International Journal of Scientific Engineering and Research (IJSER)
ISSN (Online): 2347-3878
Index Copernicus Value (2015): 62.86 | Impact Factor (2015): 3.791

An Intelligent ANN Approach for Short Term Electric Load Forecasting

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Abstract: ***As conventional approaches like the regression model and the time-series based models, are not much suitable because of the complexity and labour involved in modelling. So in this proposed work, to fulfil the requirement of accurate electric load forecast, an Artificial Neural Network (ANN) approach was used to forecast the next hour electric load for Safdarjang, New Delhi region. To accomplish the abovementioned task, initially appropriate weather variables were selected for the aforementioned region, on the basis of correlation coefficient. Then different forecasting models with several combinations of weather variables were prepared and tested. Simplest and well known ANN i.e. Multilayer Feed-Forward Neural Network with back-propagation algorithm was used.Finally, from this research work, appropriate input variables were specified to forecast the next hour electric load. The forecasting model, containing temperature and pressure as input weather variables was most appropriate one for the aforementioned region. An important observation of this research work was that those weather variables were appropriate for accurate forecast, which were highly correlated with load.***

Keywords: Artificial neural network, back-propagation algorithm, input variables, multilayer feed-forward neural network, short term electric load forecasting

1. Introduction

Electric load forecast means to predict electric load. Electric load forecasting helps an electric utility to make important decisions like purchasing and generating electric power, load switching, and infrastructure development [1]. Major factors affecting the load behaviour of the power system are: weather, time, economic factors and random disturbances.

The concern of power system planning and economic generation has become an amenity due to a large and continuously-changing difference between electricity cost and price produced by constant tariff scheme. To overcome this problem accurate electric load forecasting is a field of great importance.Load forecasting may be long - term, medium – term and short – term. Different forecast horizons have their own advantages and disadvantages. The load prediction period of STELF may be time up to an hour (or one day) to one week ahead. [2].

STELF is more important in comparison of other type of load forecast because of instant operational decision requirements for the applications associated with it. It is very important to daily maintaining of power plant.Rapidly changing load behavior enhances the need of STELF [3-8].It helps in estimating the load flows [9]. Here electric load is dependent variable whereas the independent variables are like weather variables, time factors, population etc.

As Statistical or traditional approaches like time series, regression and similar day lookup approachesare inappropriate to forecast in highly non-linear electrical environment, some modern or Artificial Intelligence (AI) approaches were tried to predict the electric load. ANN is one of the best AI approach for forecasting electric load.Many papers have been published in the field of load forecasting using ANN.

Rui and El-Keib (1995) presented six most important factors which affect the accuracy and efficiency of the load forecast, that are: the BP network structures, input variables of BP network, selection of training set, modification of the BP algorithm, number of hidden neurons and parameters of the BP algorithm. The surveyed publications and the authors' own experience lead to the conclusion that these parameters were mainly system dependent [10]. Kalaitzakis*et al.* (2002)presented the development and application of advanced neural networks to face successfully the problem of the short term electric load forecasting [11]. Kandil*et al.* (2006) demonstrated ANN capabilities in load forecasting without the use of load history as an input [12]. Hayati and Shirvany (2007) explored the application of neural networks to study the design of STELF systems for Illam state located in west of Iran [13]. Manohar and Reddy (2008)developed a method using ANN based technique for STLF. The technique was tested on real time data collected from a 220 KV / 132 KV / 33 KV / 11 KV Renigunta Sub-Station, A.P., India [14].

The organization of the paper is as follows: The methodology of the proposed work is described in section II, different testing cases and results are presented under Section III. The conclusions are inferred in last section i.e. Section IV.

2. Methodology for the Proposed Work

The methodology followed for the proposed research work was summarized as below.

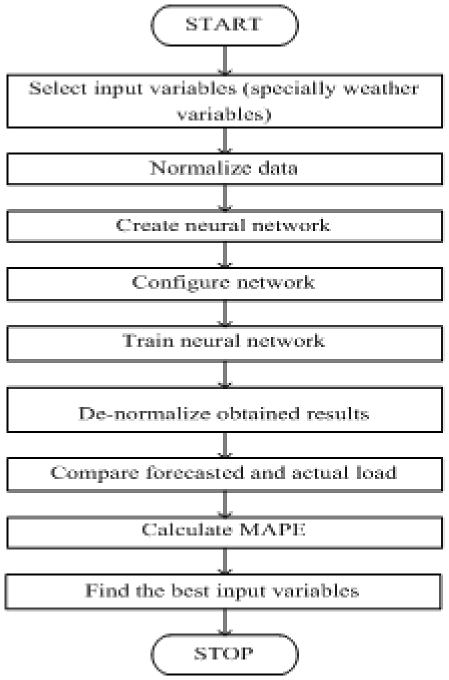

Figure 1: Sequence of work

A. Selection of Input Variables

Initially we had five weather variables i.e. atmospheric temperature, relative humidity, atmospheric pressure, wind speed and rainfall. The first step was to select the relevant input variables (especially weather variables). This was done by finding correlation between each weather variable and load. Formula (1) was used to calculate correlation coefficient of two variables.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \quad (1)$$

where r is the correlation coefficient; n is number of elements; x is first score (independent variable); y is second score (dependent variable); Σxy is sum of the product of first and second scores; Σx is sum of first scores; Σy is sum of second scores; Σx^2 is sum of square first scores; Σy^2 is sum of square second scores.

On the basis of correlation coefficient, only three weather variables i.e. temperature, pressure and humidity were selected as input variables.

Table 1: Correlation coefficient of various weather variables

Weather Variables	Correlation Coefficient	Strength
Atmospheric temperature	0.6716	Strong positive
Relative humidity	0.3704	Moderate negative
Atmospheric pressure	0.6425	Strong negative
Wind speed	0.2289	Weak positive
Rainfall	0.0409	Negligible

The correlation was also determined between past hour load and current load as shown in Figure 2.

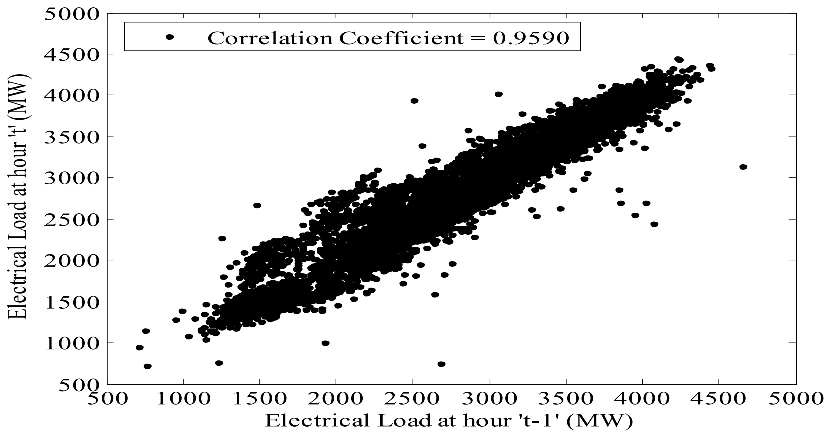

Figure 2: Correlation coefficient of $(t-1)^{th}$ and $(t)^{th}$ hour electrical load

Data analysis was carried out from different point of views: hourly data analysis, average load of each day analysis and analysis based on average load of every weekday for whole year, average load of every hour for whole year etc. On this basis, other input variables were selected like day type, hour and date value. Finally, the following input output schematic was prepared to forecast next hour electric load.

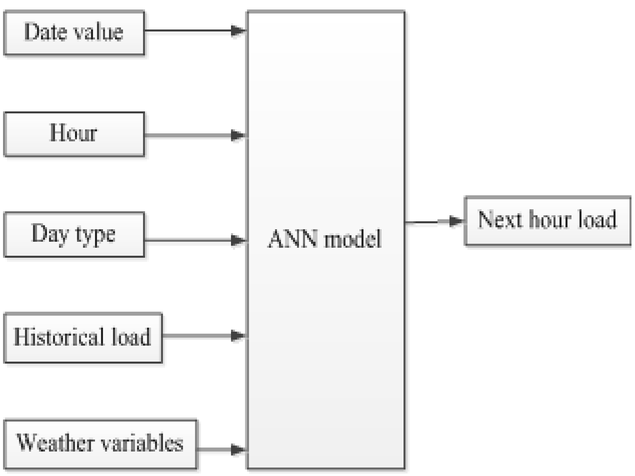

Figure 3: Input output schematic of system

B. Description of Different Forecasting Models

Based on the above inference, total eight models were prepared and tested, out of which seven models were with different combinations of selected weather variables (atmospheric temperature, atmospheric pressure and relative humidity), whereas one model was without weather information.

Table 2: Different Forecasting Models

ModelNo.	Combinationsof input variables	Totalno. Of input vectors
Model 1	• Hour • Date value • Day type • Humidity at $t^{th}$and $(t-1)^{th}$ hr • Load at $(t-1)^{th}$ hr	**6**
Model 2	• Hour • Date value • Day type • Pressure at $t^{th}$and $(t-1)^{th}$ hr • Humidity at $t^{th}$and $(t-1)^{th}$ hr • Load at $(t-1)^{th}$ hr	**8**
Model 3	• Hour • Date value • Day type • Temperature at t^{th} and $(t-1)^{th}$ hr • Humidity at $t^{th}$and $(t-1)^{th}$ hr • Load at $(t-1)^{th}$ hr	**8**
Model 4	• Hour • Date value • Day type • Temperature at $t^{th}$and $(t-1)^{th}$ hr • Pressure at t^{th} and $(t-1)^{th}$ hr • Humidity at $t^{th}$and $(t-1)^{th}$ hr • Load at $(t-1)^{th}$ hr	**10**
Model 5	• Hour • Date value • Day type • Pressure at t^{th} and $(t-1)^{th}$ hr • Load at $(t-1)^{th}$ hr	**6**
Model 6	• Hour • Date value • Day type • Load at $(t-1)^{th}$ hr	**4**
Model 7	• Hour • Date value • Day type • Temperature at $t^{th}$and $(t-1)^{th}$ hr • Load at $(t-1)^{th}$ hr	**6**
Model 8	• Hour • Date value • Day type • Temperature at $t^{th}$and $(t-1)^{th}$ hr • Pressure at t^{th} and $(t-1)^{th}$ hr • Load at $(t-1)^{th}$ hr	**8**

C. Training of Neural Network

Input and target matrices were imported from excel sheets and then normalized using the following formula (2).

$$x_n = (m-n)\frac{(x_0 - x_{min})}{(x_{max} - x_{min})} + n \qquad (2)$$

Where x_n is the normalized data; x_0 is the original data; x_{min} and x_{max} are the minimum and maximum values along the column and row respectively; n and m are the range of normalization.

To normalize the whole data set i.e. all matrix, in-built *mapminmax* function was used in MATLAB. This function processes matrices by normalizing the minimum and maximum values of each row to [Y_{MIN}, Y_{MAX}].

After that neural network was created and configured using simplest ANN i.e. Multi-layer Feed Forward Back Propagation Neural Network (MLFFBPNN). To train MLFFBPNN Levenberg-Marquardt (LM) algorithm was applied to get faster convergence. The selection of activation function was on hit and trial basis. But at least one activation function must be non-linear, so sigmoid activation function was used for input and hidden layer and purelin for output layer. Number of hidden layers was selected on hit and trial basis. But it should be as less as possible. Hidden neurons were also selected on hit and trial basis.MSE i.e. Mean square error was selected as a performance function. It is the measurement of all errors (training, testing and validation). Whatever data is given to ANN for training purpose, it divides this data for training, validation and testing in the ratio of 70%-15%-15% respectively. MSE is the performance measurement of these training, testing and validation of ANN.

This all process was done in ANN tool box. Thus ANN was created and configured. Then it was trained for the given input – target matrix. The NN generated, was finally saved. Thena new input set (unknown set) was given to the trained NN, for which it generated a normalized predicted output. The predicted data matrix was denormalized using the *reverse function* of *mapminmax*.

D. Performance Evaluation of Forecasting Models

The forecasted load (output) was noted and compared with the actual load by calculating Mean Absolute Peecentage Error (MAPE). Formula of MAPE is given as below:

$$\text{MAPE}(\%) = \frac{\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|}{n} \times 100 \qquad (3)$$

Where A_t is actual load at t^{th} hour, F_t is forecasted load at t^{th} hour and n is number of samples.

The whole process was repeateduntill the best/suitable input variables set is determined, such that the MAPE obtained for the NN lies within satisfactory limits.

3. Test Cases and Results

Eight different models were tested. There MAPE comparison plot is shown below.

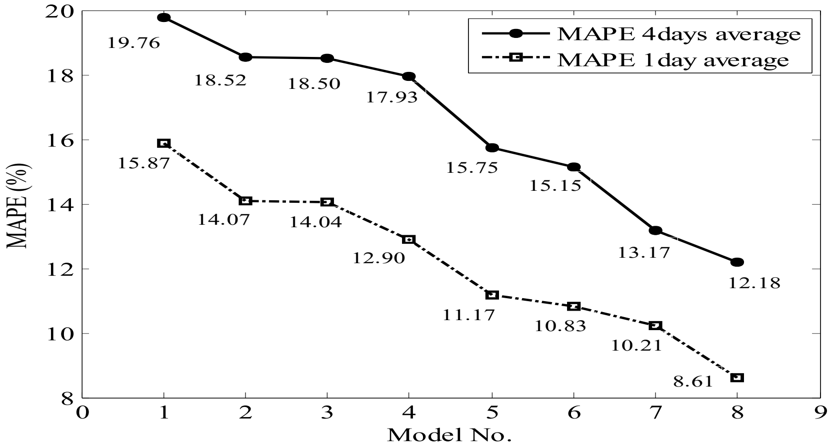

Figure 4: MAPE comparison plot of eight different Models

Finally, on the basis of MAPE, Model 8 was proved to be the best forecasting model because it has least MAPE. As seen from Figure 5, the MAPE is more during abrupt changes in actual loads, and less in other parts of the plot.

Figure 5 compares the actual and forecasted load for four days. Figure 6 compares the load for only one day i.e. 28th Dec, 2009. And, it can be seen that for the first day, the error is within satisfactory limits. The error cumulates for forth coming days and may or may not be used for prediction purposes, depending on the tolerable limits. Model 8 was summarized in Table 3.

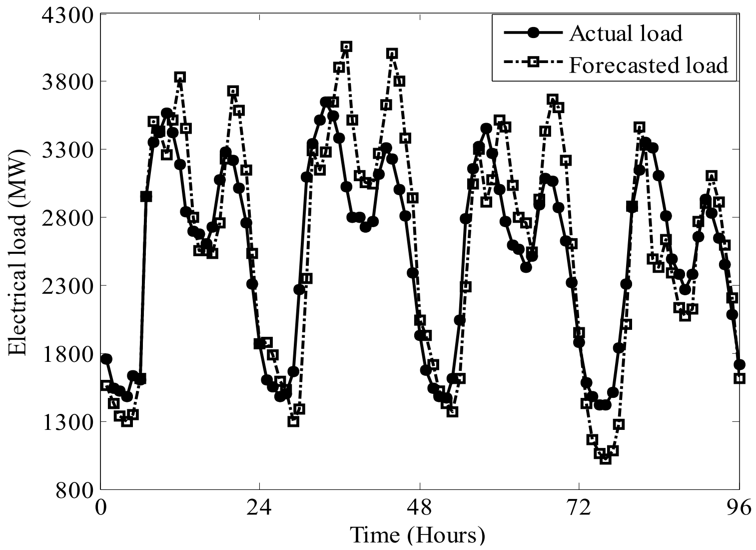

Figure 5: Comparison of actual and forecasted load of Model 8

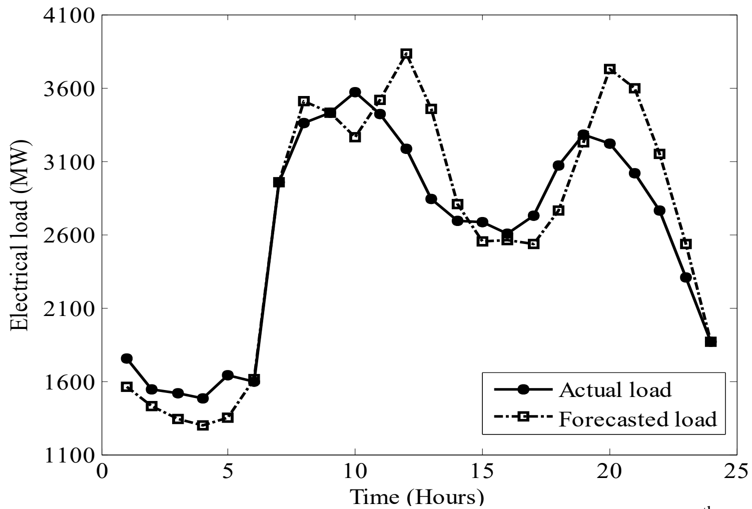

Figure 6: Comparison of actual and forecasted load of Model 8 (28th Dec, 2009)

Table 3: Summary of Model 8

Model Name	Input vectors	Hidden neurons	Date	Oneday MAPE (%)	4days MAPE (%)
Model8	8	20	28	8.6160	12.1899
			29	15.6124	
			30	12.1755	
			31	12.3557	

As seen from Table 3, MAPE is least i.e. 8.61 % as forecasted for 28th Dec, 2009. It increases on 29th then decreases. But according to literature, MAPE should increase in forthcoming days because forecasting accuracy decreases as lead time increases. But this was due to more variations in data. If more precise data will be available, then we may have improved results.

4. Conclusions

Load forecasting is very important for decision processes in the electricity sector. STELF provides an accurate estimate for the operating of the power system and also a basis for energy transactions and decision making in energy markets. It is also very important for daily maintenance of power plants because most of the decisions, like the unit commitment, load shedding and the economic load dispatch is necessarily based on forecasts of future demands.

As conventional methods are not appropriate for non - linear electrical environment, in this proposed work, an ANN approach was adopted to forecast the next hour electric load.One year hourly data was collected of New Delhi region, containing five weather variables i.e. temperature, atmospheric pressure, relative humidity, wind speed, rainfall. Initially appropriate weather variables were selected, on the basis of correlation coefficient. On the basis of data analysis, other input variables like hour, date value and day type were decided.

Then different forecasting models with several combinations of weather variables were prepared and tested. Simplest and well known ANN i.e. Multilayer Feed-Forward Network with back-propagation algorithm was used. Finally, from this research work, appropriate input variables were specified to forecast the next hour electric load for New Delhi region. The forecasting model, containing temperature and pressure as input weather variables was most appropriate one for the aforementioned region. The model without weather information was proved to be better than the models which were tested with the least correlated weather variables. So an important observation of this research work was that those weather variables were appropriate for accurate load forecast, which were highly correlated with load.

It would give better results if some other structures of ANN (i.e. RBF, ELMAN etc.) would be used with the combination of these input variables and to forecast the next hour electric load, on-line training may be preferred. So that after training of ANN once, data will be updated for each new hour and forecasting will be more accurate. Besides this, more accurate data should be arranged so that forecasting of electric load will be more accurate.

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