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Short-Term Load Forecasting By GRF Methodology

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ABSTRACT: Short-term load forecasting method is the basis of optimizing the operation for power systems. Accurate load forecasting is helpful to improve the security and economic effect of power systems and can reduce the cost of generating electricity. Therefore, finding an appropriate load forecasting method to improve accuracy of forecasting has important application value. For this we have proposed a revised radial basis function (RBF) network combined along with the genetic algorithm. Fuzzy inference system is used in addition with this modified RBF network to include the sudden changes in load values. The proposed method is compared with feed forward neural network.

Keywords : Genetic algorithm, radial basis function (RBF) network, fuzzy system, short-term load forecasting

1 INTRODUCTION

Load forecasting of power systems is an important research area in power market analysis and forecast, and plays an important role in the operation, control and planning of power systems. Its essence is the forecast of power market requirements. Load forecasting is defined as the method of confirming a load value at a certain time while utilizing a series of methods of dealing with past and future load with a certain accuracy, considering some important system performances, capacity enlargement and natural conditions. Short-term load forecasting is an important basis of the safe and economic operation in power systems. Although load forecasting has a very long research history, it still explores new methods constantly with the improved requirement of power system operation towards load forecast accuracy and the improvement of relevant theories. Correct load forecast is helpful to promote the security and stability of power system and to reduce power generating cost. With the development of power industry, short-term load forecast will play a more and more important role in future. Traditional forecast models have their own limitations because of the description with mathematic representations. In fact, the change of load is affected by weather situation and social activities, thus nonlinear relation make it difficult to denote them with explicit formulations. Therefore, combining fuzzy theory which has the ability to process data and the neural network method which is good at dealing with nonlinear mapping is an effective forecast technology. Several researches have focused on increasing the precision of load forecasting. A group of the approaches are regression based and time series methods [3]–[7]. However, when the environmental and social factors affect the load pattern, they do not work properly [8]. Hence, the intelligent algorithms based on expert systems, evolutionary programming, fuzzy systems, and artificial neural networks (ANN) and the composition of them have been applied for short-term load forecasting [9]–[24].The expert systems perform based on the rules built up from the human knowledge [9]. In these systems, the parameters such as extreme changes in climate or sophisticated social parameters may be modeled. However, finding the appropriate rules for such an expert system is a complex task [10]. Among the intelligent approaches, the ANNs are widely used for short-term load forecasting due to their high performances [11]. The major accomplishment of the ANNs is their ability to find nonlinear relationships between the load (output) and the parameters that influence the load (inputs) using only the data set and without any structural model [12]–[15].Among the ANNs, the radial basis function (RBF) networks have good organizations for short-term load forecasting. They are easy to train, computationally fast, and compared to other neural networks, they are general approximations [16].Furthermore, the combination of the neural networks with the other intelligent systems such as fuzzy and neuro-fuzzy systems may be a strong tool for load forecasting. Because by using the expert knowledge of a fuzzy system, one can model the complicated relationships between the social/environmental factors with the hourly load pattern in an area, which are difficult to find using only ANNs [18]–[22]. In [23], the RBF network and dynamic neural network are used for short-term load forecasting. In addition a combined neuro-fuzzy network is designed and the performance of the hybrid network is examined. In [24], the combination of ANNs and adaptive neuro-fuzzy network is used for load forecasting. In this network, forecasting contains two steps: first the ANN forecasts the total demand of the next day; second the ANFIS estimates the hourly load of the next day. In [25], the RBF network is used for load forecasting as well, where a genetic algorithm is used for estimating the model parameters. A faster convergence and more precision are claimed in comparison with the gradient-based methods.

2 PROPOSED METHOD

2.1 Basis Structure of RBF Network

RBF is a three-layer neural network. The input layer is made up of the signal source node. The second tier is hidden layer, as described in its modules are based on the needs and problems. The third tier is the output layer, which responded to the role of imported models. If the network input modules is n, q and m is crackdown module and output modules, its topology is shown in Figure 1. Input selection is one of the most important processes in system identification and prediction. For the load forecasting, there are various inputs to be considered such as: load values of the previous days, day code, temperature, humidity, and so on. In this paper, the load profile of the previous day (24inputs) and the load profile of one week ago (24 inputs) are considered as the main inputs. The load of the previous day is chosen because is the nearest available data to the forecasting load and is highly correlated to it. Also, the load profile of one week ago has high correlation with the fore-

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casting day due to the same day code feature.

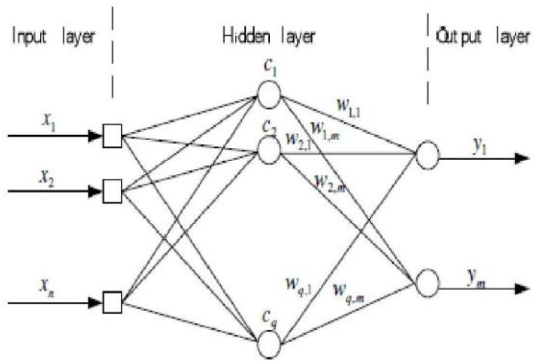

Fig 1: Topology of RBF neural network

Also, the maximum temperature of the previous week and the forecasted maximum temperature of the forecasting day are included as the inputs to the fuzzy prediction correction system. In this paper, the effect of the load variation is considered through the load of the previous day and the effect of environmental variations is considered via the corrective fuzzy system. The function of the fuzzy system is to shift/scale the forecasted load up/dawn based on the temperature increment/decrement. This way of cascading the two predictive and corrective systems is due to the knowledge gained from the history of load patterns provided during training phase.

2.2 Genetic Algoritham

Genetic Algorithm comes from the natural law of survival of the fittest genetics and biotechnology, is a group operation. The operation targeted to individual groups of all, through choice, crossover and mutation operators produce a new generation of groups, until the results are satisfactory. It is based on natural selection and natural genetics adaptive probability based on the iterative search algorithm. In the solution space, the genetic algorithm has more random search of solutions, and to identify the optimal solution. Due to the random genetic algorithm, a search of all solutions is possible, so they can find the global optimum.

Proposed genetic algorithm has following steps

Step 1: Initialization
- Set mutation rate, cross over rate, learning rate
- Check preconditions

Step 2: Selection
- Equation(i) gives initial weight values
- Fitness value ranges between 1 and -1

Step 3: Reproduction
- Mutation and Cross over
- Go to Step 2

Step 4: Termination
- Stop after fixed number of iteration

Equation (i) gives the weight values corresponding to the input data

$$Wt[i] = \sum_{i=1}^{n}(data[i] - Ymin) * Factor - 0. \quad \text{(i)}$$

where data[i] represents the input load values. Ymin is the minimum value of the input values and is obtained from the graph.Factor = 1.7/ Range Y length.

Equation (ii) is used to calculate the predicted load data

$$Load[i] = \left(\frac{Compute[i] + 0.85}{Factor}\right) + Ymin \quad \text{(ii)}$$

Compute is a function which gives the best weight value corresponding to every output neuron. Using equation (i) the initial weight values are calculated and given to the genetic algorithm where the values are selected based on the fitness. This selection process keeps on repeating until the required number of weight values is calculated.

2.3 Fuzzy System

Load sequence of power system takes on a cyclic variation. However, many random factors lead to a difficult confirmation of load forecast accuracy. In short-term load forecast, its movement trend depends on not only history load, but also current environment situation. Many factors impact on it, and the information is fuzzy. Therefore, fuzzy sets are introduced in order to make a precise load forecast. In this theory, a group of “if-then” regulations are used to signify the nonlinear mapping between input and output of the system. Fuzzy reasoning system can be connected to arbitrarily complicate nonlinear system through division of input and output space. There are many similarities among the development of different substances. In many cases, present development process of forecast object may be similar to its development situation at past certain time. Therefore, people can forecast future changes of objects according to the known development process and situation. In load forecast, some days with similar elements (such as meteorology and day type) can be selected to forecast load days according to feature value of fuzzy clustering.

2.4 Comparisions of Results

Results show that the proposed method is better than the previous feed forward network used. The prediction error for the proposed GRF methodology was 0.008 where as the prediction error for feed forward neural network was 0.036. The error rate has been reduced almost to a quarter of previous value. The weight values generated with respect to GRF method are shown in the next figure. Since genetic algorithm is used for the calculation of weight values they are equally distributed within range of 1 to -1. This uniform calculation of weight values helps increase the accuracy rate further. Graph shows that the combination of RBF along with genetic algorithm and fuzzy system will yield better results

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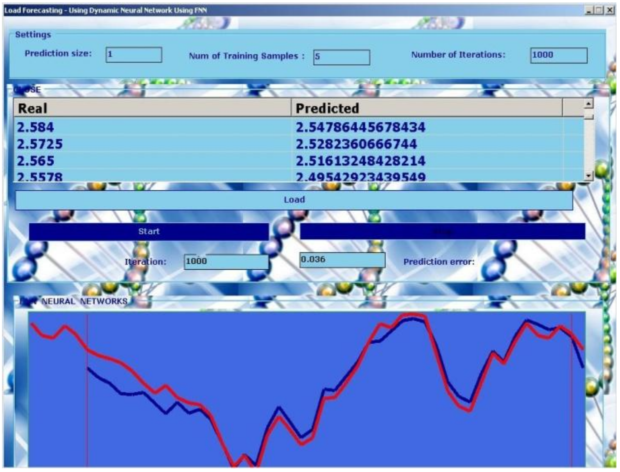

Fig 2: Load forecast results of Feed-forward Neural (FNN) network

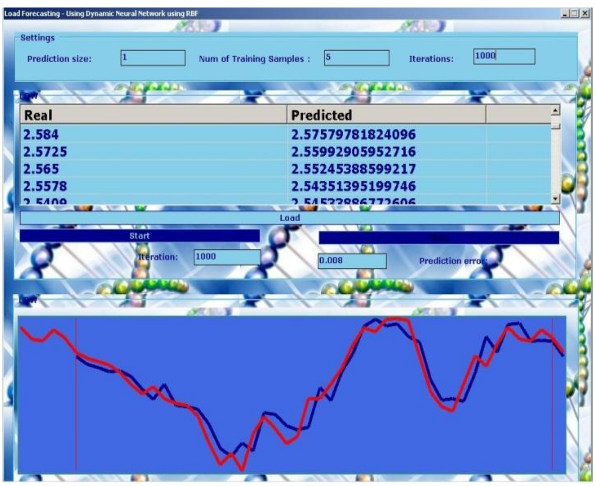

Fig 3: Load forecast results of GA-RBF-Fuzzy (GRF)

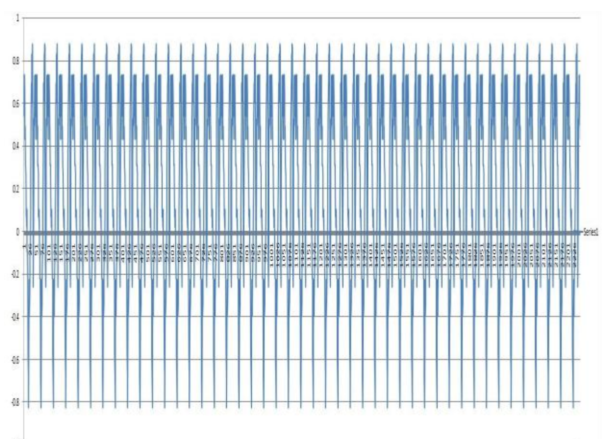

Fig 4: Weight values generated with respect to the proposed method

3 Conclusion

In this paper, a new load forecasting system based on RBF neural network was proposed and genetic algorithm was applied to calculate the weights of the neural network. Fuzzy inference system was used to incorporate the sudden changes in load values. Results show that the forecasting accuracy and convergence speed of the proposed model are better than feed forward neural networks.

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