Investigation of One Day Ahead Load Forecasting for Iraqi Power System

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ABSTRACT
Power stations must supply the electrical load demands to achieve optimal power system operation. To meet the future load, the power system dispatcher use load forecasting techniques to schedule unit generation resources. In this paper the short term load forecasting (STLF) using feed forward Artificial Neural Network (ANN) and Multiple Linear Regression (MLR) techniques for Iraqi power system (IPS) is presented. The ANN and MLR techniques are used to forecast one day ahead load for summer and winter season. The ANN gives a very small mean absolute percentage error (MAPE) compared with MLR but it takes a longer time for training process.

Keywords
Short Term Load Forecasting, Artificial Neural Network, Multiple Linear Regression, Mean Absolute Percentage Error.

1. INTRODUCTION
Power system load forecasting is an important subject both in power system planning as well as in on-line power system operation[1]. Short term load forecasting (STLF) refers to the prediction of load demand for future times from the next hour to a week. The main objective of the STLF is to provide the load prediction for basic generation scheduling functions, for assessing the security of system operation, and for timely dispatcher information[2-3]. Various STLF models have been proposed based on statistical techniques[4-7], artificial intelligence techniques[8-10], knowledge based expert systems[11-12] and Hybrid Techniques[13-15]. Among the artificial intelligence techniques, Artificial Neural Network (ANN) has received more attention because of its clear model, easy implementation, and good performance [2]. ANN-based approaches are often preferred for STLF problems because (ANNs) are capable of generalization and learning non-linear relationships between variables[16]. The other important feature of ANNs is their capability to adjust the weights between layers.

Among statistical technique, One of the simple method used to forecast the load is Multiple Linear Regression (MLR) technique. Regression analysis is a modeling technique for analyzing the relationship between a continuous (real-valued) dependent variable and one or more independent variables. The goal in regression analysis is to identify a function that describes, as closely as possible, the relationship between these variables so that the value of the dependent variables can be predicted using a range of independent variables values In the multiple linear regression method, the load is found in terms of explanatory (independent) variable such as weather and other variables which influence the electrical load[17].

In this paper ANN and MLR techniques are used to forecast the one day ahead load for winter and summer season of Iraqi Power System (IPS). The performance accuracy of the two techniques is measured using mean absolute percentage error (MAPE).

2. PROPOSED MODEL OF ANN
The proposed model of ANN used a Multi Layer Perceptron (MLP) feed forward network with one input layer, one hidden layer and one output layer. The forecasting performance is affected by many factors such as number of input neurons, the number of hidden neurons, training methods ..etc and these factors need to be chosen carefully.The number of neurons in the input layer are 6 and represent the input variable. The input variables was obtained from yearly historical load and represented by number of month, number of day, day of week, number of hour, same hour load of previous week and same hour load of previous day.The number of neurons in the hidden layer was set at 6 neurons. The activation function used in the hidden layer neuron was sigmoid function.The number of output neurons, which represent the 24 hours load forecasting results, was 1 neurons. The activation function used in the output neurons was pure linear function. The architecture of the proposed ANN model is shown in Fig.1. The Levenberg-Marquardt back propagation algorithm was used to train the ANN model . The algorithm tries to minimize the difference between the desired and actual output by adjusting the weights of the network.

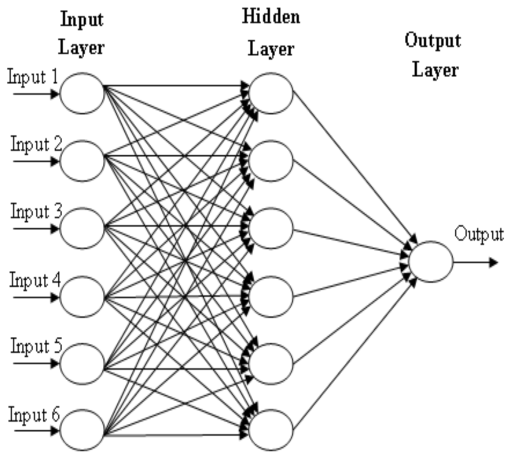

Fig 1: Architecture of the Proposed ANN Model

3. PROPOSED MODEL OF MLR
Linear regression is a form of regression analysis in which data are modeled by a least squares function which is a linear combination of the model parameters and depends on one or

more independent variables. In this technique the load is expressed in the form as [17,18]:

$$y = \beta_0 + \beta_1 . X_1 + \beta_2 . X_2 + \ldots\ldots + \beta_k . X_k + \epsilon \qquad ..(1)$$

Where:

y: load value (dependent variable)

X: explanatory input variable (independent variables)

β: regression parameters relating the y to the X

ϵ: random error

k: number of input variable

Eq.1 can be rewritten in general form as[12]:

$$y = \beta . X + \epsilon \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

The first step in multiple linear regression analysis is to determine the vector of least squares estimators, $\hat{\beta}$, which gives the linear combination $\hat{y}$ that minimizes the length of

The error vector. This implies that the correlation between each Xi is small. Now, since the objective of multiple regression is to minimize the sum of the squared errors, the regression coefficients that meet this condition are determined by solving the least squares normal equation given below[18]:

$$X^T X \hat{\beta} = X^T y \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

and $\hat{\beta}$ will be :

$$\hat{\beta} = (X^T X)^{-1} X^T y \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

The explanatory input variable of the proposed model of the MLR are same hour load of previous day, same hour average load of previous day, number of day and day of week

4. FORECASTING ACCURACY

The forecasting accuracy of the ANN and MLR techniques is measured using mean absolute percentage error (MAPE) which given as [2] :

$$MAPE(\%) = \frac{1}{n} \sum_{i=1}^{n} \frac{|P_{Ai} - P_{Fi}|}{P_{Ai}} . 100 \qquad \ldots\ldots\ldots\ldots\ldots (5)$$

Where:

P_{Ai} : actual load (MW)

P_{Fi} : forecasted load (MW)

n : number of forecasted hours (in our case 24 hours)

5. RESULTS AND DISCUSSION

5.1 Winter Season Load Forecasting

The actual historical load data of IPS for one year was used for testing the ANN and MLR techniques to forecast one day ahead load. The date February-1-2016**,** which represented winter season, is selected to forecast its load. The actual historical load from February-1-2015 to January-31-2016 was used for winter season.

All simulation results are conducted using MatLab release 2015a.The training process, performance and scatter of the proposed model of ANN are shown in Fig.2 , Fig.3 and Fig.4 respectively.

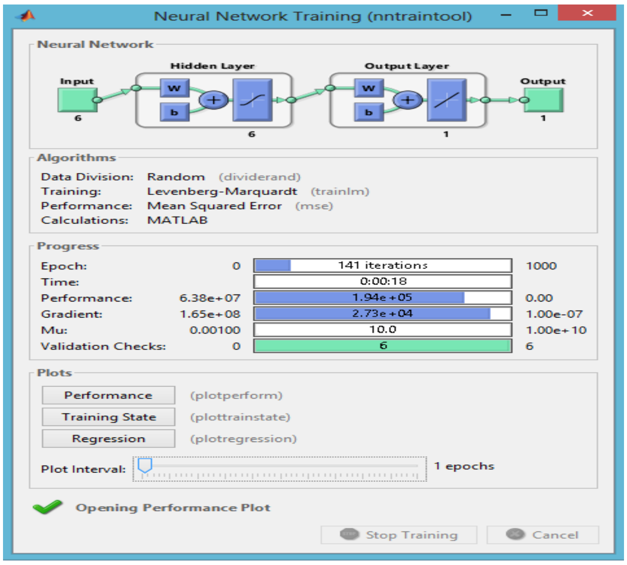

Fig 2: Training Process of ANN of Winter Season (February-1-2016)

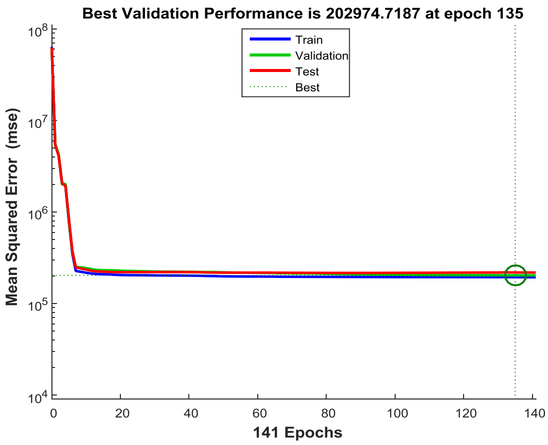

Fig 3: Performance of the ANN during Network Training of Winter Season (February-1-2016)

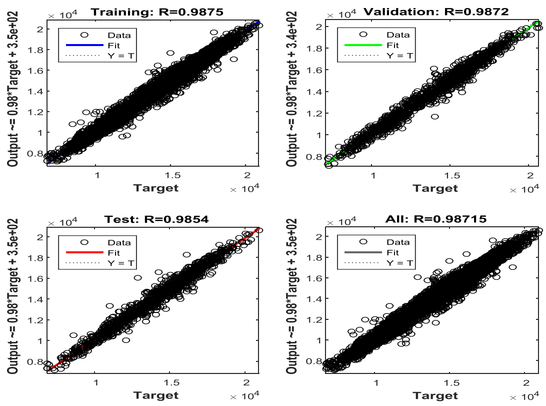

Fig 4: Scatter of the ANN of Winter Season (February-1-2016)

The actual load and ANN forecasted load is compared as shown in Fig.5. It can be noted that the forecasted load is very close to the actual load and the MAPE is 0.593%. Fig.6 shows the absolute and mean absolute percentage error. The actual historical load and predicted load is shown in Fig.7 and the MAPE is 2.511%.

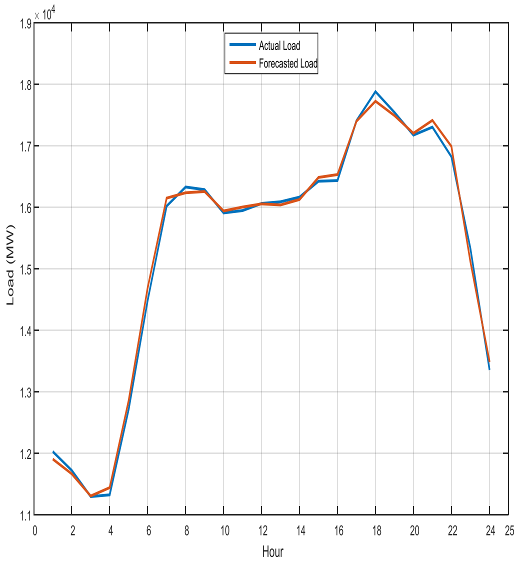

Fig 5: One Day Ahead (February-1-2016) Actual and ANN Forecasted Load

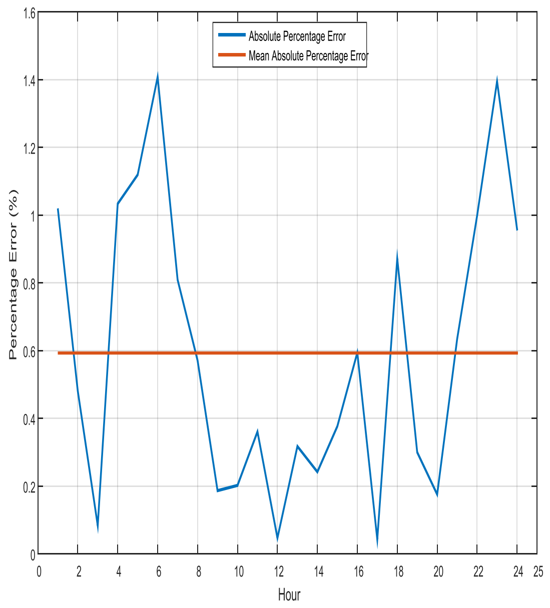

Fig 6: Absolute and Mean Absolute Percentage Error (MAPE) of One Day Ahead Load (February-1-2016) based ANN

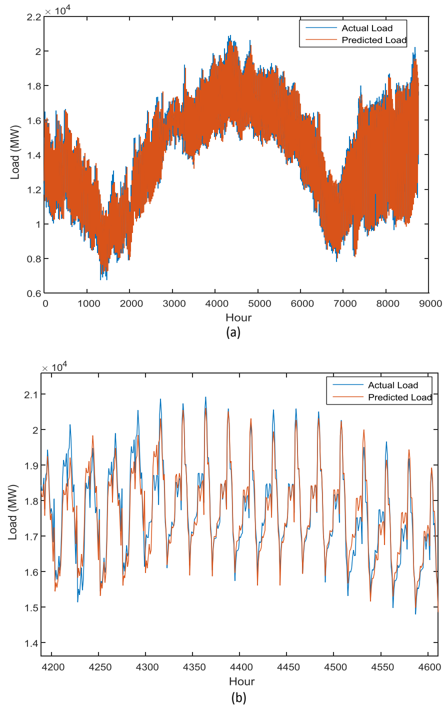

Fig.7 (a) Actual and ANN Predicted Historical Load (February-1-2015 to January- 31-2016) (b) expand view

Regarding MLR technique, the simulation results are illustrated in Fig.8, Fig.9 and Fig.10. It can be noted that the corresponding MAPE of MLR forecasted load is greater than that of ANN forecasted load. The MAPE of one day ahead load is found to be 2.024% while that of historical predicted load is 2.671%.

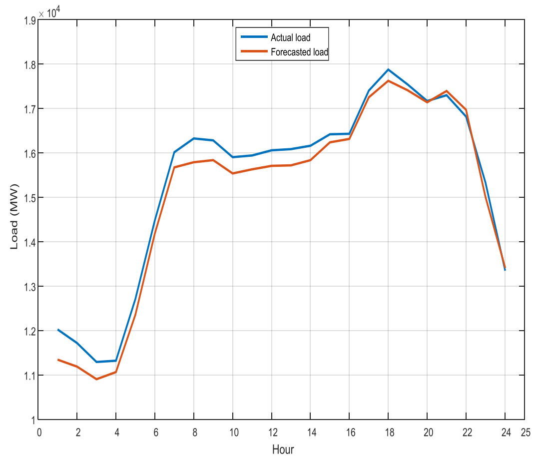

Fig 8: One Day Ahead (February-1-2016) Actual and MLR Forecasted Load

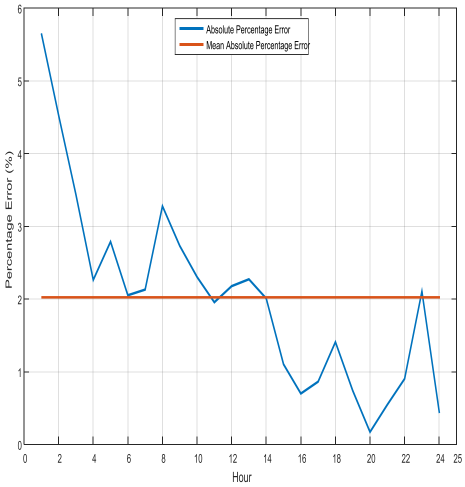

Fig 9: Absolute and Mean Absolute Percentage Error (MAPE) of One Day Ahead Load (February-1-2016) based MLR

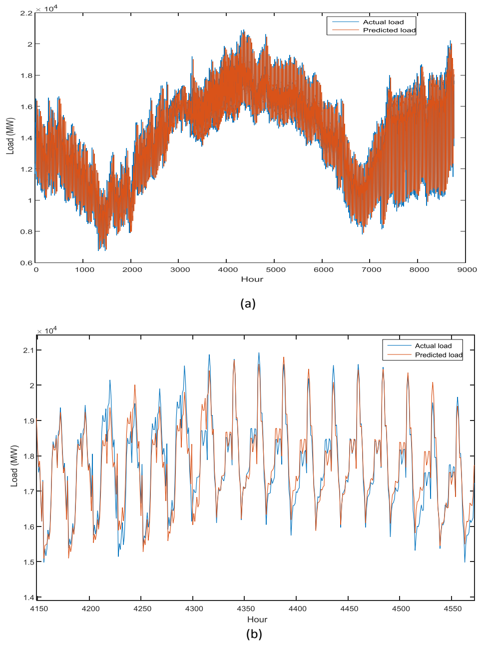

Fig.10 (a) Actual and MLR Predicted Historical Load (February-1-2015 January- 31-2016) (b) expand view

The MAPE and elapsed time of ANN and MLR simulation results for winter season are given in table1.

Table.1 MAPE and Elapsed Time of ANN and MLR Simulation Results for Winter Season

		ANN	MLR
MAPE (%)	One Day Ahead Load	0.593	2.024
	Historical Load	2.511	2.671
Elapsed Time		24 (minutes)	0.269 (seconds)

It can be noted that the MAPE of one day ahead load based ANN technique is very small compared with that of MLR while the MAPE of the historical load is approximately equals. The ANN technique takes a longer time compared with MLR because of the training process.

5.2 Summer Season Load Forecasting

The date July-1-2016**,** which represented summer season, is selected to forecast its load. The actual historical load from July-1-2015 to June-30-2016 was used for summer season.

The actual load and ANN forecasted load is compared as shown in Fig.11. It can be noted that the forecasted load is very close to the actual load and the MAPE is only 0.297%.

Fig.12 shows the absolute and mean absolute percentage error.

The actual historical load and predicted load is shown in Fig.13 and the MAPE is 2.598%.

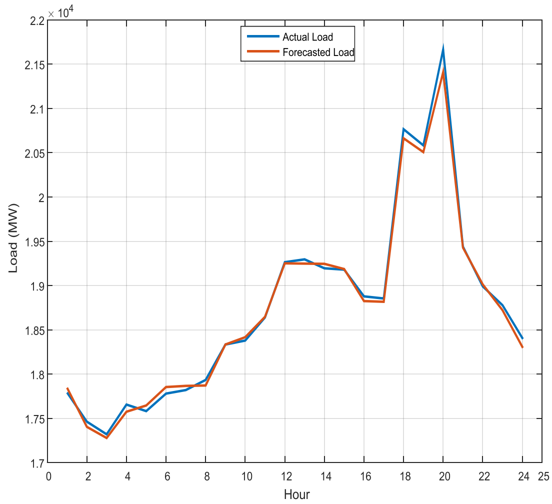

Fig 11: One Day Ahead (July-1-2016) Actual and ANN Forecasting Load

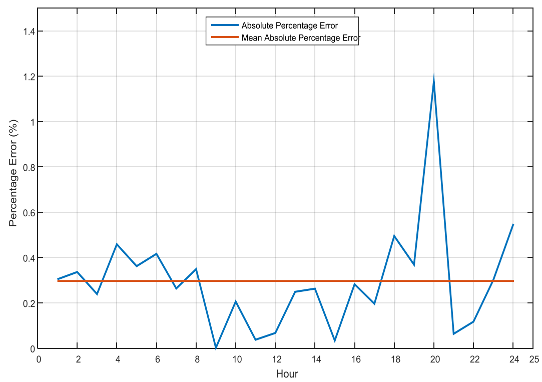

Fig 12: Absolute and Mean Absolute Percentage Error (MAPE) of One Day Ahead Load (July-1-2016) based ANN

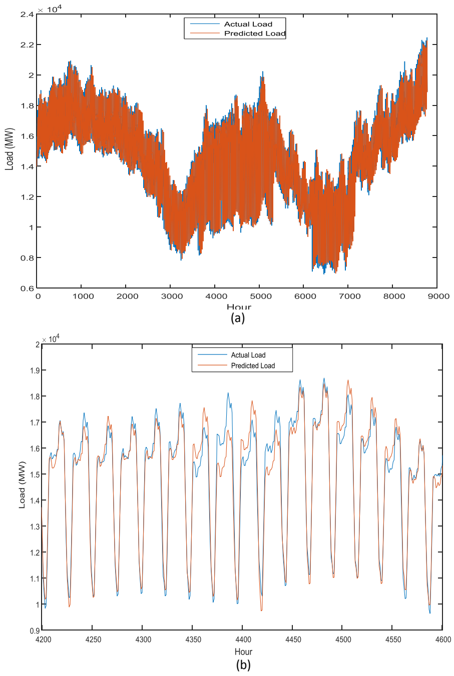

Fig.13 (a) Actual and ANN Predicted Historical Load (July-1-2015 to June-30-2016) (b) expand view

The simulation results of MLR for summer season are illustrate in Fig.14, Fig.15 and Fig16. The MAPE of one day ahead load is found to be 1.686% while that of historical predicted load is 2.598%.

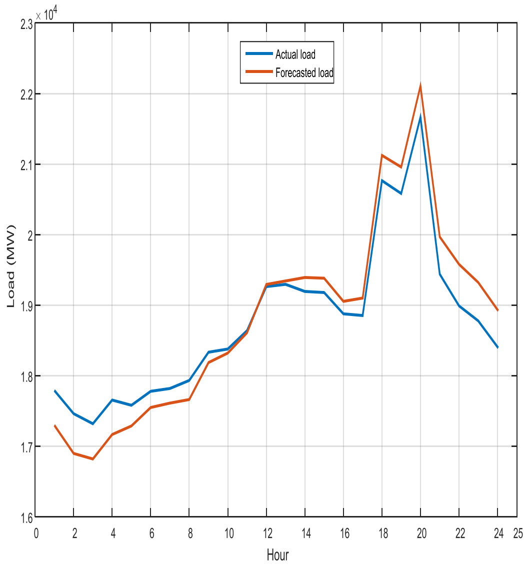

Fig 14: One Day Ahead (July-1-2016) Actual and MLR Forecasting Load

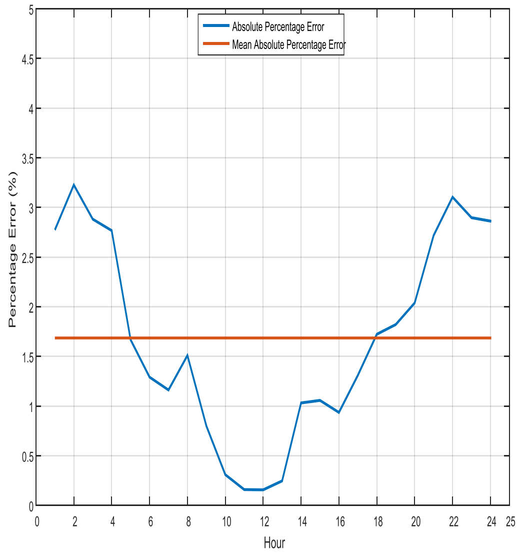

Fig 15: Absolute and Mean Absolute Percentage Error (MAPE) of One Day Ahead Load (July-1-2016) based MLR

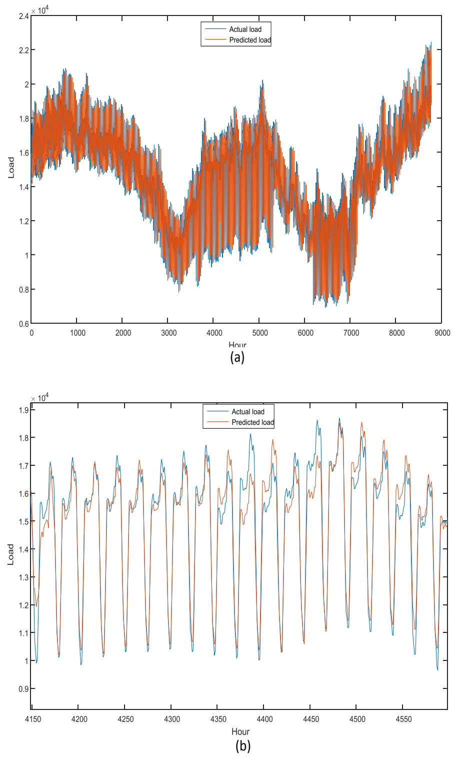

Fig.16 (a) Actual and MLR Predicted Historical Load (July-1-2015 to June-30-2016) (b) expand view

The MAPE and elapsed time of ANN and MLR simulation results for summer season are given in table2.

Table.2 MAPE and Elapsed Time of ANN and MLR Simulation Results for Summer Season

		ANN	MLR
MAPE (%)	One Day Ahead Load	0.297	1.686
	Historical Load	2.958	2.598
Elapsed Time		40 (minutes)	0.312 (seconds)

In winter season, the MAPE of one day ahead load based ANN technique is very small compared with that of MLR but It takes a longer time compared with MLR because of the training process.

6. CONCLUSION

In this paper, the investigation of one day ahead load forecasting using ANN and MLR techniques for winter and summer season of IPS is represented. Both techniques have been tested using input variables which were obtained from actual yearly historical load data. The MAPE of the proposed model of ANN for winter season is 0.593% while for summer season is 0.297%. The proposed model of MLR gives a MAPE of 2.024% for winter season and 1.686% for summer season. The results of ANN indicated that the ANN has an excellent performance to forecast STLF and represents a high degree of accuracy. On other hand, The required simulation time of the MLR technique is much less than that of ANN technique because the ANN needs long time for training process.

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