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Short-Term Load Forecasting Using Adaptive Neuro-Fuzzy Inference System (ANFIS)

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Abstract*: Electric load forecasting is a real-life problem in industry. This report presents the development of an Adaptive Neuro Fuzzy Inference System (ANFIS) based short-term load forecasting model which forecast the electric load. This report presents prediction of electric load by considering various information like time, temperature and historical load data. Historical load data is taken from MPEB Jabalpur and weather data is taken from the website www.worldweatheronline.com. ANFIS is a class of adaptive networks that are functionally equivalent to fuzzy inference systems. 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. Motivated by this advantageous feature of soft computing based load forecasting, the present work focuses on building a model for an ill defined real world system based on its available record of input-output data using ANFIS. From the analysis carried out on the ANFIS-based model; Mean absolute percentage error (MAPE) for a particular Tuesday was found to be 5.705 %. Results and forecasting performance obtained reveal the effectiveness of the proposed approach and shows that it is possible to build a high accuracy model with less historical data using a combination of neural network and fuzzy logic which can be used in real time.

***Keywords:* ANFIS, Load forecast, MAPE, APE.**

1. INTRODUCTION

Load forecasts allow utilities to plan their operations such as unit commitment and generator maintenance beforehand, and thus, serve their customers with more reliable and more economically efficient electric power [1]. The geographical location, population, social factors, and weather factors have different effects on the systems and therefore these systems have different types of load patterns. The financial consequences for forecast errors are so significant that even a small fraction reduction in the forecast error can cause major financial benefits for the utility [2].Accurate forecasts lead to substantial savings in operating and maintenance costs, increased reliability of power supply and delivery system, and correct decisions for future development. The load dispatcher at main dispatch center must anticipate the load pattern well in advance so as to have sufficient generation to meet the load requirements. Overestimation may cause the startup of too many generating units and lead to an unnecessary increase in the reserve and the operating costs. Underestimation of the load forecast results in failure to provide the required spinning and standby reserve and stability to the system, which may lead into collapse of the power system network. In the real-time dispatch operation, forecasting error causes more electricity purchasing cost or breaking contract penalty cost to keep the electricity supply and consumption balance. Hence accurate forecasting of the load is an essential element in power system .The purpose of this paper is to present a short term electric load forecasting model using an adaptive neuro-fuzzy inference system (ANFIS).

2. 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 [3] 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 fuzzy inference system that we have considered is a model that maps

– input characteristics to input membership functions,

– input membership function to rules,

– Rules to a set of output characteristics,

– Output characteristics to output membership functions, and

– The output membership function to a single-valued output, or

– A decision associated with the output.[4]

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.

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.

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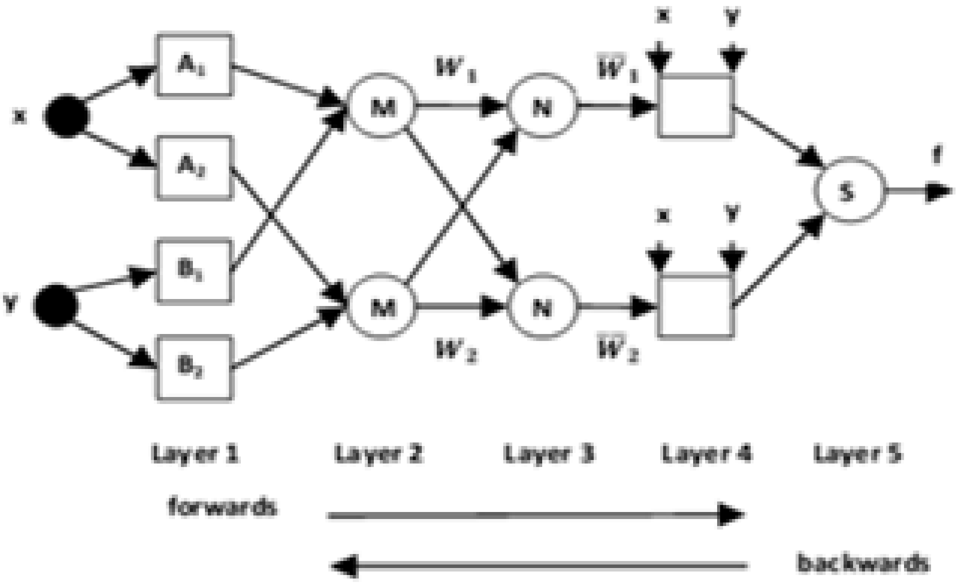

Fig. 1 ANFIS Structure

The first layer of the structure (Fig.1) is called fuzzification. In the second layer, the weight of each rule has to be computed by means of a fuzzy AND operation. In the layer 3, it is made the normalization of the values and in the layer 4 the defuzzification process. Finally in layer 5, the overall output of the system is obtained [5-8].

3. LOAD FORECASTING WITH ANFIS

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. The training method that is utilized for the proposed forecasting model is a hybrid training algorithm; it uses forward and back propagation to estimate values for the parameters. In order to speed up the process, the number of inputs was kept low in the proposed model. The relationship between the inputs and the computational time for the model training depends on the parameters to be estimated. In a large system with many inputs, the computation time can be quite large. The proposed model uses the hours of days, and temperature as its inputs.

3.1 Data analysis:

The data used in this research is the hourly load data obtained from MPEB,Jabalpur during time span Apr 1st, 2012 - Apr 30, 2012. At first, a statistical load data study was performed with the corresponding weather parameters, mainly to get an idea of variations in loading. During the initial statistical analysis, the average hourly loading on each of the weekdays was examined. We were able to draw conclusions that the hourly loading on the working days is quite consistent. On the other hand, weekend day loading patterns differ from the working days. Thus, decision was made to only consider the data from the working days in the forecast models at this initial stage of research due to the relatively small sample size of data.

A matrix of 360*3 is generated, with the row number matching the number of hours for time span Apr 1st, 2012 - Apr 21, 2012 (excluding Saturday and Sundays). The first (2) columns represent the inputs to the anfis model i.e. hour of the day and temperature. The last column represents the output to the anfis model. 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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3.2 Design of the ANFIS-Based Model:

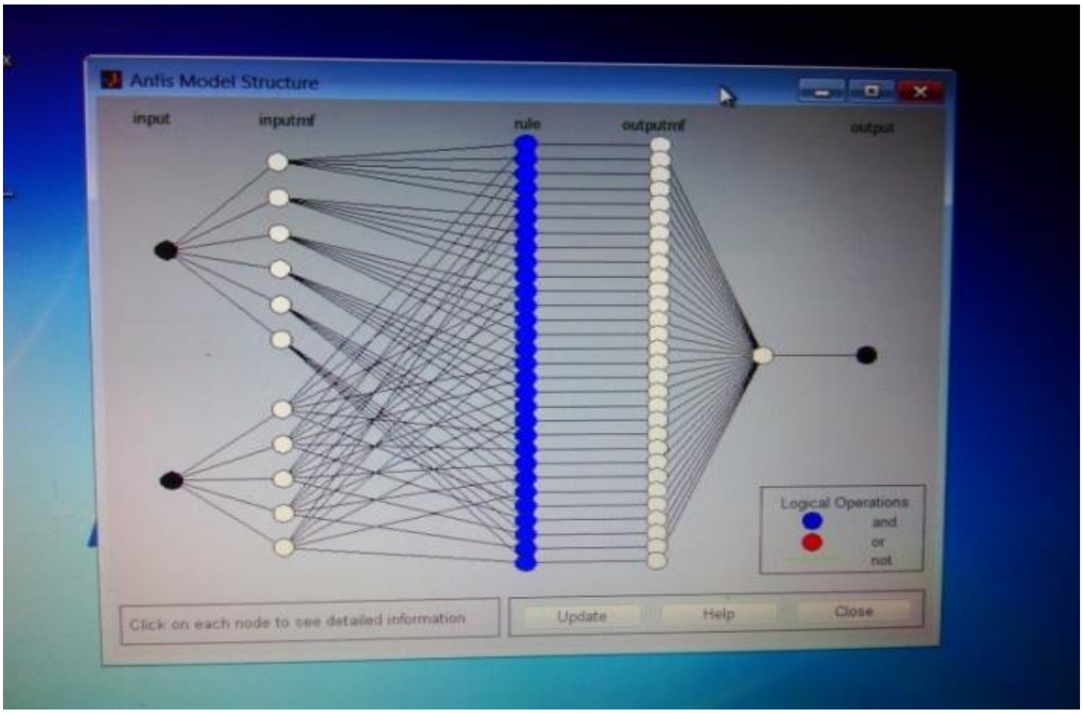

Fig 2: Structure of a 2 input ANFIS system

3.3 Generating the Fuzzy Rules and Choosing the Membership Function:

For the design of the ANFIS model, selections of the following listed parameters were made.

- Membership function type

- Number of membership function

- Learning algorithm

- Epoch size

- Data size.

- Number of input variables

The listed procedures below was adopted at the ANFIS Graphical user Interface (GUI) for the design of the model.

- Obtaining training data

- Data sizing

- Data partitioning

- Loading data sets.

- The ANFIS modeling criterion was adopted to effectively tune the membership function so as to minimize the output error and maximize performance index. The ANFIS structure obtained by the aforementioned parameters choosen is shown in fig 2.

After successfully loading the training data, the rules are generated by the grid partition method. Grid partitioning is an approach for initializing the structure in a fuzzy inference system. In this method it generates rules by enumerating all possible combinations of membership functions of all inputs. The training process automatically adjusts the membership functions based on input patterns.

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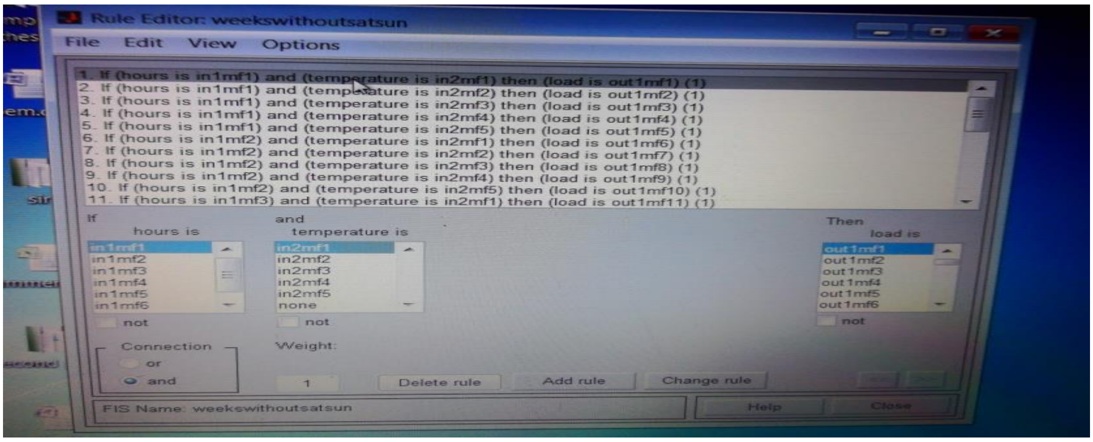

Fig 3: The dialog box for the rule editor

4. RESULTS AND DISCUSSION

In this case study ANFIS trained the data set of three weeks (from Apr 1st to Apr 21, 2012) without considering Saturday and Sunday. After the ANFIS network training is completed it is tested on Tuesday,Apr 24,2012. The graph shows(fig. 4) the comparison between training and testing datasets with the FIS .

The output of model is compared to the actual recorded load, and the performance is evaluated by statistical Mean of Absolute Percentage Error (MAPE) which is generally the statistical method used in load forecasting studies to evaluate forecasting performance . 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.

Table 1: Actual and Forecast Load for Tuesday, Apr24, 2012

Hours	Actual Load	Anfis Forecast	APE
1	1971	1660	15.779
2	1818	1620	10.891
3	1893	1610	14.95
4	1893	1560	17.591
5	1797	1640	8.737
6	1513	1490	1.52
7	1270	1320	3.937
8	1022	1090	6.654
9	1117	1180	5.64
10	1157	1260	8.902
11	1414	1420	0.424
12	1458	1380	5.35
13	1373	1250	8.958
14	1446	1350	6.639
15	1404	1440	2.564
16	1418	1400	1.269
17	1236	1250	1.133
18	1117	1180	5.64
19	1666	1690	1.441
20	1904	1950	2.416
21	2144	2180	1.679
22	2110	2140	1.422
23	1924	1890	1.767
24	1850	1820	1.622

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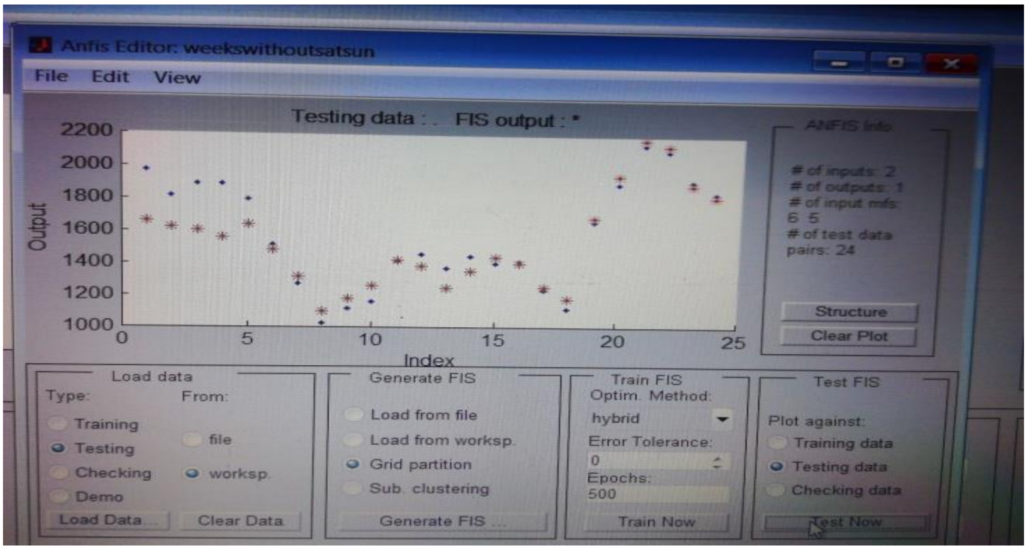

Fig 4: Testing data plot

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.(9)

Mean Absolute Percentage Error (MAPE) is defined as:

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

Here N_h shows number of hours.

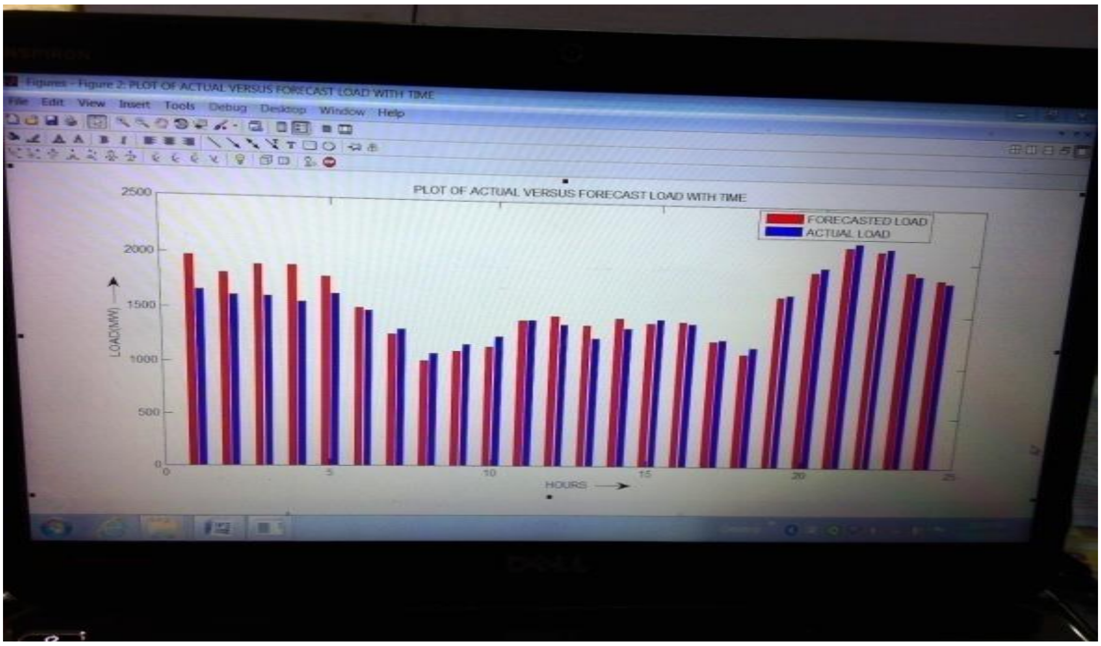

Figure 5 Plot of the actual load and Forecast load with time

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5. CONCLUSION

This paper presents a short term load forecasting methodology using ANFIS, which takes into account the effect of temperature and day type on load. To verify the forecasting ability of the proposed methodology, we trained the data set from APR 1st,2012 to APR 21,2012 without Saturday and Sundays and results for Tuesday, Apr 24,2012 is given. The results obtained shows that the proposed forecasting methodology, which proposes the use of weather variables i.e. temperature ,and including only weekdays(Monday to Friday) gives load forecasting results with considerable accuracy, with 5.705**%** MAPE. Results obtained are satisfactory Therefore, the proposed methodology will be helpful in using more weather variables, 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 additional information such as season of the year and other parameters like wind speed, humidity sky cover and rainfall etc. into the network so as to obtain a more representative forecast of future load.

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