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Short Term Weather -Dependent Load Forecasting using Fuzzy Logic Technique

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Abstract

Electric load forecasting has become a very decisive in power system studies for its systematic functioning. Precise short term load forecasting aids the electric utilities for the determination regarding unit commitment, reducing spinning reserve capacity, maintenance schedules and other optimal energy exchange plans properly. Conventional methods suffer from the problem of complexity of the estimation procedure and substantial database support requirements. In this paper, a feasibility study of the implementation of fuzzy logic model for short term load forecasting is carried out. The proposed methodology uses fuzzy reasoning decision rules that capture the nonlinear relationships between inputs and outputs. The input data includes historical load (hourly & daily), physical variables hourly data like temperature, humidity and wind speed. The proposed fuzzy based logical model has been used to estimate the daily peak load forecasts over one week period comprising four working days and two days of weekend. The model is tested with two different set of membership functions namely triangular and trapezoidal with different amounts of function overlapping on the actual data obtained from the state load dispatch centre. Test results for daily peak load forecasts based on historical data indicate that the generated forecasts is quite similar in accuracy to more complicated methods and a mean absolute percentage error less than 3% is reported.

Keywords: Short term load forecasting, fuzzy logic, membership function

Introduction

Electric Short term Load forecasting is functional tool for electric utilities in several applications incorporate security analysis, unit commitment, economic allocation of generation, optimal energy interchange between utilities and maintenance scheduling. Any rectification in the validity of load forecasts can results in significant financial savings for utilities and co-generators.

Various load forecasting approaches have been proposed in the last few decades. Those models include: time series [1,2], multiple linear regression [3,4] and expert system (ES) [5]. The time series model uses the historical load data for the forcast of loads. It is a non-weather sensitive approach with the assumption that the load is a stationary time series and has normal distribution characteristics. The historical load data does not support this condition, which results in low accuracy in forecasting the load. The estimation of the order of the polynomial in this model is specifically dependent upon the experience of the expert. This gives rise to the difficulties in application. Consumer habits and weather behaviour regression models derive linear models for the system load. The main principle behind regression is to use the common link between everything included in the model in order to anticipate the relative change in one item or variable according to changes in another item or variable. This approach is applied to short-term weather forecasting using weather data, such as temperature, humidity etc., to establish multiple variable values for the linear regression models between itself and the load. The expert system method is a rule-based approach for load forecasting, using the logic of a power system operator to evolve mathematical equations for forecasting. The main disadvantage of these methods is knowledge acquisition, i.e. experts habitually have difficulty in expressing their knowledge in the required qualitative terms.

Fuzzy logic models have been proposed as an alternative forecasting method [6,7]. Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a truth value of “0” or “1”.

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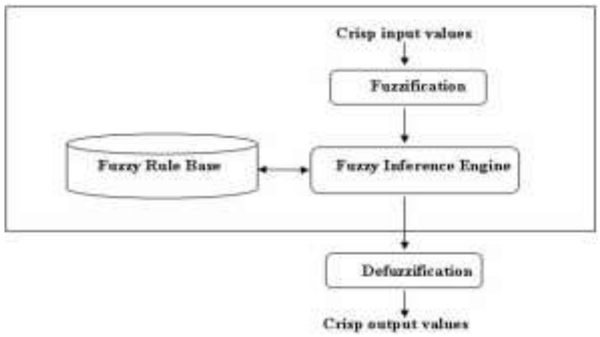

Figure 1. Basic Configuration of Fuzzy System

The mathematical complexity, while designed to capture the nonlinear relationships between inputs (past load, past and predicted temperature) and outputs (predicted load), does not offer the user an instinctive understanding. If these mathematical relationships could be reduced to a logic table, such as a set of IF-THEN statements (e.g. IF temperature is high, THEN load demand is high), then there is the possibility that the user would gain confidence in the model and therefore use it to generate, or assist in generating, the system forecasts.

Description of Fuzzy Logic Model

For Short term load forecasting, the proposed fuzzy logic based algorithm consists of four stages

(a) Design of fuzzy rule base

Based on the methodology proposed by Wang and Kosko[6,8] is used here. The approach consists of five steps as described below:

Step 1. Compile a provisional list of input and output variables using statistical analysis, engineering judgments and/or operator experience. There are four input variables which are used to forecast electric load as an output are:

- Temperature
- Humidity
- Wind speed
- Time

Step 2. Normalization of the input and output variables is defined as a graph that defines how each point in the input space is mapped to the membership value [0,1].

Step 3. Select the shape of the fuzzy membership for each variable; namely the triangular, trapezoidal and bell shape membership function. The membership function is selected by trial and error method.

Step 4. For each input and output variable, tentatively define the number of fuzzy membership functions. For example, all variables represents three functions. The lengths of the regions under the functions for a given variable need not be equal, nor must the number of functions for all variables be equal.

Temperature data is fuzzified into three main fuzzy sets described as: cold, normal and hot

Humidity data is fuzzified into three main fuzzy sets described as: dry, humid and very humid

Wind speed data is fuzzified into three main fuzzy sets described as: below normal, normal and above normal

Time data is fuzzified into three main fuzzy sets described as: morning, mid-day and night

Step 5. Construct the fuzzy rule from each pair of input-output data, also called training data[6,9]. For example: IF 'temperature' is hot and 'humidity' is humid and 'wind speed' is above average THEN 'load' is above average.

(b) Compute the point forecast value

A fuzzy inference system implements a nonlinear mapping from its input space to output space. This mapping is accomplished by a number fuzzy if-then rule, each of which describes the local behavior of the mapping.

Defuzzification is performed to dictate the point estimate of the forecast from the fuzzy forecasts. Centroid of area method approach produces a numerical forecast sensitive to all the rules.

Centroid of area $Z_{COA} = \frac{\int_Z \mu_A(Z) dZ}{\int_Z \mu_A(Z)\, Z\, dx}$

where, $\mu_A(z)$ is the aggregated output MF.

(c) Test the performance of the rule base

Forecast accuracy is tested using a different set of historical data set (test set) from the one used to obtain the rule base. If it is unsatisfactory, then the number of fuzzy membership functions and/or shape of the fuzzy membership functions can be changed and a new fuzzy rule base is obtained. The iterative process of designing the rule base, choosing a defuzzification algorithm, and testing the system performance may be repeated several times with a different number of fuzzy membership functions and/or different shapes of fuzzy memberships. The fuzzy rule base that provides the minimum error measure for the test set is selected for real time forecasting. The above method, known as 'Train and Test method', works very well when the size of the test set is sufficiently large. It is assumed (as in all modeling of systems based on historical data) that, if the test set is sufficiently large, then the observed test set error rate will be close to the anticipated real-time forecasting error rate [10].

I. **(d) Evaluate and update the fuzzy rule base**

The new rule designed from the new observation does not conflict with any rules already in

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the rule base, then the new rule can be immediately added to the fuzzy rule base. When there is a conflict, the THEN part associated with the rule may be modified based on the conflict resolution methods described above [10].

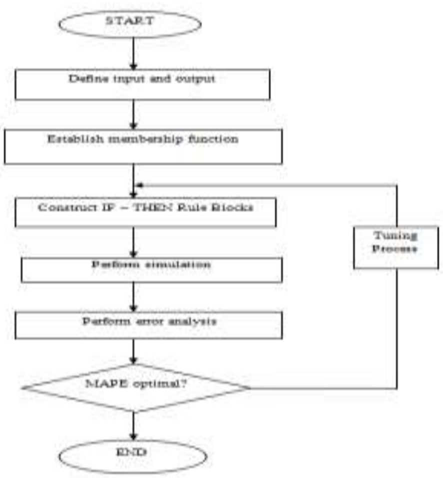

Figure 2. Process Flowchart of Modeling using fuzzy logic

Numerical Results

The performance of a load forecasting system based on this fuzzy logic methodology is demonstrated using data from Jodhpur Vidyut Nigam for different day types is used for training and load forecasting. JVN data is the complete load / demand taken from State Load Dispatch and Communication Center, Rajasthan Vidyut Parasaran Nigam. The forecasted load is compared with the actual load and percentage error is also calculated. Forecasted weather data and day type for the days for which the load is to be forecasted is used for classification. In this study, we used the load data from 14 November 2011 to 20 November 2011 of Jodhpur.

The following four cases are investigated to validate the proposed methodology. In these cases, experiments were conducted using the rules and the results for the fuzzy forecasted load are compared between triangular type and trapezoidal type membership function with the change in the number of membership function.

Case 1- LF for post holiday i.e. Monday
Case 2- LF for working day i.e. Tuesday
Case 3- LF for pre-holiday i.e. Saturday
Case 4- LF for holiday i.e. Sunday

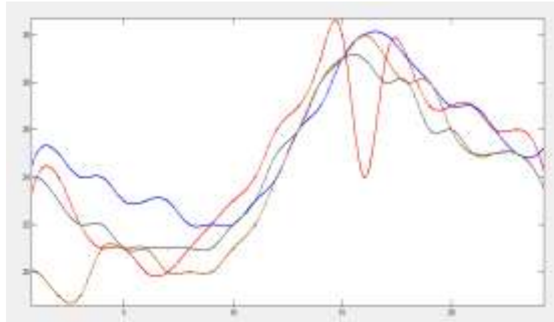

Fig. 3(a): Hourly data for four days

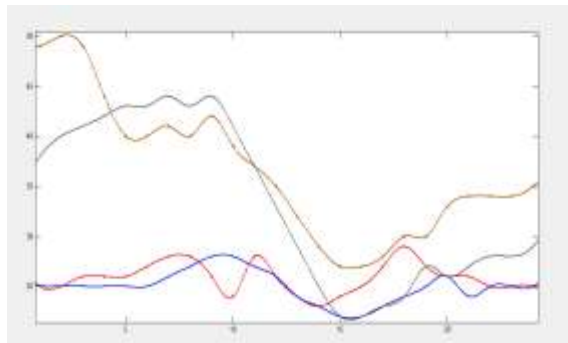

Fig. 3(b): Hourly temperature data

Hourly temperature (^{0}C) data for four days is marked as:
Red bar- hourly temperature data for case 1
Blue bar- hourly temperature data for case 2
Brown bar- hourly temperature data for case 3
Black bar- hourly temperature data for case 4

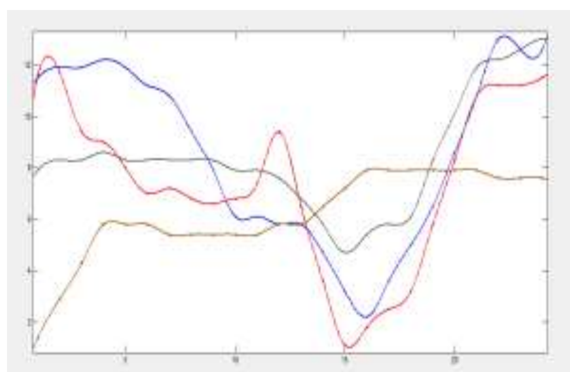

Fig. 3(c): Hourly Humidity data

The hourly humidity data for four cases given above.
Red bar- hourly humidity (%) data for case 1
Blue bar- hourly humidity (%) data for case 2
Brown bar- hourly humidity (%) data for case 3
Black bar- hourly humidity (%) data for case 4

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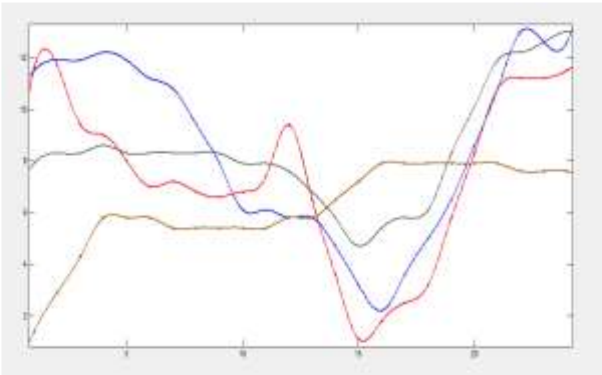

Fig 3(d): Hourly Wind speed data

The hourly wind speed data for four cases given above.

Red bar- hourly wind speed (km/h) data for case 1
Blue bar- hourly wind speed (km/h) data for case 2
Brown bar- hourly wind speed (km/h) data for case 3
Black bar- hourly wind speed (km/h) data for case 4

Results

The fuzzy rule base generated for peak load forecasting for the day of Monday when all the four input variables are divided into three fuzzy regions (k=3), is given below:-

IF t is norm AND h is humid AND ws is fast AND tm is morning THEN load is abv-avg
IF t is norm AND h is humid AND ws is fast AND tm is morning THEN load is bel-avg
IF t is norm AND h is humid AND ws is avg AND tm is morning THEN load is bel-avg
IF t is norm AND h is humid AND ws is avg AND tm is morning THEN load is avg
IF t is cold AND h is humid AND ws is avg AND tm is
morning THEN load is avg
IF t is norm AND h is wet AND ws is avg AND tm is mid-day THEN load is avg
IF t is norm AND h is humid AND ws is avg AND tm is mid-day THEN load is avg
IF t is norm AND h is humid AND ws is slow AND tm is morning THEN load is avg
IF t is norm AND h is dry AND ws is avg AND tm is mid-day THEN load is abv-avg
And so on…

As each input variable is divided into three regions, the number of possible fuzzy rules is 64 (4^3).

Case -1:

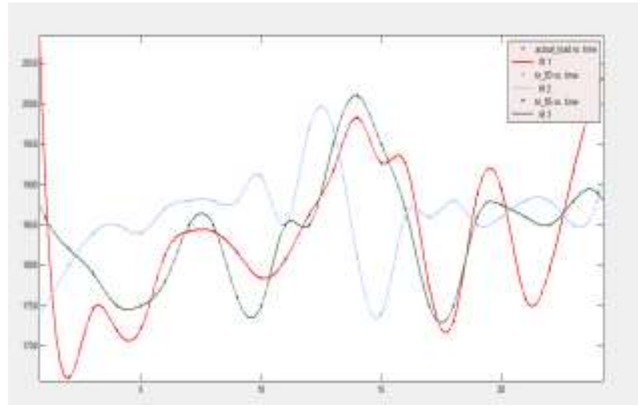

Fig 4(a): Comparison between Actual and Forecasted Loads (using triangular membership function with K=3 and 5) for Monday

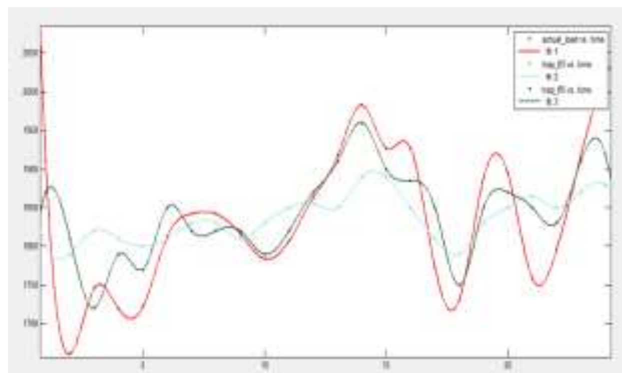

Fig. 4(b): Comparison between Actual and Forecasted Loads (using trapezoidal membership function with K=3 and 5) for Monday

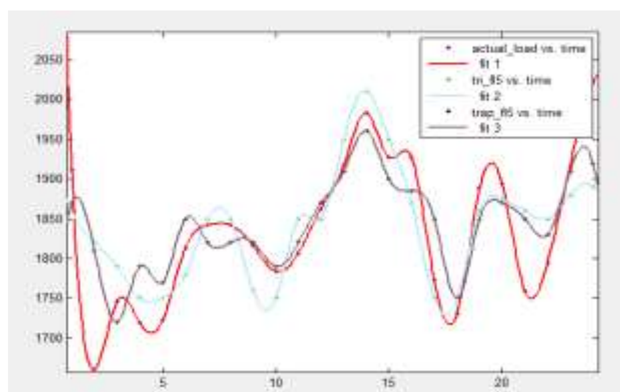

Fig. 4(c): Comparison between Actual and Forecasted Loads (using triangular and trapezoidal membership function with K= 5) for Monday

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Case -2

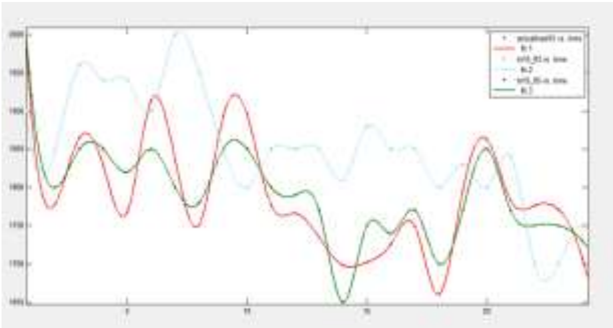

Fig.5(a): Comparison between Actual and Forecasted Loads (using triangular membership function with K=3 and 5) for Tuesday

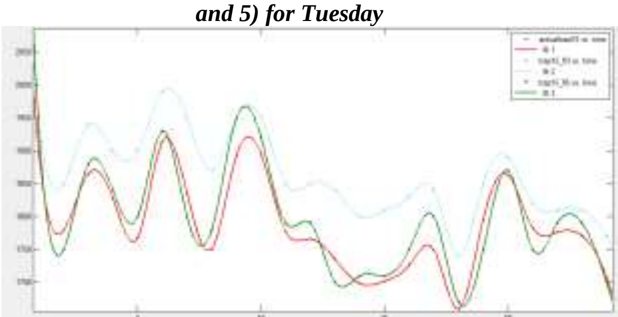

Fig.5(b): Comparison between Actual and Forecasted Loads (using trapezoidal membership function with K=3 and 5) for Tuesday

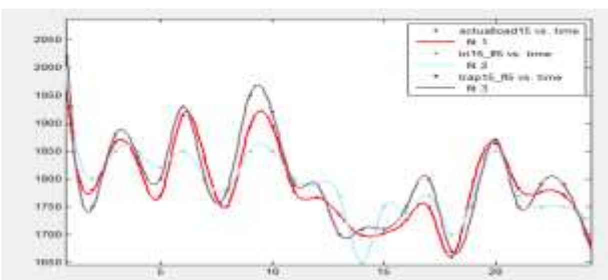

Fig. 5(c): Comparison between Actual and Forecasted Loads (using triangular and trapezoidal membership function with K= 5) for Monday

Case -3

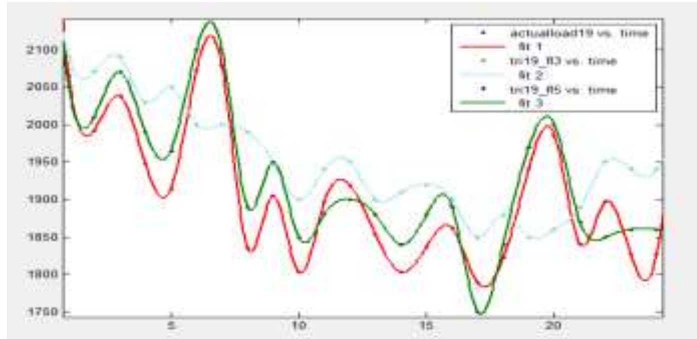

Fig. 6(a): Comparison between Actual and Forecasted Loads (using triangular membership function with K=3 and 5) for Saturday

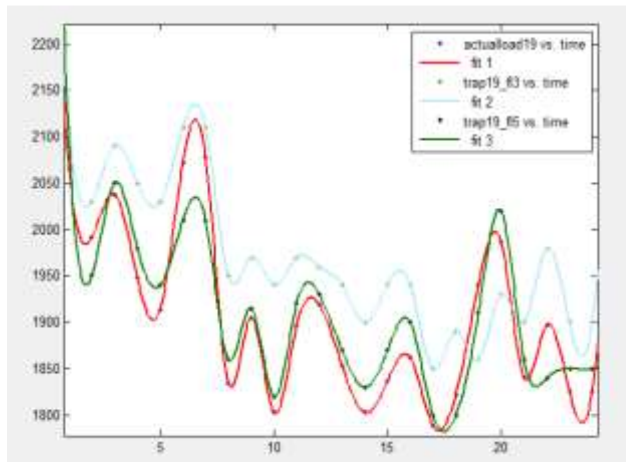

Fig. 6(b): Comparison between Actual and Forecasted Loads (using trapezoidal membership function with K=3 and 5) for Saturday

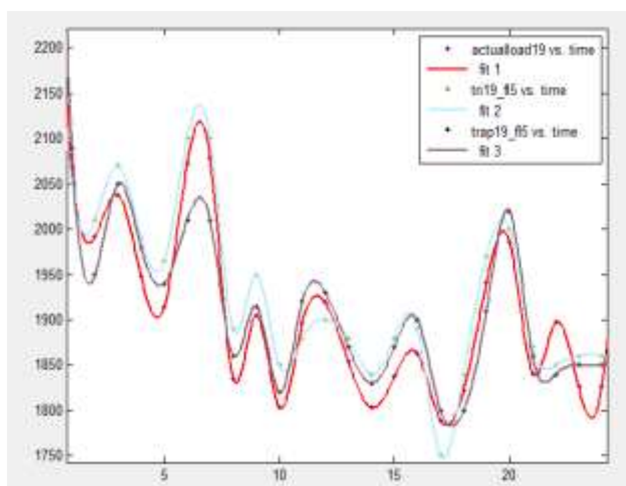

Fig. 6(c): Comparison between Actual and Forecasted Loads (using triangular and trapezoidal membership function with K= 5) for Saturday

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Case -4

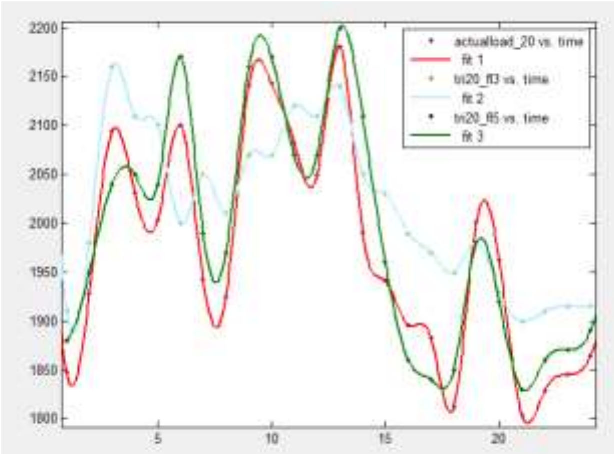

Fig. 7(a): Comparison between Actual and Forecasted Loads (using triangular membership function with K=3 and 5)for Sunday

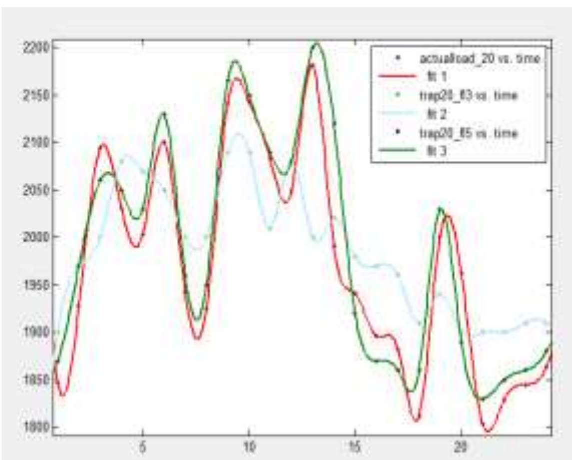

Fig. 7(b): Comparison between Actual and Forecasted Loads (using trapezoidal membership function with K=3 and 5) for Sunday

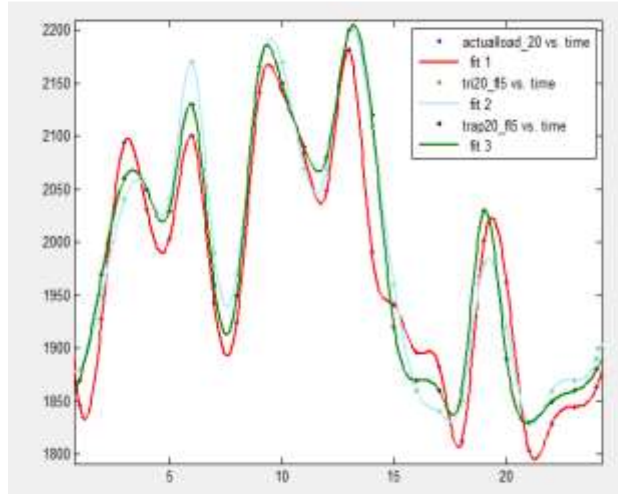

Fig. 7(c): Comparison between Actual and Forecasted Loads (using triangular and trapezoidal membership function with K= 5) for Sunday

Accuracy of Forecasts

To ensure the system accuracy, the relative error between the forecasted load and the real load consumption are obtained on daily basis. A positive value of error will indicate an over forecast, means that the forecasted load is larger than the actual load. In contrast, a negative value indicates under forecast, where the forecasted load value is less than the actual value [20].

Absolute Percentage Error (APE)

$$= \frac{Forecasted\ Load - Actual\ Load}{Actual\ Load} * 100$$

The mean absolute percentage error (MAPE) is the average of APE.
The accuracy of the results for peak load obtained in calculated and tabulated given in table 1.

Case	Actual Peak Load(MW)	Forecasted Peak Load(MW)	Absolute Percentage Error(%)
1	2020	1920	5.20
2	1914	1930	.830
3	2078	2010	3.38
4	2181	2200	.863

Table1: Comparison based on APE Calculations for K=5 and trapezoidal(M.F)

Case	MAPE(triangular M.F)		MAPE(trapezoidal M.F)	
	K=3	K=5	K=3	K=5
1	5.22	2.39	3.25	2.25
2	4.98	1.71	4.09	1.65
3	3.92	1.68	3.76	1.50
4	3.62	1.78	3.23	1.53

Table 2: Comparison based on MAPE

Conclusions

STLF is a very useful tool for security analysis, unit commitment, and economic allocation of generation. Therefore, the accurate forecasting of the load is an essential element in power system. Economy of operations and control of power systems may be quite sensitive to forecasting errors. Both positive and negative forecasting errors resulted in increased operating costs.

Based on this APE, it is concluded that fuzzy approach Trapezoidal MF with K = 5 is more effective and gives a better forecast accuracy. Because each hour is represented by a different fuzzy rule base, the fuzzy rule bases for different hours can be obtained using the optimum K value for the appropriate day.

It involves no mathematical complexity. It offers a logical set of rules, readily adaptable and understandable by an operator, may be a very good solution to the implementation and usage problem.

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