580 bonus recipients. In FY01, 219 of the 1,153 specialties were offered SRBs, with 21,356 takers (GAO, 2002, November). Additionally, in FY01, the Navy awarded SRBs to more enlistees than the other services, though it was offered to the smallest percentage of occupational specialties (GAO, 2002, November).

2. Program Specifics

a. Skill Eligibility

The current DoD Directive states that the sailor must have or agree to be trained for a military skill that is designated as “critical” by the Secretary of the Navy (SECNAV) and must reenlist for at least three years (PDUSD(P&R), 2005). The DoD Instruction explains in further detail the types of skills that are awarded SRBs. Skills may be designated “critical” by the SECNAV only if they meet at least one of the following criteria (PDUSD(P&R), 2004):

- History of critical personnel shortages in three or more adjacent year groups within bonus zones. Parameters to define “critical shortages” are determined by SECNAV and include such factors as potential impact on ability to accomplish mission.
- Skill retention is below established retention goals.
- Skill is considered “relatively arduous or otherwise unattractive” compared with other military or civilian occupations.
- Expected return to investment is justified.

b. Sailor Eligibility

As previously stated, to be eligible for an SRB, sailors must either possess the skill or commit to training for the skill for which the SRB is offered, as well as reenlisting for an additional three years of obligated service. Additional requirements are as follows:

- Must qualify for skill prior to termination date of SRB award, unless in training for skill. If in training, eligibility for award amount established at time of reenlistment in effect until training completed.
- Paygrade E-3 or higher.
- Must reenlist or voluntarily extend enlistment on active duty for a minimum of three years.
- Reenlistment must be no later than three months (or fewer, as determined by SECNAV) after discharge or release from active duty service.
- Veterans with break in service of three months to four years may qualify for broken service or prior service re-entry SRB program. Regulations defined by SECNAV.
- Existing obligated service contracts (such as extensions) cannot be used to attain eligibility.
- Eligibility cannot be obtained by combining extensions.
- Reenlistments or extensions to achieve minimum obligated service in order to qualify for an officer program are not SRB eligible.
- Must meet any additional requirements prescribed by SECNAV.

Enlisted careers are broken down into three reenlistment zones, and by law, each sailor is allowed to reenlist for an SRB only once in each zone (providing, of course, that he/she is eligible for the SRB at the time of reenlistment). Zones are broken down as follows:

- Zone A: Individual must have at least 17 months of continuous active duty service but not more than 6 years of active duty on the date of reenlistment.[1]
- Zone B: Individual must have completed at least 6 but not more than 10 years of active service on the date of reenlistment.
- Zone C: Individual must have completed at least 10 but not more than 14 years of active service on the date of reenlistment.
- Sailors with more than 14 years of service are not eligible for an SRB and are sometimes referred to as Zone D sailors.

[1] Note: Though regulations state that individuals must have 17 months of service for eligibility for an SRB, the ROGER model does not differentiate 0-17 months of service, but includes all personnel from 0-6 YOS.

c. Award Amounts

The amount of bonus is determined as the product of: (1) the enlistee's current monthly basic pay multiplied by (2) the number of years of additional obligated service, multiplied by (3) the pre-determined SRB multiple. Twice each fiscal year, the Secretary of the Navy determines which specialties will be eligible for the SRB and determines the applicable multiples. In general, those occupational specialties designated as most critical, hardest to fill, or those with the highest training costs usually have the highest multiples. Additionally, the Navy considers the civilian wages that some specialties can earn outside the military when determining the appropriate size of the bonus multiple for an occupational specialty.

Although congressional authorization designates the maximum allowable multiplier and bonus amount (which varies year to year), the individual services set their own limits each fiscal year. For example, in fiscal year 2001, the congressional limits were set at a $60,000 bonus and a multiple of 15; however, the Navy determined their limit to be $60,000 and 8, respectively (GAO, 2002, November, p. 8). Over the years, the method in which SRBs are paid out has changed. Prior to 1979, SRBs were paid in annual installments over the reenlistment period, then from 1979-1982 in lump-sum amounts at the time of reenlistment. Currently in the Navy, 50% is paid lump-sum at the time of reenlistment and the remainder is distributed in annual installments over the contract period (Goldberg & Warner, 1982, p. 10).

B. Purpose of Thesis

As previously stated, SRB expenditures have consistently been underestimated, and this is a result of predictions made by the ROGER model. The prediction model uses an ACOL econometric framework. The ACOL model is a behavioral retention model designed to estimate how expected future pay changes and economic conditions affect the current propensity of enlisted personnel to reenlist. In addition to including the effects of military pay and unemployment rates, it also includes civilian wage levels and other factors in predicting current estimated reenlistment rates. The ACOL model is discussed in detail in Chapter II.

There are multiple issues with the accuracy of the current forecasting model (commonly referred to as ROGER[2]) utilized in the Navy's SRBMS. According to prior studies, the problems begin early in the model's process, with the identification of those sailors who will be eligible for the SRB in the coming fiscal year. In many cases, the population of SRB-eligible sailors is under-estimated, leading to an under-prediction of the number of sailors who will elect to reenlist for the SRB award. This leads to an over-expenditure of SRB program funds in the execution year and necessitates the reprogramming of funds from other enlisted programs to meet SRB program costs.

Multiple problems stem from inaccurate projections in the SRB Model. Besides creating budgetary issues that necessitate the reprogramming of funds amongst various manpower accounts to sustain the current year's SRB expenditures, the lack of accuracy of the forecasting model can also lead to personnel shortages or surpluses in certain occupational specialties. These manning problems can affect command performance and fleet readiness. Commands can find themselves with a shortage or a surplus of sailors if reenlistment rates are substantially different than predicted, which affects fleet readiness and ability to perform mission.

In analyzing the current forecasting model and its processes for use in today's military environment, identifying ways to improve the accuracy of the output is more relevant than ever. In the current climate of budgetary constraints and constantly changing manpower needs, the Navy is continually being asked to do more with less. Updating the ROGER model and the SRB process will greatly contribute to the Navy's ability to maintain readiness and retain highly skilled sailors in critical ratings,

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[2] ROGER is not an acronym, but was named after the person who originally used it, according to sources at OPNAV.

as well as provide more reliable estimate of the required SRB budget to support the program without taking away from other programs.

C. Scope and Methodology

This thesis conducts a thorough review of prior studies that are relevant to the SRBMS process. In addition, the thesis analyzes issues that are vital to the system input and forecasting model within the ROGER model. Prior studies include those that have previously identified shortcomings of the SRBMS, the ROGER model itself, and the variables utilized in current estimations, as well as those relating to retention behavior. The amount of literature available on related topics is extensive, and far beyond the scope of this thesis. Therefore, only those studies that were most pertinent to the researchers' particular area of study were selected for review.

In evaluating the input sources and estimation methods of the current ROGER system and the model's output, this thesis will identify potential areas for improvement to the current model. In particular, the thesis seeks ways: (1) to improve the identification of the SRB-eligible sailors; (2) to improve the accuracy of the projected number of SRB takers; and (3) to provide suggestions for constructing new Navy occupational groupings that will be more current and more accurate in terms of reflecting similar civilian occupations and wage levels.

The methodology utilized in this thesis is as follows: (1) a thorough review of a selected group of relevant articles, studies, papers and theses; (2) interviews with the Enlisted Community Managers (ECMs) and major stakeholders to the SRBMS; (3) an analysis of the current variables, performance, and role of the ROGER model in the SRBMS; (4) validation of the reenlistment forecasting model (which is based on the ACOL methodology); (5) an analysis of the identified issues with the current ROGER model; and (6) recommendations for improvements to the current model and process in order to provide more accurate projections.

D. Organization of Study

The thesis is organized into the following sections.

Chapter II. Overview of the SRB Process. This chapter provides an overview of the SRBMS process and the history of the occupational groupings used in prior studies.

Chapter III. The ACOL Reenlistment Model and Prior Studies. This chapter continues a review of literature pertinent to the Annualized Cost of Leaving (ACOL) model and reviews studies relevant to the forecasting model currently in use by the Navy (known as ROGER).

Chapter IV. Model Assessment. This chapter describes the assessment of current accuracy of the current ROGER model and examines the algorithms that identify the population of SRB eligibles and the occupational groupings.

Chapter V. Improvements to the Current Model. This chapter provides specific recommendations for improvements to the model in the following categories: (1) identification of SRB-eligible sailors; (2) updated variables to be used in the ACOL and ROGER models; (3) revised occupational groupings.

Chapter VI. Conclusions and Recommendations. This chapter summarizes the findings of the analysis and research, as well as providing recommendations for follow-on studies.

II. Overview of the SRB Process

The SRB process begins with the Enlisted Community Managers (ECMs, BUPERS-32) at the Bureau of Naval Personnel and involves ongoing collaboration with the Office of the Chief of Naval Operations (OPNAV) N1, DCNO (MPT&E) Manpower and Personnel. To manage their inventory and predict necessary retention, the ECMs use Inventory Continuation Trackers (ICTs). ICTs are based on information from the Enlisted Master Records that are imported into the Skilled Inventory Personnel Projection for Enlisted Retention (SKIPPER). Once the data is imported, continuation rates are estimated and compiled into easy-to-read formats. The ECMs' primary goal is to establish and meet their reenlistment goals to maintain Enlisted Programmed Authorizations (EPA) by each zone,[3] and the SRB is a retention tool used to help manage their inventory.

The ICT data and metrics are updated monthly and provide a graphic depiction of the following fields, by zone, for a selected rating (Kramer, 2006):

- EPA for as long as 4 fiscal years in the future (current year + 3), which can be broken down by FY and month.
- Number in current inventory.
- Number of sailors with Soft EAOS[4] (SEAOS) who have obligated service (OBLISERVE[5]) into the next zone.

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[3] As discussed earlier, Zone A is 17 months to 6 YOS; Zone B is 6-10 YOS; and Zone C is 10-14 YOS.

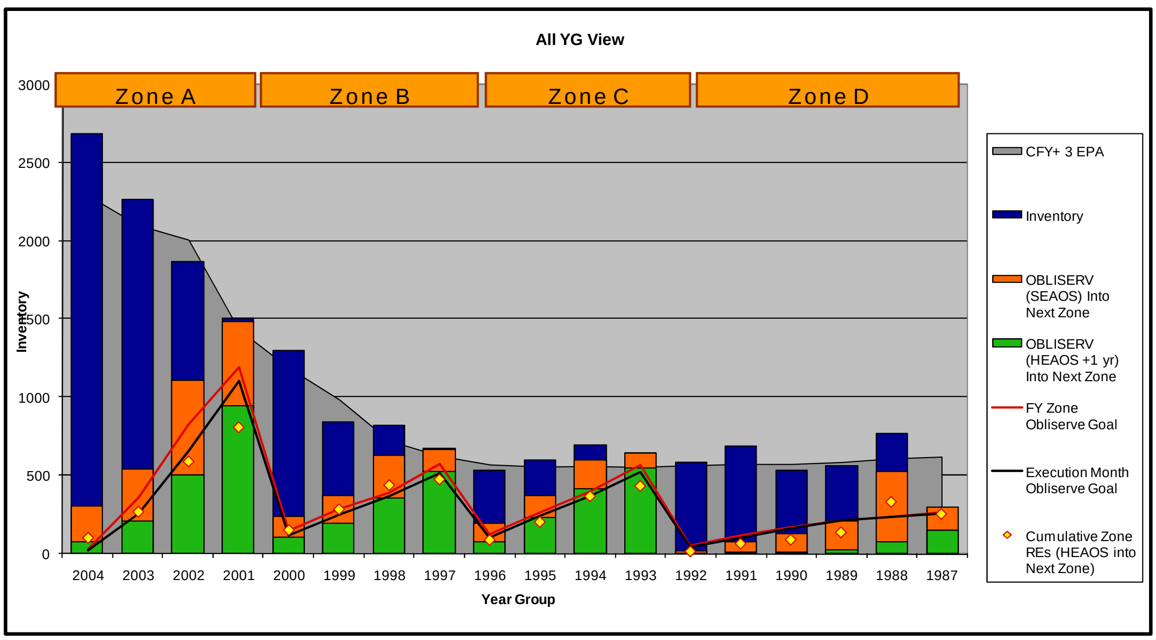
[4] The soft EAOS (SEAOS) is the last day of the sailor's total active duty obligation, including any executed agreements to extend enlistment or active duty (whether or not they have become operative).

[5] OBLISERV refers to the "Obligation to Serve." or the additional service time that a sailor must commit to complete, often in exchange for something from the Navy (e.g., a PCS move, training, or bonus money).

- Number of sailors whose Hard EAOS[6] (HEAOS) is more than one year of OBLISERVE into the next zone.
- FY zone OBLISERVE goal.
- Execution month OBLISERVE goal.
- Cumulative zone reenlistments with HEAOS into next zone.

Figure 2 is an example of an ICT and shows the inventories for the current fiscal year plus the next 3 years (gray trend line in the background), as well as inventories broken down by HEAOS and SEAOS in the bars. Additional lines are OBLISERV goals. There are a number of different views available to the ECMs; however, only one is provided in this thesis due to the large file size and difficulty with legibility in the converted file.

Figure 2. Example of an Inventory Continuation Tracker
(BUPERS-32, 2007)

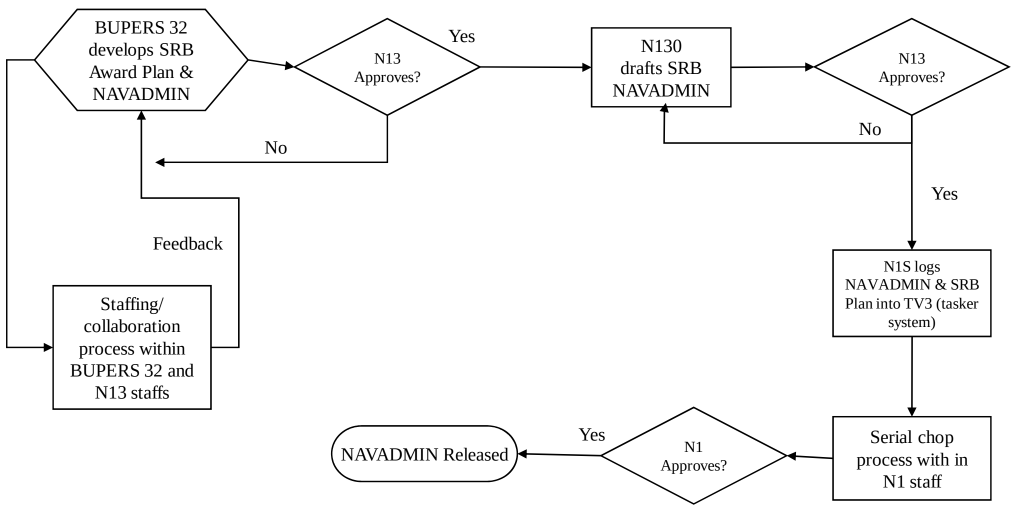


[6] The Hard EAOS (HEAOS) is the last day of the sailor's enlistment contract and does not include any agreements for extension of active duty. For example, if a sailor has a 4-year contract with a 2-year extension, his/her HEAOS is at the 4-year mark, and his/her soft EAOS (SEAOS) is at the 6-year mark.

The ICTs provide updated and necessary metrics to gauge OBLISERV behavior and determine where manning shortages are most likely to occur, thereby identifying where SRBs might be needed to meet EPA requirements.

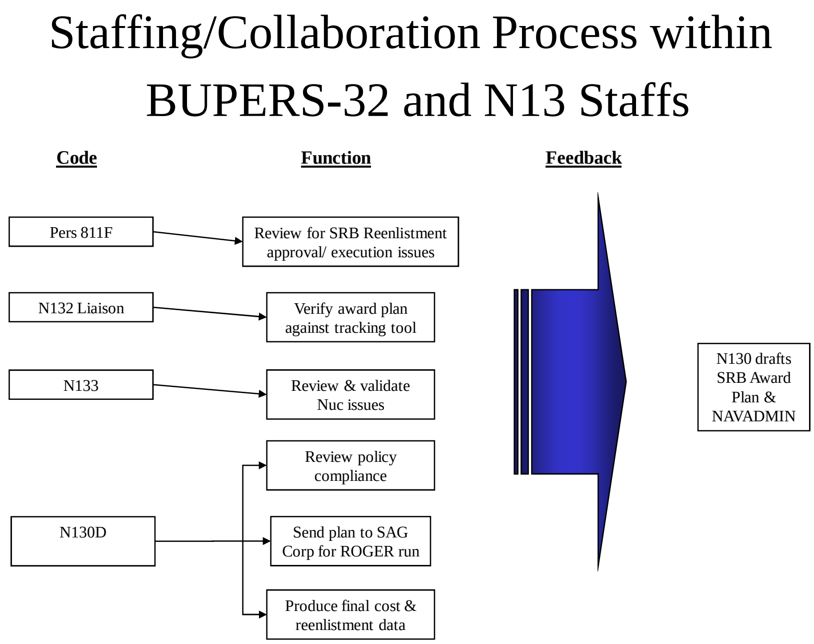
Using the ICTs and projected inventories, the ECMs and BUPERS-32 develop a proposed SRB Award plan and a Naval Administrative Message (NAVADMIN), which begins the SRB process, as diagrammed in Figure 3.

Figure 3. Overview of SRB Process
(OPNAV, N13 and BUPERS-32)



The ECMs determine the final multiple they feel is necessary for each of their respective communities, ratings, and critical NECs. Each ECM is fighting for a limited amount of funding to maintain adequate manning levels. During this process, there is staffing and collaboration between the BUPERS-32 and OPNAV N13 staffs, as mapped out in Figure 4.

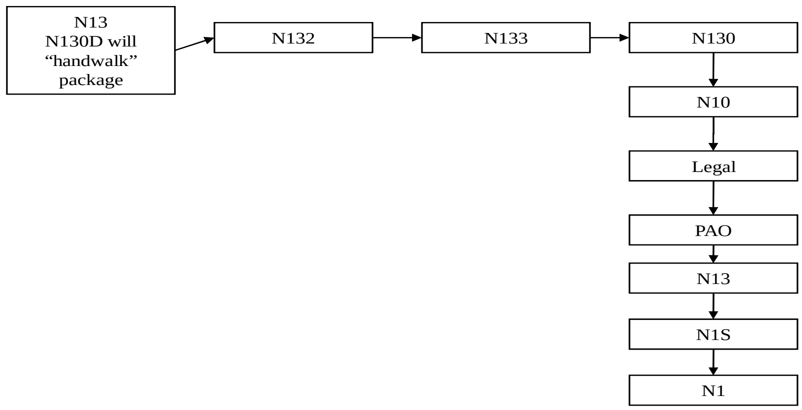
Figure 4. Staffing/Collaboration of BUPERS-32 and OPNAV
(OPNAV, N13)



It is throughout this process that issues with policy compliance, execution issues and issues with the nuclear program are resolved. Additionally, the award plan is verified against the tracking tool, and the proposed plan is sent to the SAG Corporation (the Navy's contractor for the ROGER model). SAG Corporation runs the plan through the model to calculate the estimated SRB costs. First, the population of sailors who are eligible for an SRB is identified from the EMR, then that number is multiplied by the retention formula, resulting in an estimated number of SRB takers per rating or skill set. This number is multiplied by the applicable Final Multiple Score (FMS) and then multiplied by the average length of contract to produce an estimated dollar amount of SRB expenditures (Mackin, et al., 1999).

Once approved by BUPERS-32, the plan and NAVADMIN go to N13 for approval. If approved, N130 drafts the SRB Plan and NAVADMIN and sends back to N13 for approval. After approved, the NAVADMIN and SRB Plan are logged into a tasker system, and the serial chop process within OPNAV N1 begins (as depicted in Figure 5), with N130D hand walking the package through the following codes for approval: N132, N133, N130, N10, Legal, PAO, N13, N1S, and finally, N1. Once N1 approves, the NAVADMIN is released. Figure 5 shows the path of the proposed SRB plan as it moves through OPNAV N1.

Figure 5. Serial Chop Process of SRB Plan through OPNAV N1
(OPNAV, N13)



Currently, the ICT is the best method to predict future inventory, and the ECMs must make their best estimate of retention behavior and what final multiples will be necessary to reach desired manning in each zone and to meet EPA. Unfortunately, the ECMs do not have any forecasting tools or databases to predict reenlistments or estimate return on investment. SKIPPER reportedly has a module that can estimate the predicted number of reenlistments for a rating when a final multiple is entered by using a model with weighted moving averages. At this time, however, the module is inoperative, and so its accuracy is unknown. If this model proves to be accurate (or even close), it would be an invaluable tool for the ECMs.

In attempting to predict reenlistment behavior, there are a number of factors that influence a sailor's decision that must be proxied or estimated in the ACOL model embedded in ROGER. Some of these factors include non-pecuniary factors and civilian job opportunities and wages. Additionally, estimates that feed into the model, such as pay elasticities, must be reflective of current wage levels in order to reach a relatively accurate prediction. An examination of each of these factors follows.

III. The ACOL Reenlistment Model and Prior Studies

A. The ACOL Model

The ACOL model is a behavioral retention model designed to estimate how changes in expected future pay and economic conditions affect the current propensity of enlisted personnel to reenlist. The basic premise of the model is that individuals make voluntary decisions to remain in or to leave the Navy based on which choice maximizes their total utility. Basic labor economic theory assumes that individuals will weigh all long- and short-term monetary costs and benefits of each possible occupational alternative, and will make a choice based on which option provides the greatest utility. However, it is important to note that when this evaluation is being done, non-pecuniary factors, such as medical care and sea duty, are considered in the evaluation, as well as long-term benefits, that include the military retirement system and lifetime medical benefits. For this reason, although some enlisted personnel may have alternative civilian employment options with higher wages, they may elect to stay in the Navy to reap their retirement benefits.

To estimate reenlistment decisions, retention models attempt to mirror the individual's decision process. The model weighs future expected costs and benefits by discounting future earnings to present values. The discounting process adjusts earnings that occur in the future to carry less weight than current earnings in the calculations (Mackin, 1996). Although there are other reenlistment models available, such as the Dynamic Retention Model (DRM), the bulk of the literature on economic retention behavior focuses on the ACOL framework. ACOL models calculate ACOL values for each possible reenlistment horizon, which is based on the number of years of the reenlistment contract (i.e., 3-, 4-, 5- or 6-year horizons). The ACOL model determines the value for each horizon in order to determine the point at which the ACOL value is a maximum (Mackin, 1996). This ACOL value is then used as a predictor of the reenlistment rate.

One of the major barriers to retention prediction is that it is difficult, if not impossible, to determine the expected or actual value of non-pecuniary factors, such as medical care or working conditions. For example, a sailor who is single and has no significant health issues may place a low value on the benefits of military healthcare, whereas a sailor who has had multiple surgeries, long-term medical issues or who has family members with medical needs is likely to place a significantly higher value on medical benefits. Likewise, various job characteristics associated with the military, such as family separation, deployments, frequent moves, and hazardous duty have varying effects on each sailor.

In order to account for these types of "unobserved" factors, the ACOL model estimation approximates the value of preferences when plausible. The monetary equivalents of non-pecuniary benefits are also termed the “taste factor” and it varies amongst individuals and reflects the sailor’s preference for military or civilian life. This taste factor is based on an individual’s values, such as a preference for time with family while on shore duty versus a larger net income while on sea duty and away from family.[7] Individual characteristics that appear to be correlated with a preference for the military, such as family history of service, race, marital status, and gender are variables that are used as proxies for preferences. The model works on the assumption that the unobserved distribution of these varying tastes is randomly distributed across all sailors in the given population. The taste variable takes into consideration all non-pecuniary costs and benefits of alternative employment choices over multiple years and represents the "net" value (Mackin, 1996). It is important to note, however, that this taste factor exists in economic theory only. There is no specific variable in the ROGER model that approximates the taste factor, though other studies have used proxies to approximate for taste, such as sea/shore rotation, current duty station, and separation pay (Hansen & Wenger, 2002).

[7] While on sea duty, sailors collect sea pay, and if away from port, also collect family separation pay. If they are in a hazardous duty zone, they also collect hazardous duty pay. This makes the net pay while on sea duty greater than that of shore duty.

Ultimately, each sailor has a taste value that factors heavily into his/her retention decision. In the ACOL model, the retention decision rule states that a sailor will stay in the Navy *only* if the ACOL value is greater than his/her net distaste for the Navy.

1. Importance of ACOL

The behavioral-based approach ACOL is the driving force behind the ROGER model and provides the theoretical basis for estimating the impact of a change in bonus levels on the number of reenlistments. The ability to forecast the effects of policy and economic externalities on enlisted retention is a powerful tool for Navy manpower analysts to use. This model enables prediction of retention behavior and future force inventory in order to ensure appropriate manning levels (Mackin, 1999, Appendix B, p. 18).

Prior to the development of ACOL, inventory models were non-behavioral and determined by historical rates, usually based on weighted averages. Although the non-behavioral method was (and is) useful to predict changes in total retention behavior due to force composition changes, the approach is inherently static and does not allow for changes in retention rates due to changing factors such as pay and unemployment rates. More importantly, these static models do not allow for prediction of the effects of these various changes on current enlisted retention.

The ACOL model in ROGER allows the Navy to assess its future force needs and the Navy's ability to achieve and maintain the requisite quantity (and quality mix) of enlisted personnel over the period of the POM. Over time, as the force changes, the retention models provide analysts the ability to re-estimate the quality, strength and experience mix as needed. The key is that the behavioral model predicts how sailors will respond (their retention behavior) as a result of changes in pay, external economic factors (such as unemployment), or SRB amounts (Mackin, 1999). According to Mackin (1999), the ACOL retention model predicts reenlistment rates given the following:

- The anticipated future of the economy [as summarized by the unemployment rate projections of the Office of Management and Budget (OMB)].
- The growth in civilian pay (projected by OMB).
- The pay raises programmed in the Defense Guidance and the POM.
- The SRBs and other special pays programmed by the Navy over the period of the POM.

2. History of the ACOL Model

The ACOL model was initially developed in 1978 by Enns, Nelson and Warner to analyze the effect of changes to the military retirement system for the President's Commission on Military Compensation (PCMC). PCMC had proposed an alternative military retirement system that provided financial encouragement for members to serve at least ten years, but reduced the financial incentive to stay in the service for 20 years. One of the primary questions in the study was whether the military member's horizon for the first-term reenlistment decision (the period over which military and civilian pay would be compared) should include all years to the 20-year point or be limited to only the next term of service (Mackin, 1999, Appendix B, p. 21).

ACOL remedies the horizon issue by selecting the horizon for which the annualized difference between projected military and civilian earnings is the greatest. The assumption is that sailors will choose not to reenlist for any horizon if they would not reenlist for the horizon at which the ACOL is at its maximum. This is sometimes referred to as a "maximum regret" solution (Hogan, Tsui, Chandler, & Espinosa, 2005, p. 2).

Hogan and Mairs were the first to recommend using the ACOL model to project retention effects of changes in pay, bonuses and the unemployment rate over the period of the Program Objective Memorandum (POM). Modifications made by Warner enabled ACOL to analyze changes in pay, as well as changes in the retirement system, and the Department of the Navy used ACOL to analyze POM 82 (Mackin, 1999, Appendix B, p. 22).

The original version of ACOL estimated by Warner was a random utility function based on a cross-sectional regression of aggregate retention rates by years of service (YOS) on an ACOL variable (Warner, 1999, Appendix B, p. 22). The ACOL variable was constructed by using average promotion points to project future expected military earnings, and collective age-education-earnings profiles from Current Population Survey (CPS) data to project future expected civilian earnings. Since this original regression was based solely on a single year of data with no change in unemployment data, the unemployment rate was not included as an explanatory variable (Mackin, 1999). However, since then, the unemployment rate has been incorporated into the model.

The functional form of the model is a logistic curve, similar in shape to the cumulative normal distribution, but "thicker" in the tails.[8] When transformed to the logarithm of the odds of remaining in service, it becomes linear, and is expressed as follows:

Equation 1: $$\ln\left[\frac{r_{n,t}}{1-r_{n,t}}\right] = \alpha + \beta \cdot ACOL_{n,t} + \delta \cdot \mathrm{U_t} + \varepsilon$$

In which:

- $r_{n,t}$ is the retention rate at YOS n at time t for those at an EAOS point;
- $ACOL_{n,t}$ is the annualized cost of leaving at YOS k at time T (computed as the annuitized difference between military and civilian pay over the future length of stay that maximizes ACOL);
- U_t is the unemployment rate at time t;
- and α, β and δ are behavioral coefficients estimated from data containing observed behavioral responses (retention decisions) to changes in military and civilian wages and unemployment (Mackin, 1999, Appendix B, p. 19).

[8] In a normal distribution curve (picture a bell curve), most of the probability mass lies in the center of the bell, while the "tails" quickly taper off, and so the probability of "tail" events is small. In this case, however, the tails are thicker, which indicates that "tail" events are not as rare.

Warner's original estimate of pay elasticities was obtained from a reenlistment model estimated via ordinary least squares (OLS) using grouped data. For those in their first term, Warner found pay elasticities to be between 2.0 and 3.0, which means that a 10% increase in pay leads to a 20%-30% increase in reenlistment rates. Due to varying cohort size, heteroskedasticity produced biased estimates of the standard errors. Data was pooled across skills, demographic characteristics and terms of service, as well as across Services, putting stringent constraints on the estimated coefficients. Specific tests for homogeneity and the efficacy of the data pooling were not made, and dummy variables were used to control for selectivity bias[9] (Mackin, 1999).

Though the ACOL model vastly improved estimation abilities, there was a major criticism of the model: the model failed to account for self-selection as sailors moved through multiple terms of service. Once a cohort passed through the first decision point, the preferences of the remaining sailors had changed. Generally, these sailors will have had a greater taste for the military than their counterparts who elected to leave the Navy. If the ACOL decision rule were strictly adhered to, then as long as the ACOL value increased at each decision point, every sailor would be retained. The argument holds that the pay effects in the ACOL model are biased upward due to its inability to account for selection effects. This credits pay effects for the increase in reenlistments that are actually due to self-selection (Mackin, 1999, p.4).

Other dynamic models, such as the Dynamic Retention Model (DRM) and ACOL-2 have been proposed to predict retention behavior and also account for the taste factor as cohorts proceed through the personnel system. However, these models require details of the complete history of a cohort's retention behavior—data that is difficult to obtain. These models are "best suited for the analysis of long-term

[9] Black and Hogan (1987) found that dummy variables for term of service produced similar results to random effects procedures in controlling for selectivity in the analysis of Navy enlisted reenlistment behavior.

changes in the compensation system in a hypothetical steady-state" (Mackin, 1999, Appendix B, p. 23).

3. Other Studies Relating to ACOL

Since the ACOL model was first estimated in 1978, numerous studies have attempted to improve the original estimates. In 1982, Goldberg and Warner used grouped data and weighted least squares (which adjusts for heteroskedasticity) to estimate a conditional logit model of sailors' reenlistment behavior.[10] In estimating both first- and second-term reenlistment decisions (now more commonly referred to as Zone A and Zone B), they found their estimates of the pay elasticity were in the same range as the original Warner estimates (Goldberg & Warner, 1982). As previously discussed, numerous versions of the ACOL model have been estimated, and first-term pay elasticities are typically close to 2.0 (Mackin, 1996).

The first study to use longitudinal data to estimate an ACOL-like model of reenlistment behavior was Black, Hogan and Sylwester (1987) who found a first-term pay elasticity of 1.0. Their model corrected for unobserved heterogeneity (self-selection) using a random-effects method (Mackin, 1999).

In 1999, Mackin, et al., of the SAG Corporation used data from fiscal years 1978 through 1989 and re-estimated the ACOL model using the conceptual model used by Warner and Goldberg. Instead of using OLS, however, they used maximum-likelihood estimation of individual data, and included models to project retention decisions of third-term and retirement-eligible individuals in addition to first- and second-termers.

4. Data Requirements for the ACOL Model in ROGER

Though specific variables may vary by study, the basic model used for the Navy's SRBMS (ROGER) includes an ACOL variable, the unemployment rate, race, gender, and marital status. Race and gender are represented by dummy variables,

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[10] The Navy's working ACOL model employs this specification of retention behavior.

with race being either white or nonwhite. The ACOL variable represents the pay and is constructed based on the following variables:

- military civilian experience (an interaction term for cumulative work experience)
- military experience
- military experience squared
- civilian experience
- civilian experience squared
- long-term inflation rate
- discount rate
- military basic pay table
- military Regular Military Compensation (RMC) value
- base length of reenlistment (LOR) distribution for each LOS three through six years
- Current Population Survey (CPS) multiplier[11] **(**for each age one through six)[12]
- unemployment rate
- lump sum percentage to be paid out
- Current Price Index (CPI)

The specific components of the ACOL variable are determined in the following methods. Military pay is based on Regular Military Compensation (RMC), considering anticipated promotion path and annualized over the horizon. Regular Military Compensation was defined by Congress in 1974 and includes four elements: (1) basic pay; (2) an allowance for housing (paid either in cash or as government-supplied bachelor or family housing); (3) an allowance for food (paid either in cash or as meals in military dining facilities); and (4) an implicit payment known as the federal tax advantage (since the food and housing allowances are not subject to

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[11] This multiplier adjusts the civilian earnings estimates by age cohort to account for differences between the time the estimates were made and the analysis year in the model

[12] The age categories are ages 15-17, 18-24, 25-34, 35-54, 55-64, and 65 and over.

federal income tax). Additionally, special duty pays, bonuses and incentives are included in the RMC for sailors who are eligible or entitled (this includes pays such as hazardous duty pay, family separation pay, and SRBs). Civilian pay is projected based on age-earnings profiles derived from CPS data. Differences in earnings due to race, education and mental group are adjusted based on the distribution of backgrounds of the personnel in each category, or cell.[13] Then the annualized value is computed using the same discount rate and horizon used for the calculation of military pay. The ACOL value itself is the annualized difference between expected future civilian earnings and military pay, both annualized over the same horizon (Goldberg & Warner, 1982).

B. Non-pecuniary Factors

Warner and Goldberg (1984) analyzed the effects of monetary and non-monetary effects on "stay or leave" decisions for United States Navy enlisted personnel. Theorizing that the amount of time spent on sea duty would be inversely related to the pay elasticity, Warner and Goldberg divided the Navy into 16 different occupational groups (based on similarity of training, job requirements and working conditions), and examined sailors at the end of their first term of military service.

Using basic economic theory, Warner and Goldberg assumed that each sailor would make his/her decision by evaluating the utility of each option (staying or leaving) and choosing the most personally beneficial. The utility of each option is the sum of the present value of the income associated with that option and the present value of the monetary equivalent of the non-pecuniary aspects of the option (such as sea duty and health care). As previously discussed, the monetary equivalents of the non-pecuniary benefits are reflected in a "taste factor" which varies amongst individuals and reflects the sailor's "taste" for military or civilian life.

[13] Cells in this study are defined by fiscal year, rating and length of service. (Goldberg & Warner, 1982, p. 2)

Once sailors have determined the values for each option, the assumption is that they would choose the option with the larger monetary value (maximizing their net gain).

Goldberg and Warner estimated a probit reenlistment model based on data gathered from the Defense Manpower Data Center (DMDC), which contained all 220,606 Navy enlisted personnel making a first-term reenlistment decision between fiscal years 1974 and 1978. The model included the following variables: (1) the Annualized Cost of Leaving (ACOL) model calculated over a 4-year reenlistment horizon, (2) marital status (as a dummy variable), and (3) the civilian unemployment rate for 20- to 24-year-old males in the month of the reenlistment decision (Warner & Goldberg, 1984, p. 29).

In effect, the study determines the ACOL values for sailors and finds that as long as their ACOL is greater than their net taste for a civilian lifestyle, they would prefer to stay in the military (Warner & Goldberg, 1984). This study is relevant to the SRBMS in that sailors of the same paygrade and length of service are essentially paid the same amount, with the SRB being the only significant difference in their monetary compensation. Therefore, to induce sailors to stay, the amount of SRB offered must be greater than their net distaste for military service (or their net preference for civilian life).

C. Occupational Groupings

As previously discussed, the model uses the ACOL variable to predict reenlistment rates based on differences in military and civilian earnings for enlisted sailors. Due to the vast number of skills in the Navy, from ratings to Navy Enlisted Classifications (NECs), it is extremely difficult to forecast expected civilian earnings for each individual skill (discussed in detail in the next section). Therefore, Navy skills have been grouped into broad occupational groupings that share similar characteristics and have comparable occupations and civilian wage levels. These groupings are used in calculating the ACOL variable and in estimating pay elasticities in the reenlistment model.

The importance of using accurate occupational groupings in the ROGER model cannot be overstated. If ratings with high-paying civilian opportunities, such as SEALS and divers, are grouped with ratings with few civilian opportunities and lower civilian wages, such as Yeomen, the resulting estimated pay elasticity will not be accurate, nor will the resulting reenlistment predictions. The occupational groupings are crucial to the model's accuracy, and the current nine occupational groupings used in the Navy retention model have not been analyzed or updated since 1982, when they were initially established.[14] The pay elasticities, however, have been updated more recently.

The ROGER model currently uses nine occupational groupings; however, there are a number of different grouping schemes found amongst the various studies in the literature. The number of groups can range from as few as two to as many as sixteen, though one study examined as many as 61 individual civilian occupations as they compared to 96 different Navy ratings and skill sets.

1. Goldberg and Warner, 1982; Goldberg, 1985; Goldberg and Warner, 1984

Goldberg has been one of the primary researchers to analyze enlisted retention behavior. His 1982 study with Warner, "Determinants of Navy Reenlistment and Extension Rates," established the nine occupational groupings still in use in the current ROGER model. The groupings were established solely based on their judgment of ratings with comparable job characteristics, such as tasks performed, skills required and similar work environments. Table 2 shows the nine occupational groups used in "Determinants of Navy Reenlistment and Extension Rates" (Goldberg & Warner, 1982).

Over the next few years, however, the occupational groupings used by Goldberg varied. In his 1985 study for CNA, "New Estimates of the Effect of

[14] At times, minor adjustments have been made and some ratings have been moved, but the aggregate groupings have not been updated or analyzed for current accuracy.

Unemployment on Enlisted Retention," he used the same groupings established in his 1982 study. However, in his 1984 paper with Warner, "The Influence of Non-Pecuniary Factors on Labor Supply: The Case of Navy Enlisted Personnel," which examined the relationship between sea duty and pay elasticities, the 80 Navy ratings were categorized into 16 occupational groups (as depicted in Table 3). As in the 1982 study, these classifications were based on similar job characteristics, such as training, working conditions and job requirements (Warner & Goldberg, 1984).

Table 2. Occupation Groups Used in Goldberg and Warner's 1982 and Goldberg's 1985 Studies
(Goldberg & Warner, 1982) (Warner & Goldberg, 1985)

Number	Occupation group	Ratings
1	Non-electronics	BT, EM, EN, GMG, GMM, GMT, HT, IC, IM, MM, MN, MR, OM, PM, TM
2	Electronics	AE, AT, AW, AX, DS, ET, EW, FTB, FTG, FTM, MT, OT, STG, STS, TD
3	Aviation maintenance	AD, ADR, AME, AMH, AMS
4	Ship/aircraft support	ABE, ABF, ABH, AO, ASE, ASH, ASM, BM, PR
5	Health care	DT, HM
6	Logistics	AK, DK, MS, SK
7	Construction	BU, CE, CM, EA, EO, SW, UT
8	Cryptology	CTA, CTI, CTM, CTO, CTR, CTT, IS
9	Administration, Media and Other	JO, LI, LN, MU, NC, PC, PN, YN

Table 3. Occupation Groups Used in Goldberg and Warner's 1984 Study
(Warner & Goldberg, 1984)

	Occupation group	Ratings
1	Ship Maintenance	HT, IM, ML, MR, OM, PM
2	Health care	DT, HM
3	Logistics	AK, DK, MS, SK
4	Marine Engineering	BT, EM, EN, IC, MM
5	Weapons System/Control	ET, FT
6	Aviation Maintenance	AC, AD, AE, AM, AO, AT, AQ, AV, AX
7	Construction	BU, CE, EA, EO, SW, UT
8	Administration	LM, NC, PC, PN, YM
9	Ship Operations	OS, QM
10	Communications/Sensor Systems	AW, EW, OT, RM, ST
11	Aviation Ground Support	AB, AS, PR
12	Data Systems	DP, DS
13	General Seamanship	BM, SM
14	Ordnance	GM, MN, MT, TM
15	Cryptology	CT, IS
16	Media	JO, LI, PH

2. Quester and Thomason, 1983

In a 1983 CNA study titled "Projecting the Retention of Navy Careerists," Quester and Thomason used civilian occupations as they relate to military ratings in a different fashion. In a quest to study retention over the long term, they examined the relationship between civilian job growth (instead of wage levels) in civilian occupations deemed comparable to each Navy rating. They then looked at the relationship between occupational job growth on reenlistment rates rather than the relationship of civilian wages to Navy reenlistment rates.

Matching approximately 80 Navy ratings to comparable civilian positions (termed "crosswalking") for their study, they obtained the projected future growth in each civilian occupation from the Bureau of Labor Statistics. A total of 163 civilian occupations were looked at for matches, and most of the Navy ratings were matched to one of 61 civilian occupations. Some ratings were matched with two or more civilian counterparts, and for some ratings, no match was found. Matching of military and civilian occupations was done by two Naval officers and the Deputy Director, Occupational Classification Review, Naval Military Personnel Command, and each match had to be agreed upon by all three individuals (Quester & Thomason, 1983, p.4). Fifteen of the ratings did not have a match identified (Quester & Thomason, 1983, Appendix B). The effects of civilian job growth on retention were estimated both for the major groups ("highly technical" and "less technical") and the individual occupations.

After controlling for other factors, the study found a correlation between highly technical Navy ratings and an increased probability of leaving the Navy. Additionally, results suggested that enlisted personnel are motivated by future job prospects (based on projected growth) as well as civilian wages levels. More importantly, it identified the large number of equivalent civilian job counterparts to the Navy ratings.

3. Hansen and Wenger, 2002

In their 2002 CNA study "Why do Pay Elasticities Differ?" Hansen and Wenger used occupational groups very similar to the 16 groups used in Warner and Goldberg's 1984 study. Since the data used to establish the original occupational groupings was from the 1970s, Hansen and Wenger made minor modifications to update the groupings by placing ratings that were not in existence at the time of the original study into the current group that seemed to be most closely related. Additionally, since the primary duties of some ratings, such as radioman (RM), had changed significantly since the 1970s, they were reclassified into more appropriate groups. Table 4 shows the construction of the Occupation Groups in the Hansen and Wenger study (2002).

Table 4. Occupation Groups Used by Hansen and Wenger, 2002
(Hansen & Wenger, 2002)

	Occupation group	Ratings
1	SEABEE Construction	BU, CE, CM, EA, EO, SW, UT
2	Non-SEABEE Construction*	CN, EO*
3	Marine Engineering	BT, EM, EN, GSE*, GSM*, IC, MM
4	Ship Maintenance	DC*, HT, IM, ML, MR, OM, PM
5	Aviation Maintenance	AC, AD, AE, AME, AMH, AMS, AO, AT, AQ
6	Aviation Ground Support	ABE, ABF, ABH, AG*, AS, ASE, ASH, ASM, AW*, AZ*, PR
7	Media	DM*, JO, LI, PH
8	Logistics	AK, DK, MS, SH, SK
9	Administration	LM, MA*, PC, PN, YN
10	Data Systems	DP, DS, RM*
11	General Seamanship	BM, OS*, QM*,SM
12	Healthcare	DT, HM,
13	Cryptology	CTA, CTI, CTM, CTO, CTR, CTT, IS
14	Ordnance	FT*, FTB, FTG, GM, GMG, GMM, GMT, MN, MT, STS*, TM, WT*
15	Communications/Sensor Systems	EW, OTA, OTM, STG
16	Weapons System/Control	ET, FC

* indicates an add or change from Goldberg and Warner's 1984 model

D. Estimated Pay Elasticities

All of the above studies estimated the pay elasticities of military enlisted personnel. These elasticities are estimated by determining the magnitude of the relationship between changes in relative compensation and reenlistment behavior, while controlling for other factors that might contribute. The end result is the estimation of pay elasticities of reenlistment, which measures the expected percentage change in reenlistment due to a 1% increase in pay. Identifying accurate pay elasticities is vital to predicting retention. The elasticities are imbedded into the ROGER model and used for reenlistment predictions, so if they are incorrect, the reenlistment predictions will be over- or under-estimated. Additionally, these elasticities are used by policy makers to set SRB multiples and forecast reenlistment rates, making them crucial to all aspects of manpower planning and force shaping (Hansen & Wenger, 2002). As demonstrated in Table 5, Navy enlisted pay elasticities vary significantly from study to study.

Table 5. Pay Elasticities from Prior Studies
(Goldberg, 1996)

Study	Pay Variable	Sample	Pay Elasticity First Term	Pay Elasticity Second Term	Pay Elasticity Third Term
Enns, Nelson and Warner (1987)		All	0.33-2.71		
Cooke, Marcus and Quester (1992)	Mil/Civ pay index; SRB	Navy enlisted	1.6		
Goldberg and Warner (1982)	Total retention; mil pay alone (RMC)	Navy enlisted; by occupational group	1.1-2.7		
Hosek and Peterson (1985)	Mil/civ pay index; SRB	Enlisted males, all four services	3.8	1.7	
Mackin, et al. (1996), conditional logit model	Reenlistment; mil pay alone	Navy enlisted; by occupational group	0.2-1.5		
	Total retention; mil pay alone		0.2-0.9		
Mackin (1996)	ACOL-2; elasticity of reenlistment with respect to military pay	Navy enlisted	1		
Black, Hogan and Sylwester (1987)	ACOL-2; elasticity of reenlistment with respect to military pay	Navy enlisted	0.95	0.33	0.27
Shiells and McMahon (1993)	Mil/civ pay index; SRB	Navy enlisted	1.9		
Warner and Goldberg (1984)	Mil pay alone (SRB)	Navy enlisted; by occupational group	1.1	3.4	

1. Warner and Goldberg, 1982

The initial elasticities used for the nine occupational groupings in the ROGER model were first estimated by Warner and Goldberg in 1982 in their CNA study titled “Determinants of Navy Reenlistment and Extension Rates.” The first study to distinguish extensions from reenlistments, it specifically focused on the separate effects of both RMC and SRBs on the probabilities of sailors’ reenlistments and extensions. As discussed above (and illustrated in Table 3), Warner and Goldberg classified each Navy rating into one of nine groups, based on what they considered to be similar job characteristics, tasks performed, general work environment, and skills required (Goldberg & Warner, 1982, p. 2). In this analysis of first-term and second-term reenlistment and extension rates, Warner and Goldberg estimated pay elasticities for each of the nine occupational groups and each Zone, based on a number of factors.

In the Warner and Goldberg 1982 study, retention data for first- and second-term enlistees for fiscal years 1974 through 1980 were obtained from the Defense Manpower Data Center (DMDC). First term was defined as Length of Service (LOS) 3-6 years, and second term was defined as LOS 7-10 years. Each cell was defined by fiscal year, rating and LOS, for which DMDC computed the reenlistment and extension rates of all sailors having less than 13 months remaining on their contract at the beginning of the given fiscal year. For the purposes of their study, Warner and Goldberg defined the reenlistment rate as the number of sailors who reenlisted for three or more years of additional service divided by the number eligible to reenlist in each cell. Sailors who obligated for less than three years of additional service were treated as extenders (Goldberg & Warner, 1982, p. 2).

They then calculated the average values of personal and military background characteristics for the sailors in each cell making retention decisions. The following variables were computed: average paygrade, percent black, percent married, frequency distributions of mental group and education level, and percent of all enlisted (not just those at the decision point) assigned to sea duty (computed by LOS) (Goldberg & Warner, 1982, p. 8).

In order to estimate the pay elasticities, the researchers analyzed the impact of economic variables and SRB multiples in effect at the decision points. The variables utilized for this study included the annual average unemployment rate of males age 20 and above, indices of consumer prices, civilian earnings, basic military pay and RMC. Additionally, for each cell, Warner and Goldberg used the average bonus multiples for both first- and second-termers in each occupational group for each fiscal year of data. The average multiple used was the one that each sailor in the occupational group could have received if they had all reenlisted, so the actual average multiple paid to those who did reenlist may vary (Goldberg & Warner, 1982, p. 9).

To establish the overall utility of each option (reenlist, extend, or leave), the researchers forecasted the future income stream over each reenlistment period and the annualized monetary value of non-pecuniary factors. For each cell, Warner and Goldberg calculated the average values of the projected military and civilian pay options over the applicable horizons, as well as the monetary equivalents of non-pecuniary factors (Goldberg & Warner, 1982).

To convert expected future earnings to present values, it is imperative to apply a discount rate, which is based on an individual's or group's preference for money today as opposed to future cash flow. In this study, discount rates used were based on previous literature on the subject. Gilman (1976) and Cylke, et al. (1982) estimated the first-term enlistee's personal discount rate to be 20%, and Gilman (1976) estimated the second-termer's discount rate to be only 10%. Therefore, these discount rates were used in the analysis to reflect the sailor's estimated discount rate (Goldberg & Warner, 1982, pp. 22-23).

Civilian earnings were predicted based on a number of variables (age and experience, for example) and the March 1977 Current Population Survey (CPS) data. The CPS data was adjusted for changes in average hourly earnings for each fiscal year from 1974-1980, then deflated by the consumer price index to fiscal year 1980 dollars (Goldberg & Warner, 1982, p. 24). The average expected civilian earnings were computed by cell based on average education level, race and mental group, as well as expected earning variances by the member's LOS. The same discount rate and time horizons were used in both civilian and military pay calculations (Goldberg & Warner, 1982).

Finally, in order to estimate the reenlistment extension model, all variables were included in a logit regression equation. Warner and Goldberg identified potential sources of bias and made adjustments in order to eliminate or minimize bias. The three possible options (reenlist, extend, leave) were mutually exclusive (Goldberg & Warner, 1982).

The weighted average of the estimated coefficients of this study for first-termers was found to be similar to Warner's 1979 estimate of the all-Navy pay elasticity. The estimate for second-termers, however, was 14% higher (Goldberg & Warner, 1982). At the time of this study, Warner's 1979 all-Navy elasticity estimate was being utilized for all ratings and Zones in the ACOL model. Due to this, Warner and Goldberg suggested that these newly estimated elasticities for each occupational group and Zone be incorporated into the Navy ACOL model for increased accuracy of future predictions. As stated by Warner and Goldberg,

> If bonus managers identify a manning shortage in a particular rating, they require rating-specific (or at least occupation-specific) pay elasticities to determine the bonus increase that would alleviate the shortage. The all-Navy pay coefficient would give misleading results when applied to ratings with unusually high or low pay responsiveness. (Goldberg & Warner, 1982, p. 1)

2. Hansen and Wenger 2002

Based on the wide range of estimated elasticities for enlisted personnel in the literature, Hansen and Wenger analyzed what factors might explain differences in pay elasticities across a number of studies, each of which were completed in different years. Their study analyzed whether the variations were due to differences in research methodologies or due to actual changes over time in the responsiveness of enlisted personnel to changes in pay.

The data sample used by Hansen and Wenger was retrieved from the Enlisted Master Record (EMR) and was comprised of male enlisted sailors reaching their first decision point in fiscal years 1987-1999. The sample excluded those in nuclear specialties and those in paygrades E-1 to E-3. Outliers were excluded by limiting the sample to 19- to 40-year olds in paygrades E-3 to E-6. To account for self-selection bias, those sailors who were ineligible to reenlist were included in the sample, on the underlying assumption that actions leading to ineligibility were a reflection of a sailor's desire to leave military service (Hansen & Wenger, 2002, p. 2).

Definitions of reenlistment are different for the various studies, but for this particular study, reenlistment was defined as extending or reenlisting for a minimum of 36 months. This reenlistment definition falls between those who include all extensions and those who exclude all extensions. In the study's analysis of success, however, they examine whether pay elasticity estimates are sensitive to the difference in the definition of "reenlistment" (Hansen & Wenger, 2002).

Hansen and Wenger began by specifying a baseline logit estimation model based on the ACOL framework. They calculated expected future earnings in both military and civilian jobs based on sailors' personal characteristics, such as marital status, number of children, AFQT score, age and gender. Then, the predicted earnings were matched with additional information, such as YOS, paygrade, rating group, and sea/shore rotation, to estimate the relationship between compensation and retention.

The baseline estimates were calculated and compared with other estimates in the literature derived from various empirical specifications to isolate the effects of each study's empirical specification on the reenlistment estimates. To evaluate whether the pay elasticity actually changed over time, the researchers then compared variations over time in the estimates with the variations in estimates found using the different models in the literature (Hansen & Wenger, 2002, p. 2).

To establish relative success of the different empirical models, they used half the sample (randomly generated) to calculate estimates of the pay elasticity of reenlistment. The other half was used to compare actual and predicted reenlistment in the various models.

The study's results indicate that differences in estimated pay elasticities are more likely attributed to differences in empirical specifications in each study than to changes over time in sailors' responsiveness to pay. The baseline model developed by Hansen and Wenger obtained a pay elasticity of 1.5, indicating that a 1% increase in military pay leads to a 1.5% increase in the reenlistment rate. Additionally, they found that a 1% increase in the SRB multiplier increases reenlistments by 2.5 percentage points. These estimates both lie within ranges estimated for Navy enlisted personnel in the literature. Previous estimates range from 0.8 to 3.4, with the bulk of them between 1.2 and 2.2 (Hansen & Wenger, 2002, p. 23).

Different specifications of the model resulted in a wide range of estimated pay elasticities, as well as a significant variation in the association between the SRB multiple and predicted reenlistments. Since identical data was used for all models, differences in the estimation were not due to actual changes in responsiveness to pay, but to variation in the amount of responsiveness attributed to pay in the models.

In examining the pay elasticities over time, Hansen and Wenger found almost no variation, except for during the military drawdown in the early to mid-1990s. This provided strong evidence that the differences in elasticities in the literature reflected the modeling approaches used by each study and not to actual changes in the reenlistment behavior of enlisted personnel over time. The question then remains: what is the best (most accurate) method of estimation?

Hansen and Wenger's findings are summarized as follows:

> Models designed to predict reenlistment behavior for particular subsets of the data generate the most accurate predictions for these subsets. However, these models also do the worst job at predicting reenlistment for even a slightly different subset of the data. In general, the baseline model[15] performs fairly well at predicting reenlistment rates for different groups of ratings. (Hansen & Wenger, 2002, p. 3)

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[15] Hansen and Wenger's baseline model was a logit regression model using the ACOL framework and an empirical specification consistent with most previous studies. Variables for future estimated military and civilian earnings as measures of preference for military service. The resulting elasticity from their baseline model was 1.5.

Their baseline model uses broad occupational categories, but does not account for differences in compensation or job conditions, which are thought to be contributors to retention decisions. They further state that if the sailor's rating is controlled for, there can be substantial differences in the pay elasticities. When Hansen and Wenger compared their results for the skill groups to the Warner and Goldberg 1984 study, they found both similarities and differences in the corresponding pay elasticities for each group. Hansen and Wenger propose that differences could be due to changes in working conditions and civilian opportunities for the skill groups, and/or the differences in number of variables used in the two models (Hansen & Wenger, 2002, pp. 34-35).

For this reason, in a model such as ROGER, in which reenlistment rates are based largely on occupational groups, it is important that sailors are grouped appropriately to achieve more accurate predictions. The elasticities estimated for the 16 occupational groups are shown in Table 6, and indicate that sailors in different occupational groups respond differently to changes in pay.

Table 6. Elasticities for Hansen and Wenger's 2002 Occupational Groups
(Hansen & Wenger, 2002, p. 34)

Rating	Reenlistment rate	Pay elasticity	SRB effect
SEABEE Construction	0.29	0[a]	0[a]
Non-SEABEE Construction	0.28	0[a]	0[a]
Marine Engineering	0.29	2.8[b]	4.2[b]
Ship Maintenance	0.25	3.8[b]	6.1[b]
Aviation Maintenance	0.32	0.7[b]	1.3[b]
Aviation Ground Support	0.27	0.5[b]	0.6[b]
Media	0.26	1.9[c]	2.1[c]
Logistics	0.34	3.3[b]	4.8[b]
Administration	0.34	3.1[b]	4.1[b]
Data Systems	0.39	1.5[b]	3.2[b]
General Seamanship	0.28	3.2[b]	4.5[b]
Health Care	0.31	2.6[b]	3.7[b]
Cryptology	0.46	0.2[c]	0.6[c]
Ordnance Systems	0.43	0.3[b]	0.7[b]
Communications/Sensor	0.31	2.0[b]	3.1[b]
Weapons Systems/Control	0.41	1.3[b]	2.8[b]

a. No significant effect of pay on reenlistment.
b. Zero lies outside the 99-percent confidence interval for this estimate.
c. Zero lies outside the 95-percent confidence interval for this estimate.

3. How Elasticities Fit into the ROGER Model

The elasticities represent fixed values in the ROGER model. Once estimated, they are "residents" of the model and are not continually updated. They were originally estimated in 1984, re-estimated in 1992, and most recently re-estimated in 1999. When predicting reenlistment, the pay elasticities are multiplied by the ACOL value, which changes based on current information on military and civilian pay. It is important that the elasticities are estimated based on the civilian earnings in the particular occupational group to which the Navy skill or rating is most closely matched. Therefore, as discussed earlier, if the occupational groupings do not reflect current comparable civilian occupations for each Navy rating or skill group, the elasticity estimates may not accurately predict reenlistment behavior. This is because in general, sailors in ratings with no comparable civilian occupation tend to be less responsive to bonuses (i.e., lower elasticities) than sailors in ratings with comparable civilian occupations.

E. Chapter Summary

The SRB process involves constant interplay and collaboration between BUPERS-32 and OPNAV N1 staff. The ECMs primarily determine the ratings that require SRBs to meet EPA and the SRB multiples that need to be offered. Due to a limited amount of funding, the ECMs have to give and take in order to attempt to meet each of their manning goals. OPNAV has the final approval, as the program falls under the responsibility of the DCNO.

In order to estimate reenlistment behavior, it is necessary to understand that non-monetary factors are an important influence on a sailor's decision to stay in the Navy. Sailors determine the relative value of benefits and certain other aspects of their rating, such as medical care and time at sea and include those values in their comparison of military and civilian options. These factors are weighted differently by each sailor; therefore, they are difficult to predict, but must be considered in the taste factor in order to improve the accuracy of the prediction of the ACOL model.

Besides the relative value of non-pecuniary factors, the occupational groupings used have a major effect on the estimations of the ACOL model. Though the studies discussed in this chapter may vary in regard to different independent variables and their effects on retention, they all involve estimating retention rates by occupational groups. It appears that in the literature, groupings were established based on perceived similarities by the authors and may have been accurate at the time. However, ratings have changed, merged, been added, and been disestablished at an increasing pace over the past 15 years. Operational tempo

(OPTEMPO) and national security have increased dramatically since 2001, contributing to further refining of rating responsibilities and job definitions.

The civilian sector has also changed dramatically over the last 15-20 years, with some occupations experiencing dramatic job growth, new ones emerging and others becoming obsolete. Whether the current occupational groupings are accurate, there is little question that they need to be examined as a possible factor contributing to the inaccuracy of predictions in the ROGER model. The question remains as to what specific grouping will result in the most accurate predictions in the ROGER model. Although a detailed assessment of the occupational groups was beyond the scope of this thesis, it is certainly a topic for future research.

Pay elasticities, an integral component of the retention model, have been estimated over a wide range of values in the literature. Predictive accuracy of the model is highly dependent upon accurate estimation of the elasticity of pay.

In researching pay elasticities across several studies, Hansen and Wenger (2002) found that pay elasticities were apparently falling over time, suggesting that sailors were becoming less responsive to pay. However, they found that differences in pay elasticity estimates from various studies were more likely caused by the differences in empirical specifications of the models than to changes in sailors' behavior over time. This finding is important in that, if true, pay elasticities should not need to be constantly updated. However, this does not address the issue of ensuring that pay elasticities are estimated for the appropriate occupational grouping.

In addition to the pay elasticity, the ACOL value is an important component of the retention equation. In accordance with economic theory and assuming that sailors make rational decisions, most would argue that ACOL is the single most important factor in a sailor's decision to reenlist. The ACOL value (including both monetary and non-monetary factors) measures the net benefits or costs of remaining in the military for one more term in comparison with leaving the Navy immediately. Theoretically, the monetary costs of leaving must exceed a taste factor, which is a sailor's relative preference for the service.

For an accurate retention prediction and a proper budget allocation for SRB needs, all variables in the retention model must be as accurate as possible. As is often heard in the world of computers: garbage in, garbage out. Models are no different. Therefore, it is important to validate the current model specifications and determine if changes can be made to improve the model.

IV. Model Assessment

A. Lewin Group Study

According to the study by Moore, Hogan and Espinosa of the Lewin Group (2003), "in recent years, the SRBMS has apparently failed to project accurately" (Moore, et al., 2003, p. 1). Contracted by the Navy to provide an independent assessment of the accuracy of SRBMS, the Lewin Group tested the SRB model as a whole as well as its primary components and provided recommendations on areas that appeared to have estimation errors. The study found a number of inaccuracies in the SRB process, which led to a severe underestimation of eligibles. However, the study did not evaluate the econometric basis for the SRB model or directly assess the ability of the model to predict program costs (Moore, et al., 2003).

1. Identification of Eligibles

The initial step in the SRBMS process is to identify the sailors who are eligible for the SRB in a given fiscal year. Based on information such as rating, NEC, EAOS and Zone, each eligible sailor is assigned to a pre-determined occupational skill group. The list of eligibles is created from a snapshot of the Navy Enlisted Master Record (EMR), based on the current fiscal year's reenlistment policy. In general, it includes 4-year obligors (4YO) sailors who will reach the end of active obligated service (EAOS) during the fiscal year of the SRB program, as well as those in selected critical skill groups with 6-year obligations (6YO) who are eligible to reenlist early (Moore, et al., 2003).

2. Reenlistment Rates

In order to forecast reenlistment rates, the SRBMS uses the ACOL model to determine the effect of the chosen SRB level. As previously discussed, the ACOL model is designed to estimate the difference in military and civilian pay and benefits for the SRB-eligible sailors if they leave or stay. As SRB values increase, military compensation and the cost of leaving increases. If military compensation exceeds expected civilian compensation by an amount that is sufficient to compensate for the distaste for the military lifestyle, it is expected that the sailor will reenlist.

The ACOL model, originally estimated separately for each of the nine occupational groups identified by Warner and Goldberg in 1982, was updated in 1999 and reflects the expected change in reenlistment rates based on a change in the SRB multiple. Reenlistment rates will differ across the skill groups for a given SRB multiple due to the differing values of the ACOL variable (Moore, et al., 2003)

Initially, in figuring the reenlistment rate for a program year (to determine the anticipated budget), the ROGER model determines the reenlistment rates for each skill set in a given (base) year by including actual reenlistment rates from the previous years. Then, using the ACOL framework, the model compares the differences in military and civilian compensation, the national unemployment rate, and the SRB level between the base year and the program year to calculate the projected reenlistment rate for the upcoming program year (Moore, et al., 2003).

3. Estimation of SRB Takers and SRB Program Costs

Once the estimated reenlistment rate is applied to the eligible pool for each occupational group, the model forecasts the number of sailors in each specialty who are expected to reenlist for the bonus. As previously discussed, the bonus amount for each sailor is the product of monthly basic pay multiplied by the contract length multiplied by the bonus multiple.

Bonus amount per sailor is estimated in three steps:

(1) Basic pay is computed by YOS, using the paygrade-weighted average in each cell, and is updated annually;

(2) Length of reenlistment estimates are made based on parameters estimated in Warner and Goldberg’s 1984 study;

(3) Cost of contracts for the current execution year are computed based on current payout policy. At this time, 50% of the bonus is paid as a lump-sum, upfront amount at the time of reenlistment (Moore, et al.,

2003). Then, for total program cost, the cost is projected for the aggregate pool of the projected takers.

4. Issues Identified by Lewin Group Paper

The Moore, Hogan and Espinosa study (2003) identified several key issues with the estimations and predictions of the ROGER model. Their study tested the model as a whole to identify possible problems and potential errors affecting the model's output. Their study identified the following issues: (1) the under-prediction in the identification of sailors eligible for an SRB in the fiscal year; (2) the under-prediction of SRB takers; and (3) the under-estimation of reenlistment contract length.

a. Identification of SRB-eligible Sailors

According to the Lewin study, the ROGER model does not capture all the sailors who are eligible for the SRB. In FY00, 23% of the sailors who reenlisted for the SRB were not correctly identified as being in the eligibility pool (Moore, et al., 2003, p. 11). Though perfect identification cannot reasonably be expected due to changing Navy policies and the shifting of manpower and skills (not to mention rating mergers and the like), under-prediction of the eligibles was attributed to two primary factors.

The first factor, which accounted for 36% of the FY00 takers (and as high as 90% of the HMs in Zone 1) who were identified as non-eligibles, was due to recent skill acquisition. Many sailors gain the rating, NEC or skill that qualifies them for an SRB during the current fiscal year. Therefore, when the prediction of the eligible population is made at the beginning of the fiscal year, they are not identified because they acquired the skill later that same year. However, the study theorized that if information from Navy training pipelines and schoolhouses could be captured and integrated into the model, the impact of this particular problem on under-prediction could be lessened (Moore, et al., 2003).

The second factor contributing to the mis-identification of eligibles is the number of sailors who reenlist "early" or prior to the time they are in the "reenlistment eligibility window". This problem is difficult to solve because sailors can re-enlist early for numerous reasons. Though not all reasons for an early reenlistment can be identified, the major three identified in the Lewin Group study were (1) Permanent Change of Station orders; (2) for those sailors holding nuclear specialty skills (particularly in Zones B and C); and (3) sailors with submariner skills (Moore, et al., 2003, p.16). It is important to note, however, "that over one-half of early reenlistments remain unexplained" (Moore, et al., 2003, p.6).

b. Prediction of SRB Takers

Once the eligibility errors were corrected in the Lewin Group study for the FY00 data, the model still under-predicted the number of reenlistments by 14%, as shown in Table 8. However, if the members who were not identified as eligibles and who actually took the SRB had been included in the study, the reenlistment projection error would have been even greater (Moore, et al., 2003, p. 18). It can be assumed that the 14% error rate is downward biased because there were a significant number of sailors who took the SRB and were not identified as eligible. The error rate varied by zone, with Zone A predictions at 14.4% below the actual reenlistments, Zone B at 11.9% below, and Zone C at 22% below (Moore, et al., 2003).

The results of the Lewin Group study (2003) are displayed in Table 7, which shows the following for each zone in fiscal year 2000:

- Column 1: the zone;
- Column 2: the number of sailors in the applicable zone who were predicted to reenlist for the SRB;
- Column 3: the number of sailors in each zone who actually reenlisted for an SRB;
- Column 4: the difference between the number predicted to reenlist for the SRB and the number who actually reenlisted for the SRB = (Col 2)-(Col 3);

- Column 5: the percentage difference between predicted numbers and actual numbers, using the average of actual and predicted values as the base.

Table 7. Actual and Predicted SRB Takers, by Zone, FY00 in Lewin Study
(Moore, et al., 2003, p. 19)

(1)	(2) Predicted	(3) Actual	(4) Difference	(5) Percent Difference
Zone A	6,489	7,493	- 1,004	- 14.4%
Zone B	2,584	2,911	- 327	- 11.9%
Zone C	996	1,242	- 246	- 22.0%
Total	10,069	11,646	- 1,581	- 14.5%

Note: The percentage difference uses the average of actual and predicted values as its base.

There was significant variation in the difference between the predicted takers and the actual takers amongst the nine different occupational groupings, with the bulk of the under-prediction of takers in a small set of skills. For instance, as Table 8 indicates, in Zone A, 50% of the error was attributed to the following ratings and NECs: Electronics Technician (ET), Fire Control Technician (FC), Nuclear NECs, Divers, Missile Technician (MT), Fire Control Technician (FT) and Builders (BU) (Moore, et al., 2003, p. 6). It is important to note that the occupational groups currently being used were originally established 25 years ago. Since then, new ratings have been created (such as Diver) and they have been assigned arbitrarily into an existing occupational group. Each of the groups has its own specific pay elasticity, based on the assumption that civilian skills and employment opportunities for each skill in the group are similar. Though there have been minor adjustments and re-estimations, the groupings currently in use may need to be examined.

For each Zone and Occupational Groupings, Table 8 shows the following:

- The "Pred" columns show the number of SRB reenlistments predicted by the model.
- The "Actual" columns show the number of sailors who actually reenlisted for an SRB.

- The "% Diff" columns show the percentage of difference between the predicted and actual numbers, using the average of actual and predicted values as the base.

Table 8. Predicted and Actual Reenlistments by Zone and Occupation Group
(Moore, et al., 2003, p. 21)

Occupation Group	Zone A			Zone B			Zone C		
	Pred	Actual	%Diff	Pred	Actual	%Diff	Pred	Actual	%Diff
Non-electronic maintenance	1,704	1,867	-9.1%	340	316	+7.3%	191	173	+9.9%
Electronic maintenance	1,776	2,304	-25.9%	584	699	-17.9%	355	361	-1.7%
Aviation maintenance	643	570	+12.0%	201	147	+31.0%	1	9	+160.0%
Ship/Aviation support	1,276	1,362	-6.5%	542	686	-23.5%	42	150	+112.5%
Healthcare	122	141	-14.4%	240	242	-0.8%	28	34	+19.4%
Logistics	208	263	-23.4%	103	79	+26.4%	-	-	NA
Construction	253	353	-33.0%	207	266	-24.9%	1	1	0.0%
Cryptology	361	395	-9.0%	161	188	-15.5%	60	104	-53.7%
Admin, media and other	146	238	-47.9%	206	288	-33.2%	318	410	-25.3%

Note: The percentage difference uses the average of actual and predicted values as its base.

5. Under-prediction of Contract Length

The third major problem identified by the Lewin Group (2003) is the under-prediction of contract length by an average of 3.6 months. This under-estimation has a significant impact in terms of under-predicting projected financial cost for the SRB program. In Zone C, however, the model slightly over-predicts contract length.

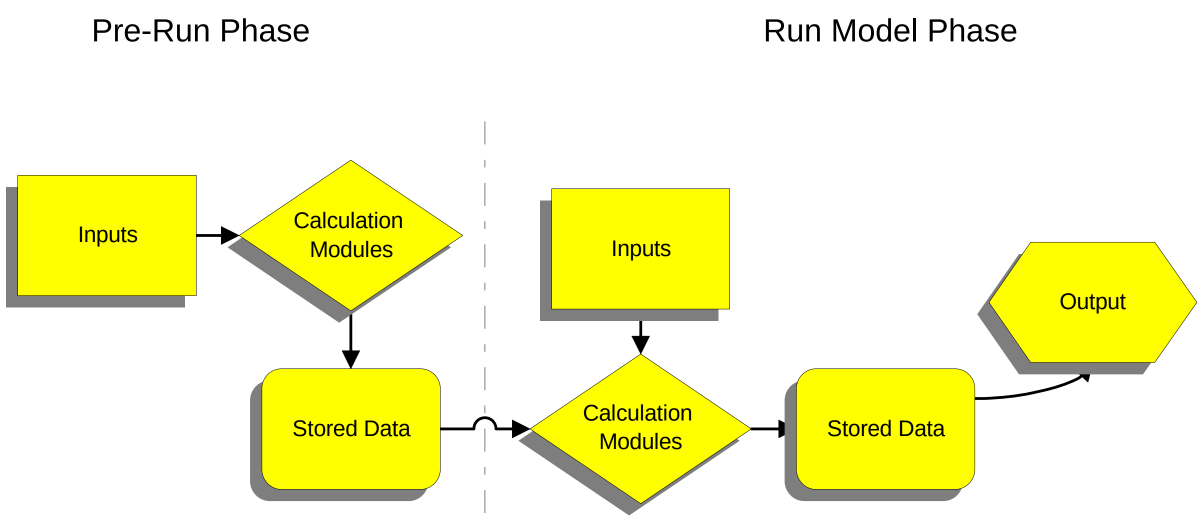
B. Overview of the SRBMS ROGER Model

The ROGER model provides the Navy with the capability to predict the effects of proposed changes in the Selective Reenlistment Bonus (SRB) plan on the size and shape of the enlisted force. An equally important feature of ROGER is the capability to project budget expenditures and manpower inventory effects associated with alternative SRB plans. The model predicts the effects of bonus payments on reenlistment rates at both the rating and NEC (skill) levels.

As previously discussed, the Lewin Group study (Moore, et al., 2003) identified several potential sources of error in the SRBMS. Since the Lewin study appeared, there have been numerous other changes in the Navy policies that may have affected the performance of the model in predicting reenlistments. New ratings have been created; other ratings have been changed and merged; the ROGER model has been enhanced; competing incentive programs and policies are continually changing; and there have been dramatic changes in civilian wage and employment prospects in many occupational fields. Additional issues addressed in the Lewin study were that generated budget costs associated with the initial SRB program continue to under-predict actual expenditures, resulting in fiscal year budgetary problems.

The structure and flow of the ROGER model are divided into “Pre-Run” and “Run Model” components. Figure 6 below describes the inputs, procedures and outputs for each of these components.

Figure 6. ROGER: Primary Components
(Mackin, 1999, Appendix B, p. 4)



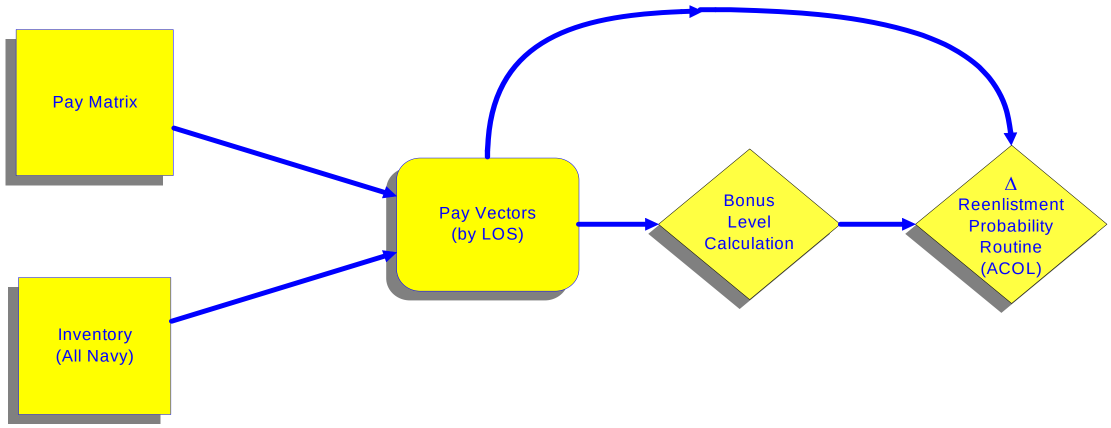
In the “Pre-Run” phase, several primary inputs must be entered prior to running scenarios. These inputs include:

- Pay tables.
- All-Navy inventory data.
- CPI deflator.
- SRB lump sum percentage.
- The analysis file (which contains information such as SRB Multipliers for each skill and 6YO flags).

The model is structured so that the “pre-run” phase does not have to be opened each time a new scenario is run, but only when data requires updating, which usually occurs several times a year (Mackin, 1999, Appendix B, pp. 4-5).

As illustrated in Figure 7, pay tables and all-Navy inventories must be entered for both the baseline year and the analysis year. ROGER filters the inventories into length of service groupings because the model only recognizes zone, not grade. The information from the length of service groupings is then used in the “*bonus level calculation routine,*” which measures the reenlistment bonus amount for a length of service (0-12 years) and Length of Reenlistment (3-6 years) and any SRB multiplier from 0 to 10. The model then converts pay and bonus amounts into base year dollar values that are utilized in other processes in the model to estimate cash amounts for current ACOL dollar values (Mackin, 1999, Appendix B, p. 5).

Figure 7. Pre-Run Pay and Inventory Inputs
(Mackin, 1999, Appendix B, p. 5)

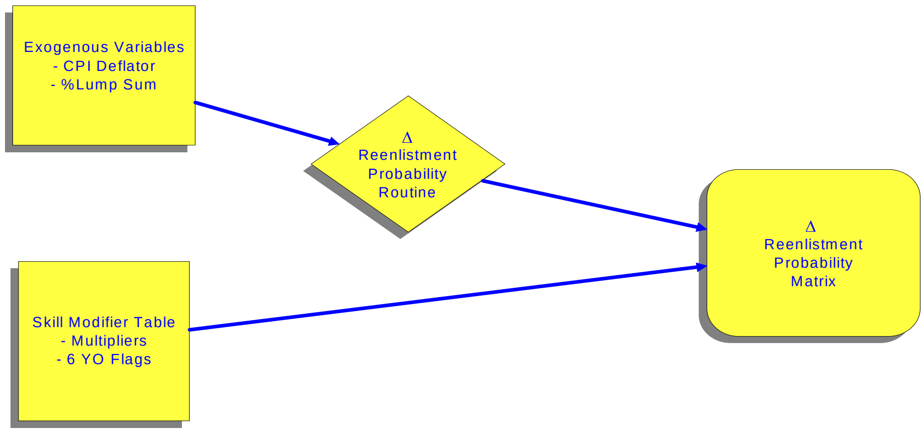


Several "exogenous variables" must be updated by the user. These variables include:

- Current CPI data needed to deflate pay and bonuses to base year values (required for projection of the ACOL effect);
- Percentage of SRB paid as a lump sum is required to calculate present value of the awards (currently at 50%);
- Baseline SRB multiplies is entered in the *skill modifier table* by skill and zone. (Mackin, 1999, Appendix B, p .5)

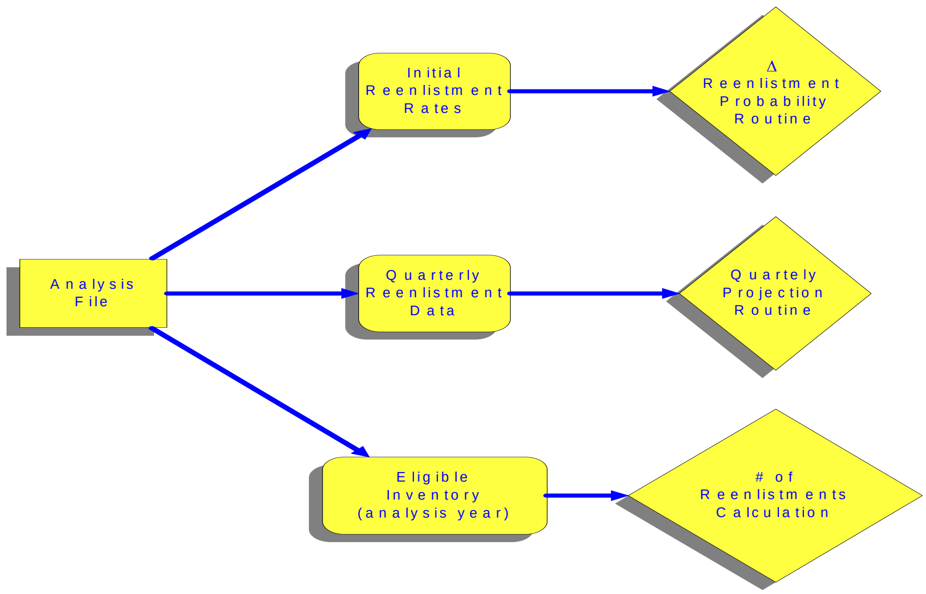
Figure 8 illustrates the flows of the exogenous variables. The SRBMS predicts the changes in the number of reenlistments from the baseline for any of the skill groups in response to the SRB Multiple proposed for that skill. This information is then stored in the reenlistment probability routine and can be used later when developing new scenarios without having to recalculate reenlistment probabilities each and every time (Mackin, 1999, Appendix B, p. 5).

Figure 8. Additional Pre-Run Inputs
(Mackin, 1999, Appendix B, p. 6)



The last part of the "Pre-Run" Phase, illustrated in Figure 9, uses the previously generated analysis file (data set produced by the Retention Reporting System that contains individual level SSN, LOS, skill identifiers, EAOS used in constructing inventories) to create initial reenlistment rates for each specialty. The initial reenlistment rates are then fed through the reenlistment rate routine and multiplied by the eligible inventory to project the number of reenlistments, which is used for planning and ultimately for fiscal year cost/ budget forecasting (Mackin, 1999, Appendix B, p. 6).

Figure 9. Analysis File Data Generation
(Mackin, 1999, Appendix B, p. 6)



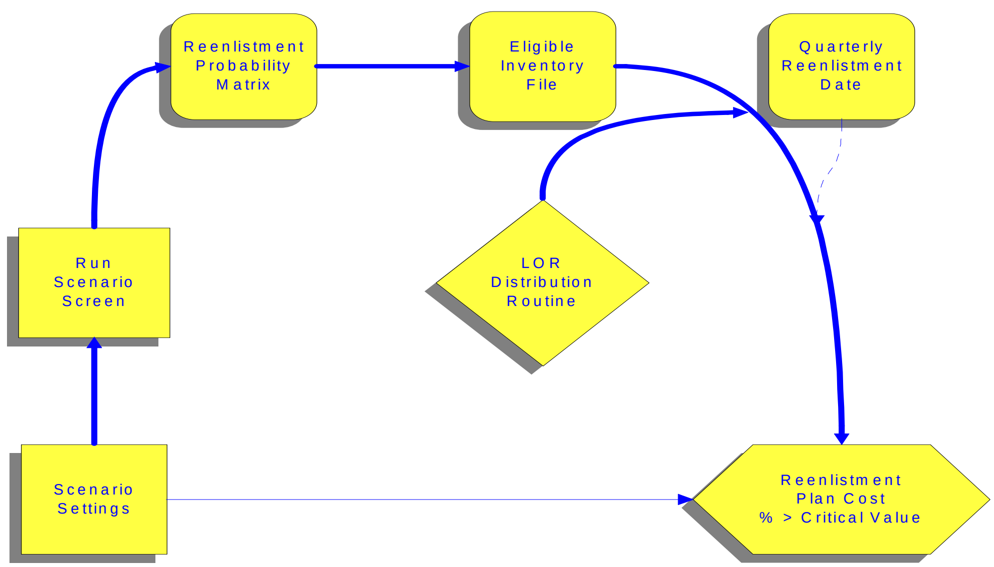
The “Run” phase begins once the user has completed the “Pre-Run” phase and is ready to run proposed SRB scenarios, and the current year analysis has been entered in the plan or scenario. The user then has the ability to enter different SRB multiplies for each skill, maximum bonus amounts and any fencing (protection from changes in SRB multiples) of skill groups. The features that can be set include:

- the highest changes of multiplier from any given base year.
- the period for which the analysis should be run (baseline, quarter, partial year), and
- the maximum amount of bonus payable for any particular skill group (Mackin, 1999, Appendix B, p. 7).

As illustrated in Figure 10, the reenlistment probabilities associated with any given plan or scenario is “Run” against the relevant inventories of eligible sailors previously identified from the “Pre-Run” phase. The model then updates itself by calculating actual Average Length of Reenlistment (*ceteris paribus,* observing indifference curves to identify maximum utility) and reenlistment rates from previous analysis periods. These enhancements and procedures are then stored and applied to a plan to generate bonus taker rates and projected plan costs. The summary output can then be displayed by:

- Projected number of reenlistments for each skill group.
- Projected reenlistment rate for each skill group.
- Budget cost of proposed SRB plan.

Figure 10. Run Model Structure
(Mackin, 1999, Appendix B, p. 7)



C. Assessment of the SRBMS ROGER Model

1. Methodology of Analysis

Even though the model projects the number of reenlistments and then the budget cost of the SRB plan in two phases (pre-run/run), the functions will be organized into a three-phase operation for the purpose of the model assessment:

- Identification of sailors eligible for reenlistment and SRB
- Categorization of ratings/NECs into occupational groupings and application of associated pay elasticities (from the ACOL model)
- Forecast of number of reenlistments and costs of the SRB plan

The assessment of the performance of the ROGER model in this thesis utilizes data on all Navy enlisted active duty inventories for fiscal years 2004-2007, and listings of sailors who actually received new SRB awards during those same fiscal years. The reason for using the four-year period is to capture any changes in the performance of the model due to enhancements the ROGER model or policy shifts affecting reenlistments that occurred over time.

For this simulation, the researchers used two primary data extracts from the Enlisted Master Record (EMR), both containing unique personal identifiers. To ensure the researchers were using the same data as used in the ROGER model for each year's predictions, they acquired the data directly from SAG Corporation, the contractor that maintains the ROGER model for the Navy. Data was then converted into ".dta" format for use in Stata statistical analysis software. The first data set, which will be referred to as the *All-Navy File*, was an extract of all Navy enlisted personnel on active duty as of 30 September, the last day of the previous fiscal year, for fiscal years 2004-2007. The second, hereafter referred to as the *Takers File*, was a file of all Navy enlisted personnel who reenlisted for an SRB in a given fiscal year. A third file, which will be referred to as the *Eligibles File,* is obtained by applying the algorithms in ROGER that identify SRB-eligible sailors to the *All-Navy File (inventory)* to predict the eligibles for a given year. In principle, this approach should provide identical results to the predictions that were produced by ROGER for each fiscal year.

2. Identification of Eligibles

As mentioned above, the ROGER model begins by identifying sailors who are eligible for reenlistment and for an SRB based on data taken from an extract of the EMR. This includes, under current reenlistment rules, those who are at the end of active obligated service (EAOS) during the fiscal year of the SRB program, and those in selected skills with six-year obligations who have a wider window to reenlist. Rating, NEC and other information, in addition to Zone and EAOS, are used to identify who is eligible and to assign them to the correct occupational group. Specifically, two principal criteria define eligibility for the SRB in a given year:

- The skills the sailor holds (rating and NEC) for which the Navy is offering SRBs, and
- Whether they are within 13 months of SEAOS (for 4-year obligors) or 48 months from SEAOS (Zone A, 6-year obligors).

Based on these two criteria, the algorithm in ROGER that identifies SRB-eligible sailors is fairly clear. It simply examines each sailor's record in the EMR to identify ratings and NECs held and matches them to any NEC/rating on the SRB list. Prior to FY04, if a sailor had more than one NEC, the model used only the primary NEC. If a sailor were eligible for an SRB under a different NEC (many sailors hold multiple NECs), the model did not recognize it. After FY04, however, an enhancement to the algorithm included the ability to look at all of the NECs (up to eight) that each sailor holds and, for estimation purposes, selects the one that would result in the largest bonus. This enhancement helps in the projection of the cost of the SRB plan so that the maximum bonus for each reenlistee is accounted for, even though he or she may choose to reenlist for an NEC with an SRB of a lower amount (sailors who reenlist for an SRB NEC are required to utilize that NEC over the period of enlistment).

For the simulation and analysis, the researchers used data over several years in order to catch any relevant trends. The data taken from the EMR included all Navy enlisted personnel on active duty at the beginning of the fiscal year (for fiscal years 2004-2007), as well as a listing of the sailors who actually reenlisted that fiscal year for an SRB (hereafter referred to as "takers"). In theory, the process should result in the correct identification of all eligibles; however, defining who is actually in the eligibility window becomes more difficult when put into practice. This is due to the multitude of existing policies created to handle various requirements, including Permanent Change of Station (PCS) moves, Tax free zones, vacating inoperative extensions, Selective Training and Reenlistment Program (STAR), Special Duty Assignment Pay (SDAP), and OBLISERV to Train (OTT), just to name a few.

Generally, sailors reenlist for an SRB during the same FY as their EAOS; however, there are always exceptions. For instance, acceptance of a PCS move requires a minimum of obligated time. If sailors who accept PCS orders do not have the time remaining on their contract, they can vacate an inoperative extension and reenlist, or they may extend, or they may be allowed to reenlist early. Those who must OBLISERV to execute a PCS move may reenlist any time within the same fiscal year as their PCS detachment month, but no later than the date of detachment from the last intermediate duty station. Therefore, there may be a large window in which the sailor is eligible to reenlist early, depending on the number of intermediary duty stations. OBLISERV must still be obtained prior to transfer, and normally within 30 days of receipt of orders (30-day rule) (MILPERSMAN 1306-106 and MILPERSMAN 1160-040).

A sailor may not transfer without the required OBLISERV indicated in the orders prior to departure from their present Permanent Duty Station (PDS). In cases where a possible loss of SRB would occur if the member reenlisted prior to transfer, extensions are usually granted. Members may cancel up to 24 months of any non-operative extension (or extensions, total time not to exceed 24 months) with no loss of SRB under certain circumstances. But, it is not certain if service members are aware of the option to obtain extensions or decide to wait until the maximum benefit is available. Even with the latitude given to SRB reenlistees, there are certain sailors who cannot reenlist without incurring a loss of SRB. These individuals who are selected as being eligible but unable to wait until an SRB window opens are:

- <u>OBLISERV to Train and then reenlist (OTT)</u>. This option is for those who have an NEC qualifying school en route, or are changing rates, and is limited to those sailors who are NOT already SRB-eligible and whose EAOS (as extended) is prior to their graduation date.
- <u>Waiver of 30-day rule</u>. This occurs when a sailor can reenlist prior to departure from their present command, but are unable to reenlist within the 30 days without potential loss of SRB. Waivers are normally granted, provided the sailors can obligate prior to transfer from their present command.

- Use of a combination of one or more extensions and/or page 13 entry in lieu of (all) hard OBLISERV. If sailors are not qualified for the OTT program and there is still potential for SRB loss, commands/Personnel Support Detachments (PSDs) are authorized to use two extensions if needed--one conditional extension to extend the service member's EAOS past the graduation date from a school that will result in an SRB-qualifying Navy Enlisted Classification (NEC) being earned, and a second conditional extension for up to 24 months.

The STAR program offers career designation to first term enlisted members who enlist or reenlist and thereby become eligible for certain career incentives, such as guaranteed schools, automatic advancement upon completion of schooling, or SRBs. To be eligible for the STAR program, the sailors must be on their first enlistment, with more than 21 months active duty and fewer than 6 years active duty. The standard eligibility window for reenlistment applies, and in some cases, those reenlisting under the program could lose potential benefits. For example, a sailor requesting a "C" School under STAR, which will earn an SRB-eligible NEC, could lose considerable SRB entitlements.

Some sailors may reenlist early in order to fill a "hard-to-fill" billet or special assignment that entitles them to Special Duty Assignment Pay (SDAP). SDAP applies specifically to individual billets that are difficult or challenging assignments and require an extra degree of effort to perform. Since these billets are awarded through the detailing process like all other billets, those who elect to take them may need to obligate additional time for a PCS move or to meet a minimum time requirement in the billet. The SDAP is a competing incentive program that may influence a sailor to take an SRB early and combine this with SDAP to maximum income.

Early reenlistment is available to sailors with non-operative extensions, so those sailors obligated for more than 4 years often reenlist early. The SRBMS includes a number of user-definable parameters to expand the eligibility window for skills that are likely to include 5- and 6-year obligors (5- and 6-YOs). This option is available for Zone A only.

This variation is accounted for in the ROGER model by a "6-YO flag" option. In order to activate the 6-YO flag it must be selected in the *Skill Modifier Table* for the applicable NEC/Rating. The user must indicate the months of service spanned by the eligibility window by checking the corresponding box. For skills with the 6-YO flag checked, the SRBMS searches the EMR for individuals who are under extended obligations. This is indicated by a difference between the HEAOS and the SEAOS displayed in the member's record. If the sailor appears to be serving under a 5- or 6-year obligation, the model applies the user-defined eligibility window. If the Navy grants early eligibility to 4-YOs, the SRBMS will not detect these sailors automatically. The 6-YO flag can be manually selected, which will cause the model to treat those sailors similarly to the 5- and 6-YOs, but the risk is that if used indiscriminately, the pool of eligibles would be over-estimated, which would cause a severe overestimation of eligibles. Note that as for the 5- and 6-YOs, the 6-YO flag can only be selected for Zone A. The model would need to be modified to activate this option for Zone B or C. For the purpose of this simulation the researchers activated the 6-YO flags for:

- Ratings and NECs in the Nuclear Field (NF), Advanced Electronics Field (AEF), or Advanced Technical Field (ATF), which have 6-year obligations.

Due to the various reasons that sailors may reenlist early, there is no definitive way to identify these sailors given the current model configuration and the data source. For this simulation, the authors set the window of eligibility to 24 months through 72 months of active service for the NF and 13 months from EAOS for all other skills.

When assessing the predictive accuracy of the ROGER model, the researchers compared the file of predicted SRB eligibles with an official record of sailors who actually took the SRB in FY04-07. All data was extracted from the EMR. The official record of those who took the SRB contains the SRB effective date, bonus level, length of reenlistment and SRB skill. They then performed a social security number (SSN) match between the model's pool of identified eligibles and the actual takers. Zero error would indicate that all of the SSNs in the *Takers File* also appeared in the model's predicted list of eligibles. On the other hand, if the SRBMS failed to identify a large number of actual takers as eligibles, this would signal a problem with the model's algorithm, input data, or both.

As seen in Figure 11 and Table 9, in FY04, of the 13,652 sailors who reenlisted for an SRB (in all zones), 3,448 were not identified in SRBMS as having been eligible for reenlistment, an error rate of 25.25%. Zone C had the largest percentage of error in FY04 (43.4%), while Zone A had the largest number of takers (1,539) who were not identified as eligible. Overall, the model did not correctly identify as eligibles at least 25.25% of all the actual SRB takers in FY04 (for all zones).

Figure 11. FY04 SRB Reenlistments and Percent SRB Reenlisters Incorrectly Classified

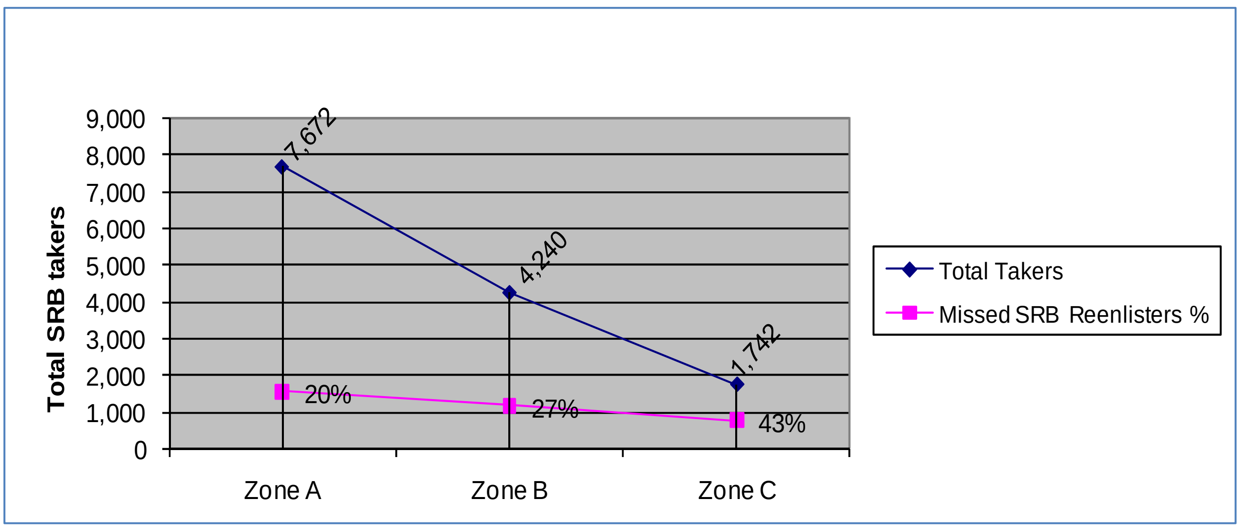


Table 9. FY04 Snapshot of Eligibles, Takers and "Missed"

(1)	(2) Total SRB Takers	(3) Identified SRB reenlisters	(4) Missed SRB reenlisters = (2)-(3)	(5) Percent Error
Zone A	7,672	6,133	1,539	20.06%
Zone B	4,240	3,088	1,152	27.17%
Zone C	1,742	985	757	43.46%
Total	13,654	10,206	3,448	25.25%

Figure 12 and Table 10 display the results of comparing actual takers to the number of predicted eligibles from the ROGER model for FY05. As Table 11 shows, 4,057 of the 16,973 sailors accepting SRBs were not identified in the eligibility pool. As in FY04, Zone C was the largest error percentage-wise (48.4%), and Zone A contained the largest number of takers not identified as eligibles. Overall, the model did not correctly identify at least 23.9% of the SRB takers, which is nearly the same overall (all zone) underprediction rate as in FY04. However, it is noteworthy that the underprediction of Zone A takers fell from 20.06% in FY04 to 16.29% in FY05.

Figure 12. FY05 SRB Reenlistments and Percent SRB Reenlisters Incorrectly Classified

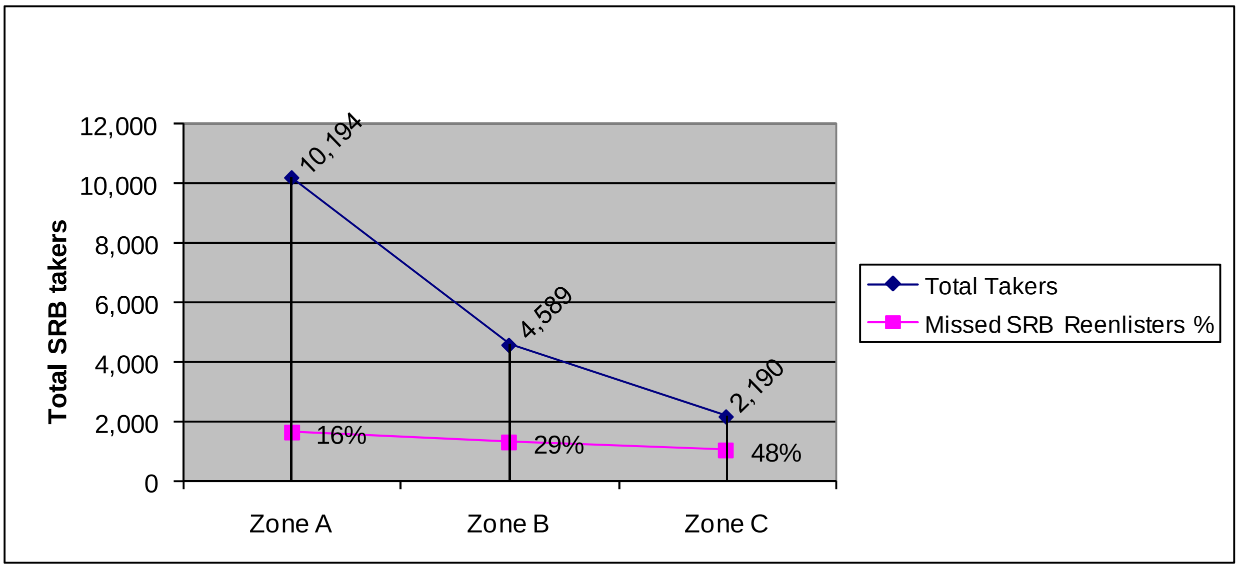


Table 10. FY05 Snapshot of Eligibles, Takers and "Missed"

(1)	(2) Total SRB Takers	(3) Identified SRB reenlisters	(4) Missed SRB reenlisters= (2)-(3)	(5) Percent Error
Zone A	10,194	8,533	1,661	16.29%
Zone B	4,589	3,255	1,334	29.07%
Zone C	2,190	1,128	1,062	48.49%
Total	16,973	12,916	4,057	23.90%

Figure 13 and Table 11 display the analysis of SRB takers and eligibles for FY06. FY06 was similar to FY04 in that 3,529 of the 13,389 reenlistees were not correctly identified, for a total of almost 21% of eligibles missed by the model (in all zones). The underprediction of Zone A takers fell to only 11.83% in FY06 (compared to 20.06% in FY04 and 16.29% in FY05).

Figure 13. FY06 SRB Reenlistments and Percent SRB Reenlisters Incorrectly Classified

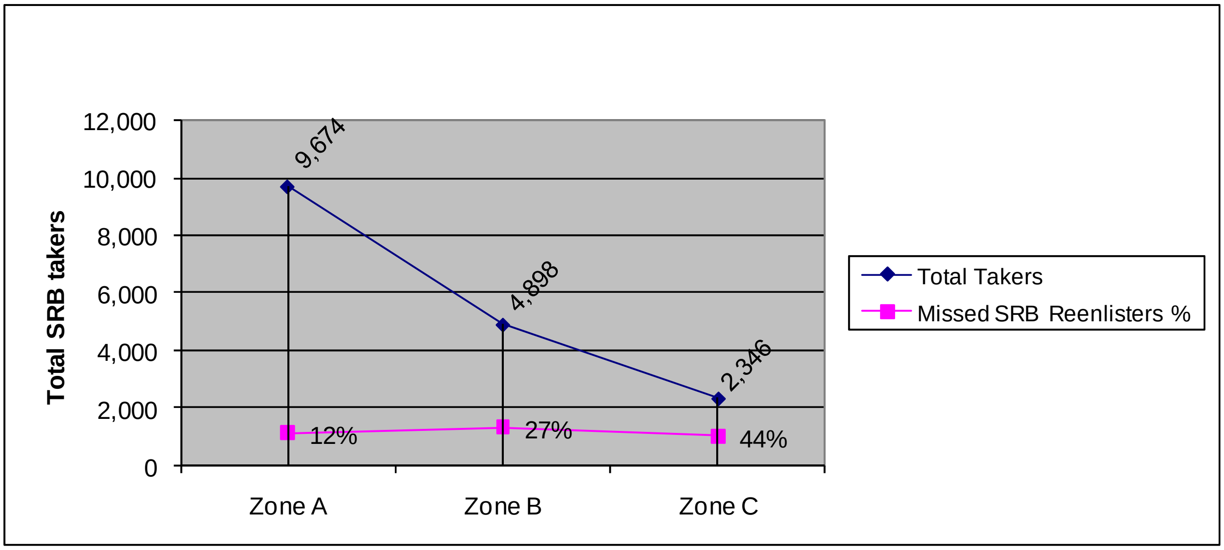


Table 11. FY06 Snapshot of Eligibles, Takers and "Missed"

(1)	(2) Total SRB Takers	(3) Identified SRB reenlisters	(4) Missed SRB reenlisters= (2)-(3)	(5) Percent Error
Zone A	9,674	8,530	1,144	11.83%
Zone B	4,898	3,555	1,343	27.42%
Zone C	2,346	1,304	1,042	44.42%
Total	16,918	13,389	3,529	20.86%

Figure 14 and Table 12 display the analysis of takers and eligibles for FY07. Of the 13,414 reenlistees, 3,733 were not identified correctly by the model as being eligible. Overall, the model did not correctly identify at least 27.8% of all actual SRB Takers in all three zones. The underprediction of Zone A sailors increased from 11.83% in FY06 to 14.75% in FY07. The underprediction of Zone C also increased and was 50.81% for FY07.

Figure 14. FY07 SRB Reenlistments and Percent SRB Reenlisters Incorrectly Classified

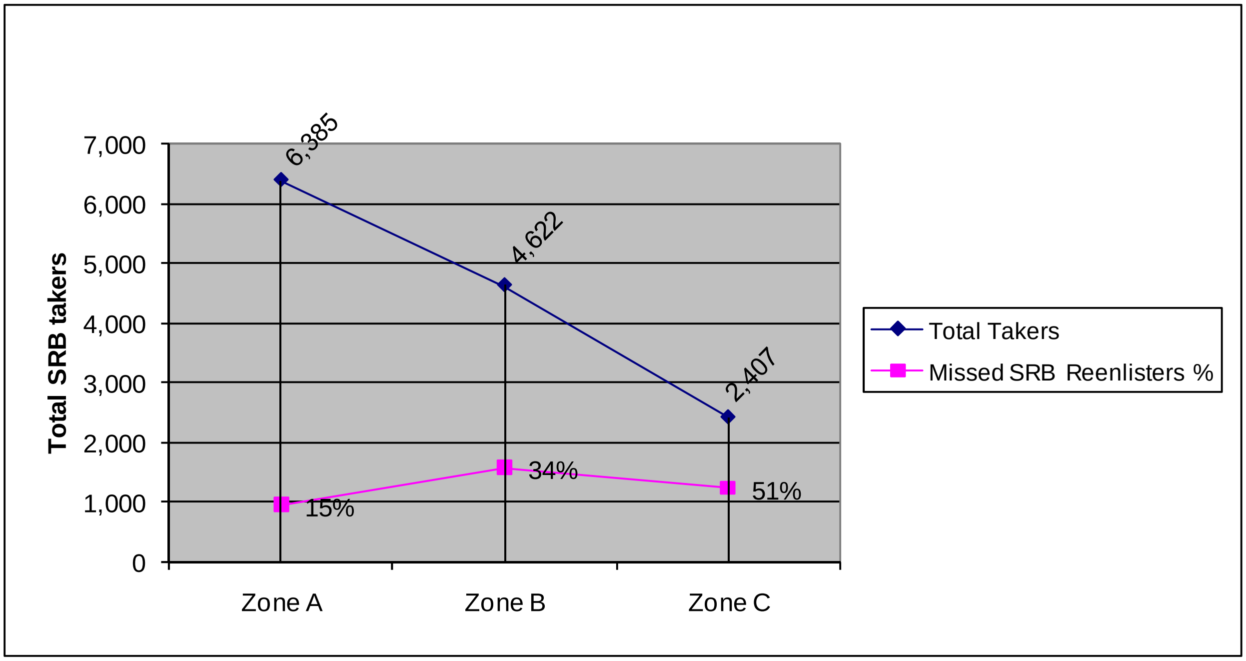


Table 12. FY07 Snapshot of Eligibles, Takers and "Missed"

(1)	(2) Total SRB Takers	(3) Identified SRB reenlisters	(4) Missed SRB reenlisters= (2)-(3)	(5) Percent Error
Zone A	6,385	5,443	942	14.75%
Zone B	4,622	3,054	1,568	33.92%
Zone C	2,407	1,184	1,223	50.81%
Total	13,414	9,681	3,733	27.83%

In attempting to determine the reasons the SRBMS under-predicts eligibles, the Lewin Group study (2003) found that 25% of eligibles were missed because they acquired a new skill during FY00 and therefore were not treated as being eligible. The study considered this to be a major contributing factor for under-prediction. Sailors may acquire new skills by completing training programs (such as A- or C-Schools), converting to other ratings, or qualifying for additional NECs. The researchers attempted to reproduce the Lewin Group study with newer data to ascertain whether new skill acquisition was responsible for the missed eligibles in the newer-years data. The researchers performed the following steps with the FY07 data:

- They matched individuals in the *Takers File* with the corresponding individual file in the All-Navy file (based on unique personal identifiers),
- Using Stata, they looked for matches between the primary and secondary NECs in each file,
- They generated a new variable that identified the occurrence of NEC mismatches in either field for each sailor.
- If none of the NEC fields matched, then the sailor either was assumed to have acquired the SRB-qualifying NEC during FY07 or the SRB NEC was missing from the file (data entry error).

Based on their analysis of FY07 data, the researchers found only 12% (plus any portion of the 1.8% data error) of all non-identified eligibles was due to new skill acquisition during the year. This dramatic shift from the 25% figure in CY00 (in the Lewin Group study) could be in part attributed to the enhanced ROGER algorithm that allows for selection of NECs other than only the PNEC, or it may be possible that the current data is more accurate. Overall, the total percentage of unidentified takers remains fairly consistent with the Lewin Group study; however, the reasons for the missed eligibles seem to have shifted over time. Since the data for FY04, FY05 and FY06 were relatively similar, the remainder of this chapter will refer to the FY07 data only.

To determine reasons for missed eligibles, the researchers applied the following method:

- Because the eligibility window is set at 13 months prior to EAOS (by policy, exceptions noted below), they created dummy variables to designate whether a sailor had a soft EAOS within 13 months of 30 September
- Those with an EAOS within 13 months were determined to be eligible to reenlist in FY07
- Exceptions: those in nuclear fields in Zone A can reenlist as early as 48 months out, so for nuclear ratings, they looked for a soft EAOS within 48 months of 30 September

As depicted in Figure 15 and Table 13, the researchers found that for FY07, 3,221 of the 3,733 takers (86%) were not identified as eligible because they were outside established eligibility windows, according to the model's specifications. Additionally, almost all of the missing eligibles with newly acquired skills were in Zone A. Of the 3,733 takers who were not identified as eligible by the model, 12% gained a new skill in FY07. For that reason, they would not be identified at the beginning of the fiscal year when the eligibility pool is identified. Another 13% were outside of the eligibility window, and were in Zone A, while 73% were outside of the eligibility window and were in Zones B or C.

Figure 15. Reasons Why FY07 SRB "Takers" are Not Identified as Eligible

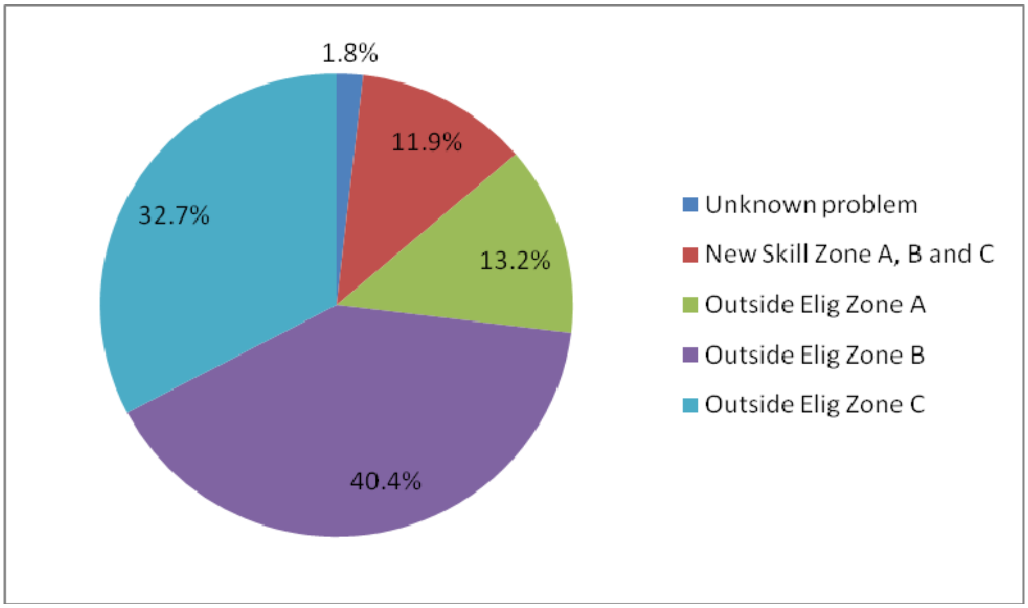


Table 13. FY07 Causes of Under-prediction of Eligibles

FY07 Causes of Under Predictions of the 3,733 SRB- Eligibles

	Number Missed	Percent of all Missed
Unknown problem	68	1.8%
New Skill Zone A, B and C	444	11.9%
Outside Elig Zone A	493	13.2%
Outside Elig Zone B	1,508	40.4%
Outside Elig Zone C	1,220	32.7%

In summary, the vast majority of error was due to sailors who reenlisted prior to their eligibility window (early reenlisters). Errors due to sailors being outside the eligibility window are very difficult to identify because there are so many exceptions to the 13-month window and they cannot be generalized in the ROGER model without risk of overestimation. For example, one reason for error is the increasing benefit of reenlisting for an SRB during deployment to tax-free geographic areas (e.g., Iraq, Afghanistan, etc.). If a sailor reenlists while in a tax-free area, both the lump sum and the annual installments are tax-free. Therefore, the present value of a small tax-free SRB can exceed that of a larger taxable bonus. For this reason, a number of sailors may elect to vacate an inoperative extension and reenlist prior to their eligibility window. However, there is no way to identify how many sailors could take advantage of this opportunity as the incidence is difficult to predict accurately.

The timing of eligibility was mostly a problem in Zones B and C. Only 53% of the takers who were “missing” for this reason were in Zone A. In Zone B and C, 96% of the “missing” takers fell outside the eligibility window, and in Zone C, 99%. This may be due to the increase in OPTEMPO and deployments over the last several years and increasing opportunities for sailors to reenlist early while in tax-free regions.

3. Skill Groups and Application of ACOL Pay Elasticities

After the eligibles population has been identified, the model automatically sorts the eligibles into their corresponding nine occupational groups based on NEC, rating and zone. Table 14 below displays the nine occupational groups and the rating and NECs associated with each. Table 14 also includes the estimated ACOL pay elasticity by occupational group and zone.

Table 14. Current Occupational Groups and Inclusive NECs

	ACOL Elasticity				
OCC Group	ZoneA	ZoneB	ZoneC	Rating	NEC
1. Non-electronic Maintenance	0.000032	0.000065	0.000067	NUC-MM, HT, MM, MR, MMSS	3365, 3366, 3355, 3356, 3396, 3385, 3386, 4946, 4955, 4503, 4502,0000
2. Electronic Maintenance	0.000021	0.000085	0.000068	NUC-ET, NUC-EM, ETSW, FC, FC AGEIS, EM, IC, ETSS-NAV, ETSS-COMM	3363, 3364, 3353, 3354, 3359, 3393, 3394, 3383, 3384, 3389, 1428, 1456, 1465, 1468, 1510, 1511, 1568, 1570, 1571, 1572, 1579, 1589, 1590, 1592, 1654, 1685, 6673, 9509, 9604, 9606, 9610, 1104, 1105, 1107, 1115, 1119, 1136, 1143, 1144, 1157, 1318, 1322, 1326, 1331, 1332, 1333, 1334, 1335, 1336, 1337, 1339, 1615, 1624,1625, 1628, 1658, 4672, 4675, 4755, 4756, 4747, 4746, 4712, 14CM, 14CM, 14EM, 14TM, 0000
3. Aviation Maintenance	0.00008	0.000083	0.000047	Aircrew, ABE, ABF, AD, AE, AM, AME, AO, AS, AT	8207, 8215, 8220, 8226, 8235, 8251, 8252, 8284, 9402, 6673, 8306, 8341, 0000
4. Ship/Aviation Support	0.000031	0.000059	0.00002	SO, EOD, SB, ND, BM, GM, IT, MN, OS, QM, STG, TM, ABH, AC, AG, AW, AZ, PR, DC, EN, GSE, GSM, FT, MT, STS, MA	5326, 5323, 5320, 5337, 5336, 5335, 5334, 5333, 5332, 5352, 5351, 5350, 5341, 5342, 5343, 0979, 0981, 0880, 0879, 2379, 2779, 2780, 2781, 9547, 2735, 0107, 0325, 0410, 0490, 1212, 0324, 0319, 0318, 0304, 0415, 0416, 0429, 0430, 0455, 0466, 0507, 0523, 0527, 7412, 7815, 7841, 7846, 7861, 4811, 4805, 4324, 0000
5. Health Care	0.000027	0.000015	-0.000014	HM	8402, 8403, 8427, 8425, 8491, 8492, 8494, 8494, 8505, 8401, 8404, 8406, 8407, 8408, 8409, 8416, 8432, 8434, 8445, 8446, 8452, 8451, 8454, 8463, 8466, 8478, 8479, 8482, 8483, 8485, 8486, 8489, 8496, 8503, 8506, 8541, 8783, 8765, 8753, 8752, 8732, 8708, 8703
6. Logistics	0.000029	-0.000008	-0.000044	CSSS, SKSS, IS, CS, SH, SK	3926, 3925, 3924, 3923, 3912, 3910, 3905, 3131, 2830, 2831, 0000
7. Construction	0.000121	-0.000015	0.000005	CB, BU, CE, CM, EA, EO, SW, UT	5633, 5933, 5931, 5932, 0000
8. Cryptology	0.000152	0.00006	-0.000009	CTA, CTI, CTM, CTN, CTR, CTT	9209, 9211, 9212, 9216, 9192, 9193, 9194, 9197, 9201, 9202, 9203, 9204, 9208, 9213, 9215, 9313, 2780, 2735, 9302, 9188, 9301, 9224, 9225, 9229, 9238, 9249, 9283, 9289, 9295, 9296, 9297, 9103, 9307, 9306, 9305, 9149, 9147, 9138, 9105, 8296, 8295, 9170, 9168, 9141, 9135, 9102, 1781, 1738, 1737, 1736, 1734, 1733, 0000
9. Admin, Media and other	0.000045	0	-0.000003	YNSS, MC, LN, MU, NC(CRF), NC, PS, PC	3803, 3814, 2186, 2905, 0000

Source: Information extracted from the ROGER model

This sorting of eligibles into occupational groups is vital to the operation of the ROGER model because it implies that each skill in the group reacts similarly to pay, as depicted by the pay elasticity for that group and zone. For example, since SEALS (SO) and Boatswain's Mates (BM) are both in Occupational Group 4 (Ship and Aviation Support), they are hypothesized to react the same to a $10,000 SRB (provided they are in the same Zone). Additionally, as previously discussed, grouping them together is based on the assumption that each occupational group has comparable civilian occupations.

In the ROGER model, once the eligibles are organized into the correct NEC, rating and occupation group, the user has the ability to design various SRB plans using different multiples to project the number of SRB takers. The number of eligibles in each group is then multiplied by the reenlistment rate predicted from the logit ACOL model:

$$r_{n,t} = \frac{1}{1 + e^{-\alpha + \beta \cdot ACOL_{n,t} + \delta U_t}},$$

In which:

- $r_{n,t}$ is the retention rate at Year of Service (YOS) n at time t for those at an EAOS point;
- $ACOL_{n,t}$ is the annualized cost of leaving at YOS n at time T (computed as the annuitized difference between military and civilian pay over the future length of stay that maximizes ACOL);
- U_t is the unemployment rate at time t;
- and α, β and δ are the logit coefficients estimated from data containing observed behavioral responses (retention decisions) to changes in military and civilian wages and unemployment (Mackin, 1999, Appendix B, p.19).

The functional form imposed upon the model is the logistic curve and the most recent parameter estimates (α, β and δ) come from Mackin (1999).

4. Projection of SRB Reenlistments and SRB Program Budget Costs

After all eligibles are defined in each specific skill group, pay tables are adjusted, and all other yearly inputs have been updated, the model is run to determine the projected number of reenlistments that correspond to any proposed SRB plan. The operation of the model works in the following manner:

- SRB multipliers are entered for the baseline and the proposed plan on the run scenario screen and are linked (by skill and zone) to the eligible inventory file (created by the model from the *analysis file*).
- Changes in baseline reenlistment rates (which are the observed reenlistment rates from the past year) are calculated using the *"Δ reenlistment probability matrix (skill × LOS × multiplier)*" generated from the ACOL routine.
- Eligibles are run through the *Length of Reenlistment* routine to determine Average Length of Reenlistment
- Projected reenlistments are aggregated across reenlistment zones and become available in summary output then stored in skill/LOS/LOR cells, then aggregated across LOS into zones and displayed on the *Run Scenario* screen in zone/skill space. (Mackin, 1999)

The percentage of the eligible inventory predicted to reenlist is based on a reenlistment probability that is skill- and YOS-specific. This probability is based on the base year probability plus the change in that probability implied by the change in the ACOL value (which reflects any changes in pay and the SRB multiple).

To predict the number of reenlistments for each rating/NEC and Zone that were offered a bonus in FY07, the researchers followed the subsequent steps:

- They reviewed the generated reenlistment baseline predictions at the beginning of FY07 and compared the numbers to the actual SRB takers for FY07.
- They compensated for the missing eligibles by multiplying the percent of missed eligibles across each zone to get a better picture on how well predictions of reenlistments were calculated after compensating for misidentification of eligibles. User-defined parameters were the same in the reenlistment simulation as in their analysis of eligibles.

As detailed in Table 15 and Figure 16, the model under-predicts total SRB reenlistments, or takers, by 12% in all zones if there are no corrections made for the missing eligibles, however, the size of the error differs by zone. In Zone A, the model predicted 6,019 reenlistments, 2.93% fewer than the 6,385 actual bonus takers. This contrasts markedly with a prediction error of 20.13% in Zone B and 22.43% in Zone C. Even so, the model predicts much better than would have been expected due to missing eligibles projections in all Zones. This can be attributed to the intense attention by the SAG Corporation to adjust small cell problems manually. Generally, rating-wide or community-wide rates are used when problems are suspected due to small cell sizes. As stated by one of the analysts at SAG Corporation during interviews, if their predictions for eligibles vary substantially from the estimates of eligibles the ECMs have for their respective communities, the SAG Corporation analysts apply ECM estimates. These estimates are then fed manually into ROGER and used to predict the number of SRB takers.

Figure 16. FY07 Predicted SRB Reenlisters vs. Actual Takers

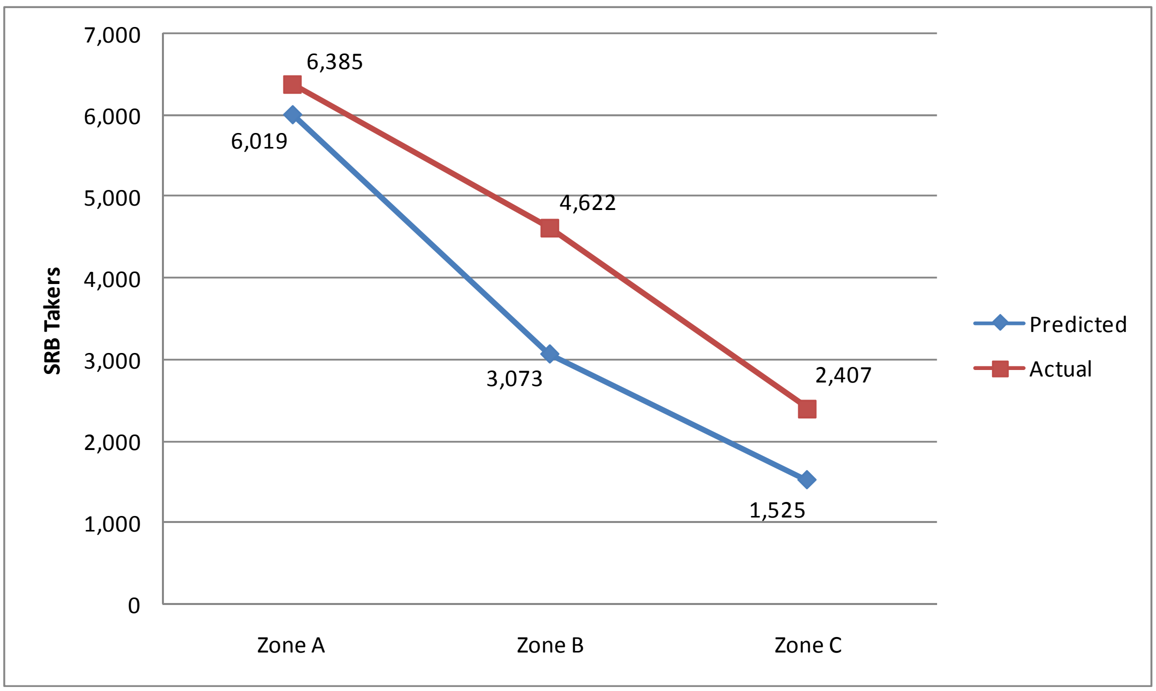


Table 15. Actual and Predicted SRB Takers, by Zone, FY07

(1)	(2) Predicted	(3) Actual	(4) Difference	(5) Percent difference
Zone A	6,019	6,385	-366	-2.95%
Zone B	3,073	4,622	-1,549	-20.13%
Zone C	1,525	2,407	-882	-22.43%
Total	10,617	13,414	-2,797	-12%

Source: ROGER Model

On the other hand, as seen in Table 16 and Figure 17, after the researchers correct for missing eligibles by extrapolating missed eligibility error rates across zones, the predictions become much closer to the actual number of takers across all zones. The corrected outcome is achieved by applying the "eligibles missed" rates in each zone to the actual prediction in each zone for FY07. For example, in FY07 Zone C the ROGER model predicted that 1,525 sailors would accept the SRB while in fact 2,407 sailors actually took the award. Reviewing the FY07 data, it was determined that 51% of the sailors who took the award were not identified as SRB eligible. When that rate was applied to the ROGER-projected 1,525 SRB- taking sailors, there was a gain of an additional 778 sailors that should have been projected SRB takers, resulting in a grand total of 2,303. In the case of Zone C, the change is drastic, with the prediction error decreasing from 22% to only 2.21%. In Zone A, prediction error changes from an under-prediction of 2.95% to an over-prediction of 4.03%.

Figure 17. Corrected Prediction vs. Actual

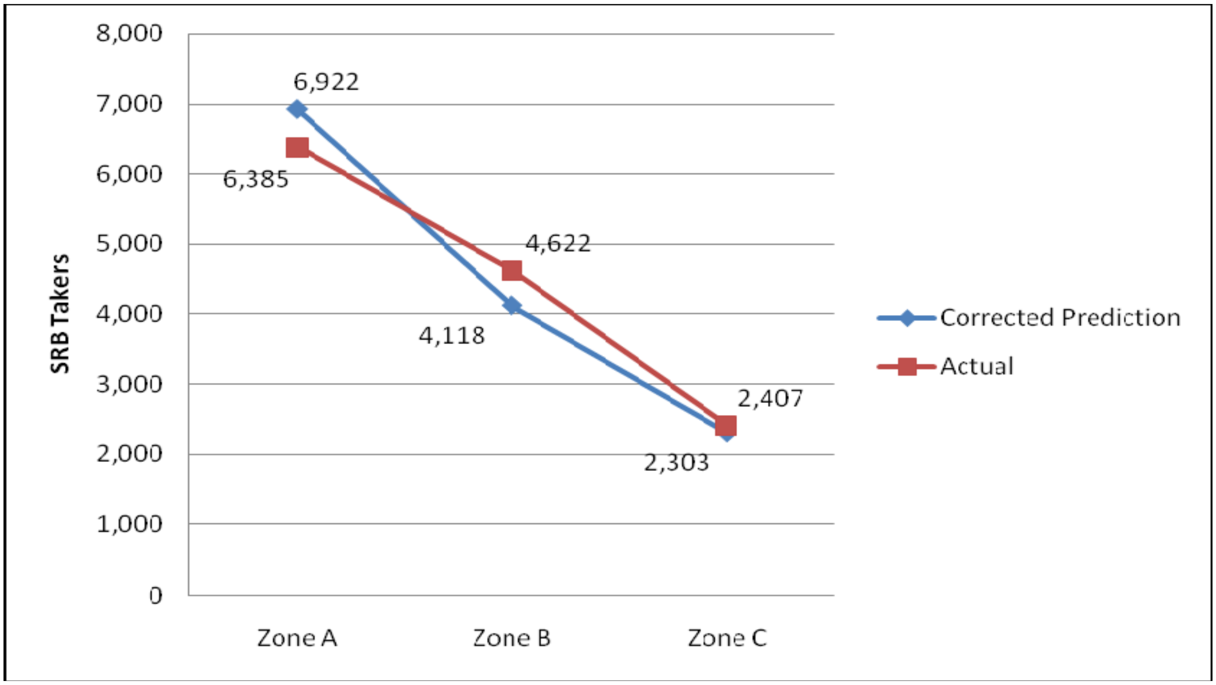


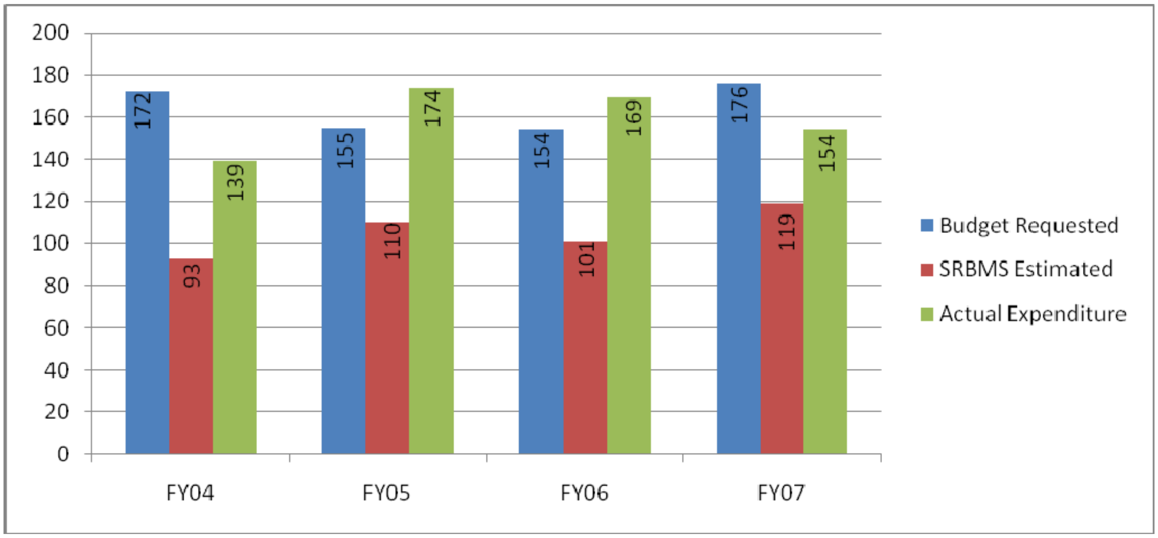
Table 16. Actual and Predicted SRB Takers after Correcting the Eligibles, FY07

(1)	(2) Predicted	(3) Actual	(4) Difference	(5) Percent difference
Zone A	6,922	6,385	537	4.03%
Zone B	4,118	4,622	-504	-5.77%
Zone C	2,303	2,407	-104	-2.21%
Total	13,342	13,414	-72	0%

Note: The percentage difference uses the average of actual and predicted values as its base.

The ROGER Model also calculates the cost of the proposed SRB plan in current year dollars, based on the projected number of bonus “takers.” The Selective Reenlistment Bonus increases the probability that a sailor will reenlist and also affects the length of reenlistment. As illustrated in Figure 18, the estimated, projected and actual costs have error projections similar to the predicted SRB takers for FY04-FY07. The costs cannot help but reflect the rest of the model because of the calculation algorithm of the SRB payments. The algorithm multiplies the number of SRB payments by the predicted number of reenlistments in a skill × LOS × Average Length of Reenlistment (ALOR).

Figure 18. Budgeted Costs vs. ROGER Estimated and Actual Expenditures



D. Chapter Summary

Currently, the ROGER model operates in a pre-run and run phase requiring specific user inputs to produce projected reenlistments associated with different SRB scenarios. Projected reenlistments in each relevant NEC/Skill are then multiplied against Length of Service and Average Length of Reenlistment to develop current fiscal year costs. The assessment of the performance required measuring projected reenlistment eligibles, takers and costs.

On average, the ROGER Model did not correctly identify 24% of the reenlistment eligible sailors across all zones for the period FY04-07. This is primarily due to sailors either: (1) not being in the universally accepted "13-month from EAOS eligibility window" or “48-months from EAOS eligibility window for Zone A NUC” (86%); and/or (2) acquiring a listed SRB skill in the current fiscal year. The under-prediction of eligible sailors results in a reenlistment prediction error of 12% across all zones, as depicted in Table 15. The underestimation of eligibles leads to an underestimation of predicted SRB takers, and in turn, leads to inaccurate predictions of associated SRB budget outlays.

V. Model Enhancement

As observed in the previous chapters, this thesis indicates that the projections of ROGER-generated baseline SRB reenlisters are not accurate, or at the very least, are not within an acceptable error margin from projected outcomes. There are a plethora of explanations for the faulty projections of SRB Takers, which include:

- Misidentification of eligibles
- Mischaracterization of baseline reenlistment rates
- Inaccurate pay elasticities
- Inappropriate grouping of Navy skills (rating/NEC)
- Fluctuations of civilian employment (e.g. change of unemployment rate)
- Missing or deficient data
- Unforeseen events affecting behavior (e.g., increased deployments to tax-free areas).

This thesis has focused on the argument that the primary cause of the projection error comes from the mis-identification of the SRB-eligible population. Addressing the identification of eligibles in the ROGER model has been demonstrated to have the largest single impact on the overall accuracy of the model's reenlistment predictions. There are multiple reasons for the inability to identify which sailors are actually members of the SRB-Eligible population, but the primary reasons that they are not identified by ROGER are:

- they are beyond 13 months from SEAOS for most sailors; or beyond 48 months from SEAOS for Zone A Nukes; or
- they have gained a new NEC in the current fiscal year.

In attempting to identify enhancements to the algorithm that selects the eligible population, there cannot possibly be a single solution that completely resolves the problem. There are simply too many characteristics of each skill group to find one element that changes the function across all the skills and zones.

Over the past few years, the projection of SRB takers has been “adjusted” by a "miss" rate. In FY06, an adjustment rate of 30% above projections was applied to attempt to account for some of the under-predictions of the model. In FY07, an ad-hoc adjustment rate of 33.5% was applied for non-NUCs and 0% for the NUC population. These ad-hoc adjustments have certainly aided in accounting for the overall mis-projections of all SRB takers and have aligned the projections closer to the actual outcomes. It is recommended that the best after-run adjustment seems to be the extrapolation of the error rate of the mis-identification of the eligible population in each zone. In the short term, the best “fix” for the model is the continued application of the missed-eligible population to the projected SRB takers. This “fix” seems to work in the aggregate until small cell size becomes an issue.

As illustrated in Chapter IV and listed below in Table 17, if the researchers were only concerned with the overall number of SRB takers, then utilizing the "missed" rate in each zone of eligibles seems to bring the projections closer to actual results. This appears to be at least a temporary working solution, given that over the past four years the error has been fairly consistent. The researchers would recommend the initial ROGER-generated baseline of projected SRB takers be adjusted upward by the following percentages, which are based on the average error rate over the last four fiscal years data:

- Zone A: 15.73%
- Zone B: 29.40%
- Zone C: 46.79%.

Table 17. FY04-07 Missed Eligible Error Rate

	Zone A	Zone B	Zone C
FY04	20.06%	27.17%	43.46%
FY05	16.29%	29.07%	48.49%
FY06	11.83%	27.42%	44.42%
FY07	14.75%	33.92%	50.81%
Average	**15.73%**	**29.40%**	**46.79%**

But these aggregated "fixes" have a lot of internal problems that do not permanently solve the issues with ROGER. First, they do not capture any systematic changes in the performance of the model (such as how reenlistment is affected by an increase or decrease in the individual Skill/NEC). Additionally, they are not useful at the small cell level because they do not allow the ECMs to see the effect of increasing and decreasing multiples for any particular skill group.

In order to demonstrate some of the issues that occur when dealing with small cell sizes, the researchers will highlight the rating/NEC HM-8404 (Field Medical Service Technician). As seen in Table 18, the rating HM with the NEC 8404 over the last four years has followed no discernable rate of eligible mis-identification. The error rate at the small cell size appears to be suffering from some type of unforeseen shock that perfectly identifies each individual in a small group and then mis-identifies that same skill set of sailors the next year by over 30%.

Table 18. FY04-07 HM-8404 Missed Eligible Error Rate*

FY 04 HM8404	Total SRB Takers	Identified SRB Reenlisters	Missed SRB Reenlisters	Percent Missed
Zone A	108	90	18	16.67%
Zone B	86	54	32	37.21%
Zone C	35	13	22	62.86%
Total	229	157	72	31.44%
FY 05 HM8404	**Total SRB Takers**	**Identified SRB Reenlisters**	**Missed SRB Reenlisters**	**Percent Missed**
Zone A	59	59	0	0.00%
Zone B	45	45	0	0.00%
Zone C	26	26	0	0.00%
Total	130	130	0	0.00%
FY 06 HM8404	**Total SRB Takers**	**Identified SRB Reenlisters**	**Missed SRB Reenlisters**	**Percent Missed**
Zone A	86	86	0	0.00%
Zone B	78	78	0	0.00%
Zone C	36	36	0	0.00%
Total	200	200	0	0.00%
FY07 HM8404	**Total SRB Takers**	**Identified SRB Reenlisters**	**Missed SRB Reenlisters**	**Percent Missed**
Zone A	75	41	34	45.33%
Zone B	105	84	21	20.00%
Zone C	89	47	42	47.19%
Total	269	172	97	36.06%

*Note: Although this is the data received, the perfect correlation between takers and reenlisters in FY05 and FY06 is highly suspect. The probability of a perfect prediction is so low that a corruption of the data is almost certain.

In order to deal with this unforeseen shock, several changes in the eligible identification algorithm were analyzed to attempt to account for the variation in the identification of the eligibles. The modifications in the algorithm theorized to have the greatest impact on the identification of the eligible population were:

- Changing the window of eligibility from 13 months to 24 months.
- Using the sailor's hard EAOS vice soft EAOS.
- Projection of NEC school historical graduates.
- Utilizing PRDs of individual sailors.

In order to analyze the level of improvement that each of these modifications might have on the overall ability to more accurately identify the eligible population, each was analyzed as to the impact on the FY07 HM-8404 community. As illustrated in Table 19, increasing the window of eligibility from 13 months to 24 months from SEAOS failed to identify any of the missing eligibles in Zone A, but correctly identified 9 of the takers in Zone B, and 4 additional takers in Zone C. Overall, the change in the eligibility window increased the identification of an additional 13 sailors, or 13%, in HM-8404. Unfortunately, at the same time, the number of sailors who were not originally identified by the algorithm as being eligible increased in each zone, yielding an increase of the total eligible population to 786 sailors (21%) in the HM-8404 skill set.

Table 19. FY07 HM-8404 - Increasing Eligibility Window from 13 Months to 24 Months from SEAOS

FY07 HM8404	Total Identified Eligibles	New Number of Identified Eligibles using 24 Months vs. 13 Months from SEAOS	Percent Increase of all Eligibles	Total Missed SRB Takers	New Number of Previously Unidentified Eligibles using 24 Months vs. 13 Months from SEAOS	Percent Increase in Eligible Identification
Zone A	2,590	109	4%	34	0	0%
Zone B	963	345	36%	21	9	43%
Zone C	221	332	150%	42	4	10%
Total	3,774	786	21%	97	13	13%

With this outcome in mind, it would only be beneficial to consider expanding the eligibility window for the purpose of SRB identification to 24 months in Zone B, but leave Zones A and C as is. The increase of newly-identified eligible population is worrisome until the overall eligible identification is recalled as being consistently 20% lower than expected. But, before enacting this recommendation, each of the small skill sets should be studied to assess the impact on each group.

As illustrated in Table 20, if there is an attempt to change the identified eligibility period from a HM-8404's SEAOS to the HEAOS, the number of missed SRB reenlisters is decreased by only one individual in each of the three zones. This is not in itself is an important finding, but when coupled with an increase in newly identified eligible population of 444 sailors or 12%, this appears to be an adjustment that would provide only a minimal improvement in the identification of missing takers, while at the same time adding a large number of sailors into the eligibles' pool.

Table 20. FY07 HM-8404 - Changing Eligibility Window from SEAOS to HEAOS

FY07 HM8404	Total Identified Eligibles	New Number of Identified Eligibles using HEAOS vs. SEAOS	Percent Increase of all Eligibles	Total Missed SRB Takers	New Number of Previously Unidentified Eligibles using HEAOS vs. SEAOS	Percent Increase in Eligible Identification
Zone A	2,590	89	3%	34	1	3%
Zone B	963	58	6%	21	1	5%
Zone C	221	297	134%	42	1	2%
Total	3,774	444	12%	97	3	3%

In FY07, 654 graduates were expected to complete the HM-8404 curriculum and be awarded the 8404 NEC. To test the theory that adding the expected number of annual school graduates for a particular NEC to the eligibles pool would improve the prediction of takers, the number of HM-8404 graduates for FY07 was added to the number of identified eligibles. This is illustrated in Table 21. Then the number of ROGER-identified eligibles was compared against the "test" number, which included those gaining the NEC in FY07. The number of missed takers was reduced by 5, or 5%. It is important to note that using this technique could result in an over-prediction of eligibles, as there is no way to know if an individual sailor is double-counted. There is a risk of double counting sailors if the school data were factored into the ROGER model, since there is no way to pre-determine which sailors would be attending Navy schools and gaining SRB-eligible NECs. Sailors could potentially be double-counted if they already held an SRB-eligible NEC at the beginning of the FY, then went to 8404 school and gained the 8404 NEC which was also an SRB-eligible skill.

Table 21. FY07 HM-8404 - Changing Eligibility to Include Projected 8404 Field Medical School Graduates

FY07 HM8404	Total identified eligibles	New number of identified eligibles using projected school graduates	Percent increase of all eligibles	Total missed SRB reenlisters	New number of previously unidentified eligibles using projected school graduates	Percent increase in eligible identification
Zone A	2,590	622	24%	34	3	9%
Zone B	963	26	3%	21	1	5%
Zone C	221	6	3%	42	1	2%
Total	3,774	654	17%	97	5	5%

As illustrated in Table 22, in FY07, 592 HM-8404 sailors had a PRD in FY07. Of those 592, 512 (86%) had already been identified as being eligible (meaning that they were at least within 13 months of their SEAOS). It was hypothesized that the other 78 newly-identified eligibles would have made up the bulk of the mis-identified eligible sailors. The assumption was that as sailors were getting ready to transfer, they might reenlist in order to execute PCS orders (for minimum time on station, for training en route, or to attend a school). Unfortunately, at least in the case of HM-8404s, PCS dates do not seem to be a major contributor to the early reenlistment problem. It was noted, however, that the newly-identified eligible population of 78 sailors resembles the ROGER baseline mis-identification of eligibles.

Table 22. FY07 HM-8404 - Changing Eligibility to Include Projected Rotation Dates (PRD)

FY07 HM8404	Total Identified Eligibles	New Number of Identified Eligibles with using Projected Rotation Dates	Percent Increase of all Eligibles	Total Missed SRB Reenlisters	New Number of Previously Unidentified Eligibles using Projected Rotation Dates	Percent Increase in Eligible Identification
Zone A	2,590	15	1%	34	0	0.00%
Zone B	963	7	1%	21	0	0.00%
Zone C	221	56	25%	42	0	0.00%
Total	3,774	78	2%	97	0	0.00%

In summary, the identification of the eligible population is the largest single cause of the under-prediction of SRB takers. The aggregated predictions can be adjusted for error by extrapolating historical eligibility error rates. These “fixes" do not completely solve the problem; however, as the group gets disaggregated into smaller cells, the error rates are not consistent from skill to skill or from year to year. These smaller cells appear to be affected by some type of unforeseen shock that allows for perfect identification one year and then large errors the next.

To address this shock, four possible enhancements to the identification were analyzed using FY07 actual data for HMs. Each of the four enhancements changes the composition of the eligibles pool and the missed eligible population. None of them, however, appeared to work to any great degree by themselves. The best answer probably lies with the inclusion of the PRD as an identifier for the eligible population. Even though the research in this thesis failed to identify any previously unidentified missed eligibles in FY07 for HM-8404, the inclusion of the PRD seemed to indirectly mirror a good portion of the overall missed eligibles, at least for the HM-8404 population. It would be interesting to see if this "coincidence" happened across a number of the skill sets or if this was merely an isolated event in this particular rating.

VI. Conclusions and Recommendations

A. Conclusions

Although several potential solutions for improving the predictions of the ROGER model were examined in this thesis, none of them improved predictive accuracy of the model as much as desired. Even so, the findings are significant in that they help eliminate potential factors that contribute to the mis-predictions of the model. A significant number of likely contributors remain to be analyzed but were beyond the scope of this particular thesis.

One of the primary areas for future research is an analysis of occupational groups used in the ROGER model. Due to the large number of changes both in the Navy and the civilian sector, as well as the fact that the current Navy occupational groups were originally established in 1982, this area is a prime candidate for future evaluation. There is certainly a question as to whether the current occupational groups in the ROGER model are numerous enough or if the ratings are accurately assigned to each occupational group. Additionally, Quester and Thomason's (1983) study indicated that job prospects and growth should be considered, as well as civilian wage levels.

Due to the extreme flexibility of reenlistment policies and numerous reenlistment and pay programs within the Navy (each having its own guidelines) it is impossible to expect perfect prediction of the SRB-eligible population in a given year. Without perfect eligibility prediction, perfect cost estimates are also beyond reach. The model's predictions can be more closely estimated in the short run by including an average "error" rate adjustment. In the long run, as research identifies the cause of the identification errors, the model will continue to become more accurate. As the identification of eligibles is improved, and an updated Length of Reenlistment algorithm is incorporated, budget forecasts will more closely approximate the true expenditures required for the SRB program.

B. Recommendations

1. Policy

One of the identification issues with early reenlisters stems from the difference between hard and soft EAOS, because sailors are allowed to vacate inactive extensions and reenlist early for an SRB. In interviews with the ECMs in Millington, this seemed to be a particularly common issue with the Hospital Corpsmen. The researchers recommend the Navy consider 5- and 6-year enlistment contracts, vice 4-year contracts with 1- or 2-year obligatory extensions to aid in the identification of eligibles. For Nuclear specialties, because they have an extended window already, the HEAOS/SEAOS is not such a large issue.

Other possible policy consideration for the future includes consideration of extending the reenlistment eligibility window to 24 months and/or consideration of indefinite reenlistments at a certain career point, as currently used in the Army. If enlisted sailors are required to provide a resignation, this provides an increased ability to predict which sailors are staying. For those communities that have high-wage civilian opportunities, the SRBs can be converted to retention bonuses past the designated career point. Due to the limited scope of this thesis and the numerous studies in the literature, Army studies were not reviewed. However, these policies may prove beneficial upon further research.

The authors also recommend review of current reenlistment policies to determine if there are any specific policies that encourage reenlistments that occur more than 13 months prior to EAOS. This may help determine some of the reasons for early reenlistments and assist in their identification. Policy review may also identify programs in which sailors are more likely to reenlist early, which might also help in the identification of methods to identify these sailors in the model.

2. SRB Process

In interviews with the ECMs, it was apparent that most concepts were learned on-the-job, and the ECMs were expected to hit the ground running. The primary recommendation for the SRM process is to implement structured training and education for ECMs to include the basics of economics and labor economics, the theory behind the ACOL model, and training on any applicable models and programs (ROGER, SKIPPER, etc.). This will enable the community managers to understand the workings behind the model, and will give them a better understanding of the entire process. Hopefully, it will lead to greater confidence in the model and an understanding of why perfect predictions are impossible. Furthermore, ECMs are the best to identify trends in their communities and recommend changes to the model to help improve the accuracy of model predictions. As the ECMs become better acquainted with the model and their communities, they can better determine what adjustments might improve the model's predictions.

Another benefit of a structured training pipeline is the standardization of several elements of the process. It was apparent in the interviews with the ECMs that each has an individual method of estimating eligibles in their community, as well as an individual process for determining the SRB multiple necessary for each rating or skill level. The researchers recommend that the following elements of the process become standardized across the communities: (1) definition of "eligible"; (2) method of estimating eligibles; and (3) method of determining required SRB multiple to reach desired manning goals. The use of computer programs, possibly Excel-based models, would most certainly aid in the standardization, as now many calculations are done by hand and some involve guesswork. If the SKIPPER or ROGER models are used at all in this process, the ECMs need to be trained to use them. Time to play with the models and learn as they go is not a luxury available to the ECMs.

Additionally, due to the high turnover rate of ECMs and the current lack of training, the researchers recommend considering civilianizing one or two positions in the Enlisted Community Management shop to provide consistency and continuity of the process. This creates a "knowledge bank" for those newly assigned ECMs who do not have an understanding of the theory or the basics or who are awaiting training. Due to the fast pace of the ECM positions, it is often difficult for them to obtain answers from others as everyone is always busy and requests for information are often short-fused. There are two analysts on-site who provide information to the ECMs, but they are also often tagged for other short-fused requests and projects. Ideally, the authors recommend hiring a full-time civilian analyst for the Enlisted Community Management Division and provide him/her with the ROGER model and a working knowledge of it to perform on-site scenario runs and to instill confidence in the ECMs regarding the process. Additionally, it might be beneficial for an analyst to investigate the utilization of the SKIPPER model and the possible coordination of future efforts between SKIPPER and ROGER.

Another issue that may contribute to the under-identification of eligibles is that the entering of NECs into a sailor's record does not appear to be standardized. Based on the information the authors received, in some cases, the NEC is entered into a sailor’s record at the school upon graduation; in other cases, the student reports to a new command and requests that it be entered. Timeliness of a new NEC being entered into a sailor's record is a vital factor in identifying whether a sailor is SRB-eligible. The researchers recommend a standardized procedure to ensure accurate and timely entry of newly-gained NECs into records to ensure that sailors are not missed during the eligibles-identification process due to missing NEC data. Additionally, as historical data is used to examine retention behavior, there needs to be a reliable way to identify the SRB-related skill. Currently there is no way of identifying for which NEC the sailor reenlisted. Therefore, since the PNEC should be the NEC required for the job the sailor is currently performing and for which the sailor should have received the SRB, the researchers recommend a standardized process in which the SRB NEC is entered as the PNEC in the EMR.

Due to the constantly changing environments both in the Navy and in the civilian sector, it is unrealistic to expect a model like ROGER to maintain accurate predictions without consistent updates. The researchers highly recommend establishing an annual review process for the model so that a certain number of re-estimations are done each year. This review process would: (1) spread the costs of model improvements over the years to avoid necessitating a large one-year outlay to reestimate the entire model; and (2) provide opportunities to use current data, recent studies, and recent behavior to enhance the accuracy of the model. The ECMs should also be involved in this process in order to identify trends in their respective communities and provide feedback to SAG Corporation and OPNAV N1 analysts to help improve accuracy. Additionally, the authors recommend establishing a procedure to determine appropriate occupational groups after ratings have merged or new ratings/skills have been created by looking at civilian opportunities and wages to ensure that Navy skills are included in the appropriate occupational groups.

Since the main problem in identifying SRB-eligible sailors stems from identifying those who are reenlisting early, tracking reasons why sailors are re-enlisting early should help determine methods to make future projections more accurate. These statistics could later be used to track historical trends and allow for improved accuracy of the model, once trends are identified, by including adjustments or rules in the model's algorithms and methods. This may also identify policy changes that might be beneficial in managing the early reenlistment issue. It would be valuable to know if there are certain circumstances which encourage early reenlistment and policy does not prohibit it, or if there are benefits to changing any policies to limit early reenlistments in order to increase the accuracy of predictions. This might involve a cost-benefit analysis of the trade-offs. One question that arises is that with the increase of deployments to tax-free zones in the last few years, have early reenlistments surged as sailors have taken advantage of the opportunity for additional tax-free income? If so, how could that behavior be predicted and implemented in ROGER?

In a world of constantly diminishing resources, budgetary resources are always a concern. Based on the authors' conversations with OPNAV, they believe that there could be significant cost savings in having the ability to run the model at the Navy Annex. Although the Navy "owns" ROGER, the model does not reside on a Navy computer. While NMCI is an obstacle, the program can be run on a laptop quite easily, as the researchers were able to run it themselves. The authors recommend that OPNAV maintain the ROGER model at the Navy Annex and train someone to run the model. For continuity purposes, it would make sense for this person to be a civilian. This would allow alternative scenarios to be run on-site. The researchers recommend the program be run locally, but SAG Corporation be retained to make adjustments and improvements to the model. The researchers anticipate that this would reduce the associated costs of each scenario run and result in significant cost-savings. Additionally, this would free additional funds that could be used to refine and improve the model as problems are identified. The model is not difficult to run. The authors ran it for their analysis, and in fact, the Army runs their model (which is similar, but not identical, to ROGER) themselves.

In interviews with the analysts at the Naval Personal Research Studies and Technology (NPRST), the researchers discovered that the SKIPPER model contains a reenlistment estimation module that had not been fully developed, but that appeared to have the features that ECMs had requested. Specifically, it had the ability, when functioning, to estimate the numbers of predicted reenlisters when an SRB multiple was entered for a skill group. Estimated cost of completion of this module (according to NPRST) was one-half of a man-year, or approximately $68,000. The researchers recommend consideration of funding this project. If effective, this would greatly facilitate the SRB process for the ECMs and provide some standardization amongst the ECMs. The intent would not be to replace ROGER with SKIPPER, but to provide a complementary service to specifically assist each ECM in identifying the appropriate multiple to meet EPA needs.

3. ROGER Model

There are changes that can be made in the ROGER model itself that have the potential to significantly improve the model's predictions. These recommendations are based on observations, interviews with the ECMs, OPNAV and SAG, and information gleaned through the literature review and the model assessment performed in this thesis.

The ROGER model process of sorting sailors into rating and NEC “bins” is built on a hierarchical system, and involves a lot of planning and manual adjustments on the part of SAG Corporation analysts. However, the analysts at SAG Corporation have no prior Navy service or experience in enlisted ratings and job skills. Often, they have to rely on their own judgment. Research is time-consuming (and costly to the Navy) and the necessary information is not always readily available. To assist in making this process more transparent and to minimize the potential for error in the hierarchical structure, the researchers recommend the following: (1) that each ECM provide lists of ratings and applicable NECs to SAG Corporation; and (2) that each ECM provide a “step-ladder” of NECs and skills, outlining any career progression or advancement "rules" within the rating, such as, "one must hold the NEC for an HM Dental Laboratory Technician, Basic (8752) before holding the NEC for an HM Dental Laboratory Technician, Advanced (8753)." This alone will provide a significant time-savings for the SAG Corporation, which should ultimately result in cost savings for the Navy.

In conjunction with the recommendation above, the researchers strongly recommend improved communication lines and consistent, three-way communication between SAG Corporation, the ECMs, and OPNAV. Although each entity has a good basic grasp of part of the puzzle, the coordination and understanding of the process among all three groups appears to differ.

As discussed in the literature review, the occupational groups currently in use are out-dated. The researchers highly recommend updating the occupational groups based on recent reenlistment behavior and current comparable civilian occupations, then recalculating pay elasticities for the new occupational classifications. They also recommend determining the appropriate number of groups, and re-assessment on a regular basis. Again, review of the Army literature and SRB program may provide some information as the Army has a larger number of skill groups than the Navy.

The Average Length of Reenlistment (ALOR) algorithm is an integral component of the cost estimation in the ROGER model. The current ALOR in the ROGER model dates to the early 1980s. It was recently reestimated by the Lewin Group in 2002. The researchers recommend funding for SAG Corporation to update the model with the new LOR estimate, which should significantly improve the cost estimates of the model.

4. Follow-on Studies

There are so many studies and issues with retention and SRBs that numerous follow-on studies are recommended. Of primary importance, data must be readily available and obtainable in order for these recommendations to be pursued. The authors highly recommend providing a relevant data source (PERSMART, EMR, etc.) that is accessible to NPS faculty and students. Not only will this provide much-needed data sources for students and faculty, but also will allow them to become familiar with data sources that are commonly used in Navy planning models.

The following suggestions are provided as recommendations for follow-on studies:

- The researchers recommend an investigation of the use of MODCOMP/LIMDEP to update the ROGER model more easily and frequently. MODCOMP (used to update SKIPPER) is similar to the ACOL model but is easier to update on a regular basis. SAG Corporation has worked with MODCOMP and identified “glitches” that need to be resolved for ease of use. They also recommend further study on the feasibility of integrating MODCOMP into the ROGER program to facilitate updates.
- They recommend that a method be found to estimate and track SRB execution by month to find if it is accurate and if reenlistment goals are being met. One possibility is to find a way to use the Pre-authorization

process to track the number of reenlistments and use as a tool in planning and adjusting for the FMS.

- They recommend researching the capabilities of the reenlistment prediction module of SKIPPER, which is currently not functional due to lack of funding.
- The researchers recommend an analysis of the Army's current SRB program. The Army currently has a 24-month reenlistment eligibility window and uses the ACOL methodology (in a model which is similar to the Navy ROGER model and maintained by SAG Corporation) for their reenlistment program. Additionally, it has indefinite reenlistments at a certain career point and numerous skill groups. An analysis of the Army's SRB Program might yield further ideas on model improvement.
- They recommend consideration of studies investigating the possibilities of a coordinated effort of the ROGER and SKIPPER models. The scope of this thesis did not include a detailed assessment of SKIPPER, but from the researchers' limited knowledge, they believe that the models might complement each other. Since SKIPPER looks forward and projects the force and ROGER works for the execution year only, if the capabilities could be integrated, it might provide the "big picture" to ECMs and analysts.
- The authors recommend obtaining school-based data, specifically the average number of graduates per year for each program, and include that figure in the model to predict eligibles with newly acquired NECs. SAG Corporation analysts have determined a method to avoid the possibilities of double-counting individuals (under both a current NEC and a new skill) as eligible (due to the impossibility of determining who will attend schools).
- They recommend an examination of the effects of GWOT and deployments to tax-free areas on reenlistments. Are sailors encouraged and/or not discouraged from reenlisting early for the additional tax-free benefit? If so, how can such early reenlisters be identified and accounted for in the prediction of the ROGER model?

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