FORECASTING OF UNIVERSITI TUN HUSSEIN ONN MALAYSIA'S ELECTRICAL LOAD BY USING HOLT'S LINEAR TREND & HOLT-WINTERS TECHNIQUES

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ABSTRACT

The best planning of electricity consumption is needed in order to sustain the increasing of development activities. An important way to achieve that goal is to have the best forecasting model that could accurately modelling the pattern usage of electricity by using the data from January 2009 until December 2017 and forecast for the electricity consumption from January 2018 to December 2018. The purpose of this paper is to apply two differences forecasting method to forecast the electricity consumption Universiti Tun Hussein Onn Malaysia (UTHM). This paper compared the performance of Holt's Linear Trend method and Holt-Winters method both in long-term forecasting. The results show that both methods performing well and Holt-Winters' with the lowest error compared to Holt's Linear Trend method. The mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) were calculated and pointed as a bench mark for both methods applied.

Keywords: holt's linear trend, holt-winters, mean absolute error, mean absolute percentage error, mean square error, root mean square error.

INTRODUCTION

More recently, electricity has become the most important part in modern life and as references in developing the country. Electricity forecasting give huge contribution for solving the problems about energy management and the most important things is for development in the future. Electricity load forecasting can be classified into three categories which is short-term load forecasting (STLF), medium-term load forecasting (MTLF), and long-term load forecasting (LTLF) [1]. The LTLF mean predicts the load demands of a year at least or several years times interval. Electricity demand forecasting is a central and integral process for planning periodical operations and facility expansion in the electricity sector. Its play a big role in power system management such as power system control, economics pattern prediction, and generator maintenance schedule [2].

Time series forecasting is one of the research topics of time series data mining. Time series forecasting like linear forecasting method needs statistical data and past observations of the same variable. All of them are collected and analysed to develop a model describing the relationships [3]. It can be classified into two categories which is classical approach and artificial intelligence (AI) based technique [4]. Some of classic approaches are smoothing techniques, regression models and auto-regressive moving average models [5].

Paul [6] stated that exponential smoothing technique is one of the most significant quantitative techniques in forecasting. The accuracy of forecasting of this technique depends on exponential smoothing constant. In this work, trial and error method was used to determine the optimal value of exponential smoothing constant to minimize the error in forecasting. The selection of the optimal value of exponential smoothing constant is necessary minimize the mean square error (MSE) and mean absolute deviation (MAD).

Taylor [7] stated that the double seasonal Holt-Winters method performing the best followed with principle component analysis (PCA) and ARMA method. The Holt-Winters method is impressive as exponential smoothing method that particularly show the process with simplicity. Hence. This method seems very attractive as it is simple to understand and implement, and it has been shown the best performance in STLF. Furthermore, this method is also highlighted because of existence of an underlying statistical model that easy to be understood.

Kavanagh [8] forecasted a supply company's demand using Double Seasonal Exponential Smoothing variation of the Holt-Winters method resulting in an average daily mean absolute percentage error (MAPE) of 2.99% over a period of nearly four weeks. It was found that a Double Seasonal Exponential Smoothing model gave a MAPE of 0.4 - 1.2%; a Neural Network model resulted in 0.4 - 2.1%, Double Seasonal ARIMA in 0.4 - 1.6%; Regression method in 0.5% - 1.4%; Seasonal Random Walk in 0/4 - 2.25% and Error Modelling Seasonal Random Walk in 0.5 - 1.7% by Taylor. Thus, he decided to pick Double Seasonal Exponential Smoothing to forecast the electricity.

Tirkeş *et al*. [9] compared the performances between Trend Analysis, Decomposition and Holt-Winters (HW) models for the prediction of a time series formed. Data comprised the series of monthly sales from January 2013 to December 2014 obtained from a food production company. The author analysed the three methods in term of their trend, seasonality and cyclic. The research showed the strength and weakness of each method.

Yapar [10] showed that although the form of initialisation and loss functions used for other exponential smoothing models did not produce any major changes in post-sample prediction accuracy, they were particularly important for the Holts linear trend for long-term projections. Even if this is not the case, the fact that trying to find an optimum initial value complicates and prolongs the optimization process cannot be overlooked. The modified simple exponential smoothing model proposed helps deal with these problems but still lacks the ability to deal with possible trending behaviour that may be present in the data.

TIME SERIES

Time series forecasting is one of the methods which using an ordered sequence of values recorded over equal intervals of time. The analysis of time series can be divided into two section which is by understand the pattern of the existing data and the second one is fitting the best model to make the prediction data [11].

The time series data will be analysed in order to extract statistic or pattern of the data so the prediction process can be done. A time series data usually will be decomposed according to the following three components [11].

a) Trend - The general movement that the variable exhibits during the observation period without taking the seasonality and irregularities into account.

b) Seasonality - This is the periodic fluctuation of the variable subjected to analysis. It consists of effects that are stable along with time, magnitude and direction.

c) Residual - This is the remaining, mostly unexplainable part of the time series. These can be sometimes high enough to mask the trend and seasonality.

HOLT'S LINEAR TREND METHOD

Holt's Linear Trend method is also known as double exponential smoothing. This method is the extension of exponential smoothing which adds the second exponential smoothing model to capture the trend of the time series data. There are three equations used in the process: the first equation for smoothing time series, the second equation for smoothing trend, and the third equation is the combination of above two equations. The equations are defined as:

$$u_i = \alpha y_i + (1-\alpha)(u_{i-1} + v_{i-1}) \quad (1)$$

$$v_i = \beta(u_i - u_{i-1}) + (1-\beta)v_{i-1} \quad (2)$$

$$\hat{y}_{i+1} = u_i + v_i \quad (3)$$

Where α is used as a level smoothing constant. There is a second constant, β being added in this method which acts as a trend smoothing constant. u_i is the trend smoothed constant process value for period i and v_i is the smoothed trend value for period i.

HOLT-WINTERS METHOD

Holt-Winter method is triple exponential smoothing that considered the trend and seasonality. Three parameters must be considered which is equation for level u_i, trend v_i and seasonal s_i. All of this will be combined in order to forecast future data. The equations are defined as:

$$u_i = \alpha\left(\frac{y_i}{w_{i-c}}\right) + (1-\alpha)(u_{i-1} + v_{i-1}) \quad (4)$$

$$v_i = \beta(u_i - u_{i-1}) + (1-\beta)v_{i-1} \quad (5)$$

$$s_i = \gamma\left(\frac{y_i}{u_i}\right) + (1-\gamma)s_{i-c} \quad (6)$$

$$\hat{y}_{i+1} = (u_i + v_i)w_{i+1-c} \quad (7)$$

It will be same as HL which use the α and β as smoothing constant for level and trend but with added of γ as the seasonal-smoothing constant and s_i is the smoothed seasonal value for period i.

ERROR ANALYSIS

The performance of each method can b calculated by using mean absolute error (MAE), mean absolute percentage error (MAPE), mean square error (MSE), and root mean square error (RMSE) as below:

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \quad (8)$$

$$MAPE = \frac{\frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{y_i}}{n} \times 100\% \quad (9)$$

$$MSE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|^2}{n} \quad (10)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|^2}{n}} \quad (11)$$

Where,

$$e_i = y_i - \hat{y}_i \quad (12)$$

Here $\hat{y}_i$is actual load, while $\hat{y}_i$ is forecasted load. MAE is a measure of all the indication data by assumed it all as equal weight [12]. If the forecasting method is good and the error of comparison with past data is near to zero. MAPE is a relative measure that corresponds to MAE. It is the measurement of accuracy used in quantitative method forecasting. If MAPE is less than 10%, it is considered as accurate forecasting, between 20%-30% good forecasting, between 20%-50% as acceptable and more than 50% is assumed inaccurate forecasting [13]. MSE is also measure

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the overall accuracy by gives an indication of degree but with additional weight [14]. Compare to MSE, RMSE will be squared root to give the smaller value if the weight is large and particularly undesirable.

RESULTS AND DISCUSSIONS

Figure-1 shows the electricity consumption pattern 12 months for every year start from 2009 until 2017. The electricity consumption shows the increases rapidly at the last quarters in 2009. The data given fluctuates for each month. The data in 2010 shows that the most average electricity consumption compared to the other years. This increasing pattern stopped at November2014 as the highest data electricity consumption recorded with the value 3258.29 MWh. Commonly, the reading between July until September for every year got the lowest value because of it is semester break for 3 months. In 2017, 3 faculties have been moved to Pagoh campus and affected the electricity consumption that decreasing.

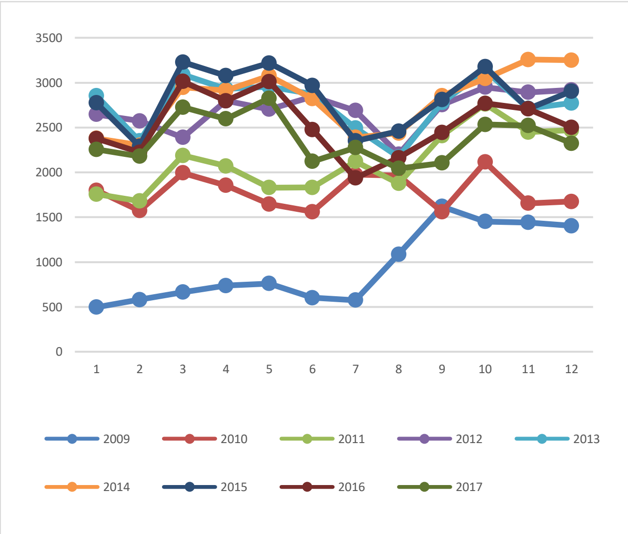

Figure-1. Actual load for each year.

Figure-2 shows the time series of electricity consumption from January 2009 until December 2017. The pattern seems going increasing and having a peak load in November 2014. It slowly decreasing from 2015 to 2017. Even several faculties have been moved to Pagoh campus, the development still in progress and this load pattern needs to be continuously determined.

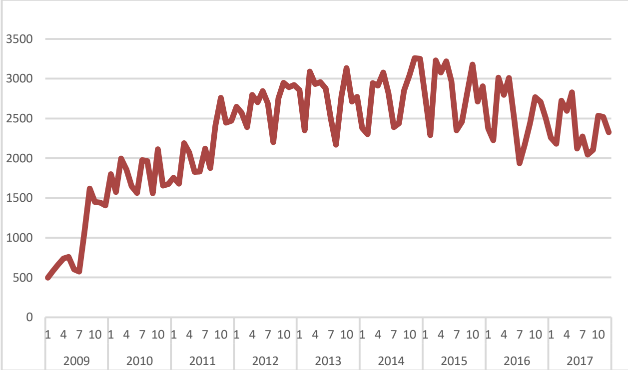

Figure-2. Actual load from 2009-2017.

HLT with $\alpha = 0.2571$ and $\beta = 0.2981$ were plotted in Figure-3. In HLT, the forecasted value slightly decreasing which is based on decreasing trend pattern started from 2015. The future forecasted value for 2018 is quite linear compare to actual data.

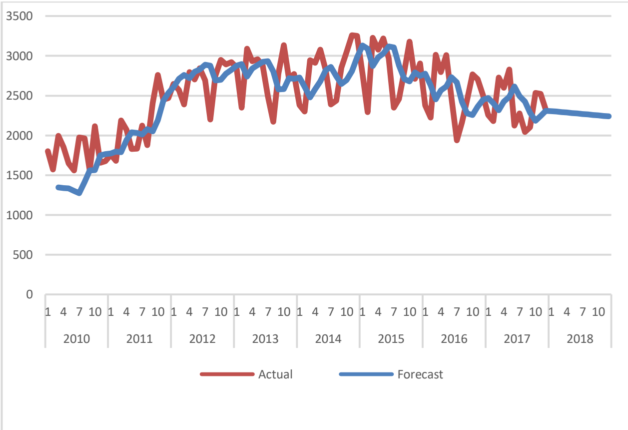

Figure-3. Actual load and forecasted load (HLT).

HW with $\alpha = 0.5691$, $\beta = 0.1198$ and $\gamma = 1$ were shown in Figure-4. This method is using the first 12 months data as seasonal trend to start forecasting in January 2011. Based on this method, the next 12 months electricity consumption data for 2018 can be forecasted. Thus, the forecasted values may more accurate compare to HLT. The forecasted value no longer linear but the pattern of electricity consumption still decreasing.

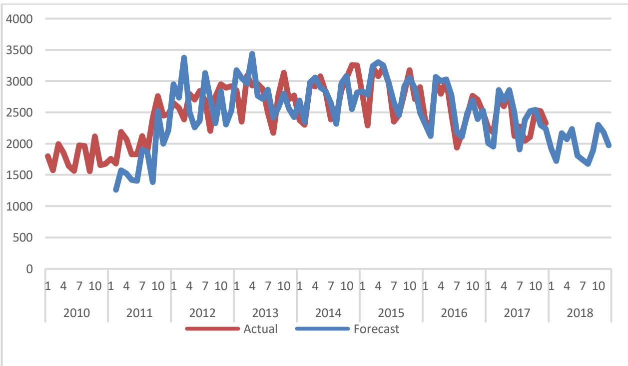

Figure-4. Actual load and forecasted load (HW).

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Figure-5 and Table-1 shows the comparison between the actual data of 2018, forecasted data for 2018 using HLT and forecasted data for 2018 using HW. The way to prove which method is accurate, the comparison with actual load consumption data of 2018 is needed. The forecast data using HLT is much more linear compare to the actual data load consumption. The HW forecast result is following the pattern of actual data but the value is a bit lower for all months in 2018.

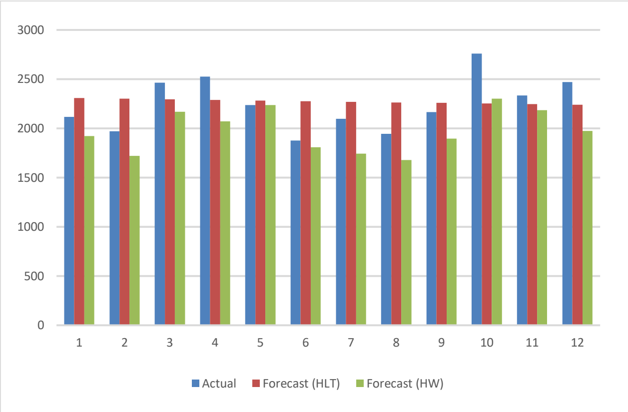

Figure-5. Comparison of actual load, HLT and HW for 2018.

Table-1. Forecast method value comparison (MWh).

		Actual	HLT	HW
2018	1	2117.23	2306.70	1920.93
	2	1968.91	2300.57	1720.66
	3	2463.97	2294.45	2167.29
	4	2525.48	2288.32	2071.75
	5	2236.96	2282.20	2235.74
	6	1876.52	2276.07	1809.19
	7	2096.15	2269.95	1742.80
	8	1944.97	2263.83	1677.45
	9	2164.70	2257.70	1893.88
	10	2757.58	2251.58	2300.28
	11	2334.59	2245.45	2184.45
	12	2471.50	2239.33	1973.24

Table-2 shows the forecast evaluation of MAE, MAPE, MSE and RMSE for both methods. HW give the lowest result of error analysis with MAE (234.2618), MAPE (9.4635), MSE (113535.6640) and RMSE (336.9505).

Table-2. Error analysis.

	MAE	MAPE%	MSE	RMSE
HLT	287.3025	11.9659	120686.2627	347.3992
HW	234.2618	9.4635	113535.6640	336.9505

CONCLUSIONS

HLT and HW were applied on Universiti Tun Hussein Onn Malaysia from January 2009-December 2017 to forecast monthly 2018 electricity consumption. Forecast result of 2018 has been compared with actual electricity consumption of 2018 and HW performed the best performance. Hence, HW gives the lowest of MAE, MAPE, MSE and RMSE. Based on literature review, forecasting method that gives an error less than 10% is the method to apply. Since the several faculties has been moved to Pagoh campus, the pattern of electricity consumption start to decrease. But the development in UTHM still in progress by several new building is under construction. HW can be used to forecast the future electricity consumption and it is need to be done as the facilities expanded.

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REFERENCES

[1] B. Koo, M. Kim, H. Lee, J. Park and C. Kim. 2013. Using Data Mining Technique. IEEE Conf. Publ. pp. 153-157.

[2] H. Seifi and M. S. Sepasian. 2011. Load Forecasting. Power Syst. 49(45–67).

[3] I. Khandelwal, R. Adhikari, and G. Verma. 2015. Time series forecasting using hybrid arima and ann models based on DWT Decomposition. Procedia Comput. Sci.4(C): 173-179.

[4] N. Amjady. 2001. Short-term hourly load forecasting using time-series modeling with peak load estimation capability. IEEE Trans. Power Syst. 16(4): 798-805.

[5] R. Weron. 2014. Electricity price forecasting: A review of the state-of-the-art with a look into the future. Int. J. Forecast. 30(4): 1030-1081.

[6] S. Kumar Paul. 2011. Determination of exponential smoothing constant to minimize mean square error and mean absolute deviation. Glob. J. Res. Eng.11(3): 30-34..

[7] J. W. Taylor and P. E. McSharry. 2007. Short-term load forecasting methods: An evaluation based on European data. IEEE Trans. Power Syst. 22(4): 2213-2219.

[8] K. Kavanagh, M. Barrett and M. Conlon. 2017. Short-term electricity load forecasting for the integrated single electricity market (I-SEM). 2017 52nd Int. Univ. Power Eng. Conf. UPEC 2017. 2017-Janua: 1-6.

[9] G. Tirkeş, C. Güray and N. Çelebi. 2017. Demand forecasting: a comparison between the Holt-Winters, trend analysis and decomposition models. Teh. Vjesn. - Tech. Gaz. 24(no. Supplement 2): 503-509.

[10] G. Yapar, S. Capar, H. T. Selamlar and I. Yavuz. 2018. Modified holt's linear trend method. Hacettepe J. Math. Stat. 47(5): 1394-1403.

[11] C. Deb, F. Zhang, J. Yang, S. E. Lee and K. W. Shah. 2017. A review on time series forecasting techniques for building energy consumption. Renew. Sustain. Energy Rev. 74(February): 902-924.

[12] E. Ostertagová and O. Ostertag. 2013. Forecasting using simple exponential smoothing method. Acta Electrotech. Inform. 12(3).

[13] Lewis C.D. 1982. Industrial and Business Forecasting Methods,. London, Butterworths.

[14] Jarret J. 1991. Business Forecasting Methods. Cambridge, MA: Basil Blackwell.