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ELECTRICAL LOAD FORECASTING USING GENETIC ALGORITHM BASED BACK- PROPAGATION METHOD

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ABSTRACT

Forecasting is the way of knowing the future value based on some past records. In electrical power systems, there is a great need for accurate forecasting of the future load and energy requirements. Accurate load forecast provides system dispatchers with timely information to operate the system economically and reliably. It is also necessary because availability of electricity is one of the most important factors for industrial development, especially for a developing country like India. It is required to be careful that the energy forecast is neither too conservative nor too optimistic. Artificial Intelligence techniques have shown promising results in many systems. Recent progress in the applications of Artificial Neural Networks (ANN) technology to power systems in the areas of forecasting has made it possible to use this technology to overcome the limitations of the other methods used for electrical load forecasting. In this work, the GA-BPN model is used for extracting the best weight matrices for different layers of BPN thus forecasting the future power demand more accurately. For this reason, this work introduces evolution of connection weights in ANN using GA as means of improving adaptability of the forecasting.

Keywords: short term load forecasting, genetic algorithm, back propagation.

1. INTRODUCTION TO ELECTRICAL LOAD FORECASTING

A power station feeds different types of consumers such as domestic, commercial, industrial and agricultural etc. A modern power station takes several years for completion and the power system planning has to be done several years before in advance. Accurate models for electric power load forecasting are essential. Load forecasting helps to make important decisions including decisions on purchasing and generating electric power, load switching and infrastructure development. Load forecasts are extremely important for energy suppliers, financial institutions, and other participants in electric energy generation, transmission, distribution and markets. According to Karabulut *et al*. (2008), load forecasts can be divided into three categories:

- Short-term load forecasting (usually from one hour to one week)
- Medium-term load forecasting (usually from a week to a year)
- Long-term load forecasting (longer than a year)

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.

A variety of methods, which include the so-called similar day approach, various regression models, time series, neural networks, statistical learning algorithms, fuzzy logic, and expert systems have been developed for short-term forecasting. A large variety of mathematical methods and ideas have been used for load forecasting. The development and improvements of appropriate mathematical tools will lead to the development of more accurate load forecasting techniques. The accuracy of load forecasting depends not only on the load forecasting techniques, but also on the accuracy of input data.

Wang X. *et al*. (2004), specify that though there are many factors influencing electric demand, it is impossible to Figure out all of them and check all their influences on electric load, especially when some of the information is difficult to obtain. Therefore it is assumed that most of the information is integrated in load history and recent data can help us to extrapolate future load.

2. RESEARCH OBJECTIVE

In this research work, an attempt has been made to develop a genetic algorithm based back propagation (GA-BPN) model for short term load forecasting (STLF). The specific objective of this research is to improve the efficiency of back propagation method by hybridizing genetic algorithm (GA) with back-propagation network (BPN) for determination of optimum weight set under different number of neurons in the hidden layer and different population size.

3. RESEARCH METHODOLOGY

The methodologies adopted in this research are explained below:

- Construction of different ANN architectures.

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- Hybridization of BPN with GA. i.e., extraction of weights for BPN by implementing genetic algorithm.
- Training of the GA-BPN network with different values of population size.
- Finding the best value of population size for GA-BPN forecasting.
- Finding the forecasted values for the best value of population size.

4.0 GENETIC ALGORITHM

Genetic Algorithm (GA) belongs to a class of population-based stochastic search algorithm that are inspired from principles of natural evolution known as Evolutionary Algorithm (EA) (Schoenauer and Michalewicz, 1997). Other algorithms in the same class include Evolutionary Strategies (ES), Evolutionary Programming (EP) and Genetic Programming (GP).

4.1 GA based weight determination

The success of any neural network (NN) architecture depends on the search for the optimized weights for given training data set. GA has been shown in practice that it is very effective at function optimization and can perform efficient searching for the approximate global minima. Thus, GA can be effectively utilized for NN weight selection.

Before a GA is executed, a suitable coding for the problem needs to be developed. The fitness function, which assigns merit to each of the individuals in the population, has to be formulated.

Rajasekaran *et al*. (2007) describes a model for calculation of fitness value as shown in Figure-1 below.

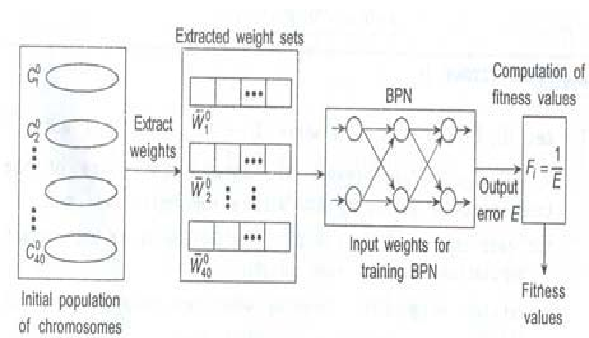

Figure-1. Fitness calculation.

5. RESULTS AND DISCUSSIONS

Two different experiments have been carried out to analyze the results.

Experiment-1

In this experiment, the GA-BPN has been implemented by taking two different architectures (3-2-1 and 3-3-1), with different population size. For each value of population, the program has been executed 5 times and the RMSE value has been calculated.

Various parameters used in this research are:

Architecture: 3-2-1 and 3-3-1
Number of hidden layers: 01
Number of input neurons: 03 (previous three days data)
Number output neurons: 01
Selection: Based on fitness value
Fitness function: 1/ (MSE)
Crossover: Two point Crossover
Stopping criteria: when fitness converged

The training results are shown in Figure-2 and Figure-3 below:

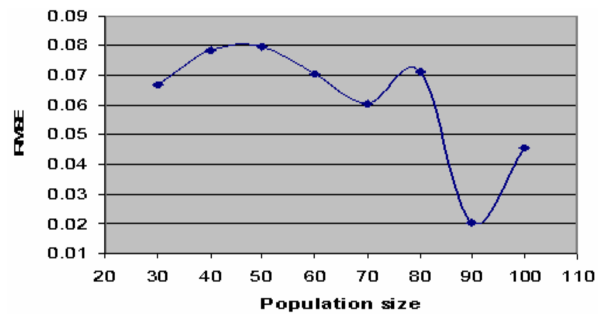

Figure-2. Population size versus error rate (GA-BPN-3-2-1).

Figure-3. Population size versus error rate (GA-BPN-3-3-1).

The training error calculated for various architectures are shown in Figure-4 and Figure-5 below.

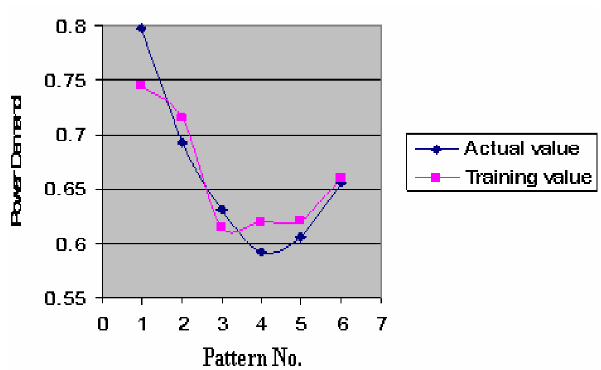

Figure-4. Daily power demands, actual vs trained values (GA-BPN 3-2-1).

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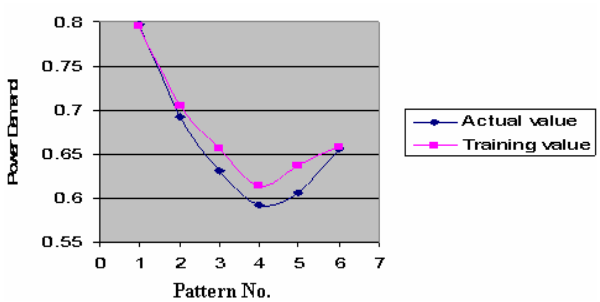

Figure-5. Daily power demands, actual vs trained values (GA-BPN 3-3-1).

5.1 Forecasted values (GA-BPN single hidden layer)

Once the training is over, the forecasted values for next days have been calculated. The values are given in Table-1 below.

Table-1. Forecasted values, GA-BPN 3-2-1 and 3-3-1 architecture.

Techniques	Actual/target value	Forecasted value	Squared error	Error (RMSE)
Genetic algorithm based back propagation method architecture: 3-2-1, population size=90	0.5876	0.585405	4.82E-06	0.020585
	0.6672	0.687654	0.000418	
	0.6892	0.718321	0.000848	
Genetic algorithm based back propagation method architecture: 3-3-1, population size=60	0.5876	0.574182	0.00018	0.02373336
	0.6672	0.668198	9.96E-07	
	0.6892	0.728043	0.001509	

It can be observed from the table that, for our research, GA-BPN with two neurons in hidden layer performs better than that of three neurons in hidden layer.

Experiment-2

In this experiment, The GA-BPN has been implemented by taking two different architectures (3-2-1 and 3-3-1), with different population size. For each value of population, the program has been executed 5 times and the RMSE value has been calculated.

Various parameters used in this research are:
Architecture: 3-3-3-1 and 3-2-2-1
Number of hidden layers: 02
Number of input neurons: 03 (previous three days data)
Number output neurons: 01
Selection: Based on fitness value
Fitness function: 1/ (MSE)
Chromosome: Real coded chromosome of length 5
Crossover: Two point Crossover
Stopping criteria: when fitness converged

The performance of the architectures under various population sizes are shown in Figure-6 and Figure-7.

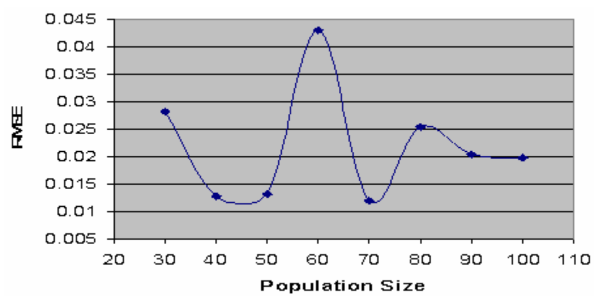

Figure-6. Population size versus error rate (GA-BPN-3-3-3-1).

Figure-7. Population size versus error rate (GA-BPN-3-2-2-1).

5.2 Forecasted values (GA-BPN two hidden layers)

Once the training is over, the forecasted values for next days have been calculated. The values are given in Table-2 below.

Table-2. Forecasted values, GA-BPN 3-3-3-1 and 3-2-2-1 architecture.

Techniques	Actual/target value	Forecasted value	Squared error	Error (RMSE)
Genetic algorithm based back propagation method architecture: 3-3-3-1, population size =70	0.5876	0.601256	0.000186	0.011996
	0.6672	0.653031	0.000201	
	0.6892	0.682530	4.45E-05	
Genetic algorithm based back propagation method architecture: 3-2-2-1, population size = 60	0.5876	0.605177	0.000309	0.010400
	0.6672	0.666389	6.58E-07	
	0.6892	0.693057	1.49E-05	

5.3 Comparison of all results

Results from various simulations and implementations used in this research are summarized below.

Table-3. Result comparison.

Techniques	Actual/target value	Forecasted value	Error term
GA-BPN: 3-2-1,	0.5876	0.585405	0.020585
	0.6672	0.687654	
	0.6892	0.718321	
GA-BPN: 3-3-1,	0.5876	0.574182	0.023733
	0.6672	0.668198	
	0.6892	0.728043	
GA-BPN: 3-2-2-1,	0.5876	0.605177	0.010400
	0.6672	0.666389	
	0.6892	0.693057	
GA-BPN: 3-3-3-1,	0.5876	0.601256	0.011996
	0.6672	0.653031	
	0.6892	0.682530	

6. CONCLUSIONS

This paper and its results show that the GA-BPN represents a powerful tool for decision making in electric load forecasting. This is based on a methodological selection of variables, a prior study of the problem to be solved, and the processing that the ANN can make in the temporal aspect.

The results obtained fulfilled the main and specific objectives of the work. The concept of hybridization of ANN and GA worked here better. The GA-BPN results are having least forecasting error and are found as the most suitable forecasting tool. All these means that the model constructed makes it possible to determine the short term load with acceptable accuracy, as required by the electric distribution companies.

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