International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 2 Issue 9, September - 2013

Weather Sensitive Short Term Load Forecasting using fully connected Feed Forward Neural Network

Richa Mantri
VJTI, Mumbai

H.A. Mangalvedhekar
VJTI, Mumbai

Pragati Gupta
VJTI, Mumbai

Abstract

A short-term electric load forecasting method using Feed Forward Back Propagation (FFBP) is proposed in this paper. Feed Forward Back Propagation has been proven to have robust abilities in modelling and predicting time series. Experiments are conducted on load data provided by RInfra Mumbai. The forecasted result is then compared to actual data for validation.

1. Introduction

Electric load forecasting plays a very important role in many operating decisions for power systems such as optimum generating unit commitment, economical load dispatch, need to maintain scheduling and fuel constraints. However load forecasting is difficult and challenging problem because of the variability and nonstationarity of load data. Therefore, the developments of accurate load forecasting models receive a considerable attention from many researchers.

In recent years, a wide variety of techniques have been proposed for the load forecasting problem. Weron[1] presents in depth review of different statistical tools used for electricity load and price forecasting. In [2], ARIMA is used with ANN to identify a combined forecasting model for electricity loads. Many electric power companies have adopted conventional prediction methods for load forecasting. However, these methods cannot represent the complex nonlinear relationships that exist between the load and series of factors that influences it [3]. Recently, artificial neural networks (ANN) have been successfully applied to short-term load forecasting [4].

The main objective of this paper is to propose a neural network model for predicting the future power demand. This includes:

- Training of the model (using back propagation algorithm) so that each input produces a desired output.
- Testing of the developed model to get the values of future power demand.

2. Artificial neural network

Neural network techniques are black-box modelling techniques. That is, they require no understanding of the physical process underlying the data [5]. An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous system, such as brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems.

Multilayer feed forward neural networks, as universal approximation machines, are very suitable for load forecasting because they have remarkable ability to approximate nonlinear functions with any desired accuracy. Selection of the input-output training data and input vector of the neural network play a crucial role [6].

3.Feed forward neural networks

In a typical feed forward neural network, also known as a Multi-Layer Perceptron (MLP), the neurons are arranged in layers. The network has N inputs which are first fed into a layer of neurons called hidden layer. The output of hidden layer is fed forward to the final layer of neurons called the output layer.

3.1. Training algorithm

The most common training algorithm used for the MLP is called the Back Propagation (BP) algorithm. This algorithm can be implemented in several steps [7]:

The training data (previous inputs and associated known outputs or targets) are presented to the network,

- The error between the network outputs and the targets is calculated,
- The error is used to estimate the derivatives of the weights and biases with respect to the errors,

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 2 Issue 9, September - 2013

- The weights are adjusted, using the derivatives, in the direction of fastest decent of the errors.
- The whole process is repeated until the error has reached a desired level or maximum number of epochs has been exceeded.
- Both the desired error level and maximum number of epochs are user defined.

4. Forecasting procedure

This section includes 4.1 actual data, 4.2 input data and 4.3data processing.

4.1. Actual data

The data used in model are the historical load data on 15 minutes interval from April 2012 through June 2012. Figure 1 shows the comparison between loads of different weekdays.

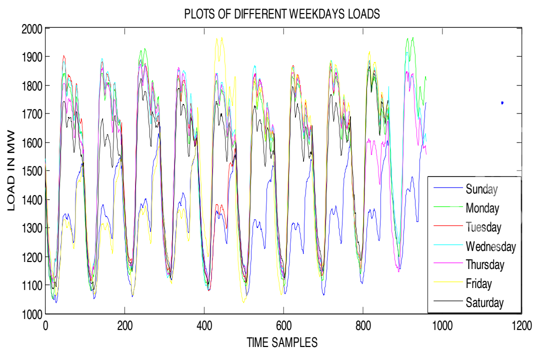

Figure1.Comparison between loads of different weekdays

4.2. Input data

For the forecasting model Sunday, Wednesday and Friday is chosen. The inputs used in model are the historic data for Sundays, Wednesdays and Fridays of each week on 15 minutes interval from April 2012 through June 2012. This historic data include load, temperature and humidity. The data set is divided into two parts. The first part is used to construct the forecasting model, while the next part is used to evaluate the forecasting process.

4.3. Data processing

Pre-processing of dataset is performed prior to training and testing. Input/output dataset was normalized to lie between -1 and 1. Normalized dataset was divided into training and testing datasets.

5. Results

In neural network the architecture and training are determined using back propagation approach. Several attempts were made until the proper number of hidden layers and numbers of neurons in a hidden layer were reached. The resultant number of neurons in a hidden layer for load forecasting that produces minimal MAPE error in both training and testing is 10.
The proposed network structure has an input layer composed of 20 neurons, a hidden layer of 10 neurons and an output layer with one neuron. The network is implemented using MATLAB neural network toolbox.

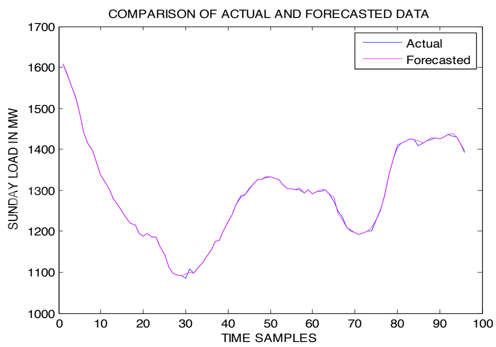

Figure2.Forecasted load for Sunday

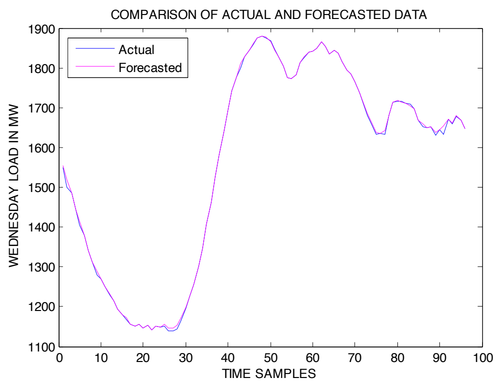

Figure3. Forecasted load for Wednesday

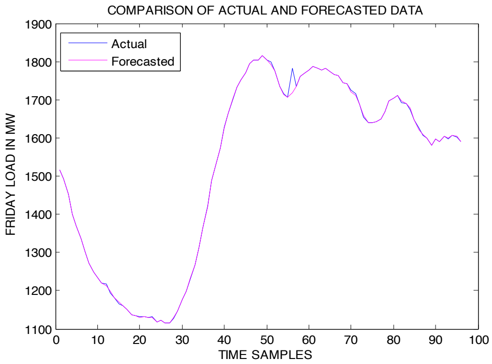

Figure4. Forecasted load for Friday

Table 1 shows the performance indices.

Table 1. Forecasting performance indices

WEEKDAY	RMSE	MAPE
Sunday	8.635	.417
Wednesday	9.527	.534
Friday	10.362	.792

6. Conclusion

The modelling and design of neural network architecture for load forecasting purposes is investigated in this research paper and is successfully implemented. The results, shown in the section 5 (Figures 2-4), show the effectiveness of the developed method. The neural network is able to establish the nonlinear relationship of the load with the historical data supplied while training and simulation phase of the network.

7. References

[1] R. Weron, *Modeling and Forecasting Electric Loads and Prices: A Statistical Approach,* 2006.
[2] J.C. Lu, D. X. Niu, and Z. Y. Jia," A Study of Short-Term Load Forecasting based on ARIMA-ANN," *in Proc. 2004 International Conference on Machine Learning and Cybernetics,* Vol. 5, pp. 3183 – 3187.
[3] Irisarri, G.D., Widergren, S.E. Yehsakul, P.D," Online load forecasting for energy control centre application*, IEEE Transactions on Power Apparatus and Systems,PAS*101, 1971, pp. 900-911
[4] Sanjib Mishra, "Short Term Load Forecasting Using Computational Intelligence methods", *Master's thesis, National Institute of Technology Rourkela,* 2008
[5] Aussem, A., 1999, Dynamical recurrent neural networks towards prediction and modelling ofdynamical systems, *Neurocomputing, 28, 207-232.*
[6] A.A. Rasool, A.A. Fttah, I.B.Sadik ,"Short Term Load Forecasting for Erbil Distribution System Using ANN and Wavelet Transform",*International Journal of Computer and Electrical Engineering,* Vol. 1, No. 3, August 2009
[7] Chihocki, A., Unbehauen, R., 1993, *Neural networks for optimisation and signal processing,* JohnWiley and sons