A fuzzy logic controller based mid-term load forecasting with renewable penetration in Assam, India

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Abstract: ***An accurate mid-term load forecasting (MTLF) tool is an essential part of power systems planning and sustainable development. In order to compensate the extra uncertainties, the power systems with high renewable penetration need even more accurate MTLF tool. The electric load demand is highly prejudiced by the thermal inertia due to the local climatic factors. Therefore, the accuracy of an MTLF method is highly dependent on the incorporated climatic factors. This paper proposes a fuzzy logic comptroller based MTLF method with renewable penetration. In order to achieve a higher degree of forecasting accuracy proposed method incorporated several climatic factors in the forecasting process. The study is done in Assam, a state of India and the proposed method is utilized to forecast the daily average load demand for one month. The forecasting accuracy of the proposed method is compared with one of most commonly used tool for MTLF called artificial neural network (ANN). The empirical results affirm the superiority of the proposed method over the ANN.***

Keywords: Mid-term load forecasting, Fuzzy logic controller, Climatic Factor, Mean absolute percentage error**.**

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1. Introduction

Load forecasting is an essentialtask for providing a sustainable solution to the electric power systems [1], [2]. It is also important for some fundamental power systems operations like hydro-thermal scheduling, interchange evaluation, unit commitment, optimum spinning reserve capacity, scheduled maintenance, and security assessment [3]–[6]. Based on the forecasting durations, the load forecasting is divided into four categories [7].

• Very short-term load forecasting: forecast up to few hours.

• Short-term load forecasting: forecast up to seven days.

• Mid-term load forecasting: forecast up toone month.

• Long-term load forecasting: forecast up to few months.

While the very short-term and short-term load forecasting is important for fundamental operations of power systems the long-term and mid-term load forecasting are basically executed towards planning a new power station or transmission line [4]. Owing to these great interests, various methods for load forecasting are proposed in the recent years. The examples of those methods are: ARMA [8], [9], seasonal ARIMA [10], gray forecasting model [11], Kalman filters approach [12], [13], artificial neural network [14], [15], expert systems [16], and the fuzzy logic [3], [17]. Among these methods, fuzzy logic is one of the established techniques in the area of load forecasting.

There is a strong correlation between the thermal comfort inside a build environment and the electric load demand. This thermal inertia primarily depends on the climatic factors like temperature, humidity, wind speed etc. [18]–[20]. So, it is very much essential to incorporate these climatic factors in the forecasting technique. Many attemptshave been made to incorporate these climatic factors in the forecasting method. In [21]–[23], the authors predominantly implemented temperature as a climatic factor in the proposed forecasting techniques. In [24], authors implemented temperature, humidity, and solar gain and in [25], authors considered temperature as well as humidity in the forecasting techniques. This work proposed a fuzzy logic controller based mid-term load forecasting (MTLF) considering several climatic factors. The study is done in the Assam state of India and the proposed method is targeted to achieve a high forecasting accuracy.

1.1 Power scenario in the study area

The study area for this work is the state of Assam, India and it is located at the longitude of 89.42° E to 96.0° E and the latitude of 24.8° N to 28.2° N. In Assam, only 37% of the total households have access to electricity and has a peak shortage of 189 MW power supply as on March 2016. The per capita electricity consumption in Assam is only 314 kWh, whereas the Indian national average is 1010 kWh[26]. As on July 2017, the total installed capacity of power utilities in Assam is 1599.65 MW. Out of which the total installed capacity of conventional (coal and gas based) power utilities is 1122.53 MW and the total installed capacity of renewable power utilities is 477.12 MW [31]. With the view to enhancing the renewable penetration across the country, the Government of India aims to install 20,000 MW of solar power by the year 2022 [32]. So, in the upcoming years, installed capacity of renewable power utilities in Assam will definitely grow. The load forecasting becomes more challenging with renewable penetration as it already involves a huge amount of uncertainties [27]. This paper proposesa fuzzy logic controller based mid-term load forecasting (MTLF) where daily average load demand of Assam is forecasted for one month. This method incorporated temperature, humidity, and wind speed as the climatic factorsand it is proposed to generate high-quality forecasting results under alocal environment in the studied region. Two case studies are made and the results of the proposed method are compared withthe one of most commonly used tool for load forecasting called artificial neural network (ANN).
The rest of paper is organized as follows: in Section 2, we discuss the architecture of the proposed method. Section 3 discussed the fuzzy logic implementation. In section 4, the appropriate case studies and the relevant forecasting results are analyzed. Finally, the conclusions are presented in Section 5.

2. Architecture of the proposed method

In the recent years, the applications of the fuzzy logic controllers are in the hotspot of many research areas in the domain of power engineering. The usability, simplicity, and accuracy make it popular in the load forecasting research. The fuzzy inference system maps a set of input variable to a set of output variables. It is based on the heuristics; the fuzzy logic controller is capable of incorporating human reasoning and intuition. The fuzzy method uses the fuzzy sets that assisted us to condense the huge amount of data into asmaller set of variable fuzzy rules [3], [7]. The architecture of the proposed solution is given in Fig. 1 below. The input-output combinations for the fuzzy logic controller are clearly indicated by the Fig. 1. The inputs to the fuzzy controller are: (a) similar day average load demand (MW), (b) forecasted temperature of the day on which we need to forecast the daily average load demand (^{0}C), (c) forecasted humidity of the day on which we need to forecast the daily average load demand (%), (d) forecasted wind speed of the day on which we need to forecast the daily average load demand (km/hour), and (e) binary set of input which decides whether it is a holiday or workday (day type). The similar days are the past historical days those have the same climatic factors profile corresponding to the forecast day. The output of the fuzzy logic controller is the forecasted values of the daily average load demand. The implementation of the fuzzy logic for the proposed solution is described in Section 3.

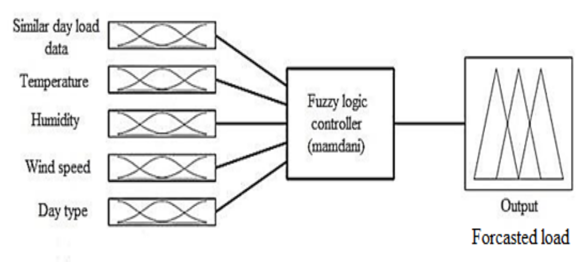

Figure 1: Architecture of the proposed method**.**

3. Fuzzy logic implementation

The fuzzy logic implementation can be divided into three steps which are described in the next page.

3.1 Assigning fuzzy values to the input and output parameters

The fuzzy logic controller input & output unions are shown in the Fig. 1. Every input and the output is shared in the number of fuzzy sets by assigning membership functions as shown in Fig. 2- Fig.7. The first input parameter, the similar day historical load data is divided into seven membership function which shows the degree of consumed load amount as follows: very very low daily average load demand (VVL), very low daily average load demand (VL), low daily average load demand (L), normal daily average load demand (N), high daily average load demand (H), very high daily average load demand (VH), and very very high daily average load demand (VVH). The similar day historical load data is used in the input to train the fuzzy logic controller based on the similarity index. The values of such similar days daily average load demand areshown in Fig.2 and these are within the range from 1100 MW to 1300 MW which denotes the minimum and maximum daily average load demand respectively. The other input parameters data (temperature, humidity and wind speed) and the output parameter (forecasted load) data are also divided into seven membership function in the similar fashion. The Gaussian sets division of the temperature, humidity and wind speed are shown in Fig. 3, Fig. 4, Fig. 5 respectively and were within the ranges from 15 to 37 ^{0}C, 24% to 99 %, and 1km/hour to 68 km/hour respectively. The day type is a binary set of input within range 0 to 1 which decide whether day on which we need to forecast the load is a holiday or workday. The day type is divided into two membership function as shown in the Fig. 6. The membership function for forecasted load output (MW) is also divided into seven as shown in Fig. 7.

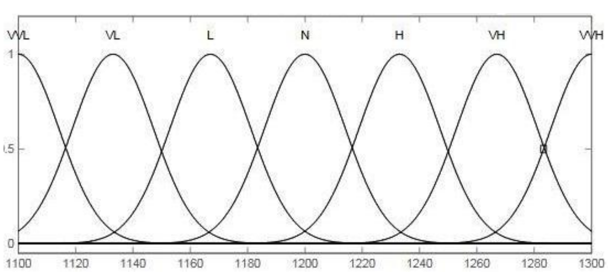

Figure 2: Membership function for the similar day load data input (MW).

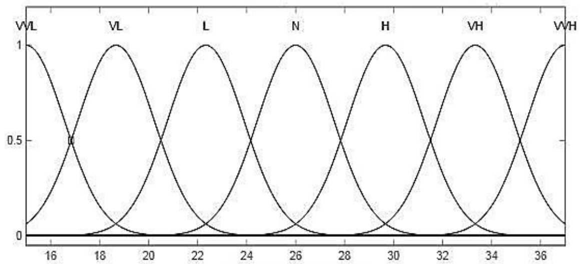

Figure 3: Membership function for the temperature data (^{0}C).

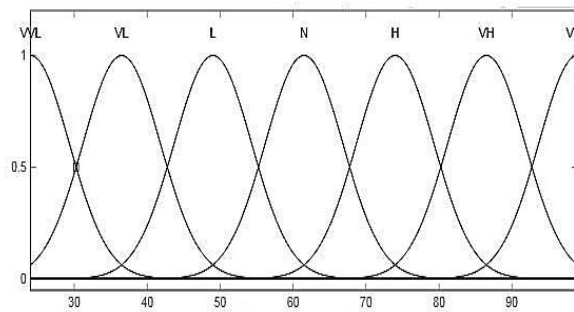

Figure 4: Membership function for the humidity data (%).

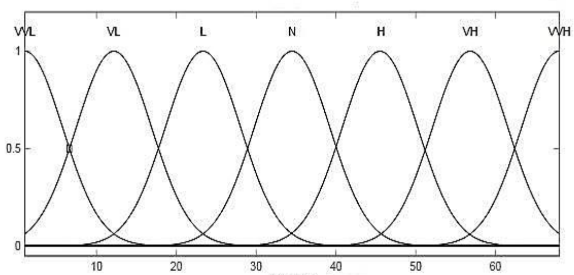

Figure5: Membership function for the wind speed data (km/hour).

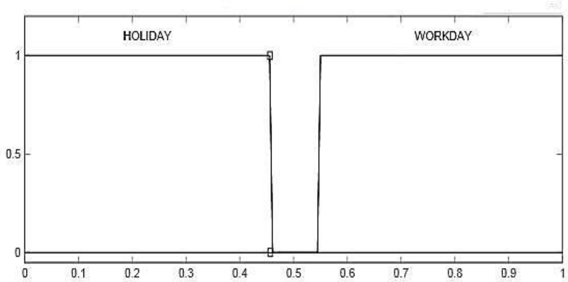

Figure 6: Membership function for the Day type.

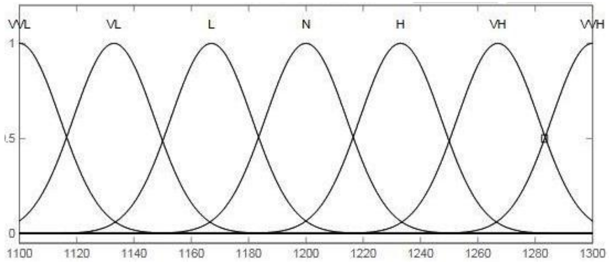

Figure 7: Membership function for forecasted load output (MW).

3.2 Assigning fuzzy rule in the system

After assigning fuzzy values to the input and output parameters the fuzzy rule can be constructed. The fuzzy rules capture the nonlinear relationship between the input data sets (load, temperature, humidity, wind speed, and day type data) and the output (forecasted load). The fuzzy rules are basically some if-then statements (eg: if temperature and humidity both are very high then load demand will be very high). In this research 53 fuzzy rules are applied to forecast the daily average load under the effect of different input data sets.

3.3 Executing the fuzzy inference into the proposed solution

The fuzzy inference is the procedure of articulating the mapping from a given input to the output using the fuzzy logic. After that, the mapping provides a base from which decisions are prepared. The fuzzy inference process involves membership functions, linguistic variable, fuzzy logic controller, and some if-then rules [3], [7]. In this proposed method the mapping from the input values to the output values contains four steps namely data pre-processing (similar day data), fuzzification (assigning fuzzy values), aggregation (constructing the rules), and defuzzification (defuzzified values of output). The assigning of the membership function and construction of the fuzzy rules are based on the past historical similar days data collected from the state load dispatch center (SLDC), Assam, India. The daily average load demand, temperature, humidity, wind speed, and day type data of three years (the year 2013 to 2015) are considered for this purpose. The climate factors forecast is not a part of this work and these are received using web service from the weather forecast provider.

4. Case studies and the forecasting results

The generated forecasting error is basically the evaluating indicator of a forecasting method. In the area of load forecasting, there are many method evaluation pointers among which mean absolute percentage error (MAPE) is a commonly used one [28]. This work also presents the forecasting accuracy in terms of MAPE. The MAPE is described as:

$$MAPE = \left(\frac{|A_i - F_i|}{A_i} \right) \times 100 \qquad (1)$$

Where A_i represents the actual value of load at time instance i and F_i represents the forecasted value of load at time instance i.

Two case studies are carried out in this study and the proposed model is employed for mid-term load forecasting (MTLF). The forecasting performance of the proposed method is compared with one of most commonly used tool for forecasting called artificial neural network (ANN). Here the ANN is trained using the Levenberg-Marquardt algorithm. This work is simulated on MATLAB 7.1, ver. 2016, Windows 7. In both the case studies, both ANN and the proposed method are employed for MTLF. The detail findings and the necessary analysis of the cases are described below.

Case 1: In this example, the MTLF is performed in the winter season and the period chosen for this case study is the January 2016. Fig. 8 presented the actual load, forecasted load using ANN and forecasted load using the proposed method. It can be observed from the Fig. 8 that there are significant deviations between a load of ANN and the actual load. On the contrary, a load of the proposed method follows the actual load with minor deviations. Among the individual time points, the maximum, minimum and average load deviations generated with ANN are 66 MW, 1.5 MW, 23.91 MW respectively and that of the proposed method are 35 MW, 0.75 MW, and 15.24 MW respectively.

Case 2: This case study is conducted in the summer season and the period chosen here is the month of July 2016. Fig. 9 presents the actual load, forecasted load using ANN and forecasted load using the proposed method. The analysis shows significant deviations between the actual load and forecasted load using ANN. In this case, also the load of the proposed method follows the actual load with minor deviations. Among the individual time points, the maximum, minimum and average load deviations found with ANN are 78 MW, 27.4 MW, 4 MW respectively and that of the proposed method are 41 MW, 13.31 MW, and 2.25 MW respectively.

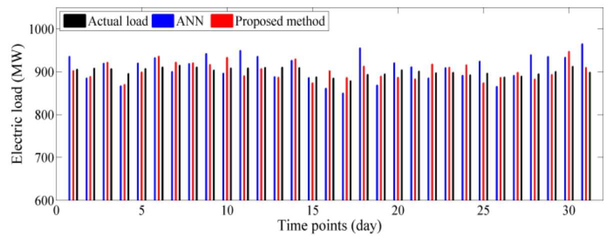

Figure 8: Forecasting results for the case 1.

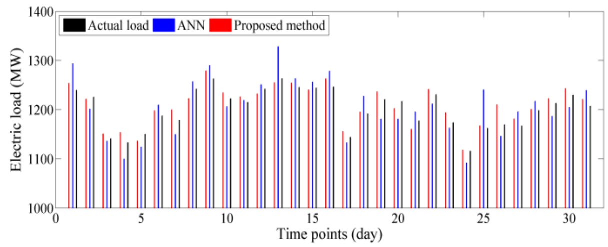

Figure 9: Forecasting results for the case 2

The tabular overviews of the forecasting performance of the ANN and the proposed methods are presented in Table 1. The results indicate that in both the cases the proposed method outperforms the ANN.

Table 1 Comparison of MAPE for the cases

Cases	*MAPE ((%)*	
	ANN	*Proposed Method*
1	2.58	1.67
2	2.19	1.06

5. Conclusions

An accurate load forecasting method is an essential part of energy transaction, market shares, and profits in the modern-day deregulated electricity market [4], [29], [30]. An accurate load forecasting method is essential for tackling the challenges in the load forecasting with renewable penetration [27]. Therefore, this paper proposes a fuzzy inference system to gain high-quality forecasting results. Two case studies are considered where forecasting accuracy of the proposed method is compared with the ANN. It is found that the proposed method provides better forecasting accuracy in both the cases. Therefore, the major contributions of this study can be summarized as (a) a fuzzy logic controller based MTLF method is proposed, (b) to address the environmental thermal comfort which has a huge impact on electricity load demand, various climatic factors (temperature, humidity, and the wind speed) are incorporated in the forecasting process, and (c) the MTLF is performed with both ANN and proposed method and the comparison of the obtained forecasting results are analyzed. The validation of the proposed method is also delivered by presenting the maximum, minimum and average load deviations among the individual time points. The results affirm that the proposed method outperforms the ANN in both the cases. So, it can be concluded that the higher forecasting accuracy of the proposed method can translateinto thefinancial performance of the energy utilities under high renewable penetration in future.

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References

[1] C. Cecati, J. Kolbusz, P. Ró˙zycki, P. Siano, and B. M. Wilamowski, “A Novel RBF Training Algorithm for Short-Term Electric Load Forecasting and Comparative Studies,” *IEEE Trans. Ind. Electron.*, vol. 62, no. 10, pp. 6519–6529, 2015.

[2] R. V. Kale and S. D. Pohekar, “Electricity demand and supply scenarios for Maharashtra (India) for 2030: An application of long range energy alternatives planning,” *Energy Policy*, vol. 72, pp. 1–13, 2014.

[3] R. Mamlook, O. Badran, and E. Abdulhadi, “A fuzzy inference model for short-term load forecasting,” *Energy Policy*, vol. 37, no. 4, pp. 1239–1248, 2009.

[4] Ö. F. Ertugrul, “Forecasting electricity load by a novel recurrent extreme learning machines approach,” *Int. J. Electr. Power Energy Syst.*, vol. 78, pp. 429–435, 2016.

[5] N. Amjady, “Short-term hourly load forecasting using time-series modeling with peak load estimation capability,” *IEEE Trans. Power Syst.*, vol. 16, no. 4, pp. 798–805, 2001.

[6] S. Mirasgedis *et al.*, “Models for mid-term electricity demand forecasting incorporating weather influences,” *Energy*, vol. 31, no. 2–3, pp. 208–227, 2006.

[7] D. Ali, M. Yohanna, M. I. Puwu, and B. M. Garkida, “Long-term load forecast modelling using a fuzzy logic approach,” *Pacific Sci. Rev. A Nat. Sci. Eng.*, vol. 18, no. November, pp. 1–5, 2016.

[8] S. J. Huang and K. R. Shih, “Short-term load forecasting via ARMA model identification including non-Gaussian process considerations,” *IEEE Trans. Power Syst.*, vol. 18, no. 2, pp. 673–679, 2003.

[9] S. S. Pappas, L. Ekonomou, D. C.

Karamousantas, G. E. Chatzarakis, S. K. Katsikas, and P. Liatsis, "Electricity demand loads modeling using AutoRegressive Moving Average (ARMA) models," *Energy*, vol. 33, no. 9, pp. 1353–1360, 2008.

[10] M. De Felice, A. Alessandri, and F. Catalano, "Seasonal climate forecasts for medium-term electricity demand forecasting," *Appl. Energy*, vol. 137, pp. 435–444, 2015.

[11] P. Zhou, B. W. Ang, and K. L. Poh, "A trigonometric grey prediction approach to forecasting electricity demand," *Energy*, vol. 31, no. 14, pp. 2503–2511, 2006.

[12] H. M. Al-Hamadi and S. A. Soliman, "Short-term electric load forecasting based on Kalman filtering algorithm with moving window weather and load model," *Electr. Power Syst. Res.*, vol. 68, no. 1, pp. 47–59, 2004.

[13] C.-N. Ko and C.-M. Lee, "Short-term load forecasting using SVR (support vector regression)-based radial basis function neural network with dual extended Kalman filter," *Energy*, vol. 49, pp. 413–422, 2013.

[14] M. Mordjaoui, S. Haddad, A. Medoued, and A. Laouafi, "Electric load forecasting by using dynamic neural network," *Int. J. Hydrogen Energy*, pp. 1–9, 2017.

[15] M. Barman and N. B. D. Choudhury, "Artificial Neural Network Based Electricity Price Forecasting Using Levenberg-Marquardt Algorithm," *Int. J. Control Theory Appl.*, vol. 10, no. 19, pp. 127–136, 2017.

[16] M. S. S. Rao, S. A. Soman, B. L. Menezes, P. Chawande, P. Dipti, and T. Ghanshyam, "An expert system approach to short-term load forecasting for Reliance Energy Limited, Mumbai," *2006 IEEE Power India Conf.*, vol. 2005, pp. 763–768, 2005.

[17] A. Azadeh, M. Saberi, and O. Seraj, "An integrated fuzzy regression algorithm for energy consumption estimation with non-stationary data: A case study of Iran," *Energy*, vol. 35, no. 6, pp. 2351–2366, 2010.

[18] B. Yildiz, J. I. Bilbao, and A. B. Sproul, "A review and analysis of regression and machine learning models on commercial building electricity load forecasting," *Renew. Sustain. Energy Rev.*, vol. 73, no. December 2016, pp. 1104–1122, 2017.

[19] S. Rahman, "Formulation and Analysis of a Rule-Based Short-Term Load Forecasting Algorithm," *Proc. IEEE*, vol. 78, no. 5, pp. 805–816, 1990.

[20] D. C. Park, M. a. El-Sharkawi, R. J. Marks, L. E. Atlas, and M. J. Damborg, "Electric load forecasting using an artificial neural network," *IEEE Trans. Power Syst.*, vol. 6, no. 2, pp. 442–449, 1991.

[21] P. Mandal, T. Senjyu, N. Urasaki, and T. Funabashi, "A neural network based several-hour-ahead electric load forecasting using similar days approach," *Int. J. Electr. Power Energy Syst.*, vol. 28, no. 6, pp. 367–373, 2006.

[22] T. Senjyu, H. Takara, K. Uezato, and T. Funabashi, "One-hour-ahead load forecasting using neural network," *Power Syst. IEEE …*, vol. 17, no. 1, pp. 113–118, 2002.

[23] I. Drezga, "Short-term load forecasting with local ann predictors," *IEEE Trans. Power Syst.*, vol. 14, no. 3, pp. 844–850, 1999.

[24] A. H. Neto and F. A. S. Fiorelli, "Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption," *Energy Build.*, vol. 40, no. 12, pp. 2169–2176, 2008.

[25] A. Jain, E. Srinivas, and R. Rauta, "Short term load forecasting using fuzzy adaptive inference and similarity," *2009 World Congr. Nat. Biol. Inspired Comput.*, pp. 1743–1748, 2009.

[26] M. Barman, S. Mahapatra, D. Palit, and M. K. Chaudhury, "Performance and impact evaluation of solar home lighting systems on the rural livelihood in Assam, India," *Energy Sustain. Dev.*, vol. 38, pp. 10–20, 2017.

[27] S. Sepasi, E. Reihani, A. M. Howlader, L. R. Roose, and M. M. Matsuura, "Very short term load forecasting of a distribution system with high PV penetration," *Renew. Energy*, vol. 106, pp. 142–148, 2017.

[28] A. Hussain, M. Rahman, and J. A. Memon, "Forecasting electricity consumption in Pakistan: The way forward," *Energy Policy*, vol. 90, pp. 73–80, 2016.

[29] E. Ceperic, V. Ceperic, and a. Baric, "A Strategy for Short-Term Load Forecasting by Support Vector Regression Machines," *IEEE Trans. Power Syst.*, vol. Early Acce, no. 4, pp. 4356–4364, 2013.

[30] G. Dudek, "Pattern similarity-based methods for short-term load forecasting - Part 1: Principles," *Appl. Soft Comput. J.*, vol. 37, pp. 277–287, 2015.

[31] CEA (Central Electrical Authority). http://www.cea.nic.in/,2017;[Accessed on 17th September, 2017].

[32] MNRE (Ministry of New and Renewable Energy). http://www.mnre.gov.in/, 2017; [Accessed on 19th September, 2017].