Calhoun
Institutional Archive of the Naval Postgraduate School

Calhoun: The NPS Institutional Archive

Theses and Dissertations | Thesis and Dissertation Collection

2016-09

An exploratory analysis of projected Navy officer inventory strength using data farming

Bazalaki, Peter

Monterey, California: Naval Postgraduate School

http://hdl.handle.net/10945/50586

DUDLEY KNOX LIBRARY

Calhoun is a project of the Dudley Knox Library at NPS, furthering the precepts and goals of open government and government transparency. All information contained herein has been approved for release by the NPS Public Affairs Officer.

Dudley Knox Library / Naval Postgraduate School
411 Dyer Road / 1 University Circle
Monterey, California USA 93943

http://www.nps.edu/library

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

AN EXPLORATORY ANALYSIS OF PROJECTED NAVY OFFICER INVENTORY STRENGTH USING DATA FARMING

by

Peter Bazalaki

September 2016

Thesis Advisor:	Samuel E. Buttrey
Second Reader:	Thomas W. Lucas

Approved for public release. Distribution is unlimited.

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE			*Form Approved OMB No. 0704-0188*

Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.

1. AGENCY USE ONLY ***(Leave blank)***	**2. REPORT DATE** September 2016	**3. REPORT TYPE AND DATES COVERED** Master's thesis

4. TITLE AND SUBTITLE AN EXPLORATORY ANALYSIS OF PROJECTED NAVY OFFICER INVENTORY STRENGTH USING DATA FARMING	**5. FUNDING NUMBERS**
6. AUTHOR(S) Peter Bazalaki	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000	**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) N/A	**10. SPONSORING / MONITORING AGENCY REPORT NUMBER**

11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB Protocol number ____N/A____.

12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release. Distribution is unlimited.	**12b. DISTRIBUTION CODE**

13. ABSTRACT (maximum 200 words)

U.S. statutory policy requires the armed services to continuously balance manpower inventory with congressionally authorized requirements. Inaccurate forecasts put the Navy's budget at risk and degrade overall mission readiness. Navy policymakers must be able to rely on accurate inventory forecasts to develop necessary manpower plans that steer inventory to match planned authorizations. Strength planners, in turn, rely on forecasting models like the Officer Strategic Analysis Model (OSAM) in an attempt to accurately predict future inventory levels.

This study utilizes applications of data farming to OSAM to simulate Unrestricted Line Officer (URL) inventory over a seven-year period. Additionally, the research utilizes applications of Design of Experiments (DOE) to project Surface Warfare Officer (SWO) inventory across a variety of assumptions, including a proposed Enhanced Probationary Officer Continuation and Re-designation (EPOCR) policy. Analysis finds that current policy will reduce FY2016 URL inventory by 8% over a seven-year period, and over-execute SWO inventory authorizations by 40%. We find that EPOCR reduces operating strength deviation (OSD) in total SWO inventory strength by 12% by FY2022. Additionally, implementing a low accession plan and a high transfer plan is the most robust in correcting OSD. When implemented correctly, EPOCR has the potential to decrease OSD to modest levels with minimal risk of under-execution.

14. SUBJECT TERMS Manpower, end strength, design of experiments, simulation, Officer Strategic Analysis Model (OSAM), inventory projection, data farming. Robust Analysis, Meta-Modeling	**15. NUMBER OF PAGES** 109
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	**18. SECURITY CLASSIFICATION OF THIS PAGE**	**19. SECURITY CLASSIFICATION OF ABSTRACT**	**20. LIMITATION OF ABSTRACT**
Unclassified	Unclassified	Unclassified	UU

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release. Distribution is unlimited.

AN EXPLORATORY ANALYSIS OF PROJECTED NAVY OFFICER INVENTORY STRENGTH USING DATA FARMING

Peter Bazalaki
Lieutenant, United States Navy
B.A., San Diego State University, 2011

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
September 2016

Approved by: Samuel E. Buttrey
Thesis Advisor

Thomas W. Lucas
Second Reader

Patricia A. Jacobs
Chair, Department of Operations Research

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

U.S. statutory policy requires the armed services to continuously balance manpower inventory with congressionally authorized requirements. Inaccurate forecasts put the Navy's budget at risk and degrade overall mission readiness. Navy policymakers must be able to rely on accurate inventory forecasts to develop necessary manpower plans that steer inventory to match planned authorizations. Strength planners, in turn, rely on forecasting models like the Officer Strategic Analysis Model (OSAM) in an attempt to accurately predict future inventory levels.

This study utilizes applications of data farming to OSAM to simulate Unrestricted Line Officer (URL) inventory over a seven-year period. Additionally, the research utilizes applications of Design of Experiments (DOE) to project Surface Warfare Officer (SWO) inventory across a variety of assumptions, including a proposed Enhanced Probationary Officer Continuation and Re-designation (EPOCR) policy. Analysis finds that current policy will reduce FY2016 URL inventory by 8% over a seven-year period, and over-execute SWO inventory authorizations by 40%. We find that EPOCR reduces operating strength deviation (OSD) in total SWO inventory strength by 12% by FY2022. Additionally, implementing a low accession plan and a high transfer plan is the most robust in correcting OSD. When implemented correctly, EPOCR has the potential to decrease OSD to modest levels with minimal risk of under-execution.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF FIGURES

LIST OF TABLES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF ACRONYMS AND ABBREVIATIONS

ANOVA	Analysis of Variance
BA	Billets Authorized
BOY	Beginning of Year
DOD	Department of Defense
DOE	Design of Experiments
DOPMA	Defense Officer Personnel Management Act
ES	Enlisted Specialty
EOY	End of Year
EPOCR	Enhanced POCR
FY	Fiscal Year
FYDP	Future Years Defense Program
GUI	Graphical User Interface
HR	Human Resource
HPC	High-Performance Computing
LH	Latin Hypercube
MPN	Military Personnel, Navy
MPTE	Manpower, Personnel, Education, and Training
MYS	Multi-Year Summary
N100	Navy's Strategic Resourcing Branch
NESP	Navy Enlisted Strength Planning Model
NFM	Navy Officer Personnel Planning System Forecasting Model
NOLH	Nearly Orthogonal Latin Hypercube
NOPPS	Navy Officer Personnel Planning System
NPS	Naval Postgraduate School
POCR	Probationary Officer Continuation and Re-designation
RSCM	Rating Supply Chain Model
OOE	Officer Over-execution
OPA	Officer Programmed Authorization
OPNAV	Office of the Chief of Naval Operations
OSAM	Officer Strategic Analysis Model

OSD	Operating Strength Deviation
PII	Personally Identifiable Information
POM	Program Objective Memorandum
RSCM	Rating Supply Chain Model
RCMOP	Requirements-Driven Cost-Based Manpower Optimization
RL	Restricted Line
SECNAV	Secretary of the Navy
SEED	Simulation Experiments & Efficient Designs
SQL	Structured Query Language
SWO	Surface Warfare Officer
U.S.	United States
URL	Unrestricted Line
VBA	Visual Basic for Applications
VV&A	Verification, Validation, and Accreditation
YCS	Years of Commissioned Service

EXECUTIVE SUMMARY

U.S. statute requires the services to balance their manpower inventory to congressionally authorized requirements. As a result, Navy strength planners, community managers, and policymakers plan and manage the Navy's end-strength, skill inventories, promotions, and accessions to meet the congressionally mandated end strength. To do so, they must continuously and accurately predict the Navy's inventory strength by designator and paygrade throughout the fiscal year. Inaccurate prediction and resulting policies put the Navy's budget at risk and degrade mission readiness.

Strength planners rely on the accuracy of complex simulation models to correctly predict the Navy's future inventory strength. Models help Navy leadership understand the potential impacts and risks inherent in current and planned policies to the force inventory structure.

The Officer Strategic Analysis Model (OSAM) is an entity-based stochastic simulation model that allows for projection of annual future officer inventory and losses across communities by applying various historical trends and force-shaping policy to current inventory. The current version of the model, as used by strength planners, however, is stripped of its stochastic capability, which limits assessing risk in the model's results. Additionally, OSAM, as currently used by strength planners, simulates only one scenario at a time, making the simulation model ineffective for the large-scale implementation necessary for investigating effects of manpower policies.

This thesis uses concepts of design of experiments (DOE), data farming, and a stochastic enhancement of OSAM to forecast Unrestricted Line (URL) officer inventory. Data farming is used to simulate 100 replications of a base-case scenario that projects Navy Unrestricted Line (URL) officer inventory over a seven-year period. The base-case scenario assumes that current manpower policies and loss rates prevail over the projected period. We use the base case to gain insight on the expected trend of URL inventory strength and the risks in future SWO inventory strength assuming the Navy continues with current manpower policy. We find that total operating inventory strength falls by an average of 8% over the seven-year period from 24,815 officers at the beginning of 2016, to 22,890 ± 13 officers at the end of 2023. The mean end strength results in the base case have extremely small standard deviation values, suggesting little value in OSAM's stochastic enhancement. More importantly, base-case results show SWO inventory strength will over-execute OPA by more than 40% in grade O3 over the entire projected period.

Additionally, the study uses concepts of data farming, design of experiments, and High-Performance Computing (HPC) to simulate surface warfare inventory using key factors and assumptions, including a proposed enhanced Probationary Officer Continuation and Retention (EPOCR) policy. We use historical loss rate categories, accession plans, transfer plans, and three user-added force-shaping plans corresponding to EPOCR losses. The current year promotion plan is used and an auto-promotion method that constrains inventory to the Defense Officer Personnel Management Act (DOPMA) guidelines is assumed. Using resources available at the Naval Postgraduate's Simulation Experiment and Efficient Design (SEED) Center, a Nearly Orthogonal Latin Hypercube Design for three discrete factors corresponding to EPOCR losses is crossed with a Full-Factorial Design for three categorical factors corresponding to the historical plans. A "landscape" of output is farmed, collected, and analyzed for insight.

We use graphical and statistical analysis, meta-modeling, and robust analysis to gain insight from the results. We find that implementing EPOCR significantly reduces grade O3 over-execution by FY2022, and levels the average operating strength in all grades to match OPA. Total operating inventory strength is reduced by 12% over the seven-year period, from 8,365 officers at the beginning of FY2016 to an average of 7,375 ± 739 officers at the end of FY2023. However, we also find EPOCR greatly elevates the risk of over-execution. To

mitigate this risk, we use robust analysis and metamodeling to find robust policies that control OSD. We find that implementing a low accession plan and a high transfer plan is the most robust in correcting OSD. Finally, we find when implemented correctly, EPOCR has the potential to decrease OSD to modest levels with minimal risk to OSD.

THIS PAGE INTENTIONALLY LEFT BLANK

ACKNOWLEDGMENTS

This thesis owes its existence to the assistance and inspiration of several people. I would first like to express my sincere gratitude to my thesis advisor, Dr. Sam Buttery, whose door was always open whenever I hit a wall or had a question about my research or writing. He consistently allowed this paper to be my own work, but steered me in the right direction whenever he thought I needed it.

I must express my profound gratitude to my second reader, Dr. Thomas Lucas, for introducing me to the topic and for his support along the way. Without his broad knowledge in the areas of simulation modeling and design of experiments this work could not have been completed.

I also owe a debt of gratitude to the SEED center for the resources it provided that made this research a reality, I am grateful to Mr. Steve Upton, whose exceptional technical expertise produced the tools necessary to run my simulations, and to Mrs. Mary McDonald, for lending her intellectual insight and analytical prowess to my research. Mr. Upton and Mrs. McDonald's tireless work and dedication to the SEED center's efforts are truly key to its success in enhancing DOD research.

I would also like to thank the teams at OPNAV N100 and N1Z4 for their hospitality during my thesis tour and for their continued support, with particular thanks to CDR Clark, LCDR Saluke, and Mr. Rinde.

Last, but not least, I would like to thank my family for the support they provided me through my entire life. In particular, I must acknowledge my significant other and best friend, Vanessa, without whose love, encouragement, and unfailing support throughout my studies, none of this would have been possible, and to my son, Anthony, whose very existence inspired me through this work and everything I do. This accomplishment would not have been possible without them. Thank you.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

A. PROBLEM STATEMENT

During the last decade, operating inventory, the available number of officers within the Navy's Unrestricted Line (URL) Community, has continually exceeded its authorized billets (BA), particularly within its junior pay grades. This phenomenon, termed by Navy inventory strength planners as Officer Over-Execution (OOE), has imposed large financial costs on the Navy's budget (Parcell, 2015). Comparisons of operating inventory to officer programmed authorizations (OPA), the authorized end strength, for four URL communities are depicted in Figure 1. Over-execution is particularly profound within the Navy's Surface Warfare Community (SWO). The SWO community, like most URL communities, has a closed-loop personnel system. This, coupled with historically low retention at the mid-level grades, has traditionally led to more SWO accessions than is authorized. However, the large number of accessions, "apparently" needed to sustain the low retention rate, has resulted in manpower operating inventory overages in the junior ranks (Huff, et al., 2015). A paygrade profile for the SWO community comparing operating inventory to authorizations from 2012 to 2015 is shown in Figure 2. Grades O1 and O2 have high historical overages, but even more startling is the over-execution in grade O3, which exceed 40% in FY2014 and FY2015. If left uncorrected, over-execution is likely to persist. However, naively fixing over-execution by lowering accessions introduces risks to mission readiness as required billets may go unfilled. Any sound solutions require accurately projecting and predicting future operating inventory based on the inherently unpredictable future behavior of personnel.

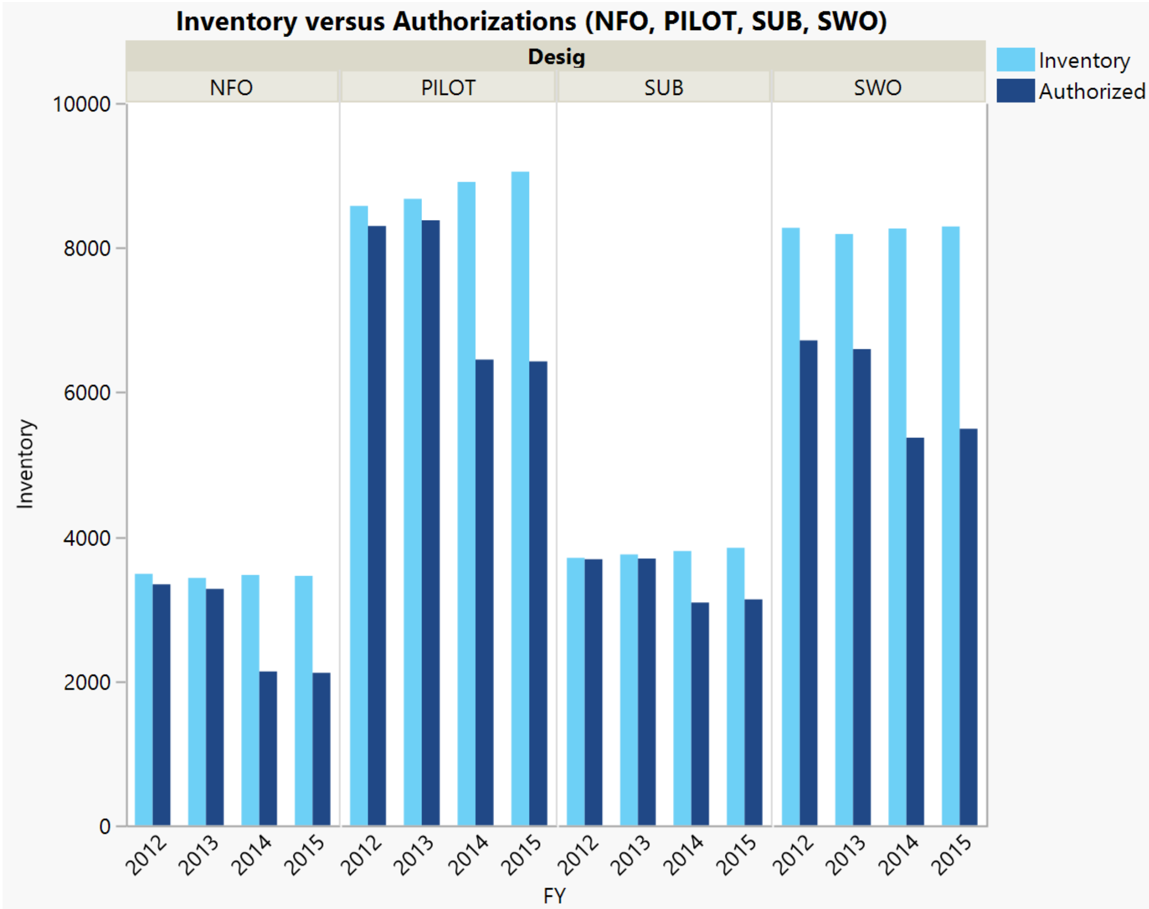


Figure 1. URL Profile Display of Operating Strength Inventory versus Authorized End Strength

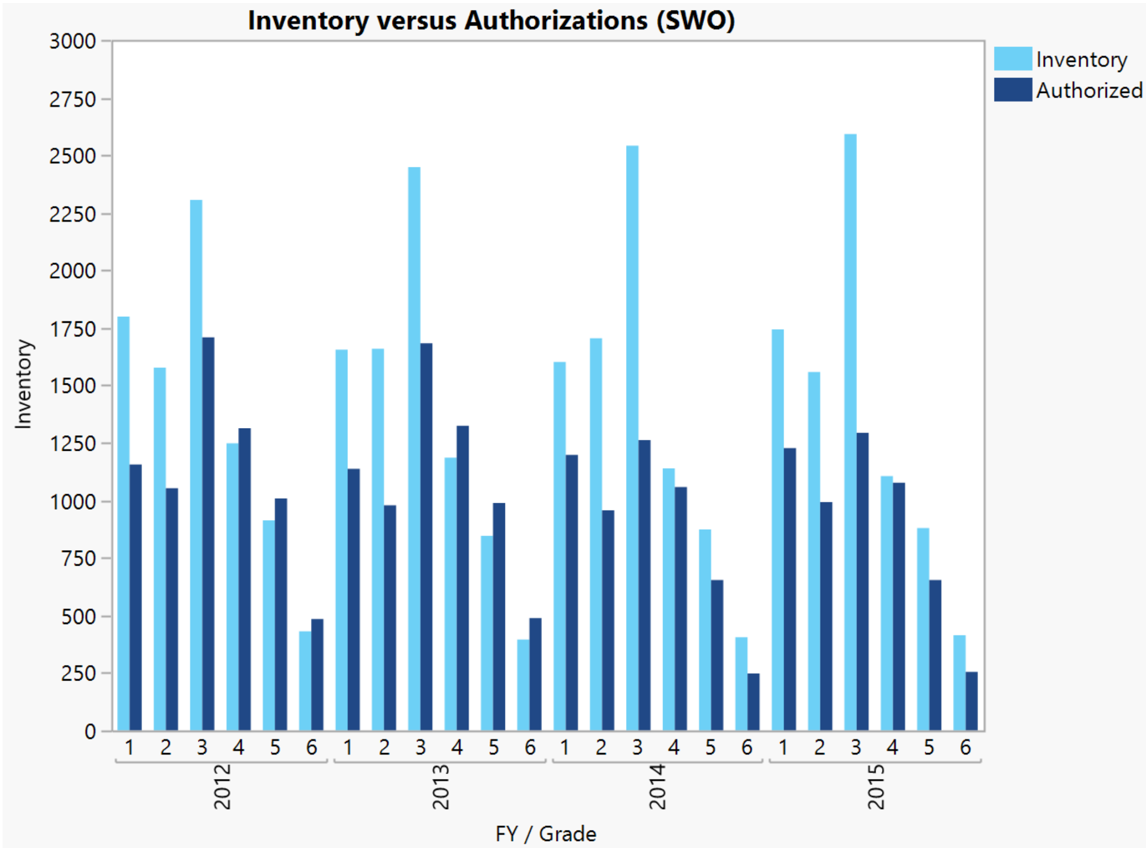


Figure 2. SWO Paygrade Profile of Inventory Strength versus Authorizations

As part of their long-range planning and programming tasks, officer strength planners at the Navy Strategic Resourcing Branch, N100, rely on powerful and complex manpower inventory models like the Officer Strategic Analysis Model (OSAM) to predict long-term trends in Officer Inventory. OSAM is an entity-based deterministic simulation model used to perform annual forecasts of officer inventory over the Future Years Defense Program (FYDP). Using OSAM for strength projection, however, is limited to single small-scale scenarios that provide limited insight to strength planners. Additionally, as a deterministic model with no variation in its results, OSAM does not provide any assessments on the risk associated with its results (Saluke, personal communication, April 26, 2016). This thesis enhances OSAM's utility by introducing randomness to the model and by using proven simulation techniques to run thousands of OSAM scenarios.

B. BACKGROUND

The Navy's manpower costs have historically constituted a large proportion of the Department of the Navy's budget and this proportion is expected to grow over the next fiscal years. The military personnel budget for active naval personnel (MPN) was $29.35 billion in FY 2016. This constituted the second-largest appropriation of a total Navy budget of $155.40 billion. This amount funded manpower requirements of 54,333 officers and 268,524 enlisted personnel for a total end strength of 322,857 (Department of the Navy, 2016).

Title 10 of the United States code mandates that services regulate their inventory to authorized end strength, the number of uniformed personnel set by congress allowed on the final day of each fiscal year. The Defense Officer Personnel Management Act further places numeric constraints on the distribution of active-duty officers in grades O4 through O6 for any authorized officer end strength. Additionally, authorized end strength must be balanced to budgetary fiscal constraints. This responsibility requires a concerted effort among policy makers, community managers, and strength planners to continuously plan, manage and monitor the Navy's officer accessions, promotions, transfers, and skill inventories.

Steering current operating inventory levels requires accurately projecting and predicting future inventory strength using current and future policy and other assumptions. The Office of the Chief of Naval Operations (OPNAV) Manpower, Personnel Training, & Education (MPT&E) Resource Management Division, Strategic Resourcing Branch, N100, is responsible for projecting current Navy officer inventory to end strength and developing, assessing, and recommending personnel strength management policies and force-shaping initiatives that will correct officer inventory strength to authorized end strength. Personnel policy derived from inaccurate projections may lead to over-execution, in turn affecting the Navy budget and mission readiness.

C. NAVY STRENGTH MANAGEMENT

Strength management concerns aligning operating inventory strength to authorized end-strength through manpower management policies encompassing accessions, promotions, transfers, and force-shaping initiatives. This section describes terms relating to Navy strength management and applicable to this study.

1. Manpower versus Manning

Manpower, also referred to as "spaces," drives the need for inventory. Manpower encompasses unconstrained minimum quantitative and qualitative positions needed to fulfill all Navy missions and functions. Navy resource managers derive manpower requirements by translating national defense strategies and force structure policy decisions into manpower needs. In general, requirements are written to minimum skill, pay grade, and quantity for each unit or Navy platform. However, budget constraints further obligate policymakers to decide on which missions and associated requirements to fund. The process ensures that sufficient funds have been set aside to pay for "spaces" when personnel are assigned to a "space." The number of authorized requirements is referred to as end strength. Specifically, end strength is the number of uniformed personnel set by congress allowed on the last day of each fiscal year, and is the target to which strength planners strive to match inventory.

Manning, also referred to as "faces" or operating inventory, is the specific inventory of personnel at an activity, unit, or platform in terms of numbers, grades, and occupational groups or skills. Each year, the Chief of Naval Operations, through the Department of Defense (DOD), must submit proposed end-strength to congress for approval and funding. Fiscal constraints on authorized end strength and how well the Navy manages accessions, promotions, transfers, and to some extent, losses, directly affects the inventory that is allocated to funded requirements.

2. Operating Strength Deviation

Fiscal constraints, manpower management, and policy create differences between authorized end strength (spaces), and the operating inventory, the number of personnel available to fill authorizations (faces). The difference between the “spaces” and the “faces” is what this study refers to as operating strength deviation (OSD). Over-execution is deviation when operating inventory strength exceeds authorized end strength, the converse being under-execution. Strength planners have to be cognizant about operating strength deviation throughout the fiscal year. Deviation in end-strength exists in both enlisted and officer communities and is tracked by skill and grade. Once deviation has been identified, community managers implement strength management policies and force-shaping plans to guide future inventory levels, or strength, to authorized end strength. This thesis focuses on operating strength deviation within the officer Unrestricted Line (URL) community.

3. Navy Strength Planning

Navy strength planners are tasked with determining the effects that current and future accessions plans, promotion plans, and losses will have on the ability to balance personnel inventory to authorized end strength. Officer strength planners predict, plan and manage total gains and losses by skill and grade for each fiscal year to meet Officer Programmed Authorizations (OPA), the number of officers, by grade and designator, programmed to meet end strength. Strength planning is founded on predicting losses and gains, and generally follows the equation

$$Strength_{p,t} = Strength_{p(t-1)} - Losses_{p(t-1)} + Gains_{p(t-1)}, \qquad (1.1)$$

where *p* and *t* are subscripts representing pay grade and time, respectively.

Strength planning is a proactive approach that can identify future operating strength deviations and provide justification for policies that ensure matching future inventory strength to authorized end strength. Strength planning is, however, a delicate and complex task requiring strength planners to rely on complex personnel inventory strength projection models such as OSAM.

4. Inventory Strength Modeling

The use of inventory strength projection models for military purposes dates back to the conception of military operations research (Abrams, 1957). Navy Strength Planners and Manpower analysts use these models, to predict how current manpower inventory levels evolve over time. The models help in assessing the risks associated with current and planned manpower policies. The Department of Defense uses various inventory strength models employing varied inventory projection methods and techniques. These models generally follow the projection structure of Equation 1.1, but they differ in purpose and design. The following sub-section discusses some of the key modeling methods with relation to OSAM.

a. Aggregate versus Disaggregate Models

DOD aggregate models project inventory as an aggregate of inventory across all specialty skills (Schank et al., 1997). Disaggregate models, such as OSAM, further partition projections by individual inventory attributes like occupation or skill, years of commissioned service, and pay grade, thus providing more detail than aggregate models (Schank et al., 1997). This study uses OSAM to project URL inventory strength by designator, pay grade, and years of commissioned service.

b. *Short-Term versus Long-term Models*

Short-term inventory strength models make monthly projections within a specified period in a given fiscal year. Long-term inventory strength models project inventory in annualized time steps, from the end of one fiscal year to another for periods longer than one year. OSAM is a long-term inventory strength model capable of producing annual inventory forecasts for periods beyond seven years (Schank et al., 1997). This study uses OSAM to project URL officer inventory from FY 2016 to FY 2023.

c. *Deterministic versus Stochastic Models*

A model is deterministic if the output of the model is wholly determined by the assumptions and input settings selected by the user. In a deterministic inventory model, each unique set of inputs will always produce the same inventory output, which makes it unnecessary to run the model more than once for a particular set of input values (Lucas, 2000). Stochastic models have randomness in their output results. OSAM uses pseudorandom processes in its modeling process to assign losses, promotions, accessions, and transfers, inherently making a stochastic model. Updates to the latest version of the model, however, removed the model's random characteristics, effectively making it deterministic (Mundy, 2014). Using OSAM deterministically, however, subjects results to the “flaw of averages,” where single number averages are fallaciously used to represent uncertainty (Savage, 2009). This study utilizes a modified version of OSAM that reinstates randomness. Chapter III of this thesis discusses this modification to OSAM.

d. *Static versus Dynamic Models*

A static inventory model does not depend on the time factor but rather describes the inventory at a specific set time and assumes an identical flow of inventory over time (Law & Kelton, 2000). Dynamic models such as OSAM project inventory from one period to another, making the time component integral to and explicit in the modeling process (Law & Kelton, 2000). This thesis uses

OSAM to study the evolvement of Unrestricted Line Officer inventory strength, including Surface Warfare Inventory, over a seven-year period.

D. PROPOSED SOLUTIONS TO OVER-EXECUTION

The prevalent over-execution within the unrestricted line community, and chiefly within the SWO community, has emerged in importance and focus to Navy leadership, particularly due to recent budget cuts. As such, Navy leadership tasked N100 for solutions. One such solution is lowering SWO accessions to a level that is just enough to cover authorizations within the junior ranks. However, naively fixing over-execution by lowering accessions introduces risks to mission readiness as future mid-level requirements may go unfilled, given the SWO community's low retention rates.

Another proposed solution is the Enhanced Probationary Officer Continuation and Re-designation (EPOCR) Board. EPOCR is a proposed force-shaping initiative that extends retention and continuation board eligibility to SWO officers with four, five, and six years of commissioned service (P. Saluke, personal communication, April 26, 2016). The Navy uses continuation and retention boards to separate from service or transfer to other communities officers who no longer have viable progression career paths within their parent communities. The SWO community typically reserves probationary force-shaping policy to officers with less than four years of commissioned service. As proposed, the policy will refer to the EPOCR board up to 120 officers with four, five, or six years of commissioned service. This study investigates the impact of a low accession plan and the EPOCR policy on projected SWO inventory.

E. PURPOSE AND OBJECTIVE

The author's efforts are focused on utilizing OSAM's inventory projections capabilities to provide a quantitative approach to understanding the risk associated with different manpower policies to the future composition of URL inventory, including the Surface Warfare inventory. Specifically, the study projects FY 2016 URL inventory to 2023, assuming current manpower policy and loss rates, and measures the deviation of operating inventory to planned authorizations by FY and designator. Additionally, the study assesses the implications of a low accession plan to SWO inventory. The EPOCR policy is also investigated to determine its impact on SWO future operating inventory. Stochastic enhancement to OSAM enables us to produce confidence intervals for projected inventory strength results.

F. RESEARCH QUESTIONS

The scope of this thesis is guided by the following research questions posed by N100.

1. What is the expected short- and long-term trend in URL inventory strength assuming current policy and prevailing loss assumptions?

OSAM's dynamic application can produce inventory evolvement over a specified period. Stochastic enhancement of the model will allow construction of confidence intervals on inventory strength results.

2. What are the long-term risks in inventory strength for the SWO community associated with current policy?

OSAM's disaggregate methodology allows us to focus analysis on an individual designator. Its long-term annualized projection allows us to track inventory strength trends for periods of great lengths.

3. What is the impact of the Enhanced Probationary Officer Continuation and Re-Designation Board on SWO inventory strength?

OSAM is flexible to the extent that one can model additional force-shaping plans using its force-shaping option. This thesis uses OSAM's force-shaping option to model losses corresponding to officers referred to EPOCR.

The insight gained from answering these research questions will identify risks in current manpower plans and provide justification for adopting sound policies and plans that will guide operating strength to authorized end strength. Analyzing the effects of various accession plans will also provide an understanding of the effect of reducing SWO accessions to future operating inventory strength.

G. METHODOLOGY AND SCOPE

This thesis combines data farming and the efficiency of design of experiments (DOE) with a stochastic version of OSAM to obtain analyzable data from the model. Applications to support data farming and the stochastic version of the model are developed and provided by the Naval Postgraduate School (NPS) Simulations, Experiments, and Efficient Designs (SEED) Center, a research center within the school's Operations Department that focuses on enhancing DOD Research via simulation design and analysis (https://harvest.nps.edu). First, the OSAM input factors that contribute the largest variation in the output of interest are identified from the model, and with guidance from N100 manpower analysts. With operating strength as the response variable of interest, loss rate categories, transfer plans, and accession plans are chosen as the explanatory variables. We introduce three additional force-shaping factors for SWO inventory with four, five, and six years of commissioned service (YCS), respectively, as a way to control future SWO operating inventory strength. The latter represents a proposed policy that increases the number of junior SWO officers referred for lateral transfer or re-designation via the Probationary Officer Continuation and Re-designation Board (Borozny, 2015). The number of factors and their corresponding levels dictate the type of design used for the experiment since complexity is limited by available computing power (Kleijnen et al., 2005). A stochastic modification of OSAM is adapted to utilize multi-cluster computing and further scripts are developed to consolidate the model's output to desired specification. The model's output is analyzed using advanced statistical techniques incorporating regression tree analysis, robust analysis, and metamodeling to explore the relationship between OSAM's input factors and projected inventory strength.

H. BENEFITS OF RESEARCH

OSAM's utility as an inventory strength projection tool is largely untested, and its value largely underestimated. This research extends previous studies by Sibley (2012), Borozny (2015), and DeHollan (2015) by studying, validating, and improving upon OSAM's utility as an inventory projection tool. Insights gained will enable manpower analysts to effectively use the model to accurately project officer inventory strength. The methods used in this research can subsequently identify the true effects of OSAM's inputs on end strength results, and measure risks associated with current and planned manpower policies to future inventory strength profiles. Additionally, the study will gain insight into the implications of the proposed EPOCR policy to future SWO inventory.

I. LITERATURE REVIEW

Human resources are the most valuable, yet more complex, and often most expensive asset of most organizations. Due to the uncertainty of human behavior, organizations often resort to simulation models to emulate their manpower systems and predict the short- and long-term composition of their future personnel inventory strength. A large amount of research has been conducted to support the development or improvement of manpower models for inventory strength projection and optimization within the context of the military. Sibley (2012) offers an extensive summary of such research. Whereas numerous manpower models exist within and outside of military application, there is little research that applies the concepts of data farming and design of experiments to manpower models. In fact, Antony (et al. 2012) finds that little attention has been given to the application of DOE outside the manufacturing context. The literature reviewed in this section focuses on some of the few studies applying data farming and DOE to military manpower models.

Blosch and Antony (1999) apply design of experiments to the Rating Supply Chain Model (RSCM) to study risk in the United Kingdom's Navy manpower planning. Specifically, their study uses DOE to identify key variables that cause gapping, referring to a job that is not filled by a competent and qualified person, while on sea rotation. RSCM is a stochastic queuing inventory model that represents the flow of inventory through manpower positions and their interrelations with events such as recruitment, promotion, and losses. The model takes as input nine covariates and outputs distributions on queue lengths and waiting times within the queuing process. The study designed an experiment to evaluate the effects of three variables, sea-shore ratio, length of sea-draft, and billet ratios, and their interactions using one of Taguchi's orthogonal array designs. Results from the experiment allowed for analysis using analysis of variance (ANOVA) and other statistical techniques to determine the factors that influence gapping at sea. Although Blosch and Antony were conservative in the number of variables, their study revealed a promising application of DOE to manpower modeling within the military arena.

Erdman (2010) applies the concepts of design of experiment to the U.S. Army's Enlisted Specialty (ES) model. Erdman uses DOE to identify the variables with the greatest effect on minimizing the deviation between projected personnel inventory and authorized end strength. ES, like OSAM, is a dynamic inventory model that projects military inventory by grade and skill over a multi-year planning horizon. With 800,000 variables, ES adds an optimization application with 224,473 constraints to the inventory modeling process. Erdman evaluates 52 objective function coefficients of the model that place the greatest weight on decision variables and he uses the Plackett-Burman (Plackett & Burman, 1946) approach to construct his experimental design (Erdman, 2010). The findings from his analysis for the Army's G1 showed a possibility of a 14% reduction in deviation, or an average drop of 8,355 misalignments (Erdman 2010).

Nelson (2010) uses DOE to evaluate the Navy's Bureau of Personnel Metrics and Analytics Branch (BUPERS-34) Reenlistment model. The reenlistment model uses linear regression to forecast the expected reenlistment rate for the Navy's prescribed three reenlistment zones, based on years of completed service, assuming current conditions. Nelson uses DOE to determine the most influential variables in the model that predict the reenlistment rate for each zone. He uses a 3-factor, 2-level full factorial design for each zone and analyzes experimental results using multivariable regression and other statistical techniques. Nelson identifies a number of insignificant variables in the model and recommends alternative models that improve robustness and fit for each of the three enlistment zones (Nelson, 2010).

The thesis research of Sibley (2012) provides the foundations on which this thesis is based, and is the earliest literature known to this author utilizing the concepts of data farming and DOE on OSAM. Sibley seeks to evaluate and improve the prediction capability of an earlier version of OSAM by examining the performance across the simulation model's loss adjustment factors for the lateral transfer variable. With 90 factors of discrete levels, Sibley uses a randomized Latin Hypercube (LH) design and a Nearly Orthogonal Latin Hypercube design to vary lateral transfer rates and loss adjustment rates among the SWO and Human Resource (HR) officers for pay grades O1-O6. Data farming and DOE allowed for efficiently exploring a factor space that would otherwise have been computationally impossible to explore. Sibley's work, the first application of data farming and DOE to OSAM, not only lays the groundwork for continuing work, but also provides proven analytical solutions to OSAM's limitations adopted in the current version of the simulation model.

DeHollan (2015) advances the work of Sibley (2010) by applying concepts of data farming and design of experiments to an updated version of OSAM, enhanced with randomness. DeHollan measures the stochastic variation in the enhanced model and determines the effects of an improving economy on the four largest designators of the URL community, specifically focusing on pay grades O3 through O6. His work differs from that of Sibley (2010) in that in addition to using data farming and DOE to validate OSAM's behavior, he uses the model itself to analyze behavior and future composition of officer inventory based on a given real-world scenario. Since OSAM's existing platform does not have the intrinsic capability to model economic factors, DeHollan simulates a three-year period of an improving economy by introducing forced losses for three consecutive years. He uses a 257-design point NOLH design to vary 27 factors representing forced losses per pay grade per designator per year. He analyses the relationships among the factors from the results of his experiment using metamodeling and other statistical techniques.

Borozny (2015), who did her thesis research on OSAM concurrently with that of DeHollan, uses data farming and DOE to project Navy Surface Warfare officer inventory over a six-year period. Using the same modified version of OSAM as DeHollan, Borozny studies the interactions among OSAM's accession modeling methods; loss rates; and an aggregated force-shaping plan representing an EPOCR policy. Borozny finds that OSAM's different loss rates cause little to no variation in the model's end strength output, holding all else constant. Additionally, the loss rates resulted in counterintuitive results where higher loss rates increase end strength and vice versa. Borozny does not provide an analytical explanation for this surprising result, but this author suspects that varying accessions by accession methods, rather than by accession plans, over-compensates for the losses in end strength inventory induced by the loss rates. The current thesis research differs from Borozny (2015) by varying the accession plans available in OSAM rather than the accession methods. Additionally, this study models EPOCR force-shaping transfers at a disaggregated level, representing each of the three affected YCS with independent factors.

The works of DeHollan and Borozny provide the literature that serves as proof of concept for augmenting OSAM's inventory strength projection capabilities with data farming and DOE to answer questions relating to officer manpower policies, force-shaping, and personnel strength planning.

J. NAVY STRENGTH PLANNING MODELS

Navy strength planners and policy makers use a variety of strength planning models, some of which are discussed briefly in the following sections.

1. Navy Officer Personnel Planning System Model

N100 currently utilizes the Navy Officer Personnel Planning System (NOPPS) model for its officer strength planning and projection purposes. The model is used in conjunction with accession and promotion models to develop officer inventory management plans that will guide inventory to authorized end strength. NOPPS uses historical loss rates and average inventory to predict monthly inventory across the Future Years Defense Program (FYDP). The forecasting utility of NOPPS is, however, inadequate and limiting, forcing strength planners to calculate forecasts outside of the model (Frank, 1993).

2. Navy Enlisted Strength Planning Model

The Navy Enlisted Strength Planning (NESP) model, also utilized by N100, is an event-based deterministic tool used to forecast the Navy's enlisted end strength (DeSousa, 2015). NESP determines enlisted losses for a given year by applying historical loss rates to the number of enlisted sailors eligible to leave the Navy within that year. Much like NOPPS, discussed earlier, NESP's forecasting ability is also limited in that strength planners need to calculate loss rates externally (DeSousa, 2015).

3. Officer Strategic Analysis Model

The Officer Strategic Analysis Model (OSAM), utilized for this study, is the primary inventory strength projection model used by Navy strength planners to project long-term annualized projections of active officer inventory strength by pay grade, skill, and fiscal year. The model is described in Chapter III of this thesis.

This chapter gives an overview of the problem that is the focus of this research, inventory over-execution within the URL community, and describes it within the context of inventory strength planning. The chapter poses the specific research questions and the quantitative methods by which these questions are explored as well as the relevance of this research. The next chapter discusses OSAM, the inventory strength simulation model employed for this study.

THIS PAGE INTENTIONALLY LEFT BLANK

II. OFFICER STRATEGIC ANALYSIS MODEL

This chapter gives a basic overview of OSAM, including a general description, the model's design, its development, and a general description of the model's analytic approach and processing steps. DeHollan (2015) gives an in-depth description of the model's development and architecture.

A. MODEL OVERVIEW

The Officer Strategic Analysis Model (OSAM) is a dynamic entity-based long-term simulation model used to project annualized personnel inventory strength by skill and grade over a user-specified time period. The model is one of many decision tools available to Navy manpower analysts and the primary model used by Navy strength planners to project long-term annualized active officer inventory strength. OSAM simulates inventory, dynamically, in yearly time-steps, by applying historical loss rates, accession plans, transfer plans, promotion plans, and user-defined forced losses to the beginning of year (BOY) inventory. The model applies current Defense Officer Management Act (DOPMA), DOD, and Secretary of the Navy (SECNAV) policies and constraints to its yearly inventory strength projections.

B. DEVELOPMENT

OSAM was developed in 2007 to fill a Navy void of decision tools capable of projecting active officer inventory. The model was developed by LMI, a government-consulting group, specifically for the Navy's N14 (Manpower, Personnel, Training, and Education Catalog, 2015). As of the date of this writing, OSAM has not completed the Verification, Validation, and Accreditation (VV&A) process required for all simulation models intended for DOD use. Nevertheless, it has undergone extensive upgrades from its original version and has not only contributed to effectively supporting planning and budgeting of long-term officer inventory strength but also made it possible to convert the model into one that is data farmable. The executable application of OSAM was originally built in

Microsoft Visual Fox Pro, a defunct database language available only on government computers, limiting OSAM's usefulness (DeHollan, 2015). Another limitation of the original version was that the model's input was decentralized to multiple file locations, requiring manual adjustment of each file to adjust scenario settings, a tedious process that was prone to error (Sibley, 2012).

The latest software version is built in Microsoft Visual Basic (VBA) and houses its data files in Microsoft Access. The transition to VBA and Access circumvents government restrictions, expanding OSAM's access and use by Navy strength planners and manpower analysts. The current version also consolidates OSAM's input data to a single database, removing the need to individually edit each file when adjusting scenarios and pushing the models toward conforming to data farming standards.

C. SOFTWARE ARCHITECTURE

OSAM follows the general structure of a typical simulation model. The model's architecture comprises an input component, a simulation module, and output component. The input component is a set of permanent source tables built and stored in MS Access files. When a simulation is executed, the input section links to the module comprising a user interface and simulation algorithms. The interface captures and transfers user input settings and parameters to the simulation module that drives the simulation algorithms. Each scenario's inputs and parameters are stored in text files outside the confines of the model, allowing for easily accessing and rerunning or modifying scenarios. After each simulation, the model saves output data as two database tables. The first table is a multi-year summary (MYS) report of forecasted inventory data pertaining to promotions selections, loss counts, transfers, and accessions. The second is a flow point table that includes detailed promotion data including the number of vacancies, promotions, and flow point estimates for each competitive category and control grade (O4, O5, and O6). A scenario Analysis Tool built in Excel is included as part of OSAM's software. A representation of OSAM's interconnecting systems is shown in Figure 3.

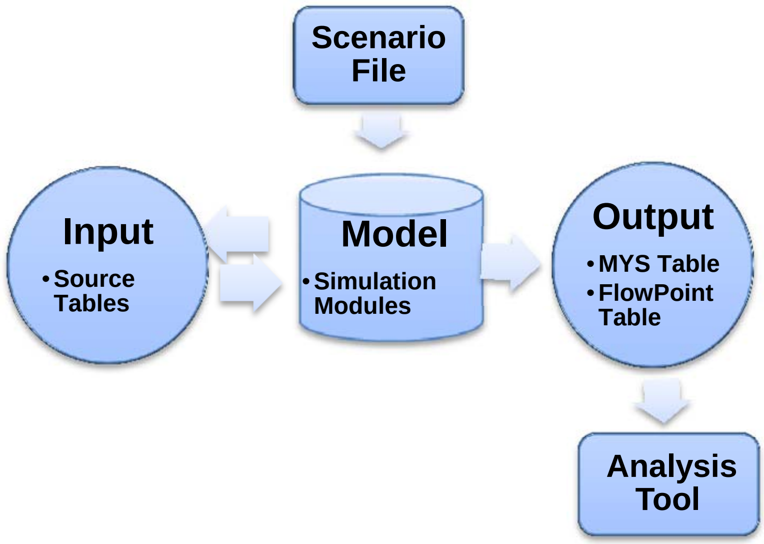


Figure 3. OSAM Database and Model Component Structure

D. SIMULATION MODELING OVERVIEW

OSAM's simulation process is similar in design and structure to Equation 1.1 displayed in Chapter I of this thesis, expressing the relationship between beginning inventory, losses, accessions, and the end strength. The analytical process begins with a beginning of year (BOY) inventory that accounts for each active duty officer brought forward from the previous fiscal year (FY), and represented by pay grade, designator, year of commissioning, and date of rank. The model subtracts inventory from BOY based on forecasted losses and user specified losses, and applies accessions and promotion algorithms to determine the end of year (EOY) inventory. For a multi-year forecast, EOY inventory for the previous year is the BOY inventory for the subsequent year. Since OSAM is a dynamic long-term disaggregate model, this process is repeated for each year for each designator and pay grade, for all years defined by the user. Figure 4 shows an overview of OSAM's analytical process.

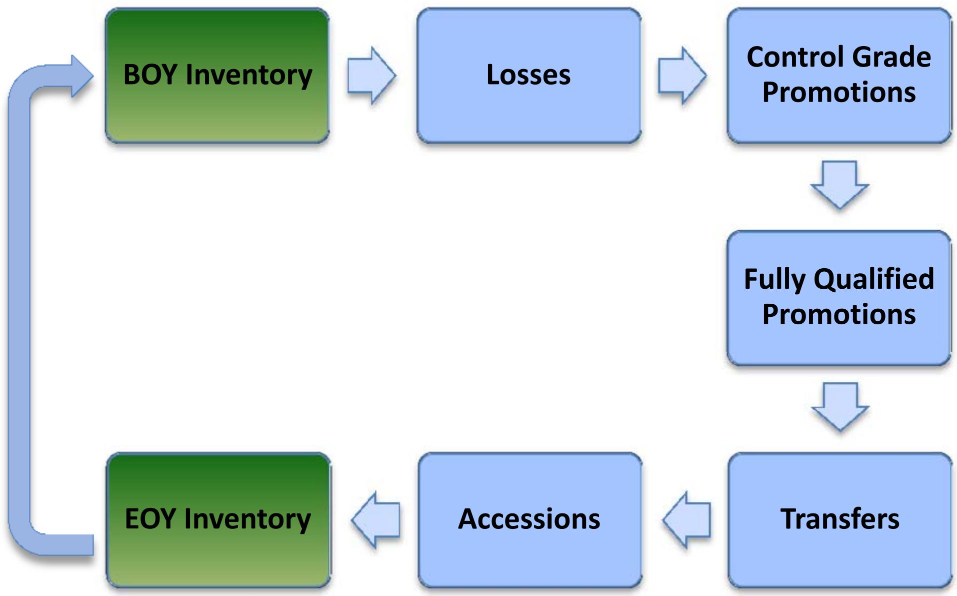


Figure 4. Overview of OSAM's Simulation Process. Source: Mundy (2014).

E. OSAM MODELING PROCESSES

This section discusses how OSAM models losses, promotions, accessions transfers, and accessions to forecast officer inventory

1. Losses

Forecasting losses represents the most complex aspect of personnel inventory strength projection and is the first analytical task of OSAM's modeling process. Navy officer strength planners categorize a loss as either natural or forced, depending on whether the loss was deliberately contrived through a force-shaping policy. OSAM categorizes losses in a similar way as Natural losses and Force-out losses and adds an option to define user-added losses.

a. Natural Losses

Officer natural losses, strictly speaking, comprise losses other than those due to force-shaping policies. These include officers who discontinue their service through voluntary retirement, resignation, and discharge. The natural losses in OSAM are an aggregate of natural losses, losses due to other than force-shaping policy and behavioral losses. OSAM derives natural losses using historical loss rates predetermined by the Navy Officer Personnel Planning System (NOPPS) Forecasting Model (NFM). NFM estimates loss rates by FY, loss types, designator, paygrade, and years of commissioned service (YCS) group. OSAM models natural losses by multiplying the historical loss rates derived from NFM by the beginning of year (BOY) inventory as denoted as

$$Losses_{Proj}\left(g,d\right) = LossRate\left(g,d\right) \times Inv_{BOY}\left(g,d\right) \tag{2.1}$$

where $Losses_{Proj}$ *(g,d)* represents the projected number of losses in pay grade *g* for a specified designator *d*. *LossRate* represents the applied loss rate, and Inv_{BOY} is the inventory at the beginning of the projection year.

b. Force-out Losses

Forced or Force-out losses are driven by force-shaping plans which are policy decisions stipulated by law and Navy leadership to compel personnel to leave service. The primary force-shaping plan for Navy officers is higher-year tenure, which limits the number of years of commissioned service at any specific pay grade. Navy promotions occur within specified YCS groups, and the percentage of officers promoted within each group must fall within minimum and maximum percentages established by law (SECNAVINST, 2006). The flexibility to balance promotions with higher year tenure creates an effective force management tool for Navy policy makers and officer strength planners that can be used to shape the inventory composition of any officer community. OSAM accounts for forced losses by applying maximum YCS conditional constraints to each pay grade designator combination:

$$\left[g \geq 4\ AND\ YCS \geq YCS_{RETIRE}\left(g,d\right)\right] OR \left[g \leq 3\ AND\ YCS \geq YCS_{MAX}\left(g,d\right)\right] \tag{2.2}$$

where, for each officer, *YCS* represents years of commissioned service group, YCS_{Max} is the maximum allowable YCS group for grade *g* and designator *d*, and

YCS_{RETIRE} represents the maximum allowable YCS group allowed prior to retirement (Mundy, 2014).

c. User-Added Losses

In addition to natural and forced-out losses, OSAM's flexibility allows a user to add additional loss constraints by either adding or reducing losses by pay grade, designator, YCS, or FY, using the force-shaping utility. The model adds user-added loss constraints by adding or decreasing the number of losses after force-out and natural losses have been applied to BOY (Mundy, 2014). One can specify user-added loss constraints by FY, pay grade, YCS group, designator, and community. For instance, selecting to increase losses by 20 applies 20 additional annual losses in each FY of a specified year range, and distributes the losses within the specified grades, YCS, and designators specified. OSAM applies the losses and additions stochastically using distributions proportional to inventory at the BOY of the specified FY. This thesis uses OSAM's force-shaping utility to enforce user-added losses representing SWO officers referred to the EPOCR board.

2. Promotions

The second step in OSAM's modeling process is determining and setting promotions. OSAM models promotions in two phases, representing control-grade and fully-qualified promotions.

a. Control Grade Promotions

Control-grade promotions apply to grades O4 to O6. Promotions to these grades is subject to stipulations in DOPMA, which provides limits on the authorized end strength and the minimum time in grade or flow-points in each of these grades. DOPMA also establishes promotion zones. Zones are correlated with an officer's time in grade and officers eligible for promotions are categorized as either "in zone" or "above zone," depending on whether they have already been considered for promotion. DON guidelines further regulate promotion percentage rates to these grades (SECNAVINST, 2006). All naval officers compete for promotions with other officers of the same competitive category, regardless of their designator. Surface Warfare, Submarine Warfare, Naval Aviator, and Naval Flight Officers, the designators that are the focus of this study, belong to the Unrestricted Line (URL) competitive category. The designators compete against one another for available promotions by grade at each selection cycle.

OSAM provides four methods for modeling promotions. The first models promotions based on a predetermined promotion plan. The second sets promotions according to predicted vacancies. The third method promotes to the number of vacancies or until flow-points reach minimum thresholds. The fourth, “Auto-Promote,” promotes to the number of vacancies while remaining within DOPMA/DOD/SECNAV guidelines. This thesis uses the FY2016 promotion plan to project FY2016 and FY2017 BOY inventory, and “Auto-Promote” to model subsequent years.

b. Fully Qualified Promotions

Fully qualified promotions refer to officer promotions to the grade of O2 and O3. Nearly all eligible officers will promote to these grades. OSAM automatically promotes officers to these grades without the need for user input.

3. Transfers

The third modeling process applies transfer rates to inventory. A transfer refers to the reassignment of an officer from one designator to another. Naval officers may transfer by way of upward mobility from a training designator to a primary designator, or laterally through a lateral transfer or re-designation board. OSAM applies upward mobility transfers from a training to parent designator automatically without user input. The model applies lateral transfers based on a user-specified transfer plan. Additionally, the model constrains transfers to only grades O1-O6 and mimics historical transfer patterns by YCS and pay grade.

4. Accessions

The last step of OSAM's modeling process is applying accessions or gains to obtain the end of year (EOY) inventory. An accession refers to personnel entry into the Navy manpower system from the civilian sector. OSAM uses accession plans that are based on historical data of prior accession plans executed by the Navy. The plans specify the number of officer accessions by community and paygrade. Alternatively, users can choose either unconstrained or constrained accession methods to model accessions for each projected FY. The unconstrained method sets the number of accessions so that approved end strength is met or exceeded. The constrained method uses the same logic as the unconstrained, but restrains accessions so that total personnel inventory does not exceed approved end strength. This study uses an accession plan for each projected FY.

F. USER INTERFACE AND SCENARIO SETTINGS

OSAM's graphical user interface (GUI), named the scenario editor and shown in Figure 5, provides a convenient way to build and run a simulation scenario. Each scenario is a set of input parameters and settings that include a user's choices of preset input tables referred to as plans; methods for applying accessions, promotions, and transfers; and Structured Query Language (SQL) statements that are used as options to program any further deviations from the originally set parameters (Mundy, 2014). The GUI allows users to easily set input parameters, define the modeling options, and specify desired output for each scenario. The GUI's simulation building process exposes the user to the various input parameters and modeling options via the Parameters, Promotions, Accessions, and Force-Shaping tabs, as shown in Figure 5.

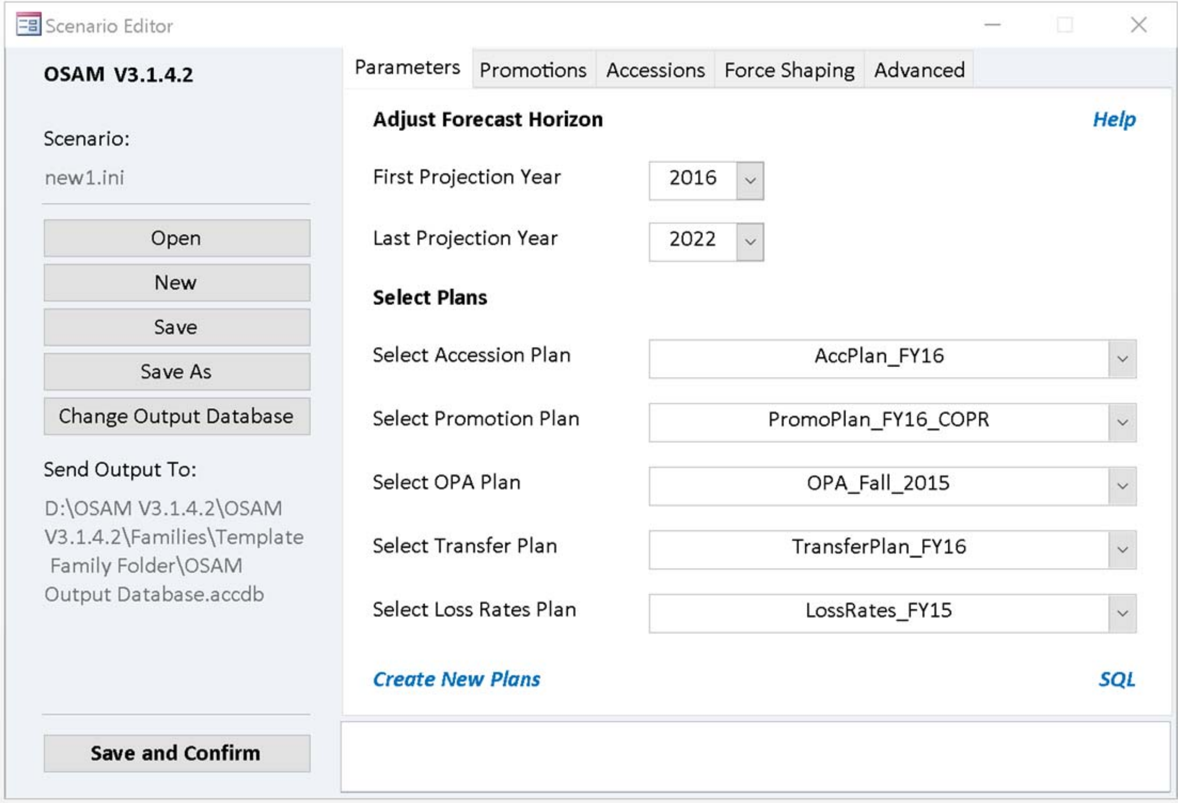


Figure 5. Officer Strategic Analysis Model Graphical User Interface

1. Input Parameter Settings and Modeling Methods

The primary input parameters are specified via the Parameters and the Force-shaping page. On the Parameters page, users can specify the length of the forecasting horizon and select from a variety of input tables for accessions plans, promotion plans, Officer Programmed Accession (OPA) or end strength plans, transfer plans, and loss rates categories. The force-shaping page allows users to add or constrain losses in addition to the losses resulting from the loss rates.

The Promotion page, shown in Figure 6, Accessions page, and Advanced page allow users to choose among the different modeling methods by which OSAM calculates or determines promotions and accessions, and transfers, respectively. On the promotion and accession page, users may elect to use pre-existing plans in the OSAM database or choose among the model's modeling methods to determine promotions and accessions, respectively. The advanced page allows users to specify outbound transfers by community and paygrade.

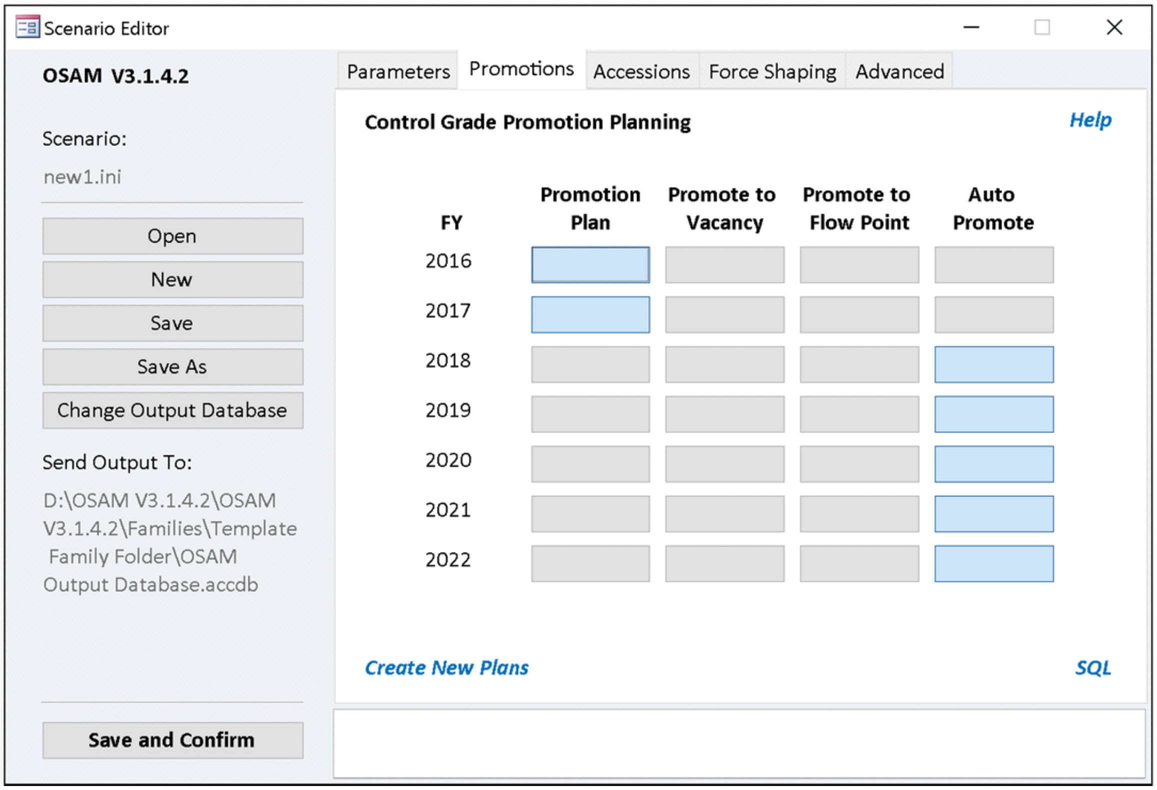


Figure 6. Officer Strategic Analysis Model Promotion Methods

2. Simulation Model Output

Once each simulation scenario is completed, OSAM consolidates and aggregates all output into multi-year summary (MYS) tables and flow point tables containing entity level information for every simulation year. MYS tables produce aggregated forecast data from which counts of beginning of year (BOY) inventory, end of year (EOY) inventory, losses, promotions, transfers, and accessions are generated. Flow point tables include detailed promotion data that includes the number of vacancies, promotions, and flow point estimates for each competitive category and control grades O4, O5, and O6 (Mundy, 2014). The

OSAM software package also includes an analysis tool, built in Microsoft Excel, which is used to analyze and track differences in scenario output.

The basic software version of OSAM and the analysis tool, however, are not suited for large-scale experiments involving thousands of iterations as needed for this study. Data farming tools are built to enable running multiple OSAM scenarios without the need for user interaction.

G. OSAM SIMULATION RUNTIME

The runtime for a single iteration of an OSAM scenario depends on the length of the forecasted horizon and the computing power of the machine on which OSAM is housed. A one year forecast scenario takes approximately two minutes on a 64-bit windows computer with an Intel 2.4 GHZ processor. A seven-year forecast takes approximately eight minutes on the same machine.

THIS PAGE INTENTIONALLY LEFT BLANK

III. METHODOLOGY AND IMPLEMENTATION

This chapter discusses the two primary methodologies used in this study, Design of Experiments and Data Farming. Design of Experiments (DOE) is used to generate and explore a broad range of OSAM scenarios. Data Farming substitutes OSAM's GUI with computing scripts that automate the process of iteratively running and collecting data from OSAM scenarios. Additionally, the chapter discusses supplemental software tools used to transform OSAM into a data farmable model.

A. DESIGN OF EXPERIMENTS

1. Definition and Applications

Design of Experiments (DOE) allows for systematically determining the relationships between a factor, an input affecting a process or system, and the response, the output of that process or system, using computational experimentation. Varying input factors singularly, as by haphazardly choosing one scenario at a time in OSAM, is time wasting, limits insight, and may produce inconclusive or even disastrous results (Kleijnen et al., 2005). With DOE, one can carefully and efficiently make controlled changes to the input factors in order to gain maximum insight on how the factors affect the outcome variable. The design is specified as a matrix where columns correspond to factors and rows to a unique combination of factor levels, referred to as design points (Kleijnen, et al., 2005). The response surface generated from the designed experiment is then studied and analyzed through metamodeling to gain insight on which, and to what extent, the simulation model's inputs affect the model's output.

2. Relevant Input Factors

A fundamental initial step in the design process is identifying and selecting relevant input factors (Sanchez et al., 2014). A factor, in the context of simulation, is an explanatory variable to a process or system's output that is manipulated by the experimenter. Decision factors are variables that can be controlled in the real world by a decision maker as opposed to noise factors that happen randomly, and are therefore uncontrollable.

The choice of factors to vary depends on the factors' characteristics, available computing resources, and the intent of the underlying experiment (Kleijnen et al., 2005). This research seeks to use OSAM to study the impact of accession plans, and the EPOCR policy characterized forced losses of SWO officers with four, five, and six years of commissioned service. Loss rate categories, transfer plans, accession plans, and force-shaping plans serve as the primary input variables of interest. Table 1 lists a summary of the factors used in our experimental design and their associated levels. A discussion of the factor ranges follows.

Table 1. Experimental Design Factors and Corresponding Levels

Factor	Variable Type	Levels
	Controllable Factors	
EPOCR 4 YCS	Discrete	[0, 120]
EPOCR 5 YCS	Discrete	[0, 120
EPOCR 6 YCS	Discrete	[0,120]
Transfer Plan	Categorical	FY[09_10, 14, 15], No Transfer
Accession plan	Categorical	FY[12, 13, 14, 15]
	Uncontrollable Factors	
Loss Plans	Categorical	FY[06 ,07, 10, 13, 14, 15]

3. Factor Range

In order to build an experimental design, it is necessary to determine the ranges for the relevant input factors. This section lists and gives a general description and the range determination for all the decision factors and the uncontrollable factor used in this study.

a. Decision factors

This section describes the decision factors used in this study.

(1) Transfer plans

URL communities depend on upward mobility transfers and to some extent lateral transfers to grow their non-accession inventory. Transfer plans are determined yearly and are effectively determined and controlled by strength planners and policymakers. OSAM programs inbound and outbound transfers for grades O1 to O2, dimensioned by pay grade, community, and FY of execution. Grades O1 to O6 transfer via training to parent designators or via probationary officer continuation retention (POCR) boards, whereas grades O3 to O6 laterally transfer into other communities. For this study, five transfer plans were chosen with guidance from N100 strength planners (P. Saluke, personal communication, April 26, 2016).

(2) Accession Plans

Accessions are the primary method by which communities get new personnel inventory. One of the primary objectives of this study is to determine the risk in future inventory posed by a low accession plan. As with transfer plans, Navy policy makers determine and have control over what accession plans to implement, and therefore are categorized as control factors for the purpose of this study. OSAM programs accession using predetermined tables that represent historical accession plans dimensioned by designator and the FY in which they were implemented. For this study, we selected four accession plans by choosing the plans that correspond to the most recent plan, the highest accession rate, the lowest accession rate, and a moderate accession rate.

(3) EPOCR (Four, Five, Six YCS)

EPOCR policy is simulated as user-added losses. OSAM's flexibility allows users to increase or decrease losses by community, pay grade, FY and YCS after the natural losses are applied via its force-shaping functionality. This thesis uses OSAM's force-shaping functionality to model losses representing SWO officers referred to the EPOCR board. Each YCS group is represented as an independent factor corresponding to SWO officers with four, five, and six years of commissioned service. We model EPOCR losses with a range of 0 to 120 losses for each YCS category. This range represents the proposed total number of officers referred to the EPOCR board.

b. Noise Factors

This section describes the uncontrollable factors used in this study

(1) Natural Loss Rates

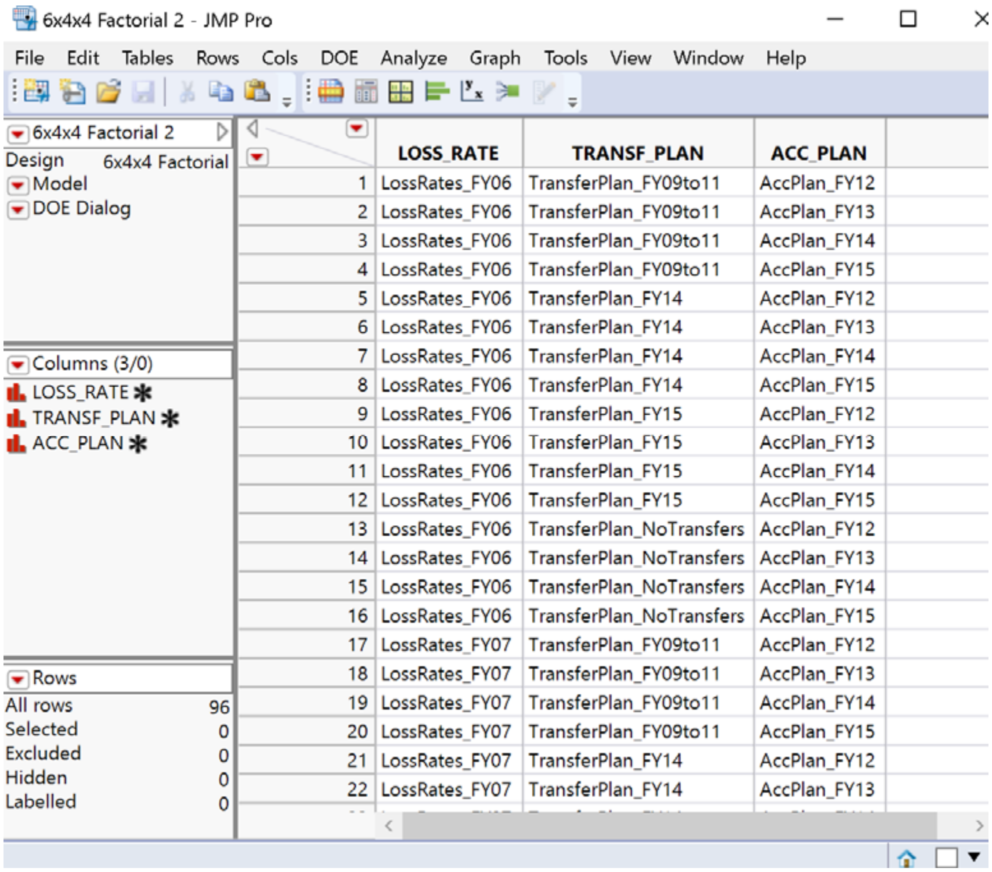
Natural losses represent the uncontrollable factors in manpower modeling caused by inherent uncertainty in human behavior. For this reason, they are often the most complex factors to model. OSAM uses tabulated historical loss rates dimensioned by pay grade, community, and the FY or period in which the loss happens. (See Chapter .I) This study seeks to determine the variability in OSAM's personnel end strength inventory projection over the uncontrolled losses. The study uses seven loss rate categories that represent a varied continuum of years with minimal losses to years with severe losses over the past ten years.

4. Choice of Experimental Design

Many competing design exist in the field of simulation analysis. The choice for which design to use, however, is significantly influenced by the number of factors, type of factors, and available computing resources (Kleijnen at al., 2005, Sanchez & Wan, 2012). This study uses a combination of three multi-level categorical and three discrete factors with a wide range of values. The relatively small number of factors, both categorical and, calls for a mixture of a gridded design and an efficient space-filling design applied to the categorical and discrete variables, respectively. Such a crossed design ensures all combinations of categorical factors are captured and reveals interactions and other possible nonlinearities within the results. A full factorial design is appropriate for the categorical factors as it will examine the categorical factors at all levels and guarantee that all main effects and interactions are captured (Sanchez & Wan, 2012). Nearly Orthogonal Latin Hypercubes (NOLH) arise as the most suitable design for the discrete variables given the broad range of values for the SWO forced losses. These designs, developed at the Naval Postgraduate School, offer excellent space-filling properties with minimal sampling (see Sanchez et al., 2012, and Cioppa & Lucas, 2007). They also enable analysts to fit a broad range of meta-models and generate a diverse set of graphs. For additional families of NOLHs, see Hernandez et al., 2012 and MacCalman et al., 2016.

5. Experimental Design Construct

A full factorial design for the categorical variables is generated using the Full Factorial Design tool in JMP Pro 12.0.1 (JMP, 2015). The three categorical factors with six, four, and four levels, respectively, are crossed to get a design matrix of 96 design points. Figure 7 depicts the first 22 of the 96 design points for the full factorial design.



	LOSS_RATE	TRANSF_PLAN	ACC_PLAN
1	LossRates_FY06	TransferPlan_FY09to11	AccPlan_FY12
2	LossRates_FY06	TransferPlan_FY09to11	AccPlan_FY13
3	LossRates_FY06	TransferPlan_FY09to11	AccPlan_FY14
4	LossRates_FY06	TransferPlan_FY09to11	AccPlan_FY15
5	LossRates_FY06	TransferPlan_FY14	AccPlan_FY12
6	LossRates_FY06	TransferPlan_FY14	AccPlan_FY13
7	LossRates_FY06	TransferPlan_FY14	AccPlan_FY14
8	LossRates_FY06	TransferPlan_FY14	AccPlan_FY15
9	LossRates_FY06	TransferPlan_FY15	AccPlan_FY12
10	LossRates_FY06	TransferPlan_FY15	AccPlan_FY13
11	LossRates_FY06	TransferPlan_FY15	AccPlan_FY14
12	LossRates_FY06	TransferPlan_FY15	AccPlan_FY15
13	LossRates_FY06	TransferPlan_NoTransfers	AccPlan_FY12
14	LossRates_FY06	TransferPlan_NoTransfers	AccPlan_FY13
15	LossRates_FY06	TransferPlan_NoTransfers	AccPlan_FY14
16	LossRates_FY06	TransferPlan_NoTransfers	AccPlan_FY15
17	LossRates_FY07	TransferPlan_FY09to11	AccPlan_FY12
18	LossRates_FY07	TransferPlan_FY09to11	AccPlan_FY13
19	LossRates_FY07	TransferPlan_FY09to11	AccPlan_FY14
20	LossRates_FY07	TransferPlan_FY09to11	AccPlan_FY15
21	LossRates_FY07	TransferPlan_FY14	AccPlan_FY12
22	LossRates_FY07	TransferPlan_FY14	AccPlan_FY13

Figure 7. Full Factorial Design for the Three Multi-level Categorical Variables Generated Using JMP Pro 12.0.1

An NOLH design is generated using Excel spreadsheet design template, created by Professor Susan Sanchez at NPS and available at the SEED center's website *https://harvest.nps.edu.* The particular design template used generates 33 design points and can accommodate up to 11 factors, more than sufficient for our three discrete factors. Figure 8 shows the complete design matrix with the 33 design points, where, for instance, YCS_4 is a variable representing SWO officers with four years of commissioned service who have been referred to the EPOCR board.

low level	**1**	**1**	**1**
high level	**120**	**120**	**120**
decimals	**0**	**0**	**0**
factor name	**YCS_4**	**YCS_5**	**YCS_6**
	120	12	53
	109	120	16
	105	53	109
	68	105	120
	113	5	57
	116	113	38
	83	57	116
	64	83	113
	79	31	27
	90	79	34
	87	27	90
	94	87	79
	72	20	23
	101	72	46
	75	23	101
	98	75	72
	61	61	61
	1	109	68
	12	1	105
	16	68	12
	53	16	1
	8	116	64
	5	8	83
	38	64	5
	57	38	8
	42	90	94
	31	42	87
	34	94	31
	27	34	42
	49	101	98
	20	49	75
	46	98	20
	23	46	49

Figure 8. NOLH Design—3 Factors and 33 Design Points

The design point matrix for the categorical factors is then crossed with the design point matrix for the discrete factors using JMP. The crossing generates a mixed design matrix with 3,168 design points. Figure 9 depicts a scatter plot matrix revealing the space filling properties of the resulting crossed design. Each subplot within the scatter plot matrix shows a two dimensional projection of the entire design and the levels used for each factor.

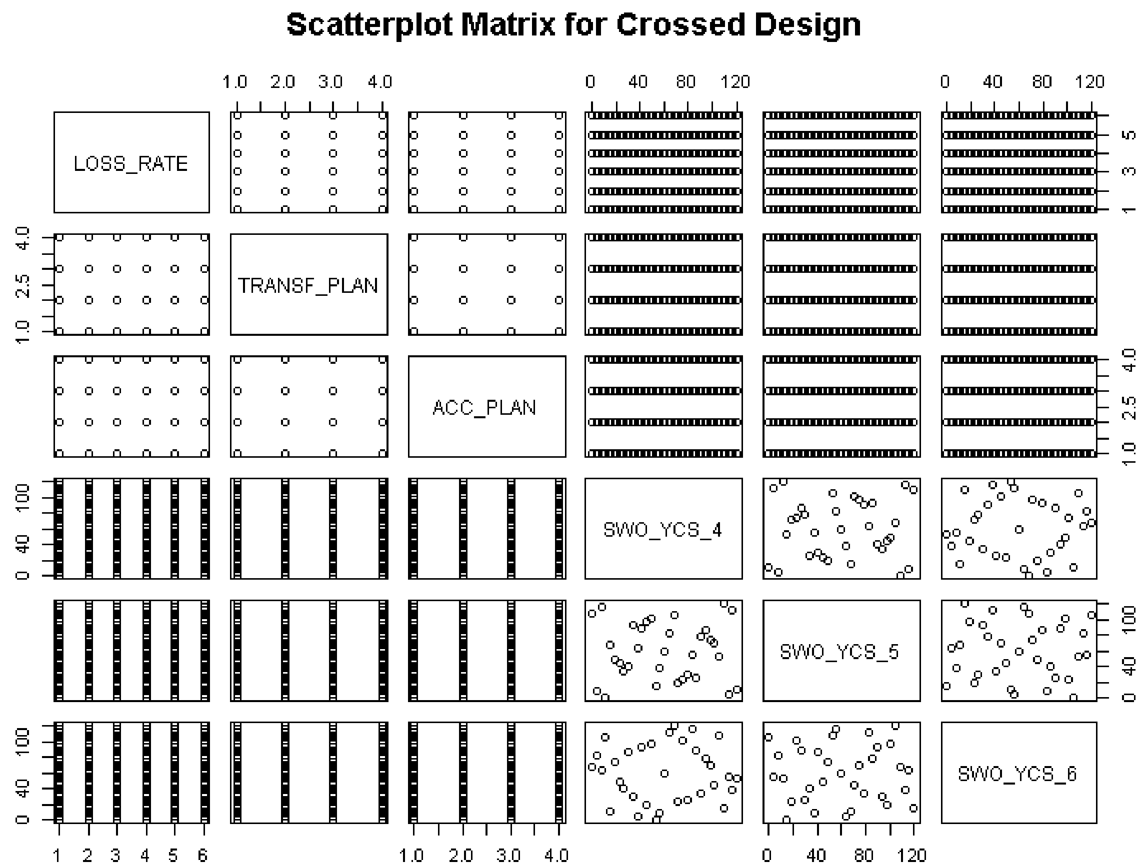


Figure 9. Scatter Plot Matrix for the Full Factorial Categorical Design Crossed with the Discrete Variable NOLH Design

6. Replication

Replication is the repeating of the entire design matrix in a simulation experiment. Replication is necessary to gain precision in its output results and to estimate the experimental error in the design if using a stochastic model (Cavazzuti, 2013). However, a tradeoff between the number of replicates per design point and the number of total design points is considered when constructing a design (Kleijnen et al., 2005). Previous studies using the stochastically enhanced version of OSAM have shown the model to depict very little random variation in end strength results. Borozny (2015) used 100 replications for her experimental design and found little stochastic variation in

OSAM's end strength results. DeHollan (2015) found similar results using 100 replications for a single base case design point. This thesis considers these findings, as well as conclusions from a base case scenario simulated for this study, in deciding a tradeoff between replications and the total number of design points to simulate. We use five replications for each of the 3,168 design points for a total of 15,840 simulation runs.

B. DATA FARMING

Data farming, in technical terms, is the process of using rapid prototyping, simulation modeling, experimental design, high-performance computing, and data analysis to study questions of interest with large possibility spaces (Horne et al., 2014). The process is analogous to agricultural farming. Where farmers manipulate the environment and cultivate land to maximize agricultural yield—pest control, irrigation, fertilizer, etc.—data farmers manipulate simulation models with designed experimentation to produce a landscape of output. A model is data farmable if it is possible to programmatically modify its input and automatically start an instance of that model, usually with a computer's command-line interface (Horne et al., 2014).

OSAM in its original version is not configured for data farming as the model is incapable of running multiple scenarios or replications of single scenarios successively without user interaction. The external software is necessary to data farm OSAM. Steve Upton, a Faculty Associate for research at NPS's SEED Center developed OSAMFarmer, a supplemental data farming wrapper that is a collection of two key software programs, OSAMRunner and SimpleFarmer. Together, these programs "wrap" around OSAM to make the simulation model data farmable.

1. OSAMRunner

OSAMRunner strips out the graphical user interface and allows a user to run successively one or more replications of an OSAM scenario by feeding input specifications to OSAM via a command line interface. The program takes as input; the model file; a configuration file specifying OSAM input parameters and settings for a specific scenario; and a seed argument, where the number of seeds corresponds to the number of desired replications. The program automatically saves the model's output from each completed replication and successively starts the next simulation until all replications are exhausted. A user can then consolidate and analyze the model's output.

2. SimpleFarmer

The second of the two programs, SimpleFarmer, concurrently schedules and manages a set of predefined tasks on a single, multi-processor machine by distributing tasks across individual processors. The program takes as input two task files, one that labels the names and locations of OSAM input task elements including the experimental design, and another containing a set of tasks corresponding to the simulated design points. SimpleFarmer schedules and executes tasks based on predefined dependencies and the number of available processers. Since SimpleFarmer distributes OSAM runs across processors, one can use the software to take advantage of parallelized processing on high-performance computer cluster nodes to cut down on the model's run-time.

3. Base Case

In addition to the experimental design, this study includes a base case scenario to serve as a baseline for comparison of the experimental results. The base case contains the same input factors and parameter settings used for the experimental design and uses the most recent and prevailing manpower policies as represented in OSAM. No force-shaping policies are specified in the base case scenario. Input parameters include the FY 2016 accession plan, FY 2016 transfer plan, and FY 2015 loss rates. The promotion method is set to FY 2017 promotion plan for FY 2016 and 2017, and auto-promote for successive years. We replicate the base case scenario 100 times to further explore the stochastic variation in end strength results, and employ OSAMRunner to data farm OSAM.

C. EXPERIMENTAL RUNTIME

The runtime for a single iteration of an OSAM scenario depends on the length of the forecasted horizon and the computing power of the machine on which OSAM is housed and run. Consequently, for this study, the total experimental runtime is the total time it takes to run all 15,840 of the simulation runs specified in the experimental design, each projected to seven years. A seven-year projection of OSAM takes approximately eight minutes to run using a 64-bit windows computer with an Intel 2.4 GHZ processor. Without the benefits of parallelized cluster computing, this experiment would take approximately 88 days. With the help of NPS's SEED center resources, this study takes advantage of OSAMFarmer's task distribution and scheduling properties to utilize a High-Performance Computing (HPC) multi-processor cluster system housed at NPS's SEED center. The HPC reduces the total experimental time to nine days (S. Upton, personal communication, July 14, 2016).

This chapter explains and gives justification for the methodologies chosen to explore the research questions posed in Chapter I. This chapter specifically describes the approaches taken to generate simulated data from OSAM. The next chapter presents and analyzes the results.

THIS PAGE INTENTIONALLY LEFT BLANK

IV. ANALYSIS OF RESULTS

This chapter presents and discusses the output from the base case scenario and the experimental design using graphical and statistical tools. We analyze the base case output to determine the degree of stochastic variation in projected operating strength. Additionally, we use results from the base case to determine the expected trend in URL inventory strength assuming current policy and most recent loss rates. We then analyze experiment data to gain insight on the effect of accession plans, transfer plans, and loss rate categories on operating inventory strength. We further study the impact of EPOCR policy. Using robust design, regression tree analysis, and meta-modeling, we determine the policy's implications on operating strength deviation (OSD).

A. ANALYTICAL TOOLS

We use R version 3.3.0 (R Core Team, 2016) to consolidate, filter, and organize the results from the base-case simulation. R is also used for initial exploratory analysis of the base case results. We use JMP Pro Version 12.0.1 (JMP Pro 2015) to process, organize, and filter the raw experimental output data into analyzable form as well as for initial exploratory analysis. JMP's analytical and graphical tools are used to further explore the base case and experimental data for insight.

B. ANALYSIS OF BASE-CASE RESULTS

Output from the base-case scenario is used to assess the stochastic variation induced by the modification of the latest version of OSAM used for this study. Additionally, the base case gives a projection of the expected operating inventory strength using standing policy and assuming the most recent applicable loss rate category. This helps to determine the expected direction of current operating inventory assuming the assumptions prevail over the projected period. Specifically, the base case simulates 100 replications of a single design point with FY2016 accession plan, FY2016 transfer plan, FY2015 loss Rate, and

FY2017 promotion plan for FY 2016 and 2017, and auto-promotion method set for successive years.

1. Data Processing and Collection

OSAMRunner saves the output from each of the 100 design points as a separate CSV file. Each file contains multi-year summaries, for all 70 designators, from which counts of beginning of year (BOY) inventory, end of year (EOY) inventory, losses, promotions, transfers, and accessions by designator and pay grade are generated. We use R to consolidate the CSV files and filter the multi-year summaries to inventory strength counts of the specific URL designators of interest, SWO, SUB, PILOT, NFO, and their corresponding training designators. We further group the data by design point, FY, Grade, and Designator. Training designators are summed together with their corresponding primary designators. For instance, SWO trainee is grouped and summed with SWO.

2. Stochastic Variation

To determine stochastic variation in the base case, counts of inventory strength are summed over all designators, grouped by FY, and averaged across the 100 replications. The results show that OSAM produces very little variation in URL projected inventory strength results across the 100 replications of the base case scenario. Figures 10 and 11 depict the variation in the URL and SWO inventory strength, respectively, projected across the 100 replications over a seven-year period. The lines depicted in the figures correspond to different replications. Variance in the total projected inventory increases in later years in both cases although the variance is small relative to the total inventory.

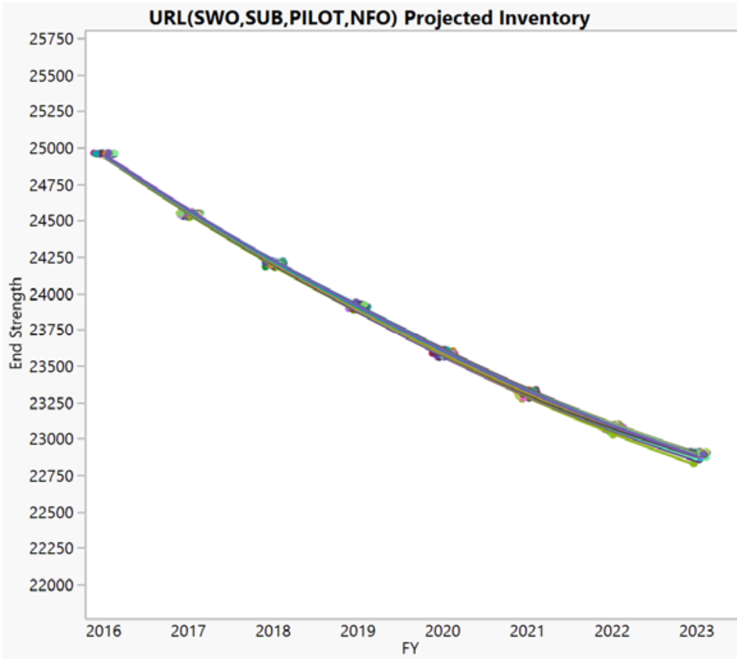


Figure 10. URL Total Inventory Strength Projected across 100 Replications of Base Case Scenario

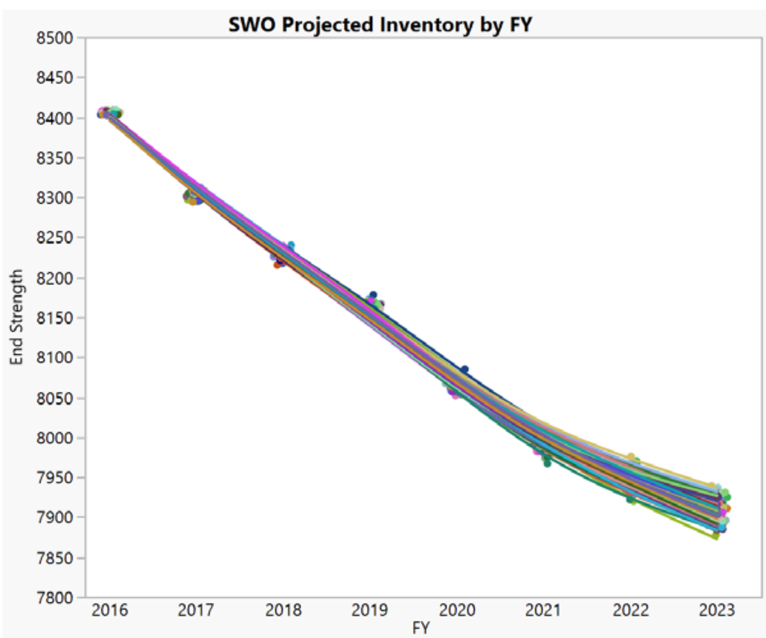


Figure 11. SWO Inventory Strength Projected across 100 Replications of Base Case Scenario

Summary statistics for URL inventory for each projected year are shown in Table 2. The standard deviation measures the variability of the projected values from the mean. FY 2023 has the highest variation in projected strength with a standard deviation of 12.49 and a mean of 22,890 officers, suggesting that stochastic enhancement of OSAM accounts for less than 0.06% of the variation in projected inventory strength. Similar results for SWO projections are shown in Table 3.

Table 2. Summary Statistics of URL Projected Inventory Strength across 100 Replications of Base Case Scenario

FY	Mean Strength	Std. Dev.	Min	Max	25th Quantile	75th Quantile
2016 (BOY)	24815	-	-	-	-	-
2016	24958	2.75	24952	24965	24956	24960
2017	24545	6.28	24521	24556	24541	24549
2018	24204	8.57	24176	24222	24199	24210
2019	23911	10.67	23884	23936	23903	23918
2020	23587	11.27	23558	23618	23579	23594
2021	23304	12.42	23271	23334	23295	23312
2022	23073	12.72	23023	23101	23066	23081
2023	22890	12.49	22826	22909	22885	22899

Table 3. Summary Statistics of SWO Projected Inventory Strength across 100 Replications of Base Case Scenario

FY	Mean Strength	Std. Dev.	Min	Max	25th Quantile	75th Quantile
2016(BOY)	8365	-	-	-	-	-
2016	8405	1.8	8402	8409	8404	8407
2017	8302	3.84	8294	8312	8300	8305
2018	8229	5.1	8215	8240	8225	8232
2019	8161	5.89	8148	8178	8156	8165
2020	8066	7.03	8052	8085	8061	8072
2021	7993	8.29	7967	8010	7987	7999
2022	7950	10.3	7920	7976	7943	7957
2023	7910	12.41	7878	7939	7902	7918

3. SWO Operating Strength Deviation-Base Case

One objective of this study is to determine the risk in operating strength deviation presented by current policy. Since the base case parameters are set to reflect current manpower management policies, we use SWO inventory strength output from the base case to determine inventory risk by comparing projected operating strength to planned Officer Program Authorizations (OPA). SWO OPA given by grade and FY and programmed to FY 2022 are given in Table 4.

The mean of the projected operating inventory strength by grade and FY compared to planned authorizations is shown in Figure 12. The total inventory strength composition for the SWO community is largely unchanged for FY2017 and beyond. Standing out is grade O3 inventory, which over-executes authorizations by more than 40% in all projected FYs. There is significant increase in FY2017 OPA for grade O1, causing significant under-execution in this grade that persists to the end of the seven-year projection period.

Table 4. SWO Officer Programmed Authorization by Grade and FY
Source: N100 (2016)

. FY	ENS	LTJG	LT	LCDR	CDR	CAPT
2016	1528	1091	1388	1096	657	256
2017	2289	1371	1570	1082	651	243
2018	2152	1379	1596	1096	654	241
2019	2104	1442	1608	1111	660	241
2020	1993	1442	1623	1103	661	238
2021	1988	1441	1624	1101	661	238
2022	1988	1441	1624	1101	661	238

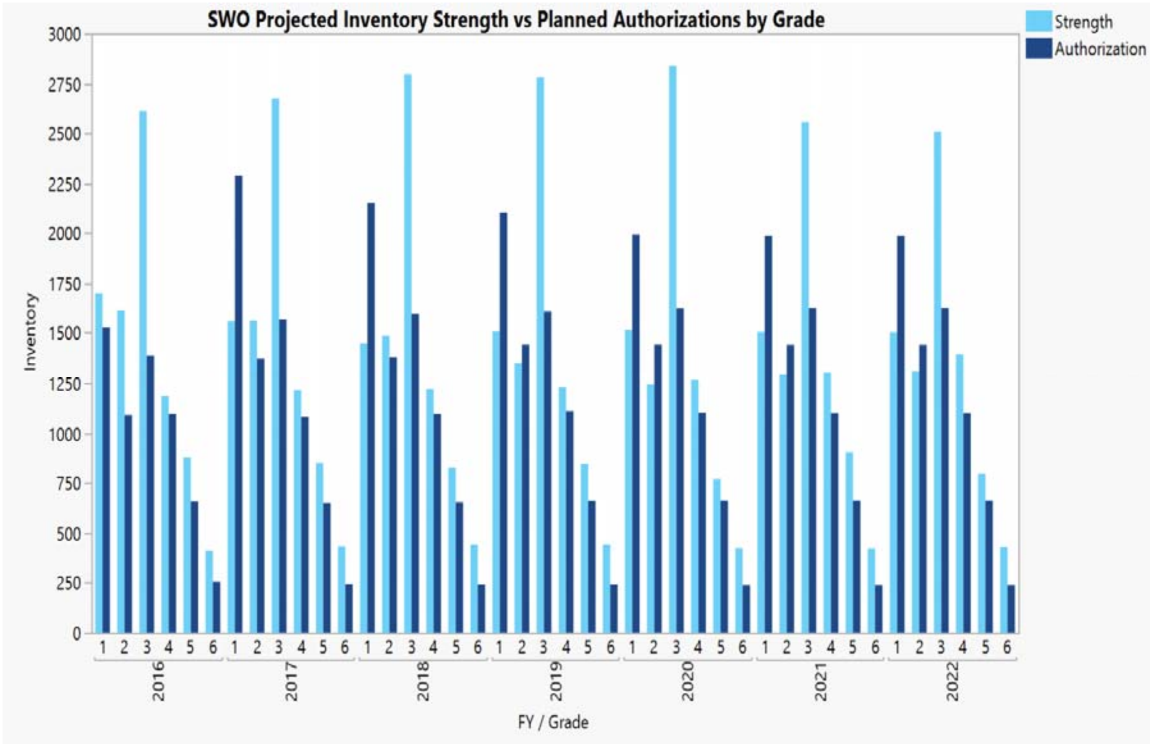


Figure 12. Projected SWO Inventory Strength against Officer Programmed Authorization by Grade and FY (Base Case)

C. INITIAL ANALYSIS OF EXPERIMENTAL DESIGN DATA

This section describes and assesses the experimental design data, with EPOCR policies, generated by the constructs of data farming and design of experiments described in the previous chapter. Whereas the experimental data is used, in the context of this research, to assess the implications of manpower policy plans and EPOCR policies on future Surface Warfare inventory strength, the initial analysis assists in finding insightful information and extracting elementary conclusions from the experimental data itself. We describe the collections and processing of the experimental design data and analyze the effects of the key input factors on operating inventory strength. Regression tree analysis is used to determine the significant contributors to FY2022 total operating inventory strength, for all replications in the experimental design.

1. Data Processing and Collection

Experimental data is consolidated and saved as Comma-Separated Values (CSV) file. The output file contains results for all the 15,840 design points, with each row in the CSV file corresponding to a design point. The data is structured as a multi-year summary report containing all designators and from which counts of beginning of year (BOY) inventory, end of year (EOY) inventory, losses, promotions, transfers, and accessions by designator and pay grade are generated. The file also includes a column for the random seed used for each design point, and columns representing each of the six factors in the experimental design. A format of the raw dataset produced from the experimental design is shown in Table 5. Since the raw dataset is all-inclusive, containing strength and loss counts for all 78 officer designators, and paygrades, including flag officers represented as grade O7, we use JMP to subset the raw data to retain only SWO and SWO trainee inventory counts for grades O1-O6, and further filter the count status to inventory strength rather than loss counts. The resulting dataset is treated as a parent dataset from which subsequent datasets are constructed for further analysis. The format of the resulting parent dataset showing the first 10 observations is shown in Table 6.

Table 5. Raw Data Format of Experimental Design Results

	DP	LOSS_RATE	TRANS_PLAN	ACC_PLAN	EPOCR (YCS_4)	EPOCR (YCS_5)	EPOCR (YCS_6)	seed	FY	Grade	Skill	Status	EOY_Totals
1	1	FY10	FY09_11	FY14	120	11	53	25841483	2016	1	111x - Surface Warfare	1 Loss - Natural	2
2	1	FY10	FY09_11	FY14	120	11	53	25841483	2016	1	111x - Surface Warfare	4 Loss - Force-Out	1
3	1	FY10	FY09_11	FY14	120	11	53	25841483	2016	1	111x - Surface Warfare	5 Loss - User Ad...	2
4	1	FY10	FY09_11	FY14	120	11	53	25841483	2016	1	111x - Surface Warfare	8 No Change	167
5	1	FY10	FY09_11	FY14	120	11	53	25841483	2016	1	112x - Submarine Warfare	8 No Change	35
6	1	FY10	FY09_11	FY14	120	11	53	25841483	2016	1	113x - Special Warfare	8 No Change	57
7	1	FY10	FY09_11	FY14	120	11	53	25841483	2016	1	114x - Special Operations	8 No Change	7
8	1	FY10	FY09_11	FY14	120	11	53	25841483	2016	1	116x - Surface Warfare Trainee	1 Loss - Natural	33
9	1	FY10	FY09_11	FY14	120	11	53	25841483	2016	1	116x - Surface Warfare Trainee	7 Accession	795
10	1	FY10	FY09_11	FY14	120	11	53	25841483	2016	1	116x - Surface Warfare Trainee	8 No Change	683

Table 6. Data Format of the Filtered "Parent" Dataset Derived from the Experimental Design

	DP	LOSS_RATE	TRANS_PLAN	ACC_PLAN	EPOCR (YCS_4)	EPOCR (YCS_5)	EPOCR (YCS_6)	seed	FY	Grade	N Rows	EOY_Totals
1	1	FY10	FY09_11	FY14	120	11	53	5732676	2016	1	3	1653
2	1	FY10	FY09_11	FY14	120	11	53	5732676	2016	2	4	1539
3	1	FY10	FY09_11	FY14	120	11	53	5732676	2016	3	4	2560
4	1	FY10	FY09_11	FY14	120	11	53	5732676	2016	4	2	1178
5	1	FY10	FY09_11	FY14	120	11	53	5732676	2016	5	2	897
6	1	FY10	FY09_11	FY14	120	11	53	5732676	2016	6	2	413
7	1	FY10	FY09_11	FY14	120	11	53	5732676	2017	1	3	1558
8	1	FY10	FY09_11	FY14	120	11	53	5732676	2017	2	4	1492
9	1	FY10	FY09_11	FY14	120	11	53	5732676	2017	3	4	2480
10	1	FY10	FY09_11	FY14	120	11	53	5732676	2017	4	2	1214

2. Initial Assessment of Experimental Results

Since data farming generates a large amount of data, it is worth first exploring the output data graphically to get an initial understanding of OSAM's modeling behavior. This section assesses OSAM's results by visualizing the total inventory composition and measuring the effects of the explanatory input factors on projected inventory strength for all replications of the experimental design.

We start by visualizing the total projected operating inventory strength profile across graders for the projected period. Box plots of projected SWO inventory strength for grades O1–O6 by FY across all design points are shown in Figure 13. The boxplots reveal how variation in inventory strength changes over the projected FY. A smoother is added to emphasize the mean trend in inventory strength by FY. For grades O1 and O2, variation increases in the first few FYs before declining and leveling off beyond 2019 and 2021, respectively. Grades O4, O5, and O6 appear to have a gradual increase in variation over the projected years. Grade O3 depicts the most variation, which also increases with FY. The large variation in this grade is partly due to the range of input values corresponding to the EPOCR policy. Grades O1, O2, and O5 appear to have a slightly negative trend while grade O3 has a more negative trend across all projected FYs.

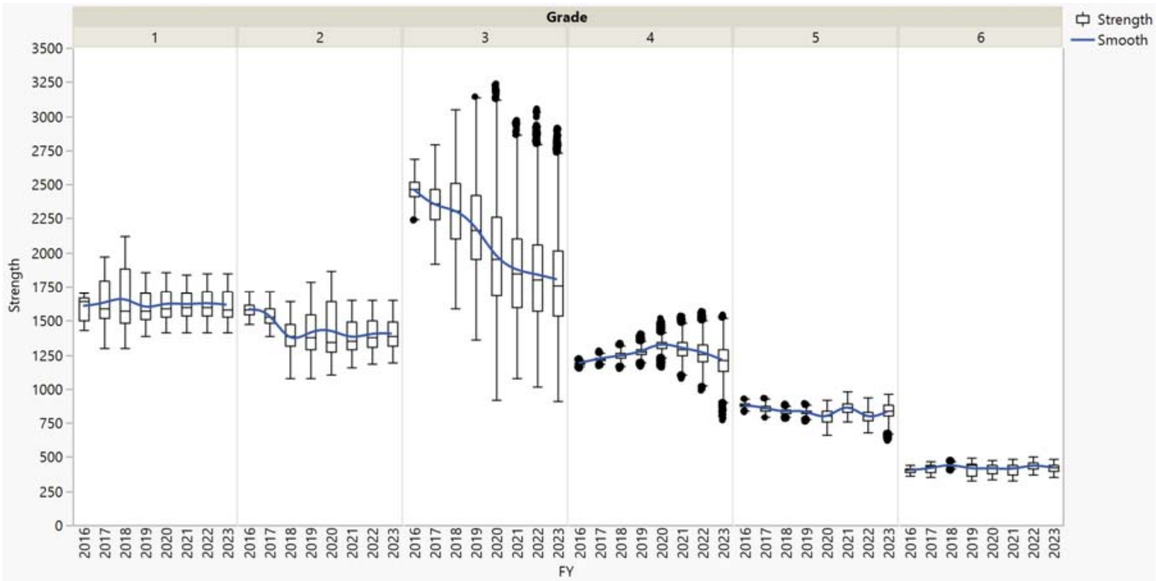


Figure 13. Box Plots of SWO Projected Inventory Strength by Grade and FY for Experimental Design

Additionally, of particular importance to N100 strength planners, is how OSAM's different loss rate categories affect long-term inventory strength projections. Box plots again provide a manner in which to compare and contrast the variability in inventory strength results due to each loss rate category. Box plots in Figure 14 depict the variability in mean total inventory strength for FY2023 across all design points. The FY2010 loss rate appears to produce the lowest mean in total FY2023 projected inventory strength while FY2006 produces the highest mean. The variation in FY2023 projected total inventory strength is lowest with the FY2007 loss rate and highest with FY2015 loss rates. Appendix A contains inventory strength distribution plots and summary statistics corresponding to these plots.

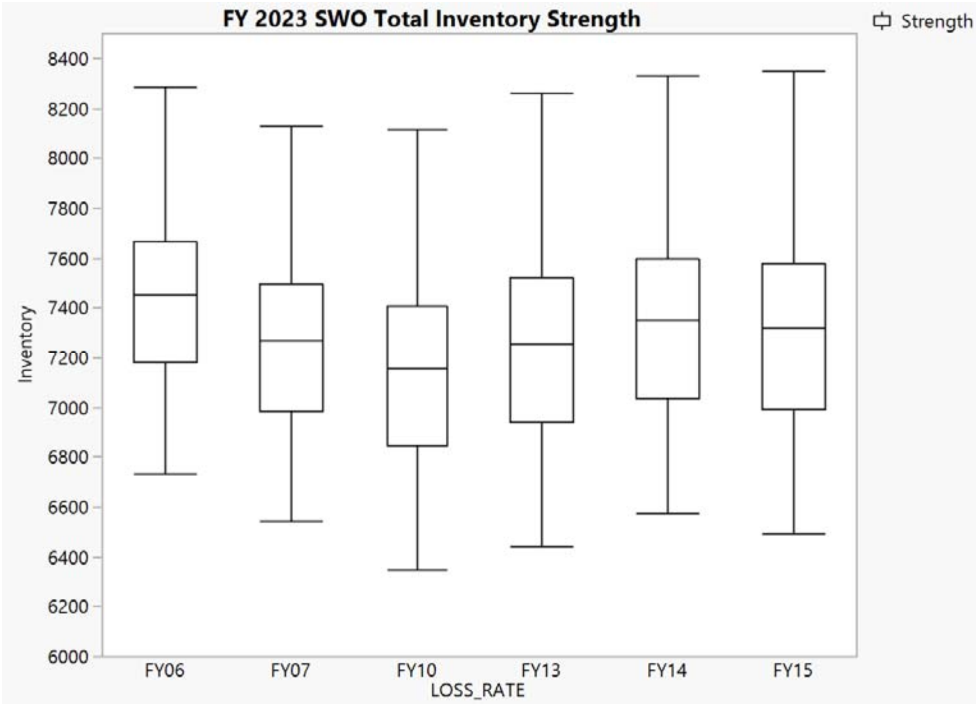


Figure 14. Box Plot of SWO Total Mean Inventory Strength for FY 2023 by Loss Rates for Experimental Design

We further need to determine whether the differences in the mean total inventory strength results due to the different loss rate categories are caused by the effects of the loss categories rather than random effects in the modeling process. We cannot deduce such information from the box plots and a more robust statistical test is needed. The hypothesis tested is:

- H_0 : There is no difference in the mean of total inventory strength results in FY2023 due to OSAM's loss rate categories, that is, μ_1=μ_2=…… μ_6, where the six populations refer to the six different OSAM loss rate categories or levels chosen for the study.
- H_A: There is a difference in the means, that is, at least two means are different.

We use One-way Analysis of Variance (ANOVA) to test the hypothesis stated above. ANOVA tests differences in means between groups by partitioning the overall variance in the response into that due to each of the measured groups and the errors (Faraway, 2005). First, we test the assumptions of ANOVA to our data specifically that the mean inventory strength results across the loss rates categories are normally distributed and that the variance in the results is equal across the loss rate categories. We see in Figure 14 that these conditions are generally met, that is: (1) all the box plots depict a similar spread, suggesting equal variance among the loss rate category results; and (2) all the box plots appear symmetrical with centered interquartile ranges, suggesting normally distributed inventory strength results. An excerpt from the results of the ANOVA test is depicted in Figure 15. The y-axis is the mean total inventory strength results across all design points. The vertical span of the diamond shapes represents a 95% confidence interval around the mean of each loss rate category. The mean is represented by the center vertical line in each diamond. The size of the intersection of the circles measures the statistical difference in the mean total inventory strength results among each paired loss rate category, where the larger the intersection, the smaller the difference in means. Visual inspection of the ANOVA test reveals significant differences among the means. Statistical results shown in Figure 16 reveal a significant F-statistic, *p-value* < 0.001, which supports the visual conclusion that there are significant differences in the inventory strength results produced by the loss rates.

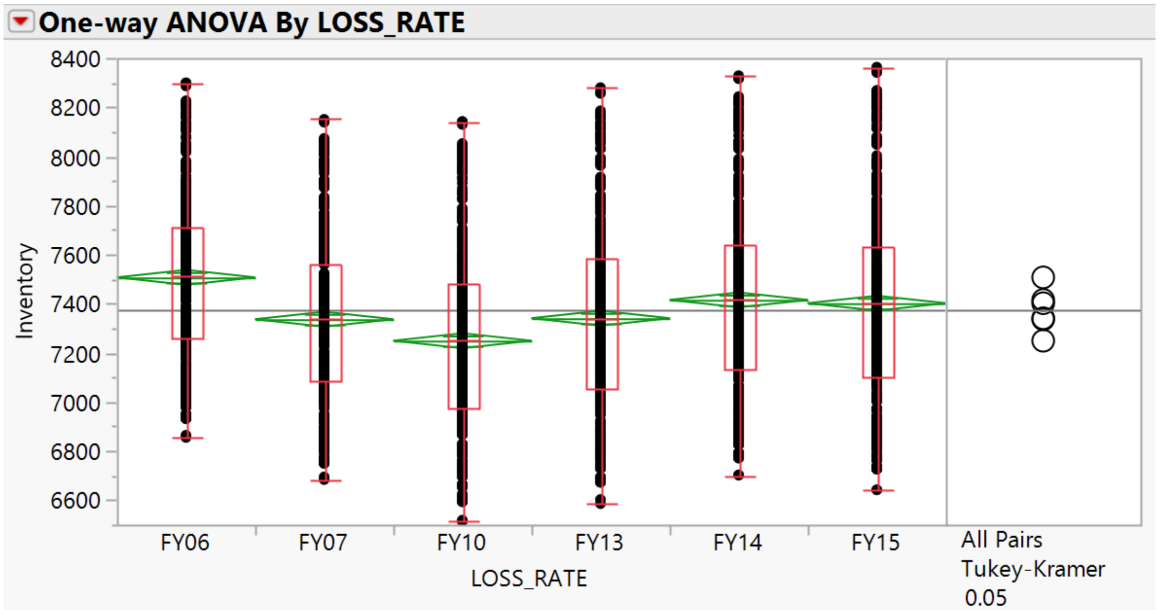


Figure 15. One-way Analysis of Mean Variance of FY2023 Total Inventory Strength by Loss Rate

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
LOSS_RATE	5	25488285	5097657	34.2947	<.0001*
Error	3162	470007562	148642		
C. Total	3167	495495847			

Figure 16. ANOVA Statistical Test for Loss Rates

Similar ANOVA hypotheses are tested for transfer plans and accession plans to determine the variables' respective effects on projected inventory strength. One interesting observation from Figure 17 is that having no transfers produces a significantly higher projected inventory strength value than when using a transfer plan. One-way ANOVA results by accession plans are shown in Figure 18. Projected inventory strength values for FY 2015 and 2014 accession plans are statistically indistinguishable and have the lowest mean. FY2012 accession plan has the lowest projected inventory strength value, which is also statistically different from the values from the rest of the accession plans.

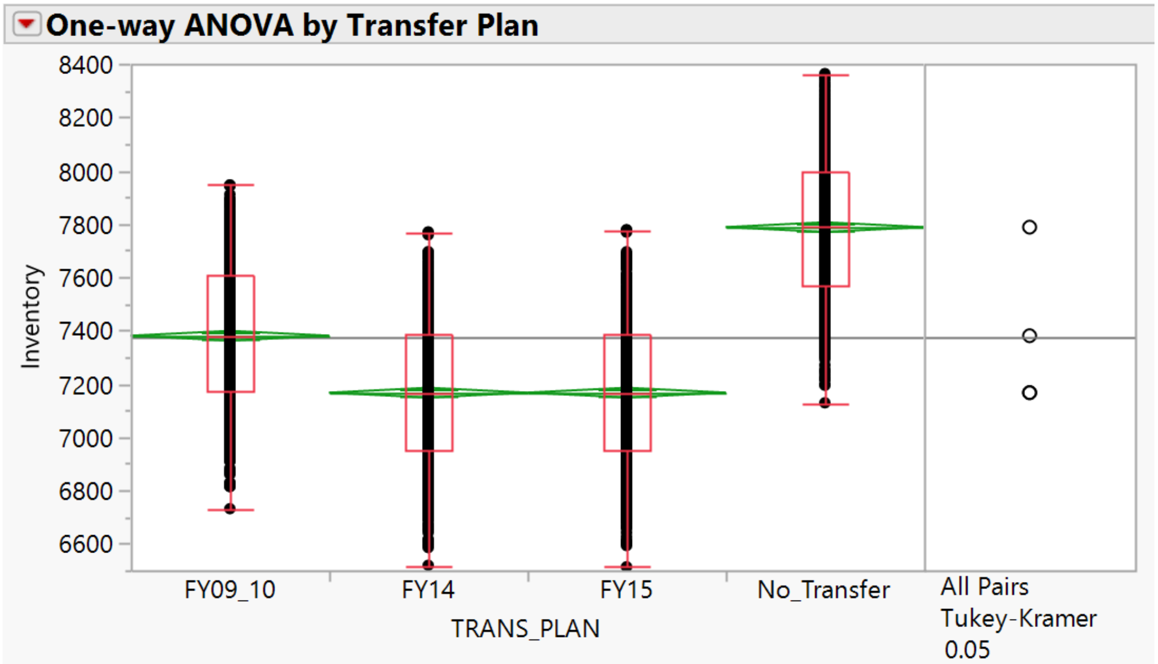


Figure 17. One-Way Analysis of Mean-Variance of FY2023 Total Inventory Strength by Transfer Plan

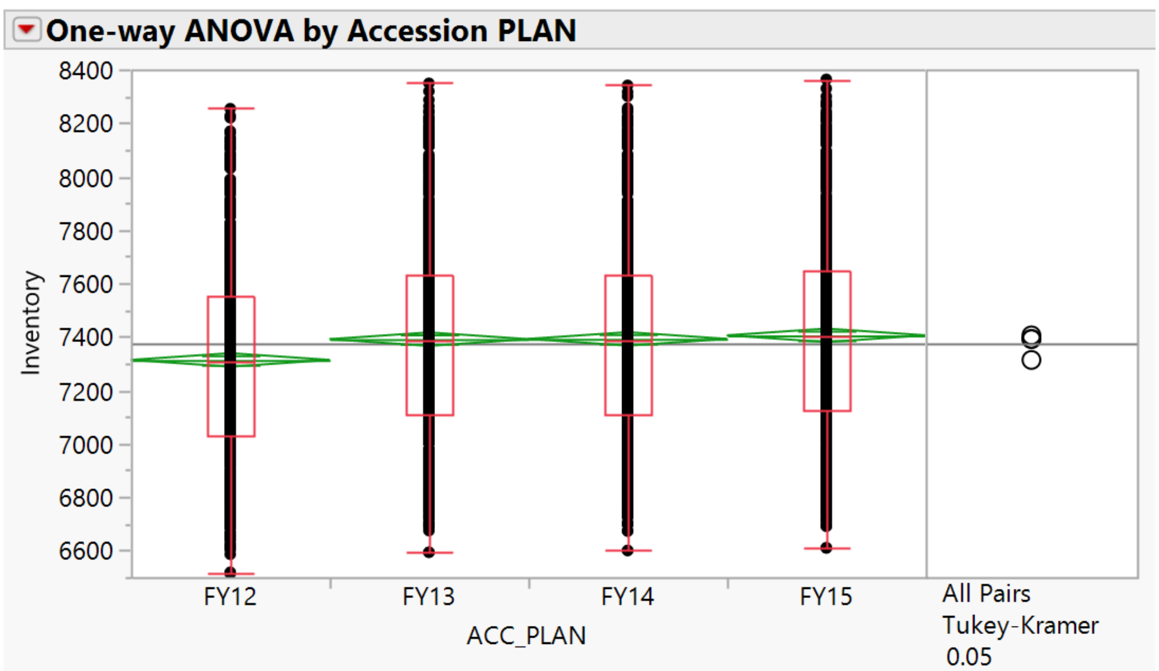


Figure 18. One-Way Analysis of Mean-Variance of FY2023 Total Inventory Strength by Accession Plan

3. EPOCR Policy

We continue our initial analysis by determining the effects of implementing an EPOCR policy to operating inventory strength projections. For this, we summarize the mean inventory strength results across the design space by grade and FY and compare the results to Officer Programmed Authorizations (OPA). A composition of SWO inventory strength by grade and FY with Projected inventory strength compared against OPA is shown in Figure 19. We observe over-execution persisting in grade O3 in FY2016-2019, and gradually decreasing to healthy levels by FY 2022. FY2022 inventory strength summary statistics for each pay grade is shown in Table 7.

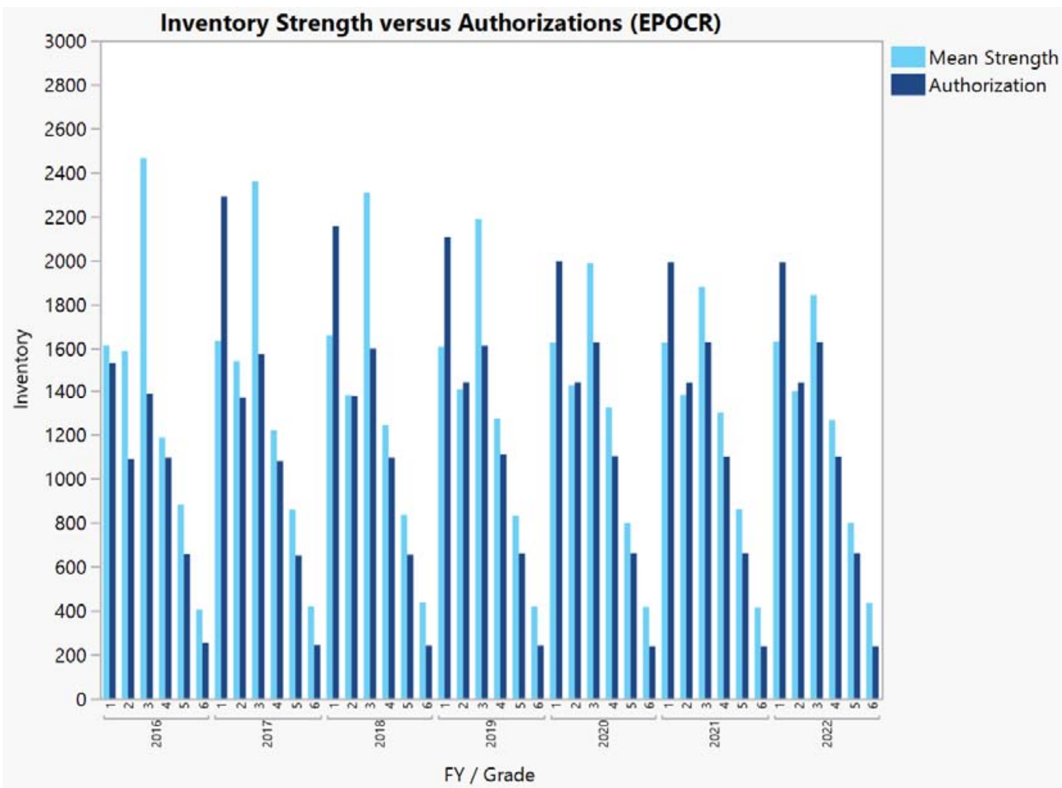


Figure 19. Projected SWO Inventory Strength with EPOCR Policy Against Officer Programmed Authorization by Grade and FY

Table 7. Summary Statistics of Mean SWO FY 2022 Projected Inventory Inventory Strength Composition Using EPOCR Policy

Grade	Strength	Std. Dev.	Min	Max	25th Quantiles	75th Quantiles	OPA	Deviation
1	1628	110.06	1427	1834	1540	1719	1988	-360
2	1402	107.64	1202	1648	1310	1500	1441	-39
3	1840	358.24	1028	3036	1574	2061	1624	216
4	1269	93.72	1031	1551	1205	1322	1101	168
5	802	44.23	709	900	759	832	661	141
6	435	24.81	386	484	408	457	238	197
Total	**7375**	**738.70**					**7053**	**322**

Figures 20 and 21 show projected inventory strength profiles for the lowest (FY2012) and highest (FY2015) accession plan, respectively. An interesting thing to note is that there is minimal difference between the low and high accession plan inventory projection profiles for grades O2 and O3, confirming our conclusions from the one-way ANOVA results for the accession plans.

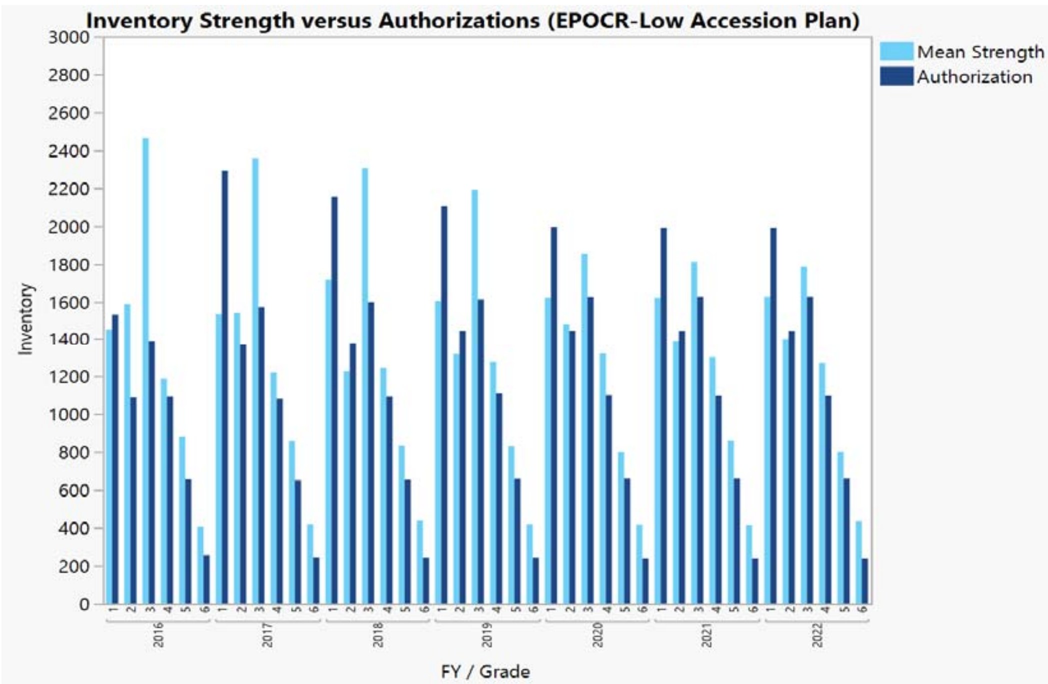


Figure 20. Projected SWO Inventory Strength with EPOCR Using a Low Accession Plan

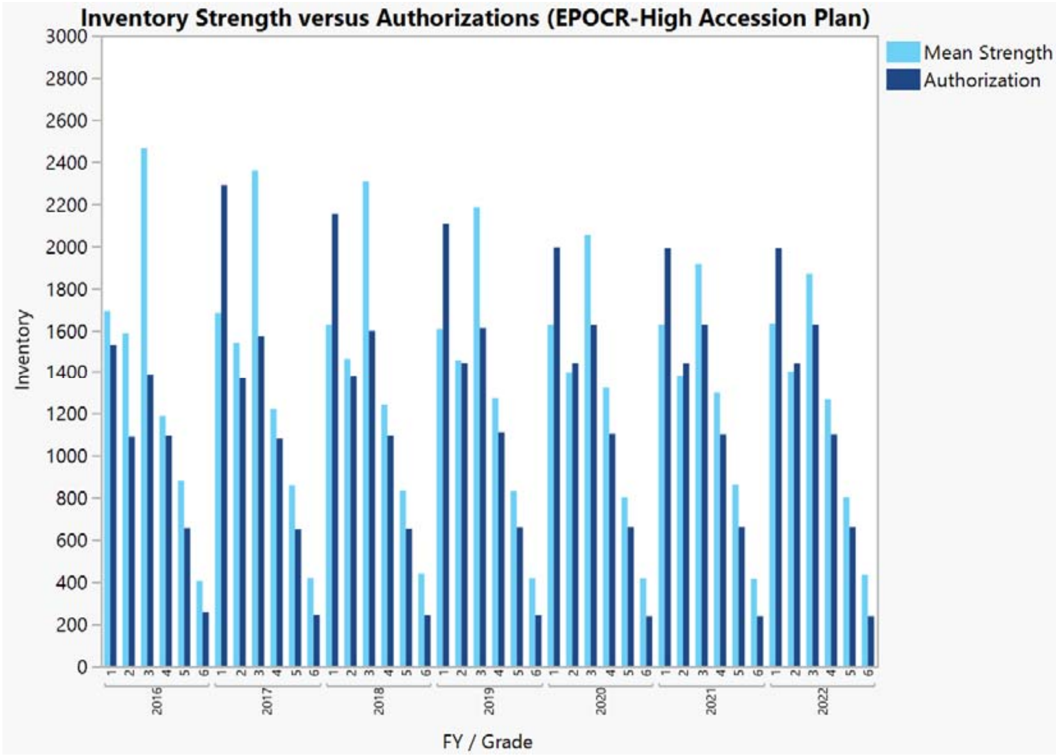


Figure 21. Projected SWO Inventory Strength with EPOCR Using a High Accession Plan

4. Regression Tree Analysis

Regression trees offer a result structure that is more intuitive and are less computationally tasking than linear or polynomial regression. Additionally, they are powerful at identifying influential factors affecting an outcome variable, as well as finding interactions among variables (Faraway, 2005). The general regression tree methodology also allows analysis for a combination of discrete and categorical predictor variables as used in this study.

We use regression tree analysis to determine the most influential factors of total SWO inventory strength for grades O1 to O6 in FY2022. The results of the regression tree model for total inventory strength are shown in Figure 22. The first node, the parent leaf, or root leaf, shows the mean and standard deviation of the total inventory strength in the entire dataset, 7,375 and 365, respectively, and the total count of all observations, 3,168. The data is recursively partitioned into regions corresponding to the distinct paths from the parent leaf to the leaves with no further splits, the terminal leaves. The intermediate cells between the parent and terminal leaves are child leaves. A predictive model is fitted for each leaf and a corresponding estimate of the mean total inventory strength is determined for that leaf. The title cell shows the number of splits and the *R-square* value, which describes how well the tree explains the variance in mean total projected inventory strength results. The most influential factors in determining the projected mean total inventory strength in order of importance in the tree are transfer plans, EPOCR policy with 4 YCS, and EPOCR with 5 YCS. The *R-Square* value of 0.733 suggests that the tree model explains about 73% of the variation in total end strength results. An expected observation, as revealed in the first split of the tree, is that having no transfer plan significantly increases the total mean inventory strength. Each distinct path from the terminal to the parent leaf also represents a sequence of interacting terms. Using a transfer plan with an EPOCR policy that refers 64 or more officers with four YCS, and 53 or more officers with 5 YCS will results in the least mean total inventory strength. On the contrary, having no transfers and referring fewer than 64 officers with four YCS results in the largest projected inventory strength value.

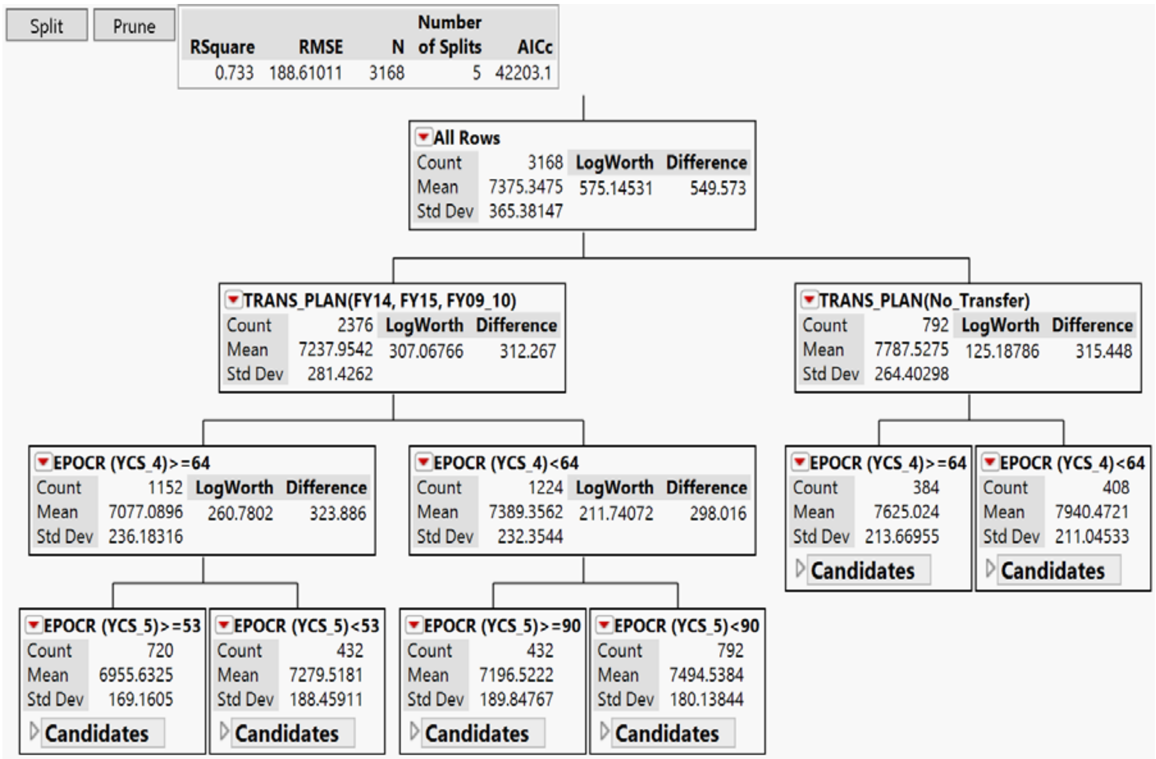


Figure 22. Regression Tree for SWO Total Inventory Strength in FY2022.

D. ANALYSIS OF OPERATING STRENGTH DEVIATION

Of importance to this research, and of interest to N100, is determining the best manpower policies that will minimize the deviation of projected SWO inventory strength from planned authorizations at a given future period. We will specifically focus on the total FY2022 projected inventory strength for grades O3 to O6. We have already determined that there is significant variation in mean total inventory strength across the different manpower policies used in this study. Furthermore, we have identified the most influential factors that affect projected total inventory strength. This section uses tree analysis to find the most influential factors that determine FY2022 total OSD for grades O3 to O6. Concepts of robust design and meta-modeling are used to determine manpower policy settings that minimize projected total OSD in these grades.

1. Regression Tree Total Operating Strength Deviation

We use regression tree analysis to identify influential factors determining total operating strength deviation (OSD) over the loss rates for grades O3 to grade O6. To set up our dataset for this analysis, we subset the parent dataset to grades O3 to O6 and FY2022 and introduce a column in the resulting dataset containing the OSD at each design point. We then sum OSD over the grades by all the input factors and random seeds. The resulting format of the data with a column for the sum of OSD represented as sum (Deviation) is shown in Table 8. We use JMP to build a regression tree model on the mean total OSD. The resulting regression tree is shown in Figure 23. The variables in the regression tree model at six splits explain about 63% of the variation in OSD. Transfer plan, EPOCR 5 YCS, and, EPOCR 4 YCS are most significant in determining the amount of OSD.

Table 8. Data Format with Inventory Strength Deviation Column

	LOSS_RATE	TRANS_PLAN	ACC_PLAN	EPOCR (YCS_4)	EPOCR (YCS_5)	EPOCR (YCS_6)	seed	N Rows	Sum (Deviation)
1	FY06	FY09_10	FY12	0	109	68	14143576	4	482
2	FY06	FY09_10	FY12	0	109	68	35989036	4	531
3	FY06	FY09_10	FY12	0	109	68	46807864	4	528
4	FY06	FY09_10	FY12	0	109	68	56621581	4	518
5	FY06	FY09_10	FY12	0	109	68	80735315	4	518
6	FY06	FY09_10	FY12	4	8	83	255496	4	864
7	FY06	FY09_10	FY12	4	8	83	29743319	4	850
8	FY06	FY09_10	FY12	4	8	83	31222864	4	821
9	FY06	FY09_10	FY12	4	8	83	68509862	4	840
10	FY06	FY09_10	FY12	4	8	83	73352979	4	838

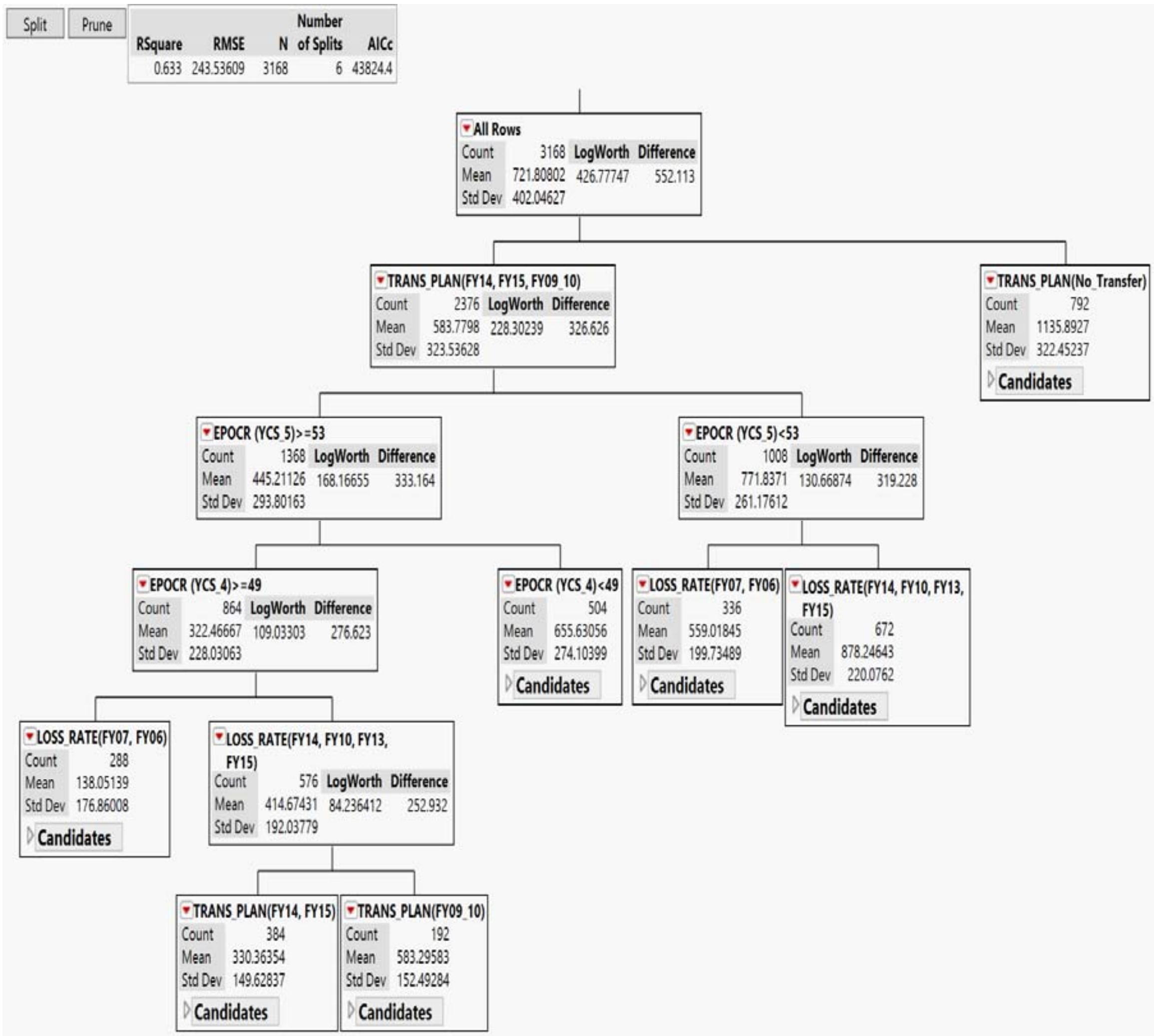


Figure 23. Regression Tree of Mean total Operating Strength Deviation for grades O3 to O6

2. Robust Design and Construct

Robust design is a powerful system optimization technique that takes the approach of finding ways to determine, with consistency, accurate and precise response values by controlling for uncertainty in the system. Both the mean and variation of the response are considered, where a system is optimized by choosing the closest mean to a target value with the smallest variance (Sanchez, 2000). The idea is to select alternatives that best approximate the desired threshold value for their mean, as well as produce a reasonably small variance around that threshold. Variability in robust analysis, then, represents a risk or cost in the system modeled.

The approach in robust analysis is to separate the explanatory factors of a response variable into controllable and uncontrollable factors and then use a loss function to find the best configuration of the explanatory factors that produces the best results with minimal variability across uncontrollable factors. The response variable of interest is the operating strength deviation and the controllable variables are represented by the manpower plans: accession plan, the transfer plan, and the three EPOCR variables. Loss rate categories represent uncontrollable factors corresponding to the uncertainty in the real world. Loss or risk is a function of the variance and mean of the operating strength deviation, and is given by the formula

$$E(Loss) = variance(deviation) + (mean(deviation))^2 \tag{4.1}$$

where *E(Loss)* is the long run cost or risk of operating strength deviation, and where zero is the best possible value of the deviation. The loss function penalizes for both a higher variance and for the mean straying away from its best possible value. In other words, if both values are low, the manpower configuration is robust and should perform consistently well in minimizing operating strength deviation. The second term is squared to level the units for both terms to units-squared.

To set up our data for robust analysis, we further process Table 8 data by averaging the mean and variance of the summed deviation over the loss rates. The resulting dataset is depicted in Table 9. We then proceed to build a meta-model on operating strength deviation.

Table 9. Data Format of Robust Design Dataset with Loss Column.

	TRANS_PLAN	ACC_PLAN	EPOCR (YCS_4)	EPOCR (YCS_5)	EPOCR (YCS_6)	N Rows	Mean (Sum(Deviation))	Variance (Sum(Deviation))
1	FY09_10	FY12	0	109	68	30	655.567	30437.426
2	FY09_10	FY12	4	8	83	30	1011.200	36346.579
3	FY09_10	FY12	8	116	64	30	615.967	30008.171
4	FY09_10	FY12	11	0	105	30	925.000	34487.655
5	FY09_10	FY12	15	68	11	30	1032.733	34342.961
6	FY09_10	FY12	19	49	75	30	816.300	32853.734
7	FY09_10	FY12	23	45	49	30	934.000	34426.897
8	FY09_10	FY12	26	34	41	30	1006.100	34183.197
9	FY09_10	FY12	30	41	86	30	760.067	32377.789
10	FY09_10	FY12	34	94	30	30	766.333	31219.126

3. Meta-Models for Mean and Variance of Operating Strength Deviation

We extend our analysis to build a meta-model that determines robust parameters for correcting FY2022 total operating strength deviation for grades O3-O6. Meta-models act as proxies to the entire simulation model by offering a more computationally efficient way of computing response estimates from the simulation model (Law, 2000). We use meta-modeling to understand the relationship between the controllable input factors' settings for the accession plans, transfer plan, and the three EPOCR variables with the response variables represented by the mean and variance of OSD. The meta-model quantifies the effects of each of the controllable variables on both the mean and variance of operating strength deviation.

Using JMP, we simultaneously fit meta-models on the mean and variance of operating strength deviation using stepwise regression and with minimum Bayesian information criterion (BIC) selected as the stopping condition for fitting the best model. We screen out less significant factors from the resulting models and use the remaining factors to fit a model using all two-way interactions and second-degree polynomials terms. We further filter out insignificant factors from the resulting models, leaving only statistically significant factors and interactions. We use data splitting to avoid over-fitting and to ensure that the models have significant prediction power. For this, the dataset used to build the model, Table 9, is randomly partitioned into a training set that is 75% of the data, and is used to build the models. The rest of the data is set aside as a test set and is used to validate the predictive power of the model.

A screen shot of summary statistics and diagnostic plots for the resulting meta-model built with the training set is depicted in Figure 24. The summary statistics indicate good predictive capability. All five input factors are statistically significant with t-statistic *p-values* < 0.01. Additionally, the model has a relatively high *R-Square* value of 0.999. The residuals are also sufficiently normal and exhibit constant variance, as evidenced by the Normal Quantile and Residual by Predicted plots, suggesting that the model has a good fit on the data. A bivariate fit of predicted values from the training and test set is shown in Figure 25. The linear diagonal fit indicates that the model has good predictive performance.

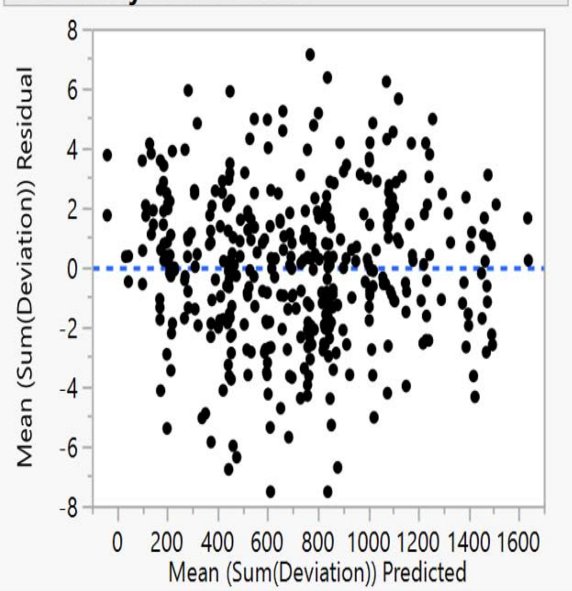
Summary of Fit

RSquare	0.999951
RSquare Adj	0.99995
Root Mean Square Error	2.577441
Mean of Response	724.2183
Observations (or Sum Wgts)	394

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
TRANS_PLAN	3	3	25392517	1274111	<.0001*
ACC_PLAN	3	3	438562	22005.57	<.0001*
SWO_YCS_4	1	1	6636151	998938.8	<.0001*
SWO_YCS_5	1	1	9553868	1438142	<.0001*
SWO_YCS_6	1	1	9559031	1438919	<.0001*

Residual by Predicted Plot



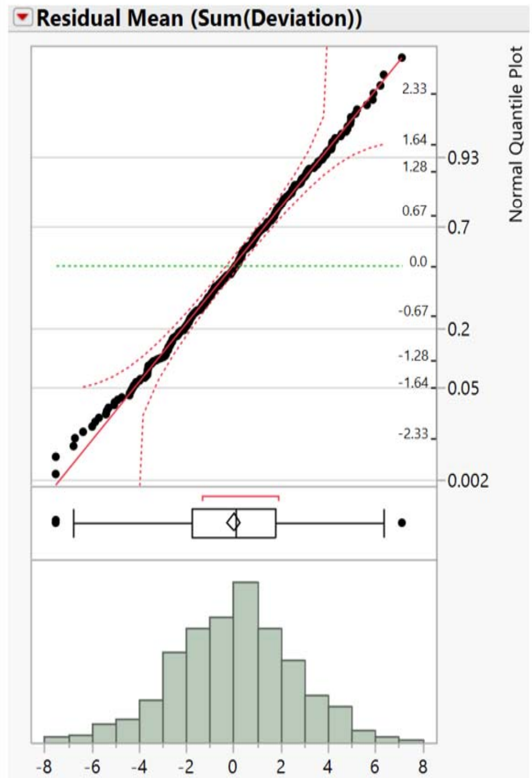


Figure 24. Diagnostic Plots for Mean Total End Strength Deviation Meta-Model Strength

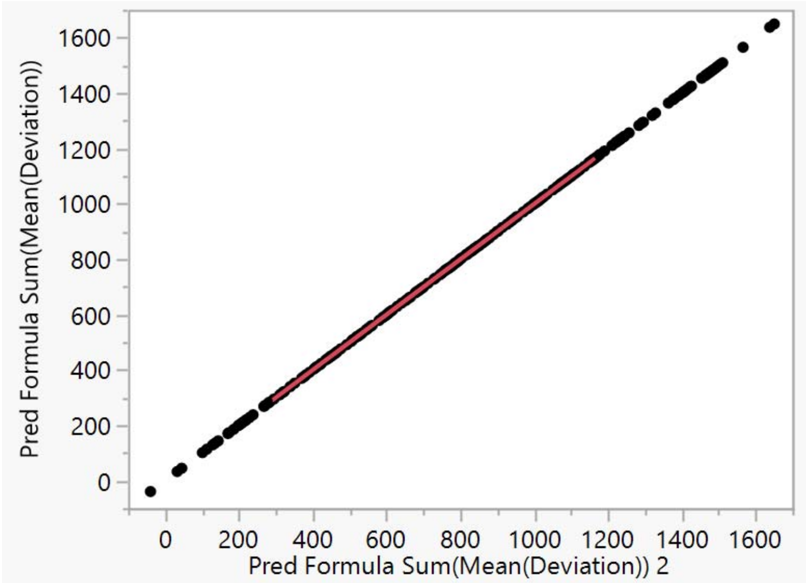


Figure 25. Actual versus Predicted Plot for Test Set Using Mean Total Inventory Strength Meta-model

4. Prediction Profiler

JMP's prediction profiler offers an interactive way of exploring a model's response surface by varying the input factors. The profiler displays the predicted mean and variance of operating strength deviation as one input variable is changed while holding the others constant. We can use the prediction profiler to find the robust settings that minimize both the mean and variance of the OSD variable. A prediction profiler with function curves for the mean and variance of deviation is shown in Figure 26. The transfer plan and accession plan are set to FY2015 and EPOCR parameters are set to zero. This corresponds to the status quo where no EPOCR policy is implemented. Shifting the input parameters on the x-axis along the deviation curves results in a marginal change in deviation proportional to the slope of the curve. Thus, a curve with a slope of zero will have no effect on the response. The response at these values indicates a mean OSD of 1261 with a standard deviation of 189, suggesting that total projected operating inventory strength in grade O3 to O6 will over-execute OPA by an estimated 1261 officers in FY2022 where an EPOCR plan is not implemented.

This again assumes that that Navy implements the respective manpower policies each year over the projected period. Shifting the transfer plan to no transfers increases the mean OSD, as does shifting the EPOCR value setting to the right.

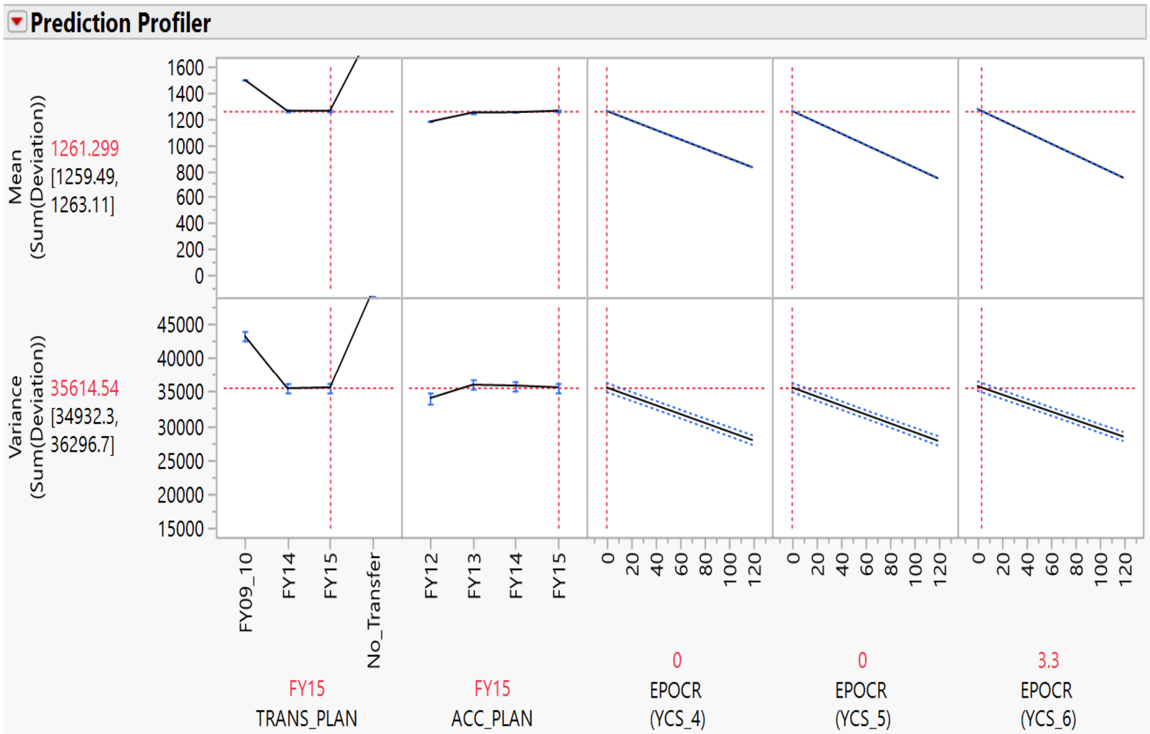


Figure 26. Prediction Profiler of Mean-Deviation Meta-Model

Figure 27 depicts a prediction profiler with transfer and accession plans set at their respective values from the robust analysis. The EPOCR parameters are arbitrarily set to a combination such that OSD is reduced to a modest level of 300 with a standard deviation of 141. This suggests that the total inventory for grades O3 to O6 will over-execute OPA by a mean estimate of 300 officers in FY2022 assuming this policy prevails over the projected period.

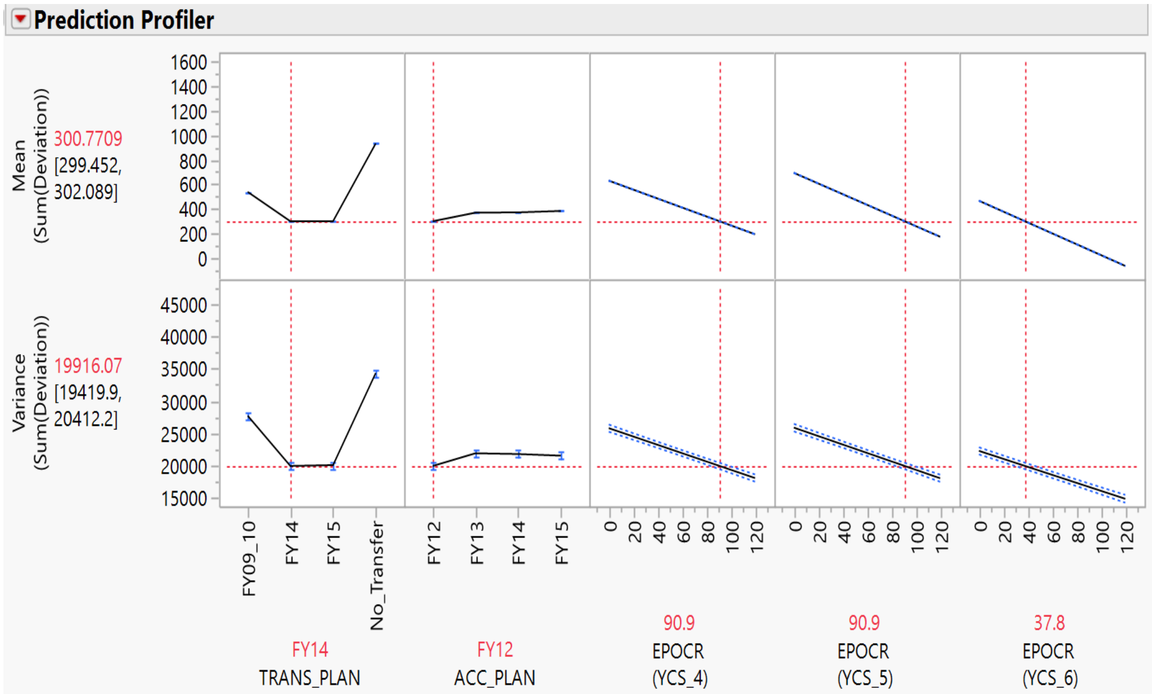


Figure 27. Prediction Profiler of Mean-Deviation Meta-Model With Robust Settings for Transfer and Accession Plans.

Figure 28 depicts a prediction profiler with robust settings for transfer and accession plans with EPOCR parameters arbitrarily set to a combination that reduces OSD to a mean estimated value of just two officers in FY2022. The standard deviation for this setting is 123 officers, suggesting an enhanced risk of under-executing SWO inventory.

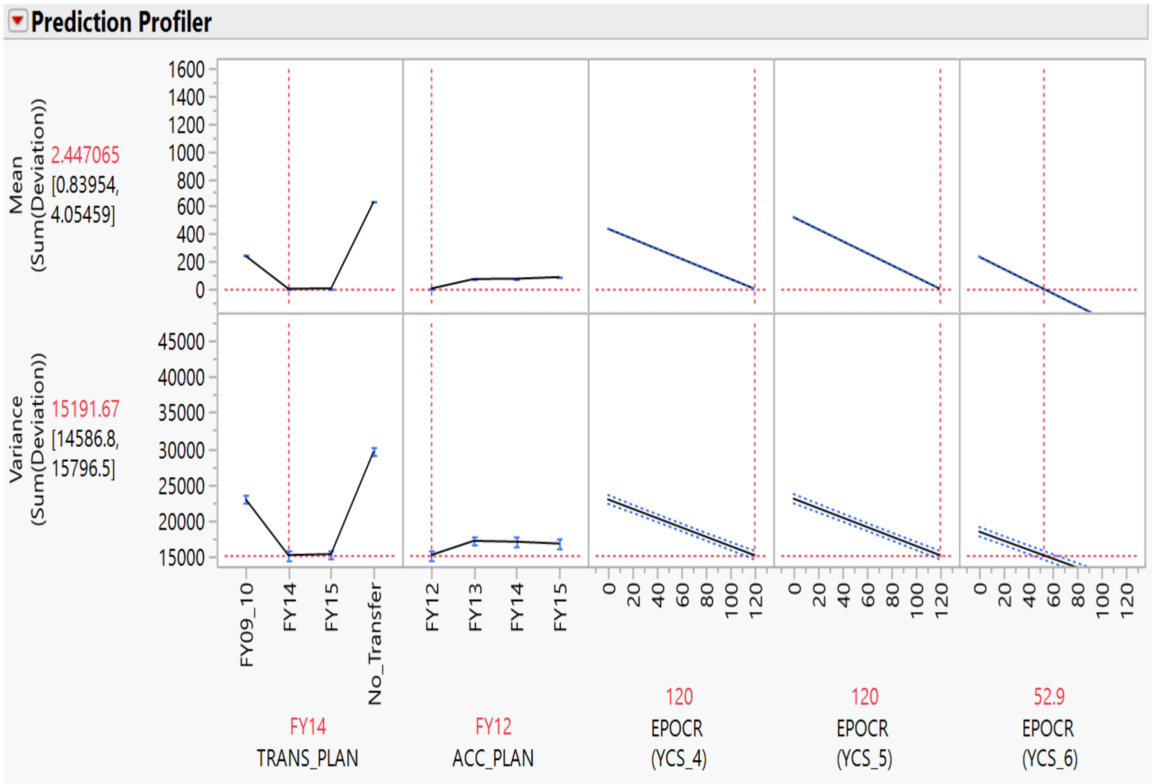


Figure 28. Prediction Profiler with Robust Settings Converging Operating Strength Deviation to two Officers

V. CONCLUSION AND RECOMMENDATIONS

This thesis extends the works of Sibley (2012), Borozny (2015), and DeHollan (2015) to enhance OSAM's utility as an inventory projection model using data farming and design of experiments. The insights gained from this study go beyond the scope of the specific questions guiding this research. To illustrate OSAM's utility, this thesis, first, analyzes the effects of current manpower policy on the future composition of URL inventory. Second, this thesis analyzes the effects of historical accession plans and the proposed EPOCR policy on surface warfare officer inventory. Finally, the study identifies the risk inherent in the EPOCR policy by measuring projected inventory deviation from planned authorizations and identifies policies that mitigate identified risk. The section that follows answers the specific research questions posed for this study

A. ANSWERS TO RESEARCH QUESTIONS

1. What Is the Expected Short- and Long-Term Trend in URL Operating Inventory Assuming Current Policy and Prevailing Assumptions?

OSAM models inventory projections dynamically over annual time-steps, and as such, provides the ability to track URL inventory over the entire projected period. The base-case projects 2016 URL inventory over a seven-year period with a key assumption that the current policy, FY2015 accessions, transfer plans, and loss rates prevail over the projected period. We find that total operating inventory strength falls by an average of 8% over the seven-year period from 24,815 officers at the beginning of 2016, to a mean and standard deviation of 22,890 and 13 officers at the end of 2023. The mean Inventory strength results in the base case have extremely small standard deviation values, suggesting little value in using OSAM as a stochastic model.

2. What Are the Long-Term Risks in Inventory for the SWO Community Associated with Current Policy?

We measure risk as operating strength deviation, the magnitude of expected deviation of operating inventory from planned authorizations (OPA). The base-case results show over 40% over-execution in grade O3 that is expected to persist over the entire projected period. We should remind the reader that the base-case assumes current manpower policy and loss rates prevailing over the projected period. In addition, the current accession plan is not enough to sustain an increase in programmed authorizations for grade O1 planned for FY2017 and beyond. Interestingly, the base case shows healthy inventory strength for grades O4, O5, and O6.

3. What Is the Impact of the Enhanced Probationary Officer Continuation and Re-designation Board on SWO Inventory?

The EPOCR results assume averages over all practical manpower policies as used in this study. Additionally, the results rest on the assumption that the policies prevail over the projected period. We find that implementing the policy significantly reduces grade O3 over-execution by FY2022, and levels the average operating strength in all grades to match OPA. Total operating inventory strength is reduced by 12% over the seven-year period, from 8,365 officers at the beginning of FY2016 to a mean and standard deviation of 7,375 and 739 officers at the end of FY2023. Total SWO over-execution is reduced to a modest 4% over FY2022 OPA from 34% in FY2015. The extremely high standard deviation on FY2022 total SWO inventory suggests a high risk of under-executing. Whereas the EPOCR policy will generally have a correcting impact on operating strength deviation, caution should be taken on how to implement it to avoid under-execution. Robust analysis of the policy can identify how to best implement EPOCR.

Focusing on the total inventory of grades O3 to O6, we use robust analysis and meta-modeling to determine the risks in implementing EPOCR, and find the best manpower policies that will correct operating strength deviation in these grades. Our initial finding suggests that using a transfer plan and implementing an EPOCR policy for surface warfare officers with 4 and 5 YCS had the most significant effect on total OSD. We find that a low accession plan, that of FY2012, and a high transfer plan, that of FY2014, are the most robust non-EPOCR policies to correct OSD. All accession plans used in the study had relatively low impact on OSD, suggesting that an economically efficient plan, a low accession plan, holds the same risk as a high accession plan. Additionally, the FY2014 transfer plan produced the lowest OSD. Prediction profilers on meta-models of OSD provide evidence that EPOCR can effectively correct operating end-strength to OPA.

The study shows that it is possible to meet future SWO manpower requirements with a conservative accession plan coupled with an aggressive transfer plan referring officers to other communities. The Navy should additionally supplement its current force-shaping tools with EPOCR to manage officer over-execution. When used correctly, EPOCR has a potential to minimize over-execution in the SWO community with minimal and measurable risk of under-executing. The number of officers within each YCS group refereed to EPOCR should be selected in such a manner to account for other constraints, assumptions, and interests external to the scope of this research.

B. RECOMMENDATIONS FOR FUTURE STUDIES

This study demonstrates the utility of OSAM as an officer projection model by applying efficient methods of extracting information from the model and providing a quantitative framework to analyze the model's results. There exists potential for research that builds on this study or improves on OSAM's utility.

1. Continuous Input Levels

Future work on OSAM can effectively enrich the factor space in the experimental design by varying beginning of year inventory, loss rates, transfer plans, and accession plans as continuous rather than categorical variables. The current version of OSAM, and as used by this study, represents these input variables as a set of pre-established tables corresponding to historical realizations of these plans, given by FY, designator, and paygrade. Since OSAM retrieves the inputs as numerical sets, loss rates, transfer plans, and accessions are modeled as categorical variables in the experimental design construct, where the factors in the experimental design correspond to the manpower plans, and the factor levels to a numeric constant for each designator and grade. The factor levels do not cover a realistic range of possibilities for the manpower plans. Additionally, we cannot prescribe numeric values for the manpower plans in our results. However, using OSAM's database structure, we can use an adjustment factor to effectively update input values for the plan parameters in the experimental design through SQL statements. For example,

```
UPDATE AccPlan_FY16 SET Accessions=Accessions*1.5 WHERE
'Community'=SWO TRAINEE
```

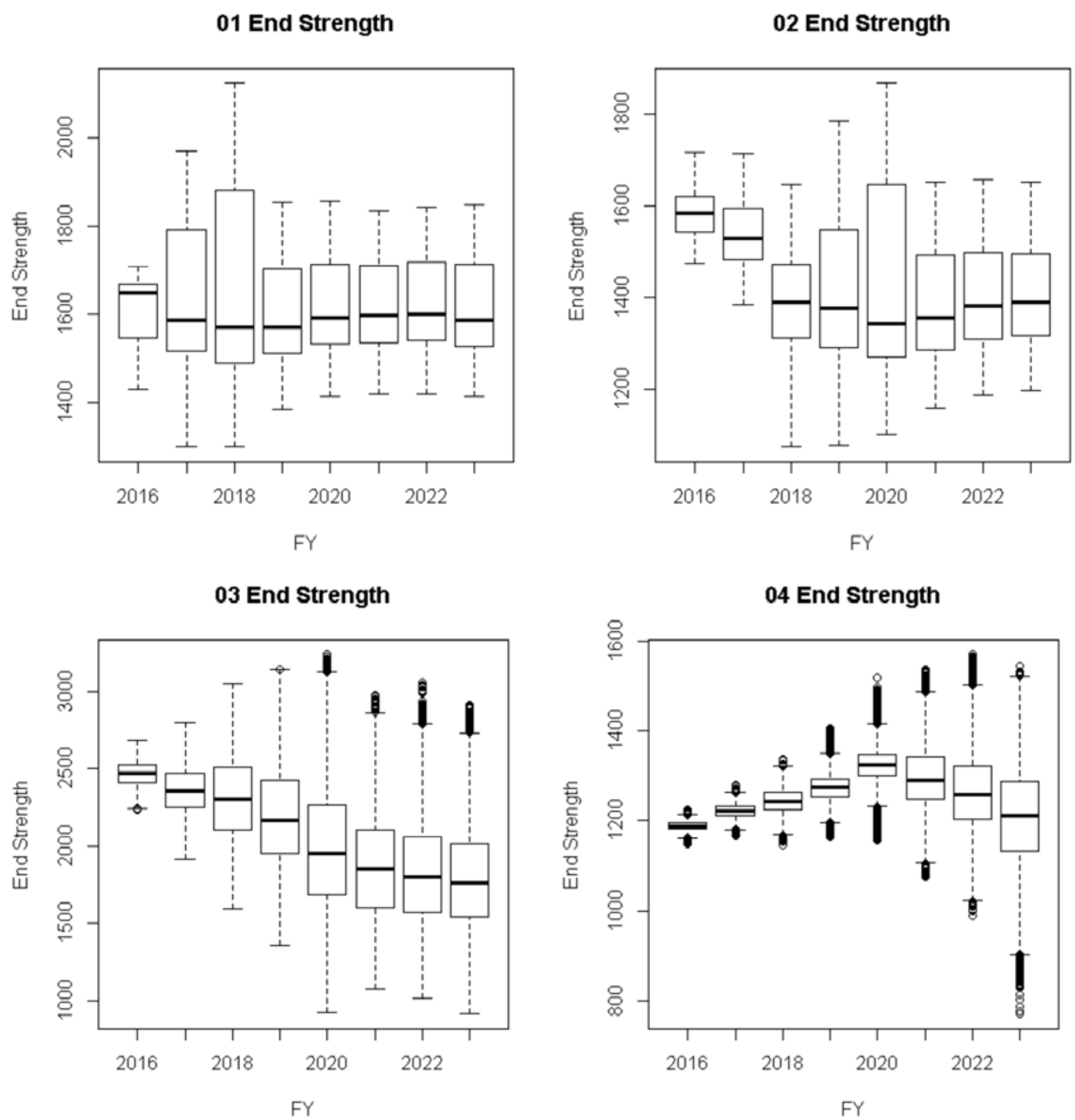
will increase FY2016 SWO accessions by a factor of 1.5. BOY inventory, loss rates, and transfer plan inputs can be adjusted in a similar way. We can then vary the adjustment factors in the experimental design to construct a realistic range of numeric values that cover the manpower plans. An experimental design varying the manpower plans as discrete factors would give a more precise assessment as to how the numeric levels of the manpower plans affect projected inventory strength.

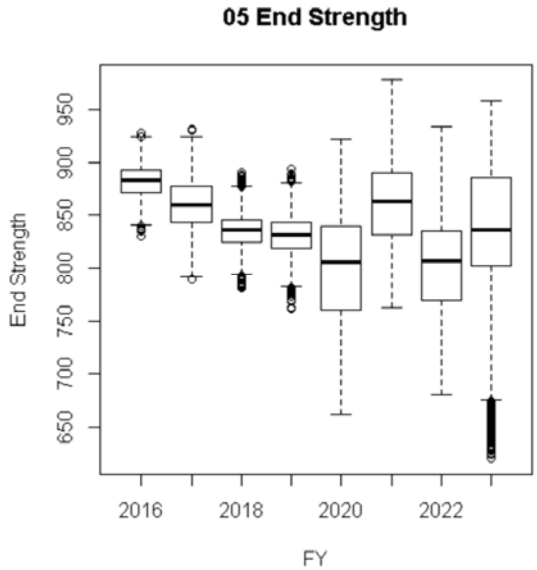
2. Fiscal Year Fixed-Effects

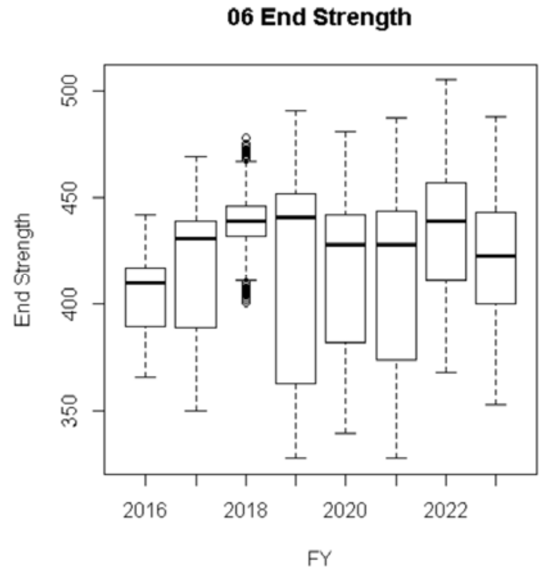
This thesis also uses linear projections of OSAM inventory over the projected window. The manpower and force-shaping plans (EPOCR) are modeled with the assumptions that the specific input parameters for each scenario are implemented linearly and annually over the projected window. Further research should consider projected year fixed-effects for each of the manpower and force-shaping plans. The advantage of such a construct is that the research can identify an optimal manpower policy for each projected fiscal year. We will add to this note that adding fixed-year effects will compound the number of factors needed by a factor proportional to the number of projected years. However, the computational resources needed to account for additional factors are minimized by using an appropriate experimental design. Additionally, since OSAM has very little variation, replication adds little value to an experiment. Construction of any designed experiment for future work should be weighted in favor of more design points rather than number of replications.

THIS PAGE INTENTIONALLY LEFT BLANK

APPENDIX A. SWO PROJECTED INVENTORY BY GRADE AND FY ACROSS DESIGN POINTS-FY2023.



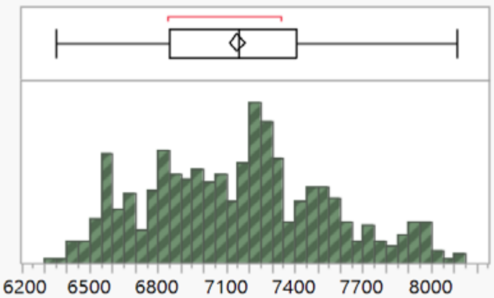

05 End Strength
End Strength
650
700
750
800
850
900
950
2016
2018
2020
2022
FY


06 End Strength
End Strength
350
400
450
500
2016
2018
2020
2022
FY

APPENDIX B. DISTRIBUTION OF PROJECTED END STRENGTH BY LOSS RATE CATEGORY-FY2023.

Distributions LOSS_RATE=FY10

Sum(Mean(Strength))

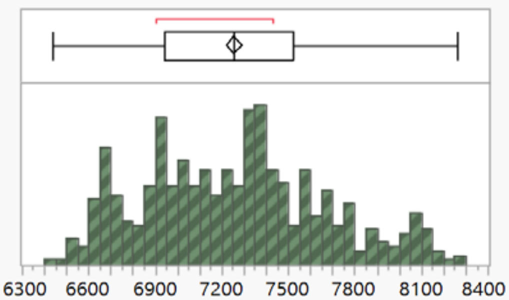


Summary Statistics

Mean	7150.1481
Std Dev	390.50635
Std Err Mean	16.994608
Upper 95% Mean	7183.5336
Lower 95% Mean	7116.7626
N	528

Distributions LOSS_RATE=FY13

Sum(Mean(Strength))

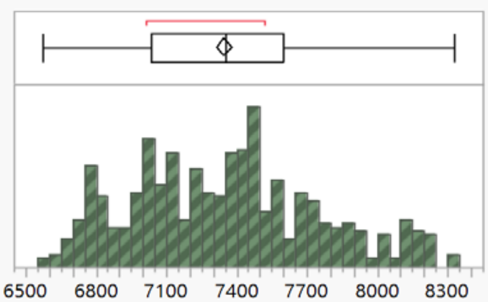


Summary Statistics

Mean	7256.6818
Std Dev	406.42045
Std Err Mean	17.68718
Upper 95% Mean	7291.4279
Lower 95% Mean	7221.9358
N	528

Distributions LOSS_RATE=FY14

Sum(Mean(Strength))

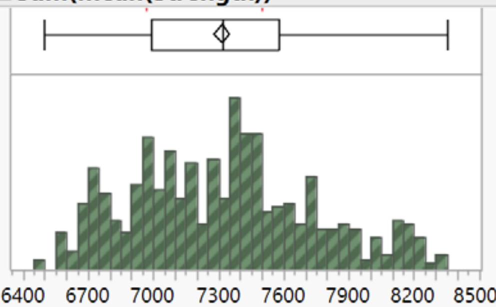


Summary Statistics

Mean	7347.9519
Std Dev	397.56849
Std Err Mean	17.301948
Upper 95% Mean	7381.9411
Lower 95% Mean	7313.9626
N	528

Distributions LOSS_RATE=FY15

Sum(Mean(Strength))

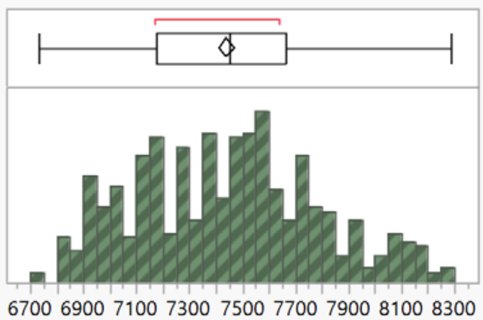


Summary Statistics

Std Dev	417.71115
Std Err Mean	18.178544
Upper 95% Mean	7353.503
Lower 95% Mean	7282.0804
N	528

Distributions LOSS_RATE=FYO6

Sum(Mean(Strength))

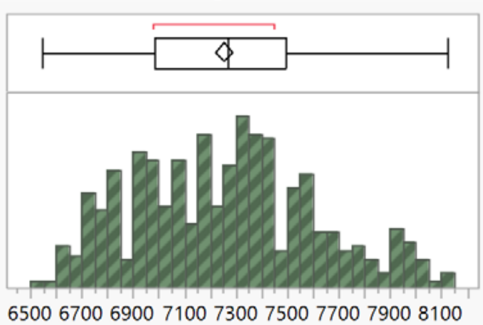


Summary Statistics

Mean	7439.6864
Std Dev	343.03445
Std Err Mean	14.928658
Upper 95% Mean	7469.0133
Lower 95% Mean	7410.3594
N	528

Distributions LOSS_RATE=FYO7

Sum(Mean(Strength))



Summary Statistics

Mean	7255.4235
Std Dev	352.08836
Std Err Mean	15.322679
Upper 95% Mean	7285.5245
Lower 95% Mean	7225.3225
N	528

LIST OF REFERENCES

Abrams, J. W. (1957). *Military applications of operational research*. Operations Research, *5*(3), 434–440.

Horne, G., Akesson, B., Meyer, T., Anderson, S., Narayanan, F., Bottiger, M. … Zimmermann, A. (2014). MSG-088 Data Farming in Support of NATO. *Final Report.* Modeling and Simulation Coordination Office, Paris, France: NATO Science and Technology Organization (STO).

Antony, J., Coleman, S., Montgomery, D. C., Anderson, M. J., & Johnson, R. T. (2011). *Design of experiments for non-manufacturing processes: benefits, challenges and some examples.* Monterey, California. Naval Postgraduate School.

Blosch, M. and Antony, J. (1998), A process-based approach to business risk analysis: The Royal Navy experience. Knowledge and Process Management *5*, 216–229

Cavazzuti, M. (2013). *Optimization methods: from theory to design scientific and technological aspects in mechanics*. Berlin, New York: Springer.

Cioppa, T. M., & Lucas, T. W. *(2007).* Efficient nearly orthogonal and space-filling Latin hypercubes. *Technom*etrics, *49*(1), 45–55.

Department of the Navy (2016) *Fiscal year (FY) 2017 budget estimates. Justification of estimates February 2016*. Retrieved from http://www.secnav.navy.mil/fmc/fmb/Pages/Fiscal-Year-2017.aspx

Department of the Navy. (2013, November). *Manpower, personnel, training, and education modeling catalog*. Washington, DC: Author. Retrieved from http://www.secnav.navy.mil/fmc/fmb/Documents/17pres/MPN_Book.pdf

DeHollan, A. N. (2015). *Investigating Naval Officer Retention Using Data Farming* (Master's thesis). Naval Postgraduate School. Retrieved from http://hdl.handle.net/10945/47245

DeSousa, W. P. (2015). *An exploratory analysis of economic factors in the Navy Total Force Strength Model (NTFSM)* (Master's thesis). Naval Postgraduate School. Retrieved from http://calhoun.nps.edu/handle/10945/47935

Erdman, R. W. (2010). *Using experimental design and data analysis to study the enlisted specialty model for the U.S. Army GI* (Master's thesis). Naval Postgraduate School. Retrieved from http://calhoun.nps.edu/handle/10945/5313

Faraway, J. (2005). *Linear models with R*. Boca Raton: Chapman & Hall/CRC.

Frank, J. A. (1993). *An assessment of the forecasting accuracy of the structured accession planning system for officers (STRAP-O) model* (Master's thesis). Naval Postgraduate School. Retrieved from http://calhoun.nps.edu/handle/10945/39789

Hernandez, A. S., Lucas, T. W., & Carlyle, M. (2012). Constructing nearly orthogonal Latin hypercubes for any nonsaturated run-variable combination. *ACM Transactions on Modeling and Computer Simulation*, 22(4), 20:1-20:17.

Huff, J. M., & Parcell D. A. (2015). *Officer overexecution: analysis and solutions (Technical Background).* Alexandria, VA: Center for Naval Analysis.

JMP Pro, Version 12.0.01 [Computer software] (2015). Cary, NC: SAS Institute, Inc.

Kleijnen, J. P. C., Sanchez, S. M., Lucas, T. W., & Cioppa, T. M. (2005). A user's guide to the brave new world of designing simulation experiments. *INFORMS Journal on Computing*, *17*(3), 263–289.

Law, A. M., & Kelton, W. D. (2000). *Simulation modeling and analysis* (3rd ed.). Boston, MA: McGraw-Hill.

Lucas, T. W. (2000). Stochastic versus deterministic argument for combat simulations: tales of when the average won't do! *Military Operations Research: Special Issue on Warfare Analysis and Complexity-the New Sciences*, *5*(3), 9–28.

MacCalman, A.D., Vieira, H., & Lucas T. W. (2016). Second order nearly orthogonal Latin hypercubes for exploring complex stochastic simulations. *Journal of Simulation,* Advance online publication. doi:10.1057/jos.2016.8

Mundy, J. T. (2014). *OSAM documentation: user manual and technical documentation for V3.1.4*. Arlington, VA: SAG Corp.

Nelson, A. (2010). *Predicting enlisted reenlistment rates* (Master's thesis). Naval Postgraduate School. Retrieved from http://calhoun.nps.edu/handle/10945/5149

Parcell D. A. (2015, August). *Officer overexecution: analysis and solutions*. Center for Naval Analysis, Alexandria, VA Resource Analysis Division.

Plackett, R. L., & Burman, J. P. (1946, June). *The design of optimum multifactorial experiments*. *Biometrika 33*(4), 305–325.

R Core Team (2016). R: A language and environment for statistical computing [Computer software]. Vienna, Austria: *R Foundation for Statistical Computing*. Retrieved from http://www.R-project.org

S. M. (2000). Robust Design: *Seeking the best of all possible worlds / proceedings of the 2000 winter simulation conference.* December 10–13, Orlando, FL

Sanchez, S. M. (2011). NOLH designs spreadsheet. Available online via http://harvest.nps.edu/ [accessed 04/05/2016]

Sanchez, S. M., & Wan, H. (2012). Work smarter, not harder: Tutorial on designing and conducting simulation experiments. In *Proceedings of the 2012 Winter Simulation Conference*. December 9–12, Berlin, Germany.

Sanchez, S. M., Lucas, T. W., Sanchez, P. J., Nannini, C. J., & Wan, H. (2012). Designs for large-scale simulation experiments, with applications to defense and homeland security. *Design and Analysis of Experiments*, volume III, by Hinckleman (ed.), Hoboken, NJ: John Wiley & Sons, pp. 413-441.

Sanchez, S. M., Sanchez, P. J., & Wan, H. (2014). *Simulation experiments: better insights by design*. Retrieved from https://libsearch.nps.edu/vufind/Record/ir-10945-44879

Savage, S. L. (2009). *The flaw of averages: Why we underestimate risk in the face of uncertainty*. Hoboken, NJ: John Wiley & Sons.

Schank, F.J., Harrell, M. C., Thie, H. J., Pinto, M. M., Sollinger. J. M. (1997). *Relating resources to personnel readiness use of Army strength management model*. Washington, DC. RAND Corporation

Secretary of the Navy Instruction (SECNAVINST) 1420.1B. (2006, March). *Department of the Navy (DoN) promotion, special selection, selective early retirement, and selective early removal boards for commissioned officers of the Navy and Marine Corps*. Retrieved from https://doni.daps.dla.mil/allinstructions.aspx

Sibley, C. N. (2012). *Analyzing Navy officer inventory projection using data farming* (Master's thesis). Naval Postgraduate School. Retrieved from http://calhoun.nps.edu/handle/10945/6868

Title 10 United States Code. Retrieved from http://uscode.house.gov/download/download.shtml

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
   Ft. Belvoir, Virginia

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, California