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LONG –TERM LOAD FORECASTING OF POWER SYSTEMS USING ARTIFICIAL NEURAL NETWORK AND ANFIS

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ABSTRACT

Load forecasting is very important for planning and operation in power system energy management. It reinforces the energy efficiency and reliability of power systems. Problems of power systems are tough to solve because power systems are huge complex graphically, widely distributed and influenced by many unexpected events. It has taken into consideration the various demographic factors like weather, climate, and variation of load demands. In this paper, Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models were used to analyse data collection obtained from the Metrological Department of Malaysia. The data sets cover a seven-year period (2009- 2016) on monthly basis. The ANN and ANFIS were used for long-term load forecasting. The performance evaluations of both models that were executed by showing that the results for ANFIS produced much more accurate results compared to ANN model. It also studied the effects of weather variables such as temperature, humidity, wind speed, rainfall, actual load and previous load on load forecasting. The simulation was carried out in the environment of MATLAB software.

Keywords: artificial neural networks (ANN), neuro-fuzzy inference system (ANFIS), weather forecasting, electrical load.

1. INTRODUCTION

Weather forecasting is essential in our world today because it gives us the early warning on weather changes. The technology and science are used to predict the case of the atmosphere for the future at a given site. Weather forecasting can also be implemented by gathering data around the present case of the atmosphere and the past or current experiences. It also plays a vital role in power system as it also used in predicting a lot of unexpected events including the different demographic factors like weather, climate, and human activate. The weather is referred to the state of air on land at a given site and time. It has many applications including predicting the case of the atmosphere in future because of its impact on human activities. The main impasse with electricity as a means of transmitting electrical energy is that it cannot be stocked such as hydrogen, gas, and oil. Because of this, the electric power company has two problems one of them technical and other economic in operation, planning, and control of electric power system. Electric power company utilizes forecasts expect the amount of energy electricity to meet future load. Several techniques have been employed for forecasts in the past; these based on different statistical methods, for instance, regression, time series, exponential smoothing and so on. In last years, research has converged towards techniques that utilize Artificial Intelligence, for example, expert systems, fuzzy logic and ANN between the artificial intelligence techniques; ANN has been received a big deal by researchers in this region because of its flexibility and adaptability in data models. In this work, ANN and ANFIS models were used to analyze data collection obtained from the metrological department for Long Term Load Forecasts (LTLF) [1,2,3].

2. TYPES OF LOAD FORECASTING TECHNIQUES INVOLVED

There are three different main kinds of load forecasting, and they are[4,3,5,6]:

a) Long -Term Load Forecast (LTLF): This is more than a year.
b) Medium -Term Load Forecast (MTLF): This is usually from one week up to 1 year.
c) Short -Term Load Forecast (STLF): This is one hour to one week.

Load forecasting for various time horizons is essential for different operations with an electric power system. The natures of types of load forecasting are various too. This research will focus on LTLF. It is used to supply electric power system with prediction of future load needs for equipment, expansion, purchases such as, for an appointed area, it is possible to predict the next (24 hours) load with an accuracy of approximately 1-3% In addition to that, it is impossible to predict the next one-year peak load with similar accuracy since accurate long-term weather forecasts are not available. It is also possible to provide the probability distribution system of the load based on historical weather observation. This work will focus only on lLTLF because it is one of the famed electrical power systems load forecasting in literature view. It has no linear correlation between the input weather variables also between variables used to long-term load forecast another affects each other. This work is one of the latest work used Malaysia weather data. The high long-term load forecast is making accurately. The more investment and planning are obtained more accurately. Data consist of seven years, current year and future year.

3. IMPACT FACTORS FOR LOAD FORECASTS

Several variables should be considered for accurate forecasting of load such as time factors, class of consumers, previous weather data and amount of load increment so on. Factors influencing loads expectations play a vital role in calculating the demand load. The time factors are a very important for Load Forecasts include the date of the hour of the day (24hour), the day of the week, and the month of the year. For long-term load forecasting many factors should be considered, such as the historical data for load, weather data such as weather, climate, and human activate of the electric load, the number of customers in unlike types, the devices in the region and their characteristics in including age and the economic and weather data and their forecasts [7].

4. METHODS OF LOAD FORECASTING

4.1 Artificial Neural Network (ANN)

ANN is always referring to a category of modules inspired by the biological nervous system. The models are consisting of many simple processing units. It is also connected to the parallel and feeding forward in many layers. Due to the quick and It is possible to get an inexpensive personal computer, the interest in ANN's has blossomed in the present digital world. The essential motive of the development of ANN to make the computer do the same work of human being. In addition, every neuron has a number to set input and one output. ANN has a group of nodes named synapses which are connected with inputs, output, or another neuron. Figure-1 shows the architecture structure of ANN which consists of three layers (input, hidden and output layers).These inputs are composed of weather variables (temperature, humidity, wind speed, rainfall, actual load and previous load) on Load Forecasting and output load forecasting. This type of structure is called Multilayered Perceptron (MLP) network which is one of the popular feed-forward networks [8,9].

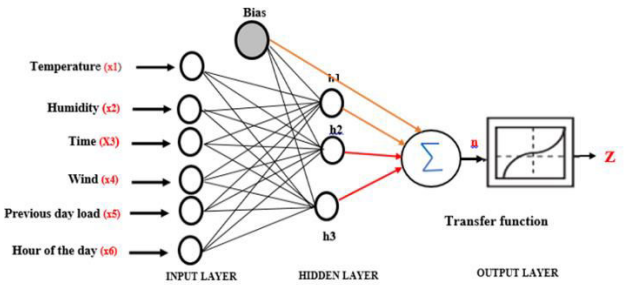

Figure-1. Architecture of ANN.

4.1.1 Types of transfer function

There are three different main kinds of the transfer function, and they are:

a) Linear Transfer Function.
b) Log-Sigmoid Transfer Function.
c) Tan - Sigmoid Transfer Function.

These transfer functions are essential for ANN because of providing improved performance with the normalized data. in this work, used tan-sigmoid transfer function Because this kind has flexibility values between -1 and 1 through separator Difference between maximum and minimum values and also has non-linear at the end of every algorithm; outputs were deformalized into the original data format for achieving the coveted result. Figure-2 shows the tan-sigmoid transfer function [1,10].

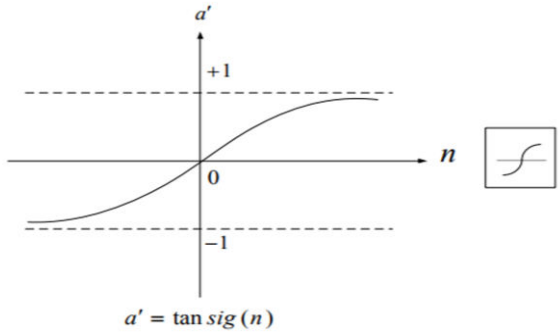

Figure-2. Tan-Sigmoid transfer function.

4.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is an integrated system, fuzzy logic (FL) and Artificial Neural Network (ANN). It is also considered one of the types of the artificial intelligent (AI) methods which can be implemented in electric load forecasting. ANFIS is a hybrids system that merges the human logic style of FL and learning style of ANN. It also can adapt to the network that consists of some nodes which are connected with links directional. Every node represents a processing unit and the links specifying between the nodes. In ANFIS some of the nodes are adaptive, and others are constant. It is also having just one output of the adaptive nodes. The adaptive nodes depend on some modifiable parameters features such as weather variables relevant to the nodes. One of most essential to learn the rule in order how to update these parameters such as minimize a prescribed error that measures the variation in the actual load (output) and target output. It has two different models are formed one of them for heating ANFIS-1, and other is for cooling ANFIS-2 energy requirements. The proposed ANFIS models can be divided into four inputs parameters, and two outputs are orientation, building form factor (FF), transparency and insulation thickness. The outputs of the models are heating and cooling for ANFIS-1 and ANFIS-2. The simple structure is illustrated in Figure-3 [11,12].

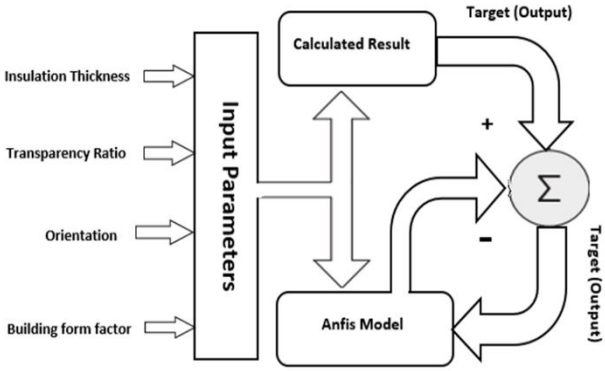

Figure-3. The simple structure for ANFIS.

5. METHODS OF LOAD FORECASTING

5.1 Data collection and implementation of ANN) for long term load forecasting (1-year)

The historical data can be divided into two categories which are actual load and the monthly weather parameters such as temperature, humidity, wind speed, rainfall. The actual load was taken from IEEE database of University Technology Malaysia [13], and it covers a period of 60 months from January 2007 to December 2011 for. Moreover, the monthly weather parameters were taken from Department of Meteorology in Malaysia for five years. Figure-4 shows the ANN block diagram representation used in this research.

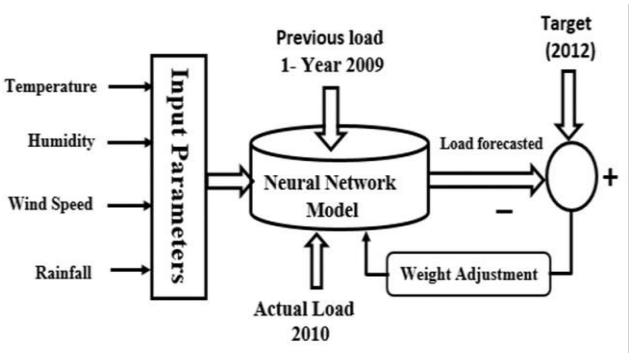

Figure-4. ANN block diagram representation.

5.2Implementation of ANN using MATLAB

Using the collected data seen in Table-1 and saved in an Excel spreadsheet. This data set spans over of 60 months, which is approximately equal to five years, the neural network has two-layer feed-forward network with sigmoid hidden neurons and linear output neurons and also used for training with Leven Berg-Marquardt backpropagation algorithm as seen in Figure-5.The next step we choose the data which is divided into two parts one of the parts is the input of weather variables such as temperature, humidity, wind speed, rainfall, actual load and previous load on load forecasting and other is output as shown in Figure 6.Training was set to 70%, validation was 15%, and Testing was 15% number of hidden neurons ten if the error is high then to minimize the error retrain is done then we can obtain plots of the implement, Train state, Fit and Regression as shown in Figure-7.Figure-8 shows the optimized ANN architecture used in this research. There are six number of inputs. These inputs are the temperature, humidity, wind speed, rainfall, data of previous load and data of the actual load. Meanwhile, there is only one ANN output which is the future load. In addition, the numbers of hidden neurons used are ten. Figure-9 shows the results of the ANN. Only seven iterations were needed by this ANN to complete the task. This ANN only consumed a small amount of time which is 0.01 seconds. The performance of the ANN is very good with a mean squared error value of 1.13e-22.

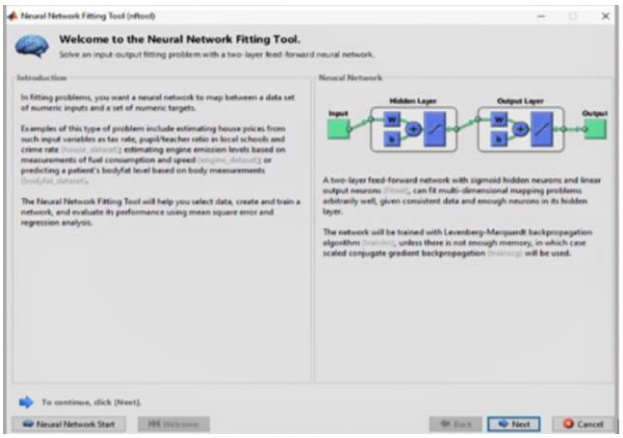

Figure-5. ANN open tool in MATLAB.

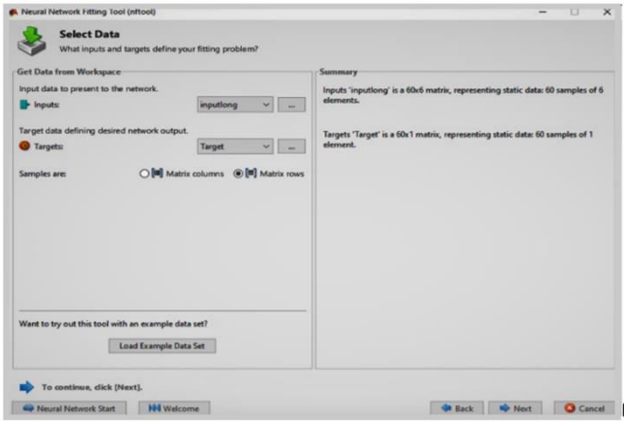

Figure-6. ANN Input data and output data preparation.

Figure-7. Training, validation and testing setting.

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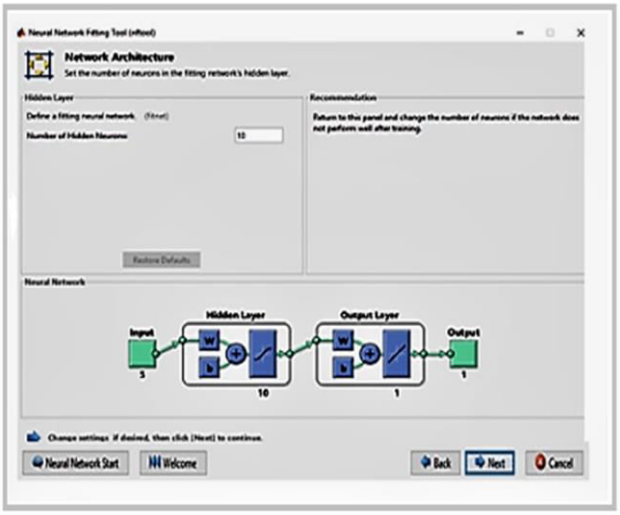

Figure-8. Optimized ANN architecture.

5.2 Implementation of the Adaptive Neuro-Fuzzy Inference System (ANFIS) using MATLAB

The ANFIS modeling standard was adapted to effectively melody the membership function so as to decrease the output error and maximize performance indicator. ANFIS Editor Display is consist of four types are. Load data, General fis, Train Fis and Test FIs, the load data is used for training, testing, and checking. Next step is to click generate FIS and choose any type such as trim and trapmf; the last step is select linear as seen Figure-9.

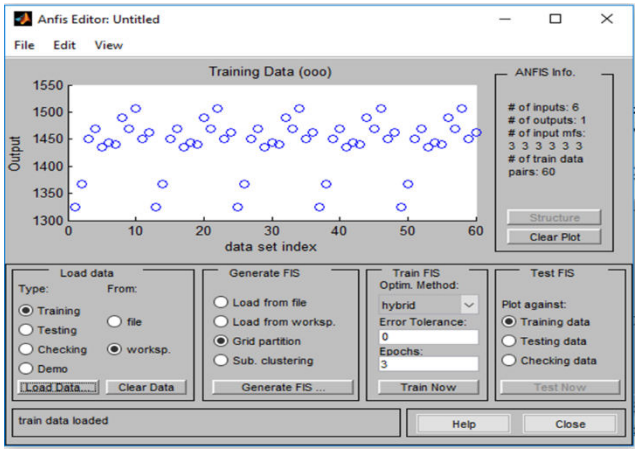

Figure-9.ANFIS editor.

5.3Generating the fuzzy rules and selecting the membership function

The first steps after successfully downloading the training data, the rules are produced by the grid division method. It has six inputs with membership function; Network partitioning is an approach for initializing the framework in a fuzzy inference system. In this way, it produces rules by recount all possible installations of the membership function of all inputs as shown in Figure-10.

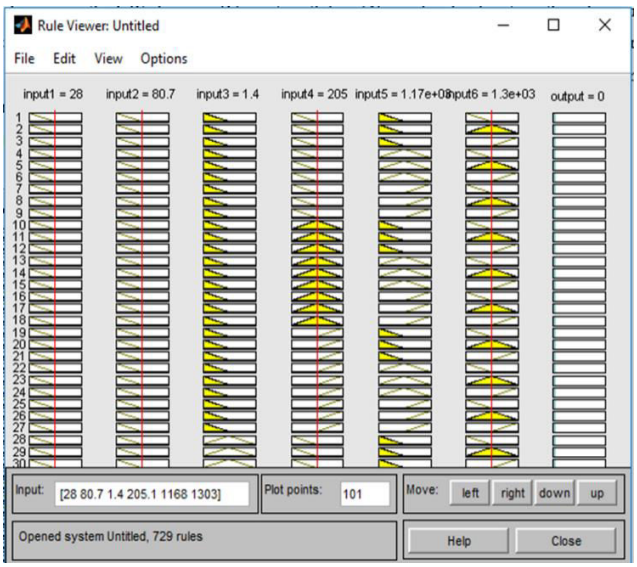

Figure-10. The dialog box of the rule viewer.

6. RESULT AND DISCUSSIONS

Figure-11 shows the results of the ANN. Only seven iterations were needed by this ANN to complete the task. This ANN only consumed a small amount of time which is 0.01 seconds. The performance of the ANN is very good with a mean squared error value of 1.13e-22. Figure-12 shows the ANN performance plot. The total number of epoch produced is 27. It also can be seen that the best validation performance is 134.2312 at epoch 21.

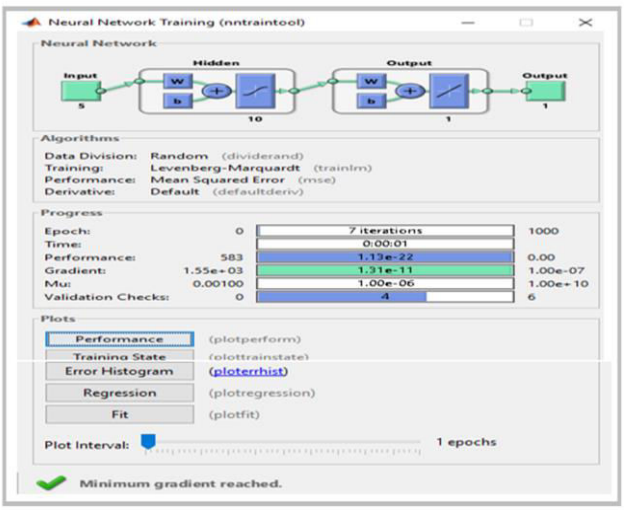

Figure-11. Results of the ANN.

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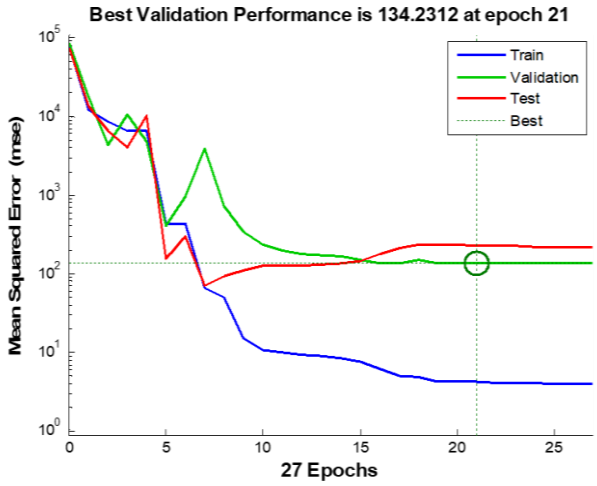

Figure-12.ANN performance plot.

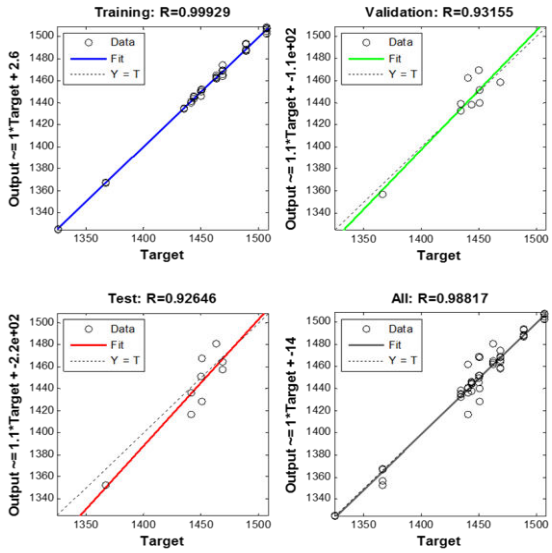

Figure-13.ANN regression plot.

Figure-13 consists of three different graphs that are test, training, and validation regression. The first plot shows the very close between the outputs and the target. The regression plot value of one (R= 1). It is also noted that the regression plot for testing is R=0.9264, for training is R=0.9992, for validation is R= 0.9315 and R= 0.9881 for all. This indicates that the neural network predicted the output satisfactorily.

Table-1 shows the relationship between the temperatures, relative humidity with the future load. It can be seen that the increase in temperature values will lead to the increase of load values. It is noticeable that the increase in relative humidity will result in the decrease of load values. Also, it can also be seen that the combination of minimum temperature with maximum humidity will obtain minimum load value. However, the result shown in Table-1 was analysed to check the accuracy of the model between the average error of ANN-BP and ANFIS are 6.7% and 0.096%, respectively.

Table-1. Data Collection from Malaysia for long-term.

Month	6-Input long-term						Target	Years		ANN				ANFIS			
	T(0c)	Humidity	Wind speed (Ms - 1)	Rainfall (mm)	Previous 1- year (2009	Actual Load (2010)	2012	2015	2020	Output 2012	Error 2012	Output 2015	Output 2020	Output 2012	Error 2012	Output 2015	Output 2020
Jan	28.4	81.0	2.6	122.4	1171.2	1202.0	1325	1534	1958	1325.09	-0.09	1565.1	1961.2	1324.8	0.249	1534.2	1957.6
Feb	27.9	78.2	3.6	178.2	1168.2	1240.0	1367	1583	2020	1356.79	10.21	1565.7	2013.8	1367.2	0.147	1582.8	2019.5
Mar	29.3	72.5	3.3	6.6	1206.3	1315.5	1450	1679	2143	1451.77	-1.772	1665.4	2130.3	1449.9	0.143	1679.5	2143.5
Apr	29.6	76.8	2.1	112.0	1232.8	1332.1	1469	1700	2170	1457.81	11.186	1711.9	2153.1	1468.9	0.066	1700	2170
May	28.8	80.6	1.6	211.0	1233.2	1301.5	1435	1661	2120	1434.56	0.435	1701.4	2102	1434.9	0.12	1660.9	2120.3
Jun	28.2	80.7	1.6	340.2	1227.5	1309.5	1444	1671	2133	1444.05	-0.054	1685.8	2102.3	1444.2	0.166	1671.4	2134.7
Jul	28	89.3	1.7	203.4	1234.5	1306.8	1441	1668	2129	1441.03	-0.029	1669	2113.6	1440.5	0.548	1667.7	2130
Aug	28.6	78.5	1.5	171.8	1207.6	1350.6	1489	1724	2200	1493.62	-4.619	1745.8	2183.5	1489	0.016	1724.1	2200
Sep	28.2	78.6	1.8	127.6	1225.4	1332.6	1469	1701	2171	1464.2	4.801	1713.1	2140.3	1469	0.046	1701	2171
Oct	28.3	78.4	2.0	188.0	1197.2	1366.6	1507	1744	2226	1502.32	4.681	1748.1	2181.1	1507	0.041	1744	2225.9
Nov	27.2	84.9	1.5	288.4	1169.4	1315.7	1451	1679	2143	1428.56	22.444	1647.1	2135.4	1451.1	0.082	1678.9	2142.9
Dec	27.3	82.6	1.9	257.6	1174.3	1326.9	1463	1693	2161	1462.08	0.919	1656.3	2136.9	1463	0.006	1693	2161

Figure-14 depicted the comparison between the target, ANN and ANFIS for 2012.It can be seen generally that the difference between the target and ANN and ANFIS predictions are close. However, it is noticeable that ANFIS prediction values are closer to the target values compared to ANN prediction values.

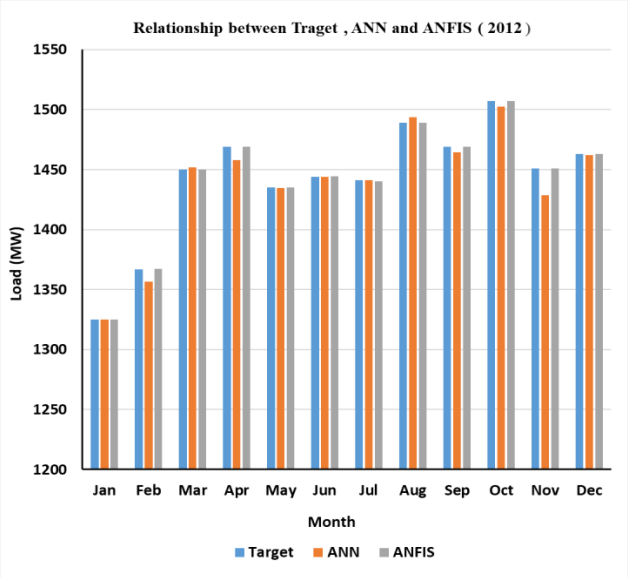

Figure-14.ANN regression plot.

Figure-15 shows the comparison between the target, ANN and ANFIS for 2015. It can be seen that ANFIS prediction values are closer to the target values compared to ANN prediction values.

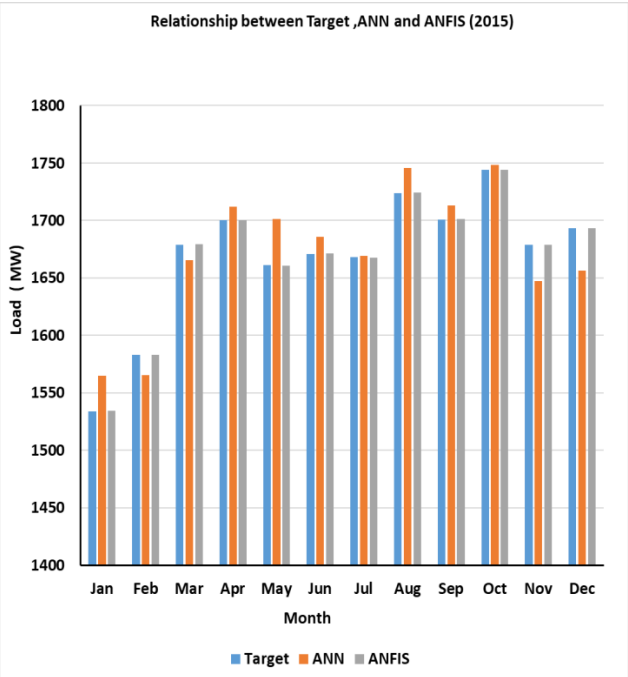

Figure-15.ANN regression plot.

Figure-16 shows the comparison between the target, ANN and ANFIS for 2020. It can be seen that ANFIS prediction values are closer to the target values compared to ANN prediction values. This proves that ANFIS is superior than ANN in term of accuracy prediction values.

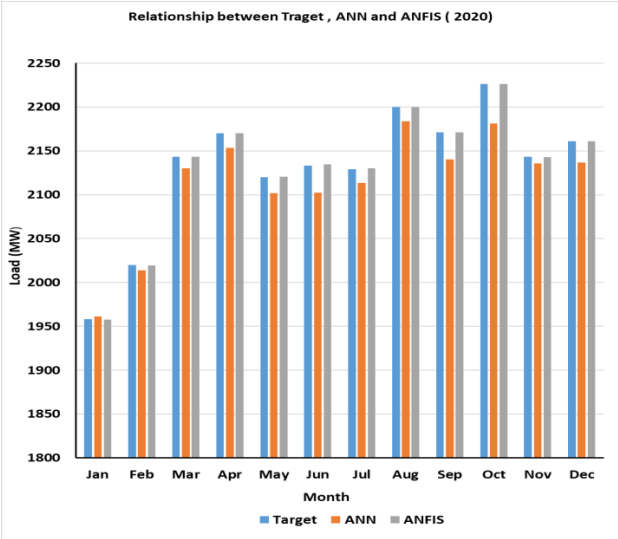

Figure-16.ANN regression plot.

CONCLUSIONS

This work presented the results of load forecasting using the ANN and ANFIS approach. This work has successfully simulated load forecasting with the use of ANN and ANFIS. From the comparison between two models utilized in this work, both of the ANN and ANFIS were able to capture the dynamic behaviour of weather variables for load forecasting. However, ANFIS produced much more accurate results for long-term compared to ANN. Furthermore, ANFIS is capable of producing its number of rules and membership functions. Finally, ANFIS could be much more a valuable tool for long-term load forecasting.

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