

Load Forecasting for Power System Planning using Fuzzy-Neural Networks

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Abstract--- A long term prediction of future load is helpful in better operation of power systems and its economical utilization. A number of algorithms have been suggested for solving this problem. In this paper neural networks and combined Fuzzy Logic, for long term load forecasting is proposed. In this paper the relationship between the humidity, temperature and load is identified with a case study for a particular region in Oman. The output load obtained is corrected using a correction factor from neural networks, which depends on the previous set of loads, number of customers etc. The data is taken for the three years and the results are obtained for the fourth year. It is further validated using the actual data from an electrical company.

Index Terms--- Neural Network, Fuzzy Logic, Load Forecasting, Fuzzy Modeling, Energy consumption.

I. INTRODUCTION

Load forecasting has been an integral part in the efficient planning, operation and maintenance of a power system. Short term load forecasting is necessary for the control and scheduling operations of a power system and also acts as inputs to the power analysis functions such as load flow and contingency analysis.[1] Owing to this importance, various methods have been reported, that includes linear regression, exponential smoothing, stochastic process, ARMA models, and data mining models. [2] 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. [3] In this paper, an approach for long term load forecasting problem, using fuzzy logic combined with ANN approach is proposed. The fuzzy logic technique has been used to classify the data's. The neural network is used to calculate the increment factor of load due to other parameters like growth in industries, increase in number of customers etc.

II. FUZZY SYSTEM

The fuzzy logic model maps the highly non-linear relationship between the weather parameters and their impact on the daily electric load peak. Here fuzzy logic model has two inputs temperature and humidity and one output load. These factors temperature, humidity has direct impact on the electric load peak. In the research it is hypothesized the temperature has the biggest impact.

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The first input to the Fuzzy logic module is temperature which have four 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. The second input to the FL module is humidity which is classified into three membership functions.

III. NEURO-FUZZY MODEL

In the area of fuzzy- neural collaborations, several forms have surfaced, 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.[4] Neural networks are essentially low-level computational structures and algorithms that offer good performance in dealing with sensory data. On the other hand, fuzzy logic techniques often deal with issues, such as reasoning, on a higher level than neural networks. However, since fuzzy systems do not have much learning capability, it is difficult for a human operator to tune the fuzzy rules and membership functions from the training data set. 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. Furthermore, the convergence of learning is usually very slow and not guaranteed.[8] Thus, a promising approach for getting the benefits of both the fuzzy systems and neural networks is to merge them in to an integrated system. This collaboration posses the advantage of both neural networks and fuzzy systems.[10] 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.[9,11] The variation of the temperature variable results in a significant variation in the load. Load demand always increases as the temperature increases demand decreases as the humidity increases.

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. This is further 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

data's like number of customers increase in the city and also various other environmental factors.

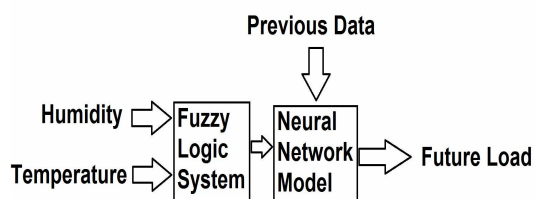


Fig.1. Block Diagram Representation

The figure 2 shows the variation of load for the year 2008, 2009 and 2010 for a particular region (Al Dhakhliya region) in Oman. It also gives the variation of temperature and humidity at the bottom.

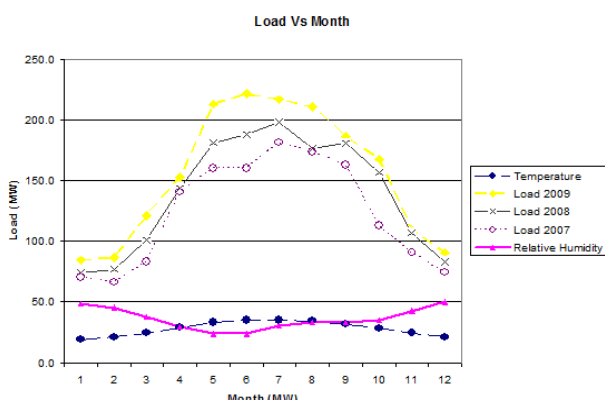


Fig. 2. Load Vs Temperature, Humidity and Load Curve

To make a detailed analysis figure 3 shows that the load increase linearly with the increase in temperature and the figure 4 shows that the load decreases with increase in humidity. Hence it is clear that the maximum temperature has low humidity and hence the load is maximum. It has also been observed that the minimum temperature has maximum humidity and the load is minimum. There is an intersection point as where the load is medium. These data's are fed to the Fuzzy system for classifying the data and to get the output.

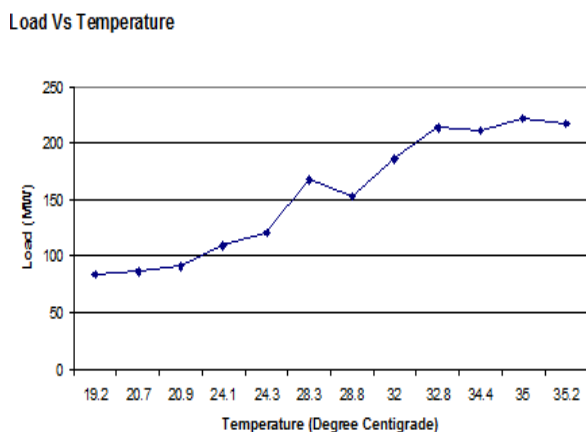


Fig. 3. Load Vs Temperature

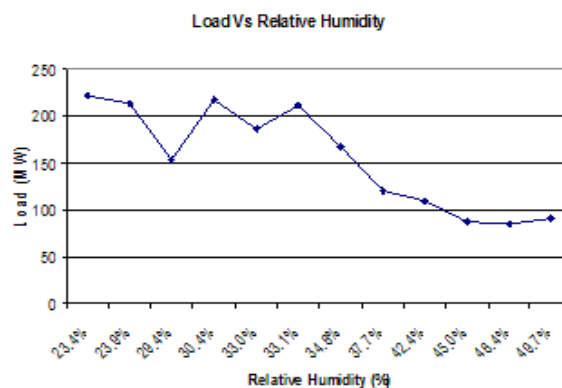


Fig. 4. Load Vs Humidity

A. Fuzzification of Input and the Outputs

In this paper the load is classified as very Low, Low, Medium and High Load. It is seen from the figure 5 and 6 that the load falls between 50 and 250 MW. From the graph

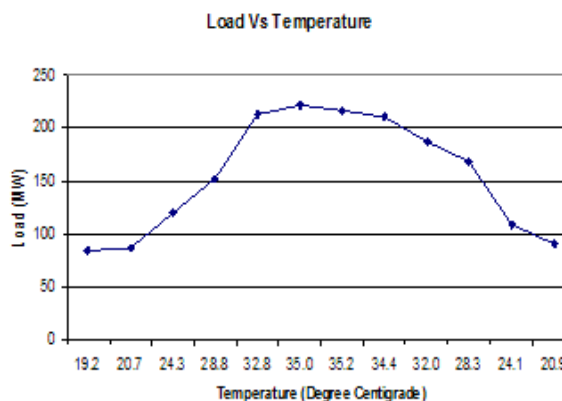


Fig. 5. Load Vs Temperature

it is clearly seen that the data can be classified as (50-100), (100-150), (150-200) and (200-250). The corresponding

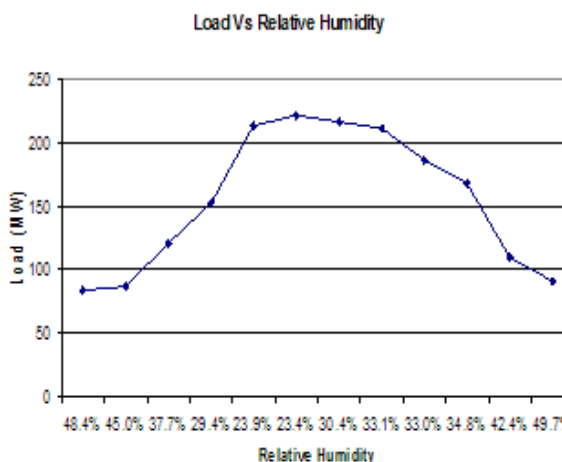


Fig. 6. Load Vs Humidity

temperature and humidity can be seen from the x-axis, which are used to classify the humidity and temperature ranges for fuzzification.

The Table I below shows how the temperature and humidity can be classified according to the load. As mentioned for the

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

Load	50-100	100-150	150-200	200-250
Temperature	19.2, 20.7, 20.9	24.3, 24.1	28.8, 32, 28.3	32.8, 35, 35.2, 34.4
Humidity	48.4, 45, 49.7	37.7, 29.4, 42.4	34.8, 33, 29.4	23.9, 23.4, 30.4, 33.3
Ranges for Fuzzification				
Classification	Very Low	Low	Medium	High
Temperature	19-21	24-27	28-32	32-36
Humidity	45-50	30-42	23-33	

various classification of load the corresponding temperature and humidity are taken. Then the ranges of fuzzification are obtained as shown in the second part of the table.

The figure 7 and 8 shows how the inputs are classified for fuzzification. It is observed that the temperatures are classified with the ranges (20-24), (23-27), (26-32), (31-40) as Very Low, Low, Medium and high respectively. The humidity is classified as (20-33), (30-42), (40-50) as Low, Medium and High respectively. The outputs are classified as

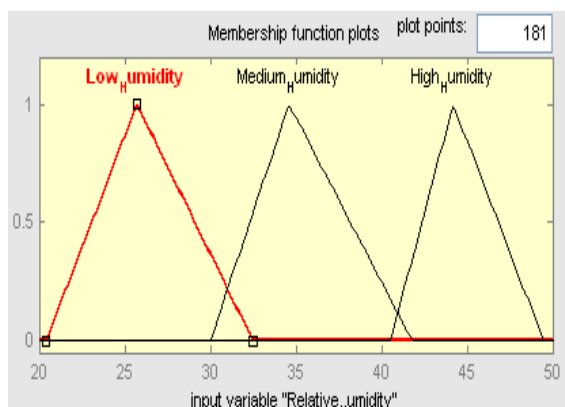


Fig. 7. Membership function for Relative Humidity

(50-110), (100-160), (150-200), and (200-250) as Very Low, Low, Medium and High Loads respectively as shown in figure 9.

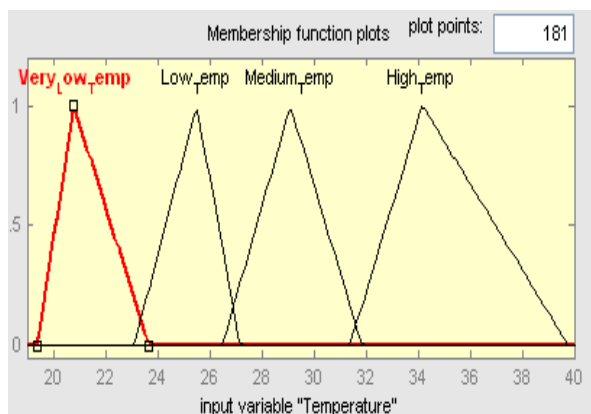


Fig. 8. Membership function for Temperature

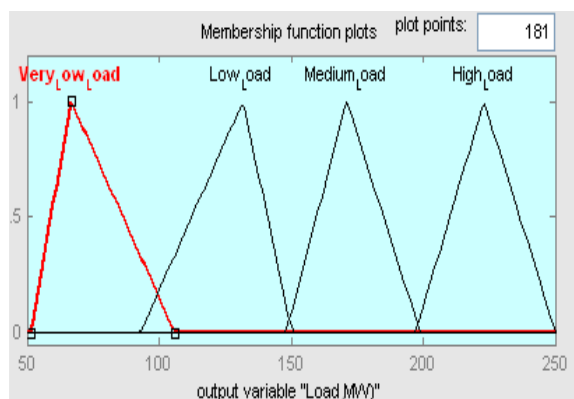


Fig. 9. Membership function for Load

TABLE II
 RULE BASE

Temperature Humidity	Very Temp	Low Temp	Low Temp	Medium Temp	High Temp
Low Humidity				Medium Load	High Load
Medium Humidity	Low Load	Low Load		Medium Load	High Load
High Humidity	Very Low Load				

The table II shows the rule base for mapping various ranges of inputs to the outputs.

The figure 10 shows the Simulink used to simulate the inputs

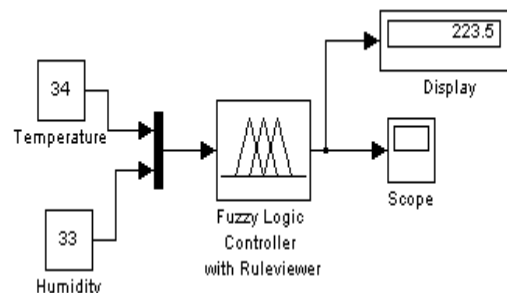


Fig. 10. Simulation of Data using Simulink

and to get the outputs. It is observed from the simulation that for a temperature of 34°C and 33% relative humidity the load is 223MW.

The figure 11 shows how the fuzzy system in MATLAB toolbox which works for the sample inputs.

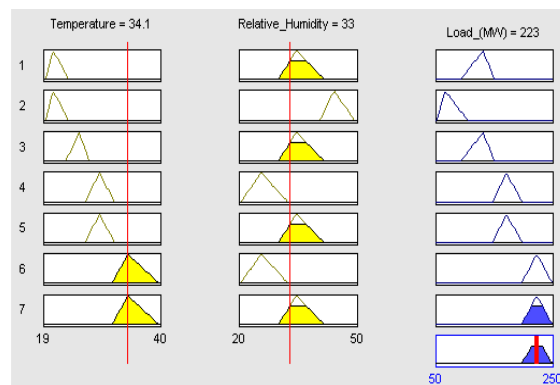


Fig. 11. Defuzzified output for one sample data

It can also be observed from the figure 11 that for a temperature of 34°C and 33% relative humidity gives an output of 223MW load. For example it is seen that the high temperature and low humidity gives an output of high load, similarly for low temperature and high humidity the output is Very Low Load. This can be cross checked with the actual load in table III which shows that the load is 210MW which

TABLE III
 TEMPERATURE, HUMIDITY VS ACTUAL/PREDICTED LOAD

Temperature	Relative Humidity	Predicted Load	Actual Load	%Error	Future Load (After ANN)
19.2	48.4%	78	84.35	7.50	128.85
20.7	45.0%	75	86.8	13.50	131.3
24.3	37.7%	123	120.65	1.95	165.15
28.8	29.4%	172	152.8	12.57	197.3
32.8	23.9%	223	213.15	4.62	257.65
35.0	23.4%	223	221.775	0.55	266.27
35.2	30.4%	224	216.7	3.37	261.2
34.4	33.1%	221	210.7	4.89	255.2
32.0	33.0%	220	186.4	18.03	230.9
28.3	34.8%	173	167.8	3.10	212.3
24.1	42.4%	122	109.15	11.77	153.65
20.9	49.7%	80	90.8	11.80	135.3
			Average % Error	7.80	

is very close to the actual value..

B. Neural Network for correction Factor

For Multilayer perceptron networks, training is normally achieved through back-propagation learning. Supervised learning involves comparing the output of a network exposed to specific input with the desired output and changing the weights of the network to achieve a proper mapping. [5] This is done by first stimulating the input nodes with a specific pattern and letting the network propagate this input through the layers. The output of the network is then compared to the desired output (i.e. the output expected for that particular input pattern).[7]The error is then back-propagated through the network, changing the internal weights along the way to produce a better match between the network predictions and the 'real' data. To facilitate this process a number of techniques can be used which include the *delta-rule* method.[6] Once the approximate load is obtained it has to be corrected using a correction factor which depends on the number of industries over the area and also the number of houses built and increase in the customers. Here back propagation algorithm is used to compare the previous set of data to correct the load for future. It is also validated using the actual data available from the Mazoon Electrical Company. The figure 12 represents the actual load for 2010, predicted load for 2010 using fuzzy system and the predicted future load for 2012 using neural networks.

Actual Load Vs Predicted Load

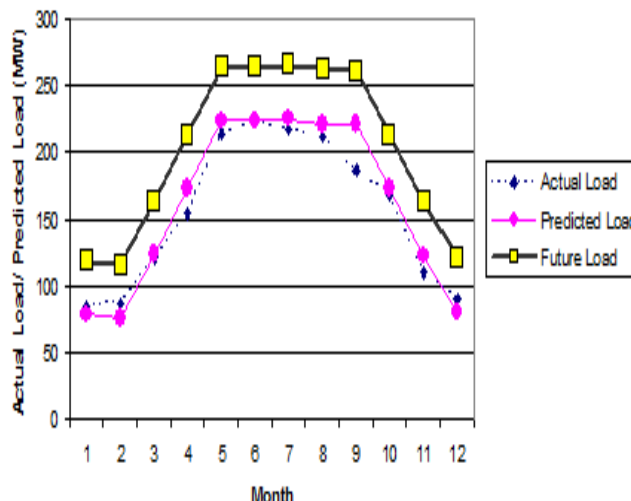


Fig. 12. Month Vs Predicted Load, Actual Load, Future Load

V. CONCLUSION

In this paper a methodology for long term load forecasting using Neuro-Fuzzy approach is presented. A new temperature and humidity relation ship with load is obtained using mamdani fuzzy logic system. The Fuzzy Logic system is used to obtain the variation of load and a correction factor is derived from an artificial neural network back propagation algorithm to predict the future load. It has been observed that the variation of predicted load from actual load has an average percentage error of 7.8%.

REFERENCES

- [1]. E. Srinivas, Amit Jain "A Methodology for Short Term Load Forecasting Using Fuzzy Logic and Similarity" *The National Conference on Advances in Computational Intelligence Applications in Power, Control, Signal Processing and Telecommunications* (NCACI-2009), Bhubaneswar, India, March 20-22, 2009.
- [2]. Gaddam.mallesham; A.N.Jha, "A Fine Load Forecasting using Neural Networks and Fuzzy Neural Networks", *Int. Conf. on Power Systems and Electromagnetic Compatibility*, Corfu, Greece, August 23-25, 2005 (pp224-229)
- [3]. Jagadish H. Pujar, Fuzzy Ideology based Long Term Load Forecasting, *World Academy of Science, Engineering and Technology* 64 2010
- [4]. K. Metaxiotis, A. Kagiannas, D. Askounis, J. Psarras, "Artificial intelligence in short term electric load forecasting: a state-of-the-art survey for the research", *Energy Conversion and Management* 44, 2003, pp.1525-1534.
- [5]. Tomonoobu senjyu, hitoshi takara,katsumi ueezato,toshihisa funabashi, "One-hour ahead load forecasting using neural network", *IEEE Trans. power syst.*, vol.17, no.1, February 2002, pp.113-118.
- [6]. Mohsen Hayati, Yazdan Shirvany, "Artificial neural network approach for short term load forecasting for Illam region", *International journal of electrical, computer, and system engineering*, vol.1, no.2, pp.121-125.
- [7]. G.A.Adepoju, S.O.A.ogaunjuigbe, and K.O.Alawode, "Application of neural network to load forecasting in nigerian electrical power system", *The pacific journal of science and technology*, vol.8, no.1, May 2007, pp.68-72.
- [8]. Bhavesh kumar chauha, amit sharma, and m.hanmandlu, "Neuro-fuzzy approach based short term electric load forecasting", 2005 *IEEE/PES Transmission and Distribution Conference & Exhibition*, Asia and Pacific Dalian, China.
- [9]. Swaroop.R, Hussein Ali Al Abdulqader, A Case study on Load Forecasting for power system planning and operation in Al Batinah Region in Oman using Neural Networks., *Journal of Engineering*

Science and Technology (JESTEC). (Accepted and will be published in August 2012, Volume 7, Issue 4)

- [10]. Cuiru wang, Zhikun cui , Qi chen, “Short term load forecasting based on fuzzy neural network”, *Intelligent Information Technology Application*, Workshop on 2-3 Dec. 2007, pp:335 – 338.
- [11]. P. Bunnoon, K. Chalermyanont, and C. Limsakul, The Comparision of Mid Term Load Forecasting between Multi-Regional and Whole Country Area Using Artificial Neural Network, *International Journal of Computer and Electrical Engineering*, Vol. 2, No. 2, April, 2010 1793-8163 334.