Short Term Load Forecasting using Neuro fuzzy

Gunjan Dave[1] Sweta J. Shah[2] Yogesh Patel[3] Merolina Christie[4] Urvish Mewada[5]
[1]Student [2,3,4,5]Assistant Professor
[1,2,3,4,5]Department of Electrical Engineering
[1,3,4,5]Ahmedabad Institute of Technology, GTU, India [2]IITE, Indus University

Abstract— Optimal day to day operation of electric power generating plant is very essential for any power utility constitution to reduce input costs and the prices of electricity. So, to generate reasonably the required power, one needs to forecast the future electricity demands since power generation relies heavily on the electricity demand. Load forecast has three different horizons: short term forecast, medium term forecast and long term forecast. The Short-Term Load Forecasting (STLF) provides information for utility program system planners so that they can come up with a short-term solution to protect the transmission and distribution systems and to better serve the clients. This article presents the development of Adaptive Neuro Fuzzy Interface System (ANFIS) based short-term load forecasting model. The fusion of neural networks and fuzzy logic in neuro-fuzzy models achieves readability and learning ability at once. This article presents prediction of electric load by considering various information like time, temperature, humidity, day and historical load data. Historical load data is taken from MGVCL and weather data is taken from the website www.timeanddate.com.

Key words: Adaptive Neuro-Fuzzy Interface System, Load Forecasting, Short Term Load Forecasting

I. INTRODUCTION

There is a growing trend towards unbundling the electricity system. This is continually confronting the different sectors of the industry (generation, transmission, and distribution) with increasing need on plan management and operations of the network. The operation and planning of a power utility company requires an adequate model for electric power load forecasting. Load forecasting plays a key role in serving an electric utility to make important decisions on power, load switching, electric potential control, network reconfiguration, and infrastructure development. [1] It helps in deciding and planning for maintenance of the power systems. By understanding the demand, the utility can know when to carry out the maintenance and ensure that it has the lower limit impact on the consumers. [2] Load forecasting is the predicting of electrical power required to meet the short term, medium term or long term demand. The reasons why businesses need STLF include energy purchasing, unit commitment, reduce spinning reserve capacity, T&D (transmission and distribution) operations and demand side management. Forecasted values are sent to day ahead planning system by demand side one day in advance. [3] This article presents the development of soft computing based short-term load forecasting model which forecast the electric load. Traditional methods have the inherent inaccuracy of load prediction and numerical instability. Further, the non-stationarity of the load prediction process, coupled with complex relationship between weather variables and the electric load render such traditional techniques ineffective as these methods assume simple linear relationships during the prediction process. [4] The prime inherent advantage associated with the soft computing techniques of not requiring a mathematical model has been a motivating factor for consideration in our present work. In soft computing technique fusion of neural networks and fuzzy logic in neuro-fuzzy models achieves readability and learning ability at once. So, this article presents the development of an Adaptive Neuro Fuzzy Inference System (ANFIS) based short-term load forecasting model which forecast the electric load.

II. BASICS OF ANFIS

The model obtained with neural network is not understandable in terms of physical parameters (black box model) and it is impossible to interpret the result in terms of natural language. On the other hand, the fuzzy rule base consists of if-then statements that are almost natural language, but it cannot learn the rules itself. To obtain a set of if-then rules two approaches are used. First, transforming human expert knowledge and experience, and second, automatic generation of the rules. The second method is intensively investigated. The fusion of neural networks and fuzzy logic in neuro-fuzzy models achieves readability and learning ability (extracting rules from data) at once. On 1993, Roger Jang [5] developed the ANFIS technique that could overcome the shortcoming of the ANNs and fuzzy systems. Neuro-fuzzy approaches have been widely applied to the short-term load forecasting (STLF). Adaptive Neuro-Fuzzy based Inference System (ANFIS), an integrated system, comprising of Fuzzy Logic and Neural Network can address and solve problems related to non-linearity, randomness and uncertainty of data. In this article the ANFIS model to STLF is presented.

The fuzzy part of the ANFIS is constructed by means of input and output variables, membership functions, fuzzy rules and inference method. The training inputs are also called energy drivers and are variables that can affect the output, such as, in case of the energy consumptions: the daily production, the climatic data, the day of the week, etc. The membership functions of the system are the functions that define the fuzzy sets. The fuzzy rules have a form of if-then rule and define how the output must be for a specific value of membership of its inputs. In general, the fuzzy systems have different kind of inference methods but ANFIS is based on a particular type of fuzzy system with Takagi-Sugeno rules as inference method. FIS basically consist of five subcomponents a rule base (covers fuzzy rules), a database (portrays the membership functions of the selected fuzzy rules in the rule base), a decision-making unit (performs inference on selected fuzzy rules), fuzzification inference and defuzzification inference.

The triangular, trapezoidal, generalized bell shaped, pi shaped, z shaped, s shaped, to mention but a few, are the various membership function that exist on the ANFIS graphic user interface. In the context of this paper work, the ANFIS used consists of Gaussian membership functions on each input. Two steps are involved in the ANFIS processes which are known as the training and testing step respectively. 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). During testing, the used data should not be seen during the training process. [6]

III. ANFIS ARCHITECTURE

The ANFIS architecture is shown in Figure 1. Using a given input/output data set, the ANFIS method constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a backpropagation algorithm alone, or in combination with a least squares type of method. This allows fuzzy systems to learn from the data they are modeling. FIS Structure is a network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs. An ANFIS can help us find the mapping relation between the input and output data through hybrid learning to determine the optimal distribution of membership functions. Five layers are used to construct this inference system. Each layer contains several nodes described by the node function. Adaptive nodes, denoted by squares, represent the parameter sets that are adjustable in these nodes, whereas fixed nodes, denoted by circles, represent the parameter sets that are fixed in the system. The output data from the nodes in the previous layers will be the input in the present layer. [7].

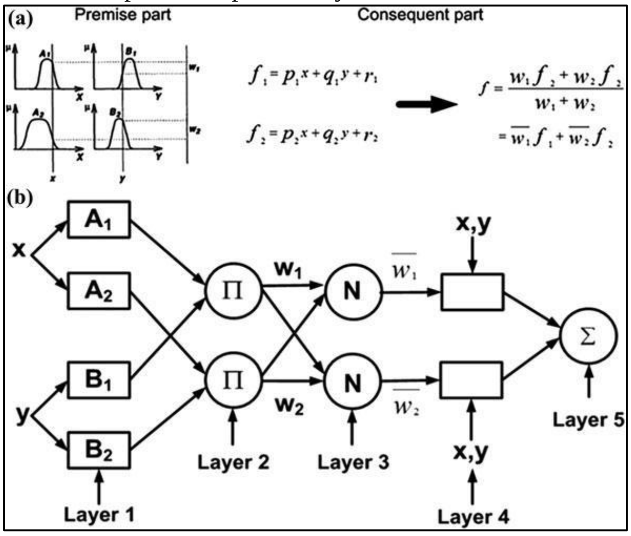

Fig. 1: ANFIS architecture

ANFIS architecture has five layers. The first and fourth layers contain an adaptive node, while the other layers contain a fixed node. A brief description of each layer is as follows: [1]

A. Layer 1

Every node in this layer adapts to a function parameter. The output from each node is a degree of membership value that is given by the input of the membership functions. For example, the membership function can be a Gaussian membership function (Eq. 1), a generalized bell membership function (Eq. 2), or another type of membership function.

$$\mu_{Ai}(x) = \exp\left[-\left(\frac{(x-c_i)^2}{2a_i}\right)\right] \qquad (1)$$

$$\mu_{Ai}(x) = \frac{1}{1+\left|\frac{x-ci^{2b}}{a_i{}^{2b}}\right|} \qquad (2)$$

$$O\mu_{Ai}(x)_{1i}=, \quad i=1,2 \qquad (3)$$

$$O_{1i}=\mu_{Bi-2}(y), \quad i=3,4 \qquad (4)$$

Where μ_{Ai} and μ_{Bi-2} are the degree of membership functions for the fuzzy sets A_i and B_i, respectively, and $\{a_i, b_i, c_i\}$ are the parameters of a membership function that can change the shape of the membership function. The parameters in this layer are typically referred to as the premise parameters.

B. Layer 2

Every node in this layer is fixed or nonadaptive, and the circle node is labelled as P. The output node is the result of multiplying of signal coming into the ode and delivered to the next node. Each node in this layer represents the firing strength for each rule. In the second layer, the T-norm operator with general performance, such as the AND, is applied to obtain the output

$$O_{2i}= w_i =\mu_{Ai}(x) * \mu_{Bi}(y), \quad i=1,2 \qquad (5)$$

Where w_i is the output that represents the firing strength of each rule

C. Layer 3

Every node in this layer is fixed or nonadaptive and the circle node is labelled as N. Each node is a calculation of the ratio between the i-th rules firing strength and the sum of all rules' firing strengths. This result is known as the normalized firing strength.

$$O_{3i} = \bar{w}_i = \frac{w_i}{\sum_i w_i} \qquad (6)$$

D. Layer 4

Every node in this layer is an adaptive node to an output, with a node function defined as

$$O_{4i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \qquad (7)$$

Where $\bar{w}_i$ is the normalized firing strength from the previous layer (third layer) and $(p_i x + q_i y + r_i)$is a parameter in the node. The parameters in this layer are referred to as consequent parameters.

E. Layer 5

The single node in this layer is a fixed or nonadaptive node that computes the overall output as the summation of all incoming signals from the previous node. In this layer, a circle node is labelled as Σ

$$O_{5i} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{w_i} \qquad (8)$$

IV. MODELING AND DEVELOPMENT

The data used in this research is the hourly load data obtained from MGVCL, during time span of 2 months. The first and most important task for designing a system for one day ahead load forecasting is the identification of input parameters. A large number of factors affect the load demand considerably. [8] Five unique inputs are used as shown in figure 2.

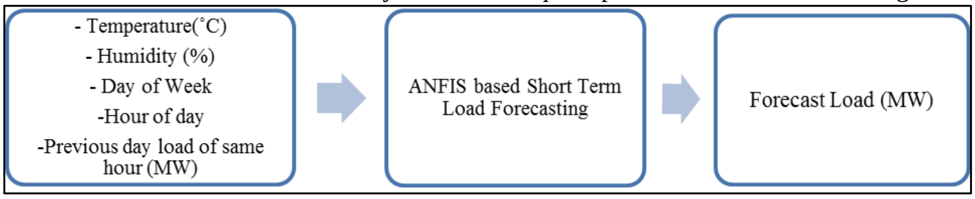

Fig. 2: Modeling & Development

Two-month load-demand data of MGVCL from 16th January 2014 to 15th March 2014 and local weather from www.timeanddate.com has been employed for the training of the ANFIS.

From the load data study concluded that hourly loading in the working days is quite consistent. On the other day week end days and festivals day loading patterns differ from the working days. So working days data (excluding Holiday and events) as a training data, as a training and checking data remaining days (weekend days and holidays) are considered.

The input sets for proposed ANFIS predictor contains a matrix of 1104 x 6 for training purpose, a matrix of 192 x 6 as testing purpose and a matrix of 96 x 6 as checking purpose with the row number matching the number of hours. The first (5) columns represent the inputs to the ANFIS model. The last column represents the output to the ANFIS model.

For the training purpose, membership functions are assigned to each input. Each input has five Gaussian membership functions. The rules are generated by the grid partition method. Since there are five inputs with five membership functions, the rule set contains 5^5, i.e., 3125 rules. The training process automatically adjusts the membership functions based on input patterns. ANFIS Structure layout is shown in Figure 3.

Hybrid algorithm is chosen for learning method as it gives accurate result. And total 100 Epoch selected for training purpose.

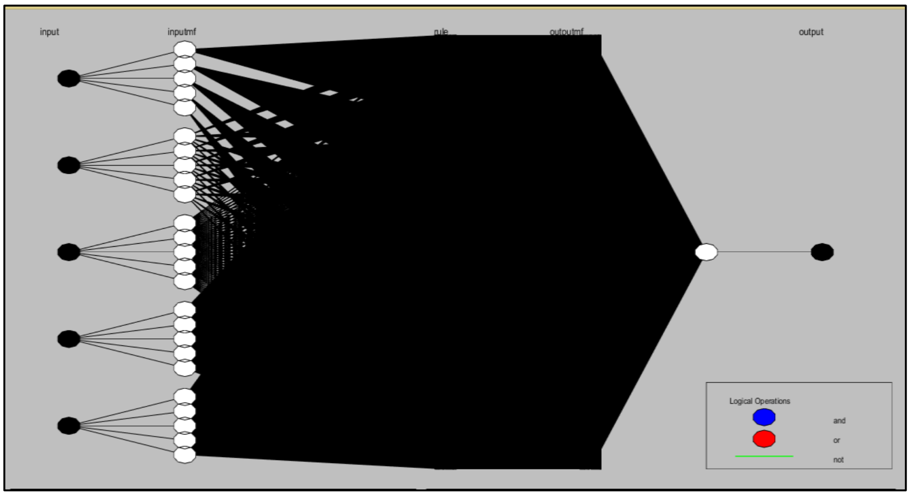

Fig. 3: ANFIS Model

Below Table shows the actual and forecasted load of randomly selected days.

	Actual (MW)	Forecast (MW)	Actual (MW)	Forecast (MW)
Day	Monday		Thursday	
Date	17/02/2014		13/03/2014	
Time				
12 to 1	984	983.11	1172	1172.38
1 to 2	987	984.1016	1156	1155.49
2 to 3	956	965.9379	1147	1146.54
3 to 4	967	967.5885	1140	1140.45
4 to 5	936	948.1872	1125	1124.82
5 to 6	993	1026.443	1153	1154.5
6 to 7	1093	1099.081	1190	1187.17
7 to 8	1188	1189.638	1195	1196.33
8 to 9	1218	1219.268	1219	1218.7
9 to 10	1247	1239.64	1280	1279.62
10 to 11	1254	1251.942	1305	1306.33
11 to 12	1267	1260.736	1350	1351.93
12 to 13	1255	1257.079	1331	1329.72
13 to 14	1228	1238.535	1315	1309.64
14 to 15	1215	1209.998	1304	1310.34
15 to 16	1204	1203.644	1282	1284.73
16 to 17	1179	1177.707	1228	1214.32
17 to 18	1161	1168.026	1203	1231.4
18 to 19	1215	1200.469	1275	1263.6
19 to 20	1210	1211.651	1302	1300.5
20 to 21	1172	1168.964	1272	1273.0
21 to 22	1146	1149.603	1226	1224.91
22 to 23	1073	1073.652	1203	1206.7
23 to 24	1034	1033.904	1149	1136.27

Table 1: Shows the actual and forecasted load of randomly selected days

Mean absolute percentage error is calculates using actual load and forecast load using equation.

$$\text{MAPE} = \frac{1}{N}\sum_{m=1}^{N}\frac{abs(Load_{forecast}(m)-Load_{actual}(m))}{Load_{actual}(m)} * 100$$

Where,
abs stand for the absolute value;
N is the total number of hours in the testing data;
m stands for the m^{th} hour in the testing data;
Load forecast (m) is the forecasted load for m^{th} hour;
Load actual (m) is the actual load for m^{th} hour.
MAPE is within 5.62% for this ANFIS Model of 16th January 2014 to 15th March 2014.
Figure 4 shows Surface plot for developed ANFIS forecast load, Temperature and day of week

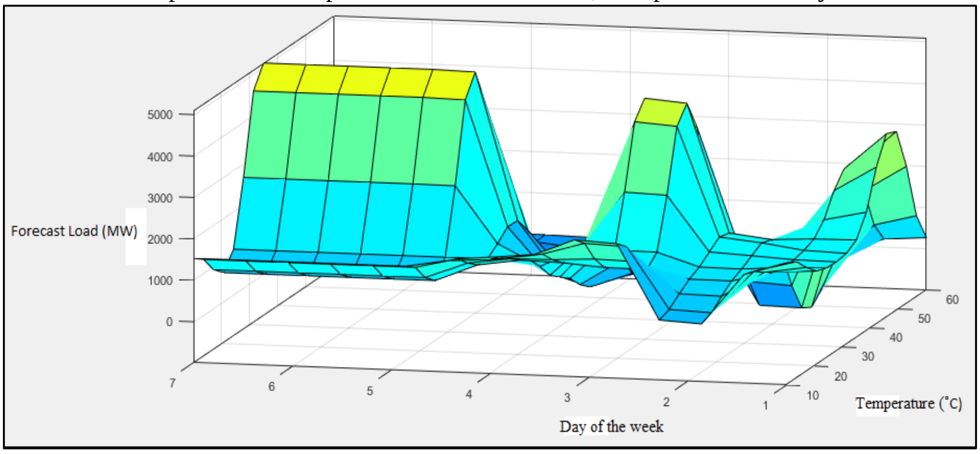

Fig. 4: Surface plot for developed ANFIS forecast load, Temperature and day of week

In this figure, we can see that there is a pattern such as: When the temperature is extreme, either too cold or too hot, and when it is weekend, then load would be very high.

Plot of actual load and forecasted load with time of 13th March 2014.

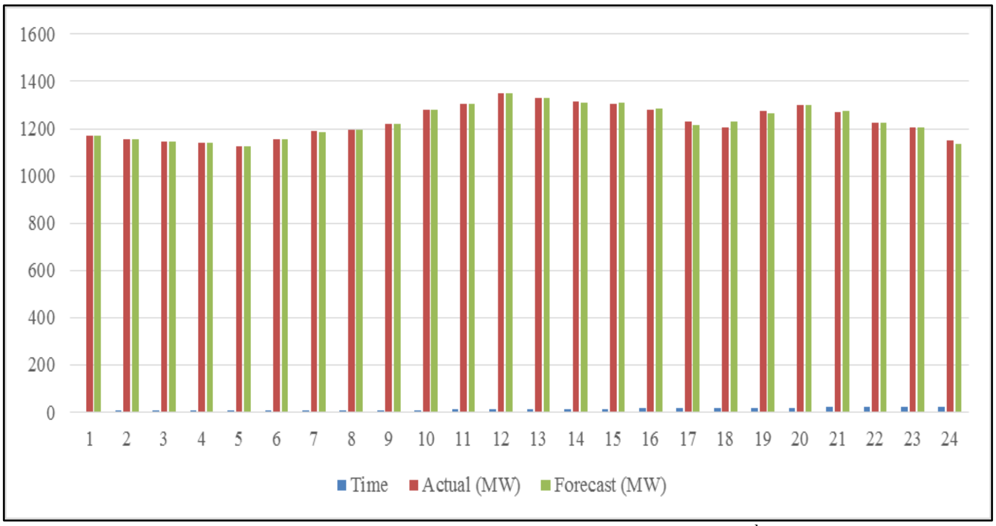

Fig. 5: Plot of actual load and forecasted load with time of 13th March 2014

V. CONCLUSION

This paper presents a short-term load forecasting methodology using ANFIS. This model proposed set of five inputs, i.e. temperature, humidity, day of the week, hour of the day, previous day load of same hour. The result obtained shows the MAPE of 5.62% for the data of 16th January to 15th march 2014.

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