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Short- Term Load Forecasting Using Artificial Neural Network Techniques

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ABSTRACT
This paper proposes a neural network approach for forecasting short- term loads. Three ANN- techniques – Radial Basis Function Neural Network, Feed forward Neural Network and Cascade- Forward Neural Network are discussed in this paper. Their performances are evaluated through a simulation study. Historical Load Data from the Load Dispatch Centre Jabalpur are used for training, testing and showing the good performance of the proposed method. The proposed model can forecast the load profile with a lead time of one to seven days.
Keywords- Artificial Intelligence, Artificial Neural Network, Back-Propagation, Load Forecasting, Power Quality.

I. INTRODUCTION

Load Forecasting is an important component for power system energy management system. Load forecasting means predicting the future load with the help of historical load data available. It is very important for the planning, operation and control of power system. It plays a vital role in the deregulated electric industry [1].

A good forecast reflects current and future trends in the power system. The accuracy of a forecast is crucial to any electric utility. That is why, accurate models for load forecasting are essential for the operation and planning of a utility company [2].

Since in power system 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 [3].

Short- term load forecasts helps in estimating the load flows. This helps in making decisions that can prevent overloading and the result deeply influence the power systems' safety and economy [4].

The short- term forecasts are not only needed for control and scheduling of power system but also used as inputs to load flow study or contingency analysis i.e. for load management program. The short term forecasting is also primarily used for the generation dispatch, capacitor switching, feeder reconfiguration, voltage control, and automatic generation control (AGC) [5].

A little increase in the percentages of short-term prediction accuracy may bring many benefits in terms of economy and reliability of power system. Therefore, precise short- term load forecasting not only enhances the reliability of power supply but also increases economic benefits [6].

The research work in this area is still a challenge to the electrical engineering scholars because of its high complexity. How to estimate the future load with the historical data has remained a difficulty up to now, especially for the load forecasting of holidays, days with extreme weather and other anomalous days. But with the recent development of new mathematical and artificial intelligence tools, it is potentially possible to improve the forecasting results [7].

Load Forecasting can be performed using many techniques such as similar day approach, various regression models, time series, statistical methods, fuzzy logic, artificial neural networks, expert systems, etc. But application of artificial neural network in the areas of forecasting has made it possible to overcome the limitations of the other methods mentioned above used for electrical load forecasting [8].

II. ARTIFICIAL NEURAL NETWORK

Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting. The outputs of an artificial neural network are some linear or non-linear mathematical function of its inputs [9].

ANN is usually formed from many hundreds or thousands of simple processing units, connected in parallel and feeding forward in several layers. Because of the fast and inexpensive personal computers availability, the interest in ANN's has blossomed in the current digital world. The basic motive of the development of the ANN is to make the computers do what a human being cannot do. The three-layer fully connected feed-forward neural network which is generally used for load forecasting. It comprises of an input layer, one hidden layer and an output layer. Signal system is allowed only from the input layer to the hidden layer and from the hidden layer to the output layer. Input variables come from historical data, which are date, hour of the day, past system load, temperature and humidity, corresponding tothe factors that affect the load. The outputs are the forecasting results. The number of inputs, the number of hidden nodes, transfer functions, scaling schemes, and training methods affect the forecasting performance and, hence, need to be chosen carefully [10].

In applying a neural network to load forecasting, one must select one of a number of architectures (e.g. Hopfield, back propagation, Boltzmann machine), the number and connectivity of layers and elements, use of bi-directional or uni-directional links and the number format (e.g. binary or continuous) to be used by inputs and outputs.

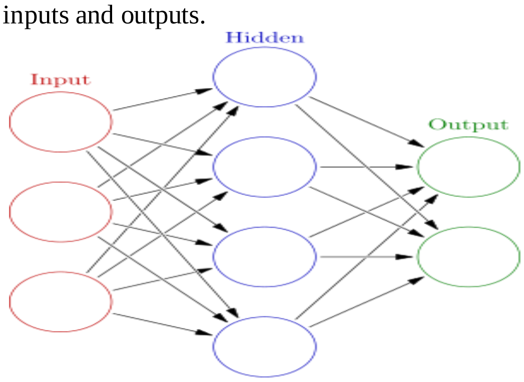

Figure 1: Structure of ANN

This is the structure of ANN. There are three layers namely, input layer, hidden layer and output layer.

III. NEURAL NETWORK TRAINING AND TESTING

In this section three types of neural network architectures are presented for short term load forecasting.

1. Radial Basis Function Network

A radial basis function network is an artificial neural network that uses radial basis functions as activation functions. Radial basis function (RBF) networks typically have three layers: an input layer, a hidden layer with a non-linear RBF activation function and a linear output layer.

The diagram below shows the radial basis function neural network architecture with input x and output y. The weights are so adjusted to give the targeted output as needed by the system.

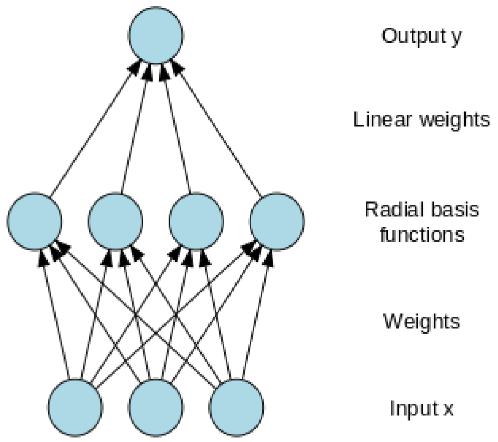

Figure 2: Architecture of Radial Basis Function Network

The input of a RBF network can be modelled as a vector of real numbers $\mathbf{x} \in \mathbb{R}^n$. The output of the network is then a scalar function of the input vector, $\varphi : \mathbb{R}^n \to \mathbb{R}$, and is given by

$$\varphi(\mathbf{x}) = \sum_{i=1}^{N} a_i \rho(||\mathbf{x} - \mathbf{c}_i||)$$

Also,

$$\rho\big(\,\|\mathbf{x} - \mathbf{c}_i\|\,\big) = \exp\left[-\beta\,\|\mathbf{x} - \mathbf{c}_i\|^2\right]$$

And,

$$\lim_{||x||\to\infty} \rho(\|\mathbf{x} - \mathbf{c}_i\|) = 0$$

Where,

N = the number of neurons in the hidden layer
$\mathbf{c}_i$=the center vector for neuron *i*
a_i= the weight of neuron *i* in the linear output neuron.

The parameters a_i, $\mathbf{c}_i$, β_i are determined in a manner that optimizes the fit between φ and the data [11].

2. Feed forward back-propagation (FB) Neural Network

Feed-forward BP Network consists of input, hidden and output layers. In a feed forward network information always moves in one direction; it never goes backwards. Back-propagation learning algorithm was used for training these networks. During training, calculations are carried out from input layer towards the output layer, and error values are fed back to the previous layer [12]. The most popular artificial neural network architecture for load forecasting is back propagation. This network uses continuously valued functions and supervised learning. That is, under supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to desired outputs (such as historical loads).

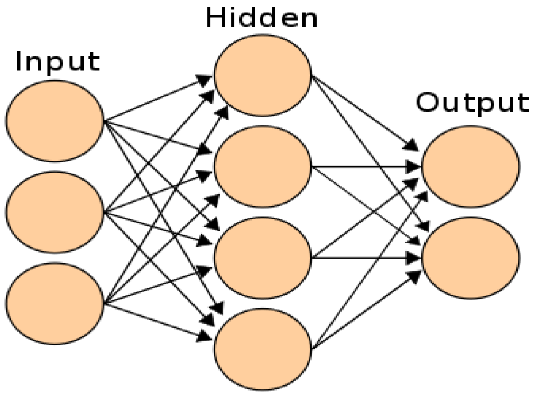

Figure 3: Architecture of Feed forward Back-Propagation Network

Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors. The linear output layer lets the network produce values outside the range –1 to +1. On the other hand, outputs of a network such as between 0 and 1 are produced, then the output layer should use a sigmoid transfer function (tansig) [13].

3. Cascade Forward Back propagation Network

Cascade forward back propagation model is similar to feed-forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. While two- layer feed-forward networks can potentially learn virtually any input-output relationship, feed-forward networks with more layers might learn complex relationships more quickly. The function newcf creates cascade-forward networks .

Cascade forward back propagation ANN model is similar to feed forward back propagation neural network in using the back propagation algorithm for weights updating, but the main nature of this network is that each layer of neurons is related to all previous layer of neurons. For example, a three layer network has connections from layer 1 to layer 2, layer 2 to layer 3, and layer 1 to layer 3. The three-layer network also has connections from the input to all three layers [12].

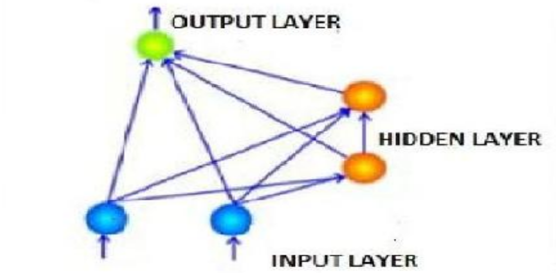

Figure 4: Architecture of Cascade forward Back-Propagation Network

Tan-sigmoid transfer function was used to reach the optimized status. The performance of cascade forward back propagation and feed forward back propagation were evaluated using Mean Square Error (MSE) [13].

$$MSE = \left(\frac{1}{n}\right) \sum_{i=1}^{n} (observed - predicted)2$$

IV. RESULTS AND DISCUSSIONS

The acceptable criteria for a particular model is based upon the

i. Mean Square Error (MSE)
ii. Training Time
iii. Detection Time

1. Performance of RBF Network

Training with RBF network for 98 epochs taking goal=0.01 and spread=1 gives good performance in terms of MSE(mean square error) equal to 1.62.

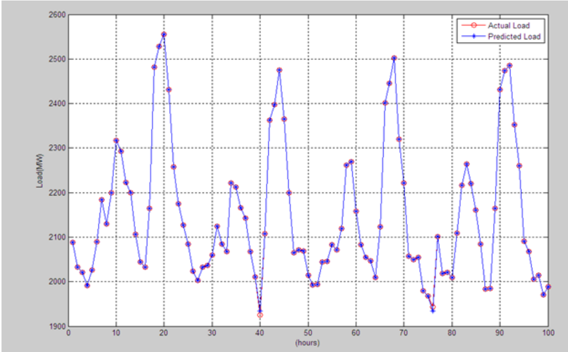

Figure 5: Performance of RBF Neural Network

Here MSE= 1.62, Training Time= 1.5744 and Detection Time= 0.0175.

2. Performance of FBPNN

For different numbers of neurons the system has been trained and tested but the exact forecast is obtained for 12,12 neurons.

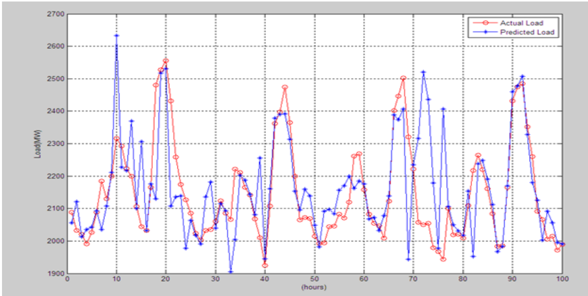

Figure 6: Performance of FBPNN

Here MSE= 1.7032e+004, Training Time= 2.4981 and Detection Time= 0.0206.

3. Performance of Cascade Forward BP Network

For different numbers of neurons the system has been trained and tested but we get the exact forecast for 15, 15 neurons.

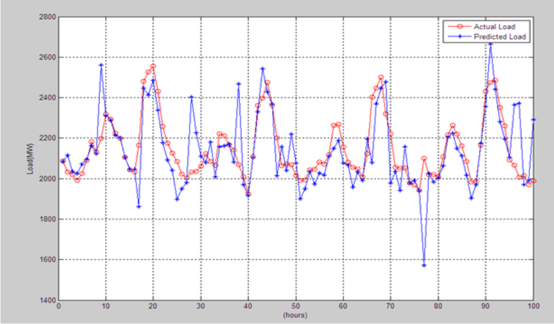

Figure 7: Performance of CF-BP Network

Here MSE = 3.2392e+004, Training Time = 15.5890 and Detection Time = 0.0254.

V. CONCLUSIONS

The result of the three neural network models (RBFNN, FFBPNN, CFBPNN) used for short term load forecast for Jabalpur region, shows that the networks has good performances and accurate prediction is achieved. Its forecasting reliabilities were evaluated by computing the mean square error (MSE) between the exact and predicted values.

The results suggest that ANN model with the developed structure can perform good prediction with least error and finally this neural network could be an important tool for short term load forecasting as well as this work incorporates additional information such as Hour of the Day, Days of the month, and different weather conditions into the network so as to obtain a more representative forecast of future load.

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