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FORECASTING CRITICAL AIRCRAFT LAUNCH AND RECOVERY EQUIPMENT (ALRE) COMPONENTS' DEMAND

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THESIS

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by

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December 2018

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13. ABSTRACT (maximum 200 words)

Demand signals across the Navy's NIMITZ Class Carrier (CVN) Aircraft Launch and Recovery Equipment (ALRE) market-basket are highly erratic and do not fit neatly into the traditional demand-based sparing construct. This causes the Naval Supply Systems Command Weapons Systems Support (NAVSUP WSS) planning efforts to continually lag behind requirements, with material often arriving late-to-need. This project attempts to develop a comprehensive and more reliable ALRE material requirement forecast model. To accomplish this effectively, a comprehensive list of historical CVN ALRE demand data were analyzed in order to identify any correlation between ALRE demand and a ship's operating phase status, and to identify whether that correlation directly drives ALRE demand. The analysis begins by collecting historical CVN ALRE demand data and identifying the improvements for the current forecasting model. After a complete analysis of the current forecasting model, we utilized multiple linear regression and evaluated various forecasting methods as the best available methods for developing/discovering an optimized and robust forecasting method. In conclusion, the extremely low demand quantities of critical ALRE components continue to make forecasting extremely unreliable, but we believe NAVSUP can improve the accuracy of ALRE demand forecast by adapting a flexible forecasting system.

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ABSTRACT

Demand signals across the Navy's NIMITZ Class Carrier (CVN) Aircraft Launch and Recovery Equipment (ALRE) market-basket are highly erratic and do not fit neatly into the traditional demand-based sparing construct. This causes the Naval Supply Systems Command Weapons Systems Support (NAVSUP WSS) planning efforts to continually lag behind requirements, with material often arriving late-to-need. This project attempts to develop a comprehensive and more reliable ALRE material requirement forecast model. To accomplish this effectively, a comprehensive list of historical CVN ALRE demand data were analyzed in order to identify any correlation between ALRE demand and a ship's operating phase status, and to identify whether that correlation directly drives ALRE demand. The analysis begins by collecting historical CVN ALRE demand data and identifying the improvements for the current forecasting model. After a complete analysis of the current forecasting model, we utilized multiple linear regression and evaluated various forecasting methods as the best available methods for developing/discovering an optimized and robust forecasting method. In conclusion, the extremely low demand quantities of critical ALRE components continue to make forecasting extremely unreliable, but we believe NAVSUP can improve the accuracy of ALRE demand forecast by adapting a flexible forecasting system.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS AND ABBREVIATIONS

ADMACS	Aviation Data Management and Control System
AES	Advanced Exponential Smoothing
AIC	Akaike Information Criterion
ALRE	Aircraft Launch and Recovery Equipment
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ASO	Aviation Supply Office
CSI	Critical Safety Items
CVN	Aircraft Carrier (Nuclear Powered)
DoD	Department of Defense
EMALS	Electromagnetic Aircrafts Launch System
ERP	Enterprise Resource Planning
ICCS	Integrated Catapult Control System
JBD	Jet Blast Deflectors
LSO	Landing Signal Officer
LSODS	Landing Signal Officer Display System
MA	Moving Average
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
NAVAIR	Navy Air Systems Command
NAVICP	Naval Inventory Control Point
NAVSUP	Naval Supply Systems Command
NAWCAD	Naval Air Warfare Center Aircraft Division
NIIN	National Item Identification Number
NIS	Not in Stock
NPS	Naval Postgraduate School
NWCF	Navy Working Capital Fund

OLS	Optical Landing System
OPTEMPO	Operational Tempo
PMA	Program Management Activity
PMA 251	ALRE Program Office, Naval Air Systems Command
PSICP	Program Support for Inventory Control Points
RAST	Recovery Assist Secure and Traverse
RMSE	Root Mean Squared Error
SCM	Supply Chain Management
SES	Simple Exponential Smoothing
SPCC	Ships Parts Control Center
VLA	Visual Landing Aid
WSS	Weapons System Support

EXECUTIVE SUMMARY

At the behest of Naval Supply Systems Command Weapons Systems Support (NAVSUP WSS), this project set out to explore opportunities to optimize the current demand-forecasting model of critical aircraft launch and recovery equipment (ALRE) components. NAVSUP WSS sponsored this research due to current low service levels, fill rates, and lead times to operational units, specifically the Navy's aircraft carriers. In order to improve existing demand forecast accuracy, the current model used by NAVSUP WSS was evaluated and compared against other models, which build upon the status-quo model framework.

NAVSUP WSS currently utilizes a forecasting method known as simple exponential smoothing (SES), which averages historical data by giving older data less relative weight and disregards irrelevant outliers. This project formulated a hypothesis that this method could be improved by taking into account a ship's operational tempo (OPTEMPO). A nuclear powered aircraft carrier's (CVN) OPTEMPO depends on where the unit is in the operational cycle. The carrier will be in one of four phases within the cycle: deployment, training, maintenance, or sustainment. In order to determine the usefulness of using cyclicality in conjunction with exponential smoothing, a correlation between operational phases and ALRE parts demand need to be examined.

This project utilized the previous six years of parts demand data along with the ship schedules of 10 aircraft carriers to run multiple linear regressions to determine the level of correlation. The results of nearly 400 regression models demonstrated virtually no correlation. This was evident by extremely low significance values and *p*-values well above the .05 threshold for null hypothesis rejection. Despite the lack of correlation between parts demand and the operational phase of the ship, four forecasting models (simple exponential smoothing, adaptive exponential smoothing, Holt-Winters, and Box–Jenkins) were evaluated for accuracy by three common evaluation methods. Those evaluation methods include the root mean square error (RMSE), the Akaike Information Criterion (AIC), and the mean absolute scaled error (MASE).

Running a forecast on all of NAVSUP's critical NIINs would be prohibitively time consuming, so the authors of this project utilized the ABC classification method to identify NAVSUP's top 10% NIINs based on annual budget consumption. Four forecasts were run and evaluated for each of the NIINs identified.

The forecasting testing conducted by this project identified the Holt–Winters model as the most accurate of the four models. The Simple Exponential Smoothing model, similar to the model utilized by NAVSUP, was second best.

In conclusion, the extremely low demand quantities of critical ALRE components continue to make forecasting extremely unreliable, but the authors of this project believe NAVSUP could benefit from more flexibility in its forecasting. It can utilize the best-fit forecast for each critical NIIN by grouping them together using demand-based criteria. The NIINs will then be grouped by best-fit forecasts once those forecasts are identified.

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I. INTRODUCTION

The United States Navy operates aircrafts that take off and land on aircraft carriers every day. The successful launch and recovery of these aircrafts is critical to the completion of air missions and safety of flight crews. Since aircraft carriers have limited launch and recovery space, they are equipped with aircraft launch and recovery equipment (ALRE). These "products include catapults, arresting gear, helicopter landing systems, wind measuring systems, aviation-based information systems, aviation marking and lighting, recovery systems and visual landing aids, aircraft firefighting equipment, and expeditionary airfield systems and related products" (Naval Air Systems Command [NAVAIR], n.d.-a).

A. BACKGROUND

The ALRE Program Office (PMA-251) located at Naval Air Systems Command (NAVAIR) in Patuxent River, MD, "provides life-cycle acquisition management for Navy and Marine Corps systems and equipment utilized for the launch and recovery of current and future fixed wing and rotary wing aircraft" (NAVAIR, n.d.-a). The ALRE Branch of Naval Supply Systems Command Weapons Systems Support (NAVSUP WSS) provides inventory support for all launch and recovery equipment.

Over the past 30 years, aircraft have continued to increase in weight while many of the ALRE systems and components have not undergone significant redesign to accommodate these higher energy loads. "The cumulative impact of heavier aircraft and other effects, including fatigue, cable dynamics, contractor manufacturing errors, and installation issues, has resulted in diminished factors of safety for ALRE critical parts" (J. Stark, email to author, May 6, 2018). In response, the Navy established the NAVAIR ALRE Flight Safe Program and designated the Support Equipment (SE) and Aircraft Launch and Recovery Equipment (ALRE) Department (NAVAIR 4.8) as overall in charge of this program. The responsibilities of NAVAIR 4.8 include final source approver, waiver & deviation issuance, and quality assurance. "The Flight Safe program ensures the safe operation of ALRE systems aboard naval vessels and shore installations by improving the quality and control of Critical Safety Items (CSI), critical processes, and ALRE interface items for production, installation, repair, overhaul, and new ship construction" (J. Stark, email to author, May 6, 2018).

"NAVSUP's ALRE branch provides sustainment support for 1,500 National Stock Numbers (NSN) of which roughly 15% are CSI items" (J. Stark, email to author, May 6, 2018). NAVAIR 4.8's current interpretation and execution of ALRE "Flight Safe" Program policy in conjunction with highly erratic demand signals across the CVNs are "impacting NAVSUP's ability to maintain healthy ALRE material pipelines" (J. Stark, email to author, May 6, 2018).

The U.S. Navy operates highly complex systems on myriad naval platforms, each with its own long list of components. One of those highly complex systems is ALRE. ALRE is composed of equipment used to launch and recover aircraft onboard CVNs. The inventory and supply chain management of the thousands of line items that support these complex systems is a robust operation. Providing necessary support involves understanding CVN operational requirements as well as having access to accurate demand data in order to reliably predict the needs of the fleet and implement effective and efficient inventory management policies.

B. RESEARCH GOALS

Demand signals across the Nimitz Class CVN's ALRE market-basket are highly erratic and do not fit neatly into the traditional demand-based sparing construct. This causes supply-planning efforts to continually lag requirements, with material often arriving late-to-need. The current demand forecasting model primarily utilizes historical component replacement rates to predict future demand. However, this construct omits changes in ship's operating phase status (deployment, sustainment, maintenance, and training).

This study utilizes both a quantitative and qualitative approach to research, gather, and analyze historical CVN ALRE demand data to see if there is any correlation between ALRE component demand and ship's operating phase status and if that correlation directly drives ALRE component demand. This research design aids in the development of a comprehensive and more reliable ALRE material requirement forecast model. The model functions to forecast which CVN ALRE assets are needed, when they are needed, an in what quantity they are needed. All required data is provided by NAVSUP WSS.

The purpose of this project is to evaluate demand signals across the CVNs ALRE market-basket to determine why this construct causes supply planning efforts to not support the unit at their time of part deficiency. Additionally, an evaluation was conducted to determine why the current model only uses past component replacement rates to predict future demand but omits changes in OPTEMPO. This could highlight the variables that drive ALRE demand and timely part replenishment.

The following are our research questions:

- Does the traditional sparing construct provide an accurate demand forecast for ALRE parts and components?
- Is there a correlation between the ALRE component demand and the ship's operating phase status?
- If there is correlation between the ALRE component demand and the ship's operating phase status, does that correlation directly drive ALRE component demand?
- Does a forecasting method exist that outperforms the current employed method of simple exponential smoothing?

C. THESIS ORGANIZATION

The body of the thesis beginning in Chapter II discusses the history of the NAVSUP Enterprise, ALRE, and the naval ship operational cycle. ALRE history is summarized along with how its role is influenced by these organizations. Next, an extensive description of ALRE systems is summarized as a significant subject of examination in efforts to identify opportunities for forecast optimization.

In Chapter III, the methodology for obtaining information along with the analysis, including explanations of statistical principles and methodologies, are used. The different forecasting models tested and the subsequent answers to the research questions, assumptions for data, and findings are also discussed. Lastly, Chapter IV summarizes the results of the analysis and provides recommendations from the authors' research.

II. LITERATURE REVIEW

A. NAVAL SUPPLY SYSTEMS COMMAND (NAVSUP)

Formally called NAVICP (Naval Inventory Control Point), NAVSUP logistically supports all components of the military in supplying weapons system parts and components. The two primary locations, both located in Pennsylvania (Mechanicsburg and Philadelphia), conjointly work together to address this issue. NAVSUP Global Logistics Support (NAVSUP GLS) Transportation and Distribution department recently realigned in 2014 to join with NAVSUP Weapons Systems Support (NAVSUP WSS). WSS's Directorate (N3) is in Norfolk, VA. These three entities are responsible for the efficient and cost-effective movement of personnel and cargo (Naval Supply Systems Command, [NAVSUP WSS], n.d.-a).

> On October 2, 1995, the Naval Inventory Control Point (NAVICP) was established with the merging of the former Aviation Supply Office (ASO) in Philadelphia and Ships Parts Control Center (SPCC) in Mechanicsburg. The purpose of this merger was to bring together all of the Navy's Program Support Inventory Control Point (PSICP) functions under a single command. The move to join the activities together as one Command, two sites, was the result of a need to reduce costs and infrastructure as well as to standardize inventory management procedures with a mission "to provide Navy, Marine Corps, Joint and Allied Forces quality supplies and services on a timely basis." (NAVSUP WSS, n.d.-a)

SPCC was the original Naval Supply Depot in Mechanicsburg established for making ships parts, specifically for aircraft engines. By 1980, ASO and SPCC became the only two remaining ICPs to provide support to the Navy (NAVSUP WSS, n.d.-a). On the NAVSUP WSS homepage, a brief description of their role in Supply Chain Management and what that entails for WSS:

> Naval Material Supply Chain Management (SCM) is NAVSUP's largest Product & Service in terms of resources invested with over 3,000 civilian, military and contractor personnel involved, $21 billion of inventory on hand and an annual material budget of over $3.5 billion. It covers the over 430,000 class IX repair part line items of supply for which the NAVSUP Weapon Systems Support (NAVSUP WSS) is responsible. NAVSUP WSS uses funds from the Navy Working Capital Fund (NWCF) to buy and repair the parts and in turn sells them to Fleet customers. In a nutshell, naval SCM

> is the collection of processes that result in Navy customers receiving the parts they need, when and where they need them, anywhere in the world. (NAVSUP WSS, n.d.-a)

NAVSUP’s two locations in Pennsylvania serve as the backbone for the Navy’s supply system. “NAVSUP WSS Philadelphia provides support for naval aviation weapons systems while the Mechanicsburg site supports ships, submarines and nuclear propulsion” (NAVSUP WSS, n.d.-a). Figure 1 is a snapshot of the NAVSUP organization:

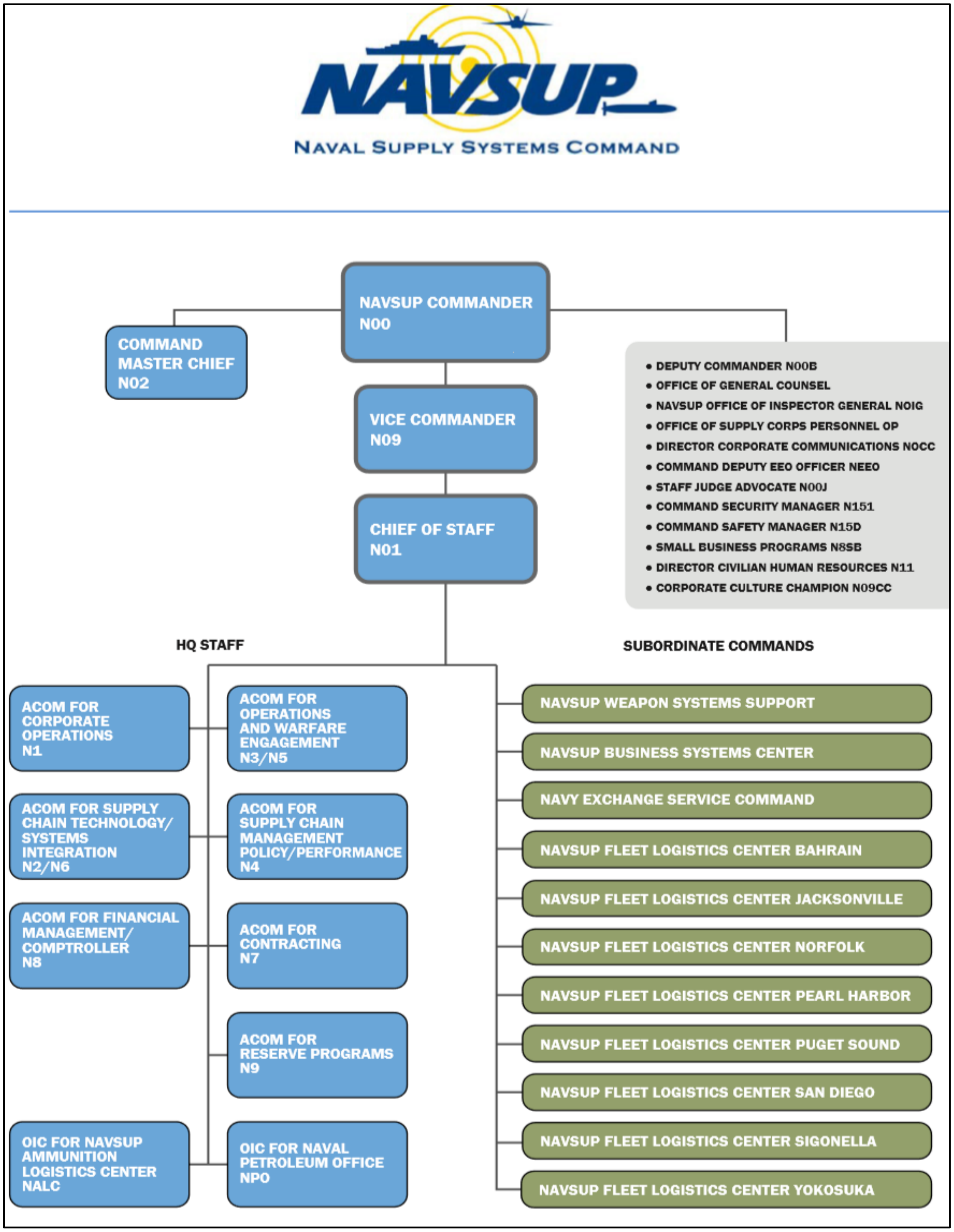

Figure 1. NAVSUP Organization in Support of Logistics Movement throughout the Navy to Include the DoD. Source: NAVSUP WSS (n.d.-b).

B. ABOUT AIRCRAFT LAUNCH AND RECOVERY EQUIPMENT (ALRE)

In order to bring offensive air strike capabilities to objectives across the global landscape, aircraft must launch from a CVN platform to be within effective striking distance. Naval aircraft carriers support success on the maritime frontier by providing a platform that enables aircraft to accomplish the mission and successfully prosecute objects by landing ordnance on target. That mission set requires jet aircraft have a ship available that will allow them to fly the distance and return safely. CVNs are equipped with this advanced ALRE to launch and recover these aircrafts while operating at sea. Without the launch and recovery systems, it could not be done.

The U.S. Navy will not have naval tactical aviation without launch and recovery. The first aircrafts launched off a U.S. aircraft carrier weighted only a couple thousand pounds. More energy is required to launch and recover the as aircrafts as they have gotten heavier over time. The initial aircraft carrier utilized hydraulic catapults (H-8 catapult), which were prone to malfunctions and explosions due to the weights of the aircrafts.

The U.S. Navy adopted the use of steam technology, which was developed by the United Kingdom, in 1698. The first steam-powered catapult installed on a carrier was the C7 catapult. Driven by the need for more energy, the internal combustion catapult (TC14 catapult) was developed with the capability to launch F-35C, F/A-18, and whatever aircrafts were developed in the future. However, it was deemed too dangerous for flight deck operations, so the Navy stayed with steam catapults.

The Nimitz-Class aircraft carriers (CVN 68 – CVN 77) are outfitted with the C-13 Mod 2 “Fat Cat.” The C-13 Mod 2’s development was led by Modest Zacharczenko, a developmental test engineer at NAVAIR, Patuxent River, MD. “His other engineering efforts were focused on the Navy’s Electromagnetic Aircraft Launch System (EMALS), which employs electromagnetic energy to propel aircraft, and is being incorporated into the latest Ford Class of nuclear-powered aircraft carriers” (Wooge, 2018).

NAVAIR’s Aircraft Launch and Recovery Equipment Program Office (PMA-251) manages an array of ALRE products. These ALRE products include launch and recovery systems, visual landing aides, and their associated information systems. The launching system includes the steam catapults, Jet Blast Deflectors (JBD), and the Integrated Catapult Control System (ICCS). "The launcher commodity encompasses not only catapults, but also the catapult control stations and jet blast deflectors" (NAVAIR, n.d.-b). "The ICCS, or 'bubble,' is a station located in carrier flight decks" (NAVAIR, n.d.-c). (See Figure 2.) It combines current remote stations to provide intercommunication during each aircraft launch. "JBDs are hydraulic-controlled panels on carrier flight decks designed to divert hot aircraft exhaust during launches" (LexLeader, 2012, para. 9). (See Figure 3.) "The panels are raised in preparation for takeoff, protecting the flight deck and other aircraft in the vicinity from the hot aircraft exhaust" (NAVAIR, n.d.-d).

Figure 2. Aircraft Shooters Watch from Inside the ICCS
Source: United States Navy (n.d.).

Figure 3. An F-14 Tomcat Preparing for Launch with the JBDs in Position to Deflect the Exhaust. Source: Avikerensky (2011).

1. Launch and Recovery Systems

Aircraft recovery at-sea is a critical piece of an aircraft carrier's mission. Landing a high-speed jet on an aircraft carrier calls for a great deal of skill and constant practice. As the aircraft approaches the carrier, the Landing Signal Officer (LSO), positioned aft on the flight deck, provides the pilot with critical information to help position the aircraft for a safe a landing. The tailhook on the bottom of the plane must engage one of four steel cables protruding only a couple of inches above the deck in order to stop the plane (Figure 4). An aircraft decelerates from 150 mph to zero within seconds upon landing on the flight deck of an aircraft carrier (LaGrone, 2014).

Current recovery systems include the carrier-based Mk-7 Mod 3/4 shipboard arresting gear system, which can stop a 50,000-pound aircraft in less than 350 feet. Air capable ships utilize the Recovery Assist Secure and Traverse (RAST) system, "which helps guide a helicopter to the deck and then secures the aircraft during the traversing phase to the hangar" (NAVAIR, n.d.-e).

Figure 4. An EA-6B Prowler, Assigned to the "Rooks" of Electronic Warfare Squadron One Three Seven (VAQ-137), Catches One of Four Arresting Wires on the Flight Deck of the Aircraft Carrier USS *Enterprise* (CVN 65). Source: Pogo (n.d.).

2. Visual Landing Aides (VLA)

Visual landing aids (VLAs) help pilots land aircrafts onboard the carrier. "Current VLAs include flight deck status and signaling systems, hover position indicators and precision approach path indicators" (NAVAIR, n.d.-f). The most critical VLA system is the Fresnel Lens Optical Landing System (OLS) (Figure 5).

> [OLS is] designed to provide a "glide slope" for aviators approaching a carrier, the lights projected through the Fresnel lenses in different colors telling the aviator when the aircraft is at the desired altitude in the approach at any distance from the ship. If the aviator sees a red light (at the bottom), it means that the aircraft is dangerously low, the subsequent flashing red light activated by the landing signal officer (LSO) indicating a wave-off requiring the pilot to go around for another attempt. (National Naval Aviation Museum, n.d.)

Figure 5. Simulation of an Aircraft making its Approach to a CVN using the Precision Carrier Landing System. Source: Olson (2012).

3. ALRE Information Systems

Like most modern technologies, ALRE is controlled by information systems that were developed by the Naval Air Warfare Center Aircraft Division (NAWCAD), Lakehurst, NJ. These systems are used to collect important data, such as wind speed, which are passed on by the LSO to the pilot. (NAVAIR, n.d.-g). ALRE information systems include the Moriah, Wind Measuring and Indicating System (WMIS), Aviation Data Management and Control System (ADMACS), and Landing Signal Officer Display System (LSODS). Moriah provides all shipboard wind related information, which is utilized for operations such as firefighting and navigation. (NAVAIR, n.d.-h). "ADMACS connects the air department, ship divisions, and embarked staff who manage the aircraft launch and recovery operations on CVN ships" (NAVAIR, n.d.-i). (See Figure 6.)

"ADMACS communicates real-time aviation and command-related data across the ship's computer networks" (NAVAIR, n.d.-i). ADMACS "also displays the status of aircraft launch and recovery equipment (ALRE), fuel, weapons and other aviation and ship related information" (NAWCAD, n.d.). The LSODS enable the LSO to assist the pilot with flight deck lighting and landing of the aircraft (Figure 7).

Figure 6. Sailors Onboard a CVN Monitoring ADMACS.
Source: NAWCAD (n.d.).

Figure 7. LSOs Watch an F/A-18E Super Hornet, Assigned to the Gunslingers of Strike Fighter Squadron (VFA 105), Land Aboard the Aircraft Carrier USS *Harry S. Truman* (CVN 75). Source: Wikimedia Commons (2010).

C. ABOUT NAVAL SHIP OPERATIONAL CYCLE

All U.S. naval ships operate in a cyclical four-phase cycle. These phases consist of deployment, sustainment, maintenance, and training. The daily operations and overall objective for each phase directly attribute to the operational tempo and subsequent usage of equipment. This is important to take into account when considering the wear and tear on the material condition of the ship as it progresses through its operational cycle. Understanding the correlation between the CVN's cyclical OPTEMPO and demand signals for repair parts is critical in forecasting the seasonality of ALRE usage and maintenance requirements. See Figure 8 below.

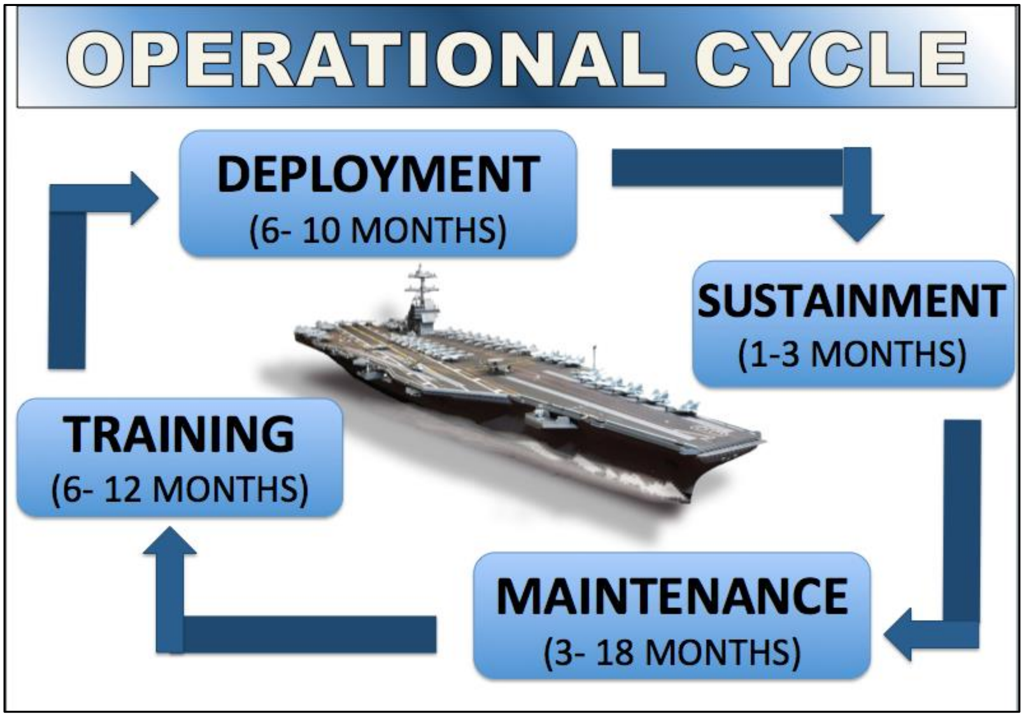

Figure 8. A U.S. Navy Ship's Typical Four-Phase Cyclical Operation Schedule.

1. Deployment Phase

The most well-known and arduous period is the deployment phase. CVN deployments typically last between seven and 10 months. During this time the ship conducts full operations at sea, which includes up to 12 hours of flight operations daily. This constant and demanding use of equipment directly correlates to extensive wear and tear, leading to increased component failure rates and subsequent replacement requirements. The amount of parts demand for corrective maintenance is typically highest during the deployment.

Special attention and consideration must be given to ALRE parts demand during this phase. If a required critical part is not in stock (NIS) then the impacts can be significant. Not only can it have a direct impact on the ships ability to conduct flight operations and therefore degrade mission readiness, but also additional transportation costs in required to expedite high value components to the ship in theater can be substantial.

2. Sustainment Phase

Once a ship returns to its respective homeport following a deployment, it immediately goes into what is referred to as the sustainment phase. This typically lasts between 30 and 90 days. The objective of this phase is to keep the ship in its current state of readiness in case it is tasked to conduct operations. This phase is generally considered an operational buffer providing Navy leadership flexibility in case of emergencies or unforeseen national defense requirements. Although the ship will technically be deployable during this time, it will not typically be conducting operations unless specifically called upon to do so.

3. Maintenance Phase

Upon completion of the sustainment phase, a ship will undergo a substantial period of maintenance referred to as an "availability." A simplistic comparison can be made to that of a personal vehicle. After a time of usage, a car needs a tune-up or even an overhaul if the wear and tear is significant. This concept holds true, but on a much larger scale, for aircraft carriers. Depending on the amount of maintenance, repairs, modifications, and upgrades needed, a maintenance availability can range anywhere from three to 18 months. Post-deployment maintenance periods typically average approximately six months.

During this time, significant work will be done throughout the entire ship, sometimes requiring it to be completely removed from the water in what is referred to as a "dry dock." The environment during an availability is most comparable to a construction zone. Hard hats, cranes, and construction shipyard workers along with their equipment fill the ship. While some critical parts for ALRE may be requisitioned to support maintenance during this period overall, the demand is extremely low. Due to the lack of operations and subsequent use of aviation systems, demand for parts is typically lowest during the maintenance phase of the ship's operational cycle.

4. Training Phase

There is a significant churn of personnel throughout the approximate 24-month operational cycle of a Navy ship. Due to this turnover of personnel, as well as the atrophy of skills and capabilities of the crew during the maintenance availability, a substantial training phase must be completed. The entire training period is broken down into three subsequent phases: basic, intermediate, and advanced.

The basic phase consists of a series of training evolutions and inspections that certify that the crew and ship can safely and effectively get underway. Examples of this include engineering certifications, damage control, force protection, and navigation. For the purposes of ALRE parts analysis, it is important to note that the material condition of the flight deck is not yet certified for flight operations until the end of the basic phase. Therefore, demand signals for corrective maintenance should still remain low. Once having demonstrated sufficient material readiness and watch standing proficiency, the ship and her crew will progress onto the intermediate phase.

During the intermediate phase, the ship will train and certify in more complex evolutions to include flight operations. As the ship and crew certify in the requisite functional warfare areas they will begin to conduct advanced integration training that mimics operations that will be executed on deployment. During this advanced phase, the ship will be underway conducting full-scale dynamic training scenarios known as deployment "work ups." The OPTEMPO during the training phase increases as the ship progresses from basic certifications through deployment work ups. Parts requirements will theoretically show a positive correlation and will increase along with OPTEMPO.

D. CONCLUSION

In conclusion, the literature review conducted describes and explains the U.S. Naval Supply organizational structure and how it provides inventory management services in support of the warfighter. One of the many equipment systems which fall under NAVSUP's purview of fleet parts support is a group of components belonging to complex systems of equipment that are responsible for the launch and recovery of aircraft. ALRE is described in detail, as its usage and forecasting difficulty are the primary focus of this thesis.

In our efforts to identify opportunities to optimize the Navy's ability to accurately forecast demand for ALRE components, we have primarily focused on the perceived correlation between the operational tempo of CVNs and replacement parts demand. Therefore, the typical operational cycle of a navy ship and subsequent phases of operation are also explained. Discovering ways to optimize and improve forecasting tools utilized by the U.S. Navy is extremely important. Accurate forecasting will ultimately reduce inventory management costs, reduce procurement and delivery lead times, and improve mission readiness.

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III. METHODOLOGY AND ANALYSIS

The purpose of this chapter is to analyze a specified group of ALRE NIINs in order to forecast demand to satisfy future operational requirements of the Navy's air capable ships. To accomplish this goal we made use of the data provided by NAVSUP WSS. This data was organized utilizing the ABC classification method to identify NAVSUP's top 10 percent NIINs based on annual budget consumption. Next, this project will utilize both the causal (multiple linear regression) and time series (simple exponential smoothing, adaptive exponential smoothing, Holt–Winters exponential smoothing, and Box–Jenkins exponential smoothing) forecasting models to forecast ALRE demand for a 12-month period.

The causal forecasting model will combine six years of historical demand data, and the historical schedules of the 10 CVNs to run multiple linear regressions, which will determine if there is a relationship between demand and OPTEMPO. The time series models will utilize the same historical demand data to uncover any trends and/or seasonality for ALRE demand. The different time series models utilized are explained in detail.

The results from the time series forecast methods will be evaluated for accuracy by two common evaluation methods: the Root Mean Squared Error (RMSE), and the Akaike Information Criterion (AIC). A third forecast error method called the Mean Absolute Percentage Error (MAPE) will also be discussed, but not utilized. MAPE limitations, which do not allow it to work with this project's low demand data is explained in further detail. The historical data utilized is the same across all models used in this project.

A. DATA COLLECTION AND ORGANIZATION

NAVSUP WSS provided six years of historical ALRE demand data for all 10 CVNs. The demand data was then combined with historical ship schedules from unclassified open source outlets (uscarriers.net) to create a spreadsheet for each ship (example in Figure 9). This was formulated by consolidating the demand for each NIIN associated with all 10 CVNs. The spreadsheet separated the demand data by month and highlighted which phase of the operating cycle the ship was in. Once complete, we used data from those spreadsheets to run multiple linear regressions and advanced exponential smoothing forecast models for each NIIN to answer the research questions for this project.

Table 1. This is a Sample of USS *Carl Vinson* (CVN 70) Demand Data Organized by Months and Operational Schedule

NIIN	12-04Apr	12-05May	12-06Jun	12-07Jul	12-08Aug	12-09Sep	12-10Oct	12-11Nov	12-12Dec	13-01Jan	13-02Feb	13-03Mar	13-04Apr	13-05May
000309452	0	0	0	0	0	0	0	0	0	1	0	0	0	0
000581381	0	0	0	1	2	0	0	0	0	1	0	0	0	0
000715184	0	0	0	0	0	0	0	0	0	1	0	1	1	5
001068440	0	0	0	0	0	0	0	0	0	0	0	0	0	0
001071654	0	0	0	0	0	0	0	0	0	0	0	0	0	0
001102604	0	0	0	0	0	0	0	0	0	0	0	0	0	0
001136177	0	0	0	0	0	0	0	0	0	1	0	0	0	0
001514355	0	0	0	0	0	0	0	0	0	0	0	0	3	0
001938859	0	0	0	0	0	0	0	0	0	0	0	0	0	1
002244686	0	0	0	0	0	0	0	0	0	0	0	1	0	0
002249023	0	0	0	0	0	0	0	0	0	1	0	0	0	0
002249098	0	0	0	0	0	0	0	0	0	2	0	0	0	0
002751898	0	0	0	0	0	0	0	0	0	0	0	1	0	0
002786951	0	0	0	0	0	0	0	0	0	0	0	1	1	0
002943617	0	0	0	0	0	0	0	0	0	1	0	0	1	1
003158906	0	0	0	0	0	0	0	0	0	0	0	1	1	0
003159101	0	0	0	0	0	0	0	0	0	0	0	0	0	1
003160033	0	0	0	0	0	0	0	0	0	1	0	0	0	1
003513815	0	0	0	0	0	0	0	0	0	0	0	0	0	1
003646970	0	0	0	0	0	0	0	0	0	0	0	1	0	0
004089800	0	0	0	0	0	0	0	0	0	1	0	0	0	0
004091435	0	0	0	0	0	0	0	0	0	0	0	0	0	1
004323430	0	0	0	0	0	0	0	0	0	0	0	0	0	0
004510011	0	0	0	0	0	0	0	0	0	0	0	0	0	1
004602936	0	0	0	0	0	0	0	0	0	0	0	0	0	1
004615366	0	0	0	0	0	0	0	0	0	0	0	1	0	0
004693398	0	0	0	0	0	0	0	0	0	0	1	1	0	0
004705269	0	0	0	0	0	0	0	0	0	0	0	0	1	0
004760009	0	0	0	0	0	0	0	0	0	0	0	0	0	1

B. ABC CLASSIFICATION

ABC classification is utilized to identify and segregate the vital inventory items in terms of budget consumption from the trivial many that may obfuscate data and are generally irrelevant for analytical purposes. The segregation and prioritization of high value units offer the ability to apply a different degree of control to those items (Dickie, 1951). The first step in classifying inventory items is to identify the items criteria to classify your inventory. With the management of a constrained DoD budget in mind, this project prioritizes NAVSUP's budget by ranking their critical NIINs based on annual budget consumption. Next, the items must be classified into groups based on that criterion. Finally, a degree of control must be applied in proportion to the importance of the group.

NAVSUP provided a list of 100 critical NIINs for evaluation. Of the 100 critical NIINs, only 55 had historical demand from the 10 CVNs. This project utilized the ABC

Classification system to classify the 55 NIINs into three groups (A – top 10%, B – middle 50%, C – bottom 40%) based on budget consumption. The “A” items consume roughly 70% to 80% of the annual budget, the “B” items consume roughly 15% to 20% of the annual budget, and the “C” items consume roughly 10% to 15% of the annual budget. (Ferrer, 2018). “Once the A’s, B’s and C’s have been identified, each category can be handled in a different way, with more attention being devoted to category A, less to B, and even less to C.” (Statistics Solutions, n.d.).

The “A” classified items contained only five NIINS. Since larger data samples lead to more accurate forecasts, the authors of this project decided to expand the “A” classified NIINs by adding the next five NIINs. This resulted in a top 10 list for the “A” category. The modified “A” classified NIINs can be seen in Table 1. Highlighted in yellow are the modified “A” classified items with the original top 10% of budget consumption delineated in red font in Tables 1 and 2.

Table 1. “A” Classified Items

CRITICAL NIIN	18-01Jan	18-02Feb	18-03Mar	18-04Apr	18-05May	18-06Jun	18-07Jul	18-08Aug	18-09Sep	Standard Price	Avg Demad	Budget	Std Dev
015334867	6	9	10	13	5	7	11	11	0	102,922.00	3.9358974	$405,090.44	6.3129
011581698	0	0	6	5	0	4	2	0	0	92,305.00	1.4487179	$133,723.91	1.5762
016485009	0	1	0	0	8	1	3	1	0	286,734.00	0.3205128	$91,901.92	1.0506
015504195	1	2	2	2	2	1	1	0	0	22,353.00	1.2307692	$27,511.38	1.2579
015504281	3	0	1	4	2	6	4	2	0	8,916.00	1.8589744	$16,574.62	1.8356
016505136	2	5	4	0	0	2	0	4	0	21,783.00	0.7051282	$15,359.81	1.5042
015512724	0	0	0	0	0	5	1	0	0	14,772.00	0.9487179	$14,014.46	1.161
015504153	0	0	3	1	0	1	0	0	0	21,485.00	0.6025641	$12,946.09	0.8877
015504283	0	0	0	0	0	0	0	1	0	30,798.00	0.3205128	$9,871.15	0.5221
013019246	3	3	0	2	0	3	0	0	0	9,394.00	0.9230769	$8,671.38	1.4121
012929791	2	4	1	0	1	0	0	0	0	17,159.00	0.474359	$8,139.53	0.9899
006900228	0	1	4	0	0	0	1	0	0	40,092.00	0.1923077	$7,710.00	0.5824
015512838	0	0	4	0	2	0	0	3	0	9,760.00	0.7179487	$7,007.18	1.0556
013126213	0	0	0	0	0	0	2	0	0	34,991.00	0.1923077	$6,729.04	0.5824

Table 2. “A” Classified Item Nomenclature

CRITICAL NIIN	NOMENCLATURE
015334867	FITTING,HOLD BACK,A
011581698	SHUTTLE ASSEMBLY
016485009	ACTUATOR,ASSY,CROV,
015504195	HYDRAULIC ACTUATOR,
015504281	DIGITAL CONTROL CCA
016505136	DISPLAY,AIRCRAFT
015512724	CIRCUIT CARD ASSEMB
015504153	VALVE,SERVO,AIRCRAF
015504283	FAILSAFE CONTROL CC
013019246	CARD ASSEMBLY CONTR

C. EVALUATING FORECASTS

Forecasting is not an exact science and a certain level of uncertainty or error is to be expected. Several mathematical methods exist that quantify the level of error in any given forecast. Armed with this error data, a forecast’s accuracy can be scrutinized as well as compared against other forecast models to determine which one provides more optimal results (Chambers, Mullick, & Smith, 1971). In this section, we present three such methods (RMSE, AIC, and MASE) that were used to evaluate the accuracy or amount of error of the time series forecasts employed in this project. A fourth method called the Mean Absolute Percentage Error (MAPE) is also discussed, but due to its inherent limitations when dealing with low demand data, it could not be used for this project.

1. Mean Absolute Percentage Error (MAPE)

The MAPE is a common method utilized to evaluate the calculated forecast error, but due to the nature of the formula, it is not applicable to this project. It is “based on the assumption that the severity of error is linearly related to its size. It is defined by and is the sum of the absolute values of the errors divided by the corresponding observed values all divided by the number of forecasts” (Jarrett, 1991, p. 32).

According to Jarrett, the MAPE formula is expressed as:

$$MAPE = \frac{1}{n} \Sigma \left| \frac{A_t - F_t}{A_t} \right| \times 100 \qquad (1)$$

where:

A_t = actual value

F_t = forecast value

n = number of time periods

The issue arises when any of the actual values in the sample is zero. Due to the actual value being the sole variable in the denominator any zero that occurs results in an undefined solution. ALRE components have low quantity and sporadic demands with many time periods experiencing zero demand therefore rendering the MAPE method unusable for the purposes of this project.

"The MAPE measures the size of the error in percentage terms. It is calculated as the average of the unsigned percentage error" (Stellwagen, n.d.). The MAPE is easy to interpret, but it can be delicate when working with low demand data.

> It is neither a resistant or robust summary measure because a few outliers can dominate it and the MAPE will not be close in value for many distributions (Hoaglin, Mosteller, and Tukey 1983: 28; Huber 1964; Tukey 1970). Therefore, the MAPE can understate forecast accuracy, sometimes dramatically. As such, it has tended to reinforce the perception of inaccurate forecasts. (Swanson, Tayman, & Bryan, n.d., p. 8)

For example, and as shown in Figure 9, the forecast for month 1 is subtracted from the actual and then divided by the actual, yielding an absolute error of 11%. Each consecutive month is calculated the same way and the average of these monthly values is calculated resulting in an overall MAPE of 17.6%.This MAPE percentage would be compared to other MAPE results for multiple forecasting methods. The lowest MAPE score would determine the type of forecasting method to utilize for that data specifically.

$$\left(\frac{1}{n}\sum\frac{|Actual - Forecast|}{|Actual|}\right)*100$$

Month	Actual	Forecast	Absolute Percent Error
1	112.3	124.7	11.0%
2	108.4	103.7	4.3%
3	148.9	116.6	21.7%
4	117.4	78.5	33.1%
MAPE			**17.6%**

Figure 9. Example of a MAPE calculation. Source: Stellwagen (n.d.).

2. Root Mean Squared Error (RMSE)

The second evaluation method is the RMSE.

> [It is the] standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points fall; RMSE is a measure of the spread of these residuals. In other words, it tells you how concentrated the data is around the line of best fit. RMSE is commonly used in climatology, forecasting, and regression analysis to verify experimental results. (Stephanie, 2016)

The model with the lowest RMSE is the best performer. According to Jarrett (1991), the RMSE formula is expressed as:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \tag{2}$$

where:

A_t = actual value

F_t = forecast value
n = number of time periods

The majority of forecasting software programs are equipped with the tools needed to calculate the RMSE, thereby alleviating the need to compute calculations manually. Referring to the whole integer values in Figure 10, the calculations using the RMSE forecast error method would appear as follows:

$$RMSE = \sqrt{\frac{(\mathbf{112-124})^{\mathbf{2}}+(\mathbf{108-103})^{\mathbf{2}}+(\mathbf{148-116})^{\mathbf{2}}+(\mathbf{117-78})^{\mathbf{2}}}{\mathbf{4}}} = 26.05 \tag{3}$$

3. Akaike Information Criterion (AIC)

The third and final evaluation method is the AIC. It "was formulated by the statistician Hirotugu Akaike; it was originally named 'an information criterion'" (Akaike information criterion, n.d.).

$$\text{AIC} = -2 \log \hat{L}\ (\hat{\theta}\ |\text{y}) + 2\text{k} \tag{4}$$

where:

$\hat{L}$ ($\hat{\theta}$ |y) = the value of the likelihood of a model's fit
k = the number of estimated parameters or variables in the model

The AIC is a complex algorithm that is used to compare the quality or effectiveness of a given set of statistical models against each other. It does not evaluate the validity or quality of a single model but is instead a tool used exclusively for model comparison. AIC essentially ranks a group of models from best to worst and is limited to comparisons between models that utilize the same data set. It is also important to note that AIC does not provide any information in regard to hypothesis testing. According to the Akaike information criterion, the model with the lowest AIC value is deemed the optimal model of the set evaluated.

4. Mean Absolute Scaled Error (MASE)

The MASE equation (equation 5) can be used to verify the forecast performance for low demand items such as ALRE because it is usually not affected by periods with no demand (Hyndman & Koehler, 2006). MASE is simply a performance metric to compare two different forecasting methods. It calculates the difference between the four forecasting methods compared to a naïve forecast. A naïve forecast is the simplest forecasting method. "According to the naïve forecasting method, demand in period t+1 should be the same as in period t. For example, if demand for specialty gray paint was 23 gallons this week, the naïve forecasting method would estimate the demand for that specialty paint to be 23 gallons next week" (Ferrer, 2018, p. 317).

"Ideally, the MASE should be close to 0. If the MASE is smaller than 1, the forecasting method performs better than the naïve method. If the MASE is greater than 1, the forecasting method performs worse than the naive method and the manager should choose another method for that item." (Ferrer, 2018, p. 360). According to Ferrer, the MASE equation is expressed as:

$$MASE_t = \left(\frac{n-1}{n}\right) x \frac{\sum_{i=1}^{n} |A_{t-n+i} - F_{t-n+i}|}{\Sigma_{i=2}^{n} |A_{t-n+i} - A_{t-n+i}|} \tag{5}$$

D. FORECASTING METHODS

Two schools of thought, causal and time series, generally delineate forecasting methodologies. Both categories of forecasting is evaluated and discussed in this section. The causal approach seeks to identify associations between variables and use these associations to predict the future behavior of dependent variables. A common example of a causal forecast method is regression analysis (Chambers, Mullick, & Smith, 1971).

Times series forecast models study historical data to identify trends and seasonality and then use that information to project trends into the future. These models are generally known to be reactive in nature since they are reliant on past events and data. Common examples of time series models include simple exponential smoothing, adaptive exponential smoothing, Holt-Winters, and Box–Jenkins.

1. Causal Approach: Regression Analysis

A primary focus of this thesis is the hypothesis that there is a direct correlation between the demand for ALRE components and the operational phase of the CVN. The initial intuitive assumption is that increased operational tempos (i.e., underway periods with sustained flight operations) such as those during deployment would cause additional wear and tear on recovery equipment. This constant usage would theoretically cause more equipment failures and subsequent requisitions for replacement parts. Conversely, maintenance periods are thought to have extremely low demand for ALRE components due to minimal equipment operation.

To test this correlation hypothesis, requisition demand data for over 100 critical NIINs from 10 CVNs for the past six years was consolidated and utilized to run four separate multiple linear regressions. The following quote explains Multiple Linear Regression.

> Multiple linear regression is the most common form of linear regression analysis. As a predictive analysis, the multiple linear regression is used to explain the relationship between one continuous dependent variable and two or more independent variables. The independent variables can be continuous or categorical. (Statistics Solutions, n.d.)

According to Anderson, Sweeney, & Williams (2013), the multiple linear regression equation is expressed below:

$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_P x_P \tag{6}$$

where:

$\hat{y}$ = the predicted value of dependent variable

b_0= the value of $\hat{y}$ when all of the independent variables (x_1 through x_P) are equal to zero

$b_1, b_2, \ldots, b_P$ = the estimated regression coefficients

$x_1, x_2, \ldots, x_p$ = the p distinct independent or predictor variables

The scenario for this study uses ALRE parts demand as the variable dependent on the particular operational phase of the ship at a given point in time. The operational phases of deployment, training, maintenance, and sustainment are, therefore, the independent variables for the purposes of a multiple linear regression analysis. The following quote explains the relationship between the independent and dependent variables. "It can be used to forecast effects or impacts of changes. That is, multiple linear regression analysis helps us to understand how much will the dependent variable change when we change the independent variables." (Statistics Solutions, n.d.). Table 3 is a visual representation of data organization implemented to run a multiple regression analysis where the "Demand for NIIN" column is the dependent variable and subsequent phase columns are the independent variables.

Table 3. Data Organization of Multiple Regression Analysis

Period	Demand for NIIN 015325728	# of Ships Deployed	# of Ships in Training	# of Ships in Maintenance	# of Ships in Sustainment
12-04Apr	0	2	5	2	1
12-05May	0	3	4	2	1
12-06Jun	1	3	4	1	2
12-07Jul	0	3	4	1	2
12-08Aug	0	3	3	2	2
12-09Sep	0	3	3	2	2
12-10Oct	0	3	4	3	0
12-11Nov	0	3	4	3	0
12-12Dec	0	2	4	4	0
13-01Jan	1	1	4	4	1
13-02Feb	0	2	6	2	0
13-03Mar	1	2	6	1	1
13-04Apr	0	3	5	1	1
13-05May	0	2	5	2	1
13-06Jun	2	3	4	2	1
13-07Jul	0	3	4	2	1
13-08Aug	1	2	4	2	2

As stated previously, four separate multiple linear regressions were run on approximately 100 NIINs that were deemed "critical" by NAVSUP WSS. The four regressions included the comparison of the following independent variables (op phase) and NIIN demand:

1. Combined correlation of all four operational phases (deployment, training, maintenance and sustainment).

2. Combined correlation between demand in relation to deployment, training, and maintenance.

3. Combined correlation between demand in relation to deployment and training.

4. Correlation between demand and deployed status only.

Tables 4–11 investigates NIINs 012929791, 012963788, 013019246, and 013102990. They show two regression results of those four NIINs. The first table for each respective NIIN illustrates the results using the primary operation cycles (deployment, training, and maintenance) as the independent variables. The second table for each NIIN shows the results of the regression that only used the ships' deployment status as the independent variable.

Table 4. Statistical Results of Multiple Linear Regression of Historical Demand Data for ALRE (NIIN 012929791) Dependent Variable and Ships' (Operational Phases) Independent Variables

NIIN 012929791: DEPLOYMENT + TRAINING + MAINTENANCE						
Regression Statistics						
Multiple R	0.227587011					
R Square	**0.051795848**					
Adjusted R Square	0.013355139					
Standard Error	0.983243307					
Observations	78					
ANOVA						
	df	*SS*	*MS*	*F*	***Significance F***	
Regression	3	3.907930295	1.302643	1.347421759	**0.265591377**	
Residual	74	71.54078765	0.966767			
Total	77	75.44871795				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.201013001	1.119411457	-0.17957	0.857980753	-2.431489018	2.029463016
# of ships deployed	0.298075032	0.184172583	1.618455	**0.109819316**	-0.06889685	0.665046914
# of ships in training	0.02405782	0.138384323	0.173848	**0.862459727**	-0.251678963	0.299794603
# of ships in maintenance	-0.024579699	0.145028145	-0.16948	**0.865879778**	-0.313554587	0.264395189

The coefficient of multiple determination, also known as "R squared" shows how closely data points "fit" along the regression line. It is a value between 0 and 1 that demonstrates how strongly the variables are correlated and how much variance among the data is explained. Generally speaking, the closer the value is to 1 the better, and anything with R square above 50% is deemed favorable since this means at least half of the variance can be explained. The R square for NIIN 012929791 in Table 4 is very weak (.051795848) and is not favorable. The next step is to analyze the *Significance F*.

The results observed in Table 4 infer that the regression is not overall statistically significant and in fact, very little correlation between the dependent variable (NIIN demand) and the independent variables (op phase) appears to exist. The model's overall significance indicator shows this, which is the highlighted value labeled as *Significance F* in Table 4.

F TEST FOR OVERALL SIGNIFICANCE

$H_o: \beta_1 = \beta_2 = \ldots = \beta_p = 0$

H_a: One or more of the parameters is not equal to zero

REJECTION RULE

p -value approach: Reject H_o if *p*-value ≤ α

Critical value approach: Reject H_o if $F \geq F_\alpha$

Figure 10. F Test for Significance (Multiple Linear Regressions) Hypothesis Test.

The *Significance F* value shows the *p*-value of the F test, which indicates whether all three independent variables are capable of predicting a correlation with the dependent variable. If the overall significance value exceeds the α of .05 then the model is not effective. This confirms that the multiple linear regression model for NIIN 012929791 is not reliable and does not show a significant relationship between the variables.

Another prominent indicator of model strength and hypothesis validity is the *p*-value. "A *p*-value is a probability that provides a measure of the evidence against the null hypothesis provided by the sample. Smaller *p*-values indicate more evidence against H_o." (Anderson et al., 2013). Anderson et al. also provide guidelines when interpreting *p*-values:

- Less than .01 – Overwhelming evidence to conclude that H_a is true
- Between .01 and .05 – Strong evidence to conclude that H_a is true
- Between .05 and .10 – Weak evidence to conclude that H_a is true
- Greater than .10 – Insufficient evidence to conclude that H_a is true

The p-values for NIIN 012929791 are all insignificant because the *p*-values are all greater than .05.

Now we are going to hypothesize that there is no correlation between demand for NIIN 012929791 and deployed status only since ALRE equipment is usually used at a higher rate when ships are deployed. The results in Table 5 indicate an R square of .048818882, a *Significance F* of .051899004 and a *p*-value of .051899004. These results mean there is not enough evidence to reject the null hypothesis and there is no correlation between demand for NIIN 012929791 and deployed status only.

Table 5. Statistical Results of Multiple Linear Regression of Historical Demand Data for ALRE (NIIN 012929791) Dependent Variable and Ships' (Operational Phases) Independent Variables

NIIN 012929791: DEPLOYED ONLY						
Regression Statistics						
Multiple R	0.220949953					
R Square	**0.048818882**					
Adjusted R Square	0.036303341					
Standard Error	0.971741491					
Observations	78					
ANOVA						
	df	*SS*	*MS*	*F*	***Significance F***	
Regression	1	3.683322054	3.683322	3.900660933	**0.051899004**	
Residual	76	71.76539589	0.944282			
Total	77	75.44871795				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.219941349	0.368359264	-0.59708	0.552226147	-0.953592406	0.513709708
# of ships deployed	0.305962854	0.154917187	1.975009	**0.051899004**	-0.002581465	0.614507173

The same analysis applies to Tables 6–11.

Table 6. Statistical Results of Multiple Linear Regression of Historical Demand Data for ALRE (NIIN 012963788) Dependent Variable and Ships' (Operational Phases) Independent Variables

NIIN 012963788: DEPLOYED + TRAINING + MAINTENANCE						
Regression Statistics						
Multiple R	0.165401949					
R Square	0.027357805					
Adjusted R Square	-0.012073635					
Standard Error	0.642927742					
Observations	78					
ANOVA						
	df	*SS*	*MS*	*F*	***Significance F***	
Regression	3	0.860367888	0.286789	0.693806886	**0.558730789**	
Residual	74	30.58835006	0.413356			
Total	77	31.44871795				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.959374123	0.731966011	1.310681	0.194018724	-0.49909999	2.417848236
# of ships deployed	0.010796718	0.120427632	0.089653	0.928805048	-0.229160576	0.250754012
# of ships in training	-0.051853461	0.09048739	-0.57305	0.56835065	-0.232153521	0.1284466
# of ships in maintenance	-0.109278628	0.094831684	-1.15234	0.252889249	-0.298234882	0.079677626

Table 7. Statistical Results (Multiple Linear Regression) of Historical Demand Data for ALRE (NIIN 012963788) Dependent Variable (Deployment) Ships' (Operational Phases) Independent Variables

NIIN 012963788: DEPLOYED ONLY						
Regression Statistics						
Multiple R	0.086377599					
R Square	0.00746109					
Adjusted R Square	-0.005598633					
Standard Error	0.640867794					
Observations	78					
ANOVA						
	df	*SS*	*MS*	*F*	***Significance F***	
Regression	1	0.234641702	0.234642	0.57130537	**0.452077061**	
Residual	76	31.21407625	0.410712			
Total	77	31.44871795				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.299120235	0.242934558	1.231279	0.222015127	-0.18472587	0.782966339
# of ships deployed	0.077223851	0.102168568	0.755847	0.452077061	-0.126262486	0.280710189

Table 8. Statistical Results (Multiple Linear Regression) of Historical Demand Data for ALRE (NIIN 013019246) Dependent Variable and Ships' Operational phases Independent Variables

NIIN 013019246: DEPLOYMENT + TRAINING + MAINTENANCE						
Regression Statistics						
Multiple R	0.122111247					
R Square	0.014911157					
Adjusted R Square	-0.025024878					
Standard Error	1.429652318					
Observations	78					
ANOVA						
	df	*SS*	*MS*	*F*	***Significance F***	
Regression	3	2.289436041	0.763145347	0.373375997	**0.772442405**	
Residual	74	151.2490255	2.04390575			
Total	77	153.5384615				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1.245372904	1.6276431	0.76513881	0.446622282	-1.997776767	4.488522575
# of ships deployed	-0.143524877	0.267790035	-0.535960486	0.593593242	-0.67710817	0.390058415
# of ships in training	-0.056683376	0.201213135	-0.281708132	0.778953621	-0.4576093	0.344242547
# of ships in maintenance	0.058220708	0.210873365	0.276093228	0.783246064	-0.361953643	0.478395059

Table 9. Statistical Results (Multiple Linear Regression) Historical Demand Data ALRE (NIIN 013019246) Dependent Variable and Ships' Deployed Operational Status Independent Variables

NIIN 013019246: DEPLOYED ONLY						
Regression Statistics						
Multiple R	0.082143841					
R Square	0.006747611					
Adjusted R Square	-0.0063215					
Standard Error	1.416549012					
Observations	78					
ANOVA						
	df	*SS*	*MS*	*F*	***Significance F***	
Regression	1	1.036017746	1.036017746	0.516302209	**0.474626651**	
Residual	76	152.5024438	2.006611103			
Total	77	153.5384615				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1.291300098	0.536973008	2.404776548	0.018616645	0.221825665	2.360774531
# of ships deployed	-0.16226784	0.225829391	-0.718541724	0.474626651	-0.612046051	0.287510372

Table 10. Statistical Results (Multiple Linear Regression) Historical Demand Data ALRE (NIIN 013102990) Dependent Variable Ships' Operational phases as Independent Variables

NIIN 013102990: DEPLOYMENT + TRAINING + MAINTENANCE						
Regression Statistics						
Multiple R	0.282965006					
R Square	0.080069195					
Adjusted R Square	0.042774703					
Standard Error	0.599099025					
Observations	78					
ANOVA						
	df	*SS*	*MS*	*F*	***Significance F***	
Regression	3	2.311741366	0.77058	2.146944	**0.101516546**	
Residual	74	26.56005351	0.35892			
Total	77	28.87179487				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.804809598	0.682067508	-1.17996	0.241797	-2.163858775	0.554239579
# of ships deployed	0.133612722	0.112218018	1.190653	0.237595	-0.089986559	0.357212003
# of ships in training	0.175880505	0.084318818	2.085899	0.040435	0.007871594	0.343889417
# of ships in maintenance	0.063037933	0.088366959	0.713365	0.477863	-0.113037075	0.239112942

Table 11. Statistical Results (Multiple Linear Regression Historical Demand Data ALRE (NIIN 013102990) as the Dependent Variable and Ships' Deployed Operational Status.

NIIN 013102990: DEPLOYED ONLY						
Regression Statistics						
Multiple R	0.077597464					
R Square	0.006021366					
Adjusted R Square	-0.0070573					
Standard Error	0.614495377					
Observations	78					
ANOVA						
	df	*SS*	*MS*	*F*	***Significance F***	
Regression	1	0.173847658	0.173848	0.460396	**0.499499852**	
Residual	76	28.69794721	0.377605			
Total	77	28.87179487				
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.105571848	0.232937532	0.45322	0.651682	-0.358363456	0.569507151
# of ships deployed	0.066471163	0.097964218	0.678525	0.4995	-0.128641487	0.261583813

2. Causal Analysis Results

After running nearly 400 regression models, the results overwhelmingly displayed a lack of significance in the regression. This means that a correlation between ALRE parts demand and a ship's operational phase status could not be quantifiably determined, demonstrated, or verified. This result can be observed by looking at tables 4–11 with the regression's statistics illustrating the numerical values of certain significance indicators, specifically the coefficient of determination (R square), Significance F, and the *p*-values.

The coefficient of multiple determination, also known as "R squared" shows how closely data points "fit" along the regression line. It is a value between 0 and 1 that shows how strongly the variables are correlated and how much variance among the data is explained. Generally speaking, the closer the value is to 1 the better, and anything with R square above 50% is deemed favorable since this means at least half of the variance can be explained. The typical results from this analysis of parts demand and a ship's operational tempo demonstrated R square values of approximately 2%-6%. These low values indicate that operational tempo alone can explain virtually none of the variance in demand data.

Tables 4–11 demonstrate results that are typical and consistent across all NIINs that were examined in this project. The results observed infer that the regression is not overall statistically significant and in fact, very little correlation between the dependent variable (NIIN demand) and the independent variables (operational phase) appears to exist. The model's overall significance indicator shows this, which is the highlighted value labeled as Significance F on the regression results tables.

The Significance *F* value shows the *p*-value of the F test, which indicates whether all three independent variables are capable of predicting a correlation with the dependent variable. If the overall significance value exceeds the α of .05, then the model is not effective. This confirms that the multiple linear regression model is not reliable and does not show a significant relationship between the variables.

Table 12. Summary of *Significance F* Values for NIINs in Tables 4–11

Regression Significance Summary ($\alpha = 0.05$)			
NIIN	**Independent Variables**	***P*-value of *F* Test**	**Conclusion**
012929791	Primary OP phases	0.26	insufficient evidence to reject H_o
	Deployed only	0.05	weak evidence to reject H_o
012963788	Primary OP phases	0.56	insufficient evidence to reject H_o
	Deployed only	0.45	insufficient evidence to reject H_o
013019246	Primary OP phases	0.77	insufficient evidence to reject H_o
	Deployed only	0.47	insufficient evidence to reject H_o
013102990	Primary OP phases	0.10	weak evidence to reject H_o
	Deployed only	0.50	insufficient evidence to reject H_o

In this analysis, the null hypothesis assumed that there was no correlation between ALRE parts demand and a ship's operational phase. In order to reject this null hypothesis a *p*-value less than significance level α (.05) is needed. The results of approximately 400 regression models consistently show *p*-values for independent variables well above this threshold, often generating *p*-values in excess of .85. This demonstrates that there is a very high probability that the *p*-values' respective variable (e.g., operational phase) generated outputs from the model by random chance. The lack of impact the variables have on one another demonstrates that a correlation between ALRE parts demand and a ship's operational cycle was not observed.

3. Time Series Approach

A software program called Forecast X was utilized to compute the time series forecasts in this project. Forecasting is not an exact science and even an advanced software program such as Forecast X is vulnerable to mathematical errors and inherent limitations. Despite such challenges associated with forecasting, Forecast X is a powerful tool. The needs to input available raw data and the software will determine which forecast method is optimal, as well as, necessary variables such as α and β.

a. Simple Exponential Smoothing Forecasting

Simple exponential smoothing is one of the most commonly used forecasting methods. The general concept is that older data is given less priority (weight) and newer data, which is seen as more relevant, is given more weight.

> Wilson and Keating explain that "It uses only past values of a time series to forecast future values of the same series and is properly employed when there is no trend or seasonality present in the data. With exponential smoothing, the forecast value at any time is a weighted average of all the available previous values; the weights decline geometrically as you go back in time"(Wilson & Keating, 1990, pp. 76–77).

They also state that

> The weights are made to decline geometrically with the age of the observation to conform to the argument that the most recent observation contain the most relevant information, so they should be accorded proportionately more influence than the older observations.

According to Wilson and Keating, the simple exponential smoothing equation as follows:

$$F_{t+1} = \alpha_t X_{t+1} + (1 - \alpha_t)F_t \tag{7}$$

where:

F_{t+1} = Forecast value for period t + 1

α = Smoothing constant ($0 < \alpha < 1$), in practice ($0.05 < \alpha < 0.30$)

X_t = Actual value now (in period t)

F_t = Forecast (i.e., smoothed) value for period t

They also explain that

> the weight of the most recent observation is assigned by multiplying the observed value by α (known as alpha), the next most recent observation by (1- α), the next observation by $(1-\alpha)^2$ α, and so on. The number we choose for α is called the smoothing constant. In using this equation the forecaster does not need to deal with every actual past value at every step;

> only the exponentially smoothed value for the last period and the actual value for this period are necessary. (Wilson & Keating, 1990, pp. 76–77)

In addition to simple exponential smoothing, NAVSUP currently sets the initial condition for the forecast using a method known as backcasting. It is a term introduced by John B. Robinson from the University of Waterloo, denoting a method to analyze future options. Dreborg (1996) states:

> The major distinguishing characteristic of backcasting analysis is a concern, not with what futures are likely to happen, but with how desirable futures can be attained. It is thus explicitly normative, involving working backwards from a particular desirable future end-point to the present in order to determine the physical feasibility of that future and what policy measures would be required to reach that point. (p. 814)

Backcasting is a complex method to determine an initial condition of a forecast, but it is not necessarily optimal when convolved with simple exponential smoothing. This is because of how SES works. Exponential smoothing keeps historical data, but data far in the past implicitly has very low weight. This dilution of the forecasts first value makes trying to perfect an initial condition several periods ago, inconsequential since it has very little impact on the quality of the current forecast. Using the first actual demand data point as the initial condition will likely be just as effective. Values from the forecasts are maintained up to two decimals without rounding in order to maintain accurate quantitative results throughout all time periods examined in the forecast. The final value may be rounded at the discretion of the inventory manager’s economic order quantity policy.

Table 13. Simple Exponential Smoothing Forecast with Six Years of Historical Demand for NIIN 015504195 (12-Month Forecast)

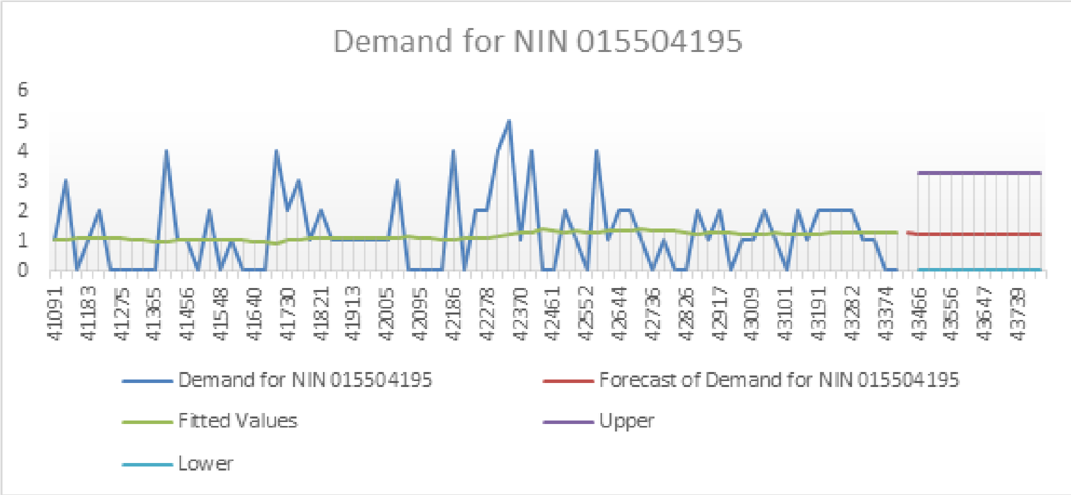
DATES	Demand for NIIN 015504195 - Actual	Simple Exponential Smoothing Forecast using α = 0.03
Jun-12		
Jul-12	1.00	1.05
Aug-12	3.00	1.05
Sep-12	0.00	1.10
Oct-12	1.00	1.07
Nov-12	2.00	1.07
Dec-12	0.00	1.09
Jan-13	0.00	1.06
Feb-13	0.00	1.03
Mar-13	0.00	1.01
Apr-13	0.00	0.98
May-13	4.00	0.95
Jun-13	1.00	1.03
Jul-13	1.00	1.03
Aug-13	0.00	1.03
Sep-13	2.00	1.00
Oct-13	0.00	1.03
Nov-13	1.00	1.00
Dec-13	0.00	1.00
Jan-14	0.00	0.98
Feb-14	0.00	0.95
Mar-14	4.00	0.92
Apr-14	2.00	1.01
May-14	3.00	1.03
Jun-14	1.00	1.09
Jul-14	2.00	1.09
Aug-14	1.00	1.11
Sep-14	1.00	1.11
Oct-14	1.00	1.11
Nov-14	1.00	1.10
Dec-14	1.00	1.10
Jan-15	1.00	1.10
Feb-15	3.00	1.09
Mar-15	0.00	1.15

DATES	Demand for NIIN 015504195 - Actual	Simple Exponential Smoothing Forecast using α = 0.03
Apr-15	0.00	1.11
May-15	0.00	1.08
Jun-15	0.00	1.05
Jul-15	4.00	1.03
Aug-15	0.00	1.11
Sep-15	2.00	1.08
Oct-15	2.00	1.10
Nov-15	4.00	1.13
Dec-15	5.00	1.21
Jan-16	1.00	1.31
Feb-16	4.00	1.30
Mar-16	0.00	1.37
Apr-16	0.00	1.34
May-16	2.00	1.30
Jun-16	1.00	1.32
Jul-16	0.00	1.31
Aug-16	4.00	1.27
Sep-16	1.00	1.35
Oct-16	2.00	1.34
Nov-16	2.00	1.36
Dec-16	1.00	1.38
Jan-17	0.00	1.37
Feb-17	1.00	1.33
Mar-17	0.00	1.32
Apr-17	0.00	1.28
May-17	2.00	1.25
Jun-17	1.00	1.27
Jul-17	2.00	1.26
Aug-17	0.00	1.28
Sep-17	1.00	1.25
Oct-17	1.00	1.24
Nov-17	2.00	1.23
Dec-17	1.00	1.25
Jan-18	0.00	1.25
Feb-18	2.00	1.21
Mar-18	1.00	1.23
Apr-18	2.00	1.23

DATES	Demand for NIIN 015504195 - Actual	Simple Exponential Smoothing Forecast using α = 0.03
May-18	2.00	1.25
Jun-18	2.00	1.27
Jul-18	2.00	1.29
Aug-18	1.00	1.31
Sep-18	1.00	1.30
Oct-18	0.00	1.29
Nov-18	0.00	1.26
Dec-18		**1.22**
Jan-19		**1.22**
Feb-19		**1.22**
Mar-19		**1.22**
Apr-19		**1.22**
May-19		**1.22**
Jun-19		**1.22**
Jul-19		**1.22**
Aug-19		**1.22**
Sep-19		**1.22**
Oct-19		**1.22**
Nov-19		**1.22**

Table 14. NIIN 015504195 Simple Exponential Smoothing Evaluation Results

AIC	256.80
RMSE	1.27
MASE	0.78



	Forecast			95% - 5%	95% - 5%
Date	**Monthly**	**Quarterly**	**Annual**	**Upper**	**Lower**
Dec-2018	1.22	1.22	1.22	3.25	0.00
Jan-2019	1.22			3.25	0.00
Feb-2019	1.22			3.25	0.00
Mar-2019	1.22	3.67		3.25	0.00
Apr-2019	1.22			3.25	0.00
May-2019	1.22			3.25	0.00
Jun-2019	1.22	3.67		3.25	0.00
Jul-2019	1.22			3.25	0.00
Aug-2019	1.22			3.25	0.00
Sep-2019	1.22	3.67		3.25	0.00
Oct-2019	1.22			3.25	0.00
Nov-2019	1.22			3.25	0.00
Avg	1.22	3.06	1.22	3.25	0.00
Max	1.22	3.67	1.22	3.25	0.00
Min	1.22	1.22	1.22	3.25	0.00

Figure 11. Simple Exponential Smoothing Forecast with Six Years of Historical Demand for NIIN 015504195 (12-Month Forecast).

The chart illustrates the upper (purple) and lower (blue) limits of a forecast with a 95% confidence interval. The simple exponential smoothing forecast for NIIN 015504195 is 95% confident that demand for each of the next 12 months will fall between the upper and lower limits above. An AIC of 256.58, and an RMSE of 1.26 means it is more accurate than the adaptive exponential smoothing forecast, which recorded an AIC, and RMSE of 274.7, and 1.45, respectively. A MASE of .78 means it performed better than the naïve forecast.

b. Adaptive Exponential Smoothing Forecast

Adaptive exponential smoothing is an advanced version of simple exponential smoothing. It "is attractive when a great many items have to be forecast. By the term "*adaptive*," we mean that this method can change the value of an unspecified α on an ongoing basis" (Jarrett, 1991, pp. 34–35).

Adaptive exponential smoothing adjusts the value of α when a change in the basic pattern is detected. A different smoothing constant is applied once a change in the basic pattern is detected. According to Jarrett, the equation for adaptive exponential smoothing is:

$$F_{t+1} = \alpha_t X_{t+1} + (1 - \alpha_t) F_t \quad (8)$$

where:

$$\alpha_t = \left| \frac{E_t}{M_t} \right| \quad (9);$$

$$E_t = \beta e_t + (1 - \beta) E_{t-1} \quad (10);$$

is the smoothed error,

$$M_t = \beta |e_t| + (1 - \beta) M_{t-1} \quad (11);$$

is the absolute smoothed error,

$$e_t = X_t - F_t \quad (12);$$

is the error, and

$\beta = 0.1$

Table 15. Adaptive Exponential Smoothing Forecast with Six Years of Demand for NIIN 015504195 (12-Month Forecast)

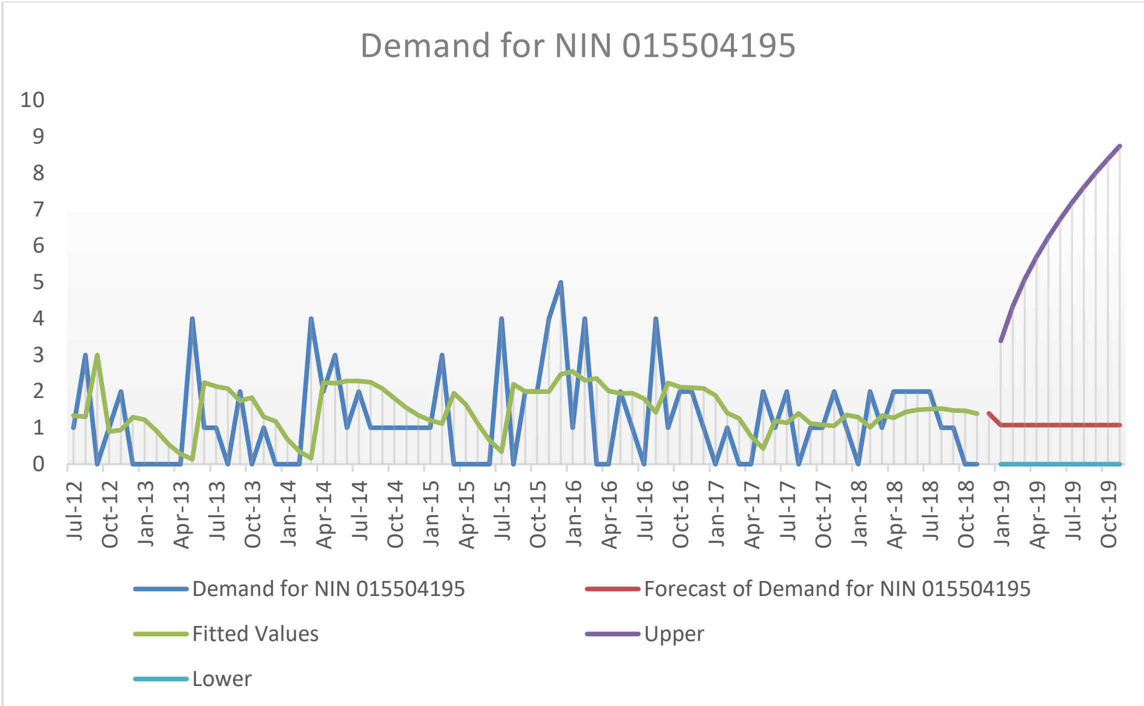
DATES	Demand for NIIN 015504195 - Actual	Adaptive Exponential Smoothing Forecast using β = 0.1
Jun-12		
Jul-12	1.00	1.33
Aug-12	3.00	1.30
Sep-12	0.00	3.00
Oct-12	1.00	0.90
Nov-12	2.00	0.94
Dec-12	0.00	1.29
Jan-13	0.00	1.22
Feb-13	0.00	0.90
Mar-13	0.00	0.54
Apr-13	0.00	0.28
May-13	4.00	0.13
Jun-13	1.00	2.24
Jul-13	1.00	2.14
Aug-13	0.00	2.08
Sep-13	2.00	1.74
Oct-13	0.00	1.82
Nov-13	1.00	1.30
Dec-13	0.00	1.18
Jan-14	0.00	0.68
Feb-14	0.00	0.35
Mar-14	4.00	0.17
Apr-14	2.00	2.24
May-14	3.00	2.23
Jun-14	1.00	2.29
Jul-14	2.00	2.28
Aug-14	1.00	2.25
Sep-14	1.00	2.07
Oct-14	1.00	1.81
Nov-14	1.00	1.55
Dec-14	1.00	1.34
Jan-15	1.00	1.20
Feb-15	3.00	1.12
Mar-15	0.00	1.96

DATES	Demand for NIIN 015504195 - Actual	Adaptive Exponential Smoothing Forecast using β = 0.1
Apr-15	0.00	1.65
May-15	0.00	1.13
Jun-15	0.00	0.66
Jul-15	4.00	0.34
Aug-15	0.00	2.20
Sep-15	2.00	2.00
Oct-15	2.00	2.00
Nov-15	4.00	2.00
Dec-15	5.00	2.47
Jan-16	1.00	2.55
Feb-16	4.00	2.30
Mar-16	0.00	2.35
Apr-16	0.00	2.01
May-16	2.00	1.94
Jun-16	1.00	1.95
Jul-16	0.00	1.81
Aug-16	4.00	1.42
Sep-16	1.00	2.23
Oct-16	2.00	2.12
Nov-16	2.00	2.10
Dec-16	1.00	2.08
Jan-17	0.00	1.89
Feb-17	1.00	1.41
Mar-17	0.00	1.26
Apr-17	0.00	0.78
May-17	2.00	0.43
Jun-17	1.00	1.19
Jul-17	2.00	1.14
Aug-17	0.00	1.40
Sep-17	1.00	1.12
Oct-17	1.00	1.08
Nov-17	2.00	1.06
Dec-17	1.00	1.35
Jan-18	0.00	1.29
Feb-18	2.00	1.01
Mar-18	1.00	1.34
Apr-18	2.00	1.27

DATES	Demand for NIIN 015504195 - Actual	Adaptive Exponential Smoothing Forecast using β = 0.1
May-18	2.00	1.43
Jun-18	2.00	1.49
Jul-18	2.00	1.51
Aug-18	1.00	1.53
Sep-18	1.00	1.48
Oct-18	0.00	1.47
Nov-18	0.00	1.39
Dec-18		**1.07**
Jan-19		**1.07**
Feb-19		**1.07**
Mar-19		**1.07**
Apr-19		**1.07**
May-19		**1.07**
Jun-19		**1.07**
Jul-19		**1.07**
Aug-19		**1.07**
Sep-19		**1.07**
Oct-19		**1.07**
Nov-19		**1.07**

Table 16. NIIN 015504195 Adaptive Exponential Smoothing Evaluation Results

AIC	274.70
RMSE	1.42
MASE	0.89



	Forecast			95% - 5%	95% - 5%
Date	**Monthly**	**Quarterly**	**Annual**	**Upper**	**Lower**
Dec-2018	1.07	1.07	1.07	3.39	0.00
Jan-2019	1.07			4.35	0.00
Feb-2019	1.07			5.08	0.00
Mar-2019	1.07	3.22		5.70	0.00
Apr-2019	1.07			6.25	0.00
May-2019	1.07			6.74	0.00
Jun-2019	1.07	3.22		7.19	0.00
Jul-2019	1.07			7.62	0.00
Aug-2019	1.07			8.01	0.00
Sep-2019	1.07	3.22		8.39	0.00
Oct-2019	1.07			8.75	0.00
Nov-2019	1.07			9.09	0.00
Avg	1.07	2.69	1.07	6.71	0.00
Max	1.07	3.22	1.07	9.09	0.00
Min	1.07	1.07	1.07	3.39	0.00

Figure 12. Adaptive Exponential Smoothing Forecast with Six Years of Historical Demand for NIIN 015504195 (12-Month Forecast).

The chart illustrates the upper (purple) and lower (blue) limits of a forecast with a 95% confidence interval. The adaptive exponential smoothing forecast is 95% confident that demand for each of the next 12 months will fall between the upper and lower limits above. A MAPE of 52.42%, an AIC of 277.79, and an RMSE of 1.45 means it's less accurate than the simple exponential smoothing forecast, which recorded a MAPE, AIC, and RMSE of 35.91%, 256, and 1.26, respectively. A MASE of .89 means it performed better than the naïve forecast.

c. Holt–Winters Double Exponential Smoothing Forecast

Charles C. Holt created a "two-parameter exponential smoothing method that is an extension of the simple exponential smoothing; it adds a growth factor (or trend factor) to the smoothing equation as a way of adjusting for the trend. Three equations and two smoothing constants are used in the model" (Wilson & Keating, 1990, pp. 84–85);

$$S_{t+1} = \alpha X_t + (1-\alpha)(S_t + T_t) \tag{13}$$

$$T_{t+1} = \beta(S_{t+1} - S_t) + (1-\beta)T_t \tag{14}$$

$$F_{t+m} = S_t + mT_t \tag{15}$$

where:

S_{t+1} = Smoothed value for period t + 1

α = Smoothed constant for the data (0 < α < 1)

X_t= Actual value now (in period t)

F_t = Forecast (i.e., smoothed) value for time period t (which is also the smoothed value for time period t - 1).

T_t = Trend estimate

β = Smoothing constant for the trend estimate (0 < β < 1)

m = Number of periods ahead to be forecast

F_{t+m} = Holt's forecast value for period t + m

Holt and Peter R. Winters worked to extend Holt's exponential smoothing method to factor in seasonality. This new method was named the Holt–Winters exponential smoothing method. The Holt–Winters method "is used for data that exhibit both trend and seasonality. An additional equation adjusts the model for the seasonal component" (Wilson & Keating, 1990, p. 90). For the purpose of this project, we used a 12-month cycle for seasonality because NAVSUP orders the critical NIINs every fiscal year. According to Wilson and Keating, the exponential smoothing equation is as follows:

$$F_t = \alpha X_t \,/\, S_{t-p} + (1-\alpha)(F_{t-1} + T_{t-1}) \tag{16}$$

$$S_t = \beta X_t \,/\, F_t + (1-\beta)S_{t-p} \tag{17}$$

$$T_t = \gamma(F_t - F_{t-1}) + (1-\gamma)T_{t-1} \tag{18}$$

$$W_{t+m} = (F_t + mT_t)S_t \tag{19}$$

where:

F_t = Smoothed value for period t

α = Smoothing constant for the data (0 < α < 1)

X_t = Actual value now (in period t)

F_{t-1} = Average experience of series smoothed to period t – 1

T_t = Trend estimate

S_t = Seasonality estimate

β = Smoothing constant for seasonality estimate

γ = Smoothing constant for trend estimate

m = Number of periods in the forecast lead period

p = Number of periods in the seasonal cycle

W_{t+m} = Holt-Winters' forecast for m periods into the future

Table 17. Holt–Winters Exponential Smoothing Forecast with Six Years of Historical Demand for NIIN 015504195 (12-Month Forecast)

DATES	Demand for NIIN 015504195 - Actual	Holt–Winters Exponential Smoothing Forecast using α = 0.12, β = 0, and γ = 0
Jun-12		
Jul-12	1.00	1.80

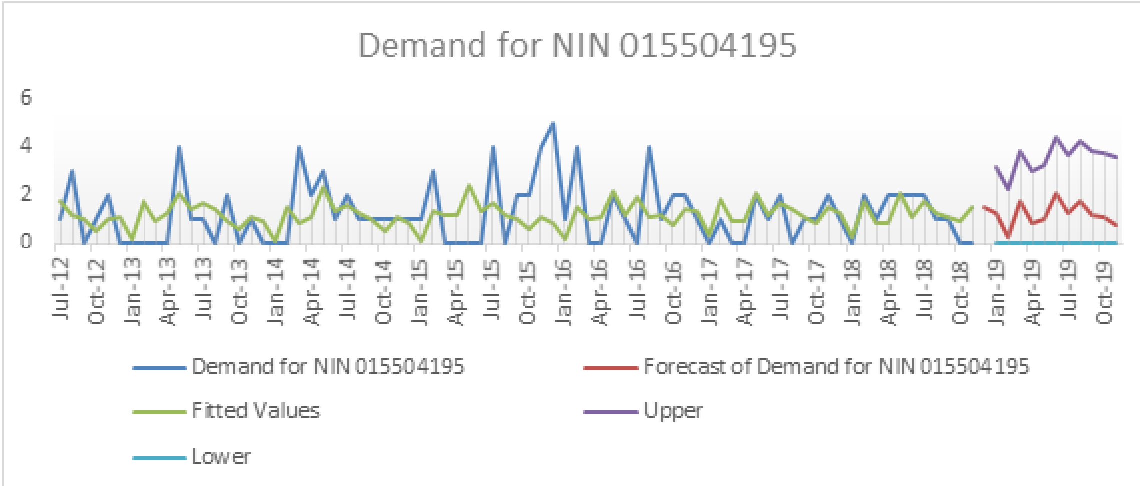
DATES	Demand for NIIN 015504195 - Actual	Holt–Winters Exponential Smoothing Forecast using $\alpha = 0.12$, $\beta = 0$, and $\gamma = 0$
Aug-12	3.00	1.20
Sep-12	0.00	1.07
Oct-12	1.00	0.57
Nov-12	2.00	1.01
Dec-12	0.00	1.10
Jan-13	0.00	0.17
Feb-13	0.00	1.74
Mar-13	0.00	0.95
Apr-13	0.00	1.29
May-13	4.00	2.15
Jun-13	1.00	1.45
Jul-13	1.00	1.71
Aug-13	0.00	1.41
Sep-13	2.00	0.94
Oct-13	0.00	0.62
Nov-13	1.00	1.12
Dec-13	0.00	0.97
Jan-14	0.00	0.15
Feb-14	0.00	1.54
Mar-14	4.00	0.84
Apr-14	2.00	1.14
May-14	3.00	2.37
Jun-14	1.00	1.40
Jul-14	2.00	1.63
Aug-14	1.00	1.24
Sep-14	1.00	1.07
Oct-14	1.00	0.55
Nov-14	1.00	1.11
Dec-14	1.00	0.86
Jan-15	1.00	0.13
Feb-15	3.00	1.37
Mar-15	0.00	1.20
Apr-15	0.00	1.24
May-15	0.00	2.44
Jun-15	0.00	1.35
Jul-15	4.00	1.67
Aug-15	0.00	1.22

DATES	Demand for NIIN 015504195 - Actual	Holt–Winters Exponential Smoothing Forecast using $\alpha = 0.12$, $\beta = 0$, and $\gamma = 0$
Sep-15	2.00	1.06
Oct-15	2.00	0.60
Nov-15	4.00	1.10
Dec-15	5.00	0.88
Jan-16	1.00	0.23
Feb-16	4.00	1.55
Mar-16	0.00	1.07
Apr-16	0.00	1.10
May-16	2.00	2.16
Jun-16	1.00	1.20
Jul-16	0.00	1.94
Aug-16	4.00	1.08
Sep-16	1.00	1.17
Oct-16	2.00	0.76
Nov-16	2.00	1.43
Dec-16	1.00	1.35
Jan-17	0.00	0.32
Feb-17	1.00	1.84
Mar-17	0.00	0.94
Apr-17	0.00	0.97
May-17	2.00	2.14
Jun-17	1.00	1.17
Jul-17	2.00	1.72
Aug-17	0.00	1.41
Sep-17	1.00	1.15
Oct-17	1.00	0.90
Nov-17	2.00	1.50
Dec-17	1.00	1.31
Jan-18	0.00	0.28
Feb-18	2.00	1.74
Mar-18	1.00	0.83
Apr-18	2.00	0.86
May-18	2.00	2.12
Jun-18	2.00	1.15
Jul-18	2.00	1.75
Aug-18	1.00	1.25
Sep-18	1.00	1.13

DATES	Demand for NIIN 015504195 - Actual	Holt–Winters Exponential Smoothing Forecast using $\alpha = 0.12$, $\beta = 0$, and $\gamma = 0$
Oct-18	0.00	0.92
Nov-18	0.00	1.55
Dec-18		**1.28**
Jan-19		**0.25**
Feb-19		**1.77**
Mar-19		**0.85**
Apr-19		**0.99**
May-19		**2.11**
Jun-19		**1.25**
Jul-19		**1.78**
Aug-19		**1.22**
Sep-19		**1.12**
Oct-19		**0.81**
Nov-19		**1.38**

Table 18. NIIN 015504195 Holt–Winters Exponential Smoothing Evaluation Results

AIC	258.13
RMSE	1.24
MASE	0.75



Date	Forecast Monthly	Forecast Quarterly	Forecast Annual	95% - 5% Upper	95% - 5% Lower
Dec-2018	1.28	1.28	1.28	3.21	0.00
Jan-2019	0.25			2.27	0.00
Feb-2019	1.77			3.87	0.00
Mar-2019	0.85	2.87		3.04	0.00
Apr-2019	0.99			3.26	0.00
May-2019	2.11			4.47	0.00
Jun-2019	1.25	4.35		3.70	0.00
Jul-2019	1.78			4.31	0.00
Aug-2019	1.22			3.84	0.00
Sep-2019	1.12	4.11		3.83	0.00
Oct-2019	0.81			3.61	0.00
Nov-2019	1.38			4.27	0.00
Avg	1.23	3.15	1.28	3.64	0.00
Max	2.11	4.35	1.28	4.47	0.00
Min	0.25	1.28	1.28	2.27	0.00

Figure 13. Holt–Winters Exponential Smoothing Forecast with Six Years of Historical Demand for NIIN 015504195 (12-Month Forecast).

β = 0 and γ = 0 because no trends or seasonality were present for the demand of NIIN 015504195. The Holt–Winters exponential smoothing forecast is 95% confident that demand for each of the next 12 months will fall between the upper and lower limits above. An AIC of 256.73 and an RMSE of 1.23 means it is more accurate than the simple exponential smoothing forecast, which recorded an AIC and RMSE of 256.58 and 1.26, respectively. Also, it is more accurate than the adaptive smoothing forecast, which recorded an AIC and RMSE of 256 and 1.26, respectively. A MASE of .78 means it performed better than the naïve forecast.

d. Box–Jenkins Exponential Smoothing Forecast

The fourth and final time series analysis forecasting method is the Box–Jenkins method.

> In time series analysis, the Box–Jenkins method, named after the George Box and Gwilym Jenkins, applies Autoregressive Moving Average (ARMA) or Autoregressive Integrated Moving Average (ARIMA) models to find the best fit of a time-series model to past values of a time series. (Box–Jenkins method, 2018)

This method

> is a statistically sophisticated way of analyzing and building a forecasting model which best represents a time series. Firstly, it is logically and statistically accurate. Secondly, the method extracts a great deal of information from the historical time series data. Finally, the method results in an increase in forecast accuracy while keeping the number of parameters to a minimum in comparison with similar modeling processes. (Jarrett, 1991, p. 317)

The Box–Jenkins model is a mixture of the Autoregressive (AR) and Moving Average (MA) models. According to Jarrett, a common approach for modeling univariate time series is the autoregressive (AR) model:

$$X_t = \delta + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-1} + A_t \qquad (20)$$

where:

X_t is the time series, A_t is white noise, and

$$\delta = (1 - \textstyle\sum_{i=1}^{p} \phi i)\mu, \qquad (21)$$

with μ denoting the process mean.

> An autoregressive model is simply a linear regression of the current value of the series against one or more prior values of the series. The value of p is called the order of the AR model. AR models can be analyzed with one of various methods, including standard linear least squares techniques. They also have a straightforward interpretation. (6.4.4.4. Common Approaches to Univariate Time Series, n.d.)

Jarrett further states “that the second part of the Box–Jenkins is the MA model, which is another way of modelling univariate time series models” (p. 317). The equation is expressed as:

$$X_t = \mu + A_t - \theta_1 A_{t-i} - \theta_2 A_{t-2} - \cdots - \theta_q A_{t-q} \quad (22)$$

where:

> X_t is the time series, μ is the mean of the series, A_{t-i} are white noise terms, and $\theta_1,\ldots,\theta_q$ are the parameters of the model. The value of q is called the order of the MA model. That is, a moving average model is conceptually a linear regression of the current value of the series against the white noise or random shocks of one or more prior values of the series. The random shocks at each point are assumed to come from the same distribution, typically a normal distribution, with location at zero and constant scale. The distinction in this model is that these random shocks are propagated to future values of the time series. Fitting the MA estimates is more complicated than with AR models because the error terms are not observable. This means that iterative non-linear fitting procedures need to be used in place of linear least squares. MA models also have a less obvious interpretation than AR models. (6.4.4.4. Common Approaches to Univariate Time Series, n.d.)

According to Jarrett, the Box–Jenkins method equation is expressed as:

$$X_t = \delta + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + A_t - \theta_1 A_{t-1} - \theta_2 A_{t-2} - \cdots - \theta_q A_{t-q}, \quad (23)$$

where the terms in the equation have the same meaning as given for the AR and MA model.

Table 19. Box–Jenkins Exponential Smoothing Forecast with Six Years of Historical Demand for NIIN 015504195 (12-Month Forecast)

DATES	Demand for NIIN 015504195 - Actual	Box–Jenkins Exponential Smoothing Forecast
Jun-12		
Jul-12	1.00	1.25
Aug-12	3.00	1.24
Sep-12	0.00	1.27
Oct-12	1.00	1.23

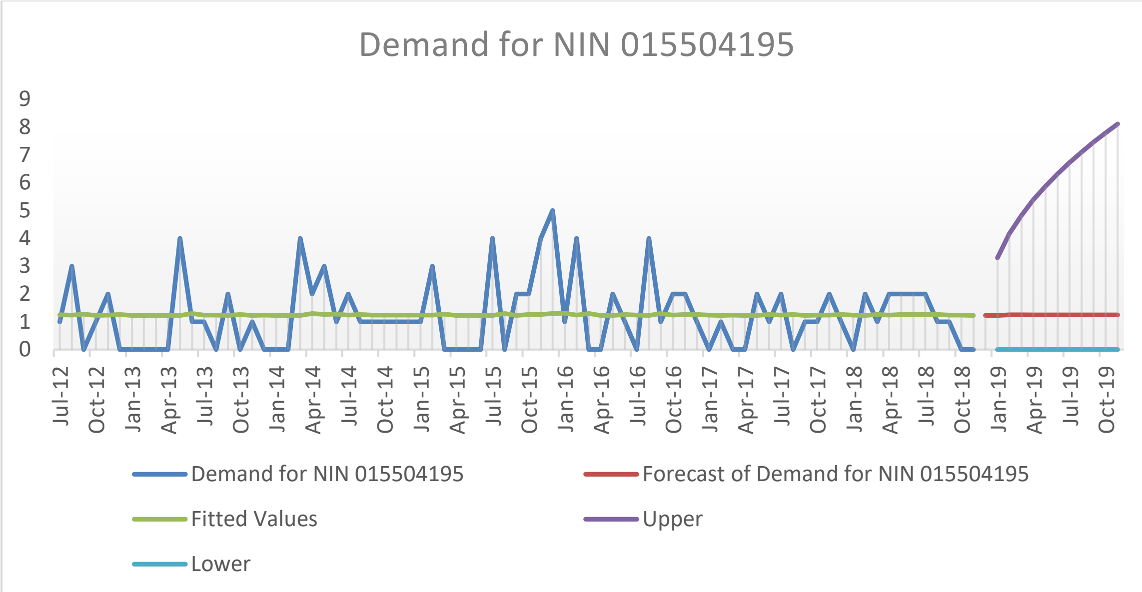
DATES	Demand for NIIN 015504195 - Actual	Box–Jenkins Exponential Smoothing Forecast
Nov-12	2.00	1.24
Dec-12	0.00	1.26
Jan-13	0.00	1.23
Feb-13	0.00	1.23
Mar-13	0.00	1.23
Apr-13	0.00	1.23
May-13	4.00	1.23
Jun-13	1.00	1.29
Jul-13	1.00	1.24
Aug-13	0.00	1.24
Sep-13	2.00	1.23
Oct-13	0.00	1.26
Nov-13	1.00	1.23
Dec-13	0.00	1.24
Jan-14	0.00	1.23
Feb-14	0.00	1.23
Mar-14	4.00	1.23
Apr-14	2.00	1.29
May-14	3.00	1.26
Jun-14	1.00	1.27
Jul-14	2.00	1.24
Aug-14	1.00	1.26
Sep-14	1.00	1.24
Oct-14	1.00	1.24
Nov-14	1.00	1.24
Dec-14	1.00	1.24
Jan-15	1.00	1.24
Feb-15	3.00	1.24
Mar-15	0.00	1.27
Apr-15	0.00	1.23
May-15	0.00	1.23
Jun-15	0.00	1.23
Jul-15	4.00	1.23
Aug-15	0.00	1.29
Sep-15	2.00	1.23
Oct-15	2.00	1.26
Nov-15	4.00	1.26

DATES	Demand for NIIN 015504195 - Actual	Box–Jenkins Exponential Smoothing Forecast
Dec-15	5.00	1.29
Jan-16	1.00	1.31
Feb-16	4.00	1.24
Mar-16	0.00	1.29
Apr-16	0.00	1.23
May-16	2.00	1.23
Jun-16	1.00	1.26
Jul-16	0.00	1.24
Aug-16	4.00	1.23
Sep-16	1.00	1.29
Oct-16	2.00	1.24
Nov-16	2.00	1.26
Dec-16	1.00	1.26
Jan-17	0.00	1.24
Feb-17	1.00	1.23
Mar-17	0.00	1.24
Apr-17	0.00	1.23
May-17	2.00	1.23
Jun-17	1.00	1.26
Jul-17	2.00	1.24
Aug-17	0.00	1.26
Sep-17	1.00	1.23
Oct-17	1.00	1.24
Nov-17	2.00	1.24
Dec-17	1.00	1.26
Jan-18	0.00	1.24
Feb-18	2.00	1.23
Mar-18	1.00	1.26
Apr-18	2.00	1.24
May-18	2.00	1.26
Jun-18	2.00	1.26
Jul-18	2.00	1.26
Aug-18	1.00	1.26
Sep-18	1.00	1.24
Oct-18	0.00	1.24
Nov-18	0.00	1.23
Dec-18		**1.23**

DATES	Demand for NIIN 015504195 - Actual	Box–Jenkins Exponential Smoothing Forecast
Jan-19		**1.25**
Feb-19		**1.25**
Mar-19		**1.25**
Apr-19		**1.25**
May-19		**1.25**
Jun-19		**1.25**
Jul-19		**1.25**
Aug-19		**1.25**
Sep-19		**1.25**
Oct-19		**1.25**
Nov-19		**1.25**

Table 20. NIIN 015504195 Box–Jenkins Exponential Smoothing Evaluation Results

AIC	256.86
RMSE	1.25
MASE	0.80



	Forecast			95% - 5%	95% - 5%
Date	**Monthly**	**Quarterly**	**Annual**	**Upper**	**Lower**
Dec-2018	1.23	1.23	1.23	3.30	0.00
Jan-2019	1.25			4.17	0.00
Feb-2019	1.25			4.83	0.00
Mar-2019	1.25	3.74		5.39	0.00
Apr-2019	1.25			5.88	0.00
May-2019	1.25			6.32	0.00
Jun-2019	1.25	3.74		6.72	0.00
Jul-2019	1.25			7.10	0.00
Aug-2019	1.25			7.46	0.00
Sep-2019	1.25	3.74		7.79	0.00
Oct-2019	1.25			8.11	0.00
Nov-2019	1.25			8.42	0.00
Avg	1.24	3.11	1.23	6.29	0.00
Max	1.25	3.74	1.23	8.42	0.00
Min	1.23	1.23	1.23	3.30	0.00

Figure 14. Box–Jenkins Exponential Smoothing Forecast with Six Years of Historical Demand for NIIN 015504195 (12-Month Forecast).

The Box–Jenkins exponential smoothing forecast is 95% confident that demand for each of the next 12 months will fall between the upper and lower limits above. An AIC of 262.25, and an RMSE of 1.29 means it is more accurate than the adaptive exponential smoothing forecast, which recorded an AIC, and RMSE of 277.79, and 1.45, respectively. Box–Jenkins generated more erroneous RMSE and AIC values than both forecasts. A MASE of .80 means it performed better than the naïve forecast.

4. Time Series Analysis Forecasting Results

The historical demand data set that we used for generating the forecasts ranged from April 2012 to September 2018. This project compares actual demand from June 2016 to September 2018 against all the four different forecasts generated. In addition, it evaluated the accuracy of four forecasting methods by using the RMSE, AIC, and MASE.

Table 21. RMSE Values for Time Series Forecasts

RMSE				
NIIN	Simple Exponential Smoothing	Adaptive Exponential Smoothing	Holt-Winters	Box-Jenkins
015334867	6.34	7.79	5.55	6.07
011581698	1.59	1.73	1.52	1.57
016485009	1.88	2.49	1.50	1.79
015504195	1.27	1.42	1.24	1.25
015504281	1.79	1.92	1.80	1.75
016505136	1.99	1.99	1.85	1.94
015512724	1.17	1.27	1.19	1.15
015504153	0.88	1.14	0.83	0.88
015504283	0.51	0.53	0.52	0.52
013019246	1.41	1.45	1.40	1.39

We see that the four methods have a RMSE less than 7.79, which is acceptable even though a RMSE as close to zero as possible is preferred. The Holt–Winters model recorded the lowest RMSE for six of the 10 NIINs. This means it performed better than the other three methods according to the RMSE criteria.

Table 22. Respective AIC Values

AIC				
NIIN	Simple Exponential Smoothing	Adaptive Exponential Smoothing	Holt-Winters	Box-Jenkins
015334867	197.98	210.30	193.92	197.37
011581698	288.13	301.41	285.59	288.00
016485009	71.68	81.24	67.97	71.95
015504195	256.80	274.70	258.13	256.86
015504281	313.97	325.04	319.36	314.71
016505136	124.30	124.33	124.08	124.60
015512724	241.56	254.41	247.79	241.38
015504153	201.29	241.17	196.48	203.28
015504283	116.65	122.41	122.42	119.79
013019246	277.47	281.20	279.89	276.71

We see that the four methods have an AIC error less than 325.04, which is very high. The Holt–Winters model recorded the lowest AIC error for five of the 10 NIINs. This means it performed better than the other three methods according to the AIC criteria.

Table 23. Respective MASE Values

MASE				
NIIN	Simple Exponential Smoothing	Adaptive Exponential Smoothing	Holt-Winters	Box-Jenkins
015334867	0.74	0.93	0.65	0.69
011581698	0.78	0.81	0.75	0.78
016485009	0.54	0.89	0.60	0.65
015504195	0.78	0.89	0.75	0.80
015504281	0.86	0.93	0.86	0.88
016505136	0.70	0.66	0.66	0.68
015512724	0.77	0.80	0.82	0.77
015504153	0.78	0.95	0.70	0.79
015504283	1.05	1.02	1.01	1.06
013019246	0.83	0.90	0.83	0.87

We see that the four methods have a MASE less than 1.06. The four methods performed better than the naïve forecast for nine out of the 10 NIINs evaluated. Of the four time series models used in this the project, the Holt–Winters model recorded the lowest MASE scores for eight out of the 10 NIINs evaluated.

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IV. FINDINGS AND RECOMMENDATIONS

A. FINDINGS

While many of our findings throughout this research are detailed at the point of discussion, the major findings of our research regarding demand and OPTEMPO correlation and forecasting accuracy are summarized here for ease of access.

After conducting detailed analysis of the results from both the causal and time series analysis forecasting, the results demonstrated that there is not a significant relationship between ALRE parts demand and ship OPTEMPO. However, a more robust forecasting method was identified.

1. No Relationship between ALRE Demand and Ship OPTEMPO

The initial motivation behind this project was the hypothesis that an essential association existed that was a significant driver of demand for ALRE components among the Navy's air capable ships. This driver was thought to be the ship's operational tempo. Six years of demand data was consolidated with ten CVN operational schedules to build and a run a causal forecasting model. Multiple linear regression analysis was used to see if a correlation between the two variables existed. The end result of approximately 400 regression models demonstrated that this was not the case and that virtually no measureable correlation between parts demand and a ship's operational tempo could be observed.

Since a causal forecast method proved to be ineffective, this project then proceeded to run the demand data through a gamut of time series models. The goal was to see if any other forecast models could provide better results than the simple exponential smoothing method that NAVSUP WSS is currently using. The results were then evaluated by multiple error determination evaluation methods. The results were encouraging.

2. Holt–Winters Forecasting Model Outperforms Simple Exponential Smoothing Model

Low-demand items are notoriously difficult to forecast, but the testing and subsequent comparison of multiple forecasting models revealed an opportunity for improvement. The Holt–Winters exponential smoothing method outperformed the simple, adaptive, and Box–Jenkins exponential smoothing methods during the RMSE, AIC, and MASE evaluations.

It is noteworthy to realize that the results varied from NIIN to NIIN with no discernable reason as to why or how. The efficacy of the forecast accuracy also depended on which evaluation method was used. This shows that flexibility in terms of inventory management methods and protocols may need to be incorporated into current business practices.

B. RECOMMENDATIONS

As we have demonstrated, the Holt–Winters forecasting model outperforms NAVSUP's current forecasting model (simple exponential smoothing) on average. The complexity of producing precise demand forecasts for such a low demand as ALRE, does not suffice for utilizing only one analytical forecasting type. NAVSUP could benefit from more flexibility in its forecasting. Inventory managers and decision makers can adopt a best-fit forecast system for their ALRE NIINs. The NIINs can be grouped by best-fit forecasts once those forecasts are identified.

Beyond the scope of ALRE components, it is recommended that NAVSUP adjust which forecast models are used based on demand similarities among NIINs. In the short term, in order to efficiently use time and resources, it is suggested that NAVSUP prioritize which NIINs to evaluate and test by the same ABC method used in this project. The top 10% NIINs with the highest budget consumption could be examined to see if any demand patterns exist among them and test those NIINs using different forecast models to identify a more optimal method.

C. LIMITATIONS

Data collection for this research was limited to the data provided by NAVSUP WSS. Although the sample size was large, the actual demand data for a majority of the NIINs across the six-year period observed were extremely low with high variability. Also, of the 100 critical NIINs, only 55 had historical demand from the 10 CVNs, which limited the forecasting evaluation.

D. FUTURE STUDIES

The current levels of demand for ALRE components are extremely low and erratic among the Navy’s 10 aircraft carriers. It is unlikely that this data is completely accurate, which degrades the efficacy of any forecasting model. Future research is recommended to assess the validity of demand data extracted through the Navy’s ERP software system as well as data reporting accuracy from the CVNs themselves. Standard practices by the end users in the fleet are not always adhered to. This is typically in reaction to long lead times and insufficient fill rates. Maintenance personnel may carry unreported safety stock to buffer against this often unavailability of parts, which obfuscates demand signals and may obscure other correlations as well. This project recommends that the informal inventory control policies and actual inventory management practices among the CVN maintenance and supply departments be examined.

In addition to researching demand signal accuracy across the fleet, it is also recommended that NAVSUP examine the viability of modifying current demand forecast processes for all NIINs, not just critical ALRE components. It may be beneficial to identify and group NIINs together based on demand similarities and utilize the most appropriate forecast for that particular group of NIINs. Parts with extremely low and sporadic demand quantities for example, may be forecasted more accurately with Holt–Winters or simple exponential smoothing forecast models as opposed to Box–Jenkins. Future studies where this hypothesis is put to the test could prove extremely useful and directly applicable to improving the U.S. Navy’s inventory management program.

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