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Industrial Engineering

FORECASTING METHODS FOR DEMAND MANAGEMENT

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Master Thesis

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By

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Ibrahim A.A.ALSHAHWANI

DEDICATION

I would like to dedicate this work to my very first teacher, my mother, my first supporter and role model, my father and my companion throughout the journey. Without you, this dream would never come true and my brothers and my sisters.

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I might want to offer my thanks to every one of the individuals who have upheld me all through the regularly extended periods of this voyage. I might want to thank my advisors, Asst. Dr. Kemal Dinçer Dingeç for being my compass notwithstanding when I believed I was lost and being in extraordinary part in charge of the zenith of this work. I might likewise want to thank my supervisors for their supportive exhortation, which incredibly enhanced the nature of this work. Finally, I thank this institution for hosting me during these years, securely earning its place as my home. I am very thankful to my mom and dad, whose values and education motivate me to keep asking questions; to my siblings and family for their infinitely appreciated love and to my country which, although inanimate, keeps me anchored and offers me an example of resiliency.

ABSTRACT

FORECASTING METHODS FOR DEMAND MANAGEMENT

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With increase the growth and development in the world became energy sector one of most important sectors therefore, most countries entered into a race to improve the energy sector and draw up a successful future policy. This study include create models to forecasting electricity demand in Turkey by using statistical techniques (Holt-Winters and box-Jenkins) to assist in decision making. We depending on two time series (annual and seasonal time series) to generate a lot of models , most this models have high accuracy but the best model to forecasting annual time series is the ARIMA (0,2,1) where Mean Absolute Percentage Error (MAPE) was 2.518% and best model to forecasting seasonal time series is SARIMA (2,1,2)X(1,1,1)where (MAPE) was 2.131%. The final results for this models show increase in electricity demand in future where in Dec-2021 the demand became 28307 (GW/h) for seasonal time series and the demand in 2027 became 398313 (GW/h), this models represent forecasting for short-term and long-term.

Therefor must be increase the production of electricity in next period to became fit with demand.

Keywords: Forecasting electricity consumption, Holt-Winters, ARIMA and SARIMA.

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LIST OF ABBREVIATION

ACF	: Autocorrelation Function
AI	: Artificial Intelligence
AIC	: Akaike's information criterion
ANNs	: Artificial Neural Networks
ANOVA	: Analysis of Variance
ARIMA	: Autoregressive Integrated Moving Average models
ARMA	: Autoregressive Moving Average models
GA	: Genetic Algorithm
GPD	: Gross Product Domestic
MA	: Moving Average
MAE	: Mean Absolute Error
MAPE	: Mean Absolute Percentage Error
MSE	: Mean Square Error
PACF	: Partial Autocorrelation Function
PAM	: Partial Adjustment Model
RMSE	: Root Mean Square Error
SARIMA	: Seasonal Autoregressive Integrated Moving Average models

1. INTRODUCTION

1.1.INTRODUCTION

Energy consumption is increase with the developing for economy. To improve the energy supplies in future we need to generate forecasting models for energy demand. The inaccurate prediction models is one of the big problems to most countries. So using hybrid forecasting models to can be deal with lack of data set could be a suitable solution [1] . Electricity is consider one of the most energy type important and consumption in the world because it has effective role in economies and societies development. So supply adequate electricity for individuals represent vital requirement in society and affecting in life directly, where it is used in a lot of application in life for example in motors , TV , radio and other applications also most developing countries became suffer from increase in electricity consumption because progress in technology, population growth and other factors [2, 3] . Decision maker for electricity and other energy sectors must be depended on accurate prediction models for load demand, so the decision maker suffer from a lot of problems for different time scales ,one of this problems is select the best techniques to create forecasting models with high accuracy[4]. Turkey is located between the 36º-42º north parallel and 26º-45º eastern parallel in the northern hemisphere and the total area 779452 Km^2, also the population lives in Turkey approximately 37 million. Where is consider natural bridge between Middle East that has energy resources, central Asian and Europe. The large growth to Turkish economy this contributing significantly to increasing energy consumption, especially electricity. Where the Gross Domestic Production (GDP) is increase about 5% between 2002 to 2012, and the expectation refers to the increase the GDP about 5.2% the next period [5]. Turkey needs to invest $4–5 billion for each year to improve its systems for electricity generation, transmission and distribution of electricity, gas, and oil because the country does not have any resources, so the forecasting models is very important [6]. Electricity supply that can be provided must me match with electricity consumption to achieve the stability , therefore we need to prediction for electricity demand in order integrated distribution system design, suitable pricing policy , effective power generation planning and demand side management [2].

1.2.RESEARCH METHODOLOGY

Figure (1.1) shows the methodology to this thesis and the techniques used to forecasting models for electricity consumption to Turkey

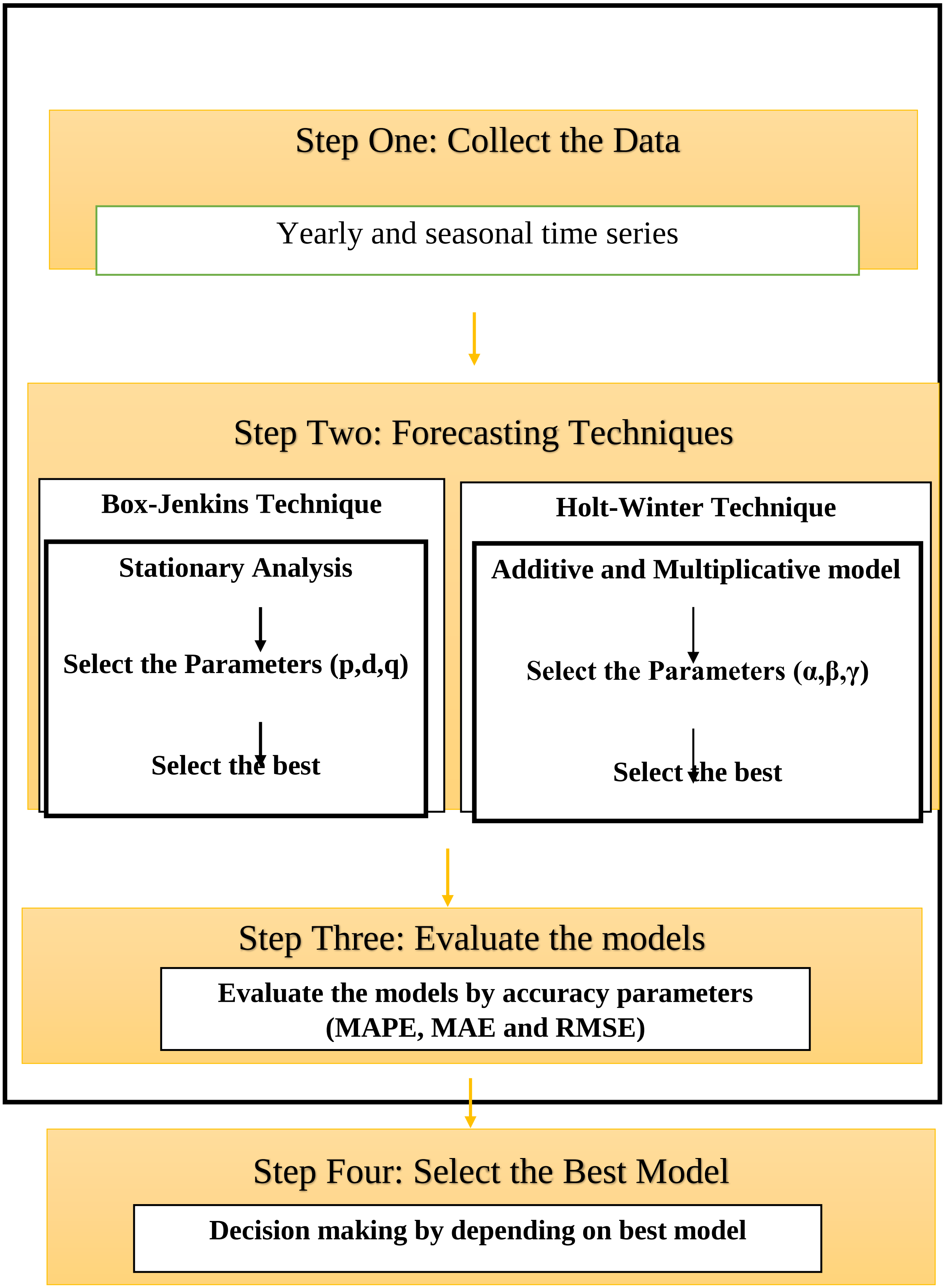

Figure 1.1: Methodology to Forecasting Electricity Consumption

1.3.THE AIMS FOR THE RESEARCH

The aims to this thesis can be show below:

1. Use statistical techniques to modelling the trends for electricity consumption in Turkey to forecasting the electricity consumption for the next periods, where we used two techniques (Holt-Winter and Box-Jenkins) to forecasting for yearly and seasonal time series for consumption.
2. Evaluate the models generated and select the best model to determine the general trend to electricity demand to assist in decision making.

1.4. STRUCTURE FOR THESIS

This thesis includes six chapters, chapter one includes the introduction, where we explain the overview of the thesis also includes the objectives and methodology. Chapter Two is composed the forecasting techniques where we explain the structure for every technique used in this thesis also we show the accuracy parameters and literature review in forecasting energy consumption. Chapter Three include create forecasting model by Hot-Winter technique, we show in this chapter the data analysis and outputs to this technique by R-software. Chapter four is composed of data analysis and we generate forecasting models by Box-Jenkins technique. Chapter Five presents the evaluation for all models generated by Holt-Winter and Box-Jenkins techniques and select the best model by using forecasting accuracy parameters. Chapter Six presents conclusions, recommendations and future research.

2. LITERATRE REVIEW

2.1.INTRODUCTION

Forecasting energy can be help the producer to generate the effective operation strategies to achieve better management [7]. The forecasting for time series is consider very important where we can collect the observations to the same variable and analysis this data to develop model to forecasting the demand or events for future. A lot of effort has been devoted in the past years to create and generate effective models to forecasting for time series [8].

The forecasting is useful to decisions makers if there is uncertainty for the future, where there are events we sure this events will happened in future so we not need to forecasting. Forecasting is very useful to many needs. Where it is help the companies and establishments to planning to the future and to make rational decisions [9] [10].

Forecasting is very useful to many needs. Where it is help the companies and establishments to planning to the future and to make rational decisions. Forecasting include several steps can be show in Fig (2.1) [9] .

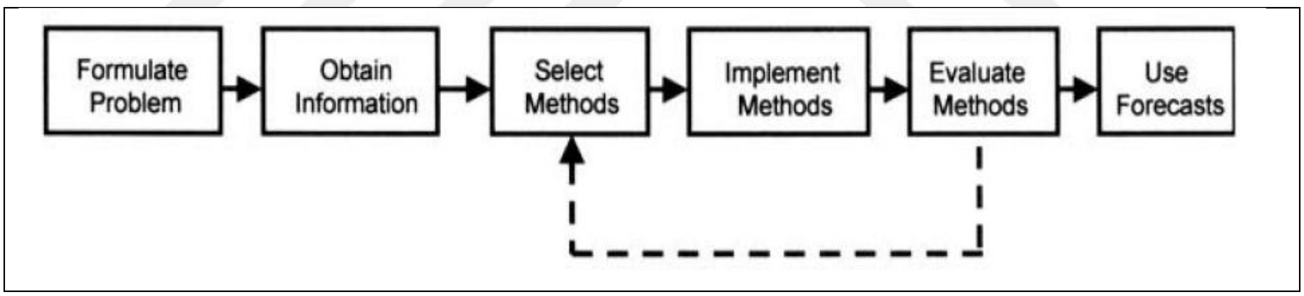

Figure 2.1: Steps to Forecasting methodology.

There are a variety of techniques can be used in forecasting , where can be classify this techniques into two categories Qualitative and Quantitate (Statistical)techniques. Also there are some factors can be used to determine the best techniques, this factors are data availability, time horizons, objectives and others[11] [9].

Quantitative techniques depending about mathematical models where their techniques are based on the analysis for the historical observations, therefore we can used past observations patterns to predict future data points. These approaches are often depending on time-series[12]. The advantages for time-series approaches are their effectiveness, simplicity and strongly, time-series prediction techniques can be categories into two basic groups: univariate and multivariate approaches. Univariate approaches include the analysis for single variable but multivariate approaches include the analysis and investigate two or more variables in same time [13] [14]. There are a lot of qualitative approaches for example Delphi approach, this method was used first time by Dalkey and Helmer, the methodology to Delphi is depending on the opinions for experts and the accumulated experience, where the collect a team of experts and specialists in a particular area and taking their views on future events. This approach very effective for long-term prediction where this method used in new environment such as forecasting to demand for new product [11] [15].

2.2.TIME SERIES TECHNIQUES

Time series include a collection of observations that can be created sequentially in time. There are a lot of application about time series such as data for electricity demand that can be registered in every day or month, weather temperature data, data for products demand and other, where used in many fields for example social sciences, engineering, economics and other. Time series data is very important for a lot of applications in economics, engineering, natural sciences and social sciences as well. The basic advantage of time series techniques is determine the dependency between the observations to create mathematical equations. If we found the mathematical model of a time series we can predict future values by depending on a historical data. Time series can be classify into two pattern discrete time series and continuous. [15] .

Time series techniques can be classified for Moving Average, Partial Adjustment Method (PAM), Exponential Smoothing, Holt's-Winter, Box-Jenkins and other techniques[16] [7].

In this study we will be focus on two techniques are Holt's-Winter and Box-Jenkins techniques

2.2.1. Holt Winter Technique

Holt-Winters (HW) used to generate linear and exponential models was proposed in 1960 by Holt and Winters where it can be predict yearly time series also mostly used to predict the seasonal time series where can be show the patterns of increasing or decreasing seasonality [17] .

HW technique is suitable to forecast time series in the short, medium and long term. HW is independent technique as a compared with other statistical techniques where it is depending about the iterative approach in generating approximate values. There are two types to HW technique additive and multiplicative models [17] [18].

The representation most popular to this technique is exponential smoothing model where this model include a predict equation and a smoothing equation for each of the components in this technique. There three components are level, trend and seasonality components .Each model is usually labeled by a pair of letters (T,S) identify the type of “Trend” and “Seasonal” components. The possibilities for each component are Trend= {N,A,A_d,M,M_d} and Seasonal={N, A,M}.For example (N, N)denotes the simple exponential smoothing method,(A,N) denotes Holt's linear method, (A , N_d) denotes the additive damped trend method,(A,A)denotes the additive Holt–Winters’ method and (A,M) denotes the multiplicative Holt–Winters’ method, to mention the most popular ones.

Can be show the equations to The Holt Winters Additive technique as follows:

$$l_t = \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{2.1}$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \tag{2.2}$$

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \tag{2.3}$$

$$\hat{y}_{t+h} = l_t + hb_t + s_{t-m+h} \tag{2.4}$$

Can be show the equations to The Holt Winters Multiplicative technique as follows:

$$l_t = \alpha\frac{y_t}{s_{t-m}} + (1-\alpha)(l_{t-1} + b_{t-1}) \tag{2.5}$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \tag{2.6}$$

$$s_t = \gamma\frac{y_t}{l_{t-1} - b_{t-1}} + (1-\gamma)s_{t-m} \tag{2.7}$$

$$\hat{y}_{t+h} = (l_t + hb_t)s_{t-m+h} \tag{2.8}$$

Where l_t , b_t , s_t are, respectively, the level component, trend component and seasonal component at time t. m stands for the period of the seasonality and h denotes the forecast horizon. Constants α, β and γ are the smoothing parameters [18] [19].

Where

$$\beta = \alpha\beta^{*}, \quad 0 < \alpha < 1, \quad 0 < \beta < \alpha, \quad 0 < \gamma < 1 - \alpha$$

2.2.2. Box-Jenkins Method

Theoretically, the Box–Jenkins is consider ARIMA model is generated from the observed time series by depending on three components: AR, integrated (I), and MA. In practice, it uses an order of AR process (p), an order of MA process (q), and a level of differencing (d) to create the most suitable fitted model to predict the time series. The Box–Jenkins prediction technique uses the following three-steps modeling method:

- Identify the model and test the data, if the data is stationary or not and after this determine the AR and MA components of the model.
- Estimate the parameters by using the computation algorithms to specify the AR and MA coefficients of the selected ARIMA model.
- Checking the model for its accuracy and good fitness [20] [21].

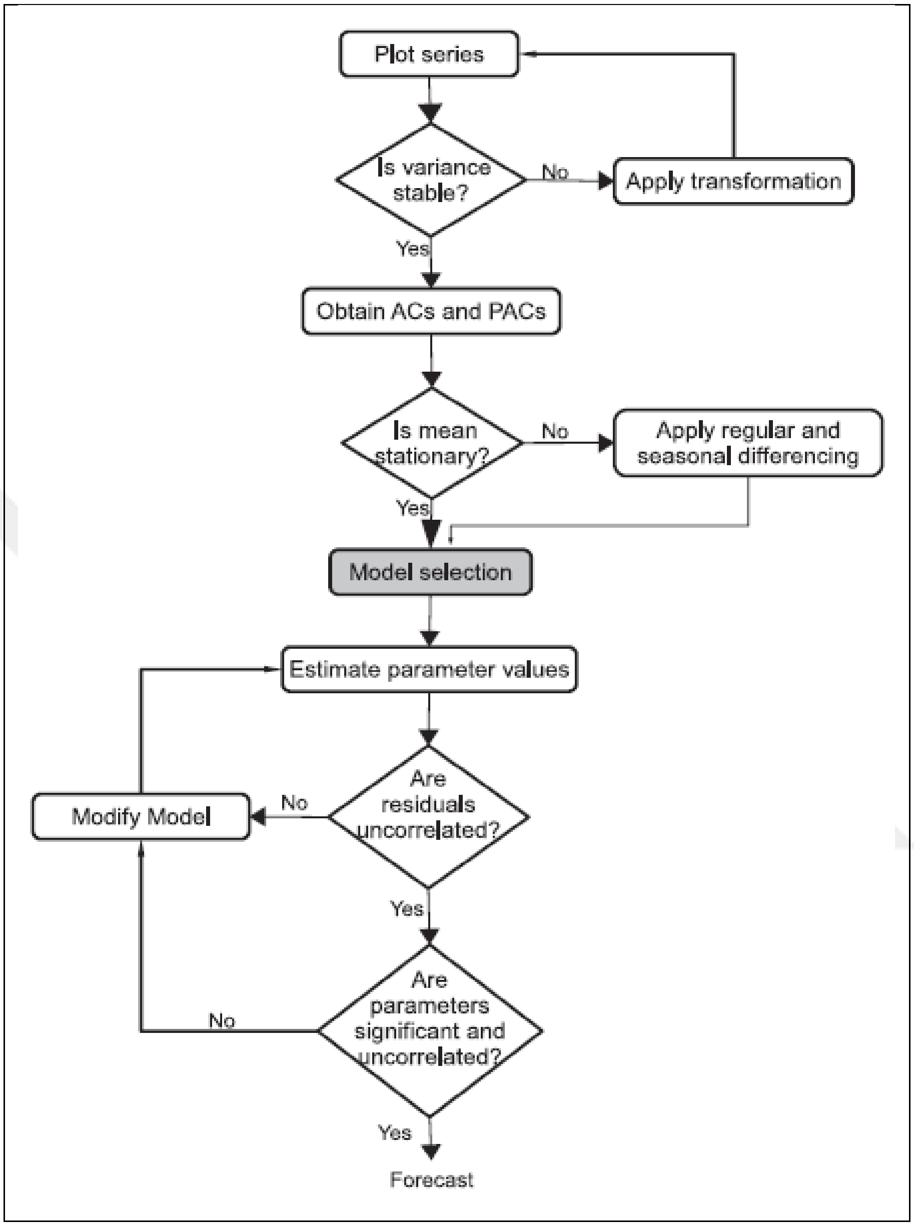

Figure 2.2: Box–Jenkins methodology

There are the a lot of models for Box–Jenkins approach but in this thesis we focus on two models autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA).

2.2.2.1.Non Seasonal ARIMA

ARIMA is considered one of the most popular statistical techniques used to linear modelling, before generate the best model we need to analysis the time series by specify the stationary, if the data is stable we can be determine the parameters (p,d,q) to forecasting or the data not stable make differencing operation to make data stable and we select the parameters. [22].

To determine the stationary for time series there are some methods, where autocorrelation function (ACF) and partial autocorrelation function (PACF) most methods used to determine the stationary of the original data. ACF determines how a series is correlated with itself at different lags, PACF is reflected as a regression of the series against its past lags [23].

ARIMA models depending on three parameters (p,d,q) we must be determine this variables to generate best model if there are no differencing we can select AR, MA or ARMA model to forecasting there is differencing select the ARIMA model as show in equation 2.9 [17].

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B) a_t \tag{2.9}$$

where $\phi_p(B) = (1-\phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p)$ (for AR(p)), $(1-B)^d$ (for non-seasonal differencing) and

$$\theta_q(B) = (1-\theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q \text{ (for MA(q))}$$

2.2.2.2. Seasonal ARIMA

SARIMA is the most famous model for prediction seasonal time series. It has great performance in both academic research and industrial applications during the last three decades. A time series $\{Z_t/t = 1,2,\ldots,k\}$ is generated by SARIMA (p,d,q) (P,D,Q)s, ARIMA model as show in equation 2.10

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D Z_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t, \tag{2.10}$$

where p, d, q, P, D, Q are integers, s is the season length;

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p,$$
$$\Phi_P(B^s) = 1 - \Phi_s B^s - \Phi_{2s} B^{2s} - \cdots - \Phi_{Ps} B^{Ps},$$
$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \text{ and}$$
$$\Theta_Q(B^s) = 1 - \Theta_s B^s - \Theta_{2s} B^{2s} - \cdots - \Theta_{Qs} B^{Qs}$$

are polynomials in B of degree p, q, P, and Q. B is the backward shift operator, and et is the estimated residual at time t. d is the number of regular differences, D is the number of seasonal differences; Zt denotes the observed value at time t, t = 1,2,. . . ,k.[18] ,24].

2.3.ACCURACY PARAMETERS

In order to evaluate the performance for the prediction models there are a lot of forecasting accuracy parameters such as mean absolute percentage error (MAPE), mean absolute error (MAE), root mean squared error (RMSE) and other [25, 26] , can be show the equations as follow:

$$MAPE=\frac{1}{P}\Sigma\frac{|yt-y|}{yt}X100\% \quad (2.11)$$

$$MSE=\frac{1}{p}\sum_{i=1}^{p}(y_t^i-y^i)^2 \quad \mathbf{(2.12)}$$

$$RMSE=\sqrt{\frac{1}{p}\sum_{i=1}^{p}(y_t^i-y^i)^2} \quad \mathbf{(2.13)}$$

Where y_{t} is actual data, y is forecasting results and P is number of observations.

2.4.LITERATURE REVIEW

There are a lot of models have been developed to forecasting electricity consumption. These model based on statistical methods or artificial intelligence methods, can be show this models as follow:

Sasan Barak et al (2016): Suggest three models to forecasting annual energy consumption in Iran, these patterns are ARIMA, Adaptive Neuro Fuzzy Inference System (ANFIS) and ARIMA–ANFIS pattern where used these pattern to handle with the lack of accurate and comprehensive data set to predict the future demand. The results indicate the performance to hybrid patterns (ARIMA-ANFIS) is best as a compared with single ARIMA and ANFIS patterns where the MSE indicator is decrease from 0.058% to 0.026% [1].

Suling Zhu et al (2011) Propose hybrid model to forecasting electricity demand in China, this model is combine between moving average and particle swarm optimization (PSO) technique. This technique is design to determine trend and seasonal adjustments, also select (SARIMA) model and compared this model with hybrid model by using same time series. The results of forecasting accuracy parameters show that our proposed model is an effective forecasting technique for seasonal time series with nonlinear trend [27].

Yuanyuan Wang (2014): develop a methodology to forecasting electricity consumption in China to help people in electricity sector make more sensible decisions. This methodology depending on the models SARIMA model, PSO and hybrid model (SARIMA-PSO), all these models are applied in Northwest electricity grid of China. The final results show three residual modification models have high forecasting accuracy [28].

Coskun Hamzac et al (2017): propose forecasting models for monthly electricity demand in Turkey. These models created by Artificial Neural Networks (ANN) and SARIMA. Where the results indicate ANN technique has high acceptability and reliability, this make successful and high-accuracy expectations according to the forecasting accuracy parameters [2].

A. Azadeh et al (2008): suggest a methodology by integrated fuzzy system in developing countries especially in Iran and China to forecasting monthly and seasonal electricity demand. In this study there are estimation algorithms generated by fuzzy logic and ARMA, where this methodology suggest used ACF and PACF to determine the stationary for time series, At last, analysis of variance (ANOVA) is used for choosing best model [29].

Serhat Kucukali and KemalBaris (2010): propose models to predict Turkey' short-term gross annual electricity consumption from 1970 to 2014 by applying fuzzy logic, where this methodology include more than variable one of the most important variable is gross domestic product (GDP). The advantage of this methodology is the ability to mimic the human thinking and reasoning, this model has high percentage of accuracy where the yielded average absolute relative errors of 3.9% [30].

3. FORECASTING ELECTRICITY CONSUMPTION IN TURKEY BY HOLT-WINDER METHOD

3.1.INTRODUCTION

In the present, the electric power sector has become very important in most areas of life in industry, trade and others. Therefore, there is a great need to establish mathematical models to predict the demand for electricity. In this chapter we will analyze the annual and seasonal time series of electric consumption in Turkey and create predictive models using Holt-Winter method. In this thesis we used R-software to forecasting electricity demand by Holt-Winter and Box Jenkins (ARIMA) methods. R language was created and developed by Ross Ihaka and Robert Gentleman in the mid 1990s. Where R-software is consider one of the best program for statistical computing to data analysis and graphics .It is designed to generate dynamic system to data analysis.

3.2.DATA COLLECTION

The data collected about electricity consumption in Turkey were in two parts: an annual time series (1979-2008) and a seasonal time series (January 2002- May 2018) [2,30] can be shown in Fig (3.1 and 3.2)

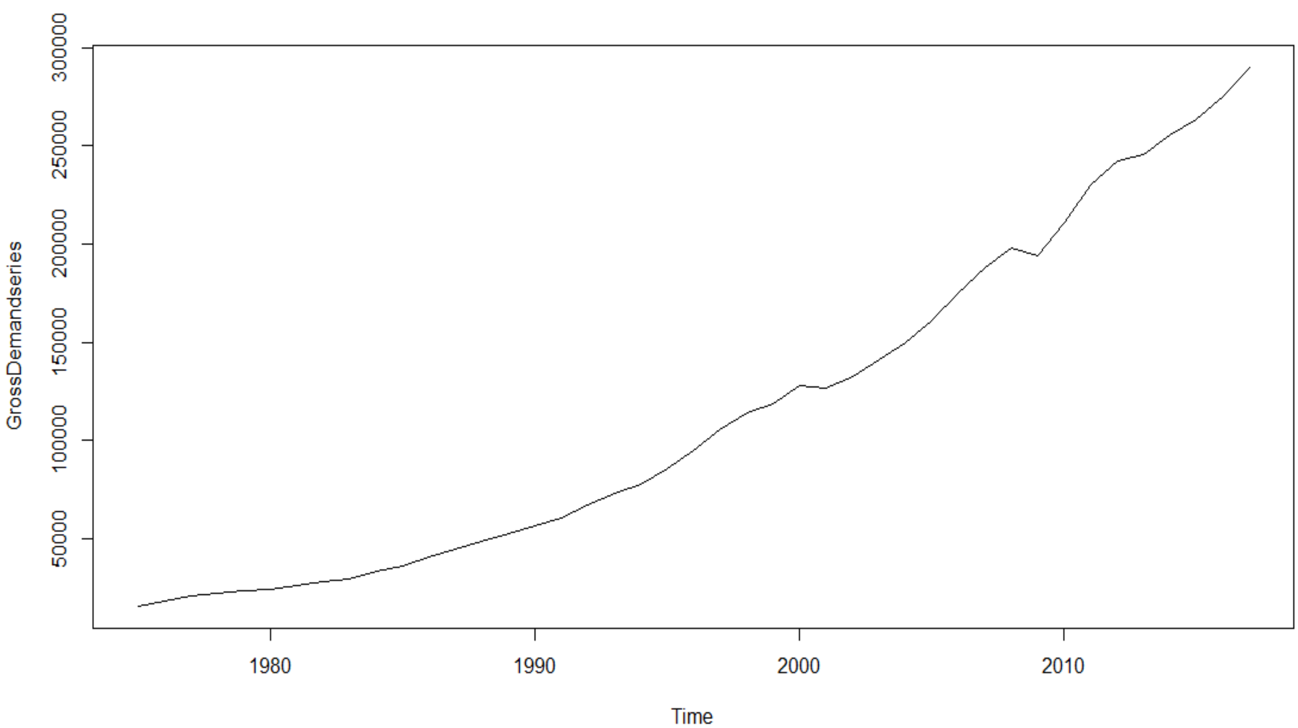

Figure 3.1: Annual Time Series from 1975 to 2017.

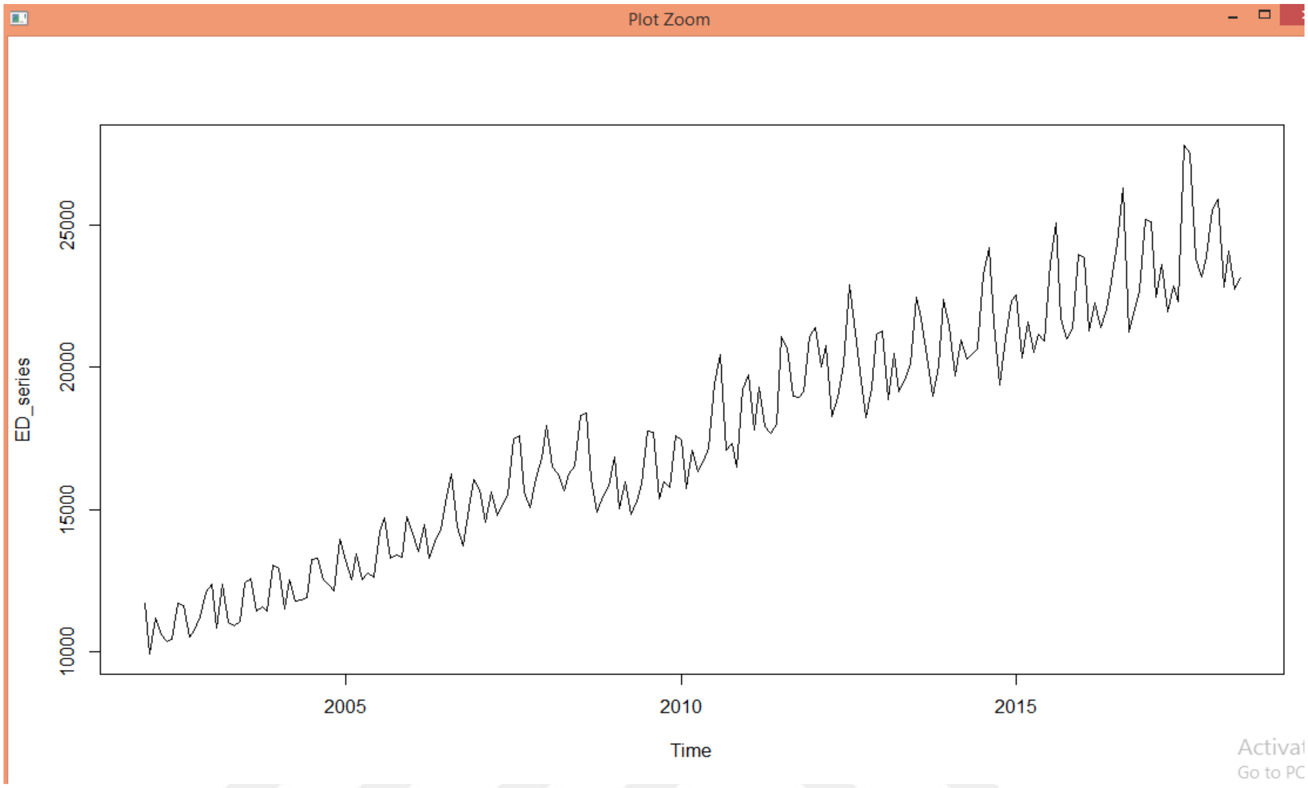

Figure 3.2: Seasonal Time Series from January 2002 to May 2018

3.3.FORECASTING BY HOLT-WINTER

The Holt-Winter forecasting method is considered one of the best to quantitative forecasting methods where it is ability to analysis annual or seasonal time series in the past to make prediction for future by using mathematical repetition functions. There are two types to forecasting by Holt-Winter are additive and multiplicative we can used two types to forecasting for annual and seasonal time series.

3.3.1. Forecasting for Monthly Data by R-software

The seasonal data are different about annual data where the seasonal data represented 197 values from January 2002 to May 2018.

Firstly we insert the data in program by using this code

```
> ED_series <- ts(ED, frequency=12, start=c(2002,1))
> ED_series
```

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2002	11694	9951	11215	10606	10386	10435	11729	11647	10506	10770	11222	12122
2003	12386	10859	12391	11045	10918	11085	12415	12561	11414	11579	11439	13057

2004	12942	11508	12539	11782	11822	11926	13243	13305	12525	12326	12150	13949
2005	13212	12524	13466	12534	12760	12603	14254	14694	13283	13407	13322	14734
2006	14172	13540	14471	13278	13876	14336	15453	16267	14395	13735	15068	16046
2007	15686	14548	15623	14786	15113	15560	17492	17580	15636	15071	16103	16803
2008	17948	16504	16245	15652	16248	16527	18309	18392	16045	14917	15446	15816
2009	16851	15010	15984	14849	15298	15900	17744	17705	15379	15990	15779	17591
2010	17422	15745	17079	16314	16712	17143	19428	20453	17094	17318	16495	19232
2011	19724	17790	19278	17923	17686	18003	21070	20674	18986	18935	19147	21090
2012	21406	19995	20758	18255	18954	20101	22880	21539	19863	18217	19244	21159
2013	21275	18842	20464	19139	19512	20133	22469	21698	20359	18965	20062	22387
2014	21409	19674	20942	20267	20424	20645	23233	24188	21552	19376	21018	22324
2015	22543	20334	21594	20520	21133	20903	23641	25050	21693	20995	21348	23953
2016	23840	21255	22271	21379	22018	23017	24369	26265	21232	21849	22683	25160
2017	25103	22452	23586	21953	22854	22304	27775	27522	23807	23162	23860	25552
2018	25872	22798	24090	22729	23136							

Now we used HoltWinters() function by R-software to forecasting electricity consumption where can be shown below the Holt-Winter model by multiplicative type.

```
> Model_1 <- HoltWinters( ED_series, alpha=NULL, beta=NULL, gamma=NULL,seasonal="m
ultiplicative")
> Model_1
```

Holt-Winters exponential smoothing with trend and multiplicative seasonal component.

Call:

HoltWinters(x = ED_series, alpha = NULL, beta = NULL, gamma = NULL,   seasonal = "multi
plicative")

Smoothing parameters:

alpha: 0.2792918

beta : 0

gamma: 0.4431466

Coefficients:

```
          [,1]
a   2.411919e+04
```

b 6.079225e+01

s1 9.786197e-01

s2 1.124332e+00

s3 1.139528e+00

s4 9.763078e-01

s5 9.483195e-01

s6 9.770553e-01

s7 1.063403e+00

s8 1.063278e+00

s9 9.468847e-01

s10 1.000540e+00

s11 9.438909e-01

s12 9.676021e-01

This is the best model to forecasting electricity consumption by Holt-Winter multiplicative type. The result for this model can be shown in Figure (3.3) and Table (A-1) in Appendix (A)

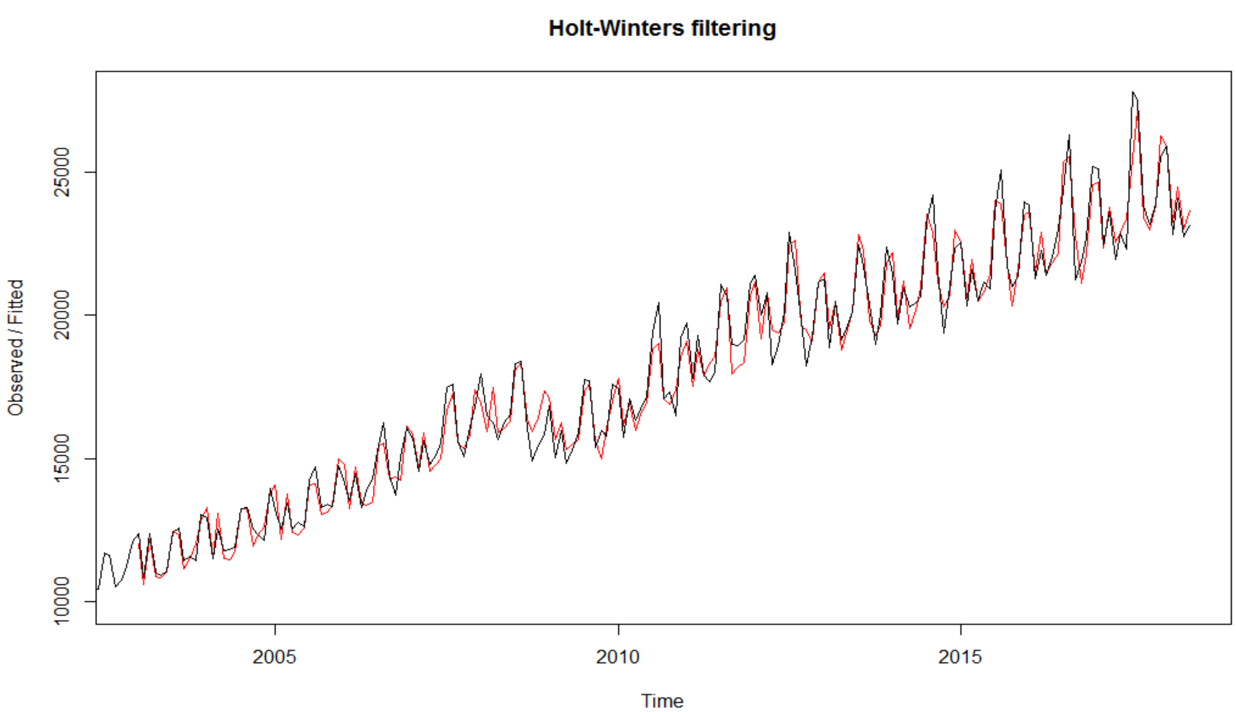

Figure 3.3: forecasting results for model 1

After we determine the best model ,now we used Model_1 to forecasting for the next period where the forecasting period from June 2018 to Dec 2021 by this code

```
> Forecast_Model_1 <- predict(Model_1, 43, prediction.interval = TRUE)
> plot(Model_1, Forecast_Model_1)
```

We can see the results in Figure (3,4) and Table (A-2) in Appendix A

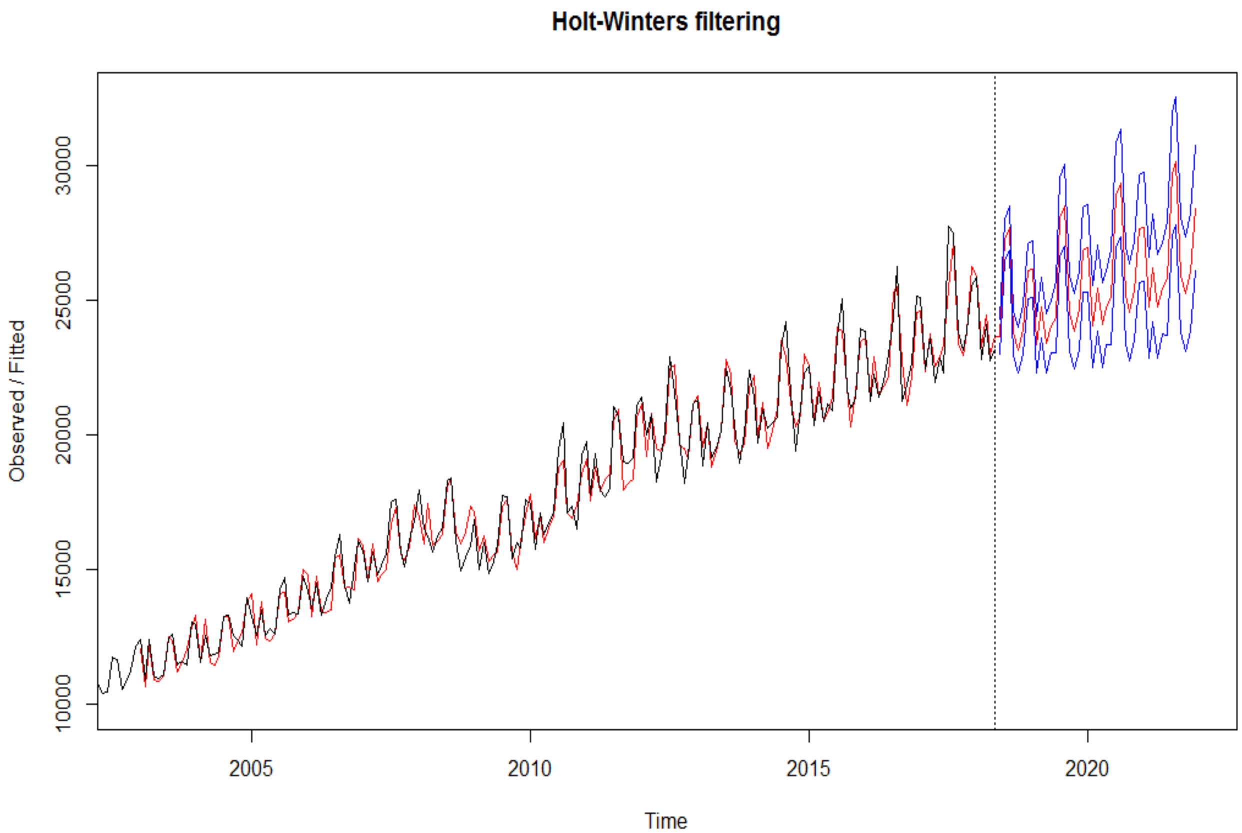

Figure 3.4: Forecasting results to the next period from June 2018 to Dec 2021 by model-1

The second model is generated by Holt-Winter additive type can be show below

```
> Model_2 <- Holt Winters( ED_ series, alpha=NULL, beta=NULL, gamma=NULL, seasonal="
additive")
> Model_2
Holt-Winters exponential smoothing with trend and additive seasonal component.
Call:
Holt Winters(x = ED_ series, alpha = NULL, beta = NULL, gamma = NULL,     seasonal = "addi
tive")
Smoothing parameters:
 Alpha: 0.28412
 Beta: 0
 Gamma: 0.5918362

Coefficients:
          [1]
a   24110.51119
b      60.79225
s1   -534.07901
s2   3022.36443
s3   3257.94292
s4   -660.16012
s5  -1173.67392
s6   -497.35605
s7   1457.38794
s8   1496.98475
s9  -1320.48151
s10   -85.57733
s11 -1395.93259
s12  -798.07371
```

Also this is represented the best model to forecasting by additive type we can show the results to Model-2 in Fig (3.5) and Table (A-3) in Appendix (A)

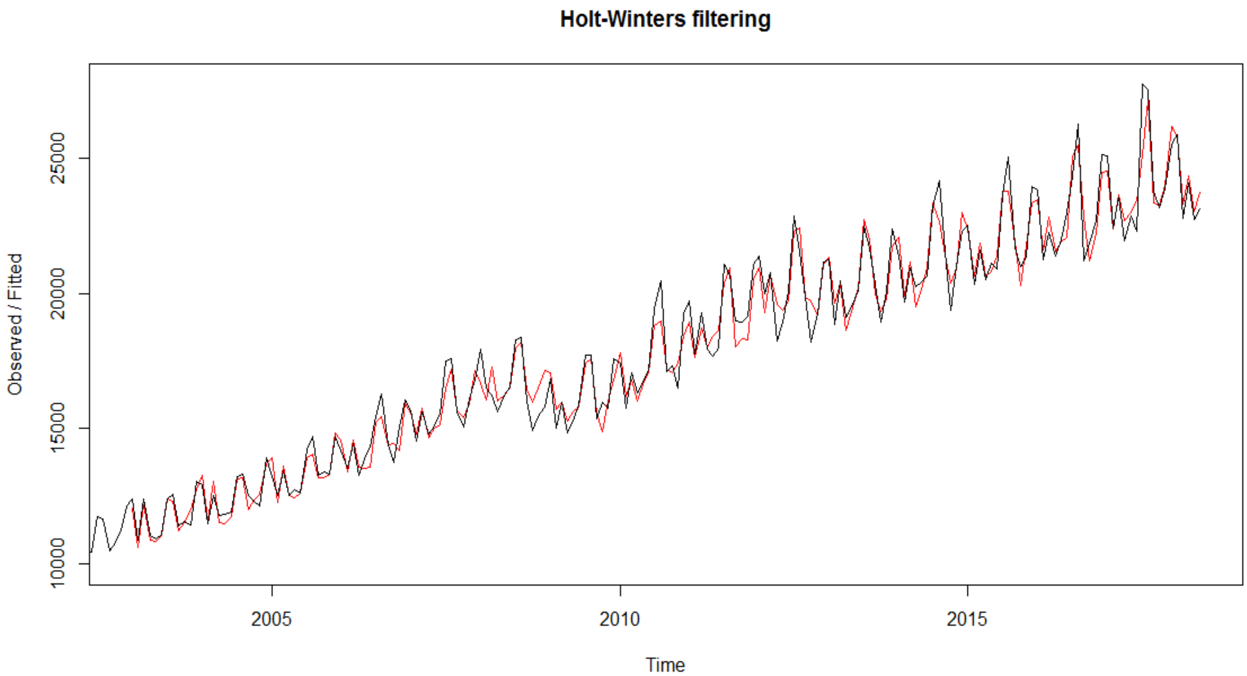

Figure 3.5: Forecasting results for model-2

After analysis the data and generate the model by Holt-Winter additive type now we get the results to forecasting for next period from June 2018 to Dec 2021 can be show the results in Fig (3.6) and Table (A-4) in Appendix (A)

```
> Forecast_Model_2 <- predict(Model_2, 43, prediction.interval = TRUE)
> plot(Model_2, Forecast_Model_2)
```

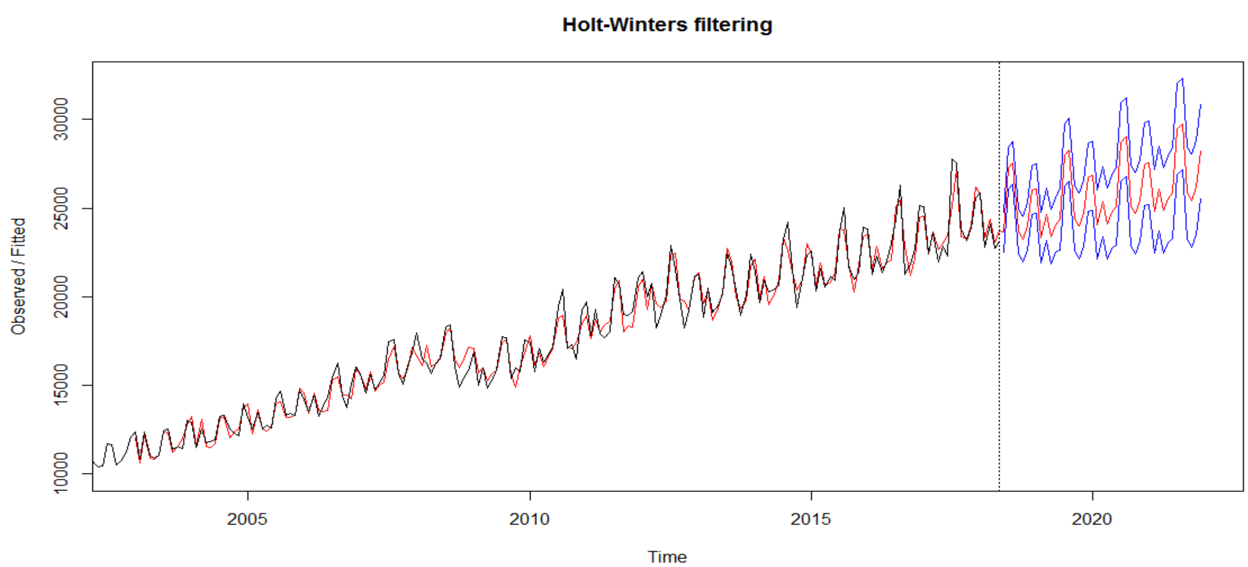

Figure 3.6: Forecasting results to the next period from June 2018 to Dec 2021 by model-2

3.3.2. Forecasting for Yearly Data by R-software

After complete the analysis for seasonal time series now we will analysis to annual time series where the data is different, therefore the parameters to forecasting annual consumption is different about seasonal electricity consumption by Holt-Winter method. We are generate two models to forecasting annual time series the first model have one parameter α = 0.999, can be show in below

```
> GrossDemandseries <- ts(GrossDemand, start=c(1975))
> GrossDemandseries
Time Series:
Start = 1975
End = 2017
Frequency = 1
[1] 15719 18615 21057  22347  23566  24617  26289  28325  29568  33267  36361
[12] 40471 44925 48430 52602  56812  60499  67217  73423  77783  85552  94789
[23]105517 114023 118485 128276 126871 132553 141151 150018 160794 174637 187942
[34] 197827 194080 210435 230306 242371 245485 255547 263708 275341 289926
> Model_3 <- Holt Winters (Gross Demand series, beta=FALSE, gamma=FALSE)
> Model_3
Holt-Winters exponential smoothing without trend and without seasonal component.

Call:
Holt Winters(x = Gross Demand series, beta = FALSE, gamma = FALSE)

Smoothing parameters:

Alpha: 0.9999512
 Beta: FALSE
 Gamma: FALSE
Coefficients:
    [1]
a 289925.3
```

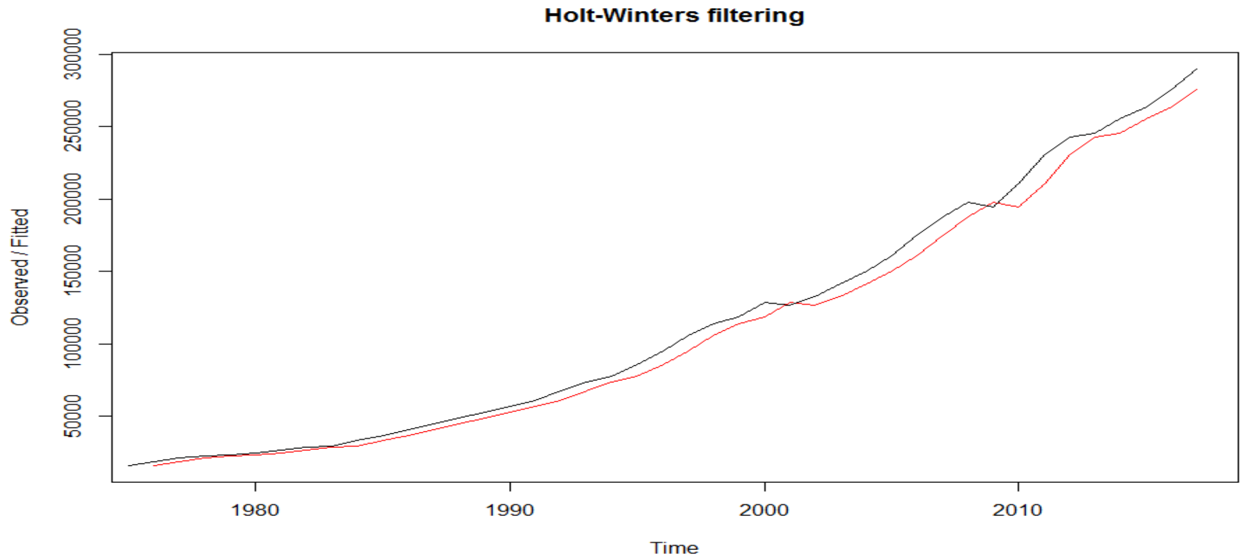

Figure 3.7: forecasting results for model-3

Fig(3.8) and Table (A-6) in Appendix A show the results to forecasting by model-3

```
> Forecast_Model_3 <- predict(Model_3, 10, prediction.interval = TRUE)
> plot(Model_3, Forecast_Model_3)
```

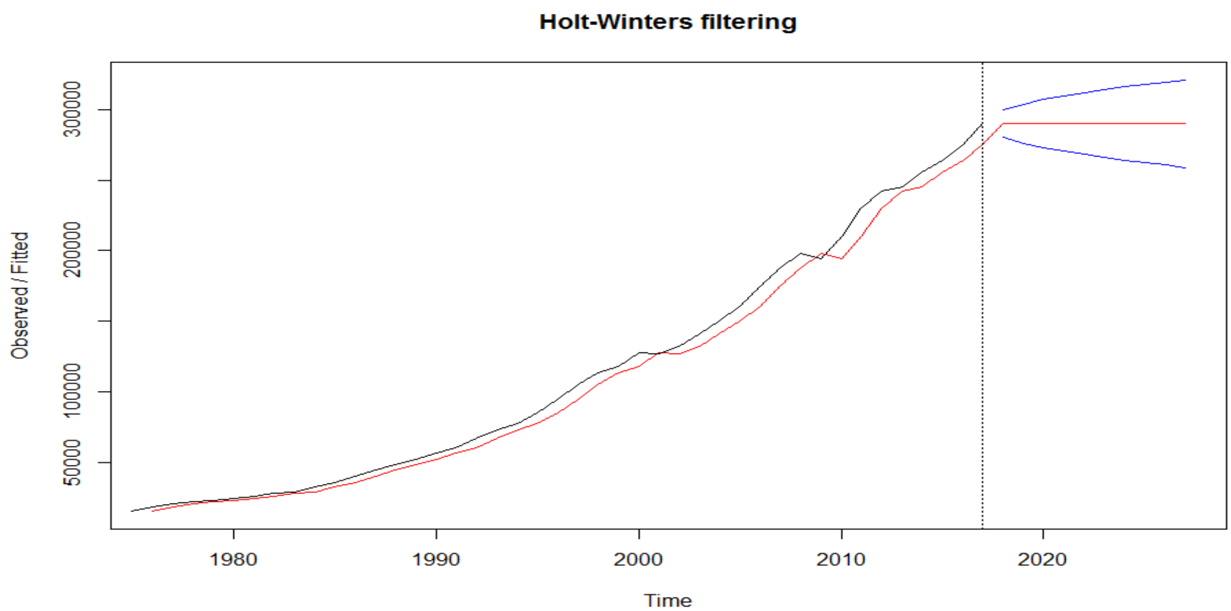

Figure 3.8: Forecasting results to the next period from June 2018 to Dec 2021 by model.

The second model to forecasting for annual time series have two parameters α=1 , β=0.19 . The r esults for model-4 can be shown in Fig (3.9) and Table (A-7)

```
> Model_4 <- HoltWinters(GrossDemandseries, gamma=FALSE)
> Model_4
```

Holt-Winters exponential smoothing with trend and without seasonal component.

Call:

HoltWinters(x = GrossDemandseries, gamma = FALSE)

Smoothing parameters:

alpha: 1

beta : 0.1900815

gamma: FALSE

Coefficients:

```
       [,1]
a 289926.00
b  10738.27
```

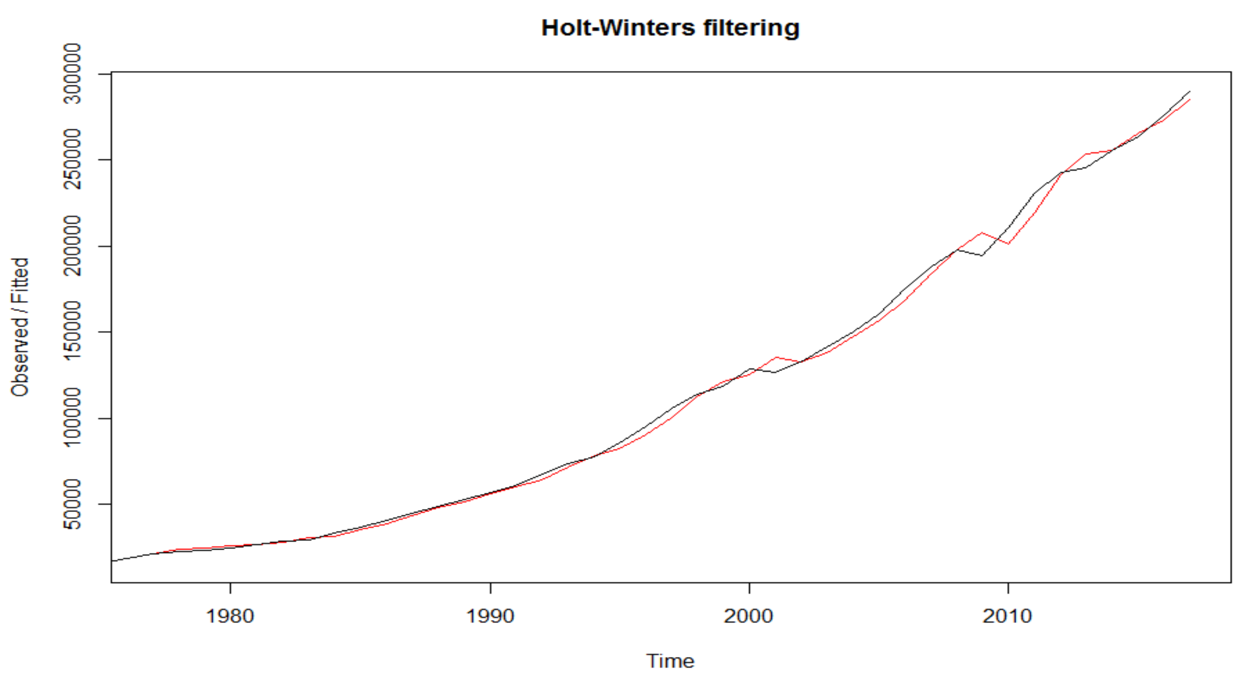

Figure 3.9: forecasting results for model-4

```
> Forecast_Model_4 <- predict(Model_4, 10, prediction.interval = TRUE)
> plot(Model_4, Forecast_Model_4)
```

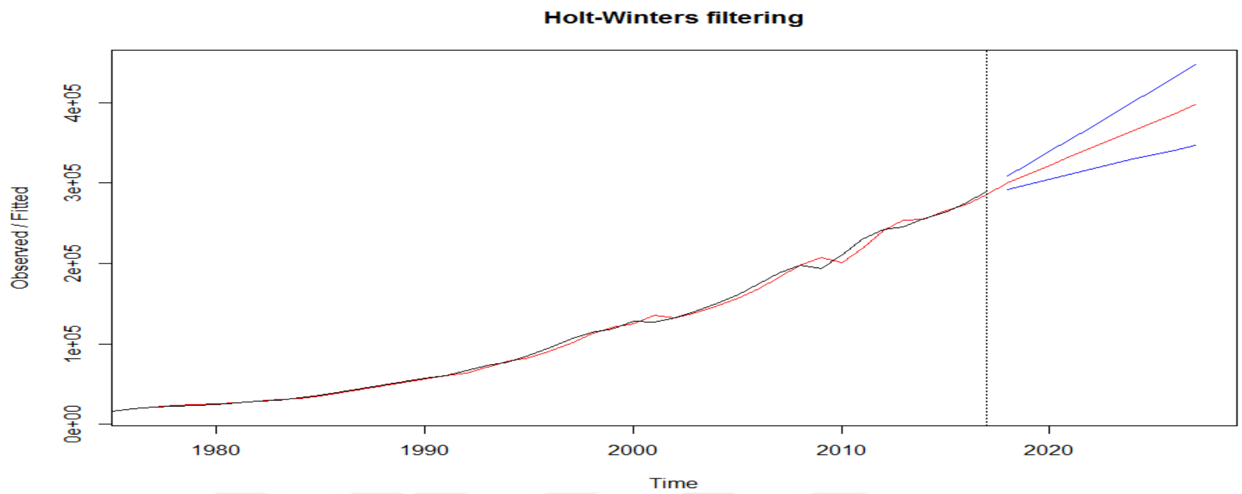

Figure 3.10: Forecasting results to the next period from June 2018 to Dec 2021 by model-4.

3.4.Validation Stage for Holt-Winter

We have a generated models to forecasting by Holt winter for seasonal time series in this stage we verify the models by divided the data into two groups the first group used to train the data where this data represented about 70% from time series and second group used to test the data and represented about 30% from time series, where can be shown that in below

```
> tain.data =window(ED_series,start=c(2002,1),end=c(2015,12))
> test.data =window(ED_series,start=c(2016,1))
> Model_1_val = HoltWinters( tain.data, alpha=NULL, beta=NULL, gamma=NULL,seasonal="
multiplicative")
> plotarimapred(test.data,Model_1_val,xlim=c(2002,2018),range.percent = 0.05)
```

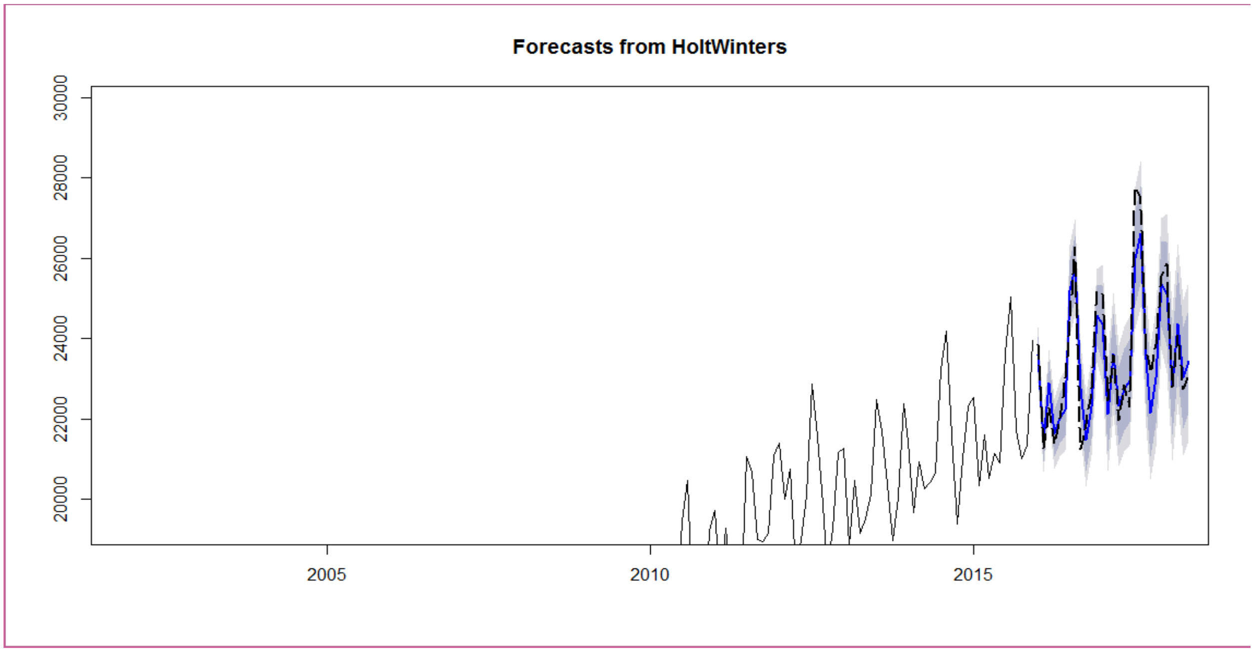

Figure 3.11: Validation process for Model-1

We see from Fig(3.11) above is the model-1 is good where the actual data and predicted data in test period is matching.

The validation process to model-2 can be shown below

```
> tain.data =window(ED_series,start=c(2002,1),end=c(2015,12))
> test.data =window(ED_series,start=c(2016,1))
> Model_2_val = HoltWinters( tain.data, alpha=NULL, beta=NULL, gamma=NULL,seasonal="
additive")
> plotarimapred(test.data,Model_2_val,xlim=c(2002,2018),range.percent = 0.05)
```

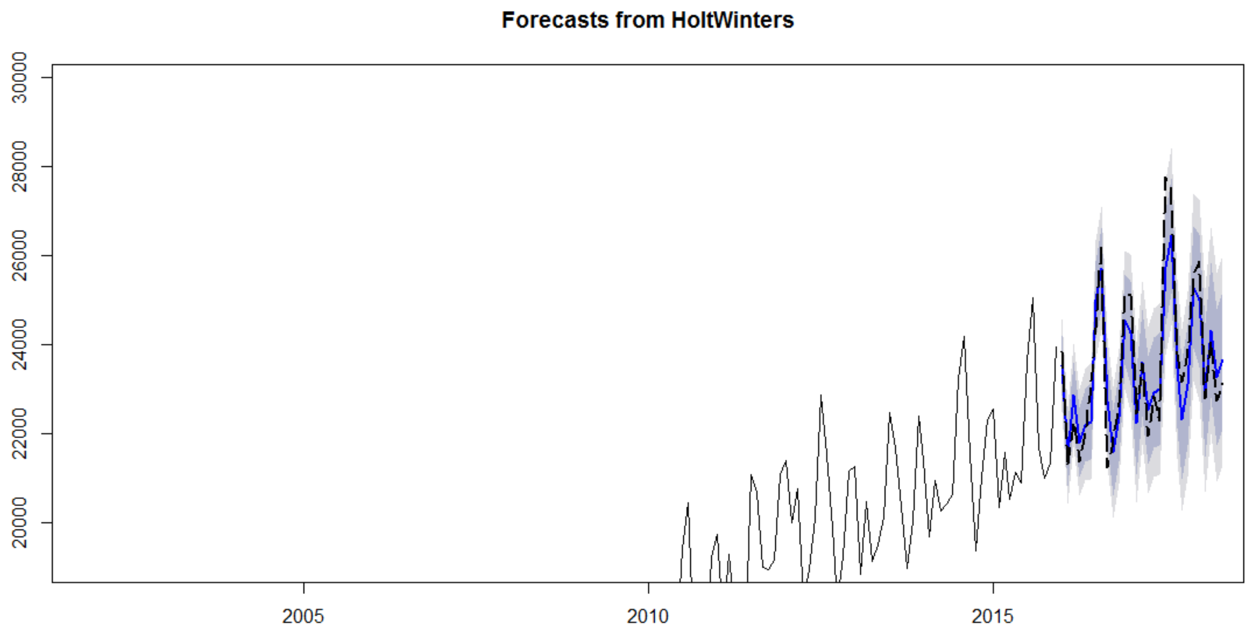

Figure 3.12: Validation process for Model-2

We see from Fig (3.12) above is the model-2 is good where the actual data and predicted data in test period is matching.

3.5 SUMMARY

This chapter is include analysis the data to forecasting the electricity consumption for Turkey by Holt-Winter where there are two types from data (annual and seasonal time series). We created four models to forecasting, Table (3.1) shown the optimum parameters (α, β, γ) to forecasting, where we used R-software to help as to determine the best parameters by <- HoltWinters function

Table 3.1: Holt Winter Parameters for Four Models

Time Series	Four Models	Holt Winter Parameters		
		α	β	γ
Seasonal Time Series	Model-1	0.279	0	0.443
	Model-2	0.284	0	0.591
Annual Time Series	Model-3	0.999	False	False
	Model-4	1	0.19	False

In Chapter six we discuss the accuracy parameters for four models (MAPE, MSE, RMSE) and comparison the results with ARIMA models to determine the best model to forecasting.

4. FORECASTING ELECTRICITY CONSUMPTION IN TURKEY BY USING BOX-JENKINS METHOD

4.1.INTRODUCTION

In this chapter we used Box-Jenkins to analysis the data where this methods has a lot of models (AR, MA, ARIMA, SARIMA and other) this is depending upon the analysis for time series. Box-Jenkins methodology is consider powerful and accuracy methodology because it has ability to analysis the trend and seasonal time series and determine the stationary for time series.

4.2.MODELLING THE DATA

There are two time series (yearly and seasonal) can be analysis and dissection to forecasting electricity consumption by box-Jenkins methods.

4.2.1. Modelling Yearly Time Series

Yearly time series have 43 values from 1975 to 2017 , where we see yearly time series in Fig (3.1) the consumption is increased this is mean the data has trend so there are for models to analysis yearly time series (AR, MA, ARMA and ARIMA).

4.2.1.1. Identification the parameters for arima model

Firstly we must be determine the parameters for ARIMA methods (p,d,q) to select the best model to forecasting to do this we used autocorrelation function (ACF) and partial autocorrelation function (PACF), this can be shown below in Fig (4.1)

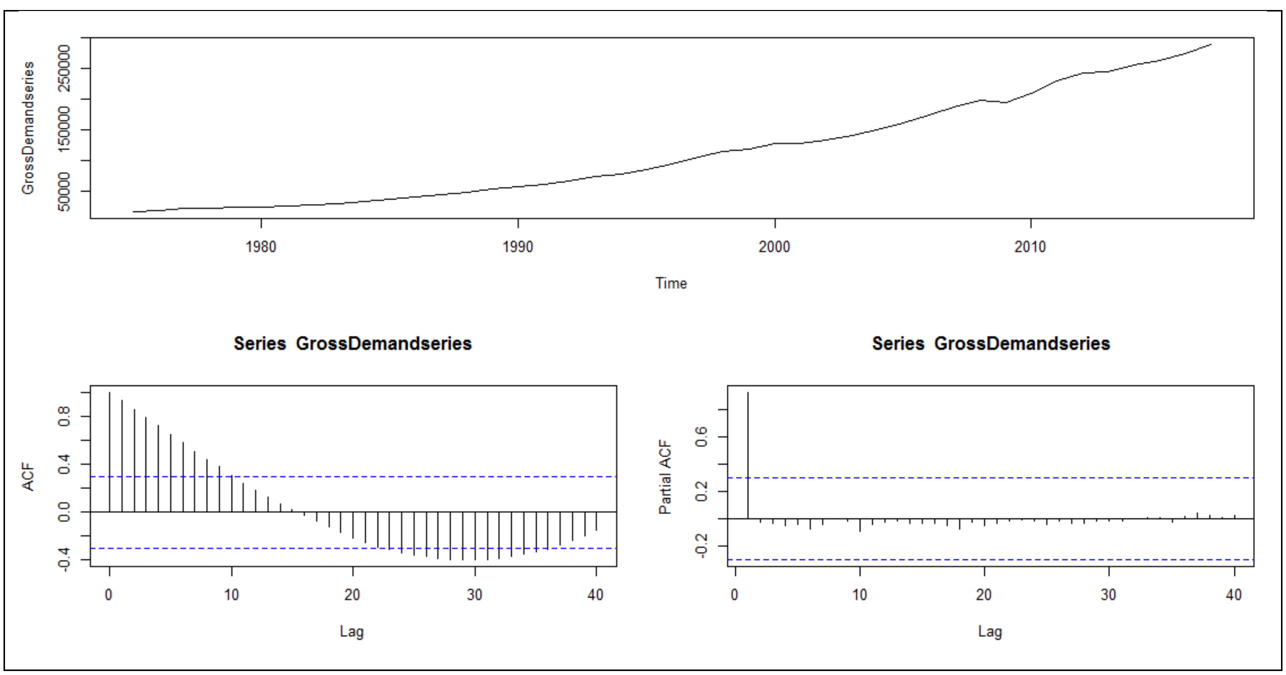

Figure 4.1: ACF and PACF to yearly time series

We see in Fig (4.1) the time series is not stationary because there are a lot of legs in ACF out of control limit so we will make difference stationary for time series , can be show that in Fig (4.2)

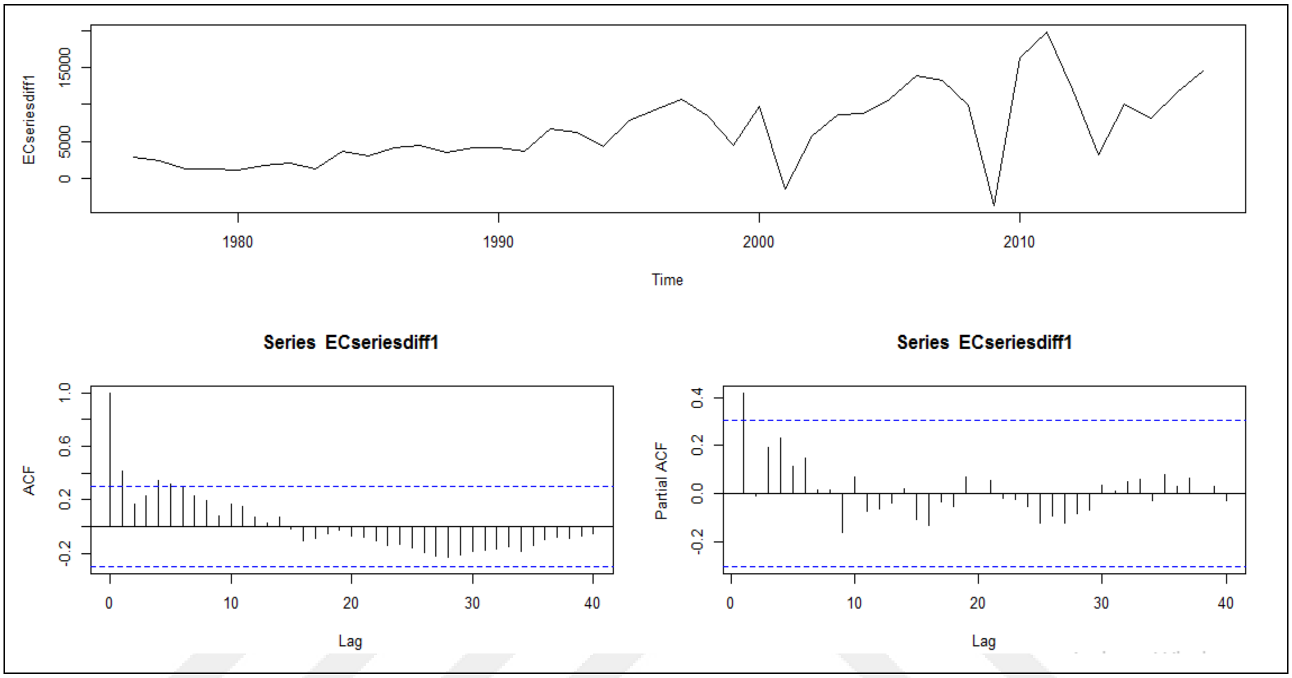

Figure 4.2: First difference to yearly time series

From Fig (4.2) we see the time series became mode stationary where there are no trend and it has good mean but also some legs in ACF is out of control limits so we need to second difference, can be shown that below in Fig (4.3).

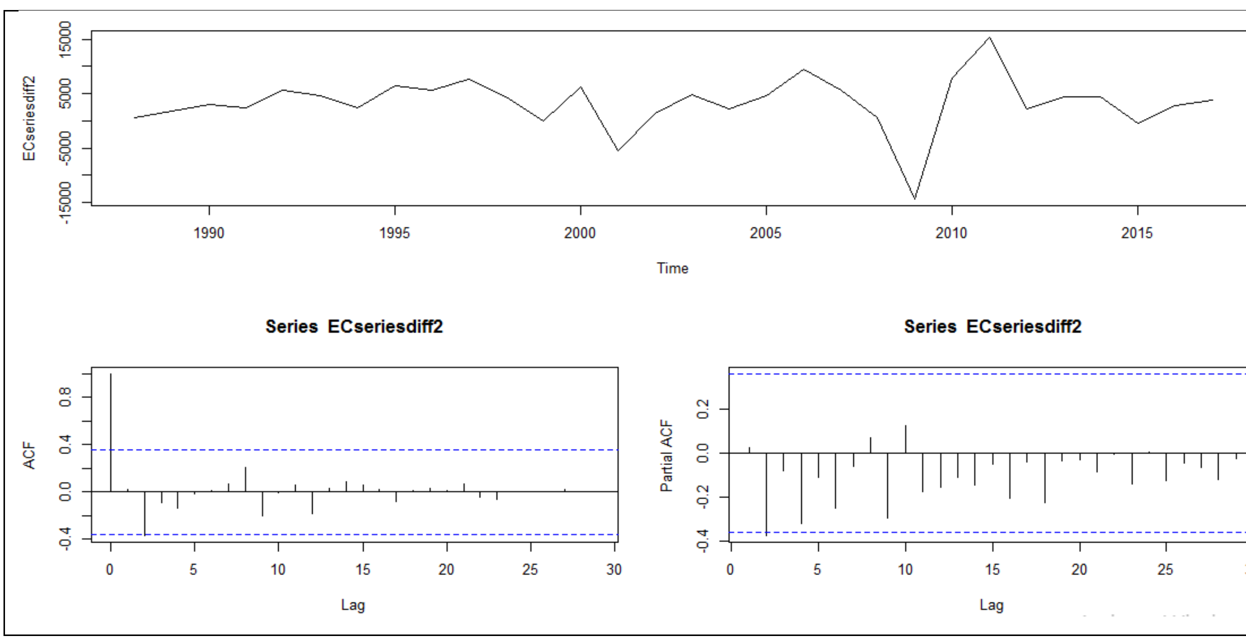

Figure 4.3: Second difference to yearly time series

From Fig (4.3) we see there are no trend to time series also all legs in ACF and PACF in control limit so the parameter (d=2)

4.2.1.2. Selection the best for arima model

Now we determine the parameters to ARIMA (p,d,q) models where d=2 but it is difficult determine (p,q) from ACF and ACF because there are a lot of models can be created from Fig (4.3). Therefore we used <- auto.arima() function in R-software to select the best model to forecasting , can be show that in below

```
Model_1 <- auto.arima(GrossDemandseries,trace = T, ic="bic")
ARIMA(2,2,2)                 : Inf
 ARIMA(0,2,0)                 : 821.9495
 ARIMA(1,2,0)                 : 822.2338
 ARIMA(0,2,1)                 : 810.7216
 ARIMA(1,2,1)                 : 813.8608
 ARIMA(0,2,2)                 : 813.322
 ARIMA(1,2,2)                 : 816.677
 Best model: ARIMA(0,2,1)
> summary(Model_1)
Series: GrossDemandseries
ARIMA(0,2,1)
Coefficients:
          ma1
      -0.7954
s.e.   0.0786
sigma^2 estimated as 18905007:  log likelihood=-401.65
AIC=807.29   AICc=807.61   BIC=810.72
Training set error measures:
               ME      RMSE      MAE       MPE      MAPE    MASE       ACF1
Training set 960.7014 4193.57 2776.30  0.813610  2.518352  0.409842  0.042221
```

We see the best model to forecasting is ARIMA (0,2,1), where the Bayes information criterion (BIC) = 810. 72 less than other models

4.2.1.3. Diagnostics the best aeima model

Residual diagnostic to the model-1 can be show in Figure 4.4. Where the standardized residual is stable and almost legs in ACF of residual in control limits, also all points for Ljung-Box in control limits this mean model-1 is good and we can used it to forecasting.

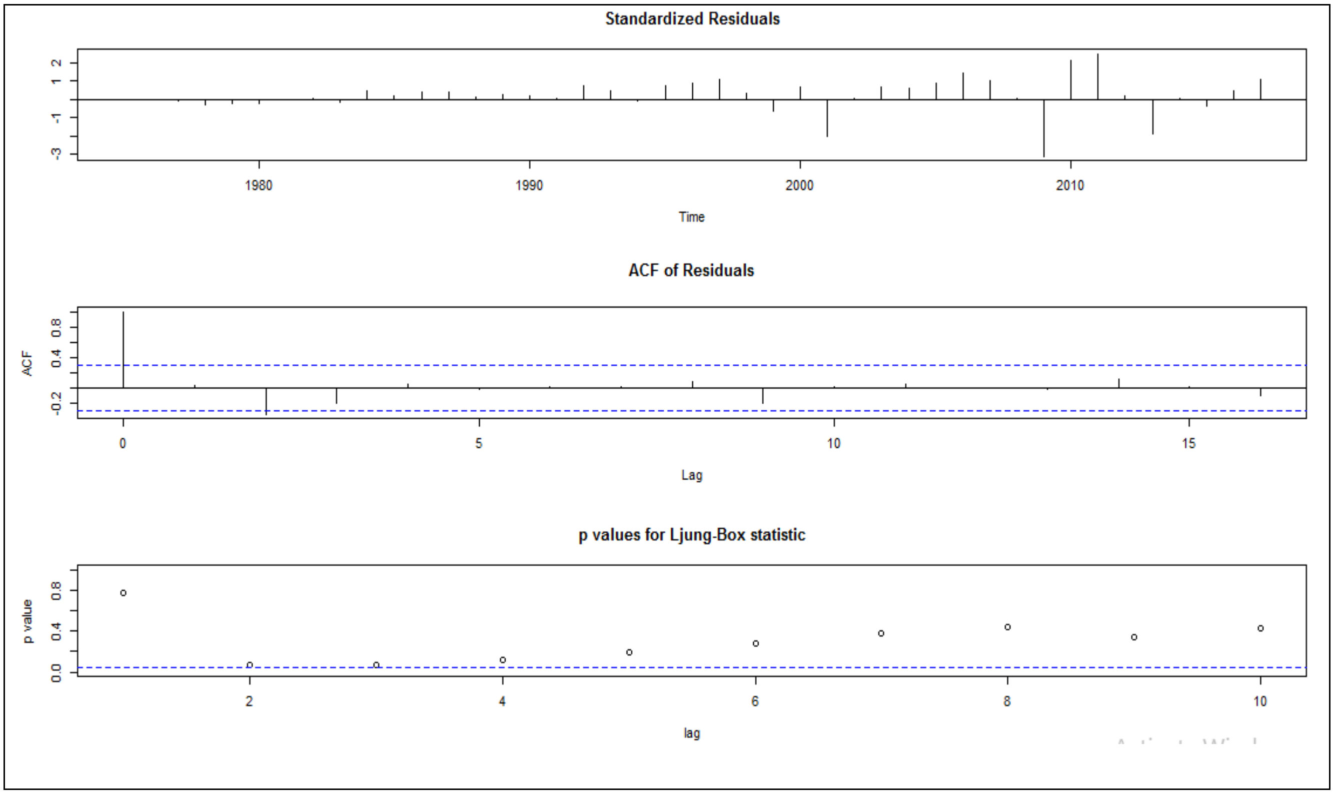

Figure 4.4: Diagnostics to the ARIMA model (0, 2, and 1)

Also we used another test tools to diagnosis ARIMA (0,2,1) model , Fig (4.6) show the normal Q-Q plot where we see most points in autocorrelation line.

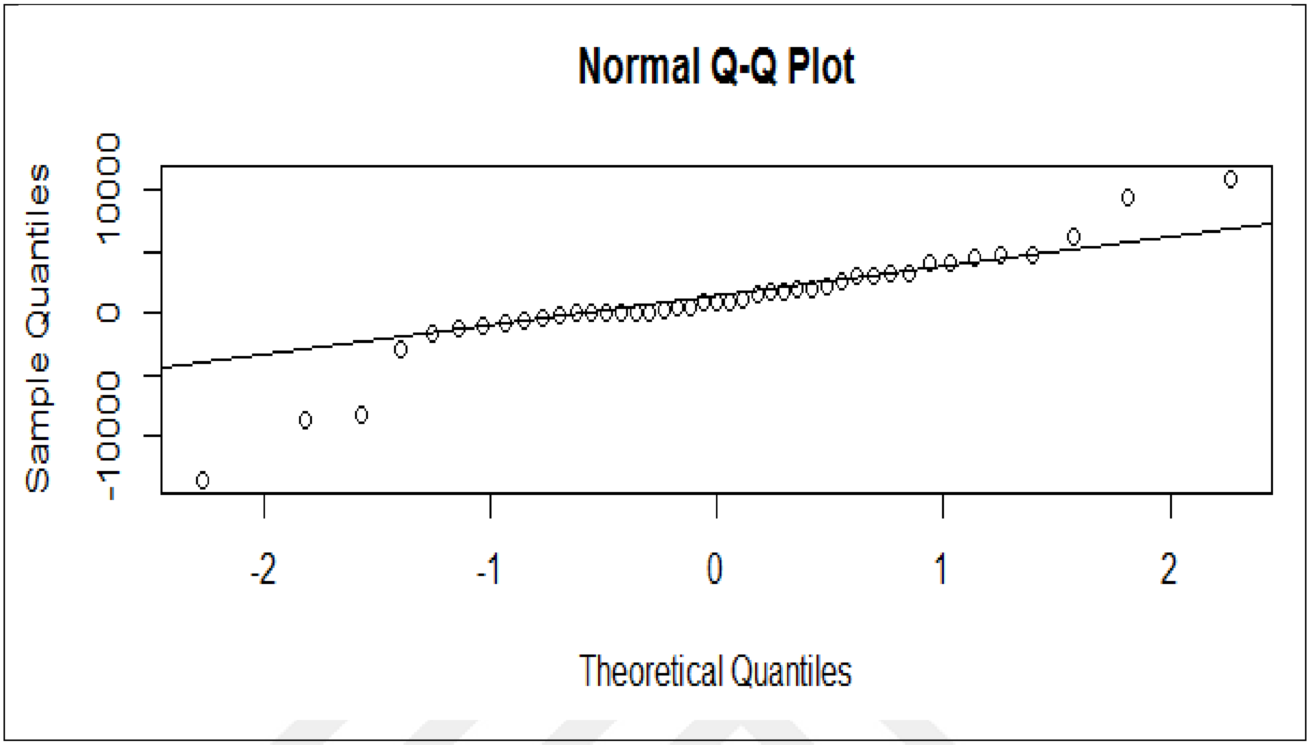

Figure 4.5: Normal Q-Q plot to the ARIMA (0, 2, 1)

4.2.1.4.Forecasting by arima model

We see in diagnosis and testing stage the ARIMA (0,2,1) model is suitable to forecasting to future for electricity consumption from 2018 to 2027, can be show below the results to forecasting by ARIMA (0,2,1) model

```
> forecast(Model_1,h=10)
     Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
2018       300764.7 295192.5 306336.8 292242.8 309286.6
2019       311603.4 302879.6 320327.1 298261.6 324945.1
2020       322442.0 310704.8 334179.2 304491.6 340392.5
2021       333280.7 318494.8 348066.6 310667.6 355893.8
2022       344119.4 326194.9 362043.9 316706.2 371532.6
2023       354958.1 333783.6 376132.5 322574.6 387341.6
2024       365796.7 341252.4 390341.1 328259.3 403334.1
2025       376635.4 348598.0 404672.9 333755.8 419515.0
2026       387474.1 355820.2 419128.0 339063.6 435884.6
2027       398312.8 362920.0 433705.5 344184.3 452441.3
```

```
> plot(forecast(Model_1,h=10))
```

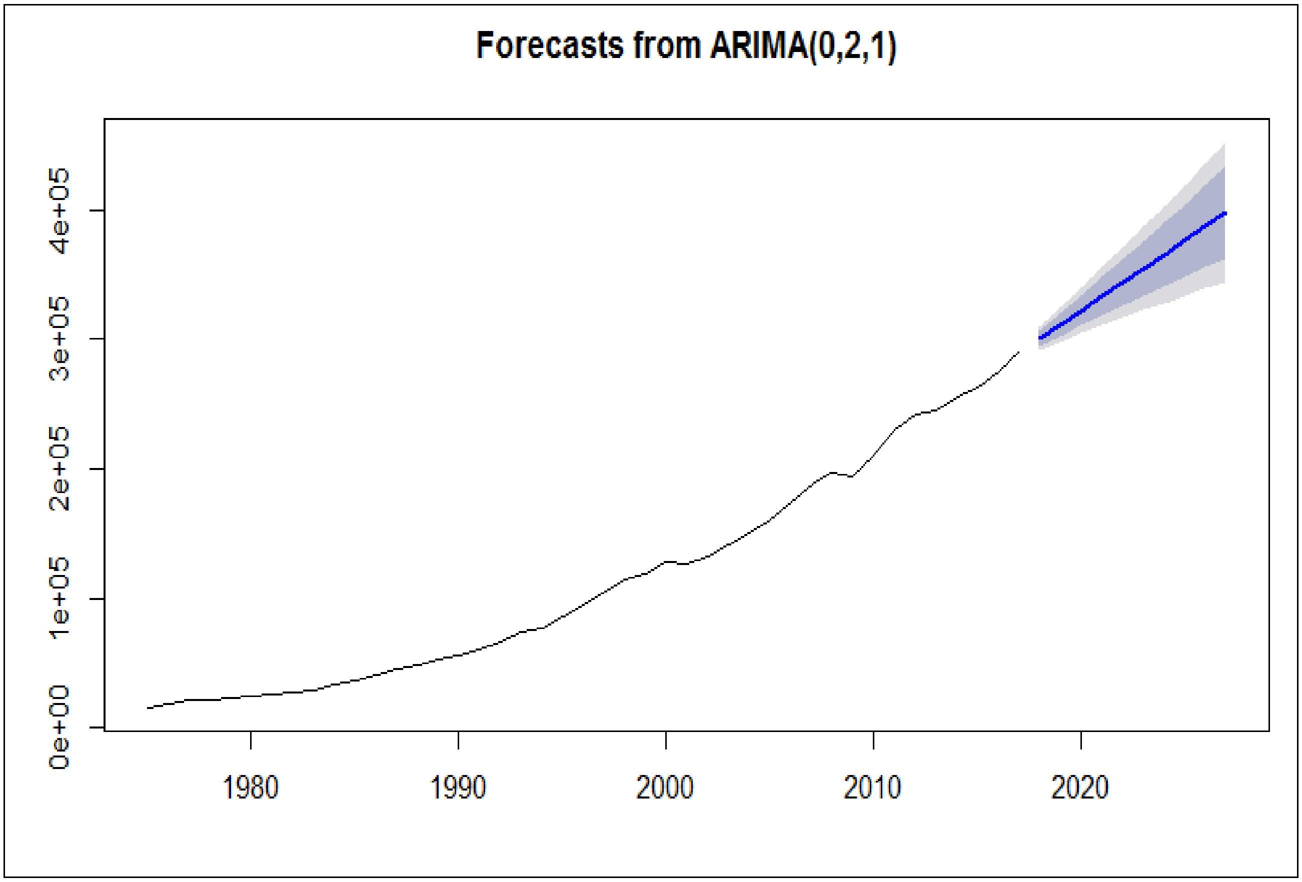

Figure 4.6: Forecasting results to ARIMA (0, 2, and 1) model from 2018-2027

From Fig (4.7) we see the forecasting to electricity consumption where the consumption is increase in every year.

4.2.2. Modelling Seasonal Time Series

Seasonal time series have 197 values from Jan 2002 to May 2018 , where we see seasonal time series in Fig (3.2) the consumption is increased this is mean the data has trend so there are a lot of models can be used to analysis this time series (SAR, SMA, SARMA and SARIMA).

4.2.2.1. Identification the Parameters for SARIMA Model

In this stage we must be determine the parameters to forecasting by (SARIMA) model where there are six parameters (p,d,q)x(P,D,Q) to represent the trend and seasonality to seasonality time series. Firstly we determine the stationary by ACF and PACF function can be show that in Fig (4.8)

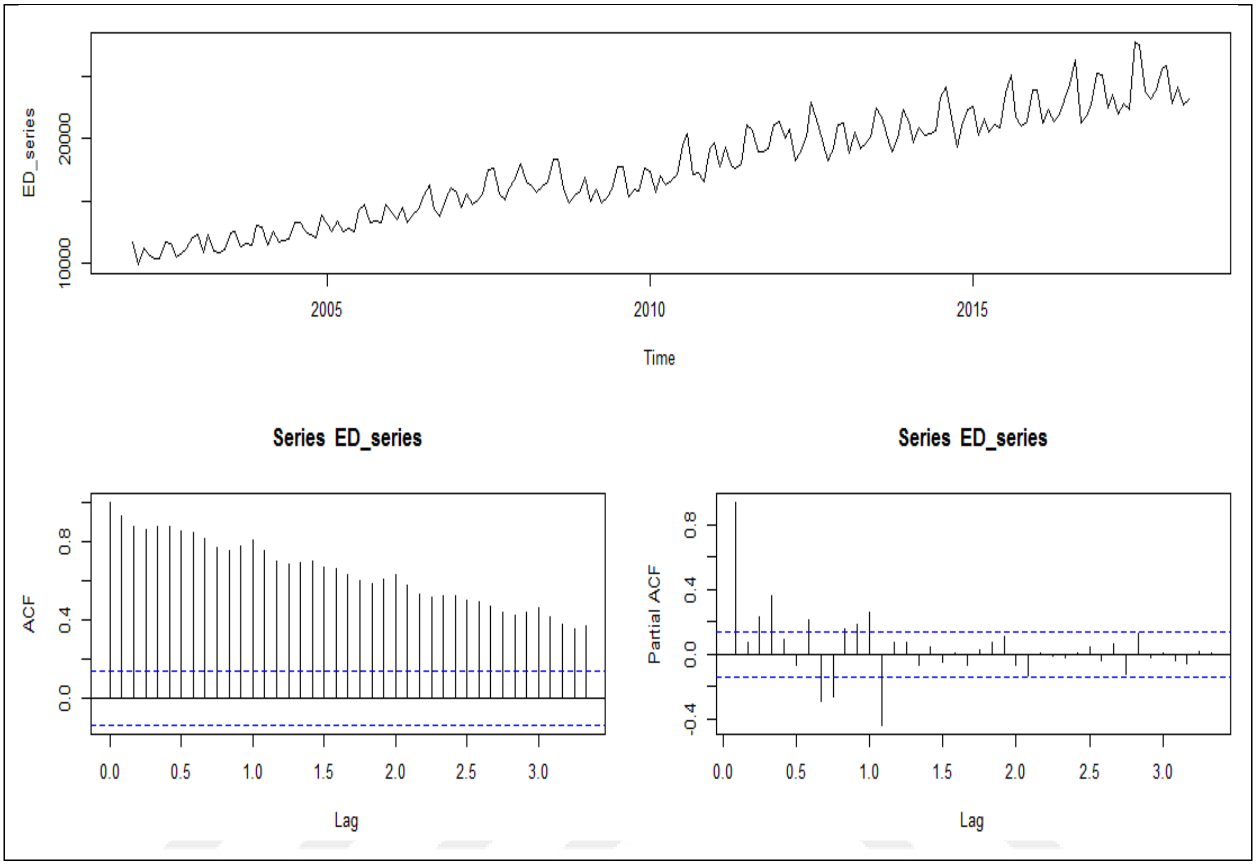

Figure 4.7: ACF and PACF to seasonal time series

We see in Fig (4.7) the time series is not stationary where there are trend and a lot of legs in ACF and some legs in (PACF) is out of control limit so we will make difference stationary for time series, can be show that in Fig (4.9)

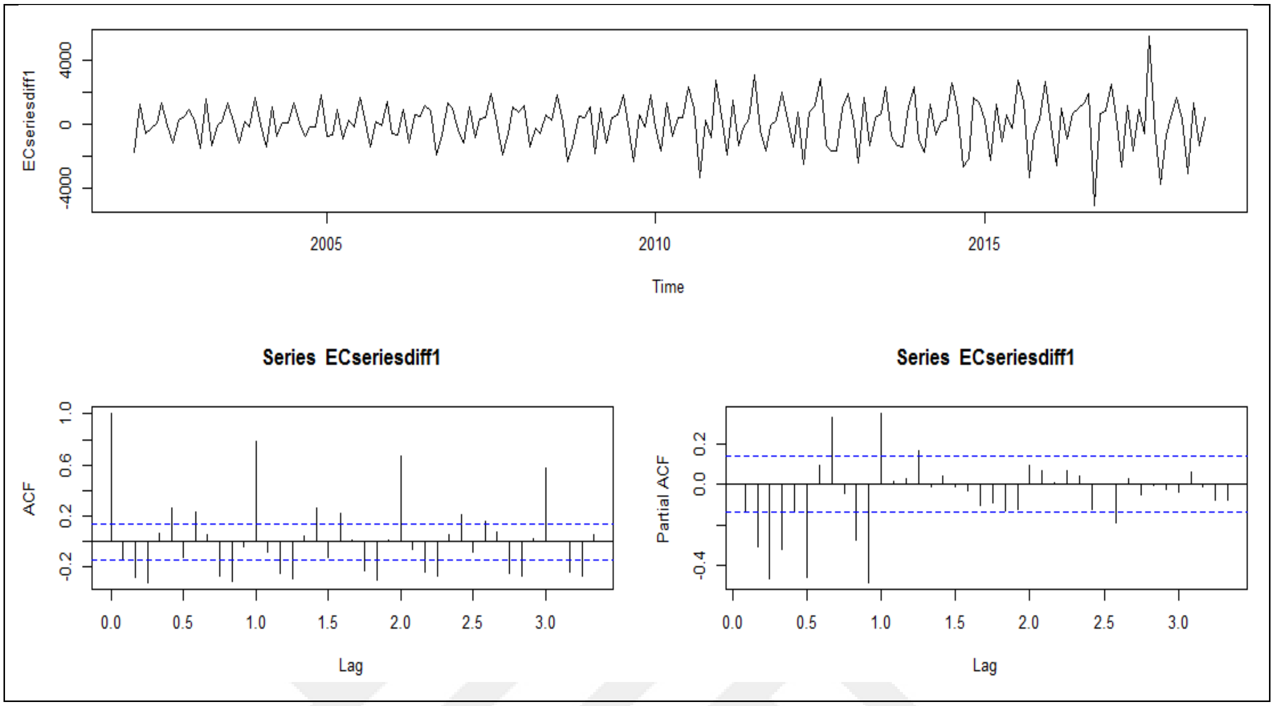

Figure 4.8: First difference to Seasonality time series

We see from Fig (4.8) the time series became more stationary but there are some legs in ACF out of control this legs are (1.0 , 2.0 and 3.0) also some legs in PACF has random distribution out of control limits because there are some seasonality so we try to remove the seasonality , Fig(4.10) can be show that

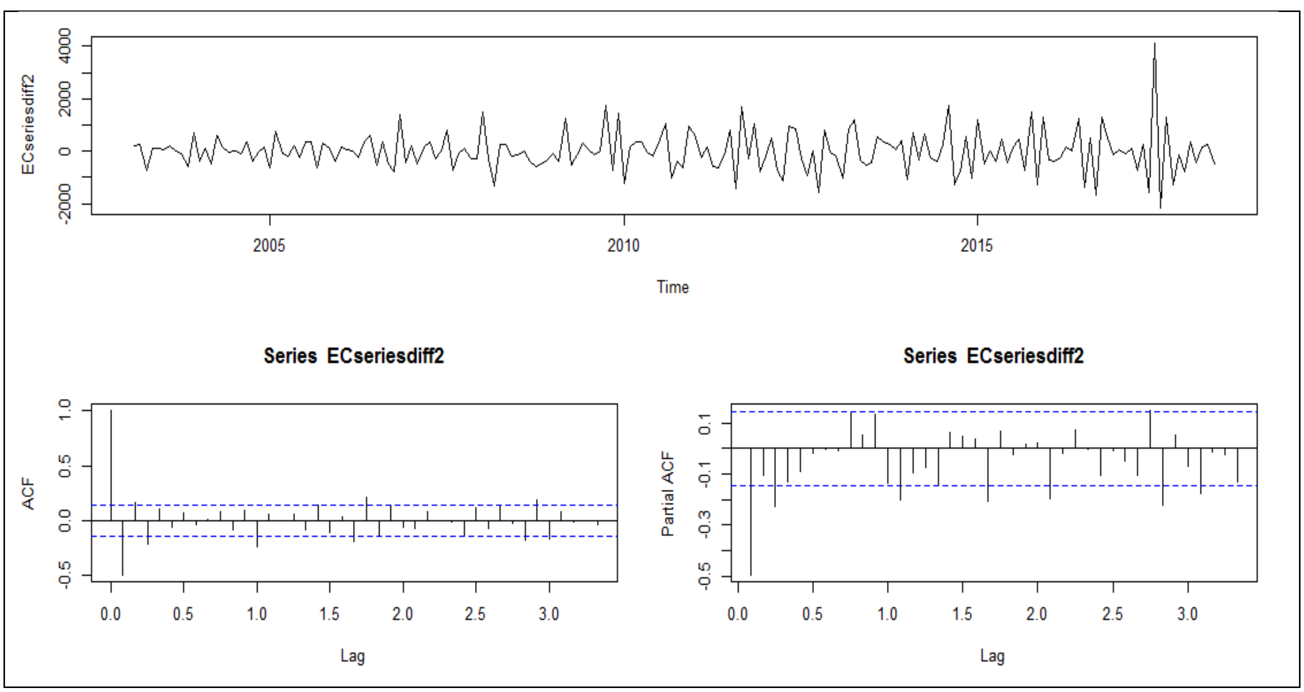

Figure 4.9: Second difference to Seasonality time series

In Fig (4.10) we see time series is stationary where there are no trend and no seasonality generated and most legs in ACF and PACF in control limits

4.2.2.2. Selection the Best for SARIMA Model

From identification stage there are trend and seasonality in time series this mean the best model to forecasting is SARIMA model so there are a lot of model , we are suggest three models to forecasting and we select the best model.

The first model can be suggested to forecasting is SARIMA (2,1,2)X(1,1,1)

```
> fit1 = arima(ED_series,order=c(2,1,2),seasonal = list(order=c(1,1,1),12))
> summary(fit1)

Call:
arima(x = ED_series, order = c(2, 1, 2), seasonal = list(order = c(1, 1, 1),
    12))

Coefficients:
         ar1     ar2      ma1      ma2    sar1     sma1
     -0.4403  0.1407  -0.2053  -0.3525  0.2100  -0.6707
s.e.   0.3725  0.1196   0.3685   0.2240  0.1304   0.0994

sigma^2 estimated as 330063:  log likelihood = -1432.45,  aic = 2878.9

Training set error measures:
                ME     RMSE      MAE      MPE    MAPE   MASE    ACF1
Training set -0.49234 555.2382 389.3063 -0.07085 2.1381 0.3500 0.00046766
```

We see from R-software output for model-1 the results is very good where the error ratio is little.

The second model suggested is (SARIMA) (2,1,1)x(2,1,1) can be show that below

```
> fit2 = arima(ED_series,order=c(1,1,2),seasonal = list(order=c(2,1,1),12))
> summary(fit2)

Call:
```

```
arima(x = ED_series, order = c(1, 1, 2), seasonal = list(order = c(2, 1, 1),
    12))

Coefficients:
          ar1     ma1      ma2    sar1     sar2     sma1
      -0.7356  0.0562  -0.4183  0.1684  -0.0161  -0.6365
s.e.   0.2428  0.2578   0.1808  0.1428   0.1017   0.1241

sigma^2 estimated as 332326:  log likelihood = -1433.04,  aic = 2880.09

Training set error measures:
                    ME    RMSE      MAE         MPE     MAPE     MASE      ACF1
Training set -1.418376 557.138 393.2081 -0.07718743 2.15492 0.353581 0.02761
```

The results to Model-2 is so good also we can depending about this results to forecasting.

The third model suggested to forecasting is Model-3 where we are used auto.arima() function to generate this model , this code help as to identification parameters automatically (p,d,q)x(P,D,Q), can be show that below

```
> fit3 <- auto.arima(ED_series,trace = T, ic="bic")

 Fitting models using approximations to speed things up...
```

```
ARIMA(2,0,2)(1,1,1)[12] with drift        : 2752.587
ARIMA(0,0,0)(0,1,0)[12] with drift        : 2825.675
ARIMA(1,0,0)(1,1,0)[12] with drift        : 2776.87
ARIMA(0,0,1)(0,1,1)[12] with drift        : 2768.129
ARIMA(0,0,0)(0,1,0)[12]                   : 2971.617
ARIMA(2,0,2)(0,1,1)[12] with drift        : 2739.839
ARIMA(2,0,2)(0,1,0)[12] with drift        : 2765.425
ARIMA(2,0,2)(0,1,2)[12] with drift        : 2742.558
ARIMA(2,0,2)(1,1,0)[12] with drift        : 2761.132
ARIMA(2,0,2)(1,1,2)[12] with drift        : 2756.899
ARIMA(1,0,2)(0,1,1)[12] with drift        : 2734.897
ARIMA(1,0,2)(0,1,0)[12] with drift        : 2762.526
ARIMA(1,0,2)(1,1,1)[12] with drift        : 2747.603
ARIMA(1,0,2)(0,1,2)[12] with drift        : 2737.649
ARIMA(1,0,2)(1,1,0)[12] with drift        : 2757.436
ARIMA(1,0,2)(1,1,2)[12] with drift        : 2751.971
ARIMA(0,0,2)(0,1,1)[12] with drift        : 2750.193
ARIMA(1,0,1)(0,1,1)[12] with drift        : 2730.257
ARIMA(1,0,1)(0,1,0)[12] with drift        : 2758.039
ARIMA(1,0,1)(1,1,1)[12] with drift        : 2742.735
ARIMA(1,0,1)(0,1,2)[12] with drift        : 2732.626
ARIMA(1,0,1)(1,1,0)[12] with drift        : 2753.52
ARIMA(1,0,1)(1,1,2)[12] with drift        : 2747.033
ARIMA(1,0,0)(0,1,1)[12] with drift        : 2748.46
ARIMA(2,0,1)(0,1,1)[12] with drift        : 2735.592
ARIMA(0,0,0)(0,1,1)[12] with drift        : 2791.725
ARIMA(2,0,0)(0,1,1)[12] with drift        : 2733.697

ARIMA(1,0,1)(0,1,1)[12]                   : Inf

Now re-fitting the best model(s) without approximations...

ARIMA(1,0,1)(0,1,1)[12] with drift        : 2902.223

Best model: ARIMA(1,0,1)(0,1,1)[12] with drift
> summary(fit3)
Series: ED_series
ARIMA(1,0,1)(0,1,1)[12] with drift
Coefficients:
        ar1      ma1     sma1    drift
     0.9045  -0.5934  -0.5470  71.0088
s.e.  0.0428   0.0746   0.0783   6.9735
sigma^2 estimated as 329795:  log likelihood=-1438.06
```

AIC=2886.12   AICc=2886.46   BIC=2902.22

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	1.21382	550.463	394.821	-0.086202	2.16740	0.392470	-0.03731

There are a lot of models generated by Auto.arima function but the best model is (SARIMA) (1, 0, 1) x (0, 1, 1).

There are three models generated to forecasting by box-Jenkins (SARIMA) method and to select the best model we used forecasting accuracy parameters (MAPE, MASE, RMSE, AIC) .Table (4.1) show the accuracy parameters for three models.

Table 4.1: Forecasting Accuracy Parameters to (SARIMA) models

SARIMA model	MAPE	MASE	RMSE	AIC
Model-1	2.138	0.35	555.238	2878.09
Model-2	2.154	0.353	557.138	2880.09
Model-3	2.167	0.392	550.463	2886.12

we see from Table (4.1) the best model to forecasting is model-1 where its has very good identifications, so we depending about model-1 and compare this model with others models in chapter 6 to determine the final model to forecasting electricity consumption.

4.2.2.3.Diagnostics the Best SARIMA Model

In this stage we are check and diagnoses SARIMA (2,1,2)X(1,1,1) where this is best model , Fig(4.11) show the acceptance level to this model

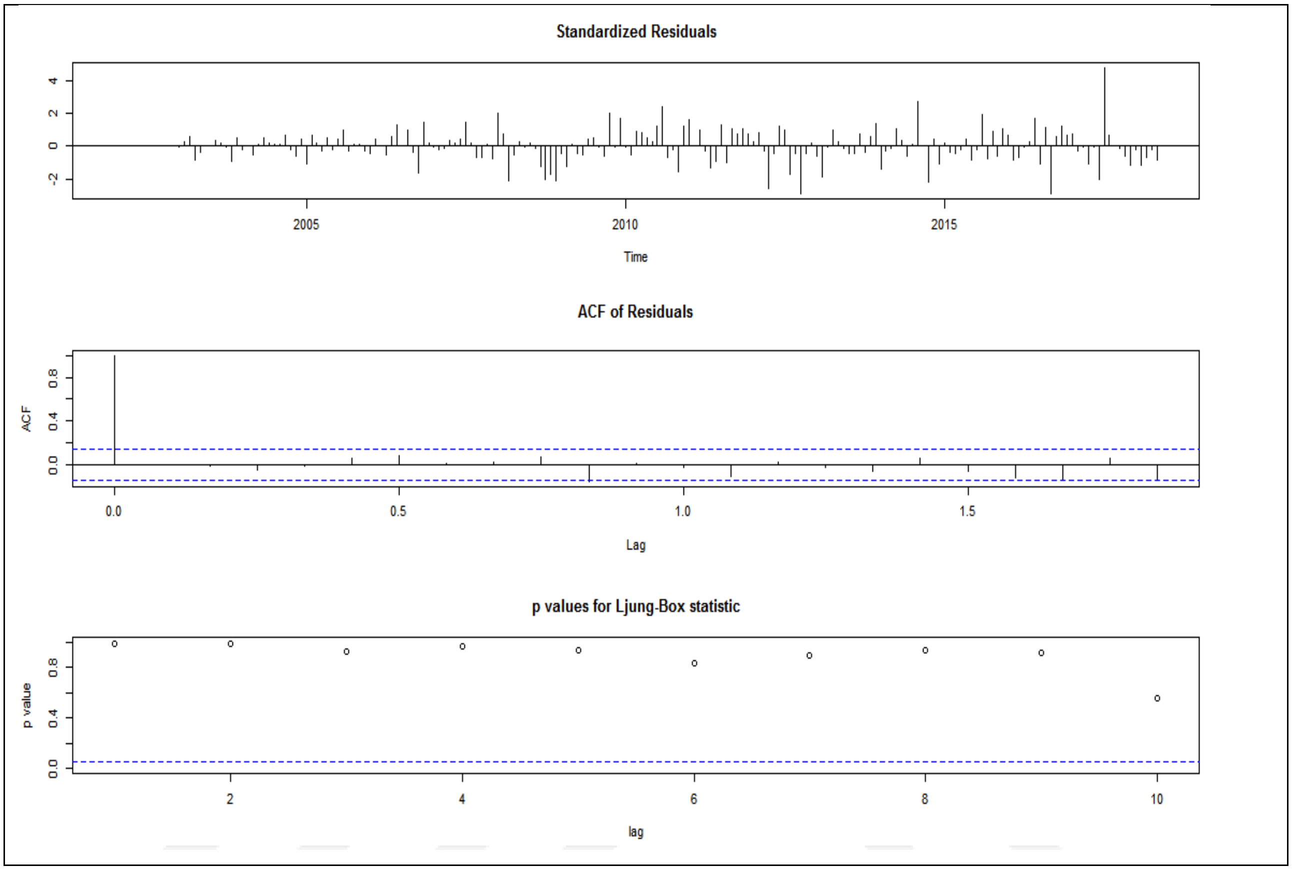

Figure 4.10: Diagnostics to the SARIMA (1, 2, 1) X (1, 1, 1) model

We are see from Fig (4.10) the standardized residuals is good because not exist big gaps in distribution and approximately all legs in ACF of residuals in control limits also all points for Ljung-Box statistic in control limits this mean the model-1 is very good and we can depended to it. Also Fig (4.12) show other normal Q-Q diagnosis.

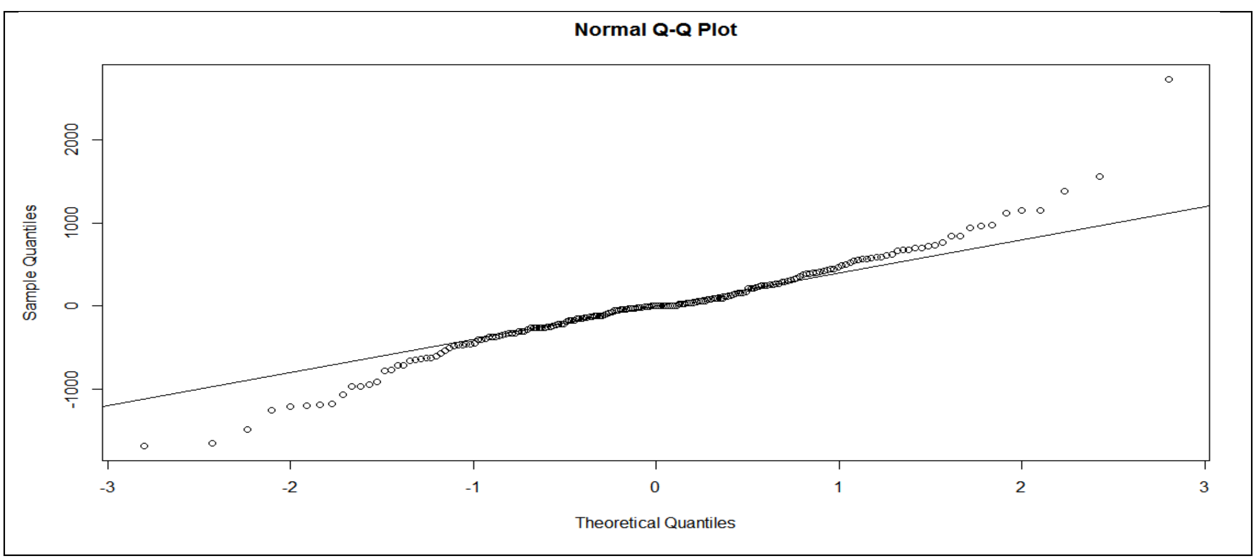

Figure 4.11: Normal Q-Q plot to the SARIMA (2, 1, 2) X (1, 1, 1)

Also we see the diagnosis for SARIMA (2,1,2)X(1,1,1) model in Fig(4.12) most points in autocorrelation line.

4.2.2.4.Forecasting by SARIMA model

We see in diagnosis and testing stage the SARIMA (2,1,2)X(1,1,1) model is suitable to forecasting to future for electricity consumption from Jun 2018 to Dec 2021, can be show below the results to forecasting by SARIMA model in Fig(4.13) and Table (1-B) in Appendix (B)

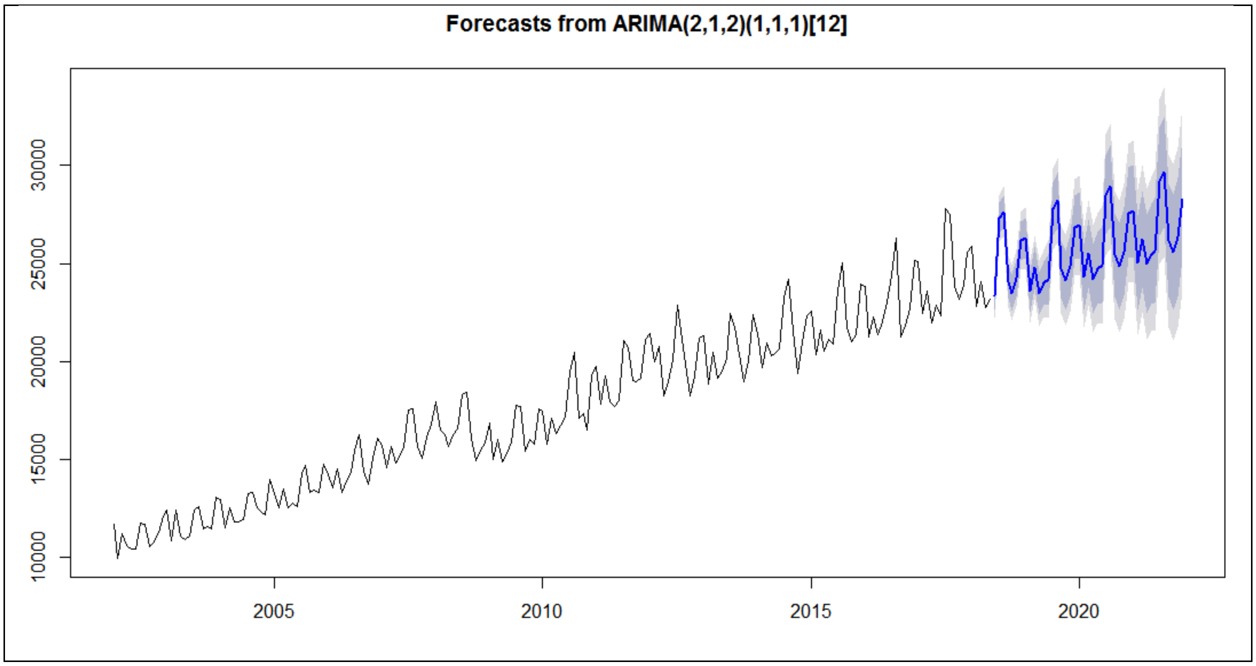

Figure 4.12: Forecasting results to SARIMA model from Jun 2018to Dec 2021

From Fig (4.12) we see the forecasting to electricity consumption where the consumption is increase gradually in trend for three years.

4.3.SUMMARY

The objective from this chapter is select the best model to forecasting by ARIMA method ,where they are a lot of models, one model to analysis yearly time series and three models generated to forecasting for seasonal time series and we select Model-1 to forecasting because it is more suitable model by depending upon accuracy parameters (MAPE,MSE,RMSE and BIC) , and the results show increase the consumption for yearly time series can be show that in Fig(4,7) and Seasonality time series in Fig (4.13).

5. DISCUSSION THE RESULTS

5.1.INTRODUCTION

Today the prediction for energy sector is very necessary where it is play important role decision making, production planning and determine the future policy, therefore we need to generate forecasting have high accuracy. In this chapter we discuss the results that can be obtain in chapter three and five to determine the best model to prediction and evaluate the performance to holt-Winter and Box-Jenkins techniques.

Also the results generated by Holt-Winter and ARIMA must be match with the trend to consumption and must be acceptance logically where in this a chapter we are show the forecasting results and discussion.

5.2.FORECASTING ACCURACY PARAMETERS

In this stage we are evaluate the performance to each model created in this thesis, there are a lot of accuracy parameters used to evaluate the forecasting models by comparison between actual data and forecasting data and select the best model it has less error ratio so we are depending about three parameters are Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), all equations to accuracy parameters shown in Chapter Two.

Can be classify the models generated for two types models to forecasting yearly time series and models generated to forecasting seasonal time series for to electricity consumption.

5.2.1. Forecasting Accuracy Parameters for Seasonal Time Series

It can be show in Table (5.1) there the five models to forecasting seasonal time series two models generated by Holt-Winters method (multiplicative and additive model) and three models generated by Box-Jenkins method where we used SARIMA model to all this models, also each model from five models is consider best model from a group of models where we select the optimize parameters for multiplicative and additive model in Holt-Winters method by using R-software also three models for SARIMA where we used Auto.arima to generate SARIMA(1,0,1)X(0,1,1) and other two models we select the best parameters by the diagnosis to ACF and PACF for general seasonal time series.

Table 5.1: The Models generated for Seasonal Time series

Types of Models	**Forecasting Accuracy Parameters**		
	MAPE	**MAE**	**RMSE**
Holt-Winter "multiplicative model"	2.379	428.207	556.336
Holt-Winter "additive model"	2.323	422.546	571.725
SARIMA (2,1,2)X(1,1,1)	2.131	389.306	555.238
SARIMA (2,1,1)X(2,1,1)	2.154	393.208	557.138
SARIMA(1,0,1)X(0,1,1)	2.167	394.821	550.463

We find in Table (5.1) all these models are suitable to forecasting where every model has very good performance but the best model from five models for forecasting is SARIMA(2,1,2)X(1,1,1) where it has less error ratio.

5.2.2. Forecasting Accuracy Parameters for Yearly Time Series

Table (5.2) show the models generated to yearly time series where we find three models generated to forecasting two models by Holt-Winters and one model by Box-Jenkins method.

Table 5.2: The Models generated for Yearly Time series

Types of Models	**Forecasting Accuracy Parameters**		
	MAPE	**MAE**	**RMSE**
Holt-Winter "α= 0.999"	7.392	6774.541	8189.411
Holt-Winter "α= 1 , β= 0.19"	2.795	2959.718	4295.524
ARIMA (0,2,1)	2.518	2776.3	4193.57

We see from Table (5.2) all models very good and suitable to forecasting but the best model to is ARIMA(0,2,1) where it is less error ratio as a compared with other.

5.3. FORECASTING RESULTS

Now we show the results of forecasting after we determine the best model to forecasting yearly and seasonal time series. Table (5.3) and Fig (5.1) show the forecasting results to seasonal time series.

Table 5.3: Forecasting Results Generated from SARIMA (2,1,2)X(1,1,1)

Month	Forecasting Results (GW/h)	Month	Forecasting Results (GW/h)
Jun-18	23349	Apr-20	24217
Jul-18	27296	May-20	24741
Aug-18	27628	Jun-20	24921
Sep-18	24073	Jul-20	28479
Oct-18	23494	Aug-20	28929
Nov-18	24221	Sep-20	25428
Dec-18	26145	Oct-20	24856
Jan-19	26288	Nov-20	25597
Feb-19	23564	Dec-20	27575
Mar-19	24791	Jan-21	27675
Apr-19	23480	Feb-21	25039
May-19	23983	Mar-21	26251
Jun-19	24169	Apr-21	24952
Jul-19	27795	May-21	25480
Aug-19	28224	Jun-21	25659
Sep-19	24713	Jul-21	29203
Oct-19	24140	Aug-21	29657
Nov-19	24879	Sep-21	26157
Dec-19	26847	Oct-21	25585
Jan-20	26955	Nov-21	26327
Feb-20	24304	Dec-21	28307
Mar-20	25519		

We see the forecasting results are increase gradually this is mean the electricity demand for the next two years are increase so this is consider very good indicator to decision maker to increase the productivity to became fit with the demand.

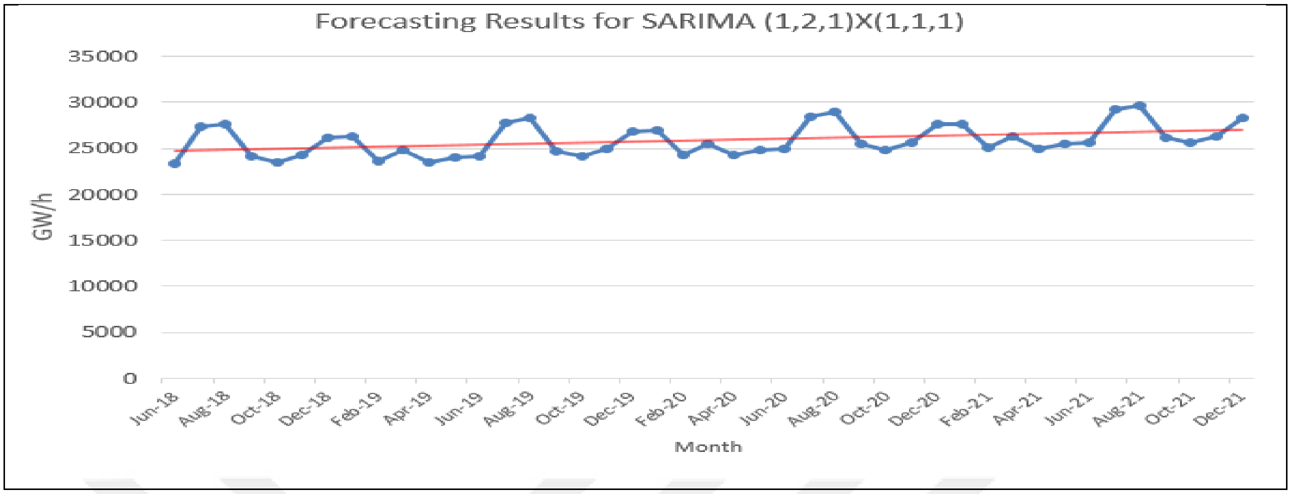

Figure 5.1: Forecasting Results for SARIMA (1,2,1)X(1,1,1)

Also we see in Fig (5.1) the general trend for results of forecasting is increase.

Table (5.4) show the forecasting results to yearly time series where we show three results (two results to models generated from Holt-Winter and one model consider the best for ARIMA method).

Table 5.4: Forecasting Results to Yearly Time Series

Year	Holt-Winter Model-1 (GW/h)	Holt-Winter Model-2 (GW/h)	ARIMA(0,2,1) (GW/h)
2018	289925	300664	300765
2019	289925	311403	311603
2020	289925	322141	322442
2021	289925	332879.	333280
2022	289925	343617	344119
2023	289925	354355	354958
2024	289925	365094	365797
2025	289925	375832	376635
2026	289925	386570	387474
2027	289925	397309	398313

From the performance evaluation in Table (5.2) the best model to forecasting is ARIMA (0,2,1) so we depending upon the results to this model.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. CONCLUSIONS

In this section we discuss the final conclusions to the thesis can be show as follow:

1. The best technique to prediction electricity demand for seasonal time series is Box-Jenkins because the SARIMA(2,1,2)X(1,1,1) model has high accuracy where (MAPE, MAE, and RMSE) are (2.131,389.306 and 555.238) best from other models, The results show an increased electricity consumption from 23349 (GW/h) in Jun-2018 to 28307 (GW/h) in Dec-2021.
2. The best method for forecasting electricity consumption for yearly time series is Box-Jenkins because the ARIMA (0,2,1) model has high accuracy where (MAPE, MAE, and RMSE) are (2.518,2776.3 and 4193.57) best from other models, The results show an increased electricity consumption from 300765 (GW/h) in 2018 to 398313 (GW/h) in 2027.
3. The forecasting results to electricity consumption in turkey show increased the demand in the next period and this increase is expected and logically, where the increase in population and developing economy sector and other factors, it causes to increased electricity demand.
4. In this thesis the best model generated by using Box-Jenkins, this is mean the ARIMA, SARIMA models are most activity as a compared with other statistical models, also box-Jenkins method has ability to analysis any time series and suggest a lot of suitable models to forecasting with less error ratio.

6.2.RECOMMENDATION FOR FUTURE WORK

Can be used other techniques to forecasting electricity demand such as fuzzy logic, ANN and other artificial intelligence techniques, also can be analysis the factors effecting on electricity demand for example population growth and GDP and other factors in order to create high accuracy models.

1. By depending about this results in thesis the electricity demand in future is increasing so must be increased the productivity for electricity plants to became the production fit with demand.

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Appendix A

Table A.1: to model-1 (Holt-Winter multiplicative type)

```
> Model_1$fitted
             xhat    level    trend    season
Jan 2003 12012.91 11006.84 60.79225 1.0854091
Feb 2003 10619.11 11163.63 60.79225 0.9460716
Mar 2003 12178.84 11295.24 60.79225 1.0724556
Apr 2003 10899.37 11411.29 60.79225 0.9500785
May 2003 10831.54 11514.89 60.79225 0.9357154
Jun 2003 11034.13 11601.49 60.79225 0.9461382
Jul 2003 12464.52 11677.30 60.79225 1.0618871
Aug 2003 12353.24 11725.06 60.79225 1.0481410
Sep 2003 11165.67 11841.22 60.79225 0.9381334
Oct 2003 11506.71 11975.94 60.79225 0.9559667
Nov 2003 12028.06 12057.85 60.79225 0.9925251
Dec 2003 12824.34 11952.88 60.79225 1.0674783
Jan 2004 13301.34 12074.55 60.79225 1.0960830
Feb 2004 11533.90 12043.78 60.79225 0.9528546
Mar 2004 13110.86 12096.98 60.79225 1.0783934
Apr 2004 11516.64 12009.67 60.79225 0.9541176
May 2004 11453.14 12148.14 60.79225 0.9380955
Jun 2004 11729.98 12318.75 60.79225 0.9475296
Jul 2004 13254.72 12437.32 60.79225 1.0605381
Aug 2004 13230.62 12495.02 60.79225 1.0537447
Sep 2004 11938.24 12575.53 60.79225 0.9447560
Oct 2004 12328.48 12809.78 60.79225 0.9578814
Nov 2004 12630.46 12869.85 60.79225 0.9767856
Dec 2004 13800.53 12793.26 60.79225 1.0736324
Jan 2005 14074.64 12892.68 60.79225 1.0865539
Feb 2005 12180.67 12731.73 60.79225 0.9521710
Mar 2005 13772.53 12893.23 60.79225 1.0631856
Apr 2005 12431.07 12873.50 60.79225 0.9610941
May 2005 12343.25 12964.20 60.79225 0.9476587
Jun 2005 12582.04 13147.82 60.79225 0.9525632
Jul 2005 14075.25 13214.76 60.79225 1.0602385
Aug 2005 14128.00 13322.64 60.79225 1.0556337
Sep 2005 13041.86 13533.18 60.79225 0.9593854
Oct 2005 13146.04 13664.17 60.79225 0.9578198
Nov 2005 13373.79 13801.06 60.79225 0.9647910
Dec 2005 14982.85 13846.86 60.79225 1.0773103
Jan 2006 14806.49 13843.13 60.79225 1.0649142
Feb 2006 13255.70 13737.52 60.79225 0.9606756
Mar 2006 14716.65 13880.97 60.79225 1.0555809
Apr 2006 13430.64 13876.76 60.79225 0.9636298
May 2006 13364.99 13893.31 60.79225 0.9577821
Jun 2006 13499.19 14103.12 60.79225 0.9530699
Jul 2006 15403.57 14409.13 60.79225 1.0645237
Aug 2006 15547.07 14482.89 60.79225 1.0689912
Sep 2006 14275.15 14731.78 60.79225 0.9650218
Oct 2006 14349.98 14827.25 60.79225 0.9638588
Nov 2006 14232.94 14709.85 60.79225 0.9635965
Dec 2006 16152.26 15012.68 60.79225 1.0715689
Jan 2007 15864.36 15045.77 60.79225 1.0501632
Feb 2007 14624.24 15059.13 60.79225 0.9672168
Mar 2007 15915.53 15097.91 60.79225 1.0499271
Apr 2007 14537.84 15080.88 60.79225 0.9601209
```

May	2007	14806.56	15213.86	60.79225	0.9693544
Jun	2007	14985.98	15362.95	60.79225	0.9716177
Jul	2007	16676.36	15588.74	60.79225	1.0656136
Aug	2007	17271.27	15863.31	60.79225	1.0845990
Sep	2007	15543.96	16003.60	60.79225	0.9676033
Oct	2007	15352.35	16090.96	60.79225	0.9505065
Nov	2007	15829.24	16069.08	60.79225	0.9813616
Dec	2007	17396.21	16207.79	60.79225	1.0693133
Jan	2008	16924.61	16113.64	60.79225	1.0463805
Feb	2008	15940.56	16447.59	60.79225	0.9656040
Mar	2008	17463.87	16671.35	60.79225	1.0437320
Apr	2008	15895.88	16405.99	60.79225	0.9653304
May	2008	16057.52	16396.22	60.79225	0.9757251
Jun	2008	16296.86	16511.53	60.79225	0.9833781
Jul	2008	18068.34	16637.69	60.79225	1.0820351
Aug	2008	18348.11	16760.60	60.79225	1.0907603
Sep	2008	16376.99	16832.63	60.79225	0.9694301
Oct	2008	15929.91	16797.78	60.79225	0.9449146
Nov	2008	16399.86	16559.18	60.79225	0.9867561
Dec	2008	17355.32	16349.99	60.79225	1.0575556
Jan	2009	17129.41	16004.26	60.79225	1.0662526
Feb	2009	15674.04	15992.13	60.79225	0.9763980
Mar	2009	16242.31	15862.98	60.79225	1.0200039
Apr	2009	15286.51	15853.04	60.79225	0.9605799
May	2009	15521.11	15786.63	60.79225	0.9794096
Jun	2009	15651.22	15783.80	60.79225	0.9877959
Jul	2009	17359.55	15914.93	60.79225	1.0866209
Aug	2009	17613.21	16074.53	60.79225	1.0915932
Sep	2009	15621.39	16158.81	60.79225	0.9631179
Oct	2009	15000.48	16149.31	60.79225	0.9253785
Nov	2009	16041.37	16508.76	60.79225	0.9681235
Dec	2009	16998.93	16493.86	60.79225	1.0268372
Jan	2010	17794.69	16715.69	60.79225	1.0606926
Feb	2010	16120.27	16678.35	60.79225	0.9630285
Mar	2010	16938.13	16630.31	60.79225	1.0148000
Apr	2010	15980.15	16729.87	60.79225	0.9517286
May	2010	16523.91	16888.63	60.79225	0.9748949
Jun	2010	16941.04	17003.31	60.79225	0.9927884
Jul	2010	18801.25	17120.92	60.79225	1.0942594
Aug	2010	19027.99	17341.68	60.79225	1.0934074
Sep	2010	17084.29	17766.46	60.79225	0.9583242
Oct	2010	16898.32	17830.09	60.79225	0.9445218
Nov	2010	17407.74	18014.97	60.79225	0.9630431
Dec	2010	18553.66	17811.06	60.79225	1.0381496
Jan	2011	19085.31	18054.35	60.79225	1.0535558
Feb	2011	17534.78	18284.45	60.79225	0.9558216
Mar	2011	18803.83	18419.82	60.79225	1.0174893
Apr	2011	17888.14	18610.77	60.79225	0.9580420
May	2011	18338.20	18681.72	60.79225	0.9784279
Jun	2011	18553.02	18556.35	60.79225	0.9965558
Jul	2011	20483.64	18462.99	60.79225	1.1058022
Aug	2011	20962.31	18671.88	60.79225	1.1190241
Sep	2011	17944.53	18660.71	60.79225	0.9584981
Oct	2011	18168.93	19024.98	60.79225	0.9519620
Nov	2011	18338.36	19310.52	60.79225	0.9466763
Dec	2011	20657.15	19609.88	60.79225	1.0501494
Jan	2012	21130.90	19785.79	60.79225	1.0647120

Feb	2012	19185.29	19918.75	60.79225	0.9602468
Mar	2012	20795.44	20215.05	60.79225	1.0256266
Apr	2012	19485.69	20265.65	60.79225	0.9586379
May	2012	19371.79	19967.88	60.79225	0.9672027
Jun	2012	19710.06	19908.03	60.79225	0.9870414
Jul	2012	22473.12	20079.45	60.79225	1.1158318
Aug	2012	22619.22	20242.08	60.79225	1.1140896
Sep	2012	19610.27	20032.07	60.79225	0.9759817
Oct	2012	19510.63	20165.19	60.79225	0.9646322
Nov	2012	19112.67	19851.43	60.79225	0.9598462
Dec	2012	21154.60	19950.44	60.79225	1.0571365
Jan	2013	21460.70	20012.39	60.79225	1.0691230
Feb	2013	19543.95	20024.67	60.79225	0.9730395
Mar	2013	20444.12	19883.98	60.79225	1.0250365
Apr	2013	18789.38	19950.19	60.79225	0.9389534
May	2013	19378.83	20114.98	60.79225	0.9605002
Jun	2013	20138.62	20214.49	60.79225	0.9932596
Jul	2013	22820.42	20273.70	60.79225	1.1222516
Aug	2013	22275.00	20247.04	60.79225	1.0968672
Sep	2013	19816.96	20160.91	60.79225	0.9799845
Oct	2013	19288.82	20376.19	60.79225	0.9438197
Nov	2013	19625.62	20341.15	60.79225	0.9619486
Dec	2013	21767.29	20528.64	60.79225	1.0572067
Jan	2014	22191.02	20753.15	60.79225	1.0661612
Feb	2014	19879.56	20609.09	60.79225	0.9617646
Mar	2014	21195.08	20610.18	60.79225	1.0253547
Apr	2014	19516.14	20602.04	60.79225	0.9445045
May	2014	20162.38	20884.86	60.79225	0.9626042
Jun	2014	20938.39	21021.56	60.79225	0.9931711
Jul	2014	23518.59	20999.85	60.79225	1.1167082
Aug	2014	22896.66	20989.22	60.79225	1.0877268
Sep	2014	21195.37	21381.58	60.79225	0.9884806
Oct	2014	20280.37	21543.14	60.79225	0.9387353
Nov	2014	20726.78	21334.86	60.79225	0.9687376
Dec	2014	22978.09	21479.62	60.79225	1.0667437
Jan	2015	22588.07	21369.16	60.79225	1.0540422
Feb	2015	20589.13	21418.01	60.79225	0.9585793
Mar	2015	21925.28	21404.46	60.79225	1.0214313
Apr	2015	20492.02	21374.67	60.79225	0.9559870
May	2015	20785.73	21443.64	60.79225	0.9665790
Jun	2015	21420.94	21604.77	60.79225	0.9887091
Jul	2015	24004.84	21519.26	60.79225	1.1123625
Aug	2015	23855.62	21488.70	60.79225	1.1070157
Sep	2015	21775.05	21850.82	60.79225	0.9937676
Oct	2015	20307.47	21888.55	60.79225	0.9251970
Nov	2015	21619.31	22156.89	60.79225	0.9730678
Dec	2015	23465.32	22139.81	60.79225	1.0569677
Jan	2016	23585.23	22329.47	60.79225	1.0533702
Feb	2016	21500.14	22457.81	60.79225	0.9547724
Mar	2016	22878.64	22446.89	60.79225	1.0164813
Apr	2016	21424.90	22340.73	60.79225	0.9564037
May	2016	21813.89	22388.12	60.79225	0.9717127
Jun	2016	22140.07	22507.58	60.79225	0.9810220
Jul	2016	25325.82	22818.03	60.79225	1.1069549
Aug	2016	25523.52	22637.41	60.79225	1.1244732
Sep	2016	22772.70	22882.37	60.79225	0.9925704
Oct	2016	21105.77	22509.63	60.79225	0.9351074

Nov	2016	22148.27	22792.41	60.79225	0.9691540
Dec	2016	24543.13	23007.30	60.79225	1.0639430
Jan	2017	24618.24	23230.02	60.79225	1.0569933
Feb	2017	22335.87	23418.91	60.79225	0.9512845
Mar	2017	23758.34	23513.79	60.79225	1.0077946
Apr	2017	22543.84	23526.82	60.79225	0.9557489
May	2017	22879.68	23414.96	60.79225	0.9746090
Jun	2017	23371.45	23468.39	60.79225	0.9932963
Jul	2017	25466.40	23229.04	60.79225	1.0934556
Aug	2017	27167.98	23879.50	60.79225	1.1348224
Sep	2017	23382.67	24027.42	60.79225	0.9707101
Oct	2017	22948.85	24210.30	60.79225	0.9455219
Nov	2017	23823.44	24334.05	60.79225	0.9765769
Dec	2017	26238.03	24405.30	60.79225	1.0724240
Jan	2018	25896.88	24287.43	60.79225	1.0636044
Feb	2018	23252.20	24341.69	60.79225	0.9528618
Mar	2018	24462.87	24269.35	60.79225	1.0054551
Apr	2018	23016.89	24226.57	60.79225	0.9476899
May	2018	23638.76	24202.52	60.79225	0.9742595

Table A.2: to forecasting results for electricity consumption by Holt-Winter multiplicative type

Jun	2018	23663.00	24319.37	23006.63
Jul	2018	27254.68	27999.39	26509.98
Aug	2018	27692.31	28501.18	26883.44
Sep	2018	23785.16	24599.82	22970.50
Oct	2018	23160.95	24020.58	22301.31
Nov	2018	23922.16	24848.16	22996.17
Dec	2018	26100.94	27124.30	25077.57
Jan	2019	26162.51	27230.63	25094.39
Feb	2019	23356.16	24389.74	22322.58
Mar	2019	24740.45	25857.26	23623.64
Apr	2019	23397.07	24511.02	22283.12
May	2019	24043.65	25018.28	23069.01
Jun	2019	24376.91	25695.80	23058.03
Jul	2019	28074.89	29549.37	26600.41
Aug	2019	28523.61	30043.04	27004.17
Sep	2019	24497.38	25900.14	23094.62
Oct	2019	23852.75	25262.85	22442.65
Nov	2019	24634.93	26105.65	23164.22
Dec	2019	26876.70	28467.78	25285.61
Jan	2020	26938.18	28558.33	25318.03
Feb	2020	24046.92	25568.41	22525.42
Mar	2020	25470.35	27082.78	23857.92
Apr	2020	24085.65	25661.02	22510.28
May	2020	24749.52	26127.86	23371.17
Jun	2020	25090.82	26836.71	23344.94
Jul	2020	28895.10	30842.82	26947.38
Aug	2020	29354.90	31345.65	27364.15
Sep	2020	25209.60	27018.41	23400.80
Oct	2020	24544.56	26343.94	22745.17
Nov	2020	25347.70	27210.10	23485.30
Dec	2020	27652.46	29656.41	25648.50
Jan	2021	27713.85	29740.89	25686.81
Feb	2021	24737.68	26624.89	22850.46
Mar	2021	26200.25	28188.36	24212.14

Apr	2021	24774.22	26703.65	22844.79
May	2021	25455.39	27143.51	23767.27
Jun	2021	25804.73	27892.02	23717.45
Jul	2021	29715.31	32041.92	27388.69
Aug	2021	30186.20	32556.32	27816.07
Sep	2021	25921.83	28060.95	23782.71
Oct	2021	25236.36	27354.66	23118.06
Nov	2021	26060.47	28245.44	23875.50
Dec	2021	28428.22	30773.45	26082.98

Table A.3: to model-2 (Holt-Winter additive type)

	xhat	level	trend	season
Jan 2003	12047.03	11006.84	60.79225	979.402778
Feb 2003	10610.46	11163.94	60.79225	-614.263889
Mar 2003	12197.95	11295.34	60.79225	841.819444
Apr 2003	10896.05	11410.98	60.79225	-575.722222
May 2003	10829.41	11514.09	60.79225	-745.472222
Jun 2003	11034.38	11600.06	60.79225	-626.472222
Jul 2003	12424.59	11675.23	60.79225	688.569444
Aug 2003	12333.99	11733.30	60.79225	539.902778
Sep 2003	11231.45	11858.59	60.79225	-687.930556
Oct 2003	11540.82	11971.25	60.79225	-491.222222
Nov 2003	12024.00	12042.89	60.79225	-79.680556
Dec 2003	12769.33	11937.47	60.79225	771.069444
Jan 2004	13263.80	12079.99	60.79225	1123.018196
Feb 2004	11601.18	12049.36	60.79225	-508.963593
Mar 2004	13068.07	12083.67	60.79225	923.609786
Apr 2004	11542.32	11994.14	60.79225	-512.615802
May 2004	11475.89	12123.03	60.79225	-707.939807
Jun 2004	11737.93	12282.16	60.79225	-605.023385
Jul 2004	13141.69	12396.39	60.79225	684.505154
Aug 2004	13182.84	12485.97	60.79225	636.082011
Sep 2004	12031.67	12581.47	60.79225	-610.586689
Oct 2004	12368.17	12782.42	60.79225	-475.044286
Nov 2004	12564.49	12831.23	60.79225	-327.534990
Dec 2004	13728.00	12774.26	60.79225	892.950048
Jan 2005	13945.31	12897.84	60.79225	986.674823
Feb 2005	12262.64	12750.29	60.79225	-548.444112
Mar 2005	13645.58	12885.34	60.79225	699.449696
Apr 2005	12544.83	12895.11	60.79225	-411.067399
May 2005	12452.32	12952.82	60.79225	-561.297081
Jun 2005	12636.48	13101.03	60.79225	-525.342385
Jul 2005	13940.53	13152.31	60.79225	727.429711
Aug 2005	14050.80	13302.17	60.79225	687.838642
Sep 2005	13204.93	13545.71	60.79225	-401.571920
Oct 2005	13196.56	13628.68	60.79225	-492.911645
Nov 2005	13306.91	13749.26	60.79225	-503.148172
Dec 2005	14861.72	13814.34	60.79225	986.582759
Jan 2006	14575.62	13838.85	60.79225	675.983380
Feb 2006	13408.05	13784.96	60.79225	-437.708098
Mar 2006	14567.40	13883.25	60.79225	623.364487
Apr 2006	13561.78	13916.65	60.79225	-415.657179
May 2006	13526.67	13896.81	60.79225	-430.937116
Jun 2006	13578.12	14056.86	60.79225	-539.528740
Jul 2006	15254.01	14332.98	60.79225	860.239968
Aug 2006	15471.45	14450.31	60.79225	960.353075

Sep	2006	14429.43	14737.13	60.79225	-368.493181
Oct	2006	14445.18	14788.14	60.79225	-403.751993
Nov	2006	14211.20	14647.16	60.79225	-496.753313
Dec	2006	15944.65	14951.38	60.79225	932.470698
Jan	2007	15606.74	15040.97	60.79225	504.974611
Feb	2007	14803.27	15124.28	60.79225	-381.801711
Mar	2007	15755.86	15112.55	60.79225	582.520432
Apr	2007	14660.49	15135.59	60.79225	-535.891414
May	2007	15009.91	15232.04	60.79225	-282.930372
Jun	2007	15164.49	15322.13	60.79225	-218.427363
Jul	2007	16500.63	15495.29	60.79225	944.548837
Aug	2007	17195.96	15837.75	60.79225	1297.413656
Sep	2007	15685.37	16007.66	60.79225	-383.080331
Oct	2007	15410.57	16054.42	60.79225	-704.643980
Nov	2007	15945.79	16018.74	60.79225	-133.739039
Dec	2007	17160.40	16124.20	60.79225	975.412406
Jan	2008	16682.79	16083.44	60.79225	538.556026
Feb	2008	16074.54	16503.71	60.79225	-489.957509
Mar	2008	17273.54	16686.52	60.79225	526.229581
Apr	2008	16033.16	16455.08	60.79225	-482.715981
May	2008	16229.12	16407.58	60.79225	-239.250731
Jun	2008	16483.67	16473.73	60.79225	-50.856929
Jul	2008	17972.21	16546.84	60.79225	1364.575313
Aug	2008	18224.24	16703.32	60.79225	1460.126608
Sep	2008	16468.57	16811.78	60.79225	-403.997274
Oct	2008	15964.50	16752.22	60.79225	-848.514698
Nov	2008	16509.06	16515.40	60.79225	-67.131431
Dec	2008	17158.94	16274.16	60.79225	823.987978
Jan	2009	17088.79	15953.39	60.79225	1074.604380
Feb	2009	15699.41	15946.62	60.79225	-308.002755
Mar	2009	15962.79	15811.54	60.79225	90.454685
Apr	2009	15294.95	15878.36	60.79225	-644.205834
May	2009	15641.99	15812.45	60.79225	-231.251541
Jun	2009	15803.80	15775.51	60.79225	-32.498786
Jul	2009	17431.69	15863.63	60.79225	1507.269637
Aug	2009	17605.15	16013.16	60.79225	1531.204152
Sep	2009	15579.65	16102.32	60.79225	-583.457705
Oct	2009	14874.57	16106.10	60.79225	-1292.323933
Nov	2009	16027.07	16483.81	60.79225	-517.532932
Dec	2009	16789.92	16474.12	60.79225	255.008085
Jan	2010	17797.16	16762.52	60.79225	973.856926
Feb	2010	16177.41	16716.72	60.79225	-600.096106
Mar	2010	16814.89	16654.65	60.79225	99.442218
Apr	2010	16018.13	16790.48	60.79225	-833.145833
May	2010	16619.14	16935.34	60.79225	-376.994609
Jun	2010	17091.57	17022.52	60.79225	8.259269
Jul	2010	18798.30	17097.92	60.79225	1639.588785
Aug	2010	18971.92	17337.62	60.79225	1573.507767
Sep	2010	17211.54	17819.22	60.79225	-668.470604
Oct	2010	17087.67	17846.62	60.79225	-819.733851
Nov	2010	17411.00	17972.85	60.79225	-622.635415
Dec	2010	18428.59	17773.38	60.79225	594.412458
Jan	2011	18938.14	18062.44	60.79225	814.905958
Feb	2011	17624.00	18346.51	60.79225	-783.301925
Mar	2011	18726.60	18454.47	60.79225	211.343223
Apr	2011	18024.92	18671.92	60.79225	-707.790505
May	2011	18426.90	18703.76	60.79225	-337.649651

Jun	2011	18644.89	18554.04	60.79225	30.050737
Jul	2011	20399.64	18432.46	60.79225	1906.381701
Aug	2011	20945.53	18683.72	60.79225	2201.016022
Sep	2011	18009.89	18667.37	60.79225	-718.270547
Oct	2011	18344.13	19005.49	60.79225	-722.148399
Nov	2011	18284.22	19234.16	60.79225	-1010.731702
Dec	2011	20535.68	19540.08	60.79225	934.804346
Jan	2012	20967.02	19758.37	60.79225	1147.861884
Feb	2012	19291.70	19943.88	60.79225	-712.971776
Mar	2012	20710.25	20204.50	60.79225	444.960889
Apr	2012	19588.67	20278.86	60.79225	-750.974414
May	2012	19369.96	19960.72	60.79225	-651.556510
Jun	2012	19722.22	19903.33	60.79225	-241.906508
Jul	2012	22322.94	20071.75	60.79225	2190.403326
Aug	2012	22437.58	20290.81	60.79225	2085.974230
Sep	2012	19852.38	20096.30	60.79225	-304.707306
Oct	2012	19749.09	20160.11	60.79225	-471.808329
Nov	2012	19201.21	19785.60	60.79225	-645.185962
Dec	2012	21089.00	19858.55	60.79225	1169.660052
Jan	2013	21333.87	19939.23	60.79225	1333.848737
Feb	2013	19629.09	19983.30	60.79225	-414.997011
Mar	2013	20346.44	19820.46	60.79225	465.191840
Apr	2013	18659.41	19914.65	60.79225	-1316.030164
May	2013	19344.70	20111.70	60.79225	-827.792132
Jun	2013	20199.40	20220.03	60.79225	-81.423574
Jul	2013	22749.17	20261.96	60.79225	2426.420129
Aug	2013	22009.20	20243.15	60.79225	1705.262320
Sep	2013	19976.10	20215.52	60.79225	-300.209109
Oct	2013	19324.96	20385.10	60.79225	-1120.930225
Nov	2013	19777.36	20343.62	60.79225	-627.055581
Dec	2013	21745.39	20485.29	60.79225	1199.316154
Jan	2014	22098.07	20728.37	60.79225	1308.905502
Feb	2014	19905.70	20593.39	60.79225	-748.475058
Mar	2014	21164.14	20588.35	60.79225	514.998188
Apr	2014	19533.98	20586.02	60.79225	-1112.837658
May	2014	20158.96	20855.08	60.79225	-756.911847
Jun	2014	20942.41	20991.18	60.79225	-109.555096
Jul	2014	23335.98	20967.47	60.79225	2307.717277
Aug	2014	22633.21	20999.00	60.79225	1573.411317
Sep	2014	21424.35	21501.54	60.79225	-137.982209
Oct	2014	20385.95	21598.60	60.79225	-1273.440836
Nov	2014	20926.78	21372.45	60.79225	-506.457180
Dec	2014	22991.10	21459.16	60.79225	1471.154114
Jan	2015	22408.16	21330.41	60.79225	1016.958296
Feb	2015	20643.66	21429.51	60.79225	-846.643513
Mar	2015	21884.00	21402.32	60.79225	420.882584
Apr	2015	20639.25	21380.72	60.79225	-802.268808
May	2015	20823.81	21407.63	60.79225	-644.620135
Jun	2015	21381.50	21556.27	60.79225	-235.564796
Jul	2015	23805.99	21481.11	60.79225	2264.087283
Aug	2015	23787.97	21495.03	60.79225	2232.152182
Sep	2015	21891.28	21914.39	60.79225	-83.900189
Oct	2015	20278.30	21918.85	60.79225	-1701.341698
Nov	2015	21776.25	22183.27	60.79225	-467.809364
Dec	2015	23371.69	22122.39	60.79225	1188.513873
Jan	2016	23483.22	22348.34	60.79225	1074.087215
Feb	2016	21593.45	22510.50	60.79225	-977.842331

Mar	2016	22833.94	22475.13	60.79225	298.014609
Apr	2016	21583.98	22375.98	60.79225	-852.791202
May	2016	21925.71	22378.53	60.79225	-513.619858
Jun	2016	22088.04	22465.55	60.79225	-438.298333
Jul	2016	25045.25	22790.28	60.79225	2194.181848
Aug	2016	25486.58	22658.93	60.79225	2766.852301
Sep	2016	22833.77	22940.89	60.79225	-167.908304
Oct	2016	21209.69	22546.59	60.79225	-1397.685736
Nov	2016	22200.56	22789.02	60.79225	-649.252019
Dec	2016	24482.48	22986.88	60.79225	1434.804901
Jan	2017	24526.21	23240.17	60.79225	1225.249795
Feb	2017	22404.39	23464.84	60.79225	-1121.238011
Mar	2017	23659.46	23539.16	60.79225	59.506681
Apr	2017	22700.23	23579.08	60.79225	-939.639133
May	2017	23013.84	23427.57	60.79225	-474.516725
Jun	2017	23459.02	23442.95	60.79225	-44.714360
Jul	2017	25144.03	23175.57	60.79225	1907.665473
Aug	2017	27141.33	23983.88	60.79225	3096.657433
Sep	2017	23367.06	24152.83	60.79225	-846.553917
Oct	2017	23272.58	24338.61	60.79225	-1126.821739
Nov	2017	23983.93	24367.99	60.79225	-444.849555
Dec	2017	26176.22	24393.57	60.79225	1721.859421
Jan	2018	25807.42	24277.01	60.79225	1469.624802
Feb	2018	23315.87	24356.15	60.79225	-1101.068374
Mar	2018	24358.98	24269.80	60.79225	28.384072
Apr	2018	23058.73	24254.17	60.79225	-1256.229553
May	2018	23739.83	24221.28	60.79225	-542.239922

Table A.4: to forecasting results for electricity consumption by Holt-Winter additive type

	fit	upr	lwr
Jun 2018	23637.22	24763.02	22511.43
Jul 2018	27254.46	28424.81	26084.11
Aug 2018	27550.83	28764.10	26337.56
Sep 2018	23693.52	24948.25	22438.79
Oct 2018	23240.80	24535.66	21945.94
Nov 2018	23977.91	25311.69	22644.13
Dec 2018	25993.44	27365.04	24621.85
Jan 2019	26093.83	27502.23	24685.43
Feb 2019	23337.16	24781.42	21892.90
Mar 2019	24632.86	26112.12	23153.60
Apr 2019	23383.29	24896.74	21869.85
May 2019	24041.94	25588.82	22495.07
Jun 2019	24366.73	26106.79	22626.68
Jul 2019	27983.97	29753.18	26214.76
Aug 2019	28280.34	30078.23	26482.45
Sep 2019	24423.03	26249.15	22596.91
Oct 2019	23970.31	25824.23	22116.38
Nov 2019	24707.42	26588.73	22826.10
Dec 2019	26722.95	28631.26	24814.64
Jan 2020	26823.34	28758.27	24888.41
Feb 2020	24066.67	26027.86	22105.47
Mar 2020	25362.36	27349.47	23375.26
Apr 2020	24112.80	26125.48	22100.12

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May 2020 24771.45 26809.39 22733.51
Jun 2020 25096.24 27284.43 22908.05
Jul 2020 28713.47 30924.92 26502.03
Aug 2020 29009.84 31244.30 26775.39
Sep 2020 25152.53 27409.77 22895.30
Oct 2020 24699.81 26979.59 22420.03
Nov 2020 25436.92 27739.03 23134.81
Dec 2020 27452.46 29776.69 25128.23
Jan 2021 27552.85 29898.98 25206.72
Feb 2021 24796.17 27164.01 22428.34
Mar 2021 26091.87 28481.21 23702.53
Apr 2021 24842.31 27252.97 22431.65
May 2021 25500.96 27932.74 23069.17
Jun 2021 25825.75 28384.76 23266.73
Jul 2021 29442.98 32021.90 26864.06
Aug 2021 29739.35 32338.04 27140.67
Sep 2021 25882.04 28500.34 23263.75
Oct 2021 25429.32 28067.08 22791.56
Nov 2021 26166.43 28823.51 23509.35
Dec 2021 28181.97 30858.23 25505.70
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Table A.5: to model-3 (Holt-Winter)

```
Time Series:
Start = 1976
End = 2017
Frequency = 1
        xhat     level
1976  15719.00  15719.00
1977  18614.86  18614.86
1978  21056.88  21056.88
1979  22346.94  22346.94
1980  23565.94  23565.94
1981  24616.95  24616.95
1982  26288.92  26288.92
1983  28324.90  28324.90
1984  29567.94  29567.94
1985  33266.82  33266.82
1986  36360.85  36360.85
1987  40470.80  40470.80
1988  44924.78  44924.78
1989  48429.83  48429.83
1990  52601.80  52601.80
1991  56811.79  56811.79
1992  60498.82  60498.82
1993  67216.67  67216.67
1994  73422.70  73422.70
1995  77782.79  77782.79
1996  85551.62  85551.62
1997  94788.55  94788.55
1998 105516.48 105516.48
1999 114022.59 114022.59
2000 118484.78 118484.78
2001 128275.52 128275.52
2002 126871.07 126871.07
2003 132552.72 132552.72
2004 141150.58 141150.58
```

```
2005 150017.57 150017.57
2006 160793.47 160793.47
2007 174636.33 174636.33
2008 187941.35 187941.35
2009 197826.52 197826.52
2010 194080.18 194080.18
2011 210434.20 210434.20
2012 230305.03 230305.03
2013 242370.41 242370.41
2014 245484.85 245484.85
2015 255546.51 255546.51
2016 263707.60 263707.60
2017 275340.43 275340.43
```

Table A.6: to forecasting results for electricity consumption by Holt-Winter (Model-3)

```
Time Series:
Start = 2018
End = 2027
Frequency = 1
          fit      upr      lwr
2018 289925.3 299731.3 280119.3
2019 289925.3 303792.7 276057.9
2020 289925.3 306909.2 272941.4
2021 289925.3 309536.5 270314.1
2022 289925.3 311851.3 267999.3
2023 289925.3 313943.9 265906.6
2024 289925.3 315868.4 263982.2
2025 289925.3 317659.6 262191.0
2026 289925.3 319341.9 260508.6
2027 289925.3 320933.1 258917.4
```

Table A.7 to model-4 (Holt-Winter)

```
Time Series:
Start = 1977
End = 2017
Frequency = 1
  xhat  level     trend
1977  21511.00  18615  2896.000
1978  23866.70  21057  2809.703
1979  24867.84  22347  2520.836
1980  25839.38  23566  2273.381
1981  26658.03  24617  2041.029
1982  28259.88  26289  1970.883
1983  30308.26  28325  1983.261
1984  31410.55  29568  1842.551
1985  35462.43  33267  2195.427
1986  38727.23  36361  2366.229
1987  43168.69  40471  2697.688
1988  47956.53  44925  3031.530
1989  51551.53  48430  3121.528
1990  55923.20  52602  3321.204
1991  60302.15  56812  3490.147
1992  64026.57  60499  3527.565
1993  71351.01  67217  4134.008
```

1994	77950.86	73423	4527.855
1995	82278.95	77783	4495.949
1996	90670.10	85552	5118.096
1997	100690.02	94789	5901.023
1998	112335.54	105517	6818.542
1999	121162.30	114023	7139.297
2000	125115.39	118485	6630.392
2001	135507.17	128276	7231.165
2002	132460.59	126871	5589.590
2003	138160.16	132553	5607.155
2004	147326.66	141151	6175.660
2005	156705.23	150018	6687.234
2006	168258.43	160794	7464.433
2007	183313.88	174637	8676.880
2008	197498.60	187942	9556.600
2009	207446.02	197827	9619.023
2010	201158.39	194080	7078.389
2011	219276.70	210435	8841.701
2012	241244.17	230306	10938.167
2013	253523.36	242371	11152.357
2014	255109.41	245485	9624.414
2015	265254.59	255547	9707.591
2016	273121.61	263708	9413.613
2017	285176.48	275341	9835.477

TableA.8: to forecasting results for electricity consumption by Holt-Winter (Model-4)

Time Series:
Start = 2018
End = 2027
Frequency = 1

	fit	upr	lwr
2018	300664.3	308950.3	292378.3
2019	311402.5	324282.6	298522.5
2020	322140.8	339365.2	304916.5
2021	332879.1	354465.3	311292.9
2022	343617.4	369669.6	317565.2
2023	354355.6	385013.4	323697.9
2024	365093.9	400512.3	329675.5
2025	375832.2	416173.0	335491.4
2026	386570.5	431997.4	341143.5
2027	397308.7	447985.3	346632.2

Appendix B

Table1.B: Forecasting Results to SARIMA model

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
Jun 2018	23349.16	22612.90	24085.43	22223.14	24475.18
Jul 2018	27296.07	26514.95	28077.20	26101.45	28490.70
Aug 2018	27627.89	26785.93	28469.84	26340.23	28915.54
Sep 2018	24072.51	23201.30	24943.71	22740.11	25404.90
Oct 2018	23494.06	22581.64	24406.49	22098.63	24889.50
Nov 2018	24221.17	23278.31	25164.03	22779.19	25663.15
Dec 2018	26144.88	25167.08	27122.67	24649.47	27640.29
Jan 2019	26287.72	25279.73	27295.72	24746.13	27829.32
Feb 2019	23564.26	22524.72	24603.79	21974.42	25154.09
Mar 2019	24791.43	23722.71	25860.16	23156.96	26425.91
Apr 2019	23480.17	22382.12	24578.21	21800.85	25159.48
May 2019	23983.45	22857.43	25109.47	22261.35	25705.55
Jun 2019	24169.62	22870.35	25468.89	22182.56	26156.68
Jul 2019	27795.14	26438.38	29151.89	25720.16	29870.11
Aug 2019	28224.00	26803.67	29644.34	26051.78	30396.22
Sep 2019	24713.31	23245.32	26181.30	22468.21	26958.41
Oct 2019	24140.30	22619.62	25660.99	21814.62	26465.99
Nov 2019	24878.85	23311.76	26445.94	22482.20	27275.51
Dec 2019	26847.68	25232.73	28462.62	24377.83	29317.52
Jan 2020	26955.62	25296.00	28615.25	24417.45	29493.80
Feb 2020	24304.26	22599.99	26008.53	21697.80	26910.72
Mar 2020	25518.81	23771.76	27265.86	22846.93	28190.70
Apr 2020	24217.34	22428.07	26006.61	21480.89	26953.80
May 2020	24741.27	22911.05	26571.49	21942.19	27540.35
Jun 2020	24921.50	22957.75	26885.25	21918.20	27924.79
Jul 2020	28479.70	26453.10	30506.29	25380.29	31579.10
Aug 2020	28928.83	26835.40	31022.26	25727.20	32130.46
Sep 2020	25427.60	23278.83	27576.37	22141.34	28713.86
Oct 2020	24855.68	22648.22	27063.14	21479.67	28231.69
Nov 2020	25596.67	23335.34	27858.00	22138.26	29055.07
Dec 2020	27574.94	25258.95	29890.94	24032.93	31116.95
Jan 2021	27675.58	25307.50	30043.65	24053.92	31297.24
Feb 2021	25039.35	22619.47	27459.23	21338.46	28740.23
Mar 2021	26251.26	23781.20	28721.31	22473.64	30028.88
Apr 2021	24951.84	22432.26	27471.41	21098.48	28805.20
May 2021	25480.11	22912.19	28048.03	21552.81	29407.40
Jun 2021	25659.08	22967.17	28350.99	21542.15	29776.01
Jul 2021	29203.14	26443.78	31962.51	24983.07	33423.22
Aug 2021	29656.53	26826.34	32486.72	25328.13	33984.93
Sep 2021	26157.29	23266.08	29048.49	21735.57	30579.00
Oct 2021	25585.60	22630.55	28540.65	21066.24	30104.95
Nov 2021	26327.10	23312.41	29341.78	21716.53	30937.66
Dec 2021	28307.36	25232.41	31382.31	23604.63	33010.09