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A hybrid annual power load forecasting model based on generalized regression neural network with fruit fly optimization algorithm

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ABSTRACT

Accurate annual power load forecasting can provide reliable guidance for power grid operation and power construction planning, which is also important for the sustainable development of electric power industry. The annual power load forecasting is a non-linear problem because the load curve shows a non-linear characteristic. Generalized regression neural network (GRNN) has been proven to be effective in dealing with the non-linear problems, but it is very regretfully finds that the GRNN have rarely been applied to the annual power load forecasting. Therefore, the GRNN was used for annual power load forecasting in this paper. However, how to determine the appropriate spread parameter in using the GRNN for power load forecasting is a key point. In this paper, a hybrid annual power load forecasting model combining fruit fly optimization algorithm (FOA) and generalized regression neural network was proposed to solve this problem, where the FOA was used to automatically select the appropriate spread parameter value for the GRNN power load forecasting model. The effectiveness of this proposed hybrid model was proved by two experiment simulations, which both show that the proposed hybrid model outperforms the GRNN model with default parameter, GRNN model with particle swarm optimization (PSOGRNN), least squares support vector machine with simulated annealing algorithm (SALSSVM), and the ordinary least squares linear regression (OLS_LR) forecasting models in the annual power load forecasting.

1. Introduction

Power load forecasting is an important part of management modernization of electric power systems, which has attracted more and more attentions from the academic and the practice. Annual power load forecasting is of crucial importance to the economic operation of electric power systems and the reliability of electric networks. Accurate annual power load forecasting can relieve the conflict between electricity supply and demand. With the increasing energy shortage pressure, many countries concentrate to transform management philosophy and promote technological innovation. The smart grid, a digitally enabled electrical grid, is taken as one of the future power grid development goals. On May 21, 2009, the State Grid Corporation of China proposed the development planning of constructing 'Strong Smart Grid' in China. With the construction and development of smart grid, the generation capacity of renewable distributed energy will be improved, which will exert significant impacts on the secure and stable operation of electric power grid. Therefore, more accurate annual power load forecasting which is quite important for maintaining secure and stable operation of electric power grid is needed. However, because annual power load has complex and non-linear relationships with several factors such as political environment, economic policy, human activities, irregular behaviors and other non-linear factors, it is quite difficulty for forecasting power load accurately.

Many annual power load forecasting methods developed by the scholars and practitioners have been proposed to increase the forecasting accuracy in the past few years. The traditional forecasting methods, such as regression models [1,2] and time series technology [3–5], have the disadvantage of poor non-linear fitting capability. In recent years, owing to the development of intelligence techniques, many new intelligence forecasting methods were used for annual power load forecasting. Wang et al. [6] proposed a hybrid model combining support vector regression and differential evolution algorithm to forecast the annual load, and this method was proved to outperform the SVR model with default parameters, regression forecasting model and back propagation artificial neural network (BPNN). Pai and Hong [7] used support vector machines with simulated annealing algorithm (SVMSA) to forecast Taiwan's electricity load, and the empirical results revealed that the SVMSA model outperforms the general regression neural networks model and the autoregressive integrated moving average (ARIMA) model. Hong [8] proposed an electric load forecasting model which combined the seasonal recurrent support vector regression model with chaotic artificial bee colony algorithm (SRSVRCABC), which

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yields more accurate forecasting results than TF-ε-SVR-SA and ARIMA models. Kandil et al. [9] implemented a knowledge-based expert system (ES) to support the choice of the most suitable load forecasting model, and the usefulness of this method was demonstrated by a practical application. Chen [10] proposed a collaborative fuzzy-neural approach which multiple experts construct their own fuzzy back propagation networks from various viewpoints for Taiwan's annual electricity load forecasting and the precision and accuracy were improved. Meng and Niu [11] applied the partial least squares method which could quantificational simulate the relationship between the electricity consumption and its factors to forecast electricity load, and it was proved to be effective. Abou El-Ela et al. [12] proposed the artificial neural network (ANN) technique for long-term peak load forecasting, and it was applied on the Egyptian electrical network dependent on its historical data. In order to predict the regional peak load of Taiwan, Hsu and Chen [13] formulated an artificial neural network model by collecting empirical data. Xia et al. [14] developed a medium and long term load forecasting model by using radial basis function neural networks (RBFNN), and the result indicated that the proposed model has a high accuracy and stability.

The generalized regression neural network (GRNN) which was developed by Specht [15] is a kind of probabilistic neural networks and also a powerful regression tool with a dynamic network structure. Because of the strong non-linear mapping capability, the simplicity of network structure and high fault tolerance and robustness, the GRNN can effectively solve the non-linear problems, and it has been widely applied to a variety of fields including pattern recognition [16], short-term load forecasting [17], the modeling and monitoring of batch processes [18], TWUSM drive system [19], medicinal chemistry [20], coal desulfurization [21], exchange rates forecasting [22], sales forecasting [23], wind speed forecasting [24], and so on. However, it is very regretfully finds that the GRNN have rarely been applied to the annual power load forecasting. This paper elucidates the feasibility of using the GRNN to forecast annual power load. However, the shortcoming of applying the GRNN model is that it is very difficult to select the spread parameter properly. Polat and Yıldırım [16] used genetic algorithm to optimize the spread parameter of the GRNN for pattern recognition, and this optimized GRNN can provide higher recognition ability compared with the unoptimized GRNN. However, most researchers selected the spread parameter by experience and a lot of experiments [17–22].

Fruit fly optimization algorithm (FOA) proposed by the scholar Pan [25] is a novel evolutionary computation and optimization technique. This new optimization algorithm has the advantages of being easy to understand and to be written into program code which is not too long compared with other algorithms. Therefore, this paper attempted to use the FOA to automatically select the spread parameter value of the GRNN for improving the GRNN's forecasting accuracy in the annual power load forecasting.

The rest of this paper is organized as follows: Section 2 introduces the GRNN and FOA methods, then a hybrid forecasting model combined GRNN and FOA for annual power load forecasting is discussed in detail. Section 3 introduces the process of the sample data used in this paper and further computations, comparisons and discussions of two examples are presented. Section 4 concludes this paper.

2. Generalized regression neural network with fruit fly optimization algorithm

2.1. Generalized regression neural network

The generalized regression neural network (GRNN) is a kind of radial basis function (RBF) networks which is based on a standard statistical technique called kernel regression. The GRNN has excellent performances on approximation ability and learning speed, and it is fast learning and convergence to the optimal regression surface as the number of sample data becomes very large. When the number of sample data is small, the GRNN still has a good forecasting result [26].

The main function of the GRNN is to estimate a non-linear or linear regression surface on independent variable (also called input vector) $X = [x_1, x_2, \ldots, x_n]^T$, given the dependent variable (also called output vector) $Y = [y_1, y_2, \ldots, y_k]^T$. The procedure of the GRNN model can be represented as

$$E[Y|X] = \frac{\int_{-\infty}^{\infty} Yf(Y,X)dX}{\int_{-\infty}^{\infty} f(Y,X)dX} \tag{1}$$

where X is a n-dimensional input vector, Y is the predicted value of the GRNN model, $E[Y|X]$ is the expected value of the output Y, given the input vector X,$f(Y,X)$ is the joint probability density function of X and Y.

The GRNN is organized using four layers: input layer, pattern layer, summation layer, and output layer, just as shown in Fig. 1.

The input layer receives information and stores an input vector X, which the number of neurons equals to the dimension of input vector. Then, the input neurons of input layer feed the data to the pattern layer. The pattern layer possesses a non-linear transformation from the input space to the pattern space. The neurons in the pattern layer (also called pattern neurons) can memorize the relationship between the input neuron and the proper response of pattern layer, and the number of neurons equals to the number of input variables. The pattern Gaussian function of p_i is expressed as

$$p_i = \exp\left[-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right] \quad (i = 1, 2, \ldots, n) \tag{2}$$

where σ denotes the smoothing parameter, X is the input variable of the network, X_i is a specific training vector of the neuron i in the pattern layer.

The summation layer has two summations, namely S_s and S_w. The simple summation S_s computes the arithmetic sum of the pattern layer outputs, and the interconnection weight equals to '1'. The weighted summation S_w computes the weighted sum of the pattern layer outputs, and the interconnection weight is w. The transfer functions can be represented as Eqs. (3) and (4), respectively:

$$S_s = \sum_{i=1} p_i \tag{3}$$

$$S_w = \sum_{i=1} w_i p_i \tag{4}$$

where w_i is the weight of pattern neuron i connected to the summation layer.

The number of neurons in the output layer equals to the dimension k of output vector Y. After the summations of neurons in the summation layer are fed into the output layer, the output Y of the GRNN model can be calculated as follows:

$$Y = S_s / S_w \tag{5}$$

Therefore, the GRNN model has only one parameter σ that needs to be determined, which is very important in using GRNN for forecasting. The parameter σ (also called 'spread' in Matlab program) determines the generalization capability of the GRNN. Many researchers selected the parameter by priori knowledge or individual experience, which may be un-efficient for forecasting. Therefore, we should develop an automatically efficiently method for selecting the appropriate spread parameter in the GRNN model.