SHORT-TERM LOAD FORECAST OF A LOW LOADFACTOR POWER SYSTEM FOR OPTIMIZATION OF MERIT ORDER DISPATCH USING ADAPTIVE LEARNING ALGORITHM

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Abstract

Short term load forecasting is one of the key inputs to optimize the management of power system. Almost 60-65% of revenue expenditure of a distribution company is against power purchase. Cost of power depends on source of power. Hence any optimization strategy involves optimization in scheduling power from various sources. As the scheduling involves many technical and commercial considerations and constraints, the efficiency in scheduling depends on the accuracy of load forecast.

Load forecasting is a topic much visited in research world and a number of papers using different techniques are already presented. The accuracy of forecast for the purpose of merit order dispatch decisions depends on the extent of the permissible variation in generation limits. For a system with low load factor, the peak and the off peak trough are prominent and the forecast should be able to identify these points to more accuracy rather than minimizing the error in the energy content. In this paper an attempt is made to apply Artificial Neural Network (ANN) with supervised learning based approach to make short term load forecasting for a power system with comparatively low load factor. Such power systems are usual in tropical areas with concentrated rainy season for a considerable period of the year.

Introduction

A large variety of mathematical methods and ideas have been used for load forecasting. Different forecasting methods are used for short-term load forecasting which include statistical techniques like regression and artificial intelligence algorithms such as neural networks, fuzzy logic, expert systems etc. [1]. Some of the methods which include the similar day approach, various regression models, time series, statistical learning algorithms, fuzzy logic and expert systems have been developed for short-term forecasting. The accuracy of load forecasting depends not only on load forecasting techniques but also on the accuracy of forecasted weather scenarios [2]. .Usually such methods minimize the error on the integral of the predicted demand, i.e. the energy difference between the forecast and actual.

Load forecasting for the purpose of merit order dispatch require more accuracy on the determination of the peak cliff and off peak trough. Another point to be noted is that the determined values shall have positive error preferably as the management of the power system with a deficit condition is not desirable. The overall error optimization may miss o ut these extremes especially are power systems having low load factor [3]. The error in projection will not affect the operation strategy of the load factor as the error can be accommodated within the operational margin of generations.

Factors Affecting Short Term Load Forecasting

For short term load forecasting (STLF) several factors to be considered, such as time factors, weather data, social factors, festivities, political factors, specialty of the day such as major cricket matches, sports events etc. and the customer profile.[4] The time factors include the period of the year deciding the climatic conditions, the day of the week and the hour of the day. There are significant differences in load between week days and weekends. The load on different weekdays also behaves differently.

Modelling

For studying the short term load forecasting of a low load factor system, Kerala power system was chosen. The system load factor is around 75% with variation in the range of 65% to 80% on seasonal basis. The system has fairly good hydel capacity which contributes to about 50% on peaking basis and 35% on energy basis. The pronounced peak and off peak indicate lack of sufficient base load. Kerala power system is inherently equipped to meet the high peak demand, but the efficiency of operation calls for the right mix of thermal and hydel generation, for which the short term load forecast is to be essentially near accurate and with positive error on the peak demand projection.

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Methodology

Several techniques are available for load forecasting and selection of method is important as the prediction is by and large heuristic for short term forecast. The historical data is available, but the information is corrupted on some days or even for some part of the year due to the imposition of load restrictions and demand side interventions. The method adopted in this paper takes care of such corruption of data in the processing by ANN.

Artificial Neural Network

A neural network is a machine that is designed to model the way in which the brain performs a particular task. The network is implemented by using electronic components or is simulated in software on a digital computer. A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects:

Knowledge is acquired by the network from its environment through a learning process.

Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge.

The procedure used to perform the learning process is called a learning algorithm, the function of which is to modify the synaptic weights of the network in an orderly fashion to attain a desired design objective[5].

Mathematical model of A Neuron

A neuron is an information processing unit that is fundamental to the operation of a neural network. The three basic elements of the neuron model are:

A set of weights, each of which is characterized by a strength of its own. A signal xj connected to neuron k is multiplied by the weight wkj. The weight of an artificial neuron may lie in a range that includes negative as well as positive values.

An adder for summing the input signals, weighted by the respective weights of the neuron.

An activation function for limiting the amplitude of the output of a neuron. It is also referred to as squashing function which squashes the amplitude range of the output signal to some finite value.

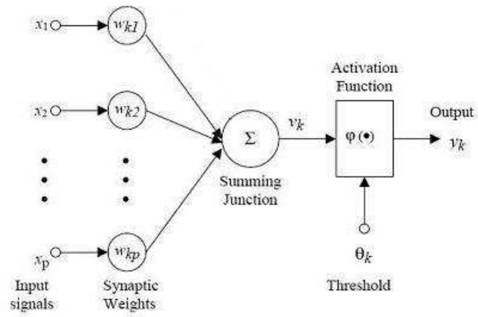

Fig (1) Model of an ANN

$$v(k)=\sum_{j=1}^{p} w_{kj}x_j \text{ and } y(k)=\phi(v_k+\theta_k)$$

In calculating the output of the neuron, the activation function may be in the form of a threshold function, in which the output of the neuron is +1 if a threshold level is reached and 0 otherwise. The various activation functions like squashing, hyperbolic tangent, sigmoid etc. can be used. Squashing functions limit the linear output between a maximum and minimum value. Hyperbolic tangents and the sigmoid functions are similar to real neural responses; however, the hyperbolic tangent is unbounded and hard to implement in hardware.The artificial neural network is made up of seven major components.

These components are summarized as:-

- Weighting Factors
- Summation Function
- Transfer Function / Activation Function
- Scaling and Limiting
- Output Function
- Error Function and Back-propagated Value
- Learning Function

Overview of Back propagation Algorithm

The back propagation network is a kind of multilayer feed forward network, and the transfer function within the network is usually a nonlinear function such as the sigmoid function. Neural Networks are widely used for load forecasting, Fault diagnosis/Fault location, Economic load dispatch and Security assessment etc in the field of power systems .The topology of back propagation network can be of 3-layers or 4-layers, the transfer function can be linear, nonlinear or a combination of both. Also, the network can be either fully connected or non-fully connected. The back propagation network structure is problem dependent, and a structure that is suitable for a given power system is not necessarily suitable for another. The typical back propagation network structure for short term load forecasting is a three-layer network, with the nonlinear sigmoid function as the transfer function [5]-[10].

In addition to the typical sigmoid function, a linear transfer function from the input layer directly to the output layer was proposed in [11] to account for linear components of the load. Because fully connected back propagation networks need more training time a non-fully connected back propagation model is proposed in [12].

Back Propagation Algorithm

Step 0: Initialize the weights (Set to small random values)

Step 1: While stopping condition is a false, do step 2-9

Step 2: For each training pair, do steps 3-8 feed forward

Step 3: Each input unit (x_i, i =1, 2….n) receives input signal x_i and broadcasts this signal to all units in the layer above (the hidden units).Step 4: Each hidden unit (Z_j, j =1, 2 …p).sum its weighted input signals.

$$Z\_in_j = v_{oj} + \sum_{i=1}^{n} x_i v_{ij}$$

Applies its activation function to compute its output signal

$$Z_j = f(z\_in_j)$$

and sends this signal to all units in the layer above (output units).

Step 5: Each output unit (Y_k, k=1, 2 ……m) sum its weighted input signals.

$$Y\_in_k = w_{ok} + \sum_{j=1}^{p} z_j w_{jk}$$

and applies its activation function to compute its output signals.

$$Y_k = f(y\_in_k)$$

Back propagation of error:

Step 6: Each output unit (Y_k , k=1, 2 ……m) receives a target pattern corresponding to the input training pattern, computes its error information term,

$$\delta_k = (t_k - y_k)\, f'(y\_in_k)$$

Calculates its weight correction term (used to update w_{jk} later)

$$\Delta w_{jk} = \alpha\, \delta_k z_j ,$$

Calculates its bias correction term (used to update w_{ok} later)

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

and sends δ_k to units in the layer below.

Step 7: Each hidden unit (z_j, j =1, 2 …) Sum its delta inputs (from units) in the layer above.

$$\delta - in_j = \sum_{k=1}^{m} \delta_k w_{jk}$$

Multiplies by the derivation of its activation function to calculate its error information term,

$$\delta_j = \delta\_in_j\, (f'z\_in_j)$$

Calculates its weight correction term (used to update v_{ij} later),

$$\Delta v_{ij} = \alpha\, \delta_j x_i$$

And calculates its bias correction term (used to update v_{oj} later)

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

Update weights and biases

Step8. Each output unit (y_k, k=1……m) updates its biases and weights (j = o …p) $_{jk}$ (new) = w_{jk} (old) + Δw_{jk}.

Each hidden unit (z_j, j =1…p) updates its bias and weights (i= o ,…… n);

$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij}$$

Flow Chart

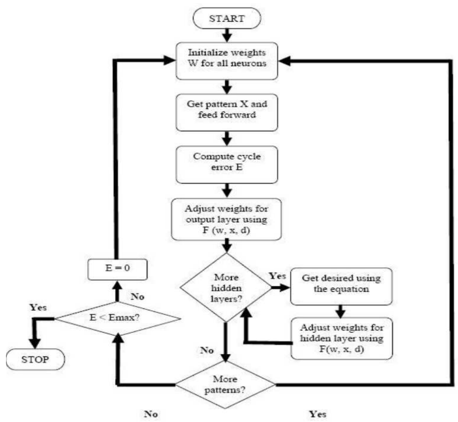

Fig (2) Flowchart showing working of BPA

The ANN architecture consists of three layers: an input layer, a hidden layer, and an output layer. Neurons in different layers are connected by the interconnecting weights W kj and the output from each neuron is multiplied by its corresponding weight before reaching the inputs of the neurons in the next layer. Each neuron consists of an activation function which is used to determine the output of the neuron from its inputs. All inputs to each hidden layer neuron are summed to make an activation function for the neuron. Likewise, the sum of all inputs to each output neuron makes the neuron activation function. For each neuron k in the hidden layer and neuron l in the output layer, the net inputs are computed as the weighted sum of all the inputs of that neuron. The training set for the ANN of any corresponding class i.e., the hourly data whose membership values of the corresponding temperature, humidity and day type categories are not zero.

Data analysis

The data collected was analysed in detail and classified. Following observations are made.

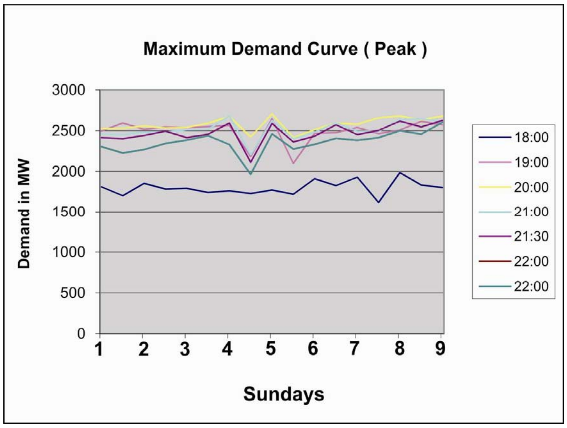

Fig (3) Maximum demand pattern – Holidays and other curves

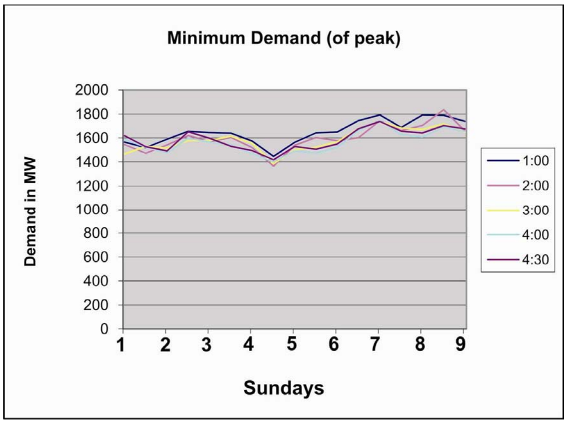

Fig (4) Minimum demand – Holidays

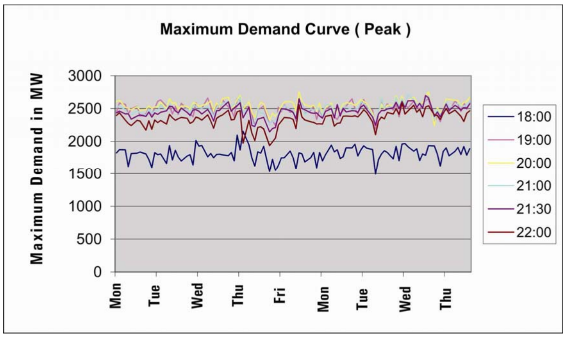

Fig (5) Maximum demand - Weekdays

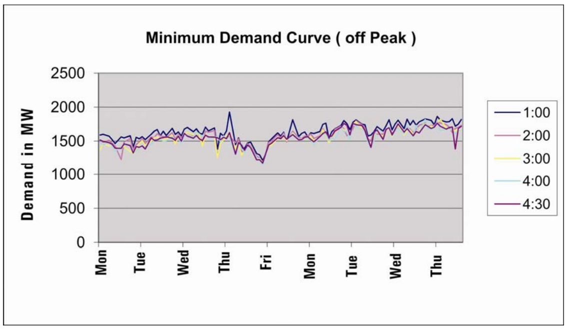

Fig (6) Minimum Demand weekdays

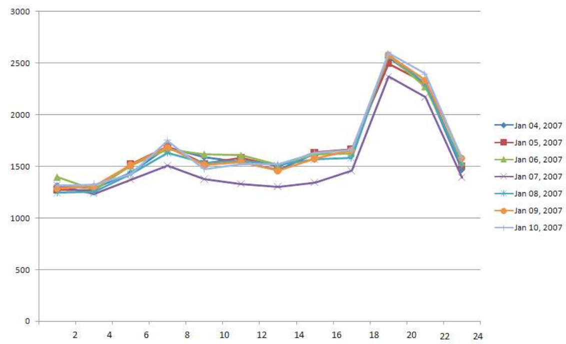

Fig (7) Load curves for a week

Implementation

The ANN to predict the hourly load was implemented using MATLAB 7. The training algorithm „Traingdx‟ was used which is an adaptive learning algorithm using the epoch method of training. The number of epochs while training was set at 1,00,000 by which point the network was sufficiently trained. The inputs considered for identifying similar day and for estimation of the load are:

1. Day of the week.
2. Hour of the day.
3. Date

4. Month
5. Year
6. Other factors- weather,temparature, humidity etc.
7. Load (normalized) of similar hour of previous three years
8. Load (normalized) of previous hour of previous three years

Thus, the architecture of the ANN has 8 inputs, 1 output and hidden neurons as shown in Fig. (8)

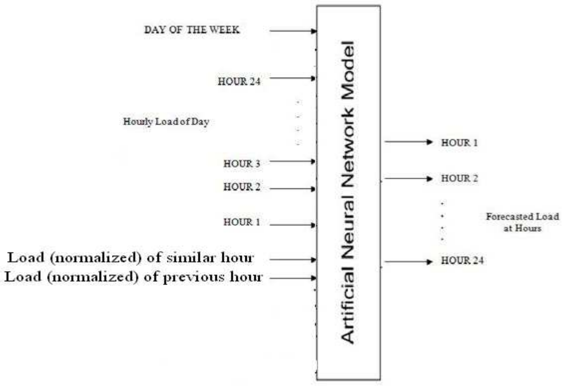

Fig (8) Architecture of ANN model used

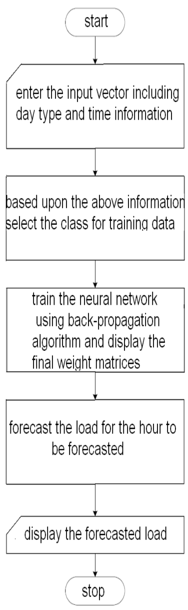

FIG (10) Input-Output Schematic for Load Forecasting

Logic of coding

12 digit codes were used for designating the data. Demand data for 1375 days were taken for training the ANN.

Digit place	Parameter
1	Day of the week-1 Sunday, 2 Monday etc
2,3	Date
4,5	Month
6,7	Year
8,9	Time
10	Indication for weather on 1 to 4 scale
11	Type of day on 1 to 4 scale. 1 for normal day,2- for special day like holiday with low load
12	Peak load curtailment

Results

Results of typical test cases were evaluated. The % error is 0.5. This is within the tolerance as hydel capacity is sufficient to accommodate such differences.

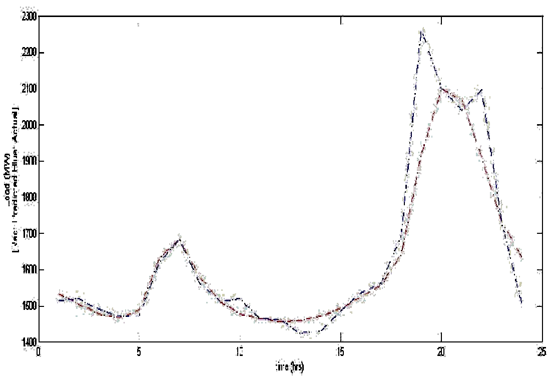

Fig (11) Test cases Day – Actual, Predicted

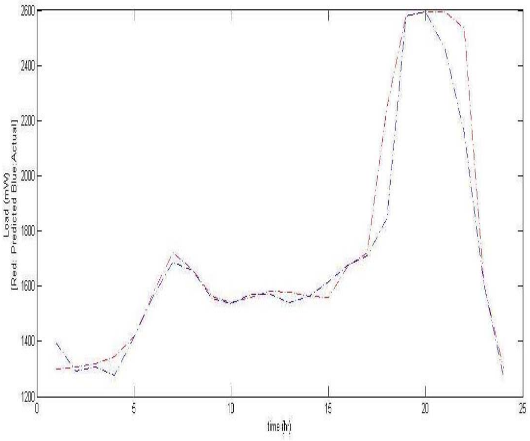

Fig (12) Test cases Day – Actual, Predicted

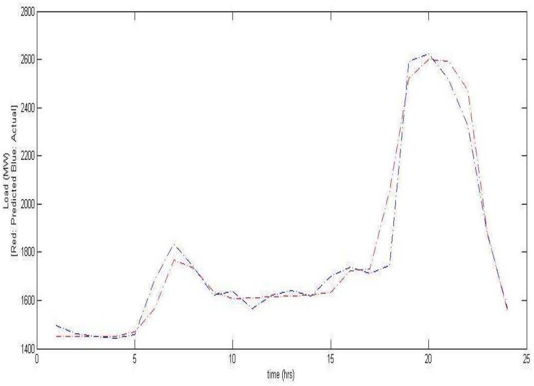

Fig (13) Test cases Day – Actual, Predicted

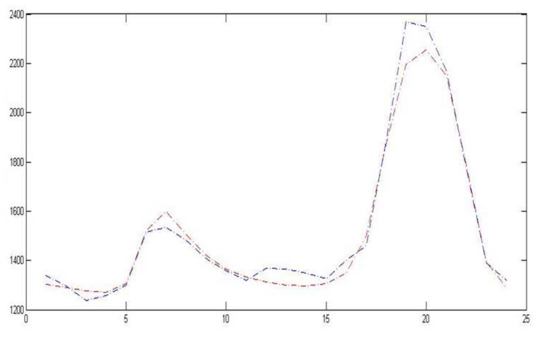

Fig (14) Test cases Day – Actual, Predicted

Conclusion

The short-term load forecasting developed is suitable for low load factor power system. In all test cases, the error obtained is on the positive side of the maximum demand. This is a necessity for planning the availability as per merit order in practical operation. The minimum demand conditions are also factually represented in the output. Thus the model is suitable for practical implementation for taking merit order dispatch instructions.

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