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Short Term Load Foreasting using ANFIS

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Abstract* — *Electrical load forecasting is an essential tool used to ensure that energy supplied by utilities meet the load plus the energy lost in the system. 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 types: short term forecast, medium term forecast and long term forecast. Since in power system the next day's power generation must be scheduled every day, day- ahead STLF is a necessary daily task for power dispatch. Its accuracy affects the economic operation and reliability of the system greatly. 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, wind speed, day and historical load data. Historical load data is taken from MGVCL and weather data is taken from the website www.timeanddate.com.

Keywords-component; Load Forecasting, Short Term Load Forecasting, Adaptive Neuro-Fuzzy Interface System, Normal Days, Weekend ad Festival Days

I. INTRODUCTION

There is a growing tendency towards unbundling the power framework. This is continually going up against various parts of the business (generation, transmission, and distribution) with expanding request on arranging administration and operations of the framework. The operation and planning of a power service organization requires a satisfactory model for electric power load forecasting. Load forecasting assumes a key part in helping an electric utility to make important choices on power, load switching, voltage control, mastermind reconfiguration, and establishment change [1] Helps in choosing and deciding for support of the power frameworks. By understanding the demand, the utility can know when to do the support and guarantee that it has the construct impact with respect to the clients. For instance, they may choose to do support on local locations amid the day when a great many people are grinding away and request is low. [2] Load forecasting is the predicting of electrical power required to meet the short term, medium term or long term demand. The reasons why organizations require STLF include energy purchasing, unit duty, lessen turning save limit, T&D (transmission and distribution) operations and request side administration. Forecasted qualities are sent to day ahead arranging framework by request side one day ahead of time. [3] This article presents the development of soft computing based short-term load forecasting model which forecast the electric load. Conventional methods have the inaccuracy of load forecasting and numerical instability [4] The prime advantage associated with the soft computing techniques is it does not require mathematical model. In Artificial Intelligence technique combination of neural networks and fuzzy logic in neuro-fuzzy models has 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 one day ahead electric load.

II. BASICS OF ANFIS

The model obtained with neural network is not understandable in terms of physical parameters and it is not possible to interpret the result in terms of natural language. fuzzy rule base consists of if-then rules 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, human expert knowledge transforming, and second, rules automatic generated. The fusion of neural networks and fuzzy logic in neuro-fuzzy models achieves readability and learning ability 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 input and output variables, membership functions, fuzzy rules and inference method. 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 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.
There are different membership functions available in ANFIS graphical user interface like triangular, trapezoidal, generalized bell shaped etc. In this paper, the ANFIS used Gaussian or triangular membership functions for each input. Two steps are involved in the ANFIS processes the training and testing step respectively. During training, membership function shapes are modified for input/output relationship to be learned. [6]

III. MODELING AND DEVELOPMENT

The data used in this research is the hourly load data obtained from MGVCL, during time span 1st November 2013 to 31st October 2014 (1 year). 70 to 75 % data taken as a training data and other as a testing and checking data. As many factors affect the load demand [7] Six unique inputs are used as shown in figure 1.

Figure 1

Here from load data study it is concluded that working days' load pattern remains same while weekend and festival days load pattern is different. For accurate load forecasting two separate models are created one is for normal day and other is for weekend days and holidays. Figure 2 shows the ANFIS model for six inputs.

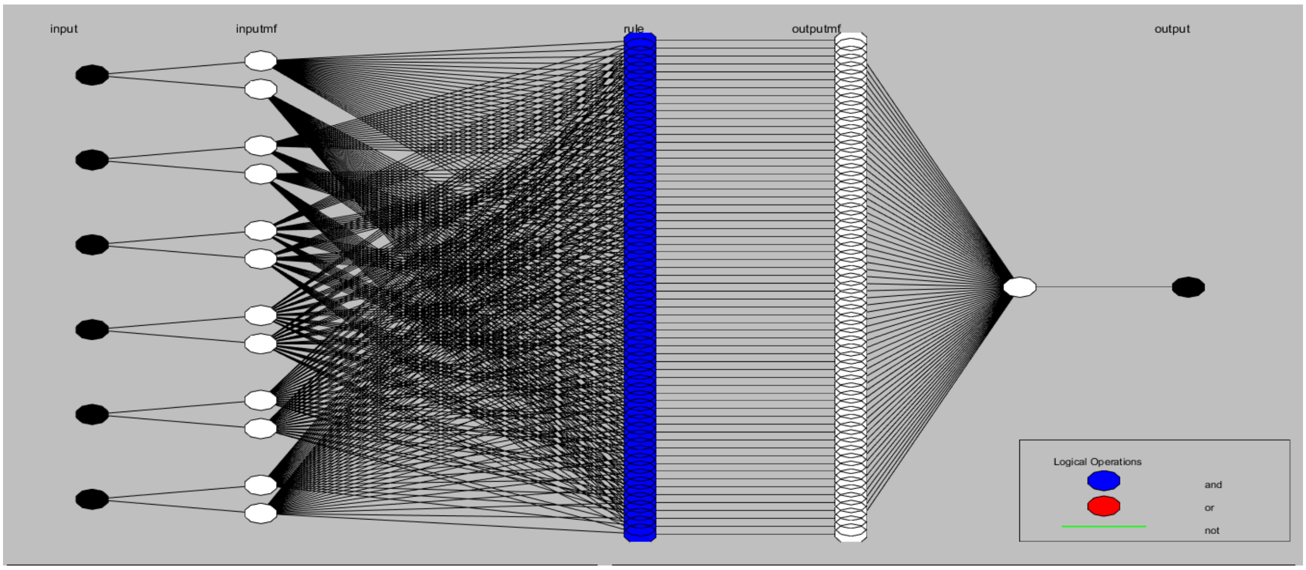

Figure 2 six input ANFIS

For training purpose membership functions are assigned to each input that is Gaussian curve or triangular shaped. Rules are generated using grid partition method. Here 2 MF function assigned to each input and total 6 inputs are given so ruled generated 2^6 i.e. 64 rules. That is shown in Figure 3. Hybrid learning algorithm is chosen as it gives accurate result.

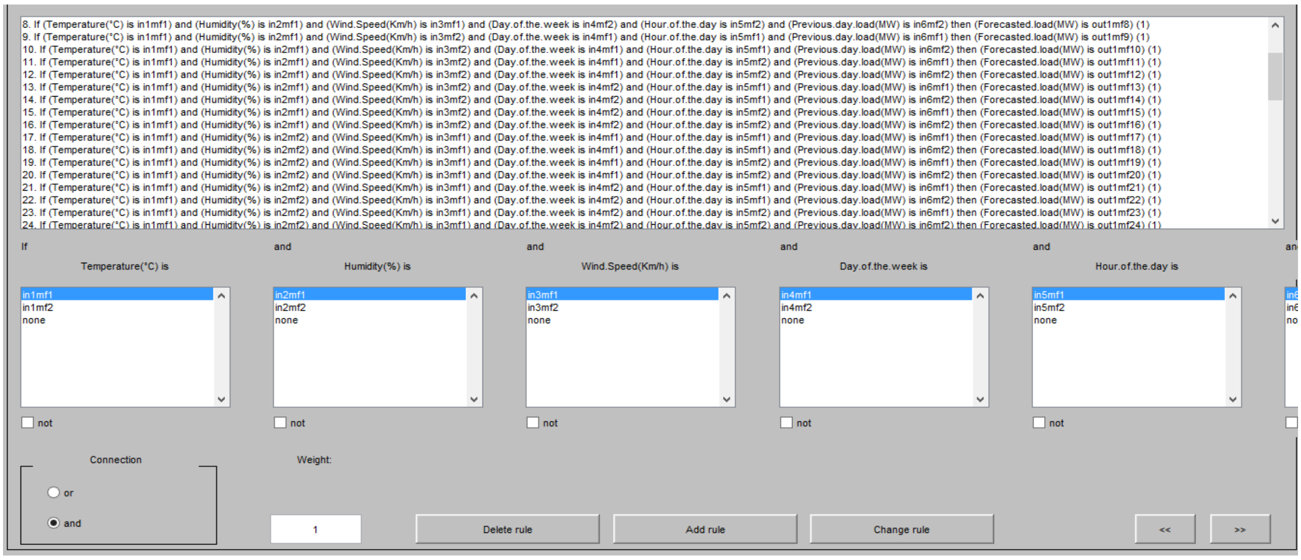

Figure 3 Generated Rules

After completion of training forecasted load is compared with the actual load and performance is evaluated by Mean Absolute Percentage Error (MAPE)

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

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

Table 1

Month	Training * Testing * Checking	Training Error	Testing Error	Checking Error	MAPE
November -13	216*7, 48*7,48*7	19.68	53.53	48.17	2.13%
December -13	336*7, 72*7, 72*7	25.82	45.42	47.26	2.04%
January -14	400*7,40*7,40*7	47.22	72.71	78.48	3.87%
February -14	302*7,65*7,65*7	37.82	65.69	51.36	3.36%
March-14	312*7,72*7,72*7	24.62	80.07	67.81	2.59%
April-14	312*7,72*7,72*7	31.18	51.11	63.29	2.34%
May-14	216*7,48*7,48*7	23.06	45.1	65.41	2.27%
June-14	336*7,48*7,48*7	34.33	36.88	61.44	2.75%
July-14	216*7,72*7,72*7	18	62.07	58.3	2.57%
August-14	264*7,60*7,60*7	26.71	109.45	45.25	2.84%
September-14	284*7,62*7,62*7	33.38	41.47	67.25	2.70%
October-14	168*7,24*7,24*7	24.44	112	100.27	2.78%

Table 1 shows the results for normal day model in that 2^{nd} column shows the training, testing and checking data matrix with row numbers matching with number of hours and 1^{st} six columns represents the input and last column represent the output. 3rd ,4th and 5th column shows the training, testing and checking error while last column shows the MAPE. Average MAPE for normal day model is 2.69%

Table 2

Month	Training * Testing * Checking	Training Error	Testing Error	Checking Error	MAPE
November -13	216*7,36*7,36*7	35.29	82.37	124.78	3.87%
December-13	184*7,40*7,40*7	16.97	67.14	49.56	2.24%
January-14	224*7,20*7,20*7	50.43	108.48	125.48	4.39%
February-14	168*7,36*7,36*7	25.55	74.1	151.9	3.78%
March-14	200*7,44*7,44*7	25.53	84.66	112.8	2.88%
April-14	180*7,30*7,30*7	25.26	62.04	81.31	2.15%
May-14	168*7,24*7,24*7	26.39	74.51	42.03	2.39%
June-14	168*7,24*7,24*7	27.26	30.37	57.41	2.32%
July-14	216*7,24*7,24*7	36.84	54.58	115.43	3.73%
August-14	144*7,24*7,24*7	18.92	38.51	61.77	1.95%
September-14	168*7,36*7,36*7	23.09	160.09	41.67	3.68%
October-14	128*7,20*7,20*7	18.38	140.97	136.39	3.46%

Table 2 shows the results for weekend and festival days model in that 2nd column shows the training, testing and checking data matrix with row numbers matching with number of hours and 1st six columns represents the input and last column represent the output. 3rd ,4th and 5th column shows the training, testing and checking error while last column shows the MAPE. Average MAPE for weekend and festival days is 3.07%.
Comparison of actual and forecasted load of normal day December month is shown in figure 4. And for weekend and festival day June month is shown in figure 5.

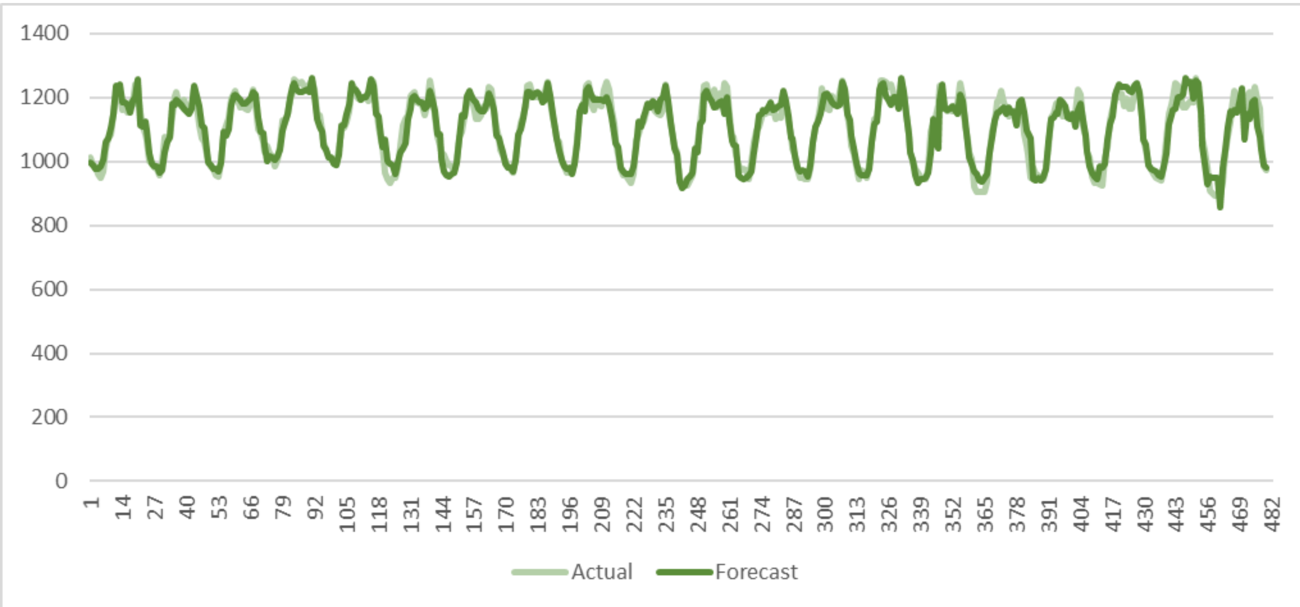

Figure 4 December Normal days

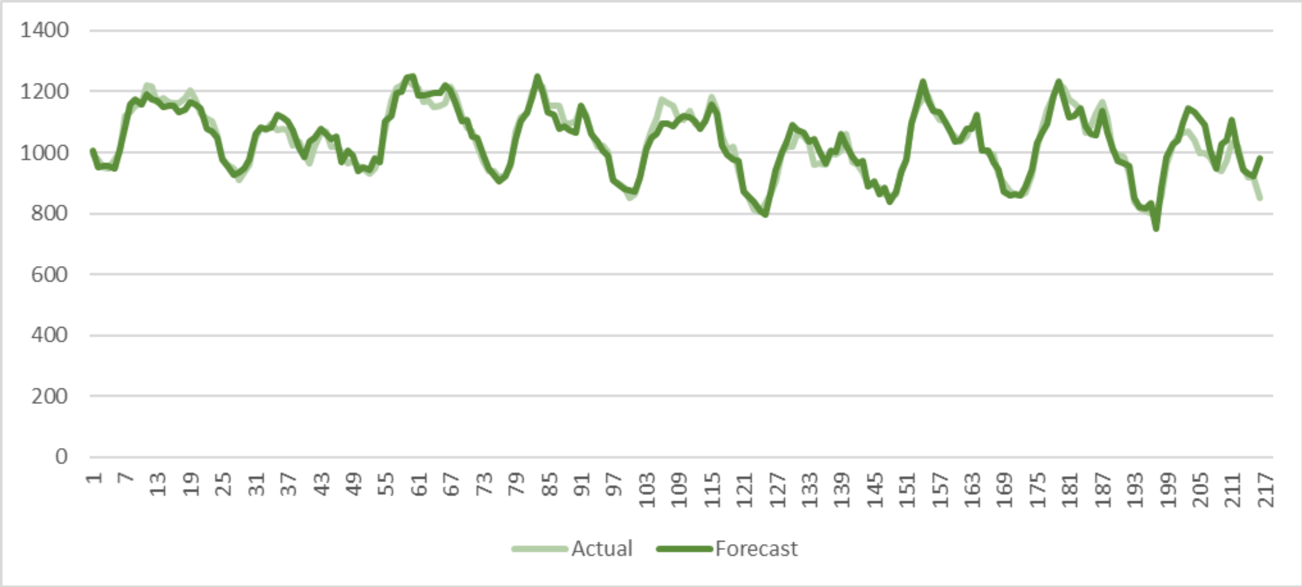

Figure 5 June Weekend and Festival days

IV. Conclusion

This paper presents a short-term load forecasting methodology using ANFIS The Result obtained for 1st November 2013 to 31st October 2014 with six unique inputs Temperature (˚C), Humidity (%), wind speed(Km/h), Day of the week, Hour of the day and two membership function for normal days has Average mean absolute error (MAPE) 2.69% and for weekend and holidays 3.07%.

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