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AN EVALUATION OF STATISTICAL METHODS FOR WORKLOAD FORECASTING AT THE DDNV MATERIAL PROCESSING CENTER

by

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Workload surges can occur intermittently throughout the year at the Defense Logistics Agency Distribution Norfolk, Virginia (DDNV) Material Processing Center (MPC). These unexpected backlogs cause receipt delays, incur extra costs for overtime and requirements for additional personnel, and negatively impact fleet readiness. The DDNV MPC is one of the largest materiel processing centers in the world, handling more than 40,000 transactions per month. Much of the workload demand is from the local fleet forces, to include more than 70 Norfolk-based Navy surface ships, submarines, numerous shore commands, and other Air Force and Army installations throughout the Hampton Roads area. Currently, there is no codified way forecasting is done aside from examining historical data and adjusting based on MPC input, and time-series analysis techniques do not work well for this type of intermittent demand. Currently, workload is forecasted using ad-hoc techniques in Excel. In this thesis, various forecasting techniques with a primary emphasis on variations of Croston’s intermittent demand forecasting were evaluated. Pertinent data were collected primarily from the Defense Logistics Agency, with additional data collected from its Distribution Standard System (DSS) and Fleet/Type Commanders. The forecasting methods were evaluated using historical data.

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AN EVALUATION OF STATISTICAL METHODS FOR WORKLOAD FORECASTING AT THE DDNV MATERIAL PROCESSING CENTER

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ABSTRACT

Workload surges can occur intermittently throughout the year at the Defense Logistics Agency Distribution Norfolk, Virginia (DDNV) Material Processing Center (MPC). These unexpected backlogs cause receipt delays, incur extra costs for overtime and requirements for additional personnel, and negatively impact fleet readiness. The DDNV MPC is one of the largest materiel processing centers in the world, handling more than 40,000 transactions per month. Much of the workload demand is from the local fleet forces, to include more than 70 Norfolk-based Navy surface ships, submarines, numerous shore commands, and other Air Force and Army installations throughout the Hampton Roads area. Currently, there is no codified way forecasting is done aside from examining historical data and adjusting based on MPC input, and time-series analysis techniques do not work well for this type of intermittent demand. Currently, workload is forecasted using ad-hoc techniques in Excel. In this thesis, various forecasting techniques with a primary emphasis on variations of Croston's intermittent demand forecasting were evaluated. Pertinent data were collected primarily from the Defense Logistics Agency, with additional data collected from its Distribution Standard System (DSS) and Fleet/Type Commanders. The forecasting methods were evaluated using historical data.

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List of Acronyms and Abbreviations

ARG	Amphibious Readiness Group
ARIMA	autoregressive integrated moving average
AVCAL	aviation consolidated allowance list
CSG	carrier strike group
COSAL	coordinated shipboard allowance list
CVN	aircraft carrier nuclear
DDNV	Defense Logistics Agency Distribution Norfolk, Virginia
DLA	Defense Logistics Agency
DOD	Department of Defense
DSS	Distribution Standard System
DTO	direct turnover
EDA	exploratory data analysis
EVA	Extreme value analysis
GPCC	Government Purchase Credit Card
INSURV	Board of Inspection Survey
LHA	landing helicopter assault
LHD	landing helicopter dock
LPD	landing platform, dock
LSD	landing ship, dock

MAG	marine aircraft group
MAPE	mean absolute percentage error
MASE	mean absolute scaled error
MPC	Materiel Processing Center
OFRP	Optimized Fleet Response Plan
PAO	Public Affairs Officer
TSA	time series analysis
TYCOM	type commander
USFFC	United States Fleet Forces Command

Executive Summary

The Defense Logistics Agency Distribution Norfolk, Virginia (DDNV) Material Processing Center (MPC) is one of the largest materiel processing centers in the Department of Defense (DOD), handling over 40,000 transactions per month. Much of the workload demand comes from local fleet forces, including more than 70 Norfolk-based Navy surface ships, submarines, numerous shore commands, and other Air Force and Army installations throughout the Hampton Roads area. Workload surges occur intermittently throughout the year at the DDNV MPC. These unexpected backlogs cause receipt delays, incur extra costs for overtime and additional personnel, and negatively impact fleet readiness.

Currently, DDNV does not use any codified workload forecasting method and relies on ad-hoc Excel-based techniques that use historical data, inputs from DDNV leadership, and recommendations from DLA directorates. Using exported historical data from Distribution Standard System (DSS) provided by DDNV, deployment data provided by the Public Affairs Officer (PAO), and ship data provided by the ship's type commander (TYCOM), we constructed exponential smoothing and autoregressive integrated moving average (ARIMA) time series analysis (TSA) models for forecasting workload. The performance of the models was compared using mean absolute percentage error (MAPE) and mean absolute scaled error (MASE) to determine goodness-of-fit and to guide final model selection.

Having found that the ARIMA model had better performance, we extended it to a dynamic regression ARIMA model with ship deployments used as a predictor, which was found to better capture workload spikes. The predictor indicates how many deployments will occur within a 28-week window, to encompass all phases and inspections of the OFRP required prior to a deployment. In the final (deployment-aware) model, all spikes in forecasted workload fell within the 80% confidence interval of the model, whereas the baseline ARIMA model using only historical data failed to capture several workload spikes.

While our research focused on DDNV, the methods and final model can be immediately implemented and utilized at other material processing centers at other distribution centers. Due to the applicability and ease at which the predictor can be tuned, we recommend that this model be used across Defense Logistics Agency (DLA) distribution centers.

Acknowledgments

I would like to express my deepest gratitude to my thesis advisor, Dr. Jefferson Huang, for his support, guidance, mentorship, and, most importantly, his patience throughout the completion of this thesis. Dr. J, I can't thank you enough for keeping me on track and reigning me back in when my mind wandered down the rabbit hole. Your commitment and willingness to push me further down my academic path is sincerely appreciated.

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To the entire cohort, thank you for setting a high bar. You are all amongst the smartest people I have ever had the privilege of meeting and working with. Working with you all forced me to think in ways I did not and could not before, allowing me to be a better officer.

I would like to express my gratitude to the entire staff at DDNV for providing the information necessary to conduct this research and the constant support and assistance they provided throughout the process. Additionally, I would like to thank the personnel in the DLA Research and Development division for sponsoring this topic.

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CHAPTER 1:
Introduction

1.1 Defense Logistics Agency (DLA)

The Defense Logistics Agency (DLA) is the nation's combat logistics support agency, managing the end-to-end supply chain needs of the entirety of the Department of Defense (DOD). The primary mission of DLA is to "deliver readiness and lethality to the Warfighter Always and support the nation through quality, proactive global logistics" (Defense Logistics Agency 2023a). This mission is accomplished over five lines of effort: Warfighter Always, support to the nation, trusted business partner, modernized acquisition and supply chain management, and future of work. Additionally, DLA supports over 40 whole-of-government agencies such as the General Services Administration, Department of Veteran Affairs, and the U.S. Army Corps of Engineers. Across all domestic and international partnerships, DLA is responsible for over five million line items encompassing all classes of supply in support of the DOD, generating over $11B in sales in 2022. DLA employs over 25,000 military and civilian personnel at the following six major sub-commands:

- DLA Troop Support, Philadelphia, PA
- DLA Aviation, Richmond, VA
- DLA Land and Maritime, Columbus, OH
- DLA Energy, Fort Belvoir, VA
- DLA Distribution, New Cumberland, PA
- DLA Disposition Services, Battle Creek, MI

This thesis is focused on one of the sites operated by DLA Distribution.

1.2 DLA Distribution Norfolk, Virginia (DDNV)

Defense Logistics Agency Distribution Norfolk, Virginia (DDNV) is the primary provider of materiel support for over 150 military commands stationed at Naval Station Norfolk and across the Hampton Roads region. The facility is part of DLA's worldwide network of 24 distribution centers. DDNV services local Air Force, Army, civilian, and Navy commands

Figure 1.1. DDNV

through their intermodal hub, handling receipt, processing, containerizing, and forward processing of materiel while also providing stevedore services for cargo loading and off-loading. Subordinate locations at Joint Expeditionary Base, Little Creek, Virginia, and Norfolk Naval Shipyard Portsmouth, Virginia, provide materiel processing services to local commands and Norfolk Navy Shipyard, respectively.

1.3 Material Processing Center (MPC)

The primary mode of support provided by DDNV to the operational fleet of Naval Station Norfolk is the Materiel Processing Center (MPC). Responsible for receipt, processing, delivery, and forward processing of materiel for 150 commands, the MPC employs a combination of military and civilian personnel. Materiel arrives via a roughly equal combination of commercial and military transportation services. On average, the MPC receives 1400 individual pieces of materiel daily. Materiel primarily consists of repair parts that make up a ship's coordinated shipboard allowance list (COSAL), a carrier air wing's aviation consolidated allowance list (AVCAL), direct turnover (DTO) materiel, and open purchase items procured via the Government Purchase Credit Card (GPCC). Personnel at the MPC focus on rapidly processing the incoming materiel to ensure on-time delivery to the end users and maintaining readiness, specifically to the operational commands.

Figure 1.2. Mark Ellefson, DDNV MPC director, left; Jack Holmes, DLA Research and Development; Dr. Jefferson Huang, Naval Postgraduate School; LCDR Adam Davidson, NPS; Danielle Williams, DLA R&D; and Jamal Smith, DLA Distribution Headquarters, visit the DDNV MPC on 12 May 2023. Photo by LCDR Robert Doggett.

1.4 Workload Forecasting for the MPC

Current forecasts of future workload at the MPC are focused on historical volume data from Excel. Predictions are based on historical averages, ad-hoc adjustments, and inputs provided from DDNV leadership and DLA directorates. Using only historical data is problematic because of the dynamic schedules of the ships serviced by DDNV, which may be different than deployment dates, which vary from year to year and are driven by the Optimized Fleet Response Plan (OFRP). The current methods are unsuitable for manpower planning purposes and effectively forecasting intermittent workload spikes that occur throughout the year. Figure 1.3 shows an example of one spike in workload that occurred in early November 2021, which took several weeks to clear requiring a significant amount of unplanned overtime and seasonal work force.

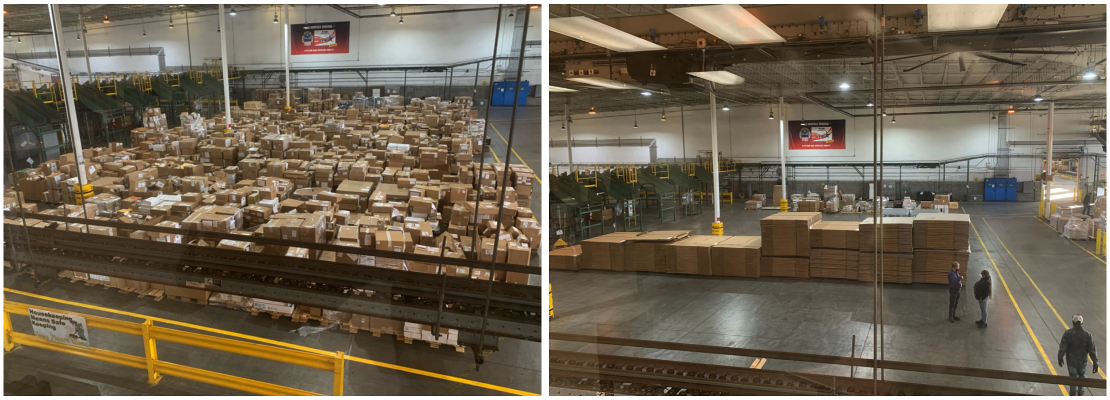

Figure 1.3. Cell 1 Receiving at the DDNV MPC on 13 October 2021 (left) and 8 November 2021 (right).

1.5 Our Contributions

1.5.1 Analysis of Distribution Standard System (DSS) Data

We conducted exploratory data analysis (EDA) on data directly exported from Distribution Standard System (DSS), the automated database to track all functional processes of materiel that is inducted at the MPC such as, receipt, storage, shipping, inventory, and workload management (Defense Logistics Agency 2023b). EDA included computing mean processing times, mean delivery times, average monthly volumes of materiel processed, and determining trend and seasonality in the workload volumes.

1.5.2 Evaluation of Time Series Methods

We compared standard time series forecasting methods applied to the data obtained from DSS. This included exponential smoothing models and autoregressive integrated moving average (ARIMA) models. The fitted models were compared using mean absolute percentage error (MAPE) and mean absolute scaled error (MASE) to measure goodness-of-fit.

1.5.3 ARIMA Model with Deployment Information

Based on the better performance of the ARIMA model, we propose incorporating information into the ARIMA model, such as deployment dates, to produce a dynamic regression model. This additional information was found to be helpful for forecasting intermittent workload spikes at the MPC, and will likely be useful in forecasting future workload.

1.6 Thesis Structure

We begin Chapter 2 with a discussion of research conducted utilizing time series analysis (TSA) in a similar fashion such as forecasting demand, mishaps, and manning requirements. Each of the referenced theses used TSA and various forecasting methods utilized in our research. We conclude Chapter 2 describing the OFRP cycle, AVCAL, COSAL and the potential effects on workload at the MPC.

Chapter 3 introduces the various methods used in the research, beginning with information on time series analysis and forecasting. We then discuss the primary forecasting models and how the best model was chosen using key performance indicators. Each of the forecasting models weights the observations in the historical data differently; a detailed explanation is provided. We also describe how to incorporate additional information, using dynamic regression models.

Chapter 4 discusses the results of the forecasting models evaluated. Test sets from the historical data were used to validate accuracy. A baseline model was evaluated and compared to a more complex model using deployment information, which was found to be significant in affecting the accuracy of the forecast.

Chapter 5 concludes with a summary of our findings, limitations of the scope of the research, and the applicability of the research. Additionally, recommendations for future work using other time series analysis techniques are presented.

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CHAPTER 2:
Background and Literature Review

2.1 Time Series Forecasting

This section reviews some prior work on applying time series methods to forecasting.

Chonko, Heiliger, and Rudge (2014) identified the inaccuracy of the causal forecast model used by DLA. Inputs into the model were estimated and variables were aggregated, which led to compounding forecast errors. Additionally, the regression model was used to predict annual workload based on only the previous twelve months of data.Applying various forecasting methods including ARIMA, double exponential smoothing, and moving averages, comparisons were made to determine which model was the best fit using mean absolute deviation, MAPE and MASE. Results of the research concluded ARIMA was the best model.

Joseph Chery (2008) uses time series analysis and various forecasting techniques to develop a model for manning requirements at Navy Medical Center, San Diego. He notes non-patient requirements for the nurses of military hospitals such as standing duty, physical readiness tests, and deployments, which add complexity to planning the requisite amount of personnel. Utilizing the Holt-Winters method, a usable forecast was generated that can be used for manpower planning.

Douglas Feiring (2006) uses univariate time series models and various forecasting techniques to evaluate the future manning inventory of various enlisted rates of the United States Marine Corps. Models tested were Holt-Winters exponential smoothing, multiplicative decomposition, and the Box-Jenkins ARIMA model. The results of each model were compared using MAPE, MASE, and the sum of squared errors to determine which was the best fit. In conclusion, each model did better than the baseline naive model, but the multiplicative decomposition model proved to be best.

Ryan Herrmann (2022) uses time series models to forecast aviation mishaps using seasonal decomposition, Holt-Winters, and ARIMA models. The models best suited for forecasting were seasonal decomposition and ARIMA due to evidence showing seasonal trends. While causality could not be determined with the research, the ability to forecast mishaps prove useful in the development of United States Air Force safety practices.

2.2 Major Deployment-Related Events

The OFRP outlines phases of deployable units broken down into five distinct phases: maintenance, basic, integrated, advanced, and sustainment (Department of the Navy 2014). The maintenance phase includes major repairs, upgrades, reconstruction, etc. and is normally conducted in a shipyard. Basic phase serves as a time period of evaluation that determines if the ship can perform core capabilities. The advanced and integrated phases include the honing of skills in tactics and mission-specific training with other ships, a carrier strike group (CSG), or an Amphibious Readiness Group (ARG). Finally, the sustainment phase is self-explanatory and is generally associated with deployments. Each of these phases requires prompt support provided by the MPC. DDNV is not aware of all the deployable units' schedules, specifically, which phase each unit is in, and the focus of this thesis is to incorporate major events (i.e., deployments and AVCAL requirement dates) as predictors to forecast potential spikes in workload. Figure 2.1 depicts and briefly explains the five phases of the OFRP cycle.

A COSAL determines the range and depth of "spares, special tools, tools, test equipment, maintenance assistance modules, equipage, and consumables required to make a ship self-sustaining for a specified period of time" (Department of the Navy 2010). This is specific to ship type, and each must be outfitted prior to joining the fleet from construction completion or availability period. The ship's COSAL are managed and maintained by Navy Inventory Control Points by extracting data based on equipment maintenance, so it is imperative shipboard personnel document maintenance properly to account for any changes in requirements.

Similar to a COSAL, an AVCAL "establishes aviation repairable and consumable allowance level inventories in support of aircraft carrier nuclear (CVN), landing helicopter assault (LHA), and landing helicopter dock (LHD)" (Department of the Navy 2017). To ensure an AVCAL can support the embarked airwing (marine aircraft group (MAG) for LHA and LHD), a composition of several squadrons of various types of fixed-wing and rotary-wing

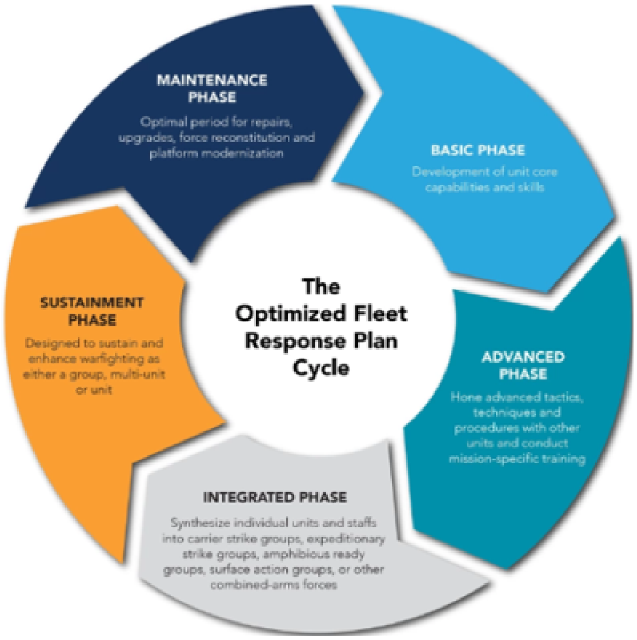

Figure 2.1. 5 Phases of the OFRP Cycle. Source: Camp (2022).

aircraft, on any of the platforms previously mentioned, a comprehensive review is done in three phases prior to deployment. This is done by analyzing the most recent eight quarters of maintenance history of the type, model, and series of every aircraft that will embark. This process can take 7-9 months with multiple inspection dates for readiness throughout. These inspections check inventory levels of the AVCAL to ensure progress is being made as the deployment date draws closer.

Throughout the OFRP cycle, a ship is mandated to maintain an adequate inventory of COSAL items in the onboard storerooms. This is most imperative when a ship is entering the fleet for the first time or reentering following a maintenance availability period (Department of the Navy 2010). While each ship is required to maintain the inventory, routine maintenance, lack of availability in Navy-wide inventory, or funding shortages limiting the ability to reorder parts may cause COSAL requirements to drop below acceptable levels. When entering the next phases in the OFRP cycle, this issue must be remedied by ordering the missing parts. Repair parts and components, which are critical in ships' readiness, must go through the MPC and can be a potential choke point in the supply chain.

When multiple ships on the waterfront place large orders simultaneously, the MPC faces an unanticipated workload spike. There are limited personnel to process incoming materiel and without proper forecasting, the MPC will not have the manpower to ensure on-time delivery. Backlogs at the MPC have been in excess of 3-4 weeks, which cause delays in readiness, increase costs due to overtime of civilian personnel, and the need to hire a tiger team to assist.

CHAPTER 3:
Methodology

3.1 Exponential Smoothing

We used the Holt-Winters seasonal method, which is comprised of a forecast equation and three exponential smoothing equations: level, trend, and seasonality with corresponding parameters (Hyndman and Athanasopoulos 2018). Forecasts are created by exponentially smoothing previous values. This is done under the critical assumption that the most recent values are more important; i.e., carry more weight. The three parameters that need to be estimated are:

- an α parameter for the level
- a β^* parameter for the trend
- a γ parameter for the seasonal component

3.2 ARIMA Models

ARIMA modeling combines differencing with autoregression and a moving average model (Hyndman and Athanasopoulos 2018). Autoregression indicates the variable of interest is regressed on itself and the forecast is generated using a linear combination of its own historical values (Hyndman and Athanasopoulos 2018). ARIMA models can be seasonal or non-seasonal. Non-seasonal ARIMA models are specified by an order p for the autoregression, an order d for the differencing, and an order q for the moving average component. Seasonal ARIMA models have p, d, q values for a seasonal component as well, where the season length m also needs to be determined. We used the *ARIMA()* function in the Forecast package in R to automatically select the p, d, q, and m values, and to fit the coefficients of the model.

3.2.1 Incorporating Additional Predictors

The previous time series models were based solely on information from past observations in the time series; however, the models can be designed to include relevant information that may lead to more accurate forecasts. External variables such as holidays, laws, competitor activities, etc. may provide explanations of the variability in the data (Hyndman and Athanasopoulos 2018). In this research, we used predictors based on the number of deployments during a certain window of time, by ship type.

3.3 Evaluating Goodness of Fit

To determine which forecasting model is the best fit, MAPE and MASE were used. The closer the MAPE and MASE values are to zero, the more accurate the model is. MAPE is used extensively throughout TSA due to its scale-independence and ease of interpretation (Kim and Kim 2016). MAPE is defined by

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - F_t}{A_t}\right|$$

where:

- N = number of data points
- A_t = actual values at data point t
- F_t = forecast values at data point t

MAPE has the disadvantage that the percentage error measurements may be infinite or undefined if there are zero values in the time series (Kim and Kim 2016).

Due to the disadvantages of MAPE, MASE can be utilized as it is independent of the scale of the data. The MASE is defined by

$$MASE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - F_t}{\sum_{i=2}^{n}\frac{A_t - A_{(t-1)}}{n-1}}\right|$$

where:

- N = number of data points
- A_t = actual values at data point t
- F_t = forecast values at data point t

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CHAPTER 4:
Analysis and Results

4.1 Exploratory Data Analysis

Materiel processing data was received from DDNV via DSS, the Naval Station Norfolk Public Affairs Officer (PAO), and the type commanders (TYCOMs), Board of Inspection Survey (INSURV), United States Fleet Forces Command (USFFC) in the form of *.csv* files. Files received from all sources contained data on important dates pertaining to ships' schedules including INSURVs, AVCAL Phase One, AVCAL requirement dates, deployment dates, and return from deployment dates. These files were processed using R and merged into a dataframe. It was cleaned by removing unnecessary columns and rows containing missing or duplicate data. The final dataframe consisted of 1,768,404 individual documents processed between FY-18 and FY-22, which was organized in the following columns:

- Document No., Document Number
- FSC, Federal Supply Code
- NIIN, National Item Identification Number
- Ship Date, Date materiel processing was completed
- Ship Week, Week of the year materiel processing was completed
- Ship Month, Month of the year materiel processing was completed
- Ship Year, Year materiel processing was completed
- Manifest Date, Date materiel was manifested for shipping to end user
- Manifest Number
- DoDAAC, Department of Defense Activity Address Directory of end user

The dataframe allowed for calculations to be done such as finding the average materiel processing time at DDNV and average delivery to the end user after processing, which was 22 days and 7 days, respectively. Average monthly processing was also calculated by grouping the documents processed by month as shown graphically in Figure 4.1. The data showed an average of 29,000 documents processed monthly.

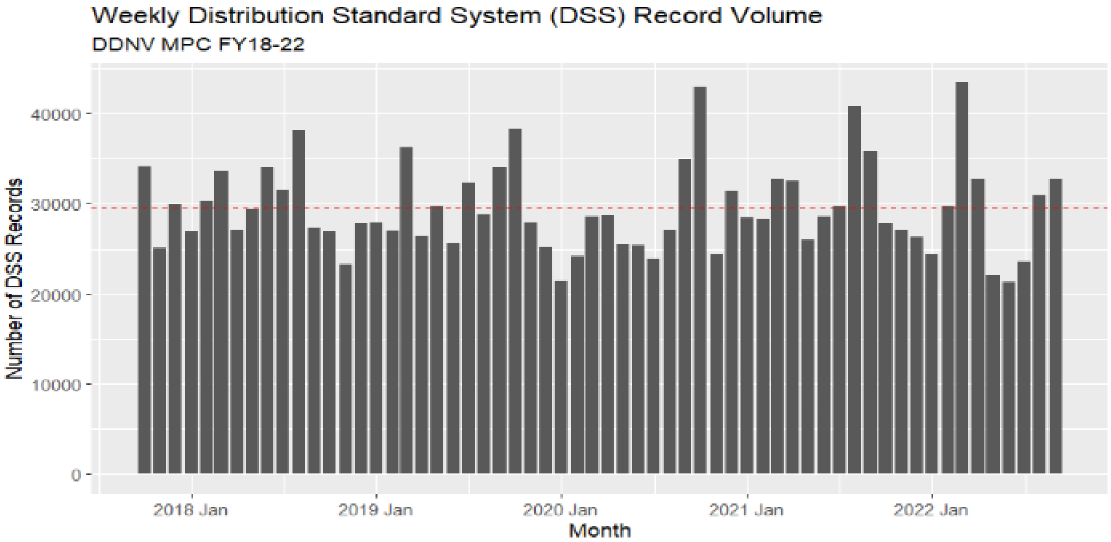


Figure 4.1. Monthly Workload Volume

Based on the workload, further analysis was conducted to determine which class of ship contributed most to overall workload. Analysis concluded CVNs contribute most of the workload with an average of 7651 documents processed monthly by the MPC. Additionally, when comparing the overall monthly workload to the CVN monthly workload, depicted in Figure 4.2, the workload spikes matched closely, which suggested some type of correlation.

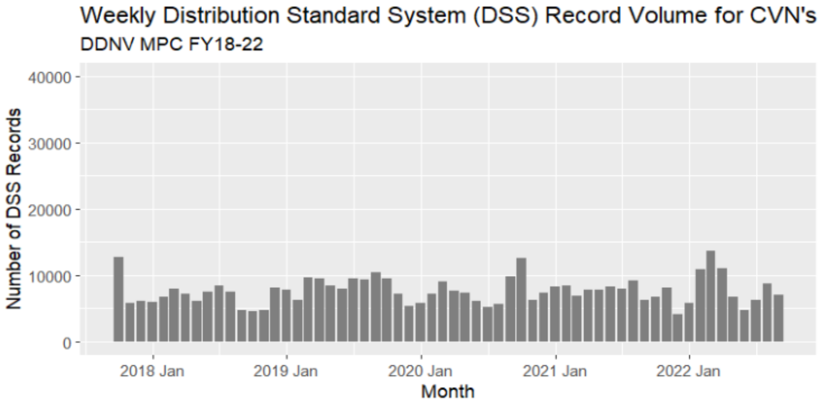


Figure 4.2. CVN Monthly Workload Volume

To determine what may be causing the correlation, we analyzed the phases of the OFRP, starting with the final phase, sustainment. Starting with the final phase gives us immediate insight into the correlation given that sustainment corresponds to deployment. When a CVN deploys, it is rarely ever "alone" in that it is accompanied by an embarked Carrier Air Wing, and a Surface Action Group comprised of Cruisers and Destroyers. Similarly, when an LHA or LHD deploys, it is a part of an ARG and accompanied by a landing platform, dock (LPD) and a landing ship, dock (LSD).

Further EDA consisted of performing a seasonal decomposition to assess the presence of trends and seasonality. The seasonal decomposition was conducted using R's *ts()* function. Using R's *stl()* function, the default "periodic" option was used to determine if a seasonal trend was present. The extracted data consisted of the seasonal, trend, and remainder components. Figure 4.3 shows the plotted extracted components.

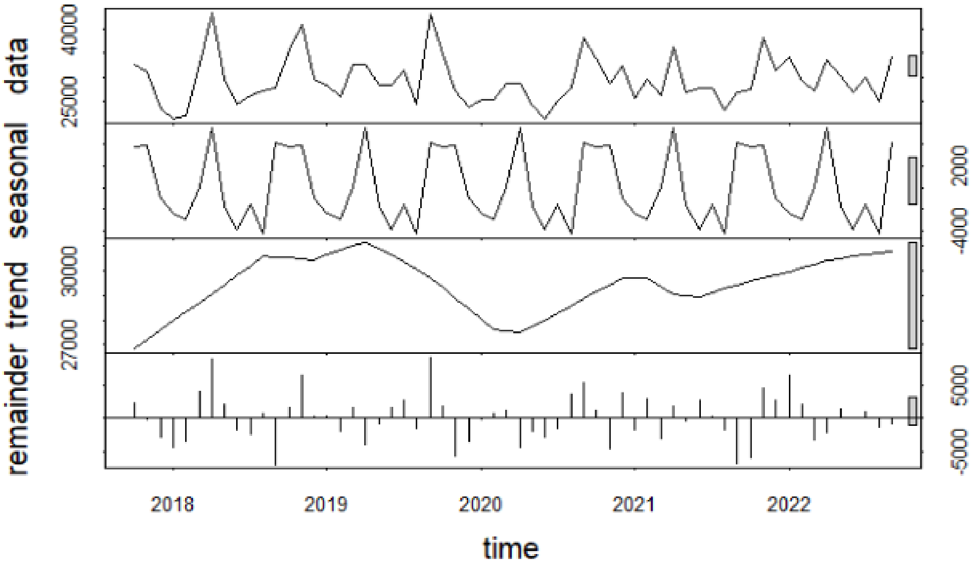


Figure 4.3. Seasonal Decomposition Components

Analysis of the data revealed strong seasonal component. Examination of the remainder component reveals a great deal of noise (randomness) due to the magnitude of the values and indicates variability that cannot be explained or captured by the seasonal or trend components. Plotting the seasonal data with a trend and fit line in Figure 4.4 show an approximately neutral trend; however, the lines fail to capture the months with extreme workloads.

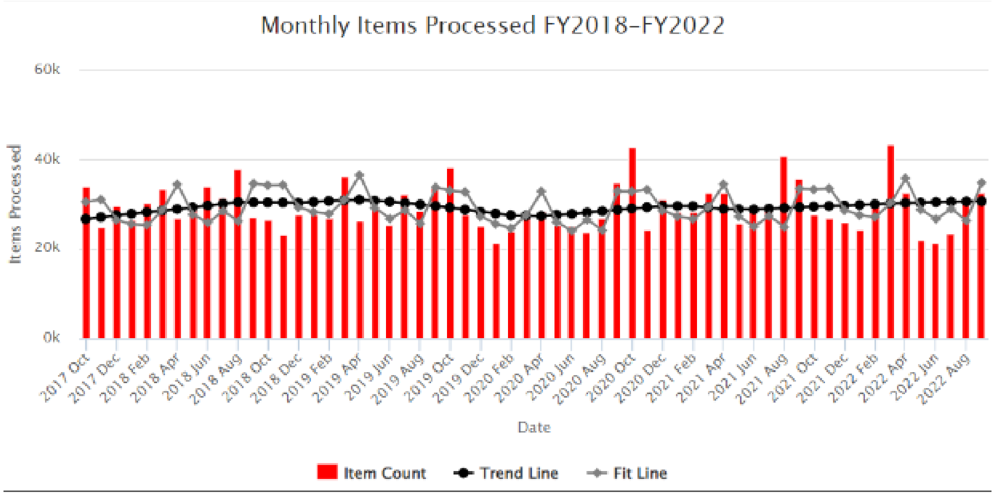


Figure 4.4. Seasonal Decomposition Plot

4.2 Models Fitted with Historical Data Only

Next, we used R to apply the Holt-Winters exponential smoothing and ARIMA forecasting methods. This analysis was conducted on models using only the historical data from DSS provided by DDNV. Figure 4.5 shows a visual comparison of the resulting fitted models plotted over the original values. Table 4.1 shows the numerical values of the actual and forecast data.

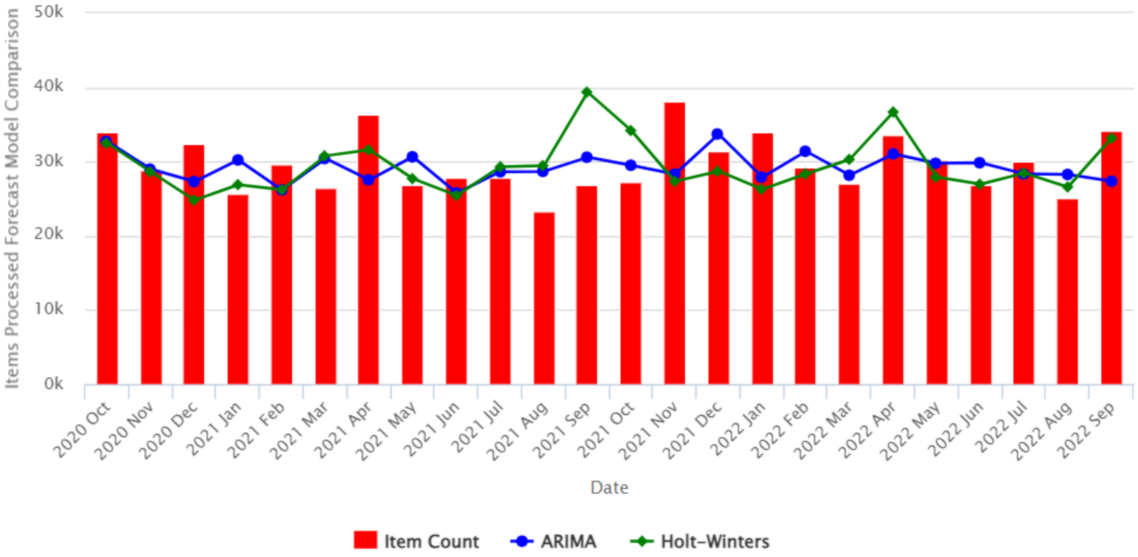
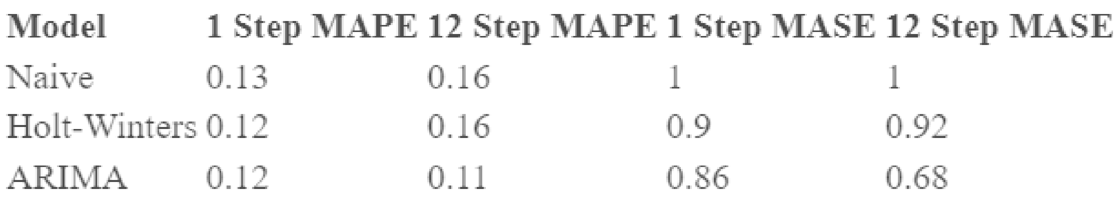


Figure 4.5. Holt-Winters and ARIMA Forecast Plot

Time	Actual	HW Forecast	ARIMA Forecast
2020 Oct	34022	32482.68	32718.10
2020 Nov	28817	28607.48	28969.48
2020 Dec	32355	24793.59	27300.35
2021 Jan	25650	26884.94	30213.23
2021 Feb	29671	26199.70	26180.64
2021 Mar	26389	30771.20	30405.21
2021 Apr	36322	31573.19	27542.43
2021 May	26959	27690.01	30636.38
2021 Jun	27866	25432.89	25762.06
2021 Jul	27780	29279.87	28619.26
2021 Aug	23296	29441.20	28673.83
2021 Sep	26856	39353.24	30581.68
2021 Oct	27336	34174.43	29496.70
2021 Nov	38091	27331.04	28297.66
2021 Dec	31505	28707.08	33703.04
2022 Jan	34053	26268.59	27891.67
2022 Feb	29316	28331.62	31381.34
2022 Mar	27092	30280.74	28155.29
2022 Apr	33678	36665.79	31025.19
2022 May	30289	27900.50	29762.01
2022 Jun	26823	26949.25	29838.29
2022 Jul	29960	28433.52	28326.29
2022 Aug	25047	26569.95	28257.36
2022 Sep	34162	33171.61	27343.97

Table 4.1. Workload Fitted Values

Both forecasts are generally close to the actual values. Visual analysis shows the ARIMA forecast closer to the actual values than the Holt-Winters forecast, especially in 2021 AUG-2021 OCT. In this time period, the Holt-Winters forecast greatly overshoots the actual values. Overall, both methods miss the peaks of workload, but for purposes of application, the MAPE and MASE values shown in Figure 4.6 show ARIMA is the better method.



Model	1 Step MAPE	12 Step MAPE	1 Step MASE	12 Step MASE
Naive	0.13	0.16	1	1
Holt-Winters	0.12	0.16	0.9	0.92
ARIMA	0.12	0.11	0.86	0.68

Figure 4.6. Holt-Winters and ARIMA MAPE and MASE comparison

4.3 Deployment-Aware ARIMA Model

4.3.1 Deployment Predictors

To create a dynamic regression model using ship's deployments as a predictor, we used information provided by the Commanding Officer of DDNV, CAPT Justin Lewis, SC, USN. In order to encompass the entirety of the deployment schedule, we needed to look back a maximum of 36-weeks prior to deployment. Contained within this range are all major inspections within the OFRP cycle required for the CVN to deploy. Due to CVNs deploying with a strike group, we utilized this time period for all classes of ships. During the analysis, the deployment predictor was tuned ranging from 28-weeks to 36-weeks. The final product was a predictor, $x_{s,t}$ where:

- s represents the number of ships of a specfic class
- t represents the week of the year

We compared this to the baseline ARIMA model. Both models are specified in the next section.

4.3.2 Model Formulation

The baseline model formulation is an autoregressive moving average time series model. This formulation does not take into account any deployment data and is solely based on historical data. Parameter values and order were selected using the Hyndman-Khandakar algorithm Hyndman and Athanasopoulos (2018), utilizing the *ARIMA()* function in the *forecast* package in *R* and estimated using data from DSS. The Hyndman-Khandakar algorithm selected $p = 2$, $d = 0$, and $q = 2$ for the non-seasonal autoregressive, integration, and moving average components, and $P = 1$ and $D = Q = 0$ for the seasonal components with a season length of 52 weeks. The model has the form

$$y_t = [c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \Phi_1(y_{t-52} - \phi_1 y_{t-53} - \phi_2 y_{t-54}) + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2}] + \epsilon_t$$

where:

- y_t represents the record count for week t
- ϕ_t represents the autoregressive parameters
- θ_t represents the moving average parameters
- Φ_t represents the seasonal autoregressive parameter
- ϵ_t represents the forecast error for week t

The parameters were estimated using data from FY18-21, and the model was tested against FY22 data. Figure 4.7 visualizes the model's test set performance. The majority of the data fell within the 80% confidence interval of the forecast; however, the forecast fails to capture the peaks in 2022 Week 8 and 2022 Week 13, which fall outside the 95% confidence interval.

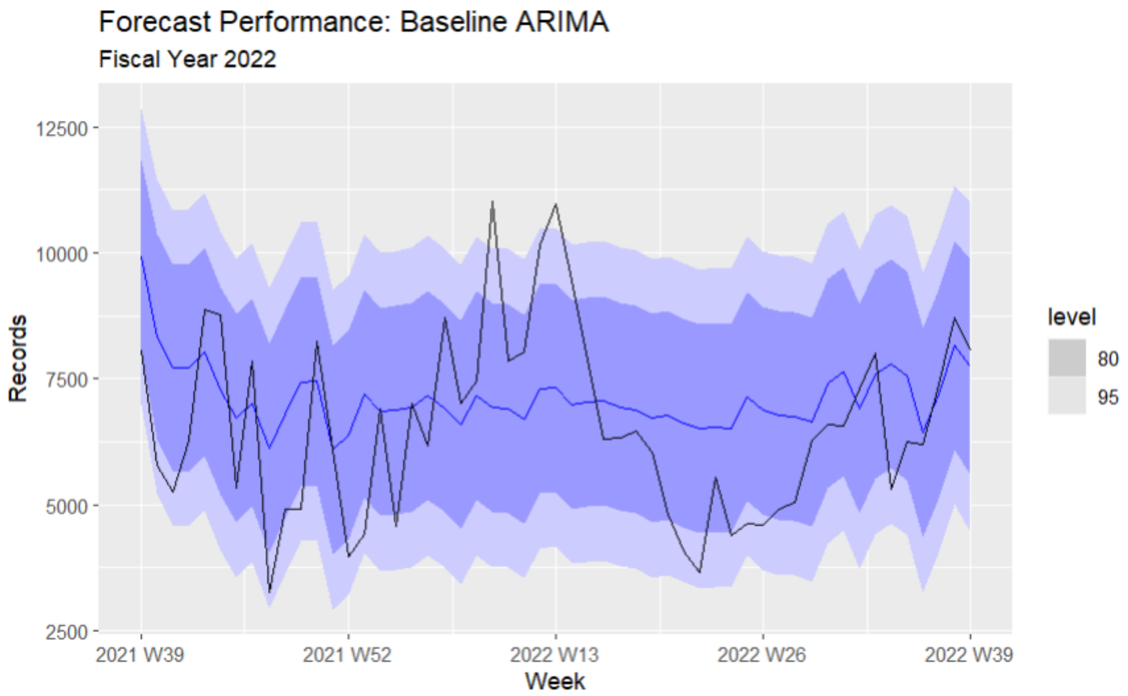


Figure 4.7. Baseline ARIMA Test Set Performance

Our deployment-aware model is a dynamic ARIMA model utilizing the DSS data and deployment predictors $x_{s,t}$. As with the baseline model, the Hyndman-Khandakar algorithm selected the lags, which were $p = 1$ and $d = q = 0$ for the non-seasonal part, and $P = 1$ and $D = Q = 0$ for the seasonal part with a season length of 52 weeks. The model has the form

$$y_t = \left[\beta_0 + \sum_s \beta_s x_{s,t} + \phi_1\eta_{t-1} + \phi_2\eta_{t-2} + \Phi_1(\eta_{t-52} - \phi_1\eta_{t-53} - \phi_2\eta_{t-54})\right] + \epsilon_t$$

where:

- y_t represents the record count for week t
- $x_{s,t}$ represents the number of deployments of ship type s in T minus 28-weeks of deployment at week t
- ϕ_t represents the autoregressive parameters
- η_t represents the regression error for week t

- Φ_t represents the seasonal autoregressive parameter
- ϵ_t represents the forecast error for week t

This model was also fitted using data from FY18-22, and tested against FY22 data. Figure 4.8 shows the test set performance.

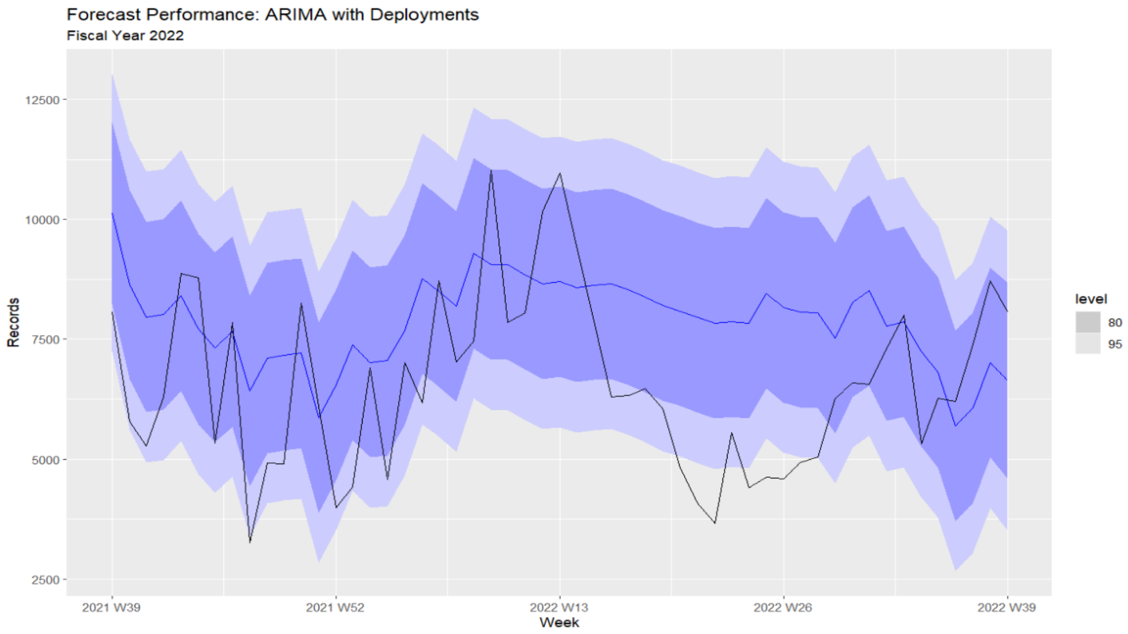


Figure 4.8. Deployment Aware ARIMA Test Set Performance

4.3.3 Comparison with Baseline

Figure 4.9 shows the test set performance of the two models side-by-side. It is clear the deployment-aware ARIMA model is better able to capture the peaks in workload than the baseline ARIMA model.

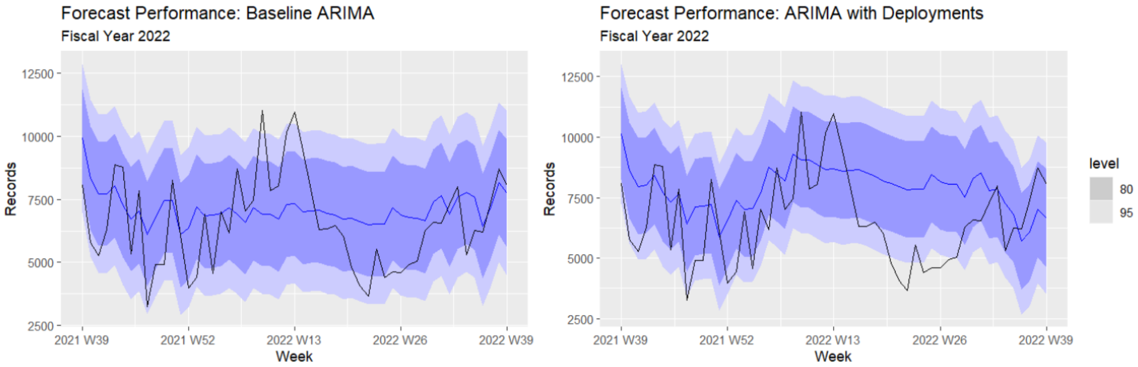


Figure 4.9. Side-by-side Comparison of Baseline and Deployment-Aware ARIMA Models

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CHAPTER 5:
Conclusion

5.1 Discussion

The findings of this research could be immediately applied to predict workload at the DDNV MPC. By using an ARIMA model with deployments as a predictor, the MPC can forecast potential spikes in workload weeks in advance and make personnel requirement decisions to maintain efficiency. Because DDNV has not used time series forecasting models in the past, the work contained in this thesis provides a foundation for quantitative forecasting at the DLA MPCs. The research can be expanded upon, using additional forecasting models, to provide accurate forecasting further into the future.

The twenty-four distribution centers operated by DLA have a direct impact on global military readiness via the logistical support that they provide. The timely processing and delivery of materiel is critical for mission success across all military branches and the whole-of-government. By implementing the methods used in this research, the distribution centers will be more able to deliver materiel on time and avoid costs associated with delays and unforeseen personnel requirements.

Throughout this thesis, the focus has been on Navy schedules; however, the methodology proposed in this thesis can apply directly to other military branches as well. Major events such as inspections, assessments, etc., can be used instead of deployments. While the events can be used in addition to deployments, caution must be exercised to avoid multicollinearity and/or unnecessarily increasing the complexity of the model.

5.2 Future Research Recommendations

This research explored several forecasting methods and modeling techniques to predict future workload. While the method used presents a way forward, there are several future research opportunities to develop upon using this research as a foundation.

5.2.1 Croston's Intermittent Forecasting Method

Widely used in inventory control, we can view the problem of forecasting spikes in workload as one of forecasting intermittent demand. Intermittent demand can be defined as a portion of a time series in which a significant amount of zero values is present. The "demand" in this case will be the spikes in workload. Croston's intermittent demand forecasting method can then be used (Croston 1972). Examples of the primary issues faced with intermittent demand are the timing of the demand and how much volume will be associated with the demand. As the data can be tailored to fit the criteria, Croston's method is a candidate for future research.

5.2.2 Extreme Value Analysis

This area of study focuses on large deviations from the median of probability. Extreme value analysis (EVA) aims to predict the occurrence(s) of events outside the range of a given data set. Natural disasters, workplace mishaps, or stock market crashes are examples of how EVA can be used. Application of one of the two main approaches, annual maxima series or peak over threshold (Davis and Resnick 1989), can lead to new forecasting models. For this research, the peak over threshold approach could be used to fit two separate distributions, accounting for the number of times DDNV would have large demand and the size of the demand.

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