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Electricity Load Forecasting using Hybrid of Multiplicative Double Seasonal Exponential Smoothing Model with Artificial Neural Network

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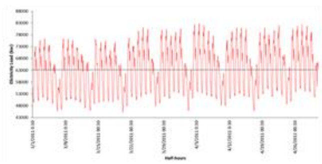
Graphical abstract



Abstract

Electricity load forecasting often has many properties such as the nonlinearity, double seasonal cycles, and others those may be obstacles for the accuracy of forecasting using some classical statistical models. Many papers in this field have proposed using double seasonal (DS) exponential smoothing model to forecast. These papers indicated that electricity load forecasting using DS exponential smoothing model has better fit. Using artificial neural network (ANN) as a modern approach may be used for superior fitted forecasting, since this approach can deal with the non-linearity components of load data. The purpose of this paper is to improve the electricity load forecasting by building the hybrid model that includes a double seasonal exponential smoothing with an artificial neural network. This hybrid model will study the double seasonal effects and non-linearity components together based on the electricity load data. The strategy of building this hybrid model is by entering ANN output as an input in double seasonal exponential smoothing model. The data sets are taken from three stations with different electricity load characteristics such as a residential, industrial and city center. The electricity load testing forecast of DS exponential smoothing-ANN hybrid model gave the most minimum mean absolute percentage error (MAPE) measurement comparing with the electricity load testing forecasts of DS exponential smoothing and ANN for all electricity load data sets. In conclusion, DS exponential smoothing-ANN hybrid model are the most fitted for every electricity load data which contains the double seasonal effects and non-linearity components.

Keywords: Electricity load forecasting; multiplicative double seasonal exponential smoothing; ANN, hybrid model

■1.0 INTRODUCTION

Electricity load forecasting is necessary to recalculate the measurement by correcting the path of load positively. Electricity load forecasting is important for economic activities such as energy generation, fuel purchasing, maintenance and investment scheduling. The magnitudes and geographical location during different periods are the main points in the electricity load forecasting. The load forecasting may be studying for yearly, weekly, monthly, daily, hourly, half-hourly or quarter-hourly.

Electricity load data often includes double seasonal cycles such as for daily, weekly, or monthly periods [1]. The double seasonal periods and the nonlinear components in the load data may be the main reasons for inaccurate load forecasting using classical approaches such as non-seasonal or single seasonal exponential smoothing approaches. Using classical exponential smoothing approaches to forecast electricity load data may produce inaccuracy in forecasting because this type of data often contains double seasonal effects. The double seasonal periods in load data will handle by using DS exponential smoothing model and result more accurate forecasting. The standard Holt-Winters exponential smoothing model may be suitable for data that has single seasonal period. DS exponential smoothing model is an updated model from the multiplicative Holt-Winters exponential smoothing model by adding other terms and considering more conditions. Choosing the best model can be measured by using the mean absolute percentage error (MAPE) measurement.

In this paper, double seasonal (DS) exponential smoothing model will be used for forecasting electricity load data. Taylor studied the short-term electricity demand forecasting for half-hourly intervals electricity demand data which contains two seasonal patterns (daily and weekly). The multiplicative seasonal exponential smoothing models have been adapted by Taylor in order to give well-specified double seasonal models with more accurate forecasting [2]. Taylor and McSharry proposed many methods to forecast intraday electricity demand data from ten European countries such as DS exponential smoothing model in addition to the new alternative exponential smoothing method and PCA method. DS exponential smoothing model concluded the best forecasting model among other proposed methods [3]. Six years of British and French load data has been forecasted by Taylor. The DSARIMA, DS exponential smoothing, and the new alternative exponential smoothing models improved to accommodate the triple seasonal cycles which include the intraday and the intraweek cycles in addition to an intrayear cycle which has also appeared in the data. The triple seasonal models outperformed the double seasonal models [4]. Souza *et al.* proposed using a variation of DS exponential smoothing method with double cycles (daily and weekly) for very short term load demand forecasting of a large electricity distributor in the southeast of Brazil [5]. Beak suggested point forecasts for two data sets of hourly time series one of them is on electricity load in New England area of the U.S. using the benchmark forecasting approaches which include Holt-Winters exponential smoothing method, and the non-benchmark approaches which include double seasonal Holt-Winters exponential smoothing method. The benchmark forecasting approaches outperformed by the non-benchmark approaches [6]. Gould *et al.* proposed a new multiple seasonal methods which used to forecast hourly data for both utility loads and traffic flows. Their data had both hourly and daily patterns. The forecasting results compared with the additive and multiplicative DS exponential smoothing methods and concluded to be the most preferred model in terms of producing the smallest forecasting error [7].

In recent studies, some researchers proposed some modern approaches based on statistical rules to determine the scientific improved approach that gives a better electricity load forecasting. An artificial neural network (ANN) approach is used for improving the forecasting accuracy of the classical statistical models of the electricity load data. ANN is a non-linear approach that is useful to handle the non-linear time series relationships and to get more accurate forecasts. Therefore, using ANN as a modern approach will improve load forecasting comparing with the load forecasting using DS exponential smoothing model. Faya *et al.* examined a combination of linear sequential and parallel neural models in a multi-time scale formulation and found that they were superior for hourly electrical load forecasting in Ireland. Many types and options have been proposed for the ANN approach which was appropriate for hourly electrical load forecasting [8]. Tee *et al.* proposed an hour a head load forecasting method using an ANN approach to improve upon previous models by using the historical load data for the 24 past hours of the ISO-New England control area. The proposed model helps ANN to build the strong relationships between the past and the current load data observations to give the superior forecasting performance [9]. Wang *et al.* proposed the back-propagation (BP) neural network for short-term load forecasting method based on "improved variable learning rate back propagation" IVL-BP in the small-sample forecasting to pass the difficulties in the application of BP neural network and to accomplish more accuracy of the load forecasting [10]. Kenya National Grid power system data were forecasted hour-by-hour for one day-ahead using developed ANN-based model by Moturi and Kioko. The performance of short-term electricity load forecasting improved with increased number of developed ANN iterations [11]. Taylor *et al.* compared many methods using a time series of hourly demand for Rio de Janeiro and a series of half-hourly demand for England and Wales. Both series appeared the weekly and daily seasonal cycles. The methods used were DSARMA modeling, DS exponential smoothing modeling, artificial neural network, and others [12].

Combining the classical statistical method and ANN approach in one hybrid model has been proposed in many recent studies. Hybrid forecasting model will take the features for both of its components those are the regular scientific structure features from DS exponential smoothing model, and the modern artificial intelligent features form ANN. Therefore, the hybrid model will improve forecasting accuracy when it will compare with other non-hybridizing forecasting approaches. In this paper, the aim of study is examine DS exponential smoothing-ANN hybrid model with the linear DS exponential smoothing model and ANN approach. There are some reports on using hybrid model combine simple exponential smoothing (SES) with ANN, but non for DS exponential smoothing-ANN hybrid model. Yu proposed SES-ANN hybrid model or a hybrid synergy model for financial time series forecasting in order to combine the linear model and nonlinear approaches together with their features to get more accuracy forecasting [13]. Samreen studied the forecasting of seven days-ahead for daily share price of KSE100 index data using hybrid SES-ANN forecasting systems. After comparing the forecasting results of ANN, SES and their hybrid, the ANN approach gave acceptable forecasting performance, but the best performance was for SES-ANN hybrid model [14].

This paper focuses on using DS exponential smoothing-ANN hybrid model to improve the electricity load forecasting comparing with its components.

2.0 MATERIAL AND METHOD

2.1 Data and Framework of Study

In this study, the electricity load data were collected from the national electricity board or Tenaga Nasional Berhad (TNB) electricity system for three Malaysian areas: Skudai, Pasir Gudang and Pusat Bandar in Johor for the period (1st/Jan/2003) until (30th/Apr/2011). As an applicable data, two months of half-hourly load data were taken for the period (1/MAR/2011 – 30/APR/2011). The last ten days of half-hourly applicable data were used for testing and calculating the testing error forecasts. The electricity load data of the three different stations: Skudai which is the residential, Pasir Gudang which is the industrial and the city center Pusat Bandar in Johor stations for period (1/MAR/2011 –30/APR/2011) are plotted in Figures 1–3.

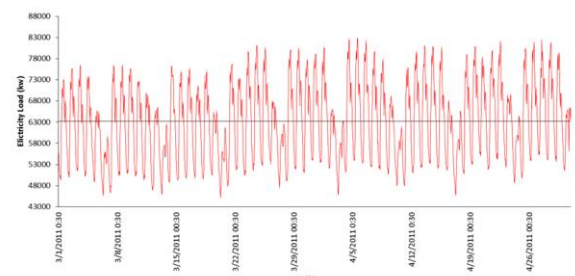


Figure 1 Electricity load of Skudai station (residential area)

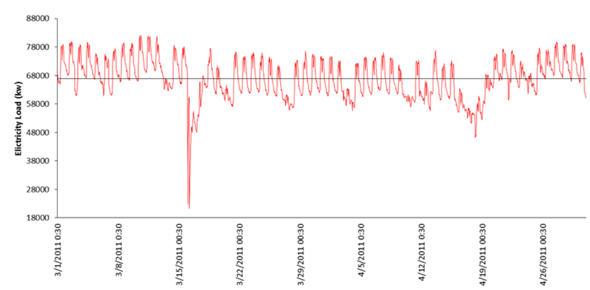


Figure 2 Electricity load of Pasir Gudang (industrial area)

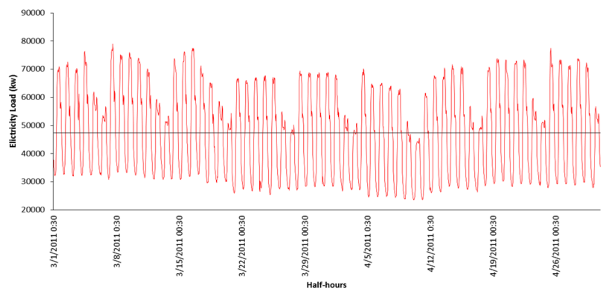


Figure 3 Electricity load of Pusat Bandar (city center)

It is clear from Figure 1–3 that all data sets have double seasonal cycles. The first cycle of the double seasonality appeared when the data repeat same peak and bottom every 48 observations or every day. Every seven days or about 336 observations, the data pattern repeated the same cycles as a weekly seasonal effect of data. Therefore, the data return back to its last behavior during two cycles: daily (every 24*2=48 time units), and weekly (every 24*2*7=336 time units).

The framework of this study contains the main points of the methodology that will be as the following:

a. Modeling and forecasting electricity load data using the most fitted DS exponential smoothing model.

b. Constructing ANN structure based on DS exponential smoothing input and output variables.

c. Constructing DS exponential smoothing-ANN hybrid model by taking the most fitted ANN output as an input variable at the current time of DS exponential smoothing model. Figure 4 explains the framework of electricity load forecasting using DS exponential, ANN and their hybrid model.

d.

Figure 4 Framework of the study

2.2 Exponential Smoothing Models

2.2.1 Classical Exponential Smoothing Models

Exponential smoothing approaches are used to smooth time series data in order to get more fitted forecasting. DS exponential smoothing model is one of the exponential smoothing family members. The exponential smoothing family includes many types of models such as simple exponential smoothing, Holt's two parameter (or double) exponential smoothing and (multiplicative and additive) Holt-Winter's exponential smoothing. DS exponential smoothing had been derived gradually from other exponential smoothing models beginning from simple exponential smoothing until the multiplicative Holt-Winter. It is an extension of multiplicative Holt-Winter's (or triple) exponential smoothing.

2.2.2 DS Exponential Smoothing Model

The natural load data often contains double seasonal period. Many papers in this field proposed many models for producing accurate load forecasting. Double seasonal (DS) exponential smoothing model will be used to model and forecast electricity load data. This method enables to study the double seasonal effects of load data [2]. Taylor updated the formula of multiplicative triple exponential smoothing model to get the DS exponential smoothing model. DS exponential smoothing model studies electricity load data with its seasonal effects and gives more accurate forecasting compared to the standard exponential smoothing methods. DS exponential smoothing can be expressed using the following formula:

$$F_{t+m} = \left(L_t + m b_t\right) D_{t+m-s_1} \times W_{t+m-s_2} \tag{1}$$

where:

$$L_t = \alpha \frac{Y_t}{D_{t-s_1} W_{t-s_2}} + (1-\alpha)\left(L_{t-1} + b_{t-1}\right)$$

$$b_t = \beta\left(L_t - L_{t-1}\right) + (1-\beta) b_{t-1}$$

$$D_t = \gamma \frac{Y_t}{L_t\ W_{t-s_2}} + (1-\gamma) D_{t-s_1}$$

and:

$$W_t = \delta \frac{Y_t}{L_t D_{t-s_1}} + (1-\delta) W_{t-s_2}.$$

Y_t is current original series. L_t is the current level estimate. α is the data smoothing constant used to smooth the data. β is the trend smoothing constant (growth factor) used to smooth the trend. γ is the seasonal smoothing constant used to smooth the daily seasonality. δ is the seasonal smoothing constant used to smooth the weekly seasonality. b_t is the current trend estimate. D_t is the current daily seasonal component estimate. W_t is the current weekly seasonal component estimate.

2.3 Artificial Neural Network

Artificial neural network (ANN) is an artificial intelligent approach which proposed to improve the electricity load forecasting. ANN can handle the problem of nonlinearity. In this paper, constructing ANN structure will be programmed by using MATLAB programming. MATLAB has been provided with some ANN tools. MATLAB ANN tools contain many types of ANN training algorithms, training functions, adaption learning functions and other ANN structure requirements. ANN structure includes determining the initial weights and bias values, and transfer functions types of hidden and output layers. Figure 5 illustrates the arithmetic processes for every neuron in ANN structure.

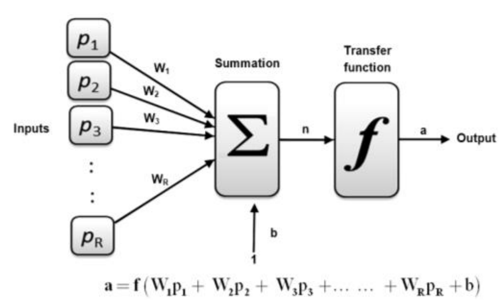


Figure 5 The arithmetic processes for every neuron in ANN

There are three types of transfer functions can be chosen. These are tan-sigmoid, log-sigmoid and linear transfer functions. Figure 6 illustrates these functions.

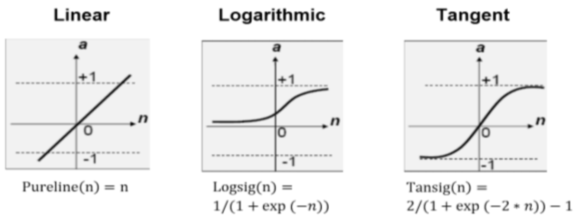


Figure 6 Types of transfer functions

The training algorithm will be selected as the multilayer feed-forward back propagation FFBP, the transfer functions have to determine as one of three types: linear, logarithmic, and tangent function. The number of neurons in hidden layer will be considered as (no. inputs*2)+1. For two input variable as example, the neural network structure may take one of the networks in the Figure 7.

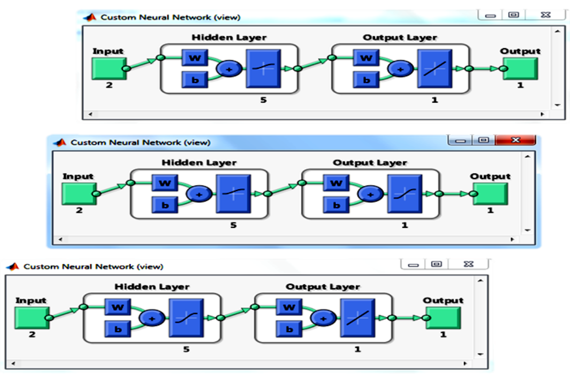


Figure 7 Neural network structures

After complete all training requirements, performing the training process will result one output variable that represents the training forecast series, and error variables which can be used to calculate the MAPE measurement of training forecasting. The best training forecast will simulate the testing forecast series. The best testing forecast will be chosen using MAPE measurement.

2.2.3 DS Exponential Smoothing-ANN Hybrid Model

In this paper, the hybrid model will hybridize DS exponential smoothing and ANN together in one model for more forecasting improving. Using the DS exponential smoothing model studies the double seasonal effects in load data, while ANN approach will study the nonlinearity in the data. DS exponential smoothing-ANN hybrid model includes updating of DS exponential smoothing model by substituting the original data with the output of ANN. The mathematical expression of the forecasting value after *m* period F_{t+m} of DS exponential smoothing-ANN hybrid model can be expressed as the following:

$$F_{t+m} = (L_t + mb_t) D_{t+m-s_1} \times W_{t+m-s_2} \tag{2}$$

where

$$L_t = \alpha \frac{\hat{Y}_t^{ANN}}{D_{t-s_1} W_{t-s_2}} + (1-\alpha)(L_{t-1} + b_{t-1}),$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta) b_{t-1},$$

$$D_t = \gamma \frac{\hat{Y}_t^{ANN}}{L_t W_{t-s_2}} + (1-\gamma) D_{t-s_1},$$

and

$$W_t = \delta \frac{\hat{Y}_t^{ANN}}{L_t D_{t-s_1}} + (1-\delta) W_{t-s_2}$$

$\hat{Y}_t^{ANN}$ is the current observation of the ANN output and other symbols in Equation (2) are defined in Equation (1).

The initial value $L_{s_1+s_2} = \sum_{t=1}^{s_1+s_2} Y_t \Big/ (s_1 + s_2)$ can be equalled to Y_1, the initial value b_s can be calculated as $b_{s_1+s_2} = \sum_{t=1}^{s_1+s_2} \frac{Y_{s_1+s_2+t} - Y_t}{(s_1+s_2)} \Big/ (s_1 + s_2)$, and the initial value D_t and W_t can be calculated as $D_t = W_t = Y_t / L_{s_1+s_2}$ (Taylor, 2003).

3.0 RESULTS AND DISCUSSION

The methodology included single seasonal and DS exponential smoothing methods, ANN approach, and DS exponential smoothing-ANN hybrid model. The aim of this study is to find the best approach that will give the best electricity load forecasting among many other approaches, and improve the forecasting of these approaches by proposing the hybrid method.

3.1 DS Exponential Smoothing Model

In the beginning, preparing electricity load data should be as a first step for analyzing of data. The electricity load data of all stations have been divided into two groups, first of them for training which contains 2448 time series observations for period (1/MAR/2011–20/APR/2011), then the second one for last 10 days (21/APR/2011 –30/APR/2011) which has 480 time series observations for testing. The second step is for determining the constants α, β, γ, δ of DS exponential smoothing model. MATLAB has been used to write M file program to determine the best testing forecast value with the minimum MAPE measurement for all possible combinations of the constants α, β, γ, δ by taking the values (0.1–0.9) for each of them, then taking the combinations for all of them. The constants α, β, γ, δ values and minimum MAPEs for DS exponential smoothing training forecast for all data stations mention in Table 1.

Table 1 The best MAPE for DS exponential smoothing training forecast for all data sets

Stations	Constants				MAPE
	α	β	γ	δ	
Skudai	0.1	0.1	0.4	0.2	12.1768
Pasir Gudang	0.1	0.1	0.4	0.1	6.6079
Pusat Bandar	0.1	0.1	0.2	0.1	14.2322

3.2 ANN Approach

Before any procedure of ANN structuring, study's data has to order as input and target variables. For good forecasting, the data has to divide for two groups: training and testing series for each of input and target variables. All possible probabilities of the training functions and transfer functions combinations have been considered in ANN structuring processes. Logarithmic and line sigmoid are determined as the best transfer functions for both of hidden and output layers respectively.

The types of transfer function have chosen depending on the linearity and nonlinearity of the data sets. Table 2 presents the training forecast performances. Determining the correct transfer function types are the main role in forecasting performance improvement using ANN approach.

Table 2 The minimum MAPE of training forecast for all data stations using ANN approach

Stations	Transfer Function		MAPE
	Hidden Layer	Output Layer	
Skudai	Log	Line	7.8549
Pasir Gudang	Log	Line	4.7569
Pusat Bandar	Log	Line	11.8430

The training forecast series by using ANN for all data sets gave more accurate training forecast compared to the training forecast of DS exponential smoothing as it is clearly in Tables 1 and 2.

3.3 DS Exponential Smoothing-ANN Hybrid Approach

Samreen proposed a new hybrid model which was built by entering the output of the best ANN for training and testing forecast series as input series (contains training and testing period) of simple exponential smoothing model [14]. In this paper, building DS exponential smoothing-ANN hybrid model can be achieved by following same procedure of Samreen by entering the output of the best ANN for training and testing forecast series as an input series of DS exponential smoothing model.

Constants consideration of DS exponential smoothing-ANN hybrid model will use same previous method, but it will be different from the constants consideration of DS exponential smoothing model, because the conditions of inputs data for each model are different. The minimum MAPE for DS exponential smoothing-ANN hybrid training forecast for Skudai, Pasir Gudang and Pusat Bandar stations, and the constants α, β, γ, δ are mentioned in Table 3.

Table 3 The minimum MAPE of training forecast and it's constant for Skudai, Pasir Gudang and Pusat Bandar stations using the hybrid model

Stations	Constants				MAPE
	α	Β	γ	δ	
Skudai	0.2	0.05	0.35	0.25	11.0758
Pasir Gudang	0.3	0.05	0.2	0.2	5.8082
Pusat Bandar	0.1	0.05	0.1	0.05	15.0959

From Table 3, the training forecast series for all data sets of the hybrid model have MAPEs bigger than those for ANN training forecast and smaller than those for DS exponential smoothing. These results mean that the most fitted training forecast is by using ANN then by using the hybrid model. Figures 8–10 include DS exponential smoothing, ANN, and DS exponential smoothing-ANN testing forecast for all data set with the same period of original series and their comparisons.

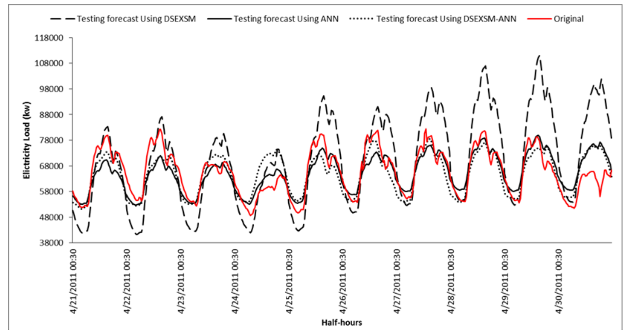


Figure 8 Comparison among DS exponential smoothing, ANN, and their hybrid testing forecast for Skudai data set

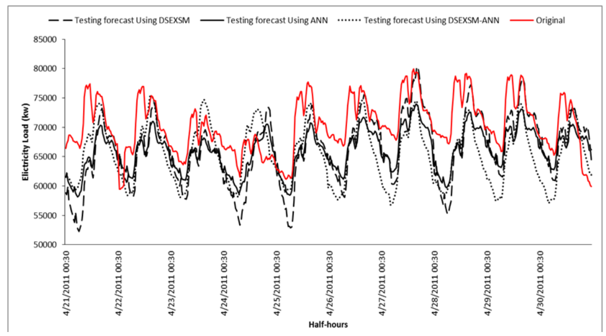


Figure 9 Comparison among DS exponential smoothing, ANN, and their hybrid testing forecast for Pasir Gudang data set

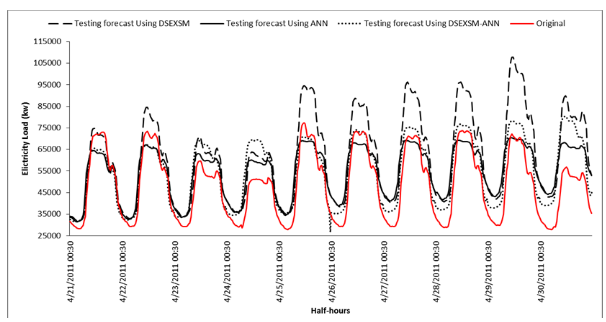


Figure 10 Comparison among DS exponential smoothing, ANN, and their hybrid testing forecast for Pusat Bandar data set

Table 4 displays the MAPEs' testing forecasts for all data sets using DS exponential smoothing, ANN, and their hybrid model. The constants α, β, γ, δ for each MAPE in Table 4 are same for those in Table 1 and 3 for DS exponential smoothing, and DS exponential smoothing-ANN methods respectively.

Table 4 MAPEs' testing forecasts for all data using all different methods

Stations	MAPE Using Different Approaches		
	DS EX. SM.	ANN	Hybrid
Skudai	14.657	6.1121	4.1254
Pasir Gudang	7.0298	6.6195	4.185
Pusat Bandar	27.157	19.9856	8.0443

Table 5 displays the MAPEs' testing forecasts for all data sets using single, double, and (multiplicative and additive) triple exponential smoothing methods. The constants α, β, γ for each MAPE in Table 5 are same for those in Tables 1.

Table 5 MAPEs' testing forecasts for all data using all classical exponential smoothing methods

Stations	MAPE of classical exponential smoothing			
	Simple	Double	Mult-Triple	Add-Triple
Skudai	12.540	93.788	184.172	168.592
Pasir Gudang	5.350	68.091	74.706	71.116
Pusat Bandar	32.862	98.758	172.928	133.862

Table 4 and Table 5 prove that DS exponential smoothing testing forecast is much better than other non-seasonal and single seasonal exponential smoothing testing forecasts such as the simple, double, multiplicative triple, and additive triple exponential smoothing testing forecasts for all electricity load data sets. Comparing DS exponential smoothing model with non-seasonal exponential smoothing models such as single and double exponential smoothing for all electricity load data sets are impossible and may cause some confusing and wrong interpreting. Table 4 summarizes that the hybrid's testing forecast were better than DS exponential smoothing and ANN testing forecasts. Figures 8–10 show the improvements in electricity load testing forecasting through applying DS exponential smoothing, ANN, and the hybrid DS exponential smoothing-ANN approaches for all data sets. In these figures, the testing forecasting accuracy using hybrid method is the best then the testing forecasting accuracy using ANN, while the DS exponential smoothing testing forecasting is the worst among others for all data sets. These results were not fitting with the training forecast results as it clear in Table 1–3. These figures also showed the under forecast and over forecast cases for all studied methods. The under and over forecasts are the other problems in electricity load forecasting that reflect the shortage or the wasted electricity generation. These figures also shown that the hybrid forecasts are much better than the others, and more similar with the original as average for both of Skudai and Pusat Bandar stations, while for same data sets DS exponential smoothing testing forecast goes a way for an over forecasting case that may cause more failure or shortage in the electricity generation. It is clear also from same figures that all proposed methods are in under forecasting case and non-similar with the original for Pasir Gudang data set and this may cause wasted electricity generation.

■4.0 CONCLUSION

The previous results confirm that the most minimum MAPE for the testing forecast errors was for the hybrid model for all data set. Studying all possible ANN structures for different transfer functions is also important to obtain the best ANN forecasting. The nature of the data plays an important role in determining the transfer function types.

In conclusion, the most fitted electricity load forecasts were the DS exponential smoothing-ANN hybrid model for all different stations. Although the ANN approach can be forecast the electricity load data very well and better than DS exponential smoothing model, ANN considered in this study is based on DS exponential smoothing model and its inputs. Therefore DS exponential smoothing is very important to study first to analyze and forecast the electricity load data then ANN can be studied secondly. DS exponential smoothing-ANN hybrid model improved both of DS exponential smoothing and ANN testing forecast results and satisfied the minimum MAPE measurements for all data sets. The correct consideration of the constants α, β, γ, δ of hybrid model may be the main reason for getting the minimum testing forecast errors.

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