Novelty Journals

ISSN 2394-9678

International Journal of Novel Research in Electrical and Mechanical Engineering
Vol. 2, Issue 2, pp: (101-107), Month: May - August 2015, Available at: www.noveltyjournals.com

Application of Adaptive Neuro-Fuzzy Inference System in Short Term Load Forecasting

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Abstract: **Load forecasts are extremely important for energy suppliers and other participants in electric energy generation, transmission, distribution and markets. Forecasting means estimating active loads at various load buses ahead of actual load occurrence Planning and operational applications of load forecasting requires a certain "lead time'' also called forecasting intervals. This paper presents an application of adaptive neuro-fuzzy inference system(ANFIS) and this paper presents prediction of electric load by considering different factors like time, day of the week and temperature. Historical load data are collected from the State Load Dispatch Center Jabalpur and weather data are collected from website www.worldweatheronline.com .From the analysis carried out on the ANFIS-based model; Mean absolute percentage error (MAPE) for a typical Wednesday (24th Dec. 2014) was found to be 3.07266.**

Keywords: **Load Forecast, ANFIS, MAPE.**

1. INRTODUCTION

In power system network load forecasting is very important part of energy management system for operation and planning purpose. Load forecasting means that the techniques for predication of electric load **[1].** In terms of lead time, load forecasting is divided into four categories: Very short term, Short term, Medium term & Long term load forecasting **[2].**Very short term- a few second to several minutes. It is used in Generation, Distribution schedules & Contingency analysis for system security. Short term- a period of one week. It is used in economic load scheduling, Scheduling of spinning reserves at generating stations & Better maintenance of generating equipments etc. Medium term - from few months to 5 years. Long term- 5 to 20 years. Thus long term & medium term forecasts help in determining the capacity of generation, transmission or distribution system expansions, annual hydro thermal maintenance scheduling etc.

There are various factors which affects the behavior of the consumer load and also impact the total losses in the transmission lines.[3] ANFIS has been widely used in automation control and other areas. Fuzzy logic (FL) and fuzzy inference systems (FIS),[4][5] first proposed by Zadeh, which provide a solution for making decisions based on indefinite, ambiguous, imprecise and missing data. So by using ANFIS a novel approach for forecasting load can be implemented. Fuzzy logic can have different meanings. Fuzzy logic in its narrow sense is a branch of FL. Even in its wider sense, fuzzy logic differs both in concept and substance from traditional multi-valued logical systems. The purpose of this paper is to present an application of adaptive neuro-fuzzy inference system in short term load forecasting (ANFIS).

2. ANFIS FOR SHORT TERM LOAD FORECASTING

The set of inputs utilized to perform STLF is non- linear, therefore an adaptive decision-making system is attempted for the purpose of accurately mapping the inputs to the output. An ANFIS based system has the merits of fuzzy logic capable of mimicking the way human beings reason, and artificial neural networks with the adaptive learning ability **[6]**. Such a hybrid system is composed of fuzzy if-then rules.

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Adaptive Network based Fuzzy Inference System ANFIS is implemented as a Sugeno fuzzy inference system. ANFIS system allows the user to choose or modify the parameters of the membership functions based on the data. The parameters are adjusted automatically by the neuro adaptive learning techniques like back propagation algorithm or hybrid method (which is a combination of back propagation and least squares method). These techniques allow the fuzzy inference system to learn information about the data set. During the learning process, the parameters of the membership functions will be changed. The computations of these parameters can be controlled by using the optimization procedure which is defined by the sum of squared difference between actual and desired outputs. Sugeno systems are more compact and computationally efficient representation than a Mamdani system. The ANFIS structure obtained by the aforementioned parameters chosen is shown in fig **1.**

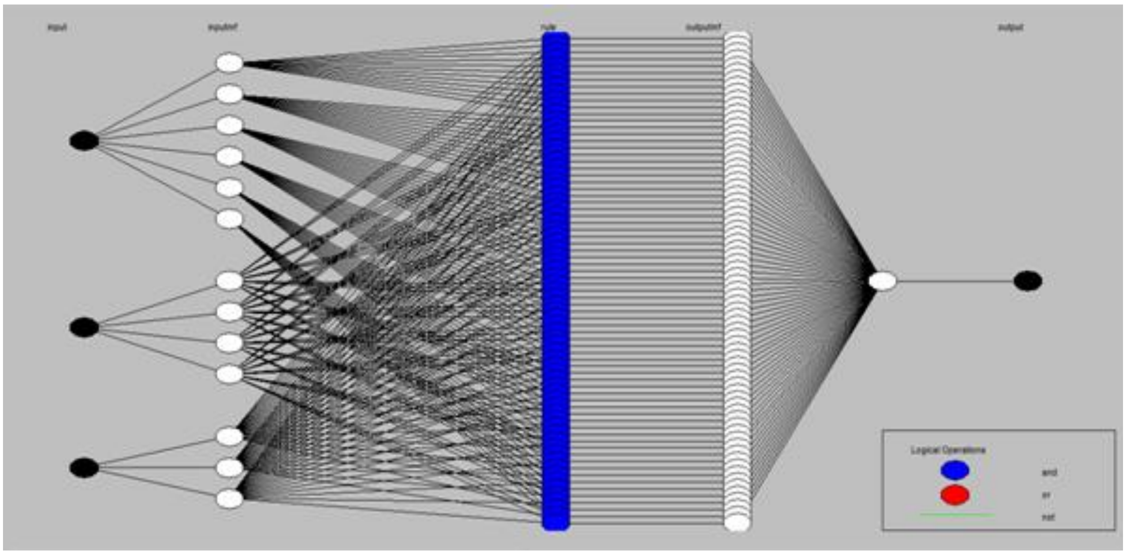

Fig.1 Structure of a three input ANFIS System

3. FUZZY INFERENCE PROCESS

There are two types of FIS: Mamdani-type and Sugeno-type. Depending upon the way outputs are determined, these two types of inference systems vary in their nature. The Mamdani FIS was first proposed by E.H. Mamdani at the University of London in 1974. It applies the system logic in a system controlled by fuzzy logic. This type of FIS results the output membership functions as fuzzy sets which needs defuzzification process to get the result in crisp form. Depending upon the number of inputs and number of outputs along with the maximum number of rules a Mamdani type FIS model can be constructed with definite grades of membership functions. A Mamdani NFS uses a supervised learning technique which is a back propagation learning to retain the variations in the parameters of the membership functions. [7]There are different layers of this type of system as:

Input Layer: Each node represents one input variable which only transmits input to the next layer.

Fuzzification Layer: Each node represents one label to one of the input variable of first layer. The output link of this layer represents the membership value. This layer specifies the degree to which an input value belongs to a fuzzy set. A clustering algorithm determines the number and type of membership functions.

Rule Antecedent Layer: The nodes in this layer represents the type of operator (T-norm operator) used in this node. The output of this layer results the strength of the corresponding fuzzy rule.

Rule Consequent Layer: This node combines the incoming rule antecedents and determines the degree to which they belong to the output label. The number nodes here are equal to the number of rules.

Combination and Defuzzification Layer: The combination of all rules consequents is done in this node and finally after defuzzification it computes the crisp output. Takagi, Sugeno and Kang proposed the Sugeno Fuzzy model when they were supposed to develop a systematic approach for generating fuzzy rules from a given input- output data set.

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In general, Sugeno-type systems can be used to model any inference system in which the output membership functions are either linear or constant. This model uses a mixture of back propagation and least mean square estimation. Different layers of this system model are as follows: Input Layer, Fuzzification Layer and Rule Antecedent Layer: These three layers function as the Mamdani type NFS model.**[7]**

Rule Strength Normalization: Every node in this layer calculates the ratio of the i-th rule's strength to the sum of all rules strength,

$W_i = W_1/(w_1+w_2)$

Where i=1, 2, 3…

Rule Consequent Layer: Every node i in this layer is with a node function,

$W_i f_i = W_i\ (p_i x_i + q_i x_2 + r_1)$

Rule Interference Layer: This layer has a single node. It computes the overall output as the summation of all incoming signals and is expressed as,

Overall output,

$$\sum_i W_i f_i = \sum_i W_i f_i / \sum_i W_i$$

4. COLLECTION OF DATA

The key to produce accurate estimates for future values with an ANFIS load-forecasting model requires past information, including load data and external parameters, such as weather, related to the past load values. For this work consider training and testing the hourly load, temperature and day of the week are consider. The hourly load data are collected from State Load Dispatch Center Jabalpur**.** The hourly weather data are collected from website www.worldweatheronline.com.

5. TRAINING OF THE SYSTEM

A Training matrix of 480*4 (i.e. 480R+4C) is generated, with the row number matching the number of hours for time span Dec. 1st , 2014 - Dec 20th , 2014 and testing matrix of 24*4 (i.e. 24R+4C) is generated, with the row number matching the number of hours for Dec. 24th , 2014(Wednesday). Table 1 show the testing data, the first three columns represent the inputs to the anfis model i.e. hour of the day, day of the week and temperature. The fourth column represents the actual output and fifth column represents the anfis forecast output and last column represents the actual percentage error (APE) of our work.

6. ANFIS PROCESS

➢ The proposed inputs were obtained from State Load Dispatch Center Jabalpur and weather website and it is used as the inputs for the ANFIS.

➢ A matrix of 480 x 4 was generated, with the row number matching the number of hours in the month of December. The first three columns represent the inputs. The last column represents the output. This matrix is then employed as the training set for the ANFIS. It takes 155 epochs to train the 72 rule-based system. The training method and steps are referred to [**8**].

➢ For the training purpose, membership functions are assigned to each input. Each input has different (i.e. 6, 4 and 3) Gaussian membership functions. The rules are generated by the grid partition method. Since there are three inputs with gaussian membership functions, the 72 rules are generated. The training process automatically adjusts the membership functions based on input patterns.[9]

As examples, Fig. 2 , Fig. 3 and Fig. 4 depict the membership functions of Hours of the day, Day-of-Week and Temperature respectively. Fig.2 shows the 6 membership function of hours (like early morning, morning, afternoon, evening, night and late night) , Fig 3 shows the 4 membership function of day type (like post holiday, working day, pre holiday and holiday) and Fig 4 shows the 3 membership function of winter temperature (like very low, low and medium).

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As expected, the eventual membership function as a result of the training process is quite different from the initial membership function.

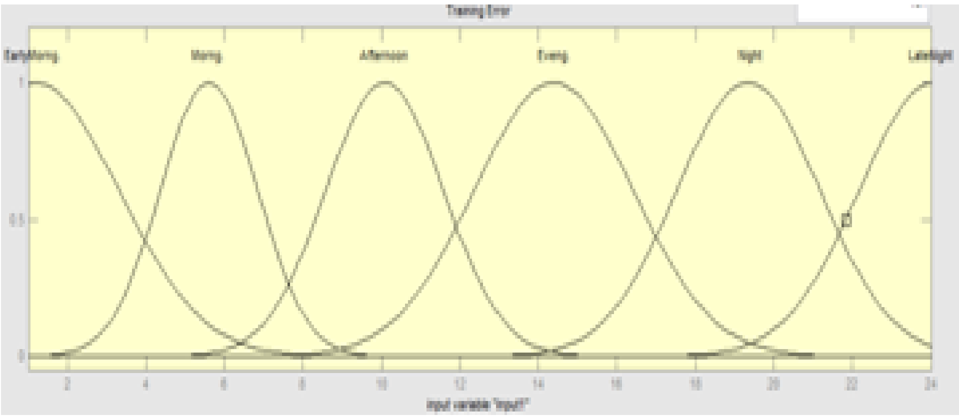

Fig. 2 Membership Function of Time

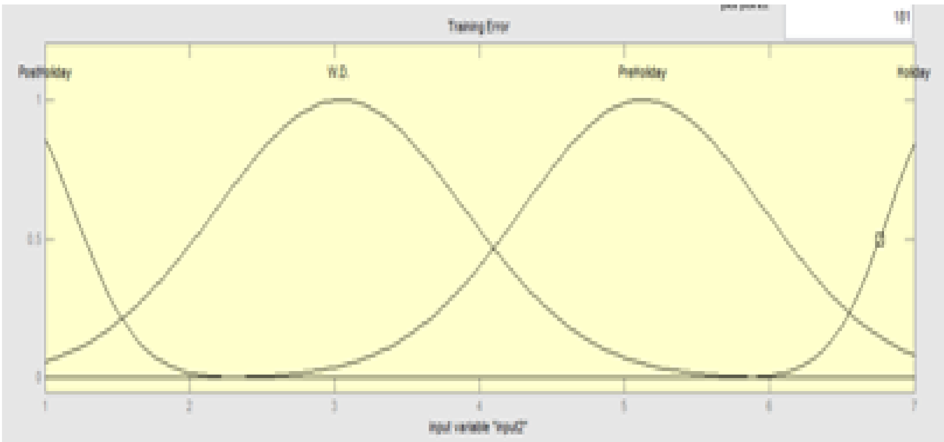

Fig 3 Membership Function of Day Type

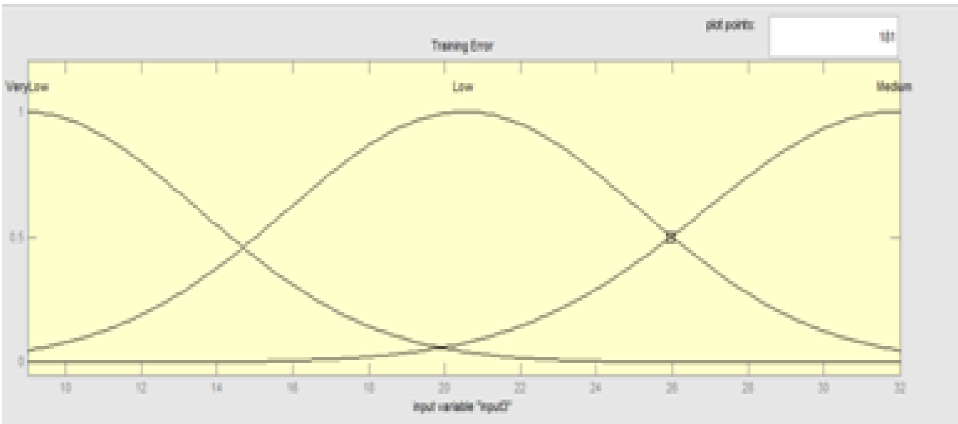

Fig 4 Membership Function of Temperature

During training, membership function parameters (membership function shapes) are modified in a manner that causes the desired input/output relationship to be learned. The training set is shown to the network many times (iterations or epochs), until converge is obtained (usually, a mean square error between output and target is minimized). The testing data set is used for model validation which is the process by which the input vectors from input/output data sets on which the FIS was not trained, are presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values. The testing data set lets you check the generalization capability of the resulting fuzzy inference system.

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7. RESULTS AND DISCUSSION

In this case study ANFIS trained the data set of three weeks (from Dec 01^{st} to Dec 20^{th} , 2014). After the ANFIS network training is completed than it is tested on Wednesday, Dec 24^{th} ,2014 .Fig.5 shows the testing data plot.

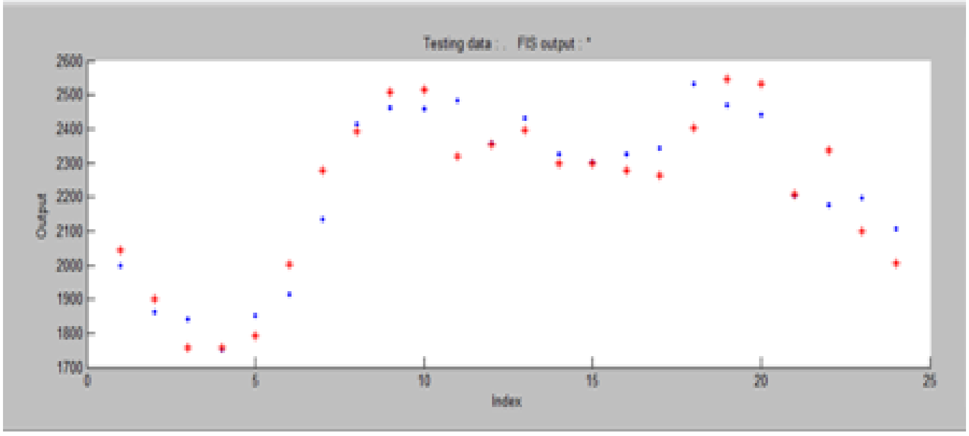

Fig. 5 Testing Data Plot

The FIS output of this work is compared to the actual load, and evaluation is done by statistical Mean of Absolute Percentage Error (MAPE). MAPE error is one of the main criteria describing the forecast method accuracy level. The model shows relatively good forecasting performance. As the error becomes smaller, the load model becomes more acceptable for the purposes of load forecasting. From the obtained result the mean absolute percentage error (MAPE) on the overall test data was obtained as shown in table 1.

The forecasting accuracy of the technique was evaluated by the average of absolute percentage errors of the hours in a day. The Absolute Percentage Error (APE) is

$$APE = \frac{|L_a - L_f|}{L_a} \times 100$$

There L_a and L_f respectively are the actual and the forecast loads of the hours in a day. The forecast results deviation from the actual values are represented in the form of MAPE.**[10]**

Mean Absolute Percentage Error (MAPE) is defined as:

$$MAPE = \frac{1}{N_h} \sum_{N_h} APE$$

Here N_h shows number of hours.

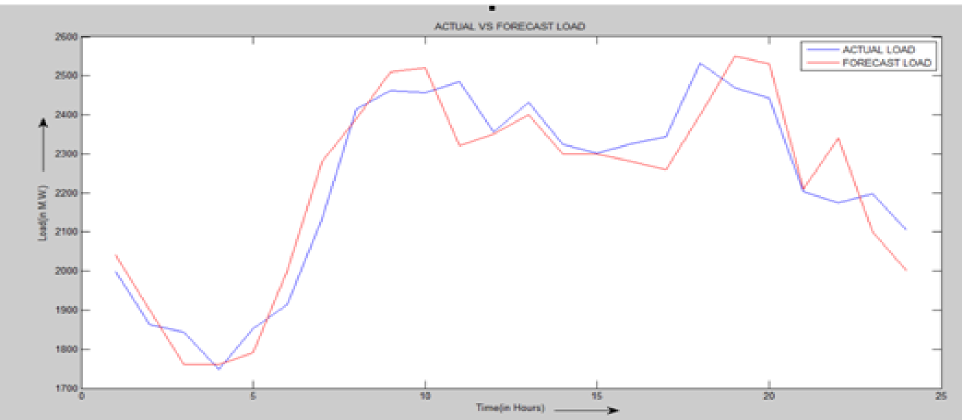

Fig. 6 ACTUAL VS FORECAST LOAD (Wednesday 24/12/2014)

Table:1 Actual and Forecast load for typical Wednesday (24/12/2014)

S. No.	Time (hours)	Day Type	Temperature (^{o}C)	Actual Demand (MW)	Forecast Demand (MW)	Absolute Percentage Error
1	1	3	14	1998	2040	2.1021
2	2	3	14	1863	1900	1.9860
3	3	3	14	1843	1760	4.5035
4	4	3	14	1749	1760	0.6289
5	5	3	13	1852	1790	3.3477
6	6	3	13	1914	2000	4.4932
7	7	3	13	2135	2280	6.7915
8	8	3	13	2415	2390	1.0351
9	9	3	21	2461	2510	1.9910
10	10	3	21	2457	2520	2.5641
11	11	3	21	2484	2320	6.6025
12	12	3	29	2356	2350	0.2546
13	13	3	29	2432	2400	1.3157
14	14	3	29	2325	2300	1.0752
15	15	3	30	2302	2300	0.0868
16	16	3	30	2327	2280	2.0197
17	17	3	30	2344	2260	3.5836
18	18	3	22	2532	2400	5.2132
19	19	3	22	2469	2550	3.2806
20	20	3	22	2443	2530	3.5611
21	21	3	18	2203	2210	0.3177
22	22	3	18	2175	2340	7.5862
23	23	3	15	2197	2100	4.4151
24	24	3	15	2105	2000	4.9881
Mean Absolute Percentage Error						**3.07266**

8. CONCLUSION

This paper presented an application of adaptive neuro-fuzzy inference system in short term load forecasting, which takes into account the effect of temperature on load. To verify the forecasting ability of the proposed methodology, we trained the data set from Dec 01st to Dec 20th, 2014 and results for Wednesday, Dec 24,2014 is given. The results obtained shows that the proposed forecasting methodology, which proposes the use of weather variables (temperature) and including day type which gives load forecasting results with considerable accuracy with **3.07266%** MAPE.

Results obtained are satisfactory therefore, the proposed methodology will be helpful in using more weather variables (like humidity, wind speed, sky cover and rainfall etc.) large dataset which will certainly be better than using only temperature as the weather variable affecting the load, in short term load forecasting and hopefully provide intellectual stimulus to research community to do further research in this direction. Further studies on this work can incorporate

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additional information such as season of the year and other parameters like humidity, wind speed, sky cover and rainfall etc. into the network so as to obtain a more representative forecast of future load.

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