Short Term Load Forecasting using Artificial Neural Network

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Abstract- **Development of artificial neural network for short term load forecasting is presented in this paper. Load forecasting is the process for prediction of electric load. Accurate load forecasting affects the economic operation and reliability of system up to great extent. If the generation is not adequate to accomplish the demand, it will lead the problem of unbalanced supply and in case of surplus generation the generating company will have to bear loss .For the optimal power system operation and planning appropriate evaluation of present and future electric load is needed. Many electrical utilities are routinely forecasting load power based on conventional methods. However, since the relationship between load power and factors influencing load power is non-linear, it is difficult to identify its non- linearity by using conventional methods. To overcome these problems load forecasting method using Artificial Neural Network (ANN) with adaptive learning rate is being used in this paper. The ANN model was trained by Levenberg Marquardt. The data used for training is collected from Gwalior region of MPSEB. The model for short term load forecasting was design and implemented with MATLAB. The result was calculated by Mean Absolute Percentage Error (MAPE) of 3.329 for the forecasted day.**

Keywords: **Short term load forecasting, ANN, MLP, MAPE**

I. INTRODUCTION

Load forecasting is an essential and primary component in the operation of any electrical utility. For optimal power system operation, electrical generation must follow electrical load demand. The generation, transmission, and distribution utilities require some means to forecast the electrical load, so that they can utilize their electrical infrastructure efficiently. For the purpose of optimal planning and operation of an electrical power system, they need proper evaluation of present load and future load demand. Precise load forecasting is required for the electric utility to make unit commitment decision, energy transfer scheduling and load dispatch. Development of an accurate STLF system is important for both electric utility and its customers to introducing higher accuracy requirements. Load forecasting plays a key role in reducing the generation cost, besides this, it is also necessary for the reliability of power system. The motivation for accurate load forecast lies in the nature of electricity as a commodity and trading article; electricity cannot be stored, which means for an electrical utility the estimate of future load demand is necessary in managing the production and purchasing in an economically reasonable way. An accurate load forecasting can bring many benefits such as reliability of power line can be enhanced, if the load is kept at an optimal level through forecasting and optimal load scheduling; the cost for supplying peak power is higher than that for supplying the average power. A reduction in peak value of electricity demand can be achieved, if we can realize load forecasting. Short term load forecasting is required for unit commitment, energy transfer scheduling and load dispatch. To development of an accurate, fast and robust STLF methodology is of importance to both electric utility and its customers, thus introducing higher accuracy requirements. However, since the relationship between load power and factors influencing the load power is nonlinear, thus it is difficult to identify this nonlinearity by conventional methods. Computational intelligence techniques have also been developed [1].

II. LOAD FORECASTING

The aim of STLF is to forecast the future system load. Good understanding of the system characteristics helps to design reasonable forecasting models and select suitable models in different situations. Since in power systems the next day’s power generation must be scheduled every day, day ahead short term load forecasting (STLF) is a necessary daily task for power dispatch. Its accuracy affects the economic operation and reliability of the system greatly. Underestimations of STLF leads to insufficient reserve capacity preparation and, therefore, increase the operating cost by using expensive peaking units. On the other hand, Overestimation of STLF leads to the unnecessarily large reserve capacity, which also leads the higher operating cost.

A. Classification of Load Forecasting

Load forecasting is divided into many types, depending upon the time period for which forecasting is carried out. The time duration for the different load forecasting methods are given in the table shown below

TABLE I
TIME SPAN FOR LOAD FORECASTING METHOD

S.N.	Load forecasting method	Time span
1.	Very Short Term Load Forecasting	Few Sec. to Few min.
2.	Short Term Load Forecasting	Few Hour to Few days

3.	Mid Term Load Forecasting	Few weeks to few month
4.	Long Term Load Forecasting	Few month to few years
5.	Very long Term Load Forecasting	Few decades prior

B. Factors Affecting the Load Forecast

Following are some factors which should be considered, as they affect the short term load forecasting:

1) Weather: Weather conditions influence the load. In fact forecasted weather parameters are the most important factors in short term load forecasts. Weather includes various factors like temperature, humidity, wind speed, cloud cover, light intensity and so on. If change occur in these factors it will causes the change in consumer's comfort feeling and in turn the usages of some appliances like space heater, water heater and air conditioner. Temperature and humidity are the most commonly used load predictors.

2) Time: Time is also an important factor which affects the load curve. For some times in a day load curve is low and during the working hours of the day it will have high peak. The weekend or holiday curve is lower as compared to the weekday curve because of the drop off in the working load. Holidays are more difficult to forecast than non-holidays because of their relative irregular occurrence.

3) Customers: Most of the electric utilities have to serve different types of customers such as industrial, commercial, and residential. The pattern of usages of electric load is different for customers of the different classes [4].

Many methods have been used for the load forecasting in the past; they are based on various statistical methods like time series, regression, exponential smoothing, Box-Jenkins and so on. However, the statistical models provide physical transparency in interpretation of data and reasonable accuracy in STLF but there is problem of limited modelling and heavy computational effort are associated with this. So statistical methods are less preferable over intelligent techniques [3]. In recent years, research has converged towards the methods which are based on artificial intelligence such as fuzzy logic, expert system, artificial neural network. Among the AI methods, artificial neural network (ANN) is most widely used method due to its flexibility in data modelling.[3].

III.STATEMENT OF THE PROBLEM

In controlling and operation of an electric system, an electric power company has to face many economical and technical challenges, for the optimal planning and operation of an electric power system; they have proper evaluation of present and future load demand. Many methods have been proposed to solve the demanding task of STLF, but they have some drawbacks. This paper therefore, proposes a new method for STLF using ANN.

IV. ANN METHOD

Since the relationship between load and factors affecting the load is nonlinear, ANN is the most widely used method for forecasting for solving these non-linearity problems, due to its self-learning and self-organizing property. Artificial neural network seems to be a good alternative to statistical methods because of their ability to act as non-linear non-parametric estimators. An approach to the development of an artificial neural network for electric forecasting has been discussed in the present work. A multilayer feed forward network using sigmoid function as the activation function, back propagation algorithm as learning method with adaptive learning rate and mean squarer error as the measure of error is used in the present work The model has been trained and tested on actual load and weather data provided by the Gwalior region of Madhya Pradesh State Electricity Board and Indian Weather Department, Indian Republic.

In the present work a three layer feed-forward ANN model has been used with error back propagation with adaptive learning algorithm. To forecast the 24-hour output for a certain day, corresponding loads of the previous day, loads of 7 and 8 days prior to the forecast day were considered as potential inputs. The temperature data of the day to be forecast was also found helpful for training. In the present work maximum temperature, minimum temperature and average temperature is considered.

1. *Input Structure of ANN*

The performance of neural network is depends on the input parameters opt for training. The accuracy of neural network is greatly affected by these parameters. Therefore, selection of these parameters is a very important task. Following are the parameters used as input in the development of ANN model.

TABLE III
INPUT PARAMETERS

S.N.	Symbol	Description of symbol
1.	$L_{max}(i)$	Maximum load of the day(i)
2.	$L_{min}(i)$	Minimum load of the day(i)
3.	$L_{avg}(i)$	Average load of the day(i)
4.	$T_{max}(i)$	Maximum temperature of the day(i)
5.	$T_{min}(i)$	Minimum temperature of the day(i)
6.	$T_{avg}(i)$	Average temperature of the day(i)

V. METHODOLOGY

A. Data Collection and Preparation

In the present work to forecast the peak load of certain day, the maximum load of the previous day, minimum load of the previous day, maximum load of the corresponding day from the previous week was considered as potential input variable. Maximum, minimum and average temperature is of the corresponding days is also considered as the input. The model has been trained and tested on actual load and weather data provided by the Gwalior region of Madhya Pradesh State Electricity Board and Indian Weather Department, Indian Republic. ANN is trained with the load data of 300 days. The performance of the trained network was tested using unseen data of 30 days.

B. Data Pre-Processing

During the training of neural network, the higher valued input variables may tend to suppress the influence of the smaller once. To overcome this problem, the network has been trained with normalized data. The raw data are scaled in the range of 0.1-0.9. The normalization is done as

$$X_n = \frac{0.8(Xactual - Xmin)}{(Xmax - Xmin)} + 0.1$$

C. Network Training And Validation

After designing of network, next step is to train the network. Training of the ANN is an iterative process that has to do with adjusting of the connection weight. In past days Back Propagation algorithm for training feed- forward neural network is used but the drawback is that it takes very long time in training due to nature of gradient descent [5]. Many techniques have been used to improve the performance of back propagation. Levenberg Marquardt is used to train the neural network. After training of the network, new data that are not used in training are feed in the network to see whether it can predict well at these unseen data.

VI. RESULTS AND DISCUSSION

The data set is normalized before training and validation. Neural network parameters used in experiment, is summarized in table given below.

Network topology: Multi-layer feed forward neural network
Input variables: Maximum, minimum load of one day prior, maximum load of seven day prior, maximum, minimum and average temperature.
Number of hidden neuron: 35,30
Number of epoch–4
Training algorithm – Levenberg –Marquardt (trainlm)
Transfer function used in the hidden layer – sigmoid function
Transfer function used in the output layer - sigmoid function

A. Analysis Of Result

Fig.1 shows the behaviour of the network during training, testing and validation. This figure shows the mean absolute error (MAE) versus epoch.

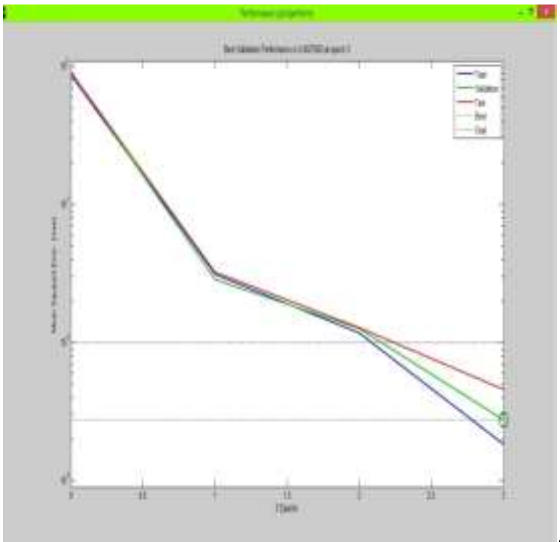

Fig.1: Performance Plot

Fig. 2 shows the closeness between the outputs and the target. Value of R=1 shows a perfect relation between target and output. From the regression plot R= 0.98328 for training, R=0.96952 for validation, R= 0.96443 for testing and R=0.97646 for all. This shows that the target and output values are very close. This means network predicted the output satisfactorily.

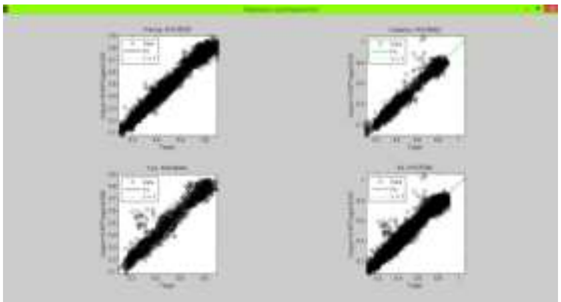

Fig.2: Regression Plot

Fig. 3 consists of three different graphs. The first plot is the learning function versus number of epochs. This shows the trend of the gradient values as the number of computational iterations increases. It is necessary in monitoring the manner in which the training progresses. The second plot is that of the learning rate (mu) against increasing number of epochs. This plot is essential in monitoring the rate at which the computed network error reduces during the progress of the training .The final plot here is that of the validation checks carried out automatically any time a sudden change is observed in the network gradient computation is carried out.

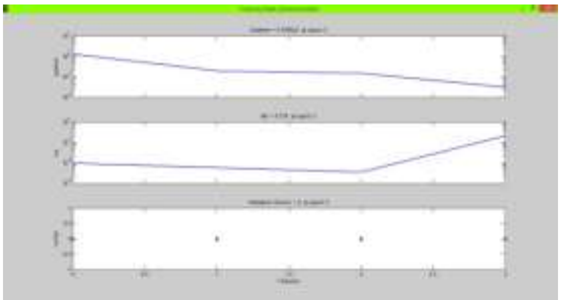

Fig.3: Training State Plot

A. *Result Evaluation*

Mean absolute error percentage error (MAPE) is used in the evaluation of the results and is defines as

$$\text{MAPE} = \left| \frac{\sum \frac{(\text{Actual Value} - \text{Predicted Value})}{\text{Actual Value}}}{\text{N}} \right| \times 100\%$$

The MAPE for the forecasting days is 3.329% and the historical load error is 4.176%

Calculation of error for the forecasted days can be calculated by the formula shown above. Error calculation for 24 hours of a sample day is shown in table III.

TABLE III

ERROR GENERATED FOR 24 HOURS

Hours	Error	Hours	Error
1	0.588	7	0.533
2	0.431	8	0.747
3	0.552	9	0.849
4	0.863	10	0.767
5	0.769	11	0.687
6	0.588	12	0.590
13	0.651	19	0.577
14	0.723	20	0.659
15	0.633	21	0.678
16	0.675	22	0.762
17	0.685	23	0.576
18	0.873	24	0.479

VII. CONCLUSION

In the proposed work, a multilayer feed-forward neural network with adaptive learning rate is used. The proposed ANN model with adaptive learning algorithm has been found to predict the next day peak load quite efficiently. For training, validation and testing of ANN, MATLAB.10 has been used. The result obtain from this work confirm the efficiency of ANN for STLF.

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