Comparative Analysis of Short Term Load Forecastsing of Solar Energy Using Anfis and Nn

KEYWORDS ANFIS, NN, load-forecasting, solar energy, FIS-Structure

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ABSTRACT *In the current scenario the optimum utilisation of renewable energy along with the grid tie up energy is gaining more importance. In the renewable energy solar is the cleanest and abundantly available energy. For cost effective and better utilisation of solar power, at present 10 solar panels has been installed at NIE IT of 0.24KW each. This makes a total capacity of 2.4KW, out of which only 1.6KW energy is utilized. The remaining energy can be made useful. So load forecasting is the important aspect for optimisation in the power. Solar energy is radiant light and heat from the sun harnessed using a range of ever-evolving technologies such as solar heating, photovoltaic's, solar thermal energy, solar architecture and artificial photosynthesis. Load forecasting is a forecast, an estimate, or a prediction of how much electricity will be needed by the residences, companies, and other institutions in the future. The data of complete one year of various weeks, months has been collected. With this reference data the calculation has been made for the prediction of future two years. The prediction results has analysed the comparative analysis has been made for theoretical analysis using neural network and artificial neural fuzzy inference system (ANFIS). With these analyses the best fit technique has been suggested in the proposed work.*

INTRODUCTION

Solar energy is radiant light and heat from the sun harnessed using a range of ever-evolving technologies such as solar heating, photovoltaic's, solar thermal energy, solar architecture and artificial photosynthesis. It is important source of renewable energy and its technologies are broadly characterized as either passive solar and active solar depending on the way they capture and distribute solar energy or convert it into solar power. Active solar techniques include the use of photovoltaic systems, concentrated solar power and solar water heating to harness the energy. Passive solar techniques include orienting a building to the sun, selecting materials with favourable thermal mass or light dispersing properties and designing spaces that naturally circulate air. The development of affordable, inexhaustible and clean solar energy technologies will have huge longer-term benefits. It will increase countries energy security through reliance on an indigenous, inexhaustible and mostly important-independent resources, enhance sustainability, reduce pollution, lower the cost of mitigating global warming, and keep fossil fuel prices lower than otherwise. These advantages are global. Load forecasting is simply what the name implies—it is a forecast, an estimate, or a prediction of how much electricity will be needed by the residences, companies, and other institutions in the future. The need for power varies from season to season, day to day, and even minute to minute. To ensure that an adequate supply of power is available to meet the demand must plan far into the future [1].

Load forecasts can be divided into three categories:
Short-term forecasts which are usually from one hour to one week.

Medium-term forecasts which are usually from a week to a year.

Long-term forecasts which are longer than a year.

Simple Neuron

The fundamental building block for neural networks is the single-input neuron. There are three distinct functional operations that take place in this example neuron. First, the scalar input p is multiplied by the scalar weight w to form the product, again a scalar. Second, the weighted input is added to the scalar bias b to form the net input n. Finally, the net input is passed through the transfer function f, which produces the scalar output a. The names given to these three processes are: the weight function, the net input function and the transfer function. For many types of neural networks, the weight function is a product of a weight times the input, but other weight functions (e.g., the distance between the weight and the input, $|w - p|$) are sometimes used. The most common net input function is the summation of the weighted inputs with the bias, but other operations, such as multiplication, can be used [2].

Multiple Layers of Neurons:

A network can have several layers. Each layer has a weight matrix W, a bias vector b, and an output vector a. The network R1 inputs, S1 neurons in the first layer, S2 neurons in the second layer, etc. It is common for different layers to have different numbers of neurons. A constant input 1 is fed to the bias for each neuron. Note that the outputs of each intermediate layer are the inputs to the following layer. Thus layer 2 can be analyzed as a one-layer network with S1 inputs, S2 neurons, and an S2 × S1 weight matrix W2. The input to layer 2 is a1; the output is a2. Now that all the vectors and matrices of layer 2 have been identified, it can be treated as a single-layer network on its own. This approach can be taken with any layer of the network. The layers of a multilayer network play different roles. A layer that produces the network output is called an output

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layer. All other layers are called hidden layers. The three-layer network shown earlier has one output layer (layer 3) and two hidden layers (layer 1 and layer 2). Some authors refer to the inputs as a fourth layer. This toolbox does not use that designation. The architecture of a multilayer network with a single input vector can be specified with the notation R − S1 − S2 −...− SM, where the number of elements of the input vector and the number of neurons in each layer are specified. The number of neurons in a layer is given by its size property. In this case, the layer has 10 neurons, which is the default size for the feed forward net command. The net input function is net sum (summation) and the transfer function is the Tausig [3].

ANFIS- Artificial Network Fuzzy Interference System

ANFIS: The acronym ANFIS derives its name from *adaptive neuro-fuzzy inference system*. Using a given input/output data set, the toolbox function anfis constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone or in combination with a least squares type of method. This adjustment allows your fuzzy systems to learn from the data they are modelling [4].

Training Adaptive Neuro-Fuzzy Inference Systems Using the ANFIS Editor GUI

The ANFIS Editor GUI window shown in the following figure includes four distinct areas to support a typical workflow. The GUI lets you perform the following tasks:

Loading, Plotting, and Clearing the Data
Generating or Loading the Initial FIS Structure
Training the FIS
Validating the Trained FIS [5].

METHODOLOGY

Analysis of data using neural network

The data of complete one year of various weeks, months has been collected. The data has been trained using NN tool for all the months of the year for power consumption and the target data has been achieved. The data collected will be entered in a suitable tabular column as compatible with the software used; this is as shown in Table 1 below. Similarly input data has been trained and target data has been achieved.

Table 1 Input and Target Data of April-2014

Month	Date	Time in hours	Power Consumed in KWH	Target Data
April	04-04-2014	12:00pm	49	61.25
	06-04-2014	12:00pm	52	65
	08-04-2014	12:00pm	37	46.25
	10-04-2014	12:00pm	46	57.5
	12-04-2014	12:00pm	55	68.75
	14-04-2014	12:00pm	51	63.75
	16-04-2014	12:00pm	47	58.75
	19-04-2014	12:00pm	38	47.5
	21-04-2014	12:00pm	46	57.5
	23-04-2014	12:00pm	49	61.25
	25-04-2014	12:00pm	51	63.75
	28-04-2014	12:00pm	45	56.25
	30-04-2014	12:00pm	43	53.75

For the collected input data the target value required is calculated as shown below and entered to the tabular column.

Prediction for 1 year:

The current utilization of solar energy can be expanded for coming year by including a classroom. One classroom consists of:

1Fluroscent lamp=36W
1Fan=48W
9fluroscent lamp=324W
6Fans=288W
Total power consumed for the classroom=612W
Total capacity of solar panel=2.4KW
Increase in power consumption = (0.612/2.4)*100 =25%
Similarly prediction for second year is done by adding another classroom which increases a power consumption of 25% on the consumed power [6].

RESULT ANALYSIS

Analysis using Neural Network

The collected data of power consumption in KWh for the year 2013-14 has been trained using nctool of neural network and the obtained result is analysed graphically with performance graph for 8 epochs, regression graph, output graph & error graph for the month of April as shown in fig 1,2,3,4 respectively.

April-2014

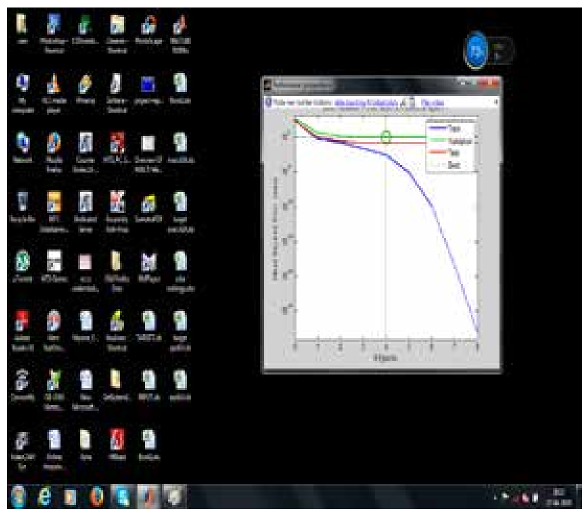

Fig 1. Performance graph of April

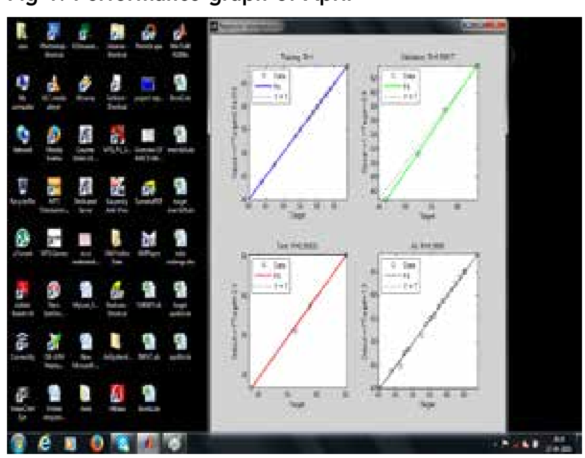

Fig 2. Regression graph of April

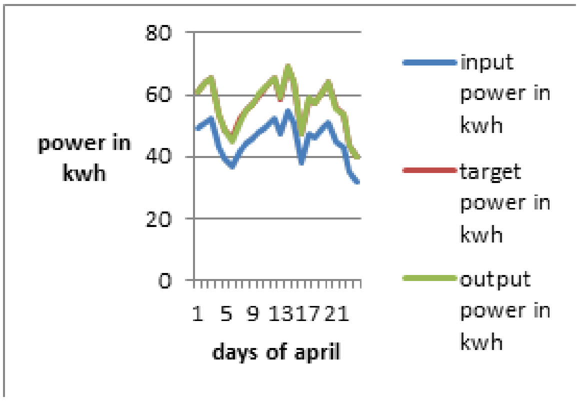

Fig 3. Output graph of April

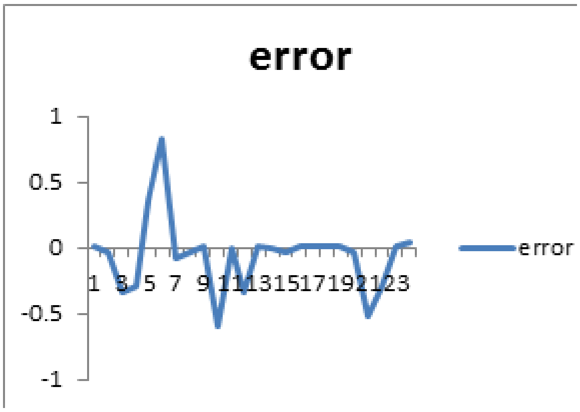

Fig 4. Error graph of April

Analysis using ANFIS

The data of complete one year of various weeks, months has been collected. The data has been trained using ANFIS tool for all the months of the year for power consumption and the target data has been achieved. The data collected will be entered in a suitable tabular column as compatible with the software used; this is as shown in Table 2 & 3 below. Similarly input data has been trained and target data has been achieved.

The collected data of power consumption in KWh for the year 2013-14 has been trained using ANFIS and the obtained result is analysed graphically with FIS-rule & error graph for the month of April as shown in fig 5, 6 respectively.

April-2014

Table2. Input, Target and Output of April 2014

input power in kwh		checking power in kwh		output power in kwh	
49	47	61.25	58.75	44.1	44.6
51	55	63.75	68.75	43.8	43.4
52	51	65	63.75	43.7	43.8
43	38	53.75	47.5	45.9	46.4
39	47	48.75	58.75	46.3	44.6
37	46	46.25	57.5	46.4	45
42	49	52.5	61.25	46.1	44.1
44	51	55	63.75	45.7	43.8
46	45	57.5	56.25	45	45.4
48	43	60	53.75	44.3	45.9
50	35	62.5	43.75	43.9	46.3
52	32	65	40	43.7	46.4

Table3. Input, Target and Output of April 2015

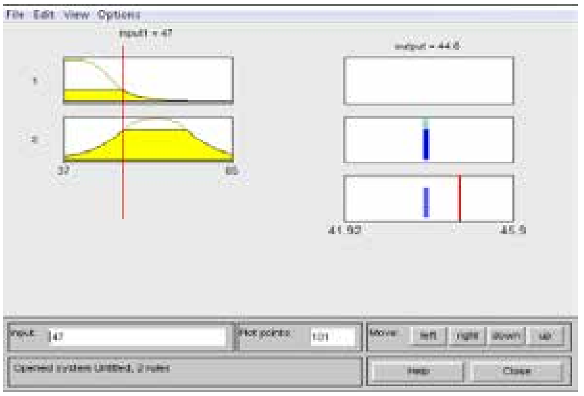

Fig5. FIS rule of April

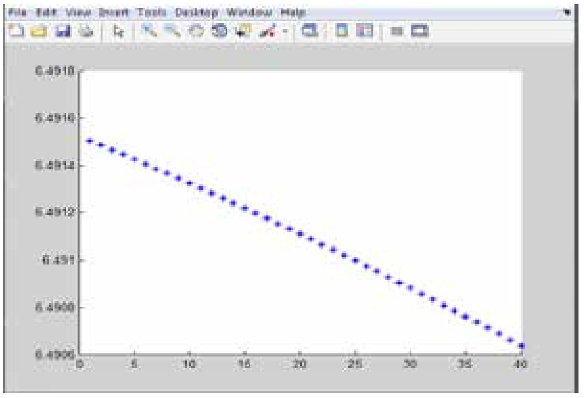

Fig6. Error graph of April

CONCLUSIONS

The learning duration of ANFIS is very short than neural network. It implies that ANFIS reaches to the target faster than neural network. When a more sophisticated system with a huge data is imagined, the use of ANFIS instead of neural network would be more useful to overcome faster the complexity of the problem.

In training of the data ANFIS gives results with the minimum total error compared to the other methods. This shows the best learning method is ANFIS among other methods. However, when the trained parameters were applied to checking data, total error of neural network is smaller than that of ANFIS.

The obtained results of average I/O and error of neural network and ANFIS for the year of 2014-15 and 2015-16 has been tabulated in table 6, 7 & 4, 5 respectively.

Table4. Average I/O & Error Of Neural Network:

Data's Of 2015-16		Prediction O/P Data's Of 2015-16		
Month	Avg. Input In KWh	Avg. Target In KWh	Avg. Output In KWh	Avg. Of Error
Mar-15	77.852	97.316	97.69	-0.38
April-15	56.745	70.932	71.217	-0.285
May-15	101.363	126.704	127.103	-0.4
June-15	146.48	183.1	182.88	0.222
Aug-15	243.189	303.98	304.815	-0.828
Sept-15	276.898	346.12	345.993	0.126
Oct-15	311.67	389.58	389.37	0.0103
Nov-15	324.67	405.841	406.265	-0.424
Dec-15	350.49	438.11	438.13	-0.034
Feb-16	727.292	909.74	908.85	0.88

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Table5. Average I/O & Error Of Anfis:

Data's Of 2015-16		Prediction O/P Data's Of 2015-16	
Month	Avg. Input In KWh	Avg. Output In KWh	Avg. Of Error
March-15	51.81	53.580	0.283
April-15	44.941	45.075	0.928
May-15	90.437	95.479	1.561
June-15	120.118	127.86	3.515
Aug-15	187.472	192.432	1.905
Sept-15	223.105	234.7296	3.8
Oct-15	254.357	264.405	3.8
Nov-15	261.934	275.2932	0.2801
Dec-15	279.67	286.3915	0.73
Feb-16	574.6674	653.972	5.44

Table6. Average I/O & Error Of Neural Network:

Data's Of 2014-15		Prediction O/P Data's Of 2014-15		
Month	Average Input In KWh	Average Target In KWh	Average Output In KWh	Average Of Error
Mar-14	45.5	56.875	56.7456	-0.055
Apr-14	43.333	54.79	54.7916	-5.3*E-15
May-14	80.916	101.1458	101.3637	-0.2178
June-14	118.375	147.9688	146.4826	0.03523
Aug-14	194.47	243.088	243.189	-0.223
Sept-14	222.62	278.276	276.896	-0.02422
Oct-14	249.362	311.703	311.67	0.0101
Nov-14	259.6792	324.599	324.6733	-0.0743
Dec-14	280.2708	350.33	350.491	-0.1528
Feb-15	582.241	727.8	727.792	-0.570

Table7. Average I/O & Error Of Anfis:

Data's Of 2014-15		Prediction O/P Data's Of 2014-15	
Month	Average Input In KWh	Average Output In KWh	Average Of Error
Mar-14	45.5	51.81	3.6595
April-14	43.333	44.941	6.49
May-14	80.916	90.437	5.335
June-14	118.375	120.118	8.045
Aug-14	194.47	187.472	1.4774
Sept-14	222.62	223.105	2.49
Oct-14	249.362	254.357	1.40625
Nov-14	259.6792	261.934	2.0625
Dec-14	280.2708	279.67	0.8095
Feb-15	582.241	574.6674	5.16

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