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Electrical Load Forecasting Using Fuzzy System

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Abstract

To cope with the demand and supply of electrical load of an interconnected power system of a country, we need to forecast its demand in advance. In this paper, we use a fuzzy system to forecast electrical load on short-term basis. Here, we consider temperature, humidity, seasons of a year and time segments of a day as the parameters, which govern the demand of electrical load. For each of the parameter, we use several membership functions (MFs) and then apply the Mamdani rule on MFs and the output is determined by using the centroid method. Finally, the surface plot reveals the real scenario of the load demand. The difference between actual load and the output of the fuzzy system is found as +1.65% to −13.76%. The concept of the paper can be applied in interconnected power system of Bangladesh to reduce power loss, especially when generation is higher than the demand.

Keywords

Defuzzification, Fuzzy Inference, Centroid Method, Surface Plot, APE

1. Introduction

Electrical load forecasting is classified as short and long-term, where the long-term deals with adjustment of demand-supply for 10 - 50 years, whereas short-term makes the adjustment for a few months to 5 years. This paper considers short-term electrical load forecasting taking daily load of Bangladesh. This section provides some previous works relevant to short-term load forecasting. A study of the short-term electrical forecasting using fuzzy logic is done in [1] to minimize the difference between actual electrical load and the forecast load. The authors have used data from PSTCL 220 kV substation V.O.P Pakhowal, Ludhiana, Punjab, India. Eight triangular membership functions (MFs) are used for input time, four triangular MFs for temperature and eight triangular MFs for output forecasted load; where input and output are linked using "if then" conditions. Finally, a comparison is made between actual load and fuzzy forecasted load graphically, where few points merge closely and few points deviate widely.

In [2], short-term load forecasting is done based on fuzzy logic, to find electrical load loss in the generation end. The authors prepare fuzzy rules based on historical data. A work is found about long term forecasting of power system in [3], where the authors use Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Interference System (ANFIS). Six parameters are used as input, which are temperature, humidity, wind speed, rainfall, data of previous load and data of actual load. A table is presented to compare the error between ANN and ANFIS, where the average error is 6.7% and 0.096% respectively.

Similar work is found in [4], based on ANN and Genetic where the data used for training and validation of the neural network is obtained from the Transmission Company of Nigeria. First 21 days load and temperature data are used for training of neural network and the remaining day's data is used for network validation. Input variables used here are hour of the day, average temperature, day of the week and the output variable is forecasted load. After the evaluation, mean absolute percentage error (MAPE) is found about 4.705% for forecasting day. The authors of [5] established another related work using ANN taking data from Duhok ELC (Control region of Iraq) of 2009 and 2010. Back propagation algorithm of ANN is used to create a set of models where the AME is found different. The next day forecast is generated using the models, where the output is found almost close to the actual value. Another work on load forecasting using fuzzy logic tool is found in [6], which uses data from PSPCL 66 KV sub-station type-c grid. It is observed that in normal days, the load does not very much. However, in weekend or holiday, the load varies. After comparison, the error margin is found between +3.67% and −3.75%. A work on long-term electrical load forecasting using Multi-layer Perceptron Neural Network and K-Nearest Neighbor (K-NN) algorithm is presented in [7]. The data is collected from Global Energy Forecasting Competition 2018. The forecasted load is compared with the actual load for obtaining the MAPE, where MAPE of NN (MLP) is comparatively less than the K-NN method.

A similar work is found in [8], where a fuzzy logic model is developed based on the weather parameters (temperature and humidity) which are collected from the Meteorological Centre of the Department of Geography of Adamawa State University, where the historical load data is collected from Power Holding Company of Nigeria (PHCN). The input parameters: humidity is divided into three MF and temperature is divided into two MF. The output parameter, load is divided into three MFs. A 6.9% MAPE is obtained from the forecasted load. Another work is found in [9], where the comparison of mid-term load forecasting between multi regional area and the whole country is made using ANN. The data information composes of peak load, energy consumption, humidity, rainfall, wind speed, consumer price index and industrial index for year 1997-2007. The experimental result shows that multi regional area model can reduce error in each month and gives more accuracy than that of the whole country model. In [10], a short-term load forecasting method is presented by utilizing neuron-wavelet method consisting of wavelet transform and soft computing technique. The soft computing technique is featured by using the Generalized Neurons Network (GNN). Finally, a comparison is shown between GNN and modified GNN, which shows that accuracy of forecasting increases in the combined model.

The prime objective of the paper is to reduce the difference between estimated power load and actual power load. At first, the actual data of energy consumption in twenty-four hours in a day for one fiscal year (2017-2018) is collected from Bangladesh Power Development Board's (BPDB) website to determine the pattern of consumption and then we analyze them as MFs of our fuzzy system. The fuzzy toolbox of MATLAB is used to create rules considering four parameters: temperature, humidity, seasons and peak hour. The output is generated from the given input parameters. Finally, 3D surface plots are designed for the perception based on the output and the obtained results are compared with the results of the BPDB's method.

The rest of the paper is organized as follows: Section 2 provides the basic theory of fuzzification and defuzzification along with the fuzzy model of electrical load forecasting, Section 3 provides the result based on the analysis of Section 2 and Section 4 concludes the entire analysis.

2. Fuzzy Model of Load Forecasting

This section deals with a Fuzzy model, where the raw weather data is used as the input and the model will provide the electrical load. The first subsection gives the basic of centroid method in defuzzification and the second subsection gives fuzzy inference model of load forecasting.

2.1. Fuzzification and Defuzzification

Fuzzy logic closely imitates the methodology in making human decision, as it deals with ambiguous and unsure information. In general, it is oversimplification of the real-world problems and based on degrees of truth rather than usual true/false or 1/0 like normal Boolean logic. Fuzzification is the process of transforming a crisp set to a fuzzy set or a fuzzy set to fuzzier set. This operation translates accurate crisp input values into linguistic variables. On the contrary, defuzzification is the process of reducing a fuzzy set into a crisp set or to convert a fuzzy member into a crisp member. Among the different methods of defuzzification, centroid method is the most preferable and appealing method. This method is given by the expression like [11] [12],

$$z^* = \frac{\sum A\bar{x}}{\sum A}. \tag{1}$$

This method is shown in Figure 1(a). Now, the expression for z^* from Equation (1) is applied to calculate the centroid of Figure 1(b), which is divided into segmented areas. Here, Table 1 shows the calculation of A and $A\bar{x}$ for each segmented areas along with $\sum A$ and $\sum A\bar{x}$.

Using Equation (1), we obtain

$$z^* = \frac{\sum A\bar{x}}{\sum A} = \frac{18.40}{3.72} = 4.90.$$

From this result, we can justify the defuzzification technique of centroid method.

2.2. Load Forecasting Using Fuzzy Inference System

In this paper, the model for electrical load forecasting is implemented by utilizing the centroid method of defuzzification in MATLAB. The collected data for each of the input parameters is processed by using "Mamdani" method and "if then" rule in fuzzy logic toolbox. Figure 2 represents the system in MATLAB. The first input is temperature and its five MFs and their ranges are low (0 - 15.5), below average (8 - 23), average (15.5 - 30.5), above average (23 - 38) and high (30.5 - 45) as shown in Figure 3. The second input is humidity, which is divided into five MFs with corresponding ranges that low (40 - 60), below average (50 - 70), average (60 - 80), above average (70 - 90) and high (80 - 100) as shown in Figure 4. The third input is season and its five MFs with ranges (in days) are winter (11 - 70), pre-summer (46 - 132), summer (103 - 217), monsoon (188 - 305) and pre-winter (283 - 374) as shown in Figure 5. The fourth input is peak hour and its three MFs with ranges (in hours) are off peak (0 - 8), day peak (8 - 16) and on peak (16 - 23) as shown in Figure 6. We notice that for the following parameters: temperature, humidity and season have two MFs as trapezoidal in shape. All other MFs are in triangular. Only pick hour has three MFs, where all of them are trapezoidal. The output parameter is the maximum load demand, which has ten MFs with ranges (in MW) and these are: base (6000 - 7200), very low (6700 - 7700), low (7200 - 8200), below average (7700 - 8700), average (8200 - 9200), above average (8700 - 9700), high (9200 - 10,200), very high (9700 - 10,700), extreme high (10,200 - 11,200) and forbidden (11,700 - 12,000) as shown in Figure 7. The output parameter has two MFs as trapezoidal, which are base and forbidden. Except those, all other MFs are in triangular.

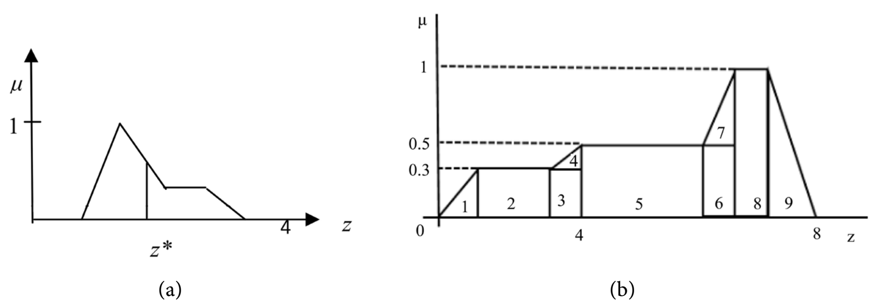

Figure 1. (a) Centroid method; (b) Defuzzification using centroid method.

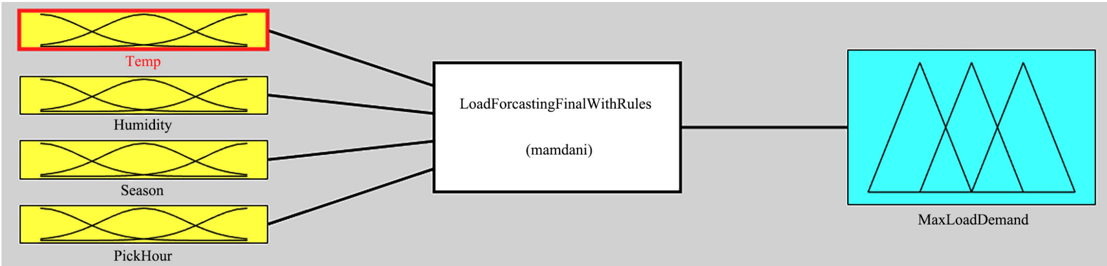

Figure 2. Fuzzy logic load forecasting system in MATLAB.

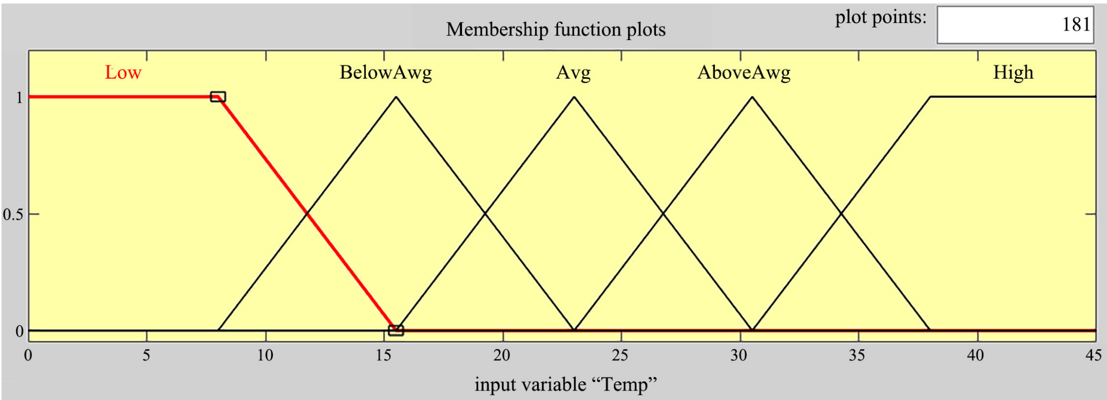

Figure 3. Input parameter temperature.

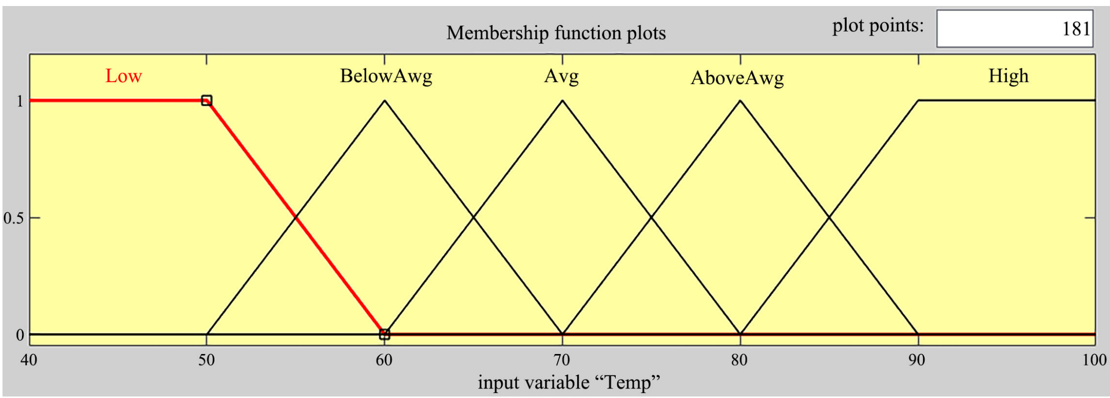

Figure 4. Input parameter humidity.

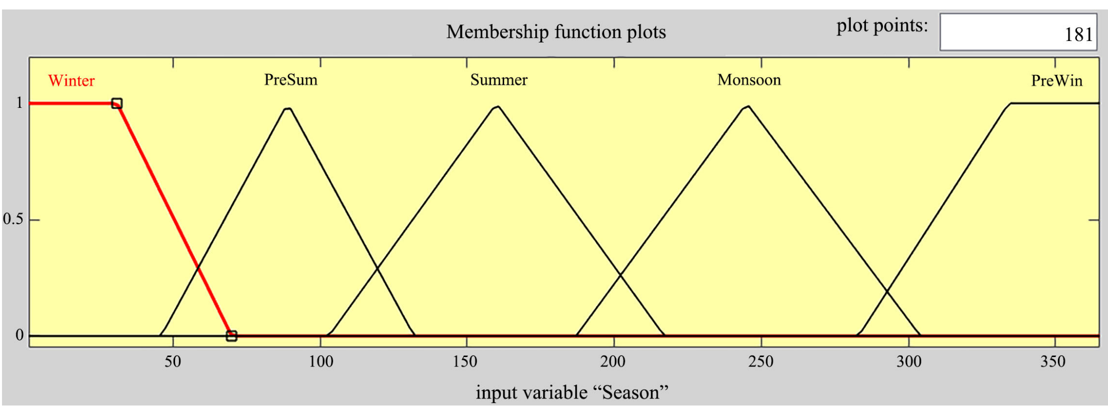

Figure 5. Input parameter season.

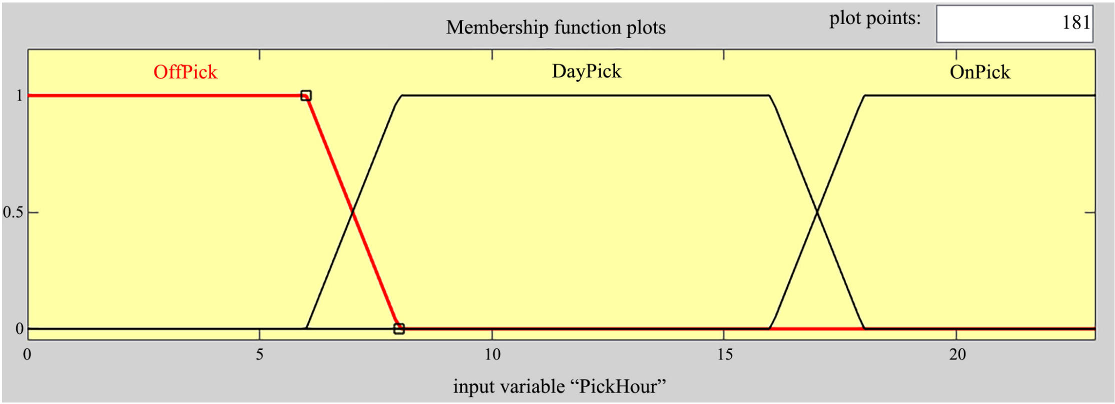

Figure 6. Input parameter peak hour.

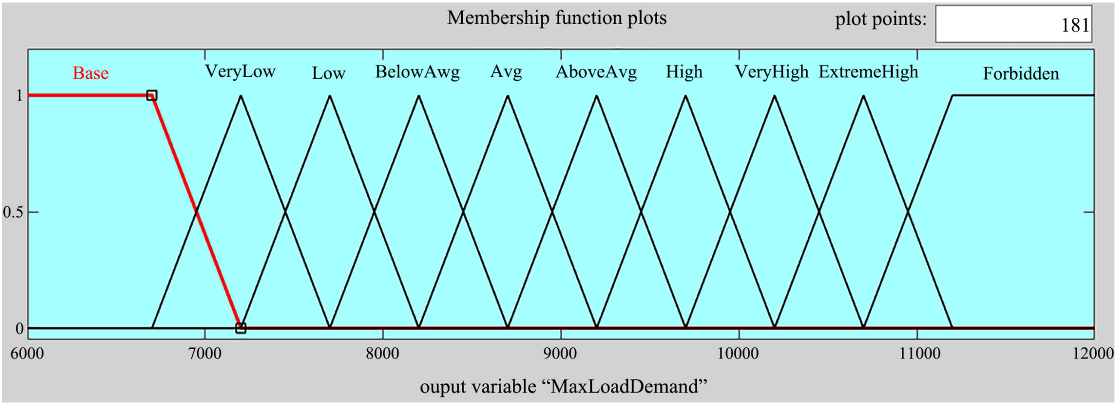

Figure 7. Output parameter maximum load demand.

Table 1. Weighted sum of areas.

Area segment no.	Area (A)	$\bar{x}$	$A\bar{x}$
1	0.5 × 0.3 × 1 = 0.150	0.670	0.100
2	2.6 × 0.3 = 0.780	2.300	1.748
3	0.3 × 0.4 = 0.120	3.800	0.456
4	0.5 × 0.4 × 0.2 = 0.040	3.866	0.154
5	1.4 × 0.5 = 0.700	4.750	3.325
6	0.6 × 0.5 = 0.300	5.750	1.725
7	0.5 × 0.5 × 0.5 = 0.125	5.833	0.729
8	1 × 1 = 1.000	6.500	6.500
9	0.5 × 1 × 1 = 0.500	7.330	3.665
	$\sum A = 3.720$		$\sum A\bar{x} = 18.400$

Now, Applying "if then" rule along with "and" condition for all the input parameter's MFs in the rule editor, a total of two hundred and forty rules are created, which is partly shown in Figure 8. In rule viewer, as shown in Figure 9, all the rules are applied for different parameters and values of their own. The rule viewer processes the input values and shows us the output value, which is applied in the input box of the rule viewer. In surface plot viewer, as shown in Figure 10, surface plot of load forecasting using fuzzy inference system is presented graphically by utilizing the given rules.

3. Results and Discussion

First, a comparison of BPDB and Fuzzy forecasting is shown in Tables 2-4 for three seasons: monsoon, winter and summer respectively. Here, we only show the results taking 10 days from each month to make the data concise for the paper. After analyzing our results, we can see significant improvements in average percentage of error when using our forecasting method compared to the method used by BPDB. Therefore, it is quite safe to assume that our fuzzy inference system is better structured and cost efficient than the BPDB's system. However, with our methodology, load forecasting of holidays shows erratic results. The BPDB's method shows similar behavior in terms of holiday load forecasting. For this reason, we subtract seven hundred MW from the ranges of the output membership function's parameters and re-create a new fuzzy inference system with all other input parameters and their MF's ranges unchanged, which is only applicable for holidays. A comparison of normal and holiday load forecasting method is shown in Tables 5-7 for three seasons: monsoon, winter and summer. A little improvement is achieved when applying holiday load forecasting method for the holidays compared to normal load forecasting method. Still, we are not able to achieve quite significant improvements, as the usage of load during holidays is very much unpredictable. It does not follow any usual patterns (abrupt variation of data), which is seen in case of normal days. In this case, one possible solution is to smooth the abrupt variation of load of holidays using multiple linear regressions (MLR) then smooth data can be applied in FIS model to improve the accuracy. This will be the extension of our work in future.

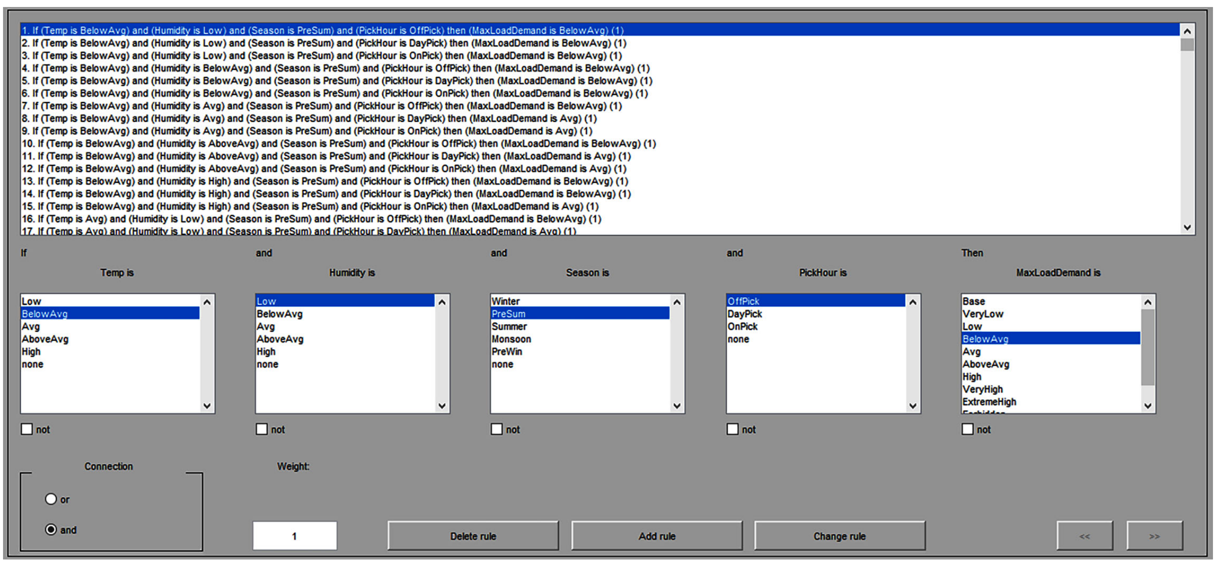

Figure 8. Load forecasting rules in rule editor.

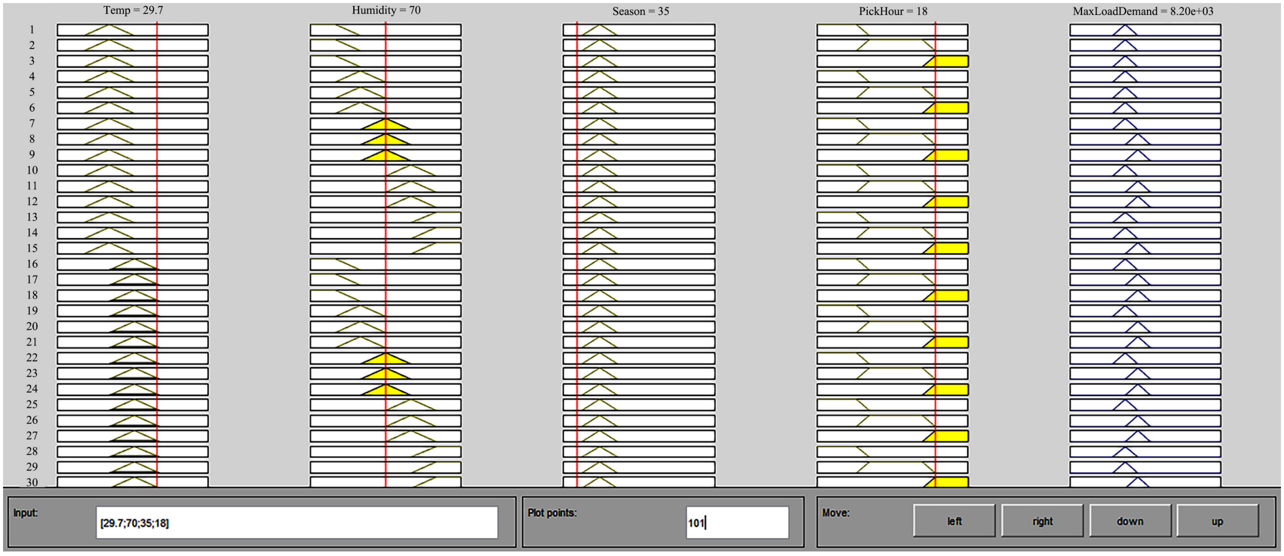

Figure 9. Load forecasting rules in rule viewer.

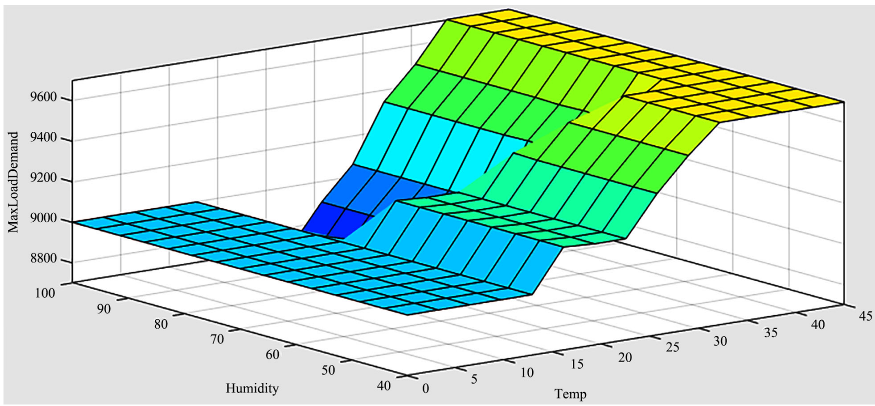

Figure 10. Surface plot in 3D.

Table 2. August' 17 comparison of forecasting data.

Date	Forecasted Temp. (˚C)	Actual maximum load (MW)	BPDB forecasted load (MW)	Fuzzy forecasted load (MW)	APE%	APE% with fuzzy
21-8-17	34.4	9318	9900	9200	−6.24	1.26
22-8-17	33	9180	10,000	9130	−8.93	0.54
23-8-17	34.2	9129	9900	9190	−8.44	−0.66
24-8-17	34.7	8986	10,000	9200	−11.28	−2.38
26-8-17	33.3	9253	9800	9200	−5.91	0.57
27-8-17	32.6	9110	9800	9200	−7.57	0.987
28-8-17	33.1	9084	9800	9200	−7.88	−1.27
29-8-17	32.6	9088	9800	9200	−7.83	−1.23
30-8-17	33.8	8980	9800	9200	−9.13	−2.45
31-8-17	33.3	8053	9700	9110	−20.45	−13.12

Table 3. February' 18 comparison of forecasting data.

Date	Forecasted Temp. (˚C)	Actual maximum load (MW)	BPDB forecasted load (MW)	Fuzzy forecasted load (MW)	APE%	APE% with fuzzy
1-2-18	25.8	8162	8350	8300	−2.30	−1.69
3-2-18	28	8109	8000	8200	1.34	−1.12
4-2-18	29.7	8139	8350	8200	−2.59	−0.74
5-2-18	29.3	8247	8350	8200	−1.24	0.56
6-2-18	28.7	7976	8400	8200	−5.31	−2.80
7-2-18	28.4	8258	8400	8360	−1.71	−1.25
8-2-18	28.3	8115	8400	8290	−3.51	−2.15
10-2-18	27.5	8144	8350	8330	−2.52	−2.29

Table 4. April' 18 comparison of forecasting data.

Date	Forecasted Temp. (˚C)	Actual maximum load (MW)	BPDB forecasted load (MW)	Fuzzy forecasted load (MW)	APE%	APE% with fuzzy
10-4-18	32.2	9355	9900	9200	−5.82	1.65
11-4-18	33.1	8943	10,000	9430	−11.81	−5.44
12-4-18	33.8	8917	9650	9560	−8.22	−7.21
14-4-18	33.4	7665	9300	8720	−21.33	−13.76
15-4-18	37.5	9961	9800	9860	1.61	1.01
16-4-18	36.4	9702	10,100	9560	−4.10	1.46
17-4-18	37	8464	10,100	9050	−19.32	−6.92
18-4-18	37.1	9758	10,000	9650	−2.54	1.10
19-4-18	32.4	9425	10,000	9300	−6.10	1.32

Table 5. August' 17 forecasted load error comparison using normal and holiday case.

Date	Forecasted Temp. (˚C)	Actual maximum load (MW)	BPDB forecasted load (MW)	Fuzzy forecasted load (MW)	APE%	APE% with fuzzy
			Normal Case			
25-8-17	34.7	8933	9800	9200	−9.70	−2.98
			Holiday Case			
25-8-17	34.7	8933	9800	8500	−9.70	4.84

Table 6. February' 18 forecasted load error comparison using normal and holiday case.

Date	Forecasted Temp. (˚C)	Actual maximum load (MW)	BPDB forecasted load (MW)	Fuzzy forecasted load (MW)	APE%	APE% with fuzzy
			Normal Case			
2-2-18	26.2	7262	7500	8200	−3.27	−12.91
9-2-18	30.4	7449	7500	8210	−0.68	−10.21
			Holiday Case			
2-2-18	26.2	7262	7500	7500	−3.27	−3.27
9-2-18	30.4	7449	7500	7510	−0.68	−0.81

Table 7. April' 18 forecasted load error comparison using normal and holiday case.

Date	Forecasted Temp. (˚C)	Actual maximum load (MW)	BPDB forecasted load (MW)	Fuzzy forecasted load (MW)	APE%	APE% with fuzzy
			Normal Case			
13-4-18	34.1	9257	9200	9420	−0.46	−1.76
20-4-18	34.1	8095	9600	9290	−18.59	−14.76
			Holiday Case			
13-4-18	34.1	9257	9200	8720	−0.46	5.80
20-4-18	34.1	8095	9600	8590	−18.59	−5.15

4. Conclusion

In this paper, we have applied microscopic approach and developed fuzzy inference model applicable in short term and long term forecasting of real life problems. Here, we have considered the concept of electrical load forecasting of Bangladesh, taking the practical data of BPDB. We have correlated the demand of electrical load with weather parameters and have found high accuracy in winter season. In future, we have the scope to apply MLR, back propagation algorithm of ANN, Long Short Term Memory (LSTM) of machine learning and convolutional neural network (CNN) of deep learning to relate the weather parameters with the actual electrical load for comparison.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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