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Prediction of Electricity Power in Indian Electricity Power System through Artificial Neural Networks

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Abstract

A precise model for electricity power load predicting are essential to the action and planning of an electricity business. Neural Networks is considered as a computational model that is capable of doing non-linear arc fitting. In our work, we use the application of neural networks to study the design of Short Term load Predicting (STLF) Systems for India. With three layered neural network architecture with back propagation algorithm is proposed to model STLF. There moods prove that neural network gives the minimum predicting error compared to the statistical predicting models and hence it can be considered as an effective method to model the STLF systems for Indian electricity power system.

Keywords: *Indian Electricity power system, artificial neural network.*

I. Introduction

The talent to accurately predict the future is important to many conclusion processes such as devel opment, predictions, acquiring, p olicy preparation, a nd policy making. There for people alwa ys try to find out accurate predicting models. This research will examine and analyze the use of neural networks as a predi cting tool for electricity load predicting and how can it be applied to the Indian Electricity Power System.

The total amount of electricity power used up by people must be bal anced with the amount of generated power. There is no r esourceful way to store large am ounts of electricity energy. To maintain this power balance between productions and in take its hold is predictions future power needs.

Load predictions can be divided into three categories: Short-term p redictions, Medium-term predictions and Long-term predictions. Natures of these predictions are different. Short-term load predicting can help to estimate load activities and to make decisions that can preve nt overloading. Timely applications of such verdicts lead to the improvement of net work reliability and to reduce t he occurrences of tools failure s. Whereas in Lo ng- term predicting helps to know the electricity load that will want in the future and take necessary actions like building more power locations, for fu lfil the needs of people in the country.

The electricity load predicting task is u sually carried out by statistical methods. This task is done by the skilled operators in electricity circulation firms. Traditional line models, such as Auto regressive (AR) and Auto-regressive Moving Average (ARMA), have been used in time series predictions in exercise. Thes e models are forth right for execution, but there are lim itations to improve predicting precision by t hese methods, because thes e models are constructed by line AR functions, and an im portant influence of Artificial Neural Networks (ANN) is that their competence to do non-linear curve fitting. ANN models are particularly powerful when applied to a very complex data set and when the structure of the model is unknown. This paper describes the use of ANN model for p redictions electricity load for Indian electricity power system.

II. BACKGROUND OF ANN FOR POWER PREDICTION

In the last few decades a many of predicting m ethods have been developed for predicting assignment. ‘End Use’ and ‘Econometric’ approaches are two mostly used methods for medium and long term predicting.

Various reversion models, time series, and statistical learning algorithms, are used fo r short term predicting. Statistical methods usually require a m athematical model that represents load as a func tion of di fferent factors such as time, weather, calendar data and c ustomer class. Additive models and multiplicative models can be introduced as such m athematical models A. Fei nberg and D. Genethliou (2005),A.Feinberg, D. Genethliou and T. Hauagos (2002), A. Feinberg, D. Genethliou and T. Hauagos (2003).

Statistical models based o n the end-use approach(8) have included report so appl iances used by customers, the sizes of t he houses, t he age of tools, technology changes, customer behavior, and population dynamic forces. These models are based on the principle that electricity demand is derived from customer's demand for cooling, heating, light, refrigeration, etc. The probl em of t hese models that; it is sensitive to the am ount and qua lity of data. Also end-use predictions require less historical data but more information about customers and their equipment.

Econometric models include economic factors s uch as each capita earnings, em ploy levels, and energy prices other than the factors included in end-use approach. It is penetrating within the historical data in few years wh ether there has a similar characteris tic to the predictions days. Similar characteristics include weather, day of t he week, and the date. The load of a si milar day is considered as a prediction.

Regression methods are used to model the relationship of load consumption and other factors such as weather, day type, and customer class F. E ngle, C. Mustafa and J. Rece (1992).

A time series is separate to be an ordered set of data values of a ce rtain variable. Time series approaches are based on t he assumption that the data have an i nternal assembly, such as auto correl ation, tendency, or peri odic difference. Time series predicting methods notice and discover such a structure. ARMA (autoregressive moving average), ARIMA (autoregressive integrated m oving average), ARMAX (autoregressive moving average with exogenous variables), and ARIMAX (auto regressive integrated moving average with exogenous variables) are the most often used time series methods. Separately from these statistical methods, it has been done some research on time series pr edicting using ANNs in T . Kolarik an d G.Rudorfer (1994), P. C ortez, J. M achado and J. Neves (1996), S. Agular, M. Rodriguez and M . Cabrera-Rios (2006).

A support vec tor machine is a more recent powerful system for solving classification and regression problems. Support vector machines perform an online are mapping of the data in to a high dim ensional space. Then s upport vector machines use simple linear functions to create linear decision boundaries in the new space. It has described a method to predictions the electricity load using this method in M. Mohandes (2002) with the development of computer power, people tried to solve load predicting problem using that efficient computing. It was ab le to discover the complication in the load data using that computer power. Rule-based and fuzzy logic expe rt systems have been used to model the complexity in the data.

In F. Atiya, M. El-Shoura, I.Shaheen and S. El-Sherif (1999), it has been descri bed a ri ver flow predicting application that has use d neural network as a p redicting tool. It has used multi-layer network, which was t rained using the back propagation algorithm. In G. Bandyopadhyay and S. C hattopadhyay (2006) it h as been executed a m ulti-layer perceptron that modeled with Generalized Delta Learning to expect the in habitants of India. Paper establishes appropriateness of non-linear ANN as predictive tool for population in India. In the paper of P. Kumar and E. Walia (2006),explains another neural network predicting application called Cash flow predicting. This system was able to predict cash necessity with reasonable precision.

According to the predicting methods conversed, it cannot be found a finest technique for predicting electricity load. Statistical methods have some limitations, because they cannot consider some of t he external factors, which are important in predicting. In st atistical methodology, predicting miscalculation is also high. But neural networks can be used as a better predicting tool. Here neural network applications confirm it by doing the predicting with less miscalculation values compared to the statistical methods.

III. IMPLEMENTATION MODEL AND DESIGING ISSUES

A feedforward Artificial Neural Network model is suggested for the short term load predicting. The network is trained by using the back propagation learning algorithm Schimann, M.Joost, R.Werner(1994) with aimpetus factor. The presentation of t he network for one-day ahead load predictions is associated with the historical data available . The data is divided into two groups called training data for train the neural network and testing data for test the ANN model (Fig.1).

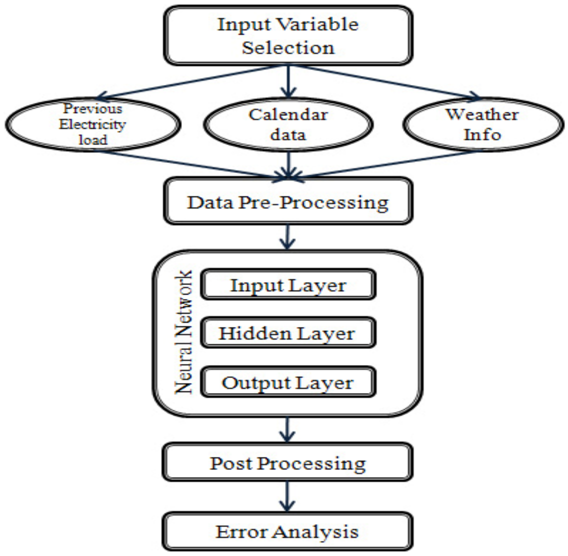


Fig. 1. Electricity load predicting system diagram

A. Preparation for input data

Variables can be characterized in to two groups, called Categorical variables (University of Idaho -Online) and Ordinal variables. Categorical variables do not have natural ordering. Sometimes these variables don't have numerical values. They should be convert ed to a numerical value for the purpose of applying to the neural network. So it can be used binary encrypting method. For example when doing electricity load predictions it can be for a particular month of the year. Therefore the month can be convert ed to a binary input as below.

January 101

February 110

March111etc...

As above, Week Days' input can be presented as 3 bytes binary code. Holiday can be represented by one byte (0or1) Ordinal Variables are vari ables having natural ordering. These variables can be directly served in to the neural networks as inputs.

In order to make the ANN model more operative, it is significant to understand the bearing and model inputs. When doing electricity load predicting a relationship can be predictable between the electri city load and the calendar data (holidays, weekdays, and wee kends) as well as the weather issues. According to the real electricity load data it can be seen a clear declining of electricity load on holidays compared to the other days. So these parameters can be used as preliminary inputs to the neural network. After that it can be recognized most relevant data for electricity load predicting, using the trial and err or method. Sometimes it may be seen that initial inputs do not directly affect the problem as it was predicted before.

Satisfying the misplaced data in the collected data set is another important task. Thes e misplaced data cannot be ignored. So i t should use ext ra pollution or i nterpolation method to fill those values. Ne xt step is data separating. Collected data set should be largely divided into two parts called training set and t est set. Training dataset is use to train the neural network and the testing set is to extent the performance of the neural network. This system used 83% of data for training determinations and the rest for testing the neural network.

Before the inputs are presented to the ANN model the data should be pre-processed. Exactness of the outputs of neural network is hinge on the data pre-processing step. Following are the steps that should be carri ed out in data pre-processing stage.

- Remove the noise from the data set.
- Normalization
- Extract main features of the dataset

B. Architecture for Artificial Neural Network

Calendar data such as day type, month type and date, historical load, minimum temperature and m aximum temperature are used as inpu ts to the neural network. Number of layers in the neural network, neurons in the hidden layer has been ch osen by using a trial and error method. Too many numbers of neurons increase the error and too less make the network disorganized to train itself to the given variable inputs.

A number of contiguous electricity load values of the time series and other inputs are plotted to the interval (1,-1) (normalizing) and gi ve them as inputs to the neural network. Then calculate the neural network output (tth value) using the weighted sum and the activation function. After that error can be cal culated using that output value and the target value (t+1th value in the series).This error is broadcast back to other layer in the network (Fig. 2).

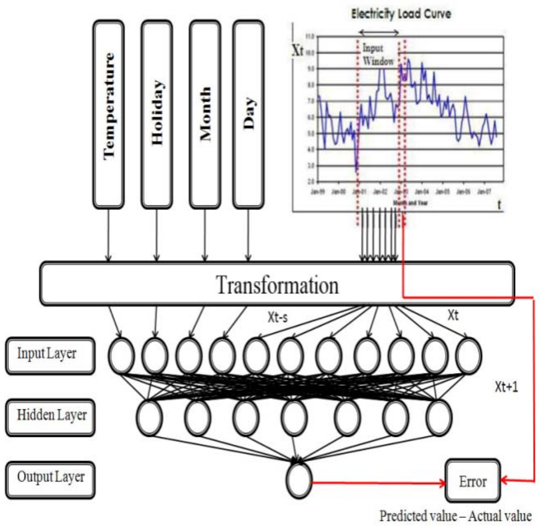


Fig.2. Fundamental Neural Network Architecture

System has im plement to gather training data from spread sheet and train the neural network. Then System has provided the functionality to give predicted value for next day by using the trained neural network.

IV. PROGRESS OF ANN FOR POWER SYSTEM

To assess the predicting consequences, two standards' were used: Root Mean Square Errors (RMSE) and Mean Absolute Errors (MAE). Also, correlation coefficient of predicted and actual dataset is measured when investigating the results. The co rrelation coefficient a impression from statistics is a measure of how sound trends in the predicted values follow trends in th e past actual values. It is a measure of how sound the pre dicted values from a predictions model acceptable with the real data.

A. Assessment Procedure

Assessment procedure is divided into several stages.

1. Fluctuating of the neural network architecture (number of hi dden neurons, number of hi dden layers, and using activation functions) find out the productivity of the neural network for electricity load predicting.

2. Evaluate the good organization of network by fluctuating the input para meters of the neural network.

3. Associate the results of neur al network predicting model with the statistical predicting models such as th e moving average and the regression.

B. Determining number of Input Nodes

When determining the amount of input nodes, as declared in the strategy, prev ious electricity loads, Month of the year, day of the wee k, maximum temperature and minimum temperature were used as preliminary inputs of the neural network. But in the testing phase some of these variables were recognized as not much affect to the load predictions. When giving the day of the week constraint as inputs, network did not give perfect predictions. Fig.3 shows the predictions load with the day of the week parameter. It gave a low correlation coefficient of 0.1545.

ActualLoad NN predictedLoad

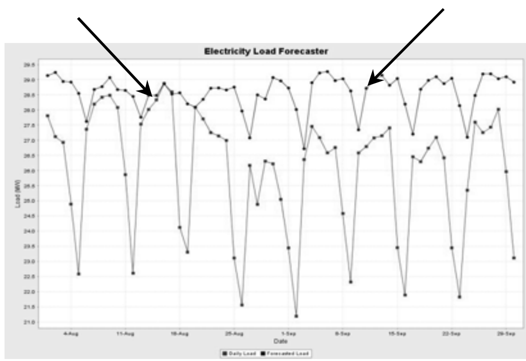


Fig.3. DayasinputtotheANN

Network model also uses t he previous14-day electricity load. Day effect is i mplicitly included in that inputs. Therefore it was definite not to comprise the day as distinct input.
It was not capable to be found a correlation among daily maximum temperature and the daily electricity load. Fig.4

shows the correlation between the maximum temperature and the electricity load.

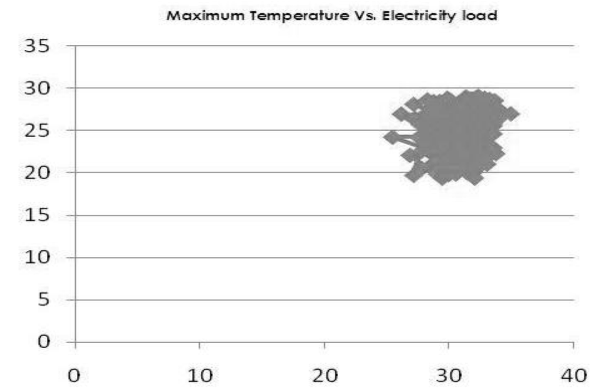


Fig.4.Electricity load Vs. Max Temperature

In India temperature fluctuates frequently within the series of 30ºC to 40ºC. So it cannot be predictable a big conclusion to the electricity load by the temperature. When associated with other countries, it can be seen a straight inspiration on temperature to the electricity load. Because, temperature of those countries are vary with in an enormous range. Sometimes it has range of -20ºC to 40ºC. So it put away enormous electricity load either to heat or to cool the environment. That's why it shows enormous correlation between the electricity load and the temperature, of those countries. Therefore the concluding neural network architecture has18 inputs. They are:

- Previous14 days electricity load
- Month of the year(3inputs encoded with binary values)
- Holiday effect (1input)

C. Determination of the Prime Number of Hidden Neurons in ANN

Next phase is to find the prime number of hidden neurons in the network. This can be complete by evaluating the error values for different number of hidden neurons. Results can be shown as Fig.5.

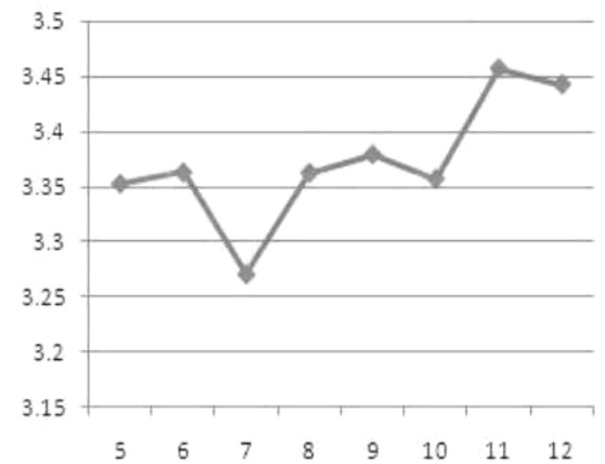


Fig.5. Present Hidden neurons Vs. RMSE

It can be clearly seen that lower most RMSE value is achieved when the neural network uses 14 hidden neurons. I fit reflects about the Correlation Coefficient of the fore told and actual electricity load data sets, a extraordinary correlation coefficient is detected when using18 hidden neurons (Fig.6).

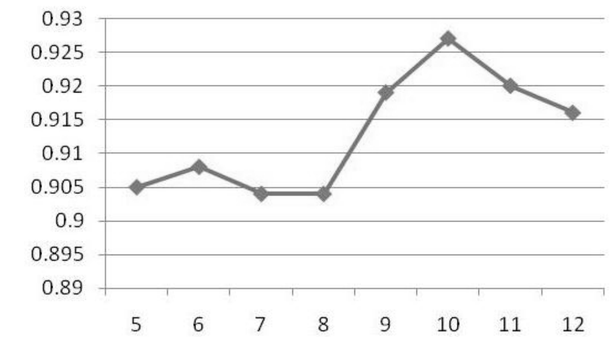


Fig.6. Real hidden neurons Vs. Correlation Coefficient

By bearing in mind the both correlation coefficient and the RMSE factors it can be determined that use of 12 hidden neurons is better. Because, the neural network gave a low RMSE value and high correlation coefficient when it is used12 hidden neurons. In peak conditions of neural network applications, 5 layered neural network architecture has been used similar to the proposed system. Analysis the network with 6 layers did not improve the results. Table I shows the performance of two architectures. Therefore this system is used three layered neural network architecture.

TABLE 1: Network Accuracy for Different Number of Hidden Layer

No. of layers	RMSE	Correlation Coefficient
5	5.499	0.9209
6	5.409	0.903

The final neural network architecture for electricity load predicting includes 13 input neurons, 11 hidden neurons and one output neuron. The sample predicting output for the neural network architecture can be shown as in Fig.7. At this stage it has not used the momentum value and learning rate was kept at 0.05.

ActualLoad ANN predictedLoad

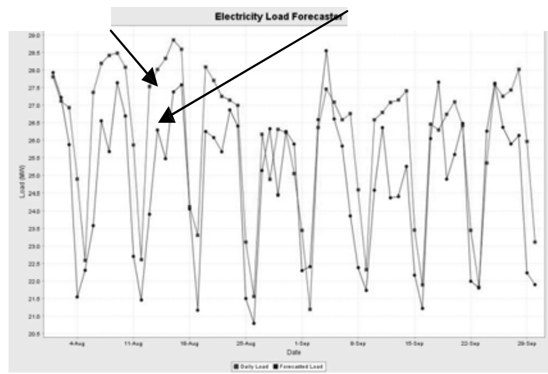


Fig.7. Prediction of Momentum factor

This pattern of t he neural network gave correlation coefficient of 0.8828. Still the network did not give accurate predicting. It can be increase the accuracy by increasing the momentum factor.

Change of momentum factor gives outputs shown in table: II

TABLE2: Effect of Momentum Factor

Momentum	Correlation coefficient	RMSE
0	0.8161	5.6623
0.1	0.8627	5.6387
0.2	0.8987	5.4496
0.3	0.8978	5.8086
0.4	0.8895	5.5990
0.5	0.869	5.6066
0.6	0.8978	5.6526
0.7	0.9015	5.5093
0.8	0.9019	5.5381
0.9	0.9179	5.4468

It can be seen whe n the momentum is inc reasing the Correlation coefficient is also increasing and the RMSE value is decreasing. By adjusting both parameters, momentum can be approximated to 0.9.

Learning rate is d irectly affects to the predicting process. Graph in the Fig.8.Shows relationship between learning rate and the correlation coefficient. It is clear tha t the low learning rate v alues lead to better predicting accuracy correlation Coeffici ent was upperm ost when the bipolar sigmoid function has been used. S o this system elected the bipolar sigmoid function as the maximum appropriate activation function. T he enhanced network with bipolar sigmoid function gave improved predictions than the initial network. It gav e correlation coefficient of 0.9251. Sample predictions values are shown as Fig.10.

ActualLoad ANN predictedLoad

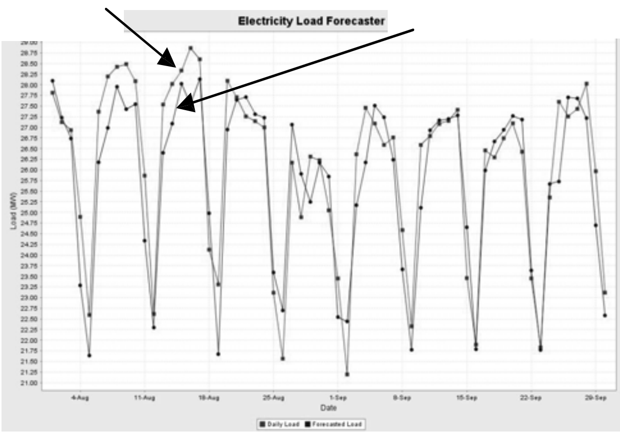


Fig.8. Improved network predictions with bipolar sigmoid function

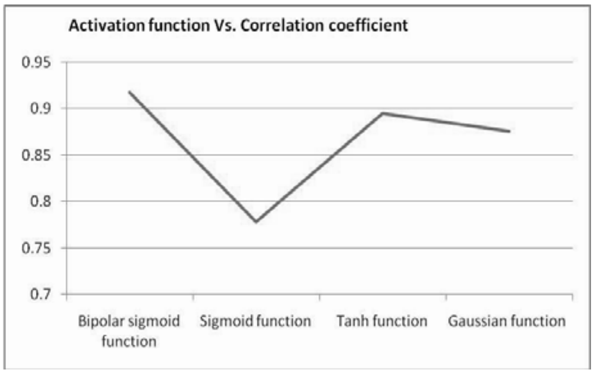
The suggested neural network electricity load-predicting model has been associated with the statis tical models. It was fo und that the neural network model is extreme superior to statistical models.

Fig.10 gives more comparable view of neural network and some other predicting models. It shows,

4 periods moving average

8 periods moving average

4 th order polynomial regression



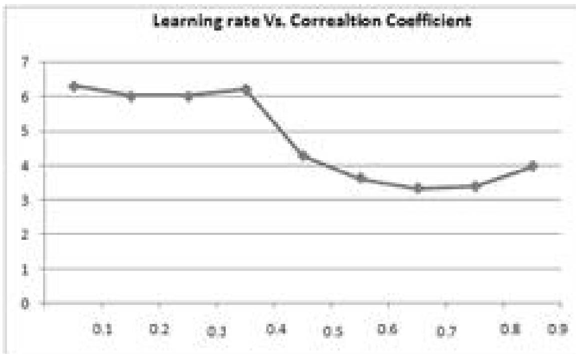


Fig.9. Learning rate Vs. Correlation Coefficient

Bearing in mind the above studies, it was decided that the suitable learning rate for th e electricity load predicting system is 0.05.

Use of di fferent activation function gave different predicting values. This system was teste d with several activation functions and the results are as Fig.10.

ActualLoad ANN predictedLoad

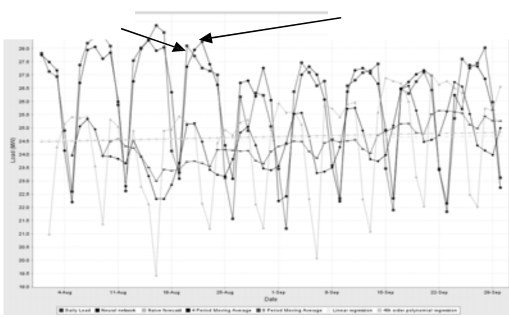


Fig.10.Comparison of Neural network predicting model with statistical models

Linear regression

Naïve and

Neural network predictions, for the same dataset.

It is very clear that rendering to the figure, conventional statistical models can't overtake the neural network model for electricity load predictions associated to the neural network model.

V. CONCLUSIONS

The existing predicting models based on statistics were studied. Advantages and disadvantages of these models were reviewed. A rep resentative neural network aided electricity load predicting model was developed. Using the data gathered from the MSEB, the neural network was trained. Results were co mpared with the ac tual electricity load. This research has fou nd out how accurateness it can be forecast the elec tricity load. Also it has investigated what the best neural network model could be for forecasting by testing with different neural network architectures and t esting with different parameters. The most suitable neural archit ecture for electricity load forecasting can be estimated as given below

No of input nodes: 11

No of hidden nodes: 10

No of layers : 5

Momentum factor : 0.9

Learning rate : 0.05

Activation function: Bipolar Sigmoid function

During the assessment phase it was ab le to draw th e following assumptions:

1. With the above arrangements, neural network can be used to predict the electricity load with Correlation coefficient of 0.9179 and RMSE 5.4468.

2. Neural network is found to be a feasible substitute in electricity load forecasting application.

3. Neural network is originated to be a more effectual and precise mean to forecas t electricity load than using conventional techniques.

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