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A New Decomposition Technique for Daily Peak Load Demand

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Abstract - This paper presents a new technique known as trend-cycle forecaster based on the popular Auto-Regressive Integrated Moving Average (ARIMA) method. The proposed technique is implemented by decomposing the time series into its various components using multiplicative decomposition. Thereafter Seasonal Autoregressive Integrated Moving Average (SARIMA) is employed on the trend-cycle to obtain a most suitable model for the data. This model is then tested using the Malaysian Electricity Peak Load data. The results obtain are promising when compared with other existing forecasting methods with an RMSE of 0.9458 and a MAE of 0.7058.

Key words: Decomposition, Peak Load, SARIMA, Trend-cycle, and Model.

1. INTRODUCTION

Electricity was discovered in the 1880's and since then has become an indispensable part of modernity (Oztura, 2007). Due to its indispensable nature, its demand has continuously increased parallel with the growing population, urbanization, industrialization, technologic deployment and enhancement of welfare (Yayar, et al, 2011). Planning has become an emerging need foci of recent researches in the electricity Supply Industry (ESI). The importance and relevance energized by daily electricity needs has positioned forecasting in a unique advantage to solving its many problems.

Forecasting is the basis for any planning and decision making. The more accurate it is, the better it is able to reduce risk associated with it in the future (Thammano, 1999). Reliable and robust forecasting method is required by the utility company to maximize profit and on the other hand satisfy the customers (Bansal*et al.*, 2010). As under forecast of electric load demand will result in shortage of supply which impacts negatively on a company's reputation and over forecast brings about incurring cost and reduced profit.

Data used in this study were obtained from the Tenaga Nasional Berhad (TNB), Malaysia. It comprises half hourly peak load demand for Malaysia from 1st September, 2005 to 31st August, 2006. Malaysia is made up of Peninsular Malaysia and the states of Sabah and Sarawak on the Island of Borneo. Malaysia has experienced a steady growth in its economy in the last decade this could be traced to the improvement in its energy sector particularly the Electricity Power Subsector (EPS), (Saidur *et al.*, 2009). Malaysian energy sector has recorded a 6.3% increase annually between 2005 and 2010 (Saidur *et al.*, 2009), this has been attributed to rural-Urban migration, higher living standards and increased per capita income. All these coupled with the fact TNB needs to meet the ever increasing challenge of power demand so as to meet up with its mandate. TNB is seeking ways of combating these rising challenges. It is in line with this that this paper proposes a new technique for forecasting Malaysian Electric Peak Load Demand is proposed known as trend-cycle forecaster based on the decomposition of the components of the time series data. See data in Chart 1.

The objective of this paper is to propose a new forecasting tool for electricity load forecasting based on the trend-cycle component of decomposed time series. The remaining part of this paper is structured as follows. Section 2 reviewed related literatures. In Section 3, we discuss decomposition technique, while Section 4 Discuss the results and Section 5 concludes the paper.

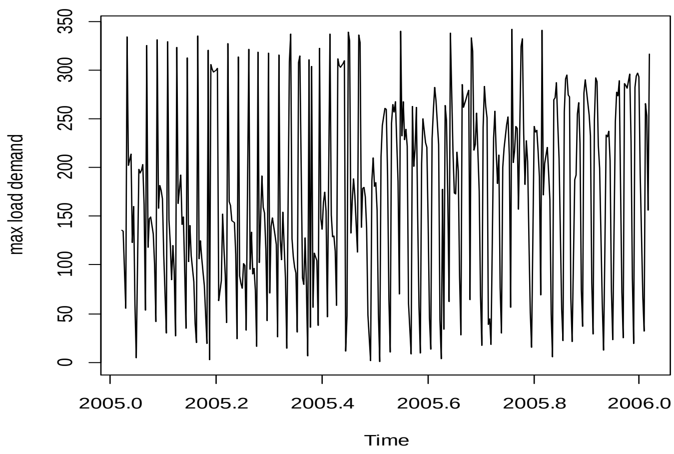

Chart-1: Time Plot of Maximum hourly peak load demand

2. RELATED LITERATURES

Energy forecasting especially electricity supply and demand has generated a lot of interest in the last decade and many studies are found in the literature on this. Many of these studies employ conventional and non-conventional techniques in forecasting load demand. There are scarcely any studies found that employ trend-cycle decomposition technique. This could be attributed to the unavailability of data as cycles require very lengthy data before its effect in a series can be observed.

In the literature it is allured to that decomposition techniques were initially developed by Pearsons (1919) to identify and isolate salient features of a time series such as trend, seasonality and cyclical patterns. Ever since their development, they have been used for analysis of economic data and are based on moving averages techniques such as time series ARIMA models (Box et al, 1978 and Gomez &Maravall, 1996).

Although decomposition methods were not developed for the primary purpose of prediction, their entrance and application is very appealing. In Theodosiou (2010) "disaggregating the various components in the data and predicting each one individually can be viewed as a process of isolating smaller parts of the overall process which are governed by a strong and persistent element, and therefore separating them from 'noise' and inconsistent variability". And by this we can learn more from these processes and possibly obtain more accurate forecast.

Al-Garni& Abdel-Aal (1997) estimated the Electric Energy Consumption of the east of Saudi-Arabia by developing a monthly ARIMA model using the univariate and Box-Jenkins time-series. Results were compared with that obtained from abductive network machine-learning models and it was shown that ARIMA models needs less data and gives better results.

Sari &Soytas (2004) employed a technique of generalized forecast error variance decomposition and arrived at the conclusion that electricity demand and variance income growth are as important as employment. (Lise & Van Monfort, 2005).

Damrongkulkamjorn & Churueang (2005) proposes a decomposition technique that uses the trend-cycle novel approach to forecast Thailand monthly energy data. The performance of the proposed decomposition technique was compared with those that project the trend-cycle using mathematical functions. Though both yielded very small APE those of the trend cycle based on S-curve is preferred to SARIMA because the ACF of the S-curve is not a white noise compared to the ACF of SARIMA which shows randomness.

Kareem &Majeed (2006) uses the traditional Seasonal Autoregressive Integrated Moving Average (SARIMA) method to forecast monthly peak-load demand for Sulaimany Governorate located in Northern Iraq for the year 2006 and obtained very good results with MAPE of 1.235

Chakhchoukh, *et al.* (2009) proposes a new robust Median -of- Ratio (MEDR) method for contaminated Gaussian SARIMA models. The proposed method uses robust autocorrelation estimates based on sample medians with robust filter cleaners that reject deviant observations. On testing its effectiveness on the French short-term load forecast it concludes that the proposed method is good considering its simplicity, computing and robust properties.

Rasak, *et al*. (2010) the paper seeks to find an appropriate forecasting technique for the moving holidays' effects in Malaysia. Such holidays include *eidulfitr*, Chinese New Year and Deepavali. The paper says these moving holidays could overlap with fixed holidays and thereby increase the complexity of the load forecasting problem. In order to achieve the objectives three methods were considered- SARIMA, constrained SARIMA and dynamic regression, the results obtained using MAPE were 4.84%, 3.85% and 2.39% for each of them respectively.

Chakhchoukh, *et al*. (2010) proposes an efficient and robust load forecasting method for prediction of up to a day-ahead. Two models were developed for achieving the purpose and these are the multivariate ratio-of-medians-based estimator (RME) and the multivariate minimum-Hellinger-distance based estimator (MHDE). Their performance were evaluated on the French electric load time series and compared with SARIMA and multiplicative double seasonal exponential smoothing models. It was found that SARIMA outperforms all the other methods.

Paretkar, *et al.* (2010) applied the popular Box-Jenkins SARIMA transfer function to implement STLF on the power flows on the transmission lines using historical data from the California hydropower of the Pacific Northwest region. The results were very promising. For the Pacific AC intertie and the Pacific DC intertie, the result showed an R^2 value of 0.961 with a MAPE of 14.9. The authors also tested for the randomness of residuals using the Ljung-Box Chi-square test and this was found to be significantly different from zero for the set of autocorrelations in the ACF and PACF plots.

Theodosiou (2010) says Combination techniques and Decomposition procedures have been applied to time series forecasting to enhance prediction accuracy and to facilitate data analysis but that their applicability is limited due to large variability associated involved in economic and financial time series. Applied decomposition technique based on STL procedures to data obtained from the NN3 and M1 competition series and concluded that the method employed outperform other statistical methods.

Theodosiou (2011) developed Seasonal Trend Loess (STL) decomposition technique which is based on the disaggregation of time series components, the extrapolation of linear combinations of the disaggregated sub-series and the re-aggregation of the extrapolations to obtain estimates of the global series. The results were compared with 4 other statistical techniques namely ARIMA, theta, Holt-Winters and Holt's Damped Trend and it was found to outperform them all using the mean absolute percentage error, median absolute percentage error, root mean square percentage error and root median square percentage error.

3. DECOMPOSITION TECHNIQUES

Decomposing time series involves identifying the individual components in the series. And for a time series it can be decomposed into four separate components and they can be identified as trend, seasonal, cyclical and residual. The trend component indicates a long time change in the data. The seasonal components are those changes that usually occur within a year and are dependent on weather and time of the year. Cyclical component are changes that occur in the data which are not fixed and most times are associated with business cycles. The general form of a decomposition technique can be expressed as:

$$Y_t = f(T_t, S_t, e_t) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (4.1)$$

Where Y_t is the value of the dependent variable at time t
T_t is the trend component in the series
S_t is the seasonal component and
e_t is the residual component or the random error

The function in (4.1) can be expressed in several forms but the two most common forms are the additive and multiplicative models which is respectively are expressed by (4.2) and (4.3)

$$Y_t = T_t + S_t + e_t \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (4.2)$$

$$Y_t = T_t \times S_t \times e_t \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (4.3)$$

- Additive Model

The additive model is used when seasonal fluctuations do not change in magnitude along the series while if changes occur in the seasonal fluctuations in the series the multiplicative model is used. The seasonal effects can be observed by simple inspection of the time plot by the increase and decrease of the magnitudes of the seasonal fluctuations. And from our time plot in figure 1 it can be seen that our series has seasonal pattern entrenched in it as revealed by the change in seasonal fluctuations. For this reason, we applied multiplicative model for the decomposition of the series.

- Multiplicative Model

The combination of the trend and cyclical components yields a trend-cycle component. To estimate this, we first apply moving averages to the data this will help smooth out the data over time. For the selected data which is a monthly energy data we choose a centered 12 MA smoother called a 2 X 12 MA (MA is moving average). Generally for moving average we center the averages of the observations and this is an easy task if the observations are odd but if they are even this is not always easy to handle. This can be handled by averaging the two consecutive averages and placing the result in the middle of the two sets of observations. For a $2 \times kMA$ smoother where k is even, we compute the compute the centered average at time t as

$$T_t = \frac{1}{2}\left(\frac{1}{k}\sum_{i=t-m}^{t+m-1} Y_i + \frac{1}{k}\sum_{i=t-m+1}^{t+m} Y_i\right) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots 4.4$$

Where T_t is the average value at time t

$m = \frac{k}{2}$, k is even and

$t > m$.

As is the case with moving average methods some values at the beginning and the end of the series are lost, the m missing values are accounted for by projecting the smoothing values to the end of the time line or allowing the averages to be computed from smaller number of observations as in Makridakis *et al.* (1998).

Having identified the trend-cycle, we excluded this from the original data to determine the seasonality. Therefore we rewrite the multiplicative model as:

$$R_t = \frac{Y_t}{T_t} = \frac{S_t T_t e_t}{T_t} = S_t e_t \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (4.5)$$

Where R_t is the ratio of the actual value to trend-cycle at time t with series is called the de-trended series and its better represented as percentages. With this achieved, we now obtained the seasonal index for each time period. We assumed the seasonal index is constant over time and the seasonal indexes obtained for all time periods are repeated to form seasonality of the series. Having identified the trend-cycle and seasonality, we obtained the residual as

$$e_t = \frac{Y_t}{T_t S_t} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4.6)$$

4. DISCUSSION OF RESULT

Though in this paper, our aim is not on ARIMA model but to achieve our set goal we need to apply ARIMA model to the original time series which is the daily peak load data for Malaysia. In order to go about this we first obtained the time plot in figure 1 above. Thereafter, we obtained the ACF and PACF so as know if the series is stationary. This is given in Chart 2a and 2b.

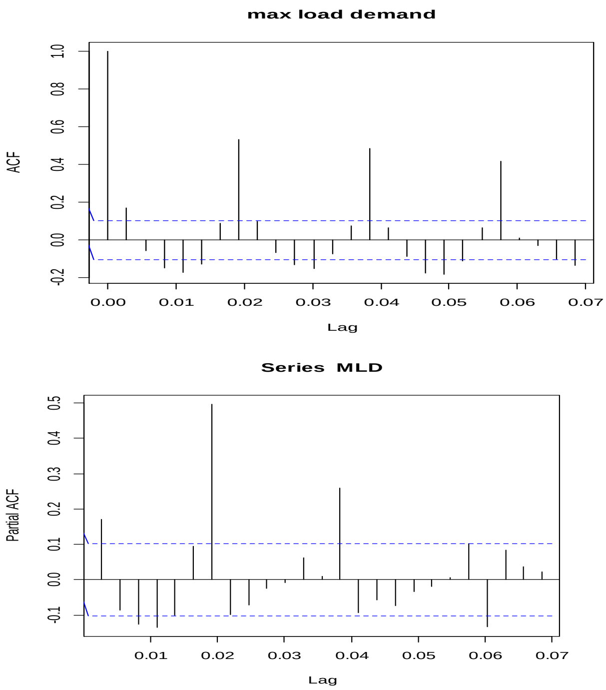

Chart -2: ACF and PACF of the series

We then took the log of the first difference because it is a necessary condition in ARIMA modeling for the series to be stationary. This is observed in series when they appear horizontal along the X-axis. We then moved on to decompose the series into its respective components as shown in Chart 3.

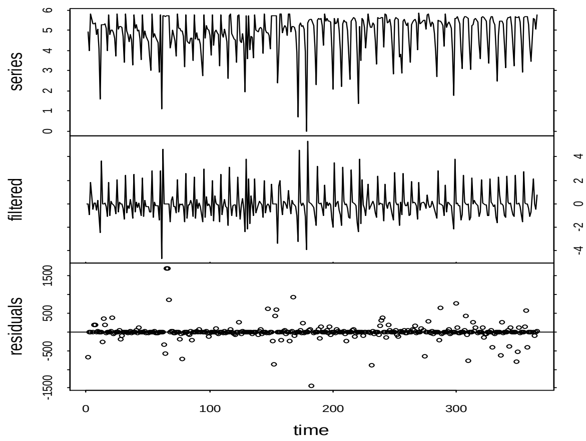

Chart- 3: Components of the Time Series

We need to mention here that the component marked filtered is the trend-cycle component of the series. These were obtained after taking the log of the first difference. With the series now stationary, we proceeded to obtain the seasonal ARIMA (SARIMA) model to be used for forecast. We obtained the following SARIMA models with zero mean

ARIMA (0, 0, 1) $(0, 0, 2)_{12}$ = 1001.995 (5.1)

ARIMA (0, 0, 1) $(1, 0, 2)_{12}$ = 1006.622 (5.2)

ARIMA (0, 0, 1) $(0, 0, 1)_{12}$ = 1002.906 (5.3)

ARIMA (1, 0, 1) $(0, 0, 2)_{12}$ = 1003.411 (5.4)

ARIMA (0, 0, 0) $(0, 0, 2)_{12}$ = 1221.127 (5.5)

ARIMA (0, 0, 2)$(0, 0, 2)_{12}$ = 1002.314 (5.6)

ARIMA (1, 0, 2) (0, 0, 2) = 1005.006 (5.7)

From these models with zero mean, we chose our best model to be the first which we write as

$$ARIMA(0,1,1)(0,0,2)_{12} \qquad (5.8)$$

Having obtained the SARIMA model, estimating the parameters of the model using least squares iterative methods. The optimal parameters and their standard errors in brackets are given below

$$\theta_1 = -0.9858\ (0.0079)$$

$$\theta_{s1} = -0.1165(0.0540)$$

$$\theta_{s2} = -0.0924(0.0525)$$

Using the SARIMA model and its associated parameters, the forecast trend-cycle of hourly peak load demand for Malaysia is computed and this is shown in Chart 4. But before this we tested the adequacy of the model. We tested the error for Normality using JaqueBera test and it was found to be highly significant with a p-value of 0.000. Furthermore, using the popular Ljung Box to test for autocorrelation of the model, this was found also to be equally highly significant with p-value of 0.000. From this we can conclude that the model is good for trend-cycle estimation. The values of RMSE and MAE are 0.9456 and 0.7058 respectively. These are low, indicating good measures of accuracy; as such we are confident that the accuracy of the model chosen for predicting the trend-cycle is acceptable.

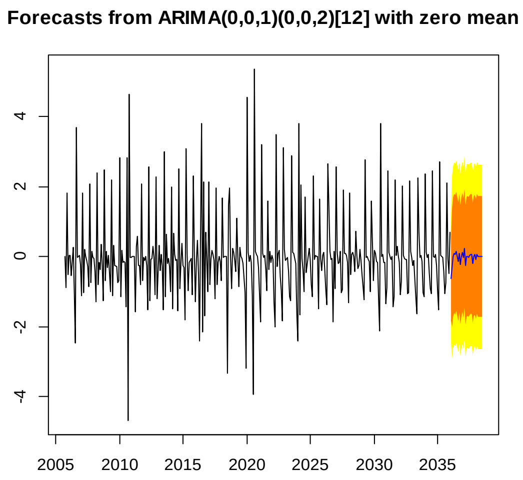

Chart- 4: Forecast of Trend-cycle

The colored area of Chart 4 is the forecast region and the smooth movement along the radix zero proves the forecast is a good one. This is more evident in that the spikes noticed earlier on in the series have leveled out.

5. CONCLUSION

A new approach based on the decomposition of the trend-cycle using ARIMA method has been put forward in this paper for forecasting the hourly peak load for Malaysia. The proposed model was applied to data obtained from TNB Malaysia. The adequacy of the model was tested using Ljung Box and it gave a good fit and the accuracy measure based on RMSE and MAE gave good results.

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