Time Series Analysis of Electricity Consumption Forecasting Using ARIMA Model

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Abstract -- **Power consumption is a very important factor in smart grids for load management process. Forecasting energy consumption is the first step in dealing with load management. For forecasting time series, the ARIMA models are one of the widely used models which showing encouraging results. In this study, ARIMA models were proposed to predict future electricity consumption. The ACF and PACF plots were used as well as stationarity of the data to identify (p,d,q) values. The results showed the accuracy and efficiency of the models and their ability to compete with current techniques for forecasting electricity consumption based on the use of the Mean Absolute Percentage Error (MAPE) to measure the accuracy of the prediction, as the model was able to predict with an error of 4.332%.**

Keywords-—— ARIMA; Electricity consumption; Forecast, Time series

I. INTRODUCTION

Libya is among the developing countries that strive to develop, advance and develop its economy, due to its direct dependence on oil, which represents about 97% of export earnings as national income. Energy is also one of the most important drivers of the economy, and among its sources is electricity, and it is considered a vital commodity. It is not possible to imagine improving the living conditions of the population and economic and industrial development except with electricity, and it has become as an economic standard that explains the progress or backwardness of a country. Today, electricity consumption is one of the most important indicators for developing governments and making good accuracy of long-term forecasting of electricity consumption is vital to increasing energy productivity and avoiding costly mistakes [1]. Power forecasting is important for good planning of the electricity consumption as well as for the implementation of decision support systems which guide the decision-making process of the power system [2]. Accurate forecasting of electricity consumption plays a crucial role for policy makers to formulate electricity supply policies. However, generally limited data and variables cannot provide beneficial information to obtain a satisfactory prediction accuracy [3]. With the recent developments in the field of modern information technology, the smart grid has become one of the main components of smart cities. In order to take full advantage benefits of the smart grid, smart planning and power planning is crucial. From a practical point of view, there are many factors that have an impact on electricity consumption, which require information integration technologies for a comprehensive understanding. For this purpose, the researchers studied methodologies to collect information related to electricity consumption and multi-factor energy consumption prediction models. In addition, conducting a comprehensive analysis and obtaining an accurate assessment of energy consumption is the basis for designing and transforming a more robust and efficient power grid [4]. Forecasting electricity consumption is an effective measure that helps power grid designers and planners build robust, adaptive, efficient, and economic smart grids. It is aimed at modeling electricity consumption under various constraints along with environmental factors and the regulations. A pre-estimated and calculated electricity demand can be obtained based on the history data including dates, economic, climate and so on [5]. This study aims to forecasted the electricity consumption in southern Tripoli Libya for two weeks based on data from Jan 1st, 2016 to Mar 24, 2016 (12 Weeks) using the autoregressive integrated moving average (ARIMA), mean absolute percentage error (MAPE) is used to select the best model performance can be used for future forecasting.

II. LITERATURE REVIEW

Many models have been developed to improve forecasting accuracy of electricity consumption. Studying the ability of the ARIMA model to compete with current technologies for forecasting electricity consumption using Mean Absolute Percentage Error (MAPE) to measure forecast accuracy [6]. ARIM models are used to predict the most appropriate period for individual household electrical energy consumption [7]. The ARIMA model was used to forecast wind speed using common error ratio measures for model prediction accuracy [8]. Six time series methods namely, simple moving average (SMA), weighted moving average (WMA), simple exponential smoothing (SES), Holt linear trend (HL), Holt-Winters (HW) and centered moving average (CMA) were applied and compared the accuracy of each to forecast monthly electricity consumption [9]. A comparative analysis of the SARIMA and ARIMA model was performed on the same data set forecasting the electricity consumption, and the SARIMA model demonstrated better performance than the

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ARIMA model [10]. Classic 'ad hoc' statistical models, advanced ensemble techniques, and neural networks were used to predict electricity power demand for a wholesale power transmission company [11]. Combining seasonal and trend decomposition using Loess (STL) and ARIMA models were proposed to monthly electricity consumption forecasting [12]. ARIMA model was used to predict electricity consumption in the Philippines, and (p, d, q) values were determined using ACF and PACF plots as well as stationarity of the data [13].

III. OVERVIEW OF ARIMA MODEL

The ARIMA model, also known as Box-Jenkins has been widely applied with time series data of variables measured over time [14]. ARIMA model includes three non-negative integers variables (p, d, q), respectively are refer to the autoregressive (AR) model shows that the value of a variable in one period is related to the values of the same variable in previous periods, integrated (I) shows the number of times that the data value have to be “differenced” to obtain a stationary data and moving average (MA) indicates to the number of lagged values forecast errors in the prediction equation [15]. Seasonal ARIMA models are usually represented as ARIMA(p,d,q)(P,D,Q)m, where m refers to the number of periods in each season, and the uppercase P,D,Q depict the autoregressive, differencing, and moving average terms for the seasonal part of the ARIMA model [16].
To estimate ARIMA model various terms values, the steps involving in finding autocorrelation and partial autocorrelation between the values of the data [17]. Autocorrelation is the correlation of a time series with a delayed copy of itself and is defined as ACF = corr (X_t, X_t+k). Here X_t and X_t+k are the current observation and the observation after k period respectively. Partial Auto-Correlation (PACF) [18] is the partial correlation of X_t+k with X_t i.e. it controls the values of the time series at all shorter lags which ACF does not. It is defined for positive lag only with values lying between −1 and +1. Table 1 gives the idea as how to make the estimation for initial values of ARIMA (p, d, q) [19].

TABLE I. MAIN CHARACTERISTICS OF ARMA (p, q) MODELS

	AR (P)	MA (q)	ARMA (p, q)
ACF	Tails off	Cuts off after lag q	Tails off
PACF	Cuts off after lag p	Tails off	Tails off

IV. METHODOLOGY

A. *Dataset Description*

Day by day demand of electricity is increasing because of uses of electrical and electronics instruments. To forecasting the electricity consumption, the electricity consumption data of in southern Tripoli from National Electricity Corporation in Libya, collected from the electricity distribution unit of it. This data set contains the electricity consumption in unit (in MWh) from Jan 1st, 2016 to Mar 24, 2016 (12 Weeks).

B. *ARIMA Model Building Process*

Figure 1. Shows schematic representation of the Box-Jenkins for ARIMA approach.

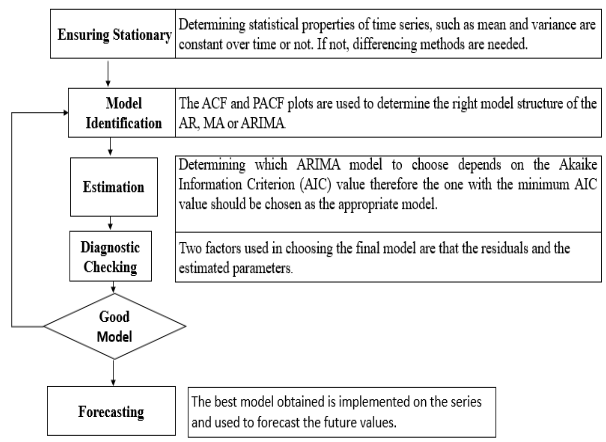

Figure 1. Schematic Representation of the Box-Jenkins Methodology for ARIMA approach

V. RESULTS AND DISCUSSION

The electricity consumption in southern Tripoli - Libya during the period from Jan 1st, 2016 to Mar 24, 2016 (12 Weeks) is depicted in Figure. 2 represents the constituents of the time series viz. are trend, seasonality and residual values. It can be seen that the electricity consumption data has a slow downward trend and has seasonality. Therefore, seasonal ARIMA was used for the forecasting.

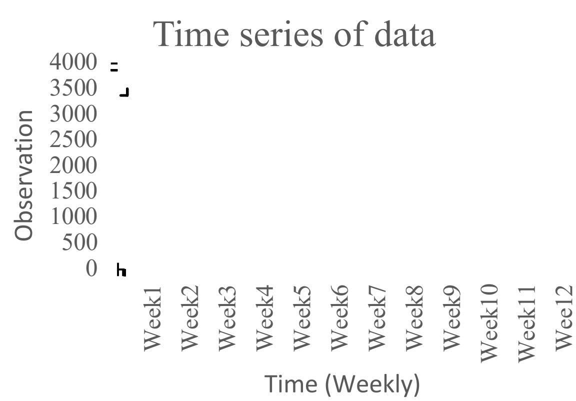

Figure.2. Electricity consumption data for 12 Weeks

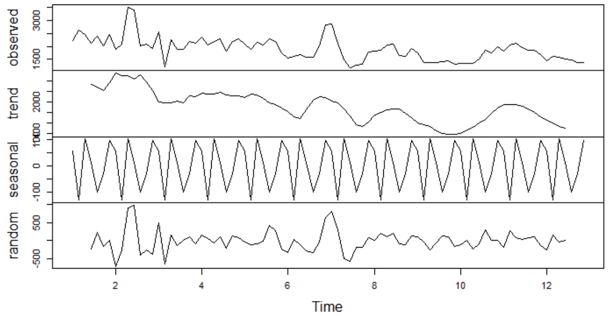

Figure 3. Decomposition of additive time series

Observing 4 graphs closely in figure 3, we can find out if the data satisfies all the assumptions of ARIMA modeling, mainly, stationarity and seasonality we note that there is seasonal, as well trend, so it is not surprising that the time series is not stationary. These patterns revealed that the series is not stationary and therefore must be transformed before attempting to form a stationary model. Therefore, the first difference of the series is analyzed, the plot of the first difference data conclude that the data is stationary after the seasonal first difference was taken as shown in Figure 4.

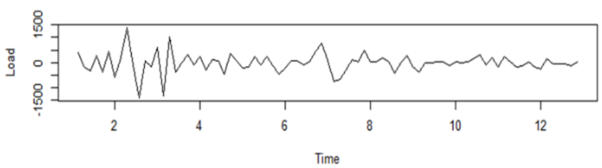

Figure.4. The first difference of data

The ACF and PACF correlogram was plotted as shown in Figures 5 and 6, to select the suitable terms for the model. From the correlograms, it was observed that both the ACF and PACF cuts the upper confidence level for the first time at lag value 0 and 6 respectively hence, the coefficients of both AR and MA terms would 6 and zero i.e. p = 6 and q = 0.

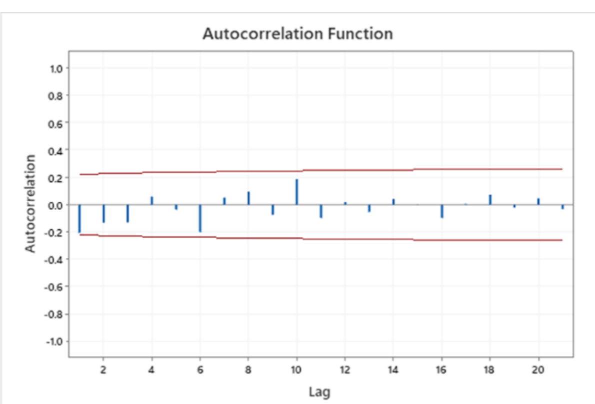

Figure. 5. The ACF graph for the first seasonal difference

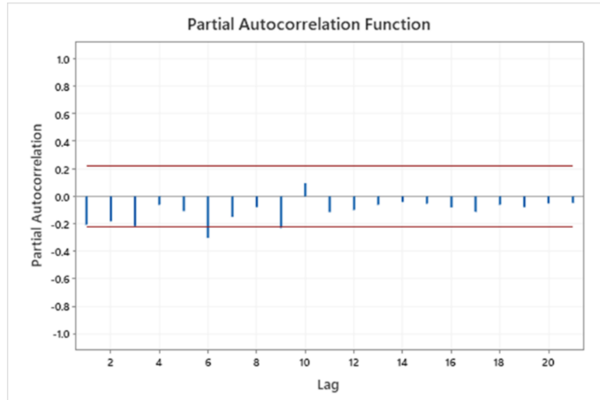

Figure.6. The PACF graph for the first seasonal difference.

A function was created using all possible combinations of parameters for fitting the models, the outcome was predicted using the models, and the model with the smallest MAPE was selected. The results showed that the best model that can be used to forecast future electricity consumption is the seasonal ARIMA model (0, 1, 6) $(1, 1, 6)_7$ with a MAPE of 4.332% as shown in Table 2.

TABLE II. FORECAST ACCURACY OF THE MODEL USING MAPE

Model	MAPE
SARIMA (6,1,0) (2,1,1)	7.193
SARIMA (6,1,0) (1,1,2)	6.872
SARIMA (6,1,0) (1,1,6)	4.332
SARIMA (6,1,0) (1,1,5)	5.206
SARIMA (6,1,0) (1,1,3)	6.460
SARIMA (6,1,0) (1,1,1)	7.187

Figure 7 shows the forecasted electricity consumption and the actual data for two weeks from Mar 25, 2016 to Apr 07, 2016.

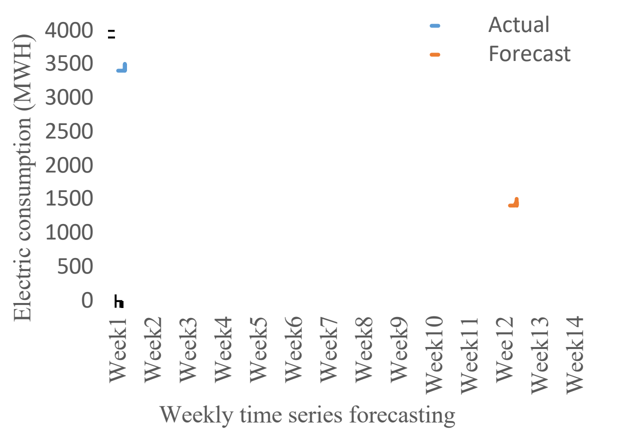

Figure.7. Actual data vs forecasted data.

VI. CONCLUSION

Forecasting the energy consumption is playing a crucial role in directing plans, programs, load management and policies within the institution. The accuracy and the simplicity of the forecasting model leads to improving proper planning and to rational policy regarding production companies. Electricity consumption in southern Tripoli - Libya during the period from January 1, 2016 to March 24, 2016 (12 weeks) was analyzed to determine the best model for forecasting electrical consumption for two weeks ahead. This study revealed that the seasonal ARIMA (0, 1, 6) $(1, 1, 6)_7$ model was the best and was able to forecast consumption with MAPE of 4.332%.

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