Short-term Load Forecasting using Neural Networks and Fuzzy Logic (Hybrid approach)

Shaive Dalela
Department of Computer Science
SRM Institute of Science and Technology (SRMIST)
Tamil Nadu, India
shavie500@gmail.com

Abstract - Load forecasting is an issue of great importance for the reliable operation of the electric power system grids. Various forecasting methodologies have been proposed in the international research bibliography, following different models and mathematical approaches. In the current work, a methodology based on artificial neural networks along with fuzzy logic is implemented, in order to obtain short-term load forecasting. In this paper, the relationship between the humidity, temperature and load is identified with a case study for a particular region in Victoria, Australia. The paper investigates the application of artificial neural networks (ANN) and fuzzy logic (FL) as forecasting tools for predicting the load demand in short term category. The extracted outcomes indicate the effectiveness of the proposed method, reducing the relative error between real and theoretical data.

Keywords: Short-term load forecasting, Artificial Neural Network (ANN), Fuzzy Logic (FL), Mean Absolute Percentage Error (MAPE)

I. INTRODUCTION

Electric short-term load forecasting (STLF) is an important guideline for providing safe schedules and economic management of power systems. [1] Under the conditions dictated by electricity markets, electric utilities have to establish reasonable economic models and competitive real-pricing according to accurate and fast forecasting results of a short-term load. [2] And thus, for a long time, STLF has been under great focus and various algorithms have been put forward.

Traditional computing approaches, such as regression and interpolation, certainly cannot provide the results that are required. On the other hand, complex algorithmic methods involving lots of calculations can converge slowly and may diverge in certain cases.

Of late, artificial neural networks have been widely employed for load forecasting. However, there exist large forecast errors using ANN when there are rapid fluctuations in load and temperatures. In such cases, forecasting methods using fuzzy logic approach have been employed.

Short-Term Load Forecasting (STLF) predicts system load by using historic load and weather data. Since system load usually differs significantly on certain days of the year, the program uniquely classifies such days to allow separate analyses of them. [3-4]

In this paper, an approach for short term load forecasting problem, using fuzzy logic combined with ANN approach is proposed. The fuzzy logic technique has been used to provide the variable load pattern to the system in hand. The neural network is used to calculate the increment factor of load without being dependent on other parameters like growth in industries, increase in number of customers etc.

II. FUZZY SYSTEM

The Fuzzy Logic module maps the highly nonlinear relationship between the increments in loads because of changes in weather parameters from time to time. The output of the Fuzzy Logic is used to determine the dependent nature of load. The past load increments is used to train the ANN. In this approach weather variables such as temperature and relative humidity are used.

The first input to the Fuzzy logic module is temperature which have three membership functions (MF) and these membership functions overlap using triangular shapes to cover all possible range of temperatures.

The shape of membership functions and the degree of overlap were chosen by trial and error. Similarly, the second input to the FL module is humidity which is classified into three membership functions.

III. NEURO-FUZZY MODEL

Various hybrid algorithms have surfaced in the area of forecasting in general. [5] Not only these combinations are different but also each and every approach has a different implementation altogether.

In this particular area of fuzzy logic and ANN, other forms are discovered including fuzzy reprocessing of neural network inputs, fuzzy post processing of neural network outputs, integrated fuzzy-neural networks and parallel fuzzy neural forecasters. Depending on the fuzzy-neural model, the selection of input/output variables and the amount of data used, forecasting errors can be very low range. Fuzzy logic and neural networks are complementary technologies in the design of intelligent systems. Each method has merits and demerits.

The ANN has the ability of self-leaning and nonlinear approximation, but it lacks the inference, common in human beings, and therefore requires massive amounts of training data, which is an intensive time consuming process. Also, because the internal layers of neural networks are always opaque to the user, the mapping rules in the network are not visible and are difficult to understand. One of the main drawbacks in building reliable ANN based forecaster lies in building inference from the training data in hand. [6-10]

The fuzzy logic inference, on the other hand, is a fast approach for fuzzy and uncertain problems. However, the traditional fuzzy system is largely dependent on the knowledge and experiences of experts and operators, and is difficult to obtain a satisfied forecasting result especially when this special information is incomplete or insufficient.

Each of these modules applied to the aspect of the problem for which it is best suited in order to produce better overall forecasting results. The variation of the temperature variable results in a significant variation in the load.

IV. METHODOLOGY

The Figure 1 shows the block diagram representation of the proposed paper. Here two parameters are considered one is the temperature and the other is the humidity. In this project the humidity and the temperature data is fed to the fuzzy logic system and the output is the load proportional to these two parameters. In the other part of the model, previous load is fed to the neural networks for training and comparing the set of past load to predict the future. This is done because the load not just depends on the temperature and humidity but also depends on the other factors like environmental factors.

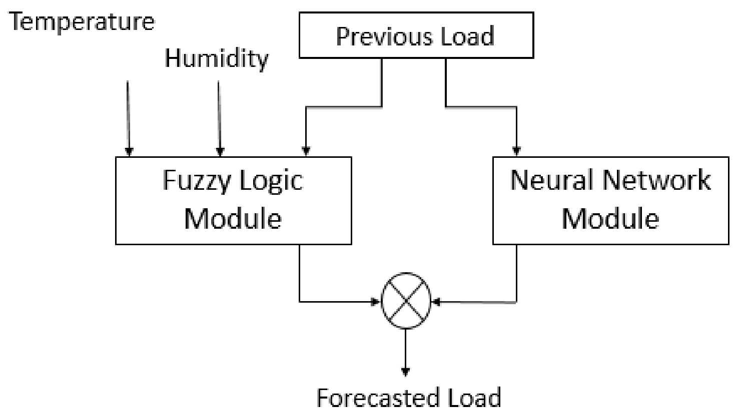

Fig.1. Block Diagram Representation

The figure 2 shows a boxplot of load for the whole year for a particular trade region of Melbourne (Australia) against days of the week.

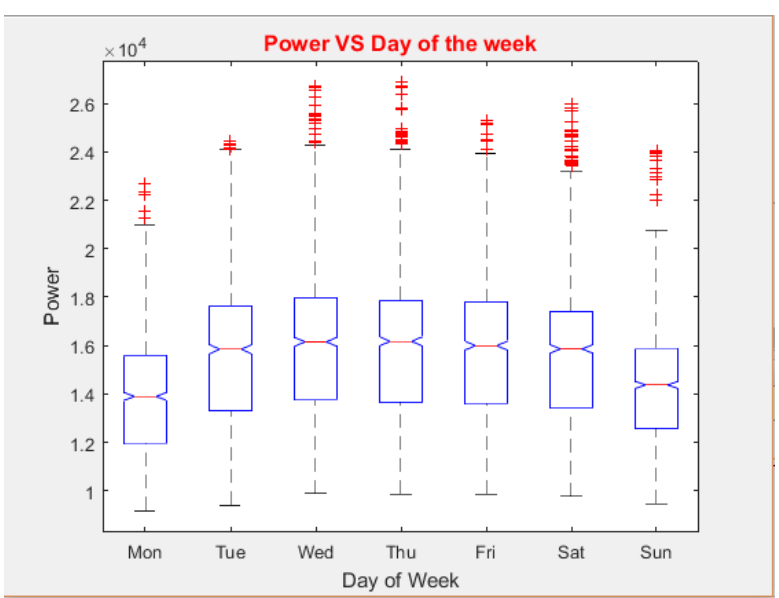

Fig.2. Load Vs Days of the Week

The figure 3 portrays a plot of load for the whole year against hours of the day.

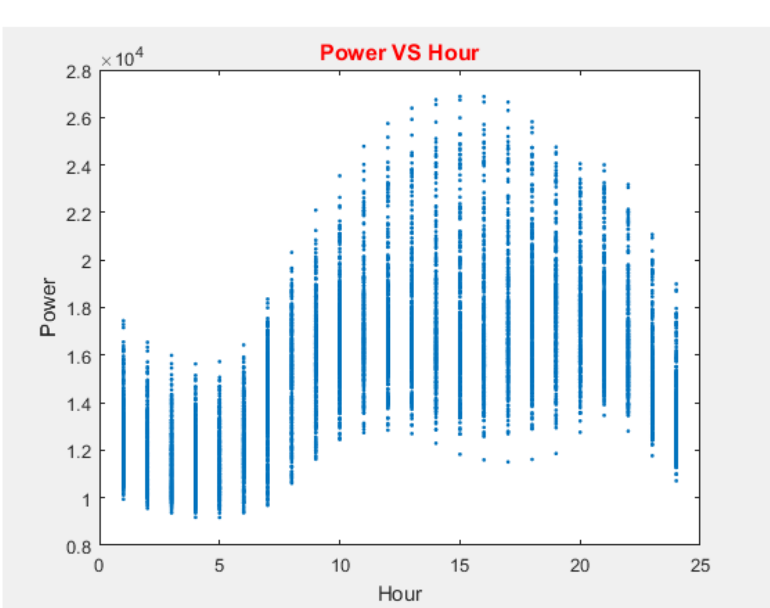

Fig.3. Load Vs Hours of the Day

In order to get the forecast with better accuracy, parameters such as temperature and humidity have been taken into consideration.

The figure 4 shows the plot of load against temperature and it can be extrapolated that as the temperature increases the load usage decreases.

The figure 5 shows that load increases linearly with increase of humidity. These data points are fed to the Fuzzy system for classifying the data and to get the output.

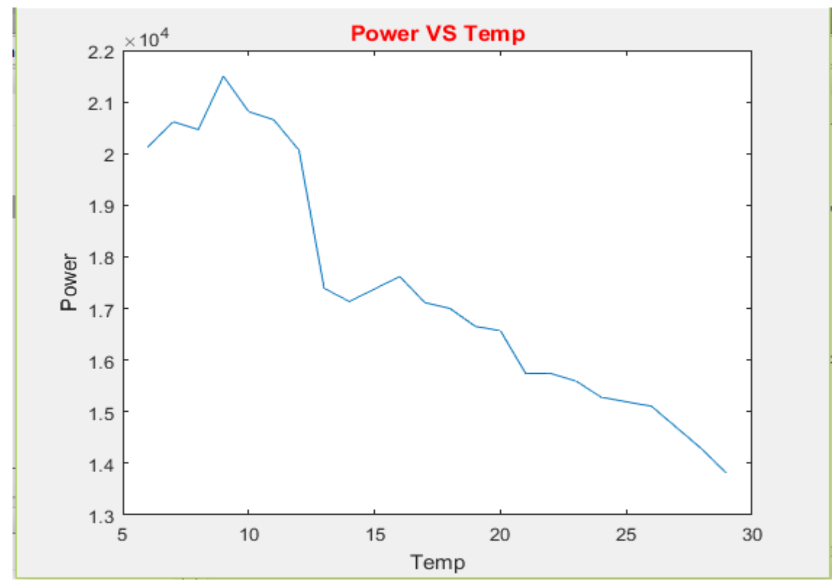

Fig.4. Load Vs Temperature

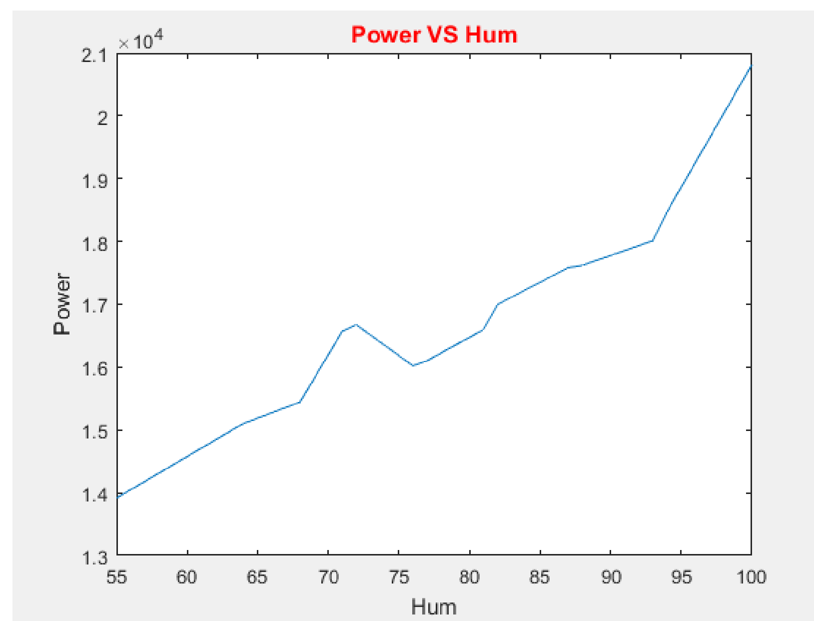

Fig.5. Load Vs Humidity

A. Fuzzification of Input and the Outputs

In this paper, the load is classified as Low, Medium and High Load. It can be seen from the figure that load lies in between 11500 to 21500 MW. The load data is classified in order to achieve appropriate density of points in each section. These three section are divided as (11500-15000), (15000-18000) and (18000-21500). The corresponding temperature and humidity is taken from the data and are used to classify the humidity and temperature ranges for Fuzzification.

TABLE I
CLASSIFICATION OF TEMPERATURE, HUMIDITY WITH RESPECT TO THE LOAD FOR FUZZIFICATION

Classification	**Low**	**Medium**	**High**
Temperature	4-12	12-17	17-29
Humidity	60-88	88-94	94-100

These ranges of fuzzification are then applied to the inputs in the fuzzy logic systems to the get the corresponding electricity load as output. The membership function for both temperature and relative humidity are shown in figure 6 and figure 7. The temperature is classified in the ranges of (4-13), (12-18) and (17-29).

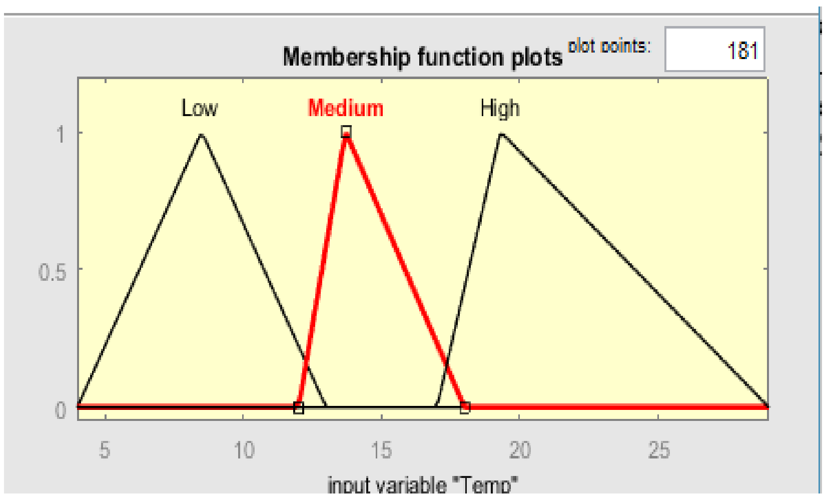

Fig.6. Membership Function for Temperature

The reason for having overlapping ranges is because the boundary conditions are also taken into consideration and the output has greater accuracy in forecasting. The membership function if both the inputs overlap using triangular and trapezoidal shapes to cover all possible range of relative load increments. The shape of membership functions and the degree of overlap were chosen by trial and error.

The humidity is classified in the ranges of (60-89), (88-95) and (94-100). The load which is taken as output has to be provided with a membership function in similar manner.

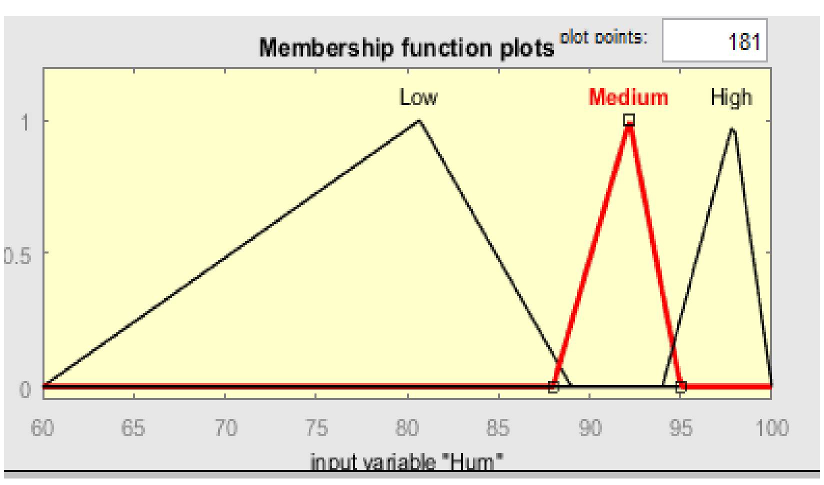

Fig.7. Membership Function for Relative Humidity

The figure 8 will provide the result for the same. The ranges for load are (11500-15500), (15000-18000) and (18000-21500).

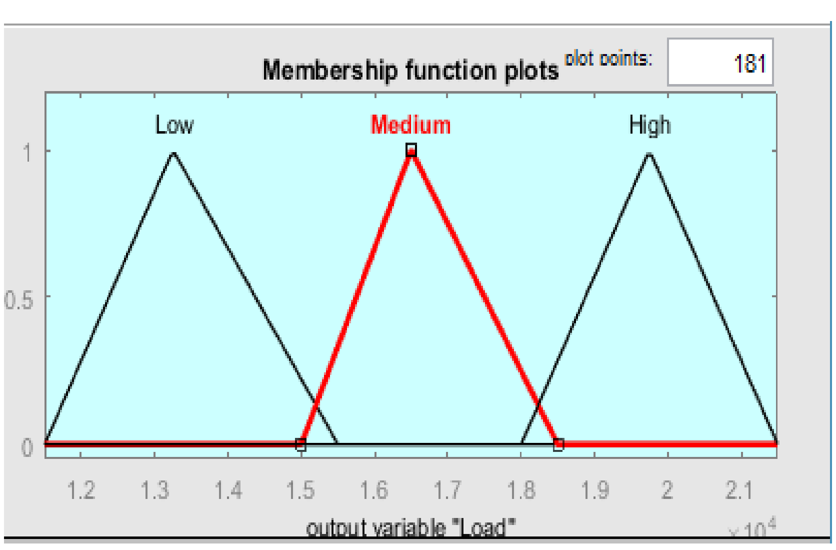

Fig.8. Membership Function for Load

The output of the Fuzzy Logic module is a control action that carries a weight between 11500 and 21500, which represent the expected change in the amount of electric load. A value greater than 11500 and less than 15500 means that low electric load will be consumed and value greater than 18000 shows that high load consumption will take place on next days.

Other than the membership functions, rules are also important in fuzzy logic system. There are 7 IF-THEN statements in the fuzzy rule base that characterize the behavior of the Fuzzy Logic Module. The choice of the rule is based on the knowledge of the variation of load relative to past load increments. The rules are mentioned in TABLE 2.

TABLE II
RULE BASE

Temperature / Humidity	Low Temperature	Medium Temperature	High Temperature
Low Humidity		Low Load	Low Load
Medium Humidity	High Load	Medium Load	Low Load
High humidity	High Load	High Load	

The fuzzy inference that was used to implement the fuzzy rules was the max-min composition and the method that transformed the inference engine rules to one crisp output was centroid defuzzification method. The output of the Fuzzy Logic module and the output of ANN module will yield the result.

According to the rules and the membership functions of the parameters under consideration, the fuzzified values are converted back to predicted values through the process of defuzzification.

Figure 9 displays the fuzzy system in MATLAB toolbox that is used to predict the values of load for future day and compared accordingly.

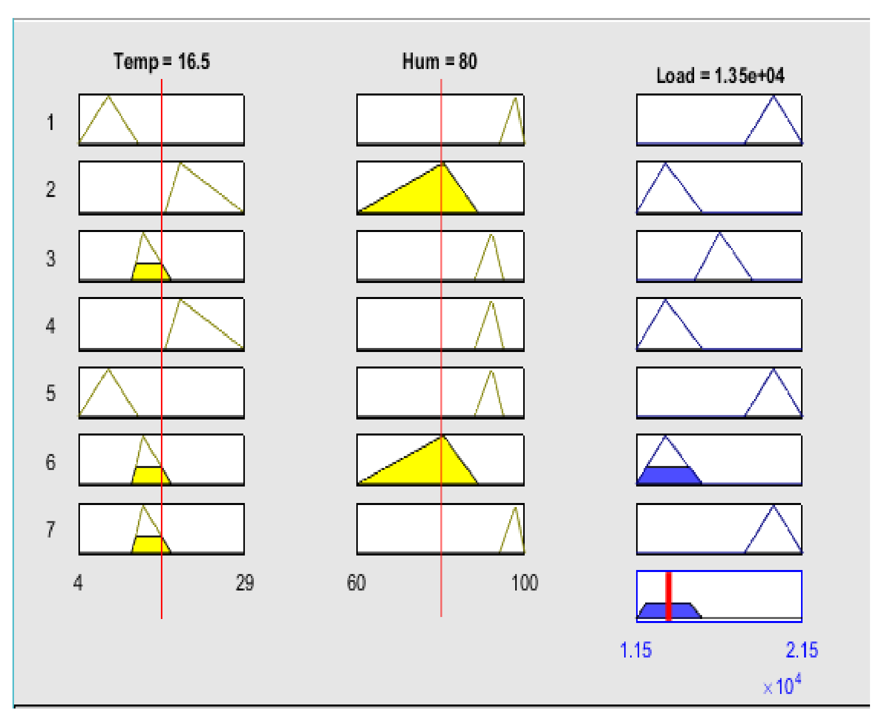

Fig. 11. Defuzzified output for one sample data

In order to determine the error in the predicted values to the actual values, some of the values of load and their corresponding values of temperature and humidity are taken and MAPE is calculated accordingly. The formula is –

$$\%\ Error = \frac{|Actual\ Load - Forecasted\ Load| \times 100}{Actual\ Load} \quad (1)$$

As the tool gives out one of the load values on the basis of temperature and humidity, we can see that at 16.5 degree C temperature and 80% of relative humidity, the load is 13500 MW of the area.

From the TABLE 3 we can see that the high temperature and low humidity gives an output of low load, similarly for low temperature and high humidity the output is high Load. These values are present in the table. It helps predicting the variability part of the load which is influenced due to weather factors.

TABLE III
TEPERATURE, HUMIDITY VS ACTUAL/PREDICTED LOAD

Temp	Hum	Actual Load	Predicted Load	Error
6	88	20129.13	19800	1.64
7	93	20615.08	19800	3.96
8	100	21500.5	19700	8.37
29	69	13796.54	13300	3.6
21	55	13916.38	16500	18.5
10	94	20813.25	19700	5.34
26	64	15105.17	13500	10.6
12	95	18475.33	19700	6.62
13	87	17389.67	16500	5.11
17	77	16102.96	16400	1.84
16	76	16020.92	13300	16.98
24	82	17134.63	16500	3.7
				7.188%

B. Neural Network Module

Artificial neural networks (ANNs) or connectionist systems are computing systems inspired based on the structure and functions of biological neural networks. The neurons take multiple inputs and just give out a single output. Each input is adjusted by a weight in order to perform mapping of training points. Such systems learn by dynamically improving performance on tasks by considering examples. They do not rely on task-bounded programming. After combining all the inputs with their corresponding weights and the threshold value, the activation function determines the output values. Backpropagation algorithm is the most commonly used algorithm in term of forecasting. Supervised learning involves comparing the outputs exposed to specific inputs thereby forming a pattern. [11-15]

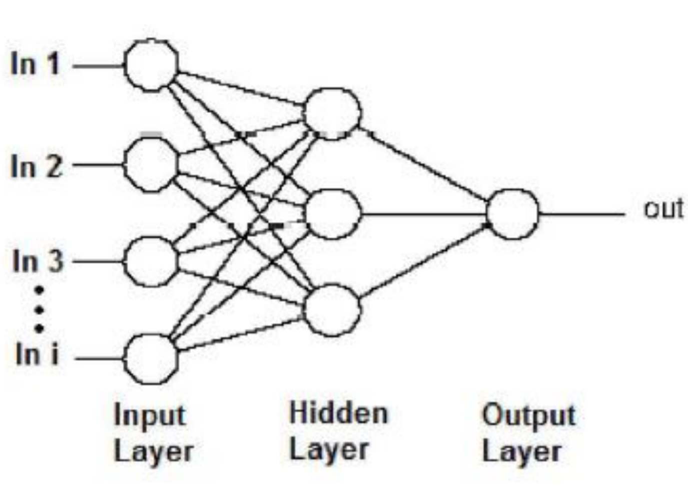

Fig. 12. Backpropagation neural network

The output of the module is basic load heft which is not based on the parameters under consideration. In order to minimize the error and improve the accuracy of the load forecaster, introduction of variability load heft is required. In the combination or hybrid module, drawbacks of both the individual modules will be covered up.

C. Combination Module (Neural Network Module and Fuzzy Logic Module)

Short term load forecasting has been implemented in many different individual as well as hybrid approaches. The approach presented in this paper is a hybrid approach of neural network, which calculates the basic load pattern and fuzzy logic, which computes the variability load pattern on the basis of parameters such as temperature and relative humidity. The combined approach not just only overcomes the disadvantages and advantages of the neural network and fuzzy logic but also shows variable nature of load when considered under certain parameters. Neural networks have self-learning capability to complete the forecasting of basic load pattern of power. Other variability causing parameters are not considered in this forecasting method. The method brings out the simplicity with which such a complex task is completed.

Fuzzy logic deals with the uncertainty part of the problem and uses the variables in such a way so as to use its reasoning to predict the forecasting load. Basic load pattern by neural network is amended by fuzzy logic system with the help of functions and fuzzy regulation base for variability load pattern which is affected by many factors.

The hybrid approach formula for calculating the forecasting load is –

$$L_F(i) = L_n(i) + L_n(i) * \frac{\alpha(i)}{100} \qquad (2)$$

i = 1, 2…24

Where, L_F is the forecasted load, L_n is the load predicted through neural network, α is the rectified percentage error, i expresses the hours of the day.

V. CALCULATIONS

Individual as well as combined approach results will be shown in this paper. These models are used to progress future 24 hour loads. It takes the help of historical data to predict the results.

The neural network takes input as the hourly load of the whole year. It only gives a single output i.e. forecasting load. The system shows variable nodes in hidden layer when the system is rebuild every single time. The MAPE produced through this method is about 4%.

The fuzzy logic in consideration of factors such as temperature and relative humidity shows variability in the load pattern. When the historical data of load, temperature and relative humidity is fed into the system along with fuzzy rules it leads to the forecasting load results. The MAPE produced as shown in TABLE III is about 7%.

The hybrid module is then considered and put into the test in accordance to the formula mentioned leading to final forecasting results. The hybrid approach considers both the basic as well as variable load heft. The MAPE produced by combination module is about 3%.

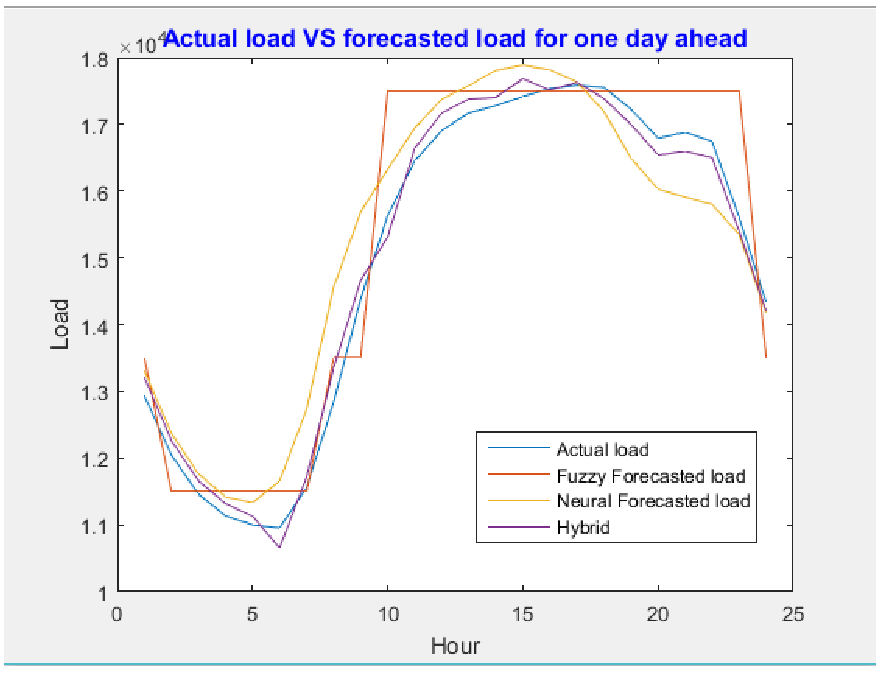

Fig. 13. Forecasted load plots

The figure 13 shows the plot of load against hours of the forecasted day i.e. 1st July 2006 as the data is from 1st June 2005 to 31st May 2006. It shows the actual load plot along with neural network, fuzzy logic and their hybrid plot.

VI. CONCLUSIONS

This paper presented a hybrid approach of neural network and fuzzy logic for short term forecasting. Neural networks in this model are only used to settle the historical load data. It helps in figuring out the advantages of NNs i.e. self-organizing and self-learning capability. As the performance of neural networks is slow, sole forecasting model can take up a lot of time. With involvement of the parameters the convergence achievement would have taken more time. Moreover, fuzzy logic considers those factors which have a great impact in load forecasting like temperature and relative humidity. The memberships and fuzzy rules are developed accordingly in order to achieve the forecasted load. The fuzzy logic system used in this is Mamdani fuzzy logic system. Factors such as weekdays, holidays, density of population can also be considered to bring about greater accuracy in the existing model.

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