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Developing a universal Navy uniform adoption model for use in forecasting

Key, Michael

Monterey, California: Naval Postgraduate School

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NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

MBA PROFESSIONAL REPORT

DEVELOPING A UNIVERSAL NAVY UNIFORM ADOPTION MODEL FOR USE IN FORECASTING

December 2015

By: Michael Key
Jeff Legg

Advisors: Kenneth Doerr
Geraldo Ferrer

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DEVELOPING A UNIVERSAL NAVY UNIFORM ADOPTION MODEL FOR USE IN FORECASTING

Michael Key, Lieutenant, United States Navy
Jeff Legg, Lieutenant, United States Navy

Submitted in partial fulfillment of the requirements for the degree of

MASTER OF BUSINESS ADMINISTRATION

from the

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December 2015

Approved by: Kenneth Doerr, Ph.D.

Geraldo Ferrer, Ph.D.

Bryan Hudgens
Academic Associate
Graduate School of Business and Public Policy

Rene Rendon
Academic Associate
Graduate School of Business and Public Policy

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LIST OF ACRONYMS AND ABBREVIATIONS

AAFES	Army and Air Force Exchange Service
AD	Active Duty
Adj.	Adjusted
ASD L&MR	Assistant Secretary of Defense for Logistics and Materiel Readiness
AVG	Average
CNO	Chief of Naval Operations
CPO	Chief Petty Officer
CRA	Clothing Replacement Allowance
CRR	Cost Recovery Rate
Cum.	Cumulative
CUM INV	Cumulative Inventory
C&T	DLA, Troop Support, Clothing and Textiles Branch
DLA	Defense Logistics Agency
DMDC	Defense Manpower Data Center
DMRR	Defense Manpower Requirements Report
DOD	Department of Defense
DWCF	Defense Working Capital Fund
EOQ	Economic Order Quantity
EXCESS INV	Excess Inventory
(F)	Female
FP	Fielding Plan
FRV	Flame-Resistant Coverall Variant
FTS	Full-time Support
FY	Fiscal Year
GAO	Government Accountability Office
LC Buy	Life Cycle
LCC	Life Cycle Costs

(M)	Male
MAPE	Mean Absolute Percentage Error
MAX	Maximum
MBA	Master of Business Administration
MCX	Marine Corps Exchange
MIN	Minimum
MP	Manpower
MSE	Mean Squared Error
NAVAIR	U.S. Navy Naval Air Systems Command
NAVSEA	U.S. Navy Naval Sea Systems Command
NAVSUP	Naval Supply Systems Command
NCTRF	Navy Clothing and Textile Research Facility
NEX	Navy Exchange
NEXCOM	Navy Exchange Command
NIIN	National Item Identification Number
NPC	Naval Personnel Command
NRF	Navy Reserve Forces Command
NSE	Non-Smoothing Exponential
NSNE	Non-Smoothing Non-Exponential
NWU	Navy Working Uniform
OPNAV N1	Office of the Chief of Naval Operations
OUSD P&R	Office of the Under Secretary of Defense for Personnel and Readiness
PDF	Portable Document Format
PTU	Physical Training Uniform
RDT&E	Research, Development, Test, and Evaluation
ROP	Reorder Point
RTC	Recruit Training Command
SDB	Service Dress Blue
SE	Smoothing Applied

SRP	Supply Request Package
SSE	Sum of Squared Errors
SST	Sum of Squares
TDP	Technical Data Package
UPMG	Uniform Program Management Group
UPMO	Uniform Program Management Office
USNR	United States Naval Reserve
VADM	Vice Admiral

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I. INTRODUCTION

A. PROBLEM BACKGROUND

In today's ever-increasing, fiscally-constrained defense budgetary environment, the need to maximize efficiency and minimize costs is more significant than ever. As pressure continues to mount on the Department of Defense's (DOD) acquisition and logistics force to increase cost effectiveness, special consideration is needed for immediate, upfront costs, and for legacy and life-cycle costs (LCCs) as well. For large acquisition programs, methods for accounting for LCCs are well established and must be included in program cost estimates. There are, however, many sizeable programs that incur significant LCCs, but are not subject to formal acquisition requirements. One such acquisition program is military uniforms (Government Accountability Office [GAO], 2012). With these programs under increased scrutiny by Congress and the Government Accountability Office (GAO), having a means to accurately forecast the demand for future uniform programs is essential for sound, total cost management.

The ability to accurately predict future demand in support of minimizing inventory costs is a challenging, yet crucial, part of proper total cost management. Inaccurate demand predictions can result in either inventory shortages, which are a detriment to the customer, or excess inventory, which results in higher inventory holding costs. There are many proven methods for determining how much inventory to carry; however, they are all dependent on accurate demand information. For mature systems or products that exhibit steady demand, determining demand is straightforward; however, with new programs, and situations where customer behavior is unknown, determining reliable demand information can be challenging.

Various methods exist for developing demand prediction models, such as causal (i.e., regressions), time series (i.e., moving average), and judgmental (i.e., instinct or experience), and with the aid of modern software, forecast models can be efficiently generated. A weak point with most classic methods is that they require the model developer to make a number of assumptions about the relationships between demand patterns and input variables (i.e., are they linear or exponential)? Often, however, this constrains the model and limits its usefulness. In many cases, the model developer may believe that a relationship between two data sets exists, but is unsure of what form that relationship takes. In such cases, significant trial and error are often needed to determine a relationship and, if the model uses multiple data sets, this process can be cumbersome. As computing power becomes cheaper and with data storage capacity growth seemingly limitless, data analytics has increased in popularity. Parallel to this increase, forecasting methods have grown more sophisticated (Venkatesan, Krishnan, & Kumar, 2004). Today, techniques such as artificial neural networks and machine learning are frequently employed; however, they are typically the realm of data scientists and statisticians. Recent software advances have improved the user-friendliness of these techniques, making these sophisticated modeling techniques widely accessible to business modelers. With these advances, business modelers can quickly develop accurate predictive models that minimize error, with little theoretical guidance on the relationships between variables. For the DOD, reducing model error directly translates to reducing costs, which, as noted, will become increasingly important in the years to come.

U.S. military uniform programs could certainly benefit from advances in modeling software. Compared to traditional weapon systems, modeling the demand for U.S. military uniform items presents unique challenges. Given that individual service members are the sole customers for a given uniform, and that the parent service mandates the quantity of uniforms each service member should own (often called an "allowance"), one might conclude that developing a demand model should be fairly straightforward if the applicable size of the military service force is known.

This specifically has not been the case for the United States Navy. Recent experience with the Navy Working Uniform (NWU) and Enlisted Service Uniform (SU) has shown that customer behavior has a pronounced role in demand patterns; adoptions of new uniforms are often not immediate and sailors frequently do not immediately purchase all their allowance. A review of actual sales data from the Navy Exchange (NEX) retail outlet system revealed that initial fielding plan forecasts substantially overestimates initial sales. This leads to substantial excess inventory, which incurs additional holding costs and ties up working capital in uniform inventory.

The life cycle of a uniform can be considered to have two, or possibly three, stages. There is the initial adoption, as commands phase in a uniform and personnel gradually acquire their allowance, marked by rapidly increasing demand, followed by a tapering of demand in the next, replacement phase. During the replacement phase, demand is more-or-less stable. Finally, no uniform lasts forever and, eventually, there will be an end-of-life phase. It is important to predict transitions between these life-cycle phases, especially if a uniform has a short life cycle, to avoid what may become permanent overages or shortages of uniforms.

B. PURPOSE OF THE STUDY

The purpose of this Master of Business Administration (MBA) project is to investigate potential improvements to demand forecast methods currently in use by the Navy Exchange Command (NEXCOM) for use in developing Supply Request Packages. This project was sponsored by the NEXCOM, with additional support provided by the Defense Logistics Agency (DLA). The goal of this project is to develop a universal Navy Uniform Adoption model, which provides demand forecasts for new, major uniform programs managed by the NEXCOM. Ideally, this model will more accurately predict uniforms' expected demand and reduce unnecessary costs. An analysis was conducted on historic uniform retail sales data for the product life cycles of two major uniform programs—the NWU Type I and the Enlisted SU. Additionally, proprietary symbolic regression software was used to discover relationships between the demand data and independent variables such as time, manpower, and uniform allowance. Further analysis was conducted on the results aimed at determining the "best fit" Navy Uniform Adoption model.

C. RESEARCH QUESTIONS AND PROJECT ORGANIZATION

Existing forecasting models in use by the NEXCOM do not fully factor in product life-cycle phases or customer adoption rates. Some customer behaviors are accounted for in their models; however, this is heavily reliant on the experience and assumptions made by the modeler. In support of developing a new forecast model, it was first necessary to determine if there is a consistent product life-cycle distribution across uniform programs. Second, whether product demand is dependent on the variables of time, manpower, and allowance and, if so, are these relationships consistent across uniform programs. Lastly, if these relationships can be exploited to develop a universal forecasting model for military uniform programs that balances accuracy and ease of use.

This project is organized as follows: Chapter II provides background on the NEXCOM and the DLA, as well as their roles in uniform production, testing, and ordering. Chapter II also outlines the specifics of the two uniforms being analyzed: the NWU and the SU. It concludes with a brief introduction of the symbolic regression software, Eureqa; our initial assumptions about potential new models; and other material relevant to forecasting and inventory management. Chapter III outlines the methodology by which the data used for analysis was collected, sorted, and normalized; along with a discussion about the unique data preparation requirements necessary for use with Eureqa. Chapter IV provides analysis of the Eureqa output results, as well as model down-selection and validation processes. Finally, Chapter V offers a summary of results, conclusions, and limitations, as well as recommendations for further research.

II. BACKGROUND AND LITERATURE REVIEW

A. BACKGROUND

The following section provides a brief background on the DLA, the NEXCOM, their relationship with each other, and their respective roles in the uniform program. The different categories of uniforms are discussed as well as the two uniform types specifically used in this research.

1. Defense Logistics Agency Overview and Its Role in Uniform Programs

As "America's combat logistics support agency" (Defense Logistics Agency [DLA], n.d.), the DLA plays the largest role in acquisition and supply chain management for the U.S. armed forces, supplying almost 90% of the military's spare parts. Typically, the DLA finds itself managing the supply chain aspects of programs developed and acquired by individual services, as is the case with Navy uniforms. When the Chief of Naval Operations (CNO) mandates a new uniform or an update is required to an existing uniform for safety or other reasons, the United States Navy is required to oversee its development. Once the design is approved and tested, the DLA will typically take over the procurement and supply chain management requirements of the new uniform.

Given the DLA's significant role in military uniform management, it created the Troop Support, Clothing and Textiles Branch (C&T), which is compartmentalized into divisions that support recruit and organizational clothing, as well as individual equipment (Moore, 2012). While used heavily, these divisions are not solely reliant on historical demand for forecasting; they have found that maintaining direct liaison with their military service counterparts is just as crucial to effectively managing accurate inventory levels. Through this liaison, the DLA can be made aware of significant program changes such as uniform cancellation, changes to sea bag allowance, or wear rules that may affect demand.

As the responsible agency for Navy uniform procurement and item management, the DLA requires the NEXCOM to provide annual forecasted sales data from the Uniform Program Management Office (UPMO). This estimate reflects the predicted annual number of uniform items sold through the NEXCOM's retail outlets, or NEXs. Items procured by the DLA for sale through NEXs are subject to holding costs, which are passed along to the NEXCOM in the form of cost recovery rates, or surcharges.

2. Navy Exchange Service Command Overview and Its Role in Uniform Programs

The NEXCOM is headquarters for the worldwide Navy Exchanges Enterprise and one of its six primary business lines is the UPMO (DLA, n.d.). The NEXCOM is an Echelon III command, falling under the Naval Supply Systems Command (NAVSUP), and is headed by a Chief Executive Officer. Within the NEXCOM, there is a Uniform Program branch with four different divisions reporting to a Navy captain: the NEX Uniform Merchandising/Call Center and Stores, Uniform Product Management Group (UPMG), Navy Clothing and Textile Research Facility (NCTRF), and the UPMO.

The UPMO, under the NAVSUP, is primarily responsible for the design, development, and testing of new uniforms and uniform changes (Gantt, 2015). Commercial items sold through NEXs are procured and managed by the NEXCOM, while government-issue (sea bag) and organizational clothing are designed and tested by the UPMO, but procured and managed by the DLA. Most items that fall under Government Issue are also available for retail sale through the NEX; government-issue uniforms sold through this channel are typically replacements for worn uniforms or outfitting purchases for service members not eligible for direct issue. In select cases, the NEXs' inventories are supplied by the DLA, or by industry vendors. Definitions and examples of different uniform categories are provided in Section 4.

Currently, no prescribed process exists for the acquisition plans of uniforms by the UPMO, other than adherence to federally-mandated acquisition policy (R. Gantt, personal communication, May 13, 2015). This is, in part, due to the variation in management practices between uniform categories and the means by which customers receive uniforms. These variations can obscure historic demand patterns and complicate forecasting. Additionally, a significant portion of uniforms are not issued and are, therefore, subject to customer behavior, which further complicates demand forecasting.

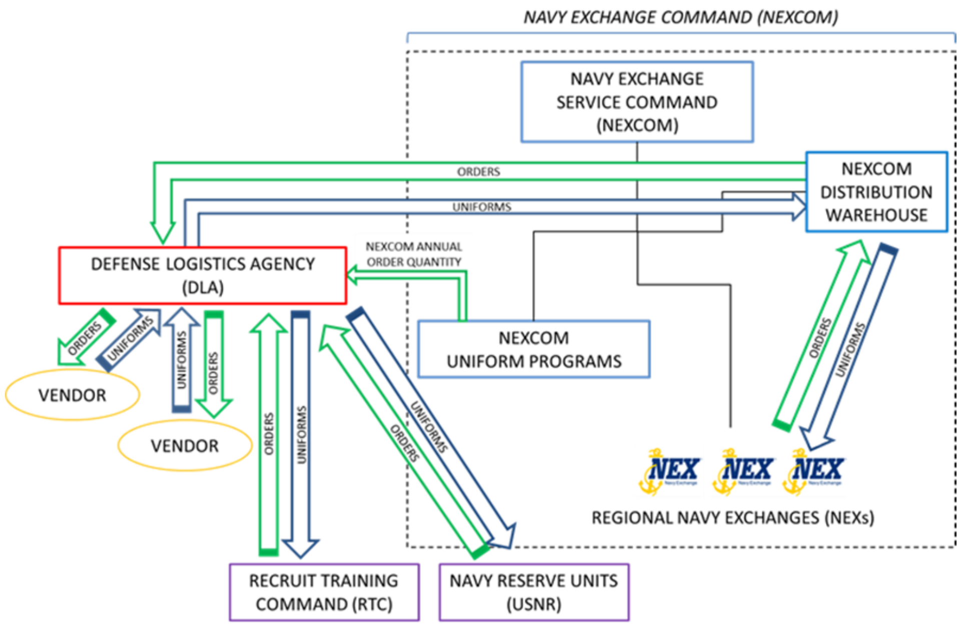
For fleet-wide uniform items, such as those that are part of the NWU Type I and Navy Enlisted SU, the DLA assumes responsibility of procurement and item management, but relies on the UPMO for annual updates to its forecasts to supplement its demand-based models. The uniform procurement and management model for these two uniforms require coordination between the DLA and the NEXCOM, as they are both commercially available through NEXs as well as government-issued to Navy recruits at the Recruit Training Command (RTC) and the Navy Reserve Forces Command (NRF). Both the NWU and SU are discussed in later sections.

3. NEXCOM/DLA Distribution Chain

The relationships among the DLA, the NEXCOM, and external agencies for uniform ordering and distribution are shown in Figure 1. As previously noted, with the exception of commercial uniforms, the NEXCOM UPMO is responsible for submitting a Supply Request Package (SRP) to initiate support for a new uniform program. Once support has been initiated, the NEXCOM provides the DLA with annual sales forecast updates for uniforms sold through the NEXs. The NEXCOM uses a multiechelon inventory model for its uniform distribution system. First echelon duties are performed by the DLA, which maintains vendor relationships, contracting and procurement, as well as wholesale inventory responsibilities. The second echelon is the NEXCOM distribution warehouse in Pensacola, Florida, which supports the retail outlets by maintaining buffer stock against recurring demand, managing stock in support of seasonal demand cycles (e.g., Chief Petty Officer [CPO] selectee frocking in September), and delivery and distribution. The distribution warehouse uses a periodic reorder system that submits orders to the DLA for any item that reaches its low-limit. Third echelon duties are the individual worldwide NEXs. The retail outlets maintain limited, on-hand working inventory, which is then sold to active duty sailors (R. Gantt, personal communication, August 5, 2015). The retail outlets also use a periodic inventory reorder system, whereby orders are sent to the NEXCOM distribution warehouse for fulfillment.

The distribution relationships between the NEXCOM, the DLA, the RTC, and NRF units are illustrated in Figure 1.

Figure 1. NEXCOM/DLA Distribution Chain.



Currently, both the Navy RTC and the NRF Command place uniform orders directly against DLA wholesale inventory for the NWU and the SU. Both activities issue uniforms according to allowance, vice selling them through retail activities. As a result, much variability (caused by the bullwhip effect) is eliminated in forecasted demand. Orders are relatively constant; they are a function of manpower levels, accessions, and individual allowance for the uniform. These orders and functions are discussed in Chapter III, Section A.

4. Definitions of Commercial, Organizational, and Government-Issue Uniform Items

NAVSUP differentiates uniforms into three separate categories: commercial uniforms, organizational clothing, and government-issue uniforms. This paper primarily focuses on commercial and government-issue uniforms; however, all three categories are described below, to make the scope of the paper clear.

a. Commercial Uniforms

United States Navy commercial uniforms consist of uniforms and uniform items typically not required for the normal execution of duties by Navy personnel, such as dinner dress uniforms, swords, formal jackets. This category also includes uniforms that are primarily worn by officers and CPOs who are not typically eligible for government-issue uniforms. Examples include the officer and CPO Service-Khaki uniforms, combination covers, and dress uniforms, including Service Dress Blues (SDBs) and Dress Whites (Chokers). Requirements and policy for Navy commercial uniform items are determined by the Deputy Chief of Naval Operations, Manpower, Personnel, Education, and Training (OPNAV N1). Capital funding is provided by the NEXCOM, and research, development, test, and evaluation (RDT&E) is performed by the NCTRF. The NAVSUP designs, develops, and tests new commercial uniforms and changes to existing uniforms (Gantt, 2015), while the NEXCOM manages the procurement. Once procured, the NEXCOM sells the commercial uniform items through the NEXs with a markup. Select commercial uniform items are also available for sale through third-party vendors.

b. Organizational Clothing

United States Navy organizational clothing is defined as "clothing issued to an individual by a naval activity, for which there is a requirement beyond authorized Navy uniforms. It remains the property of the Navy" (Gantt, 2015, slide 8). Examples include foul-weather jackets, flight jackets, and flame resistant coveralls (FRVs). The cognizant Fleet activity defines the technical requirements and provides RDT&E funding for new organizational clothing programs. RDT&E is performed by the NCTRF, with input from systems commands such as Naval Sea Systems Command (NAVSEA) and/or Naval Air Systems Command (NAVAIR), as appropriate. Procurement and item management is performed by the DLA; individual Fleet units are the end customer, with requisitions covered by operations and maintenance funds.

c. Government-Issue Uniforms

Government-issue uniforms, or "Seabag uniforms," are primarily issued to enlisted Navy sailors at boot camp and are shown in Table 1. Requirements and policy for Navy Seabag items are determined by OPNAV N1; RDT&E funding is provided by OPNAV N1 to the DLA or the NCTRF, as appropriate. The DLA manages procurement, item management, and wholesale stocks via working capital funds. Most Seabag items are also available for retail sale through the NEXCOM. After graduation, sailors in the Fleet are required to purchase replacements for worn uniforms or newly released uniforms. Enlisted sailors receive an annual Clothing Replacement Allowance (CRA) to purchase replacement uniform items from the NEX. Supplemental allowances are often provided to cover the initial purchase of a newly released uniform. No limits are placed on the quantities of these items that sailors can purchase. For their NEX inventories, the NEXCOM sources these items from the DLA. Typically, the NEXCOM charges a markup on items sold through its retail outlets, which is meant to offset NEX operating costs. For uniforms, the items are sold to the customer at the wholesale price, with OPNAV N1 covering the markup. Fleet distribution of these items at boot camp is also purchased from the DLA's inventories (Gantt, 2015).

Table 1. FY15 Seabag Items E1–E6, Male and Female.

U.S. NAVY SEABAG ITEMS (MALE, E1-E6)

ITEM	QUANTITY
Bag, Duffel, OD	1
Belt, Web, Ctn, Blk, w/chromium Clip	2
Belt, Web, Ctn, Wh,	1
w/silver clip	
Blousing Straps	2
Boots, 9"	1
Buckle, Belt, Chromium Plated	2
Cap, Garrison	1
Cap, Knit, Wl, Bl	1
Cap, 8 Point	2
Coat, All-Weather	1
Coveralls, Poly/Ctn, Utility	2
Drawers, Briefs, Ctn, Wh	8
Gloves, Leather, Blk, Unisex	1
Rating Badge Bl Poly Twl 3/4 Size	1
Rating Badge Wh Poly Twl 3/4 Size	2
Hat, White	2
Insignia, Collar, Service E2	1
Insignia, Collar, Service E3	1
Jumper, Blue, Dress	1
Jumper, White, Dress	2
Liner, Fleece	1
Mock Turtle Neck	1
Neckerchief, Blk	1
Overcoat, Mel, Wl, Bl P-coat	1
Parka	1
Shirt, Khaki	2
Shirt, NWU	4
Shoes, Black, Dress	1
Socks, Ctn/Nyl, Blk	3
Socks, , Cush Sole, Boot	5
Towel, Bath	4
Trousers, Bl, Srg, Broadfall	1
Trousers, Service	2
Trousers, NWU	4
Trousers, Tw, Ctn/Poly, Wh	2
Undershirts, Ctn, Wh	4
Undershirts, Ctn, Blue	5
Ball Cap	2
Insignia	1
PT Shirt	2
PT Shorts	2
PT Sweat Shirt (Hooded)	1
PT Sweat Pants	1
PT Shoes	1

U.S. NAVY SEABAG ITEMS (FEMALE, E1-E6)

ITEM	QUANTITY
Bag, Duffel, OD	1
Belt, Web, Ctn, Blk, w/chromium Clip	2
Blousing Straps	2
Boots, 9"	1
Buckle, Belt, Chromium Plated	2
Cap, Garrison	1
Cap, 8 Point	2
Cap, Knit, Wl, Bl	1
Coat, All-Weather	1
Coat, SDB, Gabardine	1
Coveralls, Poly/Ctn, Utility	2
Gloves, Leather, Blk	1
Grp Rate Mk Emb Bl Tw (3/4)	1
Grp Rate Mk Emb Wh Poly (3/4)	2
Grp Rate Mk Emb Bl P/C (3/4)	1
Hat, Svc, w/2 crowns	1
Insignia, Svc Hat & Cap	1
Insignia, Collar, Service E2	1
Insignia, Collar, Service E3	1
Jumper, White, Dress, CNT	2
Liner, Fleece	1
Mock Turtle Neck	1
Neckerchief, Blk	1
Neck Tab, Blk	1
Overblouse, Khaki	2
Overcoat, Mel, Wl, Bl P-coat	1
Parka	1
Shirt, Ctn/Poly, SS, Wh	1
Shirt, NWU	4
Shoes, Oxford, Black	1
Slacks, SDB, Gabardine	1
Slacks, CNT, Poly, Wh	2
Slacks, Service SU	2
Socks, Ctn/Nyl, Blk	3
Socks, Cush Sole, Boot	5
Trousers, NWU	4
Towel, Bath	4
Undershirts, Ctn, Wh	4
Undershirts, Ctn, Blue	5
Ball Cap	2
Insignia	1
Lingerie, Stockings, and Underwear	1
PT Shirt	2
PT Shorts	2
PT Sweat Shirt (Hooded)	1
PT Sweat Pants	1
PT Shoes	1
Swim Suit	1

Source: Navy Personnel Command. (n.d.). FY15 Seabag Items E1–E6, Male and Female. Retrieved from http://www.public.navy.mil/bupers-npc/support/uniforms/uniformregulations/Chapter1/Pages/SeabagActive.aspx

d. Navy Working Uniform Type I

The NWU Type I is a utility-style uniform constructed of a 50% nylon/50% cotton-twill fabric, designed to be worn by both male and female sailors, and to fulfill both sea and ashore requirements (Chief of Naval Operations [CNO], 2013). The NWU Type I consists of seven components: cap, blouse, undershirt, trousers, socks, belt, and boots. The analysis for this project focuses on the blouse and trousers, which represent the majority of the uniform's cost and are the most unique items within each uniform program. Components such as boots, socks, and undershirts can be used with several different uniforms and are often available through sources outside the DLA and the NEXCOM. As previously discussed, the NWU Type I is a government-issue uniform that is also available through NEX retail outlets. Until recently, Navy recruits at the RTC were issued four sets of NWU Type I as part of their Seabag inventory. This allowance was reduced to three. When this uniform was introduced, sailors already in the fleet were required to purchase NWU Type I through NEX outlets and maintain the same allowance in their Seabag.

NWU Type I blouses and trousers, unlike other military uniforms, are not sold as gender-specific items; however, the NWU Type I comes in many sizes to accommodate sailors' needs. The sales data for this project was aggregated into total monthly sales figures for blouses and trousers. Distribution data indicating relative demand for each uniform size—known as a tariff—was provided by the DLA and can be useful for planning when applied to a total forecasted demand number. Chapter III discusses the methods used to convert these figures into a single NWU "set" for use in developing and applying the forecast model.

The NWU Type I is required for all ranks of the United States Navy—E1-O10—and can be worn afloat and ashore according to command policy. Figure 2 provides an example of the NWU Type I.

Figure 2. Navy Working Uniform Type I.

Source: Bacon, L. M. (2014, June 23). Sailors test lightweight cammies that could become optional uniform. *Navy Times*. Retrieved from http://archive.navytimes.com/article/20140623/NEWS07/306230018/Sailors-test-lightweight-cammies-could-become-optional-uniform

e. Navy Enlisted E1–E6 Service Uniform

The Navy Enlisted E1–E6 SU is “worn year round for office work, watch-standing, liberty or business ashore” (Bureau of Naval Personnel, n.d.). The SU also consists of seven components, but requires wearing black dress shoes instead of boots. Again, the sales analysis for this project focuses on blouses and trousers as the prime components within the uniform.

Similar to the NWU Type I, the SU is provided as a government-issue uniform at the RTC and is available for retail sale through NEX outlets. Each sailor, however, is only allocated two sets as part of their Seabag inventory. In line with traditional service uniforms, the SU has gender-specific components. The provided monthly sales data for the SU was segregated between male and female figures. These figures were aggregated into total monthly sales similar to the NWU Type I. Chapter III provides additional details on the methods used to normalize the sales data for the analysis.

The SU is worn primarily ashore by sailors in grades E1 through E6, as appropriate. The NWU and SU were developed and released within a year of each; they followed similar “rollout” plans to the Fleet. Figure 3 is an example of the SU.

Figure 3. Navy Enlisted Service Uniform (E1–E6).

Source: Navy Junior Reserves Officer Training Corps. (n.d.). Navy service uniform. Retrieved from https://sites.google.com/a/navyjrotc.us/james-madison-njrotc/home/uniform-regulations-1/navy-service-uniform

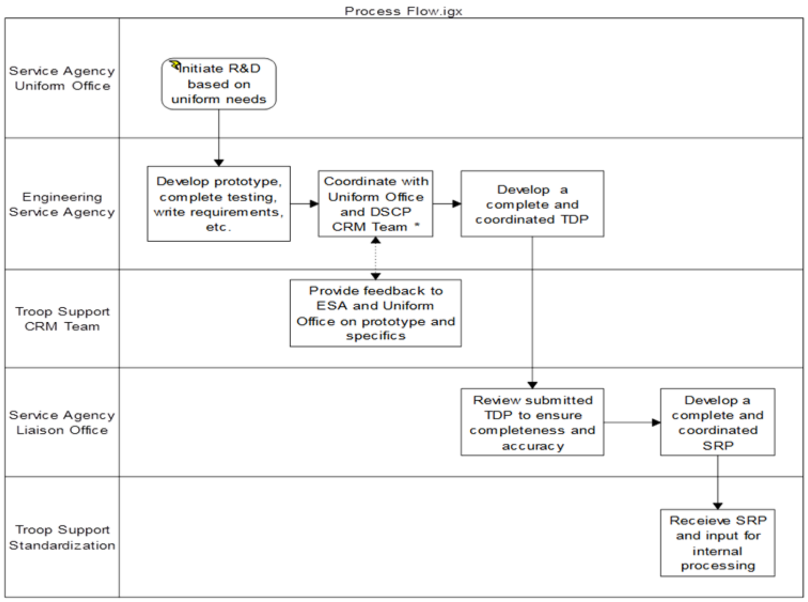
5. Establishing Support for New Uniforms

The following section briefly discusses portions of the process used to develop a new uniform and the manpower data required for selected uniform programs.

a. Supply Request Packages

Establishing support through C&T for new uniforms requires the submission of an SRP. The SRP is comprised of two primary components: the Technical Data Package (TDP) and a phasing plan, which the NEXCOM refers to as a fielding plan (DLA, n.d.). The TDP provides the detailed technical requirements for the uniform, such as form, fit, function, and durability. The TDP is developed by the NCTRF representatives assigned to C&T in Philadelphia, with input from NCTRF technical engineers. The fielding plan is developed by NEXCOM UPMO representatives. The SRP submittal is an iterative process that is based on historical demand of similar items and other factors (Gantt, 2015). Figure 4 graphically represents the SRP submittal process.

Figure 4. Supply Request Package Flowchart.



Source: Defense Logistics Agency (DLA). (n.d.). Supply request package (SRP) submission reference guide. Retrieved from https://www.troopsupport.dla.mil/clothingandtextiles/srp.asp

In keeping with increased budgetary scrutiny, the Director of the DLA is required to inform the Assistant Secretary of Defense for Logistics & Materiel Readiness (ASD L&MR) when "the residual of wholesale and retail stocks of both the end item and the constituent textiles are estimated to exceed one million dollars in value on the effective date of supply of the new item" (Department of Defense, 2014, Encl. 3, p. 17). This requirement places additional importance on accurate development of the fielding plans. The NEXCOM UPMO's process for developing these plans is discussed in the following section.

b. Fielding Plan Development

Fielding plans developed by the UPMO provide an aggregated demand forecast that covers the initial 36 months of a new uniform program. This forecast includes estimates for NEX retail sales, government-issue through the RTC, and NRF requirements. To better understand current practices, a brief walkthrough of fielding plan development for the soon-to-be-released E1–E6 Female SDBs is included below.

First, manpower numbers for the applicable service member population and time horizon are collected from the Navy Personnel Command (NPC); in this case, the applicable service member population is E1 through E6 female sailors. Phase-in for the SDB is scheduled to start in fiscal year 2017 (FY17); phase-in will be completed early in FY20. For this fielding plan, the projected manpower levels for FY17 through FY20 were averaged to create the manpower estimates. Table 2 displays the derived manpower numbers. Active component manpower was then normalized by separating RTC accessions from existing fleet sailors. RTC accessions will be a recurring annual requirement, while the pool of existing sailors requiring initial outfitting is a one-time requirement; this difference in periodicity necessitates the normalization.

Table 2. Manpower Calculations for Female E1–E6 SDB Uniform Fielding Plan.

Personnel Category	Total Manpower
Active Component	45,700[1]
Full Time Support (FTS)	1,400
Naval Reserve Forces	7,100
Total E1–E6 Female	54,200

Adapted from: Navy Exchange Uniform Program Management Office (NEXCOM UPMO). (2015). SDB Female E1–E6 Fielding Plan (6-10-2015). [Microsoft Excel data file]. Received via email from the NEXCOM UPMO.

Once the requisite manpower numbers are determined, these numbers are then multiplied by the established allowance for the uniform. In this case, the NPC set the allowance at one for the SDB, so forecasted demand equals projected manpower requirements. Table 3 shows the resulting calculations. Phase-in is often staggered over time in order to ease procurement and initial distribution. To achieve the staggered phase-in, the NEXCOM typically releases the uniform a few regions at a time; the sizes of the regions determine the percentage of Fleet sailors covered in a given year.

[1] Active Component comprises 36,800 Fleet sailors and 8,900 accessions through RTC.

Table 3. Female E1–E6 SDB Uniform Fielding Plan.

Fiscal Year	RTC	Fleet Sailors	FTS	Reserves	Life cycle Buy	Total
2017 (Q2-Q4)	8,900	10,900	500	2,000	N/A	22,300
2018	8,900	11,500	400	2,000	N/A	22,800
2019	8,900	10,800	400	2,000	N/A	22,100
2020 (1Q)	2,200	3,600	100	1,100	5,000	12,000
Total	28,900	36,800	1,400	7,100	5,000	79,200

N/A (Not Applicable) Adapted from: Navy Exchange Uniform Program Management Office (NEXCOM UPMO). (2015). SDB Female E1–E6 Fielding Plan (6-10-2015). [Microsoft Excel data file]. Received via email from the NEXCOM UPMO.

The life-cycle buy (LC Buy) captures the first round of replacements for worn uniforms. Figure 5 shows the equation currently used to determine the LC Buy requirements; in this equation, the variable *t* represents the year that the LC Buy occurs and the variable *r* represents the replacement interval. The replacement interval is set by NPC policy; in the case of the SDB, the designated replacement interval is three years.

Figure 5. Life-Cycle Buy Calculation.

$$LC_{Buy} = 25\% \cdot \left[RTC_{(t-r)} + FleetSailors_{(t-r)} + FTS_{(t-r)} \right] =$$
$$LC_{Buy} = 25\% \cdot [8{,}900 + 10{,}900 + 500] \cong 5{,}000$$

Since the LC Buy occurs in FY20 and the replacement interval is three years, the basis for the LC Buy is the FY17 combined total of RTC, Fleet sailors, and Full-time Support (FTS). This basis is than multiplied by 25% to achieve the final LC Buy numbers. The 25% is a judgment-based estimate of the percentage of sailors that actually replaces their uniforms at the three-year mark; this judgment is informed by experience.

6. Current Status of NWU Type I

In 2012, a significant defect in the NWU was made public and quickly spread via social media. An impromptu test by the NCTRF discovered that the NWU Type I will "burn robustly until completely consumed" (Patani, 2012, para. 2). When developed, the material used in the uniform was not required to be flame resistant; this requirement had been previously eliminated by the Navy in 1996 (Patani, 2012). Concerned over Fleet safety, however, the CNO directed that a replacement uniform for the NWU be created for use onboard ships. As of 2012, wear of the NWU onboard ships has been restricted; a replacement uniform, the FRV, was subsequently made available (Patani, 2012).

To date, the NWU Type I is still a uniform of record and continues to be issued and sold to sailors; however, in response to their diminished role, the Seabag allowance has been adjusted to three effective October 1, 2015 (CNO, 2015), with further allowance reductions under consideration (Bacon & Faram, 2015). The Navy is still mulling over the ultimate fate of the NWU Type I, as it weighs alternatives. Before it chooses to phase-out the NWU Type I, the Navy must consider the sizeable stockpile of NWUs still in the stock system. Estimates suggest that there is enough stock on hand to last the Navy through 2018, which means it could be costly for the Navy to abandon the uniform (Bacon & Faram, 2015).

For the purpose of this project, the authors are only analyzing sales data prior to any allowance change. Changes to the NWU wear rules should not affect the analysis.

B. LITERATURE REVIEW

The following section discusses they theory of New Product Diffusion and the associated Bass Diffusion Model. Brief summaries of different methods of forecasting are provided as well as for Eureqa, symbolic regression, holding costs, and recovery rates.

1. New Product Diffusion

Much research has been conducted on product diffusion and adoption rates; this research spans from information technology to consumer products. Diffusion is essentially the rate at which a new idea or product is adopted by society. One pioneer in product diffusion, Everett Rogers—who, in 1962, published the book *Diffusion of Innovation*—provides the following definition of diffusion:

> Diffusion is the process in which an innovation is communicated through certain channels over time among the members of a social system. It is a special type of communication, in that the messages are concerned with new ideas. Diffusion is a kind of social change, defined as the process by which alteration occurs in the structure and function of a social system. When new ideas are invented, diffused, adopted or rejected, leading to certain consequences, social change occurs. (Rogers, 2003, p. 6)

In his book, Rogers (2003) uses such examples as the QWERTY keyboard, Segway scooter, and the Internet to illustrate his diffusion theory.

Rogers also postulates that successful diffusion of products and ideas is reliant on four primary factors: innovation, communication channels, time, and social systems. The innovation is the item being diffused; it can be a physical item like a tool, a piece of software, or even art like movies and music. Communication channels refer to the availability of different methods to spread an idea, such as the availability of mass communication (e.g., radio, television, and the Internet) or reliance on more personal communication, such as word of mouth. Time plays several roles in the adoption of a new idea; successful diffusion is dependent on the time it takes a person to either decide to adopt or reject a product or idea. The social system that governs a population also holds significant sway over adoption rates; such as governments, organizational hierarchies, religion, etc., (Rogers, 2003).

While Rogers’ theory is useful as general background, this diffusion theory is not entirely appropriate for our setting for at least two reasons. First, Rogers’ model is meant to model technological diffusions or major innovations—and the way these are adopted may or may not be similar to the way new uniforms are adopted. Second, while it is clear from the data that the adoption rates of uniforms are not entirely command-driven, neither are those rates entirely consumer driven, either. Hence, even if technology adoption applied to uniform adoption, it might not apply to the adoption rate of new uniforms.

2. Bass Diffusion Model

The Bass Diffusion Model is a relevant and powerful model that has been widely used in the technology industry to forecast the rate in which new technology is adopted.

The basic assumption of the model is that “the timing of a consumer’s initial purchase is related to the number of previous buyers” (Bass, 1969, p. 215). Figure 6 shows the Bass formula. In this model, p represents the coefficient of innovation, q represents the coefficient imitation, t_i represents time since introduction, and $F(t_i)$ is the adoption rate. One weakness of the Bass model is its reliance on the q and p variables. These variables can often be hard to estimate and are reliant on historical data, estimates from similar products, or expert opinion.

Figure 6. Bass Diffusion Model.

$$F(t_i) = \frac{1 - e^{-(p+q)t_i}}{1 + \frac{q}{p} e^{-(p+q)t_i}}$$

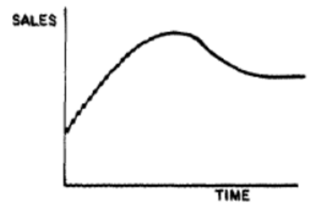
Source: Bass, F. M. (1969). A new product growth for model consumer durables. *Management Science, 15*(5), 215–227.

The Bass Diffusion Model is considered in this study when applying auto-regressive techniques for the selected Navy uniform demand curve, but not as a part of the validation process.

Like Bass, we are attempting to determine a general family of curve—a functional form, for the life-cycle demand curve. Unlike Bass, we do not proceed from a theoretical basis on what the curve “ought” to be; but rather, we will use a tool for symbolic regression to find a best-fitting curve family across multiple datasets.

Figure 7 shows Bass (1969) assumption for growth of a new product.

Figure 7. Bass Growth of a New Product Model.



Source: Bass, F. M. (1969). A new product growth for model consumer durables. *Management Science*, *15*(5), 215–227.

While researchers were unable to find any application of the Bass Model to a clothing or fashion item, Bass conducted further research that identified the "Generalized Bass Model." When applied in various areas, to specifically include forecasting, the Generalized Bass Model ultimately reduces to the original Bass Model (Mahajan, Eitan, & Bass, 1995).

Additional work included the study of the effectiveness of the model, even when it did not account for traditional economic variables, to include price (Bass, Krishnan, & Jain, 1994). This is an important consideration to this research as uniform price is not included in the model's variables either.

3. Modeling Considerations for Determining a Best Fit Curve

Several methods exist in attempting to create "best fit curves" or "smoothing" for statistical data. By fixing a curve to a dataset of points, a mathematical function is generated that best approximates the pattern of those points. The goal of the function is to predict future results of an independent variable through its interaction with a series of dependent variables. The nature of this interaction is subject to a number of factors, such as coefficient values and model form. Equation 1 provides a basic example of the relationship between independent and dependent variables. Here, *Y* represents the independent variable—the value to be forecasted—and the *x* variables represent the dependent variables, or the known factors.

$$Y = f(x_1, x_2, ...x_n) \tag{1}$$

The modeling technique to be used is subject to a number of factors including, but not limited to, degree of deviation desired, treatment of outliers, and nonnegativity constraints. Prior to applying a modeling technique, the analyst must carefully consider the appropriateness of the constraints; for example, can *Y* be a negative number? If not, a function that potentially allows negative numbers, such as linear regression, might not be a good choice. Another consideration for selecting a modeling technique may be variability in the data. Does the data to be analyzed contain outliers? If so, least squares may not be a good choice as it is highly sensitive to outliers.

The selected model can significantly affect forecasting results; therefore, extensive analysis must be performed in order to select the method that provides the greatest accuracy. That is not to say, however, that trial and error selections cannot be performed. In fact, experimenting with different modeling techniques is often recommended and can help discover a best fit model.

4. Forecasting Methods

The following is a brief summary of four different types of forecasting, including symbolic regression, which were used for this research.

a. Subjective Forecasting: Judgmental Forecasting

Judgmental forecasting is arguably the most common form of forecasting. With this method, the forecaster is relying on limited information, experience, or perhaps their "gut feeling" to set their forecasts. In a dynamic environment, human judgment is often relied on to detect change in the status quo and, once detected, determine the extent and impact of the change (Makridakis, Wheelwright, & Hyndman, 1998). Human judgment is often superior to objective models during times of rapid change, as most causal or econometric forecasting methods rely on relatively consistent patterns for their models to remain useful.

While often the only option, judgmental forecasting is subject to a number of biases. In their book, *Forecasting: Methods and Application,* Makridakis, Wheelwright, and Hyndman (1998) delineate 12 common judgment biases that frequently occur. Some examples include anchoring (i.e., extra weight given to initial information), conservatism (i.e., hesitant to change), optimism (i.e., wishful thinking), and selective perception (i.e., interpreting the problem based on personal background). To counter many of these biases, the authors suggest a statistical model be used in conjunction with human judgment. The use of a basic model can help reduce anchoring and validate the plausibility of the forecast estimate (Makridakis et al., 1998). Customer surveys, jury panels, sales force composites, and the Delphi method (where opinions are shared anonymously until consensus is achieved) are common subjective forecasting methods used in business. These methods spread the burden of the estimation across multiple experts, with the intent of reducing bias in the forecast.

b. Objective Forecasting: Causal (Econometric) Models

Causal models attempt to explain changes in an independent variable (e.g., regional sales) using a dependent variable, such as the average income for the region. The predominant form of causal forecasting is regression. The practice of regression involves fitting a curve to a data set while minimizing error; these curves can be either linear (simple regressions) or nonlinear (complex regression). With quality data that exhibits a consistent trend or pattern, regression can be an accurate and powerful tool with excellent predictive capabilities.

Regressive models do have their weaknesses, however, as they are dependent on consistent patterns for the model to remain valid. Significant shocks to the system, such as introduction of disruptive technology, can render existing models ineffectual. For example, the introduction of the personal computer eventually rendered all forecasting models for typewriters obsolete because consumer attitudes toward typewriters were fundamentally changed. Complexity can be another weakness for regression. As the number of dependent variables in the model increases, so does its complexity. In a market with quickly evolving trends, such as technology and consumer fashion, this complexity can make updating the model cumbersome; however, modern advancement in computing power has alleviated much of this issue.

c. Objective Forecasting: Time-Series

Time-series is another widely used method for forecasting. Common time-series forecasting methods include moving averages, weighted averages, and exponential smoothing. The advantages to time-series forecasting are that it is easy to use and widely understood. Drawbacks to time-series are the significant data requirements, limited range of future projection, and that it may lag behind trends. Time-series forecasts have a very limited forecasting range, which are often limited to just a few periods in the future.

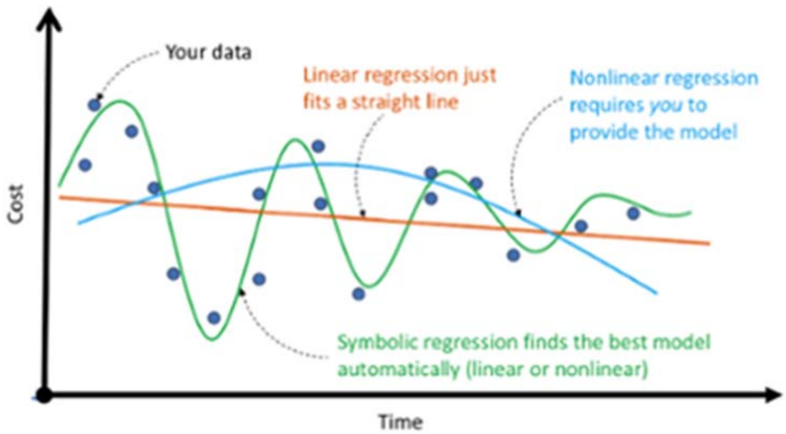
d. Eureqa and Symbolic Regression

Eureqa was initially developed in 2009 by Hod Lipson, a computer science professor at Cornell University and Michael Schmidt, at the time, a Cornell graduate student studying data science. In 2011, Eureqa was commercialized by Schmidt through his start-up, Nutonian, Inc. Branching out from its physical science and academic roots, Nutonian has begun marketing Eureqa toward businesses (Regalado, 2014).

According to venture capitalist and Nutonian investor Chris Lynch, "The Eureqa platform can identify and explain the causal relationships in big data, enabling customers to solve real-world problems where predictions alone do not suffice. In doing so, Nutonian brings the power of a team of data scientists to non-technical staff" (Burke, 2013, para. 2).

Eureqa uses a form of machine learning known as *symbolic regression*, which uses an evolutionary algorithm to progressively fit equations to a data set. Symbolic regression does not rely on the user to provide it with a model (i.e., linear) in advance (Lipson, 2013). Figure 8 provides a graphical representation of Eureqa's capabilities.

Figure 8. Different Types of Regression.



Source: Lipson, H. (2013, July 18). What is symbolic regression (and how does Eureqa use it?) [Blog post] Retrieved from http://blog.nutonian.com/bid/318620/what-is-symbolic-regression-and-how-does-eureqa-use-it

The regression is guided by a series of mathematical "building blocks" or mathematical operators, such as arithmetic, algebraic, or trigonometric, which are predefined by the user. Eureqa then applies these operators to the data set in search of a best fit. On his blog, Hod Lipson provides the following explanation of Eureqa and symbolic regression,

> We start with a bunch of simple, linear models. If these models fit perfectly, that's great. If they don't, we produce small variations to these models, and try again. These variations can include changing the form of the models adding, removing, and changing mathematical terms. We then keep testing—at a rate of 10 million equations per second—until we gradually converge. In test cases, we watched this simple algorithm find models that have taken human experts decades to discover. (Lipson, 2013, para. 3)

To our knowledge, this study is the first application of Eureqa to the problem of fitting a life-cycle demand curve for a nontechnological product.

5. Holding Costs and Recovery Rates

Holding costs are the costs associated with maintaining goods in inventory and are comprised of three primary components: cost of capital, cost of storage and handling, and cost of risk (Durlinger, 2012). Cost of capital includes financing costs for inventory procurement of manufacture, as well as opportunity costs of capital tied up in inventory. Cost of storage and handling includes any payroll, rent, utility costs, etc., directly associated with maintaining the inventory. Cost of risk includes insurance, theft, and write-downs associated with obsolescence (Durlinger, 2012). Holding costs for commercial enterprise widely range from 5%–45% depending on the type of inventory held (Durlinger, 2012).

The DLA does not publish a direct holding cost; DLA recoups inventory costs through Cost Recovery Rates (CRRs). In their FY16 Defense Working Capital Fund (DWCF) budget submission, the DLA provides the following definition of the CRR:

> The Cost Recovery Rate (CRR) is the amount added to the cost of an item to recover costs associated with purchasing and selling supplies to the customer. These costs include operating costs such as payroll, shipping, storage, accounting, and cataloging as well as recovery or return of prior year operating results and any necessary capital or cash surcharges. (Defense Finance and Accounting Services [DFAS], 2013, p. 72)

For FY15, the published CRR was 13.1%; the estimate for FY16 shows a slight increase in the CRR to 13.2%. Even with the DLA's CRR including costs not traditionally associated with holding costs, the DLA is able to maintain substantially low rates. This is primarily because DLA CRRs largely exclude cost of capital, in that the DLA does not finance its inventory nor calculate opportunity costs of foregone investment opportunities. The cost of risk does weigh heavily on the CRR; any write-downs associated with disposal for expired and obsolete material shows up as a capital or cash surcharge in DWCF operating results. These costs are recovered in future years through subsequent CRR adjustments (DFAS, 2014).

Like any cost, the DLA aims to reduce the impact of holding costs on its CRRs. To this end, DLA has launched an effort to reduce current and future inventories. According to then-DLA Director Vice Admiral (VADM) Mark Harnitchek,

> We do not do a very good job forecasting what our needs are. We buy way too much inventory that we don't use, and we keep it too long. . . . That has been a legacy problem as long as I've been in the logistics business. (Reece, 2012, p. 5)

Barry Christensen, chief of the DLA Logistics Operations’ Demand and Supply Planning Branch, provided further details on their efforts,

> Cleaning the attic is not the only focus of this effort. We need to reduce future excess inventories with better demand planning and collaboration with customers, and make improvements in our lead times internally and with our vendors. (Reece, 2012, p. 5)

Minimizing holding costs is a challenging endeavor; planners must carefully balance the cost savings associated with reduced inventories, with the potential ramifications of having inadequate inventory to meet customer needs. In order to achieve this balance, planners must have a clear understanding of future demand. For mature programs, this understanding is often gained through historic demand patterns. For new programs, however, access to reliable forecasting tools can aid in this endeavor.

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III. METHODOLOGY

A. NAVY UNIFORM ADOPTION MODEL: INITIAL ASSUMPTIONS

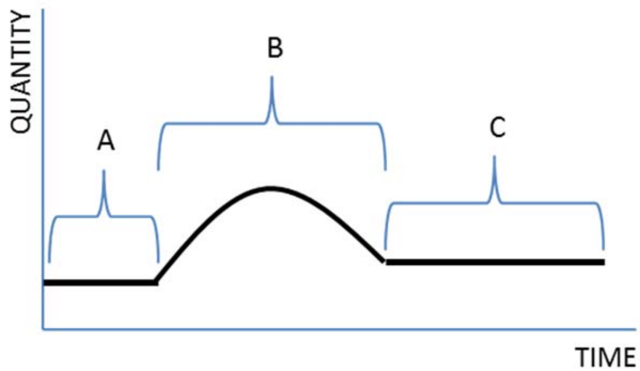
The introduction of a new Navy uniform program is subject to many elements addressed in the previous diffusion discussions. However, while uniform adoption faces constraints that most new products do not, such as compulsory ownership, consumer behavior does play a role in uniform diffusion rates. Since a large portion of new uniform distribution is accomplished through retail sales, sailors have some latitude in deciding when to purchase their uniforms and, if the allowance is greater than one, how many to purchase. Experience and retail sales data indicate that sailors often do not purchase to their prescribed allowance immediately, but purchase just enough to get by. There are enforcement systems in place, such as Seabag inspections, to ensure that sailors have their prescribed uniform allotments; however, these systems are not 100% effective.

In order to generate a Uniform Adoption Model within Eureqa, the authors had to make some determinations regarding the input variables. Initial analysis of demand history for both the NWU Type I and the SU indicated that product demand at any time (D_t) is partially explained by three variables: the size of the consumer population—manpower (*m*), the amount of time that has passed since the new uniform was introduced (*t*), and the quantity that each sailor is required to own—allowance (*a*). Equation 2 displays this premise in a basic formula. This model maintains some similarity to the Bass model, where the variables *m* and *a* together represent the total market potential for uniform sales.

$$\mathrm{D}_t = f(m, t, a) \tag{2}$$

Additionally, the researchers believe that uniform diffusion follows a relatively consistent pattern across uniforms of similar type. The researchers' assumption and description for a Fleet-wide uniform program is shown in Figure 9. This model assumes a nonoptional, Fleet-wide (i.e., not community specific) uniform that is available for retail purchase via the NEXs and, depending on the uniform, other third-party vendors. Typically, new uniforms replace existing uniform programs. When a new uniform replaces a previous version, a "cut-off" date is mandated by OPNAV N1, citing the last day on which the legacy uniform can be worn and service members must transition to the new uniform. Typically, there is an overlap period between when the new uniform is made available for purchase and the prescribed "cut-off" date. This period allows for an orderly transition and its length varies depending on the size of the uniform program.

Figure 9. Assumption for Basic Uniform Diffusion Curve.



Segment A of Figure 9 indicates the initial period following introduction of the new uniform into retail outlets. Unit demand for this period is typically low due to service member hesitancy to spend money on a new uniform for which they may already own the previous version. Segment B of Figure 9 shows the increased demand for the new item as the "cut-off" date approaches and sailors begin to adopt the new uniform more rapidly. Segment C of Figure 9 represents the tapering off and recurring demand for the uniform after the "cut-off" date has passed. This segment largely represents typical wear-and-tear replacement of the uniform items. When a uniform is eventually cancelled or replaced, a Segment D would follow. Segment D would likely realize significantly diminished demand. Knowing the current uniform is going to be phased out, sailors will buy the bare minimum necessary to get by until the new uniform is available for purchase. The uniforms studied for this project remain programs of record; as a result, the effects of a "cut-off" on tail-end demand were not studied.

B. DATA COLLECTION AND PREPARATION

In order to develop a Navy Uniform Adoption model for use by the NEXCOM UPMO, values for each of the variables contained within the basic function stated previously in Equation 2 had to be entered into Eureqa. The variables t and a are stated values. For m and D, sizeable amounts of data had to be collected to estimate them. For this analysis, two primary data types had to be collected: historic demand data (D) and manpower data (m). Sections 1 and 2 describe the data collection and preparation processes used for this analysis.

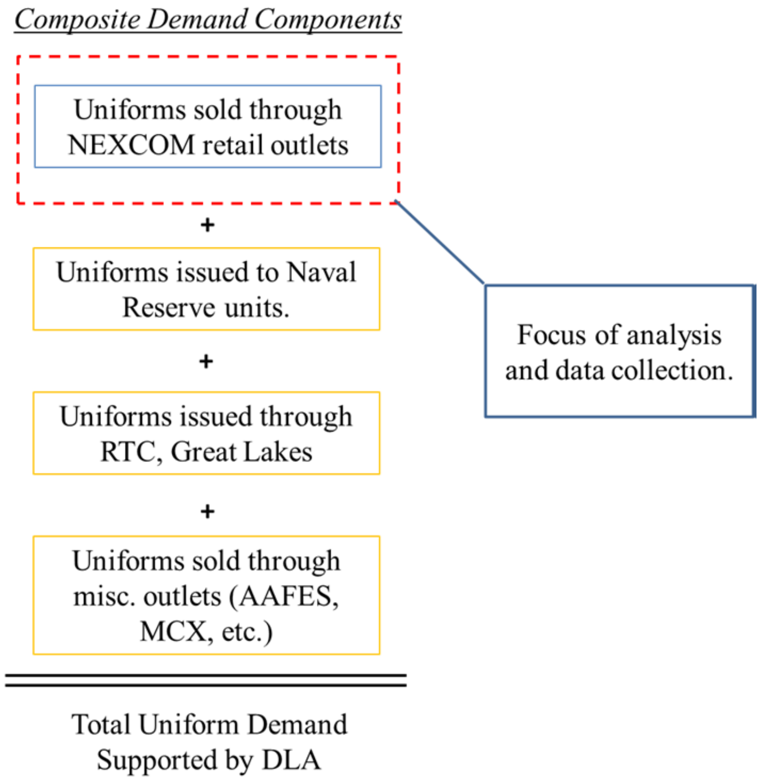
1. Demand Data

The following provides a synopsis of how the demand data was collected for this research, its initial evaluation, and how the data was combined to perform analysis.

a. Demand Data Collection

As shown in Figure 10, total demand for a major uniform program is a composite demand generated by several sources: NEXCOM retail outlets, RTC Great Lakes, NRF, and “Other.” The Other category is comprised of outlets such as the Army and Air Force Exchange Service and Marine Corps Exchanges, which typically cater to Navy personnel at joint activities; this category makes up a very small share of total demand. When submitting an initial fielding plan, the NEXCOM UPMO includes forecast information for the NEXCOM retail outlets, RTC Great Lakes, and NRF. Since both the RTC and the NRF issue their uniforms directly to sailors, many of the consumer behavior that make forecasting difficult are not present, so forecasting demand through these channels relatively straightforward. The consumer behavior of active Fleet sailors, who are expected to purchase the new uniform through NEXCOM retail outlets, has proven somewhat inconsistent with prescribed policy (buying to allowance, periodic replacement, etc.). This area of demand is the focus of the research.

Figure 10. Composite Demand Model for Major Uniform Programs.



Since the focus of the analysis centers around uniform adoption and demand for active Fleet sailors, the researchers collected monthly sales data for the NWU Type I and E1–E6 SUs that were sold through NEXCOM retail outlets. As previously discussed, both of these uniforms are comprised of several components; however, some of these components, such as belts, boots, and undershirts, can be used with more than one uniform. Additionally, items like boots and shoes are available in more than one style, which makes correlating the demand for these uniforms to the demand for the primary uniform difficult. Therefore, this study concentrated on the demand history for the prime uniform items. In this case, the prime uniform items were the components exclusive to the uniforms under analysis and comprise most of the cost. The demand for the accessory items are calculated as a derivative of the prime uniform components. Table 4 itemizes the uniform components considered to be prime uniform clothing articles for this study.

Table 4. List of Prime Uniform Components Used for Analysis.

NWU Type I
Navy NWU Trouser
Navy NWU Blouse
E1–E6 Service Uniform
Navy Women’s SU Khaki Over-Blouse
Navy Women’s SU Slack
Navy SU Men’s Khaki Shirt (Classic Fit)
Navy SU Men’s Khaki Shirt (Athletic Fit)
Navy SU Men’s Trousers (Classic Fit)
Navy SU Men’s Trousers (Athletic Fit)

During submission of the SRP, the NEXCOM UPMO’s responsibility is to provide aggregated demand estimates, while specific sizing distributions are set by the DLA C&T through their size tariffs. As such, the demand history requested and received from the NEXCOM was aggregated by uniform component and was not broken down by size. Since the NWU Type I is a gender-neutral uniform, the aggregated data provided was only categorized by blouses and trousers. Since the SU is not a gender neutral uniform, data was provided by each fit type available for sale. The researchers combined the monthly sales data for each fit type to reduce SU components down to blouses and trousers similar to the NWU Type I.

b. Initial Data Review

Both the NWU Type I and the SU were released to the Fleet in FY08; however, their releases were staggered. The NWU Type I followed the SU by a few months. In order to conduct an appropriate analysis, the monthly demand figures for each of the uniforms were normalized into sequential months since inception. For both uniforms, the review covered the first six years (72 months) of the uniform. This provided a large enough range for each program from roll out and transition into maturity.

Once the data sets were normalized for time, they were segmented into four sections in order to conduct a search for outliers. Since these were both trending data sets, an outlier analysis on the whole data set provided poor feedback. The data trends for both uniforms were consistent enough that it allowed for each data set to be segmented in the same manner. Each data set was segmented into an upswing, downswing, transition, and maturity phase. These segments were chosen based on observations; the dividing lines between the segments were chosen based on a review of the data. They represent the inflection points where the demand trend begins to shift. Figures 11 and 12 show the results of the box chart analysis for both uniforms. Both data sets exhibited significantly more variability in the initial phase, with variability reducing steadily as the program matured. The long tails on the box chart for the upswing phases indicated potential outliers in that portion of the data set. A review of the raw data showed the first few months of data returned sales of just a few dozen vice the tens of thousands that were occurring shortly thereafter. When the data sets were loaded into Eureqa for initial test runs, Eureqa's internal data preparation tool also indicated the outliers. As a result, the first three months of NWU Type I and the first month of SU data were excluded from the reviewed data set; the results can be seen in the modified upswing box charts in Figures 11 and 12.[2] Once these data points were removed, Eureqa no longer detected outliers. While this process simplified modeling, it was not without its detractions. Although these initial data points were far lower than the demand levels that occurred just a few months later, those points still represented realized demand. Models generated without these data points do not capture these initial demand levels and essentially model demand from the point where full Fleet demand begins to pick up.

[2] The dividing line between the purple and gold boxes represents the median observation within the given distribution segment for the NWU Type I. The gold box represents the spread in observations between the 25th percentile and the median; the purple represents the median to 75th percentile. The two tails represent the spread between the minimum and maximum observations.

Figure 11. NWU Type I Demand Variability Analysis.

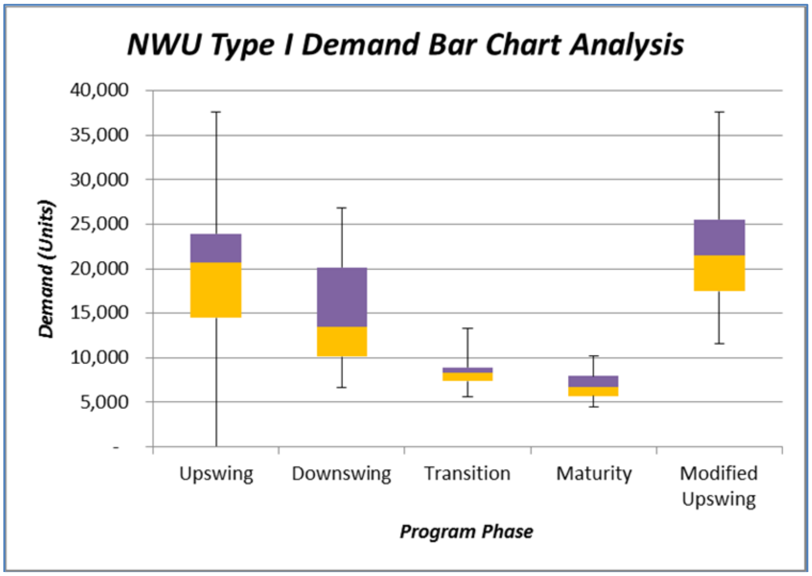
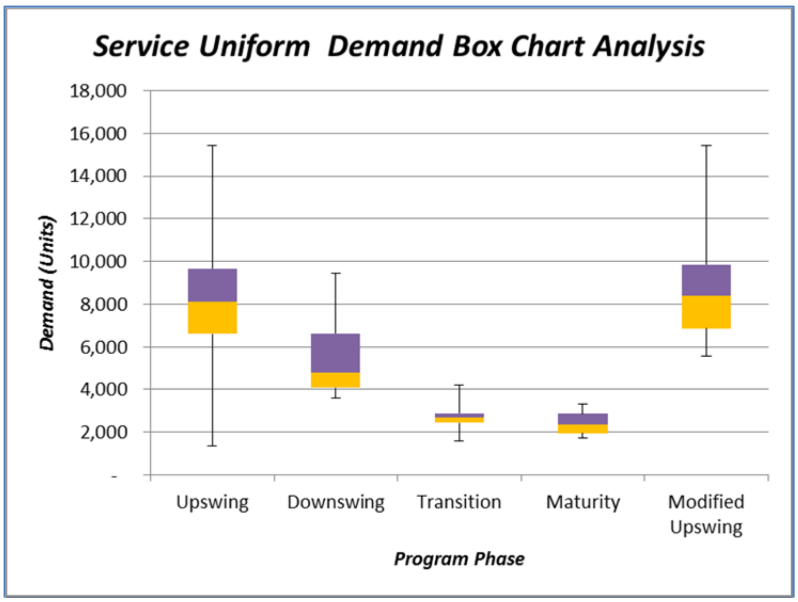


Figure 12. Service Uniform Demand Variability Analysis.



c. Defining a Uniform Set

One of the efforts underway at the NEXCOM UPMO is to treat uniforms as a complete system or set. An analysis of the demand data revealed that there is no clear cut method to define a uniform set, due largely to some divergence in the demand patterns between uniform components. The detailed analysis of this process is available in

Appendix A. Any considerations or limitations of using this method are addressed in Chapter V.

2. Manpower Data

The following provides a synopsis of how the manpower data was collected for this research, its initial evaluation, and how the data was combined to perform analysis.

a. Manpower Data Collection

Multiple sources were used to collect manpower for this research. This section briefly describes those sources and subsequent preparation and normalization of that data in order to perform the analysis.

(1) Active Duty Manpower

The active duty manpower data for this project was obtained from the Defense Manpower Data Center (DMDC), which falls under the Office of the Under Secretary of Defense for Personnel and Readiness (OUSD P&R). Each of the armed services is required to submit total active duty manpower levels to the DMDC. The DMDC publishes this data in several formats for use by manpower analysts. The DMDC’s *Active Duty Military Personnel by Service by Rank & Grade* report was used as the source for our manpower data. The DMDC website provided historical data dating back to FY98. For this analysis, the researchers collected data from FY08 to the present, which spans the product life cycles of the uniforms that are the focus of the analysis.

The manpower reports were provided by the DMDC in portable document format (PDF), which is cumbersome for analytic purposes. To streamline the collection process, these reports were converted into Microsoft Excel format and stripped of data pertaining to non-Navy services. The manpower data was then combined into a master data spreadsheet, where it could be easily normalized and prepared for use in Eureqa.

(2) Recruit Accessions Data

The accessions data for this analysis came directly from the OUSD P&R *Defense Manpower Requirements Report* (DMRR). This report provides detailed information regarding expected future accessions, as well as actual accessions results from previous fiscal years. The OUSD P&R website allows access to historical reports back through FY00. The accessions data used for this project was sourced from the "general accessions" category in the *Navy Active Duty Officer* and *Navy Active Duty Enlisted Gains and Losses* tables from the DMRR. For this analysis, the researchers collected DMRR data spanning FY08 until present.

Similar to the reports provided by the DMDC, the DMRR was also provided as a PDF. To streamline the data analysis, nonpertinent data was stripped from the file and saved for conversion. Each DMRR was converted to Microsoft Excel and the data added to the combined master spreadsheet.

(3) Combined Manpower Data

Once converted and added to the combined master spreadsheet, the manpower data was then sorted into demographic categories necessary to support further analysis. The DMDC reports do not provide female demographics in each report; however, the DMDC had annual female manpower reports available on their website. The researchers used the annual female manpower data to determine the female proportion of total manpower and applied it to the data set to estimate monthly female manpower levels. An example of the demographic breakdown used for this project can be seen in Table 15 in Appendix C; these demographics were tabulated for FY08 through FY15.

b. Manpower Data Analysis

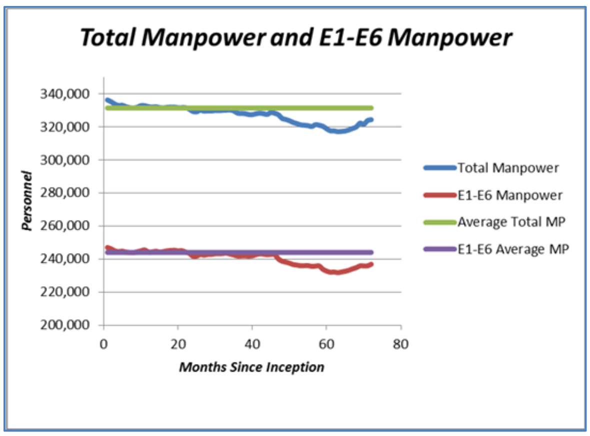
An initial review of the manpower data indicates minor year-over-year trends in total manpower; however, intra-year manpower appears quite stable. As seen in Table 5, the coefficient of variation for total manpower does not exceed 1% in any of the years included in the analysis, which supports the stable manpower hypothesis. Table 5 also demonstrates a slight increase in females as a proportion of total manpower as well as a consistent proportion for junior enlisted (E1–E6) across the data set. Figure 13 provides a graphical representation of total manpower trends across the period of analysis.

Table 5. Total Manpower Data Analysis.

	Mean	Standard Deviation	Coefficient of Variation	Female Percentage	E1–E6 Percentage
FY08	**332,979**	**1,445**	**0.43%**	**15.05%**	**73.54%**
FY09	**331,477**	**771**	**0.23%**	**15.50%**	**73.64%**
FY10	**329,652**	**524**	**0.16%**	**16.01%**	**73.46%**
FY11	**327,653**	**889**	**0.27%**	**16.42%**	**73.72%**
FY12	**321,430**	**1,555**	**0.48%**	**16.64%**	**73.39%**
FY13	**319,648**	**2,544**	**0.80%**	**17.56%**	**73.06%**
FY14	**324,088**	**889**	**0.27%**	**17.90%**	**73.11%**
FY15*	**325,651**	**540**	**0.17%**	**18.10%**	**72.83%**

*FY15 is not a complete year; it includes June 2015 through October 2015.

Figure 13. Total Manpower and Junior Enlisted Manpower Trend, FY08 through FY15.



Since the goal of a resultant model is to forecast future demand, out-year manpower estimates would be used for the input variable *m*. This data is often only available as annual estimates and for the next few years. In order to provide a model consistent with data that would be readily available to forecasters, the manpower data pertaining to the first three years of the uniform programs was averaged to create a single input variable. For total manpower m_{Total} = 331,369 and for E1–E6 manpower $m_{E1\text{-}E6}$ = 291,758; these results can also be seen in Figure 13. Due to the stability of the manpower data, the impact of this process to the final model should be minimal.

c. Uniform Purchasing Population—Adjusting for Accessions

With the primary focus of analysis aimed at uniforms sold through NEXCOM channels, it was necessary to normalize manpower into an appropriate "uniform purchasing population." This normalization process is aimed at excluding personnel that would otherwise be getting their uniforms from another source, such as direct issue via the accessions process. In order to establish the uniform purchasing population, the researchers adjusted total manpower for accessions, as well as scaled manpower according to the uniform program being analyzed. As a result of this process, two baseline uniform purchasing populations were established: Total Adjusted Manpower and E1–E6 Adjusted Manpower. The Total Adjusted Manpower would be used for the NWU Type I, while the Adjusted Manpower would be used for the SU. These categories could be further separated into male and female categories, as necessary, for use in Eureqa. Table 6 displays the DMRR sourced accessions data used for this process.

Table 6. FY08 through FY10 DMRR Accessions Data.

	FY08	FY09	FY10
Officer	2,932	2,861	3,082
Enlisted	38,244	35,506	36,208
Total	41,176	38,367	39,290
Female	6,198	5,945	6,288
Male	34,978	32,422	33,002

For the adjustment process, the annual accessions data for the first three years were averaged in the same manner as the manpower data. The accessions data were then deducted from the appropriate manpower category to create the uniform purchasing populations. This adjustment method is consistent with methods currently in use by the NEXCOM UPMO for fielding plan generation, so that it can be easily replicated in future use of the model. After adjusting for accessions, total manpower $m_{Total\text{-}Adj.}$ = 244,007 and E1–E6 manpower $m_{E1\text{-}E6\ Adj.}$ = 206,327. These would be the manpower values used for all subsequent analysis.

C. EUREQA-BASED VERIFICATION OF DEMAND PATTERN SIMILARITY

Prior to running the full analysis on both the NWU Type I and SU data sets, further validation of the similarity between the two demand patterns was necessary. In order to perform this validation, a pair of Eureqa searches was conducted; the first on the NWU Type I data set and the second on the SU data set. The resultant models were then tested against the demand history for the opposite uniform. For example, the model generated using NWU Type I data was tested against the SU demand history.

This evaluation was conducted using the statistical goodness of fit measures—coefficient of determination (R^2) and mean absolute percentage error (MAPE). If R^2 exceeded 65% and the MAPE was below 20% for both tests; it was determined that each of the data sets adequately explained one another enough to further pursue a universal Navy Uniform Adoption model. The statistical thresholds for this validation are much lower than the criteria explained in Section E; these lower thresholds were necessary due to some differences in how the data was prepared for these model searches. A detailed account of this process and the results of this analysis are available in Appendix D.

D. EUREQA MODELING PARAMETERS

The following section addresses the normalization of data required prior to use in Eureqa's symbolic regression calculations. This section also addresses how the variables and target expression were defined.

1. Normalizing Data for Use in Eureqa

Prior to entering the data sets into Eureqa for modeling and analysis, further normalization was required; in this case, the normalization was performed to control for the differing scales between manpower and demand—demand was in the tens of thousands, while manpower was in the hundreds of thousands. According to the *Eureqa Desktop User's Guide*:

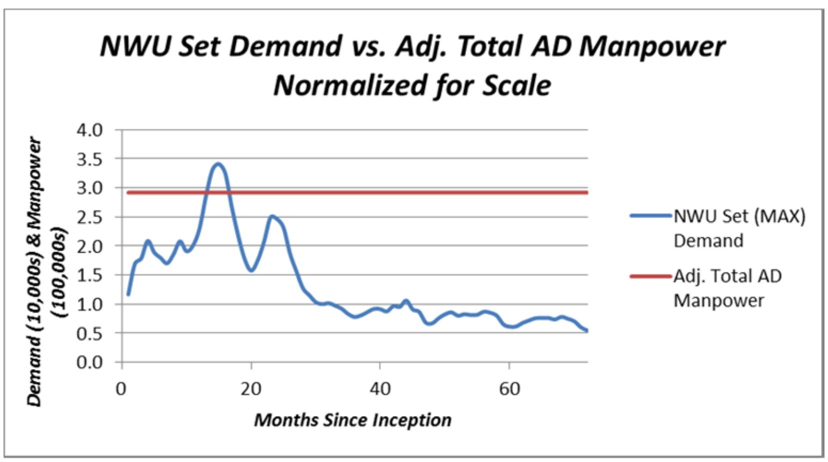
> Eureqa works best when all variables in your data have small to medium magnitudes, on the order of 1 to 100. For example, if you have variables

that range over a million, it would be best to rescale the values to larger units. (Eureqa Desktop User's Guide, n.d., section 4)

When data is entered into Eureqa, the program is unaware what each data set represents; therefore, the program treats each data set equally and does not automatically adjust for scale. If two data sets have either a significant offset or scale difference between them, it can have a "flattening" effect on the data set with the smaller values.

To control for the flattening effect, both the demand and manpower data sets were adjusted to a common scale; demand was divided by 10,000 and manpower by 100,000. After adjusting for scale, where D_t = 10,000 uniforms demand and m = 100,000 sailors, both the demand variable D_t and the manpower variable m fell within the optimal range for modeling of 1 to 100. Figure 14 displays the results of the normalization process. After normalizing for scale, the variations and trends in demand are now much more pronounced.

Figure 14. NWU Type I Set Demand and Adjusted Total Active Duty Manpower Normalized for Scale.



2. Defining the Target Expression, Variables, and Building Blocks

Using Eureqa, two basic target expressions for the demand model were evaluated; the first was $D_t = (m, t, a)$, where the dependent variable D represents monthly demand for a given uniform set. For the independent variables, m represents manpower; t represents months since uniform program inception; and, finally, a represents the established individual uniform allowance. A second, simpler expression was also evaluated: $D_t = (b, t)$, where $b = (m \times a)$ or total market potential for uniform purchases. The purpose of this second evaluation was to see if Eureqa would produce a model that uses fewer terms without sacrificing much accuracy. The desire for this evaluation was also prompted by the results from preliminary model searches; many of the top performing models only presented *m* and *a* as an interactive term ($m \times a$).

When setting the target expression in Eureqa, it is possible to be very explicit in defining what the target expression should look like. This is useful when attempting to fit coefficients to a known distribution shape, or when the modeler is confident in what the resulting model should look like. For this analysis, the target expressions were kept generic; this gave Eureqa the latitude to discover which formulas would most efficiently explain the relationships between the variables.

After setting the target expression and defining the variables, the model's "building blocks" must be selected. In Eureqa, building blocks are the various mathematical operators that it is allowed to use during the search. The available building blocks range from basic arithmetic to inverse trigonometric function. Following is a list of the building blocks used during the various model searches.

- **Basic building blocks:** Constant, input variable, addition, subtraction, multiplication, division
- **Exponential building blocks:** Exponential, natural logarithm, power, square root

Separate search runs were conducted for each target expression, both including and excluding the exponential building blocks, with the purpose of testing Eureqa's ability to discover simpler models that do not greatly sacrifice accuracy. A more parsimonious model would be easier to understand, easier to evaluate, and would more likely be put into practice for fielding plan development. Also, with simpler models, it would be easier to see the effects that a change in input variables would have on demand than if the model were very complex.

3. Defining and Entering the Data Sets

During preliminary test runs of Eureqa, where only single data sets (one uniform type) were used, the program consistently ignored two of the three independent variables—*m* and *a*. Eureqa would return results using only *t* to explain the dependent variable *D*. A search of Nutonian's Eureqa support forums yielded the following likely explanation:

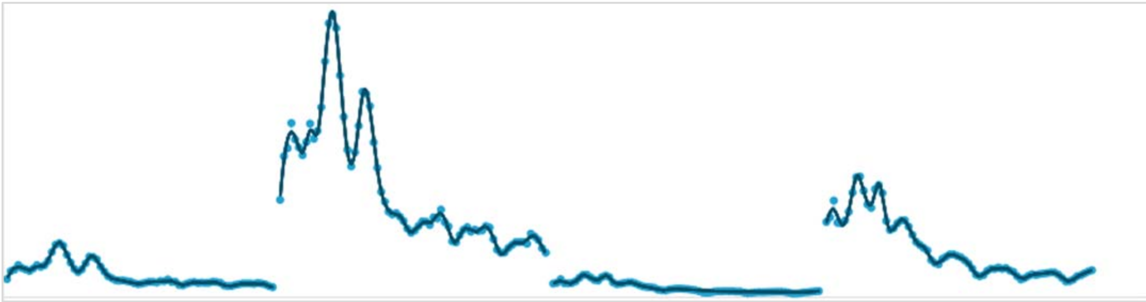
> Eureqa only uses variables with the greatest impact on the target variable. Some reasons you're only seeing one variable show up in your models might indicate that changes in only that variable have a measurable effect on your target variable. (Nutonian, 2015, para. 1)

To work around this issue[3] and speed modeling, some changes were made to the means in which data was entered into Eureqa. Since Eureqa has the capability to search and evaluate multiple data sets against a common target expression, the data was entered as four separate sets, as described below.

Presenting the data in a manner that prompted Eureqa to account for the variable *a* was straightforward; since the NWU Type I and the SU had different assigned individual uniform allowances, both data sets were entered into Eureqa. Eureqa would then associate shifts in demand with changes to *a*. When the model search involved both uniforms types, this would also solve the issue with *m*, since each uniform had different manpower levels associated with them. There were instances, however, where each uniform needed to be evaluated separately. To account for this, demand for both the NWU Type I and the SU were split using the male and female manpower ratios calculated previously. Additionally, by splitting the data in this manner, Eureqa was able to recognize that *m* can change independent of *a*; and that a change in *m* would result in a change in demand. This gave us four data sets, which can be seen in Figure 15. These data sets were subsequently matched to their associated independent variables. The manpower data set can be seen in Figure 16.

[3] Eureqa does contain a forcing function, which requires Eureqa to use the omitted variables. However, the syntax required updating each time the target expression was reset between searches. This was a time-consuming process, as the forcing function had to be manually typed in the expression field and often required minor debugging to get Eureqa to accept it.

Figure 15. Split Demand Data Sets as Seen in Eureqa Data Preview Window.



From left to right: NWU Type I Female Demand; NWU Type I Male Demand; SU Female Demand; and SU Male Demand.

Figure 16. Split Manpower Data Sets as Seen in Eureqa Data Preview Window.

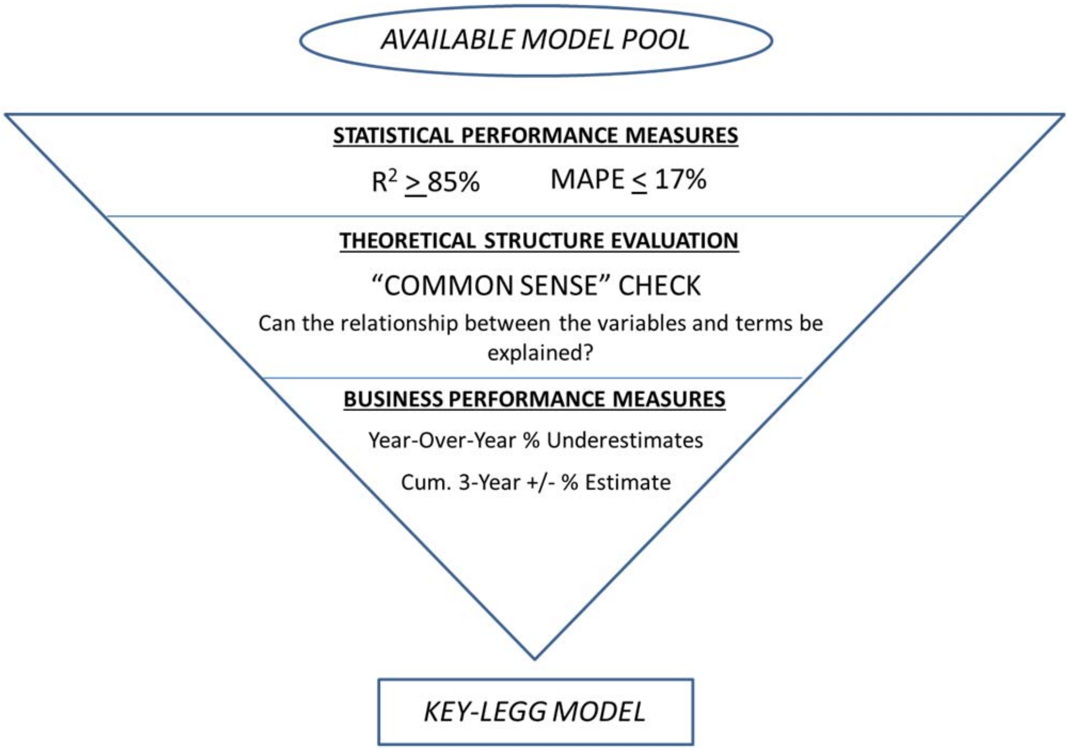
From left to right: Adjusted Total Female Manpower; Adjusted Total Male Manpower; Adjusted E1–E6 Female Manpower; and Adjusted E1–E6 Male Manpower.

By separating the data sets in this manner, Eureqa was able to associate scale changes in both *m* and *a*, with subsequent changes in the dependent variable *D*. The data for variable *t* did not require any additional adjustments, as *t* is a sequential linear representation of time, or months since inception. This data was simply repeated for each data set.

E. EVALUATION CRITERIA SELECTION

In order to evaluate and select a best-performing adoption model, a three-stage approach was used. The first stage involved an initial model evaluation using a series of statistical performance measures. The second stage provided a theoretical review of the model structure for each remaining model; the purpose of this review was to validate each model to ensure that it behaved consistently with historic observations. The third selection phase evaluated the remaining models against a series of business performance criteria to ultimately select the best-performing model. Figure 17 illustrates the process.

Figure 17. Three-Stage Selection Approach.



1. Statistical Performance Measures

Initial evaluation for the resultant models was conducted using two statistical performance measures. The Coefficient of Determination (R^2) and Mean Absolute Percentage Error (MAPE). R^2 and MAPE are two well-established, goodness-of-fit measures used in regression analysis. MAPE was chosen over other popular measures because it accounts for differences in scale—this makes comparing the results against the NWU Type I and the SU easier. First-pass model elimination was conducted using an R^2 greater than or equal to 85% and a MAPE less than or equal to 17%. Any models that failed to meet both these minimum performance standards were eliminated from further consideration. The R^2 and MAPE thresholds were determined based on observations made during preliminary model searches. The researchers noted that during most of these early searches, Eureqa would return results that met these thresholds. If necessary, second-pass model elimination was to be conducted using a Pareto method; only the best-performing methods would be analyzed further.

2. Theoretical Structure Evaluation

Once the model candidates were narrowed down, based on statistical performance, the remaining models were reviewed on a theoretical basis. The purpose of this review was to perform a “common sense” check to ensure that each term and variable behaved in an expected manner. While very sophisticated, Eureqa does not explain the relationship between the variables and terms; it only discovers them. As a result, Eureqa can return models that fit demand patterns with incredible accuracy, yet uses variables in a manner inconsistent with experience-based observations. Additionally, during preliminary model searches, Eureqa would, in fact, generate some extremely complex models; while accurate, these models were difficult to understand and test. To perform the theoretical structure evaluation, each remaining model was broken down to its component terms. Each term was individually graphed in order to review its contribution to the forecast model. Any models containing questionable terms contrary to experienced based observations would be eliminated from further consideration.

3. Business Performance Measures

After the statistical and the theoretical evaluations were completed, the remaining models were evaluated using two business performance criteria: year-over-year forecast under-estimate—a measure of stockout exposure, and cumulative percent overestimate for the first 36 months—a measure of potential for systemic oversupply of uniforms. For each Eureqa-generated forecast model, these measures were calculated for both the NWU Type I and the SU. Final model selection was conducted by evaluating each model’s relative performance using a Pareto method; the model that performed the best in most categories would be selected as the best model.

a. Year-Over-Year Percent Underestimates

As previously discussed, for any given uniform program, the shortage costs associated with stockout can be high, yet difficult to measure. In most cases, common stockout occurrences can significantly outweigh the holding costs for additional inventory. Since actual shortage costs are unknown, cost-benefit calculations would have relied on many assumptions. Instead of making financial assumptions, the models were evaluated based on their exposure to underestimated forecasts. For each year in the data range, the percentage in which the forecast was over or underestimated was calculated. The years in which an underestimate occurred were then isolated. These values were then evaluated using the Pareto method mentioned above. If both models perform equally well using this method, the model that performs the best earlier in the date range would be selected as the winner. Additional weight was given to early performance because, at this stage, sailors are still trying to purchase their initial allotment. Any significant underestimates early in the data range may lead to shortages that would preclude sailors from complying with uniform requirements.

b. Cumulative Percent Overestimate First 36 Months

The Coefficient of Determination, MAPE, and Year-Over-Year measurements evaluated the performance of each forecast model over the full range of their respective data sets. However, since one of the primary uses of these forecast models is to forecast demand for new programs, a premium was placed on initial accuracy. Significant forecast inaccuracies at this stage cannot be easily overcome, since procurement contracts are typically firm. Additionally, any significant overestimates early in the program could result in systemic oversupply for certain uniform components throughout the duration of the program.

Considering that the greatest risk for developing systemic over inventory due to forecasting errors occurs early in the program, a performance measure was devised to gauge performance during the initial roll-out phase. A review of historic uniform demand data analyzed for this project revealed that the projects begin transitioning into maturity—stable recurring demand—around three years after introduction.

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IV. ANALYSIS

A. EUREQA RESULTS: MODEL DESELECTION

The following section details the results of the Eureqa symbolic regression calculations and the subsequent application of the evaluation criteria described in Chapter III. Each subsection below outlines the separate applications of the three selection criteria phases described in the Three-Stage Selection Approach in Chapter III.

1. Establishing the Candidate Pool

In order to accommodate all of the modeling parameters, eight separate Eureqa searches were conducted. Upon completion of the model searches, the top eight models (as suggested by Eureqa) from each search were selected and added to the candidate pool for further analysis; this resulted in 64 candidate models in the base pool. Table 7 lists the various model searches conducted and parameters of the search. In addition to testing models with or without exponential operators, as discussed in Chapter III, model searches using extra data smoothing were also completed. For these searches, the data smoothing function in Eureqa was boosted to 30%; at that point, most of the peaks and valleys in the data were smoothed out. The purpose of these searches was to see if smoother data would affect resultant model complexity and accuracy.

Table 7. List of Eureqa Model Searches Conducted by Type.

Formula Evaluated	Search Parameters
D = (m,t,a)	Exponential Operators Allowed—No Extra Smoothing Applied (NSE)
D = (m,t,a)	Exponential Operators Allowed—Extra Smoothing Applied (SE)
D = (m,t,a)	No Exponential Operators Allowed—No Extra Smoothing Applied (NSNE)
D = (m,t,a)	No Exponential Operators Allowed—Extra Smoothing Applied (SNE)
D = (b,t)	Exponential Operators Allowed—No Extra Smoothing Applied (NSE)
D = (b,t)	Exponential Operators Allowed—Extra Smoothing Applied (SE)
D = (b,t)	No Exponential Operators Allowed—No Extra Smoothing Applied (NSNE)
D = (b,t)	No Exponential Operators Allowed—Extra Smoothing Applied (SNE)

2. Model Deselection Phase One: Statistical Performance

After identifying the pool of 64 potential candidates, forecasted values for each model had to be generated in order to calculate the statistical performance of each model. The program contains a function to generate and plot forecasted values using the originally modeled data set. This function was performed individually for all 64 model candidates. The generated forecast values were then exported into Excel spreadsheets for further analysis.

Once the pool of candidates was consolidated into spreadsheets, a template was developed and applied to each of the 64 forecasts, which quickly calculated R^2 and MAPE for each of the candidates. These results were further consolidated into a summary table for evaluation and application of the statistical performance criteria—an R^2 of at least 85% and a MAPE of no more than 17%.

Of the 64 candidates, 5 models met the statistical performance criteria for both the NWU and SU. Table 8 lists these models and Table 9 provides greater detail on their specific statistical performance. These five models comprise the candidate pool considered for the next stage of analysis. All five of the remaining candidates were generated using the same search parameters; no additional smoothing applied and no exponential operators allowed.

For Tables 8 and 9, NSNE denotes the search method that was used to generate the result—No Additional Smoothing and No Exponential Operators Applied. The resulting formulas were further identified using an "M" or "B"; the M formulas denote searches using the form $D_t = f(m,t,a)$, while B denotes searches using the form, $D_t = (b,a)$. The final number is a simple serial number used to identify that specific model.

Table 8. Remaining Models After Application of Statistical Criteria.

Formula ID	Resultant Formula
NSNE M2	$D = 0.0532ma + \frac{64.1m}{292 + t^2 - 22.2t - 1.66at}$
NSNE M3	$D = 0.01 + 0.0525ma + \frac{59.2m}{284 + t^2 - 22.1t - 1.67at}$
NSNE M4	$D = 0.00561a + 0.0050ma + \frac{61.2m}{288 + t^2 - 21.6t - 1.83at}$
NSNE M6	$D = 0.0057a + 0.0505ma + \frac{61.2m}{288 + t^2 - 21.6t - 1.83at} - 0.000709$
NSNE M8	$D = 0.0057a + \frac{-0.000288}{m} + 0.0505ma + \frac{61.2m}{288 + t^2 - 21.6t - 1.83at}$

Table 9. Statistical Performance of the Top Five Models.

Formula ID	NWU R^2	SU R^2	NWU MAPE	SU MAPE
NSNE M2	85.66%	91.99%	13.58%	13.09%
NSNE M3	85.42%	91.84%	13.45%	13.39%
NSNE M4	85.58%	91.78%	13.59%	13.12%
NSNE M6	85.57%	91.77%	13.59%	13.07%
NSNE M8	85.58%	91.78%	13.60%	13.09%

3. Model De-Selection Phase Two: Theoretical Structure Analysis

To perform the review of each model's theoretical structure, the remaining candidates were broken down into their component terms. Each of the terms was subsequently graphed in order to view their behavior and contribution to the overall model. A review of Table 8 reveals that each of the remaining model candidates used a common denominator form, as seen in Equation 3. In the following equations, characters in red indicate the constants.

$$Denominator = A + t^2 - Bt - Cat \tag{3}$$

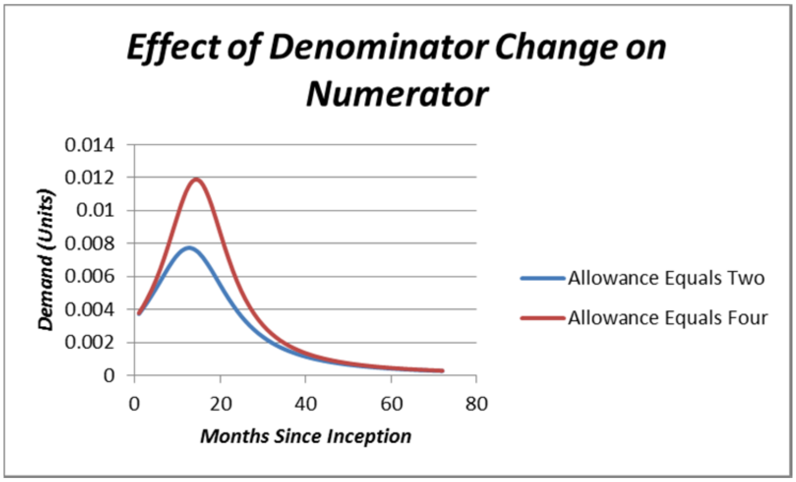
The value of the constants *A* through *C* varies slightly between the models, but variable usage does not. The shape of this denominator plays an important role in defining the shape of the overall adoption model and will be discussed first.

a. Common Denominator

The denominator gives each of the models their distinctive shape and is dominated by the variable *t*—time, which makes it primarily responsible for the distribution shape. Since reaction to mandatory uniform adoption dates was determined to be a major driver of customer behavior, it seems appropriate that the variable *t* is the primary driver of the distribution shape. Early in distribution, the t^2 term is overpowered by the ***B****t* and ***C****at* terms; at this point, the initial portion of the curve is heading downward. Eventually, the t^2 term overpowers the remaining terms and the curve begins to increase rapidly.

In addition to the variable *t*, the variable *a* is also present in the denominator. At first glance, it appears that an allowance change would have a subtle effect on the shape on the models outcome. When the inverse of the denominator is graphed, however, the effects become clear. This phenomenon can be seen prominently in Figure 18; when the allowance is increased from two to four, peak demand increases significantly. At the point in the demand distribution where peak demand occurs, most sailors are still working on purchasing their initial complement of uniforms. It makes sense that an increase in prescribed allowance would result in increased peak demand.

Figure 18. The Effect on the Numerator Given a Change in Allowance.



For this analysis, the numerator was set to 1 for both curves in order to isolate the effects of changing the allowance.

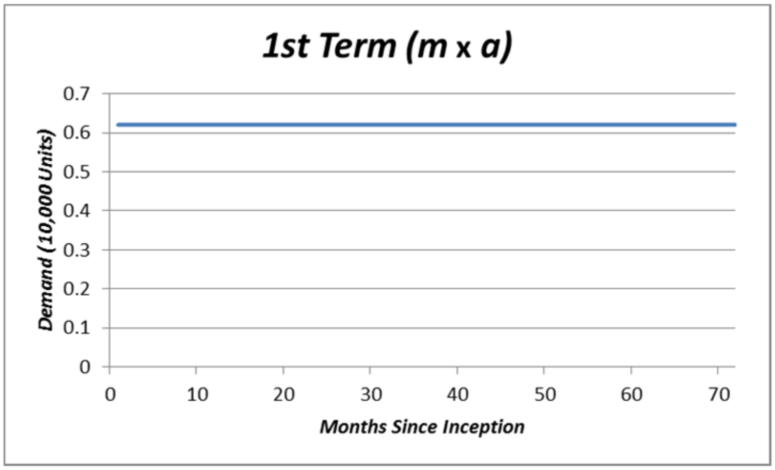
b. Model Form One (NSNE M2 and M3)

The first models reviewed during this theoretical analysis were formulas NSNE M2 and NSNE M3 from Table 8; the basic formula can be seen in Equation 4. The primary difference between models M2 and M3 is that model M3 contains an additional constant.

$$D_t = Ama + \frac{Bm}{C + t^2 - Dt - Eat} \tag{4}$$

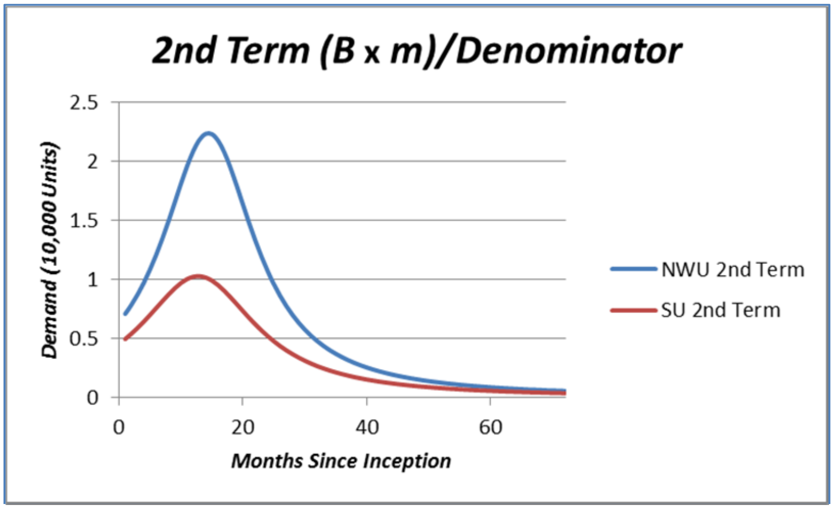
The first term reviewed was ***A**ma*, and as displayed in Figure 19; the output from this term remains constant. This term contributes to an initial demand baseline for the model, as well as provides a demand floor as the model transititions to maturity in later date ranges. The presence of a demand floor makes intuitive sense; since uniforms wear out and require periodic replacement, a minimum amount of demand will always be present, so long as the uniform program remains active. The term ***A**ma* represents the proportion of total sales potential (*m* x *a*), which is recurring and ongoing demand.

Figure 19. Theoretical Analysis: NSNE M2 and M3 Term One.



The second term evaluated is ***B****m*. On its own, the numerator provides constant output; however, when it is divided by the denominator, this term gives the distribution its distinctive shape, as seen in Figure 20. The combined second term is asymptotic; eventually the denominator begins to dominate the numerator, rendering its contribution to overall demand essentially zero. At this point, demand is supported predominately by term one, which represents minimum recurring demand. The impact of the allowance variable is further demonstrated in Figure 20 as well. As seen in this graph, the peak for the NWU Type I is far more pronounced than the SU.

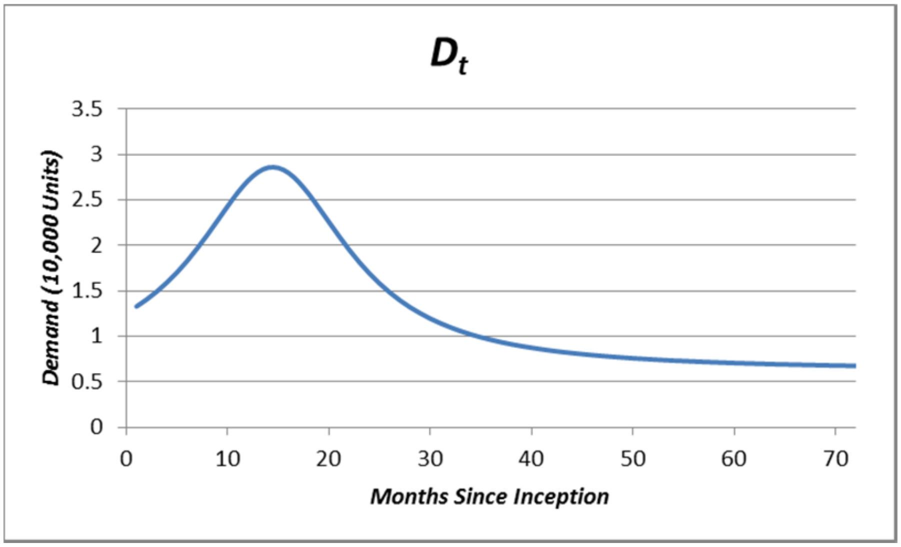
Figure 20. Theoretical Analysis: NSNE M2 and M3 Term Two.



The pattern of the second term also makes intuitive sense; when a uniform is initially introduced it is not immediately available for purchase in every outlet across the Fleet. As stock becomes available, more outlets begin to sell the new uniform and, as this occurs, demand will likely increase as more sailors are able to purchase. Additionally, the required wear dates for uniform do not typically occur immediately upon the uniform becoming available for sale; there is typically a grace period. As the required wear date approaches, demand will likely increase as sailors are forced to comply. Eventually, the Fleet will be in compliance and initial demand begins to subside; at this point, the demand curve begins to transition toward maturity and recurring demand. The second term—Bm divided by the denominator—accounts for the portion of total demand attributed to initial outfitting.

When both terms one and two are combined, they result in the distribution seen in Figure 21. This distribution shows the initial increase in demand as the new uniform is introduced, the tapering of demand, and the subsequent transition into maturity with recurring demand.

Figure 21. Theoretical Analysis: NSNE M2 and M3 Combined Terms.



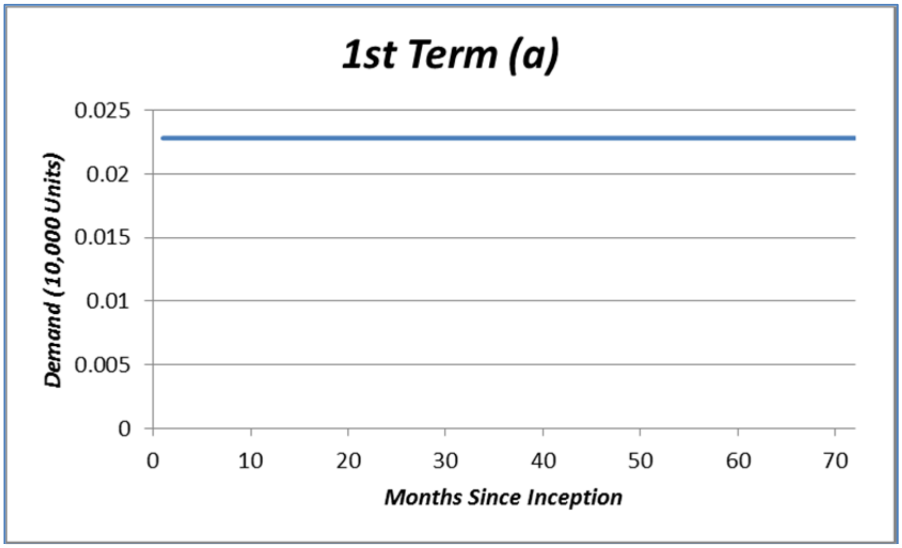
c. Model Form Two (NSNE M8)

The second model form evaluated involved model NSNE M8 of Table 8; this form is also the most complex, as it has four primary terms—two interactive and two noninteractive. Equation 5 provides the basic format of the model.

$$D_t = Aa + \frac{-B}{m} + Cma + \frac{Dm}{E + t^2 - Ft - Gat} \tag{5}$$

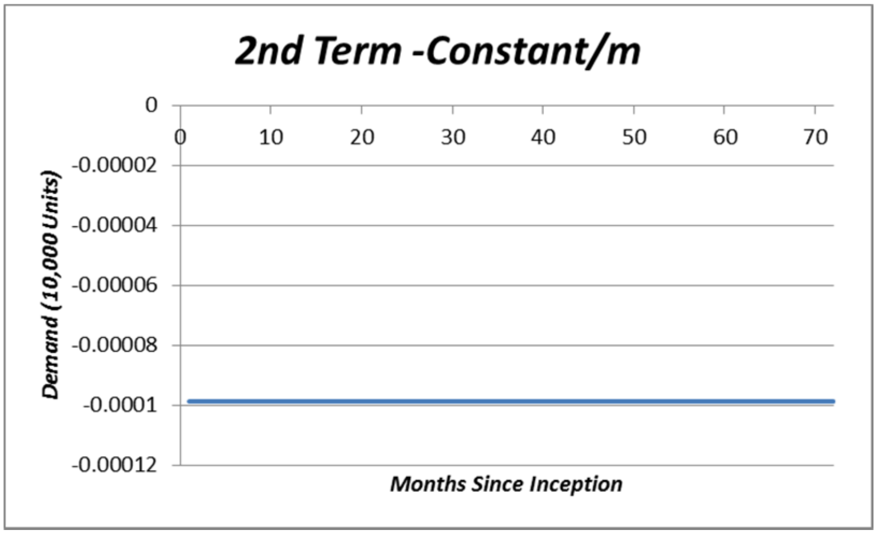
The first term reviewed was ***A****a*, which can be seen in Figure 22. Since the output of this term is constant, it contributes to recurring demand. This term seems to suggest that the presence of an allowance by *itself* is a source of demand. This term does not make as much intuitive sense. By itself, allowance is simply policy; it would not significantly affect sales potential until it is coupled with a source of demand—the customers (*m*). It is possible that this term could represent a minimal amount of internal sales, such as floor models, which would be independent of the number of sailors. This is unlikely, however, as internal sales would be more apt to be driven by geography (store locations) than the allowance.

Figure 22. Theoretical Analysis: NSNE M8 Term One.



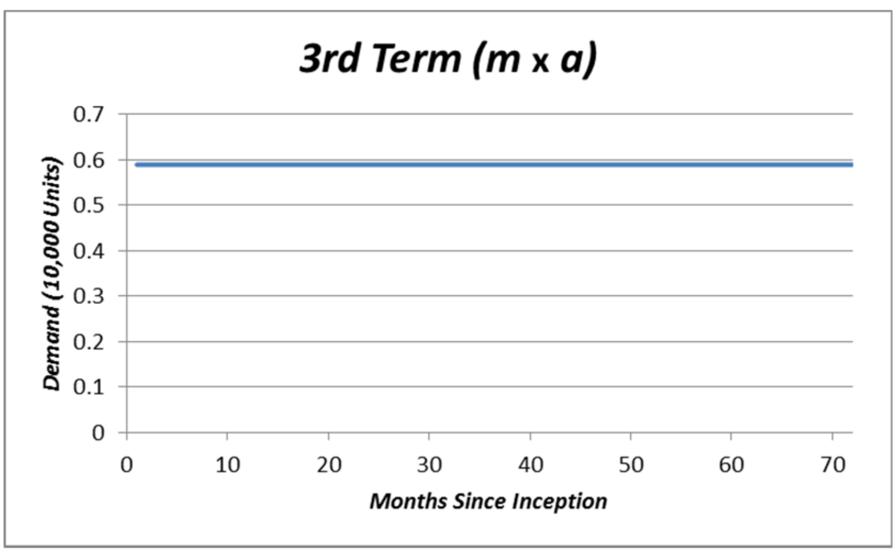
Like the first term, term two, [$^{-}$***B****/m]*, generates a constant output value, as seen in Figure 23. This term suggests that as *m* increases, demand decreases *less.* The net result is that as *m* goes up, so does demand. This term also suggests that manpower, in absence of a prescribed allowance, would drive recurring demand. While this might be possible, it does not make much intuitive sense; if the allowance for a uniform was zero, it is unlikely that customers would buy them. Lastly, the output from this term is vanishingly small. As a result, this term increases model complexity, while contributing little to the model's total output.

Figure 23. Theoretical Analysis: NSNE M8 Term Two.



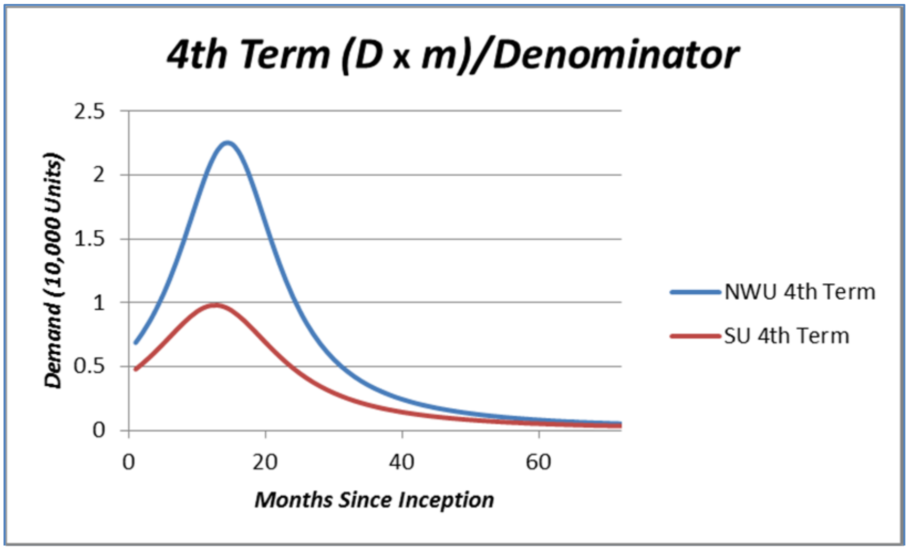
The third term in this model is an interactive term, ***C****ma*, similar to the first term in Figure 19. As previously mentioned, this term appears to suggest that recurring demand is a proportion of total sales potential (*m* x *a*); Figure 24 shows this term in graphical form; note the similarity to Figure 19.

Figure 24. Theoretical Analysis: NSNE M8 Term Three.



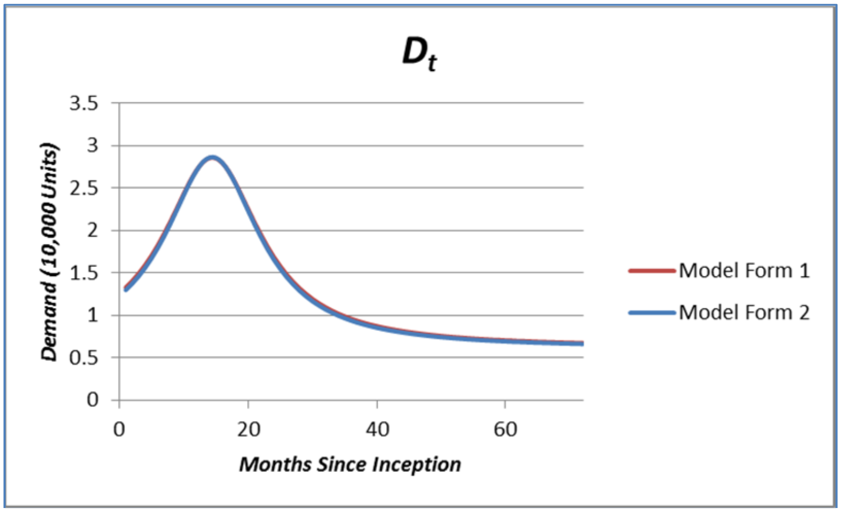
Similar to term two in Figure 20 term four, ***D****m*, provides the model its distinctive shape when it is combined with the denominator. This is illustrated in Figure 25. Similar to model form one, the greater the value of the allowance variable in the denominator, the more pronounced the demand peak becomes. This term provides the portion of demand attributed to initial outfitting.

Figure 25. Theoretical Analysis: NSNE M8 Term Four.



When all four terms are combined, they result in the distribution seen in Figure 26. This distribution shows the initial increase in demand as the new uniform is introduced, the tapering of demand, and the subsequent transition into maturity with recurring demand. For comparison, model form one is also illustrated in Figure 26. As seen in the graph, the models are nearly identical; however, model form one describes the demand with fewer terms.

Figure 26. Theoretical Analysis: NSNE M8 Combined Terms.



d. Model Form Three (NSNE M4 and M6)

The third model form evaluated covered models NSNE M4 and M6 from Table 8. These models contained two interactive terms and one non-interactive term, as seen in Equation 6.

$$D_t = Aa + Bma + \frac{Cm}{D + t^2 - Et - Fat} \quad (6)$$

Similar to the previous model form, the first term, ***A**a*, suggests that allowance by itself is a source of recurring demand. As discussed, this is unlikely because allowance by itself is a policy statement; this policy will not result in realized demand until it is directed at a customer pool (*m*). Terms two and three operate in a similar manner to the terms presented in model form one. Term two, ***B**ma*, represents recurring demand as a proportion of total sales potential (*m* x *a*), while term three, ***C**m*, divided by the denominator, represents the portion of total demand attributed to initial outfitting.

e. Model Form Selection

Of the three theoretical model forms reviewed, form one is preferred. Each of the three model forms returned nearly identical demand distributions when all component terms were combined. Theoretical model form one however, is more parsimonious in that it describes the distribution with fewer terms, without sacrificing accuracy. Furthermore, the additional noninteractive terms in forms two and three, when combined, generate a constant output; yet, they do not hold up under scrutiny as well the interactive terms. In the absence of a compelling reason to include additional noninteractive terms in the model, the researchers chose to proceed with the simpler form for the reasons stated in Chapter III.

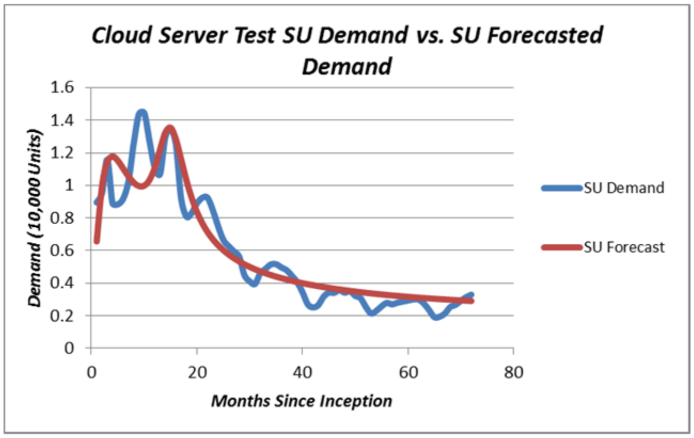
f. Achieving Parsimony

One of the challenges of choosing the "best fit" model is determining at what point the model stops explaining the distribution shape and begins mimicking nuances in the data set. Eureqa is a very powerful processing tool and makes every attempt to minimize the error between its model results and the data set. For example, during the search process, a test model search was conducted using Eureqa's commercial cloud server. During this search, Eureqa evaluated 410 *billion* potential equations; Equation 7 shows Eureqa's top model suggestion from that search.

$$D_t = Ama + \frac{Bmt}{C + t^2} + \frac{Dmat - m}{E + t^2 - Ft} \tag{7}$$

As seen in Figure 27, when applied to the SU, this model appears to be following the undulations in the demand distribution, which are unique to the data set and do not, necessarily, contribute to a *universal* adoption model distribution. When applied to NWU Type I, a similar phenomenon occurs—the model attempts to follow the variations in the data set. As a result of this mimicking behavior, when computed, the R^2 for the NWU forecast saw a 2% increase; however, the R^2 for the SU saw a 4% decrease. This reinforces the premise that additional model complexity does not necessarily produce more robust results and may introduce additional variability, which undermines the usefulness of the model.

Figure 27. SU Forecaset—Cloud Server Model.



4. Model Down-Selection Phase Three: Business Performance

With the preference of theoretical model form one, the final two models evaluated against the business performance measures were NSNE M2 and M3. The first business performance measure evaluated was year-over-year percent underestimate. As discussed in Chapter III, this measure is an evaluation of downside risk exposure, or the potential for stock shortage. For each of the six years in the data range, the over or under-estimated demand was calculated for both the NWU and the SU for both models. This created 12 points in which an underestimation could occur; an underestimate occurred in 6 of the 12 calculations. Tables 10 and 11 compare the magnitude for each error. Of these six instances, model NSNE M2 performed better on four; furthermore, NSNE M2 performs better early in the distribution range, where model accuracy is more vital.

Table 10. Business Measure: Year-Over-Year Percent Underestimate: NWU Type I.

Year Error Occurred	**1**	**2**	**3**	**4**	**5**	**6**
NSNE M2	N/A	–3.42%	–1.79%	–3.69%	–5.55%	N/A
NSNE M3		–3.6%	–3.56%	–4.14%	–5.1%	

N/A (Not Applicable) means neither model generated an underestimate in that year. The cells highlighted in green indicate the better-performing model for that time period.

Table 11. Business Measure: Year-Over-Year Percent Underestimate: SU.

Year Error Occurred	1	2	3	4	5	6
NSNE M2	–9.6%	N/A	N/A	N/A	N/A	–0.06%
NSNE M3	–10.35%					5.15%

N/A (Not Applicable) means neither model generated an underestimate in that year. The cells highlighted in green indicate the better-performing model for that time period.

The second business performance measure evaluated was the cumulative percent overestimation at Year Three. As previously stated, this metric is designed to evaluate the risk of maintaining too much inventory as a result of model estimates. Year Three was chosen because this is the point in which new uniform programs tend to transition into maturity. Of the two remaining models, neither resulted in a cumulative overage at Year Three; this can be seen in Table 12. As a result, the models were evaluated based on cumulative accuracy; this, again, resulted in NSNE M2 being the better-performing model and, subsequently, the best-performing model overall.

Table 12. Business Measure: Cumulative Year Three Percent Overage.

	NWU	SU	Average
NSNE M2	–0.18%	–2.09%	–1.14%
NSNE M3	–0.86%	–3.04%	–1.95%

The cells highlighted in green indicate the better-performing model.

B. KEY-LEGG UNIFORM ADOPTION MODEL POST-HOC ANALYSIS

The following section outlines differences between the selected uniform adoption model, NSNE M2, and the UPMO Fielding Plan for both uniforms. Further analysis is conducted in order to address inventory and cost implications in the differences between the two models for both uniforms.

1. Fielding Plan—NSNE M2 Forecast Performance Comparison

With the selection of the NSNE M2 model, a post-hoc analysis of model performance was warranted. The first post-hoc review conducted was a comparison of the model against the Fielding Plan and the actual demand for each uniform over the six-year period. Tables 13 and 14, and Figures 28 and 29, show the results of this model comparison by uniform type.

Table 13. Annual Comparison of NWU Fielding Plan, NSNE M2, and NWU Demand.

Year	Actual Demand	Fielding Plan	FP % Error	NSNE M2	M2 % Error	Cum. M2 % Error
1	222,721	602,603	171%	234,379	5%	5%
2	298,047	512,723	72%	287,854	–4%	0.28%
3	147,588	316,746	115%	144,952	–2%	–0.18%
4	105,054	N/A	N/A	101,178	–4%	–0.65%
5	93,191	N/A	N/A	88,020	–6%	–1.18%
6	79,809	N/A	N/A	82,593	3%	–0.79%

N/A (Not Applicable)—the NEXCOM UPMO Fielding Plans only project the initial three years.

Figure 28. Comparison of NWU Fielding Plan, NSNE M2, and NWU Demand.

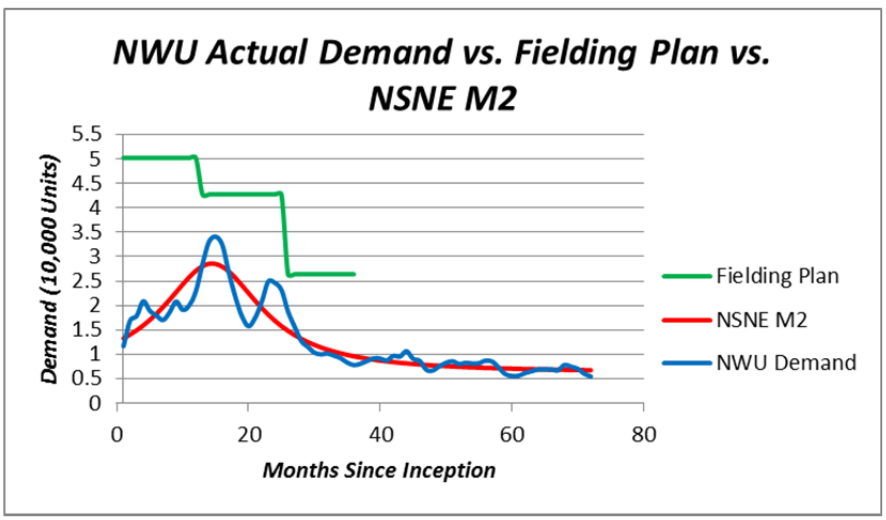
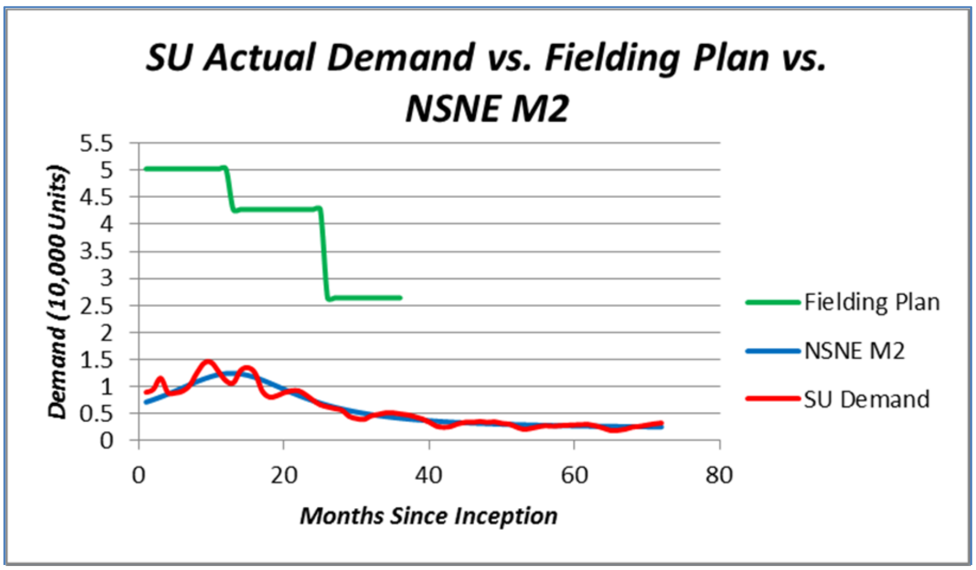


Table 14. Annual Comparison of SU Fielding Plan, NSNE M2, and SU Demand.

Year	Actual Demand	Fielding Plan	FP % Error	NSNE M2	M2 % Error	Cum. M2 % Error
1	132,404	506,187	282%	119,687	–10.0%	–10.0%
2	118,678	430,687	263%	122,731	3.0%	–3.45%
3	61,857	266,066	330%	63,982	3.0%	–2.09%
4	41,652	N/A	N/A	42,485	2.0%	–1.61%
5	33,523	N/A	N/A	34,970	4.0%	–1.10%
6	31,674	N/A	N/A	31,654	–0.1%	–1.02%

N/A (Not Applicable)—the NEXCOM UPMO Fielding Plans only project the initial three years.

Figure 29. Comparison of SU Fielding Plan, NSNE M2, and SU Demand.



2. Forecast Differences: Inventory Implications

Since reducing program cost was a primary driver of the study, further analysis of the NSNE M2 model was conducted to determine the impact on inventory levels. For this analysis, both NSNE M2 and the original fielding plans were evaluated against historical demand for each uniform type. The aim of this comparison was to determine the potential holding-cost reductions through reductions in excess inventory. As mentioned in Chapter II, holding costs incurred by the DLA are passed on to the NEXCOM as part of the CRR; any additional holding costs incurred due to excess inventory or inventory write-down charges are recovered by increased CRRs. A goal in developing the Uniform Adoption model was to provide a forecast that met the annual demand requirements, while minimizing the excess inventory, thereby minimizing holding costs.

a. Year-to-Year

A review of Table 13 shows that in four out of the six years compared, the NSNE M2 model slightly underestimated actual demand for the NWU Type I. For the SU, NSNE M2 underestimated actual demand in two of the six years; this can be seen in Table 14. These underestimates apply to aggregate *demand* for each uniform; additional factors ultimately influence the amount of inventory procured such as the application of the DLA Size Tariff, as well as safety and working stock policies. These factors, discussed in Chapter V, typically increase the quantity procured in relation to an initial demand forecast. This would mitigate potential inventory shortages.

In contrast to model NSNE M2, the original fielding plans significantly overestimated initial demand—at some points, by as much as 280% of actual demand. This overestimation can lead to systemic excess inventory and subsequent increased holding costs. This issue is compounded when the size tariff, along with working and safety stock levels, are applied. Since safety stock is typically calculated as a proportion of expected demand, if expected demand is significantly overestimated, safety stock is excessively large, adding to the systemic inventory excess. This issue is further explored in Section c.

b. Cumulative Inventory Performance

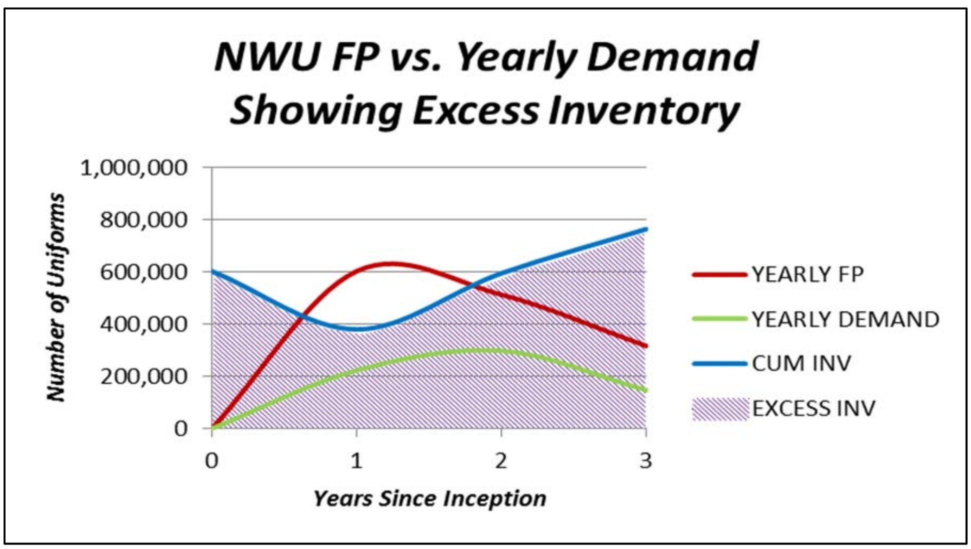
While the year-to-year comparison provided a basis for understanding the impact of forecast overestimates on inventory levels, the cumulative inventory comparison is more illustrative of the business impact. This comparison shows the "snowballing" effect of any inventory surpluses or deficits and its impact on inventory levels over time.

In order to perform this analysis, a number of assumptions were made. The first assumption was that demand prior to Time Zero was zero (i.e., no presales/orders—

demand started when the uniform was made available for general purchase). Second, it was assumed that demand not satisfied by the current year's inventory would carry over to the next year. Third, the amount of annual inventory received equaled forecasted demand for the same year and would be delivered at the start of the year. Additionally, procurement quantities were fixed for the first three years, so no adjustments could be made. Safety stock and working stock levels were not included in the analysis.

By conducting a cumulative comparison of the NSNE M2 model against the applicable uniform fielding plan, the authors were able to chart overall excess inventory at the end of Year Three (when the fielding plan ended). Figure 30 shows the cumulative excess NWU inventory incurred when the fielding plan is evaluated against actual historic demand. The cumulative inventory line represents net inventory remaining after demand was satisfied *above* any retained safety stock requirements; as a result, any additional inventory held above zero could be considered excess.

Figure 30. NWU Cumulative Inventory from the NWU Fielding Plan.



By the end of Year Three, there were 763,716 NWU uniforms in excess inventory, assuming that ordering adhered to the three-year fielding plan and no adjustments were made.

Figure 31 shows the cumulative excess NWU inventory incurred when the NSNE M2 model is evaluated against actual yearly demand. By the end of Year Three, there was a deficit of 1,171 NWU uniforms, assuming that ordering adhered to the NSNE M2 forecast model for those three years.

Figure 31. NWU Cumulative Inventory from NSNE M2.

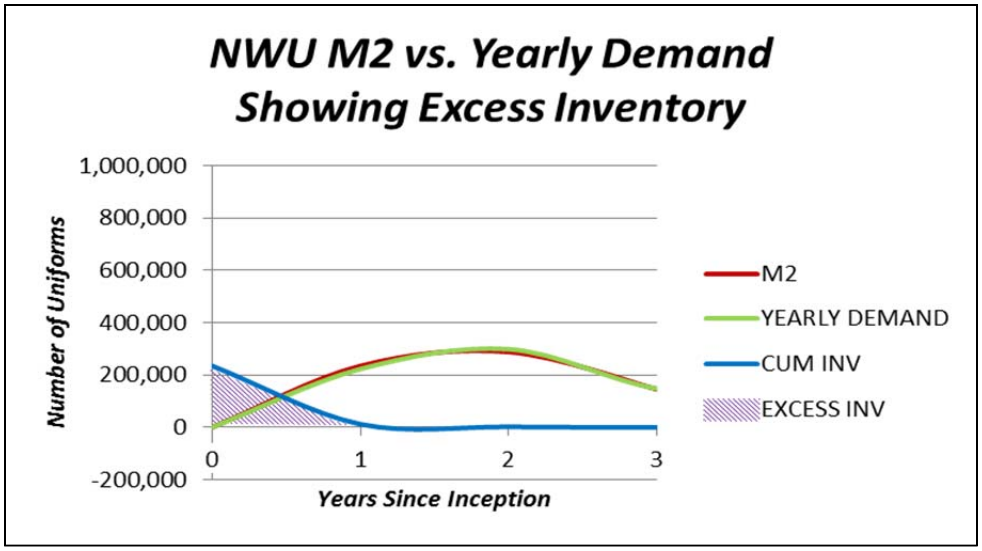


Figure 32 shows the cumulative excess SU inventory incurred when the original SU fielding plan is evaluated against historic demand. By the end of Year Three, there were 890,001 SUs in excess inventory, again assuming ordering adhered to the three-year fielding plan and no adjustments were made.

Figure 32. SU Cumulative Inventory from SU Fielding Plan.

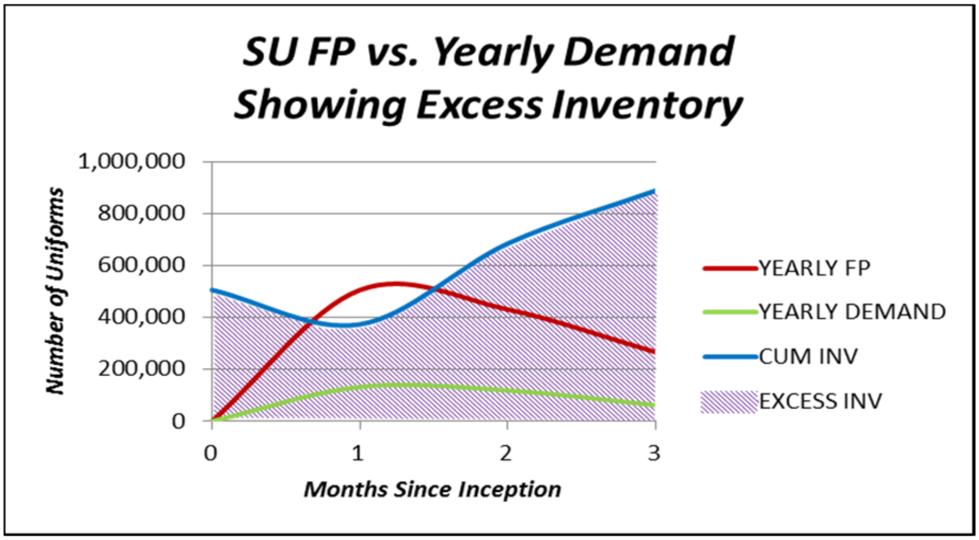
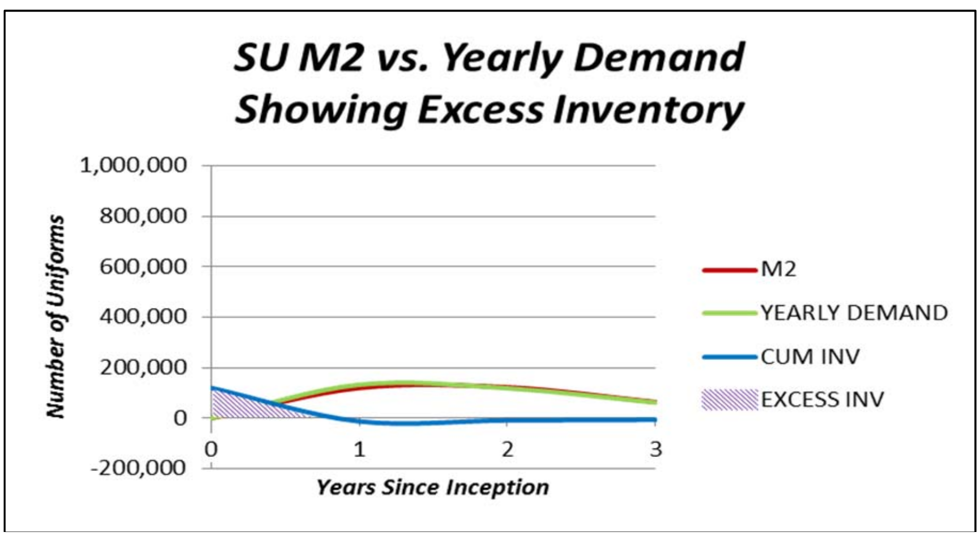


Figure 33 shows the cumulative excess SU inventory incurred when the NSNE M2 model is applied to actual yearly demand. By the end of Year Three, there was a deficit of 6,539 SUs, assuming that ordering adhered to the NSNE M2 forecast model for those three years.

Figure 33. SU Cumulative Inventory from NSNE M2.



c. Cost Implications

The application of NSNE M2 to both the NWU and SU resulted in significant *potential* excess inventory reductions—763,716 and 890,001, respectively. These excess uniforms tie up scarce working capital and warehouse space, which, in turn, can drive up CRRs and reduce readiness. While it is unlikely that no adjustments to procurement quantities could be made due to constraints such as lot sizes, production scheduling, and contractual obligations, making significant changes to procurement quantities early on in the program can be challenging and costly. Many of these aforementioned factors are set based on initial forecast guidance, which emphasizes the importance of early accuracy.

Of note, however, is that both the NWU and SU realized an overall inventory deficit of 1,171 for the NWU and 6,539 for the SU. By the end of Year Six, these deficits grew to 7,435 and 4,279, respectively; however, any deficit further out in the date range can be controlled by procurement adjustment. Again, with the application of safety stock and the DLA Size Tariff, this deficit would likely be resolved.

C. FURTHER MODEL VALIDATION

The following section explores the application of the NSNE M2 model against a third uniform type, the Physical Training Uniform (PTU), and the subsequent results.

1. Differing Uniform Types—Validation Against the Physical Training Uniform

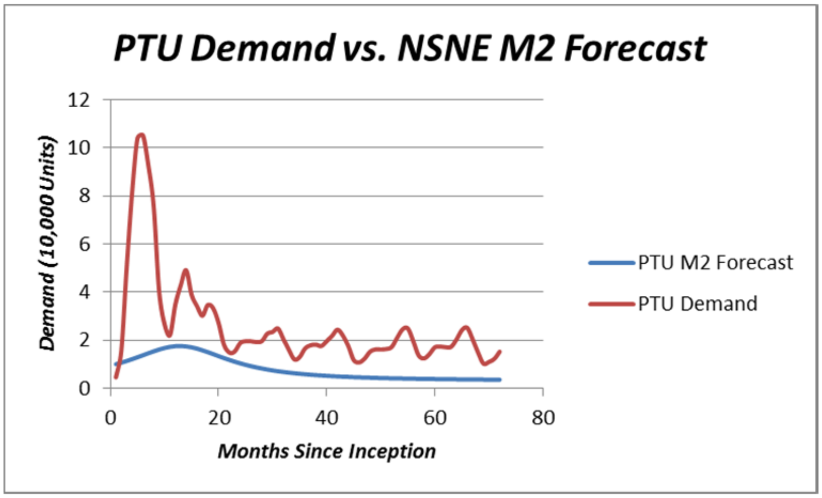
The previous analysis concentrated on validating the performance of the model against both the SU and NWU data sets, in which the model performed well on both accounts. Both the NWU and SU, however, bear a number of similarities to one another—program size, cost, timing of introduction and phase-in, etc. Since the ultimate goal is to develop a *universal* uniform adoption model, it is appropriate to test the performance of the model against a uniform that bears little commonality with the NWU and SU.

Clearly, fitting a model to many uniforms would produce a more "universal" model—capturing life-cycle factors common to all models being fit and more likely ignoring unique variance in any one uniform. As already demonstrated, however, the model proposed here represents a significant improvement over current practice. So, the question addressed is—has a model been derived that is robust enough to be used against an entirely new uniform? A benchmark that the reader should have in mind is analysis reported when using Eureqa to fit a model to one uniform (NWU or SU) and then testing that model against data from another uniform. In that case, the accuracy when applied to another uniform dropped from an R^2 of about 0.9 to an R^2 of about 0.65 (in both cases).

For this analysis, the NSNE M2 model was evaluated against the PTU. The PTU is a low-cost, athletic training uniform, which sailors use during physical fitness assessments and command-organized exercise. In addition to its officially prescribed wear requirements, the PTU is also popular among sailors for use during general athletic activity, which results in a high-use uniform.

When the NSNE M2 model was applied to the PTU data set using the *default coefficients*, the model significantly underestimated demand for the PTU; the magnitude of this underestimate can be seen in Figure 34. As a result of the stark difference in performance, further analysis was conducted to determine the cause of the poor fit. If the issue stems from the model structure itself, then this poor performance may call into question the validity of a universal model. If, however, performance can be improved through adjustments to the coefficients, then the model remains valid. The issue then becomes how to efficiently estimate new coefficients for varying uniform types.

Figure 34. NSNE M2 Forecasted PTU Demand and Actual PTU Demand.

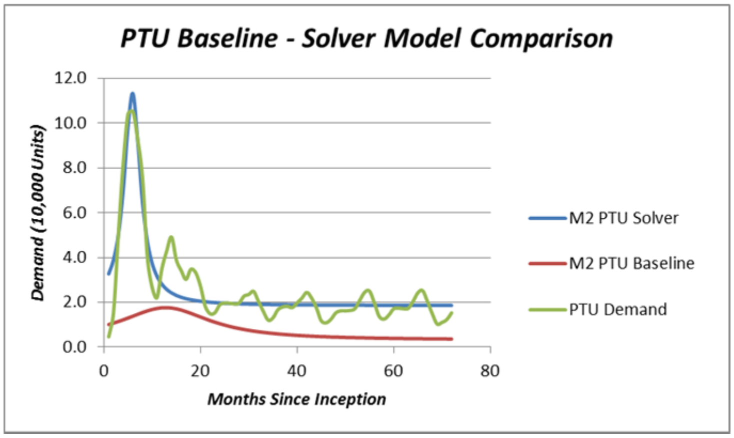


2. Estimating New Coefficients

A review of the PTU demand data reveals that PTU demand followed the same *general* pattern as both NWU and SU—an initial ramp-up in demand and subsequent drop-off and transition into recurring demand. The point at which the peak occurs, however, is several months earlier in the date range, compared to the NWU and SU. In addition to the variation in peak demand timing, there is also a significant difference in the magnitude of peak demand between the PTU demand and the demand peaks experienced with the NWU and SU programs.

In order to estimate new values for the NSNE M2 model coefficients, a basic Excel Solver model was developed that would estimate new coefficient values using historic sales data for the PTU. For this analysis, the Solver was set to minimize the Sum of Squared Errors (SSE) between historic PTU demand and NSNE M2 model output. To achieve its target, the Solver assigned new values for the model coefficients *A* through *E*, as seen in Equation 4. With the new Solver-generated coefficients, NSNE M2 was able to return an R^2 of 84.1% against the PTU data set. Additionally, the business performance measure—the percentage underestimated for the first 36 months—was reduced from 65% to 3.6%. This performance increase can be seen visually in Figure 35. The M2 Baseline curves in Figures 35 through 37, represents NSNE M2 output using the default coefficients originally generated by Eureqa.

Figure 35. PTU NSNE M2 Default and Solver-Generated Coefficient Comparison.



To further validate the Solver model result, the Solver model was also used to estimate uniform specific coefficients for both the NWU and SU. Using the Solver-generated coefficients, the R^2 for the NWU improved from 85.7% to 86.1%, while R^2 for the SU improved from 91.99% to 93.80%; these results can be seen in Figures 36 and 37. While NSNE M2 performance improved for both the SU and NWU, the improvements were marginal because default NSNE M2 coefficients were based on the SU and NWU data sets. As a result, the default variables already provided a quality fit.

Figure 36. NWU Type I NSNE M2 Model Results with Solver-Estimated Coefficients.

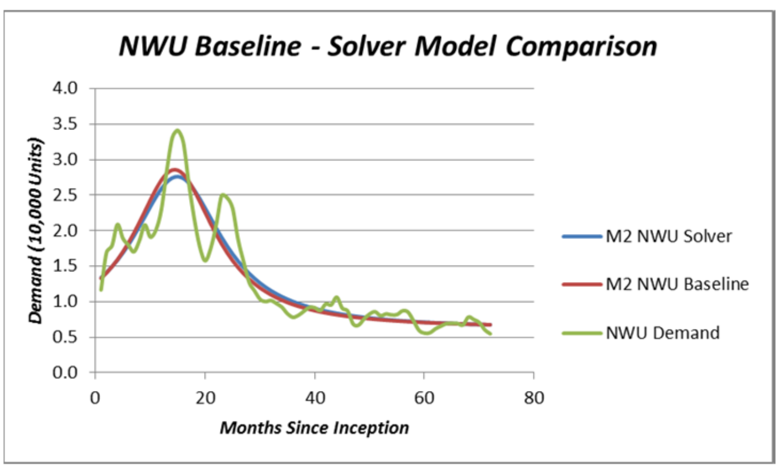
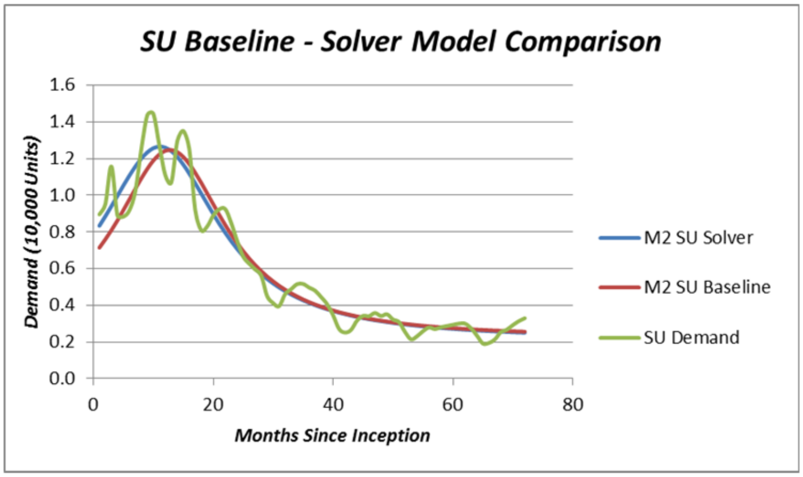


Figure 37. SU NSNE M2 Model Results with Solver-Estimated Coefficients.



Using the Solver, the performance of NSNE M2 was improved by estimating new coefficient values. Since only the values for the coefficients were changed, and the basic model form was left intact, this suggests NSNE M2, as seen in Equation 4, is a valid model and could serve as the basis for a universal adoption model. In its current form, however, the Solver model would be impractical for forecasting use because it would require the forecaster to input 72 historical data points.

A practical application of this model would involve the forecaster estimating new coefficients using as few as three points of historic sales data, from uniform programs that are the most similar in scope, type, cost, etc., to the new uniform being forecasted. During this evaluation, a form of risk analysis should be conducted, comparing the relative demand levels and determining which is the most appropriate to use in the new forecast. If there are several similar programs available, some combination of the data, such as the average between them, could be used as well. Once the appropriate demand points have been determined, these data points, along with prescribed values for *m* and *a*, would be entered into the Solver model and a forecast generated. Toward this end, the researchers developed a rudimentary tool for estimating the new coefficient values, using as few as three data points. Limited testing, however, has been conducted to thoroughly evaluate the robustness of this tool; as a result, further research in this area is recommended.

V. SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

A. SUMMARY

The purpose of this project was to investigate potential improvements to demand forecast methods currently in use by the NEXCOM for use in developing Supply Request Packages. The specific area of our focus was generating a universal Navy Uniform Adoption model that forecasts demand for Navy-wide uniforms developed by the NEXCOM and procured and managed by the DLA. The NEXCOM's existing forecast demand models resulted in an overestimate and overbuy by the DLA for the NWU and SU. The authors analyzed historical sales data for both the NWU and the SU, in order to generate a Uniform Adoption demand forecasting model for future Navy uniform fielding plans.

In Chapter II, the authors discussed the NEXCOM's and the DLA's backgrounds and roles in uniform development and acquisition. The two uniforms analyzed were examined to include their development and acquisition history. The authors also discussed multiple popular methods currently available to predict new product demand forecasting, as well as the proprietary software used in this research, Eureqa.

Chapter III detailed the methodology used to collect and prepare the data used to generate the candidate models. The process by which the data was input into Eureqa was described, to include the specifications for our desired formula output. In this chapter, the authors also discussed the selection of evaluation criteria and the three-stage, down-selection method to be applied to the Eureqa results.

Chapter IV examined the results provided by Eureqa and the application of evaluation criteria against those results. Once applied, the three-stage approach revealed the best candidate model, NSNE M2. Once selected, NSNE M2 underwent further analysis, which included overall performance and comparative performance against existing NEXCOM demand fielding plans. Additionally, the model was validated against an independent data set—the PTU. This validation process revealed that while the basic model is a sound basis for a universal adoption model, the coefficient values are not universal. Using a basic Excel Solver model, new coefficient values were calculated for NSNE M2, resulting in a significantly improved fit against the PTU. Additional research is necessary, however, to determine an efficient means to estimate new coefficient values using limited data points.

B. CONCLUSIONS

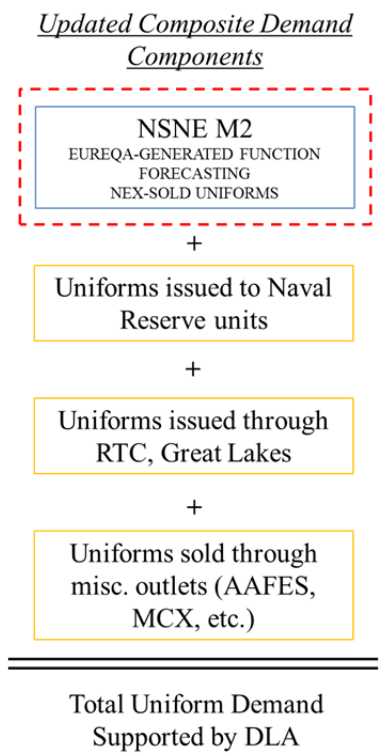
Our research posed two questions. First, could historical uniform sales data be used to develop a universal Navy Uniform Adoption model for future use with Navy-wide uniform fielding plans? Second, would this developed model predict demand for uniform sets more accurately than the NEXCOM fielding plans currently in use?

By analyzing the independent data from two existing Navy uniform programs with symbolic regression software, the authors discovered Navy-wide uniforms do follow similar demand patterns from inception through maturity. Both uniforms analyzed experienced an initial surge in demand with subsequent drop-off and transition into maturity, at nearly the same rate. Additionally, we determined that, in part, demand is a function of manpower, time, and allowance. As such, the authors were able to conclude that a Navy Uniform Adoption model could be developed using these inputs. Using either the default coefficients or those generated by the Solver model, Model NSNE M2 can be used to forecast uniforms of similar type and application to the NWU, SU, or PTU.

By comparing this formula to the existing NEXCOM uniform fielding plans, the authors were also able to conclude that, if applied to a similar type of uniform, this model would more accurately forecast the new uniform’s rate of adoption and initial demand. In some cases, when evaluated against the NWU and SU fielding plans, model NSNE M2 reduced potential excess inventory by over 2/3—which could be translated into cost savings through holding cost and working capital reductions. Since the model developed was designed to forecast demand for uniform *sets*, the authors did not conduct any specific research on the variation between demand patterns for the overall uniform set and its constituent components (i.e., belts, boots, and caps). While the authors speculate demand for these items could be safely calculated as a derivative of demand for uniform sets, the authors did not conduct any specific research on this matter.

The intended application of the NSNE M2 model is to provide a better forecasting tool for the portion of composite uniform sales demand sold through the NEXs. As shown in Figure 38, even though the retail sales component is only one of four demand sources that contribute to total uniform demand supported by the DLA, it is the component that possesses the most uncertainty.

Figure 38. Updated Composite Demand Model for Major Uniform Programs.



The most significant factor limiting full-scale adoption of the NSNE M2 model is the need to re-estimate coefficient values for uniforms that vary significantly from the ones used to derive the default coefficient values (NWU and SU). While a basic Excel Solver model has been developed that is capable of estimating new coefficient values, this model has not been adequately tested. Currently, NSNE M2 is essentially limited to forecasting uniforms programs similar to the NWU, SU, and PTU.

C. RECOMMENDATIONS

Recommendations based on this research are for the NEXCOM's operational use of this model and for further research associated with this topic.

1. Recommendations for NEXCOM

The first recommendation is for the NEXCOM to incorporate the NSNE M2 model on a trial basis into future Fleet-wide uniform fielding plans. As discussed in Chapter IV, the NSNE M2 model has the potential to generate considerable inventory cost savings due to reductions in inventory levels.

The second recommendation for the NEXCOM is the development of an auto-regressive tool to improve the accuracy of the NSNE M2 model when applied to a new uniform fielding plan. This tool compares early sales data for the new uniform against the model's initial prediction during the same time period. If the model's predictions are not consistent with initial sales data, an auto-regressive tool would efficiently revise the forecast for the program's out-years.

The final recommendation for the NEXCOM is to apply the NSNE M2 formula to other types of previously-fielded uniform items to test its adequacy to uniforms that are dissimilar to those tested during this research. If the formula adequately predicts the sales figures for those uniforms, further cost savings can be achieved by expanding the application of the model. The Excel Solver model developed during this project could accommodate this process. If during this process it is discovered that NSNE M2 does not adequately forecast, the Solver model could be used to estimate new coefficient values for these uniforms. These coefficient values could be retained to build a database of coefficient values based on uniform types that could be used to adapt the NSNE M2 model to many uniform types.

2. Recommendations for Further Research

Further areas of research for this study mainly include the continued application of symbolic regression modeling, to include additional variables and model parameters, as well as refinements and further analysis of the supporting data. This continued research would improve demand forecasting accuracy, as well as refine the methodology for applications of symbolic regression technology to other areas within the DOD supply chain. As noted, in today's limited budgetary resources, the need to maximize efficiency and minimize costs is more significant than ever. By using cutting-edge software to predict relationships and trends, the application for this technology to military uses is virtually limitless.

a. Additional Universality Testing

During this analysis, we were only able to review three data sets: the NWU Type I, SU, and PTU. We recommend that the NSNE M2 model be evaluated against additional uniform types. This would further validate or challenge the universal application of this model and identify additional weaknesses and variables that should be considered in future adaptations and development of the model. Ideally, this model should also be tested against uniforms from other services. This would help identify how close the buying habits of the services mirror one another, which would become increasingly relevant as the services potentially move toward "shared" uniforms.

b. Cut-Off Date

While briefly discussed in Chapter III, the issue of a uniform "cut-off" date was not fully explored in this research. This cut-off date would likely be a factor in the shape of the demand distribution early in the program, as well near the end, as it nears obsolescence. Its occurrence in the life cycle of a uniform program is critical in predicting the total *life-cycle* demand of the uniform.

As previously noted, a cut-off date that governs the last date in which the legacy uniform can be worn is typically mandated by OPNAV N1 when the new uniform is a replacement for an existing program. Not all new uniforms, however, replace an existing program, as was the case for the PTU. When this occurs, the aforementioned overlap of old and new uniforms would not exist; this could significantly alter the uniform adoption curve, specifically in the "Segment A," or roll-out phase of the uniform. Without an existing uniform to fulfill the requirement, the Navy would most likely field the new uniform with a shorter implementation date, thereby altering the model's forecast.

We recommend further research on the topic of cut-off dates and their effect on life-cycle demand and uniform adoption rates.

c. Disaggregating the Data—DLA Size Tariff and Uniform Sets

For the purposes of this research, the authors used aggregated sales data provided by the NEXCOM; while the demand data analyzed differentiated between components and styles (i.e., pants and trousers) but it did not differentiate by size and, in the case of the NWU Type I, gender. In general, when the NEXCOM UPMO submits its fielding plans, it does so using similarly aggregated data; demand may be separated by gender if the uniform involves gender-specific components like the SU.

When the aggregate uniform requirement is provided to the DLA as part of the SRP, or annual update, the DLA applies an existing size and gender matrix, known as a size tariff, to the aggregated number. While it is generally understood that these disaggregation processes typically inflate the quantity of uniforms procured, the exact nature of this procurement growth and subsequent impact on inventory was not studied in this analysis. The effects of this process are recommended for further research; understanding that the magnitude of potential inventory growth from this process could play an important role in fielding plan development. Any overestimates provided via the fielding plan would be universally applied to all sizes within the tariff. If true demand does match the estimate, this could lead to systemic excess inventory, especially in the more obscure sizes.

Another factor involving the disaggregation of data, which warrants further research, is the appropriateness of forecasting uniforms as a set. While the components for the NWU and the PTU tracked closely, the SU exhibited a sizeable gap between the demand for blouses and trousers. The potential reasons for this are discussed in Appendix A; however, further analysis of additional uniforms should be conducted to determine if this issue was unique to the SU or a more common occurrence.

d. *First Three Months of Data*

As discussed in Chapter III, while collecting and analyzing the data, the authors discovered that the first three months of uniform sales data received from the NEXCOM appeared to be irregular. The sales data for both of the uniforms was significantly lower during this period than the months immediately following. Several potential reasons for these low figures were discussed, such as initial intrastore transfers, charge-offs for display items, or limited presales; however, the exact explanation for these low demand points were not determined. Ultimately, these data points were omitted during modeling; as a result, model NSNE M2 may not necessarily model demand from the date of program introduction, but the date in which Fleet sales begin in earnest. Of the uniforms reviewed during this analysis, both the NWU and the SU exhibited the low initial data points; however, the PTU did not—PTU demand was robust from the outset. As a result, the authors recommend that the initial demand from additional uniform programs be reviewed to determine if a pattern exists.

We further recommend, for both NEXCOM operational use and future research, that causative research on the initial months of uniform program sales data be conducted to determine the source for such potential irregularities. This will help determine whether it is appropriate to include these data points during auto-regressive calculations or future uniform adoption research.

e. *Develop a Solver Model to Estimate Coefficients with Limited Data*

It is highly recommended that further research be conducted toward developing an improved Solver tool, which can estimate model coefficient values based on limited data—ideally, as few as three data points. Such a tool would greatly increase the usefulness and universality of the NSNE M2 model for forecasting new uniform programs. Initial research has been conducted toward this end; however, more work is required to perfect and test the model against multiple uniform types.

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APPENDIX A. DEFINING A UNIFORM SET

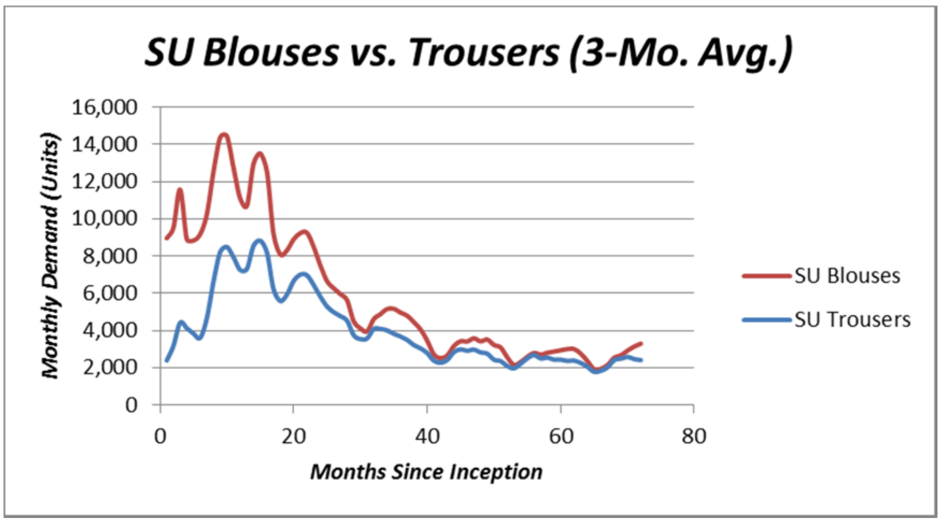
For this project, the authors were interested in developing a model that can forecast demand for uniform sets in keeping with the move toward managing uniforms as a complete system. In order to do this, they had to define a uniform set. In order to do that, the researchers evaluated three options: use the average month-to-month demand for blouses and trousers; use the maximum month-to-month demand between blouses and trousers; or use the minimum month-to-month demand between blouses and trousers.

To inform this choice, a review of the demand patterns for each of the uniform components was conducted. Figure 39 shows the three-month rolling average for monthly demand for NWU blouses and trousers over the first 72 months of the program. For this analysis, the researchers stepped into the three-month average; for the first data point, the actual observed data point was used; for the second data point, a two-month average was used; for all subsequent data points, the three-month average was used. As seen Figure 39, both blouses and trousers trend very close to one another, with trousers outselling blouses by a small margin later in the program.

Figure 39. Comparison of NWU Blouses and Trousers—Three-Month Average.

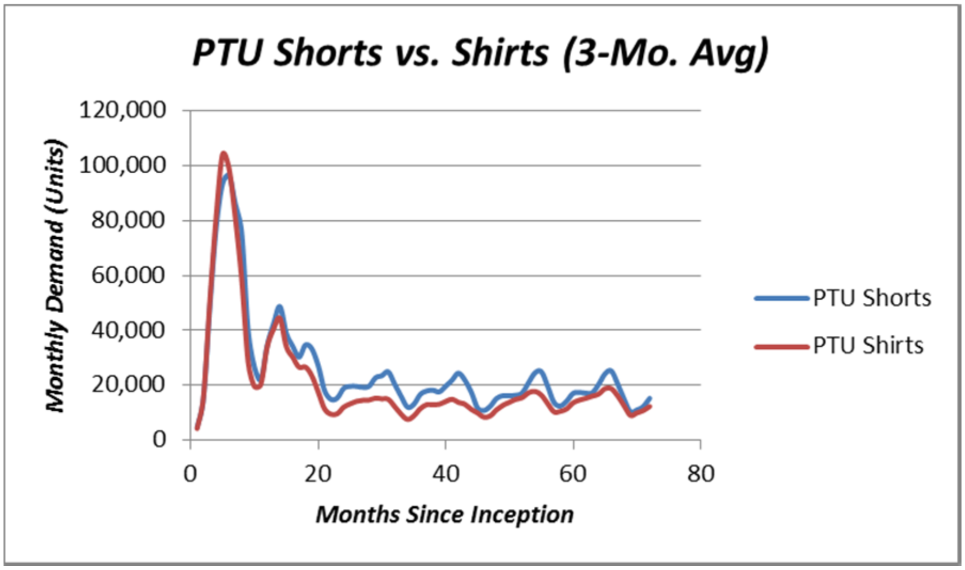
For the E1–E6 SU, the blouses and trousers did not trend together as tightly as with the NWU Type I. As seen in Figure 40, early on in the program, blouses outsold trousers by a sizeable margin; as the program matured, the two began to converge. There are a number of potential reasons for this behavior; for example, the SU trousers were nearly identical to the trousers for one of the uniforms it replaced—the working blues. It is possible that sailors whose working blues were in good condition simply reused their trousers with the new uniform to save money. However, no concrete evidence was discovered to corroborate any claims; this made deciding how to treat these differences in demand more difficult.

Figure 40. Comparison of SU Blouses and Trousers—Three-Month Average.



Since the trends for the NWU and the SU did not provide consistent results, a third uniform was reviewed. A review of monthly demand for the PTU indicated an eventual divergence in demand between the associated shirts and shorts. Figure 41 shows overlapping demand patterns early in the program; however, as time passes, shorts begin to outsell shirts and remain on top throughout the remainder of the program.

Figure 41. Comparison of PTU Shorts and Shirts—Three-Month Average.



A review of Figures 39 through 41 indicates a lack of consistency between each uniform program regarding which sells more: trousers or blouses. They do, however, display a consistent pattern across uniforms of an initial demand upswing, along with a subsequent drop-off, and transition into a stable state for both trousers and blouses.

Since there is inconsistency present, the authors believe defining demand for a uniform set as the maximum between trouser and blouse demand would be the more conservative approach. While this method may lead to overestimation of demand for some of the components incurring holding costs in the process, the cost of inventory shortage, especially early in the program, would be much higher. Included in shortage costs would be lost productivity for sailors forced to make multiple trips to the NEX to purchase uniforms, additional procurement costs associated with expedited delivery, the inability of the Fleet to conform to uniform policy, as well as potential damage to the NEXCOM's reputation. In the case of the SU, estimating demand using the minimum data set (trousers) may potentially lead to significant inventory shortages for the blouses.

In order to calculate the demand distribution for sets of uniforms, based on the maximum method, the authors used a Microsoft Excel spreadsheet. Monthly demand for trousers (column 1) and blouses (column 2) were placed in columns; with the function *=max(Column 1, Column 2)* placed in an adjacent column down each row. This was done for both the NWU and the SU; Figures 42 and 43 display the results for each uniform, with Figure 44 providing a comparison of the NWU and the SU.

Figure 42. Comparison of NWU Sets by Method.

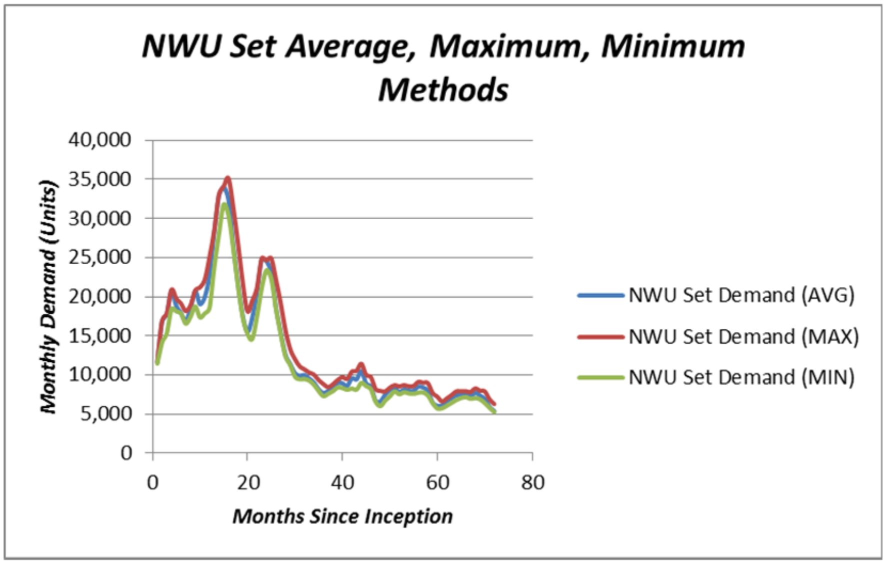


Figure 43. Comparison of SU Sets by Method.

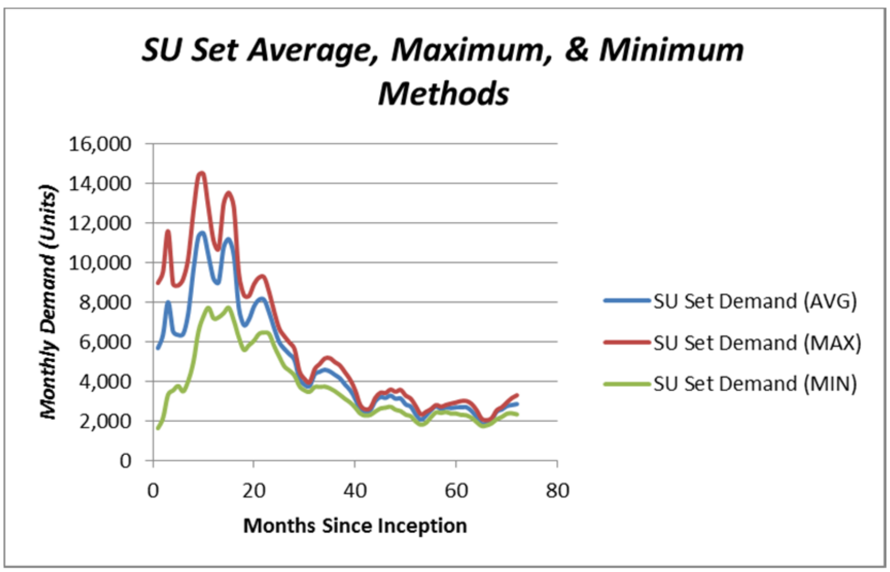
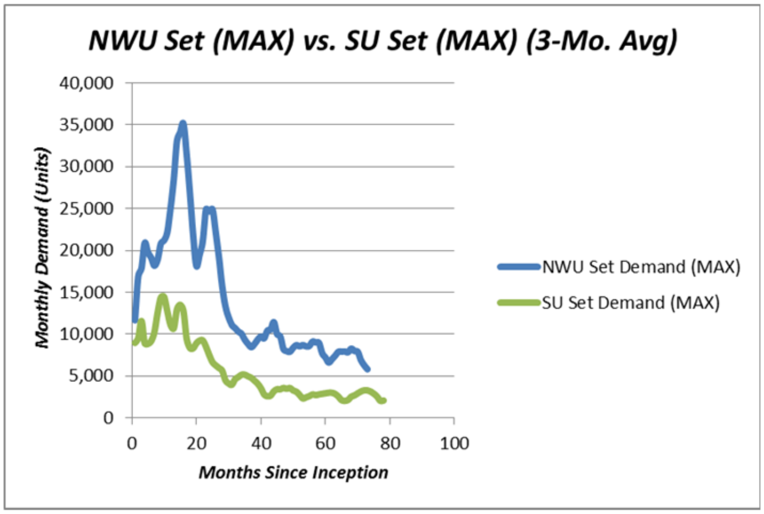


Figure 44. NWU and SU Set Demand—Three-Month Average Maximum Method.



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APPENDIX B. STATISTICAL MEASURES

A. COEFFICIENT OF DETERMINATION: R^2

The first statistical measure used in determining the best-fitting model was the coefficient of determination, commonly known as R^2. The coefficient of determination provides a measure of how much variation in the data is explained by the model; this measurement is achieved through the ratio of Sum of Squared Errors (SSE) and Total Sum of Squares (SST). SST measures the amount of variation inherent in the original data set; to determine SST, the equation $\sum (Y_i - \bar{Y})^2$ was used. This equation measures the difference between each observation in the data set and the average value of the data set. SSE measures the variation that occurs as a result of the model; it measures the difference between the observed data point and the model's forecasted data point. The equation for SSE is $\sum (Y_i - \hat{Y})^2$. Figure 45 shows the whole coefficient of determination equation; a spreadsheet model using this equation was used to evaluate R^2 for each of the Eureqa-generated forecast models under consideration.

Figure 45. Coefficient of Determination Equation.

$$\mathrm{R}^2 = \left\{1 - \left(\frac{SSE}{SST}\right)\right\} = \left\{1 - \left(\frac{\sum\left(Y_i - \hat{Y}_i\right)^2}{\sum\left(Y_i - \bar{Y}\right)^2}\right)\right\}$$

B. MEAN ABSOLUTE PERCENTAGE ERROR

The second statistical measure used for model selection was Mean Absolute Percentage Error, or MAPE. MAPE is a measure of forecast accuracy, which measures the difference in observed and forecasted values for a full data set range; this difference is presented as a ratio of observed value. Figure 46 shows the basic equation for MAPE; again, a spreadsheet model using this equation was used to efficiently measure the Eureqa-generated forecast models against their source data sets. MAPE is a useful error measure in this case, since it presents the error as ratio; since both the NWU Type I and

SU were sold on different scales, error measures that do not account for this, such as Mean Squared Error (MSE), would appear to overstate the errors in the NWU Type I data set in relation to the SU.

Figure 46. Mean Absolute Percentage Error Equation.

$$MAPE = \frac{\sum_{i=1}^{n} \frac{\left| Y_i - \widehat{Y}_i \right|}{Y_i}}{n}$$

APPENDIX C. MANPOWER DATA TABLES

Provided here, is a sample of the manpower data provided monthly by DMDC. For this analysis, the monthly reports were consolidated into annual summary tables. Table 15 provides an example of one of the annual summary tables.

Table 15. FY08 Combined Manpower.

	Officer	**Enlisted**	**Midshipmen**	**Total Active Duty**	**E1–E6**	**Officer (F)**	**E1–E6 (F)**	**Total (F)**	**Total (M)**
OCT 2007	51,265	280,565	4,384	336,214	246,967	7,718	41,988	50,601	285,613
NOV 2007	51,223	279,538	4,380	335,141	246,156	7,712	41,834	50,440	284,701
DEC 2007	51,167	278,193	4,367	333,727	244,923	7,703	41,633	50,228	283,499
JAN 2008	51,077	277,462	4,351	332,890	244,511	7,690	41,523	50,102	282,788
FEB 2008	51,079	277,605	4,347	333,031	244,772	7,690	41,545	50,122	282,909
MAR 2008	51,058	276,757	4,343	332,158	244,194	7,687	41,418	49,992	282,166
APR 2008	50,965	276,265	4,336	331,566	243,912	7,673	41,344	49,902	281,664
MAY 2008	52,153	275,960	3,270	331,383	243,814	7,852	41,299	49,818	281,565
JUN 2008	52,184	276,346	3,255	331,785	244,442	7,857	41,356	49,877	281,908
JUL 2008	51,877	276,474	4,481	332,832	244,955	7,810	41,376	50,101	282,731
AUG 2008	51,685	276,650	4,453	332,788	245,500	7,781	41,402	50,092	282,696
SEP 2008	51,383	276,397	4,448	332,228	244,332	7,736	41,364	50,008	282,220
Average Proportion of Total Manpower						15.06%	14.97%	15.05%	84.95%

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APPENDIX D. EUREQA-BASED VALIDATION OF DEMAND CURVE SIMILARITY

A. NORMALIZING THE DATA SET

As mentioned in Chapter III, Section C, prior to running the full analysis on both the NWU Type I and SU data sets, a validation of the similarity between the two demand patterns was conducted through a pair of Eureqa searches—the first on the NWU Type I and the second on the SU. The resultant models were then tested against the demand history for the opposite uniform.

Given that the data sets were run through Eureqa independently, a manual method for accounting for the individual uniform allowance had to be devised. Since the NWU Type I and SU had different allowances, failing to account for this would skew the results significantly. To complicate matters, when only one data set is entered into Eureqa, the allowance variable, *a*, is constant throughout. When this occurs, Eureqa will ignore the variable; without any variation, Eureqa cannot determine its effect on demand.

To account for this issue, the demand data was normalized by dividing the demand by its allowance to create a "core demand" driven by manpower and time. Eureqa searches were then conducted using the "core demand," and when the searches were complete, the top model, as suggested by Eureqa, was selected for each search. Once a model was selected, the output forecast would be rescaled by the appropriate allowance and validated against the applicable historical demand for goodness of fit. For this validation, Eureqa was allowed to use exponential operators in its model search.

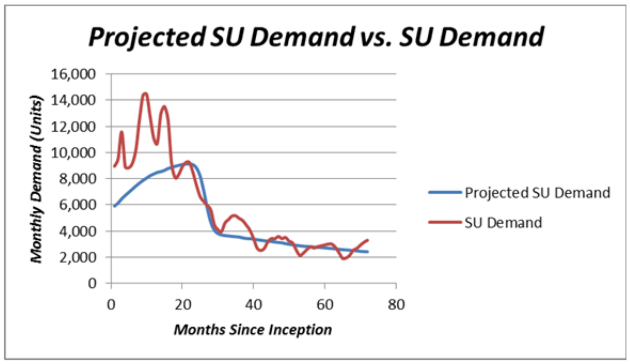
B. NWU DATA-BASED MODEL—SU FORECAST

The first data set used for preliminary demand curve analysis was for the NWU Type I. The data was first normalized using the method described in Section A; for this run, Eureqa was allowed to use exponential operators and no additional data smoothing was applied. This model search resulted in the model seen in Equation 8.

$$D_t = \frac{m}{7.63 + \exp(t - 24.5)} + \frac{4.72mt}{762 + t^2} \tag{8}$$

The model seen in Equation 8 returned an R^2 of 91.2% against the original NWU data set. When this model was used to forecast the SU, it returned an R^2 of 69.1% and a MAPE of 17.9%. Figure 47 graphically displays the generated forecast against historic SU demand.

Figure 47. Forecasted SU Demand—Historic SU Demand.



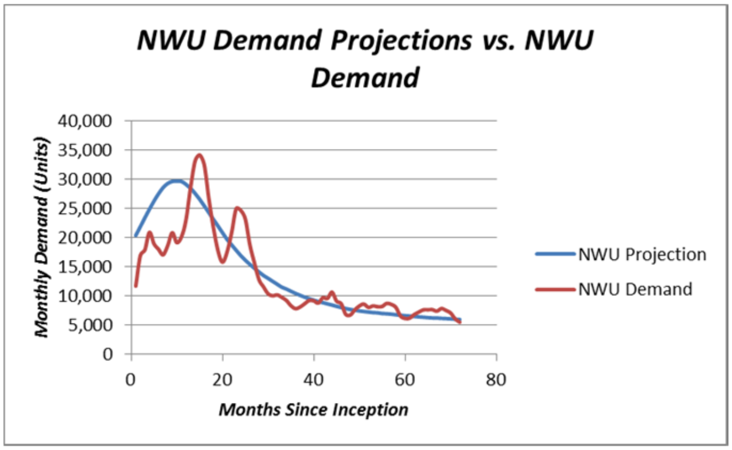
C. SU DATA-BASED MODEL—NWU FORECAST

The second data set analyzed was for the SU; again, the data was normalized prior to entering it into Eureqa. The model search criteria were set in the same manner as in the previous section. For this model search, Eureqa returned the model seen in Equation 9.

$$D_t = \frac{38m + 0.0341mt^2}{236 + t^2 - 17.4t} \tag{9}$$

This model returned an initial R^2 of 96.1% within Eureqa against its original data set. When applied to NWU data, the model returned an R^2 of 65.6% and a MAPE of 19.9%; just inside the established cut-off parameters. Figure 48 displays the goodness of fit graphically.

Figure 48. Forecasted NWU Demand—Historic NWU Demand.



D. REVIEW OF THE NWU AND SU "CORE DEMAND" PATTERN

The analysis of both the NWU Type I and SU-based models reveals that both models achieve the minimum goodness-of-fit thresholds established in Chapter III—an R^2 of 65% and a MAPE of 20%. As a result, the two models adequately explain the opposing data set to support further investigation of a *universal uniform adoption model.*

A further review of relative performance between the two preliminary models suggests that the application of individual uniform allowances is nonlinear (i.e., doubling the allowance of uniforms from two to four does not result in a doubling of demand). As seen in Figure 49, a forecast of NWU Type I demand via a SU-based model *overestimates* the forecast early in the program. In contrast, a forecast of SU demand via an NWU-based model *underestimates* demand, also as seen in Figure 49.

Figure 49. Normalized NWU and SU Demand.

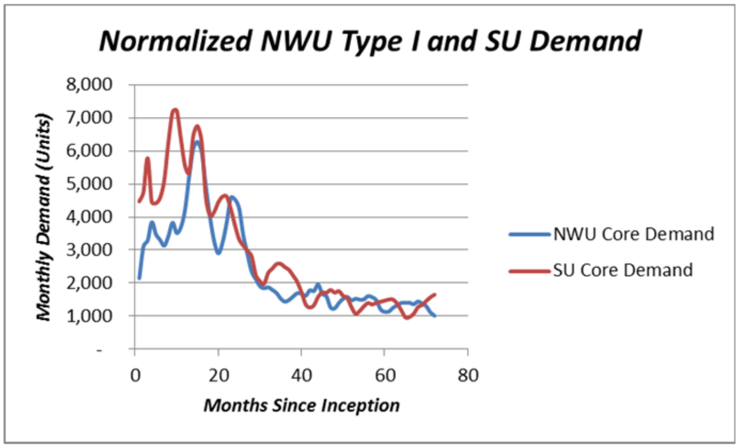


Figure 49 further illustrates this phenomenon; in this figure, demand for both uniform programs have been normalized for allowance and manpower—the NWU Type I was scaled to match the SU. The figure also shows that, after dividing by the individual uniform allowance, SU demand was higher than NWU demand for much of the program range. If compliance was 100% and every service member purchased to the prescribed allowance, the "core demand" should have looked similar to Figure 48; simply scaled down. Additionally, since the NWU dropped more significantly than the SU, it suggests that the higher the allowance, a, the less likely it is that the full allowance will be purchased.

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