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The Application of Box-Jenkins Models in Short-Term Load Forecasting

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Abstract— Short-term load forecasting (STLF) plays an important role in obtaining secure and economic operations of electric utilities in a deregulated power system. This paper presents the autoregressive (AR) Box-Jenkins model that used to perform the STLF of the Malaysian hourly peak loads. The AR Box-Jenkins model was selected based on the behaviors of the sample autocorrelation (SAC) and sample partial autocorrelation (SPAC) functions of the time series. Comparison in terms of accuracy in estimating the STLF has been made between the AR and autoregressive integrated moving average (ARIMA) Box-Jenkins models. The results have shown that the AR Box-Jenkins model is robust in forecasting the Malaysian hourly peak load for the next 24 hours with less error.

Keywords - Short-term load forecasting, autoregressive Box-Jenkins model, sample autocorrelation function and sample partial autocorrelation function.

I. INTRODUCTION

Load forecasting has always been an essential task for the electric utilities in which it may assist to an effective operational planning and security assessment of a power system. This is important to ensure that the electric utilities are operating in an economic, reliable and uninterrupted service to the customers [1]. With the advent of deregulation in electric utilities, load forecasting becomes even more important especially to the system operators and market participants in which this may assist towards organizing appropriate strategies of risk management and competitive energy trading [1,2,3]. Forecasting the future load can be classified into four main categories which are the very short-term, short-term, medium-term and long-term load forecasts [1,4]. The very short-term load forecasting (VSTLF) is performed in a very short time that is from one minute to a few minutes ahead. The determination of VSTLF is immensely important for the economic dispatch activities and Area Control Error (ACE) estimation. The short term load forecasting (STLF) is performed ranging from one-hour to one-week ahead. The STLF is required for improvising day-to-day optimal decisions on the economic and secure operations of a power system [1,5]. The economic operations of a power system involves scheduling of generating capacity, scheduling of fuel purchases, power transfer analysis and planning of market based power transfer [5,6]. On the other hand, STLF is also applied to the system security assessment whereby the system operating condition is analyzed by taking into account system contingency. The medium-term load forecasting is covering in the range from a few weeks to a few months ahead. It is required mainly for fuel allocation and maintenance scheduling. The long-term load forecasting is performed ranging over a period of five years. The long-term load forecasting is important for the system expansion planning.

The preceding years have shown immense development of load forecasting methods due to its significant impact on the economic and reliable operation of a power system. The load forecasting methods can be divided into two main categories which are the statistical approaches and artificial intelligence (AI) based techniques [3]. The hybrid Kalman Filters [7], autoregressive models [8,9], Box–Jenkins models [3,10,11], and regression-based model [3,12] can be categorized under the statistical based technique. On the other hand, artificial neural networks (ANN) and fuzzy inference system have been extensively used in forecasting the future load and it can be classified under the AI based technique [13,14,15]. Furthermore, accurate forecast of future load can be obtained by using the enhance development of AI techniques which exploits the combination of a time series and ANN techniques [16,17], combination of ANN and fuzzy inference method [18,19], principal component analysis with ANN [20], genetic algorithm based ANN [21] and wavelet based ANN [22].

Selecting an appropriate load forecasting model is important so that the future load is forecasted with less error. This paper presents the Box-Jenkins model that used to perform the short-term load forecasting (STLF) for the next 24 hours. The Box-Jenkins models are comprised of the autoregressive (AR), moving average (MA) and autoregressive integrated moving average (ARIMA) techniques. In order to identify an appropriate Box-Jenkins model for STLF therefore, the sample autocorrelation (SAC) and sample partial autocorrelation (SPAC) functions are used to analyze the behavior of the past univariate load time series [23,24]. Generally, the AR Box-Jenkins model forecasts the future load based on linear function of the past

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peak loads, the MA Box-Jenkins model forecasts the future load based on linear combination of the past peak load errors and the ARIMA Box-Jenkins model forecast the future peak load based on the combination of AR Box-Jenkins and MA Box-Jenkins models. The Malaysian hourly peak load is used as a case study in the assessment of STLF using Box-Jenkins models. The behaviors of SAC and SPAC have shown that the AR Box-Jenkins model is an appropriate approach to perform forecasting of the Malaysian peak load for the next 24 hours. Comparison has been made on the results of STLF which are obtained based on the AR and ARIMA Box-Jenkins models. This is to investigate the effectiveness of AR Box-Jenkins model in performing the STLF.

II. METHODOLOGY

The determination of short-term load forecasting (STLF) using Box-Jenkins model involves three main procedures which are the verification of stationary time series, identification of an appropriate Box-Jenkins model based on the stationary time series and STLF using the selected Box-Jenkins model [24]. The above mentioned procedures of STLF using Box-Jenkins model are explained elaborately in the following Subsections.

A. Verification of Stationary Time Series

The first procedure of STLF using Box-Jenkins model is to verify that the time series of the past hourly peak load is either stationary or non-stationary. If the past hourly peak loads are non-stationary then it should be transformed to a stationary time series. The time series of the past hourly peak load is said to be stationary if the time series fluctuate with a constant variation around a constant mean, μ. If the time series of the past hourly peak load does not fluctuate with constant variation around a constant mean, μ, then it is reasonable to believe that the time series is non-stationary. Therefore, the first differences of the past hourly peak loads should be performed in order to obtain a stationary type of time series. The first differences of the inherent time series is given by,

$$z_t = y_t - y_{t-1} \tag{1}$$

where,

y : hourly peak load.
t : time interval which begins with 2, 3,…, n.
n : total time intervals.

The second differences of the past hourly peak loads should be executed only if the first differences are still non-stationary. The second differences of the time series can be obtained by using equation (3).

$$z_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) \tag{2}$$

$$= y_t - 2y_{t-1} + y_{t-2} \tag{3}$$

where,

t : time interval which begins with 3, 4,…., n.

Then, the sample autocorrelation (SAC) function and sample partial autocorrelation (SPAC) function are obtained by taking into account the stationary time series that is either the past hourly peak loads, first differences of the time series or second differences of the time series. The following Subsection provides detail explanation of the SAC and SPAC functions.

B. Identification of an Appropriate Box-Jenkins Model for STLF

The Box-Jenkins model that used for STLF should be selected based on the behavior of stationary time series. The sample autocorrelation (SAC) function and sample partial autocorrelation (SPAC) function are used to investigate the behavior of stationary time series. The sample autocorrelation (SAC) function defined as r_k can be calculated by using equation (4).

$$r_k = \frac{\sum_{t=b}^{n-K} \left(z_t - \bar{z}\right)\left(z_{t+K} - \bar{z}\right)}{\sum_{t=b}^{n-K} \left(z_t - \bar{z}\right)} \tag{4}$$

where,

$$\bar{z} = \frac{\sum_{b}^{n} z_t}{(n-b+1)} \tag{5}$$

b : the beginning value of t. b = 1 when the stationary of past hourly peak loads is used. If the first or second differences of the time series is used then b = 2 or b = 3, respectively. This shows that the stationary of past hourly peak loads, first differences and second differences begins with the time series of y_1, z_2 and z_3, respectively.
k : lag time interval which is 1, 2,…., n-K.
K : used to specify the distance between two time intervals for k.

If the past hourly peak loads are stationary then the z_t and $\bar{z}$ that used in equation (4) are replaced by y_t and $\bar{y}$, respectively. The SAC or r_k given in equation (4) is used to measure linear relationship between the two time series separated by a lag of k time unit. The results of r_k should always be in the range between -1 and 1. The r_k value that is close to 1 indicates that the two time series separated by K have strong tendency to move together in a linear fashion with positive slope. On the other hand, r_k value that is close to -1 indicates that the two time series separated by K have strong tendency to move together in a linear fashion with negative slope. Henceforth, the r_k can also be used to verify whether the past hourly peak loads, first differences of the time series or second differences of the time series is stationary. By referring to a particular time interval, the r_k that cuts off abruptly or dies down fairly quickly implies that the time series is stationary. On the other hand, the time series is said to be non-stationary when the r_k cuts off or dies down extremely slow.

The standard deviation of r_k $\left(s_{r_k}\right)$ and t_{r_k}-statistic given in equations (6) and (7), respectively are used to identify the commencement of r_k that cuts off abruptly or dies down fairly quickly.

$$s_{r_k} = \begin{cases} \dfrac{1}{(n-b+1)^{\frac{1}{2}}} & if\ k = 1 \\ \dfrac{\left(1+2\sum_{j=1}^{k-1} r_j^2\right)^{\frac{1}{2}}}{(n-b+1)^{\frac{1}{2}}} & if\ k = 2,3,...,\ n-K-1 \end{cases} \quad (6)$$

$$t_{r_k} = \frac{r_k}{s_{r_k}} \quad (7)$$

The spikes of r_k are usually occurring before the commencement of r_k that cuts off abruptly or dies down fairly quickly. The r_k that cuts off abruptly or dies down fairly quickly inevitably yields to the value of $|t_{r_k}|$ that is less than 2 and $2(s_{r_k})$ exceeds the respective value of r_k. On the other hand, the spikes of r_k are represented by the $|t_{r_k}|$ which exceeds the value of 2 and $2(s_{r_k})$ is less than the respective value of r_k. Fig. 1 shows that the spikes exist at lag 1 and lag 2. Consequently, the r_k cuts off abruptly after lag 2.

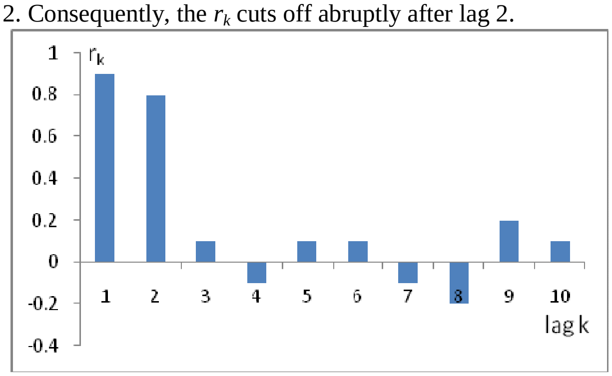

Fig. 1. SAC or r_k cuts off abruptly after lag 2

Furthermore, the SAC or r_k may sometime dies down or decreases in three different ways which are,

i) Damped exponential with or without oscillations as shown in Fig. 2 and 3, respectively.
ii) Damped sine-wave as shown in Fig. 4.
iii) Combination of both signals given in i) and ii).

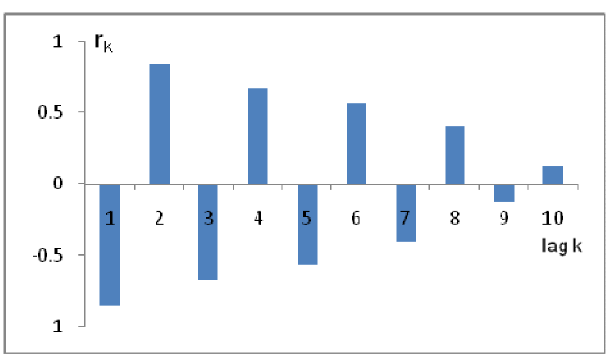

Fig. 2. Damped exponential with oscillation

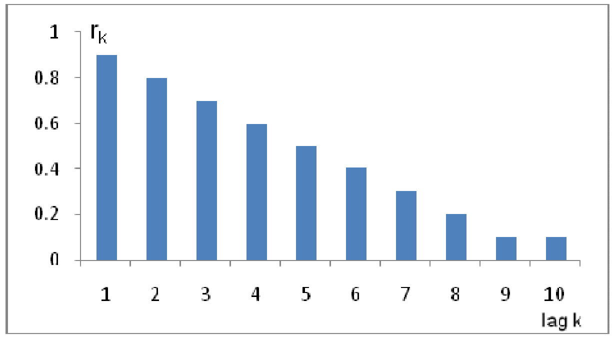

Fig. 3. Damped exponential without oscillation

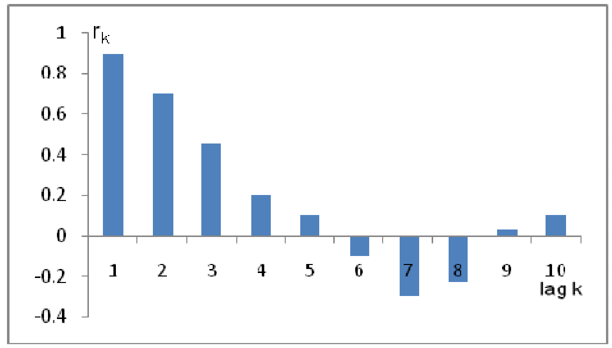

Fig. 4. Damped sine-wave

It is worth mentioning that the sample partial autocorrelation (SPAC) function is a part of the procedure in identifying an appropriate Box-Jenkins model for STLF. The SPAC function is defined as r_{kk} and it is given in equation (8).

$$r_{kk} = \begin{cases} r_k & if\ k = 1 \\ \dfrac{r_k - \sum_{j=1}^{k-1} r_{k-1,j}\, r_{k-1}}{1-\sum_{j=1}^{k-1} r_{k-1,j}\, r_j} & if\ k = 2,3,...,n-K-1 \end{cases} \quad (8)$$

where,

$$r_{kj} = r_{k-1,j} - r_{kk} r_{k-1,k-j} \qquad if\ j = 1,2,\ldots, k\text{-}1 \quad (9)$$

The r_{kk} is then used in equations (10) and (11) to determine the spikes of r_{kk} and commencement of r_{kk} that cuts off abruptly or dies down fairly quickly. Equations (10) and (11) are the standard deviation of r_{kk} $(s_{r_{kk}})$ and $t_{r_{kk}}$-statistic, respectively which are given by,

$$s_{r_{kk}} = \frac{1}{(n-b+1)^{\frac{1}{2}}} \quad (10)$$

$$t_{r_{kk}} = \frac{r_{kk}}{s_{r_{kk}}} \quad (11)$$

The spikes of r_{kk} and commencement of r_{kk} that cuts off abruptly or dies down fairly quickly are identified by using $2(s_{r_{kk}})$ and $|t_{r_{kk}}|$, which have the same procedures as the $2(s_{r_k})$ and $|t_{r_k}|$ that used in identifying the spikes of r_k and commencement of r_k that cuts off abruptly or dies down fairly quickly. Furthermore, the SPAC function or r_{kk} may sometime dies down or decreases in three different ways which are similar to the SAC function or r_k.

The SAC and SPAC functions are then used to determine an appropriate approach of Box-Jenkins model for the STLF. The moving average (MA) Box-Jenkins model should be used for STLF once the following criterions are fulfilled.

i) The SAC cuts off abruptly after several lags. The SAC given in equation (4) is tacitly similar to equation (12).

$$\rho_1 = \frac{-\theta_1}{1+\theta_1^2} \quad (12)$$

$$\rho_k = 0 \qquad \text{for } k > 1$$

where,

θ_1 : a constant that should be estimated from the sample data of time series.

ii) The SPAC dies down in a damped exponential fashion. In this case, the SPAC is represented by ρ_{kk} which is similar to the r_{kk} given by equation (8).

On the other hand, the autoregressive (AR) Box-Jenkins model should be used for STLF when the following factors are satisfied.

i) The SAC dies down in a damped exponential fashion. In this case, the ρ_k given in equation (13) is implicitly similar to equation (4) that is the SAC or r_k.

$$\rho_k = (\phi_1)^k \quad (13)$$

where,

ϕ_1 : a constant that should be estimated from the sample data of time series.

ii) The SPAC cuts off abruptly after several lags. The ρ_{kk} is similar to the SPAC or r_{kk} which is given in equation (8).

The autoregressive integrated moving average (ARIMA) Box-Jenkins model should be used for STLF if the subsequent factors are fulfilled.

i) The SAC dies down in a damped exponential fashion. For this case, equation (4) is used to calculate the SAC or r_k that is relatively similar to the ρ_k given in equations (14) and (15).

$$\rho_1 = \frac{(1-\phi_1\theta_1)(\phi_1-\theta_1)}{1+\theta_1^2-2\theta_1\phi_1} \quad (14)$$

$$\rho_k = \phi_1 \rho_{k-1} \qquad \text{for } k \geq 2 \quad (15)$$

ii) The SPAC decreases in a damped exponential decay.

The following Subsection provides elaborate explanation of each Box-Jenkins model that used for the STLF.

C. STLF Using Box-Jenkins Model

The selection of Box-Jenkins model is made by referring to the behavior of SAC and SPAC of the past hourly peak loads, first differences of the time series or second differences of the time series. This has been discussed elaborately in Section II.B. The Box-Jenkins models are comprised of autoregressive (AR), moving average (MA) and autoregressive integrated moving average (ARIMA) techniques. The AR Box-Jenkins model of order 1 that used for STLF is given by equation (16).

$$\hat{y}_t = \delta + \phi_1 \hat{y}_{t-1} + a_t \quad (16)$$

where,

$$\delta = \mu(1-\phi_1). \quad (17)$$

μ : average of the past hourly peak loads.

a_t : random shock is usually zero since $y_t - \hat{y}_t$. (18)

$\hat{y}_t$: forecasted hourly peak load at time interval t.

y_t : actual hourly peak load at time interval t.

Equation (19) is the MA Box-Jenkins model of order 1 that used to perform the STLF.

$$\hat{y}_t = \delta + a_t - \theta_1 a_{t-1} \quad (19)$$

where,

$$\delta = \mu. \quad (20)$$

a_{t-1} : random shock that is $y_{t-1} - \hat{y}_{t-1}$. (21)

The ARIMA Box-Jenkins model of order 1 that used for STLF is given by,

$$\hat{y}_t = \delta + \phi_1 \hat{y}_{t-1} + a_t - \theta_1 a_{t-1} \quad (22)$$

The δ is calculated by using equation (17).

The procedure of STLF using Box-Jenkins model is briefly described in terms of flowchart shown in Fig. 5.

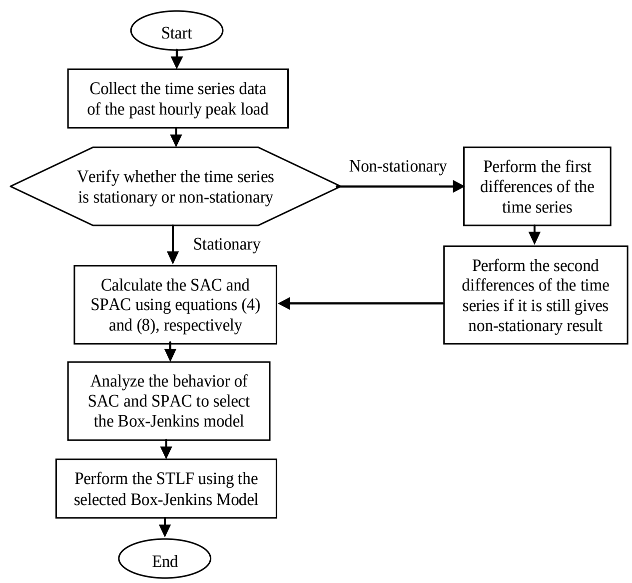

Fig. 5. Flowchart of STLF using Box-Jenkins model

III. Results and Discussion

The Malaysian hourly peak loads in the year 2002 are used as a case study in the assessment of STLF using Box Jenkins models. The Malaysian hourly peak loads are shown in Fig. 6 and it is used by the Box-Jenkins models to perform the short-term load forecasting (STLF) for the next 24 hours. It is obvious that the Malaysian hourly peak loads can be categorized as a non-stationary time series whereby it does not fluctuate with constant variation around a constant mean, μ.

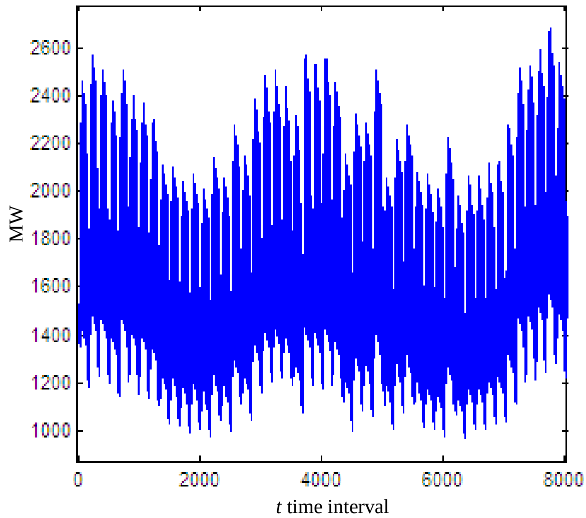

Fig. 6. Malaysian hourly peak loads

Hence, the first differences of the time series are performed by using equation (4) in order to obtain a stationary form of time series. By referring to Fig. 7, it is proven that the first differences of the time series fluctuate with constant variation around a constant mean, μ. Hence, it is reasonable to believe that the time series is stationary.

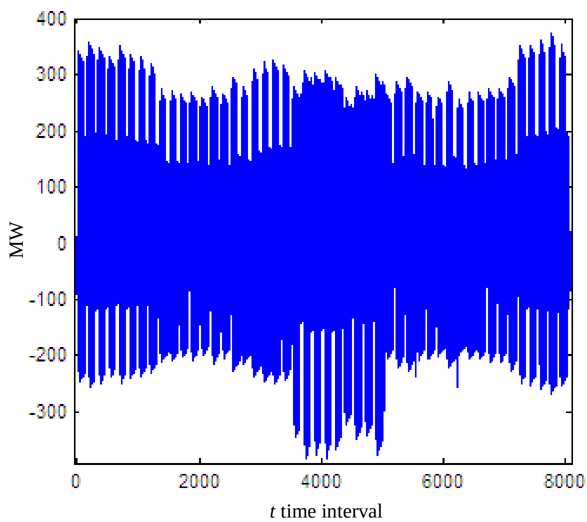

Fig. 7. First differences of the Malaysian hourly peak loads

The stationary time series is then applied into equations (4) and (8) in order to obtain the behaviors of SAC (or r_k) and SPAC (or r_{kk}), respectively. The SAC and SPAC of the stationary time series are shown in Fig. 8 and 9, respectively. It is observed that the SAC dies down in a damped exponential with oscillation and the SPAC cuts off abruptly after the first lag. Fig. 8 and 9 have shown that the behaviors of SAC and SPAC, respectively are complying with the criterions of autoregressive (AR) Box-Jenkins model. Therefore, the AR Box-Jenkins model given in equation (16) is used to forecast the Malaysian hourly peak load for the next 24 hours.

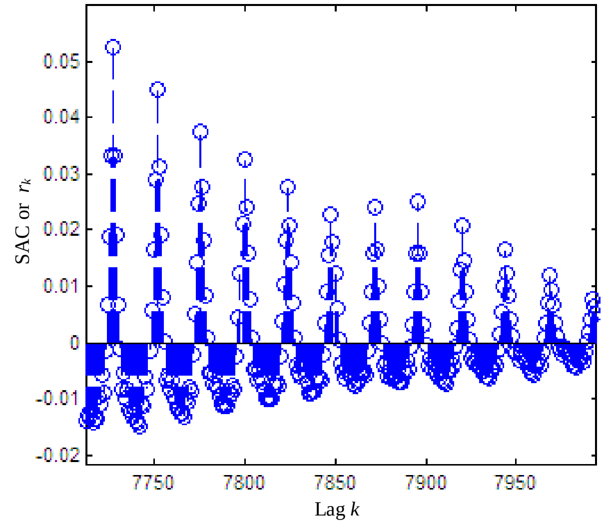

Fig. 8. SAC dies down in a damped exponential with oscillation

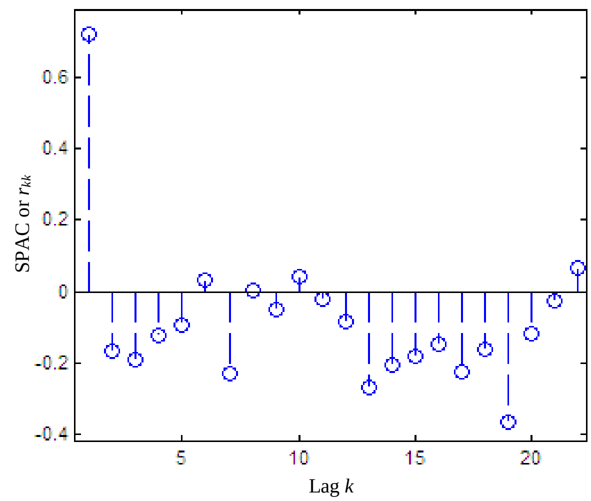

Fig. 9. SPAC cuts off abruptly after the first lag

Fig. 10 is the result of Malaysian hourly peak load forecasted consecutively for the next 24 hours using the AR Box-Jenkins model. The result has shown that the AR Box-Jenkins model is able to forecast the Malaysian hourly peak loads that are relatively similar to the actual values. On the other hand, the effectiveness of AR Box-Jenkins model in forecasting is also investigated by evaluating the mean absolute percentage error (MAPE) between the forecasted peak loads and the actual values [16]. The MAPE value of 7.9% again shows that the AR Box-Jenkins model is robust in forecasting the future hourly peak loads with less error.

Furthermore, comparison is performed on the results of STLF which are obtained by using the AR and ARIMA Box-Jenkins models. This is to distinguish the robustness of the two methods in forecasting the Malaysian hourly peak load for the next 24 hours. The result of STLF determined by the AR and ARIMA Box-Jenkins models are shown in Fig. 10 and 11, respectively. In particular, the Malaysian hourly peak load is forecasted consecutively for the next 24 hours by using the AR and ARIMA Box-Jenkins models. The results have shown that the AR Box-Jenkins model is robust in forecasting the Malaysian hourly peak loads which are relatively similar to the actual values and it is superior to the STLF results given by the ARIMA Box-Jenkins model. This can also be proven by comparing the MAPE of the Malaysian hourly peak loads forecasted by the AR and ARIMA Box-Jenkins models. It is worth mentioning that the forecasted and actual value of hourly peak loads are the two chronological variables considered in the MAPE calculation. The MAPE value for the Malaysian hourly peak loads forecasted by the AR and ARIMA Box-Jenkins models are 7.9% and 9.1%, respectively. The results again prove that the AR Box-Jenkins model is competent in forecasting the Malaysian hourly peak loads with less error compared to the ARIMA Box Jenkins model. Hence, the AR Box-Jenkins model can be used by the system operators and market participants to forecast the future hourly peak loads and this may assist towards effective operation of a deregulated power system.

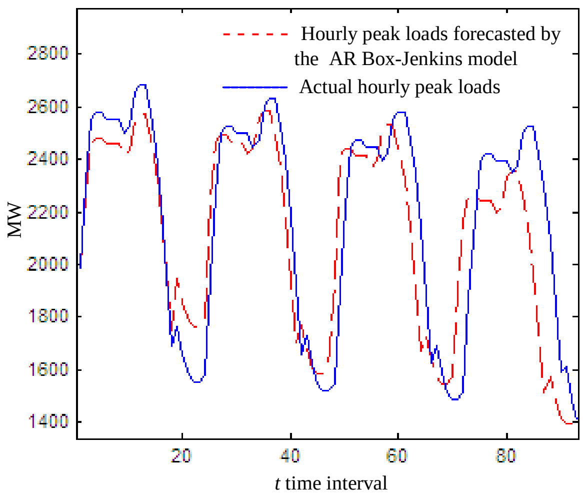

Fig. 10. Comparison between the hourly peak loads forecasted by AR Box-Jenkins model and the actual values

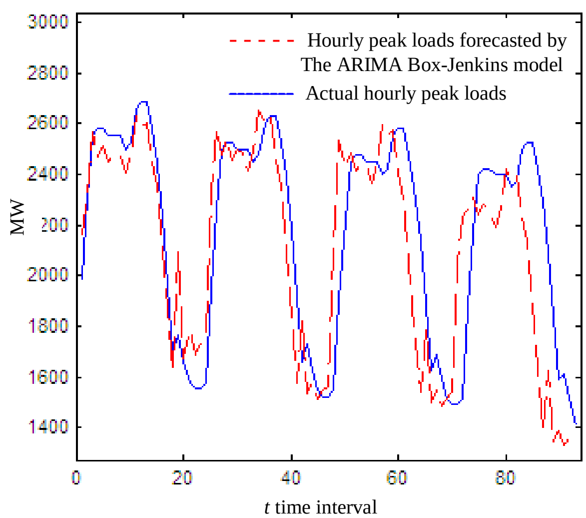

Fig. 11. Comparison between the hourly peak loads forecasted by ARIMA Box-Jenkins model and the actual values

IV. Conclusion

The application of autoregressive (AR) Box-Jenkins model in performing the short-term load forecasting (STLF) has been presented. The Malaysian hourly peak loads have been used as a case study in the assessment of STLF using AR Box-Jenkins model. The AR Box-Jenkins model that used for STLF was selected based on the behaviors of sample autocorrelation (SAC) and sample partial autocorrelation (SPAC) functions. The SAC and SPAC are representing the behavior of the stationary past hourly peak loads, first differences of the time series or second differences of the time series. The first differences of the past hourly peak loads was performed in order to obtain the stationary form of time series. If the time series is still non-stationary then, the second differences of the past hourly peak loads should be performed in order to obtain the stationary form of time series. The results have shown that the AR Box-Jenkins model is able to forecast the Malaysian hourly peak load for the next 24 hours with less error. The results have shown that the AR Box-Jenkins model is superior to the ARIMA Box Jenkins model in forecasting the Malaysian hourly peak load for the next 24 hours with less error. It is important to accurately forecast the hourly peak loads in which this may assist towards effective operational planning and security assessment of a power system.

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