MARMARA UNIVERSITY
INSTITUTE FOR GRADUATE STUDIES
IN PURE AND APPLIED SCIENCES

APPLICATION OF SALES FORECASTING TECHNIQUES FOR A COMPANY IN THE HOME APPLIANCES INDUSTRY

TÜLAY AKDAĞ

MASTER THESIS

Department of Industrial Engineering

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Asst. Prof. Dr. Kıvanç ONAN

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Tülay AKDAĞ, a Master of Science student of Marmara University Institute for Graduate Studies in Pure and Applied Sciences, defended her thesis entitled "Application of Sales Forecasting Techniques for A Company In The Home Appliances Industry", on July 26, 2019 and has been found to be satisfactory by the jury members.

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APPROVAL

Marmara University Institute for Graduate Studies in Pure and Applied Sciences Executive Committee approves that Tülay AKDAĞ be granted the degree of Master of Science in Department of Engineering, Industrial Engineering Program on 07.08.2019
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BEYAZ EŞYA ENDÜSTRİSİNDEKİ BİR ŞİRKET İÇİN SATIŞ TAHMİNİ TEKNİKLERİNİN UYGULANMASI

Zaman serisi analizi ile tahmin, bir iş ortamında, üretim planlama, satın alma, çizelgeleme ve pazarlama gibi operasyonları etkin ve verimli bir şekilde planlamak için yaygın bir istatistiksel analizdir. Beyaz eşya endüstrisinde, doğru bir satış tahmininin tüm operasyonlarda önemli bir rolü vardır. Bu tezde kullanılan veriler mevsimsel, çevrimsel ve trend modellerine sahip olan dokuz yıllık ve aylık satışları içermektedir. Amaç, soğutma grubu (buzdolabı ve dondurucu) satışlarını zaman serisi tahmin yöntemiyle tahmin ederek şirketin karar verme sürecine yardımcı olmaktır. Autoregressive integrated moving average (ARIMA) ve Nonlinear Autoregressive (NAR) Neural Network tahminleme metotları kullanılmıştır. Analizler için R, R Studio ve MATLAB kullanılmıştır. Zaman serileri, öğrenme seti (ilk 96 ay) ve test seti (son 12 ay) olarak iki gruba ayrılmıştır. Öğrenme seti, ARIMA modellerinin ve NAR ağının uydurulması için kullanılırken, test set tahmin doğruluğunu değerlendirmek için kullanılmıştır. ARIMA modelini zaman serilerine uygulayabilmek için sırasıyla Box-Cox transformasyon ve farkalma kullanılmıştır. Aynı verilere Levenberg-Marquardt geri yayılım öğrenme algoritmasına göre NAR ağı uygulanmıştır. Tahmin edilen değerler gerçek değerlerle, tahmini doğruluk ölçülerine dayalı olarak karşılaştırılmıştır. Seçilen ARIMA modelinin beyaz eşya endüstrisindeki şirketin soğutma grubu satışlarını tahmin etmede güvenilir sonuçlar verdiği görülmüştür.

ABSTRACT

APPLICATION OF SALES FORECASTING TECHNIQUES FOR A COMPANY IN THE HOME APPLIANCES INDUSTRY

Prediction through time series analysis is a common statistical task in a business environment for planning operations effectively and efficiently such as production planning, purchasing, scheduling and marketing. In white goods industry an accurate sales forecasting has a significant role in whole operation as well. The data used in this thesis include nine-year monthly sales which have seasonal, cyclical and trend patterns. The objective is to help decision making process of the company by forecasting its cooling group (refrigerator and freezer) sales by a time series forecasting method. Autoregressive integrated moving average (ARIMA) and the Nonlinear Autoregressive (NAR) Neural Network methods have been chosen to use. R software, R Studio and MATLAB have been used for the analyses. The time series have been divided into two subsets as training set (first 96 months) and test set (last 12 months). The training set is used to fit ARIMA model and NAR network, whereas the test set is used to evaluate forecast ability of the model. For applying ARIMA model, in order to obtain stationary data series in the variance and in the mean, Box-Cox transformation and differencing have been applied, respectively. The NAR network based on Levenberg-Marquardt Backpropagation training algorithm has been applied to the same data and comparisons have been done. The forecasted values have been compared with actual values based on the measures of forecast accuracy. It is concluded that the chosen ARIMA model gave reliable results for forecasting the sales of cooling group of company in the white goods industry.

SYMBOLS

a_t : White noises series with zero mean and constant variance at period t
d : The degree of differencing for nonseasonal part
D : The degree of differencing for seasonal part
m : The number of terms estimated in the model
n : The sample size
p : The order of autoregressive components for nonseasonal part
P : The order of autoregressive components for seasonal part
q : The order of moving average components for nonseasonal part
Q : The order of moving average components for seasonal part
s : Number of periods per season
y_t : The actual value of observations at period t
B : The backshift operator
μ : Parameters of the model
θ_q : Model parameters for moving average part
$\emptyset_p$: Model parameters for autoregressive part
ε_t : Error value at time t
σ^2 : Variance

ABBREVIATIONS

ACF : Autocorrelation Function

AIC : Akaike's Information Criterion

ANNs : Artificial Neural Networks

ARIMA : Autoregressive Integrated Moving Average

BIC : Bayesian Information Criterion

BP : Backpropagation

GDP : Gross National Product

MAD : Mean Absolute Deviation

MAE : The Mean Absolute Error

MAPE : The Mean Absolute Percentage Error

MSE : The Mean Squared Error

NAR : Nonlinear Autoregressive Neural Network

NARX : Nonlinear Autoregressive Neural Network with Exogenous Inputs

NN : Neural Network

PACF : Partial Autocorrelation Function

RNN : Recurrent Neural Network

SARIMA : Seasonal Autoregressive Integrated Moving Average

SCT : Special Consumption Tax

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1. INTRODUCTION

Sales forecasting is the function of calculating the expected sales amount of products and services (Merigo, et al., 2015). It is interpreted by the demand estimates of which product will be produced, what amount the customers will demand (Orbach and Fruchter, 2011). Historical sales figures are used for sales forecasting in the organizations to predict outlook performance and it is possible to obtain strategic business plans in the long and short terms (Jimeneza, et al., 2017). The data may occur from time series data such as yearly, monthly or daily sales, production records, etc. The time series is composed of series of recurrent observations on a single subject and these observations are linked on its own past values (Washington et al., 2011) and the time series data set contains generally both nonlinear and linear patterns which attend to show seasonality, fluctuations, irregular cycles, trend or variability in business, economics and kind of other scientific fields. Suhermi et al. (2018) have stated that “Time series analysis is the analysis of observational data that occurs in a time sequence and a fixed time interval”. Analyzing time series is for generalizing the dynamic patterns in the dataset and estimating effects of the known or unsuspected interventions. Generally, a retail sales time series has seasonal or periodical and strong trends and variations exhibiting defiances in generating effective predictions (Ramos, et al., 2015).

In the literature, many applications among time series forecasting are properly examined to sales forecasting due to sales forecasting applications are based upon the concept of time series (Guo et al., 2013). Sales forecasting has been used commonly for business applications and in many different ways in recent research. Sales forecasting is considerably complex because of the effect of different environments and a proper sales forecasting methodology improve the effeciency of business strategy (Lasek et al., 2016). Becasue an accurate forecast allows organizations to have better market performance, and better interpretation of the future, minimize profit losses, and organize production processes and marketing strategies more effectively (Fantazzinia and Toktamysovab, 2015).

The sales forecasting problems are approached as univariate time series forecasting problems since the studies used input data from past sales data of time series being forecasted. In researches, many important models have been presented and offered for increasing performance and the accuracy of time series estimations. One of the important and popular time series models is the autoregressive integrated moving average (ARIMA) model. In 1970s George Box and Gwilym Jenkins proposed Box-Jenkins methodology (Box, et al., 2015) for practicing ARIMA models to time series analysis (Makridakis, et al., 1998). In many research and business applications of forecasting, ARIMA method has been used widely due to its high prediction performance, accuracy, robustness, and interpretability (Orbach and Fruchter, 2011; Calster et al., 2017). Due to Box-Jenkins methodology and its statistical properties, ARIMA model has major impact on practical applications to time series modeling when there is seasonality (Zhang, 2005). The ARIMA models can present various different kind of time series like AR which is pure autoregressive, MA which is pure moving average and combined AR and MA (ARMA) series. There existences linear correlation form assumed among time series values so, there are not nonlinear patterns that captured by ARIMA models. By development of artificial intelligence techniques, artificial neural networks (ANNs) have been widely chosen as a forecasting method (Yu et al., 2011). ANNs are the approach for solving various nonlinear problems which are difficult to analyze by traditional techniques (Bhandari et al., 2016). ANNs approach inspired from human brain function, is a new technique which composed a mathematical model to approximate correlation between variables (Gairaa et al., 2015). In constrast to classical approaches, this approach is implemented without assumptions about the dispersion of the variables and no imposing a particular form to data (Gairaa et al., 2015). ANNs have three building blocks Learning Mechanism, Neural Network Architecture and Activation Function (Singh and Gill, 2014). In the practice, there are enormous amount of nonlinear systems, or the system whose attitude is flexible, dynamic and based on their actual state (Guo et al., 2011). Neural network (NN) buildings which are able to be functional in the situation of that the dynamic recurrent neural network (RNN), the nonlinear autoregressive (NAR), and the nonlinear autoregressive neural network with exogenous inputs (NARX) (Gu, et al., 2011; Seaman, 2018).

In this thesis, it has been focused on ARIMA and nonlinear autoregressive (NAR) methods to forecast cooling group (refrigerator and feezer) sales of a company in the home appliances industry with the objective of helping its decision-making process by proposing a reliable forecasting model.

Time series modeling has been used commonly in the business applications for a long time such as ARIMA or ANNs. Such forecasting techniques have been used in many fields. However, it has been really difficult to find a study on sales forecasting of white goods.

2. METHODOLOGY AND LITERATURE REVIEW

2.1. Forecasting

There exists time lag between realization of an approaching occurrence. That's why this lead time is the essential objective for planning and estimating in the case it is required to understand if an occurrence will happen or a demand will arise, by this way that relevant actions and precautions can be taken (Makridakis, 1998). In the forecasting, it is tried to estimate how sequence of data set or variables will proceed through the future. Estimating situations diversify properly in the time horizons, the factors verifying real outcomes, patterns of data and various other aspects, therefore various types of techniques have been developed to deal with mentioned diverse applications.

Major categories for forecasting methods are summarized by Makridakis et al. (1998) as quantitative (quantitative information is sufficient and available such as time series and explanatory), qualitative (qualitative knowledge exists but no quantitative information is available sufficiently) and unpredictable (little or no information is available). Time series forecasting methods identify the pattern in the historical data series and extrapolate that pattern into the future by assumption of continuity (Makridakis et.al, 1998).

Forecasting the future properly, forecasts are obtained by using all of the related useful information, such as historical records and knowledge or input of any future events which have the possibilities to impact the forecasts (Hyndman and Athanasopoulos, 2018). When a prediction is needed for the things in a manufacturing area, it is necessary to ask if the forecasts are required for all product lines or for spesific products, for each sales outlet or allocated by region. Forecaster should also be aware of the forecasting horizon. Some questions are also be answered such as if the forecasts are essential for short or long term. Different kind of models will be required depending on the forecast horizon (Hyndman and Athanasopoulos, 2018).

2.1.1. The Basic Steps in Forecasting Task

Forecasting task entails five main steps (Makridakis et al., 1998; FAO, 2019):

1. **Definition of the problem:** Defining the problem needs the understanding of the methods which will be used, how fit the functions of forecasting within the organisation and who needs the forecasts.

2. **Gathering data:** Required statistical data are obtained by interviews, questionnaries or direct observations such as sales records and so on.

3. **Preliminary analysis:** Graphing the data is the start point of this task. Many questions among the data are answered here that if there are stable patterns or if there is notable trend, seasonality or cycling, there are outliers or how strong reliationship among the variables for analysis, etc. Several tools have been investigated to assist with this analysis.

4. **Choosing and fitting models:** Best model is identified according to existence of historical data, power of correlation between variables, and the forecast methods used. For choosing the proper models, generally two or three potential models are compared. Considering different kind of data patterns is very substantial step for choosing a proper forecasting method, so that the methods allowing these patterns are able to be utilized. Horizontal, cyclical, trend and seasonal are distinguished types of time series data patterns.

5. **Model using and evaluating:** The models are used for forecasting after the models have been chosen and their parameters estimated. The accuracy of the model is only able to be appropriately measured afterwards the actual data for the forecast period have become available. Some methods have been identified to assist in assessing the performance of forecasts.

2.1.2. Time Series Forecasting

Often the past data occurs from series of observations over time. The sequence of observations over time is reffered as a time series. The methods of time series forecasting define the patterns in the past time series data and estimate these patterns through the future by assumption of continuity. Analyzing time series is for generalizing the dynamic patterns in the dataset and estimating effects of the known or unsuspected interventions.

Time series analysis is a method for analyzing the series to find out the pattern and the characteristics of the data (Gestel, 2001). In the literature several significant time series forecasting techniques have been developed and envolved (Makridakis, 1998; Gestei, 2001). ARIMA is the most popular one of the time series forcasting because of its characteristics such as simplicity and flexibility to present many variations of time series (Hamzacebi, 2008). The linear models have been applied by many researchers due to their simplicity in understanding the models as well as they are easy to implement. But some limitation of such a model is the preassumed time series linear form that becomes inadequate in many real problems and empirical cases. The real problems are generally more complex, and the data series often contain nonlinear pattern. To handle this drawback, development of machine learning and several nonlinear stochastic techniques in the forecasting of time series data have been defined in literature (Makridakis, 1998). Recently, ANN is recommended for an alternative to time series forecasting (Makridakis, 1998). Various neural network models have been trained such as Bayesian approach which was suggested for nonlinear time series forecasting techniques (McAlinn and West, 2016).

Forecasting for time series is important in making more advanced organizational, financial, individual and many other strategic decisions for long and short terms. For instance, proper bankruptcy prediction and credit scoring support for financial foundations to avoid financial crisis (McAlinn and West, 2016). Electricity load time series forecasting assists better planning for power system (Behera et al., 2010; Raza and Khosravi, 2015), time series forecasting of internet traffic assists service suppliers to improve their service (Lavrenza et al., 2018), time series forecasting of call volumes in a call center supports scheduling staff (Meade and Islam, 2015). Cortesa et al. (2018) have been studied the temporal patterns of dengue incidence by using the data between 2001 and 2014 historical records and forecasted for the next year (2015) in different Brazilian cities. Lavrenza et al. (2018) provided a survey of the art at the state in traffic safety research and examined the basic techniques in classical time series forecasting modeling.

The Time Series Definition

The time series is explained basically as a “sequential set of data points that measured over successive times and it is defined as a set of vectors $x(t)$, $t = 0,1,2,...$ where t is the time elapsed and $x(t)$ is treated as a random variable" (Raicharoen et al., 2003; Adhikari and Agrawal, 2013). The observations are taken while an occurrence in a time series are occurred in an appropriate chronological order (Adhikari and Agrawal, 2013).

If the data contains one variable it is called as univariate, but if there exists multiple variables, it is called as multivariate time series (Adhikari and Agrawal, 2013). In the practical situations, a time series data might be continuous as well as discrete. A continuous series are observed at each stage of time and a discrete time series values are recorded at discrete period of time. Generally, the discrete time series and sequential records are observed at equally spaced time periods such as yearly, monthly, daily, etc. time intervals. In general time series data might be affected by key components such as trend, cyclical, irregular and seasonal components (Adhikari and Agrawal, 2013).

2.1.3. Sales Forecasting

The retail sales management is very important for retail organizations. In the competitive environment, sales forecasting has significant impact in the global and commercial organizations (Xiao and Qi, 2008). Organizations and retailers would like to increase their profit and reduce their cost. A proper forecasting system is one of the efficent way to meet the targets as proper forecasts can improve business strategy (Aye and Balcilar, 2013). Sales forecasts are vital for many strategic actions in many operable fields such as, sales processes, production, purchasing, marketing including accounting and finance at the organizational level. Inventory management, replenishment plans, distribution strategies are also provided by sales forecasts and for commercial retail operations, accurate sales forecast directly linked to organizing and planning transportation, production, purchasing, labor force and customer services (Zhang, 2009). So, the accuracy of forecasts to predict the sales amount in the next periods leads to decisions on customer expectations, cost and waste management while increasing sales income with more efficient plans.

In the literature many papers about sales forecasting have been reported, that contain many studies in various industries, for instance, fashion industry (Sébastien, 2010; Yu et al., 2011; Du et al., 2015; Loureiro et al., 2018), as print circuit board industry (Chang et al., 2005), food industry (Chen et al., 2010; Sivanandan, 2015), apparel industry (Guo et al., 2011) and airline industry (Kim and Shin, 2016).

Sales forecasting is studied in many different ways in current reports, especially ANNs (Nunnari and Nunnari, 2017), ARIMA (Zhang, 2001; Calster et al., 2017) and among others. Some researchers studied the forecasting tasks for sales as univariate time series forecasting problem (Jimeneza, et al., 2017). These kind of reports used the past data of time series being forecasted directly, according to a main presumption which the fundamental data generating the series is constant (Jimenez et al., 2017).

2.2. Methods Used in Study

In this thesis among time series forecasting methods ARIMA and NAR methods have been chosen to use.

2.2.1. Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model is one of the most famous techniques of time series for the univariate forecasting tasks, due to its simplicity, interpretability and accuracy (Calster et al., 2017). The ARIMA models are extrapolated by ARMA models, that has been first described by Whitle (1954) and moreover popularized by Box and Jenkins (Box et al., 2015) in the 1970s. The general notation of Box-Jenkins ARIMA model with nonseasonal part (p,d,q) and seasonal part $(P,D,Q)_s$ is ARIMA $(p,d,q)(P,D,Q)_s$, where, p and P are the order of autoregressive components, d and D are the degree of differencing, q and Q are the order of moving average components for nonseasonal part and seasonal part of the model, respectively, and s is the number of periods per season (Box et al., 2015). In this study, seasonal variant of ARIMA models, the SARIMA $(p, d, q)(P,D, Q)_s$ model has been used that contains additionally seasonal variants (Box et al., 2015).

General form of ARIMA model is shown in equation (1) as follows (Wei, 2006):

$$(1-B)^d Y_t = \mu + \frac{\theta_q(B)}{\emptyset_p(B)} a_t \tag{1}$$

Where,

$$\emptyset_p(B) = 1 - \emptyset_1 B - \cdots - \emptyset_p B^p$$

$$\theta_q(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$$

$BY_t = Y_{t-1}$

Y_t: The actual value

B: the backshift operator

a_t: White noise series with zero mean and constant variance

M: Parameters of the model

d: Degree of differencing

ARIMA is a class of stochastic processes used to analyze time series. The general scheme of proposed ARIMA and general statistical methodology have been given by Contreras et al. (2003) in Figure 2.1:

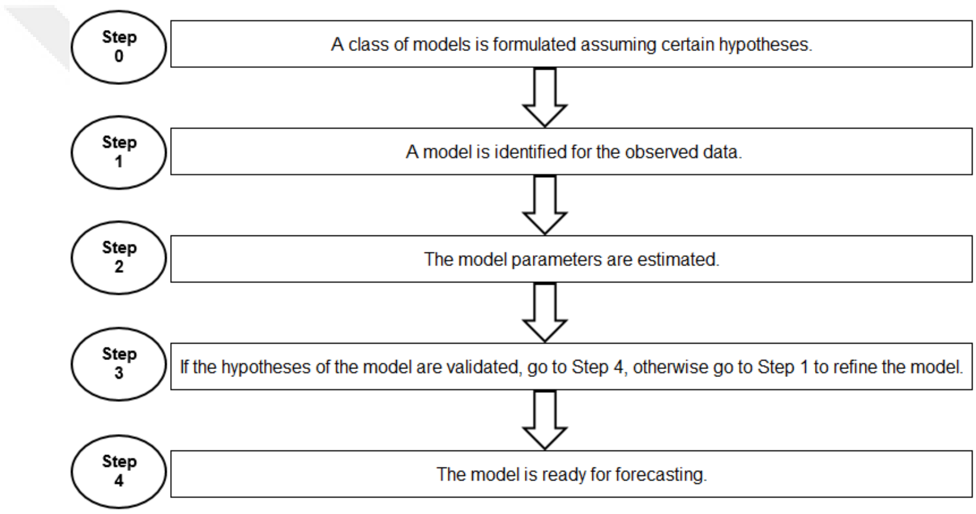

Figure 2.1. General scheme of proposed ARIMA and statistical methodology (Modified from Contreras et al. (2003)

2.2.1.1. Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model entails the steps as follows (Tseng, 2002):

(1) The ARIMA (p, d, q)(P, D, Q)$_s$ structure definition,

(2) Unknown parameters estimation,

(3) Test on the residuals,

(4) Prediction of outcomes based on the existing data.

A seasonal ARIMA model is builded with additional seasonal terms in the ARIMA model. The model is shown below:

$$\textbf{\textit{ARIMA}} \quad \underbrace{\textbf{\textit{(p, d, q)}}}_{\substack{\text{Non – seasonal} \\ \text{part of the model}}} \quad \underbrace{\textbf{\textit{(P,D,Q)}}_{\textbf{\textit{m}}}}_{\substack{\text{Seasonal part of} \\ \text{the model}}}$$

Here m equals number of periods per season, it is used uppercase notation is used for the seasonal part and lowercase notation is used for the nonseasonal part (Hyndman and Athanasopoulos, 2018). The seasonal part includes the components which are similar to the terms of nonseasonal of the model but consist of backshifts of seasonal period.

In the SARIMA model, the expected value of variables is supposed to be a linear function of random errors and past records. Basically, formed with equation (2) by Zhang, (2001) as below:

$$y_t = \theta_0 \; + \emptyset_1 y_{t-1} + \cdots + \emptyset_p y_{t-p} + \varepsilon_1 - \theta_{1\varepsilon_{t-1}} - \cdots - \theta_{q\varepsilon_{t-q}} \qquad (2)$$

Where,

y_t: Actual value,

ε_t: Error value at time t,

$\emptyset$i (i=1; 2; : : : ; p) and θj (j=0; 1; 2; : : : ; q): Model parameters,

p, q: Integers for the number of model terms.

Errors are assumed to be independently and identically distributed with a zero mean and a constant variance of σ^2. Equation 1 issues various cases of the ARIMA models. When q equals zero then equation 2 transforms AR model of order p. If p equals zero, the model transforms to MA model of order q. The main issue of the ARIMA model architecture is determining the proper model orders (p and q).

The approach according to Box and Jenkins methodology (Box, 2015) for building ARIMA models is applied to forecasting and the time series analysis. The methodology of Box–Jenkins contains three steps, respectively, model identification, estimation of parameters and diagnostic checking (Zhang, 2001).

Identification of the model means data is prepared and model is selected. Tools are available to define potential models, by corresponding the empirical autocorrelation patterns with the theoretical ones (Zhang, 2001). By analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF), the temporal correlation structure of the transformed and/or differenced data is identified. It is offered to use the PACF and ACF of the patterns as an essential tool for identifying the order of the ARIMA model (Zhang, 2001). In analyzing the series, the ACF is very beneficial statistical tool to have measures when the earlier values have some relationship with later values. PACF is defined as "correlation between a variable and a lag of itself that is not explained by correlations at all low order lags" by Men and Wang (2012). PACF is a summary of the correlation between the records in a series with measurements at the time period with the correlation of intervening records removed (Men and Wang 2012). That means the PACF at lag k is the correlation after removing the impact of any correlation due to the terms at shorter lags (Machine Learning Mastery, 2019). According to the ACF and PACF graphs, several models are defined for model selection. By examining Akaike's Information Criterion (AIC), the model is chosen as the best fitted model (Machine Learning Mastery, 2019). The formulation of AIC has been showed with equation (3) (Makridakis et al., 1998):

$$AIC = -2\log L + 2m \approx n(1+\log(2\pi)) + nlog\sigma^2 + 2m \quad (3)$$

where, m = p+q+P+Q is the number of terms estimated in the model, n is the number of observations in the series and σ^2 is the variance of the residuals.

The Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC) have very significant role in the identification step. Mostly the AIC value is used in selecting the number of terms of an ARIMA model (Fard and Zadeh, 2014).

In the identification step, initially data transformation is generally necessary in order to make the time series stationary in variance because making the data stationary is a required condition for fitting ARIMA models (Zhang, 2001). The autocorrelation structure and mean are constant over time in a stationary time series. When time series data has trend and heteroscedasticity, transformation and differencing are performed to the time series data to stabilize the variance and remove the trend before the ARIMA model fitted (Machine Learning Mastery, 2019). After a tentative model is specified, it is straightforward to estimate the model parameters and it is necessary to minimize measures of errors for the parameter estimation (Men and Wang, 2012).

According to Box-Jenkins methodology, the final step of time series modeling is the diagnostic check. Residuals of the model are examined for verification that the fitted model is adequate (Zhang, 2001; Men and Wang 2012). Diagnostic statistics and residuals' plot determine the adequacy of the fitted model and if the fitted model is not sufficient, a new temporary model might be defined (Zhang, 2001).

2.2.1.2. Box-Cox Transformation

In the case a dataset has variation such as increases or decreases with the level of the series, a transformation might be necessary for the preparation of the data. For instance, a logarithmic trasnformation can be used in the case the original observations as $y_1,\ldots,y_t$, the transformed observations $w_1,\ldots,w_2$, this shows $w_t=log(y_t)$. The logarithmic transformation is often used due to its interpretability (Hyndman and Athanasopoulos, 2018). In the literature, the other transformations are also applied, for instance, cube roots. Such a transformation is named power transformation in case they are written $w_t = y_t^p$ (Hyndman and Athanasopoulos, 2018).

In this thesis the Box–Cox transformation has been used. The Box-Cox transformation contains both logarithmic and power transformation by using the following mathematical formulation (4) (Hyndman and Athanasopoulos, 2018):

$$w_t = \begin{cases} \log(y_t) & if\ \lambda = 0 \\ (y_t^{\lambda} - 1)/\lambda & otherwise \end{cases} \tag{4}$$

where, y_t is the original observation and w_t is the transformed observation at time t. Box-Cox transformation depends on the parameter λ.

2.2.1.3. Residual Diagnostic

After defining a proper model, diagnostic checking is necessary to verify if the model is adequate. By examining the residuals, remaining patterns can be observed. Diagnostic checking is very important step for estimating the ARIMA models (Ramos et al., 2015).

For a good forecasting model, after fitting the model, the residuals should be white noise. For this purpose, ACF/PACF graphs of the residuals are drawn and according to patterns in these graphs, it is examined if there are any significant autocorrelations or partial autocorrelations. In addition, portmanteau tests can also be applied to the residuals. These tests help to verify that the model is adequate. In case a portmanteau test is significant, that means the model is inadequate. In such a situation, it is necessary to go back and revise the ARIMA model or different models should be tried. In the ACF/PACF graphs, the patterns of significant spikes may offer how the model may be revised. For instance, if there are significant spikes at seasonal lag, a seasonal component can be added. In the case of a significant spike at small lags, this time, non-seasonal components of the model may be increased (Makridakis et.al, 1998).

2.2.2. Structure of Neural Networks

Artificial neural network (ANN) methods have been offered as a technique for time series forecasting and it has been extensively used recently (Zhang, 2001). The key target of artificial neural networks (ANNs) is to build a model for simulation of the intelligence of the human brain and the networks are comprised of many interconnected nodes as the neurons in the brain (Kihoro et al., 2004). Similar to a human brain, the main operation of ANNs is the firing regulations that inform the neurons based on the inputs (Syam and Sharma, 2018). ANNs recognize rules and samples, find out from experimentation and ensure generalized outputs upon the known past information (Adhikari and Agrawal, 2013). In spite of the fact that the development of neural networks has been mostly biologically motivated, but subsequently, they have been studied in various several fields, particularly for forecasting purposes (Hornik et al., 1989).

In nature, ANNs are self-adaptive and data-driven (Hornik et al., 1989). That manner is very helpful for various empirical cases. Moreover, ANNs are intrinsically nonlinear that lets them more sufficient and precise in the modeling of complicated data patterns against traditional linear methods (Zhang, 2001). Besides, as proposed by Hornik et al. (1989) ANNs are universal functional approximators.

ANNs use parallel processing of the knowledge from the data to estimate a huge variety of functions within a well enough accuracy. ANNs can deal with cases that the inputs are inaccurate or fuzzy. A neural network is supposed to be as a network of neurons that are in layers, the inputs from the bottom layer and the forecast outputs from the top layer (Hyndman and Athanasopoulos, 2018).

Among many neural network buildings, the commonly used one in the applications is three-layer feedforward backpropagation neural networks (Akkaya et al., 2013). Mostly ANNs have three layers, that are connected by cyclic links which are called input, hidden and output layers (Syam and Sharma, 2018). There might be one or more than one hidden layer. Neural network architecture is formed by an output layer of linear neurons with linear transfer functions and a hidden layer of neurons with nonlinear functions (Durdu, 2010). As shown in Figure 2.2 the input layer unit is linked to the hidden layer units. A three-layer feedforward backpropagation architecture of ANN model is represented in Figure 2.3, where x_j (j=1,...,N) shows initial variables and n_i (i=1,…, S) shows the outputs of neurons in the hidden layer and y_t (t=1,…, L) shows the outputs of the ANN (Durdu, 2010).

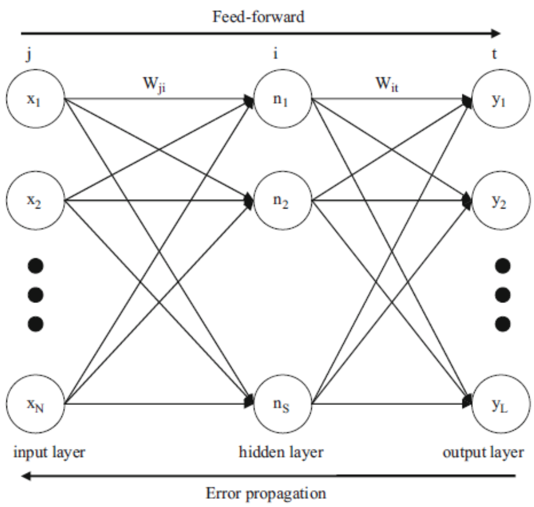

Figure 2.2 Three-layer feedforward backpropogation neural network (Durdu, 2010)

There are weights on the interconnections among the input and hidden units and in a similar manner, between the hidden and output units. The activities of the input units determine the hidden units' activities and hidden units activities determine the output units' activities (Durdu, 2010; Syam and Sharma, 2018). ANNs also have the advantage due to their capability for self-organizing, learning and adapting (Maier and Dandy, 2000).

In the training process, calculations backward through the network are performed. This process is named “backpropagation” process and it continues until the error is minimized. This error is a value for understanding how well the neural network performs. The main aim of this process is to determine weights by minimizing the difference between actual target values and network outputs. Neurons have an activation function and by applying the activation function, the output pass through the next neurons.

Cigizoglu (2004) and Wei (2008) applied the algorithms of error backpropagation (BP) for the network training in applying ANN for water resources.

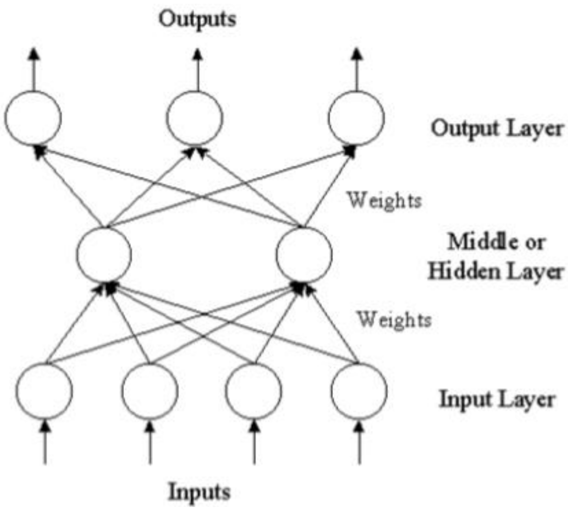

Figure 2.3 Connection weights of the layer of input, hidden and output units (Durdu, 2010)

As the major working process of BP, each error signal is able to distribute back from the output to input layer to fix the weights in order output of the network to match the objectives (Wei, 2008).

The output of the model is calculated by the following equation (5) (Zhang and Qi, 2005):

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j f\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-i}\right) + \varepsilon_t\,, \forall t \tag{5}$$

where,

y_t is the output at time t, p is the number of input nodes, q is the number of hidden nodes, f is a sigmoid transfer function.

α_j (j = 0, 1, 2, …, q) is a vector of weight from the hidden to output nodes; β_{ij} (i = 0, 1, 2, …, p; j = 0, 1, 2, …, q) are the weights from the inputs to hidden nodes; α_0 and β_{0j} are weights of arcs leading from the bias terms having values equal to 1.

In the literature, different transfer functions have been used in ANNs and sigmoid functions are generally used in the applications (Adhikari and Agrawal, 2013). Sigmoid function is a mathematical function which has "S" shaped curve. Sigmoid functions such as the hyperbolic tangent functions or logistics functions are used as transfer functions of ANNs.

The Nonlinear Autoregressive (NAR) Neural Network

The NAR network is a technique of repetitive ANNs with embedded memory, presents a robust category of networks, which can represent nonlinear dynamical mappings among various ANNs (Benmouiza and Chechnane, 2016). The mathematical formulation (6) for NAR network is:

$$\hat{y}_t = f(y_{(t-1)} + \cdots . + y_{(t-d)}) \tag{6}$$

f is a function that is determined by the network structure and connection weights.

Both ARIMA models and NAR networks forecast with lagged output variable. In the literature, several applications of time series forecasting have been employed by using statistical, classical and ANNs methods (Tealab et al., 2017; Tealab, 2018; Camelo et al., 2018; Karmy and Maldonado, 2019; Zhang et al., 2019; Yetkin and Kim, 2019; Wang et al. 2019). ARIMA models whose methodology are developed by Box and Jenkins (Box et al., 2015) are applied in several empirical studies. Statistical methods are quite simple and flexible for many temporal phenomena (Koutroumanidis et al., 2009). In the meantime, ARIMA models are linear models, this is the reason their performance have restricted in the real environment (Domingos et al., 2019). Therefore, in the recent researches, the nonlinear models are suggested alternatively (Psoni et al., 2019). ANNs have been performed for many fields such as for environmental forecasting, temperature prediction (Şahin, 2012), rainfall predictions (Mandal and Jothiprakash, 2012). Various univariate forecasting models have been studied by combining linear and nonlinear models appropriately (Zhang, 2001; Durdu, 2010; Khashei and Bijari, 2011; de Oliveira and Ludermir, 2016).

In many reports, time series forecasting with ANNs have been compared with the ARIMA models (Ramos et al., 2015; Xu et al., 2019). Wavelet-ARIMA and wavelet-ANN models have been applied to temperature time series data by Nury et al. (2017). Elkateb et al. (1998) have suggested neural network in electric load forecasting because it has better result than ARIMA models. There are some examples in the literature about NAR/NARX forecasting methods for different time series (Gairaa et al., 2015; Asgari et al., 2016; Nunnari and Nunnari, 2017; Zhenhong et al., 2018; Cheng et al., 2019; Rogier and Mohamudally, 2019).

In addition, in the literature there is wide range of studies that include forecasting benchmarks by combining different methods. In the hybrid systems, classical methods and ANNs are combined for getting better results in different fields of application (Khandelwal et al., 2015; Whang, 2017; Cortes, 2018; Safari and Davallou, 2018). Babu and Reddy (2014) and Wang et al. (2017) present in their studies hybrid approaches for time series forecasting.

2.3. Description of Measures of Forecast Accuracy

In this study, it has been used various performance measures for forecasting accuracy. For the test mean equation (7), and for the test variance equation (8) is used.

$$\bar{y} = \frac{1}{n}\sum_{t=1}^{n} y_t \tag{7}$$

$$\sigma^2 = \frac{1}{n-1}\sum_{t-1}^{n}(y_t - \bar{y})^2 \tag{8}$$

2.3.1. The Mean Absolute Error (MAE)

The mean absolute error (MAE) is calculated by equation (9). The MAE gives the average of absolute errors where forecast error at time t (ε_t) is the difference

(9)

between the actual value and its forecast.

$$\mathrm{MAE} = \frac{1}{\mathrm{n}} \sum_{\mathrm{t}-1}^{\mathrm{n}} |\mathrm{e}_{\mathrm{t}}|$$

For having a proper prediction, the applied MAE must be smaller as possible.

2.3.2. The Mean Absolute Percentage Error (MAPE)

The Mean Absolute Percentage Error (MAPE) is calculated by equation (10) below:

$$MAPE = \frac{1}{n} \sum_{t-1}^{n} \left| \frac{e_t}{y_t} \right| \times 100 \tag{10}$$

MAPE shows the percentage of average absolute error and MAPE does not display the direction of errors.

2.3.3. The Mean Squared Error (MSE)

The mean squared Error (MSE) is calculated by equation (11) and gives the average of the squared errors.

$$MSE = \frac{1}{n} \sum_{t-1}^{n} e_t^2 \tag{11}$$

MSE gives a general perspective of the error accured during forecasting.

3. STATISTICS AND FACTS OF WHITE GOODS INDUSTRY

White goods sector consists of six main products: Refrigerator, freezer, washing machine, oven, dishwasher, dryer and air conditioner. The products in this scope constitute the largest part of durable consumer goods.

The durable consumer goods sector has a rapidly growing and developing market in the world. South Korea, Taiwan, Singapore in the Far East, Finland and Spain in Europe have rapid development in the electronic and white goods industries. Moreover, according to technical developments, the market for durable consumer goods is growing very dynamically with extraordinary speed (Vakıf Yatırım Menkul Değerler A.Ş, 2018).

The sector is one of the leading industries in the world due to the huge number of workers employed.

White Goods Sector in Turkey

White goods sector is one of the most important industry in Turkey and it has a huge impact on the economy of Turkey. Additionally, Turkey has a very important position in Europe by producing energy efficiency high-quality products. That’s why the target market of the white goods sector is foreign markets beside Turkish market. Exports of durable consumer products have been increasing every year since the 90s (Türkiye Beyaz Eşya Ve Elektronik Sektörü Raporu, 2019)

In 2010, R & D expenditures in the sector were approximately 200 million dollars and the rate of the total turnover was 2%. The sustained development, renewal of itself, adapting to the global economy and new technologies are the points to the bright future of the sector. It provides directly or indirectly the subsistence of approximately 2.5 million people (Türkiye Dayanıklı Tüketim Malları Meclisi Sektör Raporu, 2014).

Production of white goods began in the 1950s in Turkey. First production facility for white goods was established in 1959, and this facility started production with a capacity of 15 units per day with 38 workers. From past to today, white goods industry has been one of the leading sectors in Turkey with environmentally friendly and most competitive production systems by exporting 70% of production volume with 28 millon products. Until the 1980s, while it was producing significant materials and components in the facilities in Turkey, at the same time the other required parts were being imported. At the beginning of the 80s, improvement studies for the quality of products was started. When the production volume increased, “one factory, one product” application became widespread in the 80s. On the other hand, licensed products were produced in original design and technology was developed in accordance with the world standards. Simultaneously, export was started for Middle East countries. In the 80s, after-sales services and customer services were developed rapidly (Türkiye Dayanıklı Tüketim Malları Meclisi Sektör Raporu, 2014).

In the 90s, R & D activities became even more important. In the same period, industrial design departments were created in the companies. In the 90s, some materials supplied from the sub-industry increased and the quality increased. Parallel to these, OEM (Original Equipment Manufacturer) production was in the forefront, in the same years the efforts for creating branded and international brands were increased and important budgets were allocated to marketing activities. In the 2000s, the product quality, technologies and environmentally friendly designs began to be recognized for in both Turkish and Europe markets. Minimum energy and water consuming products in the second half of the 2000s were presented to the world market (Türkiye Dayanıklı Tüketim Malları Meclisi Sektör Raporu, 2014).

The sector has increased its production 6 times and its export 20 times in the last 15 years. The sector has made its most important progress with environment-friendly and the energy and water savings products. The domestic material usage rate in the white goods sector is 70% and capacity utilization rate is between 75% and 85% (Beyaz Eşya Sektör Raporu 2017, İş Bankası).

Consumption expenditures, which are a function of income, constitute approximately 59% of our Turkey’s Gross National Product (GDP). This rate has historically dropped to its lowest of 58% and rose to 73% in the years when the economy is relatively better. As of 2017, Turkey is 17th in the World's GDP ranking with 851 billion dollars. Growing in population rate and in young population, white goods market in Turkey always has significant potential. There is a strong connection between the white goods sector and the performance of the national economy (Vakıf Yatırım Menkul Değerler A.Ş, 2018

The sales for white goods occur for the first purchase of the consumers and their demands for renewal or replacement. Some external factors affect the demand for white goods sales. Sales in the domestic market can be divided into three categories as the need for renewal, new house sales and demand due to marriage & divorce. It is estimated that the people change their white goods after 8-10 years period in Turkey. Especially in 2017, the share of renewal demand in white goods sales increased from 28% to 40% due to the incentive in special consumption tax (SCT) (Vakıf Yatırım Menkul Değerler A.Ş, 2018).

The increasing population and urbanization rate, marriage, divorce and housing affect the sales of the white goods industry. In particular, the factors that affecting the demand for housing demand also affects the demand for white goods. The ratio of people living alone in the population is increasing and this creates additional demand for white goods. Figure 3.1 shows that there is a strong correlation between housing and white goods sales. In Figure 3.2 shows the distribution of demand for white goods over renewal, new house sales and demand due to marriage & divorce (Vakıf Yatırım Menkul Değerler A.Ş, 2018).

The median age is 32 in Turkey and approximately 50% of the population is under 30 years. The expected human life period is 78 years, which is expected to increase to 80 years by 2025. The population between 15-64 years constitutes 64.4% of the population, which is expected to rise to 100 million in 2040. This growing of the population is supporting the demand for white goods. Compared with Europe, high population growth and young population structure are advantageous for Turkey's economy and the white goods sector in the meantime (Vakıf Yatırım Menkul Değerler A.Ş, 2018).

Refrigerator is the first white goods product that the consumers use in their home and it is the most common product in households with 96 percent. It is described as the most vibrant segment of the white goods sector. The main reason for this is the innovations in the products. Recently, the elegantly designing, digital and low energy consuming refrigerators increase the consumer's awareness about the need for renewal. Renewal demands could be postponed in times of crisis, but first purchases are not easily abandoned. For example, in the crisis of 2001, domestic sales of durable consumer goods contracted by around 40 percent, while domestic sales in the refrigerator grew by 1 percent. In 2002, domestic sales grew by 13 percent (Türkiye Dayanıklı Tüketim Malları Meclisi Sektör Raporu, 2014).

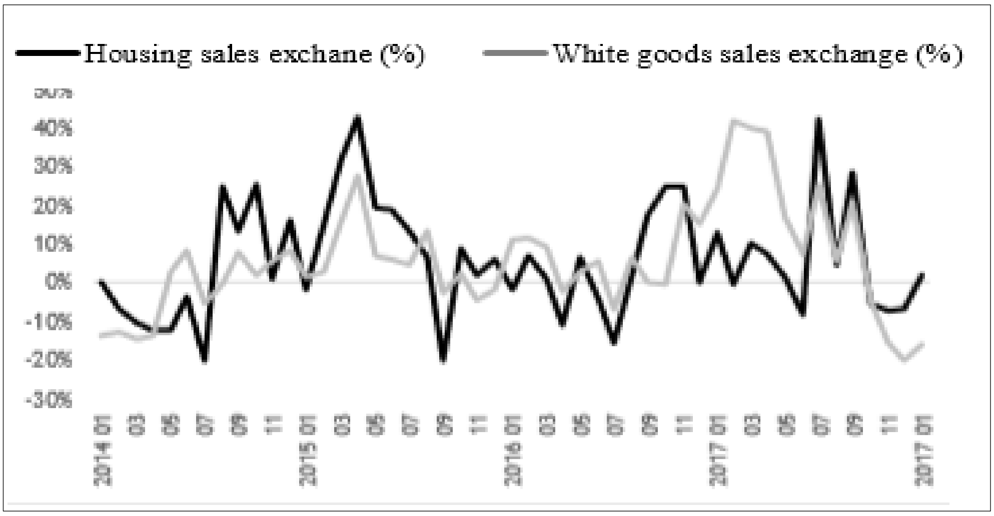

Figure 3.1. Correlation between housing and white goods sales household (Vakıf Yatırım Menkul Değerler A.Ş, 2018)

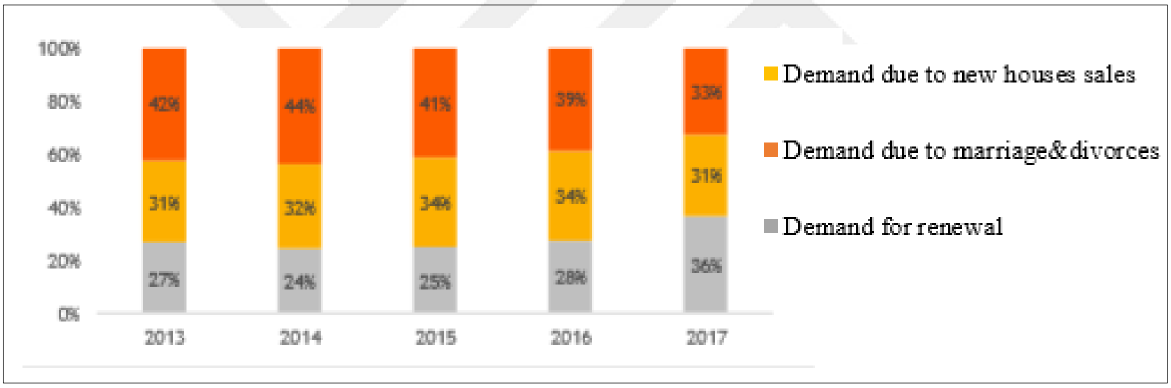

Figure 3.2. Distribution of white goods demand (%) over renewal, new house sales and demand due to marriage & divorce (Vakıf Yatırım Menkul Değerler A.Ş, 2018)

4. APPLICATION

4.1. ARIMA Modeling For Time Series Analysis

In this thesis, the cooling group of white goods (refrigerator and freezer) time series data have been used and they are divided into two subsets as training set (first 96 months) and test set (last 12 months). The ARIMA method is applied in R Statistical Software for one year ahead forecasting of refrigerator and freezer time series sales data.

The general notation of Box-Jenkins ARIMA model with non seasonal part (p,d,q) and seasonal part $(P,D,Q)_s$ is ARIMA (p,d,q) $(P,D,Q)_s$, where p and P are the order of autoregressive components, d and D are the degree of differencing, q and Q are the order of moving average components for non-seasonal part and seasonal part of the model and s is period size per season (Box et al., 2015). An ARIMA model can only be used when the data series is stationary. Since the data series used in this study is non-stationary, in order to obtain stationary data series in the variance and in the mean, Box-Cox transformation and differencing are applied, respectively.

4.1.1. Refrigerator Sales Forecasting

Since the data series used in this study is non-stationary, Box-Cox transformation is used to stabilize the variance and the parameter λ of the Box-Cox transformation is chosen as $\lambda = 0.4051379$. The transformed time series and its seasonal difference along with autocorrelation function (ACF) and partial ACF are given in Figure 4.1 Differencing removes the trend and gives a stationary mean.

In fitting the model, the first 96 months of data are used as the training set, whereas the last 12 months of data are used as the test set to evaluate prediction ability of the model. Among candidate models, ARIMA (1,0,0) $(0,1,1)_{12}$ model was chosen using Akaike's Information Criterion (AIC). The estimated parameters for this model are given in Table 4.1.

At the diagnostics phase, ACF/PACF of residuals have been checked and Ljung-Box test has been applied in order to see if the residuals are white noise. Checking of normality has been done with Shapiro test. Diagnostic testing on the residuals from the model are given in Figure 4.2. The ACF of the residuals and the residuals versus order graph show that the residuals are uncorrelated, hence the residuals resemble white noise. It is seen from the histogram that the residuals are approximately normally distributed. Therefore, the fitted model is adequate. According to Shapiro-Wilk test results for the residuals *p*-value is 0.4139. Ljung-Box test results for the residuals has been issued as follows;

data: Residuals from ARIMA (1,0,0) (0,1,1)[12]

Q* = 18.922, df = 17.2, P-value = 0.3456

Model df: 2. Total lags used: 19.2

Table 4.1. Model Summary

```
ARIMA(1,0,0)(0,1,1)[12]
Box Cox transformation: lambda= 0.4051379

Coefficients:
         ar1     sma1
      0.6061  -0.7957
s.e.  0.0966   0.1986

sigma2 estimated as 93.46:  log likelihood=-314.84
AIC=635.68   AICc=635.98   BIC=642.97

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
Training set 1192.729 4932.627 3633.519 2.189607 8.958682 0.6252022 -0.1774718
```

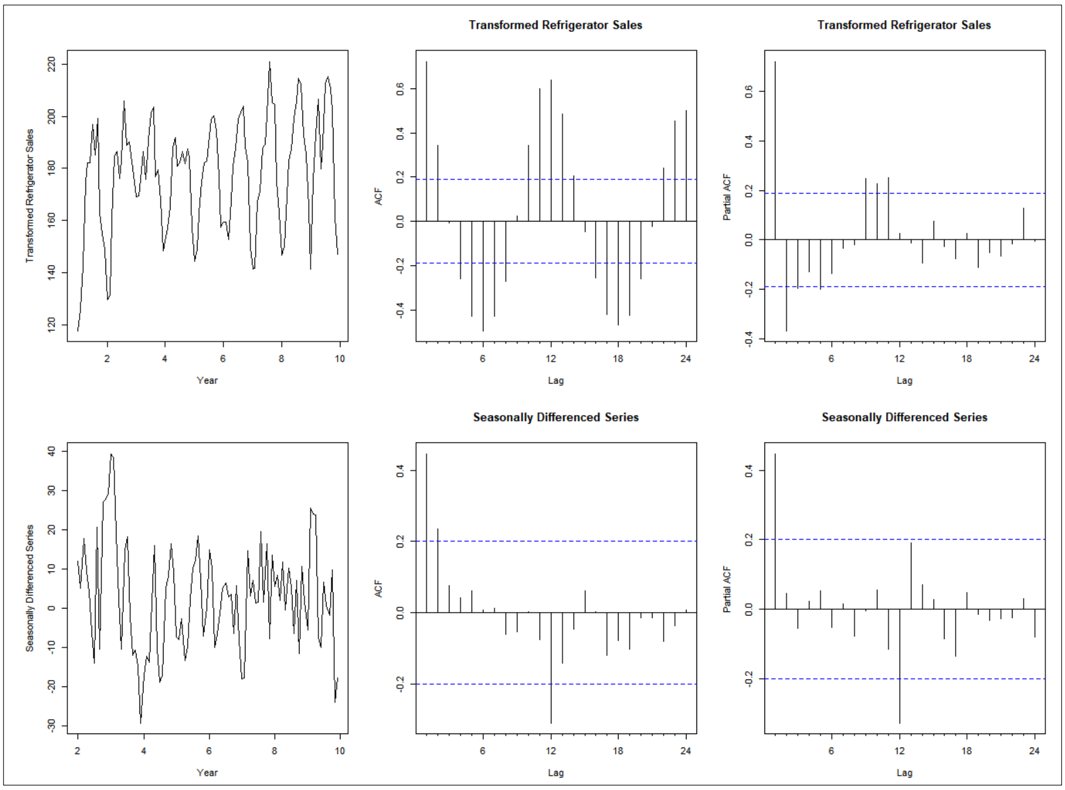

Figure 4.1. Plots of transformed and seasonally differenced series with ACF and Partial ACF.

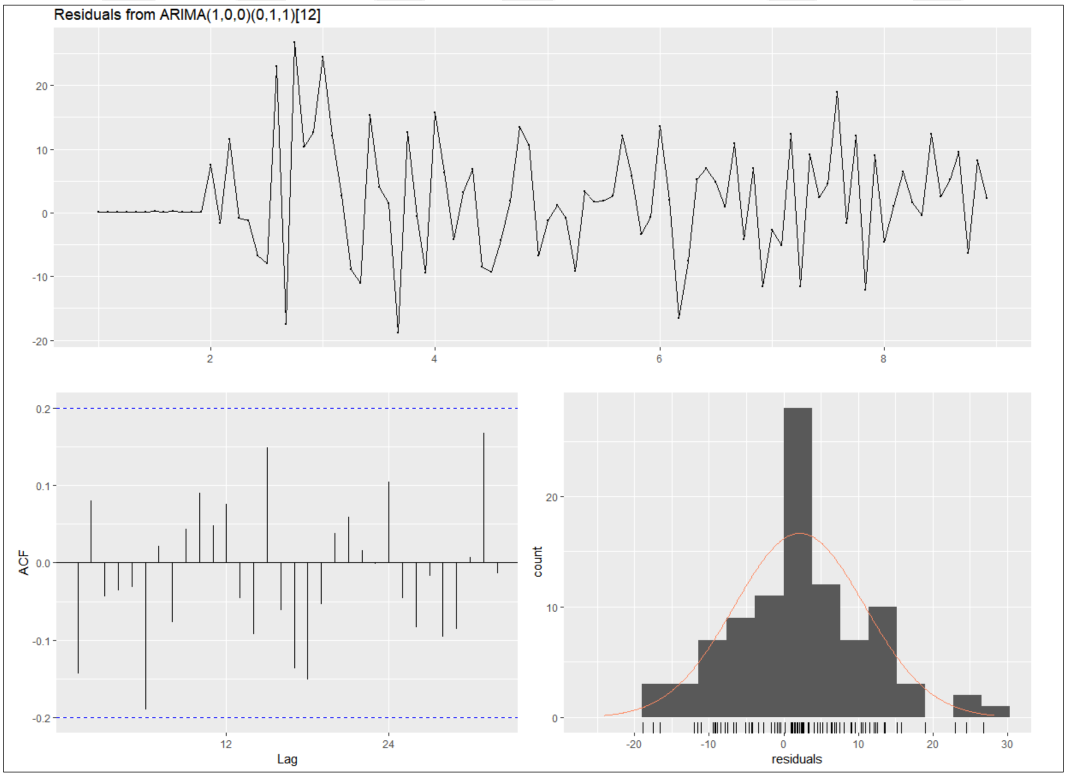

Figure 4.2. Diagnostic testing on the residuals

ARIMA (1,0,0)(0,1,1)$_{12}$ model in terms of backshift operator is calculated with equation (12):

$$(1-\phi_1 B)(1-B^{12})Y_t = (1-\Theta_1 B^{12})e_t \tag{12}$$

hence the fitted ARIMA model is (13):

$$Y_t = \phi_1 Y_{t-1} + Y_{t-12} - \phi_1 Y_{t-13} - \Theta_1 e_{t-12} + e_t \tag{13}$$

where Y_t is the observation at time t, e_t is the error term at time t, $\emptyset$ is non-seasonal autoregressive coefficient and Θ is seasonal moving average coefficient.

The forecast equation (14) of the fitted ARIMA model is used to obtain h-period ahead predictions.

$$\hat{Y}_{t+h} = \hat{\phi}_1 Y_{t-1+h} + Y_{t-12+h} - \hat{\phi}_1 Y_{t-13+h} - \hat{\Theta}_1 e_{t-12+h} + e_{t+h} \tag{14}$$

Figure 4.3 shows the plot of the time series data with 12-month ahead predictions.

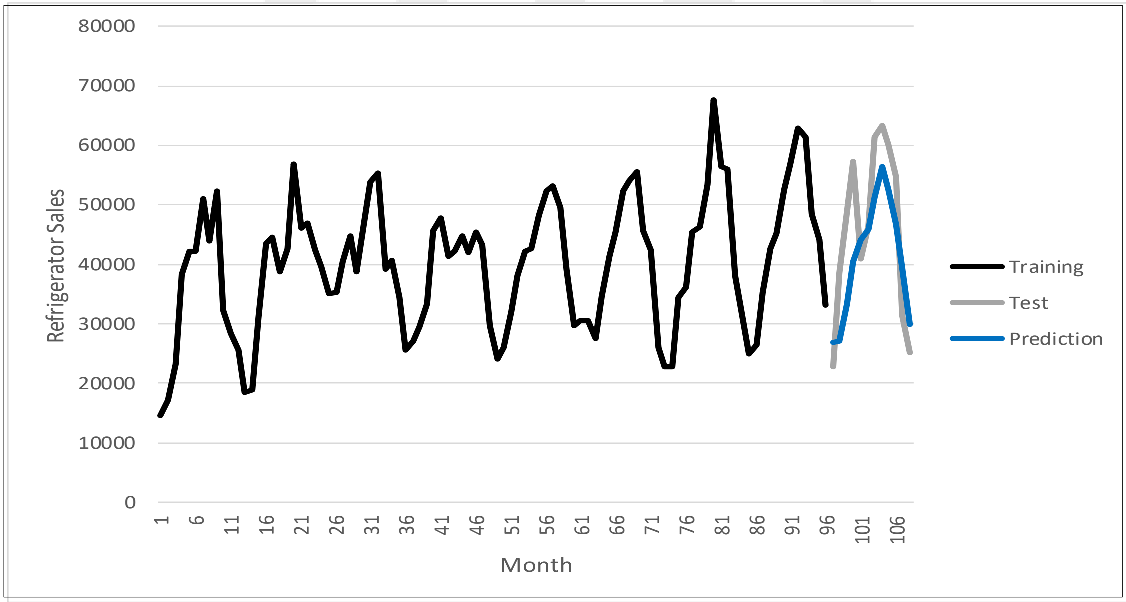

Figure 4.3. Plot of predictions from ARIMA (1,0,0)(0,1,1)$_{12}$ model

4.1.2. Freezer Sales Forecasting

Box-Cox transformation is used as well to stabilize the variance and the parameter λ of the Box-Cox transformation is chosen as $\lambda = 0.07791019$. The transformed time series and its seasonal difference along with autocorrelation function (ACF) and partial ACF are given in Figure 4.4. Differencing removes the trend and gives a stationary mean.

In fitting the model, the first 96 months of data are used as the training set, whereas the last 12 months of data are used as the test set to evaluate prediction ability of the model. Among candidate models, ARIMA $(2,1,2)(1,0,0)_{12}$ model was chosen using Akaike's Information Criterion (AIC). The estimated parameters for this model are given in Table 4.2.

Diagnostic testing on the residuals from the model are given Figure 4.5 the ACF of the residuals and the residuals versus order graph show that the residuals are uncorrelated, hence the residuals resemble white noise. It is seen from the histogram that the residuals are approximately normally distributed. Therefore, the fitted model is adequate.

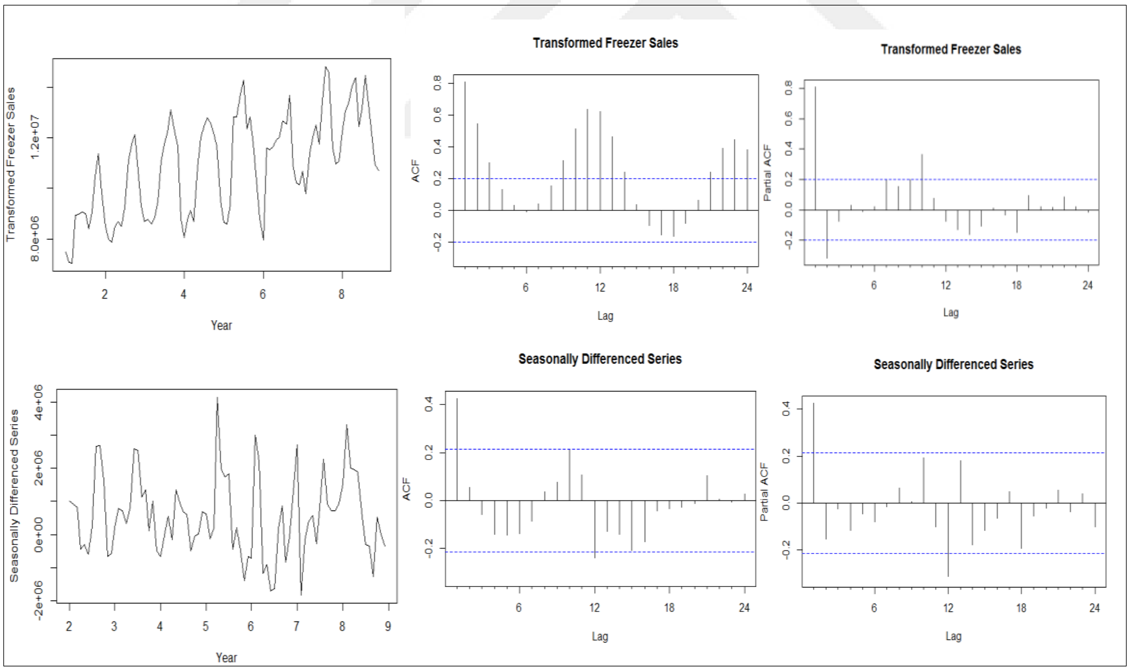

Figure 4.4. Plots of transformed and seasonally differenced series with ACF and Partial ACF.

Ljung-Box test results for the residuals has been issued as follows;

```
data:  Residuals from ARIMA(2,1,2)(1,0,0)[12]
Q* = 14.664, df = 14, p-value = 0.4015
Model df: 5.   Total lags used: 19
```

According to Shapiro-Wilk test test results for the residuals *p*-value is 0.4139.

Table 4.2. Model Summary

```
ARIMA(2,1,2)(1,0,0)[12]
Box Cox transformation: lambda= 0.07791019

Coefficients:
         ar1      ar2      ma1     ma2    sar1
      1.5953  -0.8729  -1.7746  0.8735  0.1404
s.e.  0.0596   0.0608   0.0663  0.0605  0.1242

sigma^2 estimated as 8.815e+11:  log likelihood=-1440.46
AIC=2892.92   AICc=2893.88   BIC=2908.24

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE        ACF1
Training set 111952.4 909080.3 713628.9 0.543652 6.454668 0.6974834 -0.0468617
```

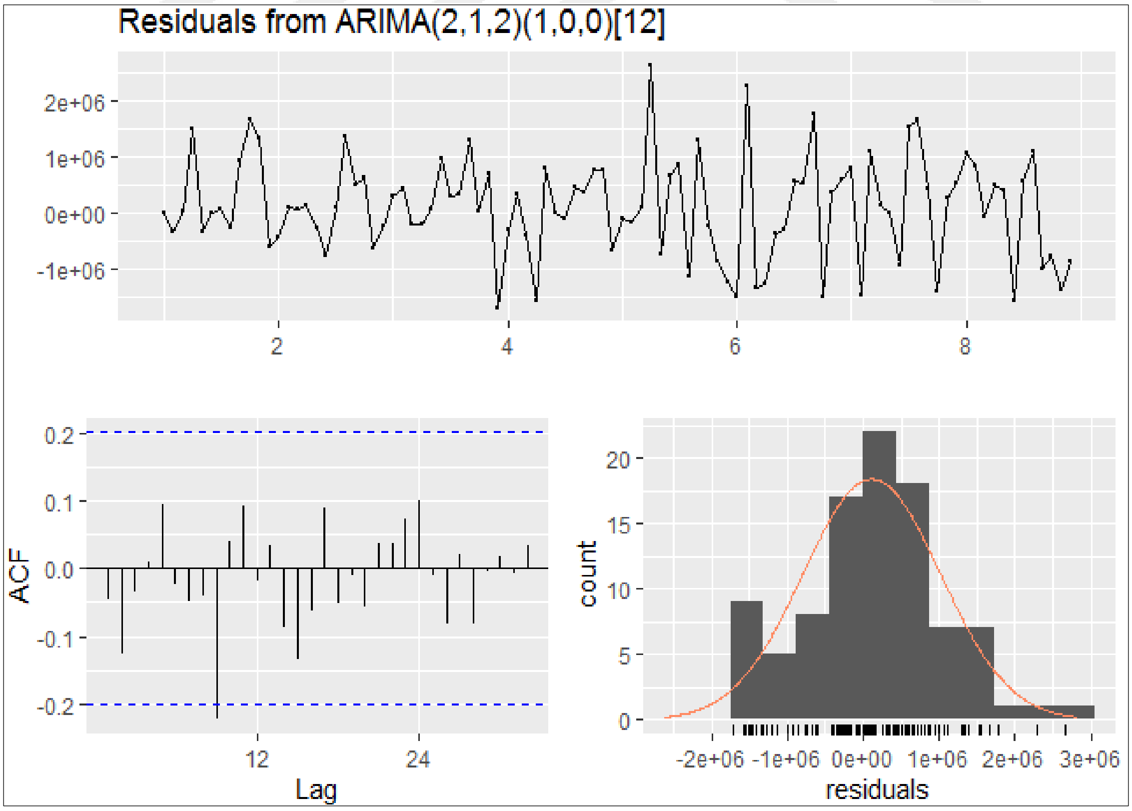

Figure 4.5. Diagnostic testing on the residuals

ARIMA (2,1,2)(1,0,0)$_{12}$ model in terms of backshift operator is equation (15):

$$(1-\Phi_1 B^{12})(1-\phi_1 B-\phi_2 B^2)(1-B)Y_t=(1-\theta_1 B-\theta_2 B^2)e_t \qquad (15)$$

hence the fitted ARIMA model is equation (16):

$$Y_t=(1+\phi_1)Y_{t-1}-(\phi_1-\phi_2)Y_{t-2}-\phi_2 Y_{t-3}+\Phi_1 Y_{t-12}-(\Phi_1+\Phi_1\phi_1)Y_{t-13}+(\Phi_1\phi_1-\Phi_1\phi_2)Y_{t-14}+(\Phi_1\phi_2)Y_{t-15}-\theta_1 e_{t-1}-\theta_2 e_{t-2}+e_t \qquad (16)$$

where Y_t is the observation at time t, e_t is the error term at time t, $\emptyset$ is non-seasonal autoregressive coefficient, Φ is seasonal autoregressive coefficient and θ is non-seasonal moving average coefficient.

The forecast equation (17) of the fitted ARIMA model is used to obtain h-period ahead predictions.

$$\hat{Y}_{t+h}=\left(1+\hat{\phi}_1\right)Y_{t-1+h}-\left(\hat{\phi}_1-\hat{\phi}_2\right)Y_{t-2+h}-\hat{\phi}_2 Y_{t-3+h}+\hat{\Phi}_1 Y_{t-12+h}-\left(\hat{\Phi}_1+\hat{\Phi}_1\hat{\phi}_1\right)Y_{t-13+h}+\left(\hat{\Phi}_1\hat{\phi}_1-\hat{\Phi}_1\hat{\phi}_2\right)Y_{t-14+h}+\left(\hat{\Phi}_1\hat{\phi}_2\right)Y_{t-15+h}-\hat{\theta}_1 e_{t-1+h}-\hat{\theta}_2 e_{t-2+h}+e_{t+h} \qquad (17)$$

Figure 4.6 shows the plot of the time series data with 12-month ahead predictions.

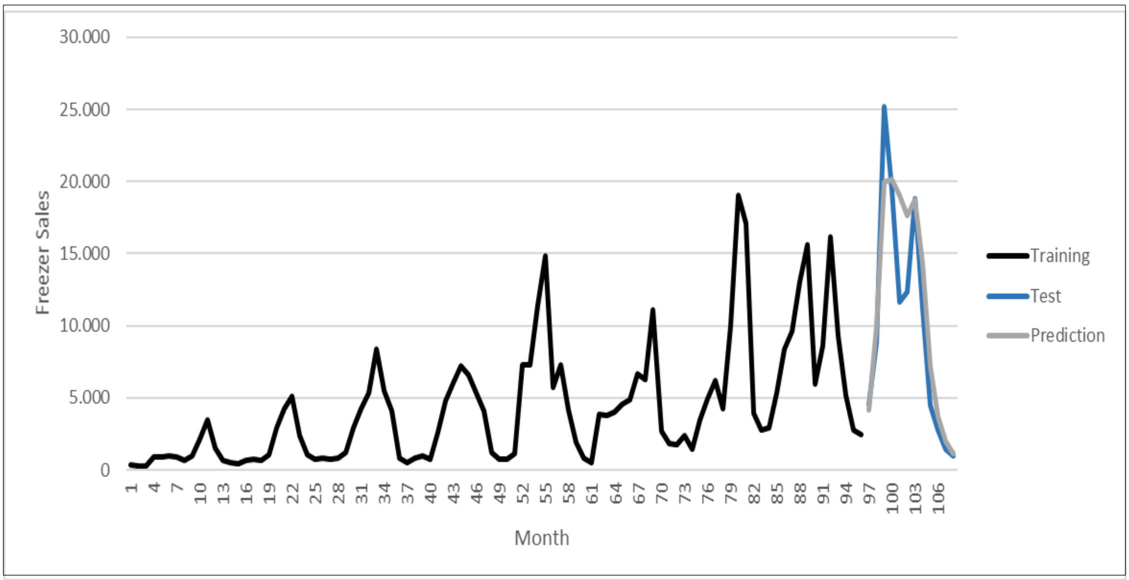

Figure 4.6. Plot of predictions from ARIMA (2,1,2)(1,0,0)12 model.

4.2. NAR Neural Network for Time Series Analysis

The NAR neural networks are applied to the refrigerator and freezer time series data using Levenberg-Marquardt Backpropagation training algorithm in MATLAB.

For the training process the observations between 1st and 78th (inclusive), for validation process the observations between 79th and 90th (inclusive) and for the test process the observations between 91st and 108th (inclusive) have been used. NAR neural network has been created with feedback delays = 1:6 and hidden layer size = 4.

As shown in the following figures, 31 iterations for refrigerator time series (Figure 4.7) and 9 iterations for freezer time series (Figure 4.8) have been applied. NAR neural network has been used with one hidden layer for both refrigerator and freezer time series as shown in figures 4.7 and 4.8.

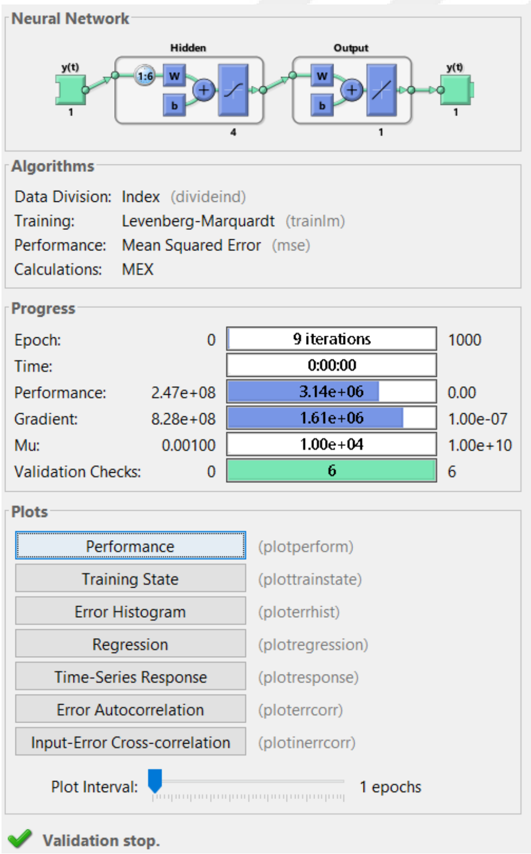

Figure 4.7. NN Training (nntraintool) for Refrigerator Time Series

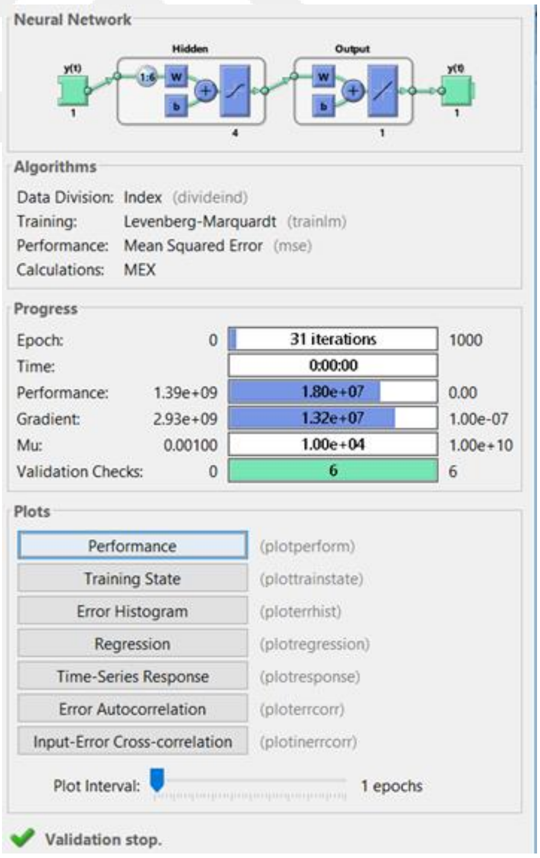

Figure 4.8. NN Training (nntraintool) for Freezer Time Series

The best validation of performances for both refrigerator and freezer time series data have been shown in Figure 4.9 and Figure 4.10. Moreover, their error histograms also given in Figure 4.11 and Figure 4.12.

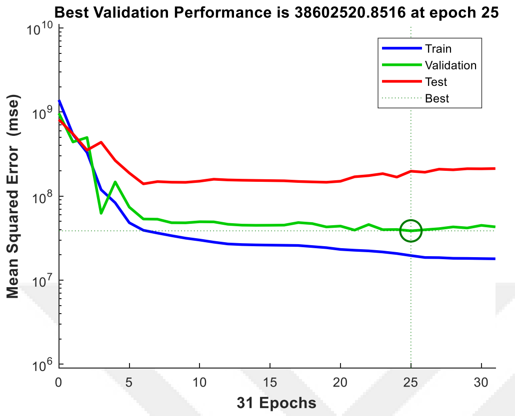

Figure 4.9. NN Training Performance for Refrigerator Time Series

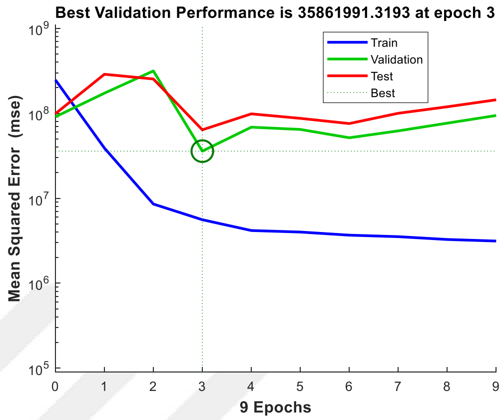

Figure 4.10. NN Training Performance for Freezer Time Series

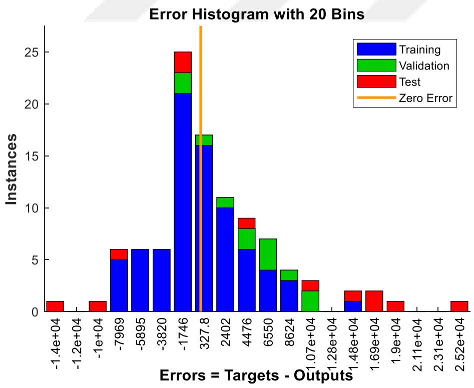

Figure 4.11. NN Training Error Histogram for Refrigerator Time Series

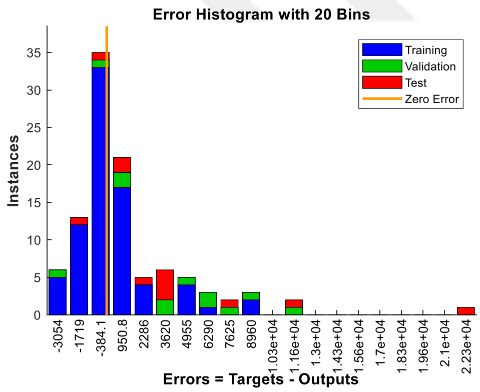

Figure 4.12. NN Training Error Histogram for Freezer Time Series

Regressions of NAR networks are shown in figures 4.13 and 4.14 for refrigerator and freezer time series. For refrigerator time series; R Training is 0.9005, R Validation is 0.93961, R Test 0.57801 and R All is 0.81747. For freezer time series; R Training is 0.79015, R Validation is 0.47463, R Test is 0.54898 and R All is 0.65909. Figure 4.15

and 4.16 show the Neural Network Training Time-Series Response and Neural Network Training Error Autocorrelation for refrigerator time series. Figures 4.17 and 4.18 show the Neural Network Training Time-Series Response and Neural Network Training Error Autocorrelation for freezer time series.

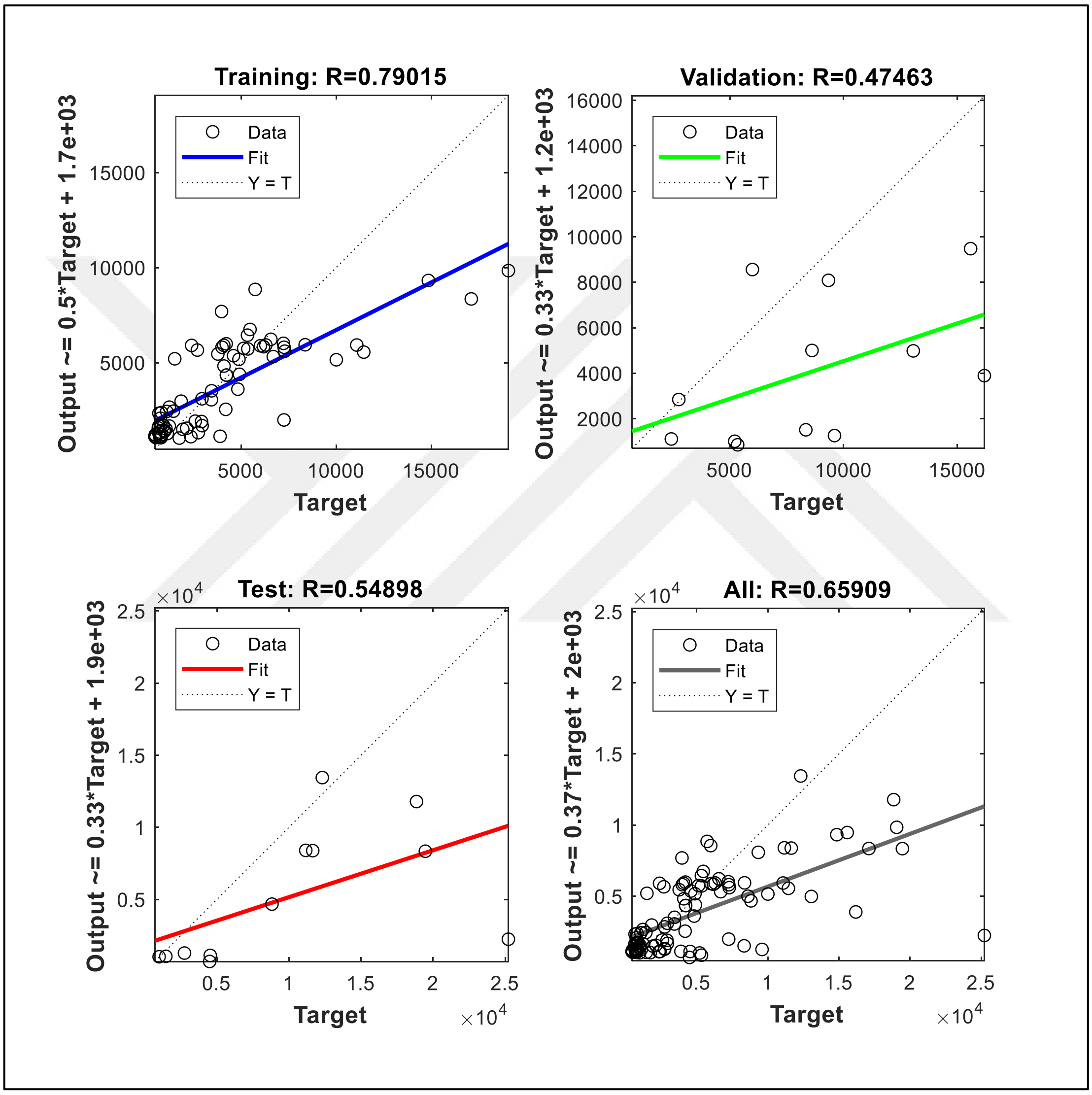

Figure 4.13. Regression Plot of Refrigerator Time Series

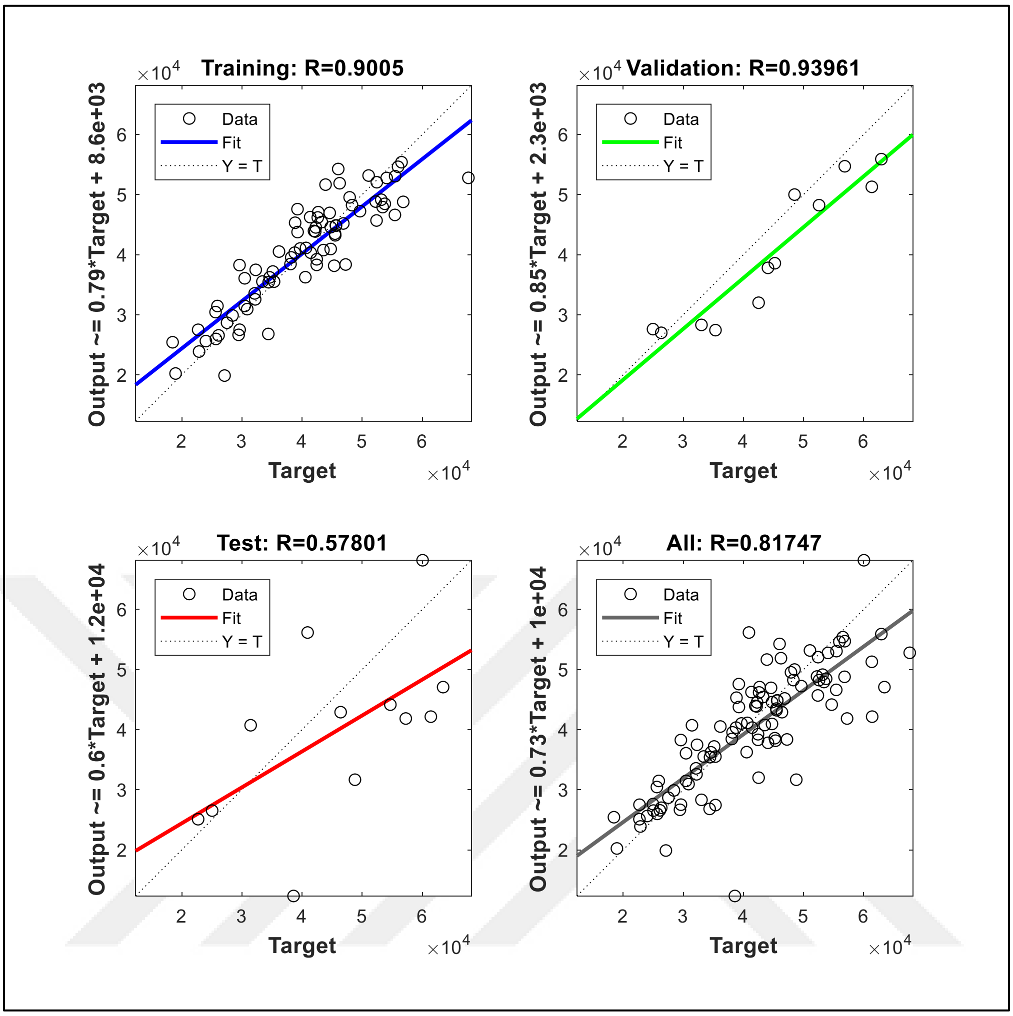

Figure 4.14. Regression Plot of Freezer Time Series

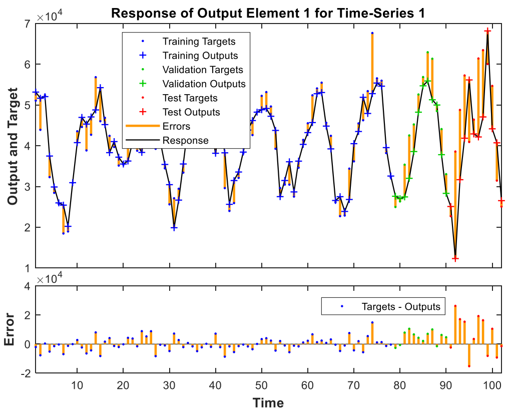

Figure 4.15. Neural Network Training Time-Series Response of Refrigerator

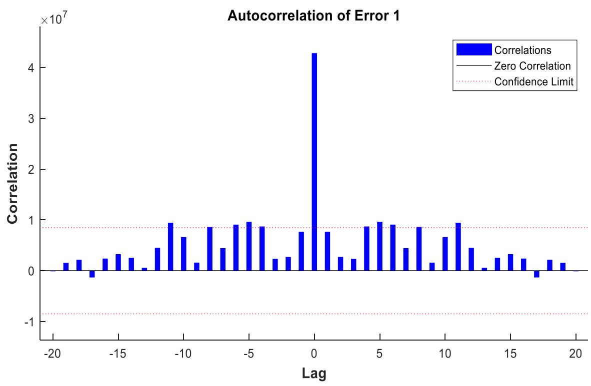

Figure 4.16. Neural Network Training Error Autocorrelation of Refrigerator Time Series

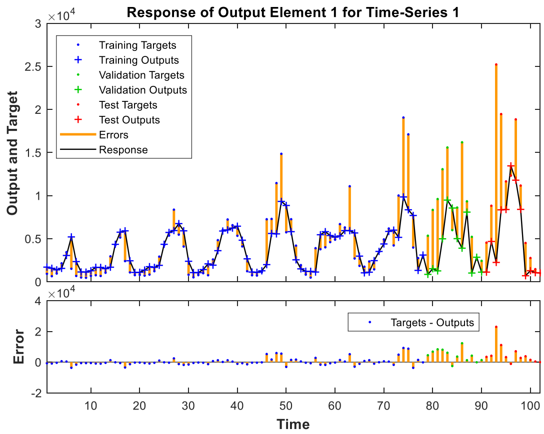

Figure 4.17. Neural Network Training Time-Series Response of Freezer

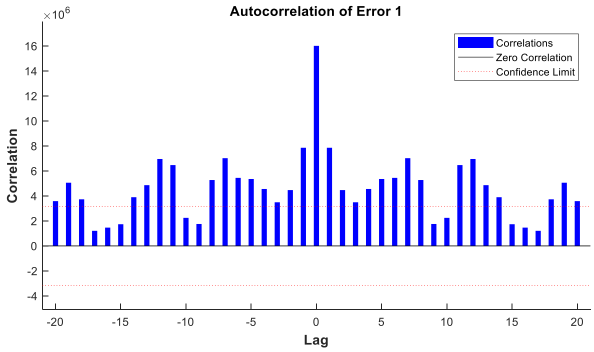

Figure 4.18. Neural Network Training Error Autocorrelation of Freezer Time Series

Figures 4.19 and 4.20 show respectively, the plot of the refrigerator and freezer time series data with 12-month ahead predictions from NAR neural network implementation.

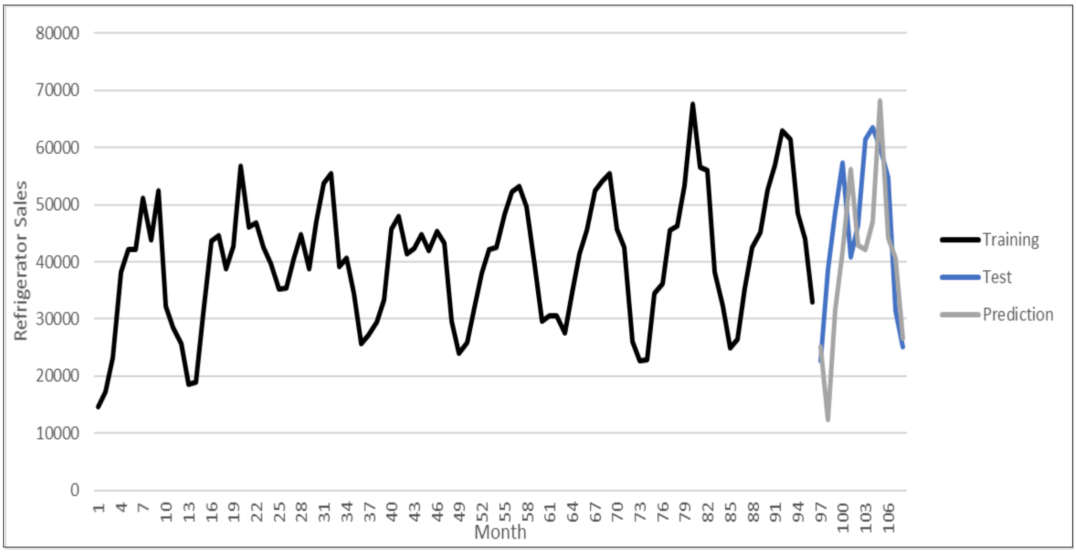

Figure 4.19. Plot of Predictions of Refrigerator Time Series

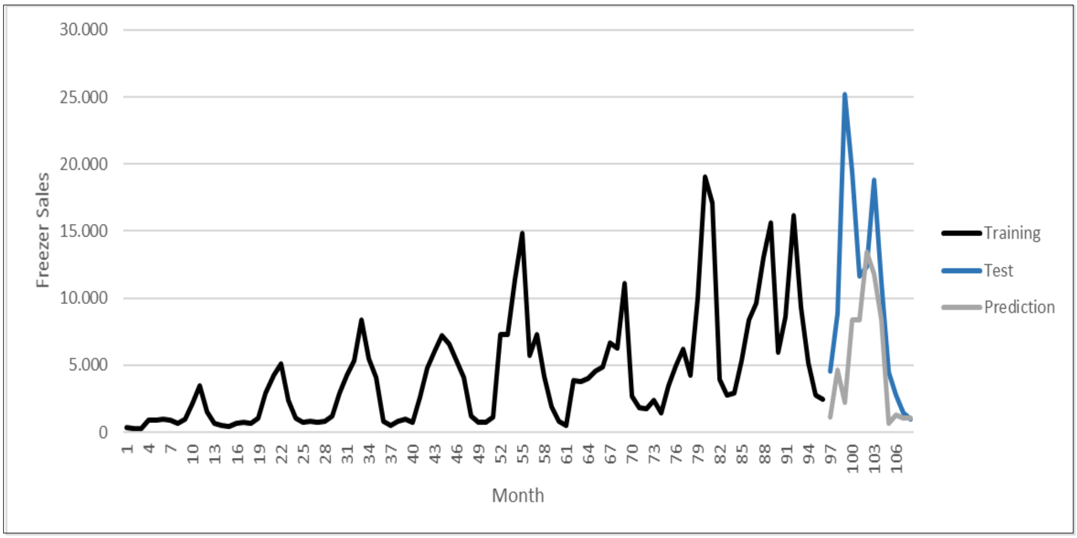

Figure 4.20. Plot of Predictions of Freezer Time Series

5. RESULTS

The data used in this thesis include nine-year monthly sales which have seasonal, cyclical and trend patterns. The objective is to help decision making process of the company by forecasting its cooling group (refrigerator and freezer) sales by a time series forecasting method. ARIMA and NAR neural network methods are used for forecasting. The forecasted values have been compared with actual values based on the measures of forecast accuracy. R software, R Studio, MS Excel and MATLAB were used for the analyses. According to accuracy measures of root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE), comparisons have been made between chosen ARIMA models and NAR networks for refrigerator and freezer time series. These results are presented at Table 5.1. According to the results, ARIMA models predict with greater accuracy than the NAR networks for both refrigerator and freezer sales for test set.

Table 5.1. Comparison of Forecasting Methods for Refrigerator and Freezer Sales for Test Set

	Refrigerator Sales			**Freezer Sales**		
Methods	**MSE_{test}**	**MAE_{test}**	**$MAPE_{test}$**	**MSE_{test}**	**MAE_{test}**	**$MAPE_{test}$**
ARIMA	9284.55	8078.97	18.09%	3308.99	2388.08	26.81%
NAR	16064.47	12078.81	25.89%	7992.89	5133.52	44.89%

Chosen ARIMA model gave better results for the training set than the test set (Table 5.2.). This forecasting accuracy difference of the model between training set and the test set was considered mainly as a result of the tax cuts in furniture and electronic goods which came into effect in the year of the test set and increased the sales. Therefore, it is concluded that the chosen ARIMA model gives reliable results for forecasting the refrigerator and freezer time series.

Table 5.2. Comparison of Forecasting Methods for Refrigerator and Freezer Sales for Training Set

	Refrigerator Sales			**Freezer Sales**		
Method	**$MSE_{training}$**	**$MAE_{training}$**	**$MAPE_{training}$**	**$MSE_{training}$**	**$MAE_{training}$**	**$MAPE_{training}$**
ARIMA	4932.627	3633.52	8.96%	909080.3	713628.9	6.45%

6. CONCLUSION

By applying forecasting methods to the historical data whose patterns are assumed to continue into the future, predictions and appropriate decisions are made by the management of a company. In light of this, forecasting in the business environment has been common statistical task to manage the processes such as production, purchasing, sales, marketing and so on. Therefore, forecasting is an important tool for the decision making process of the organizations. In the competitive environment, sales forecasting has an important impact on the companies because many strategic decisions depend on the business plan and forecasts. Sales forecasting helps to determine the sales amount in the next periods which are needed for making efficient plans and meeting customer demands.

In the white goods industry, an accurate sales forecasting has a signicant role in the whole operation as well. Inventory management, replenishment plans, distribution strategies require sales forecasts. Accurate and reliable sales forecasts are directly linked to processes related to organization and planning of transportation, production, purchasing, labor force and customer services in the white goods industry.

In the literature many papers about sales forecasting for different areas have been reported, however it has been difficult to find a study for sales forecasting in the white goods industry.

The data used in this thesis include nine-year monthly sales which have seasonal, cyclical and trend patterns. The objective is to help decision making process of the company by forecasting its cooling group (refrigerator and freezer) sales by a time series forecasting method. Autoregressive integrated moving average (ARIMA) and the nonlinear autoregressive (NAR) neural network methods have been chosen to use for the study. R software, R Studio and MATLAB have been used for the analyses of the models. The forecasted values have been compared with actual values based on the measures of forecast accuracy. It is concluded that the chosen ARIMA model gave accurate and reliable results for forecasting the sales of cooling group of the company in the white goods industry.

It is also observed that there are many internal and external factors that influence white goods sales such as demand for renewal, new house sales, marriages and divorces. Besides these factors, there is a strong connection between the white goods sector and the performance of the national economy. Additionally, the tax cuts in furniture and electronic goods in Turkey have significant effects on the amount of sales in the white goods market.

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