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How Accurate is TNB's Electricity Demand Forecast?

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ABSTRACT

Forecasting of electricity demand provides an essential input for decision making in power operation and development. In Malaysia, Tenaga Nasional Berhad (TNB) is using a well-established and sophisticated system to forecast the electricity demand. However, the reported predictive performance appears to be unsatisfactory if we compared to the other forecasting methods. Thus, this paper aims to evaluate and compare the predictive performance of TNB's forecast to the univariate time series methods of classical decomposition model, exponential smoothing, Holt-Winter smoothing and Box-Jenkins approach. The predictive performance of Box-Jenkins approach is found to be superior to TNB. Specifically, the Autoregressive Frictionally Integrated Moving Average (ARFIMA) is found to be able to reduce eighty five per cent of the TNB's forecast error.

Keywords: Electricity demand, predictive performance, classical decomposition model, Smoothers, Box-Jenkins Approach.

1. Introduction

Forecasting is a tool to minimize future uncertainty and it plays an important role in a country's power operation and development. Indeed, forecasting of electricity demand provides an essential input for decision making in power operation and development. It forms the basis for power system planning, security, reliability and development (Zuhaimy, Fuah and Azna, 2014). Due to the rapid changes of socio-economic characteristics, deregulation of electricity supply industry and the trend of increasing electricity demand, the forecasting of electricity demand is even more important that before (Nagi, Yap, Tiong and Ahmed, 2008). Overestimation in electricity demand will lead to energy wasting (excess of supply) and underestimation will lead to the electric failure (shortage of supply). Either excess or shortage of supply, it will impose a huge cost to the country. Zuhaimy and Rosnalini (2011) claimed that one per cent error in electricity load demand forecast may lead to a loss of millions of ringgit Malaysia. Thus, the importance of electricity demand forecasting is clearly shown.

In Malaysia, the power supply industry is monopolized by Tenaga Nasional Berhad (TNB). TNB serves an estimated 8.3 million customers, with almost RM87 billion worth of assets and a workforce of more than thirty three thousand persons. TNB performs three types of forecasting: short term, medium term and long term forecast for its power operation and development purposes. As reviewed by Zuhaimy, Fuah and Azna (2014), during the 1970s, TNB's electricity demand forecasting is a pure judgmental approach. In the early 1980s, the time series analysis, regression analysis and income elasticity approaches are introduced in the demand forecasting. In addition, the sectoral trend analysis and end-use method are implemented to complement the existing forecasting methods. Finally, the values that forecasted by the various methods are averaged to produce the forecasted electricity demand.

It is clear that the TNB is using a well establish forecasting system. In terms of predictive performance, the forecast error (Mean Absolute Percentage Error, MAPE) on the electricity maximum demand is 2.5% for 1-3 years forecast horizon, 10.6% for 4-7 years forecast horizon and 16% for more than 8 years forecast horizon (Electricity Demand Forecasting, p.87, 2007). These forecast errors are substantially higher than the forecast error of previous studies that use time series forecasting methods without averaging. For instance, using a time series regression model, Ismail, Jamaluddin and Jamaludin (2008) forecasted the maximum electricity demand, the forecast error, MAPE, is found to be approximately 1.71%. Lim and Yip (2014) performed a 10-step ahead forecast on the monthly electricity maximum demand in Malaysia and the MAPE is 1.09% for in-sample and 1.68% for out-of-sample. This leads to the following research questions: how accurate is the TNB's forecast on electricity demand? Using the averaging approach, does TNB obtain a better forecast (as compared to the univariate time series)? This paper attempts to answer the above research questions and aims is to access the accuracy of TNB's electricity demand forecast compared to other univariate time series methods.

In literature, there are various methods of forecasting such as classical decomposition, neural neworks, hybrid method, and fuzzy logic, and time series model. For example, Norizan and Maizah (2010) use a hybrid model to forecast the half hourly load demand in Malaysia; Aqeel Ahmed, Meysam and Gholamerza (2012) use an adaptive neuro-Fuzzy network to forecast yearly electricity demand in Johor, Malaysia; Peng and Chu (2009) use five time series forecasting methods including classical decomposition model to forecast the monthly container throughput volumes. The time series models are the popular methods because of its ability in dealing with non-stationary, seasonal patterns and signals (Intan Azmira, Shah, Mohd Sharieel and Arfah, 2012). In terms of forecast horizon, electricity demand forecasting could be broadly classified into two categories: short term and long term. According to Zuhaimy and Ronalini (2011), short term forecast is crucial for daily operations of a utility company and long term forecast is needed for strategic planning in electricity sector as the investment in this sector is capital intensive and takes long time period.

Nur Adilah, Maizah and Norizan (2013) examine the forecast accuracy of five exponential smoothing methods in forecasting the electricity load demand. It is claimed that the exponential smoothing is a leading forecasting method due to its robustness and accuracy. The double seasonal Holt-Winters exponential smoothing method is found to have the highest forecast accuracy. Moreover, the forecasting horizon also influences the accuracy and it is suggested that the one-step ahead forecasts to be used in forecasting electricity load demand. On the other hand, using the forecasting accuracy criteria of Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean absolute Relative Percentage Error (MARPE), Fadhilah, Mahedran, Amir and Izham (2009) found that the ARMA (2, 0) model is the best model for forecasting electricity demand in Malaysia.

The electricity usage of Washington, U.S., is forecasted using various univariate time series models (naïve, regression, decomposition, exponential smoothing and ARIMA) and it is found that exponential smoothing method has the best predictive performance (Javedani, Lee and Suhartono, 2011). The predictive performance of ARIMA model is found to be influenced by the presence of outliers in data. Javedani, Lee and Suhartono (2011) suggested that outliers (out-of-sample) could influence on predictive performance of models that rely highly on correlation between historical data such as ARIMA; whereas, for models that forecast using more weight to more recent observations such as exponential smoothing, will perform better in presence of these outliers.

Another univariate forecasting method that closely related to ARIMA is ARFIMA (Autoregressive Fractionally Integrated Moving Average). ARFIMA could be a useful forecasting method as well. ARFIMA suites well with the long-memory processes that normally indicated with a slowly decay autocorrelation function. ARFIMA also has a statistical advantage in terms of parsimonious parameterization (Bhardwaj and Swanson, 2003). Previous studies have found that ARFIMA is able to yield higher forecast accuracy than other time series models (Ding, Granger and Engle, 1993; Bhardwaj and Swanson, 2003). For instance, Siti Normah, Maizah, Suhartono, and Norizan (2012) show that ARFIMA performs better than the established model of ARIMA in forecasting electricity load demand. It appears that the fractional differencing of ARFIMA is able to improve the predictive performance. This forecasting method is not included in the TNB's forecasting (see Electricity Demand Forecasting, 2007). Thus, for purpose of comparison, we included ARFIMA as one of the forecasting models in the present paper.

In short, there are mixed evidences on the best forecasting methods in terms of predictive performance. It is true that TNB is using a comprehensive and sophisticated forecasting system on its electricity demand. However, TNB's forecast accuracy appears less satisfactory compared to previous studies. Due to the importance of having an accurate forecast of electricity demand, it is imperative to evaluate the predictive performance of TNB's forecast.

2. Data and Methodology

The TNB's forecasted values on electricity demand (maximum load) is obtained from the Electricity Demand Forecasting (Electricity Demand Forecasting, p.83, 2007). In summary, the TNB's forecasted peak electricity demand (MW) are increasing over the period of 2007-2013: 13,662 (2007), 14,288 (2008), 14,891(2009), 15,473 (2010), 16,071 (2011), 16,678 (2012), and 17,309 (2013). In addition, we obtain the monthly data of electricity maximum demand (MW) from January, 2002 to December, 2013, from the various issues of Quarterly Update of Malaysian Economy by Ministry of Finance, Malaysia. To be consistent with the TNB's forecast, we use the estimation sample of January 2002 to December 2006 and the forecast of electricity maximum demand is performed for the year of 2007, 2008, 2009, 2010, 2011, 2012 and 2013 (out-of-sample forecast).

Then, the predictive performance is evaluated using Mean Square Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Square Percentage Error (MSPE), and Root Mean Square Percentage Error (RMSPE) as follow:

$$MSE = \frac{\sum_{t=1}^{n} (Y_t - \hat{Y}_t)^2}{n} \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (Y_t - \hat{Y}_t)^2}{n}} \tag{2}$$

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right|}{n} \tag{3}$$

$$MSPE = \frac{\sum_{t=1}^{n} \left(\frac{Y_t - \hat{Y}_t}{Y_t} \right)^2}{n} \tag{4}$$

$$RMSPE = \sqrt{\frac{\sum_{t=1}^{n} \left(\frac{Y_t - \hat{Y}_t}{Y_t} \right)^2}{n}} \tag{5}$$

We used the time series decomposition (classical decomposition model), smoothers (single and double exponential, non-seasonal and seasonal Holt-Winter), and Box-Jenkins approach (ARIMA and ARFIMA) to forecast the electricity maximum demand. A brief discussion on the methods is presented as follow.

2.1 Time Series Decomposition

Forecasting could be performed by decompose the time series into four elements: trend (T), cyclical (C), seasonal (S) and irregular (I). Mathematically, a multiplicative classical decomposition model can be expressed as follow:

$$Y_t = (T_t)(S_t)(C_t)(I_t) \tag{6}$$

2.2 Smoothers

We used four types of smoothers: single and double exponential, non-seasonal and seasonal Holt-Winters. Forecasting could be performed using the smoothed values of a single-exponential smoothing as follow:

$$S_t = \alpha Y_t + (1-\alpha)S_{t-1} \tag{7}$$

S_t is the smoothed values and Y_t is the electricity demand. Substituting the lag values of St and lead to the following equation:

$$S_t = \alpha \sum_{k=0}^{T-1} (1-\alpha)^k Y_{T-1} + (1-\alpha)^T S_0 \tag{8}$$

The double-exponential smoothing is a single exponential smoothing on a smoothed series, as follow:

$$S_t = \alpha \sum_{k=0}^{T-1} (1-\alpha)^k Y_{T-1} + (1-\alpha)^T S_0 \tag{9}$$

The Holt-Winter forecasts a series using two parameters, α and β, as follow:

$$\begin{aligned} \hat{Y}_{t+1} &= a_t + b_t t \\ a_t &= \alpha Y_t + (1-\alpha)(a_{t-1} + b_{t-1}) \\ b_t &= \beta(a_t - a_{t-1}) + (1-\beta)b_{t-1} \end{aligned} \tag{10}$$

To incorporate the seasonal component (seasonal with period L), the Holt-Winter forecasts a series (τ step-ahead) with three parameters, β and γ , as follow:

$$\begin{aligned} \hat{Y}_{t+1} &= \{a(t) + b(t)\tau\} s(t+\tau-L) \\ a(t) &= \alpha \frac{Y_t}{s(t-L)} + (1-\alpha)\{a(t-1) + b(t-1)\} \\ b(t) &= \beta\{a(t) - a(t-1)\} + (1-\beta)b(t-1) \end{aligned} \tag{11}$$

2.3 Box-Jenkins Approach

ARIMA, also known as Box-Jenkins approach, the series could be differenced or seasonally differenced. For a series of Y_t, an ARIMA (p, d, q) could be represented as follow:

$$\left(1 - \sum_{k=1}^{p} \alpha_k L^k\right)(1-L)^d Y_t = \left(1 + \sum_{k=1}^{q} \beta_k L^k\right)\varepsilon_t \tag{13}$$

The d is the integration parameter and it takes discrete values of zero, one and above. There is stationary condition of a series in the estimation of ARIMA. To check on the level of integration needed, a modified Dickey-Fuller t test for a unit root is performed (DF-GLS). ARFIMA extends the ARIMA by allowing a fractionally integrated ARMA process using a parameter d. For a series of Y_t, an ARFIMA (p, d, q) could be represented as follow:

$$\left(1-\sum_{k=1}^{p}\alpha_k L^k\right)(1-L)^d Y_t = \left(1+\sum_{k=1}^{q}\beta_k L^k\right)\varepsilon_t \tag{14}$$

The d is the integration parameter; d is nonzero and if d is in the range of -0.5 to 0.5, the process is stationary and invertible.

3. Analysis and Results

Descriptive statistics show that during the period of 2002 to 2013, the electricity maximum demand (MW) in Malaysia is ranging from 9,870 to 16,562 with mean value of 13,315 and standard deviation of 1,697. Graphically, from Figure 1, the electricity demand shows an increasing trend during the period. However, the variance of electricity demand appears to be constant over time. We perform the DF-GLS on it and as expected, the electricity demand is found to be an I(1) series (stationary at first difference). Table 1 presents the actual and TNB's forecasted values of electricity maximum demand from 2002 to 2013. From Table 1, it is clearly shown that the forecasted values of TNB appear to be increasing and consistently over-forecast the electricity demand.

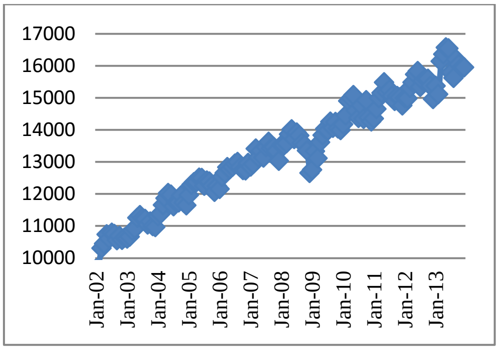

Figure 1: Electricity maximum demand (MW) Jan 2002-Dec 2013

TABLE 1: Electricity maximum demand (MW)

Year	**Actual**	**TNB forecast**
2002	10783	-
2003	11329	-
2004	12023	-
2005	12493	-
2006	12990	-
2007	13620	13662
2008	14007	14288
2009	14245	14891
2010	15072	15473
2011	15476	16071
2012	15826	16678
2013	16562	17309

We forecast the electricity demand of 2007-2013 using the multiplicative classical decomposition model, exponential smoothing (single and double), Holt-Winter (non-seasonal and seasonal), ARIMA and ARFIMA using the estimation sample (January 2002 to December 2006). For ARIMA, the autocorrelation function (ACF) and partial ACF are used to identify the order of *p* and *q*. The ACF and PACF suggest that the SARIMA (1 12 24, 1, 0). Thus, we estimate SARIMA(1 12, 1, 0), SARIMA(1 12 24, 1, 0) and SARIMA (1 12 24, 1, 1). In a similar vein, the ARFIMA(1 12, *d*, 0), ARFIMA(1 12 24, *d*, 0) and ARFIMA (1 12 24, *d*, 1) are estimated. Table 2 presents the actual and forecasted values of electricity demand.

TABLE 2: The actual and forecasted electricity demand

	2007	2008	2009	2010	2011	2012	2013
Actual	13620	14007	14245	15072	15476	15826	16562
<u>Forecast:</u>							
decomp	13564	13680	14387	14695	15205	15580	16296
sex	12954	12954	12954	12954	12954	12954	12954
dex	13537	14165	14793	15422	16050	16679	17307
hw1	13610	14266	14923	15579	16235	16891	17547
hw2	13508	14041	14574	15107	15640	16172	16705
arima1	13587	14080	14178	15325	15607	15805	16629
arima2	13579	14107	14118	15283	15481	15837	16548
arima3	13481	14000	14188	14784	15244	15595	16197
arfima1	13520	14038	14095	15115	15330	15811	16593
arfima2	13508	14031	14035	15169	15261	15882	16619
arfima3	13515	14034	14038	15170	15270	15882	16618
TNB	13662	14288	14891	15473	16071	16678	17309

Note:
1. Out-of-sample forecast 2007-2013
2. decomp=classical decomposition model; sex = single exponential smoothing; dex = double exponential smoothing; hw1 = Holt-Winter (non-seasonal); hw2 = Holt-Winter (seasonal); arima1 = ARIMA(1 12, 1, 0); arima2 = ARIMA(1 12 24, 1,0); arima3 = ARIMA (1 12 24, 1, 1); arfim1 = ARFIMA(1 12, *d*, 0); arfim2 = ARFIMA (1 12 24, *d*, 0); and arfim3 = ARFIMA (112 24, *d*, 1).

From Table 2, it is found that the forecasted values of TNB appears almost similar to the values forecasted by classical decomposition model (decomp), double exponential smoothing (dex) and Holt-Winter (hw1). On the other hand, the forecasted values of ARIMA and ARFIMA are closer to the actual values than the TNB's forecasted values.

The predictive performance of the various forecasting methods is calculated. The results are as presented in Table 3. From Table 3, it is found that the predictive performance of TNB's forecast is satisfactory if we compared it to single exponential smoothing (sex) and Holt-Winter (hw1). The TNB's percentage of forecasting error (MAPE) is found to be 3.32% which is lower than single exponential smoothing (sex) and Holt-Winter (hw1).

The TNB's predictive performance is found to be substantially lower than the Box-Jenkins approach (either ARIMA or ARFIMA). ARFIMA (1 12, *d*, 0) has the best predictive performance where the percentage of forecasting error (MAPE) is only 0.50% (arfim1). This implies that by using ARFIMA to forecast the electricity demand 2007-2013, we are able to reduce the forecasting error of TNB by 85% (i.e., (3.32 – 0.5)/3.32).

TABLE 3: Predictive Performance

	MSE	**RMSE**	**MAPE**	**MSPE**	**RMSPE**
TNB	328111	573	3.32	13.7	3.7
decomp	68036	261	1.59	2.99	1.73
sex	5047358	2247	13.11	204.22	14.29
dex	295252	543	3.07	12.13	3.48
hw1	494921	704	3.95	20.3	4.51
hw2	41461	204	1.1	1.82	1.35
arima1	13858	118	0.61	0.61	0.78
arima2	10382	102	0.5	0.48	0.69
arima3	49425	222	1.22	2.01	1.42
arfima1	8259	91	0.5	0.39	0.62
arfima2	17034	131	0.74	0.78	0.88
arfima3	16131	127	0.73	0.74	0.86

Note:
1. Out-of-sample forecast 2007-2013
2. decomp=classical decomposition model; sex = single exponential smoothing; dex = double exponential smoothing; hw1 = Holt-Winter (non-seasonal); hw2 = Holt-Winter (seasonal); arima1 = ARIMA(1 12, 1, 0); arima2 = ARIMA(1 12 24, 1,0); arima3 = ARIMA (1 12 24, 1, 1); arfim1 = ARFIMA(1 12, d, 0); arfim2 = ARFIMA (1 12 24, *d*, 0); and arfim3 = ARFIMA (112 24, *d*, 1).

4. Conclusion and Discussions

Forecasting of electricity demand provides an essential input for decision making in power operation and development. In Malaysia, TNB is using a well-established and sophisticated forecasting system which comprises of various forecasting methods. The various forecasted values are then averaged by TNB to obtain one forecasted value in electricity maximum demand. This paper compares the predictive performance of TNB's forecast method to other univariate time series methods. The predictive performance of Box-Jenkins approach is found to be substantially better than TNB. Specifically, the ARFIMA is able to reduce eighty five per cent of the TNB's forecasting error. This relatively poor predictive performance of TNB's forecast could be due to the averaging. The averaging performed by TNB is theoretical sound, for instance, it is consistent with the theory of portfolio diversification (minimize the risk). However, the averaging of various forecasted values will lead to an average predictive performance. Since there are overwhelming evidences from literature that the Box-Jenkins approach is the best approach in short and long memory time series forecasting, why averaging and why not we just choose the best model?

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