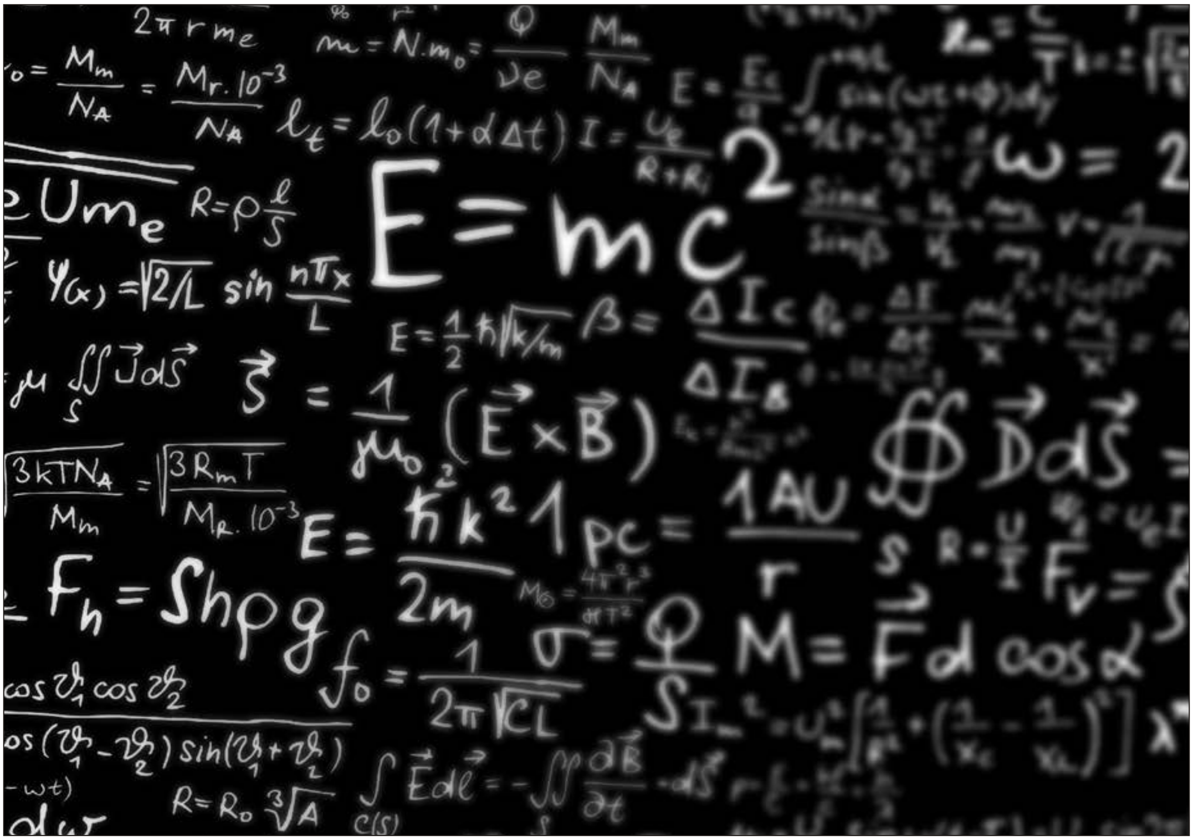

Asian Journal of Mathematics & Statistics

ISSN 1994-5418

Asian Journal of Mathematics and Statistics 1 (3): 139-149, 2008
ISSN 1994-5418

Time Series Regression Model for Forecasting Malaysian Electricity Load Demand

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Abstract: The demand of electricity forms the basis for power system planning, power security and supply reliability. Forecasting electricity demand with linear methods has always been challenging tasks, as the load time series exhibit several superimposed levels of seasonality. In Malaysia, the demand for electricity has reached over 15,000 MW for the past few years and the demand is increasing. This power demand is significantly affected by many non linear factors such as temperature, holiday, special events and other seasonality. This study investigates the impact of weather variables, holidays and other type of variables on daily and monthly electricity demand in Malaysia. A multiple regression model is developed to forecast electricity demand on weather variables, holiday types, daily and monthly seasonality. Due to the nature of the time series data, a time series regression model with autoregressive errors is developed to forecast daily peak electricity demand. The empirical study shows that the Mean Absolute Percentage Error (MAPE) for model with holiday variables is approximately 1.71% in fitting the daily load model. This study also demonstrates the forecast for one month ahead using time series regression model with load reduction weights yield better accuracy. Thus it proved the suitability of the adopted time series regression method for the forecasting short-term electricity load demand.

Key words: Forecasting, time series regression, box-jenkins, electricity demand and forecast accuracy

INTRODUCTION

There is evidence that the climate, temperature and holiday in Malaysia has an impact on electricity demand and was demonstrated by the power failure in 1995 due to the increase in demand due to prolong hot weather. The electricity power in Malaysia is provided by the Tenaga National Berhad (TNB) as the main supplier and a few other independent power providers (IPP). TNB is the largest electric utility in Malaysia. It was established in September 1990 through a corporatization and privatization exercise by the Malaysian government. The corporatization is regulated under the Electricity Supply Department within the Ministry of Energy, Telecommunications and Posts, Malaysia. TNB has more than RM 75 billion in assets and services over five million customers throughout the Peninsula Malaysia and Sabah. TNB core activities are in the generation, transmission and distribution of electricity and the main provider in electricity generation. TNB has the largest generation capacity of over 7800 MW that accounts for over 62% of the total power generation of Peninsular Malaysia (Ismail and Ahmad, 2003).

Electricity data are measurements of electricity demand or generated over a period of time, daily, weekly, monthly or yearly. A load time series is a collection of electricity peak load demand data recorded over a period of time weekly, monthly, quarterly, or annually. It is a series of values of a

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variable at successive times in statistics and signal processing, a time series is a sequence of data points, measured typically at successive times, spaced apart at uniform time intervals. The time series analysis comprises methods that attempt to understand such time series, often either to understand the underlying theory of the data points.

There are various factors that influence the load demand and among these factors are temperatures, holidays, daily and monthly seasonality. This study we proposed the development of time series regression model with each contributing factors are adjusted prior to the modeling of the data. The data used in this study comprises of daily peak electricity demand L_t (h, MW h^{-1}) in Peninsular Malaysia from January 1997 until December 2000. All sectors namely the industrial, commercial and residential sectors are included in this data as sectorial disaggregating was not available for daily peak electricity demand. Previous studies have shown that temperature is usually the most significant weather variable influencing electricity consumption (Nima, 2001). For this reason, weather variables are used with the inclusion of maximum, minimum and mean temperature as independent variables. The temperature data was collected at nine weather stations distributed across Peninsular Malaysia. Some adjustment were made to the temperature data by calculating the population weighted temperature index. The used of population weighted averages is adequate for the estimation of national electricity since energy used is usually related to the population size. The multiple regression model described in this study is shown to accurately predict the daily peak load demand under a wide range of weather conditions, holiday types and other seasonality factors. Two years of historical weather data from the Malaysian Metrological Office (MMO) as well as daily peak load data from TNB have been used in order to develop the time series regression model. The time series regression model developed in this study can be used to predict electricity load demand and it envisaged that forecast output from these models could be used in conjunction with other models such as Artificial Neural Network (ANN) (Ismail and Jamaludin, 2008) to produce short and medium peak load electricity demand.

THE DATA

In this study, the data from National Census of population in 2000 was used in the weights calculation (Census, 2000). The population weights given in Table 1 were calculated by obtaining the ratio of each states (a total of 14 states) population from the total population of Peninsular Malaysia. Population weighted temperature is obtained by summing the population weights for each stations j with the actual temperature of that station j for particular day-k as shown below.

$$T_w = \sum_{k=1} \sum_{j} P_{jk} W_{jk}$$

Where:

T_w = Population weighted temperature for day k

P_{jk} = Population weights for station j and day k

W_{jk} = Actual temperature for station j and day k

Previous studies have shown significant holidays and seasonal daily components in the electricity load series (Kermanshahi *et al*., 1993; Julián *et al*., 2005; Mirasgedis *et al*., 2006; Nima, 2001; Ismail and Jamaluldin, 2008). Examination of daily maximum load graphs for four consecutive years from September 1997 to August 2001 reveals a strong weekly effect with substantially reduced loads on the weekend (Fig. 1). In a weekly pattern, Sunday has the lowest load demand recorded. Special holidays like Eid of Ramadhan (EOR), Chinese New

Table 1: Population weights for nine weather stations

Stations	States	Population (Census, 2000)	Population weights
Alor Setar	Kedah and Perlis	1,649,756+204, 450 =1,854,450	0.0997
Bayan Lepas	Pulau Pinang	1,313,449	0.0706
Ipoh	Perak	2,051,236	0.1103
Kuantan	Pahang	1,288,376	0.0693
Kota Bharu	Kelantan	1,313,014	0.0706
Kuala Terengganu	Terengganu	898,825	0.0483
Melaka	Melaka and N.Sembilan	635,791 + 859,924= 1,495,715	0.0804
Subang	Selangor	4,188,876	
	Wilayah Persekutuan	1,379,310	
		5,568,186 (Total)	0.2994
Senai	Johor	2,740,635	0.1474
Total	Peninsular Malaysia	18,595,009	

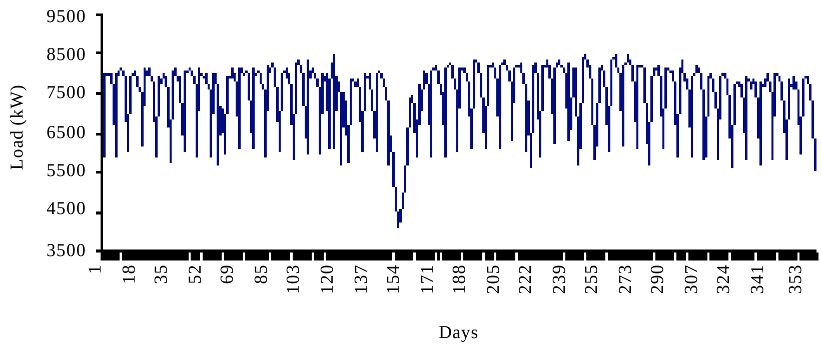

Fig. 1: Load consumption from September 1997-August 1998

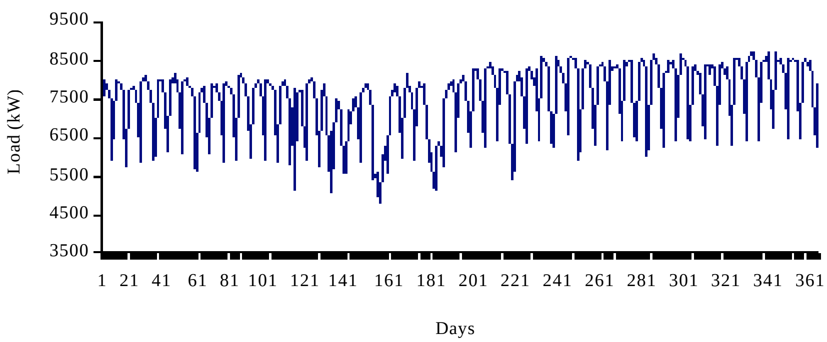

Fig. 2: Load consumption from September 1998-August 1999

Year (CNY), Christmas (CHM), Labour Day (LAB) and other special holidays all have the effect of lowering maximum load demand.

Figure 1 shows that the load pattern has a cyclical pattern throughout the year. There's a deep reduction in the load consumption in the month of January and early February that was due to the celebration of EOR and CNY that coincides where CNY fell on the 28, 29 January and EOR on 30, 31 January. These two major celebrations cause most Malaysian taking a long break at the same time and was the main reason why the reduction occurs. For other major holidays, the effect of holidays can be seen from the graph where the reduction of load occurs.

Figure 2-4 show the load consumption reveals the same pattern with big reduction on major religious holidays. All special holidays observed by the states in Peninsular Malaysia have some

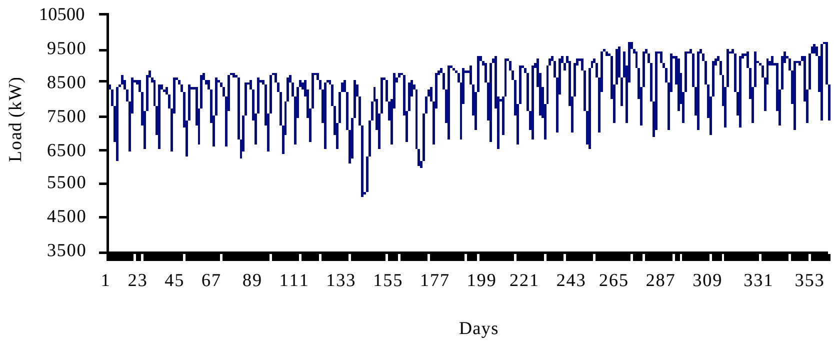

Fig. 3: Load consumption from September 1999-August 2000

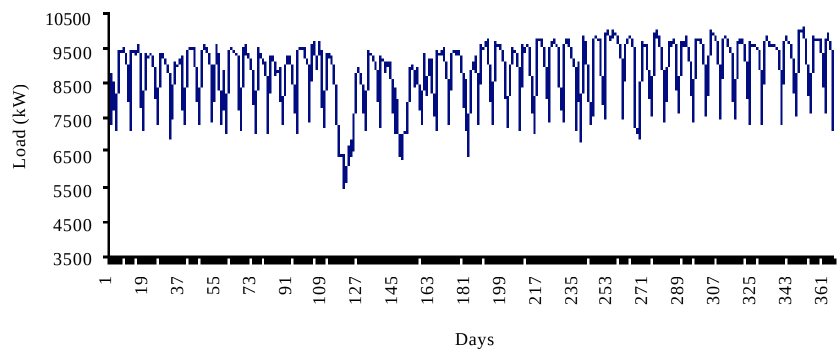

Fig. 4: Load consumption from September 2000-August 2001

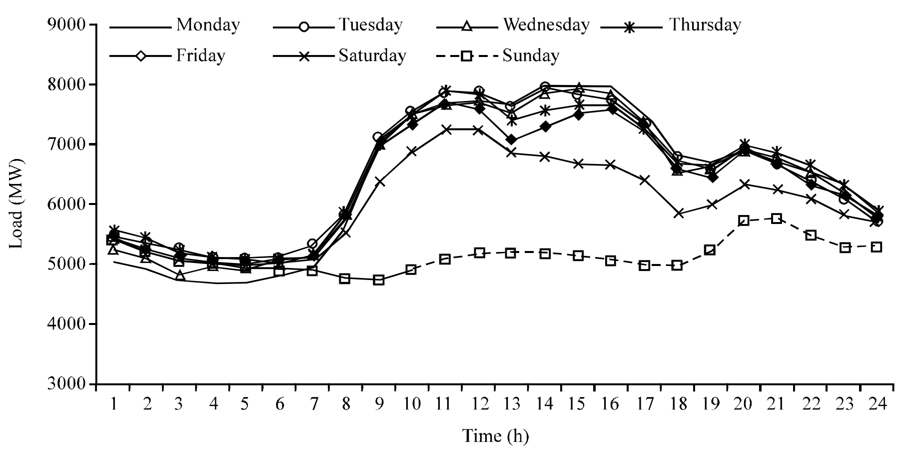

Fig. 5: Typical weekly load pattern

effects on lowering the load besides weekends. On these graphs, HRH and CNY falls, one month after EOR this can be seen, from significance reduction in load consumption from those graphs.

The effect of weekdays and weekends on load pattern can be clearly seen and the actual weekly pattern by hour on one particular week in 1999 as in Fig. 5. Variations of hourly load and variation between days in a week can clearly be identified. For hourly load, the load pattern follows the activities of the consumers. Load demand increase steadily from 9 am to 12 noon with small decrease during midday and picks up again until 4 pm in the afternoon. The demand decreases steadily after 4 pm until 7 pm and increase again around 8 pm to 9 pm. The load demand decreases gradually to the lowest load demand in the early morning. The line graphs show that Sunday has the lowest load with Saturday the next lowest and for most of the rest of the days the load variation are rather small.

In order to capture these two factors, a qualitative variable day of the week has been introduced into the model through the specification of six dummy variables (D_{it}) representing all days in a week (Tuesday, Wednesday, Thursday, Friday, Saturday and Sunday).

$$D_{it} = \begin{cases} 1, & t = \text{Tues,....,Sunday} \\ 0, & \text{otherwise} \end{cases}$$

The load demand decreases during holidays. For the model to take the decrease in to account, three additional dummy variables were introduced. First, define the variable H_{jt} where j refers to priority level given by different type of holidays as in Table 2. The priority values were chosen arbitrarily between [0,1] and were selected according to average load reduction values. Priority level one is given to CNY and EOR as these two holidays has the highest load reduction and also the longest duration of holidays. These holidays were given the highest weight reduction of one. The second category is given the next highest load reduction and were given priority level two which include EOR, LAB, National Day, CHM and Deepavali. All these are federal holidays and major religious events and the value given is 0.75 for load reduction weight. Third grouping is other federal holidays that incurred on average within 1300-1800 MW of load reduction. Last category includes all state holidays with load reduction ranging from 300-900 MW. These holidays include state holidays of Johor, Selangor, Wilayah Persekutuan and Pulau Pinang as these four states are the most populous and has the highest concentration of industrial activities (Census, 2000).

Second dummy variable H_{t-1}, which measures the effect of a day before a holiday is also added into the model. Its value also ranges from [0, 1]. These values have been selected base on historical values of average load reduction following a holiday. Another variable introduced is H_{t+1}, that also takes the value from [0, 1] when the observation corresponds to a day after a holiday or 0 otherwise. These two variables are introduced to measure the impact of proximity of holidays to load consumption.

Table 2: Priority level of holidays

Holidays	Average load reduction (MW)	Priority value	Priority level
CNY			
EOR	2600-3200	1	1
HRH			
LAB	2000-2600	0.75	2
National Day			
Deepavalli			
CHM			
New Year Day			
First Muharram	1300-1900	0.5	3
Wesak			
Maulud			
Agong's Birthday			
Thaipusam			
Wilayah	300-900	0.25	4
Nuzul Quran			
Ramadhan			
Selangor			
Johor			
Penang			

To account for the monthly seasonality, eleven dummy variables (M_{jt}) were introduced, each representing one of the months in a year and January as the base month. Thus, j refers to months of February, March until December. M_{jt} equals 1 if in the t observation the month j is found and 0 otherwise.

$$M_{jt} = \begin{cases} 1, & \text{if } j = \text{Feb, March,..., December.} \\ 0, & \text{otherwise} \end{cases} \quad \text{for } t = 1, 2 \text{ and } n.$$

TIME SERIES REGRESSION MODEL

Linear regression is useful for exploring the relationship of an independent variable that marks the passage of time to a dependent variable when the relationship is linear; that is, when there is an obvious downward, or upward, trend in the data over time. If the trend of the dependent variable over time is not linear, then linear regression will not capture the relationship. It fails to capture seasonal, cyclical and counter-cyclical trends in time series data. Neither does linear regression capture the effects of changes in direction of time series data, nor changes in the rate of change over time. For time series regression, it is important to obtain a plot of the data over time and inspect it for possible non-linear trends (Makridakis *et al.*, 1998). If we assume that the time series z_t and w_t are stationary time series, then the following assumptions applies:

E (z_t) $= \mu_z$ for all t (constant mean)
Var (z_t) $= \sigma^2_z$ for all t (constant variance)
Cov (z_t, z_{t+j}) $= \gamma_j$ for all t and arbitrarily chosen j = 1, 2, ...

Time series regression may be divided into three types namely:

- **Static Time Series Regression Model:**

$$z_t = \beta_0 + \alpha_0 w_t + u_t$$

- **Distributed Lag Time Series Regression Model:**

$$z_t = \beta_0 + \alpha_0 w_t + \alpha_1 w_{t-1} + \cdots + \alpha_p w_{t-p} + u_t$$

- **Autoregressive, Distributed Lag Time Series Regression Model: (Commonly called the ARX model)**

$$z_t = \beta_0 + \delta_t z_{t-1} + \cdots + \delta_r z_{t-r} + \alpha_0 w_t + \cdots + \alpha_p w_{t-p} + u_t$$

Time series regression is employed to forecast time series that are deterministic in nature. Such models are useful when the parameters describing a time series are not changing over time. For such model, error term is assumed to be a random variable and statistically independent. However, when we employ time series regression is employed, Residual Sample Auto Autocorrelation (RSAC) and Residual Sample Partial Autocorrelation (RSPAC) will indicate that the error terms are not statistically independent. To remedy this situation we will model the error term using Box-Jenkins model. We then forecast future values of the time series by combining the time series regression model with Box-Jenkins model. This analysis has been structured by following a stepwise scheme starting with the simplest model and adding each time new terms in order to assess separately the effect of the different factors that influence the daily electricity demand. Taking into account all the commented effects, the estimated model is finally given by:

$$L_t = c + \alpha_1 t + \beta_1 Temp_{max} + \gamma_1 Temp_{min} + \sum_{i=2}^{7} \delta_{1i} D_{it} + \lambda_1 H_t + \kappa_1 H_{t-1} + \varpi_1 H_{t+1} + \sum_{j=2}^{12} \theta_{1i} M_{jt} + e_{1t} \quad (1)$$

Where:
t = Time variable,
β_i = 1, 2,...k are coefficients to be estimated for the terms considering the different effects
e_t = The residual term

FORECASTING MODEL AND RESULTS

The results for the estimation of Eq. 1 are presented in the first three columns in Table 3. The constant and the trend are highly significant. Temperature variables are significant for maximum

Table 3: Parameters coefficients for Model 1 and Model 2

Model 1				Model 2			
Parameters	Coefficients	t-ratio	p-value	Parameters	Coefficients	t-ratio	p-value
Constant	8.431556	161.22	0.0001	Constant	8.377520	139.240	0.0001
T	0.000155	48.59	0.0001	T	0.000158	9.684	0.0001
Temp max	0.016645	13.25	0.0001	Temp max	0.010504	9.839	0.0001
Temp min	-0.003932	-1.86	0.0631	Temp min	0.006470	3.308	0.0001
Feb.	-0.014983	-2.56	0.0107	Feb.	0.003255	0.028	0.7777
Mar.	0.028861	4.80	0.0001	Mar.	0.042768	2.982	0.0029
April.	0.034987	5.65	0.0001	April.	0.054580	3.475	0.0005
May.	0.040774	6.46	0.0001	May.	0.019618	1.192	0.2336
Jun.	0.042028	6.97	0.0001	Jun.	0.030217	1.784	0.0747
July.	0.034945	5.95	0.0001	July.	0.030828	1.800	0.0720
Aug.	0.038465	6.55	0.0001	Aug.	0.022623	1.314	0.1892
Sept.	0.034580	5.82	0.0001	Sept.	0.029993	1.746	0.0811
Oct.	0.027061	4.32	0.0001	Oct.	0.031964	1.881	0.0602
Nov.	0.027441	4.33	0.0001	Nov.	0.034636	2.192	0.0286
Dec.	0.036713	5.85	0.0001	Dec.	0.046677	3.611	0.0003
Tue.	0.006450	1.43	0.1525	Tue.	0.005528	1.448	0.1480
Wed.	0.009521	2.12	0.0342	Wed.	0.009583	2.870	0.0042
Thurs.	0.002172	0.48	0.6285	Thurs.	0.001164	0.324	0.7457
Fri.	-0.010880	-2.42	0.0157	Fri.	-0.011300	-3.146	0.0017
Sat.	-0.068720	-15.31	0.0001	Sat.	-0.069255	-20.741	0.0001
Sun.	-0.268140	-59.42	0.0001	Sun.	-0.268189	-70.160	0.0001
H_{t-1}	-0.222440	-14.49	0.0001	H_{t-1}	-0.183940	-16.104	0.0001
H_{t+1}	-0.188010	-52.86	0.0001	H_{t+1}	-0.140366	-13.244	0.0001
H	-0.426600	-52.86	0.0001	H	-0.379562	-59.538	0.0001
				AR(1)	-0.369020	-13.465	0.0001
				AR(2)	-0.279870	-9.590	0.0001
				AR(3)	-0.079356	-2.735	0.0063
				AR(4)	-0.045043	-1.545	0.1225
				AR(6)	0.081559	2.871	0.0042
				AR(7)	-0.110761	-4.162	0.0001
				AR(12)	0.080786	3.105	0.0019
				AR(14)	-0.142742	-5.537	0.0001
MSE	0.001962			MSE	0.001095		
R^2	0.903200			R^2	0.946300		
DW	0.9535			DW	1.969600		
AIC	-4624.91			AIC	-5414.650		
SBC	-4499.59			SBC	-5247.550		

temperature but not significant for minimum temperature. The result shows the importance of daily seasonality in the electricity consumption especially the effect of holidays. Days with the least demands are increasingly Sunday, Saturday and Friday. From Model 1, monthly seasonality is significance and positive except for February, which is negative. The base month is January and this implies that all the other months have higher electricity consumption compared to January except for February, which has a lower electricity demand. January on average has lower electricity demand due to end of the year effect. The daily seasonality shows that Tuesday and Thursday are not significantly different from the base day, Monday. The coefficient for Wednesday is positive and significant which means that Wednesday has a higher consumption compared to Monday. All coefficients for Friday, Saturday and Sunday are negative and significantly different from Monday. This can be attributed to the weekend effect. As expected the Friday load shows the lowest demand for weekdays.

All coefficients for the dummy variables related to holiday effects are negative and significant indicating large demand decrease due to holidays, coefficients for H_{t-1} indicates that the momentum for holiday has started earlier usually a day before the holiday and this momentum is carried forward even after a holiday as shown by the significance H_{t+1} which measure a day after the holiday effect. This effect is usually true during major religious holidays like CNY, EOR, HRH and Deepavali. The excitement of holiday and the 'going back home' tradition which is strongly rooted in most Malaysian cause this before and after holiday's effect. Model 1 has a good predictive power with R^2 of 90.32%.

Serial Correlation

Despite the fact that the proposed Model 1, takes into account many seasonal and anomalous effects, it still shows large serial correlation coefficients (DW = 0.9535). The effects of serial correlation removal from the model will be examined below. In order to reduce the serial correlation observed in the first lags, various AR models have been tested using both AIC (Akaike Information Criterion) and SBC (Schwartz Criterion) as references for the selection. Finally, introducing 14-th order autoregressive process in the error term has specified the model.

$$L_t = c + \alpha_1 t + \beta_1 \mathrm{Temp}_{max} + \gamma_1 \mathrm{Temp}_{min} + \sum_{i=2}^{7} \delta_{2i} D_{it} + \lambda_2 H_t + \kappa_2 H_{t-1} + \varpi_2 H_{t+1} + \sum_{j=2}^{12} \theta_{2i} M_{jt} + \varepsilon_{2t} \quad (2)$$

Where:

$$\varepsilon_{2t} = e_{2t} - \phi_1 e_{2t-1} - \phi_2 e_{2t-2} - \phi_3 e_{2t-3} - \phi_4 e_{2t-4} - \phi_5 e_{2t-5} - \phi_6 e_{2t-6} - \phi_7 e_{2t-7} - \phi_{12} e_{2t-12} - \phi_{14} e_{2t-14}$$

The results for Model 2 are shown in the second column of Table 4. The significance of dummy variables for holidays is still maintained despite incorporating the residual autocorrelation.

Optimal Value of Load Reduction Weights

The priority values given to each holidays previously are based on intuitive judgment, the true value for weights given to each holiday groups are studied further. We fixed Group 1 holidays at 1 at all times, Group 3 at 0.5 and Group 4 at 0.25 and then changed the value of Group 2 iteratively with the values ranging from 0 to 1. Then for each value the model obtained was then use to forecast the load demand for October 2000 and the differences between the forecasted value and actual value were then measured. The process is repeated by changing the values for Group 3 and Group 4, respectively.

The optimum values for each holiday groups are Group 1 = 1, Group 2 = 0.65, Group 3 = 0.5 and Group 4 = 0.07. These values were obtained from the plot of mean average percentage error versus priority value for each group. Using these values in H_t variable, Model 2 and Model 3 were then used to forecast load demand for October 2000. During this month, two holidays occurred, that is state

Table 4: Priority level of holidays

Holidays	Priority level Model 1	Model 2	Model 3
CNY	1	1	1
EOR			
EOR			
Labour Day	Changed	0.65	0.65
National Day	iteratively (0,1)		
Deepavalli			
Christmas			
New Year Day			
First Muharram	0.5	Changed	0.5
Wesak		iteratively	
Maulud		(0,1)	
Agong's Birthday			
Thaipusam	0.25	0.25	Change iteratively
Wilayah			(0,1)
Nuzul Quran			
Ramadhan			
Selangor			
Johor			
Penang			

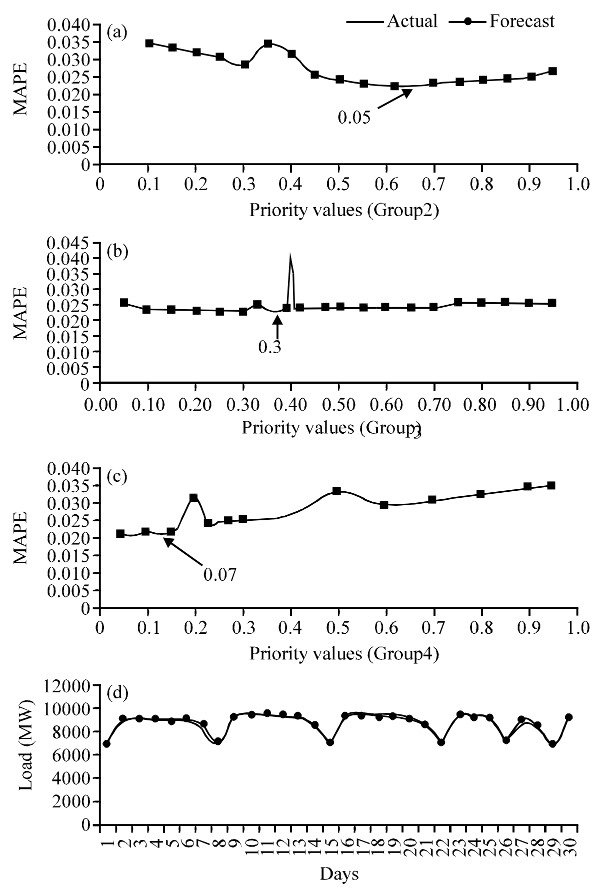

Fig. 6: Plot of MAPE vs priority value for group(a) 2 (b) 3 (c) 4 and (d) actual forecasts for October 2000

holiday of Johor and Deepavalli. The forecasted error for each predicted value shows that Model 3, has better accuracy and manage to predict the load when holidays occurred fairly accurate with 1.184 and 1.143% error for Johor state holiday and Deepavalli in October 2000. The forecasted versus actual values were plotted in Fig. 6d. Model 3 achieved a satisfactory result with MAPE of 1.74 percent as compared to 2.41 percent using the intuitive values of Model 2.

CONCLUDING REMARKS

In this study, all the important factors that are affecting load demand have been included in the time series regression models. Three models were being developed: Model 1 is the basic model, without taking into account serial correlation factor of load data and this model shows large serial correlation coefficients (DW=0.9535). The effect of serial correlation removal from the model is examined through Model 2, where the serial correlation was modeled using Box-Jenkins auto regressive error. Model 2 was satisfactory and adequate with 2.41 percent forecasting error. Searching the best priority values of each holidays grouping carries out further refinement of the model. Once these values were obtained they were used again in Model 3 and this model achieved a satisfactory forecasting error of 1.71% (Table 5).

From these results, it can conclude that, holidays play a major role in determining the load demand. Searching the true value of load reduction weights for each holidays grouping manage to reduce the forecasting error to a satisfactory level. In this particular problem, this study manage to quantify the effect of holidays by grouping the holidays with similar load reduction pattern together and

Table 5: Forecasted value for October 2000 for Model 2 and Model 3

Day of week	Holiday	Model 2	MAPE (Model 2)	Model 3	MAPE (Model 3)
Sunday		6977.16	1.426952	7025.23	0.02126
Monday		9086.05	2.493514	9093.08	0.02573
Tuesday		8813.61	3.040594	9054.85	0.00387
Wednesday	Johor	8474.39	5.965490	9118.70	0.01184
Thursday		8746.49	3.214673	8942.56	0.01045
Friday		9121.56	0.723117	9186.11	0.00021
Saturday		8593.58	6.237854	8629.63	0.06684
Sunday		7160.66	2.310232	7211.84	0.01612
Monday		9270.44	0.670310	9307.28	0.00276
Tuesday		9348.15	0.783804	9383.64	0.00407
Wednesday		9426.10	0.923902	9484.69	0.00308
Thursday		9376.37	1.040950	9392.69	0.00869
Friday		9264.44	1.084348	9318.02	0.00512
Saturday		8620.78	0.921963	8643.93	0.00656
Sunday		7126.04	3.007486	7175.33	0.02337
Monday		9403.06	0.880378	9446.54	0.01347
Tuesday		9274.78	2.790274	9301.49	0.02510
Wednesday		9234.40	2.084615	9278.74	0.01614
Thursday		9200.70	2.400552	9205.28	0.02352
Friday		9049.92	3.147260	9074.99	0.02879
Saturday		8579.39	1.949829	8595.93	0.01761
Sunday		7062.39	4.536496	7099.91	0.04029
Monday		9275.36	2.946950	9307.44	0.02611
Tuesday		9263.45	2.067343	9286.23	0.01827
Wednesday		8933.31	3.963556	9202.04	0.01075
Thursday	Deepavalli	6984.13	5.003672	7267.99	0.01143
Friday		8888.56	0.949006	9112.66	0.03494
Saturday		8577.99	1.695199	8589.56	0.01832
Sunday		6934.88	2.311875	6958.90	0.01974
Monday		9203.45	1.641017	9226.53	0.01394
Avg MAPE			2.407107		1.761%

searching the best weights reduction for these groups. In this case, the load reduction weights obtained are 1, 0.65, 0.37 and 0.07 were used successfully in the time series regression model for forecasting load demand.

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