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Artificial Neural Network Based Approach for short load forecasting

Rajesh Deshmukh [1], Amita Mahor [2]
Department of Power Electronics, NRI Institute of Science and Technology Bhopal [1,2]

Abstract

Accurate models for electric power load forecasting are essential to the operation and planning of a power utility company. Load forecasting helps electric utility to make important decisions on trading of power, load switching, and infrastructure development. Load forecasts are extremely important for power utilizes ISOs, financial institutions, and other stakeholder of power sector. Short term load forecasting is a essential part of electric power system planning and operation forecasting made for unit commitment and security assessment, which have a direct impact on operational casts and system security. Conventional ANN based load forecasting method deal with 24 hour ahead load forecasting by using forecasted temp. This can lead to high forecasting errors in case of rapid temperature changes. This paper present a neural network based approach for short term load forecasting considering data for training, validation and testing of neural network.

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Load forecasting, neural network, short term, correlation analysis.

1. Introduction

Load forecasting has always been important for planning and operational decision conducted by utility companies. However, with the deregulation of the energy industries, load forecasting is even more important. With supply and demand fluctuating and the changes of weather conditions and energy prices increasing by a factor of ten or more during peak situations, load forecasting is vitally important for utilities. Short-term load forecasting can help to estimate load flows and to make decisions that can prevent overloading. Timely implementations of such decisions lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts. Load forecasting is also important for contract evaluations and evaluations of various sophisticated financial products on energy pricing offered by the market. In the deregulated economy, decisions on capital expenditures based on long-term forecasting are also more important than in a non-deregulated economy when rate increases could be justified by capital expenditure projects.

Load forecasts can be divided into three categories: short-term forecasts which are usually from one hour to one week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year. The forecasts for different time horizons are important for different operations within a utility company. The natures of these forecasts are different as well. For example, for a particular region, it is possible to predict the next day load with an accuracy of approximately 1-3%. However, it is impossible to predict the next year peak load with the similar accuracy since accurate long-term weather forecasts are not available. For the next year peak forecast, it is possible to provide the probability distribution of the load based on historical weather observations. It is also possible, according to the industry practice, to predict the so-called weather normalized load, which would take place for average annual peak weather conditions or worse than average peak weather conditions for a given area. Weather normalized load is the load calculated for the so-called normal weather conditions which are the average of the weather characteristics for the peak historical loads over a certain period of time. The duration of this period varies from one utility to another.

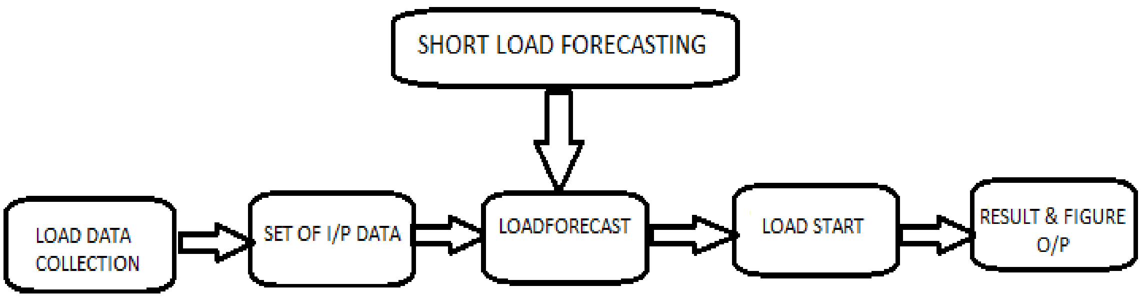


Fig.1 Short term load forecasting system

a) Load Data Collection

The historical load data and real time load data of May 2011 are obtained from state load dispatch centre Jabalpur.

b) Set of input data

Using pattern recognition theory, the data that their values are highly similar to that of predicting data are chosen as parameters and Ann's input sets. The parameters can be influenced by some kind of factors, such as temperature, humidity and day types etc. Particular time, day and week are taken as input sets.

c) Load Forecast

The two layered feed-forward artificial neural network which has the feature of memory and learning is constructed and Back Propagation learning algorithm is used to obtain load forecasting value. The load parameter setting is chosen to set load forecasting error limit and the like.

d) Load start

The maximum load, minimum load and average load in one day can be added up in this part.

2. Back Propagation Learning Algorithm

Back propagation is a systematic method for training multi-layer artificial neural network. It has a mathematical foundation that is strong if not highly practical. It is a multi-layer forward network using extend gradient based delta learning rule, commonly known as back propagation rule. BP neural network topological structure is shown in Fig. in which *V ij* is the weight between input layers and hidden layers and *Wjk* is the weight between hidden layers and output layers. V_{oj} is the bias of hidden layers and W_{ok} is the bias of output layers.

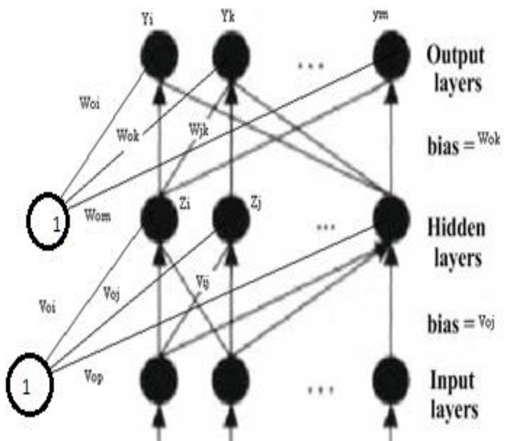


Fig.2 Back propagation neural network structure

In the above structure Xi is the input signal, Zj is the hidden layer and Yk is the output layer. The pattern recognition theory is disposed as following.

1. The value of X1 is transferred to input layers and new activated value is produced in hidden Layers.

$Z_{-inj} = V_{oj} + \sum_{i=1}^{n} X_i V_{ij}$

2. Calculate the activated value of output layer.

$Y_{-ink} = W_{ok} + \sum_{j=1}^{p} Z_j . W_{jk}$

3. Calculate the errors of output layers.

$\delta_k = (t_k - y_k)\, f(Y_{-ink})$

4. Calculate the errors of hidden layers according to errors of output layers

$\delta_{-inj} = \sum_{k=1}^{m} \delta_j W_{jk}$

5. Adjust weight between hidden layers and output layers.

$\Delta W_{jk} = \alpha\, \delta_k Z_j$ where α is learning rate between 0 to 1

6. Adjust weight between input layer and hidden layers.

$\Delta V_{ij} = \alpha\, \delta_j X_j$

7. Adjust weight of output layers.

$\Delta W_{ok} = \alpha\, \delta_k$

8. Adjust bias of hidden layers.

$\Delta V_{oj} = \alpha\, \delta_j$

Repeat above steps **until** δ_k reaches to rather small or to zero. The chosen data according to pattern recognition theory have high similitude degree. This can not only reduce the number of input neurons and hidden layer neurons, and then simplify learning algorithm, but also minis the rate of converging to local minimum and reduce the training.

3. Applications

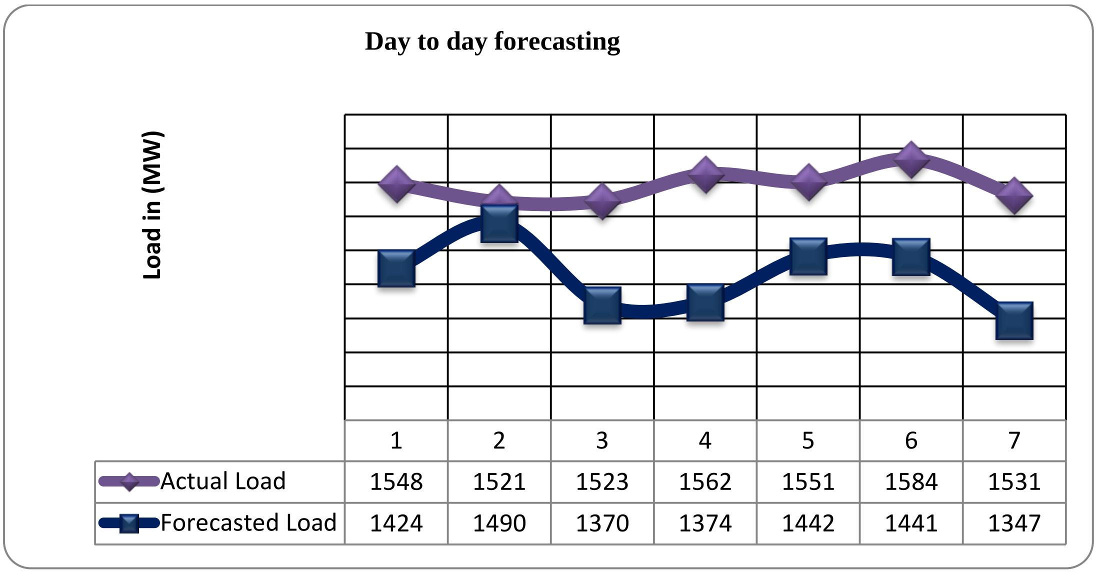
1. Adaptive learning**:** An ability to learn how to do tasks based on the data given for training or initial experience.
2. Self-Organization**:** An ANN can create its own organization or representation of the information it receives during learning time.
3. Real Time Operation**:** ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability.

4. Proposed work

The main purpose of the proposed work is to investigate application of various computational intelligence methods for short term load forecasting. Short term forecasting (STLF) using neural structures i.e. multilayer's neural network (MLNN) and back propagation training algorithm was discusses and their suitability for STLF was investigated.

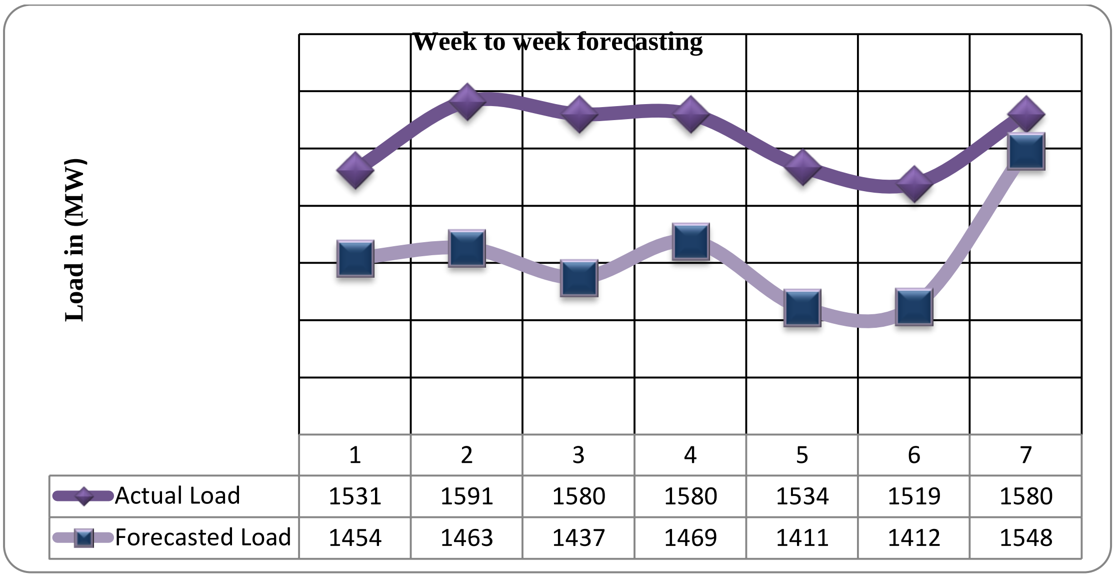
5. Results

The results obtained from testing the trained artificial neural network on data for 24 hours of a day over a one-week period are presented below in graphical form. Each graph shows a plot of both the predicted and actual load in MW values against the hour of the day. The mean of accuracy between the predicted and actual loads for day to next day 92.12%, week to next week 93.16% and hole day divided in to three intervals for 1:00 am to 8:00 am is 93.05%, 9:00 am to 16:00 pm is 93.18% and 17:00 pm to 24:00 am is 92.12% has been calculated and presented in the table. This represents a high degree of accuracy in the ability of neural networks to forecast electric load.



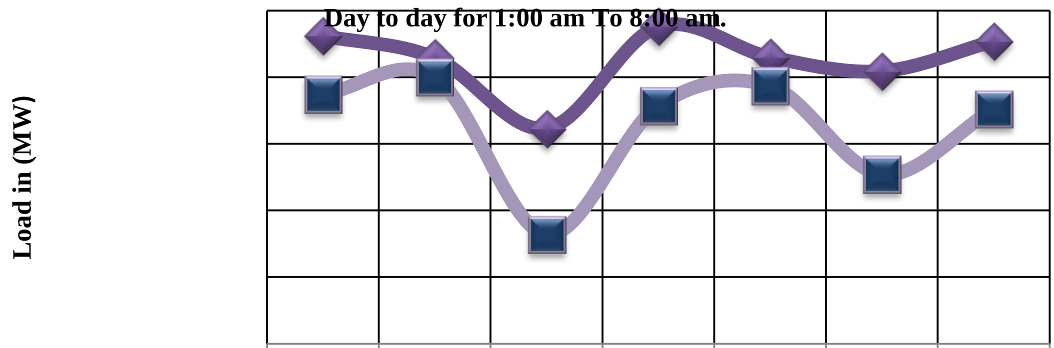
	1	2	3	4	5	6	7
Actual Load	1548	1521	1523	1562	1551	1584	1531
Forecasted Load	1424	1490	1370	1374	1442	1441	1347

Fig.3 Day to day forecasting of May 02.05.2011 to 08.05.2011



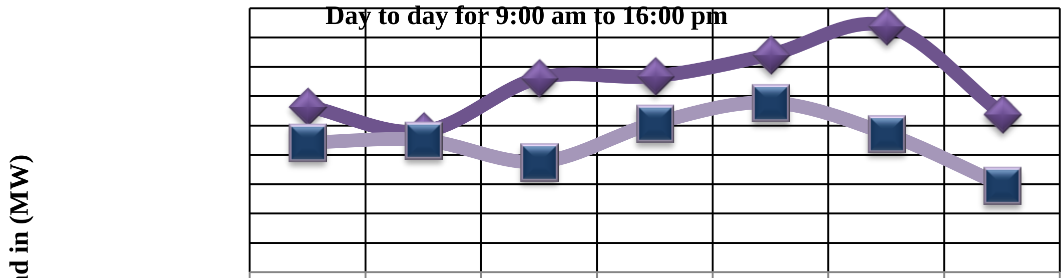
	1	2	3	4	5	6	7
Actual Load	1531	1591	1580	1580	1534	1519	1580
Forecasted Load	1454	1463	1437	1469	1411	1412	1548

Fig.4 Week to week forecasting of May 01.05.2011 to 14..05.2011



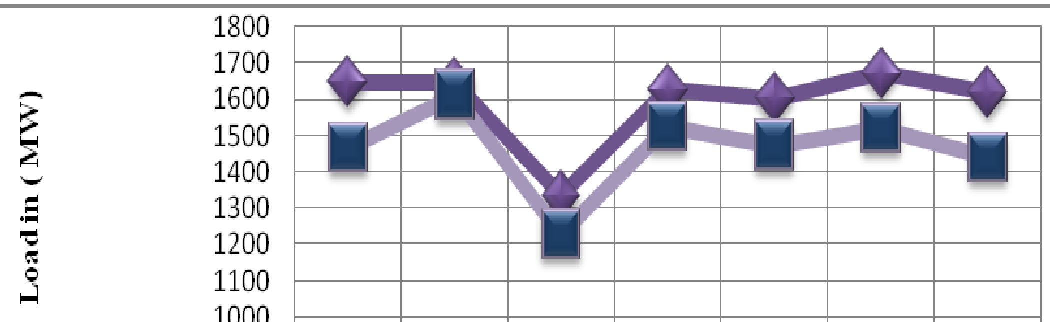
	1	2	3	4	5	6	7
Actual Load	1462	1429	1323	1476	1430	1409	1454
Forecasted Load	1374	1400	1164	1357	1387	1254	1352

Fig.5 Day to day forecasting for time 1.00am to 8.00 am. of May 02.05.2011 to 07.05.2011



	1	2	3	4	5	6	7
Actual Load	1533	1490	1581	1584	1621	1670	1520
Forecasted load	1471	1475	1438	1504	1539	1486	1398

Fig.6 Day to day forecasting for time 9.00am to 16.00 pm. of May 02.05.2011 to 07.05.2011



	1	2	3	4	5	6	7
Actual Load	1648	1645	1335	1627	1602	1672	1619
Forecasted Load	1466	1612	1227	1523	1473	1521	1441

Fig.7 Day to day forecasting for time 17.00pm to 24.00 am. of May 02.05.2011 to 07.05.2011

Table 1: Table of average results

Mode of forecasting	Accuracy in Percentage
Day to day forecasting Week to week forecasting	92.3% 93.3%
Day to day forecasting for time 1:00 am to 8:00 am.	93.05%
Day to day forecasting for time 9:00 am to 16:00 pm.	93.81%
Day to day forecasting for time 17:00 pm to 24:00 am.	91.57%

6. Conclusion

The result of MLP network model used for days, week and particular time of the day, short term load forecast for the west zone region shows that MLP network has a good performance and reasonable prediction accuracy was achieved for this model. Its forecasting reliabilities were evaluated by computing the mean accuracy between the exact and predicted values. We were able to obtain a high degree of accuracy.

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