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ORIGINAL CONTRIBUTION

Fuzzy Inference Model for Short-Term Load Forecasting

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Abstract For planning and operation of an energy management system, load forecasting (LF) is essential. For smooth power system operation (PS), LF enhances the energy-efficient and reliable operation. LF also helps to calculate energy supplied by utilities to meet the load plus the energy lost in the PS. Every day, it is necessary to schedule the power generation for the next day. So, short-term load forecasting (STLF) is used to calculate the power dispatch for the next day. In unit commitment, economic allocation of generation and maintenance schedules, STLF is also used. So, to make the STLF more effective, fuzzy logic (FL) is used here. FL is essential for weather-sensitive and historical load data for forecasting the load. The fuzzy decision rule identifies the nonlinear relationship between the input and output data. The historical load and hourly data like temperature, humidity (relative humidity) and wind speed are used for input data. For the training and testing, the hourly based load data are collected from the state load dispatch and communication center of Rajasthan Vidyut Prasaran Nigam, Jaipur (JVN). The triangular membership function of the fuzzy logic model is used to predict the load. The performance of the work is determined by the mean absolute percentage error (MAPE) and the MAPE value for pre-holiday (Saturday), holiday (Sunday), post-holiday, and working day is 0.37%, 0.24%, 0.09%, and 0.09%, respectively.

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Keywords Fuzzy logic (FL) · Membership function (MF) · Short-term load forecasting (STLF) · Mean absolute percentage error (MAPE)

Introduction

Forecasting is an integral part of the electric power system [1]. Because from a few minutes to an hour ahead or as much as 20 years into the future, load forecasts are typically programmed. There are four types of electrical load forecasting, i.e., short-term load forecasting, very short-term load forecasting, medium-term load forecasting and long-term load forecasting [2]. Predicting the load from one hour to one week is known as short-term load forecasting [3]. Short-term load forecasting is one of the most important operations for control of power generation for determining the power plant's work plan and choosing the best production group. Because the problem of economic as well as technical issues is challenging to electrical companies [4–6], these problems are removed by short-term load forecasting by deciding production of energy and purchasing, developing infrastructure and switching of load correctly for electricity providers is very much important [7–9]. By criteria regarding the quality of supply, the reliability of supply and to minimize the costs of balancing, a day ahead planning balances the forecasted hourly demand that is implemented based on providing security and system integration of operation. One day in advance, balancing the whole system is performed according to the forecasted values given by the demand side to the day ahead planning system. Otherwise, the cost will be increased by an imbalance of the load from forecasted errors.

Due to the characteristics, the behavior of the electric power system is quite different. Any forecasting method cannot achieve the best results for all power systems [10].

So other methods are adopted for load forecasting. Among them, the most commonly used methods are regression analysis, time series analysis, similar day approach, support vector machine, artificial neural network, fuzzy logic as shown in Fig. 1, adaptive network-based fuzzy inference system, genetic algorithm and some hybrid methods which are discussed as a literature survey. Statistical methods and artificial neural networks are widely adopted for load forecasting. But nowadays, hybrid methods or other intelligent approaches are also adopted for load forecast [11].

In [12], it is studied that for determining the position of the capacitor, an oppositional crow search algorithm (CSA) is used for Var planning with fuzzy logic technique. For each bus of the tested networks, i.e., IEEE 30 and IEEE 57, the fuzzy membership value is calculated based on the loss sensitivity factor. To obtain the global or near-global optimal setting of the control variable for more accuracy and reliability, modified whale optimization algorithm (MWOA) is used [13]. In [14], for optimal reactive power planning, oppositional gray wolf optimization (OGW) is used for less expensive systems with poor bu recognition by voltage collapse proximity index (VCPI). The optimization and performance toward unraveling the optimal phasor unit (PMU) placement problem (OPPP) is achieved by integrating an A-star algorithm and binary search tree. Here, redundancy measurement is considered for OPP [15]. An efficient and hybrid meta-heuristic algorithm of harris hawk-particle swarm optimization is used to solve the voltage-constrained reactive power planning problem. So, the overall operating cost and transmission loss are calculated [16]. For minimizing active power loss and system operating cost while maintaining voltage profile within the permissible limit in finding the optimal setting of all control variables, including thyristor-controlled series compensator (TCSC), the series type and Static var compensator (SVC), the shunt kind of FACTS device, the tested system is used. For this, optimization like whale optimization algorithm (WOA), differential algorithm (DE), gray wolf optimization (GWO), and Quasi-opposition-based gray wolf optimization (QOGWO) are implemented. Among them, WOA gave the best results. The statistical analyses between the different techniques are implemented by the ANOVA test [17]. In other bundle conductor arrangements for three-phase, the capacitance and inductance per unit length are determined

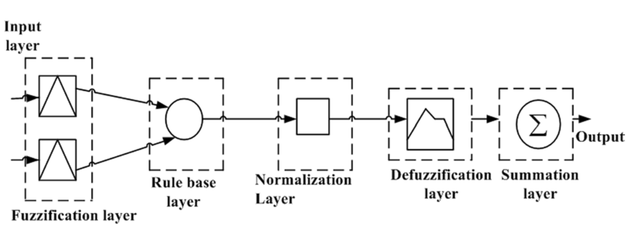

Fig. 1 Fuzzy logic model

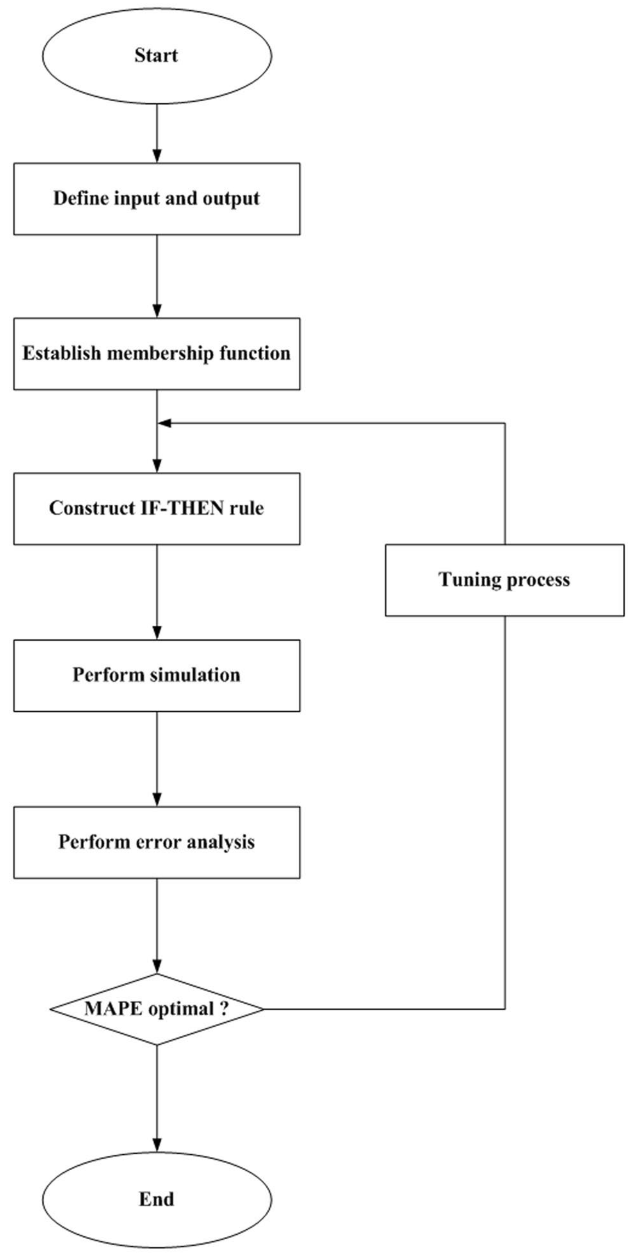

Fig. 2 Flowchart of Fuzzy logic

by the whale optimization algorithm (WOA) with the discussion for voltage stability for load modeling [18]. For the solution of voltage-constrained reactive power planning (VCRPP) of power system, ameliorated harris hawks optimization (AHHO) and harris hawks optimization (HHO) have been used [19]. To minimize the active power loss and total operating cost, opposition-based gray wolf optimization (OGWO) and gray wolf optimization (GWO) are used for IEEE 14, IEEE 30 and IEEE 57 bus systems [20].

Proposed Approach for STLF

The exact fuzzification method is Takagi–Sugeno–Kang, or Sugeno fuzzy inference uses a singleton output membership function that is a linear function of the input values. The Sugeno systems use a weighted average or weighted sum of a small number of data points during the defuzzification process rather than computing the centroid of a two-dimensional area, which results in a more computationally efficient procedure.

Work of Fuzzy Logic Model for STLF

Four steps are suggested for developing and implementing a fuzzy logic-based load forecasting system, as shown in Fig. 2.

Fuzzy Rule Base Design

Wang and Kosko have suggested this methodology because it successfully generates predictions. The five steps have concluded this method as follows:

Step 1 According to statistical analysis, engineering decisions, and operator experience, the *i*/*p* and *o*/*p* variables list has been preliminarily assembled. The following are the three input variables utilized to forecast electric load as an output [10, 11], i.e., temperature, humidity and wind speed are all factors to consider.

Step 2 Analyzing their behavior, the input and output variables are normalized, and the membership value [0, 1] is mapped to the input space [21, 22].

Step 3 For each variable, choose a fuzzy membership function shape such as triangular, trapezoidal, Gaussian, or bell shape membership. By trial and error, the membership function (MF) is selected.

Step 4 The number of fuzzy membership functions for each *i*/*p* and *o*/*p* variable is determined. In this case, all variables represent all three functions. The region's lengths in the functions are not equal for a particular variable, nor are the number of functions for all variables required to be similar. The cold, normal, and hot like three fuzzy set categories classify the temperature data [23, 24]. Similarly, the dry, humid, and very humid categories classify the humidity data. Three types of wind speed data, low, medium and high, are used to predict the load. Three fundamental fuzzy sets are used to classify the data, distinguished by the following characteristics: morning, midday, and night.

Table 1 Input details of 23rd Nov. 2013

Time (hr.)	Temperature (^{O}C)	Wind speed (m/s)	Humidity	Actual load (MW)	Forecasted load (MW)	MAPE
1	18	8	36	2596	2590	0.23
2	18	8	37	2540	2510	1.18
3	17	7	38	2465	2415	2.02
4	17	7	39	2372	2320	2.19
5	16	7	40	2428	2422	0.24
6	16	6	42	2844	2840	0.14
7	16	6	43	3206	3200	0.18
8	16	6	40	3337	3330	0.20
9	17	5	33	3329	3320	0.27
10	20	5	29	3347	3340	0.20
11	25	4	26	3079	3070	0.29
12	26	4	23	2978	2970	0.26
13	27	6	21	2842	2840	0.07
14	27	8	20	2634	2630	0.15
15	26	10	19	2564	2560	0.15
16	26	11	20	2596	2593	0.11
17	26	12	21	2693	2690	0.11
18	25	12	24	2799	2790	0.32
19	24	13	24	3084	3082	0.06
20	24	14	24	2904	2900	0.13
21	21	14	24	2745	2742	0.10
22	20	13	24	2699	2690	0.33
23	20	13	23	2662	2660	0.07
24	19	12	23	2543	2542	0.03

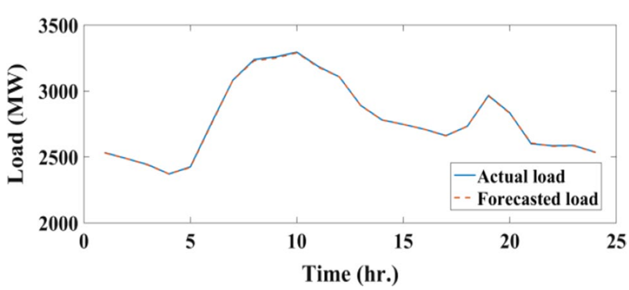

Fig. 3 Pre-holiday hourly load forecast (Saturday)

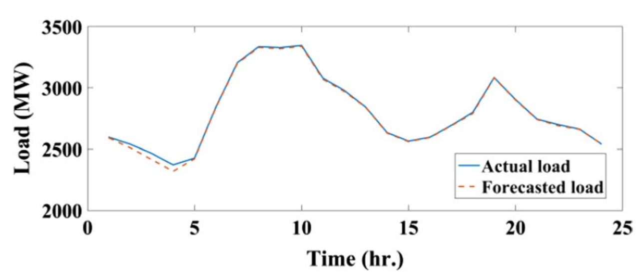

Fig. 4 Holiday load prediction hourly (Sunday)

Table 2 Input details of 24th Nov. 2013

Time (hr.)	Temperature (°C)	Wind speed (m/s)	Humidity	Actual load (MW)	Forecasted load (MW)	MAPE
1	17	5	32	2532	2530	0.07
2	16	5	34	2488	2488	0.00
3	15	4	36	2442	2440	0.08
4	14	4	37	2371	2371	0.00
5	14	5	38	2424	2420	0.16
6	14	5	37	2759	2752	0.25
7	14	4	38	3083	3083	0
8	15	4	37	3239	3230	0.27
9	20	4	29	3259	3250	0.27
10	24	4	25	3295	3290	0.15
11	25	4	21	3187	3182	0.15
12	25	5	19	3107	3107	0
13	26	6	17	2891	2890	0.03
14	26	7	16	2781	2780	0.03
15	27	8	16	2747	2747	0
16	26	9	17	2710	2710	0
17	25	9	19	2662	2660	0.07
18	24	10	23	2732	2733	0.07
19	24	11	24	2966	2963	0.10
20	24	12	26	2834	2831	0.10
21	21	13	27	2600	2606	0.23
22	20	13	29	2585	2581	0.15
23	20	12	30	2587	2585	0.07
24	19	11	31	2537	2535	0.07

Table 3 Input details of 25th Nov. 2013

Time (hr.)	Temperature (°C)	Wind speed (m/s)	Humidity	Actual load (MW)	Forecasted load (MW)	MAPE
1	19	11	32	2530	2500	1.18
2	19	10	33	2468	2468	0
3	18	10	34	2429	2429	0
4	18	10	34	2340	2342	0.08
5	18	10	35	2353	2350	0.12
6	17	10	36	2756	2752	0.14
7	17	10	37	3195	3195	0
8	18	9	37	3434	3434	0
9	20	9	33	3443	3443	0
10	24	10	28	3448	3448	0
11	25	11	25	3318	3310	0.24
12	26	12	22	3142	3140	0.06
13	27	13	21	2977	2970	0.23
14	27	14	21	2784	2780	0.03
15	27	14	20	2729	2723	0.03
16	27	14	21	2732	2731	0.03
17	26	14	23	2730	2732	0.07
18	25	13	28	2854	2850	0.14
19	25	13	29	3154	3152	3.07
20	25	12	31	2953	2951	0.03
21	25	12	32	2702	2700	0.03
22	20	11	33	2662	2660	0.07
23	20	10	34	2719	2715	0.14
24	20	10	35	2709	2709	0

Step 5 Training data consist of each pair of input and output based on the fuzzy logic rule. Consider the following scenario: IF the "temperature" is high, the "humidity" is high, and the "wind speed" is superior to the norm, THEN the "load" is higher than typical.

Calculate Value of the Point Forecast

A fuzzy inference system is used to implement a nonlinear mapping from the input to the output space. A sequence of fuzzy IF–THEN rules is used to map these data, each describing the mapping's local behavior. Defuzzification is utilized to derive the forecast's point estimate from fuzzy forecasts. Using Eq. (1) for the centroid of area (Z_{COA}) approach, a numerical prediction is generated responsive to all rules. Z_{COA} helps in the defuzzification technique. It is applied where the load will be divided into segmented ways for exact prediction of the load with minimum error by removing noisy data.

$$Z_{\mathrm{COA}} = \frac{\int_Z \mu_A(Z)\mathrm{d}z}{\int_Z \mu_A(Z)Z\mathrm{d}x} \tag{1}$$

where $\mu_A(Z)$ is the MFs aggregated output.

Evaluate the Rule Base's Performance

A different historical data set (test set) is used to test the forecast accuracy from the one used to obtain the rule base.

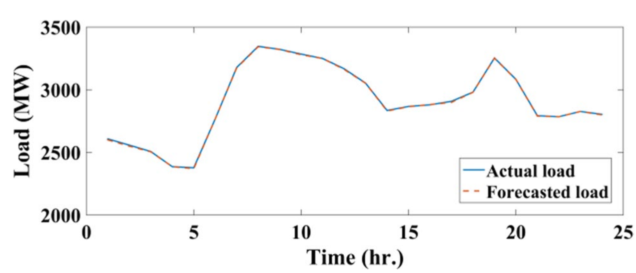

Fig. 5 Post-holiday hourly load forecast (Monday)

Table 4 Input details of 27th Nov. 2013

Time (hr.)	Temperature (°C)	Wind speed (m/s)	Humidity	Actual load (MW)	Forecasted load (MW)	MAPE
1	18	8	38	2608	2600	0.30
2	18	8	39	2558	2550	0.31
3	17	8	40	2507	2505	0.07
4	17	8	40	2386	2386	0
5	17	9	40	2377	2370	0.29
6	17	9	40	2768	2768	0
7	17	9	41	3178	3175	0.09
8	18	8	40	3347	3344	0.08
9	20	7	35	3323	3322	0.03
10	25	7	30	3285	3280	0.15
11	25	7	26	3250	3250	0
12	25	6	23	3168	3163	0.15
13	26	7	22	3053	3052	0.03
14	26	8	21	2835	2831	0.14
15	27	9	20	2867	2865	0.06
16	26	9	21	2880	2882	0.06
17	25	9	23	2908	2900	0.27
18	24	9	27	2981	2980	0.03
19	22	10	28	3254	3252	0.06
20	21	10	29	3083	3082	0.03
21	21	10	30	2793	2790	0.10
22	20	10	32	2785	2785	0
23	19	9	33	2827	2827	0
24	19	9	34	2804	2800	0.14

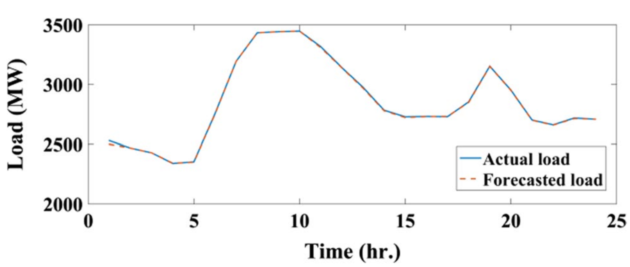

Fig. 6 A working day's hourly load forecast (Wednesday)

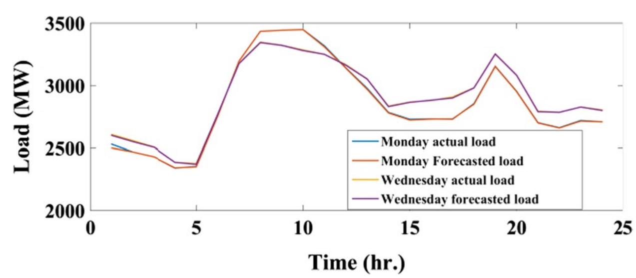

Fig. 8 Working day's hourly load forecast (Monday and Wednesday)

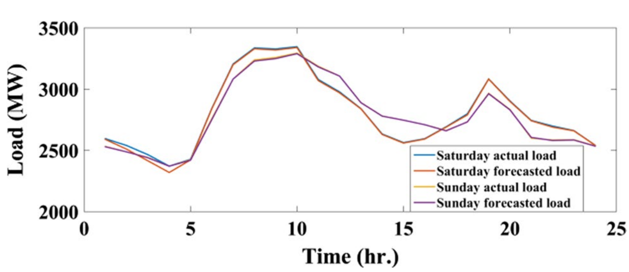

Fig. 7 Pre-holiday and holiday hourly load forecast (Saturday and Sunday)

If the shapes of the fuzzy membership functions and/or the number of fuzzy membership functions are insufficient, a new fuzzy rule base can be created. The iterative building of the rule base by selecting a mechanism of defuzzification and the performance of the evaluating system occurred systematically with different types of fuzzy memberships and/or the number of fuzzy membership functions. The test set for real-time forecasting, selected using a fuzzy rule base, has the lowest error. When the test set is large enough, the 'Train and Test method,' commonly referred to, works well. If the test set is large enough, it is expected that the observed

Table 5 Comparison of the proposed days

Period	Saturday		Sunday		Monday		Wednesday	
Time (hr.)	Actual load (MW)	Forecasted load (MW)	Actual load (MW)	Forecasted load (MW)	Actual load (MW)	Forecasted load (MW)	Actual load (MW)	Forecasted load (MW)
1	2596	2590	2532	2530	2530	2500	2608	2600
2	2540	2510	2488	2488	2468	2468	2558	2550
3	2465	2415	2442	2440	2429	2429	2507	2505
4	2372	2320	2371	2371	2340	2342	2386	2386
5	2428	2422	2424	2420	2353	2350	2377	2370
6	2844	2840	2759	2752	2756	2752	2768	2768
7	3206	3200	3083	3083	3195	3195	3178	3175
8	3337	3330	3239	3230	3434	3434	3347	3344
9	3329	3320	3259	3250	3443	3443	3323	3322
10	3347	3340	3295	3290	3448	3448	3285	3280
11	3079	3070	3187	3182	3318	3310	3250	3250
12	2978	2970	3107	3107	3142	3140	3168	3163
13	2842	2840	2891	2890	2977	2970	3053	3052
14	2634	2630	2781	2780	2784	2780	2835	2831
15	2564	2560	2747	2747	2729	2723	2867	2865
16	2596	2593	2710	2710	2732	2731	2880	2882
17	2693	2690	2662	2660	2730	2732	2908	2900
18	2799	2790	2732	2733	2854	2850	2981	2980
19	3084	3082	2966	2963	3154	3152	3254	3252
20	2904	2900	2834	2831	2953	2951	3083	3082
21	2745	2742	2600	2606	2702	2700	2793	2790
22	2699	2690	2585	2581	2662	2660	2785	2785
23	2662	2660	2587	2585	2719	2715	2827	2827
24	2543	2542	2537	2535	2709	2709	2804	2800

error rate will be close to the expected real-time forecasting error rate [25, 26].

Calculate and Update the Fuzzy Rule Database

Once an observation is made, it can be added to a fuzzy rule base as long as it does not conflict with any previously existing rules. Conflict resolution processes [27] can modify the THEN component of the rule when disagreements arise.

Analysis of Errors

Find the mean absolute percentage error (MAPE) using Eq. (2) for forecasted error between the actual and forecasted loads.

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|\text{Actual load} - \text{Forecasted load}|}{\text{Actual load}} \times 100 \tag{2}$$

where N = forecasted values.

Figure 2 explains the work of fuzzy logic for STLF, which predicts the exact load 24 h ahead followed each step.

Assumption

In this study, Sugeno fuzzy inference model is used with IMF1for STLF, where the output membership function is linear and the number of the fuzzy rule is 01. Also assumed that future trends will hold similar to historical trends.

Table 6 Performance of Saturday and Sunday

Period	Saturday			Sunday		
Time (hr.)	Actual load (MW)	Forecasted load (MW)	MAPE	Actual load (MW)	Forecasted load (MW)	MAPE
1	2596	2590	0.23	2532	2530	0.07
2	2540	2510	1.18	2488	2488	0.00
3	2465	2415	2.02	2442	2440	0.08
4	2372	2320	2.19	2371	2371	0.00
5	2428	2422	0.24	2424	2420	0.16
6	2844	2840	0.14	2759	2752	0.25
7	3206	3200	0.18	3083	3083	0
8	3337	3330	0.20	3239	3230	0.27
9	3329	3320	0.27	3259	3250	0.27
10	3347	3340	0.20	3295	3290	0.15
11	3079	3070	0.29	3187	3182	0.15
12	2978	2970	0.26	3107	3107	0
13	2842	2840	0.07	2891	2890	0.03
14	2634	2630	0.15	2781	2780	0.03
15	2564	2560	0.15	2747	2747	0
16	2596	2593	0.11	2710	2710	0
17	2693	2690	0.11	2662	2660	0.07
18	2799	2790	0.32	2732	2733	0.07
19	3084	3082	0.06	2966	2963	0.10
20	2904	2900	0.13	2834	2831	0.10
21	2745	2742	0.10	2600	2606	0.23
22	2699	2690	0.33	2585	2581	0.15
23	2662	2660	0.07	2587	2585	0.07
24	2543	2542	0.03	2537	2535	0.07

Numerical Outcomes

For training and load forecasting, the data from the Jaipur Vidyut Nigam for various day types are used, which shows the performance of the fuzzy logic methodology used for a load forecasting system. The real-time data are collected from the Rajasthan Vidyut Parasaran Nigam, Jaipur (JVN), which consists of a State Load Dispatch and Communication and the weather data such as temperature, wind speed, humidity, and humidity historical hourly load demand over a week are considered as real-time data. In this paper, 03 triangle membership functions are used. IMF1 is used to improve the accuracy of load forecasting because IMF1 achieved the highest level of categorization accuracy, and when the levels of the IMFs rise after that, performance falls. Compared to higher-order IMFs, lower level IMFs have more frequency components and faster oscillations. This analytical characteristic facilitates the analysis of non-stationary signals for load prediction.

Figure 3 explains the comparison of the actual load and forecasted load for Saturday, 23rd November 2013. The average percentage inaccuracy is calculated by comparing projected and actual loads. There are four circumstances mentioned in this essay.

- Pre-holiday hourly load forecast (Saturday)
- Holiday hourly load forecast (Sunday)
- Post-holiday hourly load forecast (Monday)
- Working day hourly load forecast (Wednesday)

Figure 4 compares the actual and forecasted loads for Sunday, 24th November 2013.Table 1 explains the predicted load and error of Saturday in 2013 for 23rd November with the effect of temperature, wind speed and humidity [28, 29].

Table 2 explains the predicted load and error of Sunday in 2013 for the 24th of November with the effect of temperature, wind speed and humidity [19, 20]. In Table 2, the forecasted load is 2530 MW because

Table 7 Performance of Monday & Wednesday

Period	Monday			Wednesday		
Time (hr.)	Actual load (MW)	Forecasted load (MW)	MAPE	Actual load (MW)	Forecasted load (MW)	MAPE
1	2530	2500	1.18	2608	2600	0.30
2	2468	2468	0	2558	2550	0.31
3	2429	2429	0	2507	2505	0.07
4	2340	2342	0.08	2386	2386	0
5	2353	2350	0.12	2377	2370	0.29
6	2756	2752	0.14	2768	2768	0
7	3195	3195	0	3178	3175	0.09
8	3434	3434	0	3347	3344	0.08
9	3443	3443	0	3323	3322	0.03
10	3448	3448	0	3285	3280	0.15
11	3318	3310	0.24	3250	3250	0
12	3142	3140	0.06	3168	3163	0.15
13	2977	2970	0.23	3053	3052	0.03
14	2784	2780	0.03	2835	2831	0.14
15	2729	2723	0.03	2867	2865	0.06
16	2732	2731	0.03	2880	2882	0.06
17	2730	2732	0.07	2908	2900	0.27
18	2854	2850	0.14	2981	2980	0.03
19	3154	3152	3.07	3254	3252	0.06
20	2953	2951	0.03	3083	3082	0.03
21	2702	2700	0.03	2793	2790	0.10
22	2662	2660	0.07	2785	2785	0
23	2719	2715	0.14	2827	2827	0
24	2709	2709	0	2804	2800	0.14

Step-1 The EMD divided the initial load data signal (24th Nov. 2013) into three separate IMFs and one residual.

Step-2 The suggested approach Sugeno fuzzy inference model is used to forecast the component signals (IMFs).

Step-3 One output node in the overall prediction model adds all of its inputs and displays the forecasted average value of the load. So in Table 2, the forecasted load is 2530 MW.

Table 3 explains the predicted load and error of Monday in 2013 for 25th November with the effect of temperature, wind speed and humidity [28, 29].

Figure 5 compares the actual and forecasted loads for Monday on 25th November 2013.

Table 4 explains the predicted load and error of Wednesday in 2013 for 27th November with the effect of temperature, wind speed and humidity [19, 20].

Figure 6 compares the actual and forecasted loads for Saturday 27th November 2013.

Figure 7 compares the actual and forecasted loads for Saturday and Sunday in STLF.

Figure 8 compares the actual and forecasted loads for Monday and Wednesday in STLF.

Table 5 explains the work of Saturday, Sunday, Monday and Wednesday, which affect the STLF for predicting the load 24 h.

Table 6 explains the work of Saturday and Sunday with errors that affect the STLF to predict the load 24 h ahead. Table 7 presents the work of Monday and Wednesday with errors affecting the STLF for predicting the load 24 h ahead. Table 8 explains the errors of different days that affect the STLF for predicting the load 24 h. Table 9 presents the work of comparison where the proposed work gives better output for the STLF with the effect of temperature, wind speed and humidity.

Table 8 Day-wise performance

Period Time (hr.)	Saturday MAPE	Sunday MAPE	Monday MAPE	Wednesday MAPE
1	0.23	0.07	1.18	0.30
2	1.18	0.00	0	0.31
3	2.02	0.08	0	0.07
4	2.19	0.00	0.08	0
5	0.24	0.16	0.12	0.29
6	0.14	0.25	0.14	0
7	0.18	0	0	0.09
8	0.20	0.27	0	0.08
9	0.27	0.27	0	0.03
10	0.20	0.15	0	0.15
11	0.29	0.15	0.24	0
12	0.26	0	0.06	0.15
13	0.07	0.03	0.23	0.03
14	0.15	0.03	0.03	0.14
15	0.15	0	0.03	0.06
16	0.11	0	0.03	0.06
17	0.11	0.07	0.07	0.27
18	0.32	0.07	0.14	0.03
19	0.06	0.10	3.07	0.06
20	0.13	0.10	0.03	0.03
21	0.10	0.23	0.03	0.10
22	0.33	0.15	0.07	0
23	0.07	0.07	0.14	0
24	0.03	0.07	0	0.14

Table 9 Comparison of the error with existing work

Work	MAPE			
	Saturday	Sunday	Monday	Wednesday
Proposed work	0.37	0.09	0.24	0.09
Existing work	10.55	9.05	10.05	11.74

Conclusion

For unit commitment, generating economic allocation and security analysis, the STLF is a helpful tool. So in the PS, accurate load forecasting is essential for minimizing forecasting error. Forecasting errors may significantly impact the economy of operations and power system control. The fuzzy logic method to STLF implementation, which gives a logical set of easily flexible rules that the operator quickly understands, could be a good fit. The MAPE between the actual and anticipated values, determined for four scenarios using three triangular membership functions, is used to examine its forecasting reliabilities. The MAPE for pre-holiday (Saturday), holiday (Sunday), post-holiday, and working day is 0.37%, 0.24%, 0.09%, and 0.09%, respectively. The MAPE in the load calculation is reduced if a proper and extensive training data set is used for fuzzy logic model training. The MAPE can be lowered by adopting the trapezoidal, Gaussian bell membership function and increasing the number of membership functions. Expert Systems and Support Vector Machines are examples of artificial intelligence approaches that can be used to lower the MAPE. It will help in contingency analysis and load shedding, and by including a factor that penalizes model complexity, the regularization technique reduces the modified cost function. The complexity of the model is determined by the load curve, which is obtained from the second derivative of output. This model can be used to forecast the load utilizing renewable energy sources.

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Declarations

Conflict of interest There is no conflict of interest.

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