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The Forecasting of Electricity Consumption in the UAE Based on ARIMA Model

'Author: Mr. Abdulsalam Elnaeem Balila; balila@graduate.utm.my'
'Author Address: Dubai, United Arab Emirates'
'Corresponding author: Dr. Ani Shabri; ani@utm.my'

1- Abstract

The increase in electricity consumption in the United Arab Emirates (UAE) has become an inevitable reality, and it can be said that with the increase of the population and climate change, the consumption of electricity will increase dramatically. It is necessary to forecast the consumption of electricity in the United Arab Emirates because it plays an important role in planning strategies and policies in the future. In this study, the UAE electricity consumption data for 1985-2019 is used to forecast the electricity consumption of UAE in the future using the Auto-Regressive Integrated Moving Average model (ARIMA). The data were divided into the training data set (1985-2014) and testing data set (2015-2019) using R software to insure the model accuracy. The ARIMA model is selected to be ARIMA (0, 1, 0) to forecast the future of UAE electricity consumption. The model is adequate and accurate. The result shows that the UAE electricity consumption will continue in increasing. Electricity consumption in 2024 is expected to reach a higher level at 15,049 GWH. The results are helpful to establish effective policies, regulations, and strategies to improve and develop electricity demand management and electricity efficiency.

Keywords: *Electricity Consumption, GWH, UAE, ARIMA, IMA, and Forecast.*

2- Introduction

Increasing demand for electricity is a result of technological advancements and the urgent need for it, which is why electricity forecasts are necessary for both short-and long-term power planning and structuring of the national economy (1), as the UAE and all other countries around the world's economies are heavily dependent on electricity. As previously reported and studied in relation to the rate of energy consumption per capita, the UAE is one of the world's highest countries with the highest electricity consumption rates.

Globally, the average person consumes between 7 and 15 kilowatt hours of electricity per day, according to 2013 data (2). Over the previous 10 years, a report from the Kuwait Financial Center stated that the UAE's electrical sector has developed consistently due to a 12 % annual growth rate in capacity for electricity generation and a present absorptive capacity of 30,000 megawatts. Over the same period, power consumption grew at an annual rate of 8%. Over the next four years, the UAE's electricity consumption is expected to expand at a rate of 5.8 % each year, according to the research from the center (2). The United Arab Emirates' rapid population and economic growth have resulted in a significant need for power, which has become one of the country's most significant difficulties. Thus, the country will be able to plan for the future and devise policies to alleviate the country's electrical supply shortages by using the projection of electricity consumption rates.

3- Problem Statement

There is a significant need for energy in the United Arab Emirates because of the country's growing population, developing economy, and environmental concerns. The country's per capita electricity consumption is among the highest in world. There are a number of factors that lead to an increase in electricity consumption in the UAE, the most important of which are: The phenomenon of climate change and the desire to reduce emissions, desire to shift towards an economy capable of creating new job opportunities, increasing demand for electricity, especially in the summer with high temperatures, and steady population increase. It means that the government, commercial entities, or individuals must use appropriate and reliable forecasting methods to guide and reduce excessive usage of electricity. Junwei Miao (3),Farjana, Arpita, Masud, and M. Sultan 2019 (4), Suat Ozturk and Feride Ozturk 2018 (5). The ARIMA model has been shown to be very accurate, stable, and suitable for estimating power use based on prior studies. It is used in this study to anticipate UAE electricity usage in the future.

4- Data Availability and Methodology

This research is based on data from the United Arab Emirates (UAE) on power use from 1985 to 2019. Data on power consumption is taken from the World Development Indicators | Data Bank (6). To assess model accuracy and sufficiency, the data were divided into two sets: training (1985-2014) and testing (2015-2019). The variable of electricity usage is expressed in gigawatt hours equivalent (GWH). The data are separated and the ARIMA models are built using the R statistical software.
ARIMA models are non-stationary time series models that are often used to anticipate future values based on data from time series. Box and Jenkins introduce the ARIMA model (7). It predicts the future values of a time series using a linear combination of the previous values (lags). In terms of mean or variance, or both, ARIMA models can be non-stationary.
Numerous transformations can be used to convert nonstationary time series data to stationary time series data.
It is possible to transform a homogeneous series (nonstationary in mean) to a stationary time series by applying the appropriate degree of difference. A nonhomogeneous time series (non-stationary in variance) can be converted to a stationary time series by taking a logarithm (log) transformation or any other variance stabilizing (8). The time series stationary in the mean is not necessarily to be stationary in the variance; but, if it is nonstationary in the mean, it will be nonstationary in the variance (9). Any additional transformations, such as differences, must be preceded by a variance stabilizing transformation in order to ensure that the difference transformation does not result in negative values. The transformation improves the approximation to the normal distribution by stabilizing the variance (10).

The Auto-Regressive Integrated Moving Average model has three parameters as follows: ‘p’ is the (AR) parameter and it represents the order of auto-regressive process, ‘d’ represents the order of differences to get the stationary series, and ‘q’ is the (MA) parameter and it represents the order of moving average process. Auto-regressive is the regressing of the target variable on its prior terms. 'd' parameter is applied when the sample data are non-stationary. If d=0, the series is stationary and the model is called Auto-Regressive Moving Average model, denoted

by ARMA (p, q), and if d >=1, the series is stationary after a proper differencing. If p=0, the model is written as ARIMA (p, 0, q), the model is called the integrated moving average model of order (d, q) and is denoted by IMA (d, q). If p=0 and q=0, the process is called white noise. The moving average model states that the variable linearly depends on the present and past values of the error term (10).
The generalized univariate ARIMA models with p, d, q parameters has the following specification (10):

$$Z_t = \mu + \Phi 1\ Z_{t-1} + \Phi_2\ Z_{t-2} + \ldots + \Phi_p\ Z_{t-p} - \theta_0 - \theta_1 a_{t-1} - \ldots - \theta_q\ a_{t-q} \quad (1)$$

Or

$$\Phi_p(B)\ (1 - B)^d\ Z_t = \theta_0 + \theta_q \quad (2)$$

Where Z_t is the transformed time series value, μ is the mean value of sequences, $\{Z_t\}$, Φ and θ are unknown parameters, and is the error term (independent identically distributed) with zero mean.

$\Phi_p(B) = (1- \Phi_1 B- \ldots - \Phi_p B^p)$ is the represent the AR operator, and $\theta_q(B) = (1- \theta_1 B- \ldots - \theta_q B^q)$ is represented the invertible MA operator, and B is a represent delay operator.

5- Model Identification

The essential phases in time series analysis are to identify and build the model based on the historical time series data. These stages necessitate a thorough understanding of the processes involved. The model identification is required to plot and match the sample ACF with the sample PACF and the features of these processes in terms of their autocorrelation function (ACF) and partial autocorrelation function (PACF). If there are decays in ACF and cuts off in the PACF, the AR model is indicated, if there are cuts off in ACF and decays in the PACF, the MA model is indicated, and if there are decays in ACF and decays in the PACF, the ARMA or ARIMA model is indicated (10).

6- Model identification Steps

Step1: Plot the original time series and choose a proper transformation (e.g., differencing, log, and square root). Any transformation must be before the differencing to avoid the log and square roots of the negative values in the differenced series.

Step2: Compute and examine the significance of the ACF and PACF of the original time series to confirm the necessary degree of differencing so that the differenced series is stationary. If the sample ACF decays very slowly and sample ACF cuts off after lag1, then it indicates that differencing is needed.

Step3: Use of unit root tests to confirm the weather of the transformed and differenced time series data is stationary or not. If it is stationary, go to step4 or repeat step2 and 3.

Step4: Calculate and examine the significance of the ACF and PACF of the converted time series to identify the orders of *p* and *q*. (10).

Figure.1: below show the forecasting structure and model accuracy

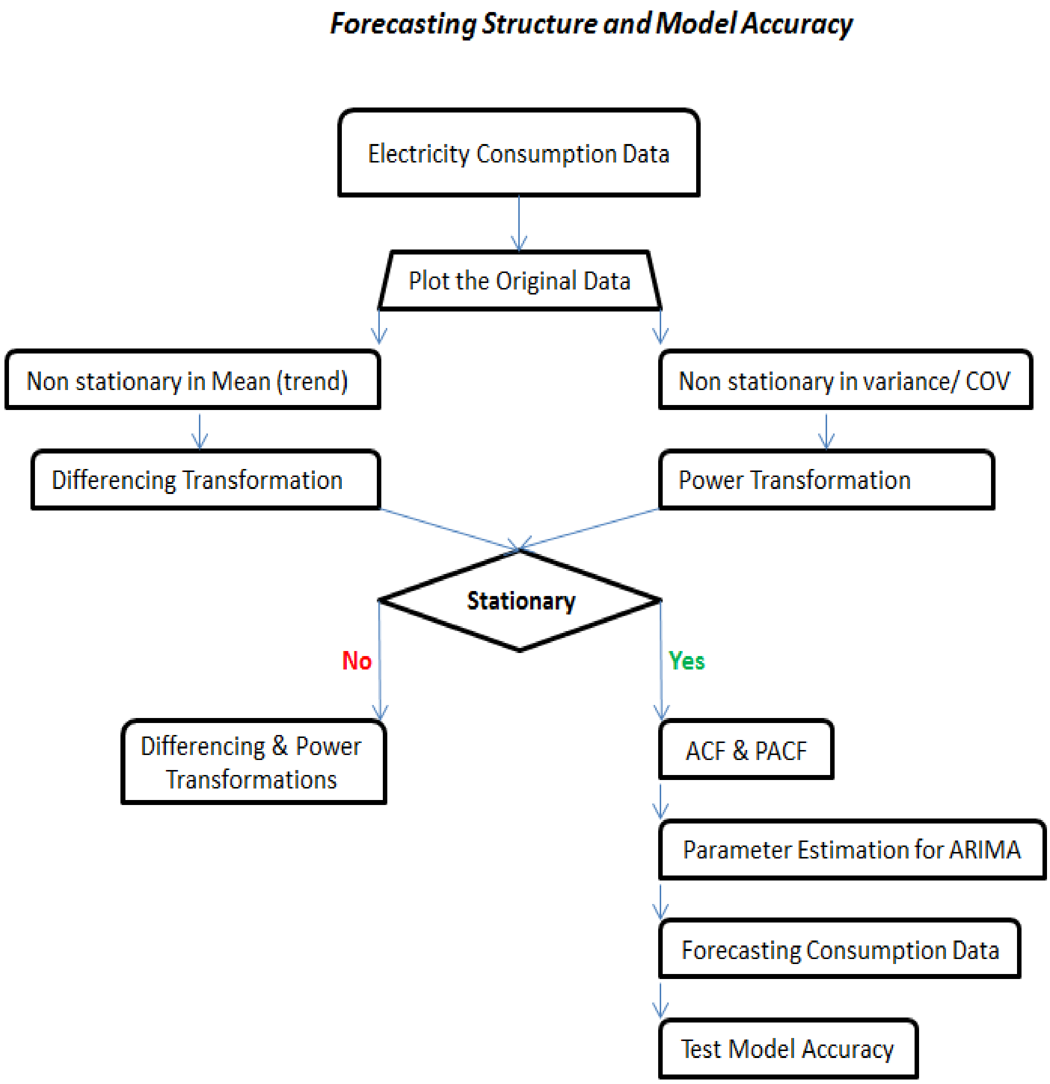


Figure.1: Forecasting structure and model accuracy

7- Results and Discussions

7.1- Unit Root Tests. The purpose of Unit Root Tests is to identify the existence of the unit root. The presence of unit roots indicates the nonstationary time series. Furthermore, the basic hypothesis underlying weak form efficiency is that successive electricity consumption changes cross the four seasons and each has its own light, temperature, and weather patterns that repeat yearly. The history of a series of changes cannot be used to predict future changes in any "meaningful" way, it will result in the spurious regression. Augmented Dickey-Fuller (ADF)

test, (KPSS) test, and Phillip Perron test are the most common methods of testing the existing of a unit roots. The time series of electricity consumption in UAE takes natural logarithm to avoid heteroscedasticity. We apply the ADF and KPSS tests to investigate the existence of unit root in UAE electricity consumption time series data. The consumption of the electricity rises indeed from 1997 to 2002, and again from 2010 to 2015.
The ADF P-value of its level is 0.5822, which is higher than the significance level of 5%. Thus, it can't reject the existence of the unit root. The P-value of the KPSS in its level is 0.01628, which is less than the significance level of 0.05. Therefore, the trend stationary hypothesis is rejected. According to the ADF and KPSS tests, the series of UAE electricity consumption appears to contain a unit root in its level. UAE electricity consumption is nonstationary time series.
The ADF P-value after the 1st difference is 0.01, which is less than the significance level of 5%. Thus the unit root hypothesis is rejected. Furthermore, the KPSS test P-value after the 1st difference is 0.1, which is higher than the significance level of 0.05. Therefore, it cannot reject the trend stationary hypothesis. All tests approve that the series is stationary after the 1st difference. The result show that it is integrated of order one, namely I (1). The results are displayed in Figure.2 below.

```
        Augmented Dickey-Fuller Test

data:  training_set
Dickey-Fuller = -1.9751, Lag order = 10, p-value = 0.5822
alternative hypothesis: stationary


        KPSS Test for Trend Stationarity

data:  training_set
KPSS Trend = 0.19925, Truncation lag parameter = 2, p-value = 0.01628


        Augmented Dickey-Fuller Test

data:  d.Log.training_set
Dickey-Fuller = -4.3908, Lag order = 10, p-value = 0.01
alternative hypothesis: stationary


        KPSS Test for Trend Stationarity

data:  d.Log.training_set
KPSS Trend = 0.10073, Truncation lag parameter = 2, p-value = 0.1
```

Figure.2: ADF and KPSS test

7.2- Model Identification. This step is to test auto-correlation (ACF) and partial autocorrelation (PACF) based on the differenced series. Figure.3 shows the results of autocorrelation analysis. According to the coefficients of the sample ACF and PACF, we will fit ARIMA (0, 1, 0) model or white noise. The series became stationary after logarithmic transformation and first-order difference methods. The auto-correlation coefficients and partial auto-correlation coefficients of the series are the first-order truncation. It is clear that the spikes of ACF & PACF are insignificant (not touching the blue dash lines) after the 1^{st} difference. Accordingly, the

ARIMA (0, 1, 0) model is constructed. The results of ACF and PACF of the differenced series are displayed in Figure.3 below.

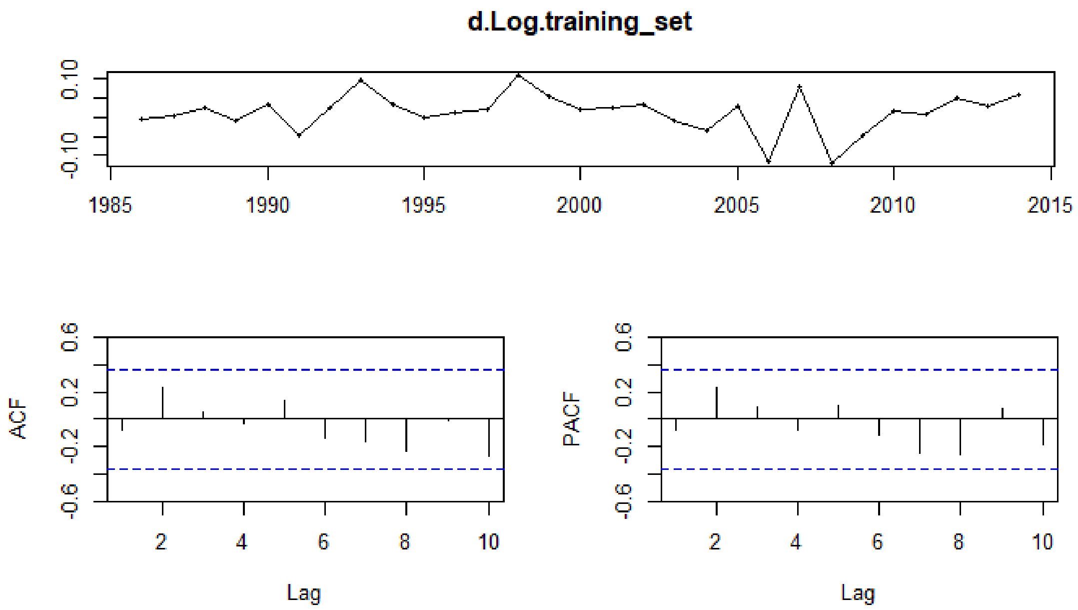


Figure.3: the 1st order differential auto-correlation and partial auto-correlation analysis

7.3- Parameter Estimation & Evaluation ARIMA model for training data. Based on the above analysis, the model of electricity consumption after the 1st difference is a white noise process as followed:

$$\Delta Z_t = \mu + a_t \qquad (4)$$

Where a_t is a white noise, which implies it is a sequence of uncorrelated random variables from a fixed distribution with constant mean, usually assumed to be zero, and constant variance. The parameters estimated are in Figure.4 below.

```
Call:
arima(x = training_set, order = c(0, 1, 0))


sigma^2 estimated as 351342:  log likelihood = -226.31,  aic = 454.61

Training set error measures:
                   ME     RMSE      MAE      MPE     MAPE      MASE       ACF1
Training set 124.5186 582.7802 428.9896 1.040009 3.757589 0.9673371 -0.1137104
```

Figure.4: The results of parameter estimation

7.4- Forecasting: The method of forecasting will be illustrated using an ARIMA (0, 1, 0) model for the UAE electricity consumption. The last five years (2015-2019) are used for a test set. The forecasts are plotted in Figure.5 below.

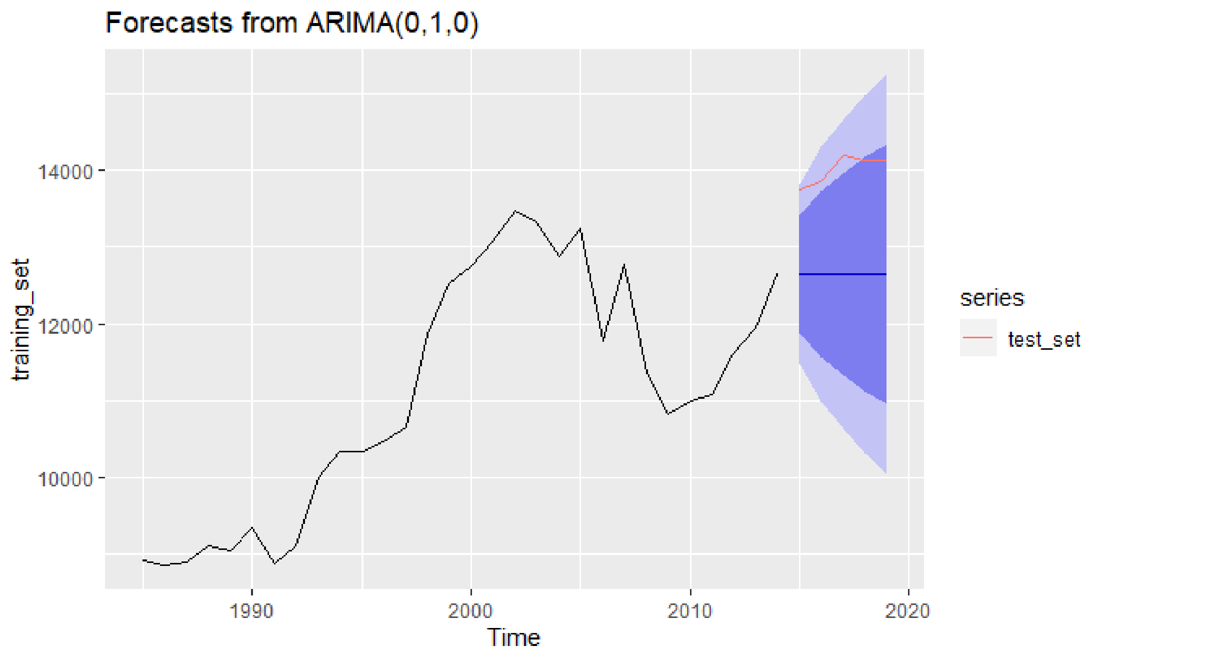


Figure.5: Forecasts from ARIMA model fitted to the UAE electricity consumption training data.

The fitted model contains an h argument to allow for h-step ahead forecast “fitted values” on the training set. Figure.6 below is a plot of one-step fitted value forecast on the training set.

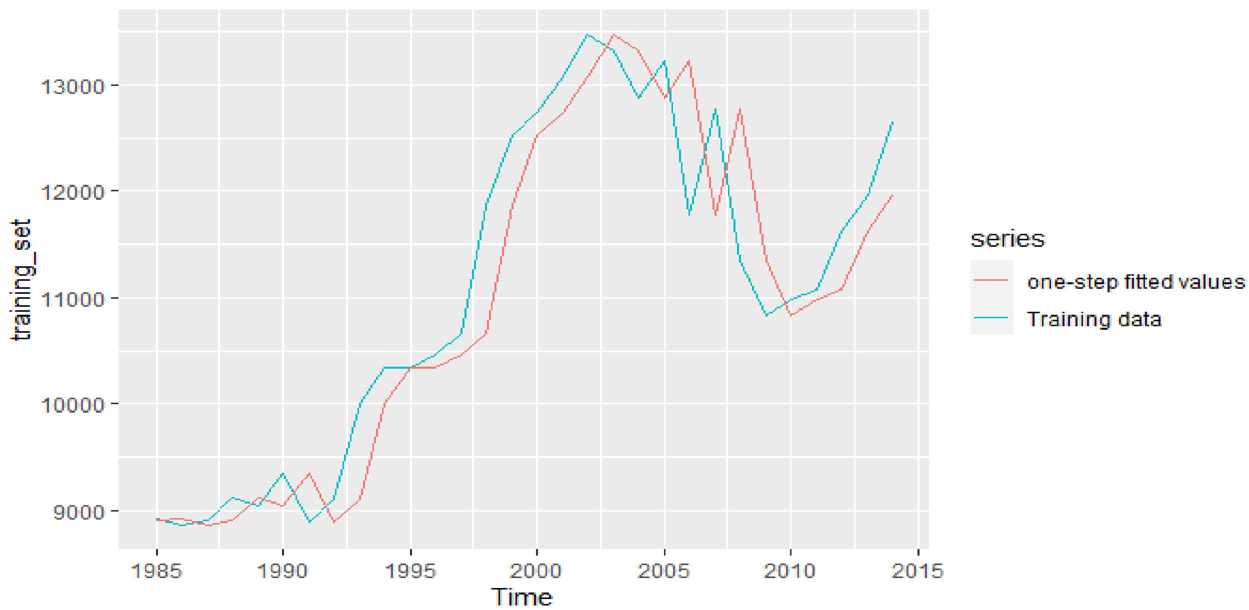


Figure.6: One-step fitted values from an ARIMA model to the UAE electricity consumption training data.

One-step forecast on the test data, in this step we will fit the model using training data and then evaluate its performance on the test data set. In the above analysis, we have used the last five observations (2015-2019) for the test data set and estimated our forecasting model on the

training data set. Then the forecast errors will be for 1-step, 2-steps, 3-step, 4-step, and 5-steps ahead. The forecast variance increases with the forecast horizon.
The solution of this issue is to obtain the first step errors on the test data. We are using the training data set to estimate all parameters, but when we compute forecast on the test data set, we will use all data (training and test data).
Using the ARIMA (0,1,0) model used above, we will apply the model to the test data set. The results are displayed in Figure.7 below.

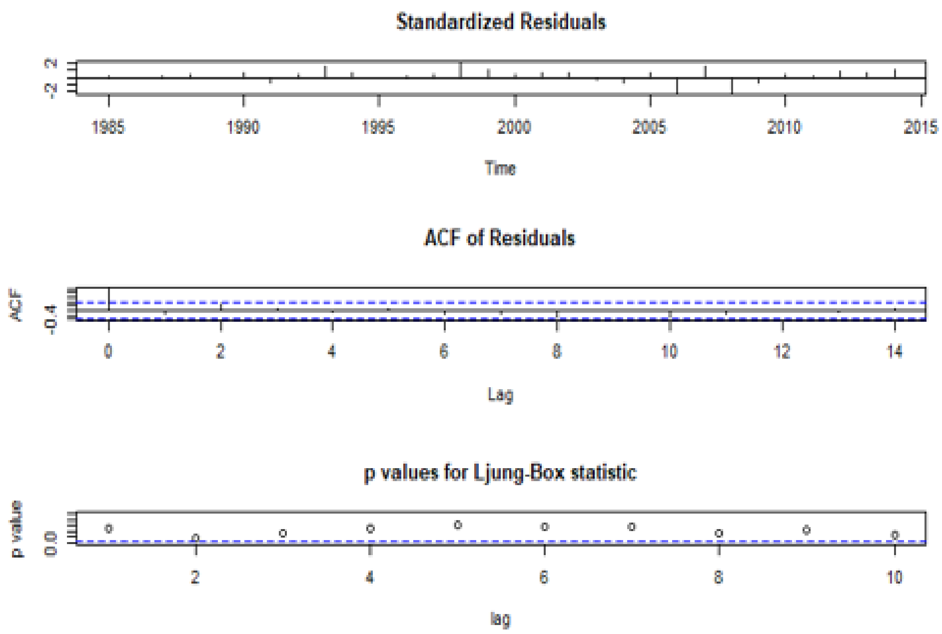
```
                   ME     RMSE      MAE       MPE      MAPE      MASE       ACF1
Training set 78.72177 159.8175 103.5874 0.5585762 0.7346691 0.8218171 -0.2453874
```

Figure.7: One-step forecasts on test data

***7.5- Model Adequacy*:** the last step is to test the model adequacy. The Box -Ljung test (or Chi-square test) tests the null hypothesis that the residual are uncorrected. From the analysis in Figureure.8, The Box -Ljung P-value at lag 10 is 0.2596, which is higher than the significance level of 5%. Thus, it cannot reject the residuals are uncorrected. The plot also showed insignificant standardized residuals, uncorrected residuals, and p-value for Ljung-Box statistic being higher than 5%. Thus, the model is adequate. The results are displayed in Figure.8 below.

```
        Box-Ljung test

data:  arima010$residuals
X-squared = 12.394, df = 10, p-value = 0.2596
```



Figureure.8: One-step forecast on test data.

8- Conclusion and Recommendation:

This paper focuses on forecasting time series data by partitioning the power consumption series into two data sets: a training data set and a testing data set to ensure that the model's accuracy and adequacy are not compromised during training. The ARIMA (0, 1, 0) or white noise model is developed to anticipate future UAE electricity demand. This forecasting result depicts the electricity demand and enables power suppliers to manage and rationalize their electric power across various industries. After the power changes and differencing, the series became stationary. Relative forecasting errors for electricity consumption were determined to be noncorrelated and minor using Box-Ljung tests and visualized ACF of residuals. This indicates that the model is accurate and appropriate. According to the findings, UAE electricity usage would continue to rise. Electricity shortages will result in increased electricity usage, which will be reflected in economic growth. To achieve a balance between economic growth and energy consumption, the country should develop and strengthen electricity demand management laws, regulations, and strategies. Electricity needs to be rationalized, with a focus on environmental sustainability. The UAE government is improving current practices in electricity through collaboration and coordination across crucial agencies and entities.

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