Short Term Load Forecasting using Neural Network trained with Genetic Algorithm

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Abstract—**A computationally efficient artificial neural network for the purpose of short term load forecasting is proposed. The major drawback of feed forward neural networks such as a multilayer perceptron (MLP) or dynamic neural network such as Hopfield, Elman, MFLNN trained with back propagation algorithm is that it requires a large amount of computation for learning. We propose a three-layer multi layer neural network trained with genetic algorithm in which the need for computationally intensive back propagation is eliminated. The results of which are better than a MLP trained by back propagation algorithm, which require more number of hidden neurons. The whole project is carried out for Orissa Power Transmission Corporation Limited, taking into the load data of Orissa.**

Index Terms—**Short term load forecasting, genetic algorithm, back propagation.**

I. Introduction

Generally, time series approaches assume that the load can be decomposed into two components. One is weather dependent, and the other is weather independent. Each component is modeled separately and the sum of these two gives the total load forecast. The behavior of these two controls the total load pattern. The behavior of weather independent load is mostly represented by Fourier series or trend profiles in terms of the time functions. The weather sensitive portion of the load is arbitrarily extracted and modeled by a predetermined functional relationship with weather variables.

Many neural net structures using different types of training algorithms have been proposed, which incorporate the temperature, & historical load. In Indian context load variation with respect to temperature variation is almost dependent upon the seasonal change. Seasonal change is always gradual, and an online Functional-Link Net is trained every 24 hours to predict next 24 hour load or trained every hour to predict next hour load. So, temperature variation due to seasonal change need not to be taken as an explicit parameter for input. Instead, surge in cooking load in morning hours and commercial, lighting and domestic load in evening hours should be incorporated appropriately as parameters for prediction.

The objective of the present approach is to study the universally accepted non-linear mapper (i.e. MLPNN) trained by genetic algorithm to identify a time-series load model incorporating the non-linearity due to hour of the day, & day of the week etc.

II. GENETIC ALGORITHM

Genetic algorithm (GA) is a directed random search technique [1] that is widely applied in optimization problems [1], [2], [3]. This is especially useful for complex optimization problems where the number of parameters is large and the analytical solutions are difficult to obtain. GA can help to find out the optimal solution globally over a domain [1], [2], [3]. It has been applied in different areas such as fuzzy control, path planning [4], & modeling & classification [5] etc.

There are two kinds of genetic operators, namely crossover & mutation. For crossover mechanisms, two-point cross over, multipoint crossover, arithmetic crossover, & heuristic crossover have been reported [1], [6]-[8]. For mutation mechanisms, boundary mutation, uniform mutation, and nonuniform mutation can be found [1], [6]-[8]. Three steps are used to generate offspring: copying the parents, determining the mutations to be performed, and mutating the copy.

Neural network was proved to be a universal approximator [9]. A three-layer feedforward neural network can approximate any nonlinear continuous function to an arbitrary accuracy. Neural networks are widely applied in areas such as prediction [10], system modeling, and control [9]. Owing to its particular structure, a neural network is very good in learning [2] using some learning algorithms such as GA [1] and back propagation [2]. In general, the learning steps of a neutral network are as follows. First, a network structure is defined with a fixed number of inputs, hidden nodes and outputs. Second an algorithm is chosen to realize the learning process. A small network may not provide good performance owing to its limited information processing power. A large network on the

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other hand, may have some of its connections redundant. Moreover, the implementation cost for a large network is high. So, a network with least number of neurons and computational complexity is always preferred.

Finally The results of an MLP trained by genetic algorithm are compared with those obtained by traditional back propagation algorithm.

III. DEMAND PATTERN IN ORISSA

A broad spectrum of factors affects the system's load level such as trend effects, cyclic-time effects, special effects, weather effects, random effects like sudden load increase or outages or a sub-station failure. Thus the load profile is dynamic in nature with temporal, seasonal, and annual variations. But for hourly forecasting, seasonal and annual load variations can be discounted for.

The peak electrical consumption of the Orissa is about 2277 mW during working day in summer. The daily demand has two peaks, i.e. one is in morning from 7 Hrs. to 10 Hrs. because of domestic cooking loads, and the other is from evening 06 Hrs. to 10 Hrs. because of domestic, commercial lighting loads. The industrial loads remain constant through out the day. The weekly pattern is comprised of the daily shapes (Monday through Sunday), reflecting the main working activities. Generally the load pattern on normal weekdays, when the work is already in full swing, remains constant with small random variations from varying industrial activities, and rain fall. The The load pattern of Monday and Saturday is different from that on other weekdays due to pickup loads on Monday mornings when all business and industries just start work, and evening loads on Saturdays, because of its proximity to the weekend. The shape of the load curve on Sundays is similar to that on holidays. The peak load decreases considerably before and after major public holidays.

IV. INPUT VARIABLE SELECTION AND MODELLING

The most important work in building our MLP based Short Term Load Forecasting model is the selection of the input variables. Actually, there is no guaranteed rule that one could follow in this process. It mainly depends on experience and is carried out almost entirely by trial and error. However some statistical analysis can be very helpful in determining the variables, which have significant influence on the system load. The input vector consists of 9 variables, i.e. the load of last three hours prior to the hour to be forecasted (hour-1, hour-2, hour-3), the load of the previous day for three hours (hour, hour-1, hour-2), & the load of the same day for three hours (hour, hour-1, hour-2) of the previous week. The training data consists of load data of 1 day including the load of the day to be predicted.

V. TRAINING AND TESTING

A three layer MLP model trained by back propagation with different momentum and learning rate, & genetic algorithm were tested. Different activation functions i.e. Logsig, Tansig, & Tanh were also tested on both type of training. The input to the MLP is data set of the day before training day. The forecasted output is compared with that of the training day load data. The error thus found is used to find the Jacobian for the hidden neurons and the output neuron. Jacobian is then used to obtain error function in case of GA and updation function in case of BP. After the training is over, the training day data set is used to forecast the next day 24 hour load pattern. The learning parameter (α) for back propagation was chosen between 0<(α)<1. The number of hidden neurons was chosen as 17 in case of MLP with BP and 4 for MLP with GA.

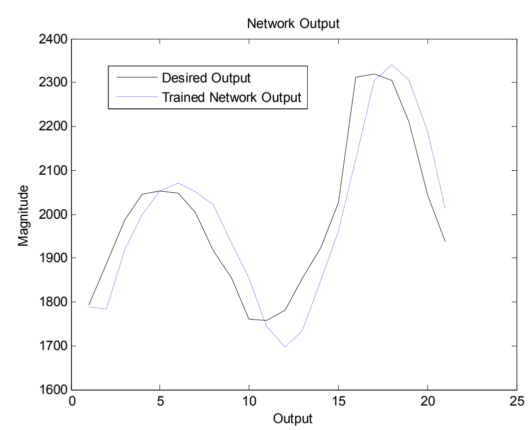
So, the novelty of this model is that it requires very few numbers of hidden neurons and very few training data set for prediction upto a high degree of accuracy. For MLP-BP logsig activation function gave the best result where as for MLP-GA tansig gave the best result.

VI. FORECASTING RESULTS

The Mean average percentage error (i.e MAPE) in case of MLP-BP was found to be 3.4453 % with logsig activation function, 17 nos. of hidden neurons, learning rate of 0.1, & Guyen-Widrow parameter initialization.

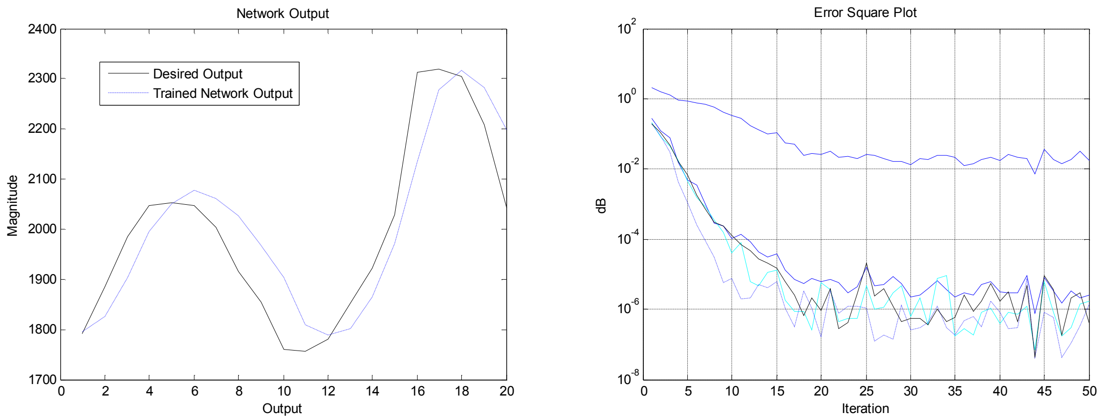
In case of MLP-GA the best result was found to be, MAPE of 3.3779 %, with 4 nos. hidden neurons, tansig activation function, random parameter initialization, population of 60 chromosomes per variable (i.e. weights & biases), 10 bit chromosomes, mating probability of 80%, and 5 point crossover.

Fig. I
MLPNN With Back Propagation training algorithm with (α) = 0.05, no of hidden neurons = 17



MAPE: 3.5543 %

Fig. II
MLPNN With genetic training algorithm, with no of hidden neurons = 4



MAPE: 3.3779 %

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