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Short Term Load Forecasting of Chhattisgarh Grid Using Adaptive Neuro Fuzzy Inference System

Saurabh Ghore[1], Amit Goswami[2]

[1]M.Tech. Student, Disha Institute of Management and Technology, Raipur, Chhattisgarh, India

[2]Assistant Professor, Disha Institute of Management and Technology, Raipur, Chhattisgarh, India

Abstract: ***Electrical load forecasting is the process of predicting future electrical load demand on the basis of given historical load information. Load forecasting is an essential and integrated process in planning and operation of electric power utilities. The basic quantity of interest in load forecasting is typically the time period in relation to the load demand studied. Power sector is highly capital intensive and entire planning of generation, transmission and distribution follows an axiomatic approach based on load forecasting. Short-term load forecasting is used in power system for real-time control, security, optimal unit commitment, economic scheduling, maintenance, energy management and power-plant structure planning etc. In this research work Short-Term Load Forecasting of Chhattisgarh Grid is done by using the data obtained from State Load Dispatch Centre (SLDC) of Chhattisgarh State Power Transmission Company Limited (CSPTCL). Adaptive Neuro Fuzzy Inference System (ANFIS) is used in MATLAB to train, test and simulate the data obtained from SLDC Chhattisgarh.***

Keywords: Short Term Load Forecasting, State Load Dispatch Centre, Adaptive Neuro Fuzzy Inference System, Training, Testing, Simulation, Grid Partitioning, Subtractive Clustering, Mean Absolute Percentage Error.

1. Introduction

A prediction scenario of future events and situations is called as forecast, and the act of making such predictions is called forecasting. Forecasting is the basic technique of decision making in different areas of life. The purpose of forecasting is to minimize the risk in decision making and reduce unanticipated cost. One of the most important works of an electric power utility is to correctly predict load requirements. Load forecasting is a method of quantitatively determining future load demand. The primary function of a power utility is to supply electrical energy to the consumers economically. Limitations of energy resources in addition to environmental factors, requires that the electrical energy should be used more efficiently [2].

Load forecasting has a vital importance in power system energy management system. Precise load forecasting helps the electric utility to make unit commitment decisions, reduce spinning reserve capacity and schedule device maintenance plan properly. Besides playing a key role in reducing the generation cost, it is also essential to the reliability of power systems. Load forecasting plays an important role in power system planning, operation and control. Planning and operational applications of load forecasting requires a certain „lead time‟ also called as forecasting intervals. Accurate models for electrical load forecasting are essential to the operation and planning of a power utility [4].

Power sector is highly capital intensive and entire planning of generation, transmission and distribution follows an axiomatic approach based on load forecasting. For this purpose, the anticipated load demand should be known. The resources available in the country for electrical power generation (thermal, hydro and nuclear power stations) can then be developed easily considering the electrical power and energy requirements and the locations or regions where demand is expected. Load forecasting is vitally important for the electrical industry in the deregulated economy. It has many applications including energy purchasing and generation, load switching, contract evaluation and infrastructure development. Short-term load forecasting is used to supply necessary information for the power system management in day-to-day operations and unit commitment. The forecasting time-period or the prediction time for short-term load forecasting can be hour-by-hour, day-by-day, week-by-week. With the recent trend of deregulation of electricity markets, short-term load forecasting has gained more importance and greater challenges [7].

The aim of this research work is Short-Term Load Forecasting of Chhattisgarh Grid by using the data obtained from State Load Dispatch Centre (SLDC) of Chhattisgarh State Power Transmission Company Limited (CSPTCL). Adaptive Neuro Fuzzy Inference System (ANFIS) is used to forecast the one day ahead load-demand requirement for Chhattisgarh grid. A complete database of load demand ranging from 5th March 2014 to 3rd March 2015 on daily 24-hour format, along with the maximum and minimum temperature data of each day of the required time period, is used for one day ahead load forecasting on date 4th march 2015. ANFIS based system has been modeled and implemented in MATLAB 2013 (a) to forecast the 24-hour load demand on required date. The hourly load forecast of 4th March 2015 is obtained by using the load-demand data of Chhattisgarh grid and Temperature data from 5th March 2014 to 3rd March 2015 respectively. The load forecast of 4th March 2015 obtained from ANFIS method is compared with the actual load of the same day obtained from SLDC, CSPTCL and average prediction error is calculated for determining the prediction accuracy of ANFIS used for short-term load forecasting.

2. Adaptive Neuro Fuzzy Inference System

An adaptive neuro fuzzy inference system (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. This technique was developed in the early 1990s. ANFIS integrates both neural networks and fuzzy logic principles and it has the potential to capture the benefits of both in a single framework. It‟s inference system corresponds to a set of fuzzy "If-Then" rules that have learning capability to approximate nonlinear functions. Hence, ANFIS is considered to be an universal estimator. ANFIS uses a hybrid learning algorithm to tune the parameters of a Sugeno-type fuzzy inference system (FIS). This algorithm uses a combination of the least-squares and back-propagation gradient descent methods to model a training data set. ANFIS also validates models using a checking data set to test for overfitting of the training data [1].

ANFIS is a type of Neuro-fuzzy model. Neural networks and fuzzy systems both are stand-alone systems. With the increase in the complexity of the process being modeled, the difficulty in developing dependable fuzzy rules and membership functions increases. This has led to the development of another approach which is mostly known as ANFIS approach. It has the benefits of both neural networks and fuzzy logic. One of the advantages of fuzzy systems is that they describe fuzzy rules, which fit the description of real-world processes to a greater extent. Another advantage of fuzzy systems is their interpretability; it means that it is possible to explain why a particular value appeared at the output of a fuzzy system. In turn, some of the main disadvantages of fuzzy systems are that expert‟s knowledge or instructions are needed in order to define fuzzy rules, and that the process of tuning of the parameters of the fuzzy system often requires a relatively long time [2].

A diametrically opposite situation can be observed in the field of neural networks. It is known that neural networks are trained, but it is extremely difficult to use a prior knowledge about the considered system and it is almost impossible to explain the behavior of the neural network system in a particular situation. In order to compensate the disadvantages of one system with the advantages of another system, several researchers tried to combine fuzzy systems with neural networks. A hybrid system named ANFIS has been proposed. Fuzzy inference in this system is realized with the aid of a training algorithm, which enables to tune the parameters of the fuzzy system.

The toolbox function ANFIS uses a given input/output data set and constructs a fuzzy inference system (FIS) whose membership function parameters are tuned using either a back propagation algorithm alone or in combination with a least squares type of method. This adjustment allows fuzzy systems to learn from the data they are modeling. A network type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map [8].

The parameters associated with the membership functions changes through the learning process. The computation of these parameters is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure. This error measurement is usually defined by the sum of the squared difference between actual and desired outputs. ANFIS uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation.

ANFIS is a data driven procedure representing a neural network approach for the solution of function approximation problems. Data driven procedures for the synthesis of ANFIS networks are typically based on clustering a training set of numerical samples of the unknown function to be approximated. Since introduction, ANFIS networks have been successfully applied to classification tasks, rule-based process control, pattern recognition and similar problems. The fuzzy inference system comprises of the fuzzy model proposed by Takagi, Sugeno and Kang to formalize a systematic approach to generate fuzzy rules from an input/output data set [3].

In the ANFIS structure, the parameters of the premises and consequents play the role of weights. Specifically, the shape of membership functions in the "If" part of the rules is determined by a finite number of parameters. These parameters are called premise parameters, whereas the parameters in the "THEN" part of the rules are referred to as consequent parameters. The ANFIS learning algorithm consists of adjusting the above set of parameters. For ANFIS, a mixture of back propagation and least square estimation (LSE) is used. Back propagation is used to learn the premise parameters, and LSE is used to determine the parameters in the rules consequents. This combination of least-squares and back propagation methods are used for training FIS membership function parameters to model a given set of input/output data.

ANFIS is one of the best combination of neural-network and fuzzy-logic principles, providing smoothness due to the FC interpolation and adaptability due to the NN backpropagation. ANFIS is capable of handling complex and nonlinear problems. Even if the targets are not given, it can reach the optimum result rapidly. ANFIS integrates both neural network and fuzzy logic methods and it has the potential to capture the benefits of both in a single framework. It has strong computational complexity restrictions and has faster convergency than typical neural networks. ANFIS uses smaller training set and has compact modelling than typical neural networks. It gives faster results than ANN in short-term load forecasting. The basic learning rule of ANFIS is the back propagation gradient descent, which calculates error signals recursively from the output layer backward to the input nodes. This learning rule is exactly the same as the back propagation learning rule used in the common feed forward neural networks [7].

3. Architecture and Working Principles of Adaptive Neuro Fuzzy Inference System

ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation. The Sugeno fuzzy model was proposed by Takagi & Sugeno in an effort to formalize a systematic approach to generating fuzzy rules from an input-output data set. A typical fuzzy rule in a Sugeno fuzzy model has the format:

IF x is A and y is B THEN z = f(x,y)

where A and B are fuzzy sets in the antecedent; z = f(x, y) is a crisp function in the consequent. Usually f(x, y) is a polynomial in the input variables x and y, but it can be any other functions that can appropriately describe the output of the system within the fuzzy region specified by the antecedent of the rule. If f(x, y) is a first-order polynomial, than model is called as the first-order Sugeno fuzzy model. If f is a constant, then it is called the zero-order Sugeno fuzzy model, which can be viewed either as a special case of the Mamdani fuzzy inference system, where each rule‟s consequent is specified by a fuzzy singleton, or a special case of Tsukamoto‟s fuzzy model where each rule‟s consequent is specified by a membership function of a step function centered at the constant. Moreover, a zero order Sugeno fuzzy model is functionally equivalent to a radial basis function network under certain minor constraints [2].

Considering a first-order Sugeno fuzzy inference system which contains two rules:

Rule 1: IF X is A1 AND Y is B1, THEN f1 = p1 x+ q1y + r1
Rule 2: IF X is A2 AND Y is B2, THEN f2 = p2 x + q2y + r2

The first-order Sugeno fuzzy inference system is shown in Figure 1

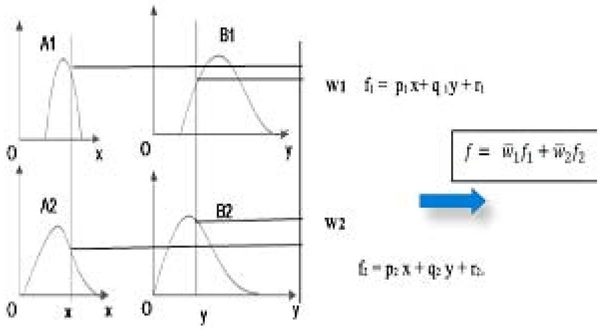

Figure 1: First-order Sugeno fuzzy inference system

To facilitate the learning of the Sugeno fuzzy model, it is convenient to put the fuzzy model into framework of adaptive networks that can compute gradient vectors systematically The fuzzy reasoning mechanism is used to derive an output f from a given input vector [x, y]. The firing strengths w1 and w2 are usually obtained as the product of the membership grades in the premise part, and the output f is the weighted average of each rule‟s output. The resultant network architecture of ANFIS that is shown in Figure 2, where node within the same layer performs functions of the same type. Here circle indicates a fixed node, whereas a square indicates an adaptive node [5].

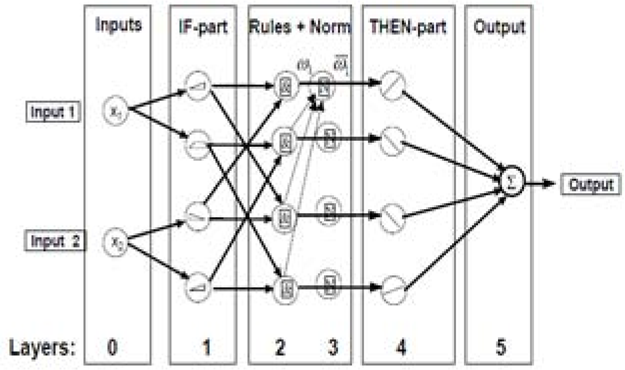

Figure 2: ANFIS architecture

The description of the various layers in ANFIS architecture is as follows [6]:

Layer 1:
Each node in this layer generates membership grades of a linguistic label. For instance, the node function of the ith node may be a generalized bell membership function:

$$O_i^1 = \mu_{Ai}(X) = \frac{1}{1+\left(\left(x\frac{ci}{ai}\right)^2\right)^{bi}} \quad , \quad i=1,2 \qquad \text{----(1)}$$

where x is the input to node i, Ai is the linguistic label (small, large, etc.) associated with this node; and {ai, bi, ci} is the parameter set that changes the shapes of the membership function. Parameters in this layer are referred to as the premise parameters.

Layer 2:
Each node in this layer calculates the firing strength of a rule via multiplication and the nodes are fixed:

$$O_i^2 = W_i = \mu_{Ai}(X)\,\mu_{bi}(Y), \quad i = 1,2 \qquad \text{----(2)}$$

Layer 3:
The nodes are fixed nodes. They are labeled with *N*, indicating that they play a normalization role to the firing strengths from the previous layer. The outputs of this layer can be represented as:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1+w_2}, \quad i = 1,2 \qquad \text{----(3)}$$

Layer 4:
The nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first-order polynomial (for a first-order Sugeno model). Thus, the outputs of this layer are given by:

$$O_i^4 = \overline{w_i}f_i = \overline{w_i}(p_ix+q_iy+r_i), \quad i = 1,2 \qquad \text{----(4)}$$

where *w* is the output of layer 3, and {pi, qi, ri} is the parameter set.

Layer 5:
There is only one single fixed node labeled with *S*. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by:

$$O_i^5 = \sum_{i=1}^{2} \overline{w_i}f_i = \frac{\left(\sum_{i=1}^{2} \overline{w_i}f_i\right)}{w_1+w_2}, \qquad \text{----(5)}$$

The basic learning rule of ANFIS is the back propagation gradient descent, which calculates error signals recursively from the output layer backward to the input nodes. This learning rule is exactly the same as the back propagation learning rule used in the common feed forward neural networks [8]. It is observed from the ANFIS architecture that given the values of premise parameters, the overall output f can be expressed as linear combinations of the consequent parameters:

$$f = \overline{w_1} f_1 + \overline{w_2} f_2 \qquad \text{-----(6)}$$

$$f = \overline{w_1}\,(p_1 + q_1 + r_1) + \overline{w_2(p_2 + q_2 + r_2)} \qquad \text{-----(7)}$$

4. Modelling and Development of ANFIS based Short-Term Load Forecasting System

The first and most important task for designing a system for one day ahead load forecasting is the identification of input parameters. Six unique inputs are used in this research work:
(1) Hour number
(2) Month number
(3) Day of the week
(4) Maximum temperature
(5) Minimum temperature
(6) Previous day load of same hour

One year load-demand data of Chhattisgarh grid from 5th March 2014 to 3rd March 2015 along with the maximum and minimum temperature data of each day has been employed for the training of the ANFIS to predict the 24-hour load on 4th March 2015. The structure of the proposed ANFIS based forecasting system is shown in Figure 3.

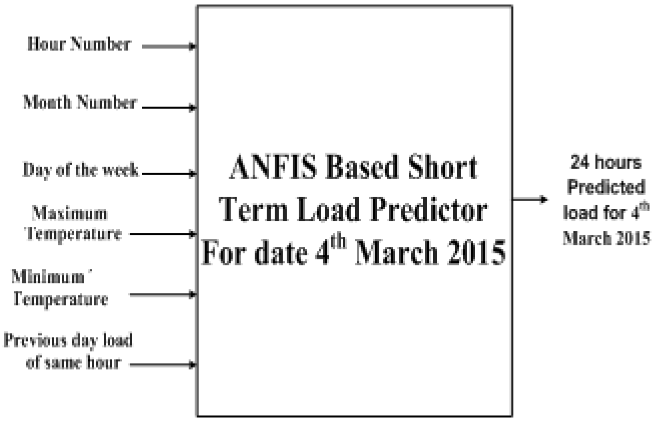

Figure 3: Structure of ANFIS based short term load forecasting system for date 4th March 2015

MATLAB 2013 (a) is used for ANFIS training and testing. The input and target data for the training and testing process is arranged as required for the modeling and development of proposed ANFIS predictor. The training data set for proposed ANFIS predictor contains all the six inputs and one target output all in separate columns. The training data set designed, contains all the six inputs and target output values for 365 days for 24 hours of each day. Hence the dimension of the developed dataset for training is 8736×7, i.e. it contains 8736 rows and 7 columns. Similarly a testing data set is also designed to test the prediction efficiency of the trained ANFIS, which includes all the six inputs for the date 4th March 2015 and having dimension of 24×6. After successful training and testing of proposed ANFIS predictor, the training and testing scenario and properties of the developed ANFIS predictor obtained are as follows:

(i) name: 'VST_FINAL_4_march'
(ii) type: 'sugeno'
(iii) and Method: 'prod'
(iv) or Method: 'probor'
(v) defuzz Method: 'wtaver'
(vi) imp Method: 'prod'
(vii) agg Method: 'sum'
(viii) input: [1x6 struct]
(ix) output: [1x1 struct]
(x) rule: [1x39 struct]

Figure 4 shows the ANFIS editor after loading input and target data.

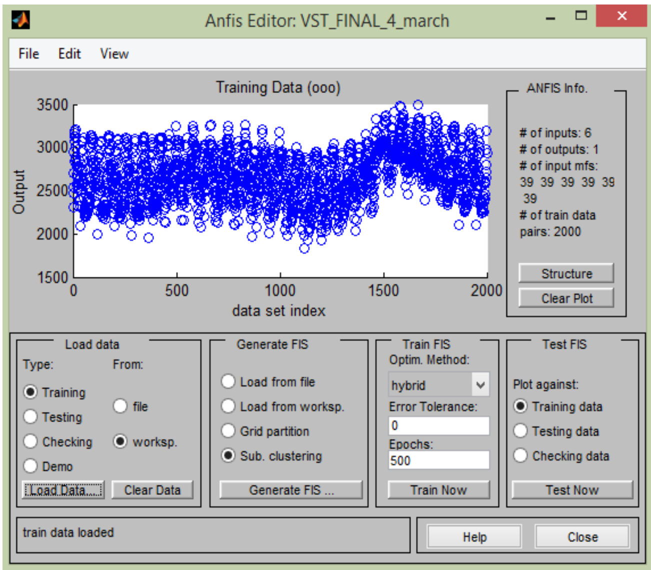

Figure 4: ANFIS editor after loading input and target data

Figure 5 shows the training process of proposed ANFIS predictor. The training error achieved is 33.1305.

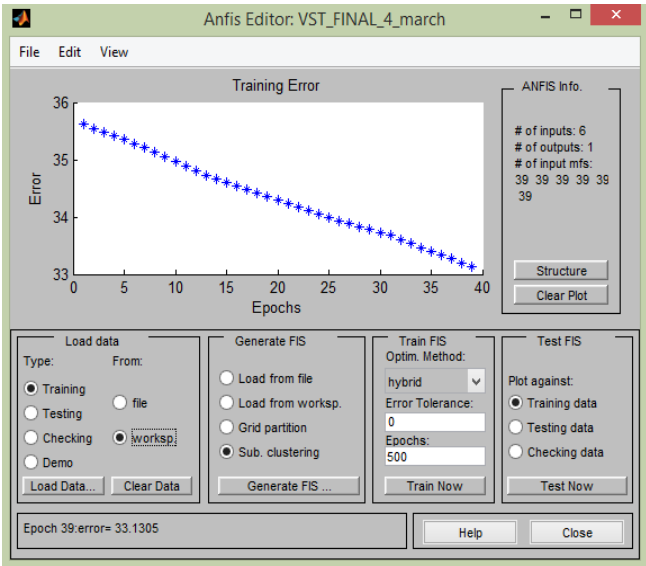

Figure 5: Training process for proposed ANFIS predictor

The Testing process for proposed ANFIS Predictor is shown in Figure 6.

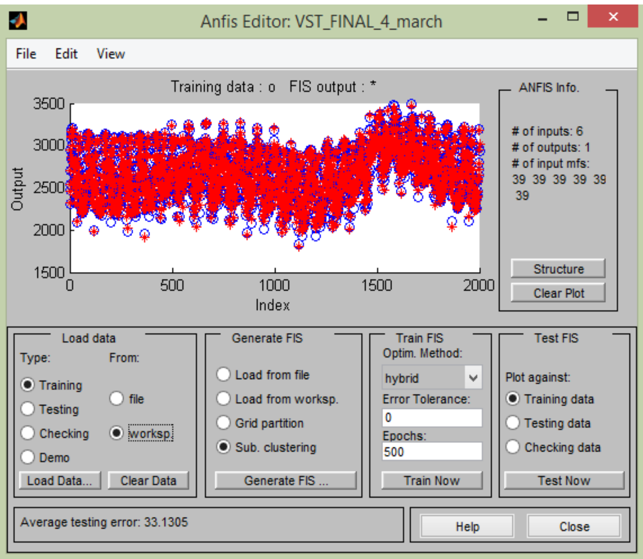

Figure 6: Testing process for proposed ANFIS predictor

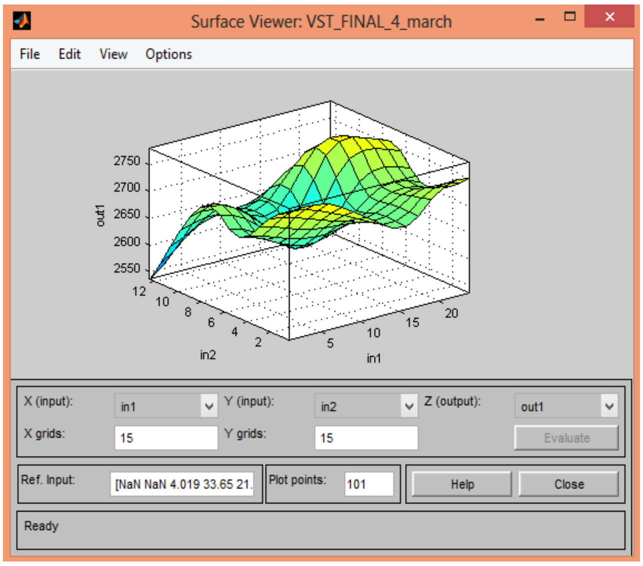

Figure 9: Surface plot of developed ANFIS predictor

ANFIS structure, layout and surface plot are shown in Figure 7, Figure 8 and Figure 9.

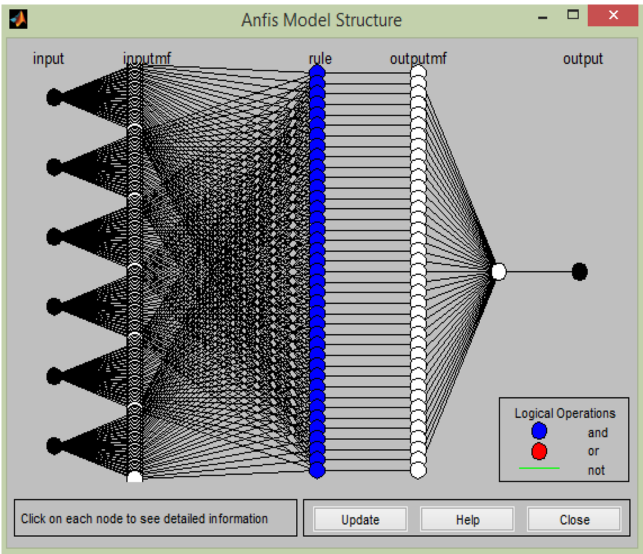

Figure 7: Structure of developed ANFIS predictor

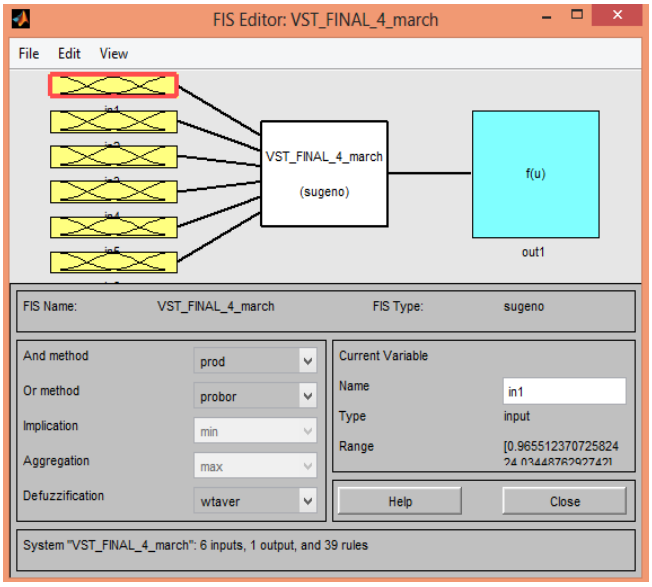

Figure 8: Layout of developed ANFIS predictor

5. Results and Conclusion

Short-Term Load Forecasting of Chhattisgarh Grid is performed successfully by using the data obtained from State Load Dispatch Centre (SLDC) of Chhattisgarh State Power Transmission Company Limited (CSPTCL). Adaptive Neuro Fuzzy Inference System (ANFIS) is used in MATLAB 2013 (a) to train and test the data obtained from SLDC, CSPTCL. The hourly load forecast of 4th March 2015 is obtained by using the load-demand data of Chhattisgarh grid from 5th March 2014 to 3rd March 2015 and the temperature data of same time period. Table 1 shows the actual load obtained from SLDC, CSPTCL on date 4th March 2015 and the forecasted load on the same date using ANFIS based prediction system along with the prediction error.

Table 1: ANFIS Load forecasting results on 4th March 2015

Hour No.	Actual Load in MW	Forecasted Load By ANFIS in MW	Difference in MW	Percent Prediction Error
1	2487	2453.253	33.747	1.357
2	2472	2429.380	42.620	1.724
3	2491	2511.385	20.385	0.818
4	2518	2533.705	15.705	0.624
5	2523	2585.605	62.605	2.481
6	2637	2674.409	37.409	1.419
7	2761	2736.153	24.847	0.900
8	2791	2802.240	11.240	0.403
9	2727	2692.690	34.310	1.258
10	2642	2601.173	40.827	1.545
11	2702	2725.986	23.986	0.888
12	2638	2610.278	27.722	1.051
13	2454	2433.480	20.520	0.836
14	2458	2503.381	45.381	1.846
15	2453	2496.118	43.118	1.758
16	2581	2527.571	53.429	2.070
17	2693	2662.112	30.888	1.147
18	2936	2904.499	31.501	1.073
19	3355	3338.972	16.028	0.478
20	3166	3193.731	27.731	0.876
21	3145	3166.986	21.986	0.699
22	2935	2971.010	36.010	1.227
23	2857	2932.375	75.375	2.638
24	2869	2884.263	15.263	0.532
Average Percentage Prediction Error for 24 Hours in MW				1.235

The load forecast of 4th March 2015 obtained from ANFIS method is compared with the actual load of the same day obtained from SLDC, CSPTCL as shown in Figure 10. The Average Prediction Error of 1.235 % is obtained which is very low and it shows the high prediction accuracy of ANFIS used for short-term load forecasting.

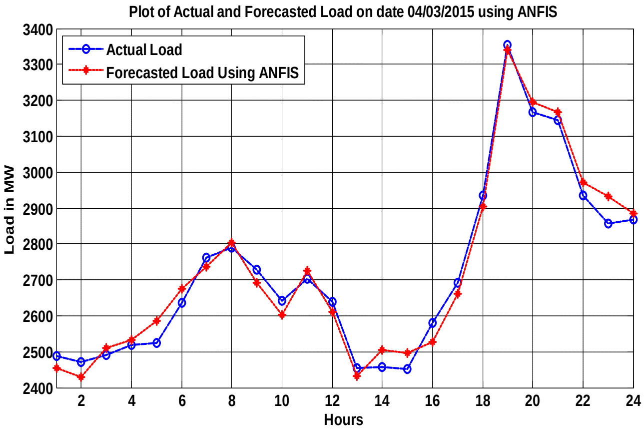

Figure 10: Plot of Actual load and Forecasted load on 4th March 2015 obtained by using ANFIS in MATLAB

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Author Profile

Saurabh Ghore was born in Bilaspur, Chhattisgarh, India on 27th July 1990. He graduated with B.E. Degree in Electrical and Electronics Engineering from Government Engineering College, Raipur, Chhattisgarh, India in the year 2012. Currently, He is pursuing M.Tech. from Disha Institute of Management and Technology, Raipur, Chhattisgarh, India. His field of interest includes Electrical Load Forecasting, Electricity Generation, Transmission And Distribution, Power System Operation And Maintenance.

Amit Goswami was born in Raipur, Chhattisgarh, India on 23rd February 1984. He graduated with B.E. Degree in Electrical Engineering from Rungta College of Engineering and Technology, Bhilai, Chhattisgarh, India in the year 2006. He received M.E. Degree in Power System from Shri Shankaracharya College of Engineering and Technology, Bhilai, Chhattisgarh, India. His field of interest includes Electrical Machines, Power System Analysis, Power System Protection and Switchgear.