CHAPTER 1

INTRODUCTION

1.1 General

Electricity is the basic requirement for the economic development of any country. In India energy crisis is one of the biggest problems not only in industrial development but also in agriculture etc. Looking to the present energy scenario of the electricity sector, India had an installed capacity of 225.133 GW as of May 2013, [1] the world's fifth largest. Out of total energy generation contribution of coal is largest after it, renewal hydropower accounts for 19%, renewable energy for 12% and natural gas for about 9%. India currently suffers from a major shortage of electricity generation capacity, even though it is the world's fourth largest energy consumer after United States, China and Russia. The International Energy Agency estimates India needs an investment of at least $135 billion to provide universal access of electricity to its population. Over 300 million Indian citizens had no access to electricity. Over one third of India's rural population lacked electricity, as did 6% of the urban population. Of those who did have access to electricity in India, the supply was intermittent and unreliable. In 2010, blackouts and power shedding interrupted irrigation and manufacturing across the country.

So looking to the above situation proper energy planning and efficient utilization of energy is very important aspect, load forecasting is a step toward this direction. It involves the accurate prediction of both the magnitudes and geo-graphical locations of electric load over the different periods of the planning horizon. The basic quantity of interest in load forecasting is typically the hourly total system load. Load forecasting is also concerned with the prediction of hourly, daily, weekly and monthly values of the system load, peak system load and the system energy. A wide variety of models, varying in the complexity of functional form and estimation procedures, have been developed for the improvement of load forecasting accuracy. Load forecasting act as important tool in the optimal utilization of energy, here an Intelligent approach for STLF has been used. In this work we are using ANN and fuzzy logic based approach and compared the predicated value with actual data.

1.2 Classification of Developed STLF Methods

On the basis of time difference, load forecasting is divided into four categories:

- Long-term forecasting with the lead time of more than one year
- Mid-term forecasting with the lead time of one week to one year
- Short-term load forecasting with the lead time of 1 to 168 hours
- Very short-term load forecasting with the lead time shorter than one day

1.3 Intelligent Approach

There are different categories of forecasting methods for different purposes. In this thesis short-term load forecasting which serves the next day(s) unit commitment and reliability analysis is focused on. The research approaches of short-term load forecasting can be mainly divided into two categories: Fuzzy logic method and artificial intelligence methods [2]. In fuzzy logic based approach the input data is normalized and on that basis its rule base is made for analyzing the data, while artificial intelligence methods try to imitate human beings' way of thinking and reasoning to get knowledge from the past experience and forecast the future load. There are various other method which belong to computational intelligence category, it include expert system [8], artificial neural network (ANN) [9], fuzzy inference [10], and evolutionary algorithm. Expert systems try to get the knowledge of experienced operators and express it in an "if…then" rule, but the difficulty is sometimes the experts' knowledge is intuitive and could not easily be expressed.

Artificial neural network doesn't need the expression of the human experience and aims to establish a network between the input data set and the observed outputs. It is good at dealing with the nonlinear relationship between the load and its relative factors, but the shortcoming lies in over fitting and long training time. Generally computational intelligence methods are flexible in finding the relationship between load and its relative factors, especially for the anomalous load forecasting.

1.3.1 Fuzzy Logic

Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a value of "True" or "False". Under fuzzy logic an input is associated with certain qualitative ranges. For instance the temperature of a day may be “low”, “medium” or “high”. Fuzzy logic allows one to logically deduce outputs from fuzz inputs. In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs.

Among the advantages of the use of fuzzy logic are the absences of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise inputs. With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting

1.3.2 Neural Networks

The Artificial neural networks (ANN) has been a widely used for load forecasting technique since 1990. Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting. The outputs of an artificial neural network are some linear or non-linear mathematical function of its inputs. The inputs may be the outputs of other network elements as well as actual network inputs. In practice network elements are arranged in a relatively small number of connected layers of elements between network inputs and outputs. Feedback paths are sometimes used. In applying a neural network to load forecasting, one must select one of a number of architectures (e.g. Hopfield, back propagation, Boltzmann machine), the number and connectivity of layers and elements, use of bi-directional or unidirectional links and the number format (e.g. binary or continuous) to be used by inputs and outputs. The most popular artificial neural network architecture for load forecasting is back propagation. This network uses continuously valued functions and supervised learning. That is, under supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical loads) in a pre-operational “training session”. Artificial neural networks with unsupervised learning do not require pre-operational training.

1.4 Significance of the STLF Process

In nearly all the energy management systems of the modern control centers, there is a short-term load forecasting module. A good STLF system should fulfill the requirement of accuracy, fast speed, automatic bad data detection, friendly interface, automatic data access and automatic forecasting result generation.

a) Accuracy

The most important requirement of STLF process is its prediction accuracy. As discussed earlier, good accuracy is the basis of economic dispatch, system reliability and electricity markets. The main goal of most STLF literatures and also of this thesis is to make the forecasting result as accurate as possible.

b) Fast Speed

Employment of the latest historical data and weather forecast data helps to increase the accuracy. When the deadline of the forecasted result is fixed, the longer the runtime of the STLF program is, the earlier historical data and weather forecast data can be employed by the program. Therefore the speed of the forecasting is a basic requirement of the forecasting program. Programs with too long training time should be abandoned and new techniques shortening the training time should be employed. Normally the basic requirement of 24 hour forecasting should be less than 20 minutes.

c) Friendly Interface

The interface of the load forecasting should be easy, convenient and practical. The users can easily define what they want to forecast, whether through graphics or tables. The output should also be with the graphical and numerical format, in order that the users can access it easily.

d) Automatic Bad Data Detection

In the modern power systems, the measurement devices are located over the system and the measured data are transferred to the control center by communication lines. Due to the sporadic failure of measurement or communication, sometimes the load data that arrive in the dispatch center are wrong, but they are still recorded in the historical database. In the early days, the STLF systems relied on the power system operators to identify and get rid of the bad data. The new trend is to let the system itself do this instead of the operators, to decrease their work burden and to increase the detection rate.

e) Automatic Data Access

The historical load, weather and other load-relevant data are stored in the database. The STLF system should be able to access it automatically and get the needed data. It should also be able to get the forecasted weather automatically on line, through Internet or through specific communication lines. This helps to decrease the burden of the dispatchers.

f) Automatic Forecasting Result Generation

To reduce the risk of individual imprecise forecasting, several models are often included in one STLF system. In the past such a system always needs the operators' interference. In other words, the operators have to decide a weight for every model to get the combinative outcome. To be more convenient, the system should generate the final forecasting result according to the forecasting behavior of the historical days.

g) Portability

Different power systems have different properties of load profiles. Therefore a normal STLF software application is only suitable for the area for which it has been developed. If a general STLF software application, which is portable from one grid to another, can be developed, the effort of developing different software for different areas can be greatly saved. This is a very high-level requirement for the load forecasting, which has not been well realized up until today.

1.5 Organization of Dissertation

The dissertation is organized as follows: Chapter 1 is the introduction of present work. Literature review is prescribed in chapter 2. Chapter 3 Fuzzy logic based approach for STLF including fuzzy based model development, data collection, data normalization, making rule base and evaluation of MATLAB results. Chapter 4 present ANN based approach for STLF including predication and evaluation of result using MATLAB. Finally, the conclusion and the future scope of the work presented in chapter 5.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter includes the literature survey related to intelligent approach for STLF. Various books and research paper related to intelligent approach for STLF have been studied, which form the back bone of the present work undertaken by me.

2.2 Literature Review

2.2.1 Fuzzy Logic based Approach

Fuzzy logic based approach is a very important tool for STLF. Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a value of "True" or "False". Under fuzzy logic an input is associated with certain qualitative ranges. For instance the temperature of a day may be "low", "medium" or "high". Fuzzy logic allows one to logically deduce outputs from fuzzy inputs. In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs. In this report we are analyzing the data using fuzzy logic based approach for that various research papers are taken as reference.

Chaturvedi [2] discussed about the various soft computing techniques including fuzzy logic, which a capability of handling uncertainty arising from, say, vagueness, incompleteness, overlapping concepts; neural networks providing machinery for adaptation and learning, genetic algorithms for optimization and learning, and probabilistic reasoning for inference were considered to be the basic ingredients of soft computing. The ability to accurately forecast load is vitally important for the electric industry in a deregulated economy. Load forecasting has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. K. Adamson [3] et.al a large variety of methods have been developed for and applied to load forecasting. In this paper various approaches to load forecasting, highlighting the importance of intelligent systems and explore the possible future directions of forecasting research. Papalexopoulos [4] et.al, described a linear regression-based model for the STLF. The model's most significant aspects fall into the following areas: innovative model building, including accurate holiday modeling by using binary variables and temperature etc. Rizwan [15] et.al. presents the Short term Electrical load forecasting using Fuzzy logic approach, the forecasting is done using the data from Shahpura, Jaipur.

Rahman [5] et al. investigates the applicability of expert systems to short term load forecasting in that an expert system based load forecasting algorithm has been developed and tested with electric utility historical data. The algorithm has been developed based on the logical and syntactical relationships between weather and load, and prevailing daily load shapes. It is robust and accurate and has yielded results that are equally good. The data and computational requirements of the algorithm are also minimal. Therefore, the expert system approach to the load forecasting problem has yielded a viable algorithm which has the desired performance, and is implementable on a microcomputer.

Rehman [7] proposed a new short term load forecasting technique which utilizes the attractive features of both the statistical and expert system based methods, but avoids their drawbacks. The priority vector based load forecasting technique uses pairwise comparisons to extract relationships from pre-sorted historical hourly load and weather records for up to two years. The pre-sorting is done to identify seasonal boundaries and to categorize the day types (weekdays, weekends, holidays, etc.). The technique is adaptive in the sense that it internally generates the coefficients of relationships among the governing variables (i.e., weather parameters) and the load. As these relationships change over lime, such coefficients are automatically updated. The resulting linear method is robust and fairly accurate.

Srinivas [11] presents a forecasting method based on similar day approach in conjunction with fuzzy rule-based logic. To obtain the next-day load forecast, fuzzy logic is used to modify the load curves on selected similar days. A Euclidean norm considering weather variables such as `temperature' and `humidity' with weight factors is used for the selection of similar days. The effectiveness of the proposed approach is demonstrated on a typical load and weather data. S. C. Pandian [12] et al. present a fuzzy approach for STLF in which the ‘time’ and ‘temperature’ of the day are taken as inputs for the fuzzy logic controller and the ‘forecasted load’ is the output. J. A. Momoh [13] et al. presents a survey of publications on applications of fuzzy set theory to power systems and the basic procedures for fuzzy set based methods to solve specific power systems problems. Srinivasan [17] et al. used the hybrid fuzzy-neural technique to forecast load .This technique combines the neural network modelling and techniques from fuzzy logic and fuzzy set theory.

Several techniques have been developed to represent load models by fuzzy conditional statements. Hsu [14] et al. presented an expert system using fuzzy set theory for STLF. The expert system was used to do the updating function. Short-term forecasting was performed and evaluated on the Taiwan power system. Al-Anbuky [16] et al. discussed the implementation of a fuzzy-logic approach to provide a structural framework for the representation, manipulation and utilization of data and information concerning the prediction of power commitments. Neural networks are used to accommodate and manipulate the large amount of sensor data.

Srinivasan [17] et al. used the hybrid fuzzy-neural technique to forecast load .This technique combines the neural network modelling and technique s from fuzzy logic and fuzzy set theory. Chow and Tram [20] presented a fuzzy logic methodology for combining information used in spatial load forecasting, which predict s both the magnitude s and locations of future electric loads. Padmakumari [19] et al. combined fuzzy logic with neural networks in a technique that reduces both errors and computational time.

2.2.2 ANN based Approach

The use of artificial neural networks (ANN) has been a widely studied load forecasting technique since 1990. Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting. The outputs of an artificial neural network are some linear or non-linear mathematical function of its inputs. In this work ANN is used for STLF, the various research paper used for reference are discussed here.

Neural networks (NN) or artificial neural networks (ANN) have very wide applications because of their ability to learn . According to Damborg [21] et al., neural networks offer the potential to overcome the reliance on a functional form of a forecasting model. There are many types of neural networks: multilayer perceptron network, self-organizing network, etc. There are multiple hidden layers in the network. In each hidden layer there are many neurons. Inputs are multiplied by weights, and are added to a threshold to form an inner product number called the net function. The method discussed by Liu [22] et al., using fully connected feed-forward type neural networks. The network outputs are linear functions of the weights that connect inputs and hidden units to output units. Therefore, linear equations can be solved for these output weights. In each iteration through the training data (epoch) , the output weight optimization training method uses conventional back-propagation to improve hidden unit weights, then solves linear equations for the output weights using the conjugate gradient approach .Sinha [23] presents an application of ANN to short term load forecasting. The proposed method works in two stages. In the first stage a load forecast with a lead time of 24 hours is done for unit commitment, generation planning etc. In the second stage the next hour forecast is refined using the latest load values and the error in their prediction.

Srinivasan and Lee [18] surveyed hybrid fuzzy neural approaches to load forecasting. Hsu and Yang [25] estimated the load pattern of the day under study by averaging the load patterns of several past day, which are of the same day type (ANN being used for the classification) . To predict the daily peak load, a feed-forward multilayer neural network was designed. Buhari [26] et al., present the development of an ANN based short-term load forecasting model for the 132/33KV sub-Station, Kano, Nigeria. The recorded daily load profile with a lead time of 1-24 hours for the year 2005 was obtained from the utility company. The Levenberg-Marquardt optimization technique which has one of the best learning rates was used as a back propagation algorithm for the multilayer feed forward ANN model. The obtained result has very less error.

Ho and Hsu [10] designed a multilayer ANN with a new adaptive learning algorithm for short term load forecasting. In this algorithm the momentum is automatically adapted in the training process. Lee and Park [27] proposed a non-linear load model and several structure s of ANNs were tested. Inputs to the ANN include past load values, and the output is the forecast for a given day. Lee and Park demonstrated that the ANN could be successfully used in STLF with accepted accuracy. Djukanovic et al. [28] proposed an algorithm using an unsupervised /supervised learning concept and historical relationship between the load and temperature for a given season, day type and hour of the day. They used this algorithm to forecast hourly electric load with a lead time of 24h.

Drezga and Rahman [29] applied another ANN-based technique that features the following characteristics: (1) selection of training data by the k-nearest neighbor's concept, (2) pilot simulation to determine the number of ANN units and (3) iterative forecasting by simple moving average to combine local ANN predictions. The logical and syntactical relationships between weather load and the prevailing daily load shapes have been widely examined to develop different rules for different approaches. The typical variables in the process are the season under consideration, day of the week, the temperature and the change in this temperature.

Chen [30] et.al. presents some of the practical techniques of using artificial neural networks for the short-term load forecasting problem. The model described in this paper is a back propagation based multilayer perceptron including the temperature factor. In order to expedite the training process, the quasi-Newton method is employed. An intelligent treatment to holiday factors in order to improve the forecasting accuracy is discussed. Vehmuri [31] et.al. used ANN technique for the evaluation of STLF. It evaluate the performance of ANN methodology for practical considerations of STLF problems. In this Data from two utilities are used in modeling and forecasting. In addition, the effectiveness of a next 24h ANN model in predicting 24 h load profile at one time was compared with the traditional next 1h ANN model.

Lie [33] et.al present the novel feed-forward two layers ANN neural network based function, this approximation model is utilized to forecast electric system hourly load. The forecast model is based on a quantitative weight assignment priority factors for the day type and daytime classes, in addition to the daily average temperature. The forecast vector utilizes scaled historical load data for eight day type classes, four day time subclasses as well as load pattern averaged one-hour, six-hour, 24-hour, and 168-hour filtered historical load. Osman [32] et.al presents an ANN based STLF method that uses the most correlated weather data for training, validating and testing the neural network. Correlation analysis of weather data determines the input parameters of the neural networks.

CHAPTER 3

FUZZY BASED APPROACH FOR STLF

3.1 Introduction

Load forecasting is vitally important for the electric industry in the deregulated economy. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. A large variety of mathematical methods have been developed for load forecasting. In this thesis short term load forecasting using fuzzy logic based modeling is presented. It has emerged as a complement tool to mathematical approach for solving various power system problems including STLF. It provides a powerful new paradigm, help us in the analysis of unknown and complex problems. Keeping in view of the aforesaid variation in the inputs, an attempt has been made to develop the fuzzy logic based model for short term load forecasting. The proposed model is simple, accurate and incorporates the uncertainties in the input variables.

3.2 Basics of Fuzzy Logic

The concept of fuzzy logic was introduced by Professor Lotfi A. Zadeh at the University of California, Berkeley in the 1960's. His goal was to develop a model that could more closely describe the natural language process. This model was intended to be used in situations when deterministic and/or probabilistic models do not provide a realistic description of the phenomenon under study. The fuzzy sets and fuzzy operators are the subjects and verbs of fuzzy logic. But in order to say something useful, we need to make complete sentences. The condition statements, IF -THEN rules, are things that make fuzzy logic useful. The fuzzy logic IF -THEN statements are used to characterize the state of a system and truth value of the proposition is a measure for how well the description matches the state of the system [1,13]. The fuzzy set can be defined as follows:

Let X, be a universal set. The characteristic function $\mu.A$ of a subset of X takes its values in the two element set {0, 1} and μ $A(x) = 1$, if $x \in A$ and zero otherwise. A fuzzy set A has a characteristic function taking its values in the interval {0, 1}. μA is also called a me membership function and μA (x) is the grade of membership of $x \in X$

in A. In fuzzy set, the transition between membership and non-membership is gradual rather than abrupt. The union and intersection of two fuzzy subsets A and B of X having membership function μA and μB respectively is defined as

1. Union: $\mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)]$
2. Intersection: $\mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)]$

Fuzzy logic describes the vague concepts such as fast runner, hot weather, weekend days etc. It is convenient to map an input to an output space. The concept of fuzzy provides a natural way dealing with the problems in which source of impression is the absence of sharply defined criterion rather than the presence of random variables. Prof. Zadeh also introduced linguistic as variables whose values are sentences in natural or artificial language.

Fuzzy logic starts with the concept of a fuzzy set. A fuzzy set is a set without a crisp, clearly defined boundary. It can contain elements with only a partial degree of membership. Fuzzy set theory exhibits immense potential for effective solving of the uncertainty in the problem. Fuzziness means vagueness. Fuzzy set theory is an excellent mathematical tool to handle the uncertainty arising due to vagueness .Fuzzy systems incorporates Fuzzy logic into their reasoning mechanism to gain a decided advantage over the crispness of boolean logic for a wide range of problems. Thus, rule-based expert systems or control systems cast their rules using fuzzy set and fuzzy operator.

3.3 Data Collection and Normalization

The hourly daily electrical load of Shahpura, Jaipur has been collected from Rajasthan Electricity Board for the purpose of short term load forecasting. The hourly daily electrical load (MW) for the month of November 2012 is presented in Table 3.1.

Table 3.1 Load Variation for the Month of November 2012

Serial No.	Input 1	Input 2	Input 3	Input 4
1.	31.9890	34.7592	32.6468	34.2988
2.	30.9881	30.7675	31.2300	33.2388

3.	31.0176	30.4974	31.0144	33.0069
4.	31.1353	30.4674	31.0452	33.1394
5.	30.6054	34.9392	32.6468	31.7150
6.	28.6331	27.7663	31.2300	31.6488
7.	21.0383	20.3532	20.4500	21.7444
8.	18.0356	17.4420	17.3700	18.4981
9.	18.4772	17.6821	17.7704	18.8294
10.	18.9776	18.2223	18.4172	19.5913
11.	19.0659	18.3723	18.4788	19.5250
12.	19.2131	18.4624	18.6328	19.7238
13.	18.0356	17.2919	17.3392	18.3656
14.	18.6244	17.8321	17.9244	19.0944
15.	20.0963	19.3027	19.5260	21.0488
16.	18.9482	18.3123	18.2940	20.3863
17.	19.2131	18.2523	19.6492	20.6844
18.	20.3906	19.6329	19.8956	21.0819
19.	23.1872	22.6641	23.0680	24.2288
20.	25.3950	24.6450	25.0700	26.3488
21.	28.6331	32.6883	33.5092	29.0650
22.	28.1621	27.4961	27.9344	29.7606
23.	28.3388	27.7062	28.1500	29.8600
24.	20.8322	20.2631	20.1420	21.4794
25.	20.4495	24.1948	12.7500	13.4300
26.	18.9188	18.1322	18.3248	19.4588
27.	18.0356	18.1623	17.6780	19.4256
28.	16.5638	16.1814	15.9840	18.3988

29.	15.1508	17.6520	15.8300	14.4900
30.	15.9750	15.1910	15.2140	16.0469
31.	14.7975	14.0505	22.7600	15.0863
32.	15.0919	14.4107	15.8300	16.7425
33.	15.0036	15.1610	15.6452	16.2788
34.	14.2382	13.6604	13.9820	14.0925
35.	14.3559	13.4503	13.5200	14.2250
36.	14.2088	13.4203	13.3968	14.4238
37.	14.0910	15.4011	15.9224	18.8625
38.	14.3559	13.4503	13.4892	14.2250
39.	14.5914	13.9005	13.8280	14.7550
40.	14.8564	14.1106	13.9820	15.0863
41.	14.0616	15.2811	21.4972	14.3906
42.	14.5620	13.7804	18.9100	16.7425
43.	15.0919	14.3207	14.8136	15.7488
44.	16.0928	16.1214	16.0456	16.1463
45.	15.5923	14.8609	14.8752	16.0800
46.	15.1213	14.2606	14.2592	15.0863
47.	14.0027	13.3603	13.8280	14.4238
48.	13.6200	12.7600	14.6288	16.5438
49.	13.9144	13.0600	13.3660	15.1856
50.	33.6375	33.2585	33.6940	36.0213
51.	36.2869	36.4699	37.1436	39.5988
52.	37.1700	36.6800	37.3900	39.9300
53.	36.9051	36.4699	37.0820	39.6319
54.	36.8756	36.6199	36.4660	39.1350

55.	35.9925	35.2694	36.1580	38.9694
56.	36.2574	29.8971	34.9568	36.9488
57.	34.2263	33.1685	34.0020	36.1206
58.	34.2263	33.7988	34.3408	36.6175
59.	34.2263	34.3690	34.6796	36.5513
60.	32.4600	31.6979	32.2464	35.4581
61.	32.7249	32.2681	32.8008	34.8950
62.	33.7847	33.4686	33.5400	35.5244
63.	33.9319	33.4686	34.3100	36.1538
64.	31.6652	26.7758	33.8788	35.0938
65.	33.0782	32.5382	33.0780	35.3256
66.	33.0488	32.4782	33.0780	35.1269
67.	33.3431	32.5683	32.6160	34.9613
68.	33.1371	25.7554	20.9428	23.4669
69.	33.3726	32.8384	33.3860	35.6569
70.	34.0202	33.4086	21.3740	24.0300
71.	33.9319	33.4386	28.9200	27.3425
72.	33.6375	26.7758	29.2588	25.4544
73.	34.2263	34.9693	34.6180	37.3794
74.	32.6661	32.1181	32.5852	34.7625
75.	31.9890	32.2681	32.1848	34.4644
76.	30.9881	28.7267	27.1336	26.8788
77.	31.2825	31.0676	31.0760	32.9738
78.	31.5769	31.3978	31.6920	33.5700
79.	28.6626	27.7362	24.7004	23.6325
80.	28.6920	28.0964	28.4580	30.3238

81.	29.2219	28.8167	26.9180	27.1438
82.	29.4868	28.9668	29.3820	31.3506
83.	29.8106	29.1768	29.3820	31.1519
84.	30.1050	29.5370	30.0288	32.0131
85.	30.9881	28.7267	23.6809	19.8894
86.	30.1050	29.6270	27.2568	24.0300
87.	30.9881	30.5274	30.9528	32.9738
88.	35.7276	35.5995	33.6940	33.2056
89.	36.8756	35.8696	30.7372	23.7981
90.	37.1700	36.4699	37.3900	39.8306
91.	36.2869	30.4674	36.5276	38.9363
92.	35.5509	35.0593	35.6652	38.2075
93.	35.4332	35.2694	35.7576	38.2738
94.	34.8150	34.6691	32.2156	26.1831
95.	35.1977	34.6691	34.3100	32.3444
96.	34.2263	34.0689	34.0020	36.9819

The input is normalized and scaled in the range of 0.1- 0.9 to avoid the convergence problem during the rules formation. The actual data is scaled by using the following expression and presented in Table 3.2

$$L_s = \frac{(Y_{\max} - Y_{\min})}{(L_{\max} - L_{\min})}(L - L_{\min}) + Y_{\min} \tag{3.1}$$

L_s =Normalized Value

L =Input Value from table

$L_{\min}$ =Min. Value in the table

$L_{\max}$ =Max. Value in the table

$Y_{\min}$ =Min. value of range (0.1)

$Y_{\max}$ =Max. Value in the range (0.9)

Table 3.2 Normalized Input value Data

S. No.	Input 1	Input 2	Input 3	Input 4
1.	0.731	0.833	0.746	0.730
2.	0.697	0.700	0.700	0.698
3.	0.697	0.691	0.693	0.691
4.	0.703	0.69	0.694	0.695
5.	0.684	0.839	0.746	0.652
6.	0.616	0.6	0.70	0.650
7.	0.355	0.353	0.350	0.351
8.	0.252	0.256	0.250	0.253
9.	0.267	0.264	0.263	0.263
10.	0.287	0.282	0.284	0.286
11.	0.287	0.287	0.286	0.284
12.	0.292	0.29	0.291	0.290
13.	0.252	0.251	0.249	0.249
14.	0.272	0.269	0.268	0.271
15.	0.322	0.318	0.320	0.330
16.	0.283	0.285	0.280	0.310
17.	0.292	0.283	0.324	0.319
18.	0.332	0.329	0.332	0.331
19.	0.429	0.43	0.435	0.426
20.	0.505	0.496	0.500	0.490
21.	0.616	0.764	0.774	0.572
22.	0.599	0.591	0.593	0.593
23.	0.605	0.598	0.600	0.596
24.	0.348	0.350	0.340	0.343
25.	0.332	0.481	0.100	0.100
26.	0.280	0.279	0.281	0.282

27.	0.250	0.28	0.260	0.281
28.	0.200	0.214	0.205	0.25
29.	0.152	0.263	0.200	0.132
30.	0.181	0.181	0.180	0.179
31.	0.140	0.143	0.425	0.150
32.	0.150	0.155	0.200	0.200
33.	0.147	0.18	0.194	0.186
34.	0.121	0.13	0.140	0.120
35.	0.125	0.123	0.125	0.124
36.	0.120	0.122	0.121	0.130
37.	0.116	0.188	0.203	0.264
38.	0.125	0.123	0.124	0.124
39.	0.133	0.138	0.135	0.140
40.	0.142	0.145	0.140	0.150
41.	0.115	0.184	0.384	0.129
42.	0.132	0.134	0.300	0.200
43.	0.150	0.152	0.167	0.17
44.	0.184	0.212	0.207	0.182
45.	0.167	0.17	0.169	0.18
46.	0.151	0.15	0.149	0.150
47.	0.113	0.12	0.135	0.13
48.	0.000	0.100	0.161	0.194
49.	0.110	0.100	0.120	0.153
50.	0.780	0.783	0.780	0.782
51.	0.870	0.890	0.892	0.890
52.	0.900	0.897	0.900	0.900
53.	0.891	0.890	0.890	0.891
54.	0.890	0.895	0.870	0.876

55.	0.860	0.850	0.860	0.871
56.	0.869	0.671	0.821	0.810
57.	0.800	0.780	0.790	0.785
58.	0.800	0.801	0.801	0.800
59.	0.800	0.820	0.812	0.798
60.	0.740	0.731	0.733	0.765
61.	0.749	0.750	0.751	0.748
62.	0.785	0.790	0.775	0.767
63.	0.790	0.790	0.800	0.786
64.	0.713	0.567	0.786	0.754
65.	0.761	0.759	0.760	0.761
66.	0.760	0.757	0.760	0.755
67.	0.770	0.76	0.745	0.75
68.	0.763	0.533	0.366	0.403
69.	0.771	0.769	0.770	0.771
70.	0.793	0.788	0.380	0.420
71.	0.790	0.789	0.625	0.520
72.	0.780	0.567	0.636	0.463
73.	0.800	0.84	0.81	0.823
74.	0.747	0.745	0.744	0.744
75.	0.724	0.75	0.731	0.735
76.	0.690	0.632	0.567	0.506
77.	0.700	0.710	0.695	0.690
78.	0.710	0.721	0.715	0.708
79.	0.611	0.599	0.488	0.408
80.	0.612	0.611	0.610	0.610
81.	0.630	0.635	0.560	0.514
82.	0.639	0.640	0.640	0.641

83.	0.650	0.647	0.640	0.635
84.	0.660	0.659	0.661	0.661
85.	0.690	0.632	0.4549	0.295
86.	0.660	0.662	0.571	0.420
87.	0.690	0.692	0.691	0.69
88.	0.851	0.861	0.78	0.697
89.	0.890	0.870	0.684	0.413
90.	0.900	0.89	0.900	0.897
91.	0.870	0.690	0.872	0.870
92.	0.845	0.843	0.844	0.848
93.	0.841	0.850	0.847	0.850
94.	0.820	0.830	0.732	0.485
95.	0.833	0.830	0.800	0.671
96.	0.800	0.810	0.790	0.811

The electrical loads of Shahpura, Jaipur are also presented graphically in Fig. 3.7, Fig. 3.8, Fig. 3.9, Fig. 3.10 and Fig. 3.11 respectively. These load curves are helpful in determining the load pattern and also in comparing the actual and the forecasted value.

3.4 Model Development

The fuzzy logic model for the short term electrical load forecasting is developed and presented. The developed model contains a set of rules which are developed from qualitative descriptions. The fuzzy linguistic variables are described as low, medium and high. The membership function for the actual load is presented in Fig. 3.1. A concern for the development of fuzzy systems is the assignment of appropriate membership functions. Construction of membership functions can be based on intuition, experience or probabilistic methods. Nevertheless, it has shown that the choice of membership degrees in the interval [0, 1], does not matter, as it is the order of magnitude that is important. In fuzzy systems, rules may be fired with some degree using fuzzy inference; whereas, in conventional expert systems, a rule is either fired or not fired. For the short term load forecasting (STLF) problem, rules are defined to determine the accuracy in terms of absolute relative error. Such rules are expressed in the following form.

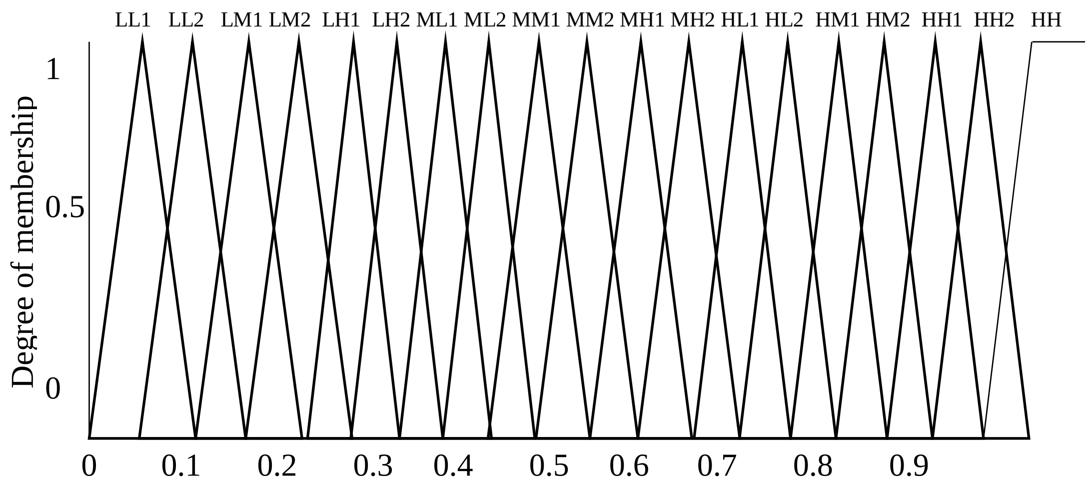

Fig. 3.1 Fuzzy subsets membership functions for electrical load

The fuzzy logic based model for short term load forecasting is presented in Fig 3.2.

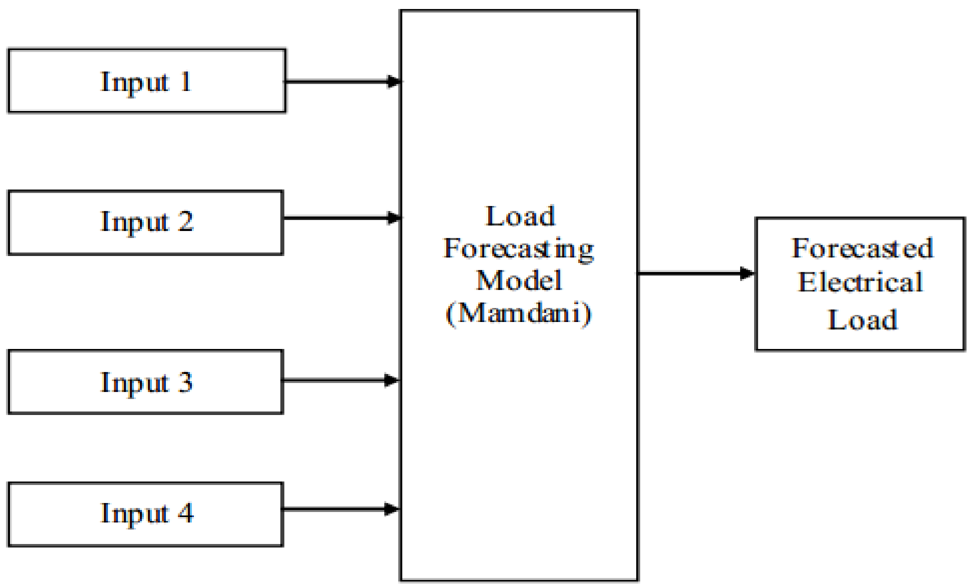

Fig. 3.2 FLC based Model for SLTF

IF premise (antecedent), THEN conclusion (consequent). For the STLF problem, a set of multiple -antecedent fuzzy rules have been established. The input to the rules is electrical load demand during 12, 13, 14 and 15 November, 2012 respectively and the output consequent is the electrical load on 16th November 2012. The rules are summarized in Table 3.3 given below.

3.4.1 Rule Base

For the predication of STLF using Fuzzy logic, a set of multiple antecedent fuzzy rules have been established. The fuzzy variable are described as Low, Medium, High and further each is subdivided into Low, Medium and High as shown in Table 3.3.

Table 3.3 Rule Base

S. No.	Input 1	Input 2	Input 3	Input 4	Output
1.	HM1	HH1	HM1	HM1	MM2
2.	HL2	HL2	HL2	HL2	HL2
3.	HL2	HL2	HL2	HL2	HL2
4.	HL2	HL2	HL2	HL2	HL2
5.	HL2	HH1	HM1	MM2	MM2
6.	MH2	MH2	HL2	HL1	HL1
7.	ML1	ML1	ML1	HL1	ML1
8.	LH1	LH1	LH1	LH1	LH2
9.	LH1	LH1	LH1	LH1	LH2
10.	LH2	LH2	LH2	LH2	LH2
11.	LH2	LH2	LH2	LH2	LH2
12.	LH2	LH2	LH2	LH2	LH2
13.	LH1	LH1	LH1	LH1	LH2
14.	LH1	LH1	LH1	LH1	LH2
15.	LH2	LH2	LH2	ML1	LH2
16.	LH2	LH2	LH2	LH2	LH2
17.	LH2	LH	LH2	LH2	LH2
18.	ML1	ML1	ML1	ML1	ML1

19.	MM1	MM1	MM1	MM1	ML2
20.	MM2	MM2	MM2	MM2	MM2
21.	MH2	HM1	HM1	MH1	MH1
22.	MH2	MH2	MH2	MH2	MH2
23.	MH2	MH2	MH2	MH2	MH2
24.	ML1	ML1	ML1	ML1	ML1
25.	ML1	MM2	LL1	LL1	MM2
26.	LH2	LH2	LH2	LH2	LH2
27.	LH1	LH2	LH1	LH2	LH2
28.	LM2	LM2	LM2	LH1	LH2
29.	LM1	LH1	LM2	LM1	ML2
30.	LM2	LM2	LM2	LM2	LM2
31.	LM1	LM1	MH1	LM1	LH1
32.	LM1	LM1	LM2	LM2	LM2
33.	LM1	LM2	LM2	LM2	LM2
34.	LL2	LM2	LM2	LM2	LM1
35.	LM1	LL2	LM1	LL2	LM1
36.	LL2	LL2	LL2	LM1	LM1
37.	LL2	LM2	LM2	LH1	LL1
38.	LM1	LL2	LL2	LL2	LM2
39.	LM1	LM1	LM1	LM1	LM1
40.	LM1	LM1	LM1	LM1	LM1
41.	LL2	LM2	ML2	LM1	LL2
42.	LM1	LM1	LH2	LM2	LM1
43.	LM1	LM1	LM1	LM1	LM1
44.	LM2	LM2	LM2	LM2	LM2
45.	LM1	LM1	LM1	LM2	LM1
46.	LM1	LM1	LM1	LM1	LM1

47.	LL2	LL2	LM1	LM1	LM1
48.	LL1	LL1	LM1	LM2	LM1
49.	LL2	LL2	LL2	LM1	LM1
50.	HM2	HM2	HM2	HM2	HM1
51.	HH2	HH2	HH2	HH2	HH2
52.	HH2	HH2	HH2	HH2	HH2
53.	HH2	HH2	HH2	HH2	HH2
54.	HH2	HH2	HH1	HH2	HH1
55.	HH1	HH1	HH1	HH1	HH1
56.	HH1	HL1	HM2	HM2	HM2
57.	HM2	HM2	HM2	HM2	HM2
58.	HM2	HM2	HM2	HM2	HM2
59.	HM2	HM2	HM2	HM2	HM2
60.	HM1	HM1	HM1	HM1	HL2
61.	HM1	HM1	HM1	HM1	HM1
62.	HM2	HM2	HM2	HM2	HM2
63.	HM2	HM2	HM2	HM2	HM1
64.	HL2	MH1	HM2	HM1	HL2
65.	HM1	HM1	HM1	HM1	HM1
66.	HM1	HM1	HM1	HM1	HM1
67.	HM1	HM1	HM1	HM1	HM1
68.	HM1	MH1	ML1	ML2	MM2
69.	HM1	HM1	HM1	HM1	HM1
70.	HM2	HM2	ML2	ML2	MM2
71.	HM2	HM2	HL1	MM2	MM2
72.	HM1	MH1	HL1	MM1	HH2
73.	HM2	HH1	HM2	HM2	HH1
74.	HM1	HM1	HM1	HM1	HM1

75.	HL2	HM1	HM1	HM1	HM1
76.	HL2	HL1	MH1	MM2	MH2
77.	HL2	HL2	HL2	HL2	HL2
78.	HL2	HL2	HL2	HL2	HL2
79.	MH2	MH2	MM2	ML2	MM2
80.	MH2	MH2	MH2	MH2	MH2
81.	HL1	HL1	MH1	MM2	MH1
82.	HL1	HL1	HL1	HL1	HL1
83.	HL1	HL1	HL1	HL1	HL1
84.	HL1	HL1	HL1	HL1	HL1
85.	HL2	HL1	MM1	LH2	MM2
86.	HL1	HL1	MH1	ML2	MM2
87.	HL2	HL2	HL2	HL2	HL2
88.	HH1	HH1	HM2	HL2	HL1
89.	HH2	HH1	HL2	ML2	MH1
90.	HH2	HH2	HH2	HH2	HH2
91.	HH1	HL2	HH1	HH1	HH1
92.	HH1	HH1	HH1	HH1	HH1
93.	HH1	HH1	HH1	HH1	HH1
94.	HH1	HH1	HM1	MM2	MM2
95.	HH1	HH1	HM2	HL1	HL2
96.	HM1	HM1	HM1	HM1	HM2

The rules listed in Table 3.3 have been implemented using fuzzy logic toolbox of MATLAB for developing the model to forecast the electrical load.

3.5 Components of Fuzzy Tool Box (FTB)

3.5.1 Fuzzy Inference System (FIS) Editor

The FIS Editor displays information about a fuzzy inference system. The FIS Editor handles the high-level issues for the system such as how many input and output variables, their names etc. Fuzzy Logic Toolbox software does not limit the number of inputs. However, the number of inputs may be limited by the available memory of your machine. If the number of inputs is too large, or the number of membership functions is too big, then it may also be difficult to analyze the FIS using the other GUI tools.

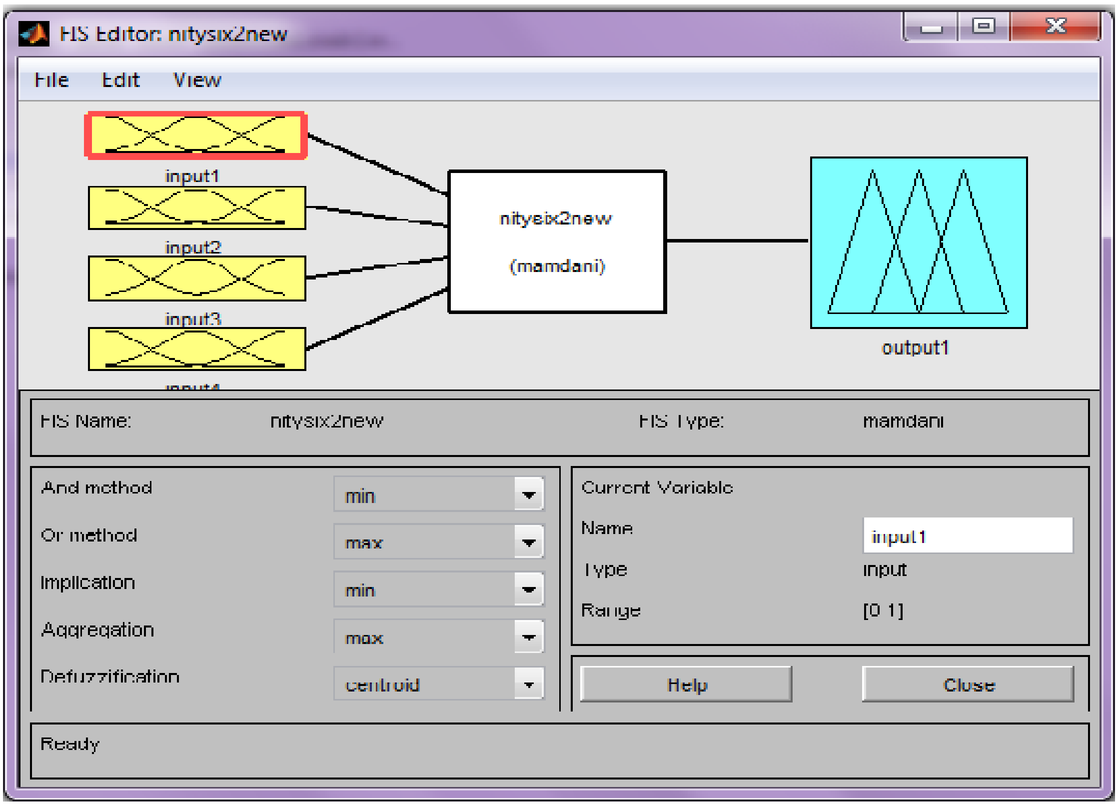

Fig. 3.3 MATLAB Model of FIS

3.5.2 Membership Function

The membership function editors is the tool that lets you display and edit all of the membership functions associated with all of the input and output variables for the entire fuzzy inference system. The membership function editor shares some features with the FIS Editor, as shown in the figure. When we open the membership function editor to work on a fuzzy inference system that does not already exist in the workspace, there are no membership functions associated with the variables that you defined with the FIS Editor, so basically membership function editor is used to define the shapes of all the membership functions associated with each variable. In Fig. 3.4, four input and outputs are provided corresponding to which membership function is formed. The input data is provided in normalized form to avoid problem of convergence.

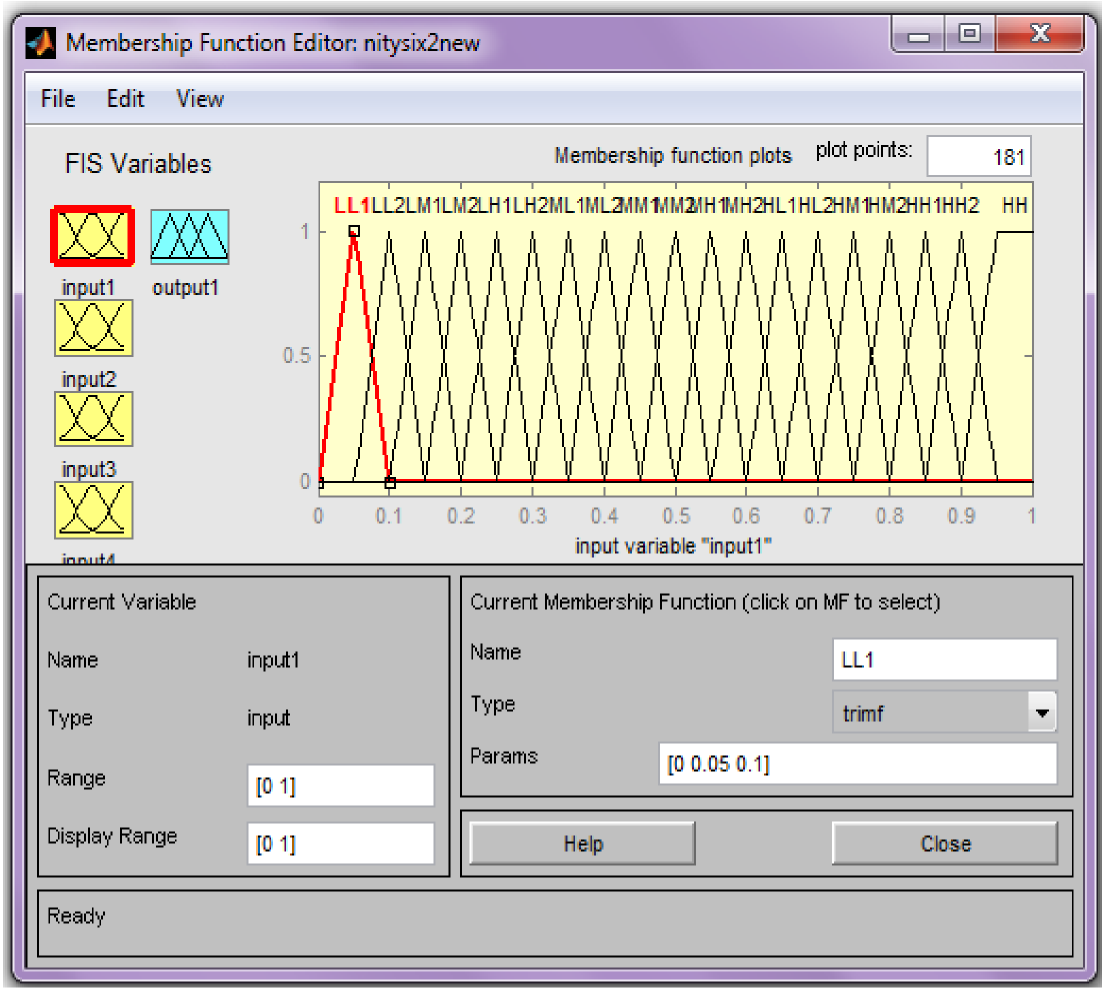

Fig. 3.4 MATLAB Model of Membership function in FTB

3.5.3 Fuzzy Rule Editor

The rule editor is for editing the list of rules that defines the behavior of the system. Based on the descriptions of the input and output variables defined with the FIS editor, the rule editor allows you to construct the rule statements automatically.it also facilitate to change the fuzzy rule base, for calculating the fuzzy output corresponding to actual output it has linguistic variable which define mathematical value into non mathematical or linguistic value. The Fig 3.5 shows the rule base of the fuzzy logic model. The fuzzy variable are defined or modified as per the requirement in the fuzzy rule editor. It provide both AND and OR connection, along with this It also provide function of add, delete and changing the rule base.

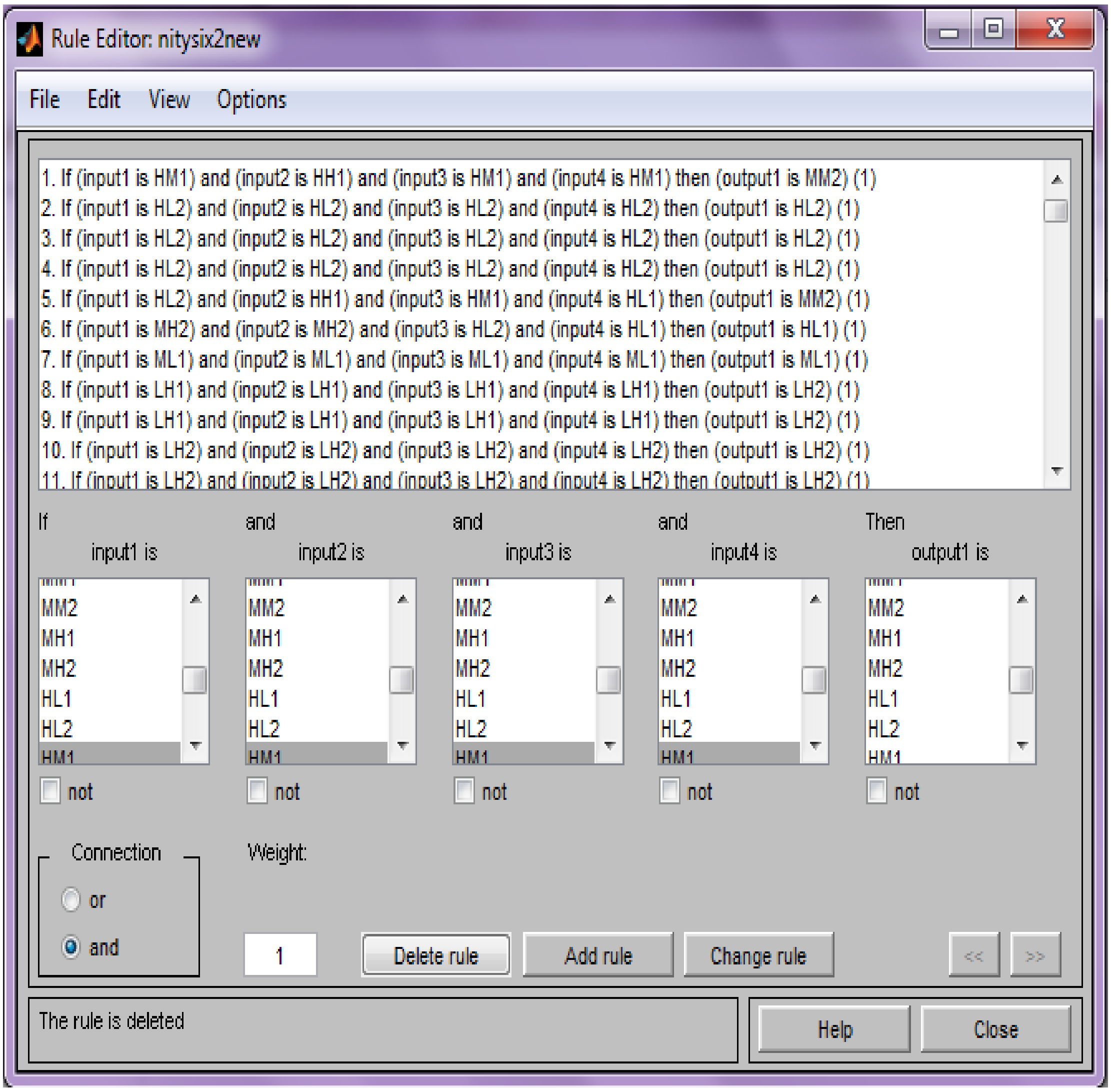

Fig. 3.5 MATLAB Model of Rule Editor

3.5.4 Rule Viewer

The rule viewer displays a roadmap of the whole fuzzy inference process. It is based on the fuzzy inference. The rule viewer and the surface viewer are used for looking at, as opposed to editing, the FIS. They are strictly read-only tools. The rule viewer is a MATLAB technical computing environment based display of the fuzzy inference diagram shown at the end of the last section. Used as a diagnostic, it can show (for example) which rules are active, or how individual membership function shapes are influencing the results. The surface viewer is used to display the dependency of one of the outputs on any one or two of the inputs—that is, it generates and plots an output surface map for the system.

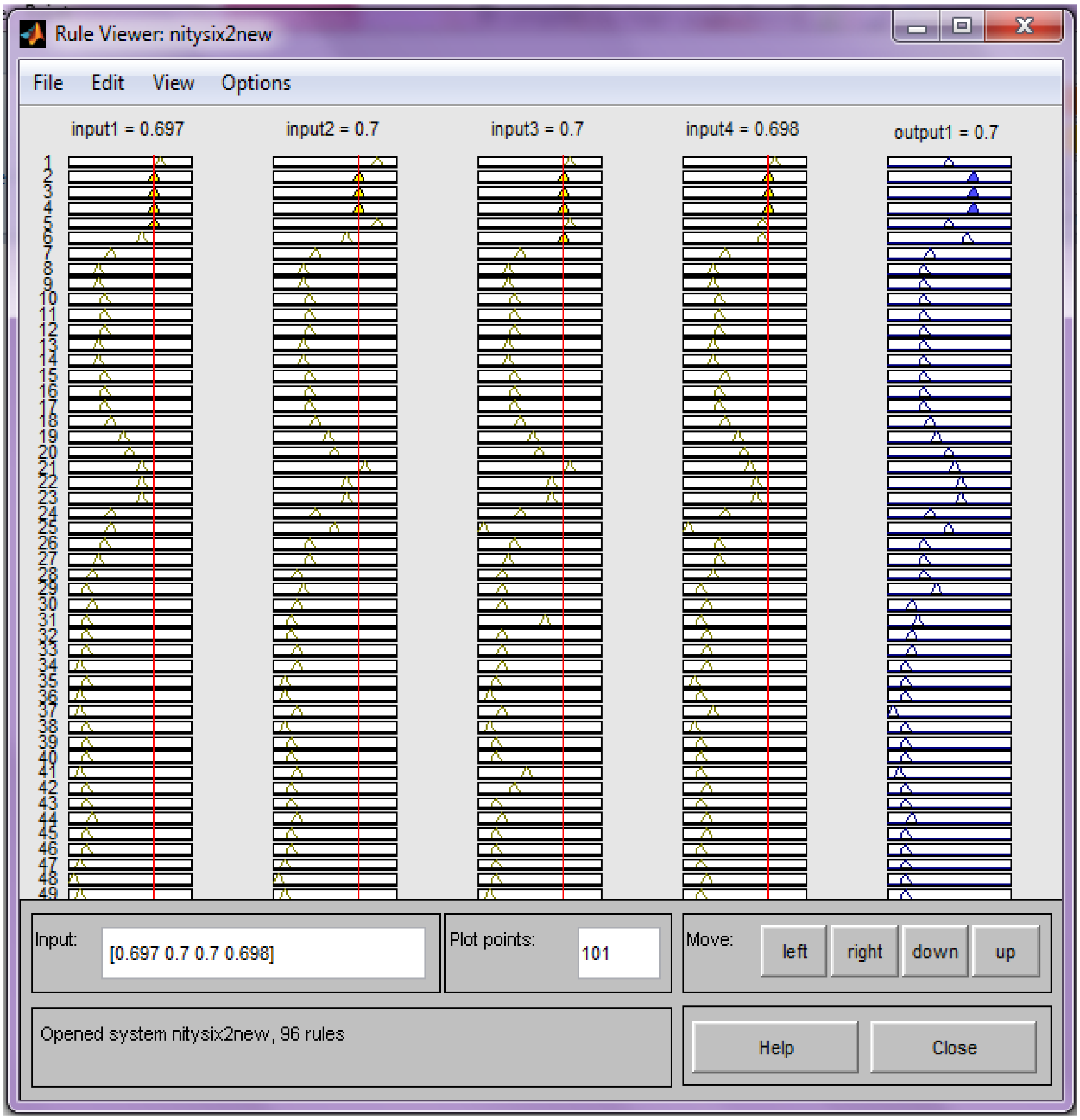

Fig. 3.6 MATLAB Model of Rule Viewer corresponding to second rule

3.6 Simulation Results

Fuzzy logic based model is developed and presented for the short term load forecasting using the above mentioned data for Shahpura, Jaipur station. The output of the model is demand of electricity on 16th of November, 2012. Various rules have been established in the development of fuzzy logic based model. The results for 2nd rule are presented in Fig. 3.6. Obtained results are de-normalized to get the forecasted electrical load. Variation of load from 12th to 16th November is shown in Fig 3.7, Fig 3.8, Fig 3.9, Fig 3.10, and Fig 3.11 respectively. Results of fuzzy logic based models are compared with the actual demand of electricity for validation.

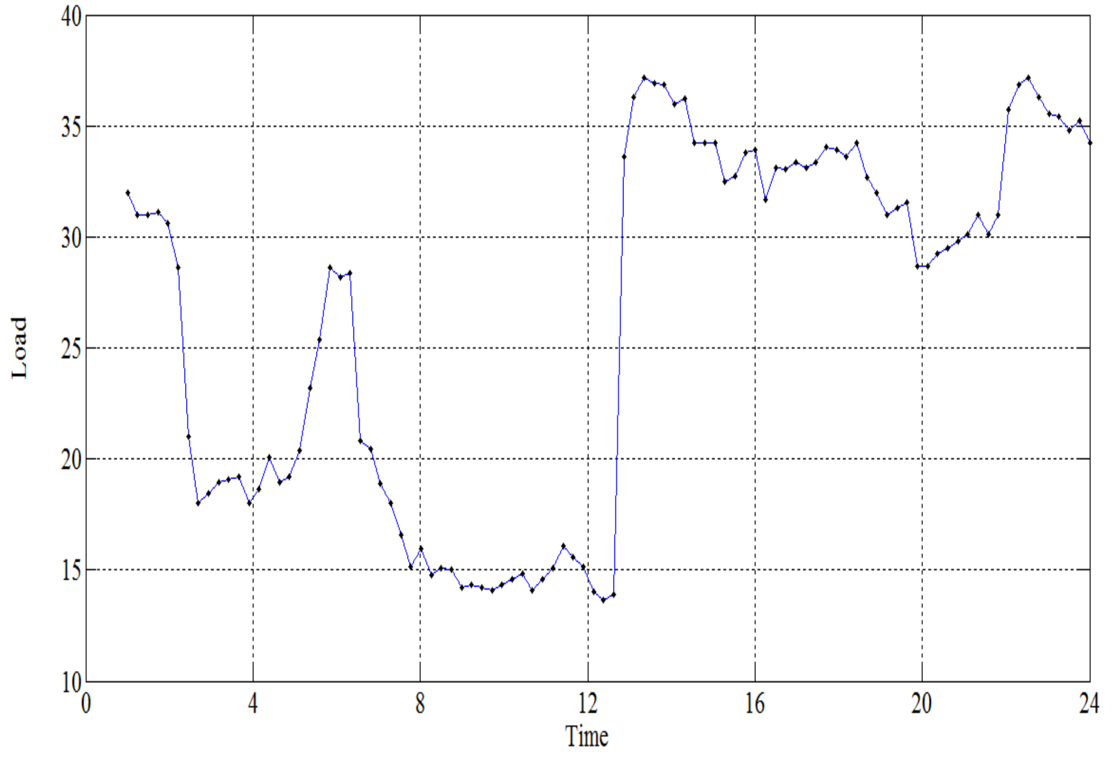

Fig 3.7 Load Variation on 12th November.

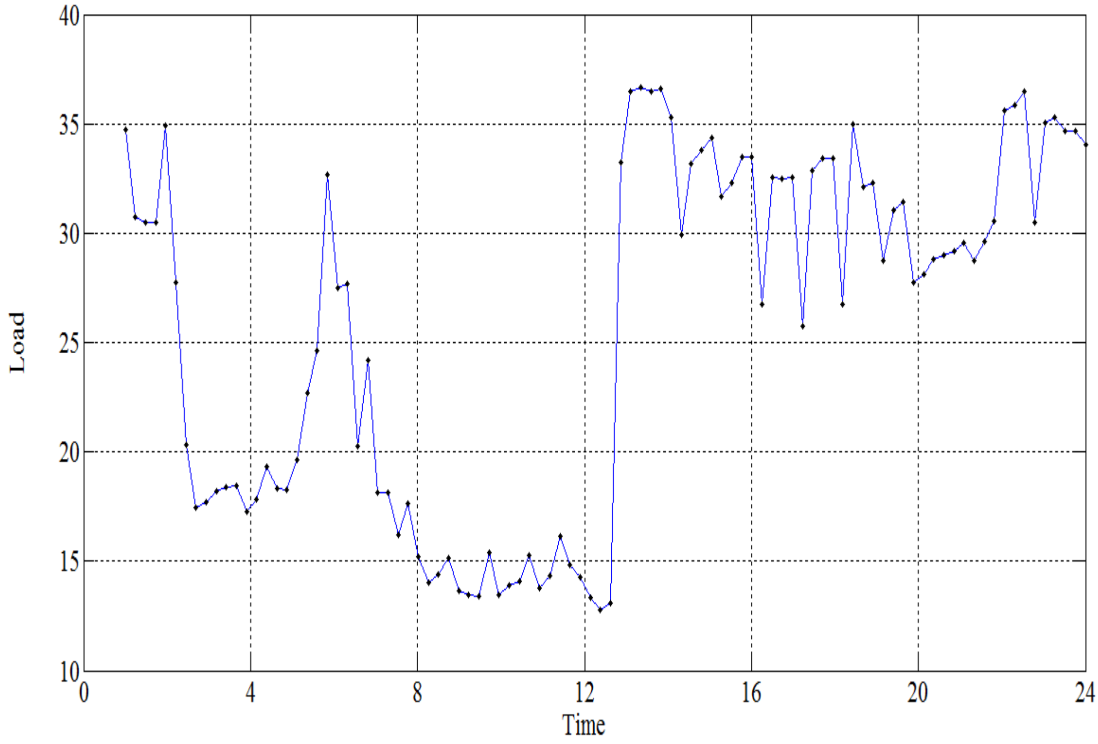

Fig 3.8 Load Variation on 13th November.

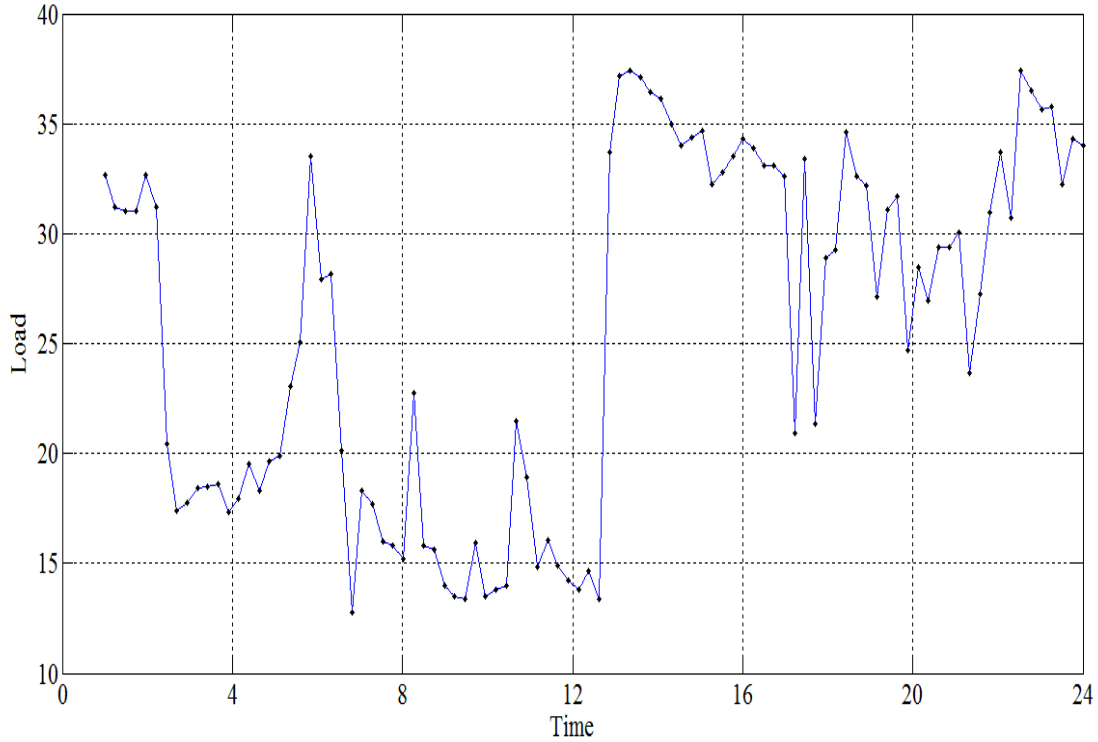

Fig 3.9 Load Variation on 14th November.

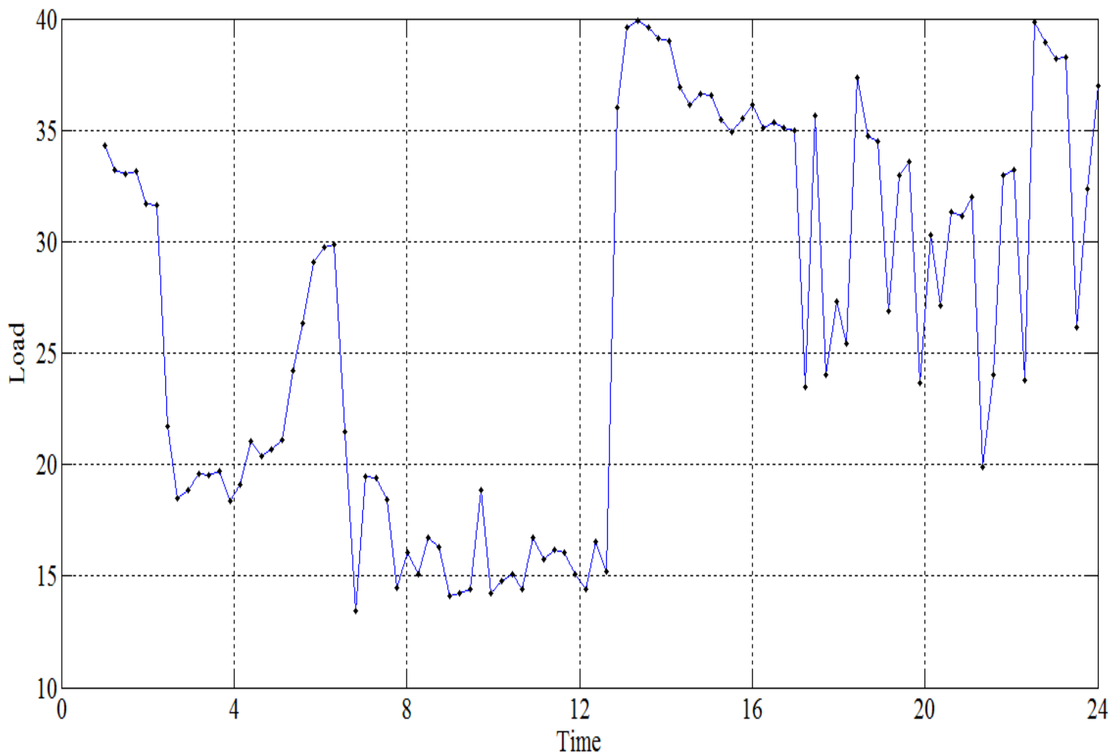

Fig 3.10 Load Variation on 15th November.

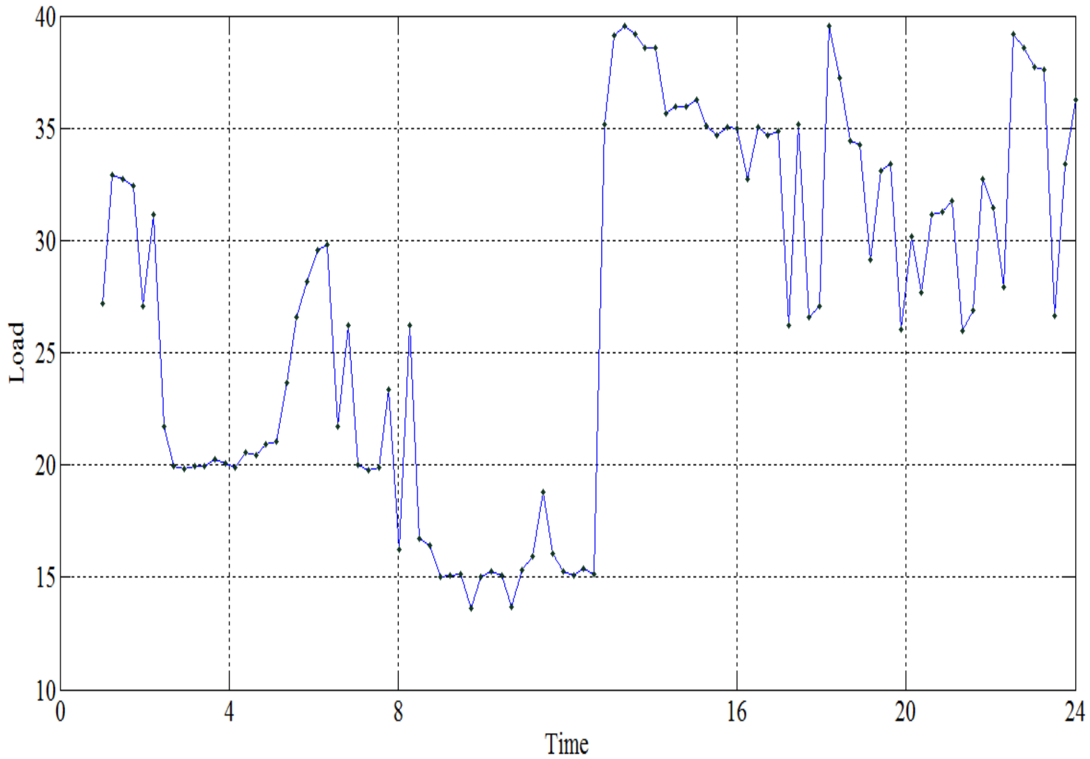

Fig 3.11 Load Variation of 16th November (Output) .

The results of fuzzy logic model are shown in Table 3.4. This table presents forecasted output in comparison with the actual data. The performance of the model is evaluated on the basis of absolute relative error and Mean square error which can be determined by using the following formula:

$$\text{Mean absolute relative error} = \frac{|P_{actual} - P_{forecast}| \times 100}{P_{forecast}} \tag{3.2}$$

$$\%MSE = \frac{\sum_{i=1}^{i=n} (P_i - Q_i)^2 * 100}{N} \tag{3.3}$$

where P_i and Q_i the actual and predicated value respectively. The absolute relative error (ARE) in the forecasted load in comparison with the actual load is also presented in Table 3.4. The output value and forecasted value are presented in normalized form in order to avoid problem of convergence. The output value and forecasted values are used to evaluate the fuzzy based model using MAPE and MSE parameters presented in Table 3.4.

Table 3.4 Percentage MAPE and MSE using Fuzzy Logic Approach

S.No.	Output	Forecasted	Normalized Output	Forecasted	% MAPE	% MSE
1.	27.2175	26.5800	0.520	0.500	3.846	0.0004
2.	32.8831	33.0600	0.695	0.700	0.720	2.5E-05
3.	32.7536	32.7684	0.691	0.697	0.868	3.6E-05
4.	32.3975	32.8332	0.680	0.700	2.941	0.0004
5.	27.0459	26.5800	0.515	0.500	2.856	0.000216
6.	31.1349	31.4400	0.641	0.650	1.404	8.1E-05
7.	21.7138	21.7200	0.350	0.350	0.000	2.39E-12
8.	19.9331	20.1000	0.295	0.300	1.695	2.5E-05
9.	19.8360	20.1000	0.292	0.300	2.740	6.4E-05
10.	19.9655	20.3916	0.296	0.300	1.351	1.6E-05
11.	19.9331	20.4240	0.295	0.300	1.695	2.5E-05
12.	20.2569	20.6184	0.305	0.300	1.640	2.5E-05

13.	20.0950	20.1000	0.300	0.300	0.000	3.08E-33
14.	19.8684	20.1000	0.293	0.300	2.389	4.9E-05
15.	20.5806	20.7804	0.315	0.322	2.222	4.9E-05
16.	20.4188	20.2944	0.310	0.300	3.226	0.0001
17.	20.9044	20.9100	0.325	0.300	7.693	0.000625
18.	21.0663	21.0720	0.330	0.330	0.000	2.39E-12
19.	23.6886	23.3400	0.411	0.400	2.676	0.000121
20.	26.5700	26.5800	0.500	0.500	0.000	1.23E-32
21.	28.1888	28.2000	0.550	0.550	0.000	2.39E-12
22.	29.5485	29.8200	0.592	0.600	1.351	6.4E-05
23.	29.8075	29.8200	0.600	0.600	0.000	1.23E-32
24.	21.7138	21.7200	0.350	0.350	0.000	2.39E-12
25.	26.2463	26.5800	0.490	0.500	2.040	1E-04
26.	19.9979	20.2944	0.297	0.300	1.010	9E-06
27.	19.7713	19.8732	0.290	0.300	3.448	1E-04
28.	19.8684	20.1000	0.293	0.300	2.389	4.9E-05
29.	23.3649	23.3400	0.401	0.500	24.688	0.009801
30.	16.2100	16.1796	0.180	0.180	0.000	3.08E-33
31.	26.2463	26.5800	0.490	0.500	2.040	1E-04
32.	16.7280	16.8600	0.196	0.200	2.041	1.6E-05
33.	16.4043	16.5684	0.186	0.191	2.687	2.5E-05
34.	15.0445	15.2400	0.144	0.150	4.167	3.6E-05
35.	15.0769	15.2400	0.145	0.150	3.448	2.5E-05
36.	15.1416	15.2400	0.147	0.150	2.041	9E-06
37.	13.6200	15.2400	0.100	0.050	50.000	0.0025
38.	15.0445	15.2076	0.144	0.150	4.167	3.6E-05
39.	15.2711	15.2400	0.151	0.150	0.662	9.98E-07
40.	15.1093	15.2400	0.146	0.150	2.739	1.6E-05
41.	13.6524	13.6200	0.101	0.100	0.991	1E-06
42.	15.3359	15.2400	0.153	0.150	1.961	9E-06
43.	15.9510	15.9204	0.172	0.170	1.163	4E-06

44.	18.8000	18.9660	0.260	0.265	1.923	2.5E-05
45.	16.0481	16.1796	0.175	0.170	2.857	2.5E-05
46.	15.2388	15.2400	0.150	0.150	0.001	2.39E-12
47.	15.1093	15.2400	0.146	0.150	2.739	1.6E-05
48.	15.4006	15.2400	0.155	0.150	3.225	2.5E-05
49.	15.1416	15.2400	0.147	0.150	2.041	9E-06
50.	35.1494	34.9392	0.765	0.775	1.307	1E-04
51.	39.0991	39.1836	0.887	0.889	0.226	4E-06
52.	39.5200	39.5400	0.900	0.900	0.000	4.93E-32
53.	39.1963	39.1512	0.890	0.890	0.000	2.39E-12
54.	38.5488	38.6328	0.870	0.872	0.230	3.99E-06
55.	38.5488	37.9200	0.870	0.850	2.299	0.0004
56.	35.6350	36.7536	0.780	0.810	3.846	0.0009
57.	35.9588	35.4900	0.790	0.775	1.899	0.000225
58.	35.9588	35.5224	0.790	0.780	1.266	0.0001
59.	36.2825	36.1380	0.800	0.795	0.625	2.5E-05
60.	35.0846	34.6800	0.763	0.775	1.573	0.000144
61.	34.6638	34.6800	0.750	0.775	3.333	0.000625
62.	35.0523	34.9392	0.762	0.775	1.706	0.000169
63.	34.9875	35.4900	0.760	0.775	1.974	0.000225
64.	32.7213	33.0600	0.690	0.700	1.449	1E-04
65.	35.0199	34.6800	0.761	0.775	1.840	0.000196
66.	34.6638	34.6800	0.750	0.775	3.333	0.000625
67.	34.8580	34.6800	0.756	0.775	2.513	0.000361
68.	26.2139	26.5800	0.489	0.500	2.249	0.000121
69.	35.1494	34.6800	0.765	0.775	1.307	1E-04
70.	26.5700	26.5800	0.500	0.500	0.000	1.23E-32
71.	27.0880	26.5800	0.516	0.500	3.101	0.000256
72.	39.5200	39.5400	0.900	0.900	0.000	4.93E-32
73.	37.2538	36.8832	0.830	0.820	1.205	0.0001
74.	34.4371	34.6800	0.743	0.775	4.307	0.001024

75.	34.2753	34.6800	0.738	0.775	5.013	0.001369
76.	29.1600	28.8804	0.580	0.600	3.448	0.0004
77.	33.0774	33.0600	0.701	0.700	0.143	1E-06
78.	33.3688	33.9348	0.710	0.720	1.408	1E-04
79.	26.0196	26.5800	0.483	0.500	3.520	0.000289
80.	30.1636	30.2088	0.611	0.610	0.164	9.98E-07
81.	27.6708	27.5520	0.534	0.550	2.996	0.000256
82.	31.1349	31.0188	0.641	0.643	0.312	4E-06
83.	31.2644	31.4400	0.645	0.650	0.775	2.5E-05
84.	31.7500	31.7964	0.660	0.660	0.000	1.23E-32
85.	25.9873	26.5800	0.482	0.500	3.734	0.000324
86.	26.8938	26.5800	0.510	0.500	1.961	0.0001
87.	32.7536	32.7360	0.691	0.695	0.579	1.6E-05
88.	31.4263	31.7964	0.650	0.655	0.769	2.5E-05
89.	27.9298	28.2000	0.542	0.550	1.476	6.4E-05
90.	39.1963	39.5400	0.890	0.900	1.123	1E-04
91.	38.5811	37.9200	0.871	0.850	2.411	0.000441
92.	37.7394	37.6932	0.845	0.850	0.592	2.5E-05
93.	37.6099	37.9200	0.841	0.850	1.070	8.1E-05
94.	26.6671	26.5800	0.503	0.500	0.596	9E-06
95.	33.3688	33.2220	0.710	0.680	4.226	0.0009
96.	36.2825	35.8140	0.800	0.790	1.250	0.0001
97.					2.551	0.0268

The predicted data of electrical load on 16th November, 2012 is compared with actual load demand and also presented graphically in Fig. 3.12.

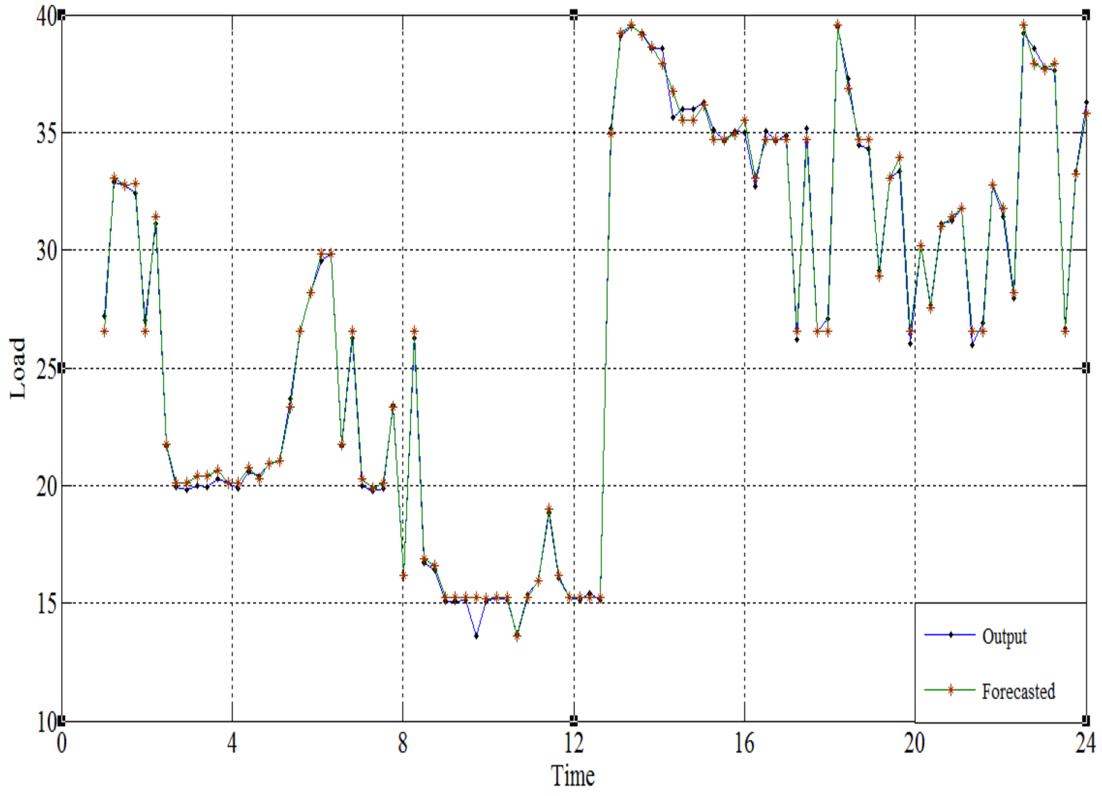

Fig. 3.12 Comparison of Actual and Predicted Load

It is clearly seen that the forecasted load on 16th November, 2012 in most of the cases is very close to the actual load. The average percentage error is found to be 2.551% in the short term electrical load forecasting.

3.7 Conclusion

The short term electrical load forecasting is an essential component of any power system planner. Therefore, an attempt has been made for STLF by using fuzzy logic. The performance of the model is evaluated on the basis of statistical indicator i.e. Absolute relative error and mean square error. The %MAPE and %MSE in the forecasted load in comparison with the desired load is 2.551 and 0.268 respectively which is very close to the desired load. Hence, it is concluded that the developed model is accurate and effective for short term load forecasting.

CHAPTER 4

STLF USING ANN

4.1 Introduction

In the previous chapter, an intelligent model based on fuzzy logic technique for the predication of STLF has been presented and this technique has shown reliable performance in STLF. Due to non-linear relationship between input and output the absolute percentage mean square error is around 2.6%. Therefore there is need to develop an alternative way for the predication of STLF. An ANN provides computationally efficient way of determine an empirical, possibly non-linear relationship between a number of inputs and output. The aim of present work is to develop ANN based model that can be used for STLF.

In this chapter multi-layered feed-forward (MLFF) neural network with back-propagation learning algorithm has been used for predicting the next day load. A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects (a) Knowledge is acquired by the network from its environment through a learning process. (b) Inter-neuron connection strengths, known as synaptic weights, are used to store the acquired knowledge. Procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objective. Like brain ANN has the ability to learn complex and non-linear relationships through a training process with the use of historical data, and weather information. In this thesis, a short term load forecasting method using artificial neural networks is presented.

4.2 Necessity of using ANN

Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze. It has following other advantages also, these include

1. *Adaptive learning*: An ability to learn how to do tasks based on the data given for training or initial experience.

2. *Self-Organization*: An ANN can create its own organization or representation of the information it receives during learning time.

3. *Real Time Operation*: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.

4.2.1 Merits of ANN

1. They are extremely powerful computational devices.

2. Massive parallelism makes them very efficient.

3. They can learn and generalize from training data, so there is no need for enormous feats of programming.

4. They are particularly fault tolerant . This is equivalent to the "graceful degradation" found in biological systems.

5. They are very noise tolerant, so they can cope with situations where normal symbolic systems would have difficulty.

6. In principle, they can do anything a symbolic/logic system can do, and more.

4.3 Mathematical Model of Neuron

A neuron is an information processing unit that is fundamental to the operation of a neural network. The three basic elements of the neuron model are:

1. A set of weights, each of which is characterized by a strength of its own. A signal x_n connected to neuron n is multiplied by the weight w_n.The weight of an artificial neuron may lie in a range that includes negative as well as positive values.

2. An adder for summing the input signals, weighted by the respective weights of the neuron.

3. An activation function for limiting the amplitude of the output of a neuron. It is also referred to as squashing function which squashes the amplitude range of the output signal to some finite value.

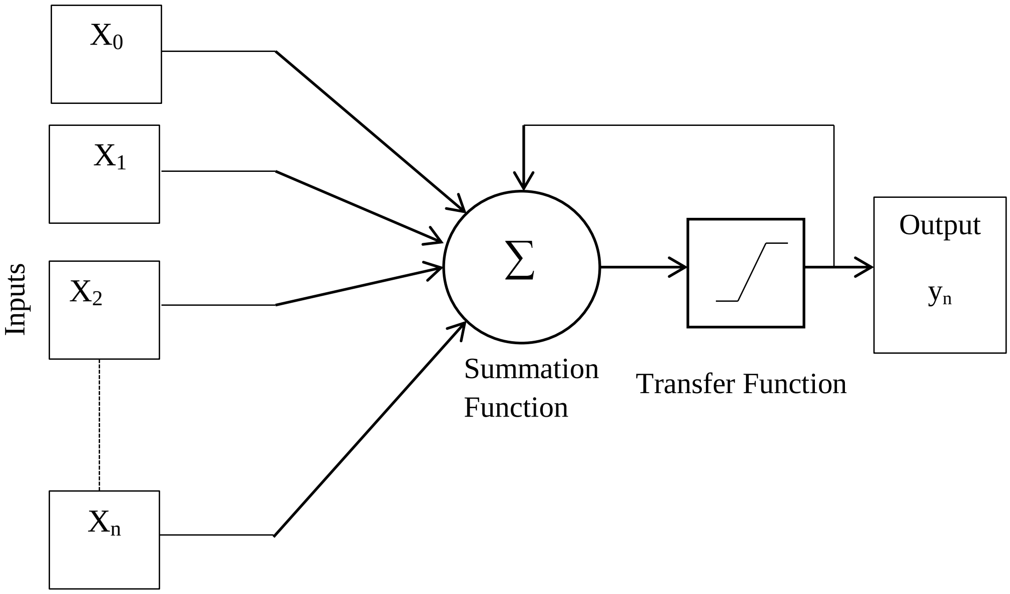

Fig. 4.3 A Neural Network

Equation for above model is

$$y_n = \sum_{n=0}^{n} w_n x_n \tag{4.1}$$

Where w_n = weight corresponding to an input.

x_n =input signal connected to neuron.

4.4 Architecture of Network

There are three fundamental different classes of network architectures:

4.4.1 Single-Layer Feed-Forward Networks- In a layered neural network the neurons are organized in the form of layers. In the simplest form of a layered network, we have an input layer of source nodes that projects onto an output layer of neurons, but not vice versa. This network is strictly a feed-forward type. In single-layer network, there is only one input and one output layer. Input layer is not counted as a layer since no mathematical calculations take place at this layer.

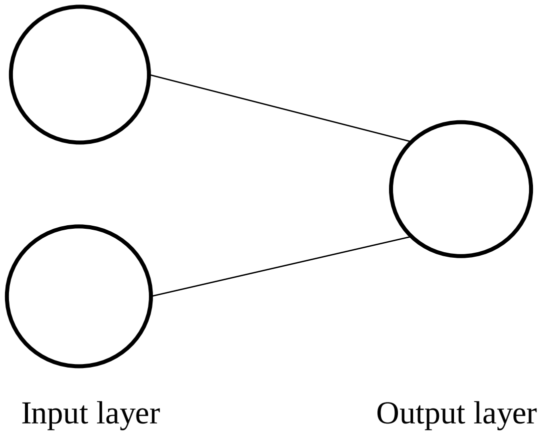

Fig. 4.4 Input – Output Layers of Neural Network

4.4.2 Multi-Layer Feed-Forward Networks-The second class of a feed-forward neural network distinguishes itself by the presence of one or more hidden layers, whose computational nodes are correspondingly called hidden neurons. The function of hidden neuron is to intervene between the external input and the network output in some useful manner. By adding more hidden layers, the network is enabled to extract higher order statistics. The input signal is applied to the neurons in the second layer. The output signal of second layer is used as inputs to the third layer, and so on for the rest of the network. In MLFF networks one of the most important, configuration issue is to select an optimal number of hidden layers. It has been shown that with homogeneous sigmoidal output functions. In MLFF networks one hidden layer is sufficient to compute arbitrary decision boundaries for the outputs and that two hidden layers are sufficient to compute an arbitrary output function of the outputs . A number of empirical tests suggest. that for simple applications there is no significant advantage in using two or more hidden layers over single hidden layer.

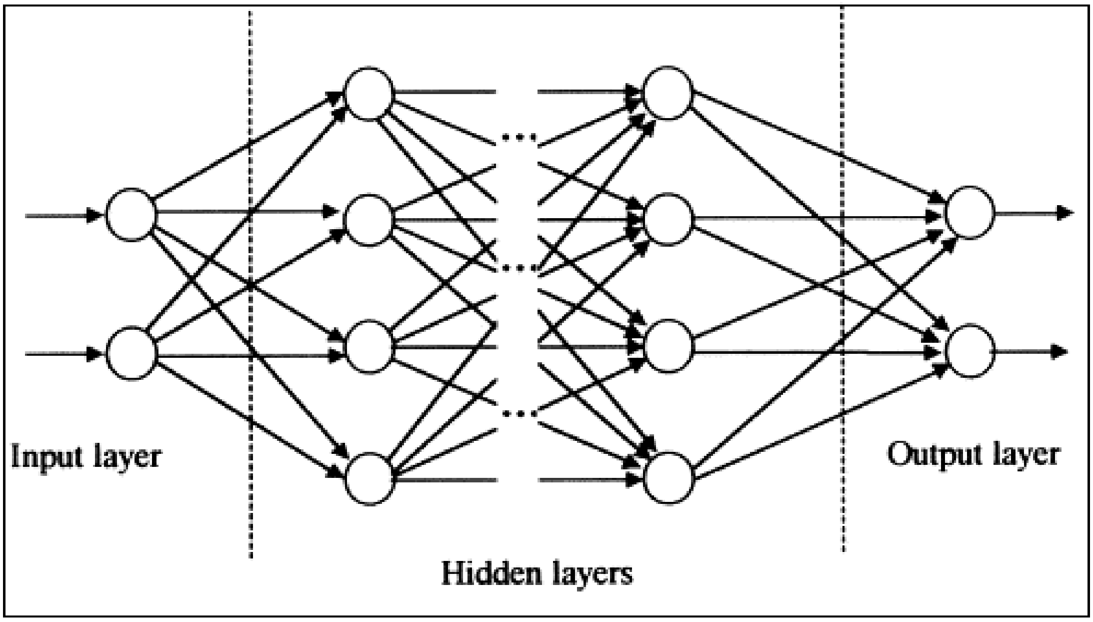

Fig. 4.5 Multi-layer Neural Network

4.4.3 Recurrent Networks-A recurrent neural network has at least one feedback loop. A recurrent network may consist of a single layer of neurons with each neuron feeding its output signal back to the inputs of all the other neurons. Self-feedback refers to a situation where the output of a neuron is fed back into its own input. The presence of feedback loops has a profound impact on the learning capability of the network and on its performance.

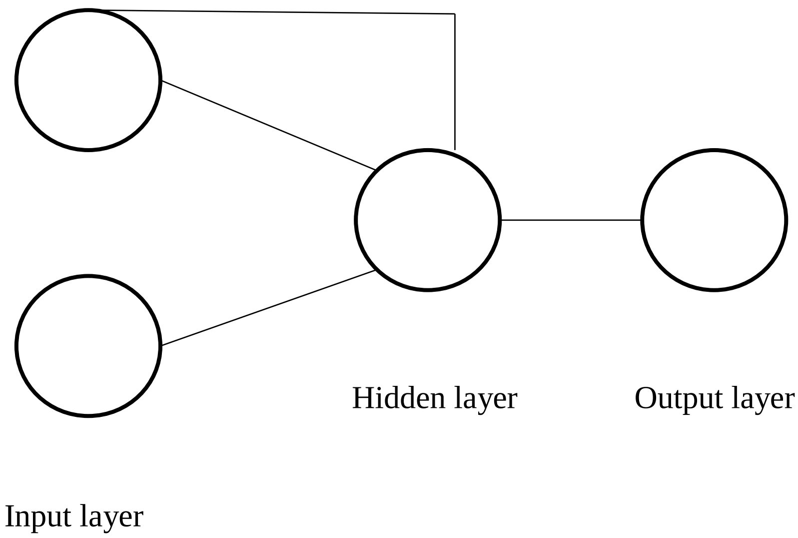

Fig. 4.6 A recurrent Neural network

4.5 Learning Processes

By learning rule we mean a procedure for modifying the weights and biases of a network. The purpose of learning rule is to train the network to perform some task. They fall into three broad categories:

4.5.1 Supervised Learning

The learning rule is provided with a set of training data of proper network behavior, as the inputs are applied to the network, the network outputs are compared to the targets. The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets.

4.5.2 Reinforcement Learning

It is similar to supervised learning, except that, instead of being provided with the correct output for each network input, the algorithm is only given a grade. The grade is a measure of the network performance over some sequence of inputs.

4.5.3 Unsupervised learning

The weights and biases are modified in response to network inputs only. There are no target outputs available. Most of these algorithms perform some kind of clustering operation. They learn to categorize the input patterns into a finite number of classes.

4.6 Back Propagation Algorithm

Multiple layer perceptrons have been applied successfully to solve some difficult diverse problems by training them in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm. This algorithm is based on the error-correction learning rule. It may be viewed as a generalization of an equally popular adaptive filtering algorithm-the least mean square (LMS) algorithm. Error back-propagation learning consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, an input vector is applied to the nodes of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass the weights of the networks are all fixed. During the backward pass, the weights are all adjusted in accordance with an error correction rule. The actual response of the network is subtracted from a desired response to produce an error signal. This error signal is then propagated backward through the network, against the direction of synaptic connections. The weights are adjusted to make the actual response of the network move closer to the desired response.

A multilayer perceptron has three distinctive characteristics:

1. The model of each neuron in the network includes a nonlinear activation function. The sigmoid function is commonly used which is defined by the logistic function:

$$y = \frac{1}{1 + \exp(-x)} \tag{4.2}$$

The presence of nonlinearities is important because otherwise the input-output relation of the network could be reduced to that of single layer perceptron.

2. The network contains one or more layers of hidden neurons that are not part of the input or output of the network. These hidden neurons enable the network to learn complex tasks.

3. The network exhibits a high degree of connectivity. A change in the connectivity of the network requires a change in the population of their weights.

4.6.1 Basic Model of Learning Process

The neural network fitting tool will help you select data, create and train a network, and evaluate its performance using mean square error and regression analysis. A multi-layer feed-forward network with sigmoid hidden neurons and linear output neurons, can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer.

The network will be trained with Levenberg-Marquardt back propagation algorithm, unless there is not enough memory, in which case scaled conjugate gradient back propagation will be used. Block diagram of neural fitting tool is given below.

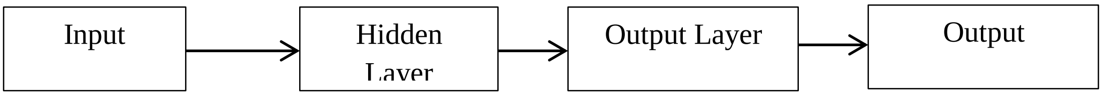

Fig. 4.7 Neural Model of learning process

4.7 Steps of using ANN for STLF

It include following steps

4.7.1 Select Data

In this input and target data is imported. Neural networks are good at fitting functions and recognizing patterns. The Fig. 4.8 below show the input and output imported data. It also provides sample orientation in rows and columns.

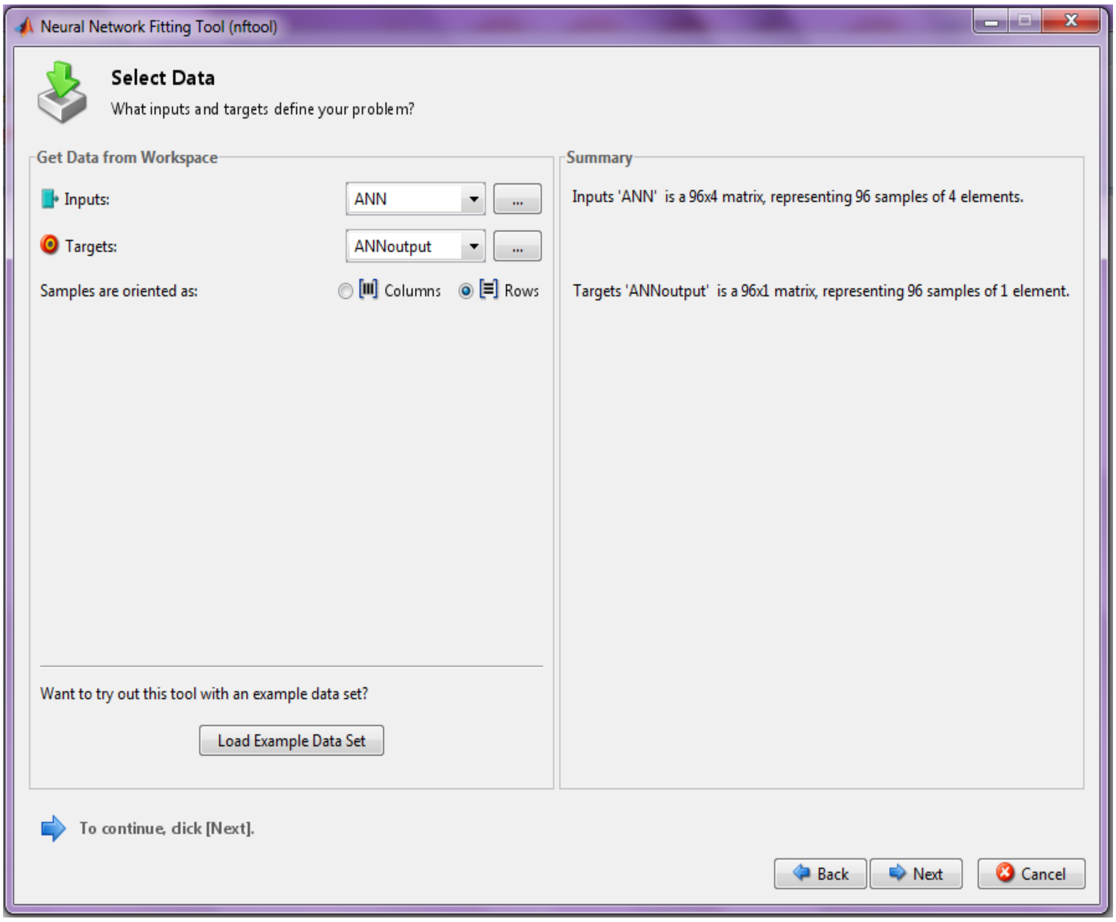

Fig. 4.8 Neural Network Fitting Tool – Select Data

4.7.2 Validation and Test Data

In this we can check the validity of data and established learning pattern by examine the validity error and validation fitting curve .It set aside few sample for testing and validation. It divide given sample into three which include testing, validity and validation.

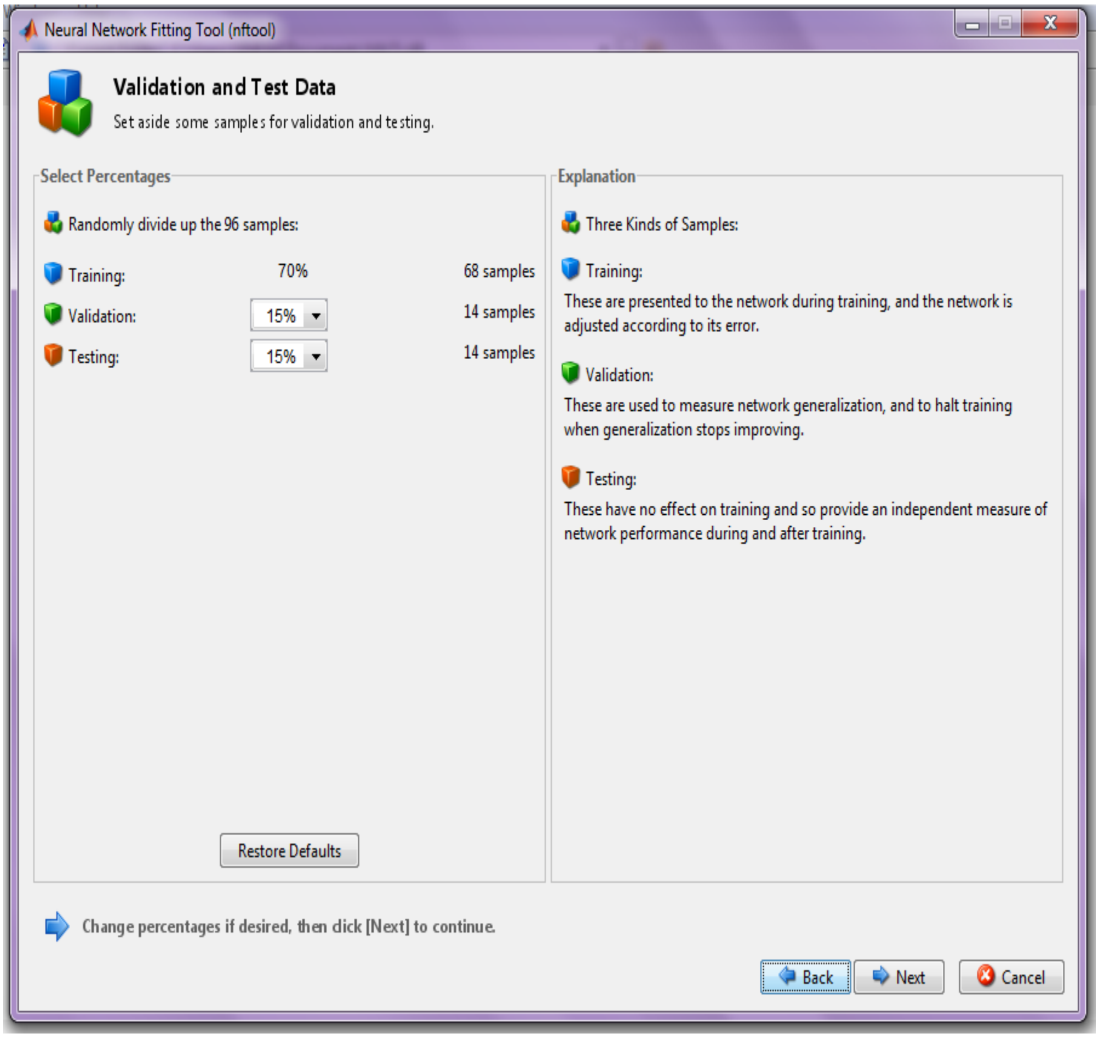

Fig. 4.9 Neural Network Fitting Tool – Training Data

4.7.3 Network Size

It is the further step in which number of neurons are decided as choosing optimal number of hidden layer neurons is perhaps the most interesting and challenging aspect in designing the configuration.in our model we are using 41 layer of hidden neurons. The training to a very large extent depends upon number of neuron layers.

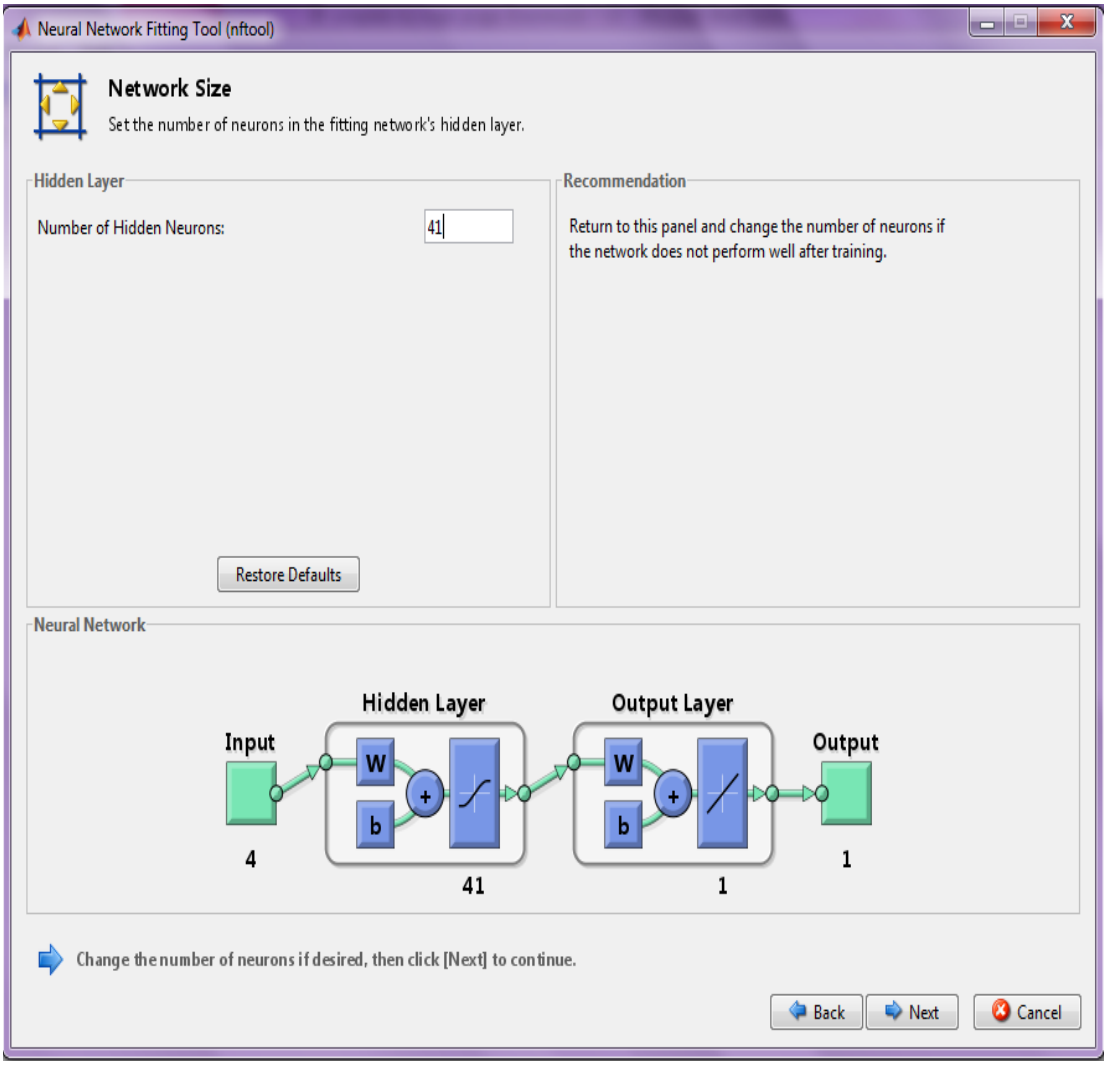

Fig. 4.10 Neural Network Fitting Tool – Neural Network

4.7.4 Train Network for Cure Fitting

When the network weights and biases are initialized, the network is ready for training. The network can be trained for function approximation (nonlinear regression), pattern association, or pattern classification. The training process used in this model is levenberg-Marquardt back propagation. During training the weights and biases of the network are iteratively adjusted to minimize the network performance function. When we train the data multiple times then it will generate better result.

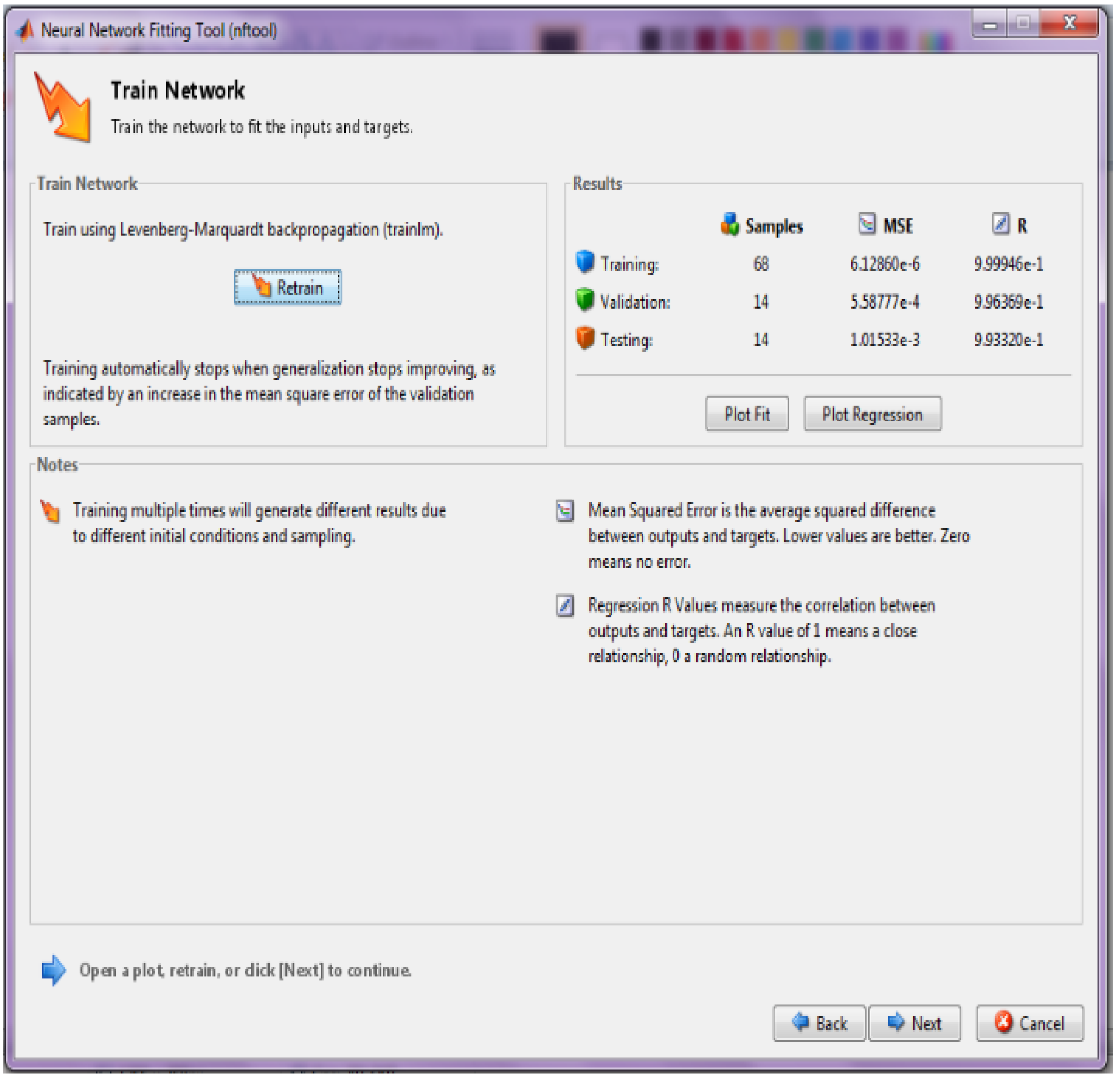

Fig. 4.11 Neural Network Fitting Tool – Train Network

4.8 Simulation Results

The use of Levenberg-Marquard training algorithm resulted in a very fast training, and the error was significantly reduced within few iterations. The MATLAB simulation results are shown which indicate a desirable validation and regression curve. The mean square error is indicated in Fig 4.17 which is below very low. The ninety six are provided as input out of which 70% value are randomly choose for training while 15% each are used for validation and testing.

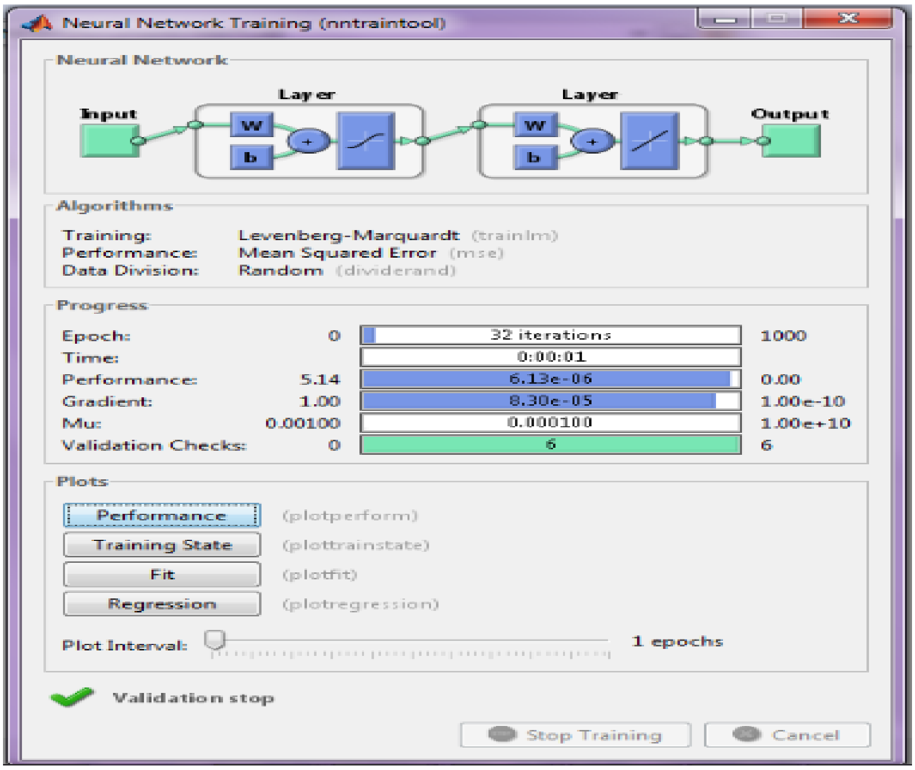

Fig. 4.12 Neural Network training

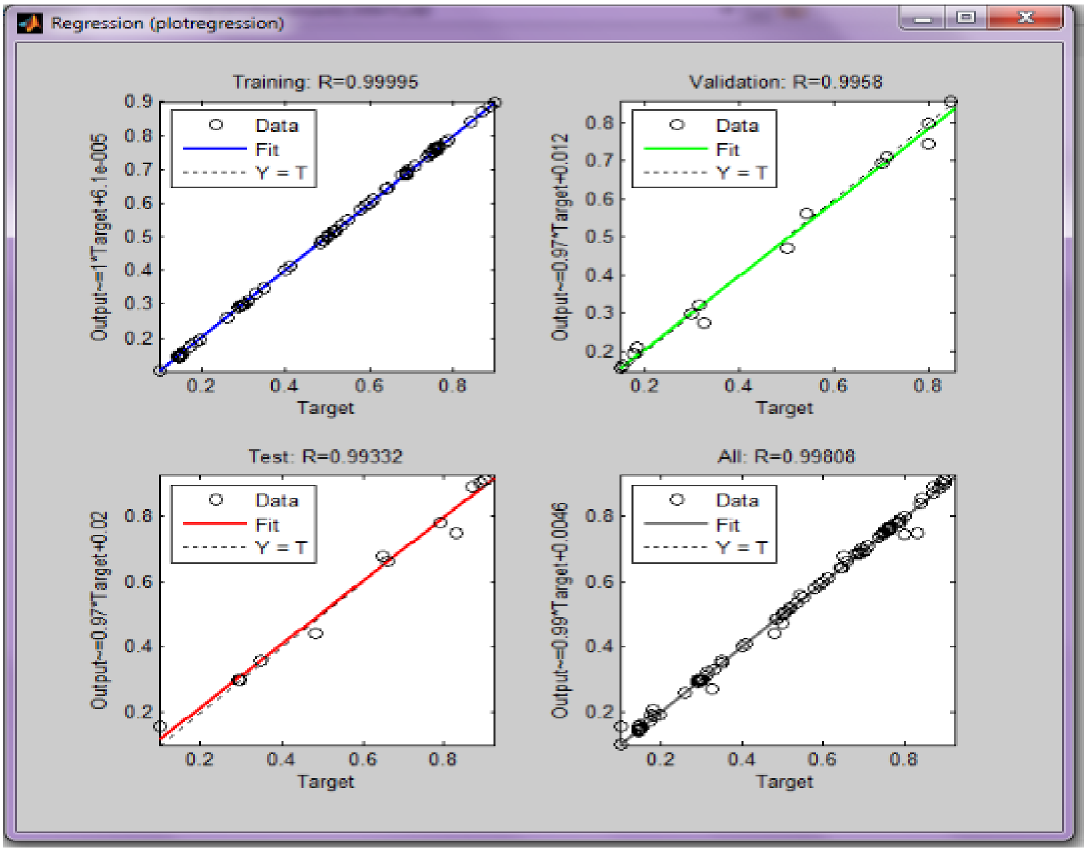

Fig. 4.13 Data fitting curves

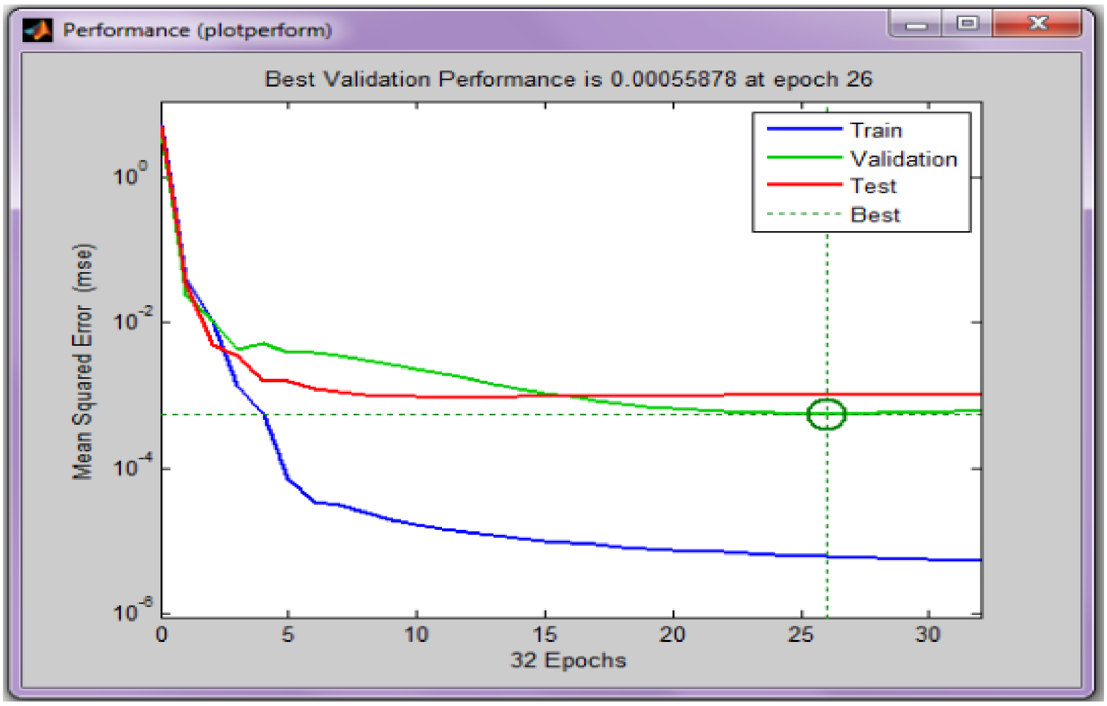

Fig. 4.14 Best Validation Performance

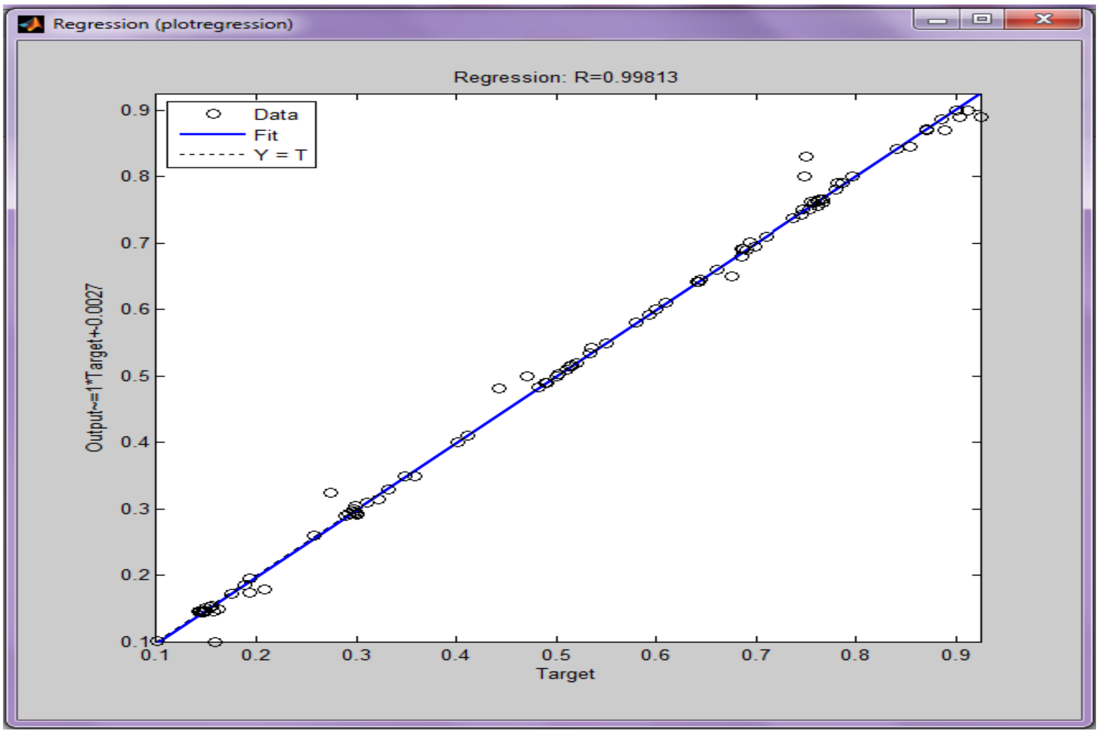

Fig. 4.15 Regression curve to best fit

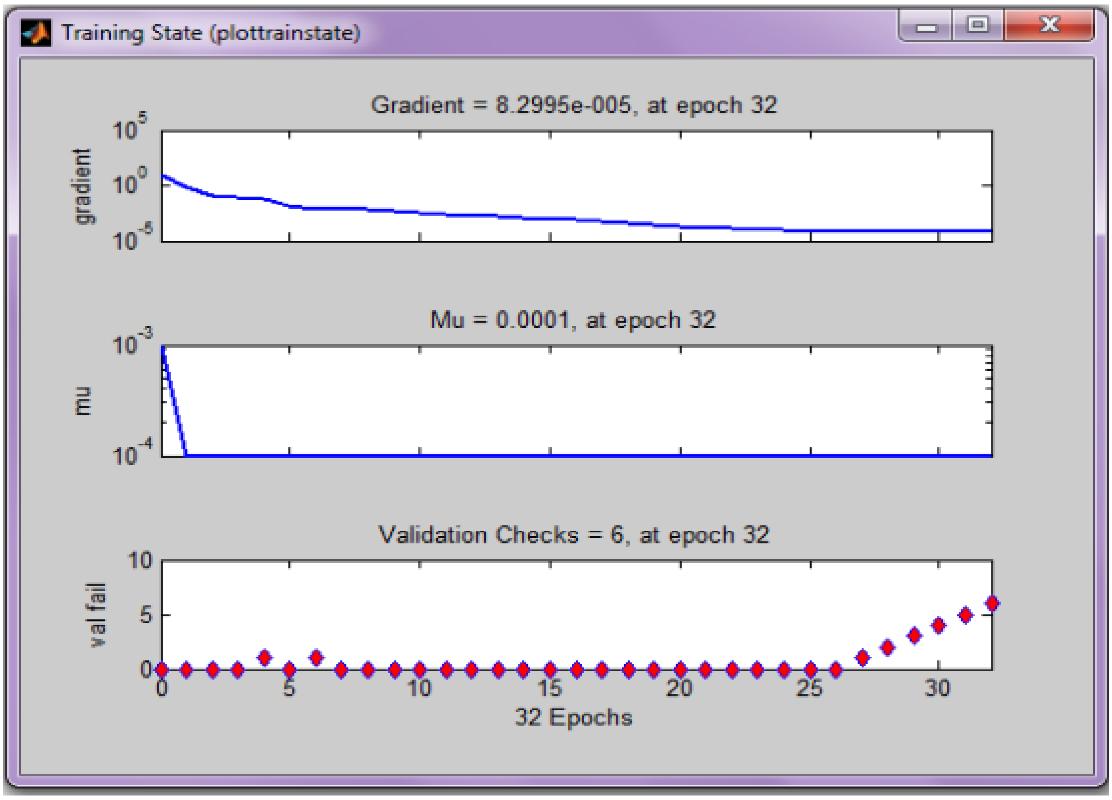

Fig. 4.16 Plot of training state

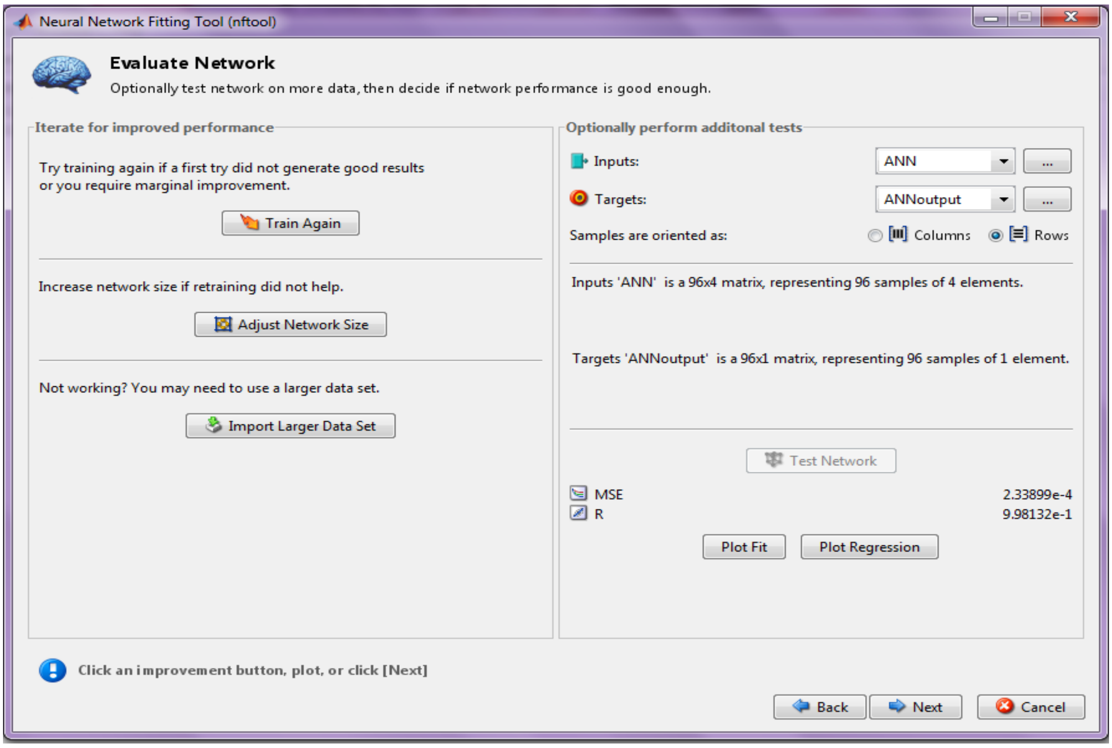

Fig. 4.17 Evaluate Neural Network

The results of ANN model are shown in Table 4.1. This table presents forecasted output in comparison with the actual data. The performance of the model is evaluated on the basis of absolute relative error and Mean square error which can be determined by using the following formula:

$$\text{Mean absolute relative error} = \frac{\left|P_{actual} - P_{forecast}\right| \times 100}{P_{forecast}} \tag{4.3}$$

$$\%MSE = \frac{\sum_{i=1}^{i=n} (P_i - Q_i)^2 * 100}{N} \tag{4.4}$$

where P_i and Q_i the actual and predicated value respectively. The absolute relative error (ARE) in the forecasted load in comparison with the actual load is also presented in Table 4.1.

Table 4.1 Percentage MAPE and MSE using ANN Approach

S. No	Output	Forecasted	% MAPE	% MSE
1.	0.520	0.521	0.125	4.24251E-07
2.	0.695	0.699	0.611	1.80138E-05
3.	0.691	0.686	0.762	2.77372E-05
4.	0.680	0.686	0.815	3.06775E-05
5.	0.515	0.515	0.036	3.45661E-08
6.	0.641	0.641	0.027	2.9507E-08
7.	0.350	0.359	2.486	7.57283E-05
8.	0.295	0.299	1.441	1.80719E-05
9.	0.292	0.301	2.943	7.38313E-05
10.	0.296	0.297	0.195	3.33405E-07
11.	0.295	0.299	1.351	1.58801E-05

12.	0.305	0.300	1.794	2.99274E-05
13.	0.300	0.298	0.684	4.21012E-06
14.	0.293	0.301	2.593	5.77215E-05
15.	0.315	0.322	2.136	4.52568E-05
16.	0.310	0.310	0.073	5.08419E-08
17.	0.325	0.275	15.394	0.002503005
18.	0.330	0.332	0.531	3.07027E-06
19.	0.411	0.411	0.003	1.47059E-10
20.	0.500	0.470	5.977	0.000893112
21.	0.550	0.550	0.002	7.02076E-11
22.	0.592	0.592	0.059	1.22746E-07
23.	0.600	0.600	0.017	1.07245E-08
24.	0.350	0.349	0.300	1.09933E-06
25.	0.490	0.490	0.001	1.02679E-11
26.	0.297	0.298	0.171	2.58297E-07
27.	0.290	0.290	0.138	1.60709E-07
28.	0.293	0.292	0.396	1.3454E-06
29.	0.401	0.401	0.026	1.1114E-08
30.	0.180	0.209	15.847	0.000813692
31.	0.490	0.490	0.008	1.63697E-09
32.	0.196	0.194	1.123	4.84106E-06
33.	0.186	0.189	1.508	7.86861E-06
34.	0.144	0.146	1.706	6.03339E-06
35.	0.145	0.146	0.614	7.91394E-07

36.	0.147	0.144	2.373	1.21644E-05
37.	0.100	0.159	58.940	0.003473939
38.	0.144	0.146	1.154	2.76331E-06
39.	0.151	0.149	1.128	2.90358E-06
40.	0.146	0.156	7.121	0.000108091
41.	0.101	0.101	0.010	1.00517E-10
42.	0.153	0.153	0.040	3.73334E-09
43.	0.172	0.175	1.828	9.88086E-06
44.	0.260	0.257	0.970	6.36246E-06
45.	0.175	0.194	10.790	0.000356553
46.	0.150	0.163	8.398	0.00015869
47.	0.146	0.142	2.476	1.30689E-05
48.	0.155	0.155	0.068	1.12478E-08
49.	0.147	0.149	1.437	4.46078E-06
50.	0.765	0.767	0.295	5.109E-06
51.	0.887	0.886	0.098	7.48014E-07
52.	0.900	0.912	1.334	0.000144231
53.	0.890	0.904	1.599	0.000202472
54.	0.870	0.871	0.071	3.77382E-07
55.	0.870	0.889	2.162	0.000353863
56.	0.780	0.780	0.021	2.58456E-08
57.	0.790	0.787	0.432	1.16615E-05
58.	0.790	0.782	1.060	7.00649E-05
59.	0.800	0.748	6.556	0.002750519

60.	0.763	0.762	0.116	7.88307E-07
61.	0.750	0.747	0.374	7.84868E-06
62.	0.762	0.756	0.844	4.13177E-05
63.	0.760	0.766	0.754	3.28511E-05
64.	0.690	0.690	0.021	2.17327E-08
65.	0.761	0.758	0.452	1.18534E-05
66.	0.750	0.753	0.368	7.61403E-06
67.	0.756	0.762	0.835	3.98944E-05
68.	0.489	0.489	0.004	3.51498E-10
69.	0.765	0.764	0.162	1.54187E-06
70.	0.500	0.500	0.007	1.3261E-09
71.	0.516	0.516	0.005	6.28641E-10
72.	0.900	0.900	0.005	1.65063E-09
73.	0.830	0.750	9.583	0.006326493
74.	0.743	0.745	0.229	2.89031E-06
75.	0.738	0.736	0.254	3.52747E-06
76.	0.580	0.580	0.004	5.59985E-10
77.	0.701	0.694	1.069	5.61052E-05
78.	0.710	0.710	0.037	7.06155E-08
79.	0.483	0.483	0.009	2.01908E-09
80.	0.611	0.610	0.156	9.04312E-07
81.	0.534	0.534	0.029	2.33168E-08
82.	0.641	0.643	0.366	5.51514E-06
83.	0.645	0.644	0.225	2.1073E-06

84.	0.660	0.661	0.124	6.65688E-07
85.	0.482	0.442	8.264	0.001586803
86.	0.510	0.510	0.007	1.37104E-09
87.	0.691	0.687	0.613	1.79592E-05
88.	0.650	0.676	4.002	0.000676765
89.	0.542	0.536	1.165	3.98519E-05
90.	0.890	0.924	3.846	0.001171884
91.	0.871	0.871	0.026	5.26073E-08
92.	0.845	0.854	1.055	7.94696E-05
93.	0.841	0.841	0.031	6.63794E-08
94.	0.503	0.503	0.005	5.14165E-10
95.	0.710	0.710	0.009	4.36279E-09
96.	0.800	0.796	0.532	1.81344E-05
97.			2.165	0.0233

4.9 Conclusion

ANN provide efficient tool in short term electrical load forecasting. The obtained % MAPE and % MSE using ANN based approach are 2.165 and 0.0233. It provides more accurate result and improvement in performance.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

In this dissertation fuzzy logic and ANN based model for the predication of STLF have been developed and presented. These models are developed on the basis of load parameter, Five consecutive days load have been selected from 12th to 16th November 2012. The data is collected from Rajasthan Electricity Board (Shahpura Sub-station), India. The obtained data is normalized to avoid the problem of convergence. Using the normalized data Fuzzy logic and ANN models are presented in Chapter 3 and 4 respectively. The performances of models are evaluated on the basis of statistical indicators such as MAPE and MSE, the MAPE and MSE for fuzzy model is 2.551 and .0268 respectively similarly. The MAPE and MSE for ANN model is 2.165 and .0233 respectively.

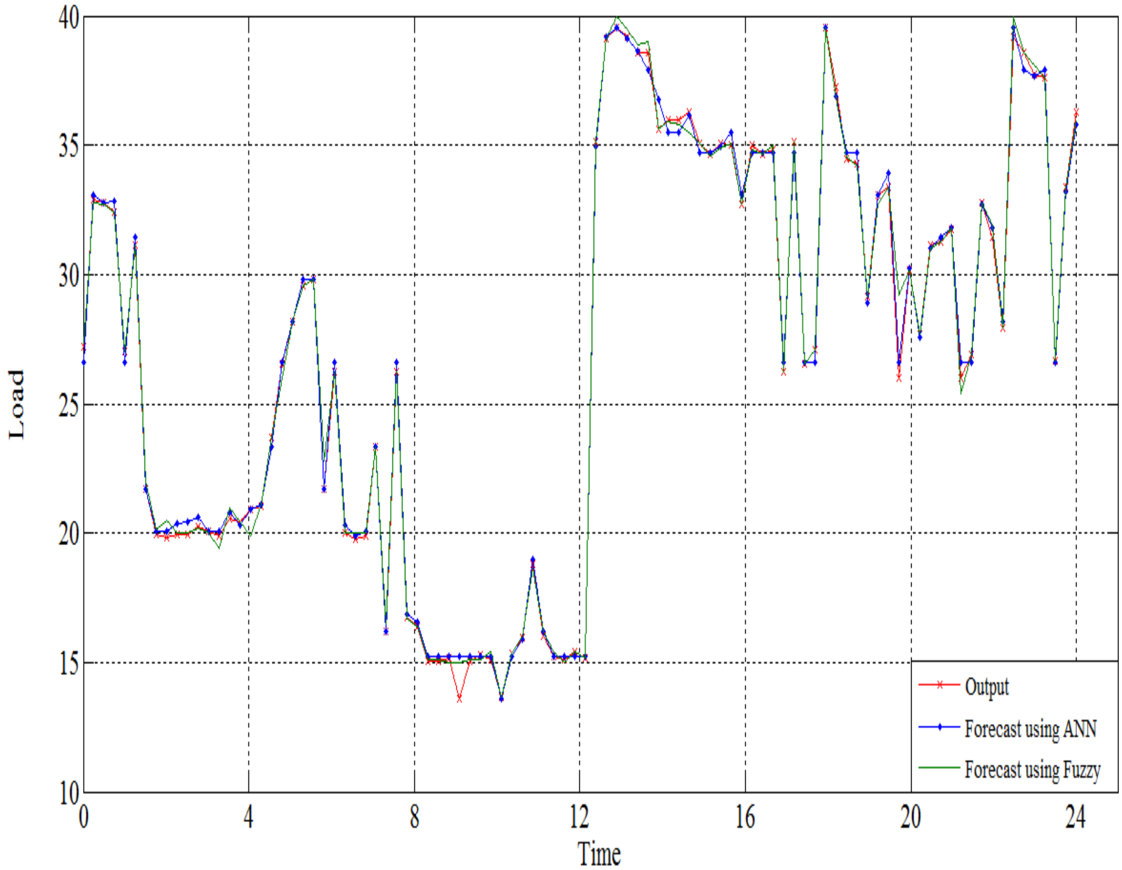

Fig 5.1 Comparison of Output, Forecasted value using Fuzzy and ANN methods.

Table 5.1 Comparison of results obtained from Fuzzy logic and ANN method.

S. No	Method	% MAPE	%MSE
1	Fuzzy logic approach	2.551	0.0268
2	ANN based approach	2.165	0.0233

Therefore it is concluded that ANN model is better as compared to fuzzy logic for the predication of STLF. The error and characteristic curve comparing actual, forecasted value using fuzzy and ANN models is shown in Table 5.1 and Fig 5.1 respectively

5.2 Future Scope

The following study based on the present research work can be extended in future. It helps to develop many other feed-forward and feedback neural structures which can be modeled for testing and analyzing the STLF. ANN using back propagation provides a efficient in method in term of forecasting load. As both the methods have its own advantages but for accurate result efforts are made for developing hybrid model and many hybrid models consisting feature of both Fuzzy logic system and ANN can be developed. Fuzzy logic provide solution of problem by linguistic variable and ANN using the ability to learn similar to brain and help and even trained to solve various complex problems so STLF using artificial intelligence method can be developed for complex system having various variables. Intelligence approach also provides various other advantages in term of proper energy scheduling, efficient utilization of energy etc. The proposed model may be useful in smart grid operation and control.

APPENDIX

```
function net = create_fit_net(inputs,targets)
%CREATE_FIT_NET Creates and trains a fitting neural network.
%
%  NET = CREATE_FIT_NET(INPUTS,TARGETS) takes these arguments:
%    INPUTS - RxQ matrix of Q R-element input samples
%    TARGETS - SxQ matrix of Q S-element associated target samples
%  arranged as columns, and returns these results:
%    NET - The trained neural network
%
%  For example, to solve the Simple Fit dataset problem with this function:
%
%    load simplefit_dataset
%    net = create_fit_net(simplefitInputs,simplefitTargets);
%    simplefitOutputs = sim(net,simplefitInputs);
%
%  To reproduce the results you obtained in NFTOOL:
%
%    net = create_fit_net(ANN,unnamed);

% Create Network
numHiddenNeurons = 41;  % Adjust as desired
net = newfit(inputs,targets,numHiddenNeurons);
net.divideParam.trainRatio = 70/100;  % Adjust as desired
net.divideParam.valRatio = 15/100;  % Adjust as desired
net.divideParam.testRatio = 15/100;  % Adjust as desired

% Train and Apply Network
[net,tr] = train(net,inputs,targets);
outputs = sim(net,inputs);

% Plot
plotperf(tr)
plotfit(net,inputs,targets)
plotregression(targets,outputs)
```

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