J. Inst. Eng. India Ser. B (October 2020) 101(5):475–495
https://doi.org/10.1007/s40031-020-00477-2

ORIGINAL CONTRIBUTION

Day Ahead Regional Electrical Load Forecasting Using ANFIS Techniques

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Received: 7 September 2018 / Accepted: 7 August 2020 / Published online: 16 August 2020

Abstract Short-term load forecasting is a powerful tool for improvement of operation, energy efficiency and reliability of power systems. Researchers are continuously working to improve outcomes of short-term load forecasting (STLF). In this paper, three different ANFIS models are developed for STLF. The proposed models are tested for prediction of load demand of Rajasthan region of India, from fifteen minutes to one week ahead for particular time of the day of year 2015. Rajasthan region has a typical load curve as it has a land area of 342,239 km^2 and population of 68 million, with acute climatic conditions. The outcomes obtained from proposed models are compared with outcomes of significant strategies available in literature based on ANN. This comparison reveals that the proposed RR (Rajasthan Region) model is a competitive technique among all other strategies. The results are compared on the basis of MAE, APE and MAPE for fifteen forecasting samples.

Keywords Load forecasting · Artificial neural network · Fuzzy logic · ANFIS

Introduction

Electrical load forecasting plays a powerful role in capacity planning, scheduling, and the operation of power systems [1]. It provides very important information for generation, control, power dispatch, maintenance, and expansion of power facility with fewer problems to their consumers [2, 3]. Decisions related to unit commitment, economic dispatch, automatic generation control, security assessment, maintenance planning, and energy exchange depend on the trends of upcoming load demand [4]. Accurate STLF results in economic and trouble free operations, improves efficiency with accurate load scheduling and reduces power system reserves and enhances reliability of power grid with reduction in possibility of overloading and blackouts [5, 6]. It decides accurate load demand, with lead times, from a few minutes to several days and schedules spinning reserve for effective control on load flow parameters [7]. Electric load prediction is difficult as it always depends on different unstable factors, like weather variables, social activities, dynamic electricity prices and nonlinear behavior of consumer demand [8].

Many techniques using different methods including artificial neural networks have been used for STLF. ANN-based models are generally used as they perform better with continuously changing environmental parameters, take short time in development and are simple and flexible in design [9]. These are efficient for online implementation in energy control centers but require large training time and pose problem of convergence for complex function approximations [10]. ANNs are unstable, depend on data, and can easily fall into a local minimum and there is no definite rule to determine number of hidden neurons; therefore it is difficult to logically determine network structure [11, 12].

Fuzzy logics are successfully used for load forecasting problems due to their capability to minimize model errors [13, 14]. But fuzzy systems also have drawbacks of determination of fuzzy rules and membership functions when the system complexity increases.

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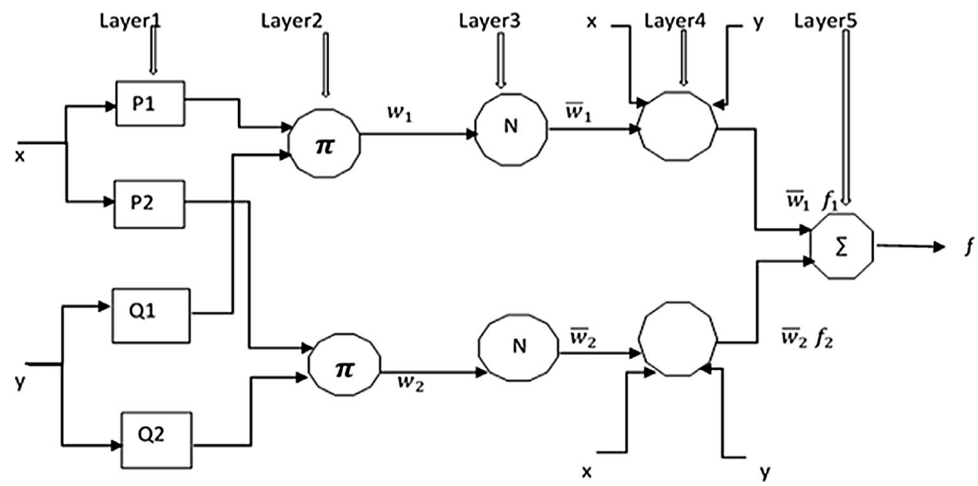

Fig. 1 Structure of ANFIS

Table 1 Details of FIS1, FIS2 and FIS3

Structure of FIS			
FIS	Generation Function	Variable parameters	Data
FIS1	genfis1	Number of membership function = 2 Type of membership function = Gauss	Training and Testing Data
FIS2	genfis2	Cluster Radius = 0.2	
FIS3	genfis3	Number of clusters = 04	

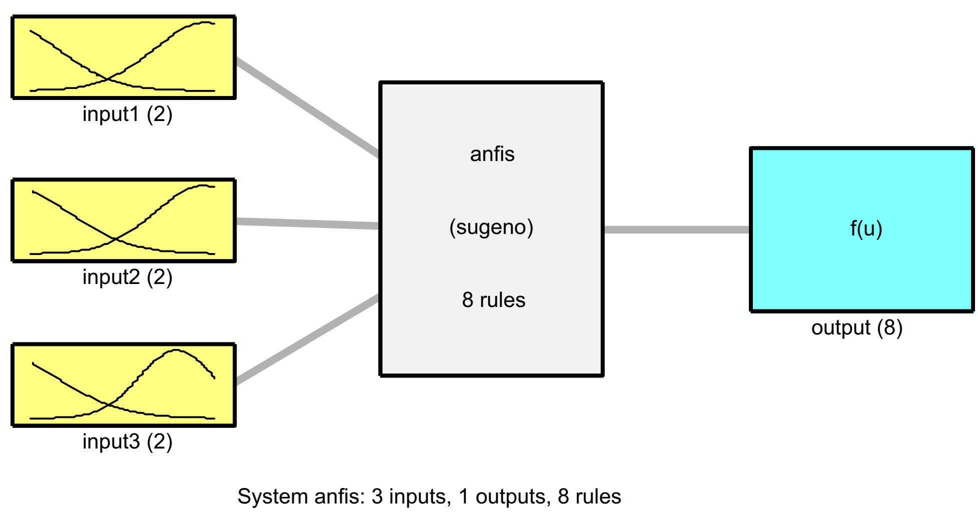

Fig. 2 Structure of ANFIS Model 1

To overcome drawbacks of ANNs and fuzzy logics and to get advantages of both, these two techniques are combined together. The combination of neural networks and fuzzy logics are known as adaptive neural network-based fuzzy inference system (ANFIS). It represents a powerful tool to model system behavior and is very effective to get solutions of those problems which have random data sequences with highly irregular dynamics [15, 16]. Using expert knowledge of fuzzy system and capability of handling complicated relationship between social, weather parameters and hourly load pattern in an area, ANFIS deals better with load forecasting problems, which is difficult in ANNs only [17]. ANFIS shows significant improved forecasting accuracy.

In this paper, we proposed three ANFIS models for load forecasting and applied on Rajasthan region of India. This region is biggest in land area in India, having area of 342,239 km^2. Its population is approximate 68 million.

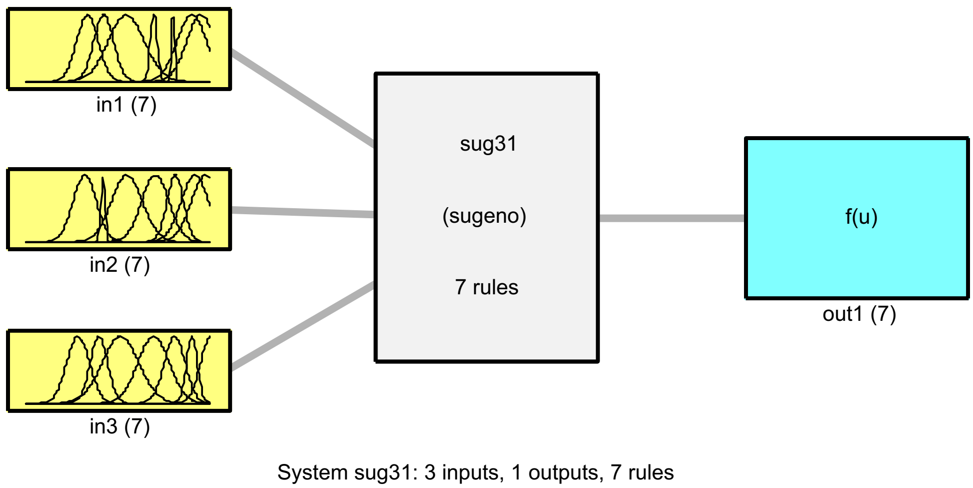

Fig. 3 Structure of ANFIS Model 2

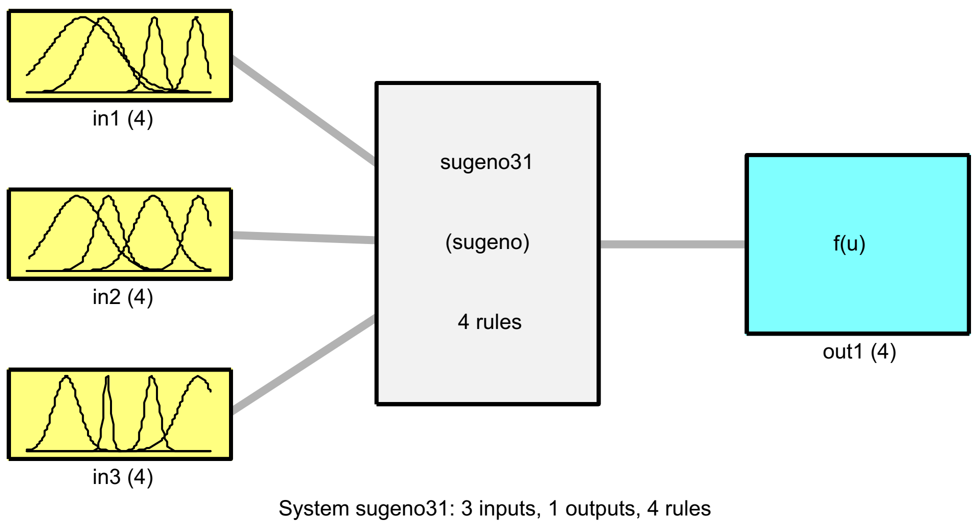

Fig. 4 Structure of ANFIS Model RR

Table 2 Structure of ANFIS

ANFIS parameters				
Structure parameters			Training parameters	
S.N.	Name	Number	Name	Number
1	Nodes	34	Iterations	500
2	Linear parameters	32	Error goal	$1e^{-5}$
3	Nonlinear parameters	18	Initial step size	0.01
4	Training data pairs	1	Step size decrease rate	0.9
5	Fuzzy rules	8	Step size increase rate	1.1

Beside this, Rajasthan have large geological and social diversities as it has desert Thar, Arawali hills, rivers Chambl, Banas and Kalisindh. Approximate half of the region suffer from lack of rain and face a temperature variation from −2 to 50 °C. Electrical load demand of Rajasthan mainly depends upon agricultural load (type of crops and cultivated area), domestic load, and load of small-scale industries. All these particularities create a

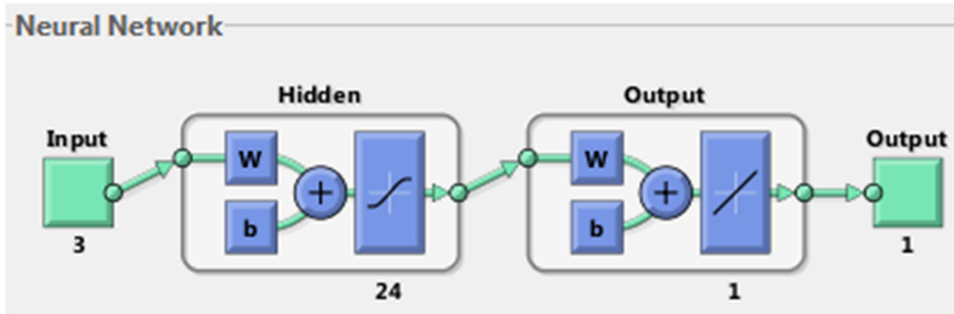

Fig. 5 Structure of ANN Model

typical load curve, having changing day to day load profile. Due to suddenly changing weather and other parameters, it is very difficult to predict upcoming trend of electrical load demand. In this research paper, such typical load demand profile has been considered for prediction and new techniques are developed.

Adaptive Neuro-Fuzzy Inference System (ANFIS) and Its Structure

Neuro-fuzzy approach combines two powerful computing techniques, first is adaptive neural networks and second one is fuzzy set theory. Neural networks have ability to learn and adapt to changing environment to achieve better performance. Fuzzy set theory is very effective to deal with imprecision and uncertainty, by using linguistic information with incorporating human knowledge, and develops the relation between input and output variables [18]. The fuzzy neural network (FNN) system is fuzzy inference system in neural network structure [19]. It is easy to design to achieve high accuracy by setting parameters of the network structure and learning algorithm of the FNN. ANFIS uses the self-learning ability of ANN with the linguistic expression function of fuzzy inference, whose membership functions and fuzzy rules are acquired from a large number of existing data rather than experience [20]. ANFIS automatically tunes its parameters with use of

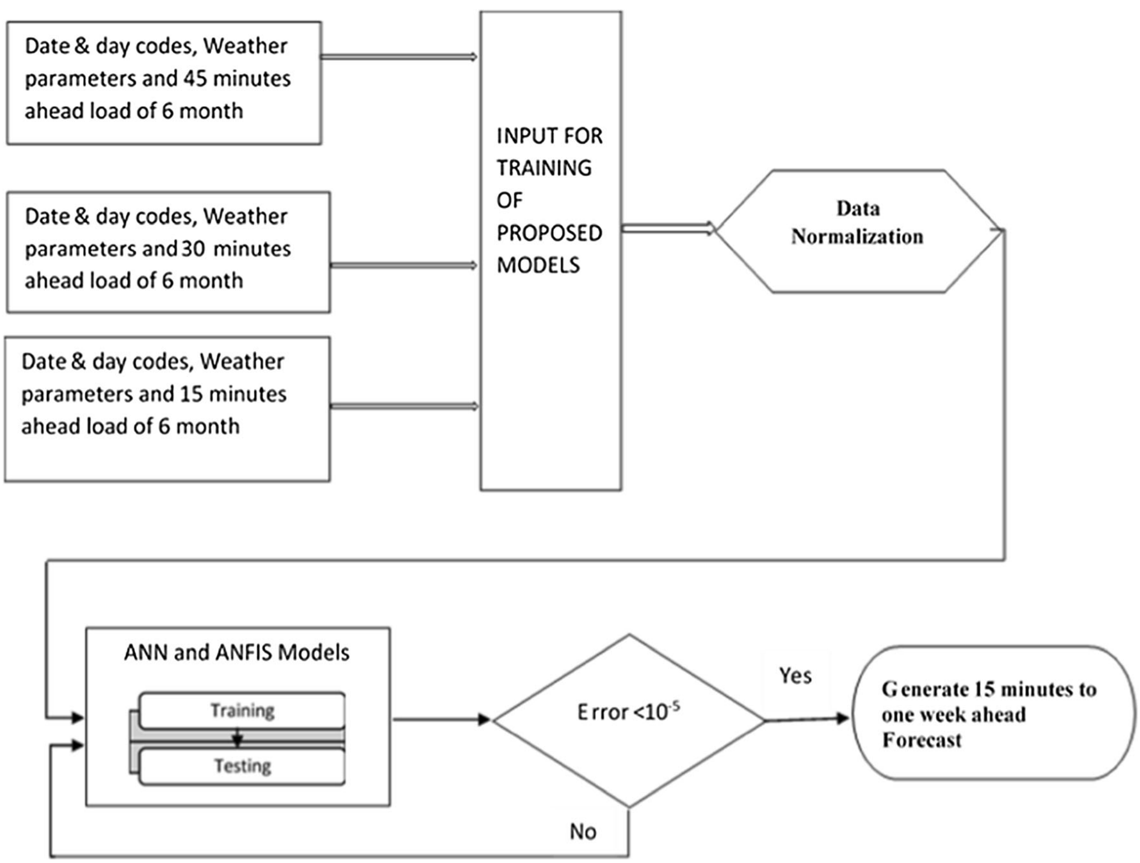

Fig. 6 Flowchart for training of proposed forecasting models

Table 3 Design of input signal to proposed models

Design of input signal to proposed models			
Input Parameter		S.N. of parameter in input signal	Total number of parameters
Date		1 -2	2 (day and month)
Day code		3	1
Max., Average & Min. Temperature of	Kota	4 to 6	3
	Jaipur	7 to 9	3
	Jodhpur	10 to 12	3
Max., Average & Min. Humidity of	Kota	13 to 15	3
	Jaipur	16 to 18	3
	Jodhpur	19 to 21	3
Each 15 minutes load of the day		22 to 117 (24 × 4 = 96)	96
Total Parameters in Input =117			

INPUT SIGNAL ⟹ ANN & PROPOSED ANFIS MODEL

adaptation procedure, possesses fast convergence, is more efficient than back-propagation (BP) neural network and can learn from the input data obtained in experiments, which is the feature of a controlled system [21]. ANFIS uses fuzzy decision rules as membership functions (MF) and learns the best fitting parameters of the MFs and applies hybrid learning rule which is much faster and reliable than the simple gradient descent learning. Basically it is a fuzzy-Sugeno model of adaptive systems whose learning and adaptation are systematic and less dependent on expert knowledge [22]. In a neuro-fuzzy system, NNs automatically extract fuzzy rules from the numerical data and through the training process, and the parameters of the membership functions are adaptively attuned [23].

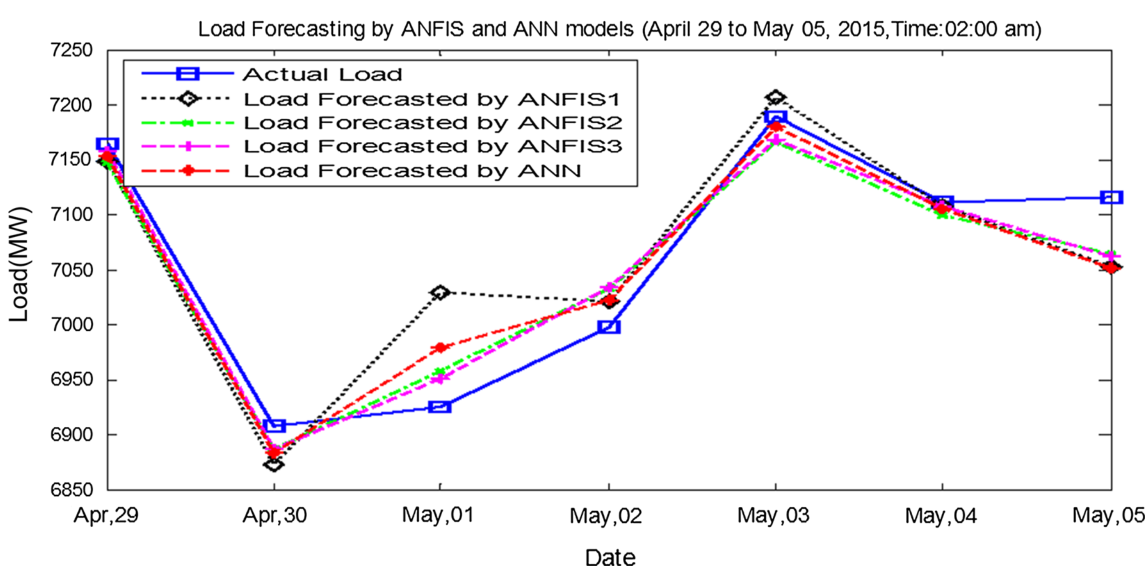

Fig. 7 Comparison of actual load and output of different models for load trend of 2:00 a.m.

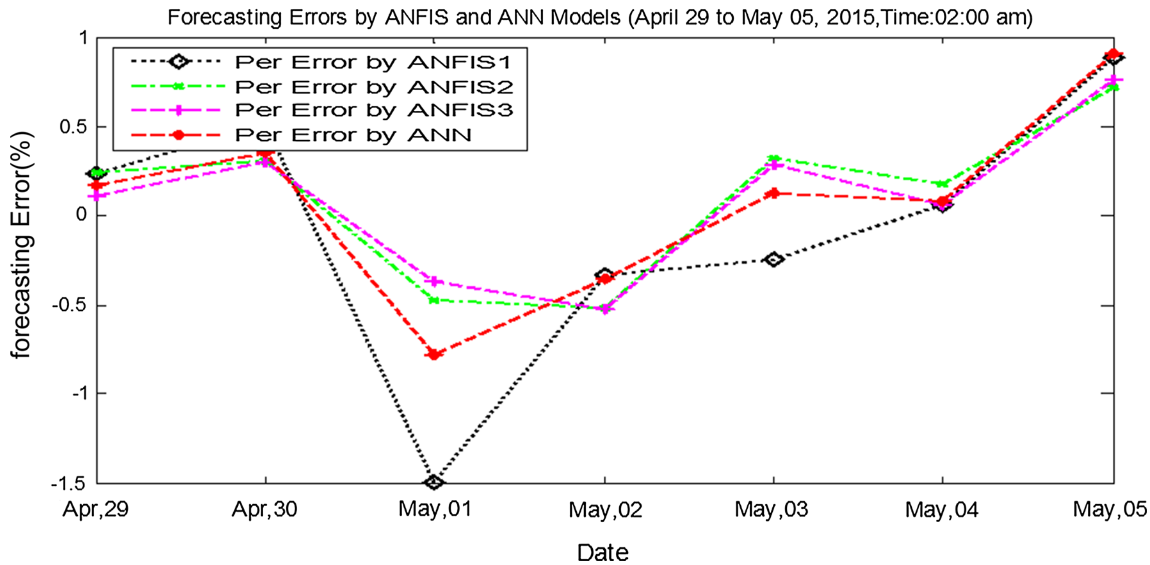

Fig. 8 Comparison of forecasting error for load trend of 2:00 a.m.

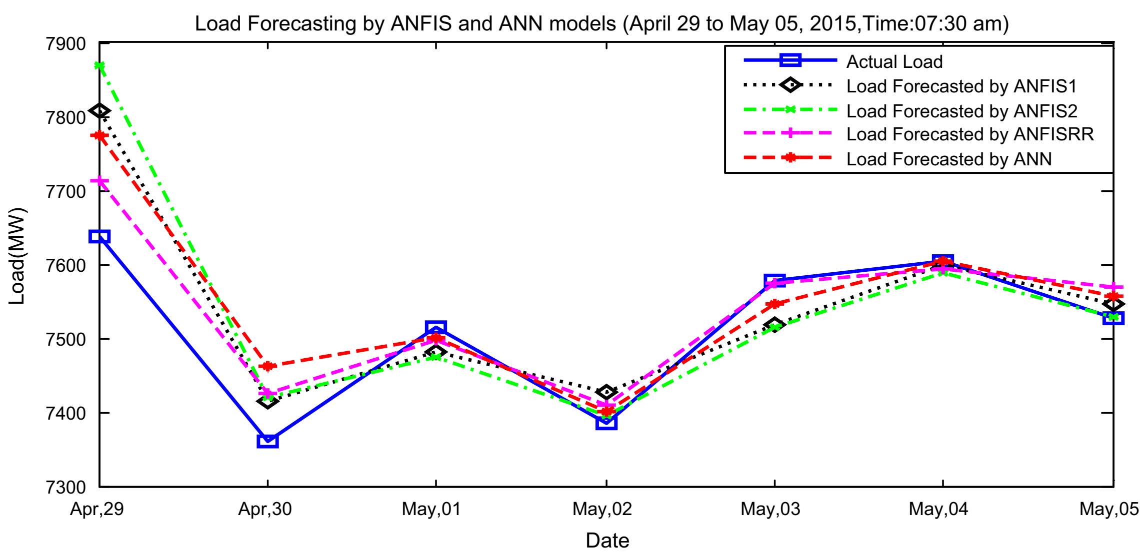

Fig. 9 Comparison of actual load and output of different models for load trend of 07:30 a.m.

In this section, ANFIS architecture and its learning algorithm for the Sugeno fuzzy model have been explained. FIS has two inputs (x and y) and one output f and a common rule set with two fuzzy if then rules is as follows:

$$f_1 = P_1x + Q_1y + \gamma_1 \tag{1}$$

$$f_2 = P_2x + Q_2y + \gamma_2 \tag{2}$$

Rule 1: If (x is L_1) and (y is $M1$) then $f_1 = P_1x + Q_1y + \gamma_1$
Rule 2: If (x is L_2) and (y is M_2) then $f_2 = P_2x + Q_2y + \gamma_2$

Here, P_1, P_2, Q_1, Q_2, γ_1 and γ_2 are linear parameters and L_1, L_2, M_1 and M_2 are nonlinear parameters. ANFIS structure according to above equations is as shown in Fig. 1. This structure consists of five layers, namely a fuzzy layer, a product layer, a normalized layer, a de-fuzzy layer and a total output layer. The relation between output and input of each layer in the ANFIS has been explained further.

First layer is fuzzy layer, in which X and Y are the input of nodes P_1, P_2, Q_1 and Q_2, respectively. P_1, P_2, Q_1 and Q_2 are the linguistic labels used in the fuzzy theory for dividing the membership functions. The membership

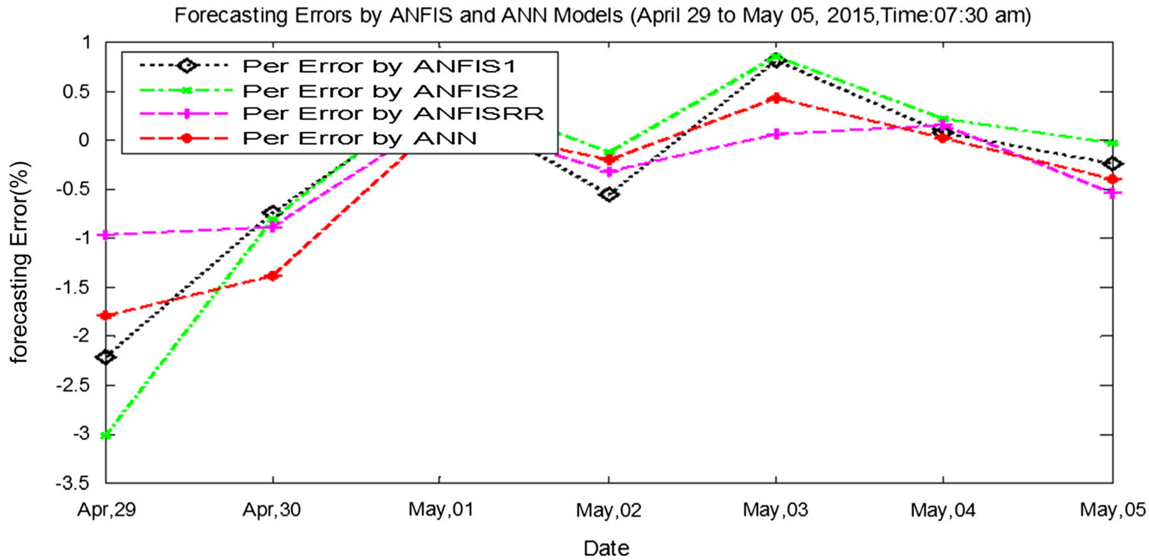

Fig. 10 Comparison of forecasting error for load trend of 07:30 a.m.

relationship between the output and input functions of this layer can be expressed as:

$$O_{1i} = mP_i(x), i = 1, 2; \tag{3}$$

$$O_{2j} = mQ_j(y), j = 1, 2; \tag{4}$$

where O_{1i} and O_{2j} denote the output functions and mP_i and mQ_j denote the membership functions.

Layer 2 is the product layer that consists of two nodes labeled п. The output of this layer is the product of the input signal, which is defined as follows:

Output of layer 2

$$O_{2i} = mP_i(x_1) \cdot mQi(x_2)i = 1, 2; \tag{5}$$

The third layer is the normalized layer, it normalizes weight functions and its nodes are labeled N. Here, w_1 and w_2 are the weight functions of the third layer.

$$O_{3i} = \bar{w} = \frac{\boldsymbol{w_i}}{\boldsymbol{w_1} + \boldsymbol{w_2}}, \quad i = 1, 2 \tag{6}$$

Layer fourth is the de-fuzzy layer, and its nodes are adaptive.

Output of fourth layer is

$$O_{4i=}\overline{w_i}f_i = \overline{w_i}(a_i + b_i + c_i) \tag{7}$$

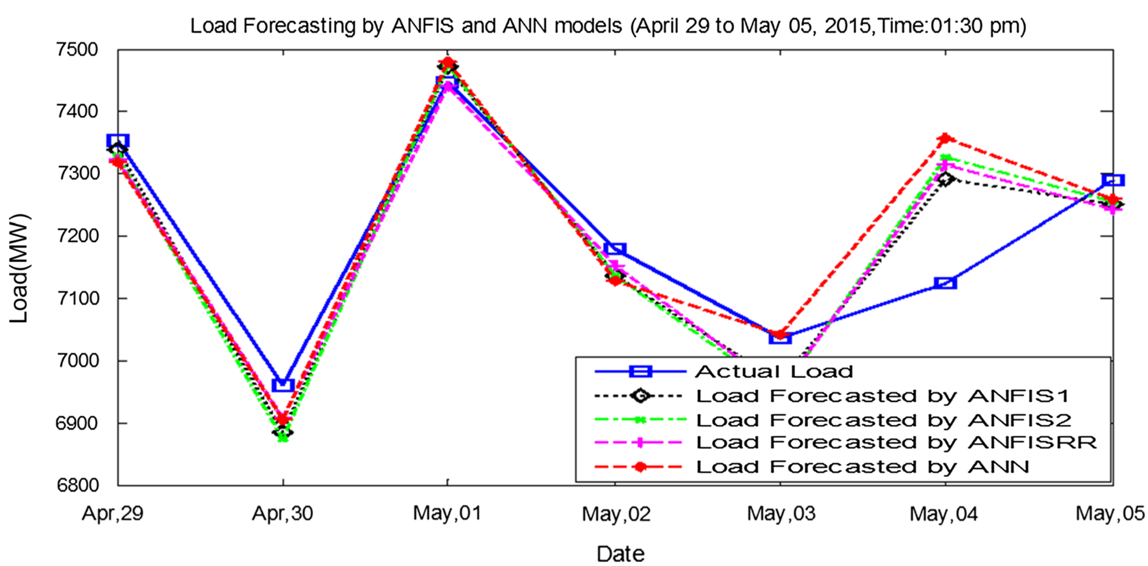

Fig. 11 Comparison of actual load and output of different models for load trend of 01:30 p.m.

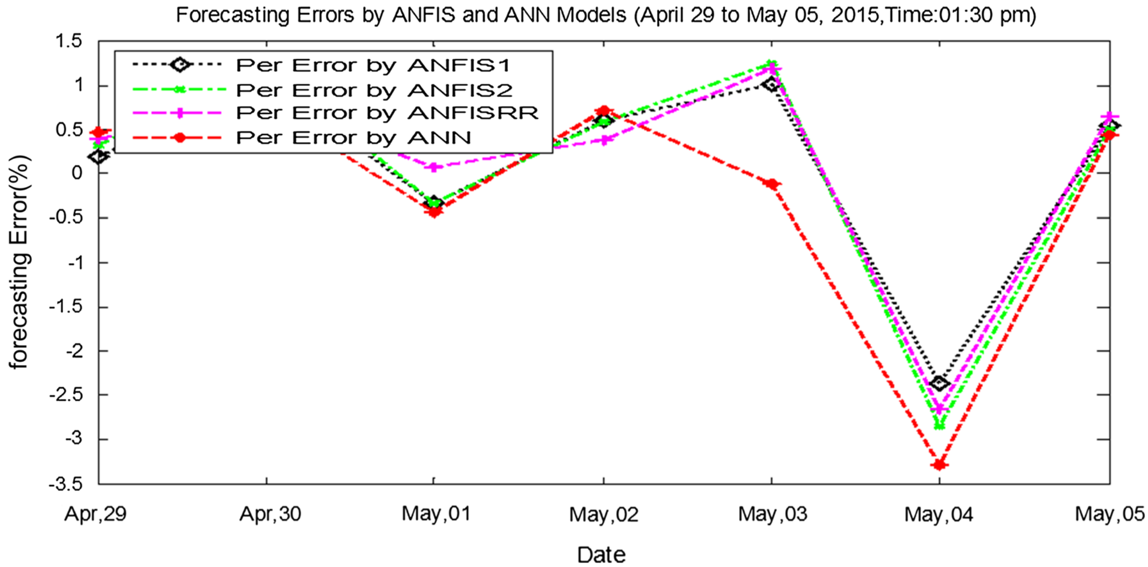

Fig. 12 Comparison of forecasting error for load trend of 01:30 p.m.

where $\overline{w_i}$ is the output of layer 3, and $(a_i + b_i + c_i)$ are consequent parameters.

The fifth layer is the total output layer, and its node is labeled Σ. Output of this layer is the summation of the incoming signals to this layer.

The output of this layer is

$$O_{5_i} = \sum \bar{w}_i f_i = \frac{\sum \boldsymbol{w_i f_i}}{\sum \boldsymbol{w_i}} \tag{8}$$

Implementation of Proposed Forecasting Models

In this research, we used two basic techniques: one is based on ANN and second is based on ANFIS.

Structure of Proposed Models of ANFIS

The FIS structure can be built with three different techniques. These are grid partition (GP), subtractive clustering (SC) and fuzzy c-means clustering (FCMC). GP uses

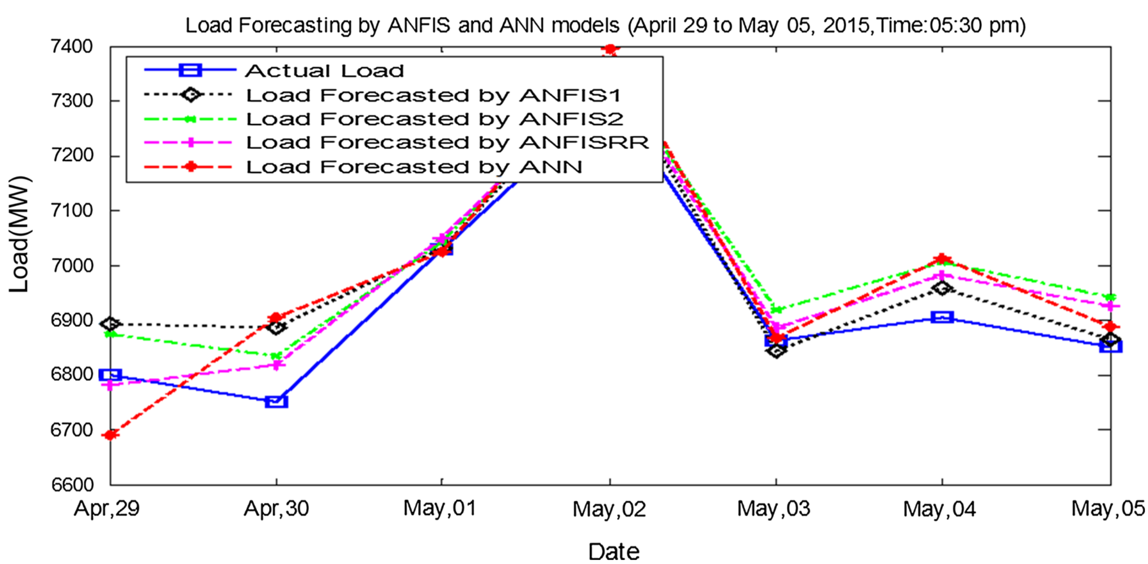

Fig. 13 Comparison of actual load and output of different models for load trend of 05:30 p.m.

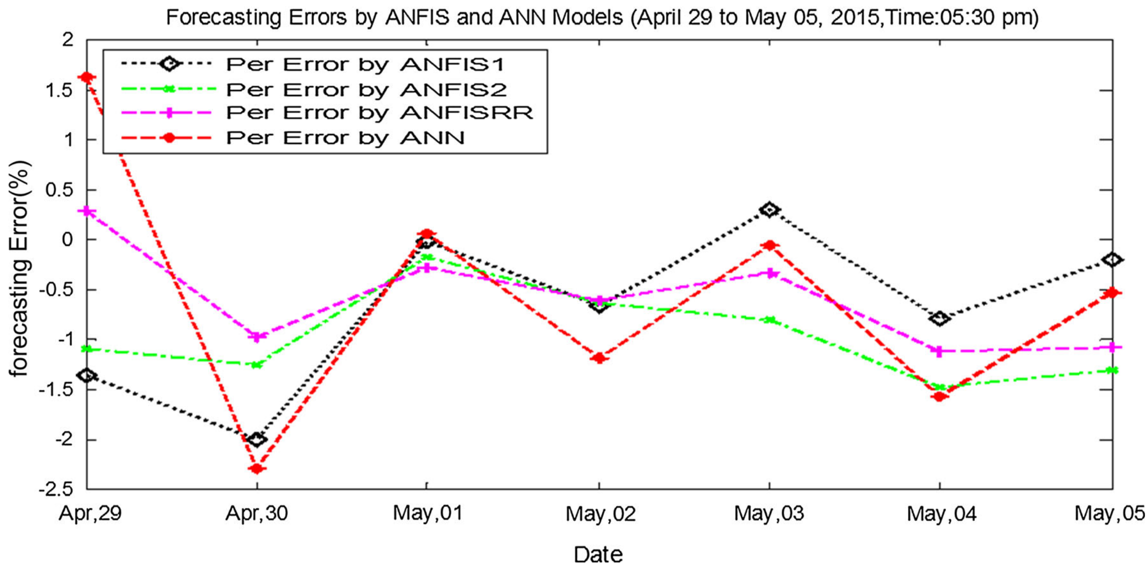

Fig. 14 Comparison of forecasting error for load trend of 05:30 p.m.

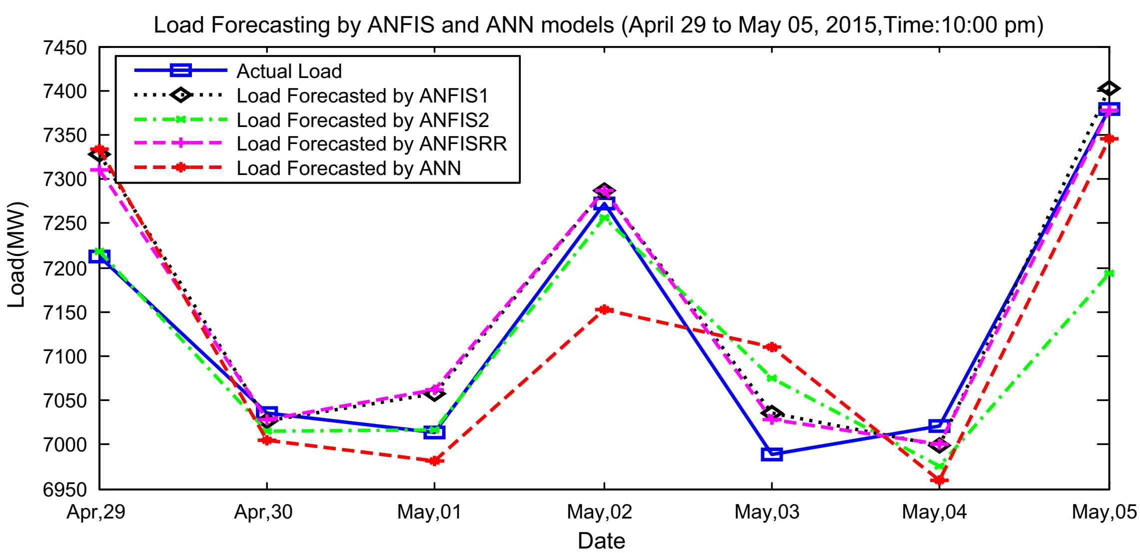

Fig. 15 Comparison of actual load and output of different models for load trend of 10:00 p.m

different type and number of membership functions, SC is a quick, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data varying the cluster radius and FCMC is a clustering methods which generates different number of clusters [24].The genfis1, genfis2 and genfis3 functions found in MATLAB are used to generate different FIS structures which describe the GP, SC and FCMC methods, respectively.

FIS1 = genfis1 (Data, Number of membership functions, Type of membership function)
FIS2 = genfis2 (Data, Cluster Radius)
FIS3 = genfis3 (Data, Number of Clusters)

Arguments used in different functions in this case are as shown in Table 1.

FIS1, FIS2, and FIS3 are ‘sugeno’ type and used for ANFIS model1, ANFIS model2 and ANFIS model RR (Rajasthan Region), respectively. After training, all three models are used to predict electrical load. Figures 2, 3 and 4 explain the structure of different models. These three figures are generated during simulation and directly imported from MATLAB. ANFIS structure and its parameters used for training are shown in Table 2.

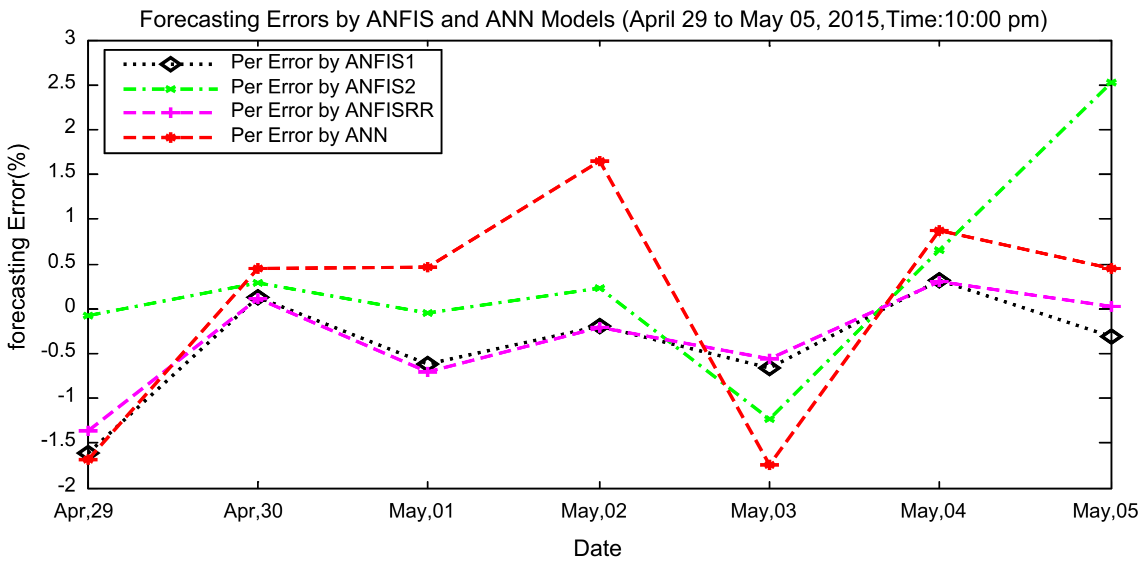

Fig. 16 Comparison of forecasting error for load trend of 10:00 p.m.

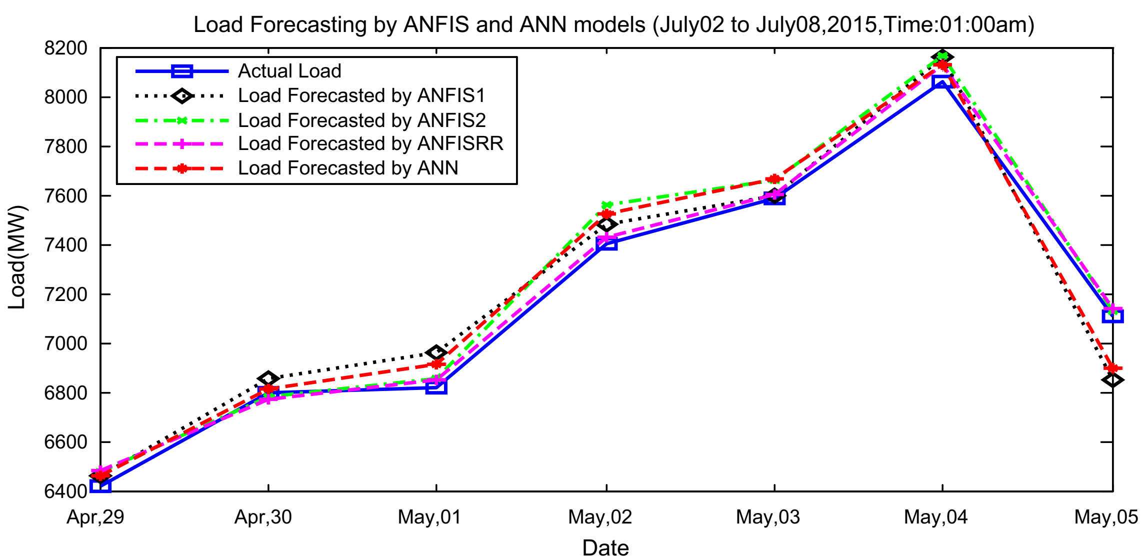

Fig. 17 Comparison of actual load and output of different models for load trend of 1:00 a.m

Structure of ANN Model

A feed-forward neural network is used as shown in Fig. 5. This figure directly taken from MATLAB, generated during simulation. It is two-layer network. In hidden layer 24 neurons and in output layer single neuron is used. Tan Sigmoid and pure line are used as transfer function. Three set of parameters are used as input. The output of ANN is one set having seven data (load of one week of particular time).

Collection of Load and Weather Parameters

Daily electrical load (with 15 min interval) of year 2015 of Rajasthan state of India collected from department of Rajasthan Rajya Vidyut Prasaran Nigam Limited (RRVPNL). Maximum, average and minimum temperature and humidity of Kota, Jaipur and Jodhpur are collected as weather variables from department of meteorology.

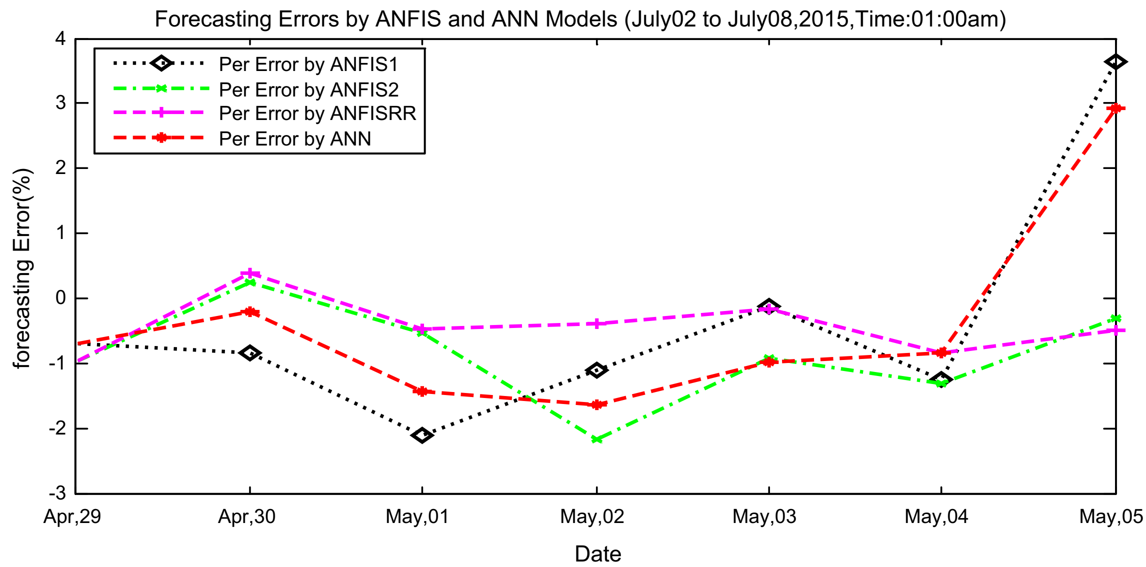

Fig. 18 Comparison of forecasting error for load trend of 1:00 a.m.

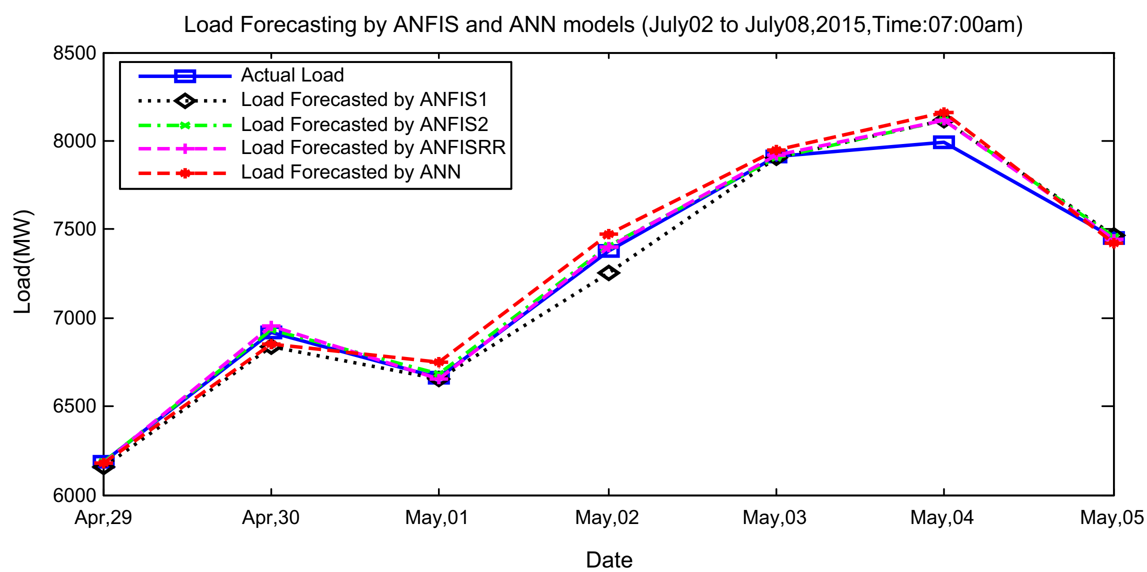

Fig. 19 Comparison of actual load and output of different models for load trend of 7:00 a.m.

Data Preparation

To ensure convergence within specified limits the original data are normalized. There is a strong correlation between power consumption and weather variables. In our case only temperature and humidity (maximum, average and minimum) of three stations are considered as weather variables as other weather parameters have weak effect on electric power consumption. In proposed models, three types of variables are used as inputs for training: (a) day indicator, i.e., date, month and day code, (b) weather-related inputs, i.e., maximum, average and minimum temperature and humidity of the day, and (c) previous load. Previous load is the load of each fifteen minutes for daily (i.e., $4 \times 24 = 96$) and for 365 days. For each day, total 117 nos. of parameters are given as input signal to the network. First and second data is the date, third data is day code, next 18 parameters are max., average and minimum temperature and humidity of Kota, Jaipur and Jodhpur, i.e., three main cities of Rajasthan. Remaining 96 data are fifteen minutes load of each day. Preparation of data to give as input to the models is shown in Table 2.

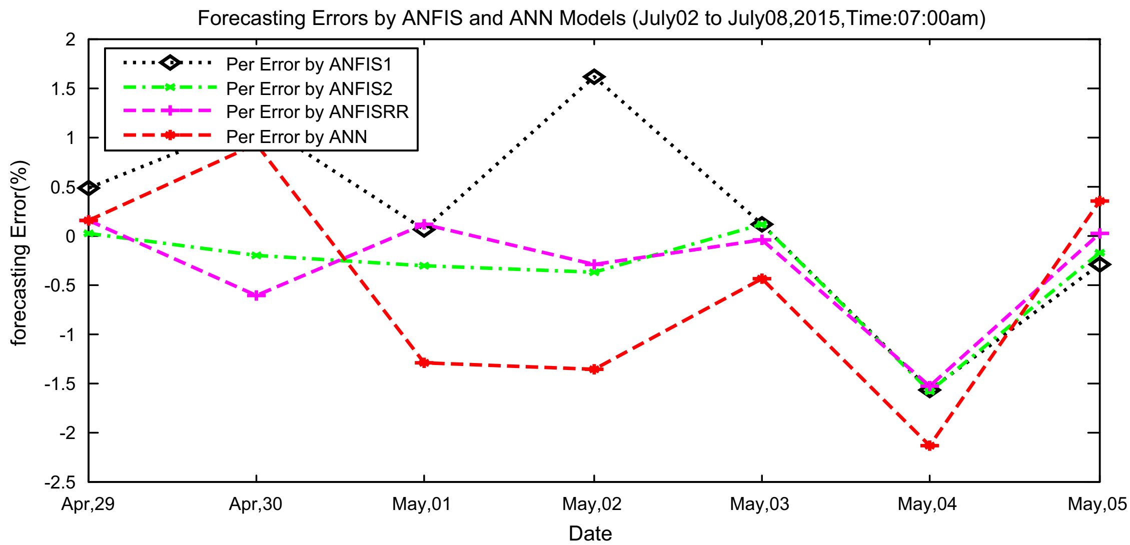

Fig. 20 comparison of forecasting error for load trend of 7:00 a.m.

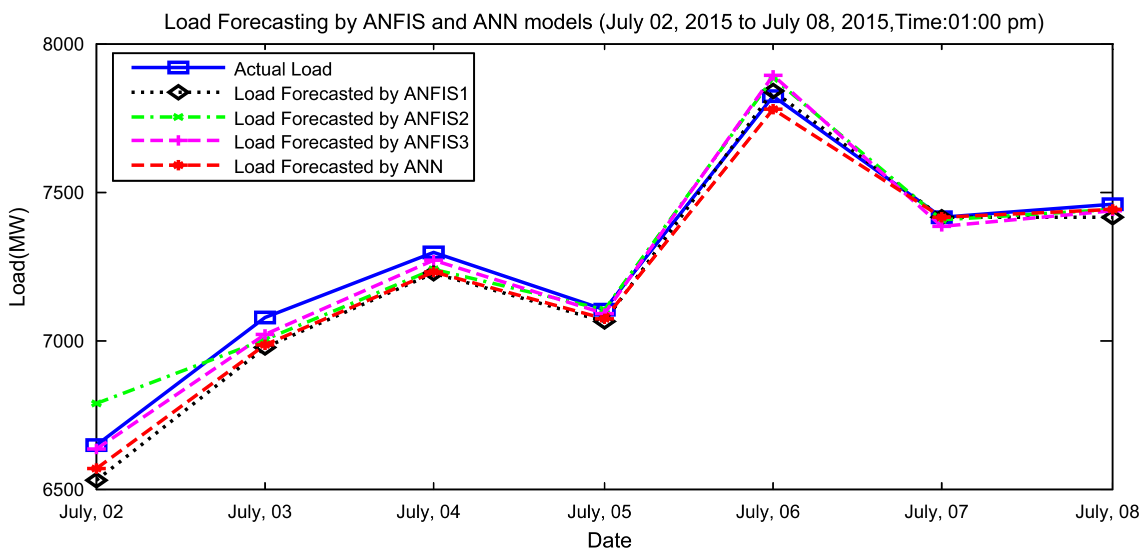

Fig. 21 Comparison of actual load and output of different models for load trend of 1:00 p.m.

Training of ANN and Proposed ANFIS Models

In our research work, most important point is that proposed forecasting models are designed to forecast the load of desired time of desired day and same time of previous six days. To train ANN and ANFIS models, three sets of parameters as input and one set as target are given to the models as explained below.

Input Signal = date, day code, weather parameters of three main cities (total 18 parameters) and $L_d(t_f - 45), L_d(t_f - 30), L_d(t_f - 15)$, where $L_d(t_f - 45), L_d(t_f - 30)$ and $L_d(t_f - 15)$ are the loads before 45 min, 30 min and 15 min, respectively, from required forecast time t_f.

Target Signal = date, day code, weather parameters of three main cities (total 18 parameters) and $L_d(t_f)$ where $L_d(t_f)$ is load at particular time on forecast day.

Training Inputs = Input signal parameters up to seven days before forecast day.

Training Targets = Target signal parameters up to seven days before forecast day.

To train the forecasting models, Training Inputs and Training Targets are given to ANN and ANFIS models and training programs are run till training error goal is achieved.

Training flowchart for all the four models is shown below (Fig. 6).

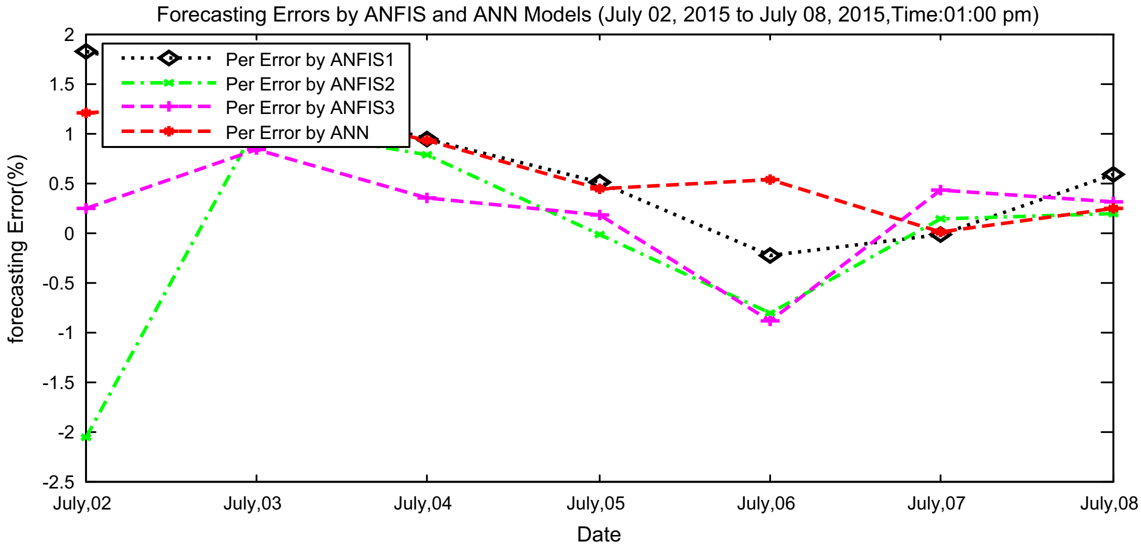

Fig. 22 Comparison of forecasting error for load trend of 1:00 p.m.

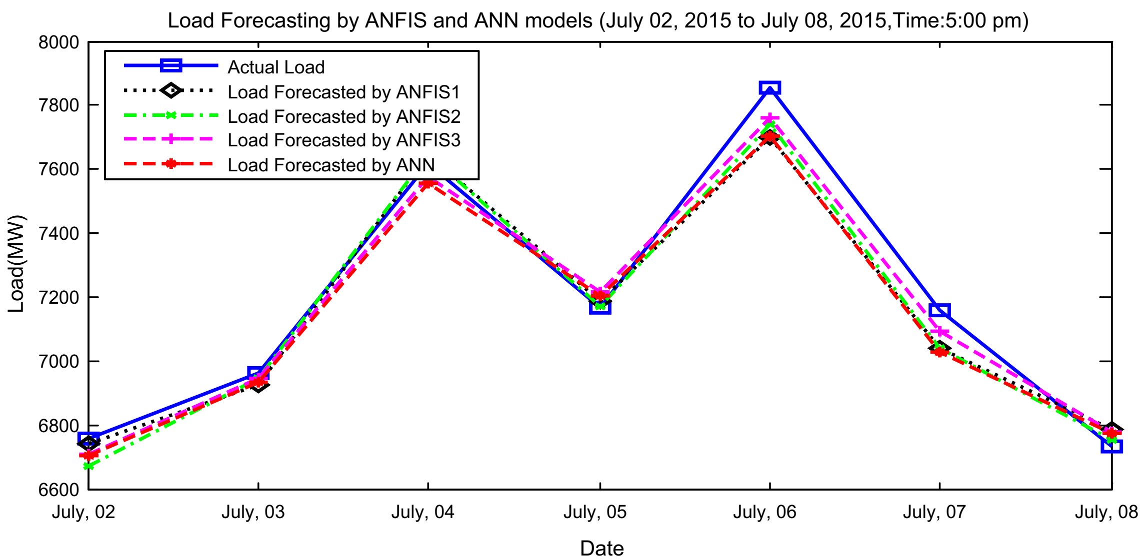

Fig. 23 Comparison of actual load and output of different models for load trend of 5:00 p.m.

Forecasting

All the models trained according to designed training parameters shown in Table 3. When a set of input data is given to the trained network, it predicts the target, and provides forecasted output. Data of one week are given as Test Input (in same pattern as in training) for prediction of load of this week at specified time t_f. The predicted output is compared to Test Targets (actual data) to check forecasting error.

Performance Metrics

The accuracy of the forecasting is measured according the following Performance Metrics

Absolute Percentage Error (APE)

$$\text{APE} = \left[\frac{L_j - Y_j}{L_j}\right] \times 100 \tag{9}$$

L_j is the jth actual value and y_j is jth forecasted value.

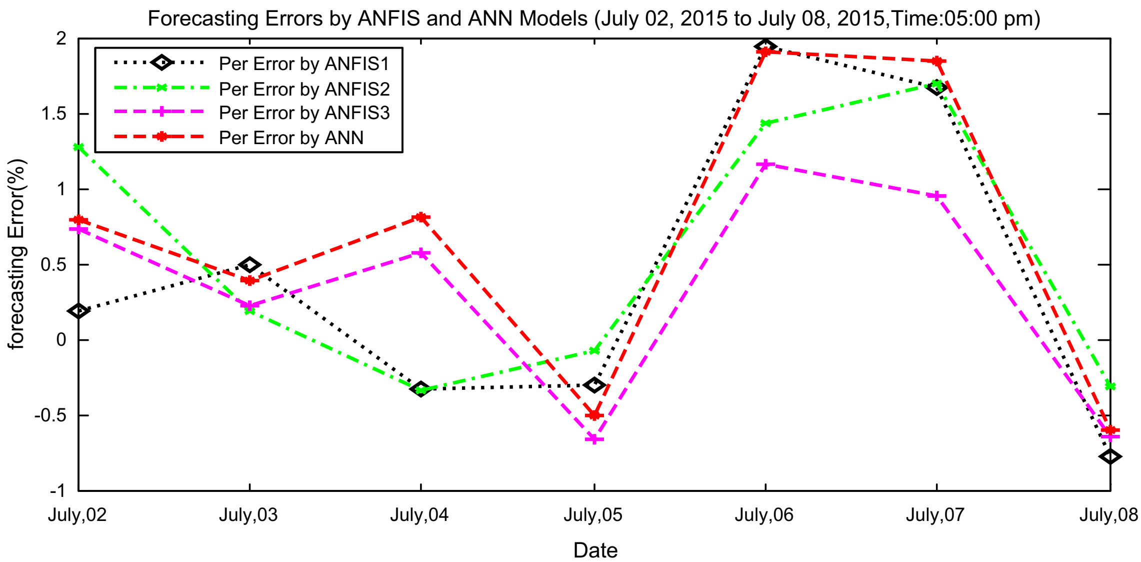

Fig. 24 Comparison of forecasting error for load trend of 5:00 p.m.

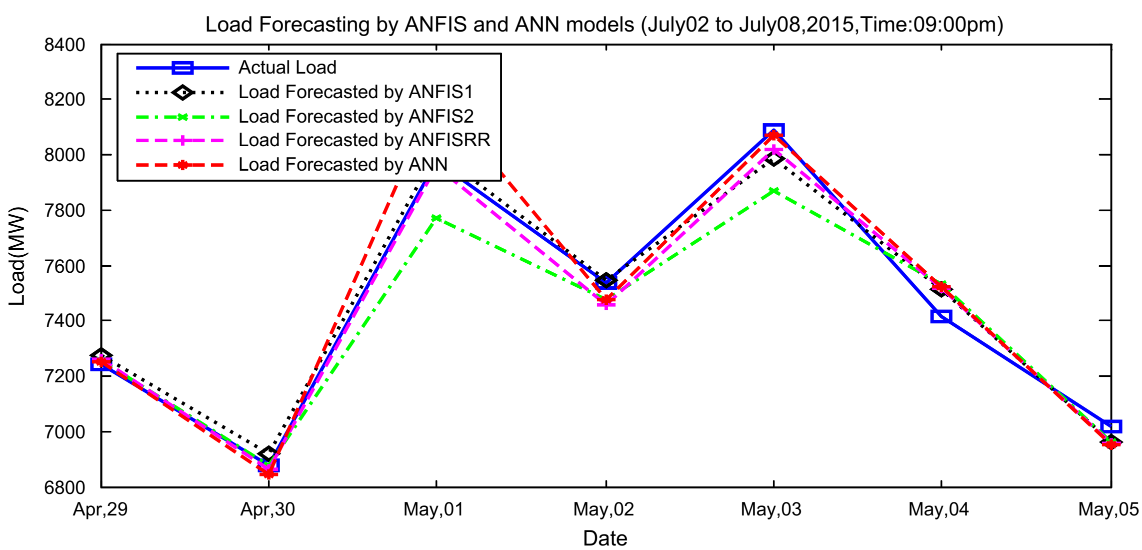

Fig. 25 Comparison of actual load and output of different models for load trend of 9:00 p.m.

Mean Absolute Error (MAE)

$$\mathrm{MAE} = \frac{1}{n}\sum_{j}^{n}\left|L_j - Y_j\right| \tag{10}$$

where n is the total number of data points.

Mean Absolute Percentage Error (MAPE)

MAPE is a common indicator in forecasting problems [25].

$$\mathrm{MAPE} = \frac{1}{n}\sum_{j}^{n}\left|\frac{L_j - Y_j}{L_j}\right| \times 100 \tag{11}$$

The MAE criterion penalizes all errors equally, whereas MAPE criterion accepts industry standard for measuring load forecast quality of all models of forecasting including ANFIS, which is considered as an effective technique and have better pridiction performance [26–30].

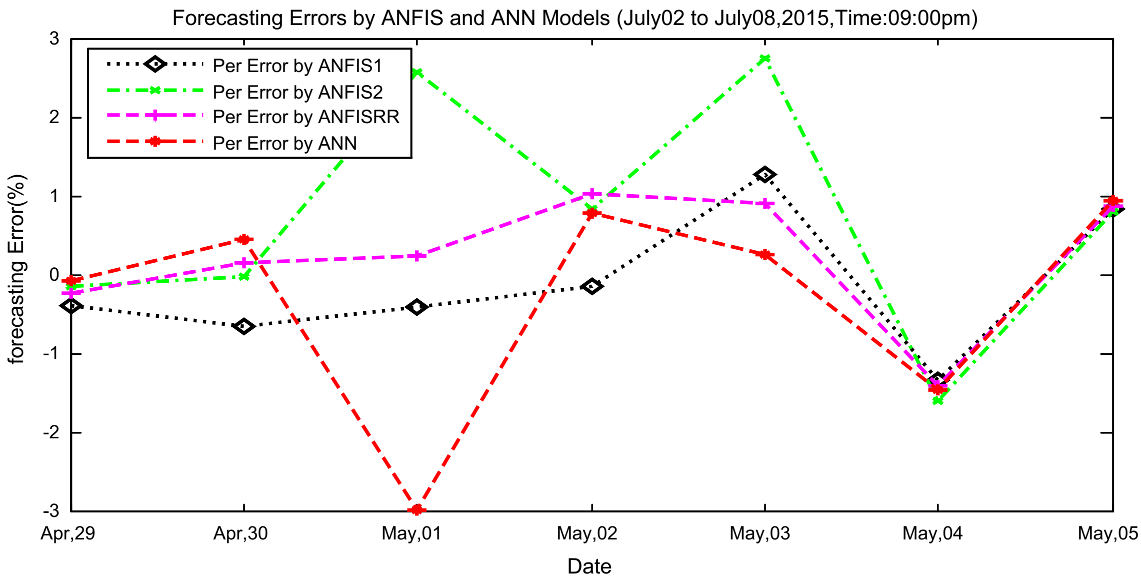

Fig. 26 Comparison of forecasting error for load trend of 9:00 p.m.

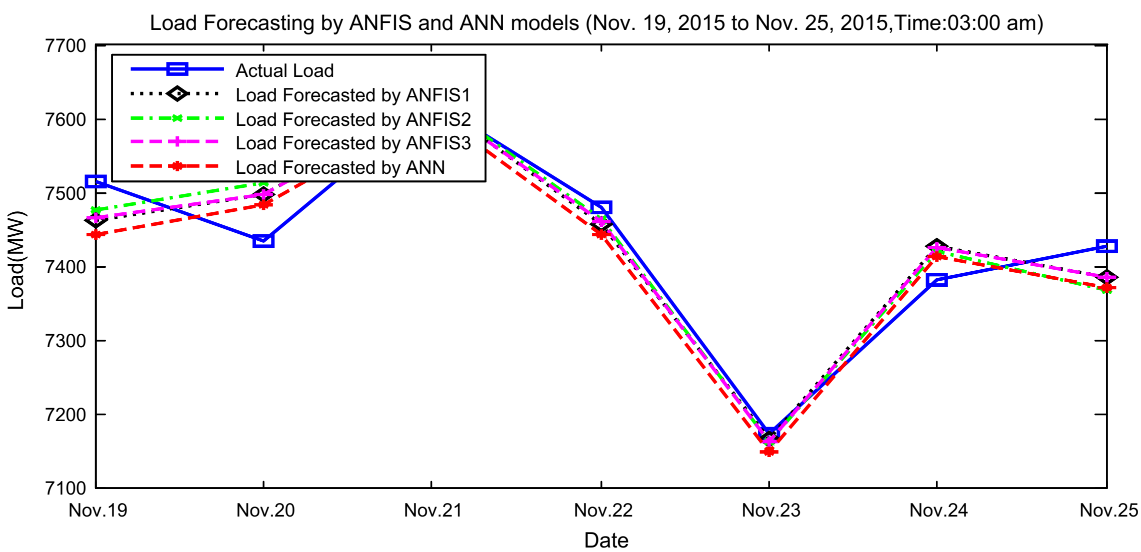

Fig. 27 Comparison of actual load and output of different models for load trend of 03:00 a.m.

Results and Discussion

ANN and ANFIS models have been tested for load data of year 2015 of Rajasthan region of India. Load forecasting of three main seasons considering days of weeks from 29 April to 05 May 2015, July 2 to July 08, 2015 and from November 19 to November 25, 2015 has been done and shown in graphical form. Time of forecasting is chosen in such a way that it covers different types of load pattern. Actual load, forecasted load and percentage forecast error for ANN and ANFIS models are also shown with help of Figs. 7 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35 and 36 and tabular form in Table 4.

Total fifteen samples are used for forecasting purpose. It is clear from graphical presentation and error comparison in Table 4 that all three ANFIS models give better performance than ANN model. Although all three ANFIS

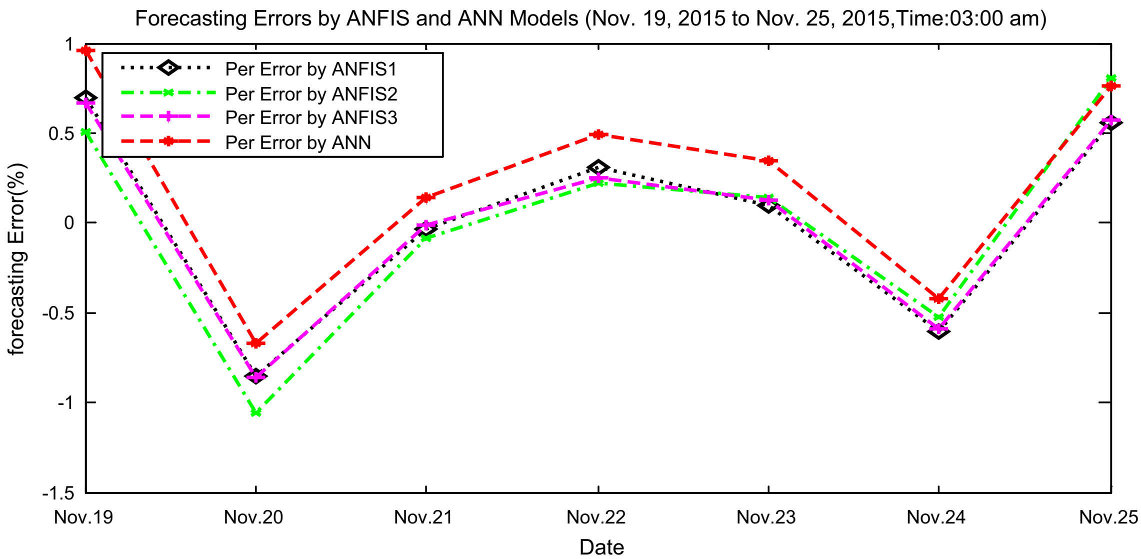

Fig. 28 Comparison of forecasting error for load trend of 03:00 a.m.

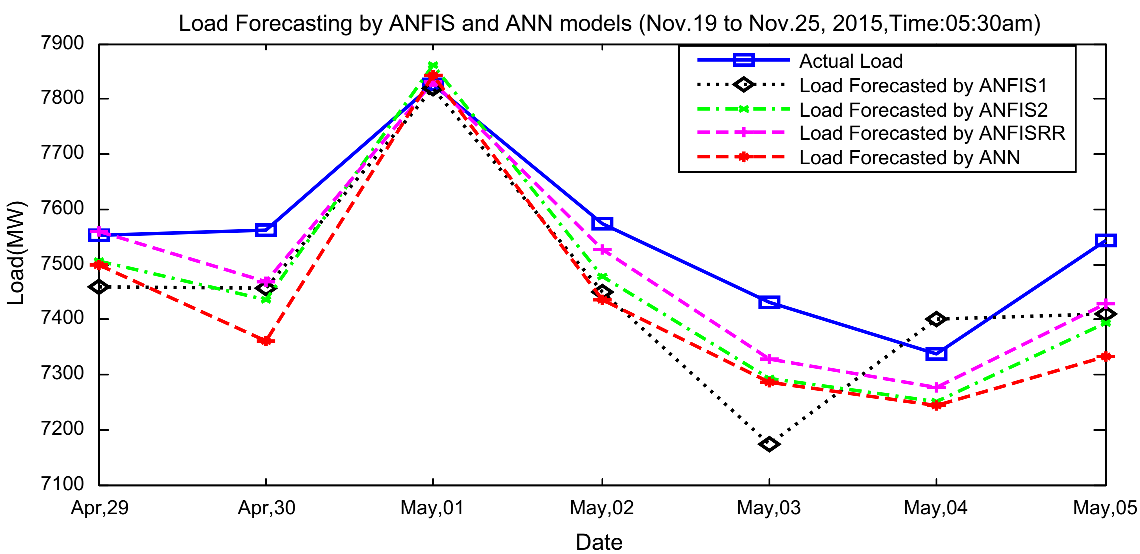

Fig. 29 Comparison of actual load and output of different models for load trend of 05:30 a.m.

models working better but model RR is more efficient as it gives smallest value of MAE, Maximum APE and MAPE for most of the times. These values are shown in bold font.

Highlights

During research, following points are noticed:

- Load profile of Rajasthan region mostly depends upon weather variables, rain, agriculture, type of crop, demand of domestic consumers and, small-scale industries; therefore it is changing in nature.
- ANFIS models have fewer values of MAE, APE and MAPE as compared to ANN model. It means ANFIS has better ability to forecast electric load.
- RR model is easy to design and implementation in comparison of other proposed models and has better prediction efficiency.

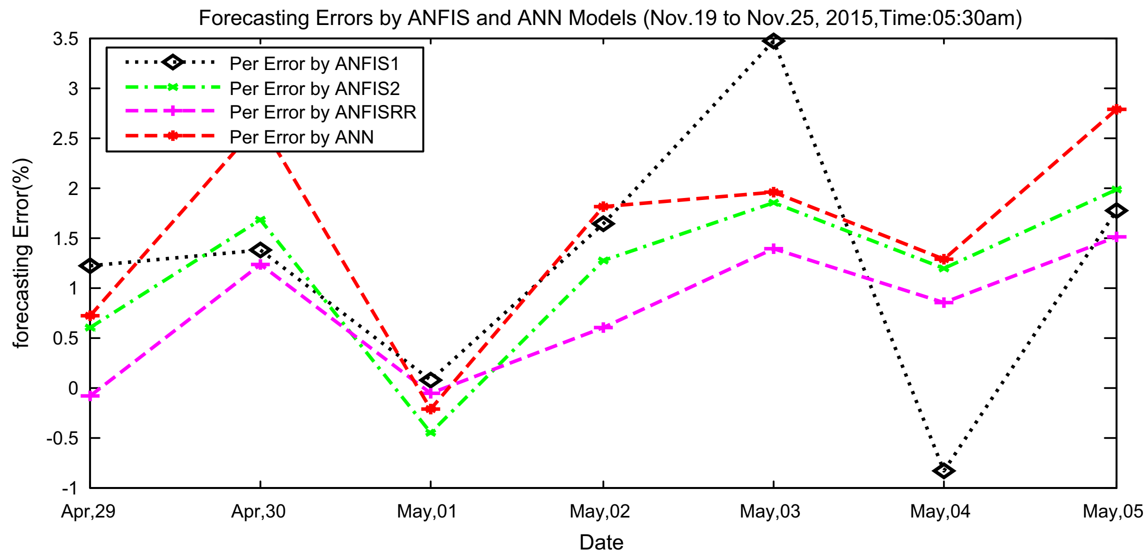

Fig. 30 Comparison of forecasting error for load trend of 05:30 a.m.

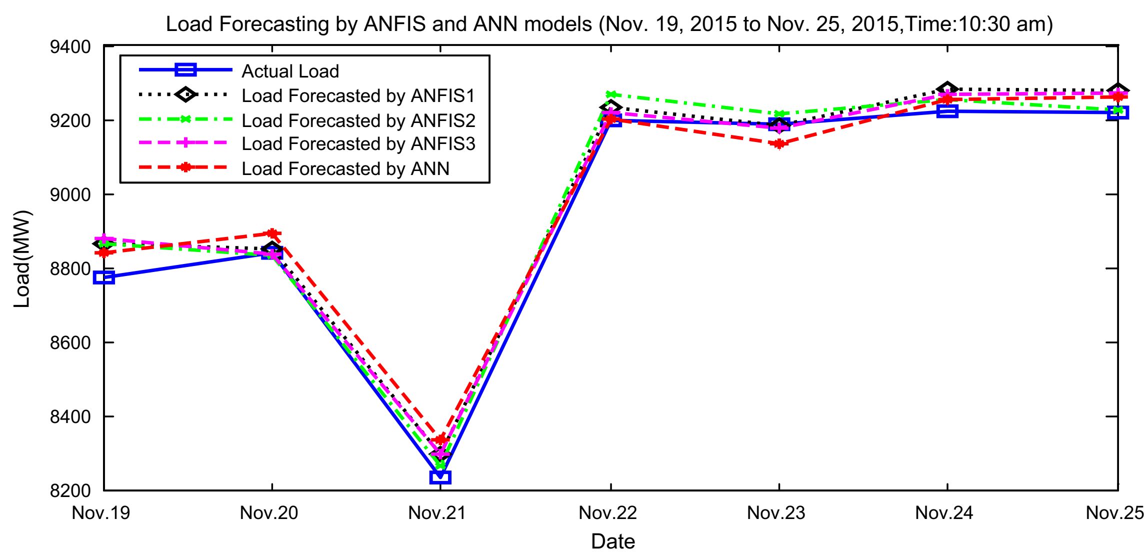

Fig. 31 Comparison of actual load and output of different models for load trend of 10:30 a.m.

- ANFIS-based forecasting techniques have been used for first time for this region.
- ANFIS model RR performs better than other ANFIS and ANN models as most of the time MAE, APE and MAPE are minimum for used samples.
- It is observed during case study that ANN model changes its results when it is repeated for forecasting of a sample, while results of ANFIS models remain unchanged. It shows that ANFIS models are more reliable and consistent than ANN model.

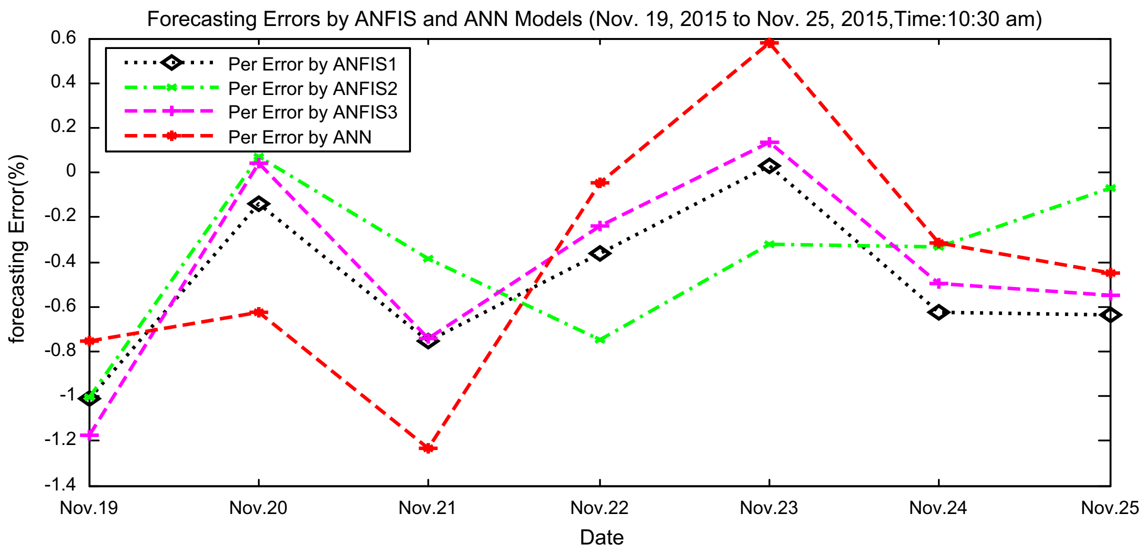

Fig. 32 Comparison of forecasting error for load trend of 10:30 a.m.

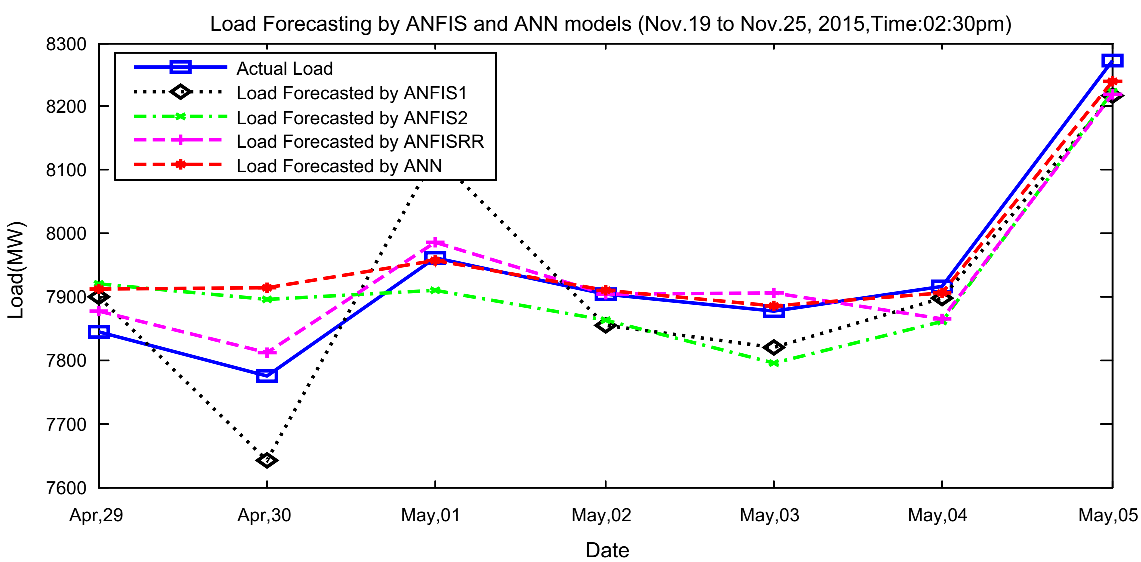

Fig. 33 Comparison of actual load and output of different models for load trend of 02:30 p.m.

Conclusion

In the recent years, many approaches for the load forecasting are developed. However, the load pattern of a particular region is different from the other, and therefore, there is no general tool is available for the forecasting. That's why, a specific technique based on ANFIS has been described in this manuscript which gives better results of load forecasting for Rajasthan state of India. It is valuable to analyze the effect of weather and other parameters such as day and date on the load consumption of Rajasthan for first time. In this paper three ANFIS models are proposed and compared with ANN model for short-term load forecasting. Proposed ANFIS models have different fuzzy

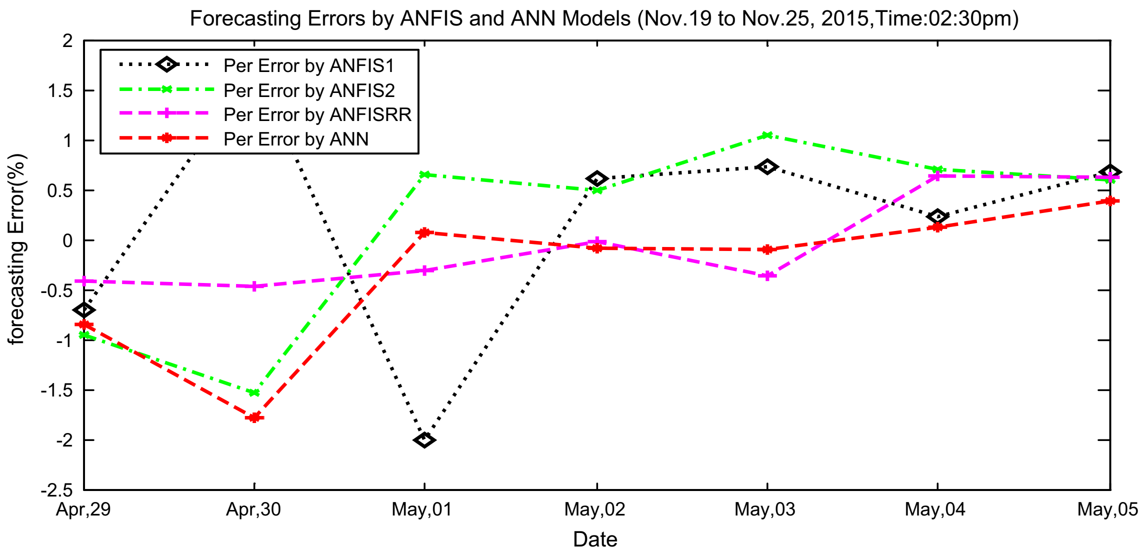

Fig. 34 Comparison of forecasting error for load trend of 2:30 p.m.

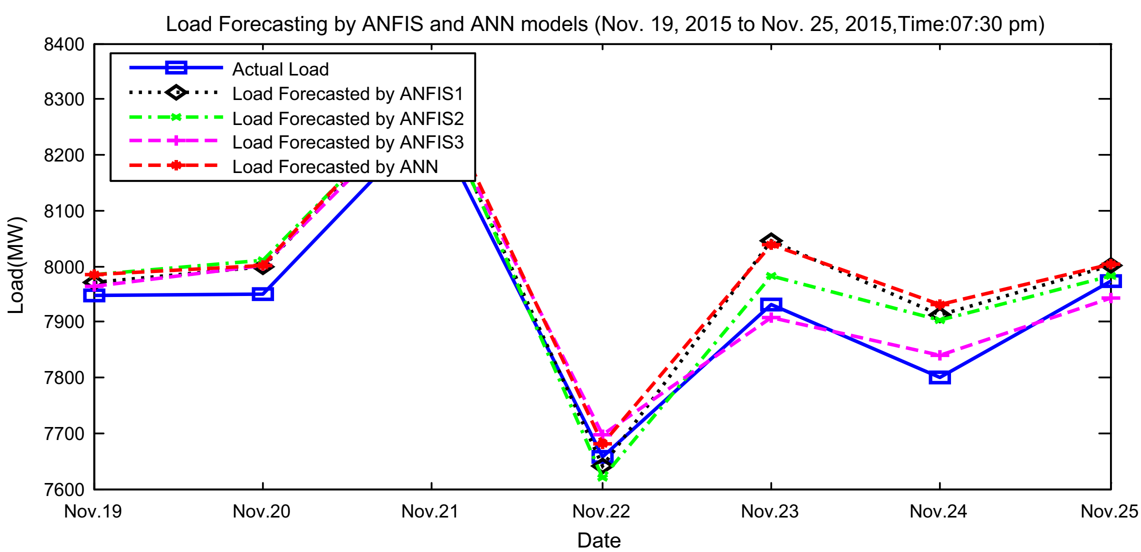

Fig. 35 Comparison of actual load and output of different models for load trend of 7:30 p.m.

structures. Model1 is based on number and type of membership function, model2 is based on radius of cluster while third model is RR model which is based on number of clusters. RR model is robust, easy to design and implement in comparison of other proposed models and has better prediction efficiency. Average values of MAE, Maximum APE and MAPE provided by RR model for fifteen testing samples are 40.5633, 1.2160% and 0.5589%, respectively, which are less than other models. The forecasting results reveal that proposed RR model for STLF provides best

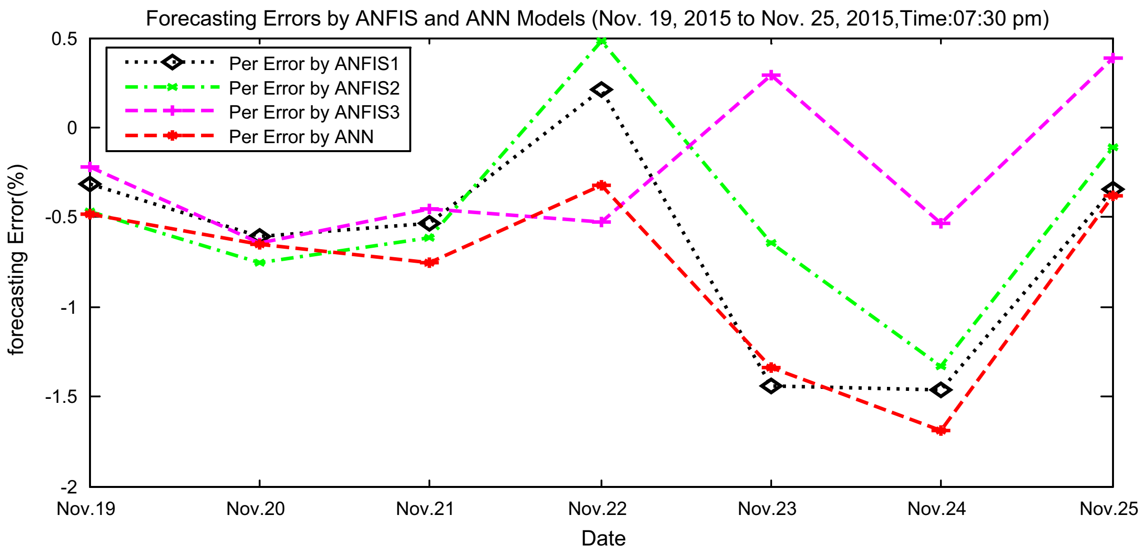

Fig. 36 Comparison of forecasting error for load trend of 7:30 p.m.

Table 4 Error comparison

Date	Time	ANFIS1			ANFIS2			ANFIS RR			ANN		
		MAE	Max. APE	MAPE	MAE	Max. APE	MAPE	MAE	Max. APE	MAPE	MAE	Max. APE	MAPE
April 29 to May 05, 2015	**02.00 a.m.**	33.22	1.1177	0.4741	27.78	**0.7215**	0.3941	**24.22**	0.7619	**0.3439**	30.71	0.8449	0.4366
	07.30 a.m.	54.77	2.2181	0.7260	60.29	3.0249	0.7966	**33.86**	**0.9688**	**0.4513**	47.32	1.7916	0.6295
	01.30 p.m.	62.38	**2.3659**	0.8754	71.62	2.8467	1.0056	**62.36**	2.6582	**0.8751**	63.74	3.2819	0.8903
	05.30 p.m.	52.30	2.0010	0.7616	66.52	1.4760	0.9660	**46.46**	**1.1228**	**0.6723**	72.20	2.2902	1.0469
	10.00 p.m.	39.30	1.6057	0.5507	51.95	2.5237	0.7208	**33.24**	**1.3570**	**0.4673**	74.42	1.7391	0.7964
July 2, to July 8, 2015	**1:00 a.m.**	99.53	3.6321	1.3957	67.61	2.1657	0.9223	**37.99**	**0.9667**	**0.5330**	89.61	2.9163	1.2450
	7:00 a.m.	55.71	1.6151	0.7575	30.42	1.5867	0.3986	**29.84**	**1.5333**	**0.3963**	70.11	2.1312	0.9496
	1:00 p.m.	55.84	1.8191	0.7922	51.42	2.0644	0.7264	**34.10**	**0.8945**	**0.4636**	47.35	2.2392	1.1528
	5:00 p.m.	59.72	1.9413	0.8143	55.08	1.9594	0.7601	**51.25**	**1.3619**	**0.7067**	71.25	1.6603	0.8368
	9:00 p.m.	54.04	**1.3453**	0.7219	96.91	2.7527	1.2483	**51.89**	1.4172	**0.6921**	75.65	2.9943	0.9948
Nov. 19, to Nov. 25, 2015	**3:00 a.m.**	33.42	**0.8501**	0.4493	35.53	1.0586	0.4780	**32.66**	0.8609	**0.4393**	40.23	1.0792	0.5716
	5:30 a.m.	111.27	3.4650	1.4838	97.01	1.9854	1.2908	**61.21**	**1.5008**	**0.8166**	122.49	2.7788	1.6298
	10.30 a.m.	45.16	**1.0119**	0.5093	**37.33**	1.6357	**0.4186**	42.61	1.5490	0.6790	50.12	1.4847	0.8029
	2:30 p.m.	75.68	2.0092	0.9561	67.58	1.5362	0.8554	**32.20**	**0.6406**	**0.4045**	38.28	1.7800	0.4868
	7:30 p.m.	55.65	1.4644	0.7024	49.81	1.3331	0.6259	**34.56**	**0.6463**	**0.4429**	63.68	2.1416	1.1286
Average Value		59.1993	1.8975	0.7980	57.7907	1.9114	0.7738	**40.5633**	**1.2160**	**0.5589**	63.8107	2.0769	0.9066

results so far for Rajasthan region and its performance is acceptable. Further, it is found that this model is more accurate as compared to other state-of-the-art techniques.

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