APPLYING FORECASTING METHODS TO REDUCE THE COST OF SPARE PARTS INVENTORY IN A COMPANY

Alper Sadık TAVUKÇU[1]*, Bahar SENNAROĞLU[2]

[1]Marmara Üniversitesi, Mühendislik Fakültesi, Endüstri Mühendisliği Bölümü, Göztepe Kampüsü, Kadıköy, İstanbul
ORCID No : http://orcid.org/0000-0003-0784-3601
[2]Marmara Üniversitesi,Mühendislik Fakültesi, Endüstri Mühendisliği Bölümü, Göztepe Kampüsü, Kadıköy, İstanbul
ORCID No : http://orcid.org/0000-0002-6809-634X

Keywords
Spare Parts,
Inventory,
Cost,
Demand Forecast,
Supply

Abstract
Any improvement on inventory cost provides financial benefits to companies and also increases customer satisfaction. In this study, it was aimed to reduce the cost of inventory of a construction equipment vendor with spare parts stock of ten thousand available out of almost fifty thousand registered items and increase in spare parts availability. The vendor company prepares spare part orders by using 12-month moving average of variable demand data. The research question was whether or not moving average method used by the company provides minimum cost and minimum lost sales. 36-month spare parts sales data were analyzed by using various forecasting methods. A sample group that best represents thousands of spare parts was selected for the analysis. A test period was picked out of 36-month time period and various forecasting methods were used for demand forecasting of this sample group. Stock on hand amount and lost sales amount were calculated for each demand forecast method and the method which provides minimum cost was determined.

YEDEK PARÇA ENVANTER MALİYETİNİ DÜŞÜRMEK İÇİN TAHMİN YÖNTEMLERİNİN BİR ŞİRKETTE UYGULANMASI

Anahtar Kelimeler
Yedek Parça,
Envanter,
Maliyet,
Talep Tahmini,
Tedarik

Öz
Envanter maliyetinde yapılacak herhangi bir iyileştirme, firmalara mali açıdan fayda sağlayacak ve ayrıca müşteri memnuniyetini arttıracaktır. Bu çalışmada, on bin kalemi stoklu yaklaşık elli bin kalem yedek parça envanter kaydına sahip bir iş makinesi satıcı firmasının stok maliyetinin azaltılması ve yedek parça bulunabilirliğinin arttırılması amaçlanmıştır. Satıcı firma, hâlihazırda yedek parça stok siparişlerini değişken talep verisinin 12 aylık hareketli ortalamasını kullanarak hazırlamaktadır. Araştırma sorusu, şirketin kullandığı hareketli ortalama yönteminin en az maliyet ve en az kayıp satışa neden olup olmadığıydı.36 aylık yedek parça satış rakamları farklı istatistiksel talep tahmin yöntemleriyle analiz edilmiştir. Binlerce yedek parça kalemini en iyi temsil eden bir örnek grubu seçilmiştir. 36 aylık periyot içinden bir test periyodu belirlenmiş ve farklı talep tahminleri yöntemleri bu örnek yedek parça grubunun talep tahminleri için kullanılmıştır. Her bir tahmin yönteminin yol açtığı stok tutma maliyeti ve kayıp satış maliyeti hesaplanmış ve mevcut talep tahmin yönteminden daha az maliyet sağlayan yöntem tespit edilmiştir.

Araştırma Makalesi		Research Article	
Başvuru Tarihi	: 16.12.2020	Submission Date	: 16.12.2020
Kabul Tarihi	: 16.08.2021	Accepted Date	: 16.08.2021

*Sorumlu yazar; e-posta : astavukcu@hotmail.com

1. Introduction

Car, construction equipment, aircraft, white goods and electronic appliances manufacturers are the largest industrial companies in the world in terms of production amounts and turnover. A report published by McKinsey in 2017 shown that labor and spare parts turnover reached 760 billion USD in 2015 around the world. More than half of this amount was obtained from spare parts sales (McKinsey, 2017). Having considered other industries, spare parts sales and inventory amounts reached significant level globally. Any improvement on inventory cost provides financial benefits to companies and also increases customer satisfaction.

Failure time of a part and spare part demand time are totally uncertain. Therefore, customer demand and inventory consumption speed are variable. There are various mathematical methods to analyze historical data and to forecast future values. Every method has weak and strong sides. For example, moving average method, simple exponential smoothing method and Holt's method do not consider seasonal pattern and ARIMA method requires long term data. Also, different methods can cause different forecasting results for the same data set. Each forecasting result will have an effect on supply process. In this study, it is aimed to reduce the cost of inventory of a construction equipment vendor with spare parts stock of ten thousand available out of almost fifty thousand registered items and increase customer satisfaction.

A sample group that best represents thousands of spare parts was selected. Sample group consists of three spare parts containing top selling first fifty parts which make up 38% of total sales. 36 months spare parts sales data was analyzed and seasonal pattern observed for these three parts. Last 12 months was picked as test period out of 36 months. Holt-Winters' and ARIMA methods were used for demand forecasting of this sample group. Stock on hand amount and lost sales amount was calculated for each demand forecast method and compared with current forecasting method in use.

In the second section of this article, a literature review is given about the spare parts demand forecasting. In the third part, forecasting methods and forecasting accuracy are explained, case study is introduced and demand forecast calculations are completed. In the final two sections, results and the conclusions of the study are presented.

2. Literature Review

Spare parts demand forecasting is a complex process and requires some steps such as collecting demand data, finding pattern on the demand, using different forecasting methods and computing forecasting accuracy. Mainly, moving average, simple exponential smoothing, Holt's method or Holt-Winter's method are used for spare parts demand forecasting. However, some researchers studied on Box-Jenkins method known as ARIMA. Businger and Read (1999) studied on US Navy spare parts inventory management. US Navy uses simple exponential smoothing method to make demand forecast. They proposed to US Navy three alternative ARIMA models; ARIMA(1,1,1), ARIMA(2,2,2) and ARIMA(3,2,3). Jiafu, Zongfang and Fang (2009) used ARIMA to model spare parts demand for a factory. They built four different ARIMA models by using seven years historical data of four spare parts group. Vargas and Cortés (2017) presented a comparative study of time series methods on automobile spare parts forecasting. They used ARIMA, ANN and ARIMA-ANNs hybrid methods for sample spare parts and compared forecasting accuracy for each simulation. Saravanan, Anbuudayasank, David and Narassima (2019) used ARIMA method on a case study for spare part demand forecasting in an automotive company. The accuracy of the forecasting was improved by 40% from the current level.

Beside time series forecasting methods, explanatory data, failure data history and life data analyses were advised to be added to spare parts inventory calculations (Cavalieri, Garetti, Macchi and Pinto, 2008). Nawzar and Sheik (2016) used multivariable regression and life data analysis to calculate spare parts demand forecasts. They also studied on a case study in Volvo Truck Company. Multivariable regression is based on big data such as population of main product, time of usage, mileage and runtime, service interval. Kim, Dekker and Heij (2017) studied on spare part demand forecasting for consumer goods using installed base information. They used multivariable regression model for spare part forecasting based on sales figures and sales region of main product. Chen, Liu and Yu (2010) proposed a Regression-Bayesian-BPNN (Back Propagation Neural Network) method to obtain spare parts demand forecast. Compared with the classical ARMA models, Regression-Bayesian-BPNN showed higher accuracy.

Another challenge for spare parts demand forecasting is intermittent demand. Since intermittent demand does not contain any pattern, it is not possible to use any time series forecasting methods. Croston (1972) proposed a forecasting method for intermittent demand. The method is based on simple exponential smoothing (SES). Beside size of demand, the method also considers intervals between demand points.

Different empirical studies, simulations and case studies with real life data have also been used frequently. Porras and Dekker (2008) suggested an empirical study on an inventory control system for spare parts at a petrochemical refinery by using different forecasting methods. Bootstrapping was given best performance. Their method dropped inventory holding cost to 6.4%. Webby and O'Connor (1996) reviewed judgmental and statistical time series forecasting methods. They analyzed empirical studies and found out that statistical and judgmental forecasting techniques give best result when they combined together. Suyunova (2018) studied on spare parts demand forecasting simulations with different parameters by using Simple Moving Average and Simple Exponential Smoothing. Regon and Mesquita (2014) conducted a demand forecasting and inventory control simulation study on automotive spare parts. They used Simple Moving Average, Syntetos–Boylan Approximation and Bootstrapping methods. They suggested spare parts demand forecast and inventory simulations every 6 month with different methods due to demand pattern change over the time. Ozcift (2018) proposed Fuzzy Clustering Model for forecasting automotive spare part demands. Fuzzy modeling inference algorithm was used for modeling the system. Suggested model performed better in terms of forecasting accuracy.

Boylan, Syntetos and Karakostas (2008) suggested demand categorization before spare parts demand forecasting. Different forecasting methods should be used on different stock keeping units (SKU's) based on demand categorization. They also applied an empirical demand categorization study on automotive, aerospace and chemical industries data which supported by a UK based software company.

Most of the studies in the literature examine only forecasting accuracy to compare forecasting methods. However, this study argues that forecasting accuracy is not enough to determine the best fitted forecasting method if thousands of stock items exist. Inventory cost should be added to the comparisons.

3. Materials and Methods

The company prepares spare parts orders by using 12-month moving average of demand. However, it is uncertain that moving average method used by the company provides minimum on hand inventory and maximum customer satisfaction or not.

Construction equipment is used in construction and mining business. Construction and mining business is highly related to weather conditions. Activity and working hours increase in good weather conditions. Quarterly gross domestic product at current prices by income approach published by TUIK shows that between 2011 and 2020, second and third quarter construction figures are higher than first and last quarter of the year (TUIK, 2021). Therefore, seasonality is observed in spare parts sales.

If seasonality is the case, moving average method is not adequate for demand forecasting. Holt-Winters' method and ARIMA models provide more accurate forecasting results. Holt-Winters' and ARIMA methods were used for demand forecasting to compare with on hand inventory amount and lost sales amount obtained by current method. In this study, research and publication ethics were followed. It is stated in this article that no legal/special permission is required.

3.1 Forecasting Methods and Forecasting Accuracy

3.1.1 Moving Average Method

Moving average is calculated by dividing the total of past values of a variable by the determined past time interval. The oldest data is leaved out from the moving average calculation and most recent data is included. Thus, forecast for the next period is obtained. The number of data points in each average remains constant and includes the most recent observations (Makridakis, Wheelwright and Hyndman, 1998).

A moving average forecast of order k, or MA (k), is given by

$$F_{t+1}= \frac{1}{k} \sum_{i=t-k+1}^{t} Y_i \tag{1}$$

3.1.2 Holt-Winters' Method

Winters (1960) improved Holt's method to obtain seasonality. Holt's method only considers trend pattern on data set. Therefore, Winters added seasonality calculations to Holt's method. There are two Holt-Winters' methods which are an additive or multiplicative way based seasonality pattern. If values of independent variable exponentially increase or decrease from season to season, multiplicative method is used. If there is a linear increase or decrease in values of independent variable from season to season, additive method is used.

The fundamental equations of Holt-Winters' multiplicative method are

$$Level: \ L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (2)$$

$$Trend: \ b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (3)$$

$$Seosonal: \ S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s} \quad (4)$$

$$Forecast: F_{t+m} = (L_t + b_t m)S_{t-s+m} \quad (5)$$

L_t : The level of the series

S : The length of seasonality (e.g., number of months or quarters in a year)

b_t : The trend

F_{t+m} : The forecast for m periods ahead

α : Smoothing parameter for the level between 0 and 1

β : Smoothing parameter for the trend between 0 and 1

γ : Smoothing parameter for the season between 0 and 1

To initialize the multiplicative Holt-Winters' method, initial values of the level L_t, the trend b_t, and the seasonal indices S_t should be calculated. At least one complete season's data set (i.e., s periods) should be used to obtain initial values of the seasonal indices. Initial value of the level is calculated by getting the average of the first season:

$$L_s = \frac{1}{s}(Y_1 + Y_2 + \cdots + Y_s) \quad (6)$$

Two complete seasons (i.e., 2s periods) should be used to obtain initial values of the trend as follows:

$$b_s = \frac{1}{s}\left[\frac{Y_{s+1} - Y_1}{s} + \frac{Y_{s+2} - Y_2}{s} + \cdots + \frac{Y_{s+s} - Y_s}{s}\right] \quad (7)$$

At last, the seasonal indices are initialized using the ratio of the first few data values to the mean of the first year:

$$S_1 = \frac{Y_1}{L_s}, \quad S_2 = \frac{Y_2}{L_s}, \quad \ldots \quad S_s = \frac{Y_s}{L_s}$$

The equations for Holt-Winters' additive method:

$$Level: \ L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (8)$$

$$Trend: \ b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (9)$$

$$Seosonal: \ S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-s} \quad (10)$$

$$Forecast: \ F_{t+m} = L_t + b_t m + S_{t-s+m} \quad (11)$$

3.1.3 The Box-Jenkins Methodology for ARIMA Models

Autoregressive - Integrated - Moving Average (ARIMA) models were frequently used by George Box and Gwilym Jenkins in the early 1970s (Box and Jenkins,1968). Box-Jenkins modeling procedure consists of three phases: identification, estimation and testing, and application. Autocorrelation measures the linear relationship between lagged values of a time series (Hyndman and Athanasopoulos, 2018). Identification phase has basically two steps; data preparation and model selection. The aim of data preparation is transforming data to stabilize variance and differencing data to stabilize mean to obtain a stationary time series. Autocorrelation function (ACF) and partial autocorrelation function (PACF) are identified to see potential models. Estimation and testing stages consist of estimation and diagnostics steps. In estimation step, parameters are estimated for potential models and suitable criterion is selected for best model. Estimation and testing stage contain some diagnostic measures. ACF and PACF of residuals should be checked, portmanteau test of residuals should be applied and white noise inspection for residuals should be done. If the test results are within the limits, chosen model can be used for forecasting.

There are four main model types; autoregressive (AR), moving average (MA), autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA).

The general non-seasonal model is explained as ARIMA (p, d, q)

AR: p = order of the autoregressive part

I: d = degree of first differencing involved

MA: q = order of the moving average part

Autoregressive model of order p, AR(p) is defined as;

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + e_t \quad (12)$$

c : constant term

ϕ_j : j th autoregressive parameter

e_t : the error term at time t

There are some restrictions on estimation of parameters. For AR(1) model ϕ_1 should be between -1 and 1 ($-1 < \phi_1 < 1$). For AR(2) model; $-1<\phi_2<1$, $\phi_1+\phi_2<1$, $\phi_2-\phi_1<1$.

Moving average model of order q, MA(q) is defined as;

$$Y_t = c + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \quad (13)$$

c : constant term

θ_j : j th autoregressive parameter
e_t : the error term at time t

Restriction on estimation of parameters for MA(1) model is $-1<\theta_1<1$ and for MA(2) model are $-1<\theta_2<1$, $\theta_2+\theta_1>-1$, $\theta_1-\theta_2<1$.

ARMA(p, 0, q) model is combination of AR(p) and MA(q) and defined as;

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + .. + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - .. - \theta_q e_{t-q} \quad (14)$$

3.1.4 Forecasting Accuracy

Different forecasting methods should be used on the same data set and forecast results should be compared using some performance measures. All accuracy measure calculations are based on error. There are two types of error; fitting errors and forecasting errors. Fitting errors computed when the model has been fitted to the known data. Forecasting errors calculated after the data for the forecast periods have become available (Makridakis et al., 1998).

If Y_t is the actual observation for time period t and F_t is the forecast for the same period, then the error is defined as

$$e_t = Y_t - F_t \quad (15)$$

If observations and forecasts for n time periods are available, n errors can be obtained. When errors are obtained, forecasting accuracy measure based on the mean squared error (MSE) can be calculated;

$$MSE = \frac{1}{n}\sum_{t=1}^{n} e_t^2 \quad (16)$$

3.2 Forecasting Methods Application in a Case Study

This study examines demand forecasting methods' applications to reduce the cost of spare parts inventory in a construction equipment distributor company. The Company tries to supply spare parts, either to meet warranty liabilities or to get profit, within shortest time and with lowest cost for demand coming from customer. There are almost 50.000 SKU's registered inventories and approximately 10.000 of them are moving SKU's. The Company has only one supplier.

The Company checks last 12-month sales figures and on hand stock every month, prepares spare parts orders by using 12-month moving average of demand and sends this spare parts order to Japanese producer's spare parts distribution center in Belgium. Spare parts distribution center in Belgium ships the spare parts order once in a month by truck. Order preparation, transportation and custom clearance takes almost 30 days which means lead time is approximately one month.

3.2.1 Spare Parts Order Preparation

The Company does not order spare parts which are not sold more than five months in a year. For the rest, it calculates maximum stock level for each item every month. Order quantity is determined by subtracting on hand quantity from maximum stock level. Maximum stock level calculation is the most important part of the order preparation (Figure 1). Maximum stock level is currently obtained by based on 12-month sales average and one month lead time.

Order Quantity = Maximum Stock Level – On Hand Quantity (17)

Maximum Stock Level = 12-Month Sales Average x Lead Time (18)

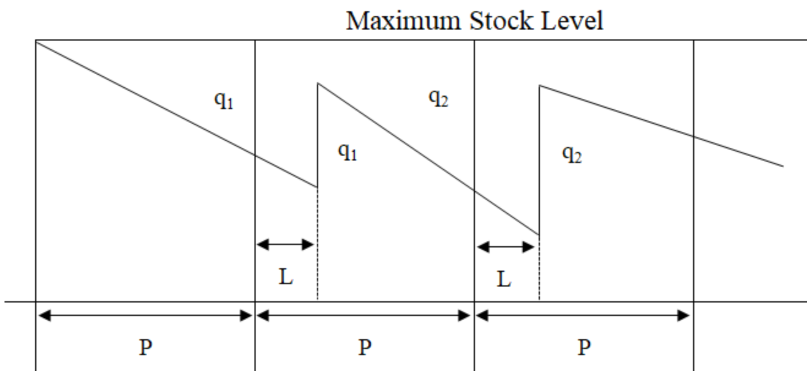

Figure 1. Periodic Review System (Chitale & Gupta, 2014)

P = Review period
L = Lead time
q_1, q_2 = Order quantities

Chitale and Gupta (2014) explain periodic inventory review in their book. Periodic inventory review is called under different names such as P system of inventory control, fixed-order-interval system, fixed-order-period system or simply the periodic system. There are two types of periodic review; deterministic and probabilistic. Demand and lead time are known and relatively constant in deterministic review whereas demand and lead time fluctuate in probabilistic review. Demand is very important input for ordering process. Spare parts demand is totally probabilistic and variable. Failure time of construction equipment and need for spare parts are uncertain and unpredictable. Therefore, maximum stock level is not stable depending on variable demand.

Because spare parts demand is probabilistic and variable, some items are not sold in an inventory control period. Therefore, time series methods cannot be used for demand forecasting due to missing demand data. The Company does not order spare parts which are not sold more than five months in a year and for the rest, uses 12-month moving average method even demand data is missing.

Beside smooth demand, Boylan et al. (2008) studied on intermittent demand. Time series methods are not applicable for intermittent demand. Other approaches are needed such as intermittent demand based simple exponential smoothing proposed by Croston (1972). However, this study considers only smooth demand data and time series forecasting methods.

3.2.2 Problem Definition and Data Set Preparation

Improvement in demand forecasting decreases on hand inventory amount and lost sales amount. Three spare parts from top selling first fifty parts with high inventory cost will be selected to represent whole inventory and to compare moving average method, which is used currently by the company, with Holt-Winters' and ARIMA methods. 36 months spare parts sales data will be analyzed and seasonal pattern will be observed for these three parts. Last 12 months will be picked as test period out of 36 months. Holt-Winters' and ARIMA methods will be used for demand forecasting of this sample group. Accuracy measures, stock on hand amount and lost sales amount will be calculated for each demand forecast method and compared with the current forecasting method in use and the method which provides maximum forecasting accuracy, minimum stock on hand amount and lost sales amount will be determined. Top selling first fifty parts make up 38% of total sales. First spare part (SP1) is a filter with 40 Euro purchase price, second spare part is a bucket tooth (SP2) with 70 Euro purchase price and third spare part (SP3) is a pin with 50 Euro purchase price.

After spare parts selection and demand data collection, seasonal pattern will be investigated. Time plot (Figure 2) is very effective way to observe patterns on the data.

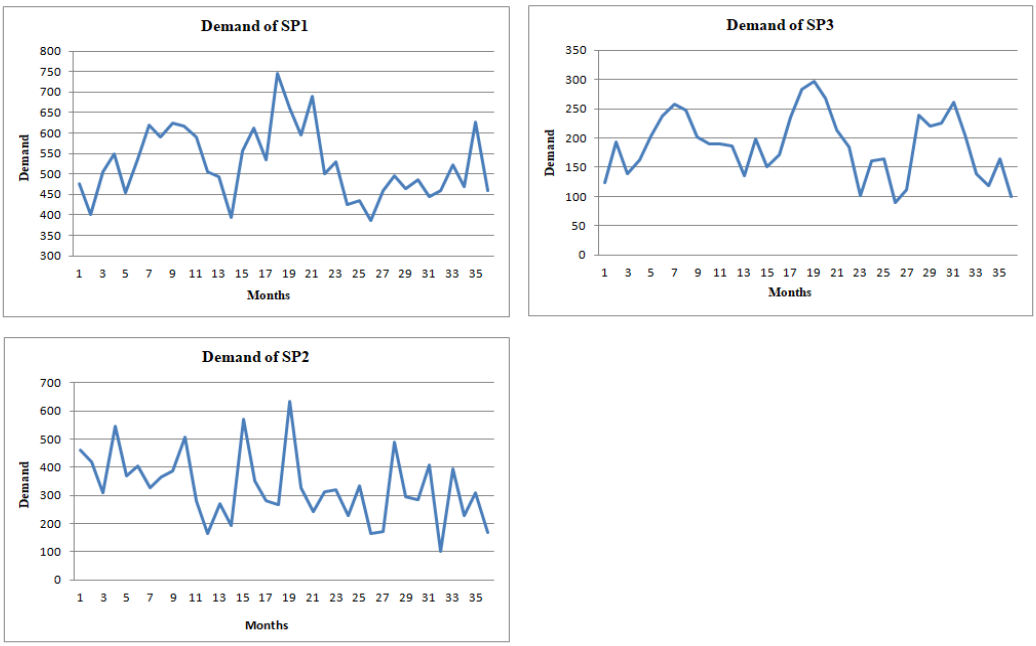

Figure 2. Time Plots of Three Spare Parts

Autocorrelation function plots (Figure 3) should also be used to analyze patterns in time series data.

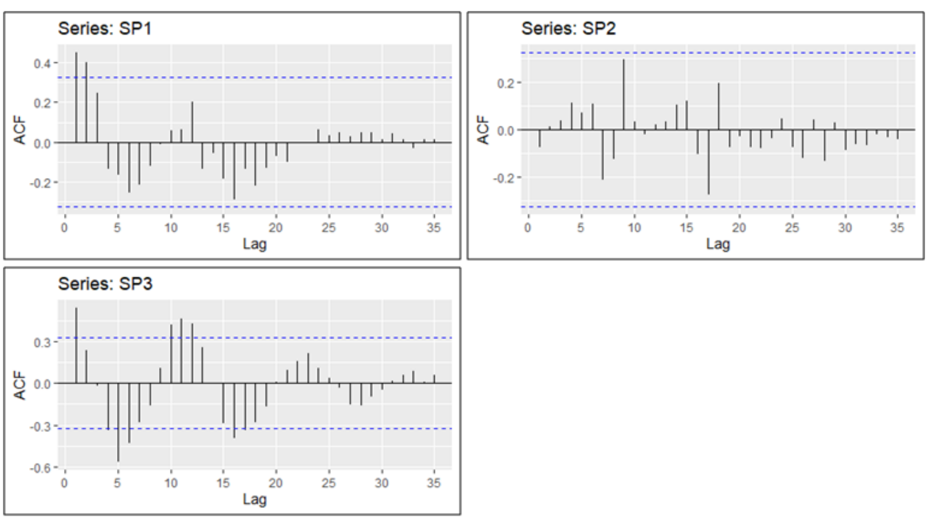

Figure 3. ACF Plots of Three Spare Parts

Seasonal pattern on the time plots and ACF plots of three spare parts is observed clearly for SP3.

3.2.3 Current Demand Forecasting of The Company

Forecasting accuracy, maximum stock level, order quantity, stock on hand amount and lost sales amount of spare parts for last 12 months as test period will be calculated by using 36 months demand data of three sample spare parts. Their demand forecasts between 25th and 36th month will be calculated by using demand data between 13th and 35th month (Figure 4).

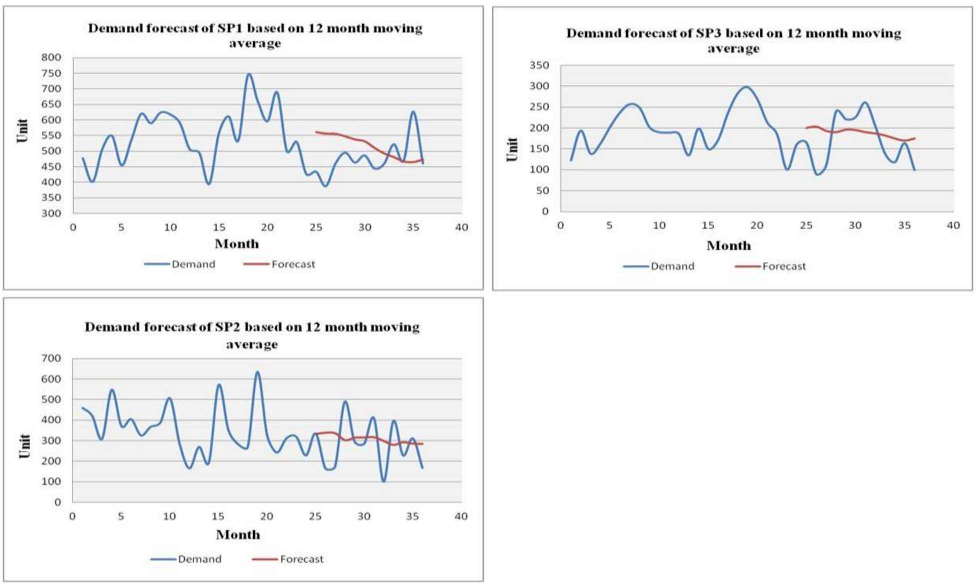

Figure 4. Demand Forecasts of Three Sample Spare Parts by using 12-Month Moving Average

Forecasting accuracy, stock on hand amount and lost sales amount were calculated for the current method. The reason to check stock on hand amount and lost sales amount at the same time is that measuring forecasting accuracy seems not enough to compare forecasting methods. Because, thousands of stock items are issued, financial results should also be considered. A forecasting method can generate better result for low cost stock items while it may not generate good results for high cost stock items. Therefore, an overall approach is needed. Target value of stock on hand amount and lost sales amount is zero for all spare parts sales and procurement operations.

After obtaining forecast values of last 12-month and rounding to integer value, stock on hand amount and lost sales amount will be computed for each part as follows;

On hand stock occurs when summation of previous month stock quantity and order quantity is greater than demand quantity. On hand quantity is multiplied by unit part cost to get on hand amount.

On hand stock = previous month stock qty + order qty – demand qty (19)

On hand amount = on hand stock x unit part cost (20)

Lost sales occur when summation of previous month stock quantity and order quantity is lower than demand quantity. Lost sales quantity is multiplied by 50% of unit part cost to get lost sales amount. Company makes up sales price by adding 50% markup to unit cost price. If on hand stock does not meet demand, company loses profit. Company does not want to lose profit and does not want to keep stock more than needed.

Lost sales qty (21)

$$= \begin{cases} \text{demand qty} - (\text{previous month stock qty} + \text{order qty}) & if\ on\ hand\ stock\ is\ negative \\ 0 & otherwise \end{cases}$$

Lost sales amount = lost sales quantity x (0.5 x unit part cost) (22)

Figure 5 shows that the company many times failed to meet customer demand because of poor demand forecasting. The company compensates stock shortage and lost sales by borrowing part from sub dealers or cannibalizing main product. In reality, it meets customer demand with very high cost and unwanted supply methods.

Figure 5. On Hand Stock & Lost Sales Quantity for Test Period with 12-month Moving Average

Table 1 shows MSE, on hand stock amount and lost sales amount of three spare parts for last 12-month test period after demand forecast calculation with moving average.

Table 1
MSE, On Hand Stock Amount and Lost Sales Amount with 12- month Moving Average

Part No	MSE	On Hand Amount (€)	Lost Sales Amount (€)
SP1	8233	27,280	4080
SP2	14,441	30,720	8460
SP3	3393	16,400	3880

On hand stock amount and lost sales amount are not direct costs but they create negative impact on financial status of the company. Because, they are costly and unwanted values, an objective function (OF) can be developed by combining them to have an overall financial approach for whole inventory. Aim of the demand forecasting should be minimizing these amounts and making the total of them close to ideal value zero.

Min. OF = On Hand Amount + Lost Sales Amount (23)

If the values on Table 1 considered, OF will be;

OF = 74,400 + 16,420 = 90,820 Euro

The aim of this study is to reduce this amount by using Holt-Winters` and ARIMA forecasting methods for the same test period.

3.2.4 Demand Forecasting With Holt-Winters` Method

There are two different Holt-Winters' methods; additive or multiplicative type. This classification is based on exponential or linear behavior of forecast variable. In this case, spare parts demand is the variable. When time plot of three spare parts are analyzed, it is difficult to determine additive or multiplicative seasonal pattern. Therefore, demand forecast of three parts will be calculated by using additive and multiplicative Holt-Winters' methods. Afterwards, MSE, on hand stock amount and lost sales amount will be computed.

Additive method; after initialization values were determined, last 12 month demand forecast of three sample spare parts were calculated by using Holt-Winters' additive method (Figure 6). Initial smoothing parameters were 0.2 for α, β and γ. Errors and MSE values were computed for last 12 months. However, smoothing parameters can get value between 0 and 1. Different combinations between 0 and 1 can reduce MSE. Forecasting accuracy can be improved by optimizing smoothing parameters (Makridakis et al., 1998). MS Excel Solver was used to optimize smoothing parameters to minimize MSE value. MSE values reduced from 4.907 to 3.069 for SP1, from 15.552 to 10.463 for SP2 and from 2.791 to 2.374 for SP3. New smoothing parameters became α = 0.577, β = 0 and γ = 1 for SP1, α = 0, β = 0.132 and γ = 0.353 for SP2 and α = 0.041, β = 1 and γ = 0.172 for SP3 after optimization.

Figure 6. Demand Forecasts of Three Sample Spare Parts by using Holt-Winters' Additive Method

Table 2 shows MSE, on hand stock amount and lost sales amount of three spare parts for last 12-month test period after demand forecast calculation with Holt-Winters' additive method.

Table 2
MSE, On Hand Stock Amount and Lost Sales Amount with Holt-Winters' Additive Method

Part No	**MSE**	**On Hand Amount (€)**	**Lost Sales Amount (€)**
SP1	3069	9760	5660
SP2	10,463	21,040	11,100
SP3	2374	10,800	3700

Objective function can be calculated to see overall effect by using values on Table 2 after obtaining on hand amount and lost sales amount for three spare parts with Holt-Winters' additive method (Figure 7).

Min. OF = On Hand Amount + Lost Sales Amount (24)

OF = 41,600 + 20,460 = 62,060 Euro

Total of on hand amount and lost sales amount decreased by almost 32% comparing to moving average method.

Figure 7. On Hand Stock & Lost Sales Quantity for Test Period with Holt-Winters' Additive Method

Multiplicative method; last 12 months demand forecasts of three sample spare parts were calculated by using Holt-Winters' multiplicative method after initialization values were determined (Figure 8). Initial smoothing parameters were 0.2 for α, β and γ. Errors and MSE values were computed for last 12 months. MS Excel Solver was used to optimize smoothing parameters to minimize MSE values. MSE values reduced from 4.441 to 2.563 for SP1, from 16.015 to 9.910 for SP2 and from 2.811 to 2.398 for SP3. New smoothing parameters became α = 0.538, β = 0 and γ = 1 for SP1, α = 0.001, β = 1 and γ = 0.284 for SP2 and α = 0.039, β = 1 and γ = 0.348 for SP3 after optimization.

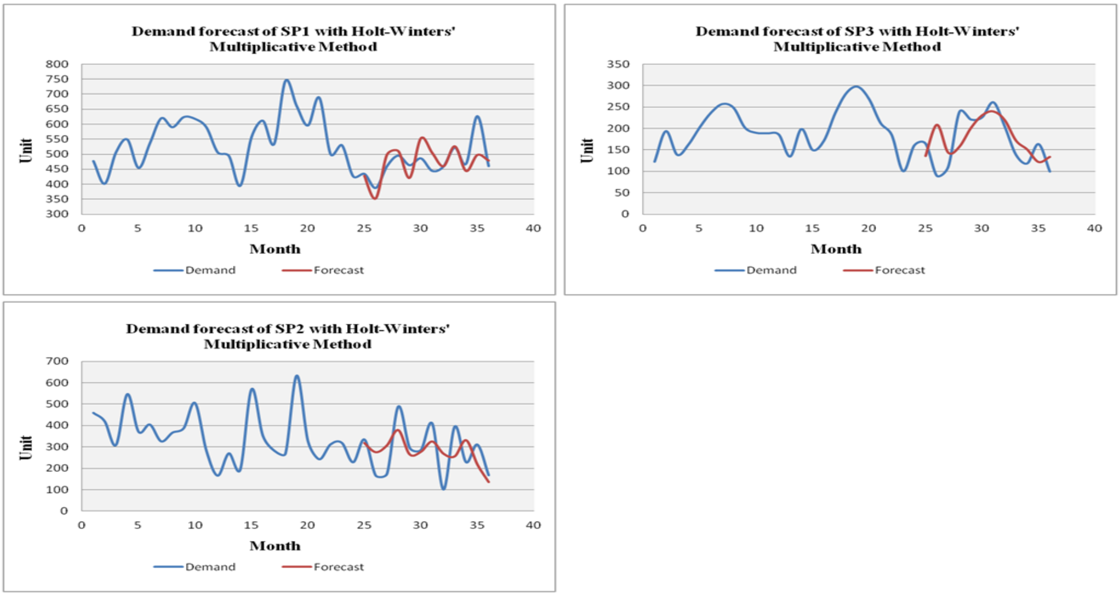

Figure 8. Demand Forecasts of Three Sample Spare Parts by using Holt-Winters' Multiplicative Method

Table 3 shows MSE, on hand stock amount and lost sales amount of three spare parts for last 12-month test period after demand forecast calculation with Holt-Winters' multiplicative method.

Table 3
MSE, On Hand Stock Amount and Lost Sales Amount with Holt-Winters' Multiplicative Method

Part No	MSE	On Hand Amount (€)	Lost Sales Amount (€)
SP1	2563	8360	4720
SP2	9910	20,720	10,180
SP3	2398	10,840	3860

Objective function can be calculated to see overall effect by using values on Table 3 after obtaining on hand amount and lost sales amount for three spare parts with Holt-Winters' multiplicative method (Figure 9).

Min. OF = On Hand Amount + Lost Sales Amount (25)

OF = 39,920 + 18,760 = 58,680 Euro

Total of on hand amount and lost sales amount decreased by almost 35% comparing to moving average method.

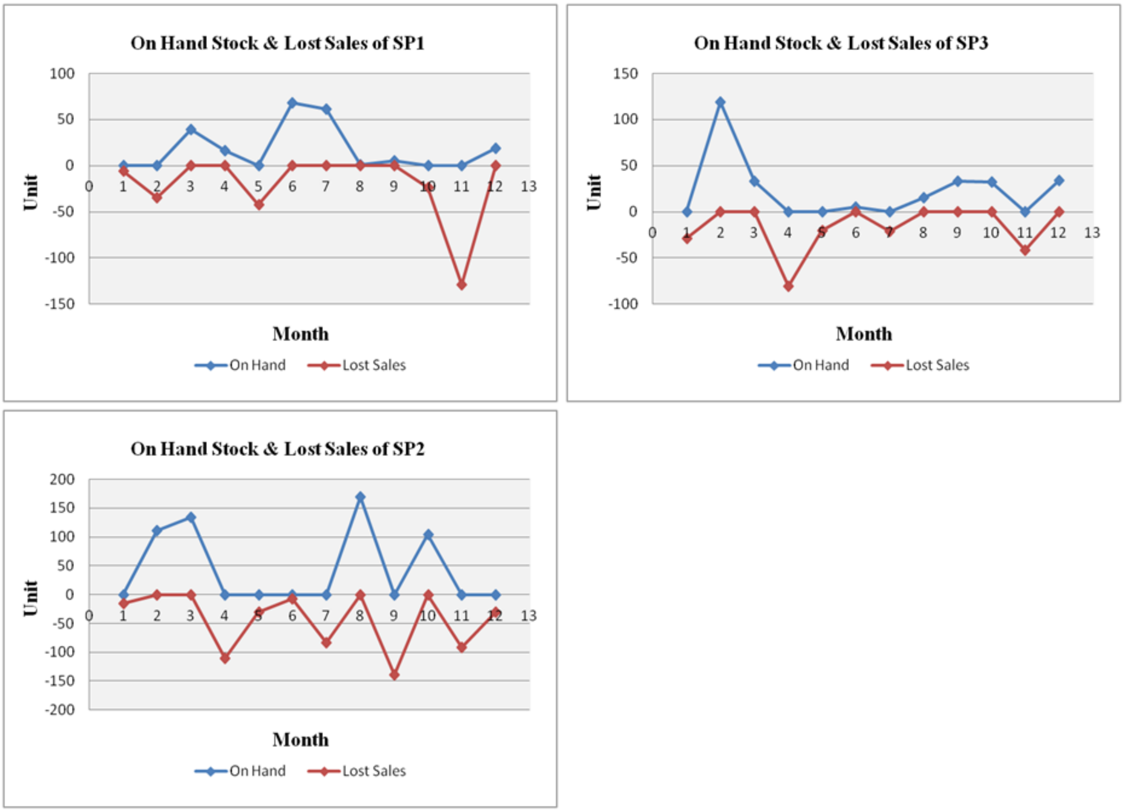

Figure 9. On Hand Stock & Lost Sales Quantity for Test Period with Holt-Winters' Multiplicative Method

3.2.5 Demand Forecasting With ARIMA Method

Demand data of three spare parts shows seasonal pattern. ARIMA gives better demand forecast result for seasonal pattern when demand data set is long enough. In order to fit a seasonal ARIMA model to a monthly data set, at least three seasons, i.e., 36 months data, are needed; generally minimum 50 observations are suggested (Schaffer, Dobbins and Pearson, 2021). In this case, there are only 24 months demand data for ARIMA model fitting. Therefore, instead of using seasonal ARIMA model, non-seasonal ARIMA model is preferred to get better result. Latest monthly demand data point is added to 24 months moving demand data and oldest monthly data point is dropped from the data set.

R software is used for calculations. Auto.arima function on R finds best ARIMA model. 12 data sets which include 24 months moving demand data prepared for three spare parts each and loaded to R. Auto.arima function analyzed first data set of each spare part and recommended (4,0,0) model for SP1, (0,0,0) model for SP2 and (1,0,0) for SP3. It is difficult to handle with different ARIMA models for inventory planners. Therefore, one ARIMA model should be selected among recommended models by R. All recommended ARIMA model combinations calculated for SP1, SP2 and SP3. ARIMA(1,0,0) model provided minimum forecast accuracy and objective function value for 12 months (Figure 10).

Equation for ARIMA(1,0,0) model is:

$$Y_t = c + \phi_1 Y_{t-1} + e_t \qquad (26)$$

Auto.arima function finds best ARIMA model and model parameters by calculating AICc value. Arima function fits ARIMA model to the data and forecast function generates forecast value for the next period by using model equation and parameters.

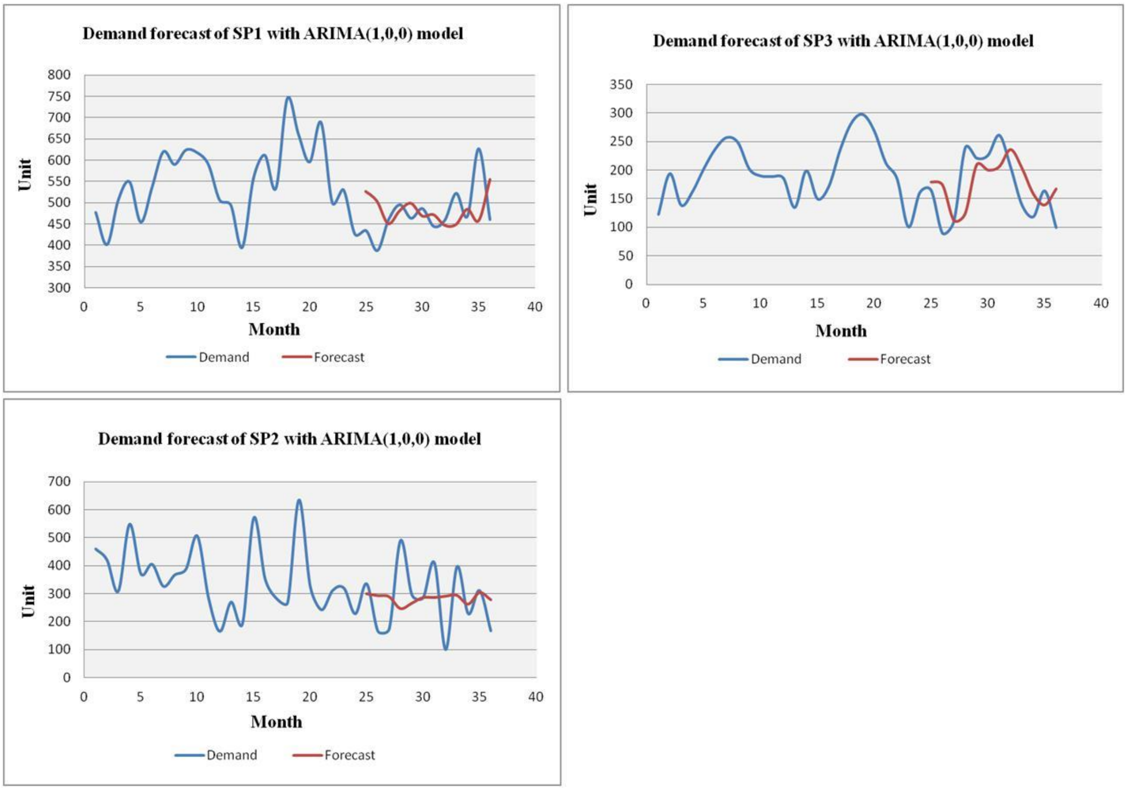

Figure 10. Demand forecasts of three sample spare parts by using with ARIMA(1,0,0) model

Table 4 shows MSE, on hand stock amount and lost sales amount of three spare parts for last 12-month test period after demand forecast calculation with ARIMA(1,0,0) model.

Table 4
MSE, On Hand Stock Amount and Lost Sales Amount with ARIMA(1,0,0) Model

Part No	MSE	On Hand Amount (€)	Lost Sales Amount (€)
SP1	5694	15,440	5880
SP2	13,934	23,440	10,740
SP3	3001	12,000	4660

Objective function can be calculated to see overall effect by using values on Table 4 after obtaining on hand amount and lost sales amount for three spare parts with ARIMA(1,0,0) model (Figure 11).

Min. OF = On Hand Amount + Lost Sales Amount

OF = 50,880 + 21,280 = 72,160 Euro

Total of on hand amount and lost sales amount decreased by almost 21% comparing to moving average method.

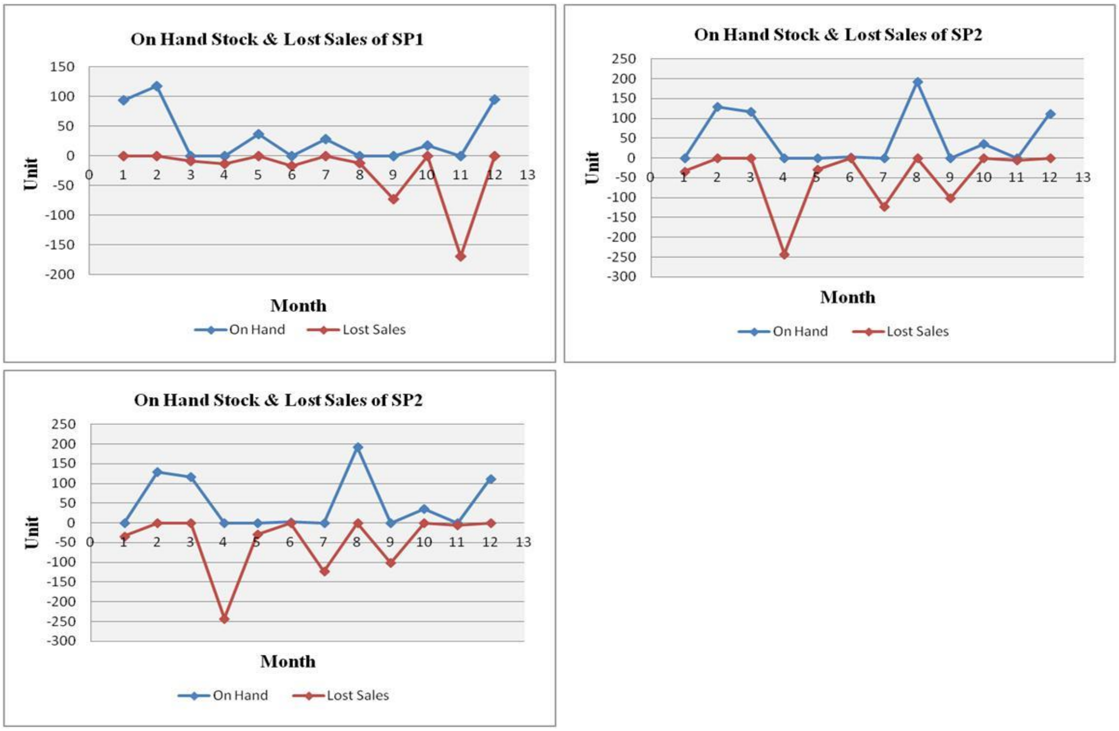

Figure 11. On Hand Stock & Lost Sales Quantity for Test Period with ARIMA(1,0,0) Model

4. Result

Holt-Winters' methods and ARIMA models were used to calculate demand forecast of three spare parts for 12-month test period. MSE value, on hand amount, lost sales amount and total of on hand amount and lost sales amount obtained and results were compared to current forecasting method on Table 5.

Table 5
MSE, On Hand Stock Amount and Lost Sales Amount Obtained by using Different Forecasting Methods for Three Sample Spare Parts on Test Period

Method	Part No	MSE	Total MSE	On Hand Amount(€)	Total On Hand Amount(€)	Lost Sales Amount(€)	Total Lost Sales Amount(€)	Total On Hand Amount(€) & Lost Sales Amount(€)
Moving Average	SP1	8233		27280		4080		
	SP2	14441	26067	30720	74400	8460	16420	90820
	SP3	3393		16400		3880		
Holt-Winters' Additive	SP1	3069		9760		5660		
	SP2	10463	15905	21040	41600	11100	20460	62060
	SP3	2374		10800		3700		
Holt-Winters' Multiplicative	SP1	2563		8360		4720		
	SP2	9910	14871	20720	39920	10180	18760	58680
	SP3	2398		10840		3860		
ARIMA(1,0,0)	SP1	5694		15440		5880		
	SP2	13934	22629	23440	50880	10740	21280	72160
	SP3	3001		12000		4660		

Holt-Winters' Additive method, Holt-Winters' Multiplicative method and ARIMA(1,0,0) model respectively provided 38.98% decrease, 42.95% decrease and 13.19% decrease in MSE, 44.09% decrease, 46.34% decrease and 31.61% decrease in on hand amount, 24.60% increase, 14.25% increase and 29.60% increase in lost sales amount and 31.67% decrease, 35.39% decrease and 20.55% decrease in total of on hand & lost sales amount comparing to current forecasting method moving average.

As a result, Holt-Winters' Multiplicative method provided the most accurate demand forecast of three spare parts for 12-month test period. It also provided lowest on hand amount and objective function whereas a slight increase in lost sales amount.

5. Conclusion

Considering thousands of stock items and millions of US dollars inventory investment, demand forecast with Holt-Winters' Multiplicative method makes significant improvement for the company. Therefore, the company will be advised to use Holt-Winters' Multiplicative method and to make similar studies periodically in the future.

The study presents an application for companies to see benefits of quantitative forecasting techniques. It explains step by step how to deal with uncertain and variable demand, importance of finding out type of pattern on the demand data, determining appropriate forecasting method based on data pattern and forecasting future values. The study takes into account minimization of on hand stock amount and lost sales amount, hence provides an approach to reduce the cost of spare parts inventory.

Companies invest millions of US dollars in their inventory to make profit and to meet customer demands. Therefore, any improvement on inventory cost provides financial benefits to companies and increases customer satisfaction.

Contribution of Researchers

In this study, Alper Sadık TAVUKÇU completed literature review, data collection, wrote the manuscript and prepared manuscript formatting. Bahar SENNAROĞLU edited the manuscript and provided R software training.

Conflict of Interest

No conflict of interest was declared by authors.

References

Boylan, J. E., Syntetos, A. A. & Karakostas, G. C. (2008). Classification for forecasting and stock control: a case study. *Journal of the Operational Research Society*, 59, 473–481. Doi: https://doi.org/10.1057/palgrave.jors.2602312

Box, G. E. P. & Jenkins, G. M., (1968). Some recent advances in forecasting and control. *Journal of the*

Royal Statistical Society. Series C (Applied Statistics), 17(2), 91-109. Doi: https://doi.org/10.2307/2985674

Businger, M. & Read, R. R. (1999). Identification of demand patterns for selective processing: a case study. *Omega International Journal Management Science*, 27, 189-200. Doi: https://doi.org/10.1016/S0305-0483(98)00039-5

Cavalieri, S., Garetti, M., Macchi, M. & Pinto, R. (2008). A decision-making framework for managing maintenance spare parts. *Production Planning & Control*, 19(4), 379-396. Doi: https://doi.org/10.1080/09537280802034471

Chen, Y., Liu, P. & Yu, L. (2010). *Aftermarket demands forecasting with a Regression-Bayesian-BPNN model*. IEEE International Conference on Intelligent Systems and Knowledge Engineering. Doi: https://doi.org/10.1109/ISKE.2010.5680793

Chitale, A. K. & Gupta, R. C. (2014). Materials management a supply chain perspective: text and cases. Third Edition, *PHI Learning Private Limited*. Retrieved from https://books.google.com.tr/books?id=oYdHBQAAQBAJ

Croston, J. D. (1972). Forecasting and stock control for intermittent demands. *Journal of the Operational Research* Society, 23, 289–304. Doi: https://doi.org/10.1057/jors.1972.50

Hyndman, R. J. & Athanasopoulos, G. (2018). *Forecasting: principles and practice*, 2nd edition. Retrieved from https://otexts.com/fpp2/

Jiafu, R., Zongfang, Z. & Fang, Z. (2009). *The forecasting models for spare parts based on ARMA*. WRI World Congress on Computer Science and Information Engineering. Doi: https://doi.org/10.1109/CSIE.2009.315

Kim, T. Y., Dekker, R. & Heij, C. (2017). Spare part demand forecasting for consumer goods using installed base information. *Computers & Industrial Engineering*, 103, 201-215. Doi: https://doi.org/10.1016/j.cie.2016.11.014

Makridakis, S., Wheelwright S. C. & Hyndman, R. J. (1998). *Forecasting: methods and applications*, Third edition. New Jersey, USA: Wiley.

McKinsey&Company Inc. (2017). The changing aftermarket game and how automotive suppliers can benefit from arising opportunities. Retrieved from https://www.mckinsey.com/~/media/McKinsey/Industries/Automotive%20and%20Assembly/Our%20Insights/The%20changing%20aftermarket%20game%20and%20how%20automotive%20suppliers%20can%20benefit%20from%20arising%20opportunities/The-changing-aftermarket-game.ashx

Nawzar, R. & Sheik, S. K. (2016). *Improving forecasting for the aftermarket through big data: A case study at Volvo Group (M.Sc thesis)*. Department of Technology Management and Economics, Chalmers University of Technology, Gothenburg, Sweden. Retrieved from https://hdl.handle.net/20.500.12380/238852

Ozcift, B. (2018). *Fuzzy clustering model proposal for forecasting automotive spare part demands* (Ph.D. Thesis). Kocaeli University The Pure and Applied Sciences Institute, Kocaeli.

Porras, E. & Dekker, R. (2008). An inventory control system for spare parts at a refinery: an empirical comparison of different re-order point methods. *European Journal of Operational Research,* 184, 101–132. Doi: https://doi.org/10.1016/j.ejor.2006.11.008

Regon, J. R. & Mesquita, M. A. (2014). Demand forecasting and inventory control: A simulation study on automotive spare parts. *International Journal of Production Economics,* 161, 1-16. Doi: https://doi.org/10.1016/j.ijpe.2014.11.009

Saravanan, A. M., Anbuudayasank, S. P., David, A. W. & Narassima, M. S. (2019). Forecasting techniques for sales of spare parts*. International Journal of Recent Technology and Engineering* (IJRTE),ISSN: 2277-3878, 8(3). Retrieved from https://www.ijrte.org/download/volume-8-issue-3/

Schaffer, A. L., Dobbins, T. A., & Pearson, S. A. (2021). Interrupted time series analysis using autoregressive integrated moving average (ARIMA) models: a guide for evaluating large-scale health interventions. *BMC medical research methodology*, 21(1), 1-12. Doi : https://doi.org/10.1186/s12874-021-01235-8

Suyunova, M. (2018). The use of demand forecasting techniques for the improvement of spare part management. *Proceedings of the World Congress on Engineering Vol I*, London, U.K.

TUIK, (2021). Gross domestic product at current prices by income approach (value, share, percentage change). Retrieved from https://data.tuik.gov.tr/Kategori/GetKategori?p=ulusal-hesaplar-113&dil=1

Vargas, G.C.A. & Cortes E.M. (2017). Automobile spare-parts forecasting: A comparative study of time series methods. *Journal of Automotive and Mechanical Engineering,* 14, 3898-3912. Doi: https://doi.org/10.15282/ijame.14.1.2017.7.0317

Webby, R. & O'Connor, M. (1996). Judgemental and statistical time series forecasting: a review of the literature. *International Journal of Forecasting* 12,91-118. Doi : https://doi.org/10.1016/0169-2070(95)00644-3

Winters, P. (1960). Forecasting Sales by Exponentially Weighted Moving Averages. *Management Science*, 6(3), 324-342. Doi : https://doi.org/10.1287/mnsc.6.3.324