DESIGN AND DEVELOPMENT OF A HYBRID INVENTORY MANAGEMENT TOOL

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ABSTRACT

DESIGN AND DEVELOPMENT OF A HYBRID INVENTORY MANAGEMENT TOOL

Düzgün, Merve

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Demand forecasting is a very important topic for companies to make plans for the next years. In this study, we propose an integrated inventory management tool which consists of forecasting and inventory control. Demand forecasting was made based on past demand values of a white goods company. ARIMA method is used for this purpose. Then, the data obtained from using the forecasting method compared with the actual data and the results were tested. The objective is to find optimum order quantity (Q) and reorder point (R) using Unified Supply Model (USM) method to minimize total supply chain cost by using actual and forecasted data. Order quantity (Q) and reorder point (R) were also calculated according to the Economic Order Quantity (EOQ) method currently used by the company. The total cost was calculated to compare both their current and recommended models. Consequently, the company could decrease total cost by approximately 66% for actual demand data and approximately 49% for forecasted demand data with the help of the USM method. We also performed some analysis and observed how the change of lead time affects customer satisfaction level and total cost and how the use of different backorder costs changed the total cost.

Keywords: ARIMA, Forecasting, Inventory Management

ÖZET

HİBRİT ENVANTER YÖNETİMİ ARACININ TASARIMI VE GELİŞTİRİLMESİ

Düzgün, Merve

Endüstri Mühendisliği Yüksek Lisans Programı

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Talep tahminleri, şirketlerin gelecek yıllar için plan yapabilmeleri adına çok önemlidir. Bu çalışmada, tahminleme ve envanter kontrolünden oluşan entegre bir envanter yönetimi aracı öneriyoruz. ARIMA yöntemi kullanılarak bir beyaz eşya şirketinin geçmiş talep değerlerine dayalı talep tahmini yapılmıştır. Ardından tahminlemeden elde edilen talep verileri gerçek talep verileriyle karşılaştırılmış ve sonuçlar test edilmiştir. Amaç, gerçek ve tahminleme yönteminden elde edilen talep verilerini ve Birleşik Tedarik Yöntemi (USM) metodunu kullanarak toplam tedarik zinciri maliyetini en aza indirmek için en uygun sipariş miktarını (Q) ve yeniden sipariş noktasını (R) bulmaktır. Q ve R şirketin hâlihazırda kullandığı Ekonomik Sipariş Miktarı yöntemine göre de hesaplanmıştır. Daha sonra toplam maliyet her iki yöntem içinde hesaplanmış ve karşılaştırılmıştır. Sonuç olarak, şirketin, önerilen USM metodunu kullanarak toplam maliyeti gerçek talep verileri ile yaklaşık %66, tahmini talep verileri ile de yaklaşık %49 azaltabileceği bulunmuştur. Ayrıca çeşitli analizler yapılmış ve teslimat süresi değişimi gibi bazı durumların toplam maliyeti nasıl etkilediği gözlemlenmiştir.

Anahtar Kelimeler: ARIMA, Tahminleme, Envanter Yönetimi

To My Family

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1. Introduction

1.1. Research Motivation

Companies are mostly focused on their core businesses, and try to optimize production and distribution systems to decrease their total costs. However, a high percentage of unit product cost comes from out-sourced materials. Therefore, material supply and inventory is an important issue for the company. Inventory control is the activity that organizes the availability of items to the customers and it coordinates the purchasing, manufacturing and distribution functions to meet the marketing needs (Wild, 2002). Having the right inventory management is an extremely effective investment for any company. There are many advantages of successful inventory management such as minimization in inventory levels, reduction in costs such as inventory holding and ordering costs, and improvement in profitability, etc. (Kontuš, 2014; p. 245).

According to Lewis (2012), it is necessary to forecast future demand to control the inventory levels (Lewis, 2012; p. 3). For this purpose, the demand forecast should be made for the next years and then inventory management methods should be applied. Thus, this study proposes an integrated inventory management tool which consists of forecasting and inventory management. This hybrid model for forecasting and inventory management can be very beneficial because this model allows companies to accurately forecast demand and perform inventory control more efficiently. Also, the successful implementation of this hybrid method can help companies about having a more efficient supply chain and reducing the total costs.

This study is conducted using a real-life data set from a white house goods company. ARIMA method is used to forecast future demand values based on past demand data and the Unified Supply Model (Ekinci, 2018) method is used to determine optimal order quantity and reorder point in order to minimize total supply chain cost. Unified Supply Model (USM) is different from other inventory management methods for uncertain demand because it takes into account inventory holding cost, backorder cost, and transportation issues like logistic costs and container loads. There are many studies in the literature that combine forecasting and inventory management, but there is no study in the literature that uses such a method and then compares it to the Economic Order Quantity (EOQ) method currently used by the company.

The main contribution of this thesis is to provide a combination of forecasting and inventory management which using the USM method for inventory control. There is no such integrated software program on the market, especially considering logistics cost, container loads, and backorder cost, so this study can be very effective in reducing the total cost by reducing backorder cost and logistic cost. If this combined method can be implemented successfully, companies could have a more effective supply chain and total costs could be reduced.

The rest of this section is organized as follows. Section 1.2 presents the forecasting methods, and Section 1.3 presents inventory management models. After, Section 1.4 explains the problem definition of this study. Research methodology of this thesis is explained in Section 1.5. The summary of this thesis is presented in Section 1.6.

1.2. Forecasting Methods

In this thesis, the objective is to determine the optimal ordering quantity (Q) and the reorder point (R) which minimize total supply chain costs. Demand quantities are used when calculating the optimal order quantity (Q) and reorder (R) point. Demands for future years based on past values can be found by the forecasting method. Forecasting is the process of making predictions of the future, given all of the information available, including historical data and knowledge (Hyndman and Athanasopoulos, 2018; p. 14). There are two types of forecasting methods which are the most accepted classification; qualitative and quantitative. Qualitative methods are used for forecasting when historical data are not available (Waters, 2008; p. 233). The five most widely used qualitative techniques are Delphi method, personal insight, panel consensus, market surveys, and historical analogy (Waters, 2008; p. 235). Quantitative methods are used when historical data available and can be performed to predict future values (Waters, 2008; p. 233). These methods are objective. Quantitative methods are also divided into two which are time series models and causal models (Chase, 2013; p. 84). Causal models consider the relationship between the variable to be forecast and the other variables when estimating the future value of a variable

(Chase, 2013; p. 86). The most common causal model is regression analysis (Chase, 2013; p. 86).

Time series methods use historical data to predict the future. There are several time series models that are moving average, exponential smoothing, and autoregressive integrated moving average (ARIMA) or Box–Jenkins, etc. (Chase, 2013; p. 84). These methods basically assume that the past will guide the future.

The time series model is a widely used method of analysis of time-dependent data obtained in the field of statistics, industry, economics, meteorology, medicine, agriculture, biology, etc. The purpose of this time series analysis is to understand the past values of the observed series and to predict the future values of the variables in the time series based on historical values (Hyndman and Athanasopoulos, 2018; p. 17). A large number of reliable data is needed to achieve the goal in time series (Chase, 2013; p. 85). To obtain good results from these data, it is necessary to provide the assumptions required for time series. In the time series study, accurate determination of the model and compliance of the model with the data is important. An incorrectly determined model does not yield correct results. The suitability of the model should be tested after the model is determined and accurate predictions can be found by establishing the appropriate model values (Hyndman and Athanasopoulos, 2018; p. 62).

Autoregressive integrated moving average (ARIMA) models which is the most advanced time series technique were popularized by Box and Jenkins in the early 1970s (Chase, 2013; p. 203). ARIMA models are applied to non-stationary series which are converted into stationary with integration. In practice, many time series exhibit nonstationary behavior. ARIMA models have an autoregressive process (AR) and a moving average process (MA). In addition to these processes, the Integrated (I) section is added to make the series stationary. Although there is not a very obvious nonstationary behavior in our data, nonstationary situations were observed when detailed examinations performed. Thus, the ARIMA method is used to predict future values of a time series in this study.

There are 4 different components that affect the time series. (Dagum and Cholette, 2006; p.16).

1. *Trend Component:* Trend is the long-term component that represents the growth or decline tendency of a variable over an extended period of time. If a time series has an upward or downward trend, it called nonstationary.

2. *Seasonal Component:* The seasonal component represents the fluctuations in time series that repeat itself each year.

3. *Cyclical Component:* The cyclical component represents the fluctuations that are not related to seasonal changes. These fluctuations often influenced by factors affecting the economy.

4. *Irregular or Random Component:* Random or irregular components are unspecified fluctuations, unlike other components. They represent erratic, nonsystematic, random fluctuations. They may result from accidents or natural disasters.

1.3. Inventory Models

Material planning which is a principle of having the raw materials, spare parts and all other materials required for production at the time when it is needed is significantly influenced the inventory management. The point at which raw materials are ordered is an issue that should be considered when making material planning. Inventory managements' main goal is to avoid holding too much stock (Agarwal, 2014; p. 233). Keeping too great or too small quantities on stock can cause some issues. Early ordering could results with overstocking or late ordering could results with out of stocks. It is also very significant how much we need to order. In summary, how much and when to order should be considered when planning material.

Inventory management is one of the most popular topics in recent years. There are many studies on inventory management models. Inventory management is divided into two groups according to demand types that are with a constant rate and uncertain rates (Nahmias, 2005). The economic order quantity (EOQ) model and its assumptions can be used when demand is assumed to be constant. The economic order quantity (EOQ) model is first developed by Harris (1913) and later Wilson (1934) further develop this work. The classical EOQ model assumes that the demand rate is constant and deterministic, there is no order lead time, and shortages are not allowed (Silver et al., 2016; p. 146). There are also extensions of the basic EOQ models developed for different assumptions (Nahmias, 2005; p. 199) One of the extensions of the basic EOQ model is the EOQ with finite production rate which assumes that units are produced internally (Nahmias, 2005; p. 218). If the production rate is considered as P, it must be greater than the demand λ in order to meet the demand (Nahmias, 2005; p. 218). In real life, if a very large quantity order is placed, the supplier is willing to charge less per unit. However, EOQ assumes that the price of each unit is independent of the size of the order and these quantity discounts should be added to the EOQ model (Nahmias, 2005; p. 220).

When the demand is uncertain, the methods that can be used are divided into two: periodic review and continuous review. Periodic review models may be for one period or multiple periods (Nahmias, 2005; p. 253). The single-period stochastic inventory model can be known as a newsboy or newsvendor problem. There is only one product in the newsboy problem and it can be used for a single period. In addition, this model only considers the overage and the underage cost (Nahmias, 2005; p. 259). The most known continuous review model is lot size-reorder point systems (Q, R). The (Q, R) model assumes that the demand is constant and stationary and there is a fixed positive lead time T. It tries to find optimal ordering quantity (Q) and reorder point (R). The classical newsvendor problem does not consider the setup cost. The (Q, R) model considers the setup cost but assumed that the inventory levels are reviewed continuously. (s, S) policy is a periodic-review model which considers the setup cost (Nahmias, 2005; p. 263). According to Silver et al. (2016), there is a continuous review system called (s, S) and an order is placed up to order-up-to-level S when the inventory position drops to the order point s or lower (Silver et al., 2016; p. 242). The (R, s, S) system is the combination of continuous review (s, S) and periodic review (R, S) systems (Silver et al., 2016; p. 244). The inventory position is checked at every R units of time, if it is at or below the reorder point s, orders are given to raise it to S (Silver et al., 2016; p. 244).

Unified Supply Model (USM) is an inventory management method to determine optimal order quantity and reorder point under uncertain demand (Ekinci, 2018). According to the USM method, an order must be placed each time the inventory level falls below the safety stock and the USM method tries to find these optimal order quantity, reorder point, and safety stock to minimize the total cost (Ekinci, 2018). The

USM may be defined as an improved version of the Economic Order Quantity (EOQ) method. The USM method has extensions for different assumptions such as uncertain demand and supply, transportation parameters and constraints, minimum order quantity constraint, supplier variance etc (Ekinci, 2018). However, this thesis focuses on a system with transportation issues like container loads, inventory holding, backorder and logistics costs under uncertain demand.

1.4. Problem Statement

Many strategic decisions such as inventory management, production planning, facility location planning, and process design interact with demand forecasts (Ivanov et al., 2017; p. 304). A demand forecast closer to actual values provides better management of the supply chain and many different advantages. Companies could reduce missed sales due to lack of products and inventory holding costs thanks to forecasting, etc. In addition to demand forecasting effective inventory management also provides companies with many advantages. Thus, this study focus on this issue and combine forecasting with inventory control.

Problem Statement: The main objective of this thesis is to find optimal ordering quantity (Q) and the reorder point (R) to minimize total cost which consists of inventory holding, backorder and logistics costs using a hybrid forecasting and inventory management environment.

For this purpose, first future demand values are found using the forecasting method and then the inventory method is applied. Inventory control is combined with forecasting for covering supply chain management. In other words, demand forecasts can be made for the following years by using past demand values, and then Q and R can be found with the inventory control method. ARIMA method is used to forecast the demand amounts for future years based on past demand data of a white goods company. After finding the demand, the Unified Supply Model (Ekinci, 2018) is used to find the optimal ordering quantity and the reorder point. The classical (Q, R) models consider setup, holding and ordering costs. However, this model considers backorder cost, logistic cost, and container load. Some algorithms are also used to calculate the optimum Q and R quantities. There is an application to show how to implement the

Unified Supply Model (USM) method by using both the actual demand values and the forecasted demand values which are obtained from the forecasting.

Having optimal Q and R can help about avoiding high costs. The optimal ordering quantity is important for the company as it can provide the order at the companies' lowest possible price. The reorder point ensures that there is sufficient stock to meet the demand until the next order arrives due to delivery time. Thus, by having an optimal reorder point, unsatisfied demand can be reduced and customer satisfaction can be increased.

This hybrid model for forecasting and inventory management can be very helpful in determining the future policies of the company since it can provide the forecasted order quantities for the future years and determine when and how much to order accordingly. Successful implementation of this hybrid method can help companies about having a more efficient supply chain and reducing the total costs.

1.5. Research Methodology

The research methodology of the forecasting part of this thesis can be defined as applied, having a descriptive empirical goal, since the forecasting model that adequately describes the causal relationships and helps to understand of real processes (Bertrand and Fransoo, 2002; p. 257). The research methodology in the inventory control part of this thesis can be classified particularly as an axiomatic quantitative research because of a mathematical modeling research method adopted in this part (Bertrand and Fransoo, 2002; p. 254).

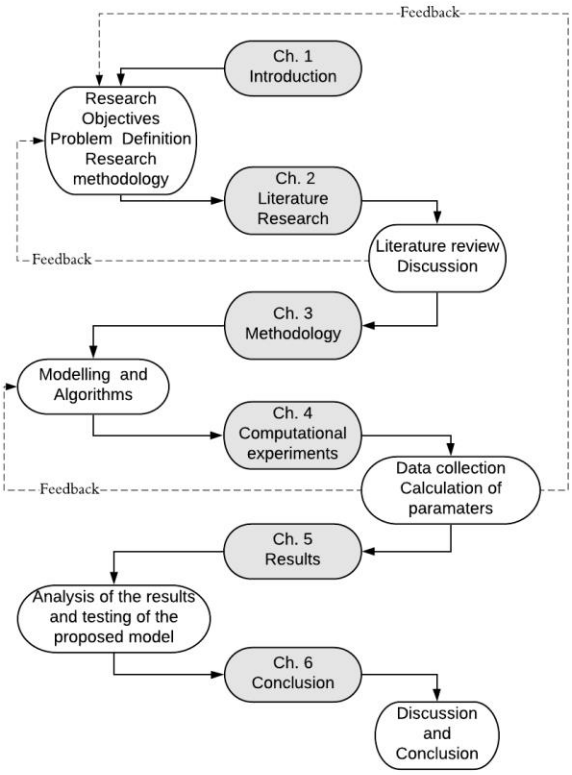

Figure 1. Research Procedure

According to Figure 1, the study starts with explaining objectives, motivation and problem definition. Then, relevant literature is reviewed. After the modeling and algorithms are provided, data collection and calculation of cost parameters are presented. Finally, the integrated tool is applied and this thesis ends with conclusions. Next section presents the outline of this study.

1.6 Thesis Summary

The remaining part of the thesis is organized as follows:

Section 2 provides a comprehensive literature review of inventory management and forecasting techniques.

Section 3 provides the solution methodology and algorithms used in this study.

Section 4 presents the data collection which is using in this study and also calculates the input data of the proposed model.

Section 5 presents and discusses the results from both forecasting and inventory management applications.

Finally, Section 6 summarizes the main conclusions and discussions of this thesis.

2. Literature Review

Section 2.1 reviews literature on forecasting methods. Section 2.2 provides a literature survey on inventory management models. Then, the survey of the literature is summarized and discussed in Section 2.3.

2.1. Literature Review on Forecasting Methods

There are numerous studies of different authors about forecasting and different forecasting methods. For example, Debnath and Mourshed (2018) propose a systematic review of forecasting methods in energy planning models. They compare fifty forecasting methods and enable researchers to select appropriate methods to meet their needs. Deb et al. (2017) present a review for forecasting time series energy consumption. They analyze the nine popular forecasting techniques and hybrid models with different combinations of forecasting techniques. Arvan et al. (2018) present a systematic review of the literature integrating forecasting methods which is a quantitative forecasting model with an experts' judgment. Aydin (2015) proposes linear and nonlinear regression analysis which is including logarithmic, power, exponential, inverse, and S regressions for forecasting global oil production.

Time series is one of the forecasting methods and assumes that the prediction of the future is based on past values of a variable (Wheelwright et al., 1998; p. 11). Tealab (2018) presents a systematic literature review of time series forecasting models using artificial neural network methodologies. Afilal et al. (2016) develop a long and short term forecasting model to predict daily attendance in an emergency department. Wang et al. (2018) propose a new neural networks-based linear ensemble framework (NNsLEF) for time series forecasting. Abhishek et al. (2012) study the Artificial Neural Network (ANN) method for weather analysis which is nonlinear and follows a very irregular trend. Bermúdez et al. (2010) propose a Bayesian forecasting approach with the Holt–Winters model, and the accuracy of the model is tested using several time series.

There are also several studies about ARIMA models which is a time series forecasting method. Ohyver and Pudjihastuti (2018) develop the time series model for forecasting rice prices using ARIMA. Silva et al. (2018) propose an ARIMA model for the time series forecasting of an emergency department of a hospital in Portugal. Cortez et al. (2010) present three time series methods which are a new neural network, adapted ARIMA method and adapted Holt-Winters method for multi-scale Internet traffic forecasting. Seasonal autoregressive integrated moving average (SARIMA) models are useful for modeling seasonal time series (Hipel and Mcleod, 1994). There are also several studies on SARIMA models. Kumar and Vanajakshi (2015) develop a model using SARIMA for forecasting traffic flow with limited data. Khashei et al. (2012) develop a new hybrid model with combining the seasonal autoregressive integrated moving average (SARIMA), artificial neural networks and fuzzy models for seasonal time series forecasting. Wang et al. (2012) compare PSO optimal Fourier method, seasonal ARIMA model and combined models of PSO optimal Fourier method with seasonal ARIMA for electricity demand forecasting in China. They obtain that the prediction accuracy of the combined model is better than the other methods. Chen et al. (2009) use Holt–Winters method, the seasonal ARIMA (SARIMA) model, and the grey forecasting model for forecasting air travel arrivals to Taiwan and compare the forecasting performance of these models'. Peng et al. (2012) propose a new hybrid method with combining echo state networks and multiplicative seasonal ARIMA model for mobile communication traffic series forecasting. Since this serial is multiperiodic and nonstationary, the proposed method is very satisfactory on the prediction accuracy. Because the proposed model uses multiplicative seasonal ARIMA to predict the seasonal part and echo state network to predict the smooth part.

In the literature, many hybrid forecasting methods are available. Models that combine two statistics and/or AI techniques, or more, can be considered as hybrid (Fajardo-Toro et al., 2019). Hybrid models often combine linear and nonlinear models. However, sometimes time series may be purely linear or purely nonlinear or combination of both. Therefore, Panigrahi and Behera (2017) develop a new hybrid methodology (ETS - ANN) by combining linear and nonlinear models. Shabanpour et al. (2017) propose a new hybrid method with combining artificial neural networks (ANN) with dynamic data envelopment analysis (DEA) to forecast the future efficiency of green suppliers. Nieto et al. (2018) develop the hybrid model that combines autoregressive integrated moving average (ARIMA), generalized autoregressive conditional heteroskedasticity (GARCH) and Bootstrap time series method for forecasting air transportation passenger demand. They combine the trend, variations, and historical distribution of data to eliminate the detrimental effects on forecasting with the help of this hybrid method. Xiao et al. (2012) develop a hybrid forecasting model that combines autoregressive integrated moving average (ARIMA) with Elman artificial neural network (ANN) and the experimental results of this study show that the forecasting performance of the proposed hybrid model is better than ARIMA model and Elman network in general.

2.2. Literature Review on Inventory Management Models

In the literature, there are many studies on Economic Order Quantity (EOQ) models. For example, Wahab and Jaber (2009) propose economic order quantity models based on Salameh and Jaber (2000) for with imperfect quality items with different holding costs. The lot size is found and compared for the models with and without the learning system with the assumption of demand is constant. Sana and Chaudhuri (2008) analyze the EOQ model for various types of deterministic demands for a retailer under permissible delays in payments and with price-discount offers. San-José et al. (2017) propose an economic order quantity (EOQ) inventory model for demand dependent on both time and price items to find the optimal price, the optimal lot size, and the optimal replenishment cycle. Cárdenas-Barrón et al. (2018) propose two economic order quantity (EOQ) inventory models with and without shortages and both models including the nonlinear demand, nonlinear stock holding cost, and trade credit. The goal of both inventory models is to determine the optimal ordering quantity and the ending inventory level in order to maximize the total profit of the retailers.

Nemtajela and Mbohwa (2017) research the relationship between inventory management and uncertain demand and obtain that there is a significant relationship between them. If demand is assumed to be constant, the classical economic order quantity (EOQ) model is highly applicable. However, when demand is uncertain, it does not work well. Some studies use advanced versions of the EOQ model when demand is uncertain. Therefore, Liao and Deng (2018) develop an extended EOQ model for cases where demand is uncertain. Balcik et al. (2016) present a literature survey about humanitarian inventory planning and management. Ziukov (2015) presents a literature review about inventory management models under uncertainty. Dai et al. (2017) propose multi-echelon inventory models with various demands which are ramp-type demand, reverse ramp-type demand, and trapezoidal-type demand to different stakeholders which are a retailer, a plant and many middlemen. When the demand modes for stakeholders are different, different inventory models should be used.

The uncertainty in most models is in demand. However, there can be uncertainty in lead time. Alawneh and Zhang (2018) propose a multi-item inventory model which takes into account the warehouse capacity constraint, demand uncertainty, and lead time uncertainty for the dual-channel warehouse to determine the ordering quantities and reordering points. Chopra et al. (2004) analyze the effect of lead time uncertainty on safety stocks.

In the literature, there are many studies on the newsboy model which is a single-period stochastic inventory model. Khouja (1999) reviews the extensive contributions to the newsboy problem. Qin et al. (2011) develop Koujas' study by considering different extensions. They focus on reviewing previous studies and developing extensions related to customer demand, supplier pricing policies, and buyer risk profile. Fard et al. (2019) develop a utility adjusted newsvendor model which can determine optimal inventory decision with the objective of maximizing expected utility based on the inventory manager’s degree of risk aversion. There are also studies about multi-period. For example, Matsuyama (2006) proposes a multi-period newsboy problem to deal with quantity unsold or unsatisfied demand. The initial inventory level of each period is tried to be determined to maximize total profit. Kim et al. (2015) propose a multi-period newsvendor model with non-stationary demand to optimize the total logistics cost for perishable products. According to the results of this study, the proposed multi-period stochastic model performs better than the EOQ and single-period newsvendor models.

Lot size-reorder point system (Q, R) is the most studied continuous review model. Handfield et al. (2009) develop a (Q, R) model in a fuzzy uncertain environment that considers uncertainty in demand, lead time, supplier yield and penalty cost. Kao and Hsu (2002) discuss a lot size-reorder point inventory model with fuzzy demands where backorders are permitted with a shortage cost. El-Wakeel and Fergany (2013) propose a probabilistic (Q, R) inventory model with partial backorders to find order quantity and reorder point which minimizes expected annual total cost.

The other periodic-review inventory model is (s, S) policy (Nahmias, 2005; p. 263). Qiu et al. (2017) develop (s, S) policies for periodic-review inventory management problems with fixed ordering costs under uncertainty. Ekren and Ornek (2015) propose an (s, S) inventory model for a paint products company with stochastic demand and lead time. There are also many studies in the literature regarding other inventory management methods but these do not be included in this study.

2.3. Discussion on the Literature Review

There is no study in the literature on the Unified Supply Model method. Since it is a new method, there are not many studies about it yet. There are many studies on the combination of forecasting and inventory management. Table 1 summarized the literature for the combination of forecasting and inventory management.

Table 1. Summary table for the combination of forecasting and inventory management.

Author	**Objective**	**Inventory Management Method**	**Forecasting Method**	**Results**
Kurawarwala and Matsuo (1996)	To obtain monthly forecasts and find procurement and average safety stock levels and effective service levels	A finite-horizon stochastic inventory model and multiple period extension of the newsboy policy	A seasonal Bass-type growth model	1st case: 43% and 21% decrease on effective service levels (ESL). 2nd case: 38% and 19% decrease on ESL.
Sani and Kingsman (1997)	To compare various periodic inventory policies and some forecasting methods with two different performance measures	Normal and power approximation, Naddor's heuristic, modified continuous review, original simple rule, mod. simple rule, original dealer rule, mod. dealer rule (1,2), (T, R) model	Croston's method, single exponential smoothing, moving average (MA), and dealer forecast method	MA is the best forecast method and Naddor's heuristic, the Power and Normal approximations are best inventory models
Rahman (2008)	To adopt the best forecasting technique resulting in minimum errors and inventory costs	An extended newsvendor model and a periodic review model	Probability Distribution model with Bayesian Techniques, ARIMA and Bayesian ARIMA Techniques, Exponential Smoothing	Bayesian ARIMA Techniques with newsvendor method is the best
Syntetos et al. (2010)	To explore forecasting and stock control for increasing service levels and reducing costs	The periodic reorder point (T, r, Q) policy, with the review period T=1	SES and SBA	Combination of (T, r, Q) and SBA is the best policy

Solis et al. (2012)	To compare the performance of forecasting methods for inventory management	(T, S) periodic review inventory control system	Simple moving average (SMA), single exponential smoothing (SES), Croston’s method, and Syntetos-Boylan approximation (SBA)	SBA is found to be best performing method and the average inventory on hand is lowest when using SBA for forecasting
Ramaekers and Janssens (2014)	To decide optimal combination of forecasting method and inventory management policy to minimize total cost	The (R, s, S) policy and the (R, s, Q) policy	Croston’s method, single exponential smoothing and 4-period simple moving averages	The combination of (R, s, Q) and MA is the best policy
do Rego and de Mesquita (2015)	To find the best forecasting and inventory control combination for each SKU	(s, nQ) inventory control	SMA, SBA, and Bootstrapping	Should revise the Stock Keeping Units (SKUs) once in a half year with taking the last 6 months of the demand records.

All of the studies in Table 1 used an integrated forecasting and inventory management system. For example, Kurawarwala and Matsuo (1996) propose an integrated framework for forecasting and inventory management of short life-cycle products. do Rego and de Mesquita (2015) present results of a simulation study on demand forecasting and inventory control to select best policies. Sani and Kingsman (1997), Rahman (2008), Solis et al. (2012), and Ramaekers and Janssens (2014) compare the performance of different forecasting and inventory management methods. Syntetos et al. (2010) develope forecasting and stock control system to increase service levels and reduce the total inventory costs include the inventory holding cost, the backlog cost and the ordering cost in a wholesaling context.

This study differs from other studies in the literature because inventory holding, backorder, and logistic costs are considered in this study. Unified Supply Model (USM) method is first introduced by Ekinci (2008) and it is defined as an improved version of the Economic Order Quantity (EOQ) method to determine optimal order quantity and reorder point under uncertain demand. The USM method has different versions for different issues such as transportation issues like container load utilization and production issues like minimum order quantity, maximum load per period, and shelf life. In this thesis, this method is used since this model takes into account container loads and demand uncertainty when considering inventory holding, backorder, and logistic costs. Another motivation for choosing this method is that no other studies are using this method in the literature.

This thesis proposes an integrated inventory management tool which consists of forecasting and inventory management. The aim of this integrated tool is determining optimal order quantity and reorder point with using forecasted demand data to minimize total supply chain cost.

3. Methodology

This chapter presents the methodology of this study. Sectin 3.1 describes the solution methodology and Section 3.2 proposes the algorithms used in this thesis.

3.1. Solution Methodology

In this study, our aim is to create an integrated inventory management tool for industrial stakeholders. The proposed model includes two main parts that are forecasting based on past experiences and quick and holistic inventory management tool. In the first part of the model, the proposed model uses an autoregressive integrated moving average (ARIMA) forecasting model to predict upcoming periods' order quantities by using dynamic data collection mechanisms. The second stage of the model tries to find optimal ordering quantities and reorder points in order to minimize total supply chain cost.

As a general definition, forecasting is the determination of future events based on historical facts and data. In forecasting, at first, all information is collected, and the method that will give the best estimation should be selected. There is not one single model that works best in all situations. It all depends largely on the availability and nature of the available data (Hyndman and Athanasopoulos, 2018; p. 16). Forecasting methods assume that the past will guide the future. Time series models generally require at least 20 observations, while in some models at least 50 observations are required (McCleary et al., 1980; p. 20).

The time series is a set of measurements that are sequenced in successive periods of time or at successive points over time (Anderson et al., 2012; p.786). The purpose of this analysis is to ensure that the future values of the time series based on historical data are well predicted.

ARIMA model is one of the two most widely used approaches to time series forecasting and ARIMA is an acronym for AutoRegressive Integrated Moving Average (Hyndman and Athanasopoulos, 2018; p. 221). The general representation of the models is ARIMA (p, d, q). Here, p is the number of time lags of the Autoregressive (AR) model, q is the order of the Moving Average (MA) model and d is the degree of difference.

The general representation of ARIMA(p,d,q) is;

$$W_t = \varphi_1 W_{t-1} + \varphi_2 W_{t-2} + \cdots + \varphi_p W_{t-p} + \alpha_t - \theta_1 \alpha_{t-1} - \theta_2 \alpha_{t-2} - \cdots - \theta_q \alpha_{t-q} \qquad (1)$$

In Equation-1, W_t, W_{t-1}, W_{t-2} ,...,W_{t-p} are differencing observation values with degree of d, φ refers to the autoregressive parameters to be estimated, θ refers to the moving average parameters which are unknown and α refers to the error term.

In this study, RStudio version 1.1.463 (2009-2018 RStudio, Inc.), the *tseries* (version 0.10-46) and the *forecast* (version 8.7) packages are used for forecasting with ARIMA.

The general flowchart of solution methodology is given in Figure 2.

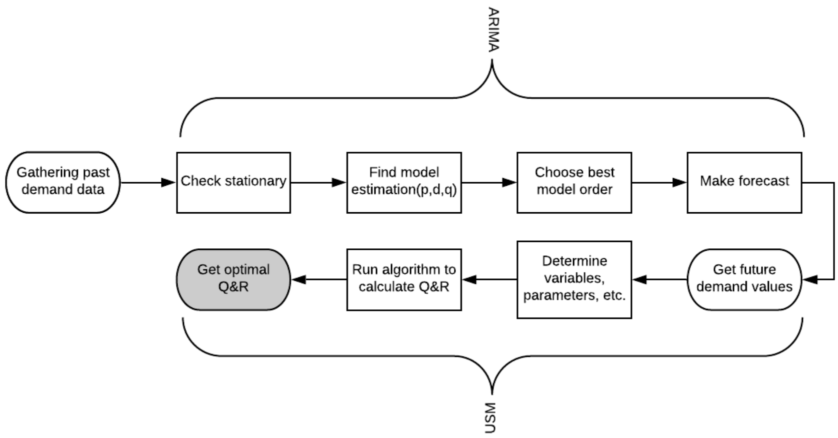

Figure 2. General Flowchart

As shown in the above figure, after gathering past demand data, the following steps can be followed to make an ARIMA forecast model:

1. *Check stationarity:* If a time series is nonstationary, it must be stationary before forecasting with ARIMA. There are several methods using in determining whether a series is stationary. The most famous one is the Augmented Dickey Fuller (ADF) test. If the p-value of the test is more than the significance level then you can not reject the null hypothesis. If the time series is not stationary, we need to make it stationary. There are several methods such as differencing method. The series is differentiated until stationary and the number of difference is called d.

2. *Find model estimation:* After finding *d* in the first step, we need to find *p* and *q* with the help of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the differenced data.

3. *Choosing the best fit model:* After determining parameters, the fitted model is found by experimenting with different parameters.

4. *Forecast using best fit ARIMA model:* Finally, forecasting is made by using the most fitted model order.

After finding predictions for demand values, the proposed Unified Supply Model is used to find optimal order quantities (*Q*) and the reorder points (*R*). Our main goal is to minimize total cost which consists of expected inventory holding cost, backorder cost, and logistic cost.

The notations used are shown in Table 2.

Table 2. Notations

Notations	Descriptions
R	Reorder Point
SS	Safety Stock
Q	Order Quantity
b	Back Order Cost
h	Inventory Holding Cost
T	Lead-time Period
K	Setup or transportation Cost
λ	Demand rate
f(x)	Probability Density Function for Lead-time Demand
F(x)	Cumulative Distribution Function for Lead-time Demand
n	Sampling amount for improper integral

From Table 2, there are three decision variables which are order quantity *Q*, reorder point *R*, and safety stock *SS*. The objective is to find optimal ordering quantity and reorder point to minimize total cost under demand λ.

There is a significant relationship between safety stock and order quantity due to their impact on holding and backorder costs. When the stock level is lower than the safety level *SS*, we need to order *Q*. The relationship between safety stock and ordered quantity can be explained in the simplest way like this. Thus, our reorder point is the sum of the *SS* and lead-time demand. According to the USM method, the general total cost function is as below;

$$TC = (hT) \lim_{n \to \infty} \sum_{i=0}^{n} \frac{\int_{-\infty}^{R+\frac{i}{n}Q} \left(R+\frac{i}{n}Q-x\right) f(x)dx}{(n+1)} + (b) \lim_{n \to \infty} \sum_{i=0}^{n} \frac{\int_{R+\frac{i}{n}Q}^{\infty} \left(x-R-\frac{i}{n}Q\right) f(x)dx}{(n+1)} + \frac{K\lambda T}{Q} \quad (2)$$

The first part of the function defines the expected inventory holding cost, the second one is about the backorder cost and the last one defines the production setup or transportation cost. The function for the expected total cost is changed since the optimum points of *R* and *Q* cannot be calculated with taking derivatives with respect to *R* and *Q*. Thus, our new function is in Equation-3.

The derivatives with respect to *R* are taken and equalized to zero.

$$\frac{dTC}{dR} = (hT) \lim_{n\to\infty} \sum_{i=0}^{n} \frac{\int_{-\infty}^{R+\frac{i}{n}Q} f(x)dx}{n+1} - (b) \lim_{n\to\infty} \sum_{i=0}^{n} \frac{\int_{R+\frac{i}{n}Q}^{\infty} f(x)dx}{n+1} \quad (3)$$

When the calculations are made, the formula in Equation-4 can be reached.

$$\lim_{n \to \infty} \sum_{i=0}^{n} \frac{F\left(R+\frac{i}{n}Q\right)}{(n+1)} = \frac{b}{(b+hT)} \quad (4)$$

And then, the derivatives with respect to *Q* are taken and equalized to zero.

$$\frac{dTC}{dQ} = (hT) \lim_{n\to\infty} \sum_{i=0}^{n} \frac{\int_{-\infty}^{R+\frac{i}{n}Q} \left(\frac{i}{n}\right) f(x)dx}{n+1} - (b) \lim_{n\to\infty} \sum_{i=0}^{n} \frac{\int_{R+\frac{i}{n}Q}^{\infty} \left(\frac{i}{n}\right) f(x)dx}{n+1} - \frac{K\lambda T}{Q^2} \quad (5)$$

When the calculations are made, the formula in Equation-6 can be reached.

$$Q = \sqrt{\frac{K\lambda T}{(hT+b) \lim_{n \to \infty} \sum_{i=0}^{n} \frac{\left(\frac{i}{n}\right) F(R+\frac{i}{n}Q)}{(n+1)} - \frac{b}{2}}} \quad (6)$$

Equation-4 and Equation-6 will be our equations in this study.

The classical EOQ formula does not consider uncertainty in demand. If the demand is uncertain, then the order optimization should consider the inventory and backorder costs, because of their effects on the inventory. According to the USM method, we should use Equation-7 to find optimum order quantity if there is container load constraint.

$$Q = \sqrt{\frac{2(K)(\lambda)}{(CSL)\,(h)}} \tag{7}$$

In Equation-8, CSL refers to customer satisfaction level. Customer satisfaction level defines how much of the demand is likely to be completed. Holding cost, backorder cost and lead time are used when calculating CSL. It is calculated with the below formula.

$$CSL = \frac{b}{b+hT} \tag{8}$$

Thereafter, it is necessary to control whether Q is greater than the container load (CL) or not. If Q is lower, this can be accepted as optimum order quantity. However, if Q is greater than CL, our logistic cost is affected so total cost, too.

$$\mathrm{Q} = \min(\mathrm{EOQ}, \mathrm{mCL}) \tag{9}$$

Thus, for solving this problem, the USM method uses the formula in Equation-9 where m is the number of containers.

After the calculation of order quantity, the reorder point can be found. Assuming that the reorder point is R and it has a coverage profile as $F(R)$ which is a number between 0 and 1. The number R that equates this F(R) to the customer satisfaction level (CSL) is our optimum reorder point. Thus, the relationship between R and CSL is like $F(R) = CSL$ and $R = F^{-1}(CSL)$. We need to make some changes when we want to consider the order quantities. If we say our order quantity is Q, then our inventory position circles between R & $R+Q$ and the coverage profile circles between $F(R)$ & $F(R+Q)$. According to the USM method, the formula to find R is in Equation-10.

$$Avg\big(F(R) + \cdots + F(R+Q)\big) = CSL \tag{10}$$

As it is shown in the above equation, if the average of the all coverage profiles between $F(R)$ and $F(R+Q)$ is equal to CSL, we have the optimum R.

The things mentioned so far were general, now our own problem will be discussed. The total cost formula is changed to fit our problem. Our own notations and indices are in Table 3.

Table 3. Customized Notations

Sets	
j	Set of product type j∈J (J=1,…,9)
Decision variables	
Q_j	Order quantity for product-j
SS_j	Safety stock quantity for product-j
R_j	Reorder point for product-j
Parameters	
λ_j	Average usage demand of product-j
std_j	Standard deviation of the demand for product-j
D_j	Mean of leadtime demand for product-j
$DStd_j$	Standard deviation of Lead-time demand for product-j
h_j	Inventory holding cost for product-j per period
K_j	Logistic cost for product-j
b_j	Back Order Cost for product-j
G	Fixed logistic cost per container
f(x)	Probability Density Function for Lead-time Demand
F(x)	Cumulative Distribution Function for Lead-time Demand
CSL_j	Customer Satisfaction Level for product j
CL_j	Container Load for product j
m	Number of containers
T	Lead-time for the production
n	Sampling amount for the mode
A	Number of periods in one fiscal year

Our aim is to find optimal ordering quantity and reorder point to minimize total cost under uncertain demand λ. The total cost consists of three parts which are inventory holding cost, backorder cost, and logistic cost. The objective function is:

$$Min\ TC_j = (h_j A)\left[\sum_{i=0}^{n} \frac{\left(R_j + \frac{i}{n}Q_j - D_j\right)F\left(R_j + \frac{i}{n}Q_j\right) + DVar_j f\left(R_j + \frac{i}{n}Q_j\right)}{n+1}\right]^{+} +$$

$$\frac{b_j}{T} A\left[\sum_{i=0}^{n} \frac{\left(D_j - \left(R_j + \frac{i}{n}Q_j\right)\right)\left(1 - F\left(R_j + \frac{i}{n}Q_j\right)\right) + DVar_j f\left(R_j + \frac{i}{n}Q_j\right)}{n+1}\right]^{+} + \frac{K_j \lambda_j A}{Q_j} \qquad (11)$$

This formula is a modified version of the formula in Equation-2 and calculates the total cost for the whole year. Because *n* is finite, the limit function is not used. The integral is not used because special formulas are used that only take positive results for the backorder and inventory amounts.

Since all these calculations will be difficult, we will use the algorithms that the USM method provided to us for calculating *Q* and *R*.

3.2. Algorithms

This section presents the algorithms used in this study.

<u>*Algorithm-1*</u>

Input: n, m, b, h, T, K, λ

Define Customer Satisfaction Level as CSL

Obtain CSL as $\frac{b}{(b+hT)}$

Define Economic Order Quantity as EOQ

Obtain EOQ as $\sqrt{\frac{2(K)(\lambda)}{(\mathrm{CSL})(h)}}$

Set founded EOQ as Q_1

Obtain R_{old} with Algorithm-2 by using $Q_x=Q_1$, CSL, n, F(x)

Obtain Q_{old} with Algorithm-3 by using $Q_x=Q_1$, $R_x=R_{old}$, b, hT, n, K, λ and F(x)

Obtain R_{new} with Algorithm-2 by using $Q_x=Q_{old}$, CSL, n, F(x)

Obtain Q_{new} with Algorithm-3 by using $Q_x=Q_{old}$, $R_x=R_{new}$, b, hT, n, K, λ and F(x)

While $[(-\frac{1}{n}) \leq \frac{R_{new}-R_{old}}{R_{old}} \leq \frac{1}{n}$ & $[(-\frac{1}{n}) \leq \frac{Q_{new}-Q_{old}}{Q_{old}} \leq \frac{1}{n}$ is not satisfied **do**

Specify R_{old} as R_{new}, Q_{old} as Q_{new}

Specify R_{new} & Q_{new} as 0

Obtain R_{new} with Algorithm-2 by using $Q_x=Q_{old}$, CSL, n, F(x)

Else Continue

Define number of containers as m

Obtain m as $\left\lceil\frac{\lambda}{CL}\right\rceil^{+}$

While $Q_{new} < mCL$ is not satisfied **do**

Specify $Q_{new}=mCL$

Else Stop. Specify R^* as R_{new}, Q^* as Q_{new}

Algorithm-2

Input: Q_x, CSL, n, F(x), T, λ

Obtain R as Tλ

Obtain z as $\frac{F(CSL\,)-T\lambda}{n}$

For (i=0, i≤n, i++)

average F(x) figures from (R) to (R+Q_x) by using $AvgCDF_{Old} = \sum_{i=0}^{n} \frac{F(R+\frac{i}{n}Q_x)}{(n+1)}$

Obtain $Diff_{old}$ as CSL-$AvgCDF_{old}$

Specify R as R+z

Specify $Diff_{old}$ & $Diff_{new}$ as 0

For (i=0, i≤n, i++)

average F(x) figures from (R) to (R+Q_x) by using $AvgCDF_{new} = \sum_{i=0}^{n} \frac{F(R+\frac{i}{n}Q_x)}{(n+1)}$

Obtain $Diff_{new}$ as CSL-$AvgCDF_{new}$

While $Diff_{new}$<0 & $Diff_{old}$>0 is not satisfied

While R+z=F(CSL) is not satisfied **do**

R=R+z

Else Specify R as Tλ , z as (-1)z, $Diff_{old}$ & $Diff_{new}$ as 0

Else Stop. R_{new}=R

Algorithm-3

Input: Q_x, R_x, b, hT, n, K, λ and F(x)

For (i=0, i≤n, i++)

average F(x) figures with weight of i and from (R_x) to (R+Q_x)

by using $WCDF = \sum_{i=0}^{n} \frac{i\,F(R_x+\frac{i}{n}Q_x)}{n(n+1)}$

Obtain Q_{new} as $\sqrt{\frac{K\lambda T}{(hT+b)WCDF-\frac{b}{2}}}$

4. Computational Experiments

Section 4.1 gives the information about dataset used in this thesis. The calculation of parameters is given in Section 4.2.

4.1. Data Collection

The data set is used in this study is a time series of the weekly demand values between 2008-2017 of a white goods company. There are demand values of 9 products for 520 weeks. Refrigerator types and their product codes are shown in Table 4.

Table 4. Refrigerator types and product codes

Product Code	Product Name
P1	French door refrigerator (4 door)
P2	Mini refrigerator
P3	Standalone upright freezer
P4	Bottom freezer refrigerator
P5	French door refrigerator (2 door)
P6	Single door refrigerator
P7	French door refrigerator (3 door)
P8	Chest freezers
P9	Top freezer refrigerator

Product codes will be used in the following sections instead of product names. The demand graphs were plotted for each of the 9 products to see their previous demand behavior. Figure 3 shows the past demand behavior of Product 1. You can see all product demand graphs in Appendix-A. And the average, standard deviation (*SD*), coefficient of variation (*CV*), maximum, and minimum numbers for 520 weeks demands of all products are shown in Table 5.

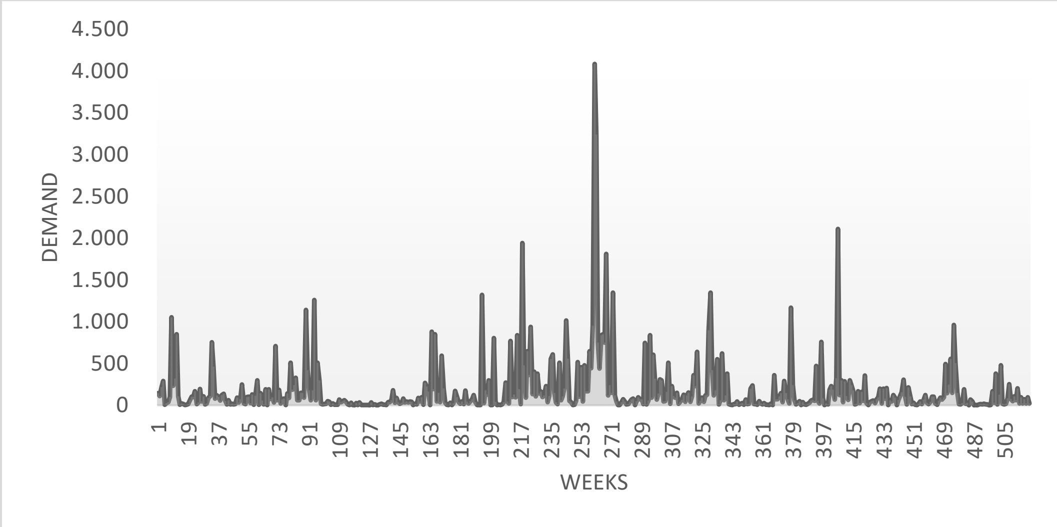

Figure 3. Plot of past demand behavior of Product 1

Table 5. Descriptive statistics for 10 years' demands of all products

	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**
Total	90.037	50.148	121.857	92.871	104.251	98.008	196.702	107.334	104.797
Avg	173	96	234	179	200	188	378	206	202
SD	346	201	515	312	392	372	787	517	630
CV	2,00	2,09	2,20	1,74	1,96	1,98	2,08	2,50	3,12
Max	4.086	2.644	6.300	2.541	3.540	3.305	8.030	5.002	5.208
Min	1	1	1	1	1	1	1	1	1

4.2. Calculation of Container Loads, Customer Satisfaction Levels, Lead Time Demand and Cost Parameters

According to the USM method, lead time demand parameters should be calculated if the lead time is greater than one period. In this study, it is assumed that the planning period is weeks, and the average lead-time is 3 weeks. Lead time demand parameters can be calculated according to formulas in Equation-12 and Equation-13 (Nahmias, 2005; p. 277).

$$D_j = T\lambda_j \tag{12}$$

$$DStd_j = \sqrt{Tstd_j^2} \tag{13}$$

These parameters are used for the probability density function. In this study, all cost calculations were made for 1 year, so A = 52. The product costs of our products are shown in Table 6.

Table 6. Product costs

Product Code	Product Cost
P1	₺ 15.000,00
P2	₺ 1.000,00
P3	₺ 3.500,00
P4	₺ 5.500,00
P5	₺ 8.000,00
P6	₺ 4.000,00
P7	₺ 10.000,00
P8	₺ 4.000,00
P9	₺ 4.500,00

The inventory holding cost is calculated by dividing the annual interest rate by 52 weeks and multiplying by the product cost. The annual interest rate is assumed to be 18% which is announced by the Central Bank of Turkey. For example, the inventory holding cost of Product 1 can be calculated as follows;

$$h = \frac{(15.000,00)*(0,18)}{52}$$

According to this calculation, the inventory holding costs are in Table 7.

Table 7. Inventory holding costs

Product Code	Inventory Holding Cost
P1	₺ 51,92
P2	₺ 3,46
P3	₺ 12,12
P4	₺ 19,04
P5	₺ 27,69
P6	₺ 13,85
P7	₺ 34,62
P8	₺ 13,85
P9	₺ 15,58

Backorder cost is a cost that occurs when a company cannot meet the demand and overtime the production to produce it. The backorder cost is assumed to be 20% of the product cost in our model and the backorder costs of all products are shown in Table 8.

Table 8. Backorder costs

Product Code	Backorder Cost
P1	₺ 3.000,00
P2	₺ 200,00
P3	₺ 700,00
P4	₺ 1.100,00
P5	₺ 1.600,00
P6	₺ 800,00
P7	₺ 2.000,00
P8	₺ 800,00
P9	₺ 900,00

Our model assumes that there is no setup cost. However, because our products are large products due to their size, logistics costs are must be considered. It is assumed to have a fixed logistics cost of 1000 ₺ per container. In addition, the number of products to be loaded into each container is different for each product because of different sizes, and these container loads should also be considered. The logistic cost for a product is the multiplication of the number of containers and the fixed logistic cost and calculated with the formula in Equation-14.

$$K_j = mG \tag{14}$$

$$m = \left\lceil \frac{\lambda}{CL} \right\rceil^{+} \tag{15}$$

The container loads are in Table 9.

Table 9. Container loads

Product Code	Container Load
P1	25
P2	60
P3	55
P4	40
P5	40
P6	45
P7	40
P8	40
P9	40

The customer satisfaction level (CSL) is calculated according to the formula in Equation-8. Table 10 shows the customer satisfaction levels of all products.

Table 10. Customer Satisfaction Levels

Product Code	Customer Satisfaction Level
P1	95,1%
P2	95,1%
P3	95,1%
P4	95,1%
P5	95,1%
P6	95,1%
P7	95,1%
P8	95,1%
P9	95,1%

5. Results

Results on forecasting are shown in Section 5.1. Section 5.2 presents the results of inventory management application.

5.1. Results on Forecasting

In this study, the ARIMA method is used to forecast demand values. The last 10 years demand values are used to forecast demand of 2018, and these are compared with actual demands to ensure the reliability of the results we receive from the ARIMA application.

When looking at the graphics of the original time series of the products, it is realized that there is not a very obvious nonstationary behavior. Augmented Dickey Fuller (ADF) test is applied to get a more precise result and find our series are stationary. In products 2,4,5,8 and 9, nonstationary situations are noticed. The first derivative is taken and the ADF test is applied again. These products now appear to be stationary. Thus, *d*, degree of differencing, is 1 for product 2,4,5,8 and 9.

After finding *d*, *p* and *q* values are needed to be found. *q* can be found with the help of the Autocorrelation Function (ACF) plot and *p* can be found with the help of the Partial Autocorrelation Function (PACF) plot of the differenced data.

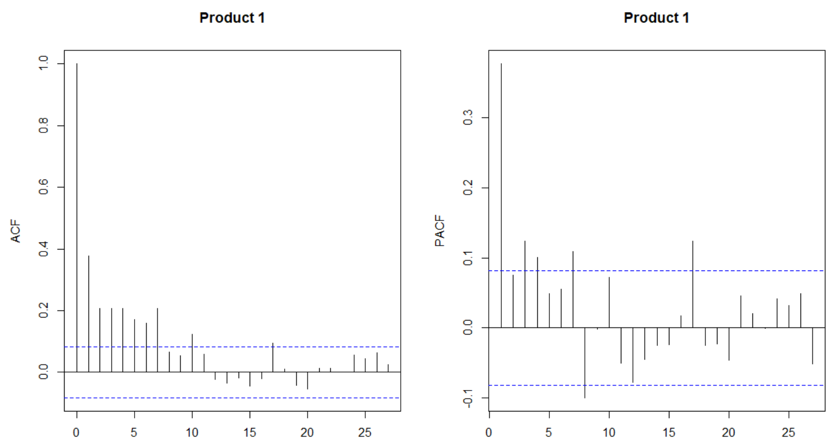

Figure 4. ACF and PACF plots of Product 1

When looking at the ACF plot of Product 1, it can be seen that there is a spike at lag 1 and 2 and it cuts off after lag 2. Thus, it means that *q* is 2. PACF plots cut off after lag 1 and it means that *p* is 1. The order of ARIMA(p,d,q,) for product 1 is ARIMA(1,0,2).

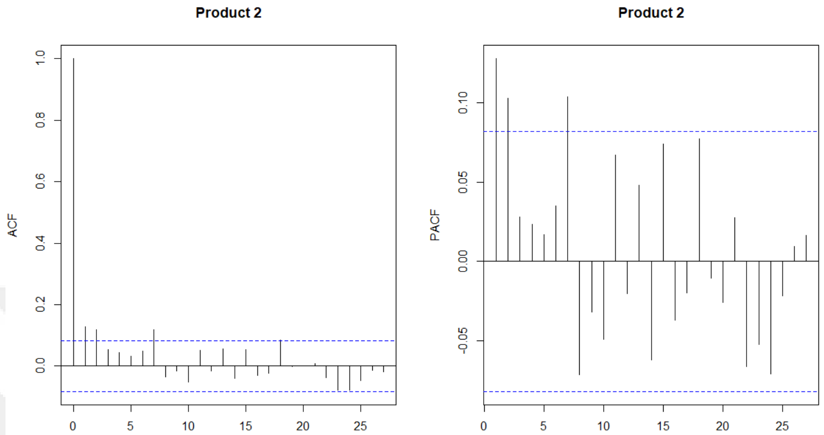

Figure 5. ACF and PACF plots of Product 2

For product 2, there is a significant spike at lag 1 in ACF plot which means that *q* is 1. In PACF plot, it can be seen that there is a cut off after lag 2, so *p* is 2. The order is 2,1,1.

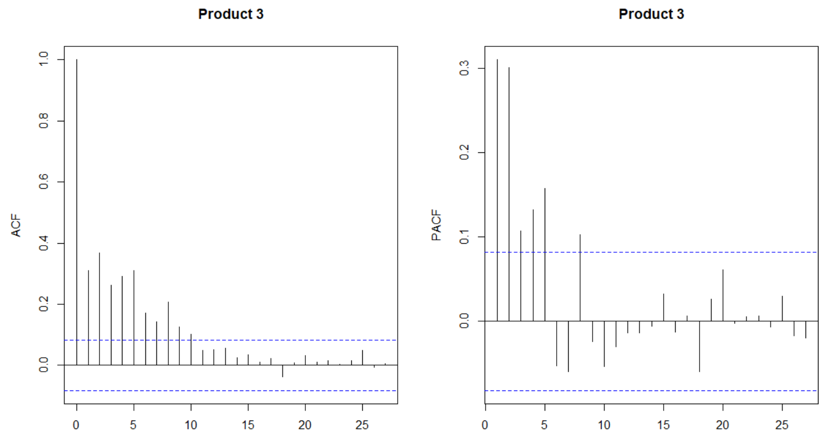

Figure 6. ACF and PACF plots of Product 3

When looking at ACF plot of Product 3, it cuts off after lag 1. PACF plot cuts off after lag 2 and it means that *p* is 2. The order of ARIMA(p,d,q) for product 3 is ARIMA(2,0,1).

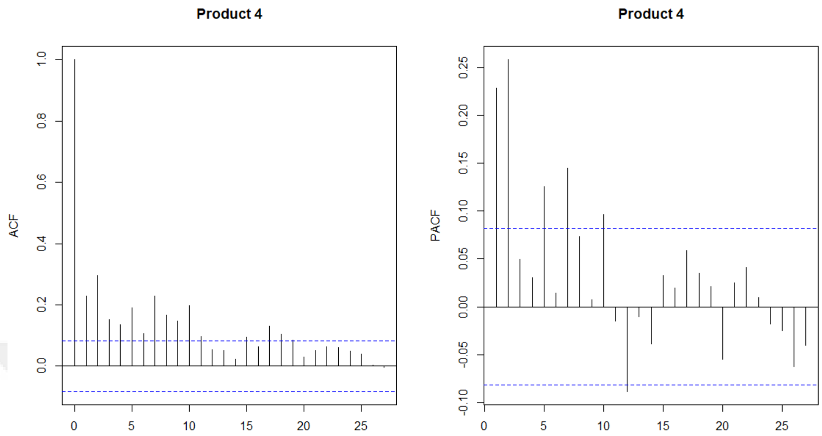

Figure 7. ACF and PACF plots of Product 4

ACF plot of product 4 cuts off after lag 1 and PACF plot cuts off after lag 2. Thus, the order of *p,d,q* is 2,1,1.

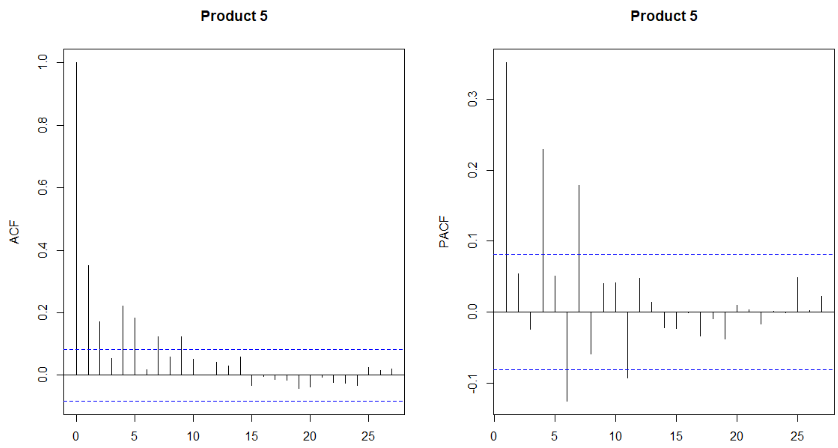

Figure 8. ACF and PACF plots of Product 5

For product 5, there is a significant spike at lag 1 in ACF plot which means that *q* is 1. In PACF plot, there is a cut off after lag 1, so *p* is 1. The order is 1,1,1.

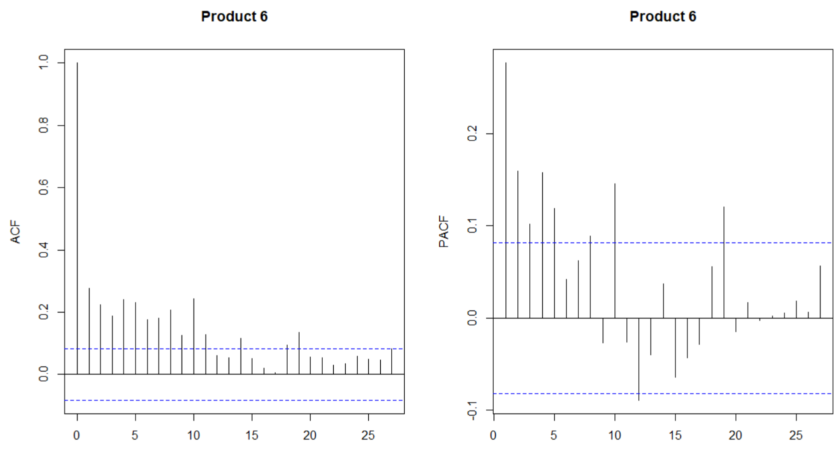

Figure 9. ACF and PACF plots of Product 6

When looking at the ACF plot of Product 6, it can be seen that there is a significant decrease after lag 1. Thus, it means that *q* is 1. PACF plot cuts off after lag 1 and it means that *p* is 1. The order of ARIMA(p,d,q) for product 6 is ARIMA(1,0,1).

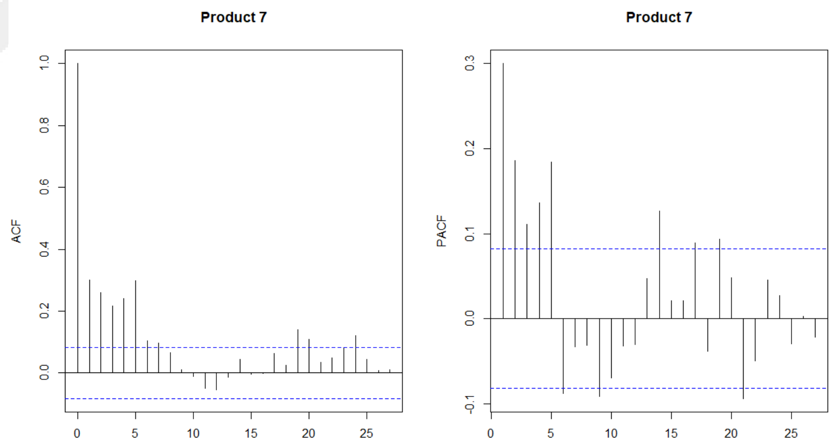

Figure 10. ACF and PACF plots of Product 7

ACF plot of product 7 cuts off after lag 1 and PACF plot cuts off after lag 2. Thus, the order of *p*,*d*,*q* is 2,0,1.

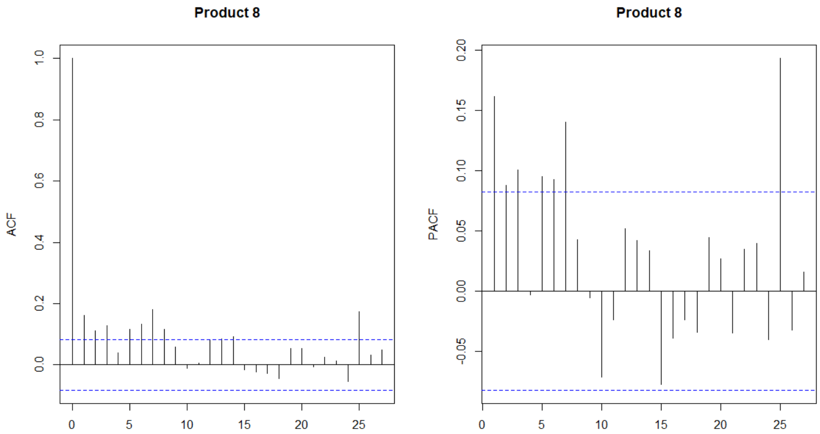

Figure 11. ACF and PACF plots of Product 8

For product 8, there is a significant spike at lag 1 in ACF plot which means that q is 1. In PACF plot, we realize that there is a cut off after lag 1, so p is 1. The order is 1,1,1.

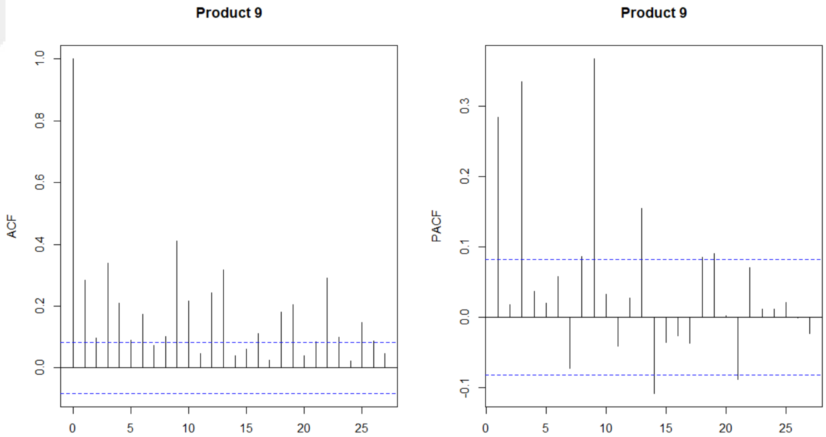

Figure 12. ACF and PACF plots of Product 9

ACF plot of product 9 cuts off after lag 2 and PACF plot cuts off after lag 1. Thus, the order of p,d,q is 1,1,2.

After determining parameters for products, the fitted model is found by experimenting with different parameters. In R, auto.arima function is used to find the best fitted model. The ARIMA orders are shown in Table 11.

Table 11. ARIMA orders of all products

Product Code	ARIMA orders
P1	1,0,2
P2	2,1,1
P3	2,0,1
P4	2,1,1
P5	1,1,1
P6	1,0,1
P7	2,0,1
P8	1,1,1
P9	1,1,2

After finding the best orders, forecasts for the demand of 2018 can be made to compare with actual demands. The comparison of actual and forecasted demand graphs of some products are in the following figures. You can see all the comparison graphs in Appendix-B.

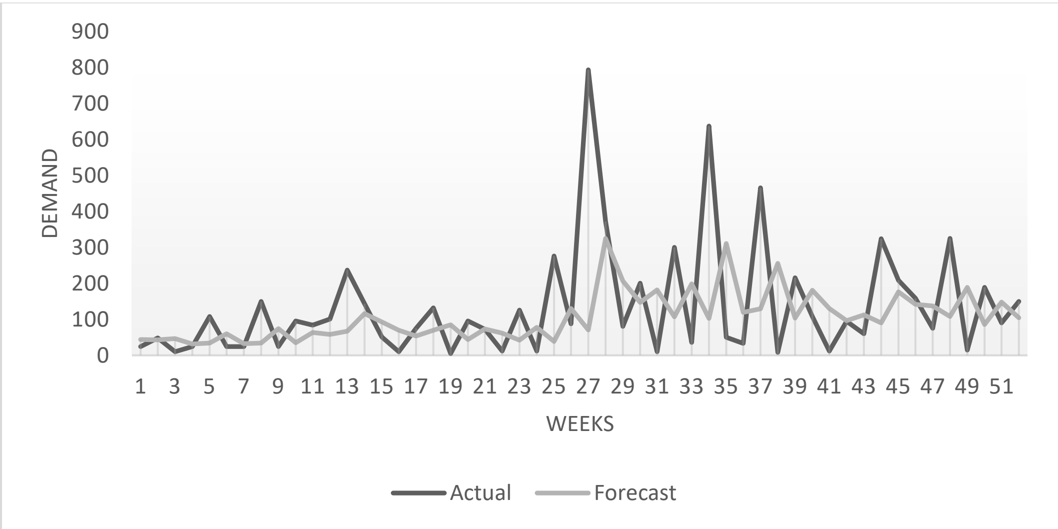

Figure 13. Comparison of actual and forecasted demand for Product 1

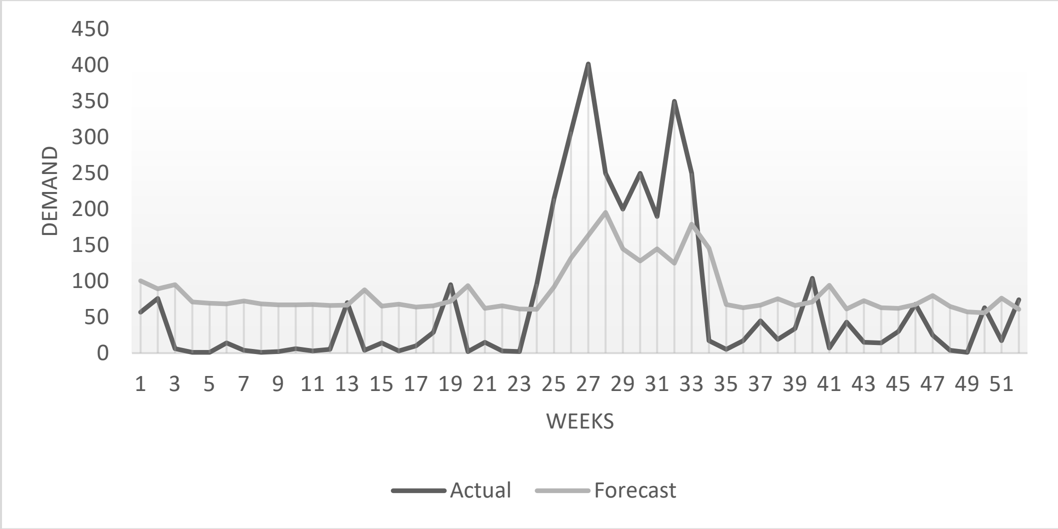

Figure 14. Comparison of actual and forecasted demand for Product 5

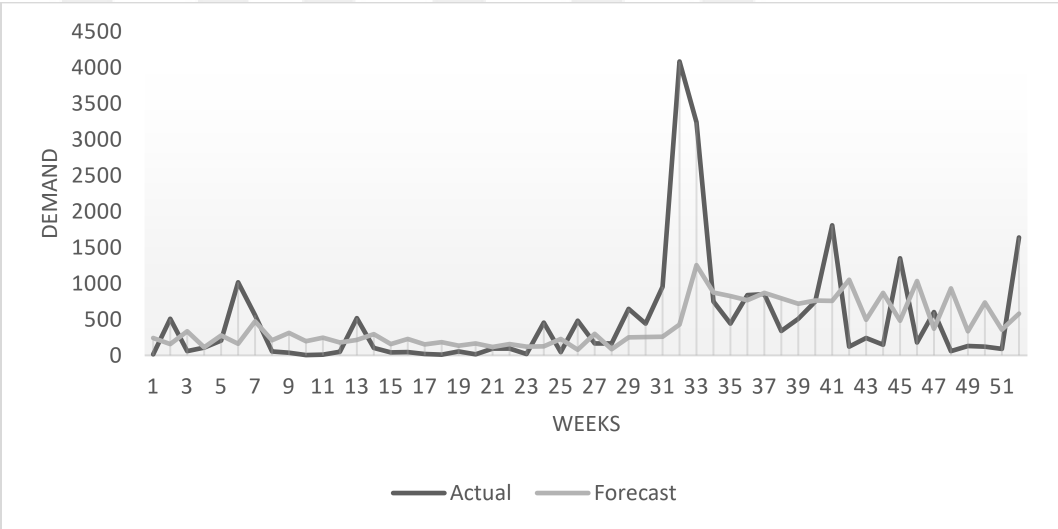

Figure 15. Comparison of actual and forecasted demand for Product 9

When these graphs are examined, it can be seen that the forecasting we implemented is quite successful. After obtaining demand values from forecasting with ARIMA, Unified Supply Model is used to find the optimal ordering quantity (Q) and the reorder point (R) to minimize total cost.

5.2. Results on Inventory Control Model

This section gives the results obtained from the inventory control model application. Average values and standard deviations of the next 1 years' demands which are found with using ARIMA forecasting are given in Table 12.

Table 12. Average and standard deviation of forecasted demand values

Product Code	Average	Standard deviation
P1	105	68
P2	93	17
P3	91	91
P4	496	199
P5	108	37
P6	140	46
P7	113	85
P8	94	16
P9	420	330

When the algorithms which are mentioned earlier are run, the *Q* and *R* values given in Table 13 can be obtained and the annual costs found using these values are given in Table 14.

Table 13. Optimal order quantity, reorder point and safety stock (using the forecasted data)

Product Code	Order quantity (Q)	Reorder point (R)	Safety Stock (SS)
P1	65	478	163
P2	120	294	14
P3	161	615	167
P4	234	1952	463
P5	80	318	63
P6	146	496	76
P7	83	544	204
P8	120	296	13
P9	237	2023	770

Table 14. Annual inventory holding, backorder, logistic and total costs (using the forecasted data)

Product Code	Inventory Holding Cost	Backorder Cost	Logistics Cost	Total Cost
P1	₺ 471.344,52	₺ 127.019,45	₺ 250.975,74	₺ 849.339,71
P2	₺ 12.689,30	₺ 2.673,76	₺ 80.720,61	₺ 96.083,67
P3	₺ 140.567,82	₺ 37.402,45	₺ 144.585,80	₺ 322.556,07
P4	₺ 512.944,06	₺ 138.129,99	₺ 661.124,09	₺ 1.312.198,15
P5	₺ 134.565,74	₺ 35.429,72	₺ 164.863,20	₺ 334.858,66
P6	₺ 98.232,18	₺ 25.268,82	₺ 199.619,39	₺ 323.120,39
P7	₺ 394.504,84	₺ 106.293,56	₺ 212.919,71	₺ 713.718,12
P8	₺ 49.899,41	₺ 10.320,56	₺ 122.943,57	₺ 183.163,54
P9	₺ 641.352,98	₺ 173.466,09	₺ 548.495,33	₺ 1.363.314,41

The costs shown in Table 14 are determined using the forecasted demand values which are found with using ARIMA. Table 15 shows the average values and standard deviations of the actual demands. If actual demand values for the same year are used, the optimal order quantity, reorder point and safety stock will be as in Table 16.

Table 15. Average and standard deviation of actual demand values

Product Code	Average	Standard deviation
P1	136	158
P2	72	93
P3	114	207
P4	623	724
P5	68	101
P6	158	179
P7	175	245
P8	95	133
P9	486	771

Table 16. Optimal order quantity, reorder point and safety stock (using the actual data)

Product Code	Order quantity (Q)	Reorder point (R)	Safety Stock (SS)
P1	74	825	417
P2	120	428	211
P3	141	869	526
P4	262	3809	1942
P5	72	458	254
P6	155	913	440
P7	103	1175	650
P8	120	609	324
P9	256	3539	2079

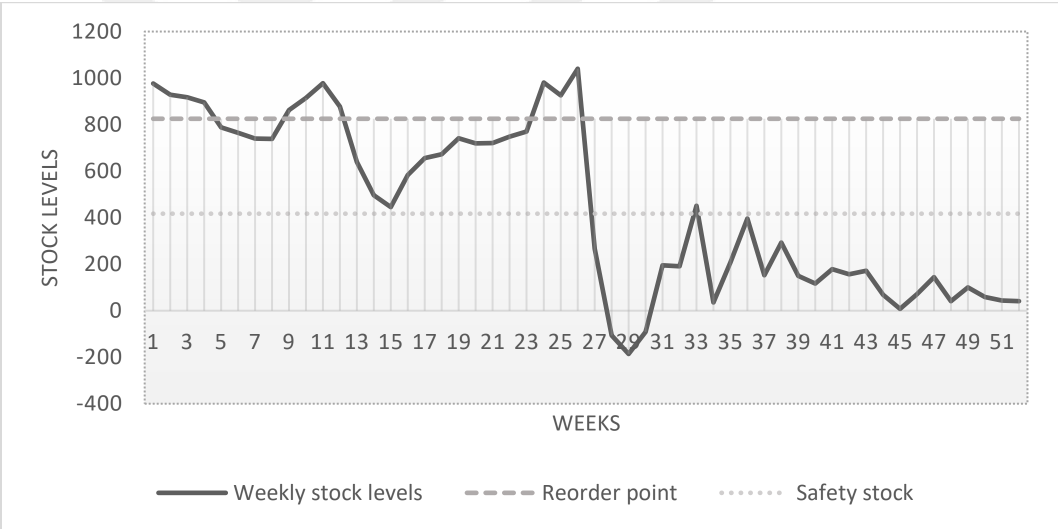

Figure 16. Stock levels of Product 1 (using USM method)

Figure 16 shows the stock levels of Product 1 for 52 weeks. The optimal order quantity is found by applying the USM method using the actual data of Product 1 is 74. An order is placed each time the stock level falls below the reorder point. When this graph is examined, it can be seen that the inventory amount is significantly higher than the backorder amount.

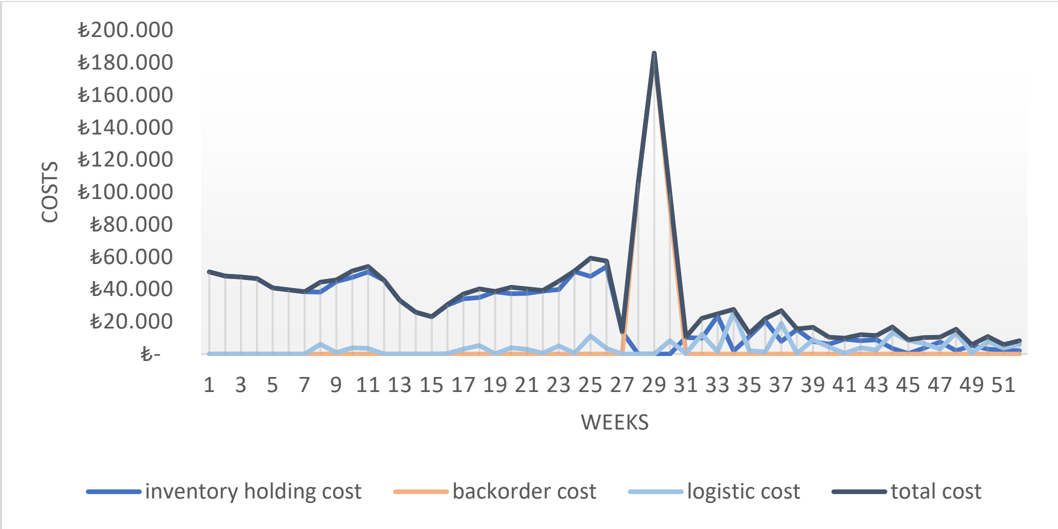

Figure 17. Weekly cost graph of Product 1

Figure 17 shows the weekly cost comparison graph of Product 1 and Table 17 shows the annual costs of all products.

Table 17. Annual inventory holding, backorder, logistic and total costs (using the actual data)

Product Code	Inventory Holding	Backorder	Logistics	Total Cost
P1	₺ 1.091.270,21	₺ 294.768,17	₺ 285.722,51	₺ 1.671.760,89
P2	₺ 43.580,24	₺ 11.723,67	₺ 62.633,33	₺ 117.937,25
P3	₺ 334.350,00	₺ 90.399,82	₺ 126.621,20	₺ 551.371,02
P4	₺ 1.824.555,18	₺ 493.880,65	₺ 863.946,19	₺ 3.182.382,03
P5	₺ 371.242,75	₺ 100.125,70	₺ 98.392,13	₺ 569.760,58
P6	₺ 332.070,79	₺ 89.586,03	₺ 211.845,99	₺ 633.502,80
P7	₺ 1.122.958,95	₺ 304.616,52	₺ 264.550,52	₺ 1.692.125,98
P8	₺ 246.533,86	₺ 66.515,30	₺ 123.300,00	₺ 436.349,15
P9	₺ 1.589.494,82	₺ 430.127,12	₺ 690.825,06	₺ 2.710.447,00

In this study, it is also observed how stock levels would change if (s, S) policy was used instead of the USM method. According to (s, S) policy method, if the level of on-hand inventory (u) is less than or equal to s, an order as S - u is placed. If u is greater than s, then no order is placed (Nahmias, 2005; p.283).

If u ≤ s, order S - u.

If u > s, do not order.

Since these s and S values are very difficult to find, (Q, R) policy can be used (Nahmias, 2005; p. 283). The relation between these values and (Q, R) are like $s=R$ and $S=R+Q$. The optimal solution of Q and R can be found with solving the below equations iteratively (Nahmias, 2005; p. 270).

$$Q = \sqrt{\frac{2\lambda\,[K+pn(R)]}{h}} \tag{16}$$

$$1 - F(R) = \frac{Qh}{p\lambda} \tag{17}$$

In Equation-16 and Equation-17, K is setup cost per order, p is the stock-out cost per unit of unsatisfied demand, h defines holding cost per unit, λ is expected demand rate and $n(R)$ represents the expected number of stock-outs incurred in a cycle.

Q and R values are calculated for Product 1 and (s, S) policy is applied. Consider the following values for the input parameters.

K= ₺200 / *order, p*= ₺3000 / *unit, h*= ₺51,92 / *unit / year,* λ=136.

The optimal solution is given below.

(Q, R)= (88,788), and so, s=788 and S=788+88=876.

The weekly stock levels of Product 1 which are calculated using these s and S values are shown in Figure 18.

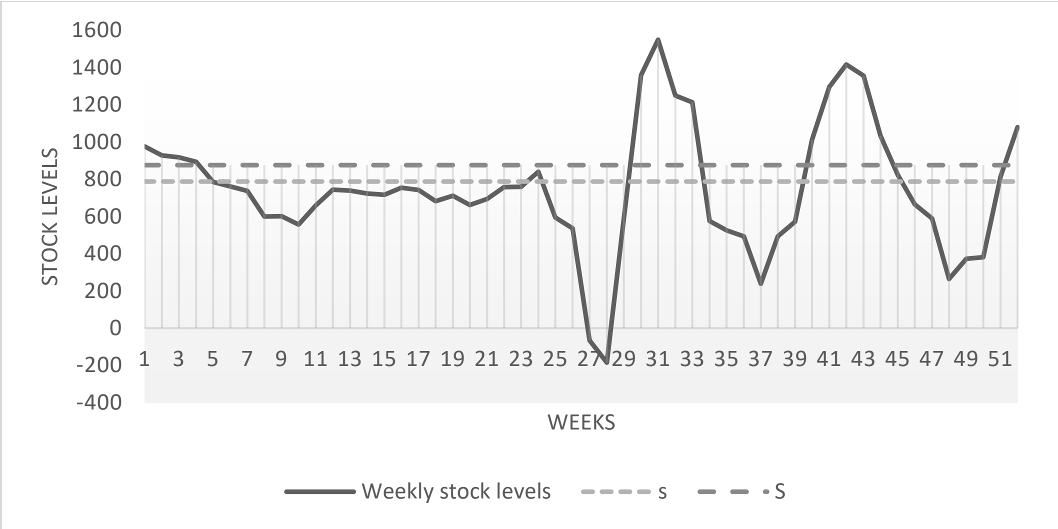

Figure 18. Stock levels of Product 1 (using (s,S) policy)

When Figure 16 and Figure 18 are compared, it can be observed that the amount of inventory when using the USM method is significantly less than the amount of inventory when using (s, S) policy.

As mentioned earlier, the backorder cost is assumed to be 20% of the product cost in our model. However, in order to analyze the effect of the backorder cost on the total cost, backorder costs should calculate with different rates. Changing the backorder cost affects the customer satisfaction level, so our optimal order quantity and reorder point changed again. Naturally, the total cost is affected. Total cost is calculated according to the USM method with different backorder rates by using actual demand values. Figure 19 shows the comparison of total costs with different backorder rates.

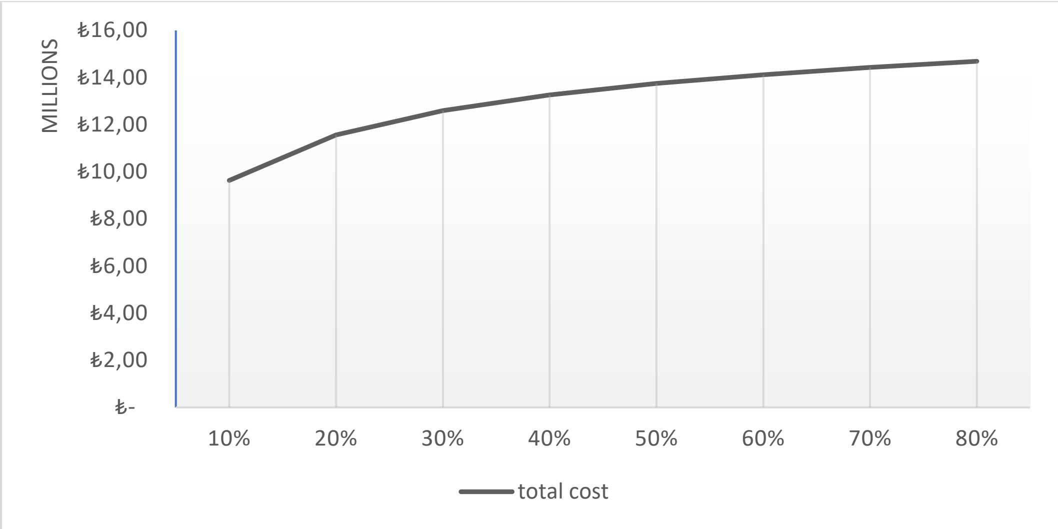

Figure 19. Comparison graph of total costs with different backorder rates

As you can see in Figure 19, the total cost increases as the return order cost increases. Assuming the backorder cost is 10% of the product cost, the CSL will be 90.6%. This is good value, but the company does not want it to remain below 95%, so the backorder rate continues to be used as 20%.

In this study, the lead time is assumed to be 3 weeks and CSL calculates with the formula in Equation-9. We wonder how CSL and total cost are affected if T changes. You can see the effect of changing T on CSL and total cost in Figure 20 and Figure 21.

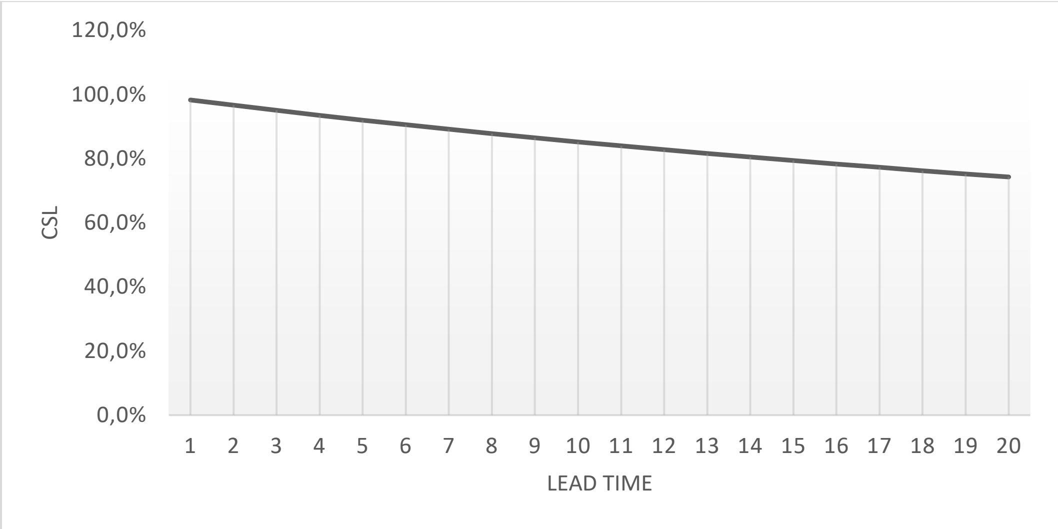

Figure 20. The effect of changing T on CSL

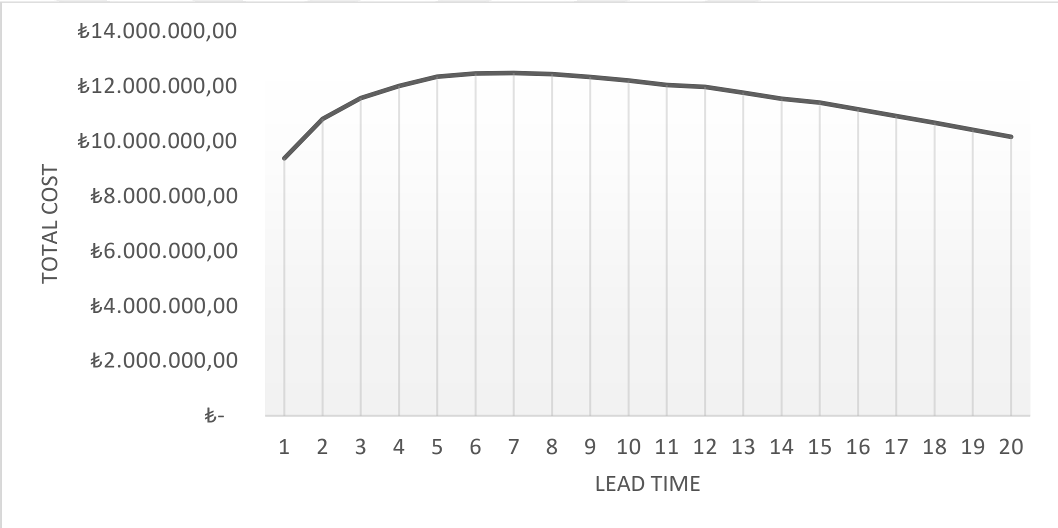

Figure 21. The effect of changing T on total cost (using actual data)

As you can see in the above figures, even if the CSL continues to decrease, the total cost increases for a while and then begins to decrease.

Before the application of this method, the company used the classic EOQ method to find *Q* and *R*. Classic EOQ formulas are shown in Equation-18 and Equation-19.

$$Q = \sqrt{\frac{2K\lambda}{h}} \tag{18}$$

$$R = (demand) * (lead\ time) = lead\ time\ demand \tag{19}$$

According to these EOQ formulas, our optimal order quantity and reorder point with using actual demand values are as in Table 18.

Table 18. Optimal order quantity and reorder point according to EOQ method (using actual demand)

Product Code	Optimal Order Quantity (Q)	Reorder Point (R)
P1	72	408
P2	204	217
P3	137	343
P4	256	1868
P5	70	204
P6	151	473
P7	100	524
P8	117	285
P9	250	1459

Figure 22 shows the comparison of the stock levels calculated using both the EOQ method and the USM method. It can be observed that the amount of backorder when using the USM method is significantly less than the amount of backorder when using the EOQ method. Also, when using the USM method, the inventory level is higher than the EOQ method.

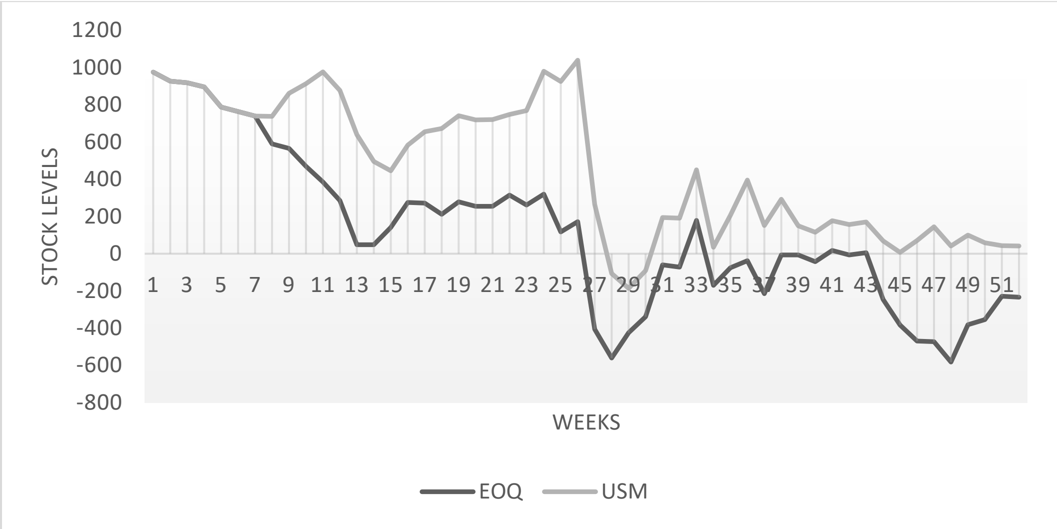

Figure 22. Comparison of stock levels

If the total costs that we obtain from the Unified Supply Model (USM) and the Economic Order Quantity (EOQ) method, in which we use forecasted and actual demand values, are compared, we can see the difference. As shown in Table 19, the company could save a significant amount of money by using the USM method effectively. You can see the detailed cost comparison for all 9 products in Appendix-C.

Table 19. Comparison of costs

		Holding Cost	**Backorder Cost**	**Logistics Cost**	**Total Cost**
Forecasted demand	***EOQ***	₺143.864	₺8.207.287	₺2.391.773	₺10.742.924
	USM	₺2.456.101	₺656.004	₺2.386.247	₺5.498.353
	Difference	**-₺ 2.312.237**	**₺ 7.551.282**	**₺ 5.526**	**₺ 5.244.571**
Actual demand	***EOQ***	₺98.096	₺30.776.212	₺2.807.034	₺33.681.342
	USM	₺6.956.057	₺1.881.743	₺2.727.837	₺11.565.637
	Difference	**-₺6.857.961**	**₺28.894.469**	**₺79.197**	**₺22.115.705**

As shown in Table 19, it is seen how much total cost will be decreased by the application of the USM method. It can be seen that a 49% reduction in total cost is achieved through the application of the USM method in the forecasted demand part of the table. In the actual demand part of the comparison table, it can be seen that there is a significant decrease on the backorder cost and an increase on the inventory holding cost, but not an equivalent amount. We also see the logistic cost change a little. To sum up, with the USM method application the company can save 22.115.705 TL.

5. Conclusion

In today's competitive world, inventory management has become very significant in terms of customer satisfaction and economic benefits provided by avoiding some issues like overstock, stockout, etc. Therefore, when and how much to order is a very important topic.

In this study, demand forecasting and inventory control are combined. The ARIMA method is used to forecast future demand values based on past demand data of a white goods company and then, these forecasted demand values are used for inventory control. Unified Supply Model is applied to find optimal ordering quantity and reorder point with the aim of minimizing total cost by using actual and forecasted demand values. In addition, the total cost is calculated according to USM and the EOQ method currently used by the company.

Thus, if the company implements the recommended USM method with actual data, they would be able to reduce their total cost from 33.681.342 TL to 11.565.637 TL which is a cost reduction of approximately 66%. For the forecasted data, the USM method application reduces the total cost of the company from 10.742.924 TL to 5.498.353 TL which is a cost reduction of approximately 49%. This recommended model is very helpful for the company to decrease the total cost by reducing the backorder cost significantly, even though the inventory holding cost increases.

This study shows that the USM method is an applicable method that provides better results than the EOQ method considering the total costs. Optimal Q and R can be achieved easily with the integrated tool compared to individual tools since more realistic inventory levels can be found by forecasting future demand successfully.

As future research directions, this study can be extended in a number of ways. First, the developed integrated model can be compared with other forecasting and inventory management methods by creating different combinations. Results can be used to measure the performance of the proposed tool. Second, in the forecasting part, the model can be tried with different demand distributions. Finally, further studies can be carried out using other previously mentioned versions of the USM method.

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APPENDICES

Appendix-A. Plots of past demand behavior

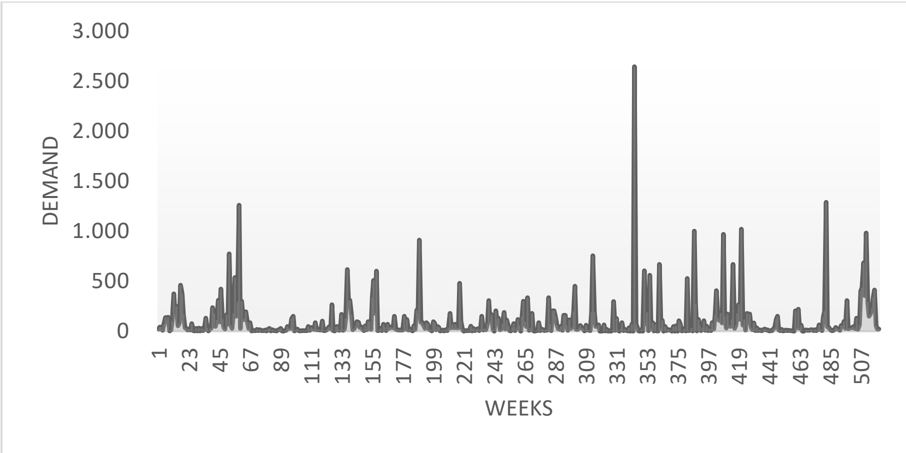

Figure 23. Plot of past demand behavior of Product 2

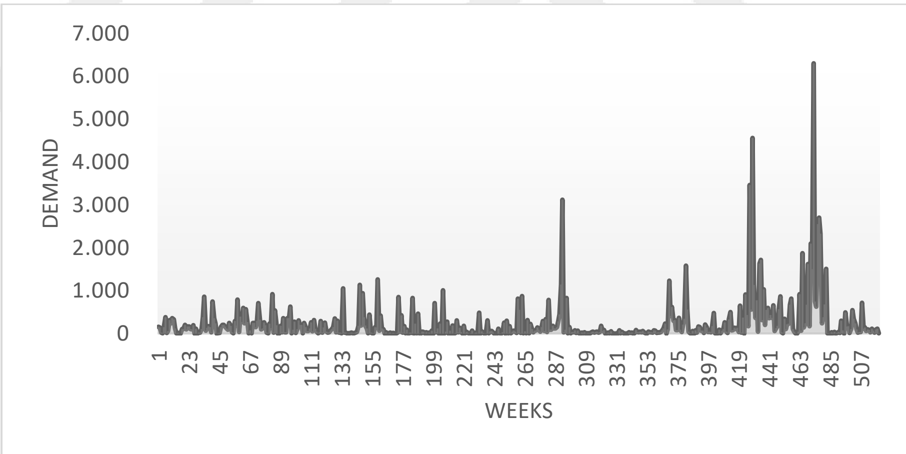

Figure 24. Plot of past demand behavior of Product 3

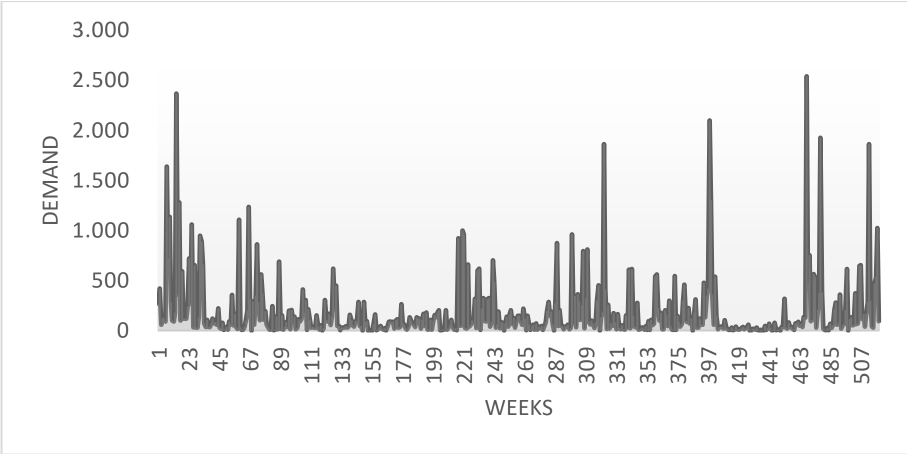

Figure 25. Plot of past demand behavior of Product 4

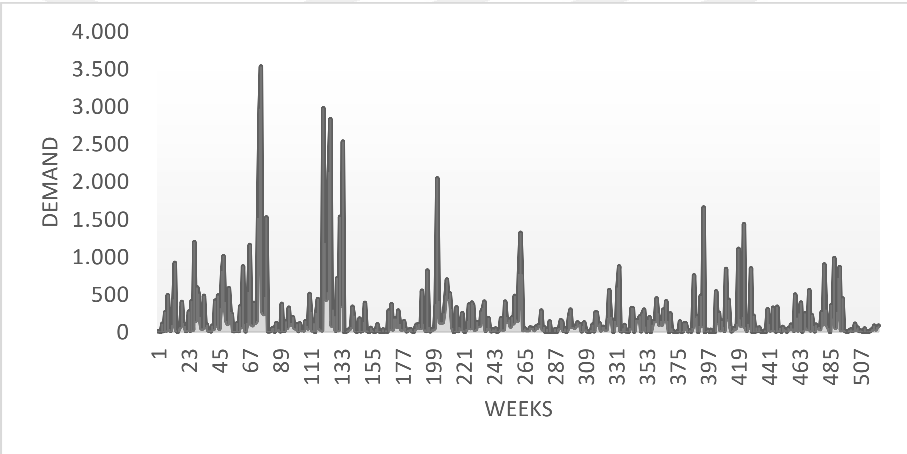

Figure 26. Plot of past demand behavior of Product 5

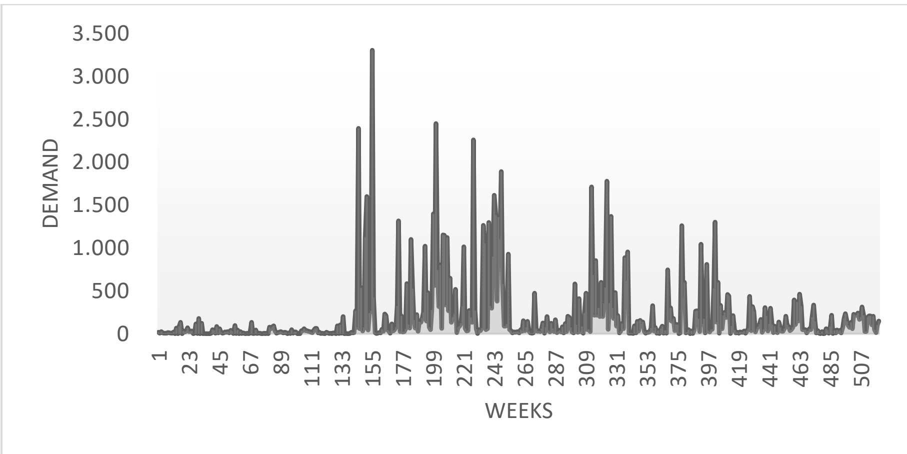

Figure 27. Plot of past demand behavior of Product 6

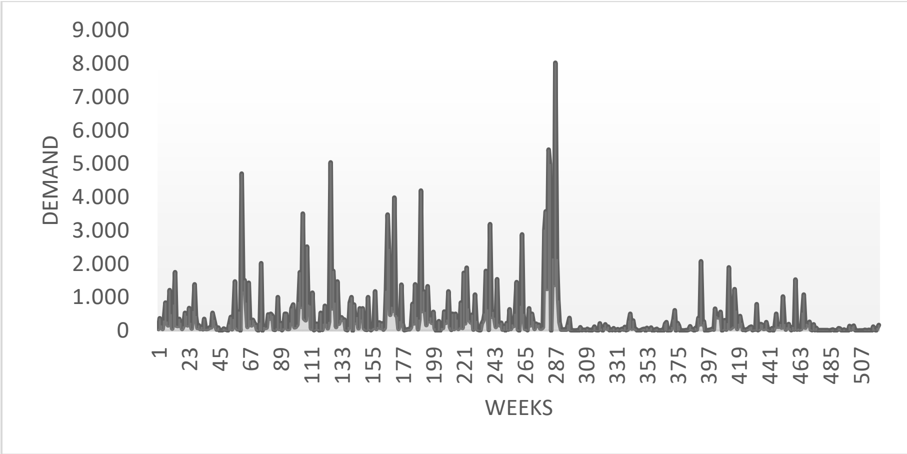

Figure 28. Plot of past demand behavior of Product 7

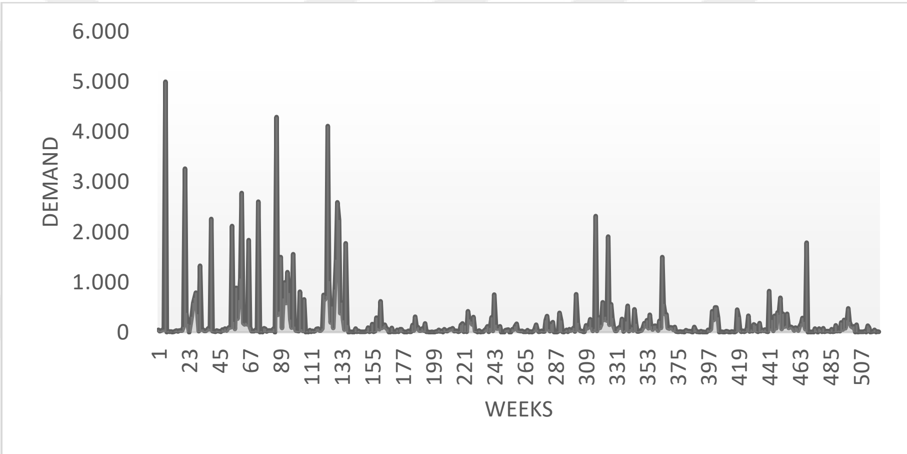

Figure 29. Plot of past demand behavior of Product 8

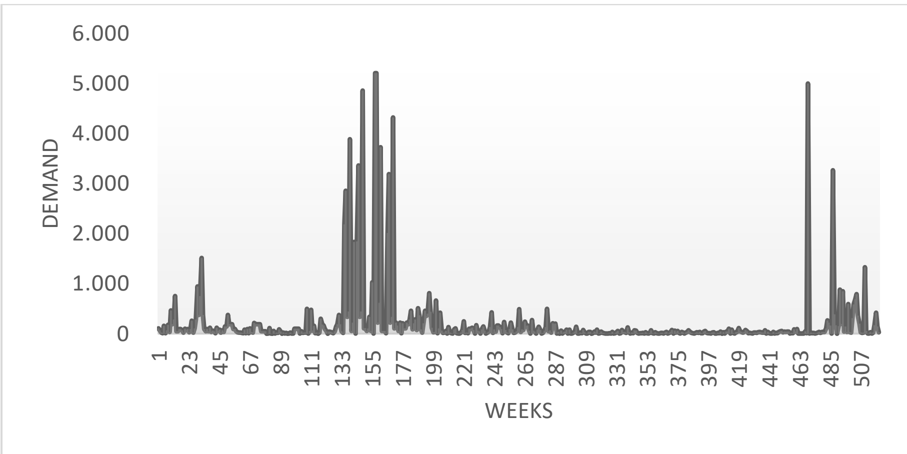

Figure 30. Plot of past demand behavior of Product 9

Appendix-B. Comparisons of actual and forecasted demand

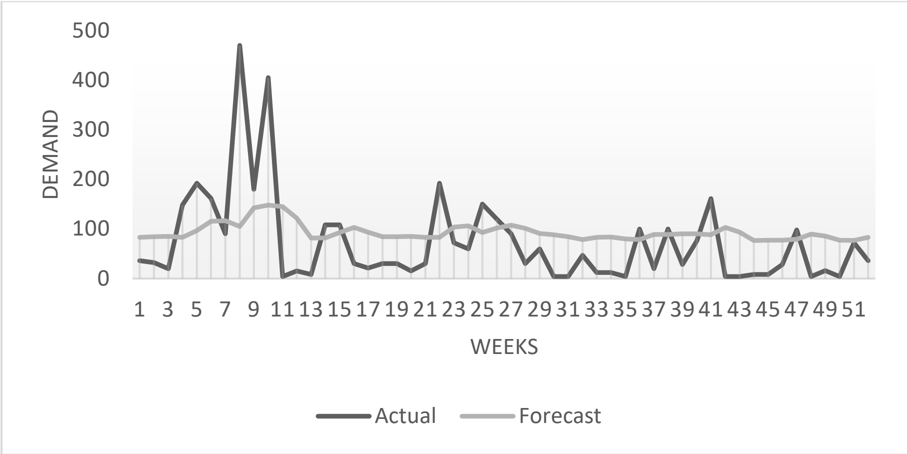

Figure 31. Comparison of actual and forecasted demand for Product 2

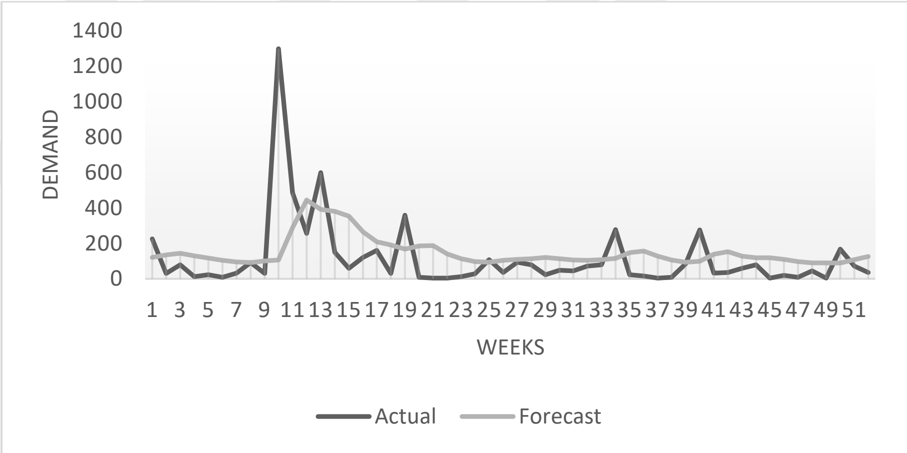

Figure 32. Comparison of actual and forecasted demand for Product 3

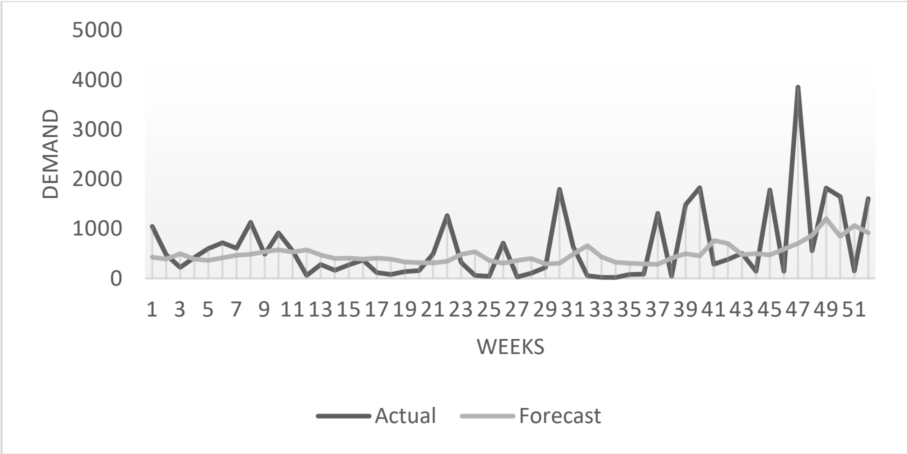

Figure 33. Comparison of actual and forecasted demand for Product 4

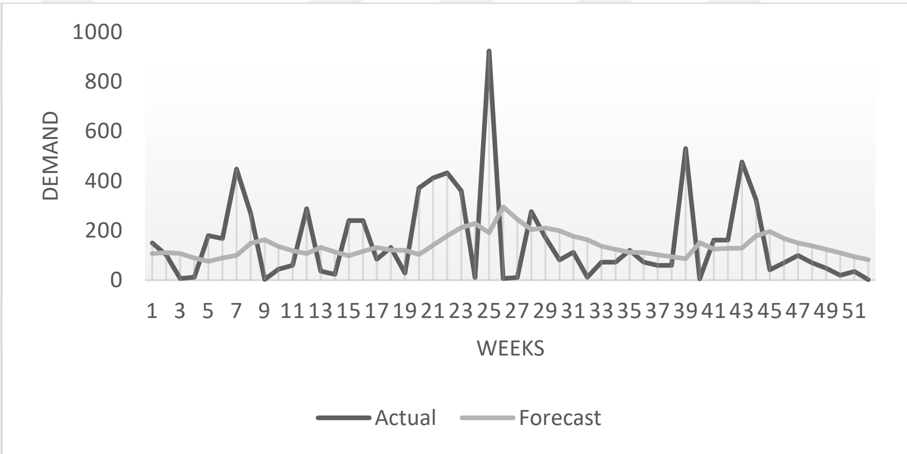

Figure 34. Comparison of actual and forecasted demand for Product 6

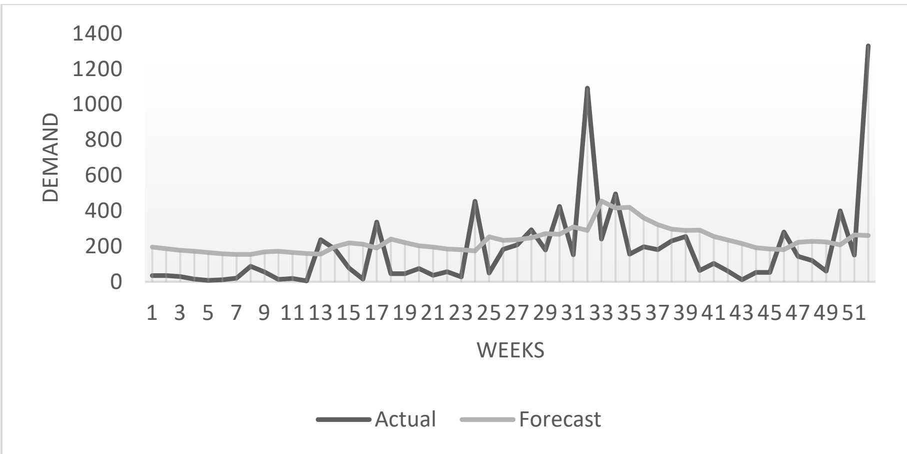

Figure 35. Comparison of actual and forecasted demand for Product 7

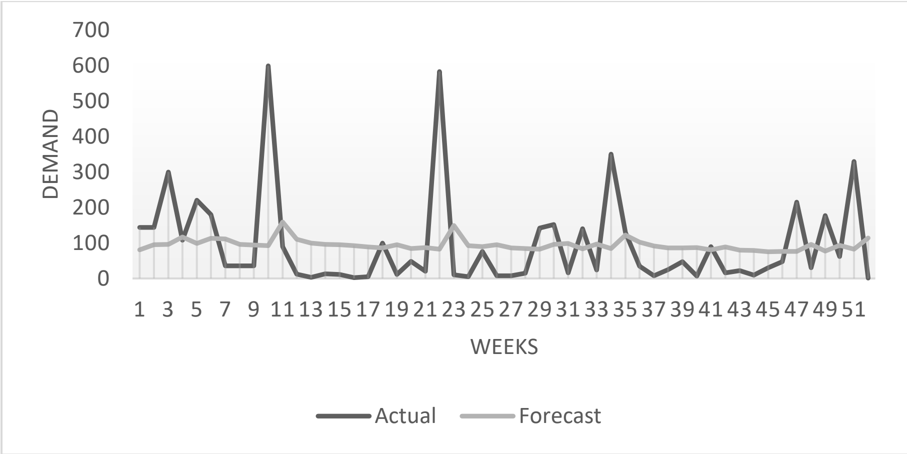

Figure 36. Comparison of actual and forecasted demand for Product 8

Appendix-C. Cost Comparison

Table 20. Cost comparison for all products

	Forecasted Demand		***Actual Demand***	
	EOQ	***USM***	***EOQ***	***USM***
Product Code	**Total Cost**	**Total Cost**	**Total Cost**	**Total Cost**
P1	₺1.978.088	₺849.340	₺5.120.721	₺1.671.761
P2	₺107.184	₺96.084	₺192.056	₺117.937
P3	₺512.004	₺275.411	₺1.502.752	₺551.371
P4	₺2.408.054	₺1.312.198	₺9.280.170	₺3.182.382
P5	₺418.513	₺372.425	₺1.603.147	₺569.761
P6	₺390.479	₺323.120	₺1.487.866	₺633.503
P7	₺1.651.039	₺713.718	₺5.333.754	₺1.692.126
P8	₺188.471	₺183.164	₺1.058.015	₺436.349
P9	₺3.089.090	₺1.422.293	₺8.102.860	₺2.710.447
Overall Costs	**₺10.742.924**	**₺5.547.752**	**₺33.681.342**	**₺11.565.637**