CHANNEL MISSIONS: FORECASTING SUSTAINMENT CARGO REQUIREMENTS

Graduate Research Paper

Katherine B. Hemken, Major, USAF

AFIT-ENS-MS-19-J-035

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

The views expressed in this graduate research project are those of the author and do not reflect the official policy of the United States Air Force, Department of Defense, or the United States Government

AFIT-ENS-MS-19-J-035

CHANNEL MISSIONS: FORECASTING SUSTAINMENT CARGO REQUIREMENTS

Graduate Research Paper

Presented to the Faculty

Department of Operational Sciences

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Operations Management

Katherine B. Hemken, BS, MA

Major, USAF

June 2019

AFIT-ENS-MS-19-J-035

CHANNEL MISSIONS: FORECASTING SUSTAINMENT CARGO REQUIREMENTS

Katherine B. Hemken, BS, MA

Major, USAF

Committee Membership:

Daniel Steeneck, Ph.D.
Chair

AFIT-ENS-MS-19-J-035

Abstract

The Department of Defense (DoD) relies on commercial air carriers as members of the Civil Reserve Air Fleet and to move cargo during peacetime operations. This research focuses on examining potential forecasting models for sustainment cargo in the Pacific area of responsibility. All four models provide viable weekly, monthly, and quarterly forecasts for the GATES cargo examined. The models developed include regression, ARIMA, Seasonal Exponential Smoothing, and Winters Method models. The models were compared based on goodness of fit measures. Then models were applied to a set of data that was withheld to determine how each performed compared to actual data. The models all provide reasonable forecasts. Overall, the monthly models are the best option because they provide relatively accurate forecasts and flexibility when applied.

To my amazing husband and family

Acknowledgements

First, I would like to thank my amazing husband who supported me throughout the year. Living together is going to be awesome. I also especially want to thank my advisor, Dr. Dan Steeneck for his patience, guidance, and willingness to explore this problem. Last but certainly not least, I would like to thank Mr. Don Anderson for his continued willingness to sponsor students and provide all the data (and then some!) needed for the project. We could not do it without you!

Katie Hemken

Table of Contents

List of Tables

List of Equations

CHANNEL MISSIONS: FORECASTING SUSTAINMENT CARGO REQUIREMENTS

I. Introduction

Background

The Department of Defense augments the military airlift fleet by contracting commercial airlift to help meet the demand to move sustainment cargo. According to Joint Publication 3-17, "National airlift policy dictates that commanders shift airlift workload to commercial carriers if surge and training requirements have been met." When used both as part of Civil Reserve Air Fleet (CRAF) and during peacetime operations, commercial carriers become a force multiplier for the military airlift capability (Joint, 2019).

Unfortunately, due to the vast scope of cargo moved and the complexity of operations, the DoD does not always accurately and effectively use the airlift capacity and capability that commercial carriers provide. In some situations, airlift is overestimated and not fully utilized. A recent Government Accountability Office (GAO) audit found that United States Transportation Command (TRANSCOM) needs to improve airlift forecasting and budgeting for commercially contracted airlift. Analysis in the report showed that over a ten-year period the forecasted workload varied and was significantly different than the actual workload. In addition to variability, the audit also identified the workload was both over and underestimated depending on the commodity being shipped and the timeframe examined. In one example referenced, the channel cargo actual workload was approximately 17% lower than the forecast in 2008. The audit identified that TRANSCOM has not yet, but needs to take steps to develop a sustainable method for accurate forecasts in the future (GAO, 2018).

As the audit identified, significant money is tied to airlift contracts. To help illustrate the importance of an accurate forecast, one congressional report identified that in the early 2000s, the DoD guaranteed millions in contracts to commercial carriers over set periods of time based on the anticipated workload. However, Air Mobility Command (AMC) spent over $2B by the time additional contracts were awarded throughout the contract period (Knight and Bolkcom, 2008). These situations drive monetary waste because the contract remains in place and the aircraft flies with a partial load or with cargo that could be shipped via more cost-effective means, such as sealift. At other times, not enough lift is contracted and "just-in-time" additional commercial lift is purchased. As when airlift is overestimated, there are negative impacts when the situation occurs. First, commercial companies do not always bid on last minute contracts because they are not perceived as profitable opportunities for the company. Second, some companies interested in bidding do not have airlift assets available on short notice to support the requirement.

In short, developing better forecasts for commercial airlift requirements can help the government plan more effectively and enable more efficient airlift operations (GAO, 2018). Additionally, better forecasts help ensure the DoD remains a viable and effective partner for commercial air carriers.

Problem statement

The DoD consistently forecasts, and then contracts for, inaccurate levels of commercial airlift to move sustainment cargo for the Pacific Theater.

Objectives

The primary objective of this research is to provide a forecast for sustainment cargo in the Pacific Theater. In order to do so, the research will use four models to develop a forecast on a quarterly, monthly and weekly basis. Additionally, this research will compare the twelve models developed and determine their viability compared to actual data.

Assumptions

In order to forecast the sustainment cargo in the Pacific Theater, several assumptions will be made. First, the level of sustainment cargo will remain relatively constant in future years. Furthermore, significant deviations to the cyclical levels of sustainment cargo in the Pacific theater are not anticipated over the next several years. As the sustainment cargo included in this research is directly tied to normal operations, this is believed to be a reasonable assumption.

Second, the research assumes that the locations originating and receiving cargo will remain consistent in the future. If additional locations are added or fewer locations are used it could impact the total amount of cargo moved. A change in basing could also impact the ability of the aerial ports to process, ship, and receive cargo.

The third assumption for this research is that the data obtained from Global Air Transportation Execution System (GATES) is an accurate and complete representation of sustainment cargo levels in the region. Although GATES is a system of record for cargo moved through the air transportation system, there is potential for some human error when entering records. To ensure the most accurate data was used in the research, this assumption is further touched on in the methodology section.

Limitations

There are several known limitations for this research. First, the data examined in the research is a small subset of data that was moved via airlift. The research relies on specific commodity codes that the researcher identified as sustainment cargo. Additionally, the research does not examine cargo within those commodity codes that were not flown on commercial missions. In some cases, the channel cargo may have historically flown on a military airframe such as a C-17 or a C-5.

Another limitation of this research is that this research does not link the forecast for the amount of cargo moved to a specific number of planes required. This is certainly an important step for TRANSCOM, however this research does not examine all the additional factors such as Aerial Port of Embarkation (APOE) or Aerial Port of Debarkation (APOD) that would be required to provide an accurate forecast for a specific number of commercial aircraft. This research did not examine the specific locations that cargo was traveling to or from and did not take enroute stops into account. For example, if an infrequently used location received cargo from a channel mission, that cargo was included in the total amount moved. While this is certainly important when examining the total amount moved, it makes it difficult to equate to a specific number of aircraft required.

II. Literature Review

Chapter Overview

This section will focus on literature that is relevant to airlift demand forecasting. It is broadly broken into four sections. The first will focus on providing an overview forecasting to discuss its importance and potential methods of forecasting. That will be followed by a brief discussion of commercial airlift and an overview of CRAF. Next, this section will include a discussion on commercial carriers in CRAF. Finally, a brief look previous studies related to CRAF demand forecasting will be provided.

Forecasting Overview

Forecasting is not a problem unique to the Air Force. Companies around the world rely on forecasts to buy, sell, and transport goods and services. Forecasting enables people to make decisions that prepare their organizations for the future (Bowerman et al., 2005). The concept of forecasting is also a relatively well known, but succinctly put, its primary objective is to determine the amount of change that is expected to occur over a given period of time (Florida, 2001). A good forecast enables leaders to base decisions on data, rather than just relying on intangible inputs or a gut feeling. As important decisions are made based on forecasts, it is important to understand some basic types of forecasts and examine some studies that relate to the problem this research paper addresses.

Many reliable forecasting models are quantitative forecasting techniques. The forecasts rely on historical data and a specific model for the forecast. Quantitative techniques use both those factors to analyze patterns and mathematically show the relationship between previous values and the current value within the dataset. In short, it is a mathematical way to predict the previous pattern into the future (Montgomery et al., 2008). There are several quantitative forecasting techniques including regression analysis, time series, regression, exponential smoothing, and Auto Regressive Integrated Moving Average (ARIMA) models. Each model examines the response of one variable to one or more independent variables (Bowerman et al., 2005). These models are frequently considered and used for time series analysis, making them potential models for the research problem discussed in the previous section.

In addition to understanding quantitative forecasting models, it is also important to understand that time-series problems are common and can be utilized in a variety of situations. As noted in Montgomery et al. (2008), trends, patterns, and shifts in data over specific periods or cycles can be revealed using time series plots. One specific type of time-series model that's frequently used is the ARIMA model. In many situations where there is both seasonality and potential trend, ARIMA models are used. Bowerman, Koehler and Pack (1990) identify that there are potentially four different approaches within the broad ARIMA model to include data transformation, double seasonal differencing, seasonal intervention, and seasonal interaction. Their research expanded on previous time-series forecast methods by examining each of the four models and developing examples to compare the models against each other. Their results lead to their conclusion that data transformation is not always necessary for increasing seasonal variation. They conclude that the other three models are all effective variations of ARIMA models and can be very useful for developing an accurate forecasting model. However, they caution that ARIMA and the four variations they discussed should not be the only models and instead should be compared against other models to determine which model construct fits the data best. (Bowerman et al., 1990). Furthermore, Bisgaard and Kulahci (2008), discuss international airline data and demonstrate that it is possible to transform data in order to examine trend over time. In order to examine the data they compiled, they used an ARIMA model and found that it was a good fit.

Commercial Airlift

Commercial companies and organizations that support commercial airlift require reliable long-term forecasts to appropriately posture and facilitate air movement. Although there are factors which make it difficult to develop an accurate long-term forecast, some forecast is required to ensure the right equipment and parts are available to meet customer demands. Although the forecasts are not always accurate, one general trend that has been noted over the past several decades is the increased requirement for air cargo shipment. Although the relative tonnage of cargo shipped is lower than other modes of transportation, the revenue from those shipments and the overall employment within that segment of the industry continues to grow (Fischer and Golich, 1991). Additionally, although it is a relatively low portion of the overall trade, the percentage is increasing. As high-value and time-sensitive items are regularly shipped via air, the value of goods shipped from a monetary standpoint make it a high portion of the overall trade (Final, 2010).

As the overall forecast of transportation of goods via airlift increases, it is important to recognize that there is a potential impact to the CRAF program. One specific concern is that the market is relatively difficult to enter due to limited resources and the saturation of the market (Fischer and Golich, 1991). As resources are limited, it could impact the number of potential companies and potentially available assets that are available to the military.

The transportation research board examined numerous aspects of commercial airlift and potential ways to forecast demand and requirement. International air cargo forecasts, broken out by 77 different commodity codes, were included as a specific area of focus. The commodity codes included cover the transportation of essentially all goods moved by air. While they used a time-series approach, they recognized that many factors such as location, route, and commodity can drastically impact the forecast. While their models do have some shortcomings, they are useful for aviation policy and the development of airport capabilities and capacity. Additionally, the information from the forecasts can help provide demand characteristics for various air cargo routes (Transportation, 2002). Although this research does not go into the specific data for each location to which AMC flies channel missions, it is possible that future research on demand could impact Air Force basing strategies and decisions.

Brief History of CRAF

The CRAF officially began in the early 1950s. Although it evolved over time, it remains an important aspect and capability for military airlift. As early as the 1970s the military recognized the need for additional cargo airlift capacity and worked with the civilian airlines to add additional cargo-capable aircraft to their fleets. The relationship with the military and the structure of the program matured with the changing landscape. In the 1970s, the military asked commercial airlines to focus on increasing cargo hauling capacity. At this point, Military Airlift Command (MAC) incentivized commercial companies to purchase cargo-capable planes by augmenting CRAF carriers business

(Crackel, 1998). Even in the earliest days of the program, leaders recognized the need for airlift capacity beyond the resources organically available in the military.

In the 1980s, the increasing need for air cargo transportation and decreasing number of assets available to the military led MAC to approach cargo-only companies such as FedEx and UPS. Although these companies were not originally part of the CRAF structure, the military saw the value of incorporating them and eventually convinced air-freight companies to join the program (Crackel, 1998). This effort increased the overall cargo capacity available in the CRAF program.

Despite all the work overcoming challenges that faced the program, CRAF was never activated in the early years of the program. The Persian Gulf War in 1990-1991 was the first time that it was partially activated. Commercial carriers helped deploy cargo and personnel to the Middle East as part of Desert Shield. Commercial carriers flew thousands of missions, and hundreds of thousands of personnel and tons of cargo. Although it was not fully activated, Desert Shield proved the importance of the program and demonstrated that commercial carriers were a critical part of the military capability (Crackel, 1998).

Over time, military strategy and commercial trends have shaped CRAF. Military strategy continues to rely heavily on the ability to quickly transport people and cargo around the world. Similarly, commercial companies are independently enticed to invest in cargo capacity because of the growing demand in the private commercial sector. (Crackel, 1998). Those two trends continue to shape CRAF today and highlight the need to partner with civilian air carriers even when the CRAF program is not activated.

Commercial Carriers as CRAF Members

Although the program has evolved over time, some of the same principles remain. One ready example is the reliance on CRAF partners for channel missions. Only carriers that participate in the program and meet the contractual requirements are able to bid on peacetime mobility missions (GAO, 2003). These peacetime missions provide some incentive for civilian companies to commit aircraft to the CRAF program. This in turn assures that the CRAF program maintains an adequate base of support if ever required to augment military airlift. Although it may seem relatively insignificant, CRAF support is relatively low cost compared to maintaining a larger organic fleet, which enables the military to invest in other requirements (Knight and Bolkcom, 2008). One important note is that the amount of peacetime airlift support commercial carriers are entitled to for business is directly proportional to the equipment and personnel that they commit to the CRAF program for mobilization during an emergency situation (Fischer and Golich, 1991).

As previously mentioned, the overall need for airlift capacity is outpacing the assets available to provide lift. This concern was evidenced during recent Executive Working Group, or meeting between CRAF leaders and AMC leaders. During an industry update, the carriers identified that in the cargo sector, civilian companies are seeing increased demand for airlift. As an example, they mentioned that tonnage flown had increased 150% on international lines between Asia, Europe and the Americas in the past five years alone. Additional aircraft are being added to cargo fleets to help support increased demand. However, the demand is outpacing the amount of additional capacity available (Clarke, 2018).

In order to purchase airlift capacity, the DoD uses two different methods. The first is called a fixed buy, which includes channel missions. The fixed buy contract includes the regularly scheduled aircraft that have set routes to Europe and the Pacific. The second method is an expansion buy. As the name implies, this method is used when the fixed buy contract does not have enough capacity to move all the cargo required to move. Expansion buys are bought after the fixed buy is already in place and are used to support exercise and growth in channel requirements (GAO, 2003).

Additionally, as briefly mentioned in previous sections, the CRAF program does have some limitations. First, there are some limitations on the type of cargo and the missions that commercial aircraft fly (Knight and Bolkcom, 2008). For example, some explosive materials and sensitive items will fly on military missions, rather than commercially contracted flights. Likewise, flights into impermissible environments will remain military missions. Another concern identified in a recent GAO study is that the cargo capacity on commercial airlift is not always well utilized. The underutilization leads to ineffective scheduling and capacity that could be more effectively managed (GAO, 2018). This specific concern ties directly to the intent of this research, which is to improve the forecast accuracy of the cargo that needs to be moved.

Channel Airlift Research

Although studies specifically focused on military airlift are relatively limited, there are several previous research efforts that address similar concerns. Although a slightly different focus area, the research completed by DeYoung (2012) and Leonard (2013) proved particularly relevant to the current research paper. In the first paper, DeYoung focused on time series forecasting for cargo going to Iraq and Afghanistan.

Many of the forecasting techniques are also applicable to data examined in this research paper (DeYoung, 2012)

In a paper completed the following year, Leonard expanded on the work done by DeYoung. He specifically focused on channel airlift missions, though his data set was broader than the data looked at in this research. The research presented showed numerous models that were replicable and useful to the current research (Leonard, 2013).

III. Methodology

Chapter Overview

This section of the paper focuses on the specific methodology used for research and analysis. It articulates the scope of the research completed and describe the dataset used to develop the forecast models. Additionally, it provides background information on the program used to develop the forecasts and some of the factors that will be examined in the analysis section of the paper.

Scope and Data Description

The initial data provided included world-wide GATES data from January 2012 through September 2017. The original data was provided in a spreadsheet with 59 columns of data including information such departure and arrival locations, Transportation Control Number (TCN), pallet dimensions, and weight among others. As data included seven years of data, there were initially over six million lines of unique data entries. After reviewing the initial complete set of data the researcher determined several ways to remove information that was extraneous to this research.

First, the researcher removed all missions that were non-channel missions. Next, the researcher defined sustainment cargo as cargo with the commodity codes of J, R, T, and U as identified by USTC. Those four codes include unaccompanied baggage, rations, household goods, and mail (Air-Commodity, 2018). Cargo identified as other commodities or non-channel missions were removed from the dataset.

The data was further scoped by identifying cargo that was identified as a Pacific Mission per the MAF ID Mission Encode/Decode table as replicated in Table 1 (Air, 2018).

Table 1 Channel Mission Second and Third Character (Air, 2018)

Second Character		Third Character	
B	Channel Cargo	A	Not Assigned
J	Positioning to first onload	B	Distribution Channel, Atlantic Region
K	Channel PAX	C	Distribution Channel, Pacific Region
L	Aeromedical Evacuation (AE)	P	Not Assigned
Q	Channel Mission (PAX and cargo)	E/Q	CPX Channel mission as assigned by AMC/A3Y
V	Depositioning from offload to new mission or home station	J/R/U W/Y/Z	Channel missions supporting Contingency Operations, Coordinate ID with 618 AOC/XOP

Specifically, channel missions with a third character of "C" are Distribution Channel in the Pacific Region (Air, 2018). Then, the researcher reviewed other channel missions and identified any missions that had a departure or arrival in the Pacific. In those cases, those missions were included in the research. Missions that did not meet either of those criteria were removed from the data set examined.

Next, the researcher removed lines of data that contained duplicate TCNs to ensure that each weight was only counted one time. This ensured that if the piece of cargo went on more than one mission or the mission had more than one leg, the weight was not erroneously included twice. The researcher also removed lines of data that were incomplete. There were enough remaining lines of data to ensure that the forecast still had a large population of data. Additionally, removing incomplete lines minimized the potential of skewed data due to erroneous information. This step minimized the amount of human error from data input.

Finally, the researcher compiled data from October 2017 through September 2018 and scoped the data using the same rule-set as previously identified. This set of data was not included in the initial forecast. This provided actual data to compare each forecast against in order to determine how each performed against real-world data.

Time Series Forecasting

In this section, the researcher provides information on four different time-series forecasting methods. Information and background on Regression, ARIMA, Seasonal Exponential Smoothing, and Winters Method models are included. Additionally, this section identifies the equations that formed the basis of each model.

Regression

One model used to develop a forecast is a regression model. Regression focuses on the relationship between an outcome and the variable that predicts that outcome. In the case of this research, the response variable is the amount of cargo moved in a specified amount of time (week, month, quarter), which is expected because the data is time series data. Following Montgomery (2008), the equation for the regression model for time series data is

$$y_t = \beta_0 + \beta_1 x_{t1} + \beta_2 x_{t2} + \cdots + \beta_k x_{tk} + \varepsilon_t, t = 1,2, \dots T, \quad (1)$$

where:

y_t = the weight of the cargo over time t,

x_{ti} = the value of the i^{th}independent variable at time t, and

β_i = the regression coefficient for the i^{th} independent variable.

Like the other models discussed in this section, regression is most effective when the parameters for the forecast remain the same over time.

ARIMA and Seasonal ARIMA

ARIMA models use past data and a series of errors to predict future values. Seasonal ARIMA models also take into account the seasonal effects of the data. ARIMA models include three variables p, d, and q with Seasonal ARIMA models including a fourth variable, s, which identifies the number of periods per season (JMP ARIMA, 2019). As the name indicates, the model is autoregressive, meaning that it is based on previous values and random shock. Additionally, it is a moving average, meaning that the forecast takes into account a specific number of previous values to determine the average used for the forecast (Box, et al., 2016).

ARIMA models take both seasonality and trend of data into account. While ARIMA models are generally very useful for time-series data, they rely on the assumption that the situation and factors that create the current data will remain the same in the future (Montgomery and others, 2008). ARIMA is an appropriate model to test with the current data, however if the conditions for movement of cargo change in the future, it will be necessary to reexamine the utility of ARIMA models.

The ARIMA model equation is (JMP ARIMA, 2019):

$$\Phi(B)(w_t - \mu) = \theta(B)a_t \tag{2}$$

where:

t = the time index,

B = the backshift operator,

w_t = the response series after differencing,

μ = the intercept or mean term,

$\Phi(B)$ = the autoregressive operator,

$\theta(B)$ = the moving average operator, and

a_t = the sequence of random shocks.

Seasonal Exponential Smoothing

Exponential smoothing model relates a new observation to a combination of previous observations. By using a combination of both the current point and previous observations, the model essentially creates a smoothed average to provide the forecast (Montgomery et. al., 2008). This is a model that is most effective when the data does not have significant trend but the average of the measured time series may have some change over the time period examined (Bowerman et al., 2005).

The equation for Exponential Smoothing is (JMP Smoothing, 2019)

$$y_t = \mu_t + s(t) + a_t \qquad (3)$$

where:

μ_t = time-varying mean term,

$s(t)$ = one of the s time-varying seasonal terms, and

a_t = the random shocks.

Winters Method (Additive)

Like the ARIMA models, Winters Method examines data that has both a linear trend and some seasonal pattern that is potentially changing over a period of time (Bowerman et al., 2005). The equation for the Winters method model is (JMP Smoothing, 2019):

$$y_t = \mu_t + \beta_t t + s(t) + a_t \tag{4}$$

where:

μ_t = the time-varying mean term,

$s(t)$ = one of the s time-varying seasonal terms,

β_t = the time-varying slope term, and

a_t = the random shocks.

Measures of Forecast Performance

In this section, the researcher will provide information on different goodness of fit measures used to compare the forecast models.

R-Squared

The R-Squared value is the coefficient of determination in the model. It indicates the amount of variation in the model that can be determined by the variable being measured. The equation for R^2 is (JMP Modeling, 2019):

$$R^2 = 1 - \frac{SSE}{SST} \tag{5}$$

where:

$$SST = \sum_{i=1}^{n}(y_i - \overline{y_i})^2,$$

$$SSE = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2,$$

n = the number of observations,

y_i = the independent variable,

$\overline{y_i}$ = the independent variable mean, and

$\hat{y}_i$ = the forecast value

The equation for the Adjusted R^2 is:

`

$$R^2{}_{adj} = 1 - [\frac{(n-1)}{(n-k)}(1 - R^2)], \qquad (6)$$

where:

k = number of independent variables

Residuals

Residuals are the difference between the predicted value at a specific point in time and the actual value at that time. When plotted, residuals should be normalized around zero and should not have significant outliers nor trend within the plot (Linear, 2019).

MAE

The Mean Absolute Error (MAE) is determined by comparing all the residual values for each data point and taking the absolute value of each. The average of the absolute values determines the MAE. The equation is: (JMP Modeling, 2019)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (7)$$

MAPE

The Mean Absolute Percent Error (MAPE) is similar to the MAE, however, as the name implies it compares percentages. Like the MAE, the MAPE measures forecast against historical data (JMP Modeling, 2019).

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \qquad (8)$$

IV. Analysis and Results

Overview

This section will examine and compare the models used to forecast cargo workload. It discusses the findings for the groups of quarterly, monthly and weekly models and discusses the goodness of fit measures for each of the models. Additionally, this section includes information on how the forecasts performed compared to the actual data from the period following the forecast dataset.

JMP

JMP is a statistical software program that enables users to interactively examine problems. This is the program used to run each model during this research. (JMP, 2019). With the refined GATES data, the researcher used JMP to develop and compare the forecasting models described in the previous sections. JMP provided outputs that enabled the comparison and review of each of the models for weekly, monthly, and quarterly time-series. JMP provides data on the following goodness of fit measures for each model.

Quarterly Models

Table 2: Quarterly Goodness of Fit Measures

Model	Rsquared	Rsquared Adj	MAPE	MAE
Regression	.877	.858	.326	.051
ARIMA (0,1,1)(0,1,1)	.877	.861	.365	.057
Exponential Smoothing	.872	.864	.370	.058
Winters Method	.861	.843	.378	.059

All four of the models that were run for a quarterly forecast produced relatively similar results. First, the coefficient of determination indicates that over 80% of the variability is caused by the variable being measured, in this case time as related to the amount of cargo moved. Although the Winters Method had a slightly lower R^2_{adj}, the model still compares well to the other three models. Interestingly, the Regression model had the highest initial R^2 value, but the R^2_{adj} falls slightly lower than the Seasonal ARIMA model.

Next, the MAPE and MAE for each model appear to indicate that the forecast was a good fit, at least against historical data. As anticipated, these values are lower for the quarterly model than the following monthly and weekly models. The forecast is the most aggregated during the quarterly models, leading to the smaller level of error.

Finally, the residuals for each model tend to be normalized around zero. In each model there are some areas where the residuals cluster slightly above zero and then slightly below zero, their overall distribution is relatively consistent. The distribution and range of residuals indicate that the model does not have significant outliers or trend that would decrease the model's applicability. In Figure 1, the regression residuals are relatively evenly distributed around zero. The residuals have a greater distribution above zero, indicating that the forecast model may have some skew.

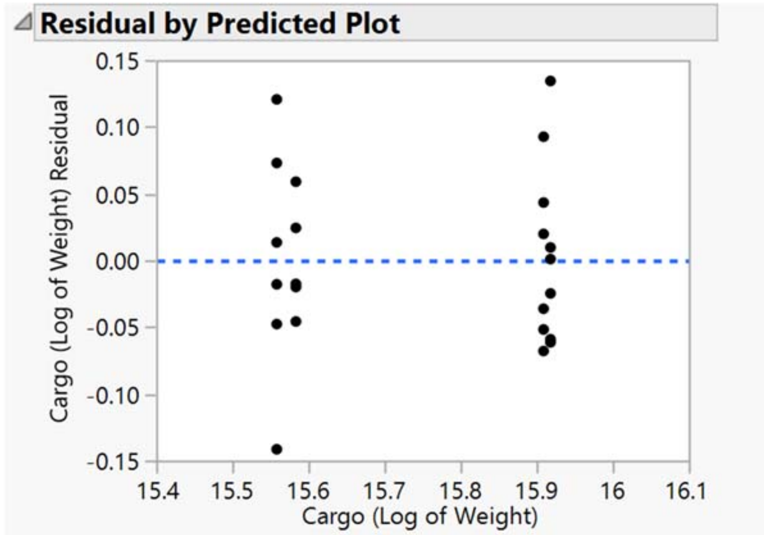

Figure 1: Quarter Regression Model Residuals

Figures 2, 3, and 4 all have similar residual properties. In each model, the residual values are normally distributed and normalized around zero. The values do not have significant trends or clusters, which supports the applicability of the ARIMA, Seasonal Exponential Smoothing, and Winters Method models.

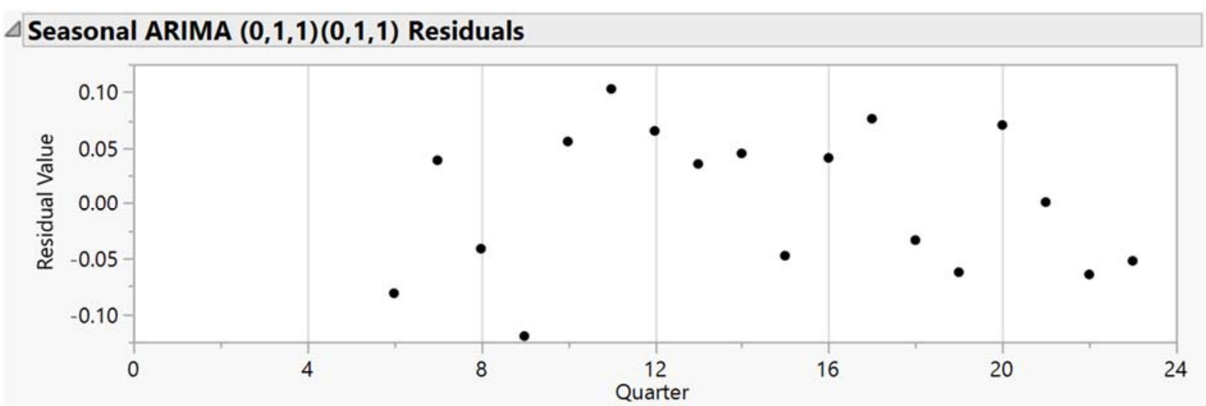

Figure 3: Quarter ARIMA(0,1,1)(0,1,1) Model Residuals

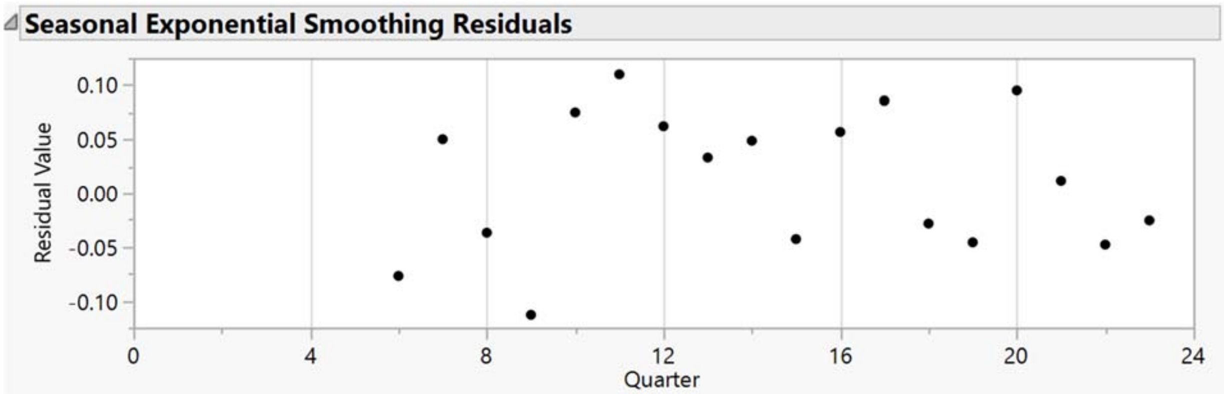

Figure 4: Quarterly Exponential Smoothing Model Residuals

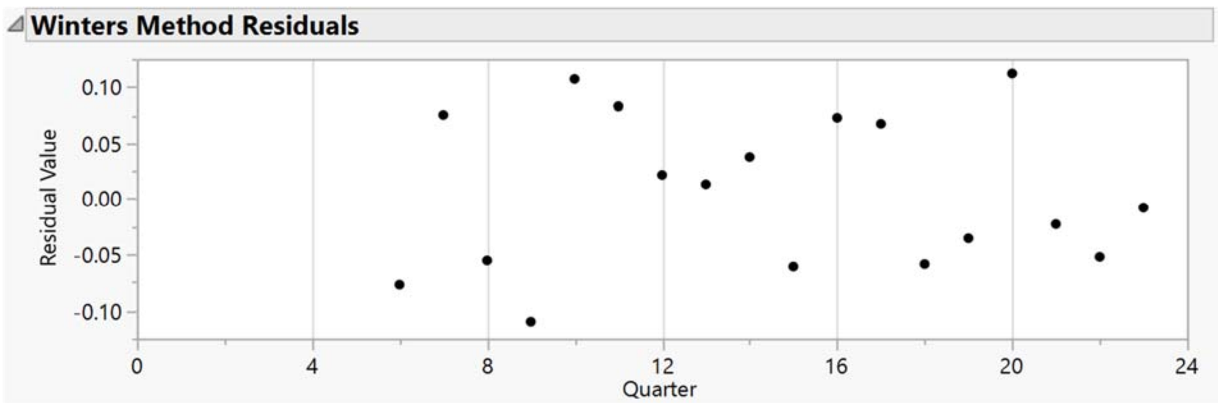

Figure 5: Quarterly Winters Method Model Residuals

Finally, the forecast values were compared to the actual amount of cargo moved, as seen in Table 3. The model slightly overestimates the total amount of cargo that will be moved each of the four quarters, however the predicted values remain relatively close to the amount of cargo actually moved in each of the four quarters examined.

Table 3: Actual Cargo Weight Compared to Model Forecasts

Quarter	Actual	Regression	ARIMA	Winters	Seasonal
4Q CY17	4,481,643	5,859,678	5,613,359	5,401,127	5,452,798
1Q CY18	5,145,243	5,714,067	5,407,949	5,141,348	5,192,081
2Q CY18	6,992,108	8,188,562	7,866,019	7,367,826	7,440,528
3Q CY18	6,899,863	8,113,620	7,910,830	7,300,395	7,372,432

One way to help compare the models against the actual values is to examine the MAE and MAPE for each model, as compared to the actual amount moved. As you notice in Table 4, the MAE is significantly higher for the ARIMA model when compared to the Winters Method and Seasonal Exponential Smoothing models, indicating that the model did not perform as well as the others for this period of time. Following the MAE, the MAPE confirms that the ARIMA model did not perform as well as the other models when compared to this set of actual data. As the table indicates, the percent error was almost twice as high as the other models during this analysis.

Table 4: Goodness of Fit for Actual Compared to Model Forecasts

	Regression	ARIMA	Winters Method	Seasonal
MAE	1,089,267	819,825	424,907	484,745
MAPE	19%	14%	8%	9%

Monthly Models

The four monthly models that were run each produced relatively similar results. A summary of the models is provided in Table 5.

Table 5: Monthly Goodness of Fit Measures

Model	Rsquared	Rsquared Adj	MAPE	MAE
Regression	.870	.845	.498	.073
ARIMA (0,1,1)(0,1,1)	.822	.816	.591	.086
Exponential Smoothing	.822	.818	.594	.087
Winters Method	.822	.815	.594	.087

Like the quarterly models, the four monthly models yielded similar results when comparing the goodness of fit measures. The R^2 and adjusted R^2 values accounted for over 80% of the variation, just like the quarterly models. However, the Regression was slightly higher than the other three models.

The MAPE and MAE are all consistent. This indicates that any of the models are likely to produce a reasonable forecast based on historical data. Both are slightly higher than the quarterly models which indicates that there is some additional variation when the model is compared to actual data.

Although the MAPE and MAE are slightly higher, the residuals indicate that the monthly models are an overall better fit for the data. Like the residuals for each of the quarterly models, the residuals are normally distributed around zero. However, the monthly models appear less clumped and more evenly distributed over the entire time period, without noticeable periods of over or underestimations. In Figure 5, the residuals for the regression model are normally distributed around zero. Unlike the quarterly model, the range is similar both above and below zero.

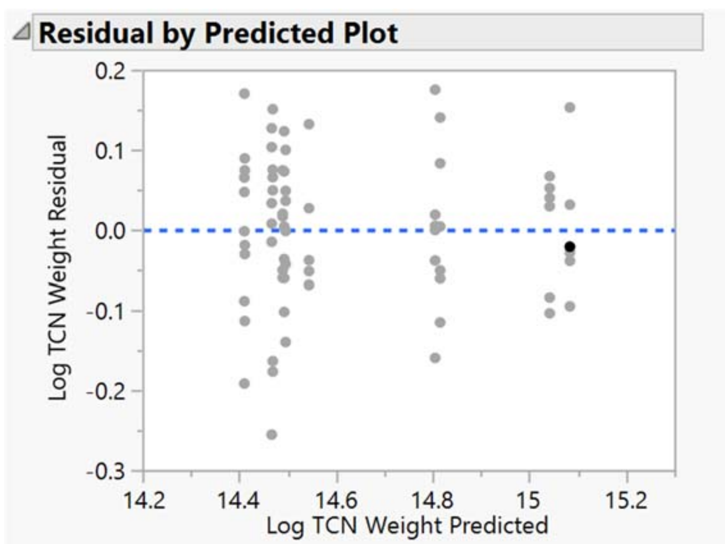

Figure 5: Monthly Regression Model Residuals

Figure 6, Figure 7, and Figure 8 provide visual representation of the remaining three models' residual values. As previously mentioned, the residuals are evenly distributed and do not appear to have significant periods of inconsistency. The residuals shown in Figures 7, 8, and 9 support the viability of each model.

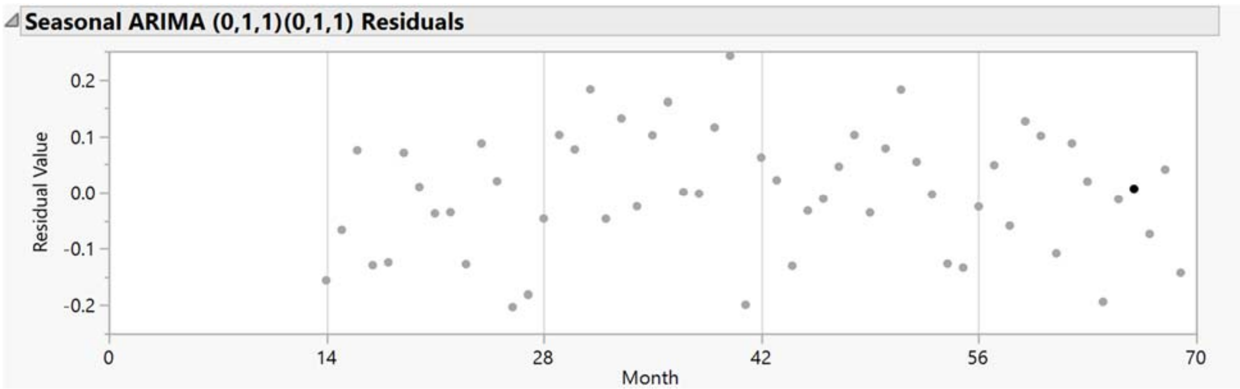

Figure 7: Monthly ARIMA(0,1,1)(0,1,1) Model Residuals

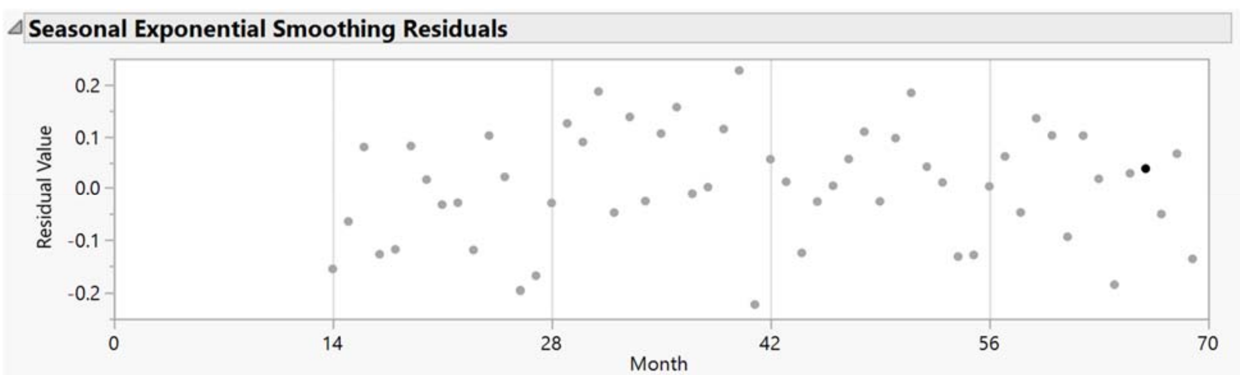

Figure 8: Monthly Seasonal Exponential Smoothing Model Residuals

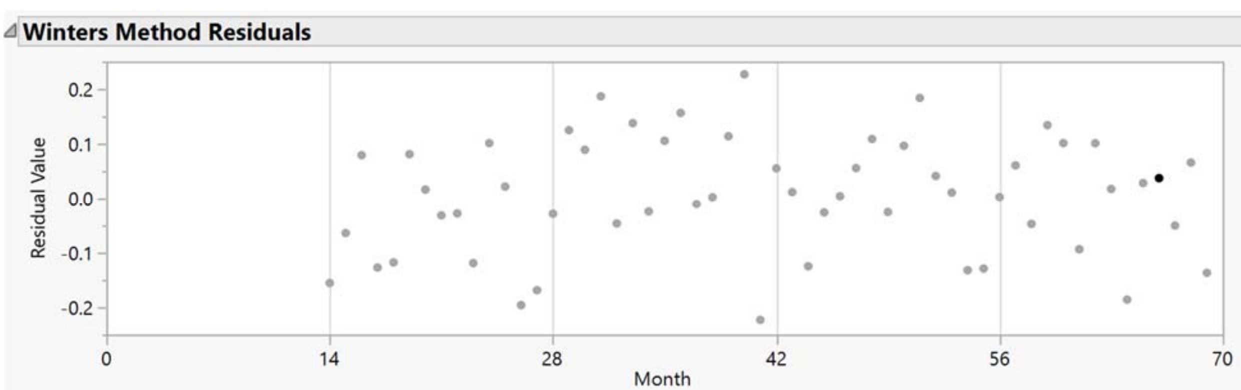

Figure 9: Monthly Winters Method Model Residuals

As indicated in Table 6, the regression model showed that some months had more significant impact to the model than others. The p-values for May, June, July, and August were all below .05 indicating high likelihood that the month had a significant impact on the amount of cargo moved. The direction of the estimate indicates the correlation of the cargo weight to the month. A positive number indicates a positive correlation and a negative estimate indicates negative correlation.

Table 6: P-Values for Monthly Regression

Term	Estimate	Std Error	t Ratio	Prob > |t|
Intercept	15.314	.213	71.85	<.0001
January	-.002	.030	-.05	.9591
February	.039	.030	1.30	.1973
March	.011	.030	.37	.7095
April	.010	.030	.34	.7359
May	-.158	.030	-5.19	<.0001
June	-.297	.030	-9.78	<.0001
July	-.276	.030	-9.10	<.0001
August	-.163	.030	-5.36	<.0001
September	-.003	.030	-.10	.9198
October	-.027	.031	-.86	.3958
November	.039	.031	1.24	.2206

Finally, the forecast values were compared to the actual amount of cargo moved, as seen in Table 7.

Table 7: Actual Cargo Weight Compared to Model Forecasts

	Actual	Regression	ARIMA	Winters	Seasonal
Oct	1,720,460	2,072,512	1,979,564	1,932,026	1,930,674
Nov	1,829,410	1,814,932	1,740,586	1,725,563	1,724,030
Dec	931,773	1,963,133	1,890,373	1,859,577	1,858,320
Jan	1,656,685	1,969,281	1,857,814	1,768,144	1,767,532
Feb	1,621,048	1,813,729	1,719,188	1,665,859	1,664,969
Mar	1,867,510	1,919,032	1,827,637	1,763,875	1,763,156
Apr	1,699,060	1,923,179	1,840,279	1,727,510	1,727,161
May	2,441,169	2,690,485	2,586,731	2,424,702	2,423,916
Jun	2,851,879	3,554,362	3,433,515	3,216,906	3,215,529
Jul	2,843,411	3,409,288	3,309,005	3,069,095	3,067,539
Aug	2,525,257	2,718,420	2,650,983	2,474,549	2,472,769
Sep	1,531,195	1,975,215	1,935,357	1,787,647	1,786,205

The monthly models performance remains relatively consistent with the quarterly models. However, it is clear that the ARIMA model performed slightly better than it did during the quarterly models. Table 8 indicates the goodness of fit measures, and demonstrates that the MAE and MAPE are both much closer to the Winters Method Model and Seasonal Exponential Smoothing Model forecasts. Although the MAPE is still slightly higher, it is within several percent of the other models, rather than almost doubled as seen in the quarterly models.

Table 8: Goodness of Fit for Actual Compared to Model Forecasts

Measure	Regression	ARIMA	Winters Method	Seasonal
MAE	361,139	292,464	203,826	203,491
MAPE	23%	19%	15%	15%

WEEKLY MODELS

Finally, weekly models were developed and compared, as identified in Table 9.

Table 9: Quarterly Goodness of Fit Measures

Model	Rsquared	Rsquared Adj	MAPE	MAE
Regression	.779	.734	.771	.101
ARIMA (0,1,1)(0,1,1)	.665	.662	.946	.124
Exponential smoothing	.666	.665	.944	.124
Winters Method	.540	.536	1.097	.144

As expected with the data used, the four weekly models examined all indicated relatively good fit based on the following factors. First, the R^2 and adjusted R^2 still indicate that the majority of the variation can be attributed to the measured variable. In the weekly modeling, the R^2 value indicates that the variation in the regression model is most attributed to the week. On the other end of the spectrum, the Winters Method model had a significantly lower coefficient of determination.

The residuals for this model appear evenly distributed and do not show trend over time. Like the monthly models, the residuals for the weekly models indicate that the models are a relatively good fit for the data. The residuals shown in Figure 9 are uniformly distributed. There are no specific or noticeable outliers, indicating the model produces a reasonable forecast for the set of data used.

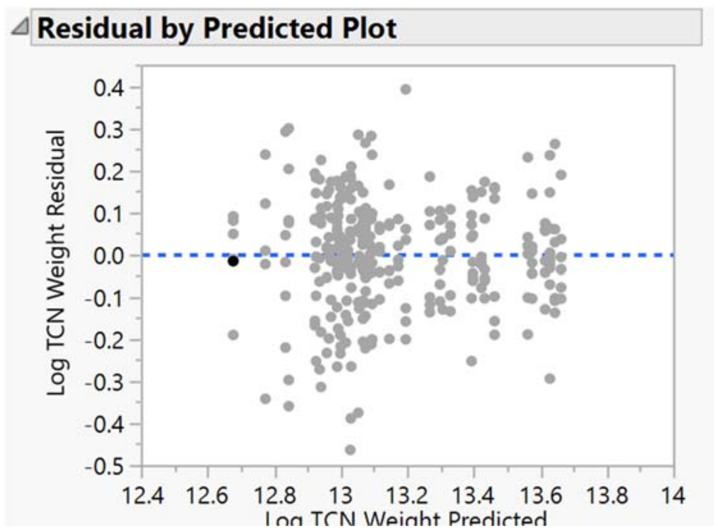

Figure 9: Weekly Regression Model Residuals

The residuals shown Figures 10, 11, and 12 indicate the ARIMA, Seasonal Exponential Smoothing, and Winters Method models are appropriate for the data used in this research. Similar to the previous models, there is uniform distribution of the residual values.

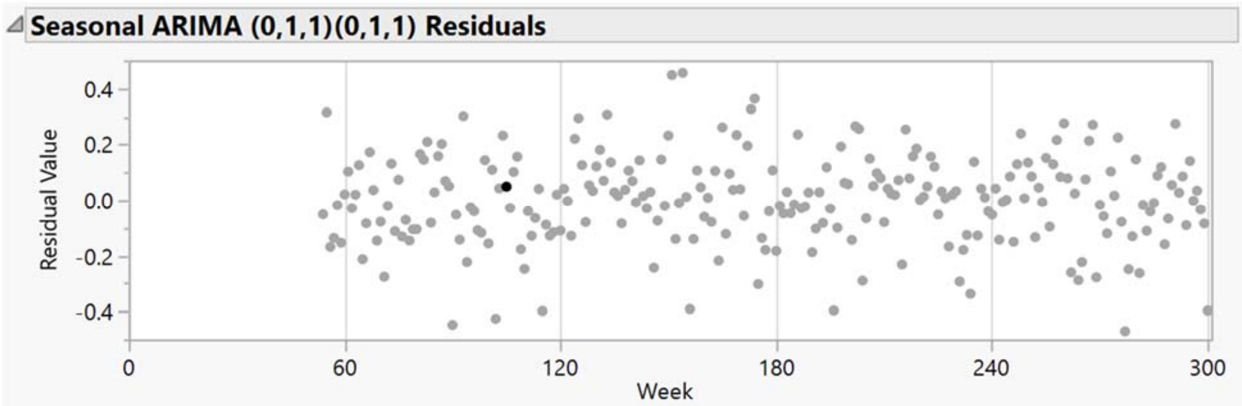

Figure 11: Weekly ARIMA(0,1,1)(0,1,1) Model Residuals

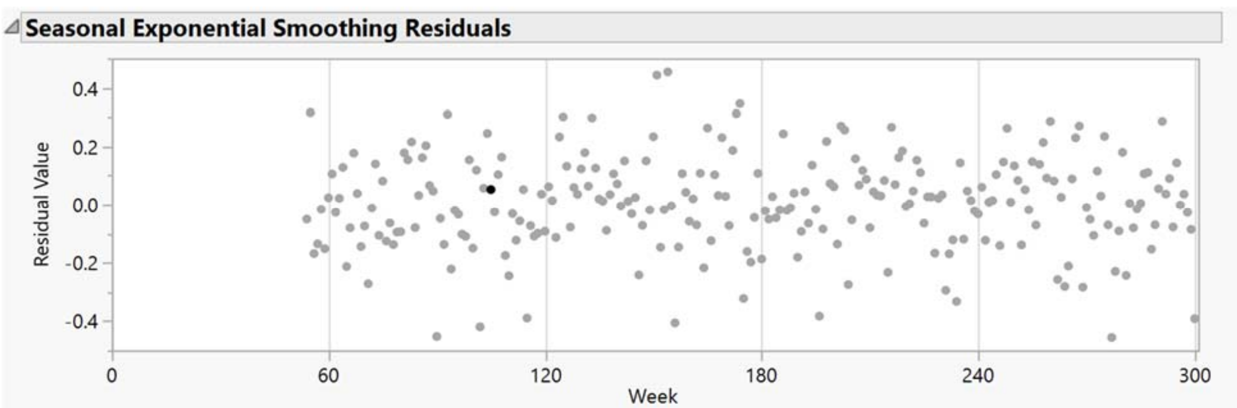

Figure 12: Weekly Seasonal Exponential Smoothing Model Residuals

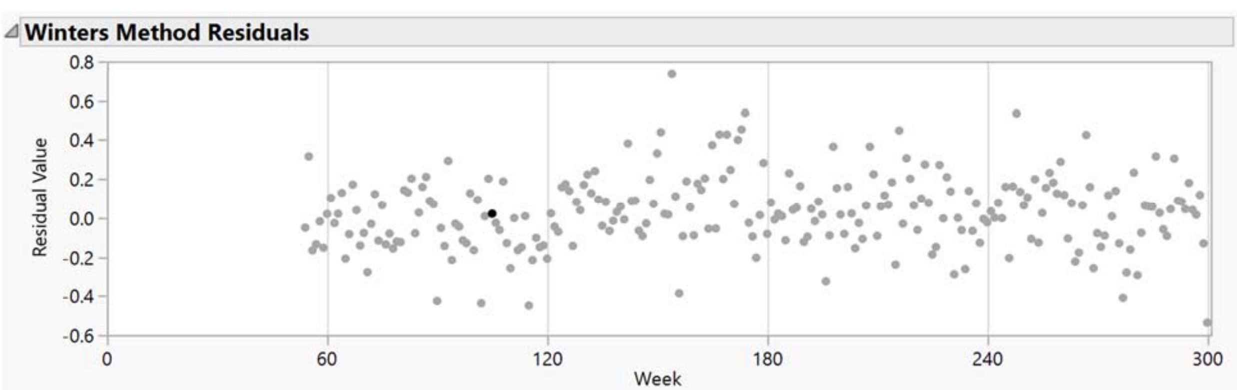

Figure 13: Weekly Winters Method Model Residuals

Finally, the forecast values were compared to the actual amount of cargo moved, as seen in Table 10. Although it is difficult to determine the actual performance from the amounts moved alone, it is clear that the models all performed relatively similar. In most instances, the models appear to forecast slightly higher amounts than the actual amounts moved.

Table 10: Actual Cargo Weight Compared to Model Forecasts

Week	Actual	Regression	ARIMA	Winters	Seasonal
1	380,066	437,630	410,715	415,488	406,694
2	373,463	456,754	434,665	482,775	432,982
3	420,733	467,820	443,972	478,983	440,031
4	351,041	476,205	447,251	413,303	439,936
5	424,891	452,507	425,196	443,989	419,072
6	318,853	427,165	409,856	412,989	407,331
7	573,176	442,141	432,901	489,392	430,987
8	383,215	374,832	347,207	330,537	334,642
9	396,786	472,694	451,600	503,510	443,512
10	351,822	455,444	445,893	532,994	440,601
11	248,911	526,101	505,870	555,792	491,311
12	176,830	352,894	342,813	434,703	333,211
13	818,560	320,411	301,397	337,281	290,392
14	253,680	512,245	466,873	407,816	442,444
15	459,143	450,634	425,172	451,735	410,290
16	383,564	424,491	387,474	326,803	367,428
17	300,362	486,304	444,364	386,686	423,720
18	372,305	449,534	421,405	451,772	407,965
19	377,741	410,918	387,096	461,814	374,689
20	381,183	417,063	402,448	507,029	392,086
21	442,945	473,265	439,773	374,194	417,576
22	438,574	439,145	414,451	421,302	397,023
23	494,179	456,102	430,286	423,753	411,209
24	476,484	429,944	400,828	375,528	380,455
25	393,860	415,386	397,480	436,623	381,688
26	371,223	442,534	419,276	434,044	399,132
27	364,111	409,447	398,664	482,259	382,700
28	401,858	437,938	417,853	408,627	394,019
29	449,148	466,550	428,428	311,602	396,309
30	386,673	485,161	456,686	381,154	429,394
31	404,537	538,208	497,006	446,564	465,073
32	529,551	615,356	584,151	640,107	555,001
33	567,155	655,922	607,967	495,297	570,000
34	603,697	658,288	624,463	601,548	593,395
35	582,678	702,825	650,242	583,617	610,865
36	658,208	842,569	781,669	734,176	738,973
37	626,040	858,256	805,541	771,904	767,700
38	738,900	829,908	776,027	799,754	739,842
39	679,552	818,231	793,715	840,627	768,404

Table 10 Cont. Actual Cargo Weight Compared to Model Forecasts

Week	Actual	Regression	ARIMA	Winters	Seasonal
40	638,519	776,619	720,793	624,790	681,657
41	695,390	786,600	748,849	689,024	717,977
42	606,693	829,959	803,242	805,593	773,416
43	636,837	682,259	665,254	787,530	639,455
44	552,924	675,321	644,017	644,193	608,989
45	644,549	601,273	580,750	607,481	551,295
46	502,961	578,622	541,804	499,540	506,243
47	500,016	596,466	577,599	629,039	548,829
48	592,655	483,374	464,767	458,739	438,149
49	480,833	497,502	480,247	486,707	452,600
50	436,296	476,609	454,621	438,800	425,233
51	467,075	477,217	458,621	425,373	430,405
52	145,115	378,639	351,034	256,872	324,668

As both the quarterly and monthly results showed, the MAE and MAPE make it easier to compare how the models performed against each other. Table 11 provides a summary of the MAPE and MAE from each of the models. In the weekly model, the Winters Method Model did not perform as well as it did during the quarterly and monthly comparisons. Additionally, the overall percent error is higher for each of the models than during the quarterly and monthly comparisons.

Table 11: Goodness of Fit for Actual Compared to Model Forecasts

	Regression	ARIMA	Winters Method	Seasonal
MAE	93,858	73,625	85,491	64,288
MAPE	30%	24%	28%	22%

V. Conclusion

Chapter Overview

This section will discuss the overall findings of the research and briefly discuss the models over each period of time. Additionally, it will provide recommendations for this research. Finally, this section will discuss ideas for further research and for future projects.

Conclusions from Research

Overall, each of the four models that was applied to quarterly, monthly, and weekly data sets provided reasonable models to address the problem identified for this research. The models all provided viable forecasts for the amount of cargo moved and performed well when actual data was compared against each model. As discussed in the previous sections of this paper, the models performed well when compared to goodness of fit measures. The quarterly models performed the best overall, as the data was the most aggregated. However, the monthly and weekly models still had strong forecasts and performed well compared to the actual amount of cargo moved. Additionally, performance against the actual data should be considered as a factor for choosing a model. Although some performed slightly worse against the actual data, none should be eliminated as potential options for developing forecasts.

The quarterly models' goodness of fit measures all indicate that the models should appropriately represent the data. The MAE and MAPE were slightly better than those produced by the monthly and weekly models, which is expected as the data is more aggregated. Additionally, other indicators for the models showed that each model can be used to forecast. Although the regression model performed slightly better than the other models, all four models are reasonable for the data. As anticipated, the forecast compared to the actual cargo moved demonstrated some models performed better over that specific time period. For the quarterly models specifically, the Winter Method Model and the Seasonal model both performed well. Based on the findings for the quarterly models, all four are appropriate options to develop a forecast for future sustainment cargo.

Similarly, the monthly models maintained positive goodness of fit measures. The regression model had the strongest MAPE and MAE, however the other three models also performed relatively well. Unlike the quarterly models, the Winters Method and Seasonal Exponential Smoothing models did not perform significantly better when applied to actual data. They still maintained slightly better MAE and MAPE, however it remained closer to the other models than during the quarterly models. Again, all four models provide appropriate representation of the data and can provide useable forecasts for future periods.

Compared to the quarterly and monthly models, the weekly models provide slightly less confidence in the forecast. The goodness of fit measures for the Regression model are strongest, followed closely by ARIMA and exponential smoothing. The Winters Method model produced slightly worse MAPE and MAE, both in model analysis and when compared to actual data. Despite slightly worse performance metrics, the weekly models' forecasts still performed reasonably well when compared to actual data. All four MAPES were at below 30% and only two are above 25%. In summary, the weekly models performed slightly worse, but could still be used to produce future forecasts.

Recommendations

After reviewing each of the models, the research supports the use of any model to predict future cargo movement. As discussed in the previous section, quarterly models, performed best, followed by monthly and then weekly models. Although this could be taken as indication to use quarterly models to forecast data, this researcher recommends using one of the monthly models to produce future forecasts. Two reasons to implement monthly models are higher fidelity of data over the time period and strong forecasts.

The first reason to use a monthly model is the data is that the forecast is more useful in smaller periods of time when implemented outside an academic scenario. The ability to forecast over a smaller period of time will help create forecasts that perform well, but break the data into periods of time that are actionable for cargo movement. While a weekly model would be most useful to planners, a monthly model will perform significantly better and should provide a more accurate forecast of the total amount of cargo needed to move when forecasting aircraft.

A second reason to use a monthly model is that the overall performance of the model performed well, even compared to quarterly models. Although the quarterly models were slightly better statistically, the difference was minimal. Using a monthly model gives the ability to adjust to more aircraft in some months and less in others, rather than a smooth flow across a quarter. Again, although a weekly model could be used, the performance was worse and the monthly model provides higher confidence in the accuracy of the overall forecast.

Areas for Further Research

Based on the research done for this paper, there are a few potential areas for further research. One potential area of research is to examine the total amount of sustainment cargo moved world-wide. This paper was scoped to only focus on the sustainment cargo moving to/from and within the Pacific Theater. However, future research could examine the total amount of sustainment cargo moved.

A second potential area of future research is to examine the total amount of cargo moved within the Pacific Theater. Sustainment cargo is only a portion of the total cargo moved within the theater and it is possible that other trends would be identified if a holistic approach is taken. This approach would be difficult due to the data being less seasonal. However, it is possible that this focus would produce a better model when all of the cargo is aggregated rather than specifying sustainment cargo. Any research done towards this topic would also need to examine the specific cargo moved as a result of limitations on the types of cargo commercial carriers can move.

Finally, future research could focus on the specific routing of the cargo. While the current research determined the total amount of cargo moved within the theater, it did not address specific locations for embarkation and debarkation nor en route stops. Breaking up the total amount of cargo moved by location could help shape the amount of commercial aircraft required for the movement, rather than just understanding the total amount of workload.

In conclusion, forecasting commercial airlift requirements to move military cargo is a complex and fluid problem. Developing forecast models helps determine the total amount of workload. However there are still numerous aspects of the overall problem that can be addressed to further TRANSCOM's ability to accurately forecast and purchase commercial airlift in the future.

Appendix A

AIR-COMMODITY Data Values

AR_CMDTY_CD	AR_CMDTY_TX
2	Arms/Weapons (All types, including inert component parts).
3	Ammunition, (all types) including inert component parts. When the primary hazard of an ammunition item is a chemical (irritant, corrosive, or oxidizer), as indicated by its proper shipping name use commodity Code C.
4	Explosives (any explosive item not included in Code 3 above) including inert component parts.
5	Nuclear Weapons Related Material (NWRM): Classified or unclassified assemblies and subassemblies (containing no fissionable or fusionable material (identified by the Military Departments (MILDEPS) that comprise or could comprise a standardized war reserve nuclear weapon (including equivalent training devices) as it would exist once separated/removed from its intended delivery vehicle. A delivery vehicle is the portion of a weapon system and delivers a nuclear weapon to its target. This includes cruise and ballistic missile airframes as well as delivery aircraft.
A	Supplies and equipment for aircraft and aerial targets including aircraft and maintenance parts, aircraft accessories, aircraft instruments, and laboratory test equipment, aerial targets and gliders, aircraft/missile technical order compliance kits, etc.
B	Construction Materials including Paint and Related Materials, Prefabricated Buildings, Wood Products, Metal and Composition Materials and Their Products, Commercial, Hardware and Miscellaneous Items, Cement, Asphalt, Building Maintenance Materials.
C	Chemical corps items and all other chemicals not covered in other classifications. Note: When an item has a chemical proper shipping name and the item is sensitive, select the special handling code from this Appendix.
D	Animals.
E	Engineer supplies, other than those listed under Code B.
F	Fuels and Lubricants including Fuel and Lubricating Supplies and Equipment, and Gases, Other Than Noxious Gases.
G	Printed Forms, Publications, Drawings, Training Guides, etc.
H	Instruments/Equipment/Supplies for Radio, Communications, Electrical, Laboratory, etc. (Includes Signal Corps)
J	Unaccompanied Baggage (ITGBL/DPM Personal Property Shipments)
K	Clothing including Clothing Equipment (Other Than Arms and Chemical Supplies), Cordage, Fabrics and Leather, Parachutes, etc.
L	Defense Courier Service Material including Communication Documents, State Department Diplomatic Material, and Cryptologic Equipment. (This code can only be used by DCS.)
M	Medical Supplies, Equipment, Samples, Records, etc.
N	Ship's Parts
O	Not to be used
P	Photographic Supplies and Equipment including Training Films.
Q	Plants, Plant Products, Insects, Mites, Nematodes, Mollusks, Soil, Meat (Other Than Rations), Animal Products or Parts, Vectors and Cultures of Animal and Plant Diseases.
R	Rations and Subsistence Supplies.
S	Office and School Supplies and Equipment including Office Machines, Furniture and Stationary.
T	**Household Goods (ITGBL/DPM Personal Property Shipments)**
U	Mail, Select a Special Handling Code from Appendix AA.
V	Trailers, Vehicles, Machinery, Shop and Warehouse Equipment and Supplies including Special Tools and Equipment, Ground Servicing and Special Purpose Vehicles, Trailers, Marine Equipment and Supplies, Repair and Maintenance Parts for the above.
W	Any material not otherwise specified that may require special handling with special instructions identified in the DI T_9 trailer data. Primarily used with channel airlift 463-L pallets.
X	Intelligence materials including maps, charts data, and information vital to military functions such as flight safety, escape and evasion, current offensive/defensive operations, foreign clearance requirements, targeting and National Aeronautics Space Administration Projects.
Y	Personnel Services. Military service records, files, or other information subject to the Privacy Act of 1974.
Z	Human Remains.

There are 29 valid records available for display.

TRDM is managed and maintained by USTC J6 (E-Mail: TRDM)

This web page was created on 02-06-2018 22:14:33

Appendix B

Channel Missions: Forecasting Sustainment Cargo Requirements

Maj Katherine Hemken
Advisor: Dr. Daniel Steeneck, PhD
Advanced Study of Air Mobility (ENS)
Air Force Institute of Technology

Introduction

The DoD augments the military airlift fleet by contracting commercial airlift to help meet the demand to move sustainment cargo. There is currently high emphasis to move cargo by commercial means first, when possible. Unfortunately, the scope of cargo moved and the complexity of operations lead to some inaccurate and inefficient use of the commercial capability.

Research Goals

The purpose of this research is to develop forecasts for sustainment cargo in the Pacific Region. The overall goal is to compare several different models over different periods of time to determine the best model.

Analysis, Conclusions, and Recommendations

Model Performance When Compare to Actual Cargo Moved

	Regression	ARIMA	Winters Method	Seasonal
MAE (qtr)	1,089,267	819,825	424,907	484,745
MAPE (qtr)	19%	14%	8%	9%
MAE (mon)	361,139	292,464	203,826	203,491
MAPE (mon)	23%	19%	15%	15%
MAE (week)	93,858	73,625	85,491	64,288
MAPE (week)	30%	24%	28%	22%

Key Findings:

1. Sustainment cargo moving to, from, and within the Pacific Theater is seasonal and does not have significant trend over time.
2. All four models developed performed well and are reasonable models to forecast future sustainment cargo movement to and in the Pacific Theater. This held true when applied to quarterly, monthly, and weekly data.
3. The monthly models provide the best balance between model goodness of fit measures and operational utility.

Significance

This research addresses the continued challenge of forecasting airlift requirements. The models examined in the research can help shape the commercial airlift purchased for sustainment cargo in the Pacific Region.

Methodology

Historical GATES data was used to develop four models to forecast future workload. The GATES data was limited to commodity codes J, R, T, and U. It was also limited to cargo that moved on channel missions in the Pacific Theater.. Regression, Seasonal Exponential Smoothing, ARIMA, and Winters Method Models were developed to examine consolidated quarterly, monthly, and weekly amounts of cargo moved. Goodness of Fit measures and the residuals for each model were used to determine the best models for the data available. Finally, the models were compared against actual data.

Future Research

This research focused specifically on sustainment cargo and only examined cargo movement within one theater. Additional research should focus on additional types of cargo moving to and within the Pacific Theater. Additionally, future research should examine cargo moved in other theaters to determine the full requirement for sustainment cargo movement.

AIR FORCE INSTITUTE of TECHNOLOGY

Bibliography

Air Mobility Command. *MAF Mission ID Encode/Decode Procedures*. Scott AFB, IL: AMC, 2018.

Bisgaard, Soren and Kulahci, Murat. "Quality Quandaries: Forecasting With Seasonal Time Series Models," *Quality Engineering*, 20: 250-260 (2008).

Bowerman, Bruce L., Koehler, Anne B., and Pack, David J. "Forecasting Time Series with Increasing Seasonal Variation," *Journal of Forecasting*, 9: 419-436 (1990).

Bowerman, Bruce L., O'Connell, Richard T., and Koehler, Anne B. *Forecasting, Time Series, and Regression: An Applied Approach* (4th edition). United States: Brooks/Cole, 2005.

Box, George E., Jenkins, Gwilym M., Reinsel, Gregory C., and Ljung, Greta M. *Time Series Analysis: Forecasting and Control* (5th edition). Hoboken, NJ: Wiley, 2016.

Clark, Peter. "Memorandum for CRAF EWG Members" Scott AFB, IL: TCJ4/J4, 2018.

Crackel, Theodore J. *A History of the Civil Reserve Air Fleet*. Washington: Air Force History & Museums Program, 1998.

DeYoung, Daniel S. *Time Series Forecasting of Airlift Sustainment Cargo Demand*. Air Force Institute of Technology, Department of Operational Sciences. Wright-Patterson AFB, OH: Air University, 2012.

GAO Report. *Defense Logistics: DOD Needs to Improve Budget Estimates and Accuracy of Forecasts for Airlift Services*. GAO-18-557. Washington: GAO, 2018.

GAO Report. *Military Readiness: Civil Reserve Air Fleet Can Respond as Planned, but Incentives May Need Revamping*. GAO-03-278. Washington: GAO, 2003.

Final Report. *Air Cargo Mode Choice and Demand Study*. California Department of Transportation, 2010.

Fischer, John W. and Golich, Vicki L. "Forecasting Civil Aviation Activity: Methods and Approaches," Transportation Research Circular, 25-35 (1991).

Florida Air Cargo System Plan. "Chapter 6 Air Cargo Tonnage: Forecast and Capacity Analysis," https://www.florida-aviation-database.com. Accessed 28 February 2019.

"JMP About Us," https://www.jmp.com/en_dk/about.html. Accessed 28 February 2019.

JMP 12.0.1 Help. *Specialized Models: Time Series Analysis ARIMA Model*. Accessed 2019.

JMP 12.0.1 Help. *Specialized Models: Time Series Analysis Modeling Report*s. Accessed 2019.

JMP 12.0.1 Help. *Specialized Models: Time Series Analysis Smoothing Models*. Accessed 2019.

Joint Chiefs of Staff. *Air Mobility Operations*. JP 3-17. Washington: JCS, 5 February 2019.

Knight, William & Bolkcom, Christopher. *Civil Reserve Air Fleet (CRAF)*. CRS Report; RL33692. Washington: Congressional Research Service, 2008.

Leonard, Taylor J. *Operational Planning of Channel Airlift Missions Using Forecasted Demand*. Air Force Institute of Technology, Department of Operational Sciences. Wright-Patterson AFB, OH: Air University, 2013.

Montgomery, Douglas C., Jennings, Cheryl L. and Kulachi, Murat. *Introduction to Time Series Analysis and Forecasting*. Hoboken NJ: John Wiley & Sons, 2008.

Nau, Robert. "Linear Regression Models," https://people.duke.edu/~rnau/compare.htm. Accessed 29 March 2019.

Transportation Research E-Circular. *Aviation Demand Forecasting: A Survey of Methodologies*. Number E-C040. Washington: National Research Council, 2002.

United States Transportation Command. "Air Commodity," https://www.ustranscom.mil/cmd/associated/dteb/files/refdata/V_Air_Cmdty.htm Accessed 2019.

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
14-06-2019

2. REPORT TYPE
Graduate Research Paper

3. DATES COVERED *(From - To)*
May 2018 - Jun 2019

4. TITLE AND SUBTITLE
Channel Missions: Forecasting Sustainment Cargo Requirements

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Hemken, Katherine B., Major

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Air Force Institute of Technology
Graduate School of Engineering and Management
(AFIT/EN)
2950 Hobson Way
WPAFB, OH 45433-7765

8. PERFORMING ORGANIZATION REPORT NUMBER
AFIT-ENS-MS-19-MS-J-035

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Intentionally Left Blank

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT
DISTRIBUTION STATEMENT A. Approved for Public Release; Distribution Unlimited

13. SUPPLEMENTARY NOTES
This work is declared a work of the U.S. Government and is not subject to copyright protection in the United States

14. ABSTRACT
The Department of Defense (DoD) relies on commercial air carriers as members of the Civil Reserve Air Fleet and to move cargo during peacetime operations. This research focuses on examining potential forecasting models for sustainment cargo in the Pacific area of responsibility. All four models provide viable weekly, monthly, and quarterly forecasts for the GATES cargo examined. The models developed include regression, ARIMA, Seasonal Exponential Smoothing, and Winters Method models. The models were compared based on goodness of fit measures. Then models were applied to a set of data that was withheld to determine how each performed compared to actual data. The models all provide reasonable forecasts. Overall, the monthly models are the best option because they provide relatively accurate forecasts and flexibility when applied.

15. SUBJECT TERMS
Models, forecasts

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
					Dr. Daniel Steeneck
a. REPORT	b. ABSTRACT	c. THIS PAGE	UU	54	19b. TELEPHONE NUMBER *(include area code)*
U	U	U			937-255-3636 ext 4702