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Double Seasonal ARIMA Model for Forecasting Load Demand

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Abstract This study investigates the use of a double seasonal ARIMA model for forecasting load demand. For the purpose of this study, a one-year half hourly Malaysia load demand from 1 September 2005 to 31 August 2006 measured in Megawatt (MW) is used. The mean absolute percentage error (MAPE) is used as the measure of forecasting accuracy. We use Statistical Analysis System, SAS package to analyze the data. Using the least squares method to estimate the coefficients in a double SARIMA model, followed by model validation and model selection criteria, we propose $ARIMA(0,1,1)(0,1,1)^{48}(0,1,1)^{336}$ with in-sample MAPE of 0.9906% as the best model for this study. Comparing the forecasting performances by using k-step ahead forecasts and one-step ahead forecasts, we found that the MAPE for the one-step ahead out-sample forecasts from any horizon ranging from one week lead time to one month lead time are all less than 1%. We thus propose that a double seasonal ARIMA model with one-step ahead forecast as the most appropriate model for forecasting the two-seasonal cycles Malaysia load demand time series.

Keywords Load forecasting; double seasonal ARIMA model; k-step ahead forecast; one-step ahead forecasts.

1 Introduction

Load demand forecasting 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 an uninterrupted energy supply for customers (Tsekouras et al. [1]). Load forecasting can be broadly classified into four main categories which are long, intermediate, short and very short term forecasts but the time scale involved will vary according to the different types of decisions and planning (operational, tactical and strategic) the forecasts are associated with.

Several forecasting methods with varying degrees of success have been implemented for load forecasting including multiple linear regression (Al-Hamadi & Soliman [2]) and nonlinear multiple regression models (Al-Rashidi & El-Naggar [3]). Artificial neural network with variety of approaches such as multilayer feedforward and recurrent neural network (Norizan et al. [4], back propagation neural network (Al-Saba & El-Amin [5]), particle swarm optimization (El-Telbany & El-Karmi [6]), dynamic artificial neural network (Ghiassi et al. [7]), Elman artificial neural network (Beccali et al. [8]) and Jordan recurrent neural network (Kermanshahi & Iwamiya [9]) have been applied. Box-Jenkins models such as SARIMA (Zuhaimy & Khairil [10]) and hybrid models (Norizan et. al [11]) have also been developed.

The current study investigates methods that are appropriate for forecasting Malaysia load demand. Due to the presence of a double seasonal pattern in the time series data, which are daily and weekly seasonality, a double seasonal multiplicative ARIMA model is proposed. The multiplicative double seasonal ARIMA model has often been used for univariate forecasting intraday load time series (Cancelo et. al [12], Darbellay & Slama [13], Taylor et al. [14]). Cancelo at al. [12] and Darbelly & Slama [13] studied the double seasonal ARIMA with polynomial of order one, Taylor et al. [14] and Taylor [15] utilized the double seasonal ARIMA with polynomials of order two and order three. Taylor [15] has also utilized 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 we consider the order of polynomial, say k, we are including all lags from lag one to lag k. However by looking at the sample autocorrelations and the partial autocorrelations, there may exist insignificance lags in between lags. At the same time, ACF and PACF might indicate the existence of significance lags after lag k where those lags were not considered in the model earlier. Therefore in this current research we focus on the subset double seasonal ARIMA model in order to include all the significance lags in our tentative model.

This paper will be organized as follows: Section two describes the Box-Jenkins seasonal ARIMA model and the forecast evaluation measures. Section three presents the results when the model is applied to Malaysia load time series data and the results are discussed in section four. In section five we produce forecasts based on the chosen model and we conclude in section six the findings of our study.

2 Methodology

A variety of different forecasting approaches are available to forecast time series data and it is important to realize that no single model is universally applicable. An approach presented here is the Box-Jenkins autoregressive integrated moving average (ARIMA) model.

Box-Jenkins ARIMA Model: For more than half a century, the Box-Jenkins ARIMA linear models have dominated many areas of time series forecasting. One of the attractive features of the Box-Jenkins approach for forecasting is that ARIMA processes are a very rich class of possible models and it is usually possible to find a process which provides an adequate description to the data. Generally, a nonseasonal time series can be modeled as a combination of past values and past error, denoted as $ARIMA(p, d, q)$ can be written as follows (Wei [16]):

$$\phi_p(B)(1-B)^d \dot{Z}_t = \theta_q(B)a_t \tag{1}$$

with

$$\begin{aligned}\phi_p(B) &= 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p,\\ \theta_q(B) &= 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q,\end{aligned}$$

where $\dot{Z}_t$ is appropriately transformed load demand in period t; $(1-B)^d$ is the nonseasonal differencing operator; B is the backward shift operator; and a_t is the purely random process. As an example let $d = 0$, $p = 0$ and $q = 1$ hence the model can be expressed as $ARIMA(0, 0, 1)$. Consider $\theta_1 = 0.27$ the model can be written as follows:

$$\begin{aligned}Z_t &= (1 - 0.27B)\, a_t \\ &= a_t - 0.27a_{t-1}\end{aligned} \tag{2}$$

The theoretical ACF and PCF of Equation 2 are presented in Figure 1.

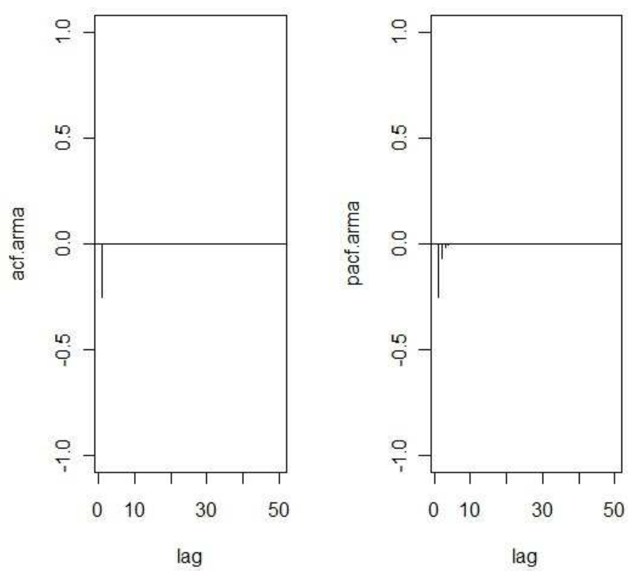

Figure 1: The theoretical ACF and PCF of Equation 2.

In practice, many time series data contain a seasonal periodic component, which repeats every s observation. To deal with seasonality, the ARIMA model is extended to a general multiplicative seasonal ARIMA (SARIMA) model which is defined as follows (Box et al. [17]):

$$\phi_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D\dot{Z}_t = \theta_q(B)\Theta_Q(B^s)a_t \tag{3}$$

with

$$\begin{aligned}\phi_p(B) &= 1-\phi_1 B-\phi_2 B^2-\cdots-\phi_p B^p,\\ \Phi_P(B^s) &= 1-\Phi_1 B^s-\Phi_2 B^{2s}-\cdots-\Phi_P B^{Ps},\\ \theta_q(B) &= 1-\theta_1 B-\theta_2 B^2-\cdots-\theta_q B^q,\\ \Theta_Q(B^s) &= 1-\Theta_1 B^s-\Theta_2 B^{2s}-\cdots-\Theta_Q B^{Qs},\end{aligned}$$

where $\dot{Z}_t$ is appropriately transformed load demand in period t; $(1-B)^d$ and $(1-B^s)^D$ are the nonseasonal and seasonal differencing operators respectively; B is the backward shift operator; and a_t is the purely random process. If the integer D is not zero, then seasonal differencing is involved. The above model is called a SARIMA model of order $(p,d,q)\times(P,D,Q)_s$. If d is non-zero, then there is a simple differencing to remove trend, while seasonal differencing, $(1-B^s)^D$ may be used to remove seasonality. As an example let $d = 0$, $D = 0$, $p = 0$, $q = 1$, $P = 0$, $Q = 1$ and $s = 48$ hence the model can be expressed as $ARIMA(0, 0, 1)(0, 0, 1)^{48}$. Consider $\theta_1 = 0.27$ and $\Theta_1 = 0.77$, the model can be written as follows:

$$\begin{aligned} Z_t &= (1 - 0.27B)(1 - 0.77B^{48})a_t \\ &= a_t - 0.27a_{t-1} - 0.77a_{t-48} + 0.2079a_{t-49} \end{aligned} \tag{4}$$

The theoretical ACF and PCF of Equation 4 are presented in Figure 2.

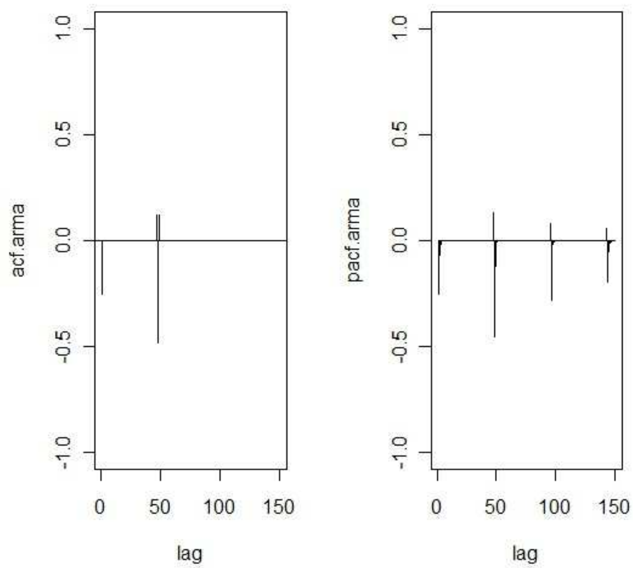

Figure 2: The theoretical ACF and PCF of Equation 4.

For the current study, due to the presence of a double seasonal pattern in short-term Malaysia load demand data, which are daily seasonal and weekly seasonal, we developed a double seasonal multiplicative ARIMA model. The general multiplicative double seasonal ARIMA model is as follows (Box et al. [17]):

$$\begin{aligned} &\phi_p(B)\Phi_{P_1}(B^{s_1})\Pi_{P_2}(B^{s_2})(1 - B)^d(1 - B^{s_1})^{D_1}(1 - B^{s_2})^{D_2}\dot{Z}_t \\ &\qquad = \theta_q(B)\Theta_{Q_1}(B^{s_1})\Psi_{Q_2}(B^{s_2})a_t \end{aligned} \tag{5}$$

where $\dot{Z}_t$ is appropriately transformed load demand in period t; B is the backward shift operator; $\phi_p(B)$ and $\theta_q(B)$ are regular autoregressive and moving average polynomials of orders p and q; $\Phi_{P_1}(B^{s_1})$, $\Pi_{P_2}(B^{s_2})$, $\Theta_{Q_1}(B^{s_1})$ and $\Psi_{Q_2}(B^{s_2})$ are autoregressive and moving average polynomials of orders P_1, P_2, Q_1 and Q_2; 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, daily seasonality and weekly seasonality are associated to the type of load data series. The daily and weekly seasonality are denoted as s_1 and s_2 respectively. For hourly load, $s_1 = 24$ and $s_2 = 168$ [14], for half-hourly load, $s_1 = 48$ and $s_2 = 336$ [13, 14], while for minute by minute load series $s_1 = 1440$ and $s_2 = 10080$ [15]. The multiplicative double seasonal ARIMA model can be expressed as $ARIMA(p, d, q) \times (P_1, D_1, Q_1)^{s_1}(P_2, D_2, Q_2)^{s_2}$. As an example let $d = 0$, $D_1 = 0$, $D_2 = 0$, $p = 0$, $q = 1$, $P_1 = 0$, $P_2 = 0$, $Q_1 = 1$, $Q_2 = 1$, $s_1 = 48$ and $s_2 = 336$, hence the model can be expressed as $ARIMA(0, 0, 1) \times (0, 0, 1)^{48}(0, 0, 1)^{336}$. Consider $\theta_1 = 0.27$, $\Theta_1 = 0.77$ and $\Psi_1 = 0.85$ the model can be written as follows:

$$\begin{aligned} Z_t &= (1 - 0.27B)(1 - 0.77B^{48})(1 - 0.85B^{336})a_t \\ &= a_t - 0.27a_{t-1} - 0.77a_{t-48} + 0.2079a_{t-49} - 0.85a_{t-336} + 0.2295a_{t-337} \\ &\quad + 0.6545a_{t-384} - 0.1725a_{t-385} \end{aligned} \tag{6}$$

The theoretical ACF and PCF of Equation (6) are presented in Figure 3.

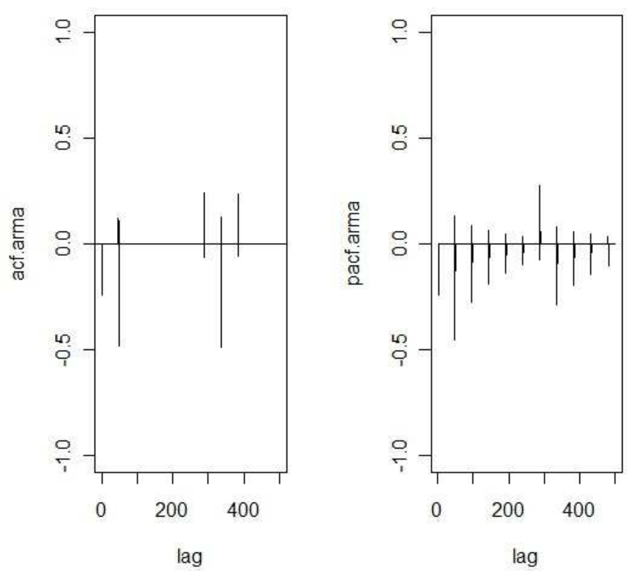

Figure 3: The theoretical ACF and PCF of Equation 6.

Box-Jenkins ARIMA Modeling Procedure: The modeling procedure of Box-Jenkins 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 optimization 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.

Measuring Forecast Accuracy: For the purpose of evaluating out-of-sample forecasting capability, different evaluation statistics such as root mean square error (RMSE), mean absolute error (MAE), mean square error (MSE), mean percentage error (MPE), mean absolute percentage error (MAPE) are often considered (Norizan et al. [18]). In the current study, MAPE is used. MAPE is the most widely used error measure in the forecasting literature. MAPE is an overall measure of forecast accuracy, computed from the absolute differences between a series of forecast and actual data points observed. This measure is commonly used in the forecasting literatures. The formula is as follows:

$$MAPE = \frac{1}{n}\sum_{i}^{n}|\frac{Z_i - \hat{Z}_i}{Z_i}| \times 100 \tag{7}$$

where Z_i is the actual values, $\hat{Z}_i$ is the predicted values and n is the number of the predicted values.

3 Data Set and Results

The data used in this study were obtained from the Malaysian electricity utility company, Tenaga Nasional Berhad (TNB), Malaysia. TNB is one of the biggest and most well-managed power companies in Asia, where this utility company has powered for decades through the generation, transmission and distribution of electricity. A one-year half hourly Malaysia load demand time series data (measured in Megawatt (MW)) from 1 September 2005 to 31 August 2006 were used in this study. The data were divided into two sets: initialization set and test set. The initialization set consists of load demand from 1 September 2005 to 31 July 2006 while the load demand from 1 August 2006 to 31 August 2006 made up the test set. Figure 4 plots the initialization set data. It is clear from Figure 4 that Malaysia load demand data is non-stationary.

Plotting the ACF and PACF of Malaysia load data in Figure 5 shows clearly the presence of seasonal pattern which is daily seasonality with length 48. Therefore pre-processing data is applied by using regular differencing ($d = 1$) and seasonal differencing ($D_1 = 1$, $s_1 = 48$) to convert non-stationary load series to stationary load series. Plotting the ACF and PACF after non-seasonal differencing ($d = 1$) and daily seasonal differencing ($D_1 = 1$, $s_1 = 48$) in Figure 6 indicates the presence of another seasonal pattern which is weekly seasonality with length 336. Plotting the load demand series after three time differencing which are non-seasonal differencing ($d = 1$), daily seasonal differencing ($D_1 = 1$, $s_1 = 48$) and weekly seasonal differencing ($D_2 = 1$, $s_2 = 336$) in Figure 7 indicates that load series is stationary series. In order words, this identification step shows that the load data have two seasonal periods, which are daily and weekly seasonality with length 48 and 336 respectively. We then present the the ACF and the PACF of stationary load demand series after three time differencing in Figure 8.

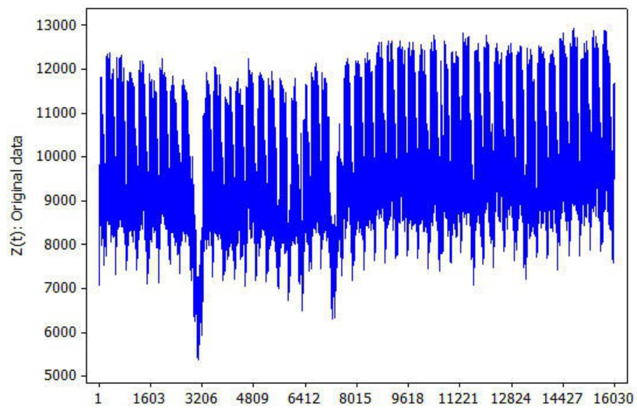

Figure 4: A half hourly load from September 1, 2005 to July 31, 2006.

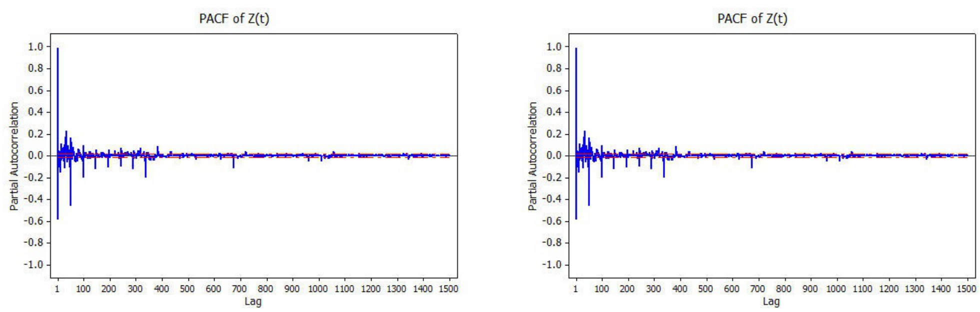

Figure 5: The ACF and PACF of Z_t.

For the purpose of this study we have to develop a program to analyze double SARIMA models since these models are not available in any statistical packages. In this study, we developed a program in Statistical Analysis System, SAS. The parameter coefficients of the model were estimated using least squares method. Three models were identified. They are as follows:

Model 1

ARIMA$([1,2,3,5,7,11,16,17,18,19,20,23,28,29,34,38,46,47],1,1)(0,1,1)^{48}$
$(0,1,1)^{336}$ All the parameters of this model are significant at alpha 0.05 significance level with white noise residuals based on Ljung-Box statistic Q^* until lags 48. This model gives 10 extreme residual values. In terms of magnitude of the residuals, these are at 11633th, 11632th, 6305th, 7265th, 3041th, 2415th, 10721th, 12659th, 11680th and 11681th observations. The model's residuals however do 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.

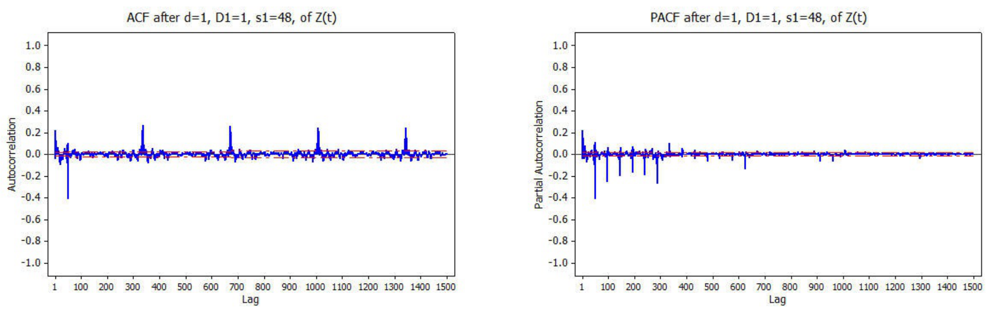

Figure 6: The ACF and PACF of Z_t after $d = 1$, $D_1 = 1$ and $s_1 = 48$.

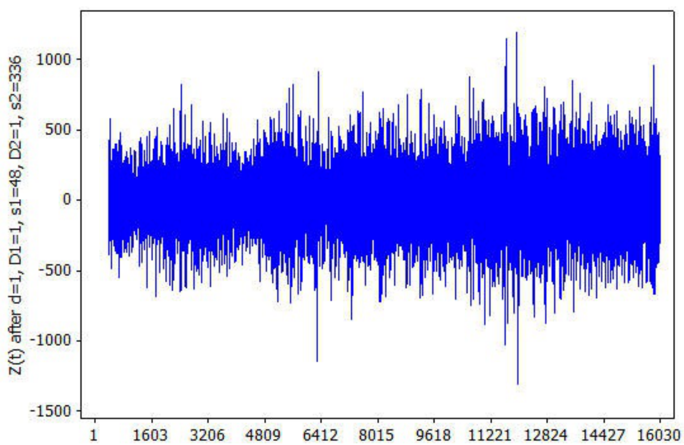

Figure 7: Load demand series after after $d = 1$, $D_1 = 1$, $s_1 = 48$, $D_2 = 1$ and $s_2 = 336$.

Model 2

ARIMA$(0, 1, [1, 2, 3, 5, 11, 16, 17, 18, 19, 20, 21, 22, 24, 28, 29, 31, 33, 34, 36, 41, 47])$
$(0, 1, 1)^{48}(0, 1, 1)^{336}$

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 statistic Q^* until lags 48. This model gives also 10 extreme residual values. In terms of magnitude of the residuals, these are at 11633th, 11632th, 6305th, 7265th, 3041th, 7456th, 11651th, 2415th, 11681th and 12659th observations. Similar to the first model, the model's residuals do not satisfy the Normal Distribution. The AIC and the SBC of this model are 194259.2 and 194435.3 respectively.

Model 3

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 statistic Q^* the residuals are not white noise. This model gives also

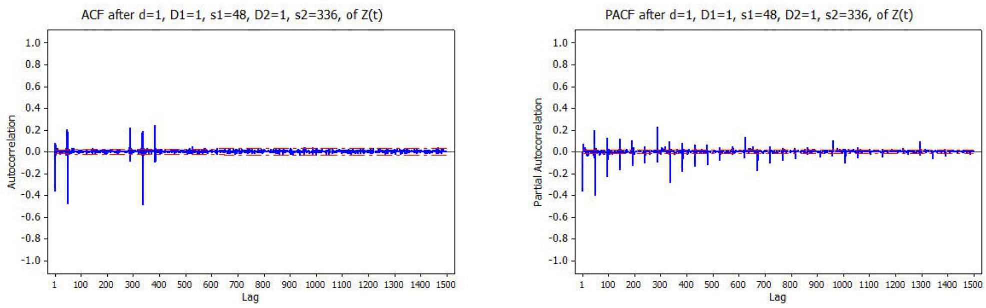

Figure 8: The ACF and PACF of Z_t after $d = 1$, $D_1 = 1$, $s_1 = 48$, $D_2 = 1$ and $s_2 = 336$.

10 extreme residual values. In terms of 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 model's residuals do not satisfy the Normal Distribution. The AIC and the SBC of the this model are 195054 and 195077 respectively.

Using the three models, forecasts were made for the following horizons: in-sample, out-sample one week, two weeks, three weeks and four weeks. The in-sample MAPE and the out-sample MAPEs of the four time horizons are summarized in Table 1. The graphical presentation of the in-sample MAPE and the out-sample MAPEs of the four time horizons are presented in Figure9.

Table 1: The MAPE of in-sample and out-sample forecasts of 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-week forecasts	21.6847	20.5402	19.1838
Out-sample one-month forecast	29.4448	27.8249	25.8641

4 Discussion of Results

One of the conclusions of the M3 Competition conducted by Makridakis and Hibon [19] was that the accuracies of various methods depend upon the length of the forecasting horizons involved. Meade [20] discovered that forecasting accuracy was less accurate for longer horizons. The results from the current study as tabulated in Table 1 supported Makridakis and Hibon [19] and Meade's [20] findings.

Model 3 is the simplest among the three models. It however outperformed model 1 and 2. The first conclusion of the M3 Competition was that statistically sophisticated or complex methods do not necessarily provide more accurate forecast than simpler ones. The results from this current study again supported that conclusion of the M3 Competition.

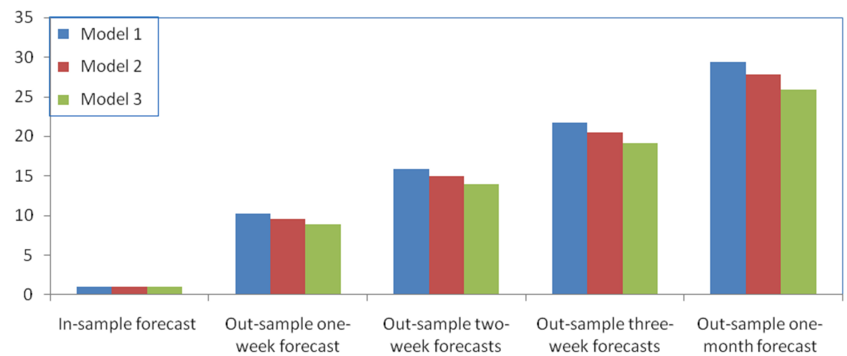

Figure 9: The MAPE of in-sample and out-sample forecasts of three models.

Model 3 is thus chosen as the best model for the current study. The SAS output of model 3 is presented in Table 2

5 Forecasting Using Model 3

The third model can be expressed as follows:

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

$$\begin{aligned} Z_t &= Z_{t-1} + Z_{t-48} - Z_{t-49} + Z_{t-336} - Z_{t-337} - Z_{t-384} + Z_{t-385} + a_t - 0.27184a_{t-1} \\ &- 0.76592a_{t-48} + 0.20821a_{t-49} - 0.85019a_{t-336} + 0.23112a_{t-337} + 0.65118a_{t-384} \\ &- 0.17702a_{t-385} \end{aligned}$$

$$\begin{aligned} Z_t = f(\quad & Z_{t-1}, \quad Z_{t-48}, Z_{t-49}, Z_{t-336}, Z_{t-337}, Z_{t-384}, Z_{t-385}, a_t, a_{t-1}, a_{t-48}, a_{t-49}, \\ & a_{t-336}, \quad a_{t-337}, a_{t-384}, a_{t-385}) \end{aligned}$$

Most statistical packages such as MINITAB, MATLAB, S-plus, SPSS and SAS provide out-sample forecasts based on k-step ahead. To calculate one-step ahead out-sample forecasts we used Microsoft Office Excel. The MAPEs of one-step and k-step ahead out-sample forecasts using model 3, ARIMA$(0,1,1)(0,1,1)^{48}(0,1,1)^{336}$ are presented in Table 3. From the table, it is clear that the one-step ahead out-sample forecasts are not as greatly influenced by lead times as the k-step ahead out-sample forecasts.

The out-sample forecasts based on k-step ahead are highly influenced by lead times as shown in Table 3. This is because the k-step ahead forecasts accumulate the error terms resulting in low accuracy in forecasting performances. We then illustrate the MAPE of k-step and one-step ahead out-sample forecasts of the third model in Figure 10; the out-samples of actual data and k-step ahead out-sample forecasts in Figure 11 and the out-samples of actual data and one-step ahead out-sample forecasts in Figure 12.

When one-step ahead out-sample forecasts are calculated and compared to k-step ahead out-sample forecasts, the MAPE are reduced with the reduction percentages of 89.3436%,

Table 2: An output SAS of model 3.

The ARIMA Procedure

Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
MA1,1	0.27184	0.0077170	35.23	<.0001	1
MA2,1	0.76592	0.0052374	146.24	<.0001	48
MA3,1	0.85019	0.0043550	195.22	<.0001	336

Variance Estimate	15181.56
Std Error Estimate	123.2135
AIC	195054
SBC	195077
Number of Residuals	15647

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	374.56	3	<.0001	-0.037	0.112	0.076	0.028	0.057	0.017
12	415.44	9	<.0001	0.000	0.006	0.014	0.013	0.039	0.025
18	597.84	15	<.0001	0.001	-0.003	-0.013	-0.037	-0.054	-0.085
24	887.81	21	<.0001	-0.077	-0.076	-0.055	-0.049	-0.013	-0.035
30	1006.04	27	<.0001	-0.010	-0.031	-0.017	-0.038	-0.061	-0.034
36	1074.44	33	<.0001	-0.038	-0.030	-0.033	0.012	0.003	0.026
42	1085.71	39	<.0001	0.016	0.008	0.002	0.012	-0.010	0.011
48	1230.59	45	<.0001	0.002	0.022	0.017	0.036	0.082	0.022

93.3132%, 95.2845% and 96.2195% at one-week forecast, two-week forecasts, three-week forecasts and one-month forecast respectively. These reduction percentages are tabulated in Table 3. Since k-step ahead out-sample forecasts are influenced by forecasting horizons, these reduction percentages are also influenced by forecast lead times. We illustrate out-samples of actual load data, k-step ahead and one-step ahead out-sample forecasts in Figure 13. It is evidenced from the figure that one-step ahead out-sample forecasts follow the actual load data more closely than k-step ahead for out-sample forecasts.

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

	k-step ahead	One-step ahead	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%

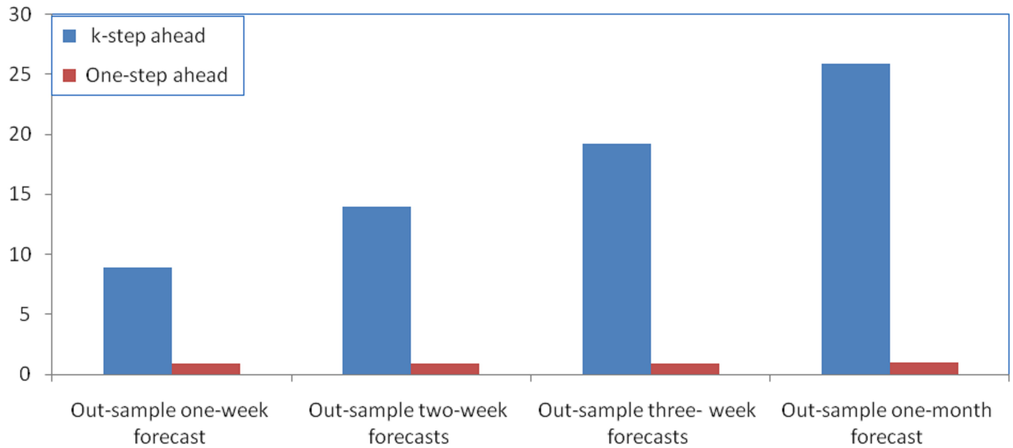

Figure 10: The MAPE of k-step and one-step ahead out-sample forecasts of the third model.

6 Conclusions

We investigated the double seasonal ARIMA model for forecasting the double seasonal (daily and weekly) Malaysia load demand time series. Comparing the forecasting performances by using k-step ahead forecasts and one-step ahead forecasts, we found that the MAPE for the one-step ahead out-sample forecasts for any horizon ranging from one week lead time to one month lead time as tabulated in Table 3 are all less than 1%. The MAPE of the k-step ahead forecasts on the other hand, increases as the time scale increases. It can be concluded that the one-step ahead forecasts are not greatly influenced by the lead times and are more accurate than k-step ahead forecasts in forecasting Malaysia load demand.

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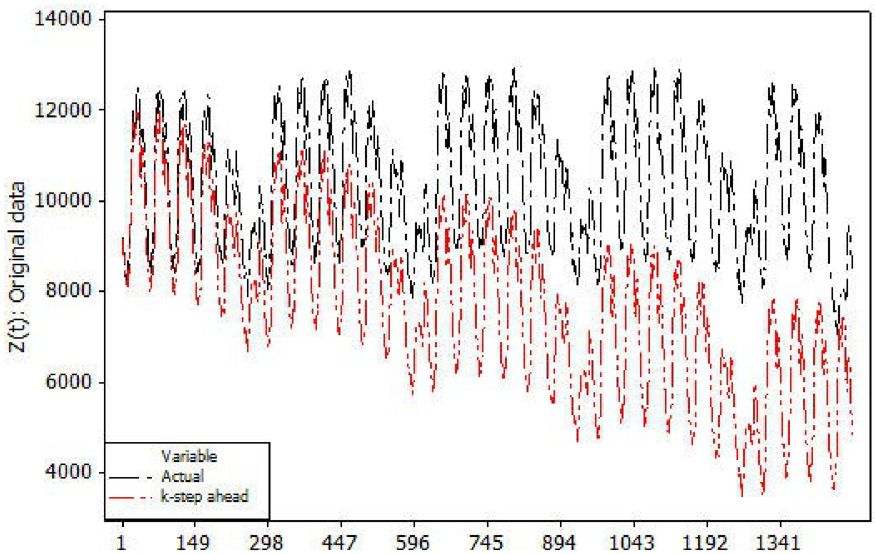

Figure 11: The out-samples of actual data and k-step ahead out-sample forecasts.

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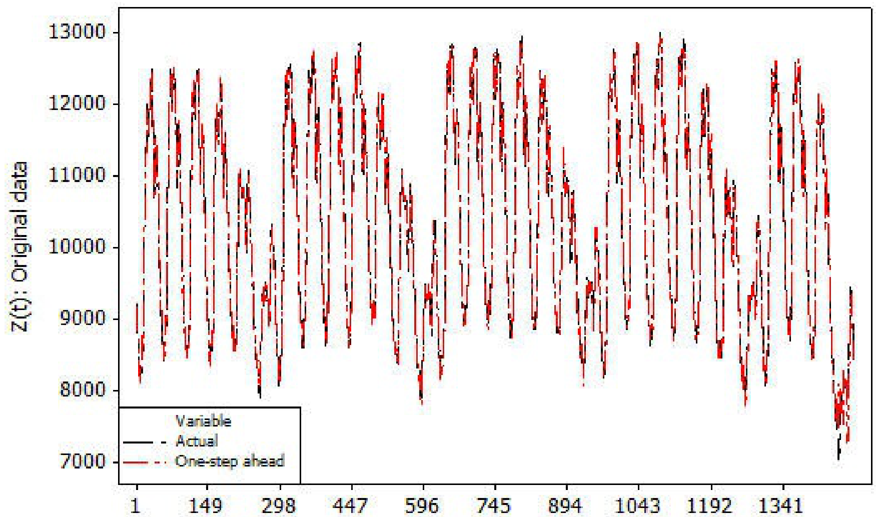

Figure 12: The out-samples of actual data and one-step ahead out-sample forecasts.

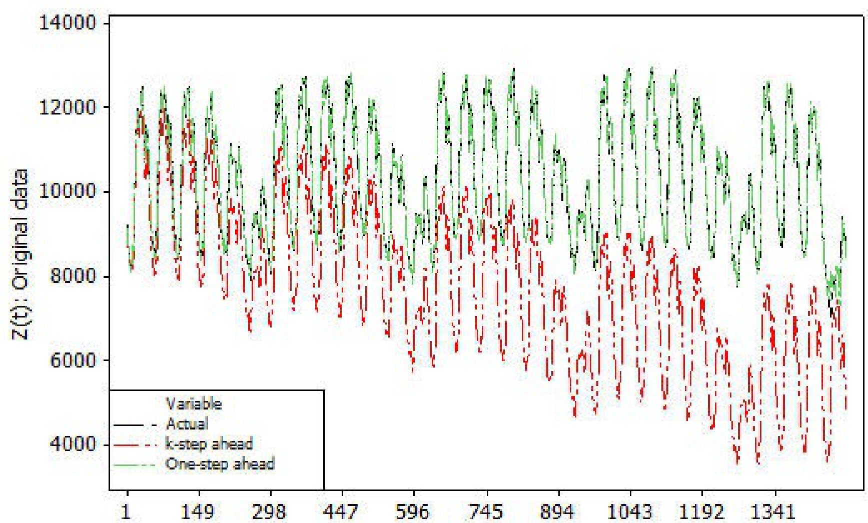

Figure 13: The out-samples of actual data, k-step ahead and one-step ahead out-sample forecasts.

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