Analysis of Short Term Load Forecasting (STLF) using Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

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Abstract

Short-term load forecasting is an essential part of load forecasting which has become one of the main research directions in the field of power systems in recent years. Problems in power systems are difficult to solve because electrical systems are graphically complex, widely distributed, and affected by many unexpected events. It considered different demographic factors such as different weather and climate. In this paper, the Artificial Neural Network (ANN) and Adaptive Fuzzy Neural Inference System (ANFIS) models were used to analyze the data. ANN and ANFIS are used for short-term load forecasting. Performance evaluations of the two models run show that the results of ANFIS give much more accurate results than the ANN model. It also investigates the impact of parameters such as temperature, next day's load, actual load and previous load on load forecasting. Simulations are performed in the MATLAB software environment.

Index Terms — Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems Load Forecasting (ANFIS).

1. INTRODUCTION

Load forecasting is a very important part of energy system energy management system. there are three Forecast vision - short, medium and long term. STLF is the hourly or hourly forecast of the load forecast from now until next week. It is mainly requested by power companies to make unit commitment decisions, reducing spinning reserve capacity, for generator type matching at determine the least expensive operation, to load the transmission. plan energy exchange and purchase. Besides utilities, other newly formed entities such as load aggregators, Electrical traders and independent system operators also need good quality of load forecasting for their operations. [1, 2]

Accuracy has a very significant economic impact. Even one a very small part of the reduction in prediction error can lead to substantial savings. Accurate prediction leads to vast saved operating and maintenance costs, increased reliability of power supply and distribution systems, and decisions for future development. Overload. Forecast lead to an unnecessary increase in reserves and operating costs. Underestimating the load forecast leads to does not providing required spin and redundancy and stability of the system, which can lead to the collapse of electrical system network.[3,4] Various factors that affect STLF are geographical location, mix of customers in business area, weather conditions, season effects, time of day, day of the week and random perturbations So far, it is very difficult to estimate future loads, especially for days with extreme weather conditions, holidays and other unusual days.

With the recent development of new mathematical tools, data mining and artificial intelligence, that is, can improve the results of the forecast. Some effects must be considered on accuracy of LF inappropriate data selection and poor data analysis drive to a decreased accuracy in types of load forecasting and focus on research as shown in Figure 1

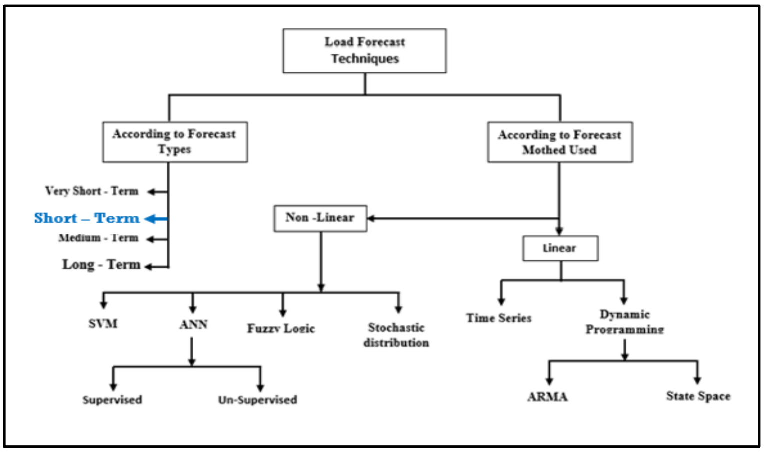

Fig. 1: Types of load forecasting and focus of paper

Various techniques have been developed for charging predicted over the past few years. Different at first Mathematical models have been proposed but they cannot to accurately model meteorological parameters, they lack strength to represent weekends and holidays and intensively calculate. The AI techniques reported in the literature are expert systems, fuzzy inference, neural network, fuzzy neural model. Between Different load forecasting techniques, applications of ANN that has loaded the forecast into the power system a lot carefully in recent years. ANN became popular because of it capable of learning complex, non-linear relationships difficult to model using conventional techniques. [5, 6]

This paper has been organized into five sections. Section 1 presents an overview of Load forecasting. Section 2 presents an overview of methods of load forecasting**.** . Section 3 presents an overview of methodology**.** The simulation result is presented and discussed in Section 4. Section 5 deals with Conclusion and future work.

2. METHODS OF LOAD FORECASTING

2.1 Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) can be defined as a giant processor capable of storing experiential knowledge. The stored knowledge is accessible for use. The neuron model can be divided into three categories as synapse, sum junction, and activation function. The first component is made up of synapses that connect the input to the composite junction. Each group is assigned a weight (W). The second component is the sum junction, where the input signals, weighted through the corresponding synapses of the neuron, are added. The third component is the activation function, which is the final process. This neuron model has been demonstrated in Figure 2. Furthermore, a neuron K can be written by equation (1.1) and equation (1.2). and Equation (3.2).[6,7]

$$\boldsymbol{v_k = \sum_{j=1}^{m} j w_{kj}\, x_j} \tag{1}$$

$$\boldsymbol{y_k = f_{(v)k}} \tag{2}$$

where,

$x_{1\,,}\ x_2\ , \dots\ x_p$ are the input

w_{k1},w_{k2}, … w_{kp} are the weights

v_k is the linear unified output

$$\boldsymbol{y_k = f(v_k)\ (v_k\ -\ b_k)} \tag{3}$$

where,

b_k is the bias

$f(v_k)$ is activation function

y_k is the output of the neuron

A series of trials were conducted on the algorithms to achieve perfect results. Levenberg-Marquardt is the fastest algorithm, but with some pressure it starts to weaken and, in this case we have to use another faster and better algorithm to approximate the function. Figure 3 shows the conjugate gradient. In this study, Tan-Sigmoid Transfer Function is used [8,9] .

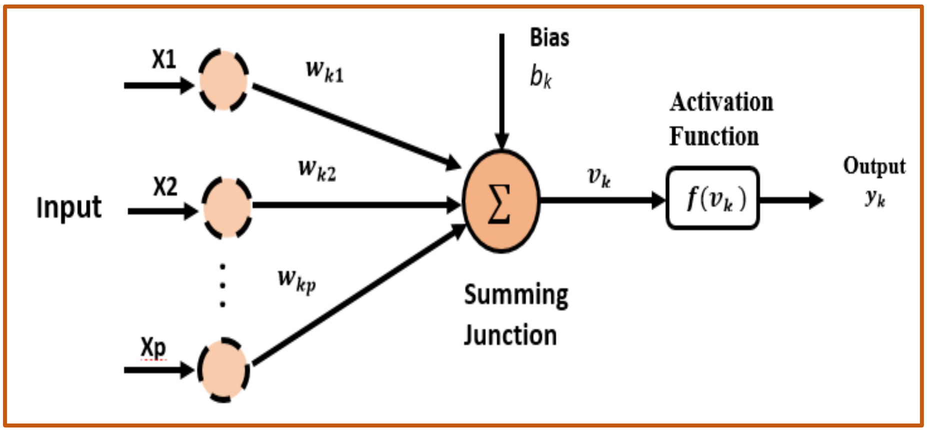

Fig. 2: Neuron model

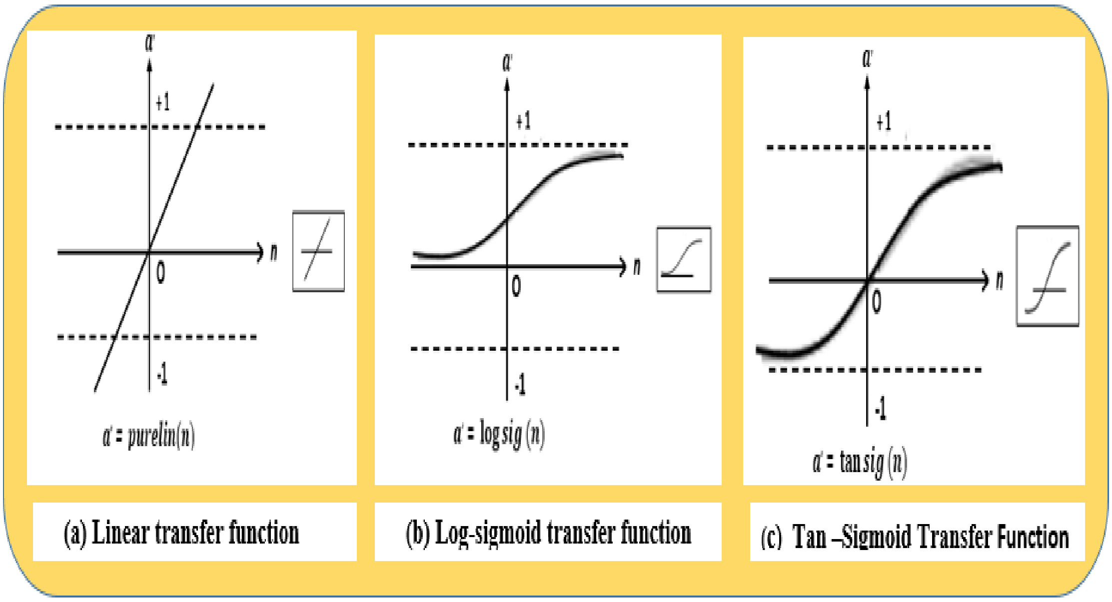

Fig. 3: Conjugate gradient

2.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is an integrated system, Fuzzy Logic (FL) and Artificial Neural Network (ANN). It is also considered as one of the types of artificial intelligence (AI) methods, which can be implemented in electricity load forecasting. ANFIS is a hybrid system that combines FL`s human logic style and ANN's learning style. It can also adapt to a network consisting of certain nodes, connected with directional links. Each node represents a processing unit and defines links between nodes. In ANFIS, some nodes are adaptive and some are constant. It also has only one output from adaptive nodes. Adaptive nodes depend on a number of modifiable parameters; such as weather t weather variables for the buttons. One of the most essential things to learn is the rule of updating these parameters, such as minimizing regulatory errors, measuring changes in actual load (output) and target output. It has two different models made up of one of them for heating ANFIS-1 and the other for cooling ANFIS-2's energy needs. [10,11]. The proposed ANFIS models can be divided into four input parameters and two output parameters namely orientation, building form factor transparency (FF) and insulation thickness. The output of the model is heating and cooling for ANFIS-1 and ANFIS-2. The simple model is shown in Figure 4

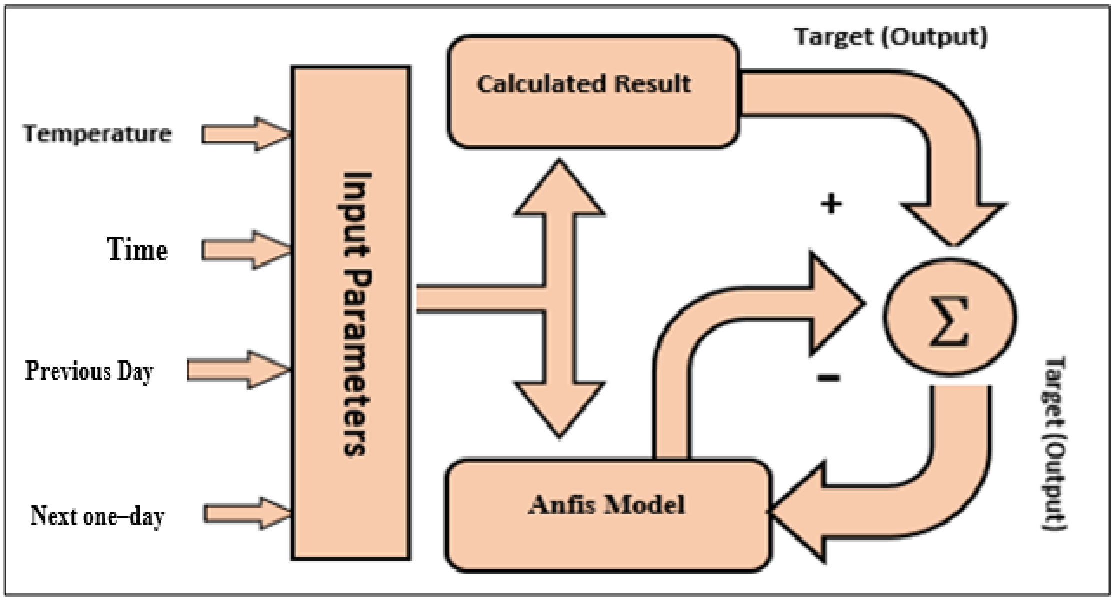

Fig. 4: The simple model of ANFIS

3. METHODOLOGY

Data for each hour was collected over a three-day period (day 1, day 2, and day 3, 2016) in two departments. Power load data was collected from maintenance department and meteorological parameters (temperature) were obtained from Department of Geography, Adamawa State, Mubi, Nigeria, as shown in Figure 5. An output is obtained and then integrated into neural networks with a future one-day load and target. The previous day's, temperature, time, next day's load, actual load, and previous load are combined. In order to obtain an accurate or suitable mapping, the output (predicted load) of the network is then compared versus the desired output.

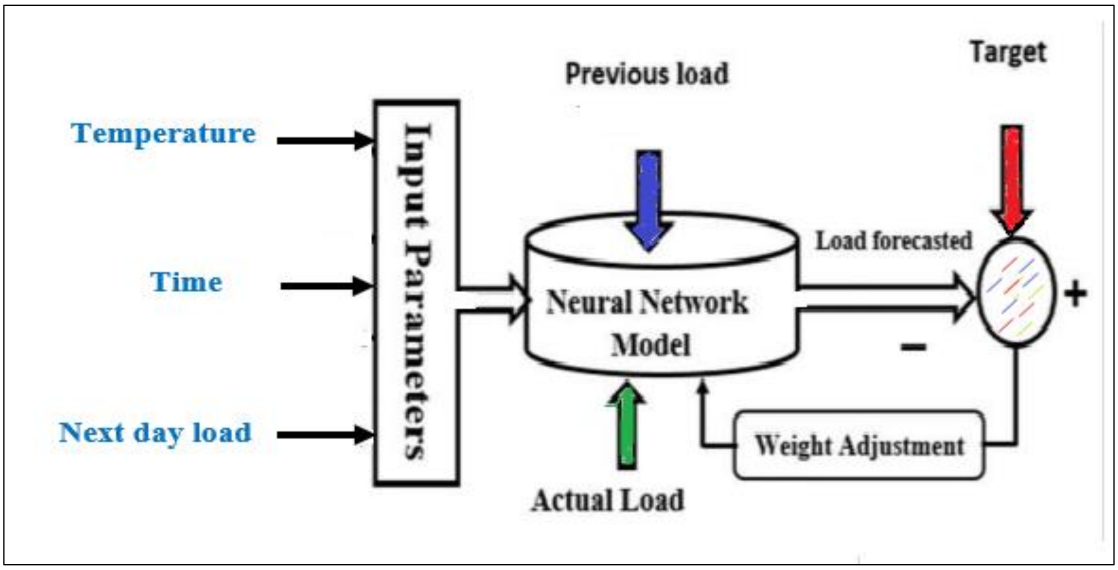

Fig.-5 Block diagram representation

3.1 Implementation of ANN using MATLAB

Using the collected data presented in Tables 1 and stored in an Excel workbook. This dataset includes more than 24 hours, roughly equivalent to a day, the neural network has a two-layer network with sigmoid hidden neurons and linear output neurons and also used for training with Leven Berg-Marquardt back-propagation algorithm as shown in Figure-6.

The following the step we select the data is divided into two parts one of the parts is the input of weather variables like temperature, time, next day's load, actual load on forecast load and other is output as shown in Figure 6. Training is set at 70%, validation is 15% and the test is 15% of hidden neurons ten if error is high, then to minimize error recycling is then we can get the instrument graph, Train Condition, Adjustment and Regression as shown in Figure-7. Figure-8 show optimized ANN architecture used in this section study. There are six items. These items are temperature, time, next day's load, actual load, and previous load. That moment, only one ANN output is the future load. IN Furthermore, the number of hidden neurons used was ten.

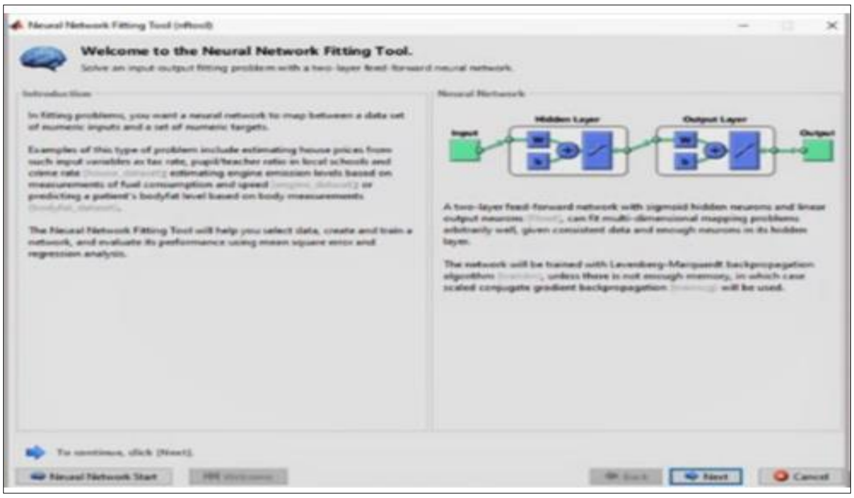

Fig-6. ANN open tool in MATLAB.

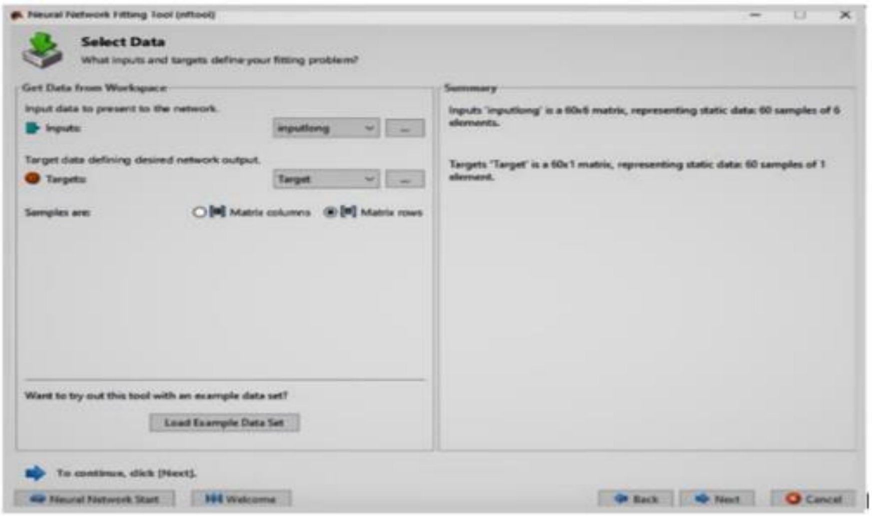

Fig-7. ANN Input data and output data preparation.

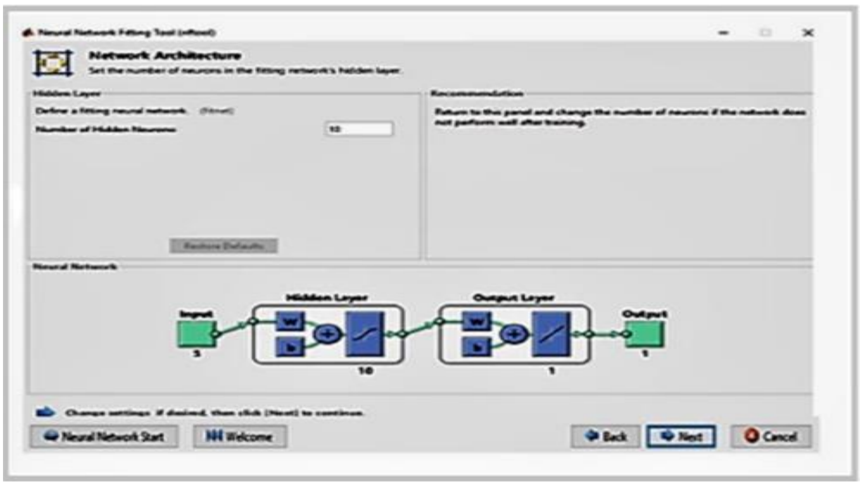

Fig-8. Optimized ANN architecture.

3.2 Implementation of ANFIS using MATLAB

In this paper, ANFIS is used to predict the customer's load demand for STLF load forecasting models based on factors such as weather variables and improve the results obtained through logic fuzzy. These variables are (temperature, time, next day's load, actual load). Similar to ANN, the MATLAB program is used to generate ANFIS. All input of desired value for time, temperature, next day's load, actual load to have forecast load and target value for ANFIS identical to input and target values used in ANN. Figure 9 illustrates the structure of ANFIS simulated in MATLAB program.

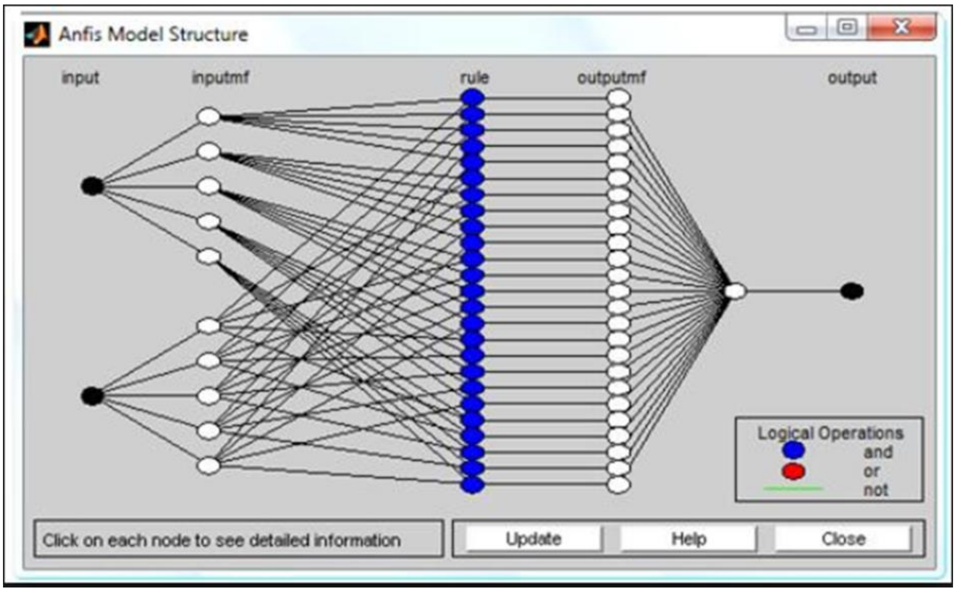

Fig. - 9 : ANFIS structure simulated in program MATLAB

The ANFIS model standard has been applied to effective tone member function to reduce output errors and maximize performance metrics. ANFIS The display editor includes four categories. Download data, General FIS, training FIS and test FIS, the load data is used for training, check and verify. The next step is to click generate FIS and choose any type, such as trim and tramf; ending is select linear as shown in Figure 10.

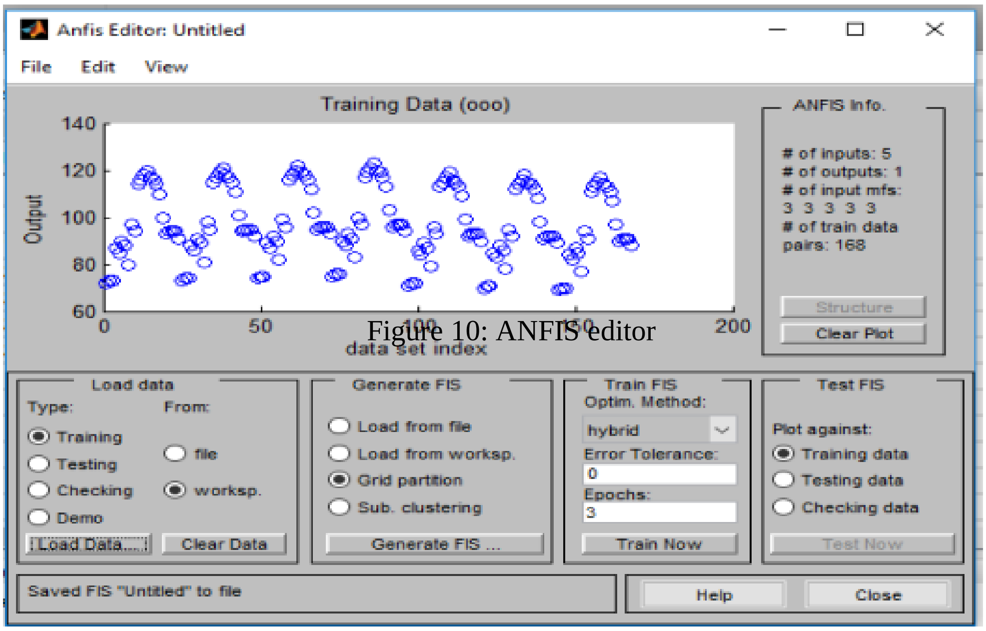

Figure 10: ANFIS editor

Fig. 10 generate FIS and choose any type

4. RESULT AND DISCUSSIONS

Figure 11 shows the results of the ANN. Only one eight iterations are required for this ANN to complete dirty. This ANN takes only a little time i.e. 0.001 seconds. The efficiency of ANN is very good with a root mean squared error of 3.06e-20. Figure 12 shows the ANN performance graph. Total the number of epochs created is 6. It can also be seen that best validation performance is 22.7037 at epoch 1. Through simulation study of short-term load forecast (24 hours) presented in Table 1, it is observed that from midnight to 6 hours the load is low and up to 8 hours the load increases.

The relationship between time and load of day is shown in Table 1. It can also be seen from Table 1 that the absolute error value is -9.54 to 10.26. Forecasting is done 24 hours a day. ANN biggest failure on January 3, 2016 was at 3:00 PM and the load peaked at 12:00 PM; This refers to temperature rises at that time. Table 1 below illustrates the results obtained from the data management and analysis performed using MATLAB in the order of the relationship between the predicted load and actual load. Table-1 was analyzed to check the accuracy of the model between the average error of ANN and ANFIS are 9.95% and 0.57%, respectively. The results show that it is very close. Finally, it is observed in Figure 13 that ANFIS is more accurate, responsive and more suitable for application versus ANN. It also to helps find the number of fuzzy rules.

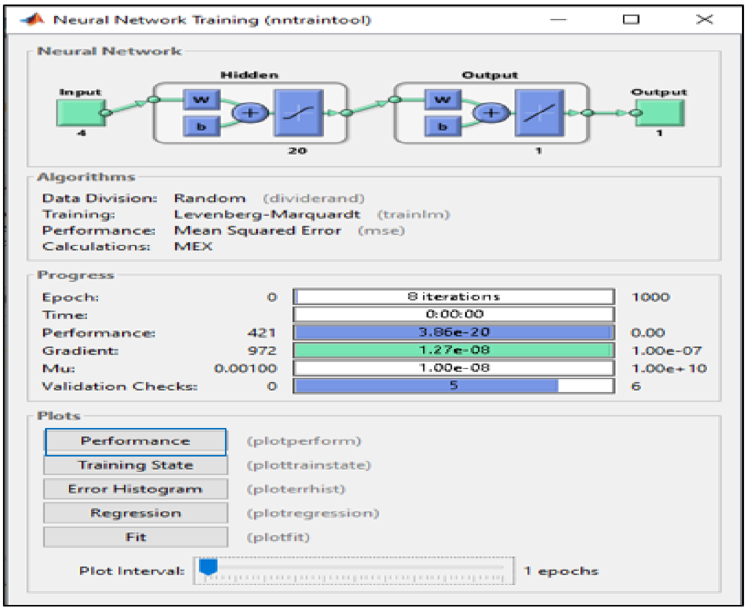

Fig.-11. Results of the ANN.

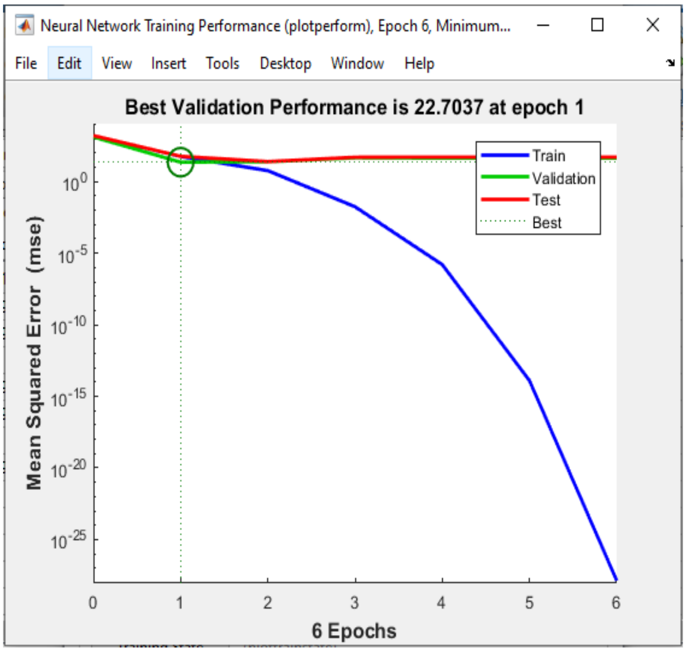

Fig.-12.ANN performance plot.

Figure 13 includes three different graphs that are test, training and validation regression. The first plot shows the closeness between outputs and Target. The value of the regression plot of one (R = 0.9482). Also note The regression plot for the test is R = 0.9929, for the training is R=0.9369, for validation R=0.93641 and R=0.9482 for everyone. This indicates that the neural network predicts satisfactory output.

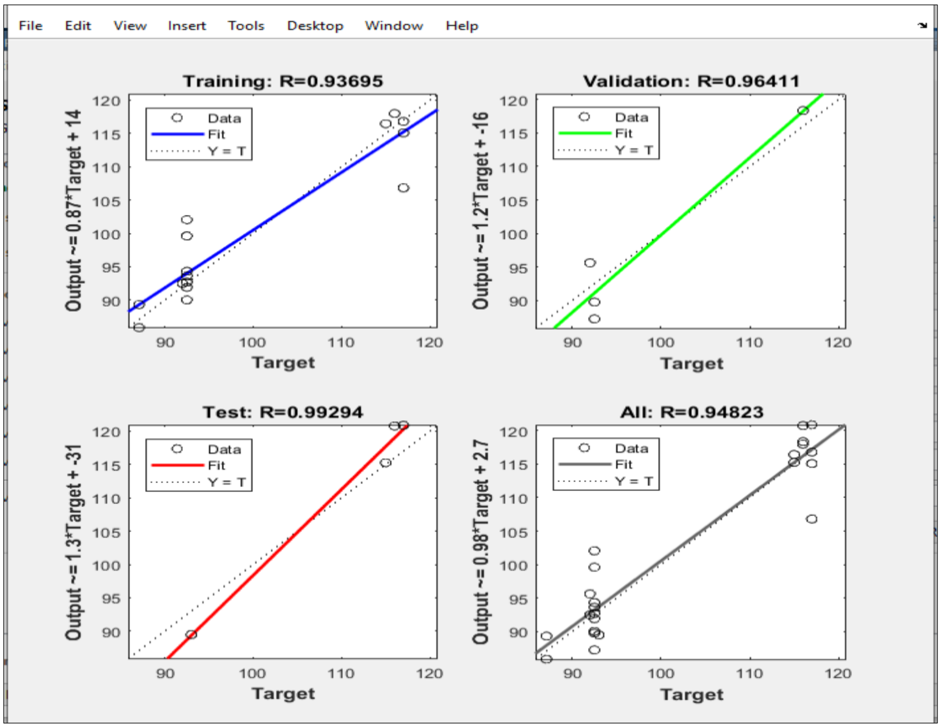

Fig.-13.ANN regression plot.

Table 1 Time - Temperature - Next day load - Previous 24-hr

4- Input data short –term					Target	ANN		ANFIS	
Time		Temperature (^{0}C)	next day load (kW)	Previous 24-hr (kW)	Target	Output	% Error	Output	% Error
Am	0.00	17	69.25	70.50	92.50	90.03	2.47	92.47	0.03
	1.00	18	70.50	72.00	87.10	89.31	-2.21	87.06	0.04
	2.00	15	69.50	69.00	87.10	85.86	1.24	87.02	0.08
	3.00	14	82.50	80.00	92.50	89.75	2.75	92.47	0.03
	4.00	14	77.75	75.50	92.50	87.25	5.25	92.41	0.09
	5.00	14	87.5	90.00	92.00	95.61	-3.61	91.99	0.01
	6.00	14	84.0	88.00	92.50	94.32	-1.82	92.49	0.01
	7.00	20	84.8	89.50	117.00	115.08	1.92	117	0.00
	8.00	24	95.0	95.00	116.00	117.98	5.02	116.00	0.00

	9.00	25	95.0	95.00	117.00	116.80	5.52	116.97	0.03
	10.00	25	112.5	105.00	116.00	118.36	-2.36	115.99	0.01
	11.00	25	116.0	110.00	115.00	116.44	-1.44	115.00	0.00
Pm	12.00	26	121.0	120.00	117.00	120.87	-3.87	117.00	0.00
	13.00	26	124.5	125.00	116.00	120.75	-4.75	115.99	0.01
	14.00	27	119.0	120.00	115.00	115.25	-0.25	114.97	0.03
	15.00	26	116.0	118.00	117.00	106.82	10.18	116.98	0.02
	16.00	25	112.5	115.00	92.50	102.04	-9.54	92.50	0.00
	17.00	24	105.0	110.00	92.50	99.62	-7.12	92.48	0.02
	18.00	24	97.5	100.00	92.50	92.70	-0.20	92.44	0.06
	19.00	24	94.0	95.00	93.00	89.48	3.52	92.99	0.01
	20.00	21	90.0	90.00	92.50	92.68	10.26	92.50	0.00
	21.00	20	89.0	90.00	92.50	93.62	-1.12	92.47	0.04
	22.00	20	89.0	88.00	92.00	92.48	-0.48	91.99	0.01
	23.00	19	85.0	80.00	92.50	91.91	0.59	92.46	0.04
Average % Error						ANN	9.95	ANFIS	0.57

5. CONCLUSIONS

This work presents the results of short -term load forecasting using ANN and ANFIS methods. This paper has successfully simulated STLF using ANN and ANFIS. From the comparison between the two models used in this work, both ANA and ANFIS was able to capture the dynamic behavior of meteorological variables for STLF. However, ANFIS produces much more accurate short-term results compared to ANNs. In addition, ANFIS is capable of produces the number of rules and its member functions. Ultimately, ANFIS can be a much more valuable tool for short-term load forecasting.

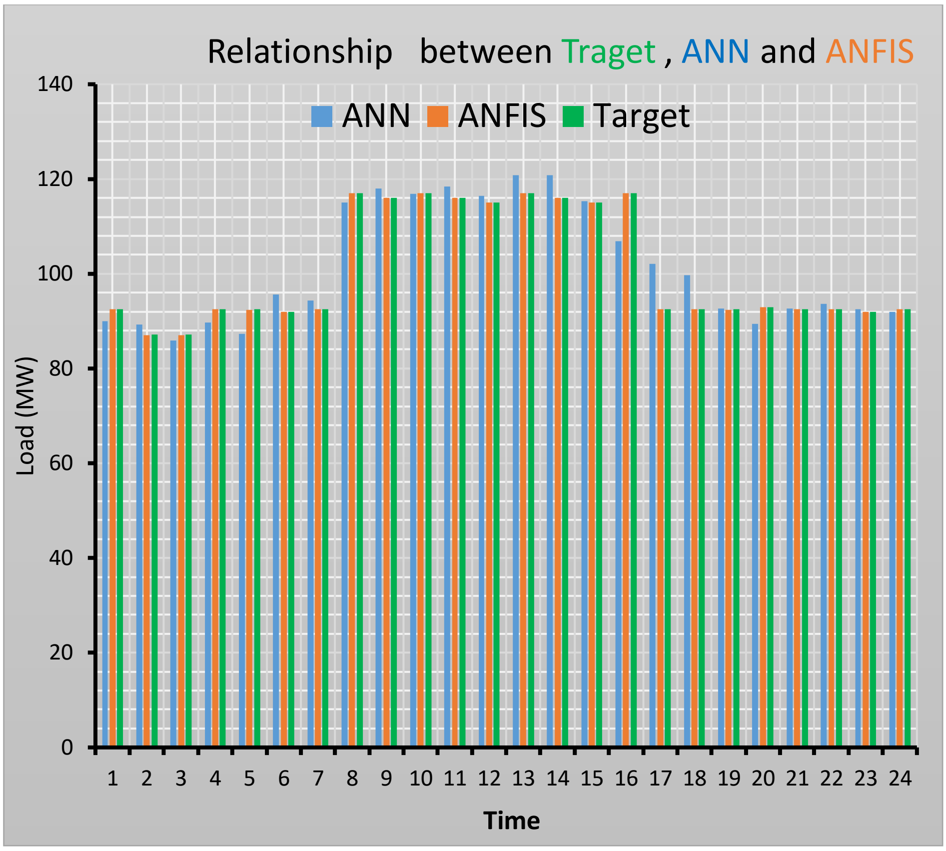

Fig.-14. Regression plot.

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