DOI:10. 13434/j. cnki. 1007-4546. 2019. 0205

Forecasting of Short-term Load based on LMD and BBO-RBF Model

HOU Luting[1], GAO Junwei[2]

(1. College of Automation and Electrical Engineering, Qingdao University, Shandong Qingdao 266071, China
2. Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing 100044, China)

Abstract: Short-term load forecasting is a basis of power system dispatching and operation. In order to improve the short term power load precision, a novel approach for short-term load forecasting is presented based on local mean decomposition (LMD) and the radial basis function neural network method (RBFNN). Firstly, the decomposition of LMD method based on characteristics of load data then the decomposed data are respectively predicted by using the RBF network model and predicted by using the BBO-RBF network model. The simulation results show that the RBF network model optimized by using BBO algorithm is optimized in error performance index, and the prediction accuracy is higher and more effective.

Keywords: short-term load; local mean decomposition; radial basis function neural network; BBO algorithm

1 Introduction

The development of society increasingly requires the power system to make reasonable economic dispatch of electric energy[1] much electrical energy is used to cause waste and too little transportation can not reach normal demand, resulting in a shortage of electricity in the region, hindering economic development and affecting social stability.

With the increase in the dependence on electricity consumption and the development of intelligent information processing, the research methods of power system are gradually deepened in the world. So far commonly used load forecasting methods includes artificial neural network[2-3], time series method[4-5] and regression analysis[6-7]. However mentioned in Document 4 about Time series method has high dependence on historical data, short-term power load forecasting is affected by weather and other factors, and it is not universal. Mentioned in Document 5 and in Document 6 about regression analysis method need us to find out quantity relationship from historical data, this method has many limitations and it is not suitable for short-term power load forecasting. The RBFNN[7] is also applied to short-term power load forecasting. RBFNN is a kind of feed-forward neural network with excellent performance, which has global approximation ability and fundamentally solves the local optimal problem, the structure is simple, training speed quickly. It has been widely used in the fields of pattern recognition and nonlinear function approximation, especially load forecasting.

Biogeography-based optimization (BBO) algorithm is a new evolutionary algorithm proposed by Simon[8] in 2008. The algorithm is raised which is based on the study of mathematical models of biological species migration and draws lessons from the frameworks of other bionic intelligent optimization algorithms. BBO algorithm has many advantages that structure is simple and convergence speed is fast, therefore, this algorithm has been widely used in the complex optimization problems of practical engineering since it was put forward[9-10].

In this paper, Local mean decomposition (LMD) is used to extract the energy characteristic signals of load forecasting, the BBO algorithm is used to optimize the RBFNN, and the BBO-RBFNN model is used to solve

Received March 20, 2019

problem of regression prediction.

2 Basic theory of local mean decomposition

Local mean decomposition, introduced by Smith[11], is a new adaptive time-frequency analysis method and firstly applied this method to EEG signal processing and achieved good results. It is a new type of signal decomposition method with good self-adaptation. The method can adaptively decompose any complex multi-component non-stationary signal into the sum of a plurality of PF components whose instantaneous frequencies are always positive, each PF component is multiplied by an envelope signal and a pure FM signal. The envelope signal is the instantaneous amplitude of the PF component and the pure FM signal can determine the instantaneous frequency of the PF component. By combining the instantaneous amplitude and instantaneous frequency of all PF components, the complete time-frequency distribution of the original signal can be obtained.

The LMD method obtains a PF component by gradually decomposing the original signal from a high frequency to a low frequency come from a series of products of a pure frequency modulation signal and an envelope signal. For any signal $x(t)$ The decomposition process[12] is as follows:

Step 1 Find out all the local extreme points of the original signal $x(t)$.

The average points m_i of all two adjacent local extreme points are connected by a straight line and then smoothed by the moving average method to obtain a local mean function $m_{11}(t)$.

Step 2 Calculate the average m_i of two adjacent extreme points n_i, n_{i+1} and envelope estimation a_i.

$$m_i = \frac{n_i + n_{i+1}}{2} \tag{1}$$

$$a_i = \frac{|n_i - n_{i+1}|}{2} \tag{2}$$

Set original signal as $x(i), i = 1, 2, \cdots, n$. Calculate the local mean value function and local envelope function by moving average, the calculating formula of moving average is as follow.

$$x_s(i) = \frac{1}{2N+1}(x(i+N) + x(i+N-1) + \cdots + x(i-N)) \tag{3}$$

Where, $2N+1$ is the moving average span, which must be odd number and one third of the longest local average.

Step 3 On this basis of local extreme point $m_{11}(t)$, the paper calculates the average $m_{11}(t)$ and envelope estimation function $a_{11}(t)$. Separate $m_{11}(t)$ from $x(t)$ and obtain $h_{11}(t)$.

$$h_{11}(t) = x(t) - m_{11}(t) \tag{4}$$

To demodulate $h_{11}(t)$, divided by the envelope function $a_{11}(t)$ and then get $s_{11}(t)$.

$$s_{11}(t) = \frac{h_{11}(t)}{a_{11}(t)} \tag{5}$$

Step 4 Judge $s_{11}(t)$ whether is a pure frequency modulation signal, which means judge whether envelope function is $a_{11}(t)=1$. If you do not meet the condition, repeat step 1 ~ step 3, until $a_{1(n+1)}=1$. Because $s_{1n}(t)$ is a pure frequency modulation signal at this time.

$$\begin{cases} h_{11}(t) = x(t) - m_{11}(t) \\ h_{12}(t) = s_{11}(t) - m_{12}(t) \\ \qquad \vdots \\ h_{1n}(t) = s_{1(n-1)}(t) - m_{1n}(t) \end{cases} \tag{6}$$

Where: $s_{1i}(t)=h_{1i}(t)c_{1i}(t)$; $i=1,2,\cdots,n$.

$$\begin{cases} s_{11}(t) = h_{11}(t)/a_{11}(t) \\ s_{12}(t) = h_{12}(t)/a_{12}(t) \\ \cdots \\ s_{1n}(t) = h_{1n}(t)/a_{1n}(t) \end{cases} \tag{7}$$

If $a_{1n}(t)$ meets the condition, which is $\lim\limits_{n\to\infty} a_{1n}(t)=1$, the iteration stop.

Step 5 Multiply all envelope estimation functions which are from iterative process to obtain the envelop signal of the first PF component.

$$a_1(t) = a_{11}(t)a_{12}(t)\cdots a_{1n}(t) = \prod_{q=1}^{n} a_{1q}(t) \tag{8}$$

Step 6 Multiply envelope function $a_1(t)$ and pure frequency modulation signal $s_{1n}(t)$ to obtain the first PF component of original signal.

$$PF_1(t) = a_1(t)s_{1n}(t) \tag{9}$$

Step 7 Separate $PF_1(t)$ from $x(t)$ and obtain a new residual signal $u_1(t)$. Take $u_1(t)$ as the new original signal and repeat the above steps k times, until the value of extreme point of $u_k(t)\leqslant 1$. So separate $x(t)$ into the sum of k PF components and a residual signal $u_k(t)$.

$$x(t) = \sum_{i=1}^{k} PF_i(t) + u_k(t) \tag{10}$$

3 BBO-RBFNN algorithm

3.1 Radial basis function neural network (RBFNN)

In 1988, Moody et al. proposed a neural network structure-Radial basis function (RBF) network, which belongs to the type of forward neural network and overlapping receptive region and uses local acceptance domain to perform function mapping. The structure of the RBF network is similar to a multi-layer forward network, which is a three-layer forward network and consists of input layer (usually composed of sensing unit), hidden layer (the role of the hidden layer is the non-linear transformation from input space to hidden layer space) and output layer, The transformation from the input space to the hidden layer space is nonlinear, while the spatial transformation from the hidden layer space to the output layer is linear and radial basis function is usually a Gaussian function. RBF network structure is shown in Figure 1.

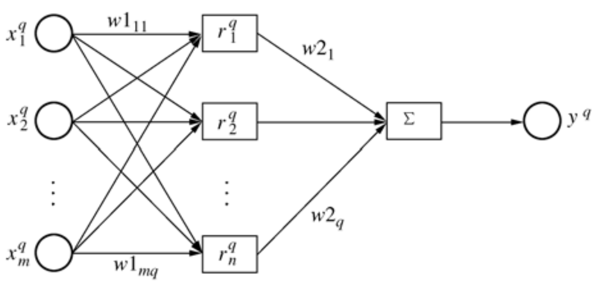

Figure 1 RBF network structure

The distance between the weight vector and the input vector of each neuron of the hidden layer connected to the input layer is multiplied by the threshold as the input of the neuron, as the shown in Figure 2. So formula (11) offers the input of neuron in hidden layer.

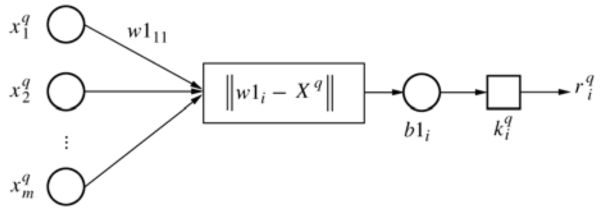

Figure 2 Input and output of hidden layer neuron in RBF network

$$k_i^q = \sqrt{\sum_j (w1_{ji} - x_j^q)^2} \times b1_i \tag{11}$$

The corresponding output expression of hidden layer is

$$r_i^q = \exp(-(k_i^q)^2) = \exp(-(\| w1_i - X^q \| \times b1_i)^2) \tag{12}$$

The input of the output layer is the weighted sum of neuron outputs of each hidden layer. Since the excitation function is a purely linear function, the output is

$$y^q = \sum_{i=1}^{n} r_i \times w2_i \tag{13}$$

3.2 Design principles of BBO algorithm

Biotic populations live in different habitats, and the habitat suitability index (HIS) is different for each habitat[8]. The characteristics associated with HIS include rainfall, vegetation diversity, geological diversity and climatic factors form a suitable index vector (SIV) to describe the habitat, each of these fitness variables is called suitable index variables (SIVs). The BBO algorithm constructed by using the distribution mechanism of biogeography solves the optimization problem which mainly depend on[9]:

1) The eigenvector of habitat corresponds to the solution of optimization problem. The habitat suitability index is a measure of the fitness of SIV, which corresponds to the metric function value of the optimization problem. Good schemes correspond to the habitat with higher HIS values.

2) Immigration and emigration mechanism of habitat corresponds to information crossover mechanism in optimization algorithms.

3) BBO algorithm can calculate the mutation rate according to the difference in the number of population in the habitat, and makes mutation operation on the habitat, so the algorithm has strong adaptive ability.

3.3 BBO-RBFNN

The basic idea of the BBO algorithm is to complete the flow of information according to the migration of species between habitats, the information sharing is achieved by adjusting the immigration rate and migration rate, migration topology, migration interval and migration strategy during the migration process. The habitat fitness is improved, and the optimal solution of the problem is obtained. For the BBO algorithm, the essence of evolutionary process is to improve the fitness of species through migration and mutation. Migration is a probabilistic operator that it adjusts the habitat H based on mobility; Variation is a probabilistic operator that it modifies the habitat H based on prior probability m. The evolutionary algebra is $G=60$, the size of the population (habitat) is $H=40$, the maximum immigration rate is $I=0.99$, the maximum migration rate is $E=0.99$, and the maximum ariation rate is $m_{\max}=0.0061$.

3.3.1 Migration

It is assumed that the maximum number of species that can be accommodated in the habitat is n, where immigration rate λ_k and migration rate μ_k are the functions of the species k in the habitat. The complex migration model which conforms to the natural law is superior to the simple linear migration model, in which the cosine migration model is the best, so the cosine migration model is selected as migration model in this paper, the formula is

$$\lambda_k = \frac{I}{2}\left[\cos\left(\frac{k\pi}{n}\right) + 1\right],\ \mu_k = \frac{E}{2}\left[-\cos\left(\frac{k\pi}{n}\right) + 1\right] \tag{14}$$

Where: I is the maximum immigration rate; E is the maximum migration rate; k_0 is the species in habitat balance. The cosine migration model is shown in Figure 3.

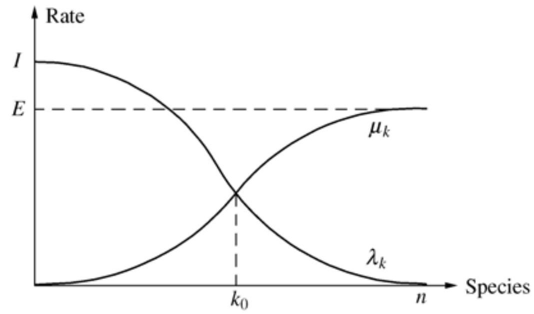

Figure 3 Cosine migration model

3.3.2 Variation

In the BBO algorithm, the probability of habitat species can be determined by the immigration rate λ_k and migration rate μ_k, the probability that the habitat has the species k is defined as P_k, then from t to $t+\Delta t$, the probability P_k changes to

$$P_k(t + \Delta t) = P_k(t)(1 - (\lambda_k + \mu_k)\Delta t) + P_{k-1}(t)\lambda_{k-1}\Delta t + P_{k+1}(t)\mu_{k+1}\Delta t \tag{15}$$

Assuming that Δt is the small enough to make more than one species, immigration rate or migration rate can be ignored, then when $\Delta t \to 0$ finding the limit of time about Formula (15), we can get

$$\dot{P}_k = \begin{cases} -\lambda_0 P_0 + \mu_1 P_1 & k = 0 \\ -(\lambda_k + \mu_k)P_k + \lambda_{k-1}P_{k-1} + \mu_{k+1}P_{k+1} & 1 \leqslant k \leqslant n-1 \\ -\mu_n P_n + \lambda_{n-1}P_{n-1} & k = n \end{cases} \tag{16}$$

The variation rate of habitat is inversely proportional to the probability of its species, so the variation rate of habitat is

$$m = m_{\max}\left(1 - \frac{P_k}{P_{\max}}\right) \tag{17}$$

Where: $m_{\max}$ is the maximum variation rate; $P_{\max}$ is the maximum of all species probabilities. After the migration and variation operation of the BBO algorithm, the optimal habitat individuals are output and the initial values of the RBFNN are trained. The load data extracted by the LMD method is used as an input vector of the BBO-RBFNN for predicting load data. Overall, the process based on LMD and BBO-RBFNN model is shown in Figure 4.

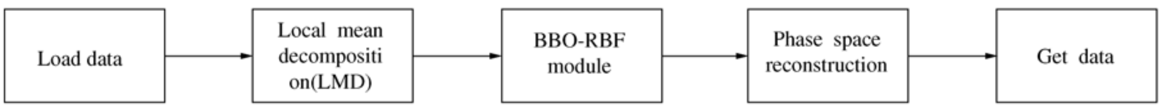

Figure 4 Overall design of prediction system

4 Experionatal result

Considering that the short-term load is affected by factors such as temperature, humidity and rainfall, a predictive model is established after considering two factors that have a large influence on temperature and humidity. Based on the influence of temperature and humidity on load data prediction, the power load data of this paper is taken from the regional load data from September 18, 2014 to October 1, 2014. This data is used as a model for predicting sample data based on LMD and BBO-RBFNN. The data is sampled every 20 minutes, the load data from 0 to 24 h is recorded. There are 3 sampling points per hour and 72 sampling points per day. The first 7 days of data were used as training samples for BBO-RBFNN, the last 7 days were used as test samples. The training input sample and the test input sample include daily maximum temperature, daily minimum temperature, daily average temperature and humidity value and day load data as characteristic indicators and the output is the sample load value point.

4.1 Extraction of feature vector by LMD

Decompose the data into signals of different frequencies by LMD and decompose the signal into $x(t)$ original data decomposition data as shown in Figure 5 and Figure 6.

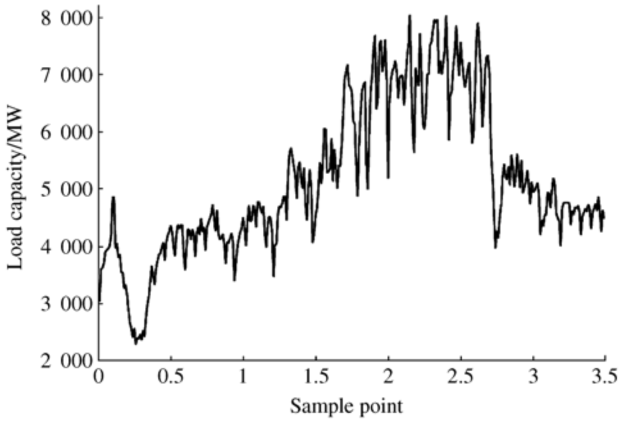

Figure 5 Original data

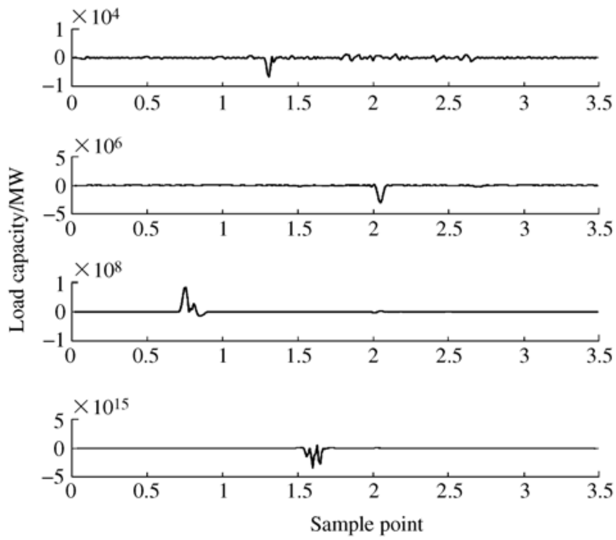

Figure 6 Decomposition data

4.2 Simulation experiment

The power load data is taken as the input data of the BBO-RBFNN. The BBO algorithm and the RBFNN algorithm are combined to train the neural network. The evolution algebra of BBO algorithm is chosen as $G=60$, the size of the population (habitat) is $H=40$, the maximum immigration rate is $m_{max}=0.0061$, the maximum migration rate is $I=0.99$. the maximum variation rate is $E=0.99$. Table 1 lists some of the outputs of the standard RBFNN and BBO-RBFNN after phase space reconstruction. The mean square error (MSE) of the BBO-RBFNN output is shown in Figure 7.

Table 1 Simulation results and absolute errors

Original data/MW	RBF/MW	BBO-RBF/MW	Absolute error
5 144.6	5 600.3	5 290.3	175.7
5 153.1	5 640.8	5 299.1	−14.6
4 894.9	5 268.8	5 041.2	20.4
5 098.8	5 562.3	5 244.7	2.0
4 977.3	5 384.8	5 123.4	32.9
4 666.7	4 913.6	4 814.0	−40.9
5 264.4	5 810.7	5 411.0	18.2
5 393.1	6 008.8	5 541.0	−59.7
5 436.4	6 068.7	5 584.7	−87.6
5 056.2	5 481.3	5 201.9	36.6
8 719.5	5 277.6	8 781.5	3541.5
5 073.3	5 524.3	5 219.2	51.3
4 907.0	5 271.0	5 053.1	68.2
5 117.6	5 578.7	5 263.4	−30.6

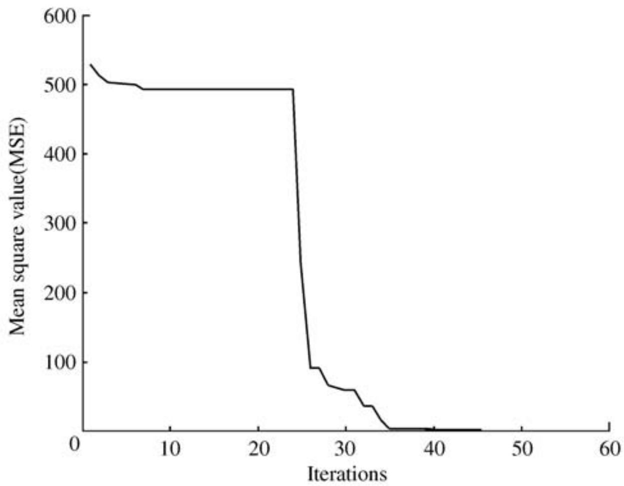

Figure 7 MSE of BBO-RBFNN output

5 Conclusions

Short-term power load forecasting has important reference value for power grid dispatching. In this paper, the load data is decomposed and reconstructed. The BBO algorithm establishes the LMD-BBO-RBFNN predictive model based on the RBFNN model. The experimental results show that the model has better optimization in error performance such as absolute error and mean square error. It has certain reference significance for studying the method of short-term power load forecasting. However, in the face of large factors such as climate, the accuracy of using the prediction method of this paper still needs to be improved. It is necessary to further explore and study the method of predicting the load by finding the relevant factors that have the greatest impact on the power load.

References

[1] Li C , Li S , Liu Y . A least squares support vector machine model optimized by moth−flame optimization algorithm for annual power load forecasting[J]. Applied Intelligence, 2016,45(4):1166-1178

[2] Liu J, Wang F, Yang Z. Transformer fault diagnosis based on RBF neural network and adaptive genetic algorithm[J]. Engineering Journal of Wuhan University. 2016:667-674,2013 (in Chinese)

[3] Lehto E, Shankar V, Wright G B, et al. A radial basis function(rbf) compact finite difference (fd) scheme for reaction-diffusion equations on surfaces[J]. Siam Journal on Scientific Computing, 2017,39(5):A2129-A2151

[4] Niu D, Hui S, Li J, et al. Research on short-term power load time series forecasting model based on BP neural network[C]// 2010 The 2nd IEEE International Conference on Advanced Computer Control, Shenyang, 2010:509-512

[5] Amini M H, Kargarian A, Karabasoglu O. ARIMA-based decoupled time series forecasting of electric vehicle charging demand for stochastic power system operation[J]. Electric Power Systems Research, 2016,140:378-390

[6] Wajima T, Fukumura K, Yano Y, et al. Prediction of human clearance from animal data and molecular structural parameters using multivariate regression analysis[J]. Journal of Pharmaceutical Sciences, 2010,91(12):

[7] Xue J, Watada J. Short-term power load forecasting method by radial-basis-function neural network with support vector machine model[J]. Icic Express Letters, 2011,5(5)

[8] Du D, Simon D. Complex system optimization using biogeography-based optimization[J]. IEEE Transactions on Evolutionary Computation, 2008,12(6):702-713

[9] Ma H, Dan S, Fei M, et al. Hybrid biogeography-based evolutionary algorithms[J]. Engineering Applications of Artificial Intelligence, 2014(12):213-224 (in Chinese)

[10] Simon D , Omran M G H , Clerc M . Linearized biogeography-based optimization with re-initialization and local search[J]. Information Sciences, 2014,267:140-157

[11] Park C J C, Looney D , Van Hulle M U , et al. The complex local mean decomposition[J]. Neurocomputing, 2011,74(6):867-875

[12] Yuan Z, Yong Q, Xing Z, et al. Roller bearing safety region estimation and state identification based on LMD-PCA-LSSVM[J]. Measurement, 2013,46:1315-1324

Brief Biographies

HOU Luting is a master candidate in College of Automation and Electrical Engineering, Qingdao University. His research direction is pattern recognition and intelligent information processing. 601303533@qq.com

GAO Junwei, Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University. His research direction is pattern recognition and intelligent information processing. qdgao163@163.com