A Comparative Analysis of Neural Network Based Short Term Load Forecast Models for Anomalous Days Load Prediction

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***Abstract*—Load forecasting plays a very vital role for efficient and reliable operation of the power system. Often uncertainties significantly decrease the prediction accuracy of load forecasting which affect the operational cost dramatically. In this paper, comparison of Back Propagation (BP) and Levenberg Marquardt (LM) neural network (NN) forecast model for 24 hours ahead is presented. The impact of lagged load data, calendar events and weather variables on load demand are analyzed in order to select the best forecast model inputs. The mean absolute percentage errors (MAPE), Daily peak error and regression analysis of NN training are used to measure the NN performance. The Forecast results demonstrate that, LM based forecast model outperform than BP NN model for performance matrices. This model is used to predict the load of ISO-New England grid.**

***Index Terms*—Short Term Load Forecasting (STLF), Neural Network (NN), Back Propagation (BP), Levenberg-Marquardt (LM), Mean Absolute Percentage Error (MAPE), Regression Analysis (RA).**

I. Introduction

Load forecasting is future load prediction which plays a very important role in the energy management and also provides a better planning for the power system. Accurate load forecasting is an integral part of energy management system, which is critical for secure, reliable and inexpensive power supply. In last decade widespread research is going on electrical load forecasting because of its applications in power system scheduling, load flow analysis and several types of contingency analysis. The affective power system operation, planning, and maintenance can be carried out by the accurate electrical load forecasting [1].

Significance of load forecast is increased because under and overestimate of load demand can affect on power system operation. Underestimating of the electrical load demand shows negative and worst affect on demand response of energy system. It's also very difficult to manage overload conditions especially where backup power storage is not available. In case of overestimation, it may create an unexpected surplus of production [2]. There are several applications which depend upon the load forecasting like energy system management, smart grid, scheduling and day to day operation of power system.

Electrical load forecast accuracy is the measure of correctness of predictability of future load demand, which plays vital role in power system operation, maintenance and planning decisions [3]. Such planning can save millions of dollars as a survey conducted for UK power system [4]. In modern era of technology, reliability of power is very crucial that is why accurate load forecasting is getting more attention by the researchers to achieve reliability of the modern power system. A small increase in the degree of accuracy may save millions dollars by implementing better energy management system [5]. Abrupt change in meteorological conditions and uncertain load demand due to change in day type, historical data requirement and type of prediction model having an affect the forecast accuracy [6, 7].

In the last few years' an extensive research is conducted in the field of load forecasting to apply in smart building energy management system. There are several techniques for short term load forecasting [1, 6] and roughly load forecasting techniques can be divided in two categories.

- Statistical techniques (parametric technique) [1, 3].
- Artificial intelligence techniques (non parametric technique).

The non parametric technique such as ANN forecast models received great attention by the researcher since the mid 1990's for load forecasting problem as a powerful computational tool. The ANN provides much better results as compared to previously implemented techniques [2, 8]. The neural network has ability to solve the complex relationship between input and output and decision making under uncertainty and prediction patterns [9-10]. A number of different methods are applied for short term load forecast such as multilayer feed forward neural network, radial basis function

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network, Bayesian regulation, adaptive neural network, quasi Newton network [11].

The paper is organized as follows: Section II examines the impact of ANN model inputs on STLF and STLF NN model inputs. Section III presents the weight update rule of Levenberg-Marquardt (LM) training algorithm. The forecast results of NN STLF model and regression analysis of LM and BP training techniques are discussed in section IV.

II. Neural Network Based Load Forecast Model

The neural network containing the neurons between the input and output layer is called multilayer neural network and neuron layer between the input and output layer is referred as hidden layer as shown in Fig. 1. The single layer network is not able to learn the complex relationship between input and output but multilayer network (MNN) have the ability to learn the complex relationship [10]. The proposed ANN based forecast model 8:20:1 neurons in input, hidden, and output layer respectively are shown in Fig. 1. There are no specific defined rule for optimal selection of network layers and neurons to produce the better forecast results. Moreover, an optimal ANN structure can be identified by applying optimization techniques to achieve the higher network performance.

However, it is most important that, selected input ANN architecture must have ability to map the input as output of network. Therefore, in order to select the optimal ANN architecture, a large number of case studies to get better forecast results. Fig. 1 shows the optimal ANN architecture for provided historical load and weather data.

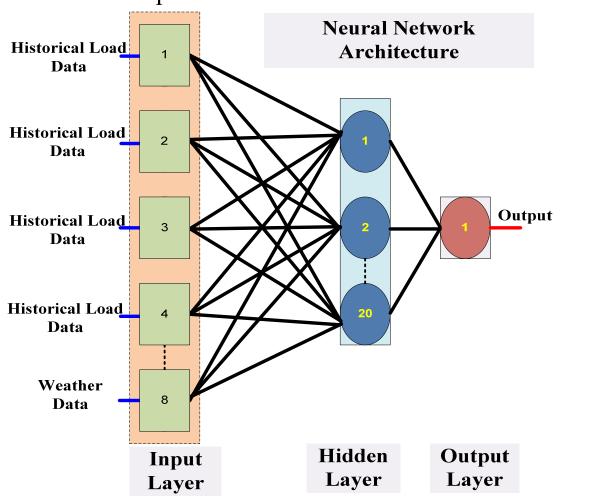

Figure 1. Proposed multilayer preceptron neural network architecture

A. Characteristics of Load Profile:

Fig. 2 shows, the graph of input load demand (MW) of five years (2005 to 2009) new-ISO England grid.

The load trend can be analyzed with load demand graph and this type of analysis can be useful for energy policy making decision [11]. Seasonality trend can be easily observed in load profile of ISO-new England grid data as demand repeats according to season of year, as the load demand in summer season is about double than the winter season. This great demand change is due to weather variation throughout the year.

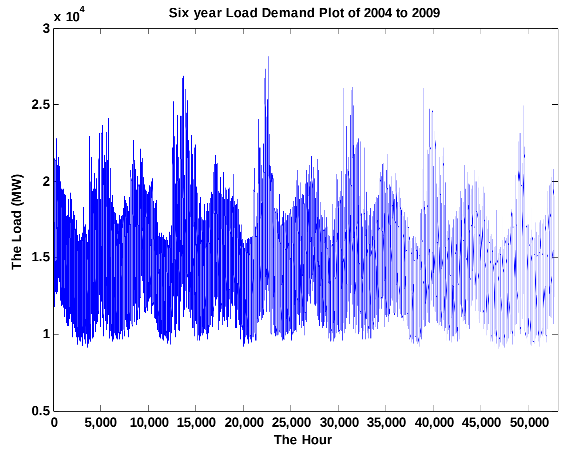

Figure 2. (2004-09) five years load profile of grid

B. ANN Training and Testing Data:

The ANN proposed model is trained by Levenberg-Marquardt training algorithm for 24 and 168 hours ahead for ISO-New England grid. The load data set is divided into two sets: first data set is used for training purpose of network and second data set for testing of forecasting results. A four year 2005-2008 24-hourly load and weather data is used to train the network called training data set and 2009 hourly load data is considered as test data set.

C. Working Day or Off Day:

The type of day refers to either a working day or an off day (weekends or special occasion). On or off days the load demand is quite different from the normal day due to the changes in human activities. In weekends, the load demand is lesser than working days because the office buildings, factories, and other working places are closed. It is observed that, people may also get up late in the morning during weekends than the working days, which also shift the peak load demand. UK grid load profile shows that, the load demand of working and weekend days (Saturday and Sunday) may also differ. It is because of change in human activities such as some of families prefer to buy the house items or family gatherings on Sunday.

During the working days, the load consumption is usually higher than off days as factories, offices, and other working places will again start their production. Therefore, the load demand pattern of working days and weekends are different. The local customs and traditions of certain locality may also affect the load pattern.

D. Day Pointer D (k) and Hour Pointer H(k):

Other inputs are day of week (Monday is day first and Sunday is seventh day), hour of the day. Fig. 3 shows that the load demand from Monday to Sunday. It depicts that, in working days the load demand is much higher than the off days (Saturday and Sunday) due higher social activities. This weekly pattern is repeated more or less throughout the year.

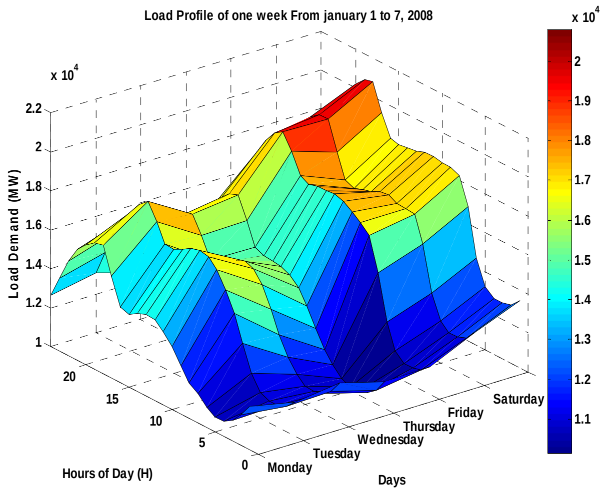

Figure 3. Load profile of January 1 to 7, 2008

A similar and cyclic repeating can be observed in one month load plot of demand with respect to hours of days and days of month.

Therefore, it can be conclude that, load demand in weekends is quite different than weekends as shown in one week and month load profile. In order develop an accurate forecast model, the type and hour of day can include as forecast model input.

E. *Forecast Model Inputs:*

Load forecast accuracy greatly depends upon the better input selection of neural networks. Moreover, most influential and highly correlated input patterns may give better forecast results. However, there is no general rule defined for input selection of forecast model. An appropriate input selection can be carried out based on engineering expertise or technical experience [12]. Some statistical and correlation analyses can be very helpful to determine the inputs, which significantly increase the load forecasting accuracy [13-15].

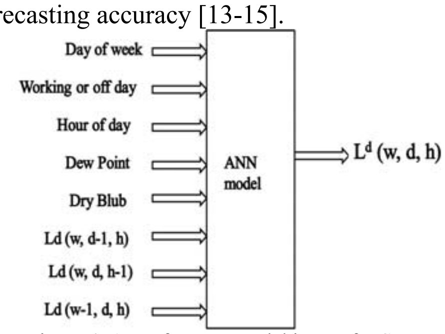

Figure 4. ANN forecast model inputs for STLF

Therefore, the inputs of ANN model for hourly load forecast model based on correlation analysis are shown in Fig. 4.

Where L_d (w, d, h) represents load demand of particular hour of the same day and same week.

1. L_d (w, d, h-1): represents the load demand of the pervious hour of the same day of the same week.
2. L_d (w, d-1, h): represents the load demand of the same hour of the previous day of the same week.
3. L_d (w-1,d,h): represents the load demand of the same hour of the same day of the previous week.
4. Day of week (day of week represents the either it is first day or second day or any other day of week)
5. Working day or off day (type of day)
6. Hour of day
7. Dew point temperature
8. Dry blub temperature

F. *Proposed ANN Model:*

The multilayer perceptron (MLP) model is used for forecasting the load demand. The network architecture is 8-20-1, 8 nodes in the input layer, 20 nodes in hidden layer and one node in output layer because the network output is one.

III. LEVENBERG MARQUARDT TRAINING METHOD FOR ANN:

The Levenberg Marquardt NN training algorithm of neural network can be derived as fellows [16-17].

$$O_p(w_{ij}+d_{wij}) = Op(w_{ij}) + \nabla O_p(w_{ij})^T dw_{ij} + 1/2 * dw_{ij}^T \nabla^2 O_p(w_{ij}) dwij \quad (1)$$

Where $\nabla O_p(w_{ij})$ and $\nabla^2 O_p(w_{ij})$ are the gradient vector and hessian matrix of the error function. dw_{ij} is

$$dw_{ij} = -\left[\nabla^2 Op(w_{ij})\right]^{-1} \nabla O_p(w_{ij}) \quad (2)$$

And hessian matrix as fellows

$$\nabla^2 O_p(w_{ij}) = J^t J + S \quad (3)$$

Where J is jocobian matrix, which contains the primary derivative of network error which is relative to weight and errors. By traditional directional propagation algorithm it can be calculated and where S represents the 2nd order derivative information in $\nabla^2 O_p(w_{ij})$.If the S is ignored then equation will be Gauss Newton method. We can also obtain results for Hessian matrix by following approximation.

$$\nabla^2 O_p(w_{ij}) = J_t J + \mu I \quad (4)$$

To get modulus weight and approximation of hessian matrix LM method is applied.

$$\nabla W = \left(J^t J + \mu I\right)^{-1} J^t O_p \quad (5)$$

To control the size of trust region μ scalar quantity is used and I is unit identity matrix.

IV. RESULTS AND DISCUSSION:

The accuracy of load forecasting is measured in term of error. The mean absolute percentage error (MAPE) is calculated as

$$MAPE = 1/M \sum_{i=1}^{m} | P_i - P_o | / P_i \quad (6)$$

Where P_i is the actual load, P_o represents forecasted load and P_i actual load denotes in the denominator. In order to access the prediction accuracy of forecasting model the mean absolute percent error (MAPE) and daily peak error is calculated.

Fig. 5 depicts the 24 hours ahead forecasted load demand of 1st April 2009 with back propagation (BP) and Levenberg Marquardt (LM) training method of NN. Analysis shows that MAPE of LM based forecast model is less in morning time and as the time is passed of a day, the MAPE becomes higher. One of the reasons is due to social activities of certain population in day time. In the ANN model, the type of day (working or off day) is considered as an input of the system because its effects on the load demand. At different events celebrations like, Eid-ul-Fitar, Eid-ul-Azha, New Year night or other public events increase the load uncertainty of the system [18]. Fig. 5 shows that the, load demand is increasing as day activities started and MAPE is also increasing.

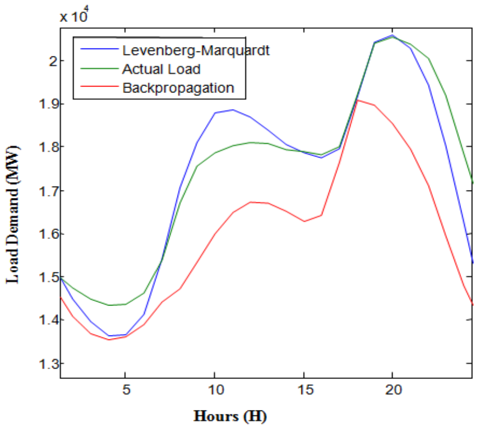

Figure 5. 24 hours ahead forecasted load using LM and BP training method

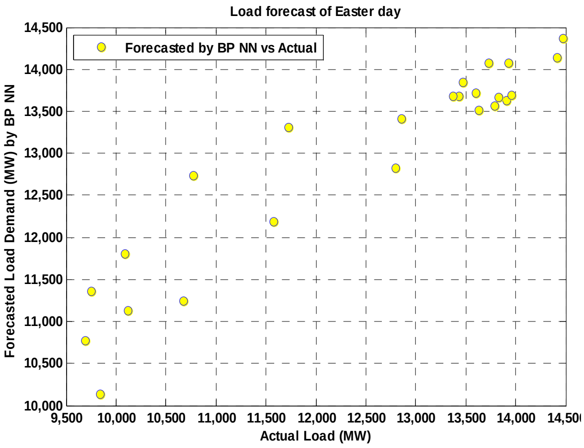

Figure 6. Scatter plot of BP_NN model for Easter day

Fig. 8 depicts the peak load forecast of LM NN based forecast model. It is observed that, the peak forecast error of model varies with passage of time. Moreover large forecast is recorded during peak consumption abrupt change in load demand.

The Fig. 6 and 7 represents the scatter plot between predicted and actual load demand by proposed LM_NN and BP_NN based forecast models for Ester day celebrated in year 2009. Where X-axis of Fig. 6 represents the actual load demand of ISO-New England grid in mega watts and y-axis shows the predicted load demand of BP_NN model.

As Fig. 7 depicts that, LM_NN based forecast model produces the better forecast results than the BP_NN based forecast model. The predicted load demand using LM_NN model is closer to actual load. Therefore LM_NN model give better forecast results and shows better capability to deal with uncertainty in load occurred during Easter day. Moreover a large forecast error is also observed during Easter day test period due to large uncertainty in load demand. Therefore, there is large dispersion in forecasted and predicted values can observed from BP_NN based forecast model. It is due lower training of the network and local minima problem. However, LM_NN based forecast model shows better forecast results due to better training of NN.

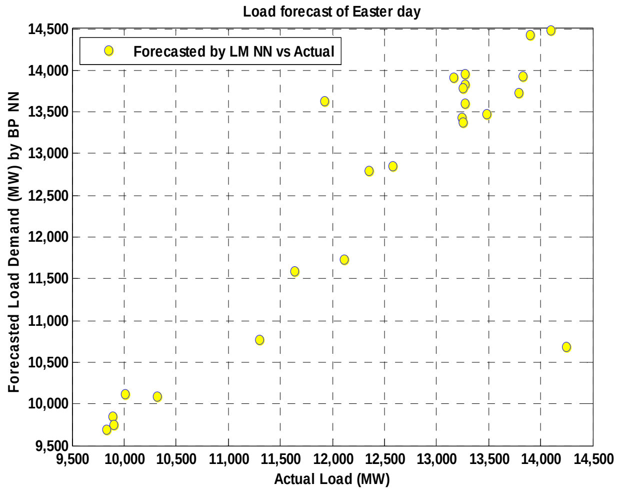

Figure 7. Scatter plot of BP_NN model for Easter day

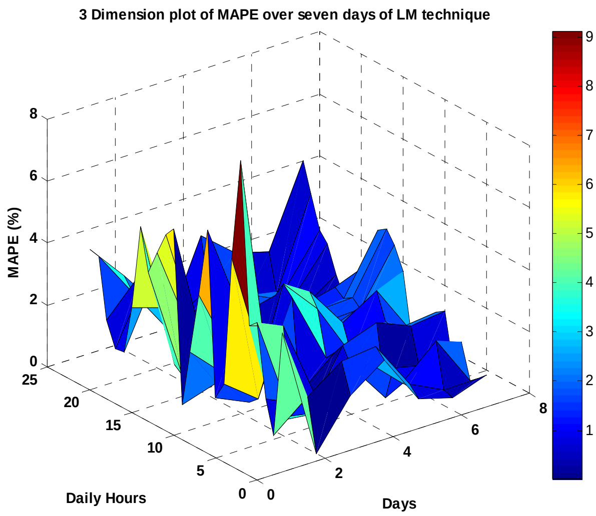

Figure 8. MAPE plot of LM based forecast model for one week ahead case study

Scatter plot of predicted and actual load demand using LM_NN and BP_NN based forecast models for Christmas day celebrated in year 2009 is shown in Fig. 9 and 10.

In Fig. 10 every point represents the predicted and respective actual load demand [19]. From BP_NN forecast scatter plot it can be observed that, predicted load points are dispersed than actual load. A similar forecast trend can observed using BP_NN based forecast model for Easter day as shown in Fig. 7.

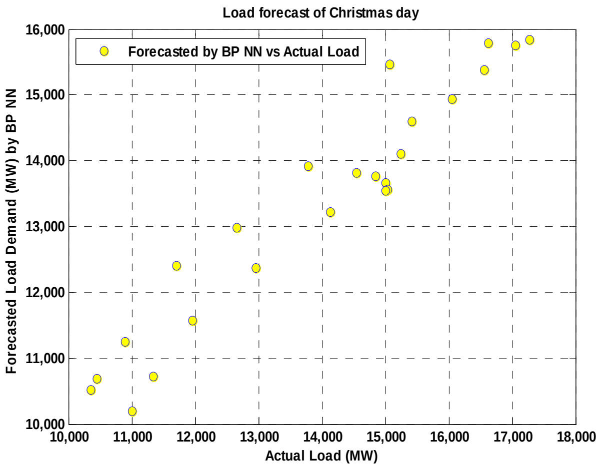

Figure 9. Scatter plot of BP_NN model for Christmas day

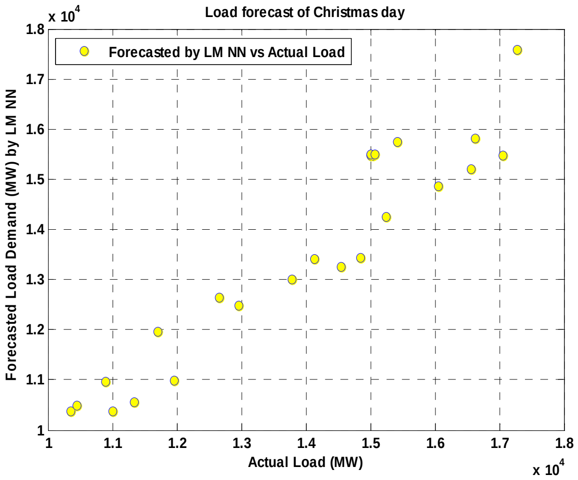

Figure 10: Scatter plot of LM_NN model for Christmas day

This indicates that, BP algorithm unable to train the network efficiently and deal with uncertainty during test day. Moreover, it leads to higher forecast error and poor performance in terms of network training. Conversely, proposed LM_NN model scatter plot shows that, the predicted and actual points are more concentrated as shown Fig. 10. This designates that, the predicted load demand is closer to actual load demand and produces higher forecast accuracy. Moreover, proposed LM_NN model have better training capability over test period as compared to BP_NN model.

TABLE I.
MAPE COMPARISON OF LM AND BP NN FOR EASTER DAY LOAD FORECAST

Easter Day Load Forecast			
Training Technique	**No. of Hidden Neural Units**	**MAPE (MW)**	**Daily Peak Error (MW)**
BP_NN	20	3.88	4.96
LM_NN	20	2.68	3.73
Christmas Day Load Forecast			
BP_NN	20	3.52	4.13
LM_NN	20	2.49	2.97

LM based forecast model produced comparatively less forecast MAPE than the BP model. In Table I, the Levenberg Marquardt NN training algorithm shows relativity small MAPE and daily peak error than for Easter day load forecast case study.

Fig. 11 depicts the regression analysis of LM training of the ANN method for STLF model with given inputs. The training process performs several times to analyze the confidence interval of training, testing, validation to the measure the overall performance of STLF model [20]. Table II shows the training, testing, validation and overall performance of training algorithm is shown. The Levenberg Marquardt (LM) shows higher confidence in training, testing, validation and overall network performance than BP training technique.

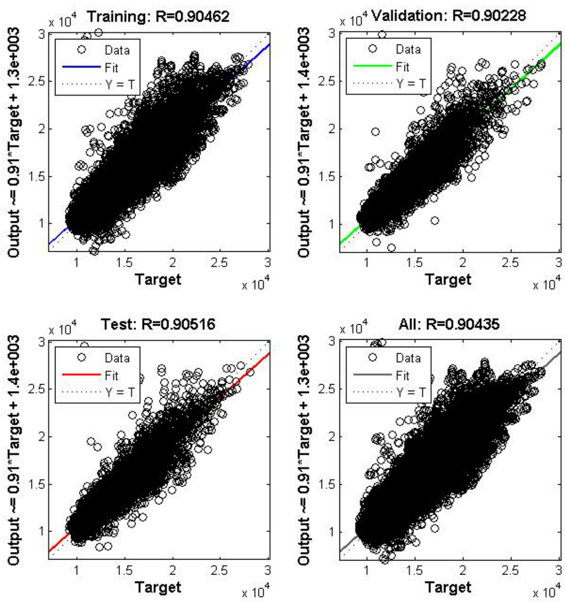

Figure 11. Regression analysis of Levenberg-Marquardt (LM) NN

TABLE II.
COMPARISON OF REGRESSION ANALYSIS OF NN TRAINING TECHNIQUES

Training Technique	Training	Testing	Validation	All
BP	0.9046	0.9051	0.9022	0.9043
LM	0.9924	0.9917	0.9929	0.9923

It can be analyzed from load forecast results that, the training algorithm and inputs having affect on the model output. Levenberg Marquardt (LM) training method shows overall better results than the Back propagation (BP).

V. CONCLUSION

This paper demonstrated the ability of Back propagation (BP) and Levenberg Marquardt (LM) training method of neural network for short term load forecasting. The historical lagged load data, type of day, day of weak, and weather variable such as dew point and dry blub temperature are considered as an input of NN based forecast model. LM based NN forecast model shows better results than the BP NN in terms of MAPE, daily peak error and overall training performance of neural network. BP training technique of NN shows the lower training capability of the network than LM technique which avoids the neural network to trap into the local minima. LM NN based model regression analysis shows that, the network achieves 95% of confidence interval for network training, testing, validation and overall NN performance. Consequently LM NN model proves that the higher forecast accuracy than BP due to strong generalization capability over a large data which increase the accuracy.

Future research focus on enhancement of forecast accuracy by including the more lagged load variables along with weather parameters as forecast model input and NN structure optimization.

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