International Journal of Technical Innovation in Modern Engineering & Science (IJTIMES)
Impact Factor: 3.45 (SJIF-2015), e-ISSN: 2455-2585
Volume 4, Issue 5, May-2018

A Novel Approach for Electricity Demand Forecasting using ANN

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Abstract— ***Demand forecasting plays an important role in electricity management system. The forecasting results can be used to determine the vulnerability of the system. There are various techniques that can forecast the demand. These techniques include parametric model, SVM, neural network techniques and genetic algorithms etc. In our approach, we are using ANN for forecasting. The ANN model allows more flexible relationship between demand and weather variables as compared to multiple regression model. Our approach performs well as compared to regression model. In this paper, we have discussed the results of artificial neural network technique for monthly demand forecasting for the Amloh city.***

Keywords— Demand forecasting, ANN, Electricity management system, CDD, HDD.

I. Introduction

Electricity demand forecasting is a significant tool that is used to ensure that the electricity generated by the system meet the demand and the electricity loss during transmission in the distribution network. It is an integral process in the planning and operation of electricity systems. Demand forecasting helps in making important decisions related to purchase and generation of electricity [1]. It is used to control decisions like transmission, fuel allocation and off-line analysis of the network. Demand forecasting decisions implemented on time results in improvement of reliability of the network and reduce number of equipment failures. It is of vital importance for electric utilities due to fluctuation in supply and demand and changes in weather conditions and increase in electricity prices during peak situations.

There are various conventional methods for forecasting. The ability of mapping complex and non-linear relationships has resulted into increase in number of applications in demand forecasting [2]. Load forecasting, fault diagnosis and security analysis are most important ones. Short term load forecasting is often carried out by using these ANN. For long term load forecasting using ANN only a few studies are carried out [3], [4].

Wavelet theory is introduced to load forecasting recently and it has received wide attention. Then analyse each components characteristic thus resulting into improved accuracy. Wavelet analysis is further extended to wavelet packet analysis for better resolution [5]. Application of wavelet analysis for load prediction is investigated in several papers.

Amjady N. et al. [6] proposed a new hybrid forecast for short term load forecasting.

Bashir Z.A et al [7] proposed a model that wavelet transformed the data during pre-processing stage and then redundant information is extracted by inserted data into neural network. One of the most recent and powerful technique for regression and classification problem is Support Vector Machines (SVMs). This was originated from statistical learning theory by Vapnik's [8].

We proposed a novel approach using the ANN and also compared the result with the regression model.

The rest of the paper is organized as follows, we describe the problem statement in section II. In section III, we present a solution to the problem proposing the architecture, schematic framework model and explaining all its components and section IV talks about the implementation and result of the proposed solution.

II. PROBLEM STATEMENT

Due to some problems in measurement or transmission of data, the historical database might have some bad or missing data, which can degrade systems performance and affects the precision of load forecasting results. Thus, we are finding a way to detect the missing data, and to evaluate the real data.

Load forecasting is one of the central functions in operation of electric power systems. The motivation for accurate demand forecasts lies in the nature of electricity to be used as a trading article and commodity. We can't store electricity; therefore, the precise estimate of the future demand is necessary for management of generation and purchase in an economically reasonable way.

In this work, we have applied the models of neural network on monthly load forecasting. The approach is comparative. The objective is to choose the most appropriate model(s). As there is need to forecast the load accurately, another objective is to process the dataset and make it suitable. The work provides the basis for an automatic forecasting application to be used in a real-time environment. There are some important properties, which are considered:

- The model should be automatic and adaptable.
- The model should be intended to use in many different cases (general).
- Updating of forecast with new data should be possible.
- The model should be reliable.
- Difficult weather conditions should be taken care of.

Electricity demand forecasting is a significant component for electricity management system. This research tries to develop a comprehensive method selection to fulfil our goal.

III. PROPOSED TECHNIQUE

A. *Weather Variables and Electricity Demand*

It has been seen that weather variables are main driving factors for forecasting electricity demand. The main weather variables are discussed below.

1) Temperature: For electricity demand forecasting, temperature is the main driving factor. Increasing temperature not only affects the demand but also restricts the load carrying capacity of distribution lines. We first plot the monthly average demand values against the mean average temperature (in India) to better understand the relationship among these. This is shown in Fig. 1.

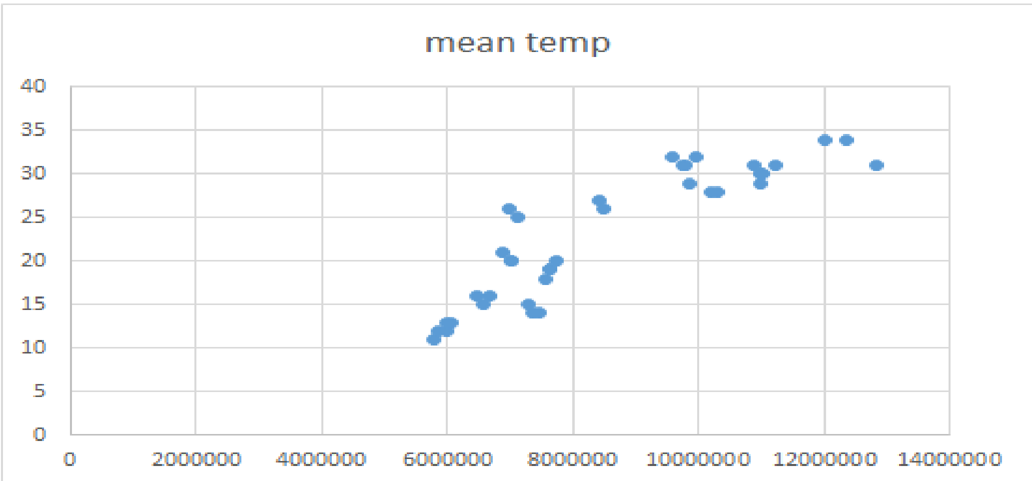


Fig. 1 Mean monthly consumption as a function of mean average temperature.

Fig. 1 shows that there is a direct relationship between temperature and demand in India. During summers, there is a significant cooling load that coincides with higher temperature. And in winters the demand tends to be lower because there is no such load of coolers and air conditioners. Also in extreme winters the demand rises due to increase in heating and lighting load. There is variation in correlation of demand with temperature over time due to non-weather-related parameters like increase in population, income etc.

2) *Degree Days:* Degree days are categorized under two classes.

- Cooling degree days- It measures the duration of hot weather and its severity. It is used to calculate the cooling needs [9]. Also called CDD.
- Heating degree days- It measures the duration of cold weather and its severity. It is used to calculate the heating needs [10]. Also called HDD.

The higher the temperature means higher is the CDD value hence more cooling is required in those days. A positive value for CDD employs electricity is required for cooling purposes whereas a positive value for HDD means electricity is required for heating purposes. Monthly demand against HDD is shown in Fig. 2. A weak linear correlation is shown among demand and HDD.

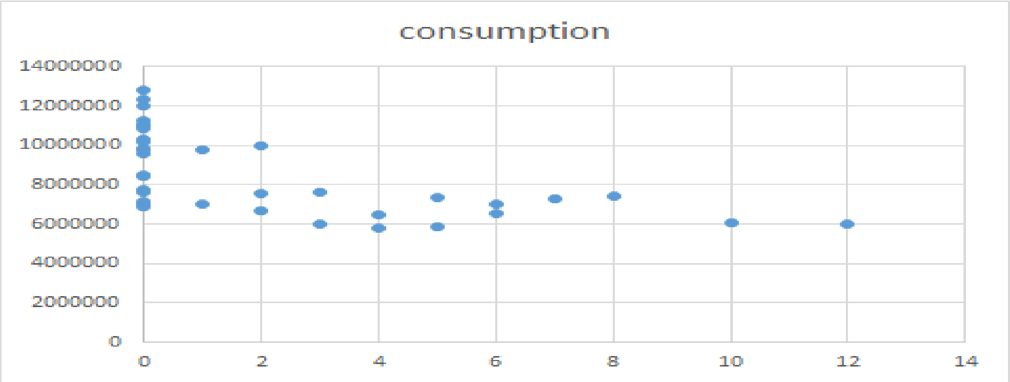


Fig. 2 Monthly demand against heating degree days

Monthly electricity demand against CDD is shown in Fig. 3.This is seen from the figure that there is strong correlation between value of CDD and monthly demand.

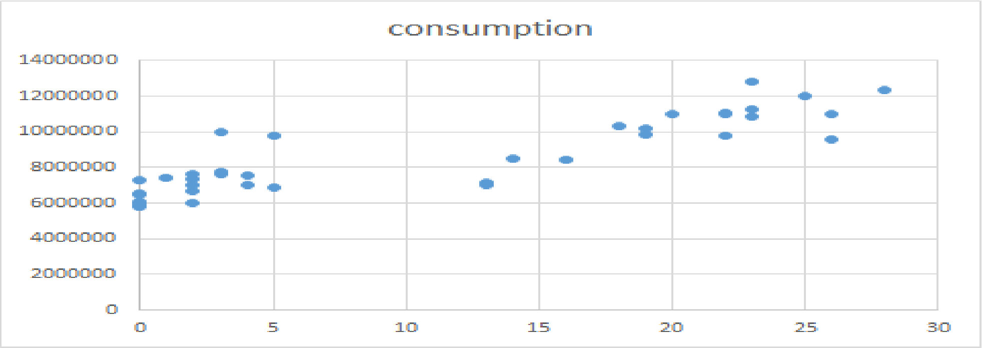


Fig. 3 Monthly demand against cooling degree days

3) *Rainfall:*Rainfall is also a crucial factor that mainly affects the domestic consumption. Rainfall is a common pheno menon in India especially in summers. Lighting and air conditioning load are directly affected by rainfall.

4) *Humidity:*Relative humidity is also one of the factors that drive demand of electricity. Demand of electricity increas es during high humidity as the air conditioning load increases.

Apart from these factors other factors like duration of sunshine and cloud cover [11] also drive the demand of electricity. As id duration of cloud cover is more, higher is the electricity require for lighting purpose.

B. ANN Technique for Monthly Demand Forecasting

The ANN technique to monthly demand forecasting has gained a great deal of interest. Its effectiveness has been reported by several researchers. The ANN techniques are applied to correlate the weather-related information and the demand variations to forecast the monthly electricity demand. The ANN used monthly historical data of the weather conditions and the load are classified according to their characteristics to create a non-linear model. Monthly demand is then forecasted by these nonlinear models.

The proposed technique for monthly demand forecasting of weather sensitive loads consist of four stages. The ANN model used a multilayer NN consisting of one input layer, two or more hidden layers and one output layer.

There is no basic rule for selection of number of input variables. Hit and trial method is used for data selection. The historical load data and weather data, forecasted average monthly weather and weather data are the required input parameters. Weather data include temperature (°c), humidity (%), Wind speed (km/h), rainfall(mm), and pressure. The demand of electricity is strongly influenced by the average monthly temperature, humidity, wind speed. Since the most recent three-year load data points are considered as part of the inputs, the corresponding three-year temperatures, humidity, and wind speed are included. In total, the temperature, humidity, wind speed data points, rainfall, load account for seven input variables. Climatic conditions fluctuate the demand.

As the historic weather data is difficult to attain and also the measurement and transmission of data can sometimes results into missing values in dataset. These missing values can degrade system performance thus a forward and backward difference mathematical model is applied to locate the missing values and substitute it with most appropriate values. Fig. 5 shows the flowchart of the whole process of training and testing.

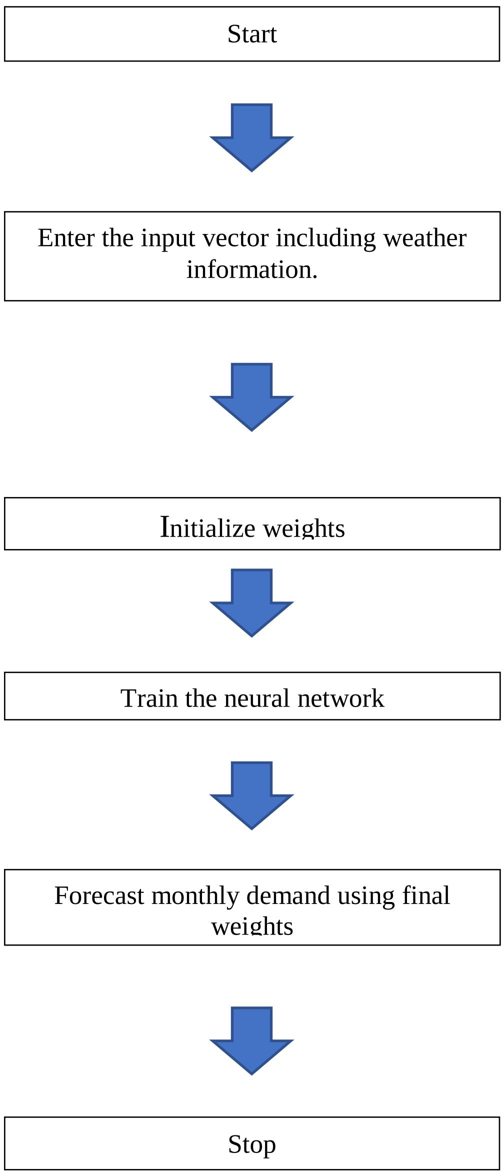
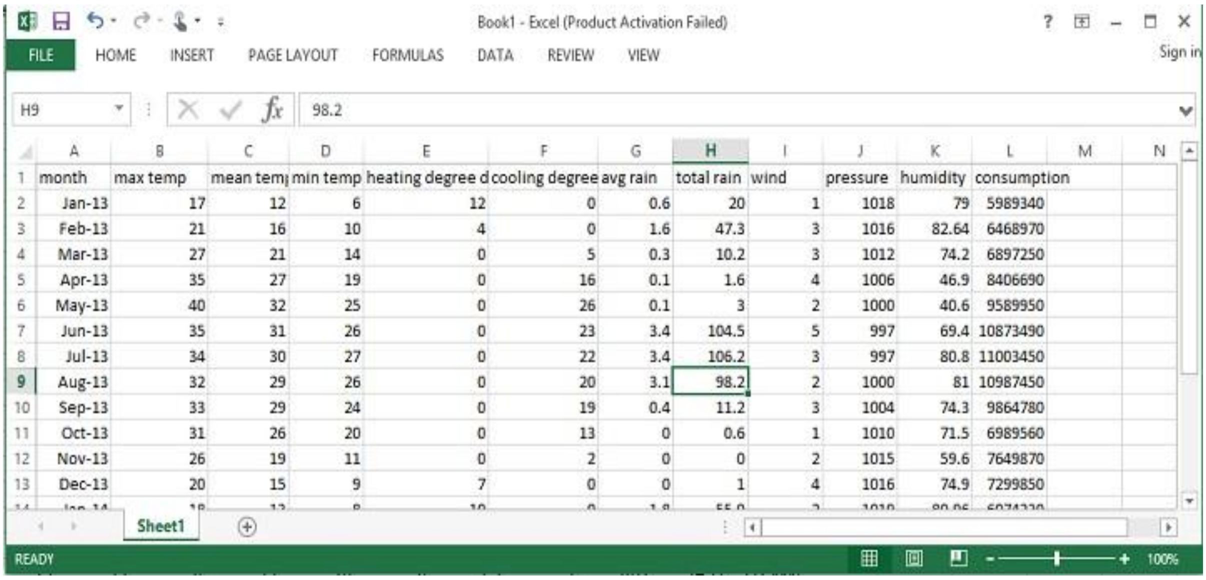


Fig. 4 Flowchart for training and testing of ANN

C. ANN Architecture

In this section, we will describe the training model for the neural network to learn from the recent three-year monthly demand data and weather-related data of Amloh as shown in Fig. 5. In order to forecast monthly future demand and for designing the network architecture, the Matlab ANN toolbox is used.



month	max temp	mean temp	min temp	heating degree d	cooling degree	avg rain	total rain	wind	pressure	humidity	consumption
Jan-13	17	12	6	12	0	0.6	20	1	1018	79	5989340
Feb-13	21	16	10	4	0	1.6	47.3	3	1016	82.64	6468970
Mar-13	27	21	14	0	5	0.3	10.2	3	1012	74.2	6897250
Apr-13	35	27	19	0	16	0.1	1.6	4	1006	46.9	8406690
May-13	40	32	25	0	26	0.1	3	2	1000	40.6	9589950
Jun-13	35	31	26	0	23	3.4	104.5	5	997	69.4	10873490
Jul-13	34	30	27	0	22	3.4	106.2	3	997	80.8	11003450
Aug-13	32	29	26	0	20	3.1	98.2	2	1000	81	10987450
Sep-13	33	29	24	0	19	0.4	11.2	3	1004	74.3	9864780
Oct-13	31	26	20	0	13	0	0.6	1	1010	71.5	6989560
Nov-13	26	19	11	0	2	0	0	2	1015	59.6	7649870
Dec-13	20	15	9	7	0	0	1	4	1016	74.9	7299850

Fig. 5 Screenshot of weather data and previous electricity consumption data stored

The layers include the input layer, the hidden layers and the output layer. The input consists of monthly demand data for last three years and weather-related data of these years. The output layer will be a monthly demand forecast for the utility company.

The network architecture is characterized by the pattern of connectivity. A two-step procedure is followed by output layer to determine its activity. First, the total weighted input Xj is computed, using the formula in equation 1.

$$Xj = \sum yi\ Wij \tag{1}$$

Where Wij is the connecting weights between ith and jth layer and yi is the activity level. Secondly, the unit calculates the activity yj using sigmoid function of the total weighted input as shown in equation 2.

$$yj= 1/ (1+ e\text{-}xj) \tag{2}$$

Then the network computes the error E, which is defined by the expression in equation 3.

$$E = \frac{1}{2}\sum (yi- di)2 \tag{3}$$

Where yi is the activity level and di is the desired output of the jth unit. The Levenberg Marquardt (lm) back-propagation algorithm consists of six computational steps. It computes the error change speed with change in the activity of an output unit. This error derivative (EA) is the difference between the actual and the desired activity as shown in equation 4.

$$EAj = \frac{\partial E}{\partial y_j} = yj – dj \tag{4}$$

Now, it computes the error change speed with change in total input received by an output unit as shown in equation 5.

$$EIj = \frac{\partial E}{\partial x_j} = \frac{\partial E}{\partial y_j} * \frac{dy_j}{dx_j} = EAj\ yj(1\text{-}yj) \tag{5}$$

Next, it computes error changes speed with change in weight on the connection into an output unit as shown in equation 6.

$$\text{EWij} = \frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial x_j} * \frac{dx_j}{dW_{ij}} = \text{EIj yj} \tag{6}$$

Then it computes the error change speed with change in activity of a unit in the previous layer. This step allows back propagation to be applied to multilayer networks. The output unit activities are affected with the change in activity of a unit in the previous layer. Hence to compute the overall effect on the error, all separate effects on the output unit are add together. But each effect is simple to calculate as shown in equation 7.

$$\text{EAj} = \frac{\partial E}{\partial y_j} = \sum_j EI_j \text{ Wij} \tag{7}$$

Next, it advances to compute the H matrix (equation 8) and the gradient (equation 9). This is necessary to approach second-order training speed without having to compute the Hessian matrix.

$$\text{H = Jt J} \tag{8}$$

$$\text{g= Jte} \tag{9}$$

where J is the Jacobian matrix and e is a vector of network errors.

At the end, the Levenberg Marquadt- lm algorithm uses approximation to the Hessian matrix in the following Newton-like update as shown in equation 10.

$$\text{Xk+1 = xk - [Jt J + } \mu I\text{]-1Jte} \tag{10}$$

Where xk+1 is the updated value of the network weight and xk is the current weight. When the scalar μ is equal to zero, this act as Newton's method, using the approximate Hessian matrix, while when μ is large, this becomes gradient descent with a small step size.

D. Training and Testing

The fully connected multilayer ANN architecture used in this study, consist of three-Layered Feed forward network using a back-propagation algorithm with gradient delta learning rule.

E. Accuracy of Forecasts

To ensure the system accuracy, the relative error between the demand generated by the model and the actual load consumption are obtained on monthly basis. A positive value of error will indicate an over forecast, means that the forecasted load is larger than the actual load. In contrast, a negative value indicates under forecast, where the forecasted load value is less than the actual value.

$$\text{Absolute Percentage Error} = \frac{generated\ \ demand\ -actual\ \ demand}{actual\ \ demand} * 100$$

$$\text{Mean Absolute Percentage Error} = (1/N) \sum_{i=1}^{N} \frac{generated\ \ demand\ -actual\ \ demand}{actual\ \ demand} * 100$$

IV. Implementation and Result

The main task of this research work is to do the preliminary investigation of feasibility and performance ANN model to carry demand forecasting on monthly basis using weather data. Real time data that includes historical monthly load demand over 5 years, and weather data in terms of temperature humidity, wind speed, is collected for the city Amloh, Punjab. This section will focus upon the results generated by the model and its accuracy.

The proposed methodology of ANN in this work consists of fully connected multilayer feed-forward back propagation network. The implementation of the proposed network undergoes following steps:

- Build the training data set including historical load data and historic weather data of temperature, humidity, and wind speed that strongly influences the load.
- Initialize the weights of connecting links to small random values to avoid saturation.
- Compute the activated output using summation principle at a neuron.
- Train the network for given number of iterations.
- Test the trained model on the test data.
- Test the models forecasting accuracy on a different set of historical data and forecast accuracy is computed.

There are number of tools available for implementation of artificial neural network. In this work, MATLAB is being used for implementation and training of artificial neural network.

As stated in earlier section, the ANN based forecasting algorithm was implemented and trained using MATLAB. The results obtained during testing of ANN model are shown in Fig.6.

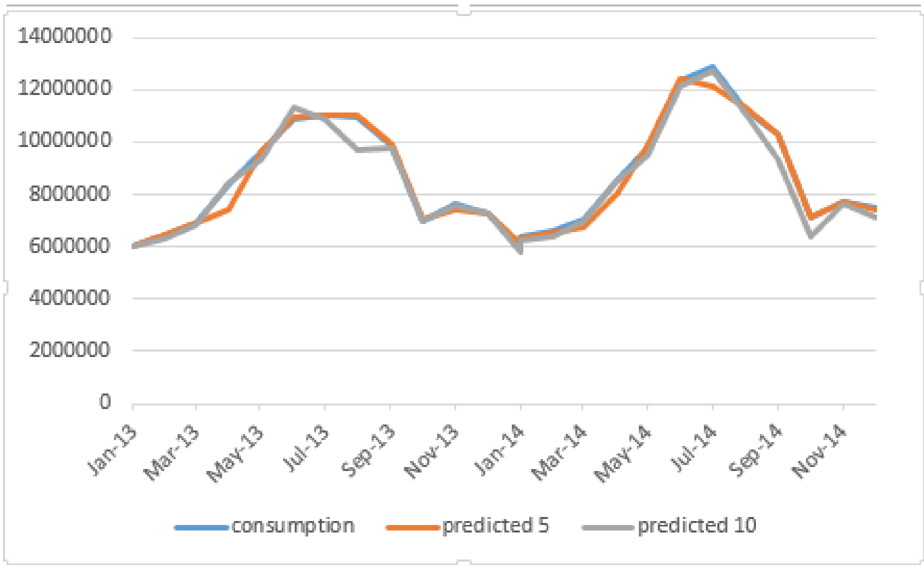


Fig. 6 ANN generated demand values against actual values.

The performance of ANN model is evaluated by computing APE and MAPE of the results, as shown in Table I. the MAPE of ANN with 5 hidden layers is 0.05 and with 10 hidden layers is 2.59.

TABLE I
COMPARING PERFORMANCE OF ANN MODEL WITH DIFFERENT NUMBER OF HIDDEN LAYERS

Actual Consumption Value	ANN generated value(5 hidden layers)	APE (5 hidden layers)	ANN generated value(10 hidden layers)	APE (10 hidden layers)
6468970	6466530	0.03	6303050	2.5
6897250	6898550	0.01	6858050	.56
9589950	9597550	0.07	9352450	2.4
10987450	11014050	0.2	9952350	9.3
7299850	7297050	0.03	7241350	.80
6551600	6569240	0.2	6388550	2.4
MAPE		0.05		2.59

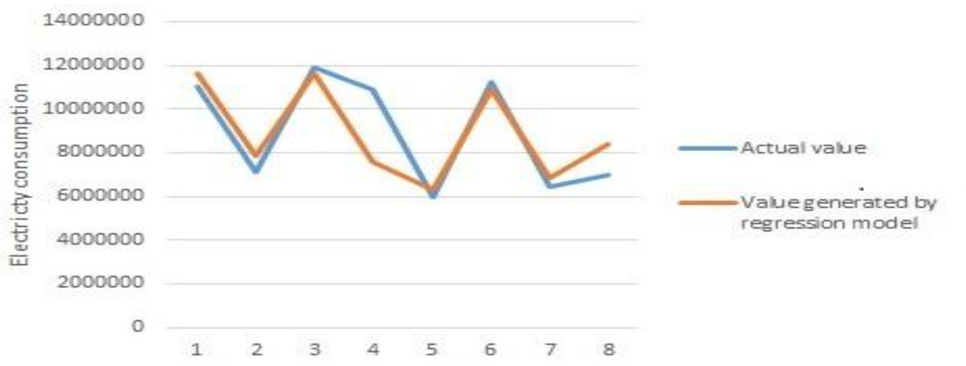


Fig. 7 Actual electricty demand against synthetic consumption using regression model in weka.

TABLE II
PERFORMANCE EVALUATION OF REGRESSION MODEL

Actual value	Value generated by regression model	APE for regression model
11003450	11670059	6.05
7125800	7864651	10.3
7023860	7690157	9.48
6468970	6849875	5.88
11235530	10908977	2.90
7023860	7610957	8.3

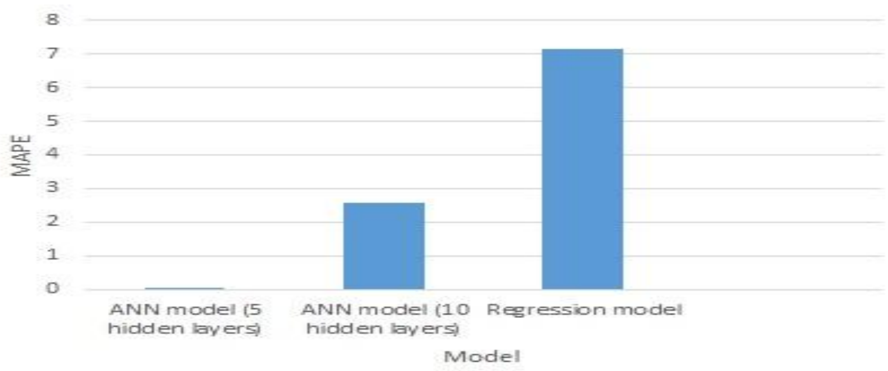


Fig. 8 Comparison of performance of ANN and regression model for electricty demand forecasting based on weather parameters.

The calculated values are very close to the actual values using less number of hidden layers by using ANN model. The difference is due to dependency of consumption on many other non- weather-related factors that are not considered while training the ANN in this model.

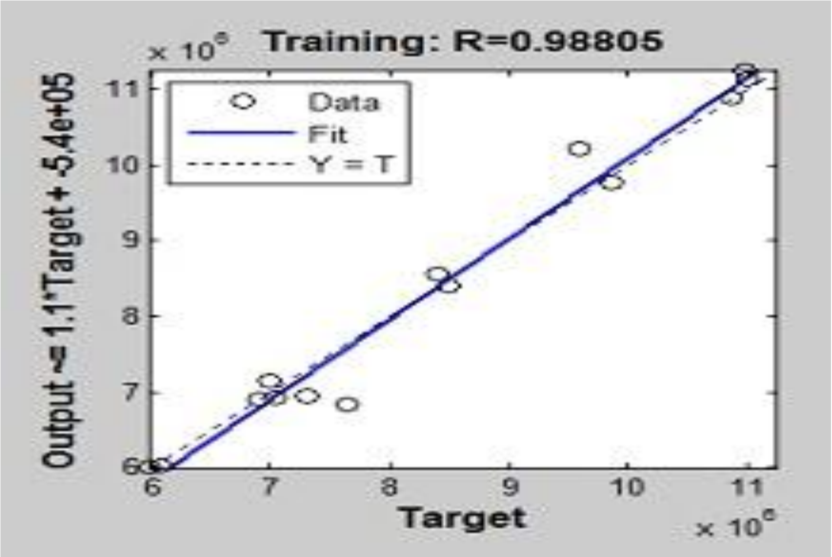


Fig. 9 Plotting performance of ANN during training of ANN.

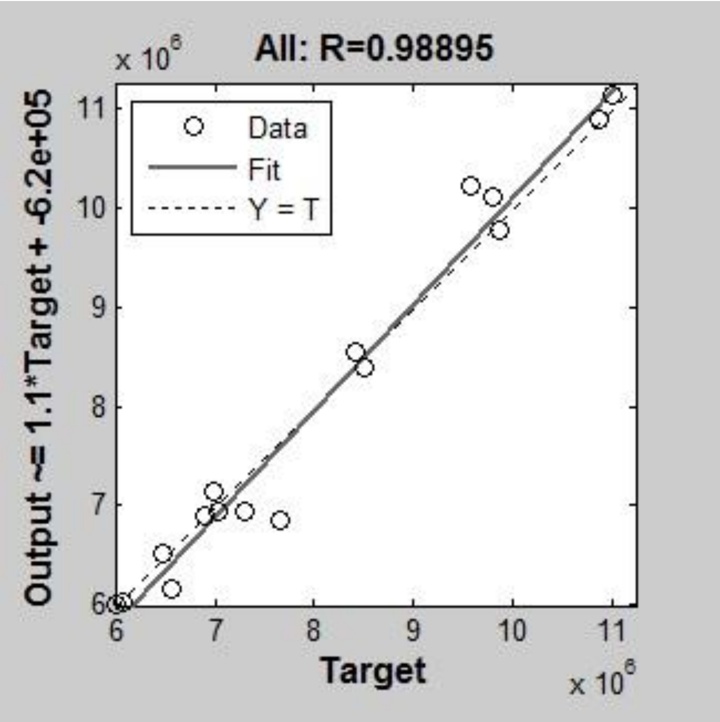


Fig. 10 Plotting performance at all levels including training validation and testing.

The results generated by regression model are shown in Fig. 7. And the closseness between values generated by regression model and actual consumption value is evaluated in Table II. The MAPE of regression model is 7.15. Therefore, the result shows that ANN provide better performance as compared to regression model as consumption values anticipated by ANN are closer to the real one as compared to values anticipated by regression model. Moreover, it is also seen that number of hidden layers should be low in order to receive better results.

V. CONCLUSIONS

The literature of Electricity demand forecasting shows that the electric load pattern is very complex. This research work has reported that every electricity network and electricity plant needs special forecasting method because each country is different in the factors affecting the electricity demand.

For effective implementation of the energy related policies forecasting electricity consumption is quite important. In this report, the monthly electricity consumption of India is modelled as a function of weather variables like temperature, rainfall, degree days and humidity. The data is pre-processed and missing values are substituted using forward and backward difference approach. These weather variables are selected using correlation coefficient. Regression analysis and ANN are used to forecast monthly consumption of electricity. It is also verified that the ANNs approach is suitable and accurate for prediction.

The results of artificial neural network technique for monthly demand forecasting for the Amloh city, are investigated and it shows that the proposed artificial neural network technique gives a good performance and reasonable accuracy. Its reliabilities were evaluated by computing the mean absolute error between the exact and predicted values

Load forecasting is still undergoing many challenges. Availability of weather data and electricity consumption data of certain regions is one of the major limitation. In developing countries like India many non-weather-related factors like carbon dioxide emission, per capita GDP, Gross Domestic saving, population and number of holidays also affect the consumption of electricity. Use of such socioeconomic factors along weather variables can yield even better results

More historical extreme cases are required in order to improve the accuracy of the forecasts. Such data might be obtained from analogues in other countries that have larger temperature extremes though care must be taken as the response may not be identical from one country to other country. The intention of this analysis was to start with a simple usable model that is capable to explain a significant amount of the variability in the electricity demand. We believe our models to be robust in order to predict electricity demand a for number of years into the future giving reliable estimates of the relevant weather-related parameters

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