A Fuzzy-Based Approach for Short Term Load Forecasting

Papia Ray and K. R. Satyajit

Abstract This paper proposes the development of a unique method of load forecasting. An essential factor in planning for developing counties in today's world is Load Forecasting (LF). In developing countries, a vast amount of power loss occurs in the generation, transmission and distribution, which is due to unpredictable load forecasting on a day-to-day basis. So, predicting accurate load forecasting has become a significant part of dropping the generation cost and optimizing the spinning reserve capability. The LF is done for managing power system energy. Earlier, many methods, Regression and Time Series, were used to forecast Load, but nowadays, intelligent methods like Fuzzy Logic (FL) are in practice, giving better forecasting accuracy. Here the presented technique for Load forecasting is FL using Mamdani Implication. From the simulation results, it has been noticed that the proposed FL-based load forecasting gives minor errors. Further, MATLAB and Simulink, Fuzzy Logic Toolbox and triangular membership function are used to obtain the forecasted load.

Keywords Load forecasting · Fuzzy logic · Actual percentage error (APE) · Mean absolute percentage error (MAPE) · Membership function

1 Introduction

Transmission of reliable power to customers is the prime duty of any utility. Consumer load demand in electric distribution systems varies because of person-to-person activities that follow daily cycles. During daylight, especially in the afternoon, the load demand is generally high due to industries and lighting. On the contrary, the demand is lesser in the evening and early morning. Load forecasting (LF) is like weather forecasting, as weather experts tell us about the weather conditions in the upcoming future [1]. Load forecasting allows the future estimation of load conditions, and power system planning can be done in the future. The energy requirement of the

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K. Namrata et al. (eds.), *Smart Energy and Advancement in Power Technologies*, Lecture Notes in Electrical Engineering 927,
https://doi.org/10.1007/978-981-19-4975-3_9

clients varies each minute because of human activities that are not the same all day [2]. Thus, a significant priority for estimation of load demand is required in the future, and LF, therefore, plays a vital part in scheduling, operation and control of electrical power systems [3]. It approximates the variable(s) of the forecasted value at a future point in time. This paper mainly focuses on FL-based short term load forecasting (STLF) [4].

1.1 Literature Review

Balancing a power system is mostly done a day ahead of forecasted values given on the side of demand [5]. In nature, several types of loads make the performance highly nonlinear, which is quite dissimilar from the nonlinearity of the power system; then comes the fault due to which the system increases the price [6]. The methods used are based on regression analysis, time analysis, artificial neural network (ANN), similar day method, fuzzy logic, etc. [7]. Neutral Networks is a prolonged convergence period and a poor capability to process a large amount of variable quantity at a time; on the other side, Fuzzy logic provides a medium for representing and processing data in linguistic standings that makes the systems easily understandable [8–10]. The fuzzy forecasting method has widely been considered for forecasting dynamic and nonlinear type data in the last decade [11, 12]. In [13]. use Mamdani implication to attempt fuzzy logic for STLF. The basic rule of Fuzzy is prepared based on time, temperature and similar previous day load. Forecasts focus on minimization of the error among the actual and forecasted values [14]. A fuzzy-based STLF method that uses Gaussian membership function, If–Then rules and fuzzy logic process and further reduces the forecasted error and the processing time [15]. A methodology on STLF contains functioning mechanisms under the different regimes of power segment in India [16]. It also demonstrates the effects of load and temperature on generation, transmission and distribution. Here load forecasting is processed by using the function of triangular membership. Also, weather parameters such as temperature can be used to predict the consumption of energy based on week/special days with a support vector machine and generic neural regression network [17].

From the above literature survey, it is concluded that LF plays a significant role in the economic operation of a power system. The conventional methods used for STLF are Multiple Linear Regression (MLR) and Time Series (TS). The significant disadvantages of the MLR method are that this model is susceptible to temperature fluctuations. It needs a very accurate temperature forecast, as a minute variation in temperature leads to a significant change in load prediction and that of the TS method is it is difficult to use and is time-consuming. This encourages the author to implement an intelligent scheme like FL, which is more effective and faster than the abovementioned schemes.

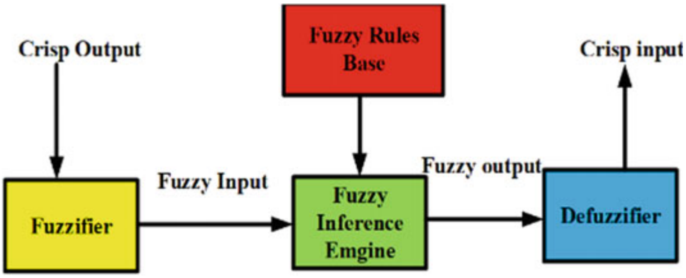


Fig. 1 Fuzzy logic configuration

2 Short-Term Load Forecasting (STLF)

The STLF is an integrated planning sector. Nowadays, demand-scheduling for several energy divisions like generation, transmission and distribution is required for designing a time-ahead power system, and STLF plays a significant role in that. It helps operators know about power systems with several decisions, including planning, generation reserve, system security, scheduling, demand side management, financial planning, and so forth. While it is essential for the time-ahead power system operation, inaccurate demand forecasting will cost the effectiveness of a spectacular financial loss.

2.1 Block Diagram and Flow Chart of the Proposed Scheme

For STLF, mathematical modelling is used for FL. The FL is multi-valued logic where the estimation of data is done according to Boolean logic (yes or no and true or false). The FL approach is one of the generalizations of Boolean logic. This logic is implemented for load forecasting weather data like temperature and humidity as the input and load as the output data. Figure 1 represents the configuration of the FL, which is implemented here. The block diagram in Fig. 2 presents an overview of FL methodology. Figure 3 presents the proposed intelligent scheme algorithm which depicts the stepwise implementation of the proposed work.

3 Model Description of Fuzzy Logic

3.1 Base Design

Make a note of the variable quantity of input and output by using arithmetical analysis with another user. This paper consists of 2 input and 1 output variable. Each variable

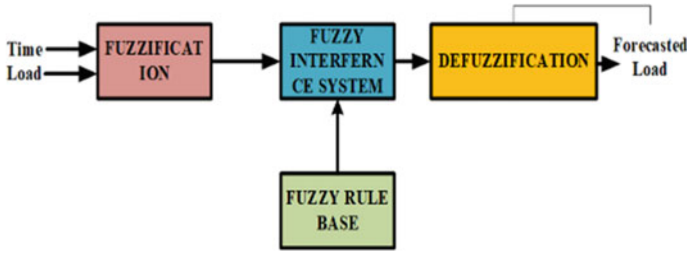


Fig. 2 Block diagram of fuzzy logic

is taken by resolving for membership value [0, 1]. After determining each variable, the input and output variable, the shape of fuzzy membership is selected and its shape can be triangular, trapezoidal, Gaussian or ballcapped. For all single variables, fuzzy membership functions are well-defined. The provided variables should not remain equal, but it is ensured that the variable must equal the number of functions. Next, the data needs to be trained in a fuzzy model. Couples of data is referred to as training sample and it is further said that if the time is midnight and the load is average, then the load is high.

3.2 *Compute the Forecast Value*

A nonlinear mapping is done by fuzzy if–Then rule implements a fuzzy inference system starting from input to output space. The centroid of the area of a numerical forecast is expressed as

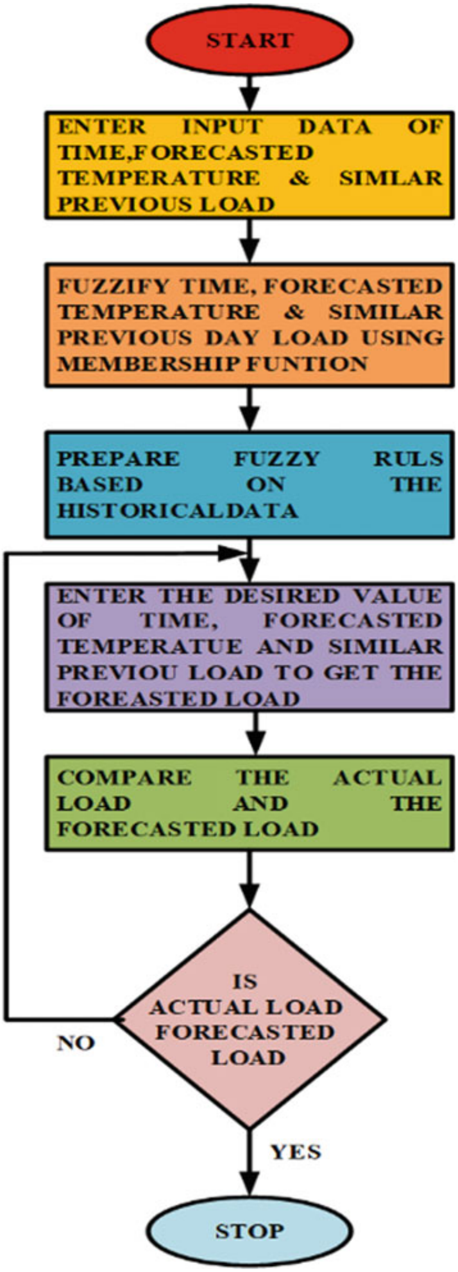
$$\text{Centroid of area, } \mathrm{M_{coa}} = \frac{\int z\mu_A(z)\mathrm{dz}}{\int z\mu_A(z)\mathrm{zdz}} \tag{1}$$

whereas membership function '*M*' that defines the fuzzy set *A* is μ, on the universe *Z*.

3.3 *Test Performance*

For obtaining the accurateness of the STLF, it is verified by using old data. If it becomes improper, the shape of the membership function of fuzzy is changed, and a new rule base is formed. The testing system and membership function shapes are tested for several periods until the correct rule base system is developed. In the "train and set" method, the lowest error is measured for forecasting, which is very useful for large data sets.

Fig. 3 Flow chart of the proposed intelligent scheme



3.4 Error Analysis

To decrease the error in the system, STLF is done.

$$\text{APE} = \left(\frac{\text{actual load - forecasted load}}{\text{forecasted load}}\right) * 100 \tag{2}$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\text{actual load}(i)\text{ - forecasted load}(i)}{\text{forecasted load}(i)}\right) \tag{3}$$

4 Modelling of FL for STLF

4.1 Fuzzification

Fuzzification can be defined as a procedure in which crisp values change the degree of membership related to the fuzzy set shown in Figs. 4, 5 and 6. The time which is divided into 6 sets of fuzzy are Midnight, Morning, Forenoon, Afternoon, Evening and Night.

4.2 Rule Base

The fuzzy rule base is considered an essential part of the fuzzy system. In this, If–then rule is used for getting the load forecasted output, some of which are mentioned below and shown in Figs. 7 and 8 as.

5 Results and Discussion

Fuzzy logic simulated for STLF is shown in Fig. 9. MATLAB software is used for simulation work. From the workshop file, actual load data and input data are taken and then simulated. The simulated diagram is shown in Fig. 9. The input data is given to the controller of fuzzy logic, block. “fis” of the fuzzy interference system is put in the fuzzy logic controller block. The controller block of fuzzy logic is prepared with the fuzzy rules, which gives the forecasted output as shown in Fig. 10.

It can be observed from Fig. 11 that the actual and forecasted load is almost identical, and significantly with less error.

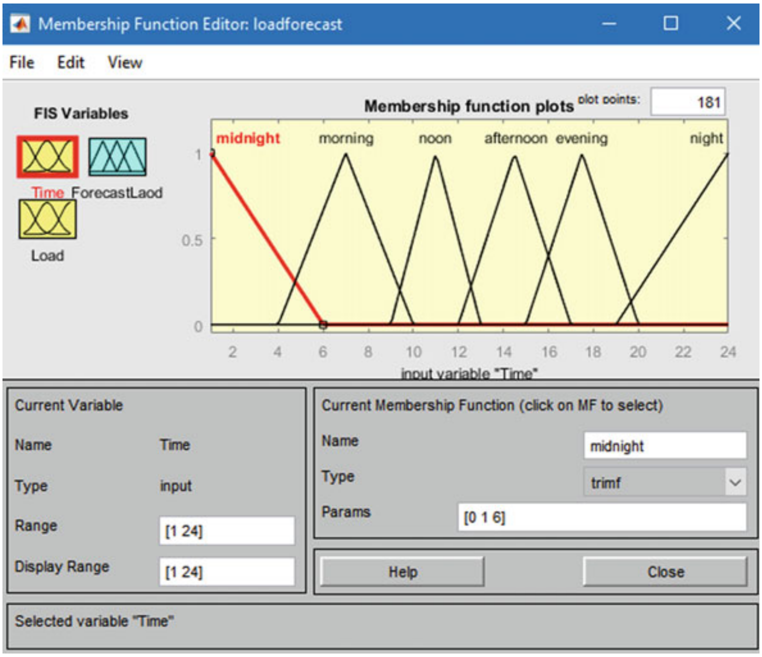


Fig. 4 Time membership function

From Table 1, it is concluded that the mean error found from the result obtained from the fuzzy logic is **1.60%** and the actual error range is between −2.63% to + 3.11%.

It is observed from Table 2 that the proposed method gives much less error as compared to other researchers' work. So, FL-based STLF is recommended.

6 Conclusion

In this report, the STLF methodology is discussed by using FL. For safety analysis of generation, STLF is a very useful tool. It has been observed that by using input data and by making a rule base, the load forecasting is predicted precisely and its margin error is between + 3.11% and −2.63%, and MAPE is 1.60%, which is relatively minor. Further, during simulation, it has been observed that the fuzzy logic toolbox is easy to understand because it works on the If–Then rule and the error can be reduced if the data is large and by using many memberships function.

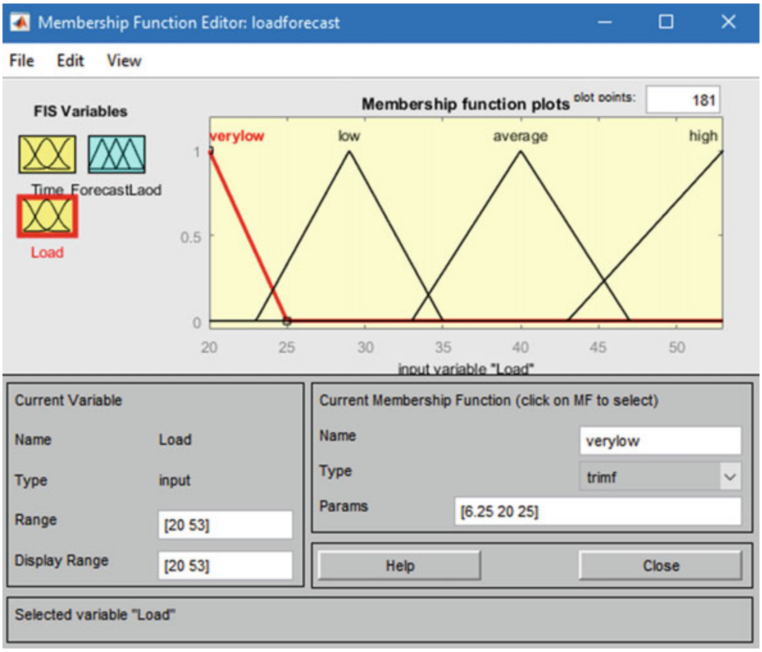


Fig. 5 Load membership functions

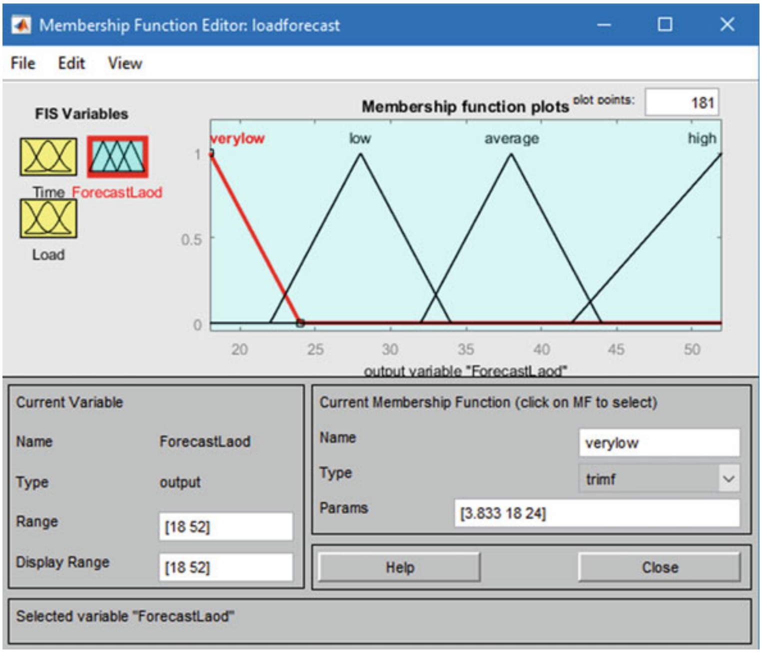


Fig. 6 Membership functions of forecasted load

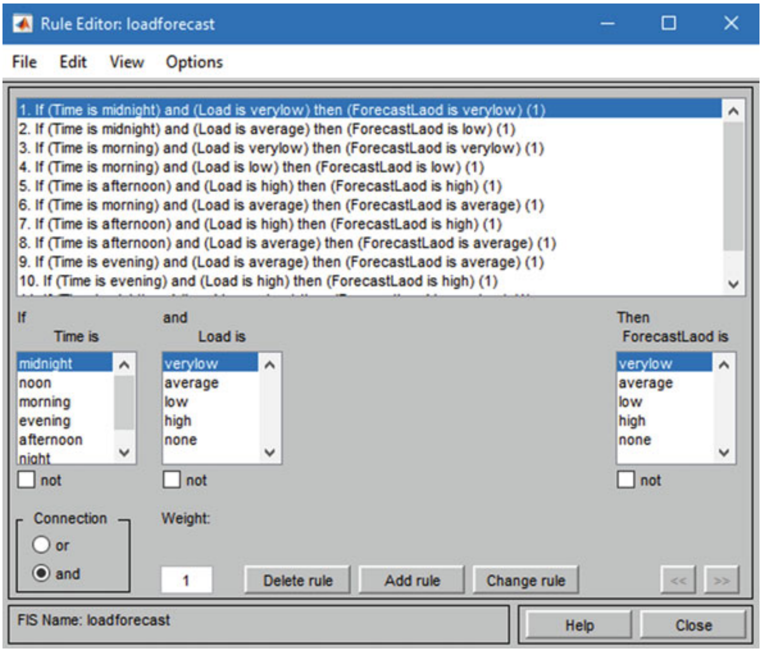


Fig. 7 Rule base of fuzzy

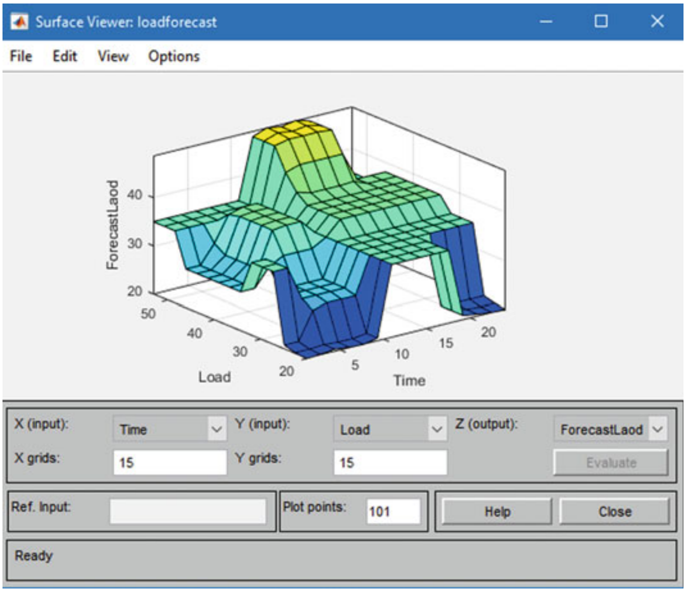


Fig. 8 Three-dimensional surface

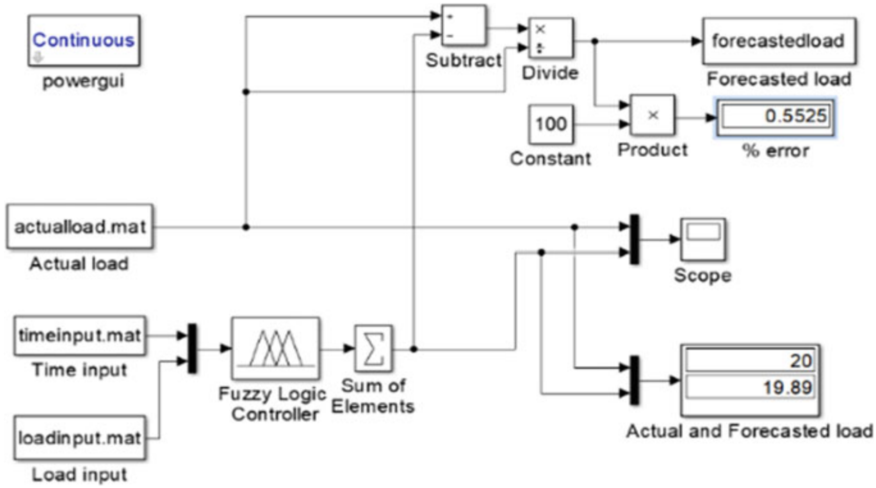


Fig. 9 Simulated FL-based STLF model

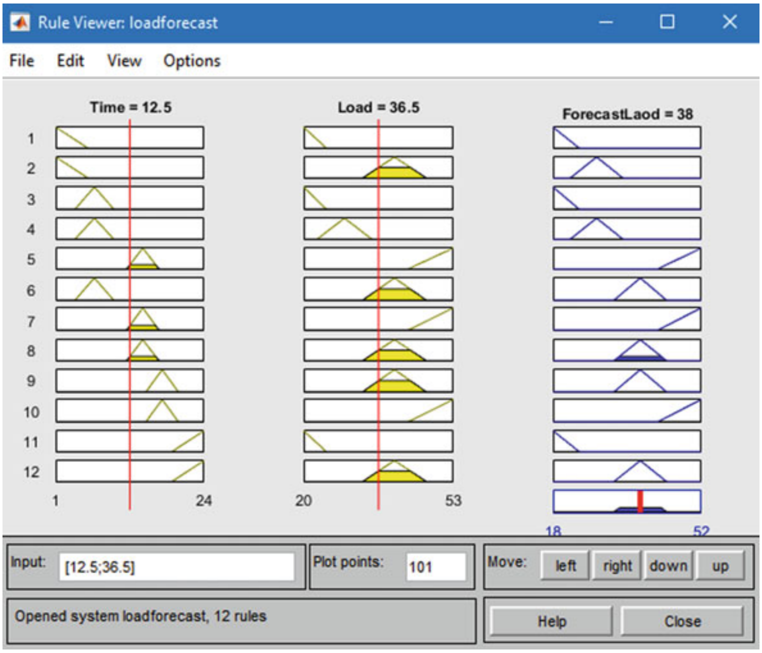


Fig. 10 Rule viewer of one sample data

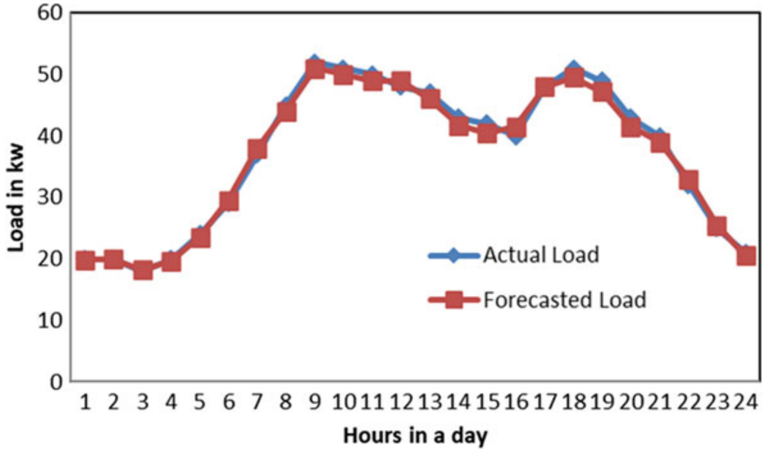


Fig. 11 Comparison of the actual and forecasted load of a day for FL

Table 1 Forecasted load and percentage error for 24 h

Time	Load	Actual load	Forecasted load	APE%
1	20	20	19.9	0.5
2	20	20	20	0
3	20	18	18.2	−1.09
4	26	20	19.7	1.5
5	31	24	23.5	2.12
6	34	29	29.5	−1.69
7	42	37	38	**−2.63**
8	53	45	44	2.27
9	49	52	51	1.96
10	48	51	50	2
11	46	50	49	2.04
12	46	48	49	−2.04
13	44	47	46.1	1.95
14	43	43	41.7	**3.11**
15	42	42	41.5	1.20
16	45	40	40.5	−1.23
17	47	48	48	0
18	53	51	49.5	3.03
19	46	49	47.8	2.51
20	39	43	42.5	1.17
21	37	40	39.7	0.75
22	32	32	32.5	−1.53
23	24	25	25.8	−0.77
24	22	21	20.7	1.44
			MAPE	1.60

Table 2 Comparison of different schemes

S No.	Scheme	MAPE (%)
1	[3]	3.75
2	[14]	2.69
3	**Proposed One**	**1.60**

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