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# SHORT-TERM ELECTRICITY LOAD FORECASTING

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**Abstract:** The purpose of this study was to develop the best model for forecasting Malaysia load demand. In this study, a half-hourly electricity load demand of Malaysia for one year, from September 01, 2005 until August 31, 2006 measured in Megawatt (MW) was used. The double-seasonal ARIMA model was considered due to the existence of two seasonal cycles in the load data. Analysis was done using SAS package. The best model was selected based on the mean absolute percentage error (MAPE), autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. The ARIMA$(0,1,1)(0,1,1)^{48}(0,1,1)^{336}$ with in-sample MAPE of 0.9906% was the best model. Comparing the one-step and *k*-step ahead out of sample forecasts performance, the MAPE for the one-step ahead out-sample forecasts from any horizon were all less than 1% . It can be concluded that the one-step ahead out-sample forecasts were more accurate. There was a reduction in MAPE percentages for all lead time horizons considered, ranging 89% to 96%. Furthermore, a time-series plot of out-samples of actual load data, *k*-step ahead and one-step ahead out-sample forecasts showed that one-step ahead out-sample forecasts followed the actual load data more closely than *k*-step ahead out-sample forecasts. The ACF and PACF plots must be considered in proving the best model for load demand and one-step ahead out-sample forecasts in forecasting load, especially in Malaysia load data.

KEYWORDS: Load forecasting, double seasonal ARIMA model, ACF and PACF plots, one-step ahead forecasts and *k*-step ahead forecasts

## Introduction

Load demand prediction is important for electric power planning and must be assessed with the greatest precision of any model. The utility power company needs forecasts for different time horizons in order to ensure uninterrupted energy supply to customers (Tsekouras *et al*., 2007). Load forecasting can be broadly classified into four main categories which are long-term forecasts, intermediate-term forecasts, short-term forecasts and very short-term forecasts. The four main categories of time horizons have been studied extensively. Long-term forecasts are investigated by Jia *et al*. (2001), Kermanshashi and Iwamiya (2002) and Carpinteiro *et al*. (2007); intermediate-term forecasts by Amjady and Keynia (2008), Elkateb *et al*. (1998) and Mirasgedis et al. (2006); short-term forecasts by Beccali *et al*. (2007), Cancelo *et al.* (2008) and Darbellay and Slama (2000); and very short-term forecasts by Taylor (2008) and Taylor *et al.* (2006). Several forecasting methods with varying degrees of success have been implemented for load forecasting including multiple linear regression (Amjady and Keynia, 2008; Mirasgedis *et al*., 2006), nonlinear multivariable regression model (Al Rashidi and El-Naggar, 2010; Tsekouras *et al.,* 2007), artificial neural network (Al-Saba and El-Amin, 1999; Ghiassi *et al*., 2006) and Box-Jenkins ARIMA model (Al-Saba and El-Amin, 1999; Ghiassi *et al.,* 2006).

The study investigates methods that are appropriate for forecasting short-term Malaysia load demand. Due to the presence of a double seasonal pattern in load-demand data which are daily and weekly seasonal, a double-seasonal multiplicative ARIMA model is proposed. The

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multiplicative double-seasonal ARIMA model has often been used for univariate forecasting intraday-load time series (Cancelo *at al.,* 2008; Darbelly and Slama, 2000; Taylor, 2008; Taylor, 2006; Taylor *et al*., 2006). The double-seasonal ARIMA with polynomial of order one has been studied by Cancelo *et al*. (2008) and Darbelly and Slama (2000). Taylor *et al.* (2006) and Taylor (2006) has utilised the double-seasonal ARIMA with polynomials of order two and order three. Taylor (2008) has also utilised the double-seasonal ARIMA with polynomial of order three and increased the order to five. However, for the reason of parsimony he deferred the consideration of higher-order models. Basically, when one considers the order of polynomial, for example if one considers the polynomial of order , all lags from lag one to lag  are being included. However, by looking at the sample autocorrelations and the partial autocorrelations, there may exist insignificance lags in between lags. It may also indicate the existence of significance lags after lag  where those lags were not considered in the model earlier. Therefore in this study focus is on the subsets of a double-seasonal ARIMA model in order to include all the significance lags in our tentative model. It is hoped that one-step ahead forecasts of short-term load demand in Malaysia obtained from a double-seasonal ARIMA model with improvement of forecasting accuracy will be shown.

This article is an extension of our previous work as reported in Mohamed *et al.* (2010a & 2010b). In those articles, a double-seasonal ARIMA model was developed and it was shown that it was appropriate to forecast short-term load demand in Malaysia. In the current study, further justification is given that our model is the best model by using autocorrelation and partial autocorrelation functions. This article is organised as follows. First the Box-Jenkins double-seasonal ARIMA model is presented. This is followed by a discussion on the detail results of the selected model. Our findings are then concluded based on the selected forecasting evaluation method for this study, which is the MAPE.

**Box-Jenkins Double-Seasonal Arima Model**

A double-seasonal multiplicative ARIMA model is presented due to the presence of double-seasonal patterns in short-term load demand data which are daily seasonal and weekly seasonal. The multiplicative double-seasonal ARIMA model (Box *et al*., 2008) is:

$$\phi_p(B)\Phi_{p_1}(B^{S_1})\Pi_{p_1}(B^{S_2})(1-B)^d(1-B^{S_1})^{D_1}(1-B^{S_2})^{D_2}\dot{Z}_t = \theta_q(B)\Theta_{Q_1}(B^{S_1})\Psi_{Q_2}(B^{S_2})a_t \quad (1)$$

where $\dot{Z}_t$ is a stationary load demand in period $t$; $B$ is a backward shift operator; $\phi_p(B)$ and $\theta_q(B)$ are regular autoregressive and moving-average polynomials of orders $p$ and $q$ respectively ; $\Phi_{p_1}(B^{S_1})$, $\Pi_{p_1}(B^{S_2})$, $\Theta_{Q_1}(B^{S_1})$ and $\Psi_{Q_2}(B^{S_2})$ are autoregressive and moving-average polynomials of orders $P_1$, $P_2$, $Q_1$ and $Q_2$ respectively; $s_1$ and $s_2$ are the seasonal periods; $d$, $D_1$ and $D_2$ are the orders of integration; $a_t$ is a white-noise process with zero mean and constant variance. The seasonal cycles, $s_1$ and $s_2$ are selected according to the type of load data series. The daily and weekly seasonality are denoted as $s_1$ and $s_2$ respectively. Generally, for hourly load, $s_1 = 24$ and $s_2 = 168$ (Taylor et al., 2006), for half-hourly load, $s_1 = 48$ and $s_2 = 336$ (Darbelly and Slama, 2000; Taylor *et al*., 2006), while for minute-by-minute load series, $s_1 = 1440$ and $s_2 = 10080$ (Taylor, 2008). The multiplicative double-seasonal ARIMA model can be expressed as $ARIMA(p,d,q)(P_1,D_1,Q_1)^{S_1}(P_2,D_2,Q_2)^{S_2}$.

The modeling procedure of Box-Jenkins double-seasonal ARIMA Model involves an iterative five-stage process as follows:

(i) Preparation of data including transformations and differencing
(ii) Identification of the potential models by looking at the sample autocorrelations and the partial autocorrelations
(iii) Estimation of the unknown parameters by some optimisation methods
(iv) Checking the adequacy of fitted model by performing normal probability plot, ACF and PACF on model residuals
(v) Forecast future outcomes based on the known data.

In this study, mean absolute percentage error (MAPE) is considered as the standard measurement to examine the accuracy of the prediction model. This measure is most commonly used in the literature to evaluate forecasting performances. MAPE is defined as (Dong and Pedrycz, 2008):

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{Z_i - \hat{Z}_i}{Z_i} \right|}{n} \times 100 \qquad (2)$$

where and are the actual values and the predicted values respectively, while $n$ is the number of predicted values.

The data used is one year half-hourly load demand measured in Megawatt (MW) from September 01, 2005 to August 31, 2006. They are gathered from Malaysian electricity utility company, Tenaga Nasional Berhad (TNB), Malaysia.

## Results

The data was partitioned into two parts. The first part from September 01, 2005 to July 31, 2006 was used for training and the second part from August 01, 2006 to August 31, 2006 was used for testing. Malaysia load data is non-stationary data which is clearly shown in Figure 1. The presence of seasonal patterns can clearly be seen in the ACF's and PACF's plots in Figure 2 and hence the data need to be differenced. After non-seasonal differencing ($d=1$) and daily seasonal differencing ($D_1 = 1, s_1 = 48$), the ACF and PACF are plotted in Figure 3. The plot indicates the presence of another seasonal pattern which is weekly seasonality with length 336. Figure 4 shows load demand series after non-seasonal differencing ($d=1$), daily seasonal differencing ($D_1 = 1, s_1 = 48$) and weekly seasonal differencing ($D_2 = 1, s_2 = 336$). It is clear from Figure 4 that load demand series is a stationary series after seasonal and non-seasonal differencing. The ACF and PACF of the stationary load demand series are plotted in Figures 5 and 6 respectively.

For the purpose of double-seasonal ARIMA model analysis, a program in Statistical Analysis System, SAS was written. The program had to be specially written since commands for such analysis are not readily available in statistical packages such as S-plus, MINITAB, MATLAB, SPSS, as well as SAS itself. The integer values $p$, $q$, $P_1$, $P_2$, $Q_1$ and $Q_2$ are identified by looking at the sample autocorrelations and the partial autocorrelations of the differenced series. The AR and MA coefficients in a double-seasonal ARIMA are estimated by the least-squares method. Finally, model validation is made through performing ACF, PACF and normal probability plot of the residuals to determine whether the residuals are white noise and normally distributed. The Akaike's information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC) are used for model selection criteria. Three models are deemed appropriate for the current data.

The first selected model is as follows:

$ARIMA([1,2,3,5,11,16,17,18,19,20,23,28,29,34,38,46,47],1,1)(0,1,1)^{48}(0,1,1)^{336}$

All the parameters are significant at alpha 0.1 significance level with white-noise residuals based on Ljung-Box statistic until lag 48. This model gives 10 extreme residual values. In terms of the magnitude of the residuals, these are at 11633th, 11632th, 6305th, 7265th, 3041th, 2415th, 10721th, 12659th, 11680th and 11681th observations. The model residual however does not satisfy the Normal Distribution because of the presence of outliers in the data. The AIC and the SBC of this model are 194170.1 and 194330.9 respectively.

The second selected model is as follows:

$ARIMA(0,1[1,2,3,5,11,16,17,18,19,20,21,22,24,28,29,31,34,36,41,47])(0,1,1)^{48}(0,1,1)^{336}$

In this model we also found that all the parameters are significant at alpha 0.05 significance level with white-noise residuals based on Ljung-Box $Q^*$ statistic until lag 48. This model also gives 10 extreme residual values. In terms of the magnitude of the residuals, these are at 11633th, 11632th, 6305th, 7265th, 3041th, 7456th, 11651th, 2415th, 11681th and 12659th observations. Similar to the first model, this second model residual does not

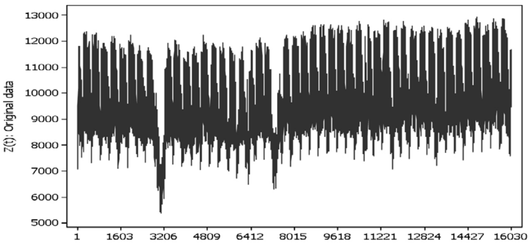


Figure 1: A half-hourly load from September 1, 2005 to July 31, 2006.

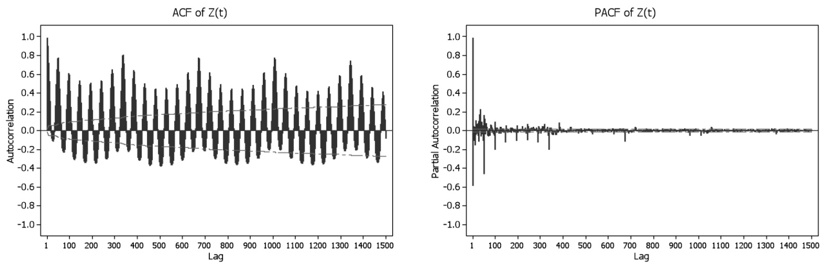


Figure 2: The ACF and PACF of $Z_t$.

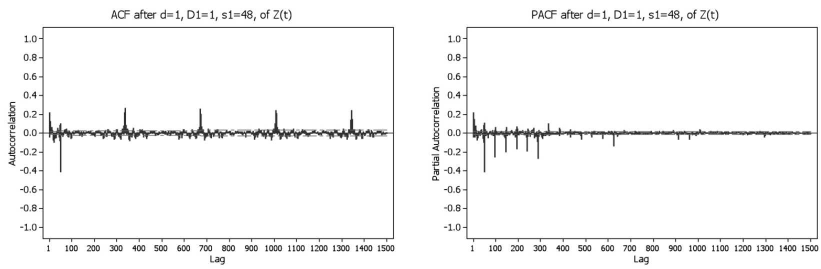


Figure 3: The ACF and PACF of $Z_t$ after $d=1$, $D_1 = 1$, $s_1 = 48$.

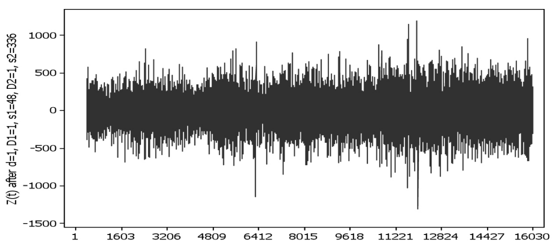


Figure 4: $Z_t$ after $d=1$, $D_1 = 1$, $s_1 = 48$, $D_2 = 1$ and $s_2 = 336$.

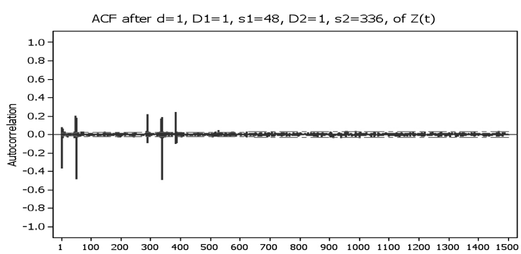


Figure 5: The ACF of $Z_t$ after $d=1$, $D_1 = 1$, $s_1 = 48$, $D_2 = 1$ and $s_2 = 336$.

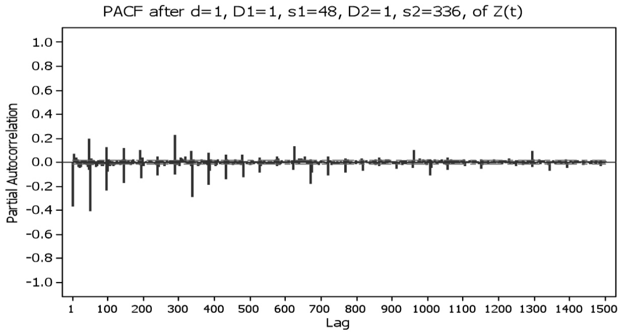


Figure 6: The PACF of after $d=1$, $D_1 = 1$, $s_1 = 48$, $D_2 = 1$ and $s_2 = 336$.

satisfy the Normal Distribution. The AIC and the SBC of this model are 194259.2 and 194435.3 respectively.

The third selected model is as follows:

$ARIMA(0,1,1)(0,1,1)^{48}(0,1,1)^{336}$

For this model, all the parameters are significant at alpha 0.05 significance level. However, based on Ljung-Box $Q^*$ statistic, the residuals are not white noise. This model also gives 10 extreme residual values. In terms of the magnitude of the residuals, these are at 11633th, 11632th, 6305th, 7265th, 2945th, 2963th, 2415th, 11652th, 11654th and 11651th observations. Similar to the first and second models, the third model residual does not satisfy the Normal Distribution. The AIC and the SBC of this model are 195054 and 195077 respectively.

## Discussion

From the PACF plot as illustrated in Figure 6, there is a fixed pattern with three moving average parameters which are (MA1,1), (MA2,1) and (MA3,1) that need to be included in our model. The estimate values of the parameters of all the three models are greater than 0.2, which are highly significant at alpha less than 0.0001 significance level. For Model 1, although all the parameters for autoregressive as listed in Table 1 are significant, the estimate values of these parameters are less than ±0.1 with exception of (AR1,1) and (AR1,2). Similar to Model 2, all the parameters for moving average are significant. However except for (MA1,2), the estimate values of all these parameters are less than ±0.1. The in-sample MAPEs and the out-sample MAPEs of four time horizons for these three models are summarized in Table 1.

Despite the fact that the third model is the simplest among all, it outperforms the first two models. Based on the performances the concept of parsimony is supported where the simplest model is the best model. For the current study, Model 3 can be expressed as follows:

$$(1-B)(1-B^{48})(1-B^{336})Z_t = (1-0.27184B)(1-0.76592B^{48})(1-0.85019B^{336})a_t \quad (3)$$

$$Z_t = Z_{t-1} + Z_{t-48} - Z_{t-49} + Z_{t-336} - Z_{t-337} - Z_{t-384} + Z_{t-385} + a_t - 0.27184a_{t-1} - 0.76592a_{t-48} + 0.20821a_{t-49} - 0.85019a_{t-336} + 0.23112a_{t-337} + 0.65118a_{t-384} - 0.17702a_{t-385} \quad (4)$$

Table 1: The MAPE of in-sample and out-sample forecasts of the three models.

| | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| In-sample forecast | 0.9680 | 0.9711 | 0.9906 |
| Out-sample one-week forecast | 10.1892 | 9.5818 | 8.8841 |
| Out-sample two- week forecasts | 15.8199 | 14.9531 | 13.9414 |
| Out-sample three-weeks forecasts | 21.6847 | 20.5402 | 19.1838 |
| Out-sample one- month forecast | 29.4448 | 27.8249 | 25.8641 |

**Autocorrelation Function and Partial Autocorrelation Function**

The autocorrelation function, ACF and partial autocorrelation function, PACF plots are also presented by using R package to support our suggestion. Based on the third model, *ARIMA*$(0,1,1)(0,1,1)^{48}$ $(0,1,1)^{336}$ there are three estimate parameters which are $\theta_1$ = 0.27184, $\theta_{48}$ = 0.76592 and $\theta_{336}$ = 0.85019 where all of these three estimate parameters are positive. To investigate the patterns of ACF and PACF graphically we propose eight combinations of these three estimates are proposed and the results are presented in Table 2.

By looking at ACF and PACF plots for all eight graphs; Figures 7, 8, 9, 10, 11, 12, 13 and 14, it was found that the Figure 7 where all of three estimate parameters are positive gives an exact pattern such as ACF and PACF of the stationary load demand series, refer to Figures 5 and 6 . Hence, the ACF and PACF plots support our suggestion that the third model is the best model in this study.

Table 2: The combination of three estimates.

| Figure | Combination | $MA(1)(1)^{48}(1)^{336}$ |
|---|---|---|
| Figure 7 | $\theta_1 = 0.27184$, $\theta_{48} = 0.76592$, $\theta_{336} = 0.85019$. | $\dot{Z}_t = a_t - 0.27184a_{t-1} - 0.76592a_{t-48} + 0.20821a_{t-49} - 0.85019a_{t-336} + 0.23112a_{t-337} + 0.65118a_{t-384} - 0.17702a_{t-385}$ |
| Figure 8 | $\theta_1 = 0.27184$, $\theta_{48} = 0.76592$, $\theta_{336} = -0.85019$. | $\dot{Z}_t = a_t - 0.27184a_{t-1} - 0.76592a_{t-48} + 0.20821a_{t-49} + 0.85019a_{t-336} - 0.23112a_{t-337} - 0.65118a_{t-384} + 0.17702a_{t-385}$ |
| Figure 9 | $\theta_1 = 0.27184$, $\theta_{48} = -0.76592$, $\theta_{336} = 0.85019$. | $\dot{Z}_t = a_t - 0.27184a_{t-1} + 0.76592a_{t-48} - 0.20821a_{t-49} - 0.85019a_{t-336} + 0.23112a_{t-337} - 0.65118a_{t-384} + 0.17702a_{t-385}$ |
| Figure 10 | $\theta_1 = 0.27184$, $\theta_{48} = -0.76592$, $\theta_{336} = -0.85019$. | $\dot{Z}_t = a_t - 0.27184a_{t-1} + 0.76592a_{t-48} - 0.20821a_{t-49} + 0.85019a_{t-336} - 0.23112a_{t-337} + 0.65118a_{t-384} - 0.17702a_{t-385}$ |
| Figure 11 | $\theta_1 = -0.27184$, $\theta_{48} = 0.76592$, $\theta_{336} = 0.85019$. | $\dot{Z}_t = a_t + 0.27184a_{t-1} - 0.76592a_{t-48} - 0.20821a_{t-49} - 0.85019a_{t-336} - 0.23112a_{t-337} + 0.65118a_{t-384} + 0.17702a_{t-385}$ |
| Figure 12 | $\theta_1 = -0.27184$, $\theta_{48} = 0.76592$, $\theta_{336} = -0.85019$. | $\dot{Z}_t = a_t + 0.27184a_{t-1} - 0.76592a_{t-48} - 0.20821a_{t-49} + 0.85019a_{t-336} + 0.23112a_{t-337} - 0.65118a_{t-384} - 0.17702a_{t-385}$ |
| Figure 13 | $\theta_1 = -0.27184$, $\theta_{48} = -0.76592$, $\theta_{336} = 0.85019$. | $\dot{Z}_t = a_t + 0.27184a_{t-1} + 0.76592a_{t-48} + 0.20821a_{t-49} - 0.85019a_{t-336} - 0.23112a_{t-337} - 0.65118a_{t-384} - 0.17702a_{t-385}$ |
| Figure 14 | $\theta_1 = -0.27184$, $\theta_{48} = -0.76592$, $\theta_{336} = -0.85019$. | $\dot{Z}_t = a_t + 0.27184a_{t-1} + 0.76592a_{t-48} + 0.20821a_{t-49} + 0.85019a_{t-336} + 0.23112a_{t-337} + 0.65118a_{t-384} + 0.17702a_{t-385}$ |

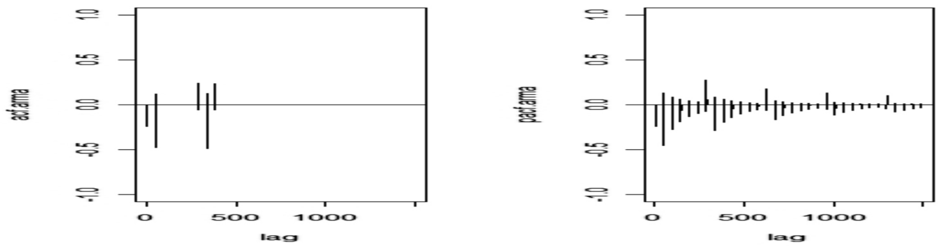


Figure 7 : The ACF and PACF plots with $\theta_1 = 0.27184$, $\theta_{48} = 0.76592$ and $\theta_{336} = 0.85019$.

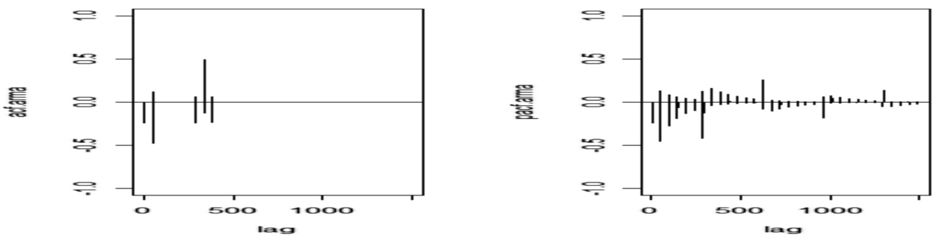


Figure 8: The ACF and PACF plots with $\theta_1 = 0.27184$, $\theta_{48} = 0.76592$ and $\theta_{336} = -0.85019$.

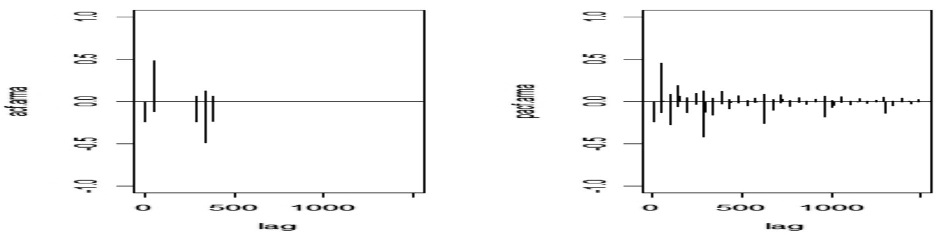


Figure 9: The ACF and PACF plots with $\theta_1 = 0.27184$, $\theta_{48} = -0.76592$ and $\theta_{336} = 0.85019$.

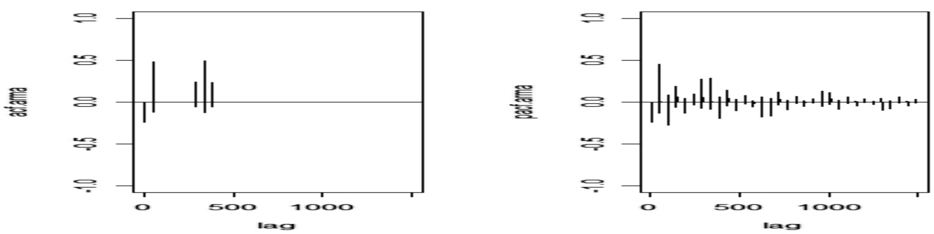


Figure 10: The ACF and PACF plots with $\theta_1 = 0.27184$, $\theta_{48} = -0.76592$ and $\theta_{336} = -0.85019$.

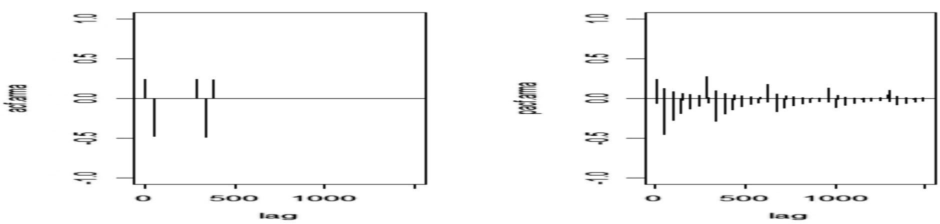


Figure 11: The ACF and PACF plots with $\theta_1 = -0.27184$, $\theta_{48} = 0.76592$ and $\theta_{336} = 0.85019$.

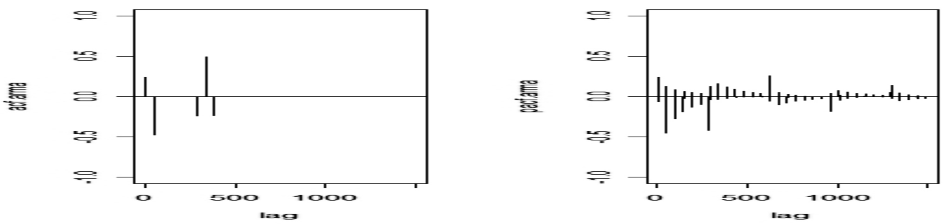


Figure 12: The ACF and PACF plots with $\theta_1 = -0.27184$, $\theta_{48} = 0.76592$ and $\theta_{336} = -0.85019$.

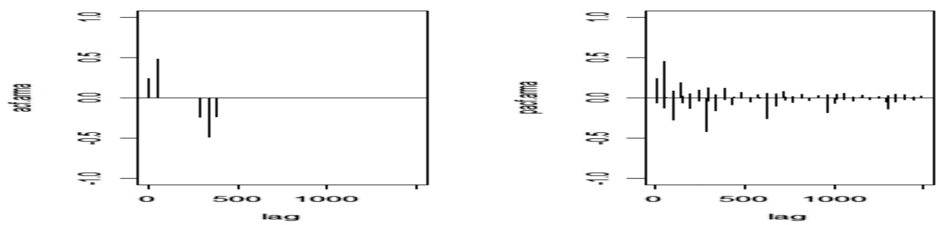


Figure 13: The ACF and PACF plots with $\theta_1 = -0.27184$, $\theta_{48} = -0.76592$ and $\theta_{336} = 0.85019$.

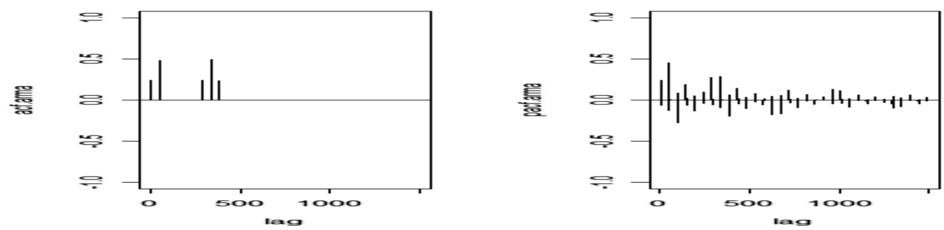


Figure 14: The ACF and PACF plots with $\theta_1 = -0.27184$, $\theta_{48} = -0.76592$ and $\theta_{336} = -0.85019$.

**Result of One-Step Ahead Out-Sample Forecasts**

A *k*-step ahead forecasting system will produce forecasts for the next *k* periods ahead. For example, $k = 4$ means that the number of periods ahead to be forecast is 4. However, the *k*-step ahead out-sample forecasts accumulate the error terms resulting in low accuracy in forecasting performances. Therefore the out-sample forecasts based on *k*-step ahead are highly influenced by lead times as shown in Table 6. However, the one-step ahead out-sample forecasts are not. The results of one-step ahead out-sample forecasts of ARIMA$(0,1,1)(0,1,1)^{48}(0,1,1)^{336}$ model which are presented in Table 6 clearly show that the one-step ahead out-sample forecasts are not influenced by the lead times. Out-samples of actual load data, *k*-step ahead and one-step ahead for Model 3 are illustrated in Figure 15. It is evidenced from the figure that one-step ahead out-sample forecasts follow the actual load data more closely than *k*-step ahead out-sample forecasts.

**Conclusion**

The ACF and PACF plots were presented to prove that the proposed model is the best model. This was done by using eight combinations of three estimates parameters in the best selected model. Results showed that the ACF and PACF plots with all three positive values of estimate parameters gave the exact patterns such as ACF and PACF of the stationary load data. The best selected model also had three estimate parameters with all positive values. It was proven that the best selected model was the best model for load data. Comparison was also made between one-step ahead out-sample forecasts and *k*-step ahead out-sample forecasts using double seasonal ARIMA model. The one-

Table 3: The MAPE of k-step and one-step ahead out-sample forecasts of model 3.

| | k-step ahead out-sample forecasts | One-step ahead out-sample forecasts | Reducing |
|---|---|---|---|
| Out-sample one- week forecast | 8.8841 | 0.9467 | 89.3436% |
| Out-sample two-week forecasts | 13.9414 | 0.9322 | 93.3132% |
| Out-sample three-week forecasts | 19.1838 | 0.9046 | 95.2845% |
| Out-sample one month forecast | 25.8641 | 0.9778 | 96.2195% |

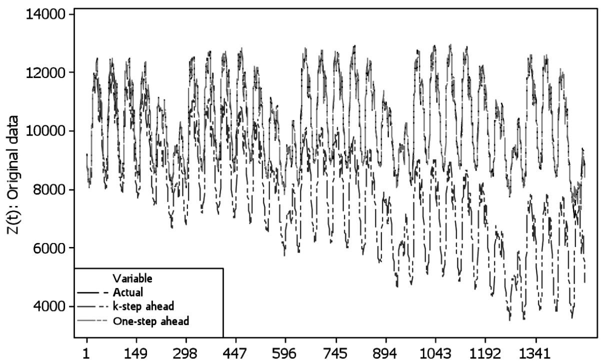


Figure 15: The out-samples of actual data, *k*-step ahead and one-step ahead out-sample forecasts.

step ahead out-sample forecasts were found to be more accurate. There was a reduction in MAPE percentages for all lead time horizons ranging 89% to 96%. Graphically, when out-samples of actual load data, *k*-step ahead and one-step ahead out-sample forecasts were plotted, the one-step ahead out-sample forecasts followed the actual load data more closely than the *k*-step ahead for out-sample forecasts. Two conclusions were therefore made: 1) the ACF and PACF plots may be considered in proving the best model that satisfies a time series data, where in the study was the load demand, and 2) apart from *k*-step ahead forecasts, the one-step ahead out-sample forecasts must also be considered in forecasting load, especially in Malaysia load data.

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