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Forecasting the Electricity Demand in Malaysia using ARIMA Model

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Abstract
Energy is essential in the economic development of Malaysia and recently is the main source in our country. Due to increasing demand of electricity in few sectors, forecasting the electricity demand is crucial because it assists decision makers in planning and operation of a power system, and can avoid the overestimation or underestimation of the demand. This also helps in maintaining the balance between the demand and supply of electricity. The purpose of this study is to determine a suitable Auto Regressive Integrated Moving Average (ARIMA) model to forecast the electricity demand for several sectors in Malaysia which are industrial, residential and commercial. According to the electricity demand data of three sectors from year 1990 until year 2018, 80% of the data are used for in-sample data for the construction of ARIMA models while 20% of the data are used for out-sample data for prediction purpose. The performance of few potential forecasting models is evaluated by using the Mean Absolute Percentage Error (MAPE), the best model is with the lowest MAPE. The best model found for each sector is then used to predict the electricity demand for all the sectors from year 2019 to year 2025. Then, the time series plots are generated to visualize and compare between the trends of electricity demand of all three sectors. Among all three sectors, we found that the industrial sector will consume more electricity as compared to the other two sectors in the future.
Keywords: Electricity demand; time series; forecasting; ARIMA

1. Introduction

Energy is the driving force of every country and it plays a vital role in the economic growth and development of the country [1]. Nyoni [1] stated that electricity is the most essential and useful source of energy since it has always been widely used in various sectors such as residential sectors and industrial sectors. A research has shown an increase in the growth for electricity during the past few years in Malaysia where the growth was mainly contributed by the strong electricity demand from domestic and commercial sectors [2]. In Malaysia, the power sector is heavily reliant on the traditional energy resources [3]. In order to have a better understanding on the future consumption of electricity, load forecasting is necessary to be carried out and discussed.

Modeling and forecasting the electricity consumption assists the electricity generation and distribution [4]. Electricity load forecasting is divided into three categories which are short-term, medium-term and long-term load forecasting. These three categories have different roles in power system. Short-term predictions (hours and days) are required in controlling and scheduling the power system, medium term predictions are required in planning the power system. Finally, long-term load forecasting (months and years) is required for the peak load capacity planning and the system maintenance scheduling. Thus, this forecasting is important for sustainable development because it helps the power system engineers and demand controllers to ensure adequate electricity supply for increasing electricity demand. Therefore, it is necessary to have an accurate electricity demand forecasting which can prevent the occurrence of energy wastage and energy outage due to overestimation or underestimation of electricity demand.

The purpose of electricity demand forecasting is to ensure an affordable and reliable energy supply. Demand forecasting helps in maintaining a balance between demand and supply of electricity in the power system and achieving energy conservation. It can also help the policymakers in making decisions and rational strategies for environmental preservation and carbon emission reduction [5]. Forecasting of electricity demand is required to be carried out since the consumption of electricity tends to change at any time in respond to customer demands [6]. It can be found that many researches and studies had been carried out for predicting the electricity consumption and analyzing the different types of forecasting models based on their forecasting performances in order to ensure an appropriate forecasting model is used for prediction [7]. As highlighted in a study, an inaccurate forecast could lead to severe technical and economic consequences where it will affect the proper allocation of resources and investments [7].

In this study, the univariate data on electricity demand for few sectors which are industrial, residential and commercial from year 1990 to year 2018 are obtained from the Malaysia Energy Information Hub (MEIH). The data are fitted into the Auto Regressive Integrated Moving Average (ARIMA) model to forecast the future electricity demand for industrial, residential and commercial sectors in Malaysia. The performance of the ARIMA model for each sector is evaluated by using the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) where the best model is with the higher accuracy and lowest MAPE value. Graphical plots are also generated to visualize and determine the sector that will consume electricity the most in future among all three sectors.

2. Literature Review

Many techniques are applied on the time series data to predict the future values based on its historical data [8]. The time series forecasting is accurate and suitable for energy prediction nowadays [5]. Series data can generally be analyzed through univariate analysis with single variable, and multivariate analysis with more variables [9]. There are several techniques that could be applied on time series data such as Autoregressive and Moving Average (ARMA), exponential smoothing, Grey–Markov method, structural time series models, ARIMA, ANN and Holt–Winters method. It can be found that ANN which uses previous data to forecast future value of multivariate time series performed well in predicting the electricity demand in Thailand [10]. However, due to the model complexity and the yearly electricity demand data used in this study is univariate time series data, the univariate Box-Jenkins model is appropriate and recommended to be used.

ARIMA models which are also referred to as Box-Jenkins models are the most popular for stochastic time series models. It consists of three parts which are Autoregressive (AR), Integrated (I) and Moving Average (MA). The three stages of ARIMA approach include identification, estimation and diagnostic checking [3]. It is able to be used for stationary data and non-stationary data where differencing is required. ARIMA model is widely used in forecasting consumption of electricity and it can be concluded that it is the suitable method for predicting electricity consumption based on many previous studies [1]. The main advantage of using ARIMA model is it can make reliable forecasts in which it does not need to depend on the demand determinants such as population, Gross Domestic Product (GDP) and temperature [7].

A study had shown ARIMA model is used in forecasting the yearly electricity demand for domestic, commercial and industrial categories in Tamale, Ghana by using data between year 1990 and year 2013 [11]. From the results, the model diagnostics which showed the residuals were random and normally distributed implied that the models selected were appropriate in forecasting the electricity demand for seven years ranging from year 2014 until year 2020. Another study which analyzed ARIMA, Seasonal Auto Regressive Integrated Moving Average (SARIMA), Autoregressive Conditional Heteroskedastic (ARCH) and Generalized Autoregressive Conditional Heteroskedastic (GARCH) in forecasting the electricity demand in Pakistan showed that ARIMA was the most accurate forecasting technique compared with others [7]. Hence, ARIMA model is suitable to be used for forecasting the electricity consumption due to its simple structure, high modeling speed and good forecasting accuracy.

3. Methodology

3.1. Description of the Data and Method

The data in this study is the electricity demand of sectors of industrial, residential and commercial in Malaysia between year 1990 and year 2018 obtained from the MEIH. The data is univariate and the unit of the electricity demand is kilotonnes of oil equivalent (ktoe). In this study, ARIMA model is used for forecasting the demand of electricity since it is reliable in predicting values based on past observations without requiring any additional variables. For the purpose of visualization, plots are generated to compare and identify the sector with the highest electricity demand for the future in Malaysia. From the electricity demand data between year 1990 and year 2018, 80% of the data will be the in-sample data while the other 20% of data will be the out-sample. The demand of electricity from year 2019 until year 2025 will be forecasted by using the appropriate forecasting model.

3.2. ARIMA Approach

ARIMA model or Box-Jenkins method can be divided into three parts which are Autoregressive (AR), Integrated (I) and Moving Average (MA). The autoregressive (AR) part shows a relationship between current value and previous value while the moving average (MA) part shows the dependency of current value and the residual value in the previous time. ARIMA model consists of three parameters *p*, *d* and *q*. The model is generally written as ARIMA(*p*,*d*,*q*) where *p* denotes the order of the autoregressive part, *d* is the degree of differencing required to obtain a stationary time series and *q* denotes the order of the moving average part of the model. The forecasting equation of ARIMA model can be expressed as

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

where

y_t is the electricity consumption,
c is the constant which represents the intercept,
p is the number of lags of the considered variable,
q is the number of lags of the error term,
ε_t is the white noise error term,
φ_i is the i^{th} autoregressive coefficient,
θ_j is the j^{th} moving average coefficient,
y_{t-i} is the series in the preceding i^{th} period,
ε_{t-j} is the preceding error term at the j^{th} period.

The mathematical formula of ARIMA model above is obtained by integrating the AR model and MA model which are expressed as

$$y_t = c + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p} + \varepsilon_t \tag{2}$$

and

$$y_t = c + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} + \varepsilon_t \tag{3}$$

respectively.

There are four steps needed to be carried out before forecasting the demand of electricity by using the ARIMA model which are identification, estimation of parameters, model selection and diagnostic checking [12].

3.2.1. Identification

To check for the stationarity of data, a unit root test which is Augmented Dickey-Fuller (ADF) test is performed to identify the existence of unit root. The presence of unit root implies that the time series is

non-stationary and differencing is required. ADF test is used since it is the most common method of unit root test and is best suited for a large sample size. The definitions of hypothesis are as follow:
H_0: There is a unit root where $\gamma = 0$.
H_1: There is no a unit root where $\gamma < 0$.
The null hypothesis will be rejected if the test statistic value is smaller than the critical value at a significance level and this implies that the series is stationary.

Differencing is required if the data is non-stationary, and this procedure helps to stabilize the mean of series by removing the difference in the level of series. At the end, the trend and seasonality in the series will be eliminated.

3.2.2. Estimation of Parameters

The parameters *p* and *q* are determined by using autocorrelation function (ACF) plot and partial autocorrelation function (PACF) plot. The characteristics of ACF and PACF functions are shown as Table 1 below.

Table 1: Characteristics of ACF and PACF functions

Model	**AR (*p*)**	**MA (*q*)**	**ARMA (*p*,*q*)**
ACF	Tails off	Cuts off after q	Tails off
PACF	Cuts off after p	Tails off	Tails off

3.2.3. Model Selection

Akaike information criterion (AIC) is used to find the model with the lowest AIC value as it indicates that it is the best model for forecasting. This step is crucial as under-fitted model may fail to capture the nature of variability in dependent variables and over-fitted model may lead to loss of generality. The formula of AIC can be expressed as

$$AIC = -2\frac{l}{T} + 2\frac{k}{T} \tag{4}$$

where
l is the log-likelihood,
k is the total number of parameters estimated,
T is the number of observations.

The formula of log-likelihood can be expressed as

$$l = -\frac{T}{2}\left[1 + log2\pi + \log(\frac{\hat{\varepsilon}\hat{\varepsilon}}{T})\right] \tag{5}$$

where
l is the log-likelihood,
T is the number of observations,
$\hat{\varepsilon}\hat{\varepsilon}$ is the sum of squared residuals.

3.2.4. Diagnostic Checking

Residual analysis is performed to check the characteristics of white noise in which they are normally distributed with zero mean and constant variance. The model is not adequate if the residuals do not have the white noise characteristics. Then, the step of estimation of parameters has to be repeated followed by diagnostic checking until an appropriate model is obtained for forecasting [1].

3.3. Evaluation of Model Performance

The Mean Absolute Percentage Error (MAPE) is used as the indicator to evaluate the performance of forecasting model. It is easy to be interpreted and understand since the error calculated is in term of percentage. The lower the value of MAPE, the higher the accuracy of model [13]. The formula of MAPE can be expressed as

$$MAPE = \frac{100\%}{N} \sum_{t=1}^{N} \left| \frac{A_t - F_t}{A_t} \right| \quad (6)$$

where
N is the number of data points,
A_t is the actual values at data point t,
F_t is the forecast values at data point t.

The interpretation of the performance of forecasting model using MAPE values is shown in Table 2 below.

Table 2: Interpretation of MAPE values

MAPE (%)	Interpretation
≤ 10	High accuracy forecasting
11 – 20	Good forecasting
21 – 50	Reasonable forecasting
> 50	Inaccurate forecasting

4. Results and discussion

4.1. Electricity Demand Trend

In constructing ARIMA model, the in-sample data used is the electricity demand from year 1990 to year 2012 while the out-sample data used for evaluating the performance of forecasting models is the electricity demand from year 2013 to year 2018. The time series plots of electricity demand for three sectors from year 1990 until year 2012 are shown in Figure 1 below. Based on Figure 1, industrial sector has the highest electricity demand from year 1990 to year 2012 followed by commercial sector and residential sector.

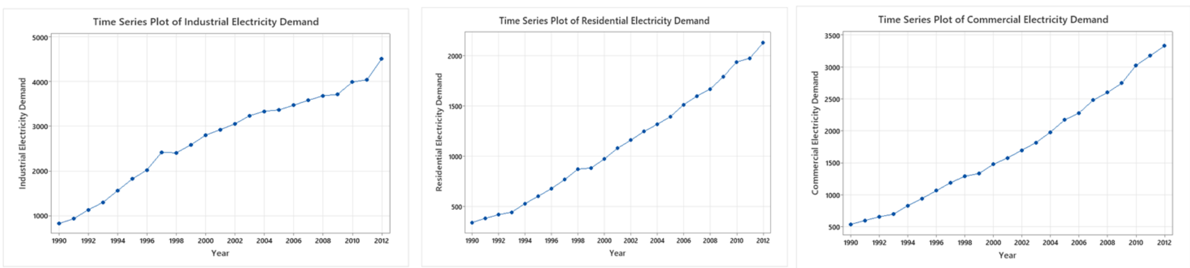

Figure 1: Time series plot of electricity demand for industrial, residential and commercial sectors

4.2. Normality of the data

In order to test the normality of the data, probability plot and Anderson-Darling test are carried out. The probability plot can be used to determine the normality of data by visualizing the fit of the distribution. The data has normal distribution if all of the points in the plot are able to form approximately a straight line. For Anderson-Darling test, the null hypothesis is defined as data follows a normal distribution while the alternative hypothesis is defined as data does not follow normal distribution. If the p-value is greater than the significance level of 0.05, it can be concluded that we do not have enough evidence to reject the null hypothesis and it implies that the data has normal distribution. The probability plots of electricity demand for industrial, residential and commercial sectors together with the result of Anderson-Darling test are shown in Figure 2 below.

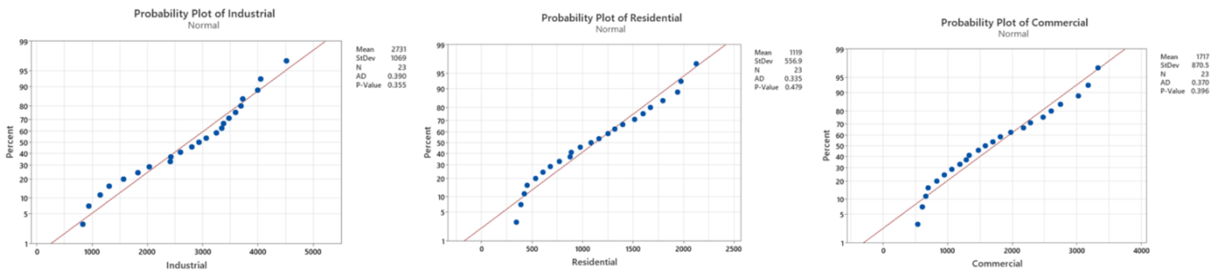

Figure 2: Probability plot of electricity demand for industrial, residential and commercial sectors

The results of Anderson-Darling test show that the *p*-values for sectors of industrial, residential and commercial are 0.355, 0.479 and 0.396 respectively. Since all the *p*-values for all three sectors are greater than 0.05, then it can be concluded that all the data follow a normal distribution. Based on the probability plots of industrial, residential and commercial sectors, all points are approximately lie on the straight line and this also indicates that the data from all sectors follow a normal distribution.

4.3. ARIMA Modeling

4.3.1. Model Identification and Model Selection

The results of ADF test for the electricity demand of all three sectors are shown in Figure 3 below. Based on Figure 3, it can be found that *p*-value = 0.4892 for industrial sector, *p*-value = 0.8545 for residential sector and *p*-value = 0.99 for commercial sector. Since all of the *p*-values are greater than the significance value of 0.05, then the null hypothesis is failed to be rejected and it can be concluded that the electricity demand data of all three sectors are not stationary. Therefore, differencing is required to be conducted.

a) Industrial sector	b) Residential sector	c) Commercial sector
Augmented Dickey-Fuller Test data: indtime Dickey-Fuller = -2.2183, Lag order = 2, p-value = 0.4892 alternative hypothesis: stationary	Augmented Dickey-Fuller Test data: restime Dickey-Fuller = -1.2595, Lag order = 2, p-value = 0.8545 alternative hypothesis: stationary	Augmented Dickey-Fuller Test data: comtime Dickey-Fuller = -0.033312, Lag order = 2, p-value = 0.99 alternative hypothesis: stationary

Figure 3: ADF test for (a) industrial sector, (b) residential sector and (c) commercial sector

a) First differencing	b) Second differencing	c) Third differencing
Augmented Dickey-Fuller Test data: dt1 Dickey-Fuller = -1.9081, Lag order = 1, p-value = 0.6074 alternative hypothesis: stationary	Augmented Dickey-Fuller Test data: dt2 Dickey-Fuller = -2.7171, Lag order = 2, p-value = 0.2992 alternative hypothesis: stationary	Augmented Dickey-Fuller Test data: dt3 Dickey-Fuller = -3.7593, Lag order = 3, p-value = 0.03862 alternative hypothesis: stationary

Figure 4: ADF test of (a) first differencing, (b) second differencing and (c) third differencing for industrial sector

From Figure 4 above, *p*-value = 0.0386 which is less than 0.05 after the third differencing implies that the data is stationary and *d* = 3 for industrial sector. Figure 5 and Figure 6 below also show that *p*-value = 0.01 and *p*-value = 0.01386 for residential and commercial sectors respectively after the first differencing. Thus, the data of residential and commercial sectors are stationary since all the *p*-values are smaller than 0.05 and both of their degree of differencing, *d* = 1.

```
        Augmented Dickey-Fuller Test

data:  dt1
Dickey-Fuller = -5.2064, Lag order = 1, p-value = 0.01
alternative hypothesis: stationary
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Figure 5: ADF test of first differencing for residential electricity demand

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        Augmented Dickey-Fuller Test

data:  dt1
Dickey-Fuller = -4.2693, Lag order = 1, p-value = 0.01386
alternative hypothesis: stationary
```

Figure 6: ADF test of first differencing for commercial electricity demand

The ACF plots and PACF plots of industrial, residential and commercial sectors are generated to identify the parameters *p* and *q*. The ACF plots and PACF plots of sectors of industrial, residential and commercial are shown in Figure 7, Figure 8 and Figure 9 below respectively. From Figure 7, it shows that there are two significant spikes in ACF plot while one significant spike at lag 1 in PACF plot. Based on Figure 8 and Figure 9, there is a significant spike in the ACF plot of sectors of residential and commercial.

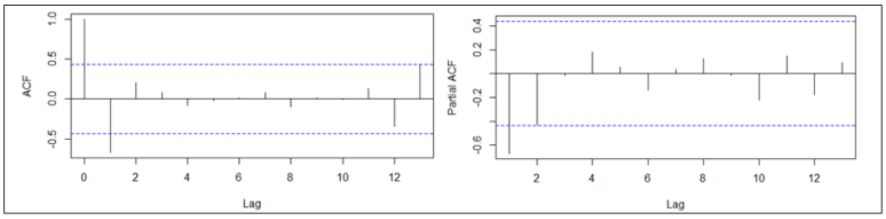

Figure 7: ACF plot and PACF plot of industrial electricity demand after third differencing

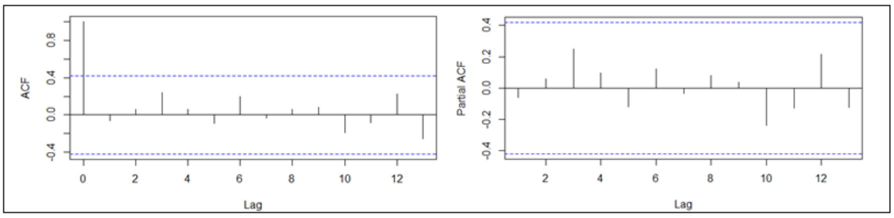

Figure 8: ACF plot and PACF plot of residential electricity demand after first differencing

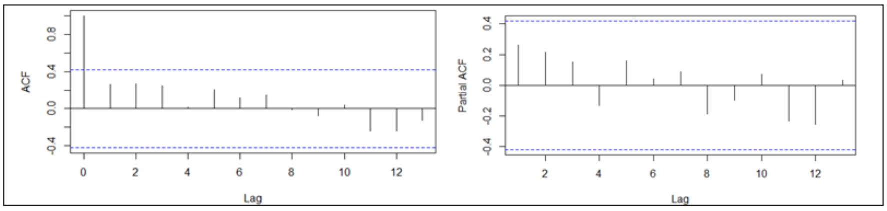

Figure 9: ACF plot and PACF plot of commercial electricity demand after first differencing

The most suitable ARIMA model that will be selected for forecasting is the model with the lowest value of AIC because it will fit the data very well. The possible ARIMA models with their values of AIC for sectors of industrial, residential and commercial are shown in Table 3, Table 4 and Table 5 below respectively.

Table 3: Possible ARIMA models for industrial sector

ARIMA (*p*,*d*,*q*)	AIC
ARIMA (0,3,0)	284.96
ARIMA (1,3,0)	269.84
ARIMA (0,3,1)	268.81
ARIMA (1,3,1)	**259.29**

Table 4: Possible ARIMA models for residential sector

ARIMA (*p*,*d*,*q*)	AIC
ARIMA (0,1,0)	261.63

ARIMA (0,1,1)	251.89
ARIMA (0,1,0) with drift	**223.49**
ARIMA (0,1,1) with drift	225.41

Table 5: Possible ARIMA models for commercial sector

ARIMA (*p*,*d*,*q*)	AIC
ARIMA (0,1,0)	280.97
ARIMA (0,1,1)	267.44
ARIMA (0,1,0) with drift	**241.01**
ARIMA (0,1,1) with drift	241.88

The results above show that the most suitable model for predicting the electricity demand for sectors of industrial, residential and commercial are ARIMA (1,3,1), ARIMA (0,1,0) with drift and ARIMA (0,1,0) with drift respectively since they have the lowest value of AIC. Therefore, the forecasting models fit the data very well.

4.3.2. Diagnostic Checking

The adequacy of the ARIMA (1,3,1) and ARIMA (0,1,0) with drift are checked by using the Ljung-Box test which is a statistical tool to determine the existence of autocorrelation in a time series. For Ljung-Box test, its null hypothesis states that the residuals are independently distributed while the alternative hypothesis states that the residuals are not independently distributed. The null hypothesis will be failed to be rejected if the *p*-value is greater than the significance value of 0.05 and this implies that the forecasting model fits the data very well. The results of Ljung-Box tests for industrial, residential and commercial sectors are shown in Figure 10, Figure 11 and Figure 12 below respectively.

```
        Ljung-Box test

data:  Residuals from ARIMA(1,3,1)
Q* = 4.1615, df = 3, p-value = 0.2445
```

Figure 10: Ljung-Box test for industrial sector

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        Ljung-Box test

data:  Residuals from ARIMA(0,1,0) with drift
Q* = 2.2435, df = 4, p-value = 0.6911
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Figure 11: Ljung-Box test for residential sector

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        Ljung-Box test

data:  Residuals from ARIMA(0,1,0) with drift
Q* = 6.9167, df = 4, p-value = 0.1404
```

Figure 12: Ljung-Box test for commercial sector

From Figure 10 and Figure 11, the results obtained show that the *p*-value for industrial sector is 0.2445 while the *p*-values for residential sector is 0.6911. Since both of the *p*-values of industrial and residential sectors are greater than 0.05, then it can be concluded that the residuals are independently distributed. Hence, ARIMA (1,3,1) and ARIMA (0,1,0) with drift fit the data of sectors of industrial and residential very well. The results from Figure 12 also indicate that the residuals of commercial sector are not autocorrelated since its *p*-value is greater than 0.05 which is 0.1404. Therefore, it can be concluded that the ARIMA (0,1,0) with drift fits the data of commercial sector very well.

4.4. Forecasting and Model Evaluation

With the most adequate ARIMA models, ARIMA (1,3,1) of industrial sector and ARIMA (0,1,0) with drift of residential and commercial sectors which are the best fitted model are selected to predict the future electricity demand from year 2013 until year 2018. The time series plot which displays the comparison between the actual data and the forecasted data of the ARIMA model of sectors of industrial, residential and commercial are shown in Figure 13 below.

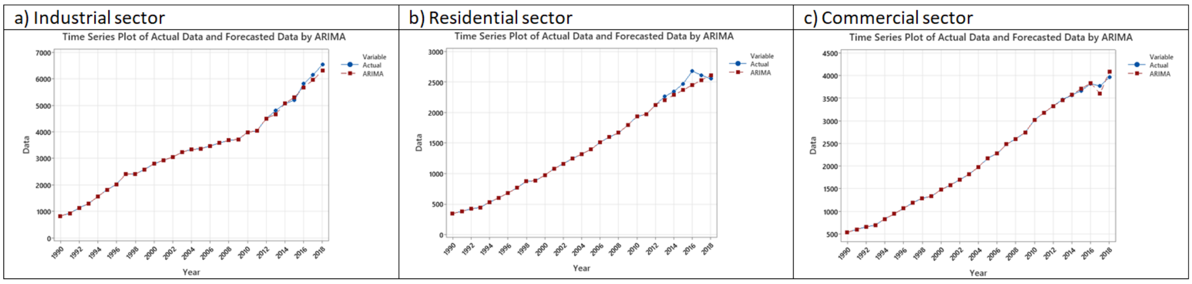

Figure 13: Graph of actual data and forecasted data by (a) ARIMA (1,3,1) for industrial sector, (b) ARIMA (0,1,0) with drift for residential sector and (c) ARIMA (0,1,0) with drift for commercial sector

By observing the graphs in Figure 13, it shows that there is no big difference between the actual data and the forecasted data for all three sectors. The performance of all three forecasting models is evaluated where the MAPE and RMSE are calculated and the results are tabulated as shown in Table 6 below. The forecasting model has higher accuracy if it has lower value of MAPE and RMSE.

Table 6: Measurement of accuracy for ARIMA models

Variable	**ARIMA models**	**MAPE (%)**	**RMSE**
Industrial	ARIMA (1,3,1)	1.5865	149.0555
Residential	ARIMA (0,1,0) with drift	3.1331	114.8089
Commercial	ARIMA (0,1,0) with drift	5.4589	86.8252

Based on Table 6 above, it can be said that all the three ARIMA models for sectors of industrial, residential and commercial have high accuracy in forecasting since their MAPE values are less than 10%.

4.5. Comparison on the Electricity Demands between Sectors

Since the selected ARIMA models are adequate and have high forecast accuracy, then the ARIMA (1,3,1), ARIMA (0,1,0) with drift and ARIMA (0,1,0) with drift are continued to be used in predicting the electricity demand of industrial, residential and commercial sectors respectively from year 2019 until year 2025 for identifying the sector that will consume more electricity in the future. The comparison graph of electricity demand of sectors of industrial, residential and commercial is plotted as shown in Figure 14 below.

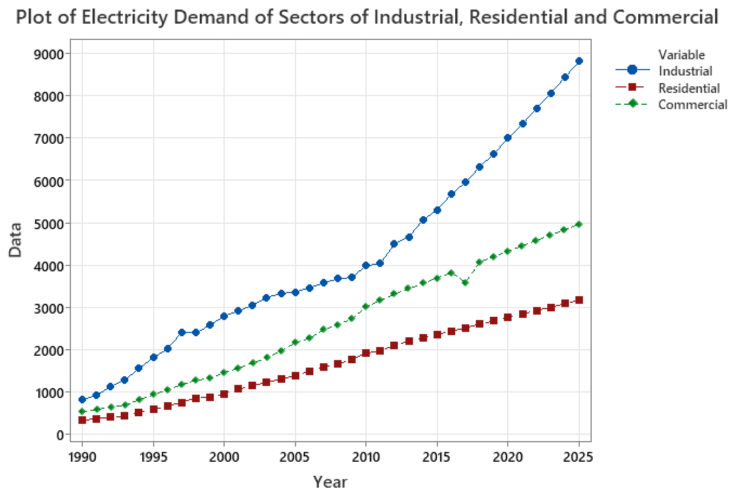

Figure 14: Comparison of electricity demand of sectors of industrial, residential and commercial

According to Figure 14 above, it can be found that all the three sectors show an increasing trend in the demand of electricity. However, there is a slightly decrease in the electricity demand for commercial sector from year 2016 to year 2017. By observing and comparing the trends of demand of electricity, it clearly indicates that the industrial sector will consume more electricity as compared to the residential sector and the commercial sector in the future. Besides, the graph shows that the difference in electricity demand between the residential and commercial sectors are increasing over time. For industrial sector, it can be observed that there is an unstable increment between year 1997 and year 2012 but the increment is at constant rate in the rest of years.

Conclusion

In this study, all the objectives are successfully achieved by using the data of electricity demand of industrial, residential and commercial sectors from year 1990 until year 2018. The most suitable ARIMA model which fits the data the best for forecasting the demand of electricity for each sector is identified. This is carried out by comparing the AIC values of the possible ARIMA models obtained for industrial, residential and commercial sectors.

Furthermore, the performance of the selected ARIMA models is evaluated by comparing the actual values and the predicted values obtained from the forecasting model of sectors of industrial, residential and commercial. The accuracy of the forecasting model is determined by using the MAPE which is an indicator in choosing the best forecasting model for each sector. The lower the value of MAPE, the higher the accuracy of the model in predicting the demand of electricity of every sector. Since all the MAPE values of industrial, residential and commercial sectors are lower than 10% which are 1.5865%, 3.1331% and 5.4589% respectively, then the ARIMA models of each sector have high accuracy in forecasting the electricity demand from year 2019 until year 2025. A comparison in electricity demand between all the three sectors is made by generating a time series plot to identify the sector which will consume the electricity the most in the future.

In conclusion, ARIMA (1,3,1) is suitable to be used in forecasting the future electricity demand for industrial sector while ARIMA (0,1,0) with drift is appropriate to be used for residential and commercial sectors since all of them have high accuracy in forecasting. The results also show that the industrial sector is the sector that will consume more electricity in the future as compared to the sectors of residential and commercial.

This research can be further developed by taking more input data such as more than 50 observations for forecasting the future electricity demand since there is only 29 observations be used in this research. A more accurate forecasting model will be generated if there are more data be considered in the process of generating the model. The future researchers can also consider the factors that affect the increase in the demand of electricity of sectors so that a more reliable forecasting model can be produced.

In addition, it is recommended that the future researchers can improve this study by focusing on the forecasting model which combines the statistical mathematical model and the artificial intelligence-based methods such as Artificial Neural Network (ANN) or hybrid model because combination of two advanced models could produce a better forecasting model with higher accuracy in predicting which would be very beneficial for the development of a country.

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