COMPARISON OF TIME SERIES METHODS FOR ELECTRICITY FORECASTING: A CASE STUDY IN PERLIS

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Abstract: This paper attempts to forecast the monthly electricity demand for the state of Perlis using three time series methods namely Box-Jenkins ARIMA, Multiplicative Holt-Winter Exponential Smoothing and Time Series Regression for the seasonal monthly data spanning from September 1996 to February 2004. The study focused only on the domestic sector because it reveals the seasonal nature of the data. The comparison is based on the forecast error which is evaluated from September 2003 onwards (six month period). This study showed that the data series did not reveal any drastic changes of electricity consumption for the forecasted period. The forecast values followed the same trend for every year, along with seasonal variation in data series. This study also found that Regression with seasonal element was the 'best' method for short term electricity forecasting in Perlis.

Keywords: Box-Jenkins, Exponential Smoothing, Regression, Electricity, Forecast

1. Introduction

Electricity is one of the main sources of energy and it is an important need in our daily lives. As a developing country, the importance of electricity in Malaysia cannot be denied. The use of electricity in all aspects of development makes Malaysia aware of the supply chain so that the energy is always sufficient. Problems will occur if the supply of energy to the customers is not sufficient or exceeds the demand. In Malaysia, the government has privatized all the aspects that are relevant to the supply of electricity. Now, the energy is managed by one of the utility companies which is focusing on the forecasting activities. These activities are very important for electricity consumption and demand especially to fulfill the needs of our country.

Parallel to the problems, forecasting of electricity demand must be done accurately as a readiness to face all the possibilities that will occur. Perlis, a state which is situated in the North of Peninsular Malaysia is experiencing rapid development in the aspects of infrastructure, social and economy. It has about 300 000 residents but the population growth is always rising and it is estimated that the population will rise at an average of 1.70% every five years (JPM, 2000). Perlis also has two main seasons which are the dry and the rainy season. The dry season starts in March and lasts until May while the rainy season is from October until December. Perlis' economy is supported by agriculture, forestry and fishing. Agriculture dominates in terms of land use, manpower and growth domestic product (GDP). The main produces are paddy, sugar cane, rubber, mango, watermelon and teakwood which contributed 32.2% to the state's GDP in 1995. Manufacturing is another major contributor to the state's GDP. Compared to other economic sectors, manufacturing reached a GDP growth rate of 11% for the period of 1995 to 2000. These positive spread out need a lot of support and control in arranging the plan for electricity demand.

Until today, the load forecasting method that has been used in Perlis is just a simple regression analysis with time (t) variable with the help of Microsoft Excel software. But the reality is, the amount of important data must be studied first before any prediction could be done. So, an accurate and correct forecasting of electricity demand should be done for Perlis.

2. Methodology

The data for this study was obtained from interviews and the review of sales reports of monthly electricity consumption for Perlis. There are about 90 series of data, equally to seven years of monthly data starting from September 1996 until February 2004. This study produced a six month period of electricity consumption forecasting starting from September 2003 to February 2004 while 84 series of the data was used to fit the models. The data was obtained for building forecasting models using Box-Jenkins, Exponential Smoothing and time series Regression method. Other than that, the forecast value of electricity consumption by Perlis's electricity provider was also used in the comparison of methods. The comparison of error was made to identify the 'best' method. Only the domestic sector was involved in this study because this sector had a big influence compared to the other sectors (commercial, industry and street lighting). The domestic sector also revealed a seasonal affect on the data pattern (Syariza, 2003). This study had three main objectives; (1) to build a model of short-term forecasting of electricity demand using Box-Jenkins, Exponential Smoothing and Regression method. (2) to produce forecast value and (3) to compare the forecast error among the methods.

3. Time Series Analysis

3.1 Box-Jenkins Method

Box-Jenkins is a set of procedures to identify, adjust and test the ARIMA model with time series data. Forecasting is made after the suitable model is identified. Box-Jenkins approach in time series analysis is an important tool to yield an accurate short-term forecast. ARIMA is flexible and suitable to show the nature of time series widely. This method needs a lot of data. If the data is nonseasonal, about 40 or more observations are needed to build the ARIMA model, while for seasonal data, about 6 to 10 years data are needed (Hanke, Wichern and Reitsch, 2001). Tsay (2000) said that the Box and Jenkins study in 1970 was a stepping stone for the time series analysis where it prepared a systematic time series approach and popularized the ARIMA model. This application was a main key to the expedition of time series methodology. Meanwhile, Chatfield (1998) identified the best forecasting method among univariate, multivariate and intuition methods based on the forecasting objectives, type of data, numbers of forecasted data and others. He found that the univariate analysis namely the ARIMA model was very suitable for short term forecasting. The study by Ghosh and Das (2002) to forecast monthly maximum demand of electricity also used the ARIMA technique and they found that the ARIMA model had long been used by researchers to forecast short term electricity demand.

There are a lot of studies in electricity forecasting using ARIMA Box-Jenkins methods. Studies by Guerrero and Berumen (1998), Calmarza and Fuente (2000), Darbellay and Slama (2000), Meetamehra (1998) and also Ekwue and Short (1990) are based on nonseasonal ARIMA to forecast electricity demand. Some of the studies involved seasonal variation such as studies by Tilak (1991), Haines, Munoz and Van Gelderen (1989), Al-Madfai, Ameen and Ryley (2000) and Barakat et al. (1990) to forecast electricity demand.

Studies by Syariza (2003) showed that the data of electricity demand for the domestic sector for Perlis was seasonal, so this study will converge only for Seasonal ARIMA (SARIMA) method. The SARIMA model, had a clear data pattern where the data fluctuated in the same pattern for every year. For seasonal monthly data, there where correlations between the observations of the same month in different years and it happened between years too. If S was the length of the seasonal period, so S=12 for monthly data and S=4 for quarterly data. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for seasonal data were not zero at the low lag (in that year) and for the multiple seasonal lag (among years). Interpretation of ACF and PACF of seasonal lag was the same with nonseasonal lag. In addition, for nonstationary seasonal series, an additional seasonal difference was often required to completely specify the model.

Seasonal Autoregressive Integrated Moving Average (SARIMA) can be written as SARIMA (p,d,q)(P,D,Q). P indicates the order of the seasonal autoregressive part, D indicates the amount of seasonal differencing and Q indicates the order of moving average for the seasonal moving average part. SARIMA (p,d,q)(P,D,Q) for this study wasre presented by equation (1) with S=12.

$$\begin{aligned} Z_t = {} & \delta + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \dots + \Phi_1 Z_{t-12} + \dots + \Phi_2 Z_{t-24} + \dots + \phi_p Z_{t-p} + a_t - \theta_1 a_{t-1} \\ & - \theta_2 a_{t-2} - \dots - \Theta_1 a_{t-12} - \dots - \Theta_2 a_{t-24} - \dots - \theta_q a_{t-q} \end{aligned} \tag{1}$$

Where;

Z_t = response (dependent) variable at time t

$Z_{t-1}, Z_{t-2}, \dots, Z_{t-p}$ = response variable at time lags *t-1, t-2,……, t-p*.

δ = constant value

a_t = random shock

$\phi_1, \phi_2, \ldots\ldots, \phi_p$ = coefficients of AR(p) model

$\Phi_1, \Phi_2, \ldots\ldots, \Phi_P$ = coefficients of seasonal AR(P) model

$\theta_1, \theta_2, \ldots\ldots, \theta_q$ = coefficient of MA(q) model

$\Theta_1, \Theta_2, \ldots\ldots, \Theta_Q$ = coefficient of seasonal MA(Q) model

Generally, Box-Jenkins approach indicates four main steps namely (1) model identification, (2) model estimation, (3) model testing and (4) forecast.

(1) Model identification: entangled with the identification of a suitable ARIMA model based on ACF and PACF. If the series is nonstationary, differentiation has to be done to get the possible value of p, P, q and Q.
(2) Model estimation: after identifying the model, estimation has to be done to determine the suitable models and choose the best model.
(3) Model testing: before the model is used, it must be tested for reliability. Five criteria of the model must be applied; (1) principle of parsimony, (2) stationary condition, (3) invertibility condition, (4) Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) and (5) the normality and randomness of error.
(4) Forecast: when the suitable model is chosen, forecasting can be done with the assumption that the upcoming data is similar to the past.

3.2 Exponential Smoothing

Exponential Smoothing (ES) is one of the most popular short-term forecasting methods. It can be used with big numbers of monthly or weekly data (Hanke, Wichern and Reitsch, 2001). This method is easy to use and understand. Alfares and Nazeeruddin (2002) said that ES is one of the classical methods used for load forecasting. The approach is first to model the load based on previous data, then to use this model to predict the future load. The Winter's method is one of several ES methods that can analyze seasonal time series directly. This method is based on three smoothing constants for stationary, trend and seasonality. Results of the analysis by Barakat et al. (1990) showed that the unique pattern of energy and demand pertaining to fast growing areas was difficult to analyze and predict by the direct application of the Winter's method. El-Keib et al. (1995) presented a hybrid approach in which ES was augmented with power spectrum analysis and adaptive autoregressive modeling. A new trend removal technique by Infield and Hill (1998) was based on optimal smoothing. This technique has been shown to compare favorably with conventional methods of load forecasting. This method needs the weight α, β and γ selected subjectively or by minimizing a measure of forecast error such as *MSE*. The four equations used in Winter's (multiplicative) smoothing are:

The exponentially smoothed series or level estimate:

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{2}$$

The trend estimate :

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{3}$$

The seasonal estimate :

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s} \tag{4}$$

Forecast p periods into the future :

$$\hat{Y}_{t+p} = (L_t + pT_t)S_{t-s+p} \tag{5}$$

Where:

L_t = new smoothed value or current level estimate

α = smoothing constant for the level

Y_t = new observation or actual value in period t

β = smoothing constant for trend estimate

T_t = trend estimate

γ = smoothing constant for seasonal estimate

S_t = seasonal estimate

p = period to be forecast in the future

s = length of seasonality

$\hat{Y}_{t+p}$ = forecast for p periods into the future

3.3 Regression

Alfares and Nazeeruddin (2002) explained that multiple regression analysis for load forecasting uses the technique of weighted least-squares estimation. Based on this analysis, the statistical relationship between total load and weather conditions as well as the day type influences can be calculated. The regression coefficients are computed by an equally or exponentially weighted least-squares estimation using the defined amount of historical data. Mbamalu and El-Hawary (1993) used the multiple regression model adapted with variables of the influence factors such as time, temperature, light intensity, wind speed, humidity and day type (workday, weekend). Moghram and Rahman (1990) evaluated that model and compared it with other models for a 24-h load forecast. Barakat et al. (1990) used the regression model to fit data and check seasonal variation.

Al-Garni et al. (1997) developed a regression model of electric energy consumption in Eastern Saudi Arabia as a function of weather data, solar radiation, population and per capita gross domestic product. Variable selection was carried out using the stepping-regression method, while model adequacy was evaluated by residual analysis. The non-parametric regression model of Charytoniuk et al. (1998) constructed a probability density function of the load and load effecting factors. The model produces the forecast as a conditional expectation of the load given the time, weather and other explanatory variables, such as the average of past actual loads and the size of the neighborhood.

Alfares and Nazeeruddin (1999) presented a regression-based daily peak load forecasting method for a whole year, including holidays. The precise forecast load throughout a year and the different seasonal factors that affect load differently in different seasons are considered. In the winter season, average wind chill factor is added as an explanatory variable in addition to the explanatory variables used in the summer model. In transitional seasons such as spring and fall, the transformation technique is used. Finally for holidays, a holiday effect load is deducted from the normal load to estimate the actual holiday load better.

The seasonal regression entangled with; (1) variable transformation, (2) dummy variables, (3) variable selection, (4) multicollinearity checking, (5) autocorrelation test and (6) regression diagnostic and residual analysis. Time series seasonal regression has dummy variables in the model. The model is in equation (6):

$$Y_t = \beta_o + \beta_1 t + \beta_2 S_2 + \beta_3 S_3 + \beta_4 S_4 + \beta_5 S_5 + \beta_6 S_6 + \beta_7 S_7 + \beta_8 S_8 + \beta_9 S_9 + \beta_{10} S_{10} + \beta_{11} S_{11} + \beta_{12} S_{12} + \varepsilon_t \quad \textbf{(6)}$$

Where,

Y_t = the variable to be forecast

t = the time index

β_i = coefficients to be estimated

S_i = dummy variable, where;

0 = nonseasonal for the month of the year

1 = seasonal for the month of the year

i = 2,3,4,5,6,7,8,9,10,11,12.

3.4 Comparison of Time Series Methods

There are a lot of studies relevant to the comparison of time series methods. An early study by Newbold and Garger (1973) found that Box-Jenkins was the most effective method for forecasting compared to 100 methods of short-term forecasting and this was proven by Michael and Ibrahim (1975). The study by Everette (1979) found that Box-Jenkins was the best method for short-term and medium-term forecasting. Carbone et al. (1983) explained that Box-Jenkins was the best method among exponential smoothing and Carbone-Longini to the time series data. Study of the comparison method was also done by Brandon, Jarett and Khumawala (1983) on nine extrapolative naïve models and found out that the Box-Jenkins model was more accurate. Other than that, Willis and Northcote-Green (1984) did their load forecast using 14 time series forecasting time series methods. J. Kirkham, Boussabaine and P. Kirkham (2002) in their load forecast study explained that Multiplicative Holt-Winter Exponential Smoothing gave the most accurate forecast which differed from the naïve and Box-Jenkins methods. Alfares and Nazeeruddin (2002) did a survey on nine techniques of load forecast. They found that multiple regression, neural network and expert system are the best three methods among the nine methods.

Error measurement is very important to determine the best forecasting model by comparing the forecasting accuracy for every technique. This study used the error measurement of mean squared error (MSE), root of mean squared error (RMSE), mean absolute deviation (MAD), mean absolute percentage error (MAPE) and mean percentage error (MPE) to evaluate the best forecasting methods.

4 Analysis

Based on the graph of electricity consumption (Figure 1), the data appeared to be an upward trend in the series and showed an increment in electricity consumption for every year. From the autocorrelation analysis, the autocorrelation coefficients at time lag of multiple 12 were significantly different from zero where (r_{12}=0.34 > 0) and (r_{24}=0.09 > 0). So, we can conclude that the electricity consumptions was seasonal on a monthly basis.

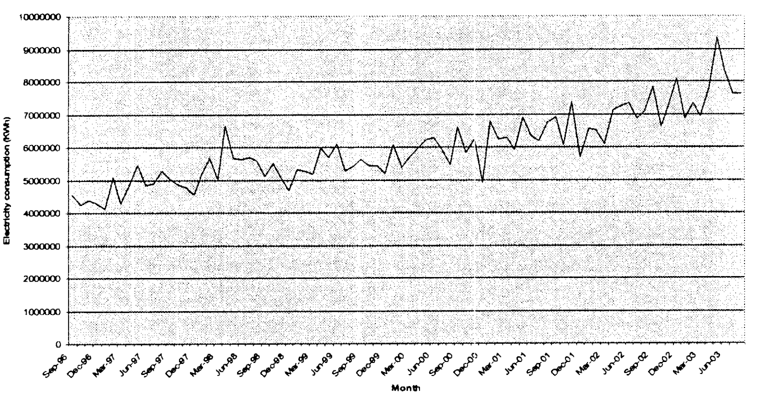

Fig. 1. Electricity consumption for Perlis state starting from September 1996 until August 2003

4.1 Box-Jenkins

The sample autocorrelation function (ACF) observed that the first several autocorrelations were persistently large and trailed off to zero rather slowly (Figure 2). So, the original observation was correct and that this time series was nonstationary and did not vary about a fixed level. The series should be different with one seasonal difference and one regular difference so that the trend could be eliminated and a stationary series created. A plot of the differenced data (Figure 3) appears to vary about a fixed level so no constant term should be include in the model. The ACF and PACF for the difference are displayed in Figure 4 and Figure 5.

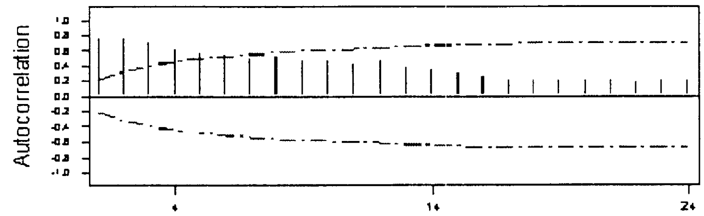

Fig. 2. ACF for electricity consumption for Perlis (September1996 – August 2003)

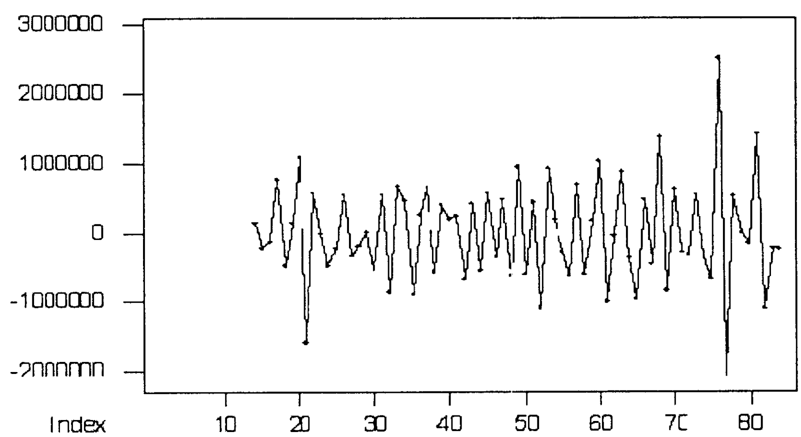

Fig. 3. A plot of the differenced data appears to vary about a fixed level

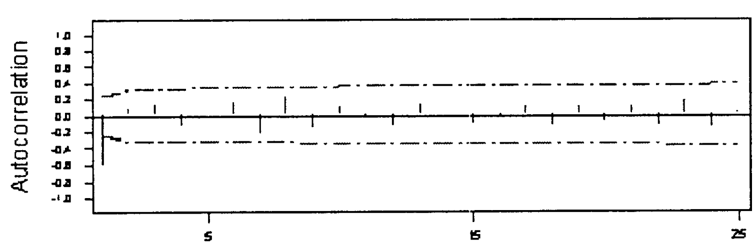

Fig. 4. ACF for electricity consumption for Perlis (September 1996 – August 2003)

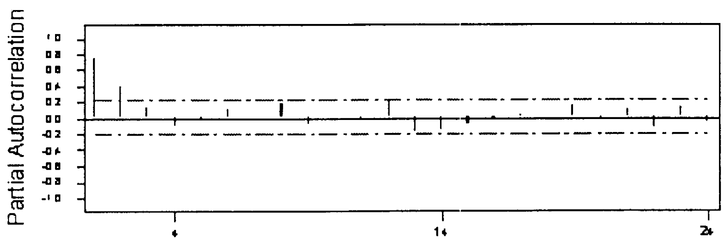

Fig. 5. PACF for electricity consumption for Perlis (September 1996 – August 2003)

The partial autocorrelations seemed to cut off after the first and second lag, consistent with the AR(1) and AR(2) and in the autocorrelations, there was a significant partial autocorrelation at the first lag. So, there were 11 models that were fixed to the ARIMA model.

- ARIMA (1,1,0)(0,1,0)
- ARIMA (2,1,0)(0,1,0)
- ARIMA (3,1,0)(0,1,0)
- ARIMA (0,1,1)(0,1,0)
- ARIMA (1,1,1)(0,1,0)
- ARIMA (2,1,1)(0,1,0)
- ARIMA (3,1,1)(0,1,0)
- ARIMA (0,1,2)(0,1,0)
- ARIMA (1,1,2)(0,1,0)
- ARIMA (2,1,2)(0,1,0)
- ARIMA (3,1,2)(0,1,0)

These models allow for no seasonal autoregressive or moving average coefficients. A plot of the series after differencing showed it varied about zero; so supposedly no constant term was included in the models. Box-Pierce test should be done to determine the appropriate model. Based on Box-Pierce test, we found that SARIMA(1,1,0)(0,1,0) was not significant. SARIMA(0,1,2)(0,1,0) was the best model based on error and AIC and BIC value. This model also fulfilled the stationary and invertability condition where the value of MA coefficient (1.0879 + (0.3157) = 0.7722) < 1. This model also fulfilled the normality and randomness of error assumption based on the plot of residuals for ACF and PACF. So, SARIMA(0,1,2)(0,1,0) was very significant to the seasonal ARIMA Box-Jenkins and the model's equation is in equation (7).

$$Z_t = 1.0879Z_{t-1} - 0.3157Z_{t-2} \tag{7}$$

4.2 Exponential Smoothing

Winter's Multiplicative was used to analyze the series based on the existing seasonal pattern and the increment of data value. From the analysis, α=0.131 was used to smooth the data to create a level estimate. The smoothing constant, β=0.097 was used to create a smoothed estimate of trend. The smoothing constant, γ =0.001 was used to create a smoothed estimate of the seasonal component in the data. The graph of the forecast value is shown in Figure 4.

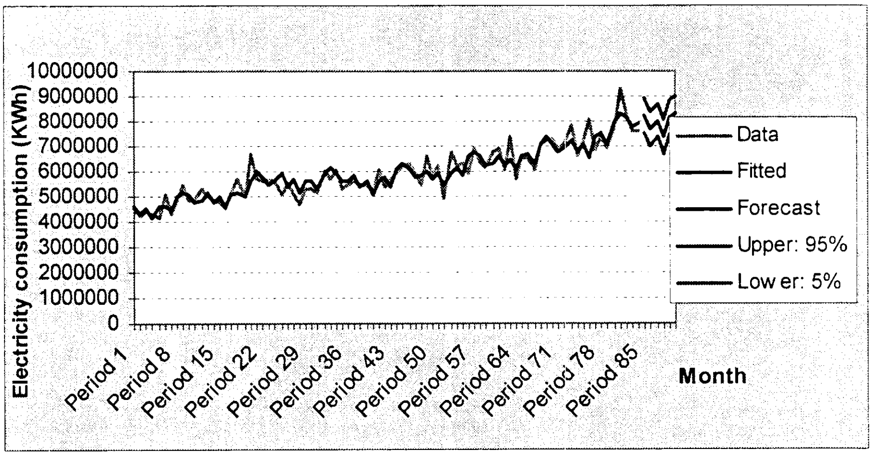

Fig. 4. Electricity consumption (September 1995-August 2002) and the forecast value using Winter's Multiplicative.

The four equations of Winter's Multiplicative are :

$$L_t = (0.131)\frac{Y_t}{S_{t-12}} + (1 - 0.869)(L_{t-1} + T_{t-1}) \tag{8}$$

$$T_t = (0.097)(L_t - L_{t-1}) + (0.903)T_{t-1} \tag{9}$$

$$S_t = (0.001)\frac{Y_t}{L_t} + (0.999)S_{t-12} \tag{10}$$

$$\hat{Y}_{t+p} = (L_t + pT_t)S_{t-12+p} \tag{11}$$

For the parameter values considered, the Winter's Multiplicative method was better than Additive in terms of minimizing forecast error (based on only RMSE and MAPE) as in Table 1.

Table 1. Forecast error for Winter's Multiplicative and Winter's Additive

	Winter's Multiplicative	Winter's Additive
RMSE	398747	399026
MAD	296024	293900
MAPE	4.89%	4.9%

4.3 Time Series Regression

The seasonality model is handled by using dummy variables in the regression function. The dummy variables are S_2, S_3, S_4, S_5, S_6, S_7, S_8, S_9, S_{10}, S_{11} and S_{12}, representing February until December. The financial year of the electricity provider of Perlis is from September until August. A normality test had been done on the model and it was found that all the variables were normal and the model was significant. But, from the regression analysis, some of the dummy variable was not significant based on the p-value. The seasonal regression model is

$$Y_t = 4585028 + 37084.476t - 483951S_2 - 233995S_3 - 726354S_4 - 263370S_5 - 207847S_6 - 543314S_7 + 105095.0S_8 + 391431.9S_9 + 122650.1S_{10} - 258039S_{11} - 190810S_{12} \tag{12}$$

Table 2. The analysis of seasonal regression model (1)

Criterion	Value
R squared (R^2)	0.848
Adjusted R squared (R_a^2)	0.822
Standard error	443603.823
Significant value	0.000

Then the regression analysis of forward selection, backward elimination and stepwise regression were done to determine the number of independent variables to be included in the new model. The analysis showed that five independent variables should be in the new model to make the model significant. The new model is

$$Y_t = 4468274 + 37106.899t - 368050S_2 - 610497S_4 - 427525S_7 + 507176.5S_9 \qquad (13)$$

Model (13) wass better than model (11) based on the criteria in Table 2 and Table 3. Model (13) was free from multicolinearity problem based on the VIF value. Using a 0.01 level of significance for k=5 and n=80 independent variables, one obtain d_U = 1.51 and d_L = 1.77. The Durbin-Watson (2.005) falls above d_U = 1.51, so the null hypothesis Ho: $\rho=0$ cannot be rejected, and it is concluded that the autocorrelation problems do not exist.

Table 3. The analysis of seasonal regression model (13)

Criterion	Value
R squared (R^2)	0.833
Adjusted R squared (R_a^2)	0.822
Standard error	442829.625
Significant value	0.000
Durbin-Watson	2.005
VIF (all variables)	less than 1.1

The normal probability plot of residual and the histogram of standard residual show that the residual of the model are normally scattered and free from heterocedasticity problems. From all the tests we can conclude that model (13) is the most suitable model for seasonal regression method. So, the fitted seasonal regression model is model (13) where S_2 is equal to the month of October, S_4 is equal to the month of December, S_7 is equal to the month of March and S_9 is equal to the month of May. We can see that seasonal has a lot of influence on the result. We know that October and December are in the rainy season and that is why the coefficient values is negative and electricity demand is predicted to be low on those month. While March and May are in the dry season but the coefficient values are negative and positive. The positive value means the electricity usage will increase on every May. Supposed in the March the usage will be increase due to warm season. Maybe other factors such as wind speed, electricity appliances or non-festive season will distract the demand forecast. Table 4 shows the real data and the forecast value using all the methods that have been discussed.

Table 4. The real data and the forecast value using all the methods that has been discussed for domestic sector for September 2003-Februari 2004.

Time	Real data	Forecast data (Perlis's electricity provider)	Box-Jenkins	Winter's Multiplicative	Seasonal Regression
Sept 2003	7,396,111	8,000,000	7,396,111	8,236,637.47	8,129,536.915
Oct 2003	7,749,495	6,900,000	7,749,495	7,690,738.209	7,659,467.314
Nov 2003	7,076,340	7,500,000	7,076,340	8,032,568.841	7,696,574.213
Dec 2003	8,064,278	8,100,000	8,064,278	7,398,889.536	7,733,681.112
Jan 2004	8,309,195	7,150,000	8,309,195	8,146,664.166	7,770,788.011
Feb 2004	7,660,784	7,550,000	7,660,784	8,327,620.527	7,439,844.91

4.4 'Best' Model Determination

Table 5 shows the measurement of forecasting error for every method. From Table 5, we know that the method with the smallest MSE, RMSE and standard error value is regression while the smallest MAD and MAPE go to the method that has been implemented by the Perlis electricity provider. The Box-Jenkins method has the lowest MPE value. Other that that, based on the rank seasonal regression give a better result. From the comparison of forecasting error and the total of rank we can conclude that seasonal regression is the 'best' method among the others. Although the forecast value used by Perlis has one of the criteria of the comparison of error, from this analysis we can conclude that the forecast is not very accurate. From this result, we could suggest that Perlis have to do something to the forecast so that electricity prediction would be more accurate. So Perlis could avoid any loss of energy or any investment. From this result also, Perlis could make a better plan of their electricity demand for the future and maybe any method that is suggested in this study could be an alternative to provide a better result.

Table 5. The measurement of forecasting error

	Forecast data (Perlis's electricity provider)	Box-Jenkins	Winter's Multiplicative	Seasonal Regression
MSE	4.37×10^{11} (3)	8.81×10^{11} (4)	4.23×10^{11} (2)	2.30×10^{11} (1)
RMSE	809798.38 (3)	938414.10 (4)	650402.41 (2)	479357.123 (1)
MAD	176033.83 (1)	825427.83 (4)	558377.988 (3)	422271.80 (2)
MPE	0.0196 (2)	-0.0805 (4)	-0.0377 (3)	-0.0068 (1)
MAPE	1.96% (1)	10.9% (4)	7.42% (3)	5.55% (2)
Standard Error	809798.38 (4)	1149317.9 (1)	796577.011 (3)	587090.177 (2)
Total	**14**	**21**	**16**	**9**

( ) – rank

5 Conclusion

Based on the result of this study, first we can conclude that electricity consumption in Perlis really has a seasonal pattern based on the plot of ACF and PACF where the partial autocorrelations seemed to cut off at lag 12. So, we can use the seasonal forecasting method to predict the short-term demand. Second, although Box-Jenkins is one of the famous methods for short-term electricity forecasting as mentioned in the literatures, the result of this method shows that it is not very suitable for Perlis and maybe other factors would have to be considered for this method. Winter's Multiplicative method is also a famous method, very easy to use and easy to account for seasonality when data have a seasonal pattern but still cannot fulfilled the forecast accuracy of Perlis. Third, seasonal regression which has dummy variables is the 'best' method among the other methods based on the forecast error measurement. It can detect which month gave the seasonal influence and gave more accurate results. Fourth, we found that the Perlis electricity demand forecast was not very accurate compared to the other three methods that have been used and maybe Perlis should introduce an alternative method such as seasonal regression (as proven in this study) to be their new tool to forecast electricity demand in Perlis. This study does not take into account of the influence factors of electricity demand such as factors of economy, social, temperature, humidity, wind speed and others. Maybe for the next research, the influence factors could be taken into account using bivariate or multivariate analysis.

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