Demand Forecasting for Food-Rations at the United Nations Darfur Mission

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SUBMITTED TO THE PROGRAM IN SUPPLY CHAIN MANAGEMENT
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF APPLIED SCIENCE IN SUPPLY CHAIN MANAGEMENT

AT THE
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2021

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ABSTRACT

Demand planning is a challenging component for organizations across a broad spectrum of industries. A key element of a successful demand plan is accurate forecasting, due in part to the operational decisions that are made based on the results of forecasting models. This is what our capstone project sponsor, Agility, has come to realize during their time-sensitive operations. Agility supplies food rations to the United Nations (UN) peacekeeping missions around the world. One particular mission, the mission in Darfur, or "UNAMID", has a unique problem related to inaccurate forecasting. UNAMID places orders for food rations approximately 80 days in advance of when they are needed, but the lead time for Agility to source and deliver these items often exceeds 150 days. Therefore, forecasting is required to ensure that food rations can be procured and delivered on time. Currently, Agility uses a simple three-period moving average forecasting method, also known as MA(3). Due to frequent errors in the order quantity forecasted using this method, Agility often incurs stiff penalties from the UN for delivering too little or too much food. This study explores how sophisticated forecasting techniques can be applied to reduce penalty costs. First, we segmented the historical order quantity data to isolate the most important SKUs. Second, we tested various forecasting methods against the currently used MA(3) to determine if a more sophisticated model would produce better results. Third, we applied the Holt-Winters Forecasting model and optimized the parameters using non-linear optimization to maximize statistical accuracy. Fourth, we added penalty costs to the model and re-optimized the parameters to minimize the projected penalty cost. Fifth, we provided a set of strategic recommendations for how Agility can use the results of this study to realize these cost savings. We found that by using our optimized Holt-Winters forecasting model, Agility could likely save at least $25,000 per year in penalty costs at UNAMID. An additional study is recommended to explore how this model can be applied to further increase cost savings at other UN peacekeeping missions.

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ACKNOWLEDGMENTS

We would like to thank several individuals that have been instrumental in this project. First, we give thanks our advisors, Chelsey Graham and Jarrod Goentzel, for providing guidance and support throughout the year. We also would like to thank members of the MIT Supply Chain Management program, notably Dr. Josué C. Velázquez Martínez for his mentorship and leadership, Dr. Chris Caplice for his forecasting expertise and for teaching us the technical skills required for this project.

Additionally, we would like to thank our sponsor company especially, Jeroen Van Heeswijk, for his guidance and feedback throughout this project.

- Landon & Shawn

I would like to thank my capstone partner Shawn for his hard work and dedication to this project throughout the year. I would also like to thank my father, who's motivation and encouragement kept me going even through the most stressful times of the SCM program. Finally, I would like to thank the rest of my SCMr cohort for their companionship throughout the program which has produced friendships I am sure will last a lifetime.

- Landon

I would like to express my gratitude to my capstone partner Landon for being a great partner going through this journey. I would like to thank my mother and my wife for the support during this challenging COVID pandemic. I would also like to express my gratitude to a life-long mentor and friend, Brian Jacobs, who enlightened and motivated me to pursue a life-changing experience at MIT. Finally, thank you for the SCM cohort for their companionship and lifetime friendship.

- Shawn

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1 Introduction

1.1 Problem Motivation

Since 2003, the region of Darfur, located in western Sudan, has been embroiled in civil conflict. Rebel militia groups, corrupt governments, and violence throughout the country has left tens of thousands of people dead and displaced nearly two million (Daly, 2007). The United Nations (UN) Peacekeeping Operations Force has stepped in to reduce atrocities during the fighting between the Sudanese government and regional rebel groups. To sustain protection of civilians and humanitarian personnel, the project sponsoring company, Agility, provides daily food rations to peacekeeping troops of UN member countries. These troops are stationed at over 90 contingents on a daily basis across various geographic locations in Darfur.

To support these troops and the efforts of the UN in maintaining peace in Darfur, Agility has been contracted to provide food to all the troops stationed in the various contingents. Accurate demand planning and agile supply chains for these food items are critical to the success of the UNAMID. One of the main challenges facing the Agility Supply Chain Operation is to accurately predict the demand for the food they supply to meet dynamic service and compliance requirements in a hostile and unforgiving environment.

1.2 Problem Statement

Agility provides an end-to-end service for UNAMID consisting of procurement, logistics, warehousing, and delivery of food rations. The UN currently places bulk food orders for UNAMID 84 days in advance, and final food orders 21 days in advance. However, the Agility Supply Chain Network has a lead time of over 150 days, which means Agility must predict and order food products almost 70 days in advance of when bulk food orders are placed by the UN.

The gap between the long lead times and when the order is placed creates a considerable amount of uncertainty, and thus requires an accurate forecasting model for Agility to serve its customer, reduce waste, and remain profitable. Currently, demand plans are created in Excel, and are based on numerous internal data sources from several proprietary systems and historical mission data. Agility has asked our team to design a model that more accurately predicts demand from the UN, and thus improves the efficiency and performance of Agility's food sourcing and delivery business.

The goal of this capstone project is to improve demand forecasting accuracy and reduce costs associated with poor forecasts by applying more sophisticated forecasting models than are currently being used.

1.3 Hypothesis

After initial review of the information and data provided by Agility, we hypothesize that demand planning at Agility can be improved through more sophisticated forecasting methods.

A more accurate forecasting model will allow Agility to better predict bulk food orders from the UN, and save money by reducing penalties attributed to forecasting related-errors.

Currently, Agility uses a basic Excel model to forecast demand. We will describe the issues with this model in more detail in the Data and Methodology section of this paper. Agility uses a simple forecasting approach to forecast demand which leads to forecast inaccuracies. Based on the contract terms, Agility incurs stiff penalties if they deliver less than 100% of the UN's bulk food order, and the UN will only purchase additional products up to 102% of their bulk food order, which means any extra product delivery beyond 102% is a loss for Agility. In reality, Agility would not deliver more than the final order, but might end up with more on hand which is accounted for in holding costs and spoilage costs. Our hypothesis is that a more accurate forecasting model will improve Agility's ability to order within this 100-102% range more frequently.

2 Literature Review

This project looks at how different forecasting techniques can be applied to better predict demand for food rations for UNAMID. This section presents our findings of literature related to the project. The review begins by discussing the concept of time series analysis and forecasting methods for demand planning. In addition, an overview of logistics and delivery in developing countries is discussed. Finally, we discuss previous research related to this topic, specifically methodologies and results achieved related to forecasting food demand.

2.1 Time Series Analysis for Demand Forecasting

Forecasting can broadly be split up into two main categories: quantitative and qualitative forecasting. Quantitative forecasting is the more widely known domain of forecasting and aims to use historical data, time-series data, or correlation information to make predictions about what will happen in the future. Qualitative forecasting, in contrast, places more weight on factors such as expert opinions, customer insights, or surveys to make predictions about the future. Our analysis will focus on quantitative forecasting, but we present an introduction to both quantitative and qualitative as our model may need to take qualitative data into consideration.

Qualitative forecasting (sometimes referred to as judgmental forecasting) is a very broad domain, but for our purposes we will briefly explain four main components associated with this practice: Expert opinion, the Delphi method, sales-force estimates, and consumer surveys (Chambers, 1971). Expert opinion refers to making a forecast based on executive judgments about the future. For example, if an executive knows that a major sponsor is going to cancel their contract with the company soon, then sales planning manually decreases their demand forecast to account for this even though the quantitative model may not be able to anticipate this change based on historical data. The second qualitative approach is the Delphi method. This is an approach that aims to forecast demand based on the opinions of a sample group of potential consumers. Next, we have estimates from the sales workforce. This is an approach that polls individual salespeople on their predictions for future demand based on their personal assessment. The final qualitative approach uses surveys to inquire customers if they would purchase a new product, or how much they would be willing to pay for a certain product and in what frequency.

In the realm of quantitative forecasting, many models and methods are used for various situations. For this project, we narrowed the scope to focus on time series forecasting, due to the type of data we have been provided, and therefore to study how it might be applied to increase forecast accuracy for Agility. Time series analysis is especially well-suited for our project given that the data provided shows order quantities over specific time intervals. Time series forecasting can generally be broken down into four main categories: Naïve approach, moving averages, exponential smoothing, and trend projections (Hyndman & Athanasopoulos, 2016). The naïve approach assumes that whatever happened most recently is going to happen again in the future. It requires very little historical data and is typically not a very accurate predictor of demand that is not "level" or steady. Moving average takes an average of a set number of periods of data and uses that as its prediction for the future. Each period, when new data becomes available, the average is updated or "moved" and the forecast for the subsequent period is updated to reflect this new average. Exponential smoothing places weights on historical data to produce forecasts for the future. This is an exceptional approach if, for example, one knows that one-year old data is much more relevant than five-year old data for a particular dataset. Exponential smoothing allows the forecaster to change the emphasis on new verses old data, whereas a non-time series approach, such as regression, places equal weight on all data. Last, trend projection takes trends in the data into consideration, such as seasonal variations, steady increases or decreases over time, or other patterns to determine a more accurate forecast for the future. Our analysis will focus mainly on combining exponential smoothing, trend, and seasonality to form an integrated forecast, as our initial investigations of the data provided to us by the sponsor have revealed such trends exist.

Within time series trend projection, we will explore a few key models in our research: single and double exponential smoothing, ARIMA, dampened trend methods, Holt-Winters method (additive and multiplicative), and machine learning forecasting techniques. We will discuss each one briefly to provide a general understanding of the models we will investigate to determine how to best forecast demand for our project. Three key terms related to forecasting that will be used in the following sections are: level, trend, and seasonality. Level is the average value in the time-series data, trend is the increasing or decreasing value in the time-series data, and seasonality is the repeating short-term cycle in the time-series data.

2.1.1 Single Exponential Smoothing

Single exponential smoothing, sometimes referred to as simple exponential smoothing, is a forecasting technique for time series data that is best used for data which has neither seasonality nor trend (Hyndman & Athanasopoulos, 2016, Chapter 7.1). In other words, this model works best at forecasting data that, while varying over time, does not have a bias towards certain periods, and does not have an overall increase or decrease over time.

2.1.2 Double Exponential Smoothing

Double exponential smoothing adds a smoothing parameter to the single model to account for a trend in the data, but not seasonality (Hyndman & Athanasopoulos, 2016, Chapter 7.2).

Double exponential smoothing might be a good choice for data that increases or decreases over time, but does not have any seasonal variations.

2.1.3 ARIMA Forecasting Models

ARIMA models, which stands for auto-regressive integrated moving average, expand on the exponential smoothing models and explain the autocorrelations or relationships between variables in the data (Hyndman & Athanasopoulos, Chapter 8, 2016). ARIMA models forecast in such a way that accounts for multiplicative changes over time in level, trend, seasonality, or any combination of the three. For Agility, it would be a relatively complex method requiring expertise in implementation and operation in comparison to other forecasting techniques.

2.1.4 Holt-Winters Method – Additive

The Holt-Winters model, also sometimes referred to as Triple Exponential Smoothing, takes into consideration seasonality, trend, and level when forecasting future data (Hyndman & Athanasopoulos, 2016, Chapter 7.3). The additive model adds together the level, trend, and seasonality factors – which allows for gradual updating of the parameters when any of the three factors change slowly in a given set of data. It sets a smoothing parameter for each of these three parameters and is best used for data that contains seasonality and trend. The additive variation of the Holt-Winters model is better used when seasonality is constant throughout the data. For example, if sales for ice cream tend to spike the same amount in the summer every year, and there is an increase in sales year-over-year, then the additive model might be a good choice.

2.1.5 Holt-Winters Method – Multiplicative

The multiplicative variation of the Holt-Winters model aims to forecast data that has varying seasonality over time (Hyndman & Athanasopoulos, ‘16, Chapter 7.3). For example, if each year sales in ice cream spike 10% more than they did the summer before, the multiplicative variation might be a good choice. This model still takes into consideration level and trend when calculating the forecasts by using the same three smoothing parameters as in the additive model. It differs from the additive model, however, in that the seasonality factor is a multiple of the level and trend parameters. This allows the model to respond quicker to changes in seasonality, which may be desirable in situations where seasonal spikes are sudden and severe.

2.2 Machine Learning Forecasting Techniques

Traditional time series and regression consider several important factors, which include trends, level, and seasonality. Another approach to forecasting is Machine Learning. Machine learning utilizes computer algorithms to determine important predicting variables from a wide range of potential factors, and is improved continuously based on cumulated data and experience (Wenzel et al., 2019). It combines learning algorithms to identify and consider unlimited demand factors to generate precise and unbiased forecasts to uncover underlying insights. Figure 1 summarizes the differences between a traditional forecasting approach and machine learning techniques (Kharfan & Chan, 2018).

	Traditional Forecasting	Machine Learning Forecasting
Number of predictor variables	Single or a few	Unlimited
Data source	Mainly demand history	Multiple
Algorithms	A number of single-dimension algorithms	An arry of integrated algorithms
Manual data manipulation and cleansing need	High	Low
Data requirements	Low	High
Technology requirements	Low	High

Figure 1. Comparison of Traditional Forecasting and Machine Learning Forecasting (Kharfan & Chan, 2018)

Machine learning is commonly divided into three groups: supervised learning, unsupervised learning, and reinforcement learning (Wenzel et al., 2019). Supervised learning algorithms study example data with target responses, then generalize rules to predict the correct responses with new datasets. Regression and classification trees are examples of supervised learning. Figure 2 shows a simple illustration of a classification tree.

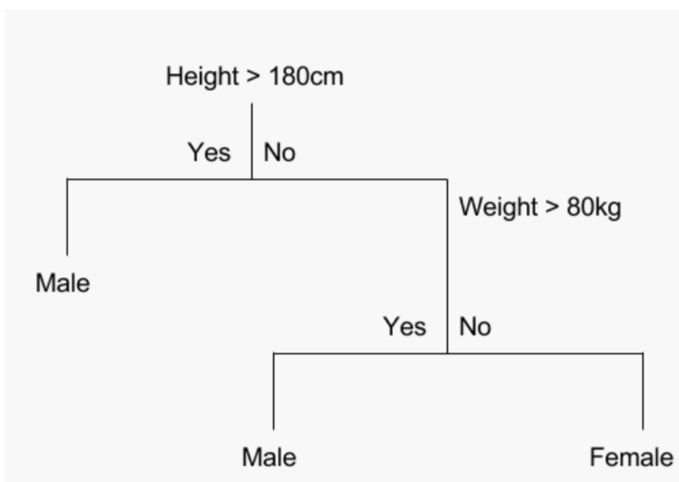


Figure 2. Illustration of Classification Trees – Height, weight example

In contrast, unsupervised learning happens when the algorithm learns from data without labels, leaving the algorithm to restructure and discover patterns on its own. This is useful to uncover insights for human understanding. Reinforcement learning is similar to unsupervised learning because the labeled data are not provided to the algorithm. However, humans can give positive and negative feedback according to the algorithm's performance and solution, and the machine in turn learns from its decisions and consequences. A study conducted by Laframboise and Vahidov (2008) compares the forecasting results between machine learning and traditional time series with monthly sales data. The findings suggest that, although some machine learning techniques show the best performance, the results were no more accurate by any statistical significance than the time series models. A study on hybrid forecasting models of ARIMA and machine learning has shown improved accuracy in demand forecasting (Aburto et al. 2007). The hybrid system outperforms pure machine learning techniques and ARIMA models, which might lead to inventory cost savings.

Three machine learning models that are commonly used to forecast time series data are Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), and Long Short-Term Memory (LSTM). MLP is a supervised learning algorithm that can learn a non-linear function approximator for either classification or regression (Shiblee, Kalra, and Chandra 2009). RNN is a machine learning algorithm commonly used for time series forecasting, which processes time series data step-by-step, maintaining an internal state from time-period to time-period. (Connor, Martin, 1994). LSTM is a machine learning algorithm that allows the network to retain long-term dependencies at a given time from many time periods before (Hochreiter, Schmidhuber, 1997).

2.3 Logistics in Developing Countries

Poor road conditions, unreliable law enforcement, and high levels of poverty are all factors that need to be considered when planning the transportation and logistics of goods in a developing country. In some countries it accounts for more than 25% of the total supply chain costs for suppliers (Khisty, 1994). Due to the UN Mission in Darfur's requirement that food rations be supplied to remote areas within the country of Sudan, we believe it is valuable to briefly cover inventory management practices related to developing countries.

Inventory management problems are fundamentally different in developing countries due to different standards of food inventory polices and a wide range of policy implementations and enforcement effectiveness (Bigman, 1986). The agricultural industry is normally the supporting pillar of the economy, and food management quality and security affect the livelihoods of local communities. Deterioration, loss, and damage lead to food waste and safety concerns. Approximately one-third of perishable products are wasted annually worldwide, and in developing countries, most food is lost at an early stage of the supply chain; much less food is wasted at the customer level (Gustavsson et al., 2011). To maintain the quality and safety of perishable items, supply chain plays an important role by creating controlled environments for optimal temperature, humidity, and other conditions (Taoukis et al., 2016).

2.4 Previous Forecasting Research

Forecasting has progressively become more sophisticated in the private sector thanks to improvements in software and ever-growing expectations of customers on product availability, varieties, and features. Increasing pressure is placed on forecasting to match supply and demand in an effort to maintain cost competitiveness (Boone et al., 2019). Humanitarian operations face more complex situations, such as response to armed conflicts, natural disasters, and uncertainties in the timing and locations of these situations. In the commercial sector, demand planning errors cost companies monetary damages in lost sales or obsolete inventory. On the other hand, forecasting errors could cause human suffering or loss of lives, making it of critical importance in the humanitarian sector (Altay et al., 2020). The most challenging problem encountered in demand planning is the uncertainty faced in an unforgiving environment, such as UNAMID’s operation (Syntetos et al., 2016). Building more safety stock inventory or capacity are practical approaches to respond to demand volatility (Meindl et al., 2001). To construct comprehensive forecasting solutions, quantitative forecasting methods will be explored; including ARIMA, Holt-Winter Models, and regression.

Put simply, demand planning is the process of generating demand forecasts (Pentz, 2019). Demand planning produces a demand plan which should specify which product quantities are required and when these products will be needed at a specific location. Demand planning is typically the first step in developing operational plans, where human knowledge and experience plays a crucial role in supply chain management. This process normally includes subjective and objective (i.e., quantitative and qualitative) forecasting methods, and Figure 3 summarizes these various forecasting methods (Caplice, 2020 a). Subjective forecasting methods are adopted when historical data is limited, and this type of forecasting is based on opinions of field experts or sample market testing. Agility has seven years of food demand data; therefore, subjective forecasting methods are not relevant for this project. In contrast to subjective approaches, objective methods such as time series analysis have shown to be more accurate in demand planning. Demand planning leverages internal and external information to generate forecasts, which is used by the organization to coordinate material sourcing, product manufacturing, and customer delivery (Zhou 2011).

Subjective	Objective
Judgmental	**Causal/ Relational**
- Sales force surveys	- Econometric Models
- Jury of experts	- Leading indicators
- Delphi techniques	- Input-Output Models
Experimental	**Time Series**
- Customer surveys	- "Black Box" Approach
- Focus group sessions	- Past predicts the future
- Test marketing	- Identify patterns

Figure 3. Summary of forecasting methods and examples (Caplice, 2020 a)

Demand planners are responsible for the forecast accuracy, which is affected by their experience, knowledge, expertise, and accessibility to information across the whole organization as well as among colleagues and external sources (Jonsson et al., 2007). Even for objective approaches, the forecasting accuracy still relies on a demand planner's expertise and well-structured accessible data within the supply chain functions. In turn, the quality of forecasting could affect the entire supply chain. The downstream supply chain departments are impacted to a more significant degree, including inventory management, product manufacturing, and finally, the customer. Demand planning technologies have become more complex to include better overall information integration and interpersonal communications. Research shows that internal information sharing and customer collaboration have a significant impact in demand planning accuracy, and there is a positive correlation between strong relationship ties and forecasting accuracy (Kaipia et al., 2017). However, subjective forecasting methods bear intrinsic pitfalls: human decision-making structures influence forecast results due to incomprehensive business understanding, lack of information and judgement, and biased perspectives (Moritz et al., 2014). Alon and Sadowski (2001) concluded that traditional methods like ARIMA and Holt-Winters model are more accurate and suitable when the data is not stochastic and when there exists trend and seasonality.

After analyzing the sponsor data, and exploring various forecasting models and techniques, we decided to use the Holt-Winters forecasting model for its applicability in Agility's daily operations, and its accuracy in predicting demand with minimal investment in software and training required. Holt-Winters is a good choice when data is not stochastic, has a trend, and seasonality. We confirmed these three conditions to be true via our initial analysis of the data provided by Agility, and through various meetings with Agility in the first months of the project. This supported our decision to use Holt-Winters as our selected forecasting model.

3 Data and Methodology

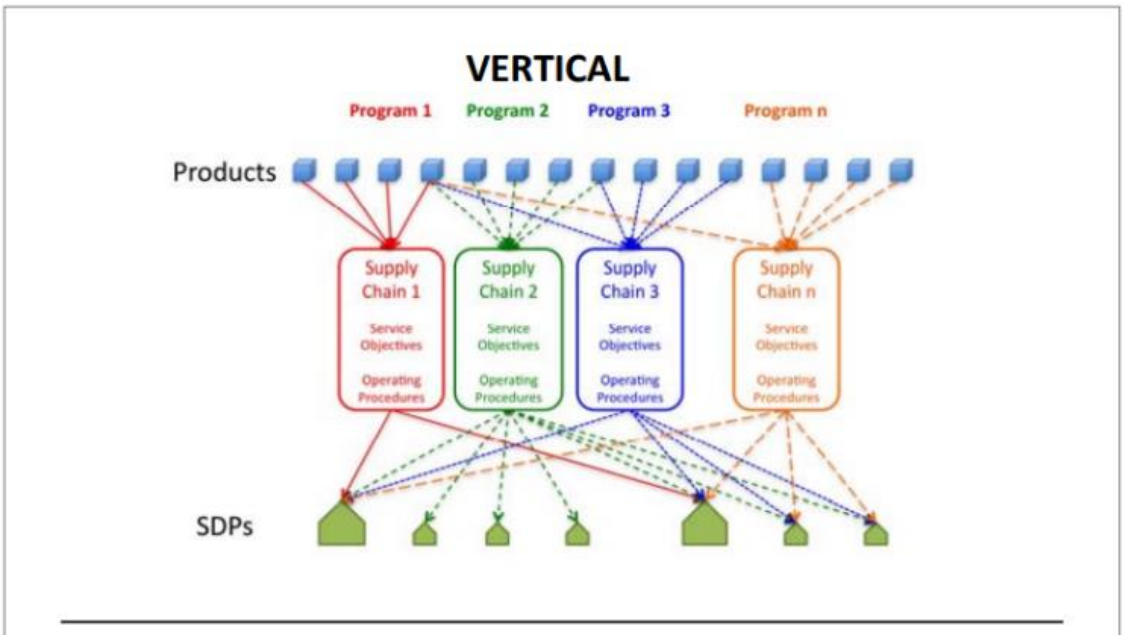
3.1 Analysis Overview

UNAMID mission carries approximately 300 products for various dietary requirements at any time throughout the year. Those dietary products have very distinct characteristics, and a complex supply chain due to certain special requirements, such as emergency stock holding, operational stock holding, and sensitivity to temperature. Another challenge posed by peacekeeping missions in hostile regions involves periodic changes in troop numbers and associated dietary restrictions, which can have implications on the design and execution of the existing supply chain network.

A one-size-fits-all forecasting approach is unsuitable to manage a distribution system for peacekeeping operations across this wide variety of products and customer requirements. Therefore, we adopt a segmentation strategy to provide a foundation for the application of demand planning and forecasting. This strategy must be generalizable and adaptable to other UN operations, as well as one that avoids excessive complexities that might hinder the effectiveness of the Agility Supply Chain Operations team.

Figure 4 illustrates the difference between a segmented supply chain system and the traditional approach of vertical and integrated strategies (Allain et al., 2010). The vertical strategy commonly involves distinctly defined service objectives and operational procedures for each individual program-based supply chain (Allain et al., 2010). Although distinct operations for all products with distinct characteristics can be beneficial to increase service levels, such tailored approaches are not always practical and are often cost prohibitive. The integrated strategy uses the one-size-fits-all approach and forces all programs to adopt the same supply chain system to minimize complexity and share resources (Allain et al., 2010). However, perishable products need to be handled in a temperature-controlled environment, unlike shelf stable items, such as rice and canned beans. If the same operating procedures were followed for all products, resources would be wasted from over-managing high volume SKUs such as rice; many products would be wasted due to expiration, temperature failures, or other inadequate special handling.

The segmented strategy combines the merits of both the vertical and integrated strategies by satisfying distinct service requirements and operating procedures, while still managing to reduce complexity and redundancies and improve utilization of shared resources (Allain et al., 2010). A clearly articulated strategy can quickly incorporate new products or programs into the segmented forecasting models, which reduces the need for newly designed forecasts for each new product/product line (Allain et al., 2010).



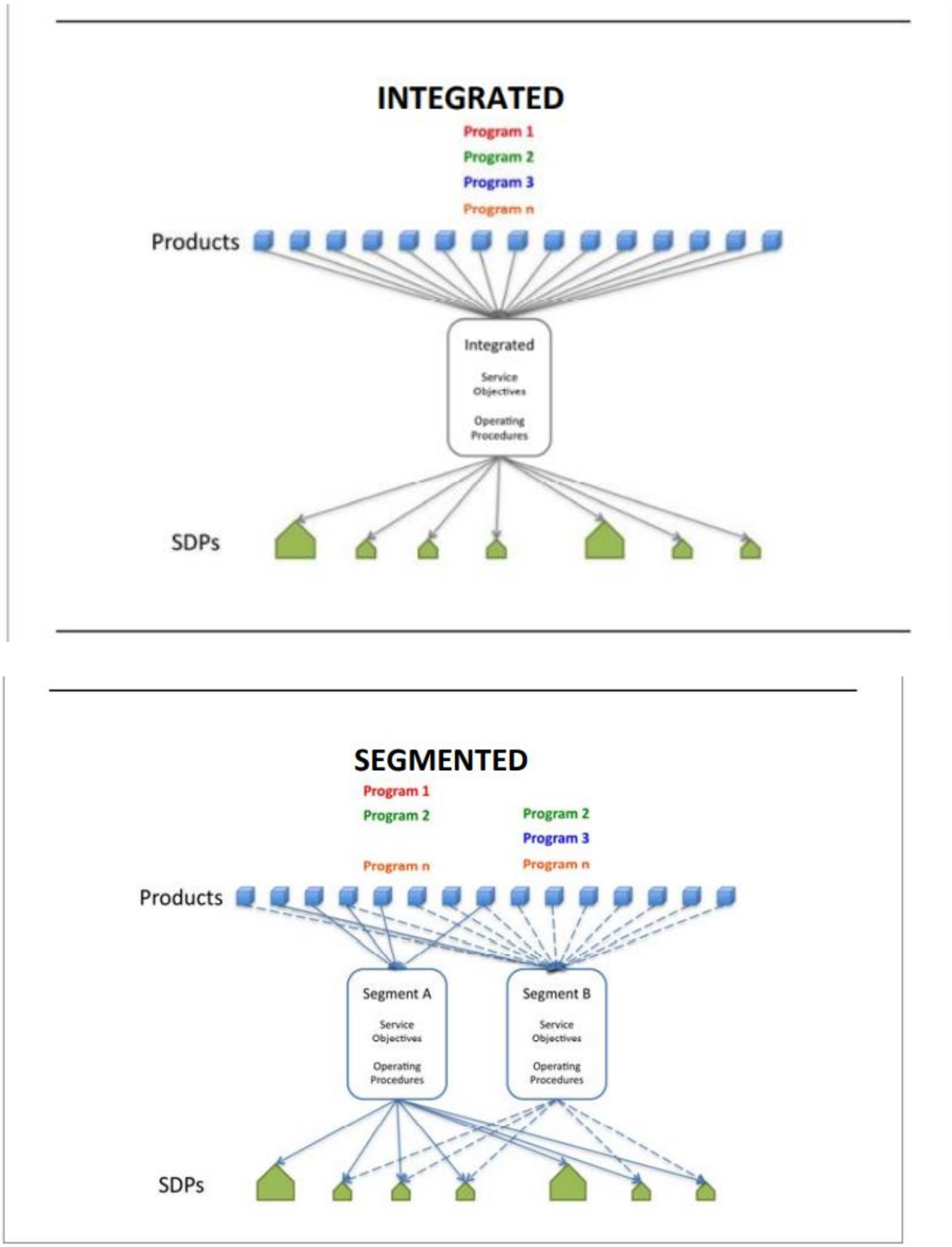


Figure 4. Simplified View of Three Common Supply Chain Structures (Allain et al., 2010)

Figure 5 depicts the forecasting framework we will apply, which we anticipate will provide greater forecasting accuracy and resilience for the UNAMID mission (Allain et al., 2010). Step 1 mainly focuses on information gathering and project establishment. Step 2 emphasizes the creation of product groups, data collection, and determination of the criteria for segmentation analysis. Step 3 is to identify service objectives and operational procedures for each segment. Step 4 is to develop an implementation strategy. In Section 3.2 we explain our methodology for following each of these steps.

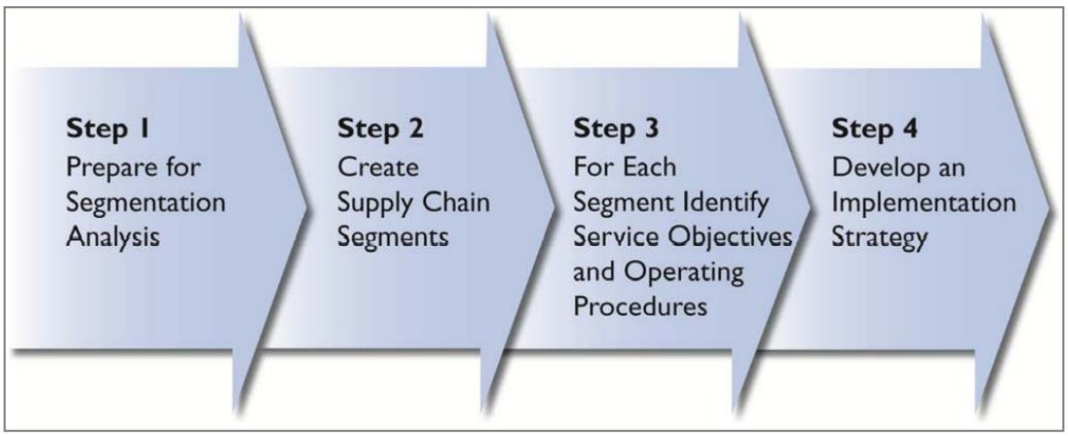


Figure 5. Developing a Strategy Using Supply Chain Segmentation Framework (Allain et al., 2010)

3.2 Project Scope

Our goal is to establish a more accurate, Holt-Winters forecasting model, which will allow Agility to order within the 100-102% range at a higher frequency and reduce contract penalty charges from the UN.

The initial scope of this project focused on forecasting bulk food order amounts for the UNAMID operation, with a subsequent goal of refining the forecast to more accurately predict food-ration order quantities than the currently used MA(3) method. The second phase of our project consisted of further refining the parameters of the new forecast to translate the more accurate order-quantity predictions into cost savings for Agility.

3.3 Forecasting

Of the 300+ SKUs that are regularly ordered by UNAMID, 20 SKUs account for approximately 55% of the total quantity ordered and 56% of the total cost to Agility. We decided, with our sponsor's guidance, to segment the forecasts into three categories: A SKUs, which represent the top 10 SKUs in terms of total cost to the sponsor, B SKUs, which represent the 11 – 20th SKUs in terms of total cost to the sponsor, and C SKUs, which represent the total remaining SKUs that can be ordered by UNAMID. Our analysis will focus mainly on the A and B SKUs.

For each of the top 20 SKUs, we began with initial analysis of plotting the data and analyzing demand trends to determine food order patterns. We discovered that trend and seasonality were present in most of these SKUs. From conversations with Agility, we also confirmed that order quantities were not stochastic, but were subject to the number of troops present at the mission. We used JMP software to test several forecasting models, such as simple exponential smoothing, double exponential smoothing, and Holt-Winters, for each of the top 20 SKUs to determine which model was the best fit for each one. Each of the top 20 SKUs had a dynamic combination of level, trend, and seasonality present in the order quantity data. To handle these three factors, we decided to use the Holt-Winters model for our forecast with optimized smoothing parameters, which we will refer to as "optimized Holt-Winters". The Holt-Winters model provides the most flexibility with variations in the data. For example, if a particular SKU shows level and trend but no seasonality, the Holt-Winters model can still successfully be applied by setting the smoothing parameter for seasonality, gamma, to zero. In the following sections we detail the specific steps taken to complete this forecasting approach. Specifically, these steps were Initial Parameter Estimation, Model Construction, and Smoothing Parameter Optimization.

3.3.1 Initial Parameter Estimation

We began our forecasting procedure by estimating the initial parameters $\hat{a}_0$ (level), $\hat{b}_0$ (trend), and F_0 (seasonality factor). To estimate the initial parameters for the Holt-Winters Model, we used the P-Centered Moving Average procedure as described by Caplice (2020 b). To demonstrate this procedure, we will outline the following four steps for one of the top 20 SKUs in our project scope, SKU 1125, frozen beef patties.

1. First the initial seasonality index is found, followed by level and trend. We calculate a P-Moving Average, where P = 13 for the number of periods Agility uses per year. This number of periods also corresponds to the annual seasonality in the data. Figure 6 illustrates the P-moving average as calculated for SKU 1125.

Order Quantity	MA(13) Center Point (Level Estimate)
5881.3	
12667.42	
12667.42	
16976.14	
14369.42	
13551.45	
18120.85	=AVERAGE(D2:D14)
13858.32	13850.17
13372.11	14011.60
13063.52	14258.73
12994.25	14216.85
13841.08	14551.54
11346.15	14943.40

Figure 6. P=13 Moving Average for SKU 1125

2. We take the ratio of actual quantity ordered over the P-moving Average to get the initial F_i values, where i is the index of the 13 periods, estimated for each periodic season. Figure 7 shows this calculation.

Order Quantity	MA(13) Center Point (Level Estimate)	Initial Fi Estimate (Seasonality)
5881.3		
12667.42		
12667.42		
16976.14		
14369.42		
13551.45		
18120.85	13285.34	=D8/E8
13858.32	13850.17	1.001
13372.11	14011.60	0.954
13063.52	14258.73	0.916

Figure 7. Calculation of the Initial Seasonality Estimates (Fi)

3. We then calculate the initial seasonality indices by averaging the F_i values for common periods (e.g., average F_i where i = 1 for 6 years of data gives an average of 6 values); this will be referred to as the "Average of F_i Estimates". We sum the F_i values and calculate

the difference between this sum and the number of periods. We then normalize the values by adjusting each F_i estimate by the difference, so that the new sum now equals the total number of periods. Figure 8 shows this calculation in detail, where the sum of the average F_i estimates was equal to 12.964. Subtracting this value from the number of periods (13) yielded a gap of 0.036. This gap value was then divided by 12 and added to each of the average of F_i estimates which resulted in a list of normalized F_i values.

Period	Average of F_i Estimates	Normalized F_is
1	0.986	**0.989**
2	0.946	**0.949**
3	1.020	**1.023**
4	1.047	**1.050**
5	1.128	**1.131**
6	0.889	**0.892**
7	1.031	**1.034**
8	1.011	**1.014**
9	1.011	**1.013**
10	1.033	**1.036**
11	0.968	**0.971**
12	0.935	**0.938**
13	0.958	**0.961**
SUM:	**12.964**	**13.000**
Gap:	0.036	

Figure 8. Calculation of Average and Normalized F_i values

4. We use the normalized F_i values from the previous step to compute the "deseasonalized" demand data. This is done simply by dividing the actual quantity ordered (actual demand) by the normalized F_i value of that period. We then use this deseasonalized data to calculate the initial estimates for the level and trend by using Ordinary Least Squares Regression (OLS). Figure 9 shows the use of OLS to generate initial estimates for the level and trend of the deseasonalized demand data for SKU 1125. For this SKU, the initial parameters that we computed and use in the next step of

our methodology were a level value of 17,908.315 and a trend value of -115.884. Our F_i average values remain the same as shown in the previous step. As seen in Figure 9, we begin with a very low Adjusted R^2. The following steps in model construction help us refine the parameters used in the model to improve this quality metric and minimize the Mean Absolute Percent Error (MAPE).

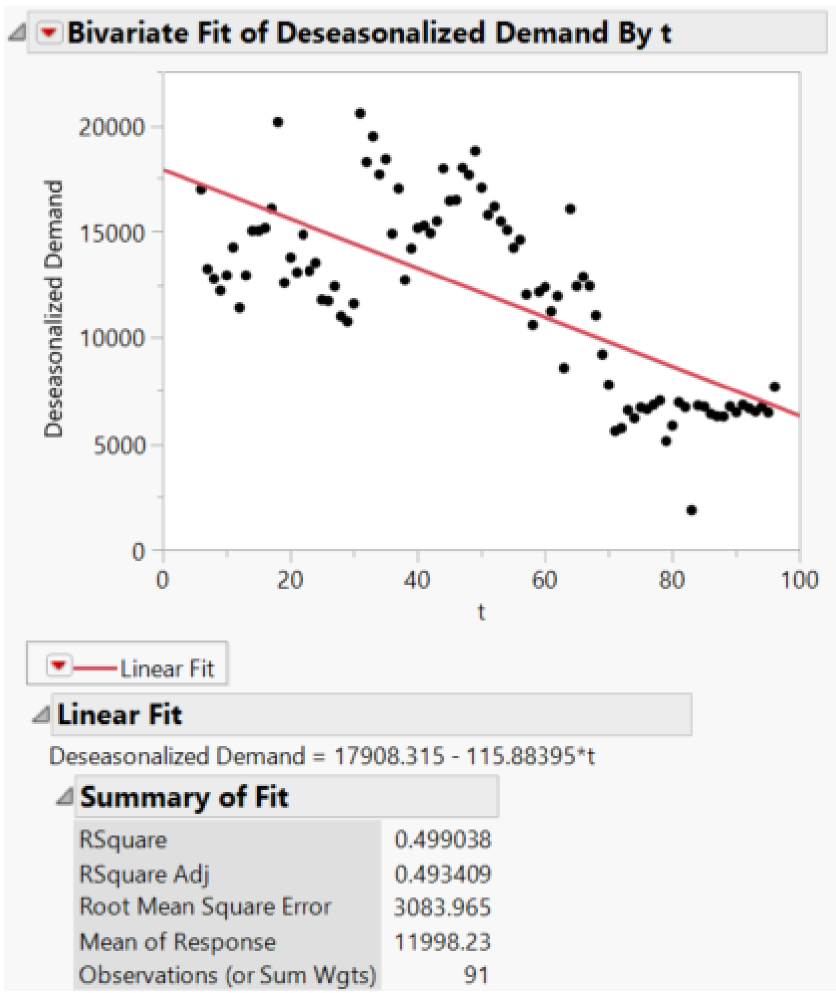


Figure 9. Calculating Initial Parameter Estimates via Ordinary Least Squares Regression using JMP Software

3.3.2 Model Construction

Now that we have initial estimates for level, trend, and seasonality, we build our Holt-Winters forecasting model. We use the following model and updating equations shown in Figure 10, and begin with common arbitrary values for our smoothing parameters of Alpha = 0.1, Beta = 0.05, and Gamma = 0.2. Alpha specifies the coefficient for the level smoothing. Beta specifies the coefficient for the trend smoothing. Gamma specifies the coefficient for the seasonality smoothing. We divide the historic order quantity data, of which we have seven years, by SKU first, and then for each SKU, we separated 70 periods for training, and the remaining 27 periods for testing. This is a generally accepted train-test split. During the second phase of our project, we pivoted our model tuning to focus on cost reduction, which led us to update our training and testing datasets to only the most recent 26 periods due to a significant drop in troop numbers at UNAMID immediately prior.

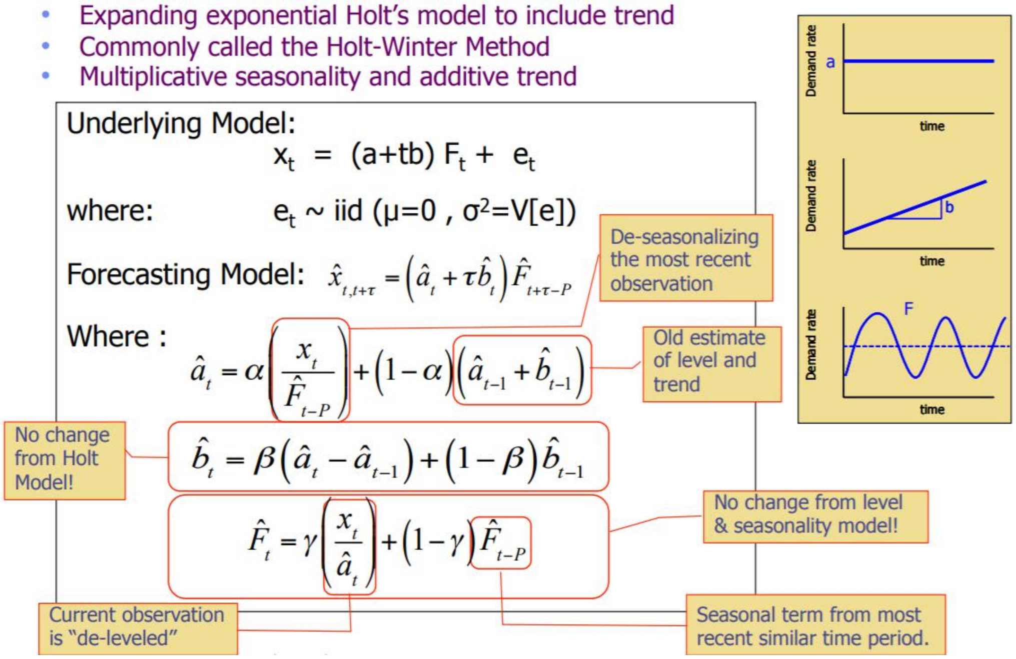


Figure 10. Holt-Winters Forecasting Model and Updating Equations

**Citation: Caplice, 2020 b, CTL.SC1x, Lesson: Exponential Smoothing with Seasonality*

In Figure 11 below, we show the partial construction of our Holt-Winters forecasting model as applied to SKU 1125. The figure shows how the thirteen $\widehat{F_t}$ seasonality factors are applied, forecasted order quantities beginning in period fourteen, and how the values of the $\hat{a}_t$ and $\hat{b}_t$ change with the updating equations as actual order quantity data is fed into the model. Tau is the difference between the period forecasting from and the period being forecasted.

					Amount Ordered	Amount Arrived			
Year	t	Period	Order Quantit	tau	x^t,(t+tau)		a^t	b^t	F^t
2013	1	1	5881.3	5			15542.00	-24.49	0.916
2013	2	2	12667.42	5			15204.66	-49.10	0.932
2013	3	3	12667.42	5			14808.52	-76.39	0.973
2013	4	4	16976.14	5			15160.70	-42.69	0.977
2013	5	5	14369.42	5			14773.00	-69.82	1.106
2013	6	6	13551.45	5			14362.26	-96.63	1.075
2014	7	7	18120.85	5			14680.04	-64.04	1.078
2014	8	8	13858.32	5			14390.25	-81.79	1.048
2014	9	9	13372.11	5			14095.81	-98.52	1.029
2014	10	10	13063.52	5			13735.08	-119.14	1.055
2014	11	11	12994.25	5			13592.17	-121.01	0.965
2014	12	12	13841.08	5			13748.64	-99.19	0.912
2014	13	13	11346.15	5			13402.06	-118.64	0.936
2014	14	1	13224.12	5	11866.85515		13470.11	-103.96	0.982
2014	15	2	14765.99	5	12494.51562		13769.35	-72.25	1.072
2014	16	3	15880.13	5	13552.2936		14124.23	-38.66	1.124
2014	17	4	16431.66	5	14182.54627		14528.70	-3.81	1.131
2014	18	5	18720.44	5	16641.26701		14916.25	26.97	1.255
2014	19	6	18645.56	5	16793.18184	11866.85515	15333.87	57.69	1.216
2015	20	7	13431.58	5	16183.58315	12494.51562	14915.34	20.24	0.901
2015	21	8	14425.06	5	15476.63132	13552.2936	14745.83	5.32	0.978
2015	22	9	13689.08	5	14863.78091	14182.54627	14516.62	-13.13	0.943

Figure 11. Holt Winters Model in Excel to Forecast Order Quantities

3.3.3 Smoothing Parameter Optimization

Once the model has been created using the 70-period training data and the arbitrary smoothing parameter values, we refine the model by adjusting these smoothing parameters. The following linear program shown in Figure 12, which was run using Excel Solver, is used to determine the optimal values for the three smoothing parameters: Alpha, Beta, and Gamma; those which maximize Adjusted R^2 of the forecast model, where $\hat{y}$ is the predicted value, y_i is the actual value, $\bar{y}$ is the average of the sample, N is the total sample size, and *p* is the number of predictors.

$$Decision\ Variables: \alpha, \beta, \gamma$$

$$Maximize\ R^2_{adj} = 1 - \left(1 - \sum_i \frac{(y_i - \hat{y})^2}{(y_i - \bar{y})^2}\right) * \frac{N-1}{N-p-1}$$

$$Subject\ to:$$

$$0 \leq \alpha \ \leq 1$$

$$0 \leq \beta \leq 1$$

$$0 \leq \gamma \leq 1$$

Figure 12. Linear Program to determine Optimal Smoothing Parameter Values

We then use the Holt-Winters model with optimized smoothing parameters to create the final forecast for each SKU in our project scope, which is applied to the remaining 20 periods of testing data. We begin in the 70^{th} period, and forecast five periods in advance, which is the time between the maximum order lead time and the receipt of the bulk purchase order from the United Nations. We then continue progressing the forecast, adding in one period of testing data at a time, allowing the model to update itself as it progresses through the data. We assume we are in each period when the forecast is made for the following period for both the optimized Holt-Winters method and the MA(3) method. Once we complete the forecast for all of the testing data, we compute the Adjusted R^2 and MAPE to determine the forecast accuracy. We then repeat this process for all of the top 20 SKUs.

4 Results and Analysis

In this section, we will discuss the results of our project in two categories: statistical results and cost reduction results. The objective of the first phase of our project was to create a forecasting model that more accurately predicted order quantities over time than the previously used MA(3) forecast. The results of this phase are presented in section 4.1. The objective of the second phase of our project was to tweak the forecasting model to show its benefit financially by reducing overall penalties. The results from this phase are presented in section 4.2.

4.1 Statistical Results

4.1.1 Determining forecast quality

Adjusted R^2 and Mean Absolute Percent Error (MAPE) were chosen as the two statistical accuracy measures for our forecast because both measures show how well a forecasting model predicts actual values. We use these two measures to compare our forecast with Agility's currently used MA(3) because they allow us to measure the difference in statistical accuracy. The R^2 value is a ratio of the sum of the residuals squared over the sum of the total error squared, and it indicates how well a model predicts responses for new observations. The Adjusted R^2 value compensates for the number of predictors used in the model. A higher Adjusted R^2 value indicates a more accurate forecast. Figure 13 shows the R^2 formula and the Adjusted R^2 formula.

$$R^2 = \frac{SSR}{SST} = \sum\nolimits_i \frac{(y_i - \hat{y})^2}{(y_i - \bar{y})^2} * \frac{N-1}{N-p-1}$$

$$R^2_{adj} = 1 - (1 - R^2) * \frac{N-1}{N-p-1}$$

Figure 13. R2 formula and the Adjusted R2 formula

The MAPE is another statistical measure of prediction accuracy. It is a frequently used measure that shows the average deviation from the actual values created by a forecasting model. Generally, MAPE is applied when there are limited extremes in the data. Figure 14 shows how the MAPE is calculated.

$$MAPE = \frac{100\%}{n} \sum \left| \frac{y - \hat{y}}{y} \right|$$

$$y: Each\ residual\ is\ scaled\ aginst\ the\ actual\ value$$

Figure 14. Formula for the Mean Absolute Percent Error (MAPE)

4.1.2 Optimized Holt-Winters vs MA(3)

Our methodology for the first objective of producing a statistically more accurate model consisted of using nonlinear optimization with JMP and Excel software aimed at minimizing MAPE, by optimizing the smoothing parameters for each of the 20 previously defined “A” SKUs. In Table 1 we show the results of this analysis. This table shows the Adjusted R^2 and MAPE values for each of the top 20 SKUs from our new forecasting model (optimized Holt-Winters) versus the currently used MA(3). Green represents the model that provides a more optimal MAPE or Adjusted R^2, while red represents less optimal.

	New Forecasting Model		Old Forecasting Model	
SKU	MAPE	Adjusted R^2	MAPE	Adjusted R^2
1115	26.65%	0.699	24.30%	0.794
1116	41.68%	0.480	43.02%	-0.089
1121	264.50%	0.500	387.43%	0.710
1125	11.38%	0.629	11.56%	0.602
1129	10.43%	0.784	11.34%	0.747
1132	17.91%	0.883	20.77%	0.678
1154	13.42%	0.512	26.48%	0.375
1156	7.87%	0.892	8.31%	0.887
1162	47.48%	0.629	54.41%	-1.135
1187	11.51%	0.755	13.31%	0.628
1189	15.14%	0.533	15.31%	0.523
2160	14.69%	0.311	17.46%	0.159
3130	6.33%	0.922	11.73%	0.657
4104	9.61%	0.805	17.88%	0.756
4114	31.13%	0.579	35.61%	0.644
4150	13.35%	0.549	17.13%	0.275
4155	19.18%	0.861	22.43%	0.699
4156	41.19%	0.473	52.09%	0.256
4157	21.48%	0.547	22.31%	0.472
4249	19.42%	0.822	24.59%	0.516

Table 1. Statistical results comparison; Optimized Holt-Winters vs MA(3)

4.1.3 Statistical Comparison Results Insight

As seen in Table 1, demand for the majority of the 20 SKUs analyzed in this project was more accurately predicted using our optimized Holt Winter model as compared to the currently used MA(3) forecast, according to these two accuracy measures. However, SKUs 1115, 1121, and 4114 showed at least one statistical measure where the MA(3) forecast performed better than our optimized Holt-Winters forecast. Here we briefly discuss the reason for this disparity.

SKU 1115 and 1121 are both frozen beef products. We hypothesize that these two SKUs are better predicted using a moving average forecast due to the high variability of demand. Beef is a relatively niche item, as many UNAMID soldiers are either vegetarian or prefer a different meat protein such as chicken or fish. Since demand for beef is more variable than that for other SKUs, a forecast such as MA(3) that only considers the most recent periods of demand will likely be more accurate. Holt-Winters model can also be manipulated to do the same, but in this case, it would be more efficient to simply use the existing model. In other words, demand for beef is likely highly concentrated on only a few contingents, whereas demand for the other SKUs is more evenly divided among all contingents. We recommend that Agility continue using the MA(3) forecasting model for these SKUs.

SKU 4114 is a canned fruit cocktail. This product is also highly variable, due to its lack of local availability during the winter months, and thus the moving average approach is more suited to forecast its demand. However, it should be noted that our forecast was extremely close in accuracy and produced a lower MAPE value.

4.2 Cost Savings

4.2.1 Cost Calculation Procedure

We performed cost calculations to quantify potential monetary savings based on the new forecasting model. The main performance metrics of Agility's operations that result in penalties includes on-time delivery, cycle service level, item fill-rate, and authorized substitutions (Figure 15). Due to the complexity and uncertainty of the supply chain, we made a few assumptions in an effort to simplify the calculations after consulting with Agility. First, we assumed that if order quantities are predicted to be correct, all the orders will be fulfilled on-time. Also, since the substitutions for shortage items have to be decided by the UN, we assume no substitutions are used for the penalty calculation. The second penalty category is line-item cycle service level (CSL), which accounts for 20% of penalty allocation. If CSL is between 92% and 98%, there will be 1.2% penalization on 40% of the contingent invoice. If CSL is below 92%, there will be 3% penalization on the entire contingent invoice. The third cost category is order quantity fill rate. If CSL is between 92% and 98%, there will be 1.8% penalization on 40% of the contingent invoice. If the fill rate is below 92%, there will be 4.5% penalization on the entire contingent invoice. To consider the effects on inventory holding and spoilage costs, we introduced two additional penalties to ensure the total penalty amount considers not only external costs but internal costs as well. Inventory spoilage cost applies to two SKUs (1129 and 4104) with perishability of one month, while the rest of the SKUs have a long enough shelf life to rotate in and out of stock via replenishment operations (Table2). Agility has a standard inventory holding cost rate at 5%, and this cost would apply to all the SKUs except for 1129 and 4104.

Performance Service Level	Allocation "A" (% service level credit)	Target %	Acceptable	Measurement Period	Band (level of performance)	% of Allocation "B"	Service Level Credit - % of invoice
1. Conformity to Delivery Schedule	20%	on time delivery	on time	weekly	1 day delay	40%	1.20%
					2 days delay	100%	3.00%
2. Conformity to Order by Line Items: Number of line items ordered is delivered (including authorized substitutions)	20%	100%	98%	weekly	95% < 98%	40%	1.20%
					<92% < 95%	100%	3.00%
3. Conformity to Orders by weight: Quantity of food order in Kg/Lr is delivered (including authorized substitutions)	30%	100%	95%	weekly	92% < 95%	40%	1.80%
					90% < 92%	100%	4.50%
4. Food Order Compliance-Availability: Number of authorized substitutions	30%	0%	3%	weekly	3% < 4%	40%	1.80%
					4% < 5%+	100%	4.50%
Methodology: Verification shall be determined by the UN in its sole discretion. The service credit shall be computed according to the followin formula: Service Level Credit = A * B * C (A = Allocation(% of at risk amount); B = % of allocation; C = At risk amount)							

Figure 15. Performance Metrics Cost Calculation

Item Code	Pack size	Net Weight - Case per UOM in KG	Total Shelf Life (Days)	No. of Periods	No. of Periods
1125	Carton +/- 20kg	20	730	24.33	24.00
1129	**30 units per tray**	**22.5**	**30**	**1.00**	**1.00**
1154	Carton 28X500GR	14	730	24.33	24.00
1156	12 X 1 LITER	12.372	365	12.17	12.00
1187	Carton 2X5 KG	10	730	24.33	24.00
1189	1 X 16-19 KG	16-19	730	24.33	24.00
2160	25 Kgs	25	730	24.33	24.00
3130	1 LTR or 5 LTR	13.8	730	24.33	24.00
4104	**18.25 KG**	**18.25**	**42**	**1.40**	**1.00**
4150	12X1LTR	12	540	18.00	18.00
1115	Carton +/- 20kg	20	730	24.33	24.00
1116	Carton +/- 20kg	20	730	24.33	24.00
1121	Carton +/- 20kg	20	730	24.33	24.00
1132	1X10X(1.3 TO 2.00 KG)	20	450	15.00	15.00
1162	100GRX12X40	4.8	270	9.00	9.00
4114	Carton 12X820GR	9.84	1080	36.00	36.00
4155	12X1LTR	12	540	18.00	18.00
4156	Carton 12X1LT	12	365	12.17	12.00
4157	12X1LTR	12	540	18.00	18.00
4249	20 Kg	20	292	9.73	10.00

Table 2. Top 20 SKUs Profile

4.2.2 Cost Optimization

To calculate the overall impact of the new forecasting model, we use the existing cost metrics to predict the cost generated from the Holt-Winters forecasting model and compare it to the MA(3) cost prediction. Based on the preliminary results, we see that Holt-Winters outperformed the MA(3) forecast in inventory spoilage and holding costs with savings at $217,000. The Holt-Winters model incurred approximately $385,000 more on cycle service level and item fill-rate. This implies that Agility's original approach of using MA(3) generated a better financial result in this scenario. Even though the Holt-Winters model performed better in adjusted R^2 and MAPE, it generated less optimal financial results. Agility has a relatively low inventory holding cost at approximately 4-5% annually, and most of the products have a long shelf life in a temperature-controlled environment. The demand from the UN fluctuates with the movement of troops frequently. Although the Holt-Winters model performs better in the long run, it does not respond well to these random fluctuations. Therefore, we updated the objective function to minimize cost, and used the Excel Solver function to optimize the cost function to make the model more suitable for the UNAMID operation. Figure 16 and Table 3 show the output of our model – a table of smoothing parameters optimized to minimize cost. Table 4 shows the corresponding cost comparison between MA(3) and Holt Winters after this optimization.

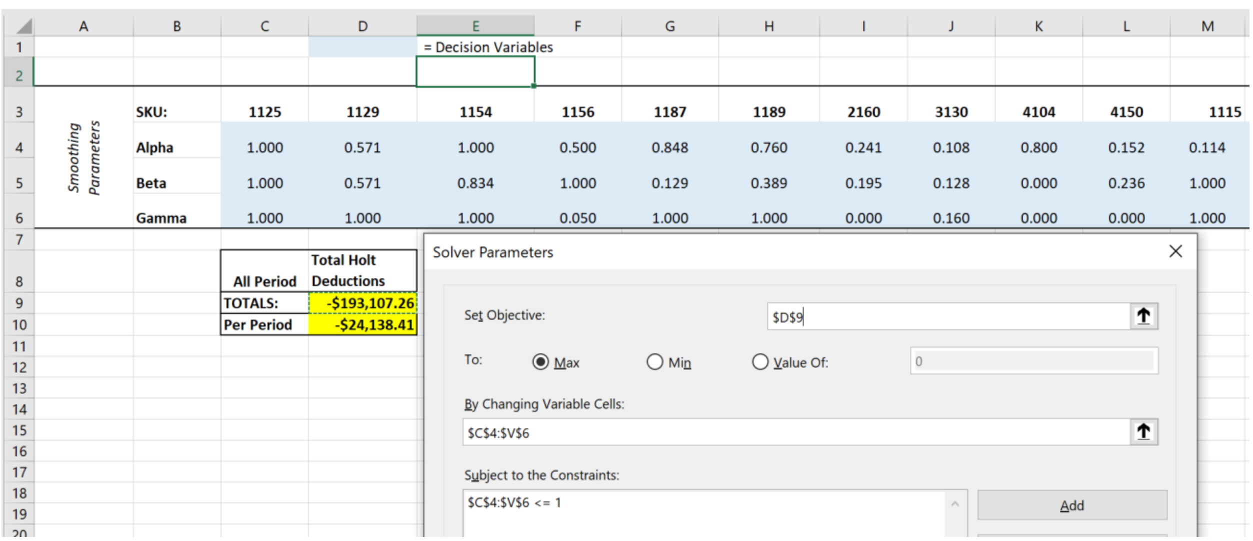


Figure 16. Smoothing Parameter Optimization (Cost Objective)

	SKU:	1125	1129	1154	1156	1187	1189	2160	3130	4104	4150
Smoothing Parameters	Alpha	1.000	0.501	1.000	0.505	0.841	0.733	0.160	0.159	0.769	0.108
	Beta	1.000	0.487	0.814	1.000	0.084	0.342	0.203	0.173	0.058	0.289
	Gamma	1.000	1.000	1.000	0.000	1.000	1.000	0.000	0.160	0.000	0.000
Smoothing Parameters	**SKU:**	**1115**	**1116**	**1121**	**1132**	**1162**	**4114**	**4155**	**4156**	**4157**	**4249**
	Alpha	0.023	0.214	0.242	0.076	0.111	0.108	0.119	0.014	1.000	0.359
	Beta	1.000	0.158	0.236	0.386	0.106	0.097	0.126	0.062	0.087	0.120
	Gamma	1.000	0.017	0.207	0.000	0.077	0.096	0.132	0.109	0.078	0.000

Table 3. Smoothing Parameters for top 20 SKUs (Optimizing on Cost)

	Line Item Cycle Service Level	Order Quantity Fill Rate	Inv Spoilage	Inv Holding	Total
Holt-Winter	(178,416)	(225,569)	(236,768)	(55,819)	(696,572)
MA(3)	(12,820)	(100,147)	(300,479)	(119,847)	(533,293)

Table 4. Cost Comparison on Holt-Winters vs. MA(3)

4.2.3 Project Value - Money Saved

After several rounds of input adjustments to the Excel Solver optimization model, we discovered that Holt-Winters would normally underperform compared to the MA(3) in highly volatile demand patterns. We found that the troop numbers had been decreasing steadily until 2019, and this reduction decreased demand for food items due to a strong correlation rate of 93.6% between the two (Figure 17). Thus, we decided to use the data from 2019 for training and 2020 for testing – which contains thirteen periods for each year with a total of 26 periods. We chose 26 periods of data because we need to use the first 13 periods to calculate the seasonality indices, and then test our model on the rest of the data. Our methodology remained the same, and we tested the model using the adjusted data frame, resulting in a potential cost savings with Holt-Winters model of $25,662.32 (Tables 5 and 6).

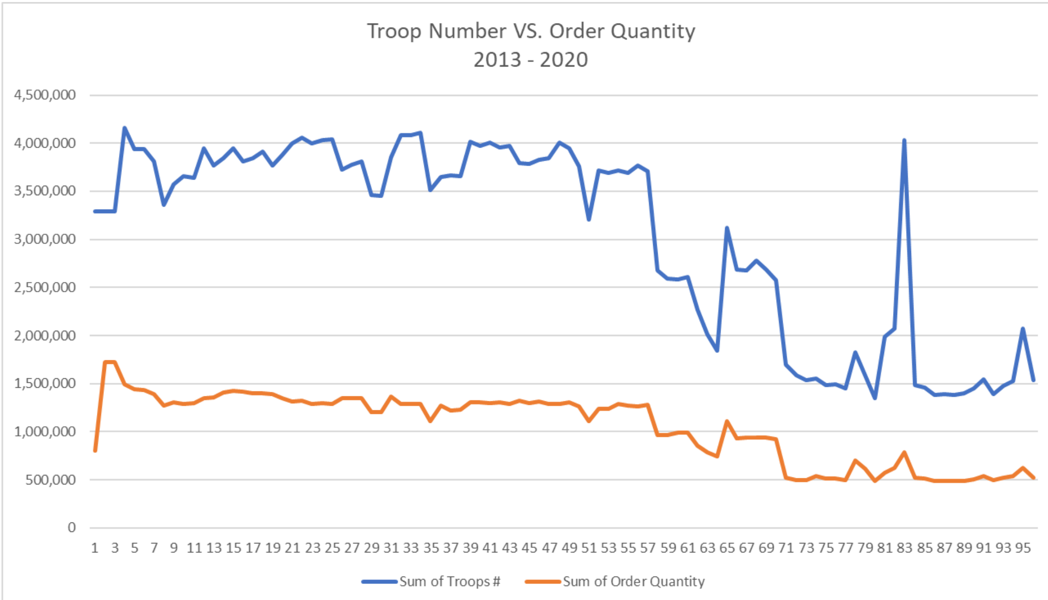


Figure 17. Troop Number vs. Order Quantity 2013-2020

Smoothing Parameters	**SKU:**	**1125**	**1129**	**1154**	**1156**	**1187**	**1189**	**2160**	**3130**	**4104**	**4150**
	Alpha	1.000	0.571	1.000	0.500	0.848	0.760	0.241	0.108	0.800	0.152
	Beta	1.000	0.571	0.834	1.000	0.129	0.389	0.195	0.128	0.000	0.236
	Gamma	1.000	1.000	1.000	0.050	1.000	1.000	0.000	0.160	0.000	0.000
Smoothing Parameters	**SKU:**	**1115**	**1116**	**1121**	**1132**	**1162**	**4114**	**4155**	**4156**	**4157**	**4249**
	Alpha	0.114	0.215	0.220	0.000	0.049	0.275	0.220	0.000	1.000	0.413
	Beta	1.000	0.113	0.211	0.346	0.049	0.226	0.203	0.067	0.087	0.088
	Gamma	1.000	0.018	0.234	0.000	0.077	0.096	0.131	0.098	0.075	0.000

Table 5. Smoothing Parameters for Top 20 SKUs (Optimized Cost and Adjusted Dataset)

	Line Item Cycle Service Level	**Order Quantity Fill Rate**	**Inv Spoilage**	**Inv Holding**	**Total**
Holt-Winter	(94,646)	(93,135)	(4,828)	(499)	(193,107)
MA(3)	(102,364)	(112,408)	(3,534)	(463)	(218,770)

Table 6. Cost Comparison on Holt-Winters vs. MA(3) (Adjusted Dataset)

These results confirmed our hypothesis that more sophisticated forecasting techniques can be applied to improve the accuracy of forecasting for food ration order quantities at the UNAMID mission. This accuracy translates into lower penalties for Agility, and thus more profit and more accurate fulfillment of food delivery orders for the troops.

5 Conclusion

Through this capstone project, we were able to analyze years of historic order quantity data for the UNAMID mission, develop a comprehensive forecasting model to predict future order quantities, optimize this model to minimize cost for Agility, and derive insights that can help Agility's business moving forward. Our analysis showed that optimized Holt-Winters forecasting with SKU segmentation can be applied to increase the accuracy of forecasting at UNAMID. By applying this model with optimized parameters, food ration order quantities can be more accurately predicted and result in reduced overage, underage, spoilage, and inventory costs. There does exist a tradeoff though between inventory holding cost, spoilage cost, and penalties. If substitutions are cheap, for example, it might make sense to optimize for statistical accuracy instead of cost, incur the penalty for under delivering, and substitute when Agility receives the food products. In the same way, if food products are locally available at a reasonable price, or inventory costs are very high, or uncertainty in delivery times is very high, it might end up being a better decision for Agility to optimize the smoothing parameters for statistical accuracy instead of pure cost minimization.

Given the aforementioned information, our recommendations are as follows:

1) Agility should conduct additional research to determine how the Holt-Winters model with optimized smoothing parameters performs against their current forecasting methodology at other peacekeeping missions;

2) Agility should use an amount of historical data to train and test the forecasting model that aligns with the longest and most recent stable period of troops at the mission. If there is a

sudden large change in the number of troops at the mission in question, Agility should temporarily use more agile forecasting methods, such as MA(3), until there are at least thirteen periods of relatively stable troop numbers – at which point they should return to using our model;

3) If the model proves to be more effective at reducing penalty costs at other peacekeeping missions similar to UNAMID, we recommend that Agility invest in the adoption of a forecasting platform that will allow for seamless input of order quantity data and output of the relevant forecast based on the optimized Holt-Winters model;

4) We recommend that Agility investigate the mission-specific and time-dependent factors that contribute to tradeoffs between using the Holt-Winters model with smoothing parameters optimized for statistical accuracy, versus the same model but with smoothing parameters optimized to minimize cost.

5.1 Limitations

The results of this study are based solely on the historical order quantity data for the UNAMID mission. While our study has shown that Holt-Winters forecasting can be applied to increase the accuracy of forecasting at UNAMID, and decrease cost penalties, this may not necessarily be the case at other peacekeeping missions where demand, lead time, local availability, and storage conditions are different.

5.2 Future Research

Additional research is recommended to determine how effective the Holt-Winters model with optimized smoothing parameters will be when applied to data from other peacekeeping missions. Agility should test the model we have created in this project against other sophisticated forecasting techniques to determine which best predicts food-ration demand at other peacekeeping missions. Once a scalable forecasting model is proven to reduce penalty costs associated with overage, underage, spoilage, and inventory constraints, a tool can then be developed that will allow for data input, model readjustment, and forecast output. This process can then be re-applied to subsequent peacekeeping missions serviced by Agility. Once a forecasting tool is in place, inventory management procedures can be investigated to reduce inventory holding costs and decrease overage penalties even further. Machine learning could also be investigated as a potential methodology to classify different SKUs based on their demand volatility, but may be an over-engineered solution given the simplicity of data currently made available by Agility.

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