Load forecasting for HESCOM using Linear Regression and Artificial Neural Network

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Abstract- *This paper presents a study of Mid-term load forecasting using Linear Regression(LR) and Artificial Neural Network (ANN) and applied it to the Dharwad and Hubli location of HESCOM (Hubli electric supply company). To study the load growth rate of both locations by considering the past 3 years load and weather data. Using linear regression analysis target values for next 3 years are determined. Considering the target values, past load data and weather data the load forecasting will be carried out in MALAB using Neural Network (NN) tool This gives load forecasts for next 3 years.*

Keywords- LR, ANN, Back propagation, Load forecasting.

I. INTRODUCTION

Load forecasting is the technique used by the power companies to predict what will be the future electric load to meet the demand and supply. At present, there's no substantial energy storage within the electrical transmission and distribution system. For ideal facility operation, electrical era should pursue electrical load request. The generation, transmission, and dispersion utilities require a few implies that to figure the electrical load all together that they will make utilization of their electrical transportation with effectiveness, emphatically and monetarily.

Purchasing and generating power, switching of loads, and creating framework; for every one of these factors load forecasting will help in taking imperative choices on electric utility. Load forecasts can be alienated into three sections: short-term forecast which gives a forecasted result from one hour to week. The Second one is midterm load forecast, these are usually from one weak to year. Lastly long term load forecast is more than a year.

The loads are for the most part influenced by climatic conditions, societal influences, monetary circumstances, different non- linear factors and some other uneven performance, which makes precise forecasting of loads a challenging task. From most recent couple of decades, efforts have been made to advance the exactness of load forecast, and quite a few state-of-the-art techniques have been developed, going from the early statistical models in light of complex artificial intelligence such as ANN.

There are four fundamental components that impact electrical load:

1. Economic
2. Time
3. Weather

1. Economic factors:

Economic factors consist of construction of new labs, buildings, and experiments which affects load on the power system; all these include investment of financial components for utility infrastructure. Utility projects, for example, ask for charges and demand organization arrange to influence the buyers' energy utilize designs amid crest periods.

2. Time factors

The aim of time viz. Occasional impacts, week by week – day by day cycle and get-away assume an imperative part in affecting load patterns. Occasional impacts demonstrate utilities topping (summer/winter) and furthermore bring out auxiliary alterations in power consumption design. Amid occasions, the load diminishes considerably.

3. Weather factors:

Temperature and precipitation are the most critical variables considered for load forecasting. Their impact on the system load varies not only within summer and winter but also between peak and valley of the same day. System load in hot and moist areas are affected by humidity. Different factors that have effect on load behaviour are wind speed, cloud cover, onset of darkness, light force and so on.

II. TARGET EVALUATION USING LINEAR REGRESSION ANALYSIS

LR analysis is a numerical process for estimating the relation between two or more variables and it is primarily used for prediction and casual forecasting. Linear regression is an approach for modelling the relationship between dependent variable and independent variable where dependent variable is taken as load and independent variable as months in time. Independent variable i.e. months are considered for the following years 2014, 2015, 2016 and 2017. The dependent variables considered are history load data. Upon considering the variables load forecasting has been carried out for next three years by using least square method.

A. Least square estimation:

Least square estimation method is a standard approach in line regression analysis. It derives that the general arrangement confines the summation of the squares of the residuals made in the delayed consequences of and every condition. Information fitting is the most critical utilization of slightest square technique. The best fit at all squares sense limits the total of squared residuals.

In linear regression analysis the relationship between variables is assumed to be a straight line. The equation of a straight is generally given by,

$y = m\,x + c$... (1)

Similarly in linear regression analysis, it is denoted by,

$Y = a\,x + b$... (2)

Where Y – Dependent variable (load).
a – Y intercept.
b – Slope.
x – Independent variable (month -year).

From Equation (1) and (2)
a = c (intercepts of y)
b = m (slope)

The least square estimation can be solved by taking into consideration the plot of history load data points with respect to month-year load data. Here the points are plotted such that the sum of the squares of the vertical distances between each data point and its equivalent data point on the line is minimized. Between data points a line is drawn which is the regression line. Corresponding to line on the x axis it has corresponding point on the regression line in relation to the load data. If the regression is extended then we can get target load values with respect to the month-year.

Another method can be adopted to find out the target values by formulae method. From formula method basically a and b values have to be find out.

$$a = \bar{y} - b\,\bar{x} \quad \text{……(3)}$$

$$\mathbf{b} = \frac{\sum xy - n\bar{x}\bar{y}}{\sum x^2 - n\bar{x}^2} \quad \text{…..(4)}$$

Where, a = y intercepts.
b = slope of the line.
$\bar{y}$ = Arithmetic mean of all y's.
$\bar{x}$ = Arithmetic mean of all x's.
n = Number of data points.

By using above equations target load data for next 3 years of Dharwad and Hubli locations are obtained.

B. Standard error of the estimate:

The standard error of the gauge is a measure of the exactness of predictions and furthermore characterized as measure of the precision of expectations made with a regression line. It is necessary to find out how the load data will fit the regression line. This estimation can be found out by figuring the standard error of the estimate spoke to as $\mathbf{S_{yx.}}$
The standard error of the estimate is same as the standard deviation (σ). Standard deviation is the measure of how broadly information focuses are scattered around the math mean. The standard error estimate reflects how widely the errors are dispersed around the regression line. The standard deviation is given by,

$$\boldsymbol{\sigma} = \sqrt{\frac{\sum_1^n (y_i - y')^2}{n-2}} \quad \text{…….. (5)}$$

Or

$$s_{y_x} = \sqrt{\frac{\sum y^2 - a\sum y - b\sum xy}{n-2}} \quad \text{....... (6)}$$

The Standard error can be calculated for both Dharwad and Hubli location using above equation.

III. ARTIFICIAL NUERAL NETWORK

An Artificial Neural Network can be defined as a mathematical implement that assumes the behaviour of thoughts like a human mind. They are portrayed as a multivariate, nonlinear, and nonparametric way which are fine in modelling confounded nonlinear systems. ANNs have best concert in data classification and function fitting. The basic processing components of ANNs are Neurons. The neurons are customized to act same as the neurons in the cerebrum by tolerating inputs, handling the sources of info, and producing an output.

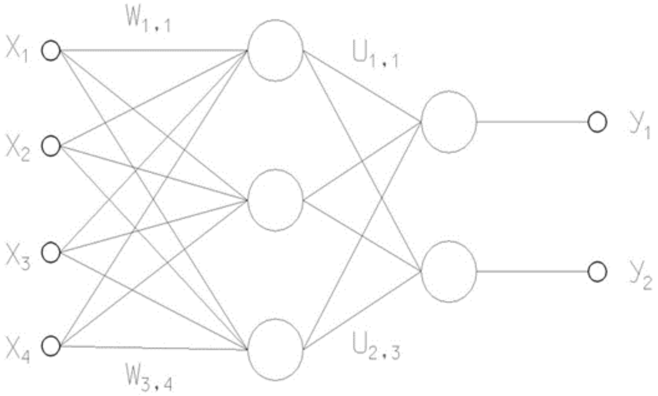

Figure 1. Two-layer, feed-forward, neural network.

Fig.1. Shows an ANN that it has two layers, an output layer and a buried layer (to be found between the output nodes and input nodes). The neurons can share inputs; so far they are not related with each other. The outputs of one layer are connected as the inputs to the next layer if the network is a feed-forward network. Right away, The single hidden layer is enough to rough any continuous function. Multiple outputs neural network depends on the network topology.

Fig.1. Can be represent mathematically as follows if the buried layer neurons activation functions are logistic, and the output layer neurons activation functions are linear.

$$y = f(\sum w_i\ x_i) \text{.......... (7)}$$

$$y = \frac{1}{1+e^{-\sum w_i x_i}} \text{......... (8)}$$

$$RMSE = \sqrt{\frac{1}{N}} * \sum_{t=1}^{N}(Y_t - yt)^2 \text{…..... (9)}$$

Where y is output and x_i inputs to the system. The weights w_i and biases of the ANN are resolute through a training algorithm that minimizes a loss function. The back propagation learning algorithm is used where the difference between an output and a estimated value shapes an error signal. The weights and biases of the ANN are changed in accordance to limit the errors between its output and target value.

A. Back Propagation Algorithm

The algorithm is derived by methods of gradient descent for non linear activation function is for the most known as back propagation algorithm. The error that is processed as back propagated and in light of that the weights are update.

The choice of back propagation neural network is,

- It under pins fast order.
- It can be used for both linear and non linear arrangement.
- It supports multi class classification.

The algorithm can be decomposed in the following five steps:

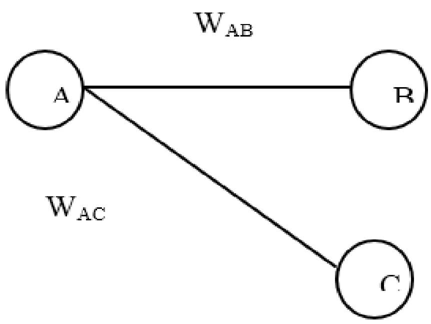

Figure 2. Two layered network.

Step 1. The network is started by setting up every one of the weights to be small numbers set between -1 to 1.

Step 2. Next work out the error for neuron B.
Error = OutputB(1-OutputB) (TargetB - OutputB)

Step 3. Change the weight. Let WAB+ be the new weight and WAB initial Weight WAB+ = WAB + (ErrorB * OutputB).

Step 4. Compute the errors for the shrouded layer neurons. Taking errors from the yield neurons and running. They back propagated trough the weights to get the concealed layer errors. If neuron A is connected to B And C to produce an error for A.

ErrorA = output (1-outputA)(ErrorB WAB + ErrorC WAC)

Step 5. Having acquired the error for the hidden layer neurons now continues as in stage 3 to change the hidden Layer weights. End of Back propagation Algorithm.

B. Load forecasting using ANN.

MATLAB by Mathworks is the PC programming used to make and implement the Midterm load forecast for

Hubli and Dharwad locations. The Neural Network Toolbox in MATLAB provides worked in capacities and applications to help in modelling nonlinear systems. It supports ANN training, validation, testing, and simulation with graphical user interface (GUI) applications.

The fig.3: shows the load forecasting flow chart which is carried out in MATLAB using ANN tool.

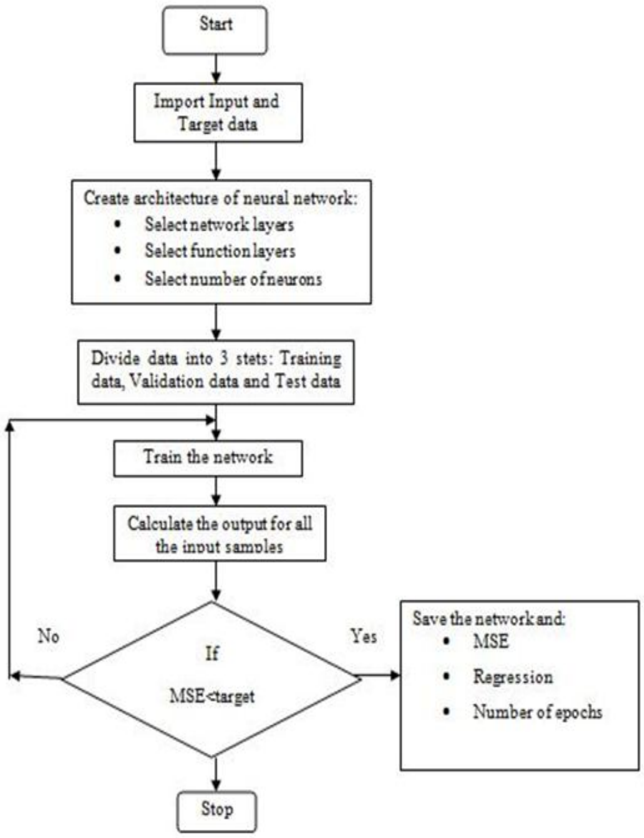

Figure 3. Flow chart for load forecasting in MATLAB.

IV. RESULTS AND DISCUSSION

A. Linear regression results

The load forecast for Dharwad and Hubli locations is carried out using past 3 years history load data and whether data. The scatter plot of history load for Dharwad and Hubli locations are given in figure 4 and 5 respectively.

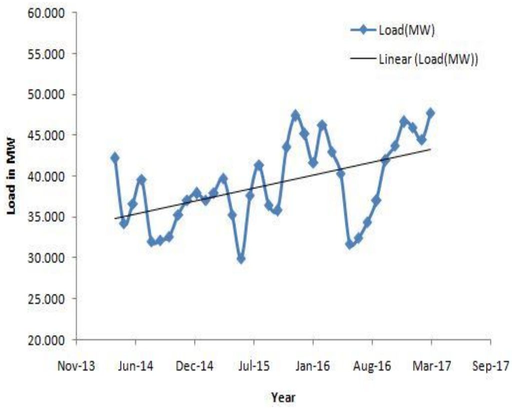

Figure 14. Scatter plot of History load for Dharwad location.

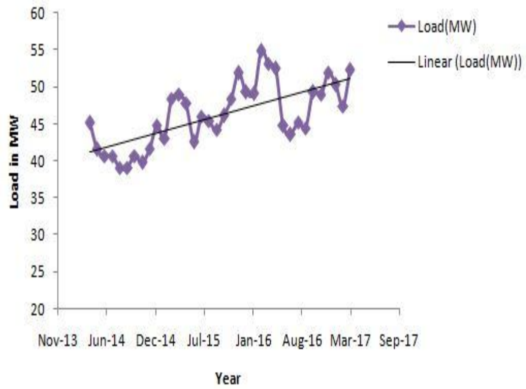

Figure 15. Scatter plot of history load for Hubli location.

The target load data for next 3 years is calculated by using linear regression equations which are given in II. The results of target load values for Dharwad and Hubli locations are given in table 1 and 2 respectively.

Table 1. 3years target load data for Dharwad location.

History data			target data		
SL no	Month - year(x)	Load in MW(y)	SL no	Month - year(x)	Load in MW(y)
1	Apr-14	42.196	1	Apr-17	42.506
2	May-14	34.225	2	May-17	42.718
3	Jun-14	36.663	3	Jun-17	27.842
4	Jul-14	39.608	4	Jul-17	29.465
5	Aug-14	32.004	5	Aug-17	38.359
6	Sep-14	32.226	6	Sep-17	40
7	Oct-14	32.623	7	Oct-17	46.037
8	Nov-14	35.247	8	Nov-17	49.296
9	Dec-14	37.071	9	Dec-17	53.283
10	Jan-15	37.872	10	Jan-18	57.977
11	Feb-15	37.111	11	Feb-18	52.081
12	Mar-15	38.007	12	Mar-18	53.711
13	Apr-15	39.756	13	Apr-18	42.924
14	May-15	35.291	14	May-18	45.77
15	Jun-15	29.971	15	Jun-18	25.371
16	Jul-15	37.673	16	Jul-18	25.904
17	Aug-15	41.365	17	Aug-18	40.785
18	Sep-15	36.463	18	Sep-18	42.386
19	Oct-15	35.825	19	Oct-18	50.667
20	Nov-15	43.518	20	Nov-18	53.53
21	Dec-15	47.382	21	Dec-18	58.074
22	Jan-16	45.178	22	Jan-19	64.603
23	Feb-16	41.629	23	Feb-19	55.753
24	Mar-16	46.237	24	Mar-19	58.572
25	Apr-16	43.048	25	Apr-19	43.342
26	May-16	40.327	26	May-19	48.822
27	Jun-16	31.719	27	Jun-19	22.9
28	Jul-16	32.482	28	Jul-19	22.343
29	Aug-16	34.43	29	Aug-19	39.572
30	Sep-16	37	30	Sep-19	44.77
31	Oct-16	41.883	31	Oct-19	55.297
32	Nov-16	43.716	32	Nov-19	57.765
33	Dec-16	46.651	33	Dec-19	62.865
34	Jan-17	45.985	34	Jan-20	71.229
35	Feb-17	44.455	35	Feb-20	59.425
36	Mar-17	47.725	36	Mar-20	63.433

Table 2. 3 years target load data for Hubli location.

History data			Target data		
SL no	Month and year(x)	Load in MW(y)	SL no	Month and year(x)	Load in MW(y)
1	Apr-14	45.11	1	Apr-17	57.139
2	May-14	41.572	2	May-17	58.141
3	Jun-14	40.71	3	Jun-17	46.66
4	Jul-14	40.619	4	Jul-17	45.26
5	Aug-14	39.126	5	Aug-17	49.385
6	Sep-14	39.106	6	Sep-17	47.9
7	Oct-14	40.659	7	Oct-17	53.96
8	Nov-14	39.759	8	Nov-17	55
9	Dec-14	41.689	9	Dec-17	58.77
10	Jan-15	44.757	10	Jan-18	53.6
11	Feb-15	42.971	11	Feb-18	50.985
12	Mar-15	48.326	12	Mar-18	56.006
13	Apr-15	48.956	13	Apr-18	61.166
14	May-15	47.772	14	May-18	63.579
15	Jun-15	42.512	15	Jun-18	48.67
16	Jul-15	45.957	16	Jul-18	46.2085
17	Aug-15	45.421	17	Aug-18	52.446
18	Sep-15	44.187	18	Sep-18	50.55
19	Oct-15	46.138	19	Oct-18	58.265
20	Nov-15	48.354	20	Nov-18	59.643
21	Dec-15	51.886	21	Dec-18	63.912
22	Jan-16	49.269	22	Jan-19	56.35
23	Feb-16	49.107	23	Feb-19	53.226
24	Mar-16	54.857	24	Mar-19	58.104
25	Apr-16	53.17	25	Apr-19	65.195
26	May-16	52.45	26	May-19	69.017
27	Jun-16	44.716	27	Jun-19	50.674
28	Jul-16	43.514	28	Jul-19	47.157
29	Aug-16	45.243	29	Aug-19	55.51
30	Sep-16	44.477	30	Sep-19	53.2
31	Oct-16	49.252	31	Oct-19	62.57
32	Nov-16	49.028	32	Nov-19	64.286
33	Dec-16	51.904	33	Dec-19	69.054
34	Jan-17	50.265	34	Jan-20	59.1
35	Feb-17	47.429	35	Feb-20	55.467
36	Mar-17	52.245	36	Mar-20	60.202

The below figure.6 and 7 shows the scatter plot for history and target values for Dharwad and Hubli locations respectively.

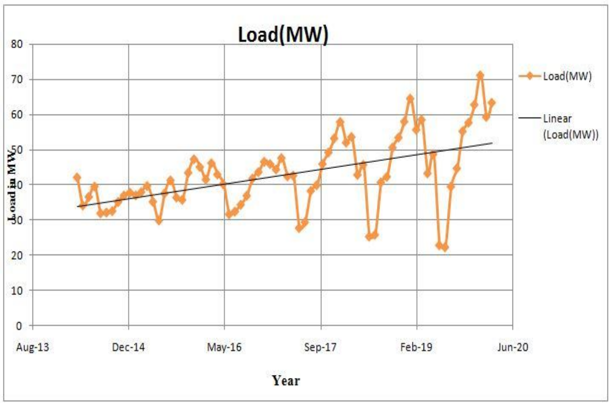

Figure 6. Scatter plot of History and Target values for Dharwad location.

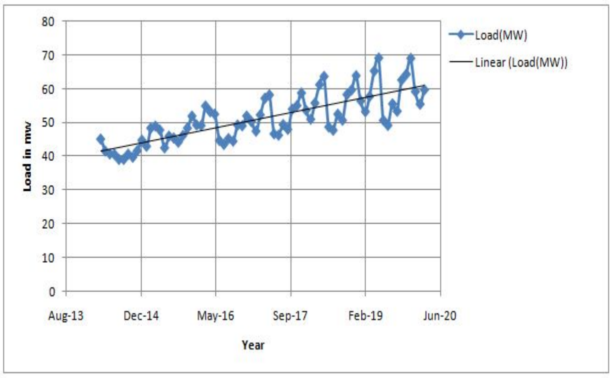

Figure 7. Scatter plot of History and Target values for Hubli location.

The standard error is estimated by using the equation 5 or 6 which shows the accuracy predictions made with the regression line. The standard error for both dharwad and hubli locations is given in table.3 and 4 respectively.

Table 3. Standard error calculation of Dharwad location.

Month	Standard error(Syx)
Jan	2.26
Feb	3.326
Mar	1.382
Apr	1.125
May	0.8147
Jun	1.58
Jul	0.681
Aug	3.326
Sep	15.133
Oct	0.583
Nov	1.614
Dec	2.255

Table 4. Standard error calculation of Hubli location.

Month	Standard error(Syx)
Jan	0.564
Feb	1.53
Mar	0.955
Apr	2.77
May	0.27
Jun	0.343
Jul	1.74
Aug	1.33
Sep	2.902
Oct	0.4087
Nov	1.6042
Dec	2.1422

A. ANN results

The results of loads forecasting completed in ANN tools are given in below figures. In ANN tool there is 3 layers input, hidden and yield layer. Inputs layer takes the 3 years history load data and predicted target load data for next 3 years. The hidden layer comprises of neurons and these neurons must be trained by utilizing the few samples of the input data, validation and testing is completed by utilizing rest of the input data. The yield layer gives the expecting load. The hidden layer neurons can be differed to get exact outcomes. The results for 10, 15 and 20 neurons are given in figure 8 to 13 for both Dharwad and Hubli locations.

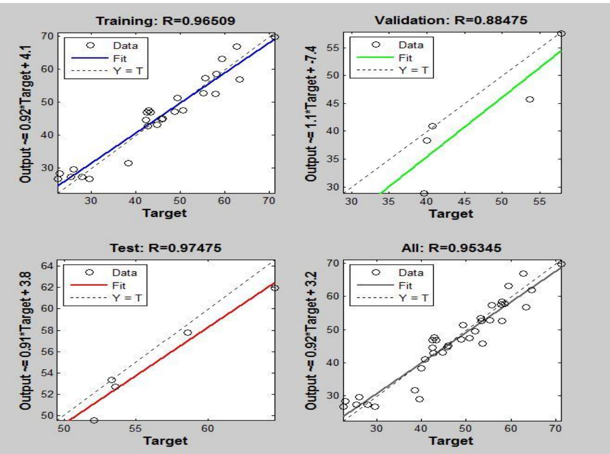

Figure 8. Regression plot for 10 neurons for Dharwad.

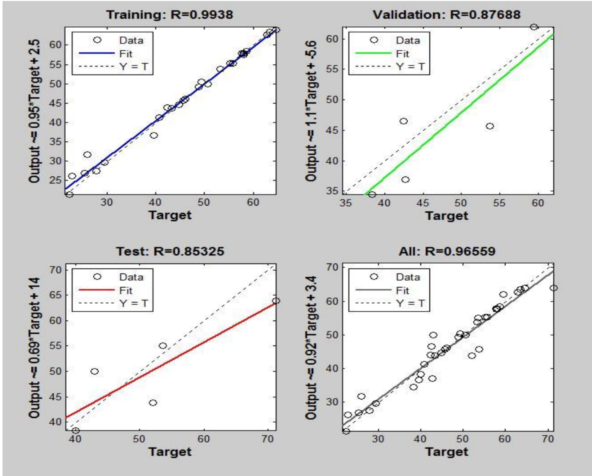

Figure 9. Regression plot for 15 neurons for Dharwad.

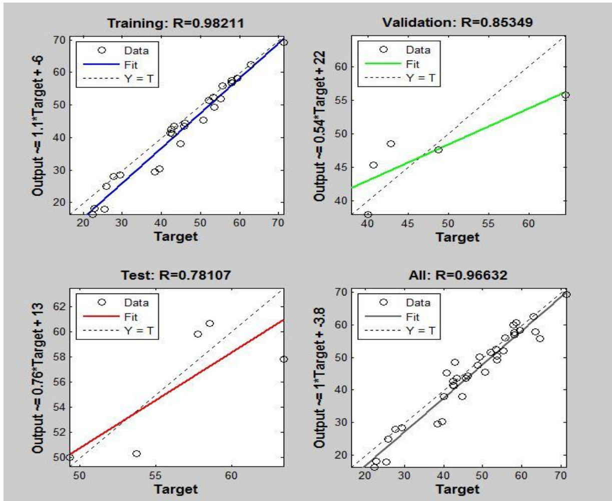

Figure 10. Regression plot for 20 neurons for Dharwad

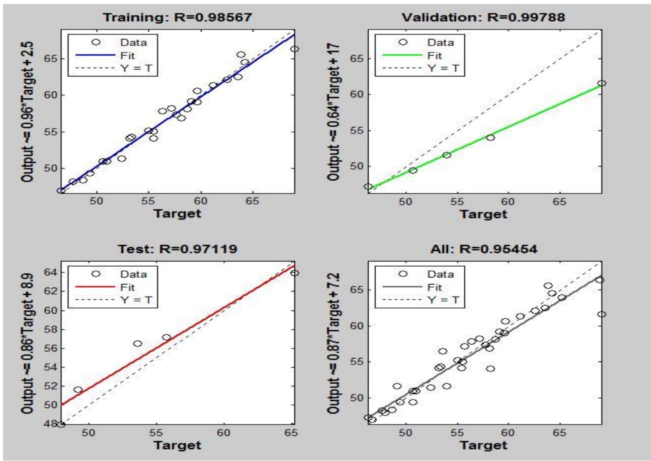

Figure 11. Regression plot for 10 neurons for Hubli.

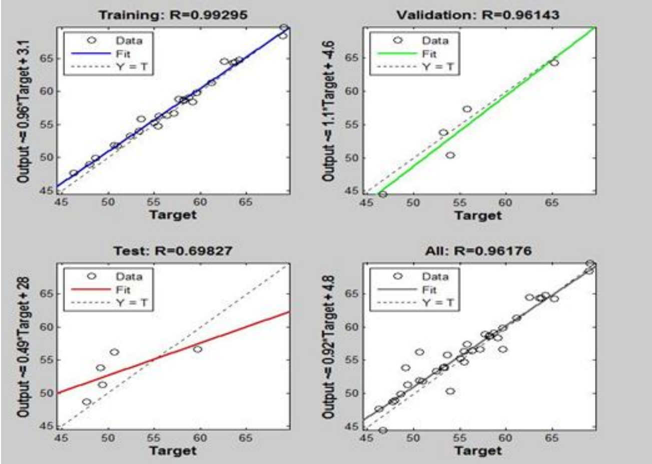

Figure 12. Regression plot for 15 neurons for Hubli.

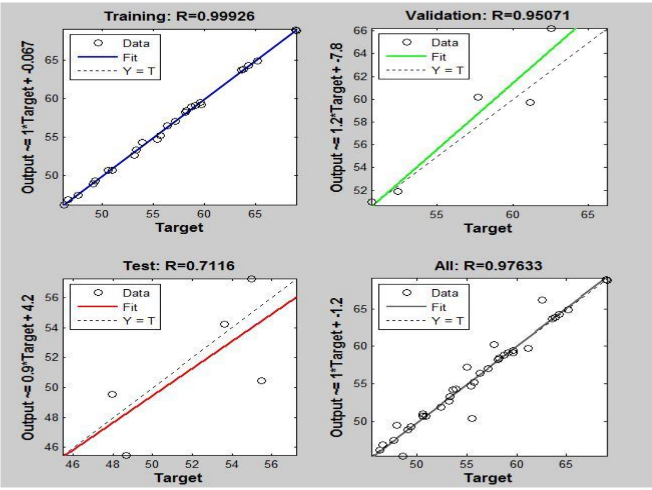

Figure 13. Regression plot for 20 neurons for Hubli.

The results of load forecasting with 10, 15 and 20 neurons for Dharwad and Hubli locations are done for next 3 years utilizing the previous 3 years, temperature, humidity, wind speed. Load data are given in table 5 and 6.

Table 5. Forecasted load data for Dharwad location.

Month-Year	Targets(MW)	With 10 neurons		with 15 neurons		With 20 neurons	
		output(MW)	errors	output(MW)	errors	output(MW)	errors
Apr-17	42.51	46.862	-4.352	46.478	-3.968	47.011	-4.501
May-17	42.72	42.765	-0.045	36.967	5.753	42.720	0.000
Jun-17	27.84	27.300	0.540	27.400	0.440	44.965	-17.125
Jul-17	29.47	26.600	2.870	29.576	-0.106	29.470	0.000
Aug-17	38.36	31.523	6.837	34.469	3.891	38.360	0.000
Sep-17	40.00	38.337	1.663	38.331	1.669	39.219	0.781
Oct-17	46.04	45.085	0.955	46.114	-0.074	46.040	0.000
Nov-17	49.30	51.295	-1.995	50.435	-1.135	49.300	0.000
Dec-17	53.28	53.353	-0.073	53.803	-0.523	53.280	0.000
Jan-18	57.98	52.543	5.437	57.554	0.426	52.274	5.706
Feb-18	52.08	49.537	2.543	43.799	8.281	52.080	0.000
Mar-18	53.71	45.754	7.956	45.738	7.972	52.040	1.670
Apr-18	42.92	47.608	-4.688	50.035	-7.115	42.920	0.000
May-18	45.77	44.737	1.033	45.766	0.004	45.770	0.000
Jun-18	25.37	27.265	-1.895	26.811	-1.441	25.370	0.000
Jul-18	25.90	29.578	-3.678	31.721	-5.821	25.900	0.000
Aug-18	40.79	40.949	-0.159	41.340	-0.550	40.790	0.000
Sep-18	42.39	44.511	-2.121	43.908	-1.518	42.390	0.000
Oct-18	50.67	47.495	3.175	49.931	0.739	42.537	8.133
Nov-18	53.53	52.665	0.865	55.114	-1.584	53.529	0.001
Dec-18	58.07	58.513	-0.443	57.782	0.288	58.068	0.002
Jan-19	64.60	61.969	2.631	63.942	0.658	64.600	0.000
Feb-19	55.75	57.376	-1.626	55.269	0.481	55.750	0.000
Mar-19	58.57	57.762	0.808	58.436	0.134	56.897	1.673
Apr-19	43.34	46.848	-3.508	43.759	-0.419	43.340	0.000
May-19	48.82	47.008	1.812	49.286	-0.466	48.820	0.000
Jun-19	22.90	28.351	-5.451	26.178	-3.278	25.189	-2.289
Jul-19	22.34	26.593	-4.253	21.445	0.895	22.340	0.000
Aug-19	39.57	28.862	10.708	36.644	2.926	39.570	0.000
Sep-19	44.77	43.142	1.628	44.554	0.216	32.725	12.045
Oct-19	55.30	52.792	2.508	55.219	0.081	55.299	0.001
Nov-19	57.77	57.533	0.237	57.809	-0.039	64.743	-6.973
Dec-19	62.87	66.968	-4.098	62.575	0.295	62.869	0.001
Jan-20	71.23	69.846	1.384	63.863	7.367	71.228	0.002
Feb-20	59.43	63.159	-3.729	61.954	-2.524	59.430	0.000
Mar-20	63.43	56.854	6.576	63.437	-0.007	63.430	0.000

Table 6. Forecasted load data for Hubli location.

Month-Year	Targets(MW)	With 10 neurons		with 15 neurons		With 20 neurons	
		output(MW)	errors	output(MW)	errors	output(MW)	errors
Apr-17	57.139	60.948	-3.809	56.595	0.544	56.861	0.278
May-17	58.143	62.404	-4.261	58.014	0.129	62.212	-4.069
Jun-17	46.652	51.599	-4.947	47.459	-0.807	44.661	1.991
Jul-17	46.258	45.490	0.768	45.526	0.732	44.736	1.522
Aug-17	49.380	46.247	3.133	48.323	1.057	45.449	3.931
Sep-17	47.961	47.129	0.832	47.189	0.772	47.632	0.329
Oct-17	53.943	53.477	0.466	53.061	0.882	53.986	-0.043
Nov-17	54.983	54.433	0.550	53.327	1.656	55.362	-0.379
Dec-17	58.708	57.556	1.152	60.094	-1.386	57.900	0.808
Jan-18	53.605	53.143	0.462	56.744	-3.139	52.691	0.914
Feb-18	50.960	51.879	-0.919	51.072	-0.112	53.784	-2.824
Mar-18	55.728	57.278	-1.550	56.608	-0.880	55.212	0.516
Apr-18	61.169	63.195	-2.026	60.491	0.678	59.872	1.297
May-18	63.582	69.665	-6.083	64.138	-0.556	62.778	0.804
Jun-18	48.655	47.340	1.315	43.258	5.397	45.801	2.854
Jul-18	47.706	50.769	-3.063	46.363	1.343	47.015	0.691
Aug-18	52.439	50.382	2.057	54.711	-2.272	51.744	0.695
Sep-18	50.646	50.074	0.572	49.942	0.704	50.194	0.452
Oct-18	58.239	59.472	-1.233	59.883	-1.644	57.186	1.053
Nov-18	59.617	56.406	3.211	59.626	-0.009	58.365	1.252
Dec-18	63.816	61.683	2.133	65.685	-1.869	65.304	-1.488
Jan-19	56.359	59.667	-3.308	58.295	-1.936	57.210	-0.851
Feb-19	53.189	55.524	-2.335	53.630	-0.441	52.706	0.483
Mar-19	57.688	61.582	-3.894	58.262	-0.574	56.222	1.466
Apr-19	65.199	71.766	-6.566	60.975	4.225	63.303	1.897
May-19	69.021	75.082	-6.061	58.723	10.298	63.230	5.791
Jun-19	50.658	47.625	3.033	49.439	1.219	50.813	-0.155
Jul-19	49.153	44.471	4.682	48.071	1.082	55.181	-6.028
Aug-19	55.497	48.110	7.390	51.086	4.414	56.121	-0.621
Sep-19	53.332	47.707	5.625	56.351	-3.019	53.857	-0.525
Oct-19	62.536	60.427	2.113	62.321	0.219	60.320	2.220
Nov-19	64.252	63.492	0.760	61.146	3.106	61.835	2.417
Dec-19	68.923	63.306	5.618	63.841	5.082	62.879	6.044
Jan-20	59.113	56.741	2.372	56.425	2.688	55.704	3.409
Feb-20	55.418	58.331	-2.913	57.009	-1.591	54.748	0.670
Mar-20	59.647	65.420	-5.770	59.661	-0.011	57.473	2.177

V. CONCLUSION

The load forecasting for dharwad and hubli locations for next 3 years has been carried out in MATLAB using ANN tool. The target values are calculated using linear regression analysis. Form the regression plots it is seen that the load forecasting results are almost equal to predicted values (target values) for 20 neurons. i.e. the output values almost fit to target values.

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