International Core Journal of Engineering Volume 5 Issue 10, 2019
ISSN: 2414-1895 DOI: 10.6919/ICJE.201909_5(10).0039

Medium and long-term wind power prediction based on artificial fish swarm algorithm combined with extreme learning machine

Xueming Zhai [1], Li Ma [2, a]

[1]School of North China Electric Power University, Baoding 071000, China;

[2]School control and Computer Engineering, North China Electric Power University, Baoding 071000, China.

[a]MikeMoma1@gmail.com.

Abstract

Accurate prediction of wind power in wind farms plays an important role in the economic operation of wind farms and the safe operation of power grids. The randomness and volatility of wind farm winds make wind power prediction more difficult. In this paper, based on the characteristics of wind farm wind, combined with the wind speed, temperature, humidity and other related meteorological data of wind farm, the ultimate learning machine model (ELM) of wind power prediction is constructed, and the artificial fish swarm algorithm (AFSA) is used to quickly optimize. Characteristics, stepwise iterative optimization of the ω and b parameters of the extreme learning machine, the cost function is minimized, the optimized parameters are obtained, and finally the ELM prediction process is performed, thereby improving the accuracy of the ELM model prediction. The constructed model is trained and predicted by the actual meteorological data and wind power data of a wind farm. The results show that the proposed method has higher prediction than the wind power prediction model of particle swarm optimization learning machine (PSO-ELM). Accuracy.

Keywords

Medium and long term wind power prediction;artificial fish swarm algorithm; extreme learning machine.

1. Introduction

Wind power forecasting is the basis for assessing the operating state of wind farms, and its stochastic fluctuation characteristics pose a challenge to the safe operation of the grid[1]. The energy and research on wind power prediction are more invested in short-term predictions, and there are few studies on the accuracy of medium- and long-term predictions, and factors such as wind power are random over time, which makes the accuracy of medium and long-term predictions face severe challenges. In order to ensure the safe and reliable operation of the power system, to achieve wind power into the network, and to reduce the frequency of power dispatching problems, it is necessary to improve the accuracy of mid- and long-term wind power prediction.

Current wind power prediction methods mainly include physical model methods, statistical regression and learning theory methods. The physical model method firstly quantifies and analyzes the meteorological data such as wind speed, wind direction, temperature and atmospheric humidity of the wind farm, and substitutes it into the power curve to find the actual wind power[2]. The wind power prediction using the physical model must rely on the mature numerical weather prediction system, and the numerical weather prediction update speed is relatively slow, which has a great

ISSN: 2414-1895 DOI: 10.6919/ICJE.201909_5(10).0039

influence on the prediction timeliness of the method. Therefore, the physical model is suitable for short- and medium-term prediction of wind power.

Both statistical regression and machine learning methods are based on historical statistics, real-time monitoring values, and output power mapping relationships. The statistical regression method requires only a time series of wind speed and power to make predictions, but the method needs to rely on a large amount of historical data to record, and for a complex and mutated weather environment, effective prediction results cannot be obtained. There are many commonly used learning methods for wind power prediction, such as artificial neural network[3], support vector machine[4], gray model [5], combined prediction method[6]. Due to their respective defects and the complexity of the algorithm, these methods can lead to slow convergence, long training time or high computational complexity.

In[7], the concept of interval prediction is proposed, and the wind power prediction model of particle swarm-extreme learning machine is established. The fast interval prediction of wind power is realized, and the learning speed and generalization ability are improved. However, the particle swarm optimization algorithm PSO lacks speed. Dynamic adjustment, easy to fall into the local optimal solution, resulting in low convergence accuracy and difficult to converge, so the iterative convergence speed of the particle swarm optimization algorithm still needs to be improved, and the model is only used for short-term wind power prediction.

In[8], based on the nonlinear and non-stationary characteristics of aircraft engine exhaust temperature margin (EGTM) data, a particle swarm optimization (PSO) based extreme learning machine prediction method is proposed, and EGTM prediction is constructed by ELM. The model is optimized by PSO algorithm to ensure the accuracy of the model. The results show that the prediction accuracy is improved compared with the traditional prediction method.

Aiming at the problems existing in the current medium and long-term wind power forecasting methods and the randomness and volatility characteristics of wind farm winds, this paper constructs an extreme learning machine model for wind power prediction using meteorological data such as wind speed, temperature and humidity , and use the artificial fish swarm algorithm to quickly optimize the input weight and offset of the ELM, find the optimized limit learning machine ω and b parameters, and finally carry out the ELM prediction process to ensure the model prediction. The accuracy of the proposed model was tested and predicted experimentally.

2. Construction of Extreme Learning Machine Optimization Model Based on Artificial Fish Swarm Algorithm

2.1 Extreme learning machine

In the extreme learning machine, the standard ELM uses the structure of the Single Layer Feedforward Neuron Network (SLFN). The composition of the SLFN includes the input layer, the hidden layer and the output layer [8], and the input of the training sample is set. The output matrix is as follows:

Input matrix: $X = [x_1, x_2, ..., x_A]^T$

Where $x_i = [x_{i1}, x_{i2}, ..., x_{in}]$ is a row vector representing the ith input sample, i ∈ [1, A]; n is the input node;

Output matrix: $T = [t_1, t_2, ..., t_A]^T$

Where $t_i = [t_{i1}, t_{i2}, ..., t_{im}]$ is a row vector representing the ith output, i ∈ [1, A]; m output node;

Input weight matrix: $\beta = [\beta_1, \beta_2, ..., \beta_L]^T$, the jth input weight vector is β_j , j ∈ [1, L];

Output weight matrix: $\omega = [\omega_1, \omega_2, ..., \omega_L]^T$, the lth output weight vector is ω_l , l ∈ [1, L].

Thus, the model for building an ELM is:

$$\sum_{l=1}^{L}\beta_{iL} f(\omega_1 x_a^T + b_l) = y_{ai} \quad . \tag{1}$$

$$Y = [y_1, y_2, ..., y_A]^T = H\beta \, . \tag{2}$$

Where: b_l is the offset of the lth hidden layer node, the actual output matrix is Y, where $y_a = [y_{a1}, y_{a2}, ...y_{an}]$ is a row vector. After introducing the penalty factor λ, the optimal objective function of the extreme learning machine can be converted to[6]:

$$U_1 = \min : \frac{1}{2}\| H\beta - T \|^2 + \frac{\lambda}{2}\|\beta\|^2 \, . \tag{3}$$

$$H = \begin{bmatrix} f(\omega_1 x_1^T + b_1)...f(\omega_L x_1^T + b_L) \\ f(\omega_1 x_A^T + b_1)...f(\omega_L x_A^T + b_L) \end{bmatrix} \quad . \tag{4}$$

2.2 Artificial fish swarm algorithm

The artificial fish swarm algorithm was proposed in by Li Xiaolei of China and other fish movements. As the process of optimization progresses, artificial fish tend to accumulate around extreme values, and more artificial fish are usually gathered around the global optimal extreme points[9].

The state of the artificial fish can be expressed as a vector, which is the variable to be optimized; the food concentration of the artificial fish at the current position is expressed as, where Y is the objective function value; the distance between the artificial fish individuals is expressed as; The perceived distance of artificial fish; Step indicates the maximum step size of artificial fish movement; δ is the congestion factor.

Artificial fish swarm algorithm artificial fish has four behaviors, namely foraging behavior, cluster behavior, rear-end behavior and random behavior.

Foraging behavior

Let the artificial fish current state be X_i, randomly select a state X_j within its sensing range, if $Y_i \prec Y_j$ in the maximization problem, go further in the direction; otherwise, re-randomly select the state X_j to determine whether it is satisfied. Advance condition; after repeatedly trying try_number (maximum number of attempts) times, if the forward condition is still not satisfied, move one step at random.

Cluster behavior

Let the current state of the artificial fish be X_i, explore the number of partners nf and the central position X_c in the current neighborhood ($d_{i,j} \prec Visable$), if it indicates that the partner center has more food and is less crowded, then towards the center of the partner Further in the direction; otherwise perform foraging behavior.

Rear-end behavior

Let the current state of the artificial fish be X_i, and explore the partner X_j whose maximum is Y_j in the current neighborhood ($d_{i,j} \prec Visable$), if it indicates that the state of the partner X_j has a higher physical concentration and the surrounding is not too crowded. , then go further in the direction of partner X_j; otherwise perform foraging behavior.

Immediate behavior

The random behavior is to randomly select a state in the field of view and then move in that direction.

The artificial fish swarm algorithm evaluates the environment in which the artificial fish is currently located according to the nature of the problem to be solved, thereby selecting an action. For example, the more commonly used evaluation method is to select the behavior that makes the maximum direction to the optimal direction in each behavior, that is, the behavior that makes the artificial fish's next state optimal in each behavior, if it does not make the next state better than the current state. Behavior, then take random behavior.

The clustering behavior can jump out of the local extremum and search for other extremums as much as possible, eventually searching for the global extremum. The rear-end behavior helps to quickly

ISSN: 2414-1895 DOI: 10.6919/ICJE.201909_5(10).0039

move toward an extreme value, speeds up the optimization, and prevents AF from stalling in local oscillations. In the process of optimization, the fish school algorithm evaluates the above two behaviors and automatically selects appropriate behaviors, thus forming an efficient and rapid optimization strategy.

2.3 Proposal of AFSA-ELM prediction model

n the ELM model, ω and b are randomly generated. The ELM prediction model was constructed by determining the number of neurons in the hidden layer and the activation function of the hidden layer neurons. The ELM model does not require complicated parameter settings. It only needs to determine the initial ω and *b*. It has the advantages of fast learning speed and good generalization performance.

In the process of wind power prediction, different parameter settings will have a greater impact on the accuracy of the prediction model [8]. At this time, if the ultimate learning machine model is constructed by a simple random selection initialization parameter method, there are some disadvantages of implicit layer node redundancy in the model construction, which affects the algorithm complexity and prediction accuracy of the ELM model. .

The artificial fish swarm algorithm has the advantages of individual independence, strong parameters and initial value robustness, and can quickly and effectively find the global optimal solution. Before the extreme learning machine predictive calculation, the initial ω and *b* parameters and the objective function are given firstly. Then, using the characteristics of AFSA's fast optimization, the ω and b parameters of the extreme learning machine are stepwise iteratively optimized to minimize the cost function. After the optimized parameters, the ELM prediction process is finally performed, thereby improving the accuracy of the ELM model prediction. Adding the artificial fish swarm algorithm to the parameter optimization of the extreme learning machine can make the initial parameters of the predictive calculation of the extreme learning machine ω and *b* from the original random selection to the optimized parameters. This method can effectively reduce the hidden layer in the model construction. Node redundancy improves the prediction accuracy of the ELM model.

2.4 Mid- and long-term wind power prediction method based on AFSA-ELM

2.4.1 Analysis of wind power influencing factors and establishment of model input and output matrix

First, observe the ability of the wind turbine to obtain wind energy, and analyze the impact factors on wind power. The capture power of the fan can be expressed by equation (5):

$$P = \frac{C_P F \rho v^3}{2} \quad (5)$$

In the formula:

P——wind turbine output power (kW);

v——wind speed (m/s);

P——air density (kg/m^3);

F——swept area of the wind wheel (m^2);

Cp - wind turbine power factor.

It can be known from equation (5) that the wind power is proportional to the cube of the wind speed, and the wind speed change directly affects the change of the wind power. Therefore, the wind speed is one of the input variables input to the ELM prediction model. The concept of wind turbine power factor, wind turbine sweeping area and air density is introduced by equation (5). These three factors also have a certain range of effects on the output power of the fan. The wind turbine power factor and the wind turbine sweeping area are fixed parameters of the wind turbine itself and are constant. Air density is determined by air pressure, temperature and humidity and can be expressed by equation (6):

$$\rho = 3.48\frac{P}{T}(1-0.378\frac{\varphi Pb}{P}) \quad (6)$$

ISSN: 2414-1895 DOI: 10.6919/ICJE.201909_5(10).0039

Where :P——standard atmospheric pressure(kPa);

T——thermodynamic temperature(K);

Pb——saturated water vapor pressure(kPa);

φ——relative humidity(%).

According to the above analysis, the wind speed, air density, wind turbine power factor and wind turbine swept area are taken as the input training sample matrix $X=[x_1,x_2,x_3,x_4]^T$ of the ELM mode, where $x_1=[x_{11},x_{12},...,x_{1n}]$ represents the first input sample: wind speed, wind speed is input in time series, and sampled data is resolved. The rate is 15min, the number of nodes is n=834557; $x_2=[x_{21},x_{22},...,x_{2n}]$represents the second input sample: air density, air density can not be directly detected, but can be calculated according to formula (6); $x_3=[x_{31},x_{32},...,x_{3n}]$ represents the third input sample: wind turbine power coefficient ; $x_4=[x_{41},x_{42},...,x_{4n}]$ indicates the third input sample: the swept area of the wind wheel.

Output matrix: $T=[t]^T$, where $t=[t_1,t_2,...,t_m]$ represents wind power; output node m = 834557.

2.5 Mid- and long-term wind power prediction method of AFSA-ELM

In the ELM model, input weights and offsets are randomly generated before training, and there are shortcomings of implicit layer node redundancy in model construction. The accuracy and time of training are affected by random selection of parameters. In this paper, the artificial fish swarm algorithm has the advantages of individual independence, parameters and initial value robustness, and optimizes the input weight and offset of ELM, that is, finds the optimal W=(a, b, β) and its cost function. E(W) is the smallest, avoiding blind training of artificial neural networks. Its mathematical model is expressed as:

$$\arg\min_{W=(a,b,\beta)} E(W)=\arg\min_{W=(a,b,\beta)} \| H(a_i,b_i)\cdot\beta-T \|^2 \tag{7}$$

$$s.t.\sum_{i=1}^{\vec{N}}\beta_i g(a_i\cdot x_j+b_i)-t_i=\varepsilon_j \tag{8}$$

Combining equations (7) and (8), the objective function of AFSA-ELM can be represented by (9):

$$Fitness(\bar{a},\bar{b},\bar{\beta})=\arg\min_{W=(\bar{a},\bar{b},\bar{\beta})} E(W)=\arg\min_{W=(\bar{a},\bar{b},\bar{\beta})} \| H(\bar{a}_i,\bar{b}_i)\cdot\bar{\beta}-T \|^2 \tag{9}$$

Where: $\bar{a},\bar{b},\bar{\beta}$ are estimates of input weights, offsets, and output weights, respectively.The

specific steps of the algorithm are as follows, and the flow chart is as shown in Fig1, see Figure.1.

Initialize AFSA algorithm parameters and ELM network structure parameters. Populationsize N, visual field visual, step size, maximum iteration number T, maximum number of

trials try_number, crowding degree δ; number of input neurons inputnum, number of hiddenlayer neurons, number of output layer neurons and outputnum .

Initialize input weights, output weights, and offsets.

The raw data is divided into training samples and test samples. The training samples

are input into the ELM. The objective function values of the artificial fish are calculated

according to the objective function (6), and the optimal state and optimality of the artificialfish individual and the global optimal artificial fish individual are sought. value.

Update the location and bulletin board of the artificial fish.

Calculate the size of the objective function and update the optimal state and optimal

value of the artificial fish.

If the number of iterations gen>maxgen, save the optimal input weight, offset and

ISSN: 2414-1895
DOI: 10.6919/ICJE.201909_5(10).0039

output weight; otherwise, gen=gen+1, return to step 4.

Bring the optimal input weights, offsets, and output weights into the ELM model for prediction.

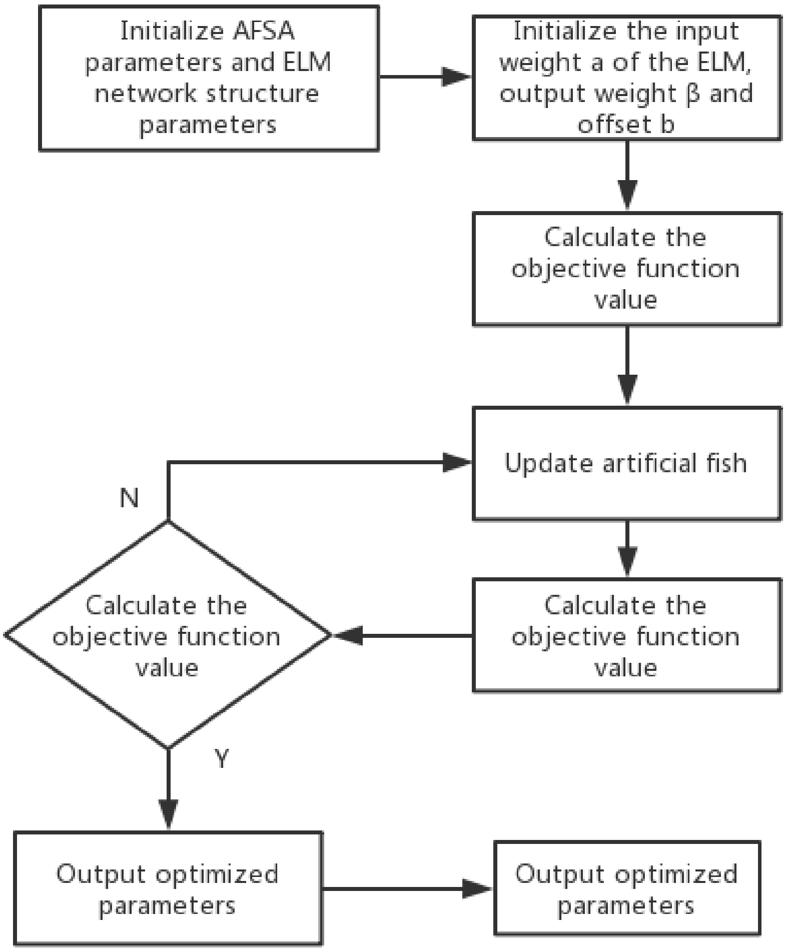

Figure.1. AFSA-ELM model flow chart

3. Experimental verification

3.1 Historical meteorological data collection

The experimental data in this paper is from historical data of weather data and wind turbine operation from a wind farm from 1980 to 2015. The wind farm wind power system has a fan capacity of 2.0 MW, providing 96 locations per day, including characteristic data such as wind speed, temperature, and relative humidity. The sampling data resolution is 15 min, and the resolution of the predicted data is year.

3.2 Wind power plant historical data processing

In actual operation, there will be some abnormal data, which may affect the accuracy of the prediction model. Raw data and retrograde preprocessing [10].

When the data is missing, it is complemented by linear interpolation; the abnormal data is replaced reasonably. ① When the output power value is too large and exceeds the installed capacity of the wind turbine, it can be replaced by the installed capacity rating. ②When the wind speed value is less than the cut-in wind speed, the actual fan output power should be 0, but the actual recorded data is not 0. Set the output power to 0 and set all wind speed values to negative to 0;

Taking the data of a power plant as an example, when selecting a sample, the data of a certain wind tower is selected as reference data. The integrity of the wind tower is good from January 1, 1980 to

ISSN: 2414-1895 DOI: 10.6919/ICJE.201909_5(10).0039

December 31, 2015. Wind speed and wind direction data for 15 minutes. Its integrity statistics are shown in Table 1 below, see Table 1.

Table 1. Wind speed data integrity statistics

Project	Height (m)	Should have data	Invalid data	valid data	Complete rate (%)
Wind speed	10	1192224	18361	1173863	98.46%
	50	1192224	36721	1155503	96.92%
	70	1192224	42801	1149423	96.41%
Wind direction	10	1192224	13983	1178247	98.83%
	70	1192224	25991	1166233	97.82%

According to the chronological sequence of the sample set, the historical data is analyzed and processed according to the wind speed power scatter plot. First, the power point and the shutdown point are removed according to the wind speed power scatter plot and the data, and then the partial autocorrelation method is used to select the most. Related stagnation, obtaining the most relevant historical data. Before and after data processing, as shown in Figures 3 and 4, the data is normalized and normalized into the interval [-1, 1], 70% of the data is used as training data, and the next 30% of the data is used as test data.see Figure.2、Figure.3.

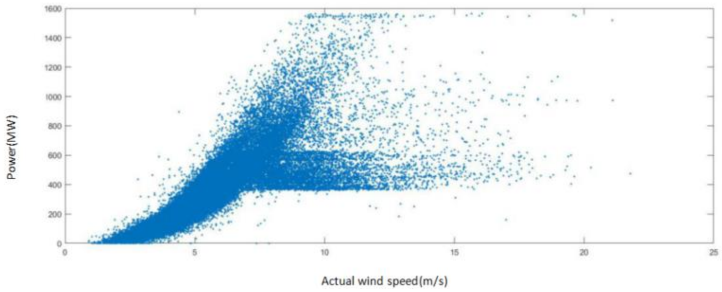

Figure.2. Original wind speed power scatter plot

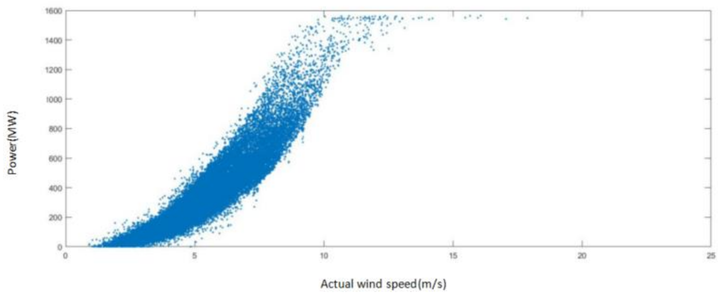

Figure.3. Wind speed power scatter plot after data processing

3.3 Experimental results

The wind power data of a wind farm is used for training and prediction. The input variable variables of the extreme learning machine predict the wind power sequence, wind speed and air density data, and the output data is the annual wind power generation. By training the ELM model, the final result is obtained. Compare the predicted results with the PSO-ELM predictions. The comparison is shown in Fig. 4, see Figure. 4.

ISSN: 2414-1895
DOI: 10.6919/ICJE.201909_5(10).0039

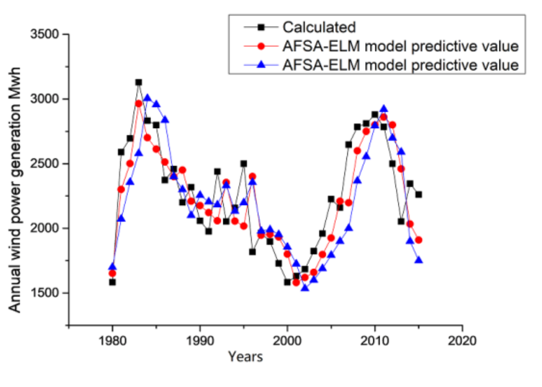

Figure.4. Comparison of AFSA-ELM prediction model and PSO-ELM prediction model results

4. Conclusion

Due to the randomness and intermittent nature of wind power generation, it is difficult to achieve high accuracy for medium and long-term wind power prediction. This paper analyzes the current wind power prediction problems. In this paper, based on the wind farm wind characteristics, combined with wind farm wind speed, air density and other related meteorological data, the wind power prediction extreme learning machine model (ELM) is constructed; artificial fish is used. The ability of the group algorithm (AFSA) to quickly optimize the ELM input weight and offset parameters is optimized to improve the accuracy of ELM prediction. Experimental results show that the proposed method has higher prediction accuracy than the wind power prediction model of the particle swarm extreme learning machine.

References

[1] YE Ｒuili ,LIU Ｒuiye,et al. Ｒeliable power outputbased on confidence interval estimation and optimal ESS configura-tion of wind farm ［J］. Electric Power Automation Equipment, 2017, 37(5) : 85-91.

[2] QIAN Zheng, PEI Yan, CAO Lixiao, et al. Ｒeview of wind powerforecasting method ［J］. High Voltage Engineering, 2016, 42 (4) :1047-1060.

[3] Fan Gaofeng, Wang Weisheng, Liu Chun, et al. Wind power prediction based on artificial neural network [J]. Proceedings of the CSEE, 2008, 28(34)：118-123(in Chinese).

[4] Cheng Qiming, Chen Lu, Cheng Yinman, et al. Short-term forecasting method of wind power based on EEMD and LS-SVM model[J]. Electric Power Automation Equipment, 2018, 38(5): 27-35.

[5] Li Junfang, Zhang Buhan, Xie Guanglong, et al. Grey predictor models for wind speed-wind power prediction [J]. Power System Protection and Control, 2010, 38(19)：151-159(in Chinese).

[6] Zhang Yihui, Wang He, Hu Zhijian,et al.A hybrid short-term wind speed forecasting model based on ensemble empirical mode decomposition and improved extreme learning machine[J]. Power System Protection and Control,2014,42(10):29-34(in Chinese).

[7] LIU Yuqi, et al. Prediction inte-rvals forecasts of wind power based on PSO-KELM ［J］. Proceedingsof the CSEE, 2015, 35(Supplement 1) : 146-153.

[8] Dai Shaowu, Chen Qiangqiang, Liu Zhihao, et al. Prediction of exhaust temperature margin based on particle swarm extreme learning machine[J]. Instrument Technology, 2019, Volume Missing (6): 10-13.

[9] Li Xiaolei. A new intelligent optimization method-artificial fish swarm algorithm [D]. Zhejiang University, 2003.

[10] Cheng Qiming, Chen Lu, Cheng Yinman, et al. Short-term prediction method of wind power based on EEMD and LS-SVM model[J]. Electric Power Automation Equipment, 2018, 38(5): 27-35.