Power Load Forecasting Based on ABC-SA Neural Network Model

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Abstract

Short-term load forecasting of power systems is related to the smooth scheduling of power systems. The accuracy of load forecasting directly affects the economics and stability of power systems, and the real-time requirements of smart grids for load forecasting are also increasing. Therefore, domestic and foreign scholars have always made short-term power load forecasting the focus of research. Artificial neural networks are intelligent algorithms that are widely used in various fields. In recent years, experts and scholars have also applied artificial neural networks to short-term power load forecasting. Among the load prediction algorithms, the most used is the BP neural network. In this paper, the artificial bee colony algorithm (ABC) is improved to improve the prediction accuracy and global convergence of the artificial bee colony algorithm. The improved artificial bee colony algorithm is used to optimize the BP neural network, namely the ABC-SA power load prediction model. Finally, the effectiveness of the proposed method is verified by comparing the predicted values with the real values.

Keywords

Power load forecasting; Artificial bee colony algorithm; Neural network.

1. Introduction

Short-term load forecasting (STLF) mainly refers to the forecast of electric load for several hours and one day to several days in the future. It is the basis for arranging the purchase of electricity plans, economic distribution load and arrangement of unit output. Load forecasting is a prerequisite for ensuring safe and reliable operation of the power grid [1]. With the development of technology and computer technology, related technologies for power load forecasting are also constantly being introduced. Currently, methods for studying short-term load forecasting at home and abroad generally have traditional basic analysis and forecasting methods as well as grayscale prediction, regression analysis and neural Intelligent prediction algorithms such as networks [2, 3]. The artificial bee colony algorithm is one of the group-only algorithms. Once the algorithm is proposed, it is more and more researchers research it because of its simple structure and easy performance. Although the artificial bee colony algorithm is excellent, it has many shortcomings of optimization algorithms - it is easy to fall into local optimum.

After the artificial bee colony reaches the end of the algorithm, the reconnaissance bee is converted to the extreme point of the bee after repeated iterations, resulting in weak search ability and even falling into local optimum. Therefore, this paper uses the simulated annealing algorithm to improve the artificial bee colony algorithm, which is called ABC-SA algorithm. Its function is to maintain the excellent solution and expand the search range of bees in the bee-keeping stage and the observation bee stage, thus improving the convergence speed. The algorithm is used in the training of optimized BP neural network, and the optimized neural network is used to predict the power load.

2. Artificial Bee Colony Algorithm and Its Improvement

2.1 Principle of Artificial Bee Colony Algorithm

In the artificial bee colony optimization algorithm, the mechanism of analog biology also contains three basic components: honey source, employment bee, non-employed bee [4].

Honey source: In different optimization algorithms, the feasible solutions are given in a certain form. In the artificial bee colony algorithm, the honey source is its feasible solution, and its biological mechanism value is from the distance of honey source, nectar How much, the merits of nectar, the value of honey source in the artificial bee colony algorithm is determined by the parameter yield.

Hire bee: It is the honey bee in the biological mechanism, also known as the lead bee. It corresponds to the number of honey sources. They pass the swing dance to the other bees to convey the information of the honey source, such as the distance of the honey source. How many advantages and disadvantages of honey source nectar, when the value of honey source is higher, the more worker bees it can lead.

Non-employed bees: that is, the bee in the biological mechanism, where the beekeeper is subdivided into follower bees and scout bees. Follow the bees in the hive waiting to lead the bees to pass the honey source information to them and select their own followers according to the greedy algorithm. The task of the scout bee is to randomly search for new sources of honey near the hive. When a bee found a honey source for a long time without a worker bee, in the artificial bee colony algorithm it is more than the limit number, at which point it will be converted into a new scout. Look for new sources of honey. The main steps of the artificial bee colony optimization algorithm are as follows:

Step 1. First establish a BP neural network.

Step 2: Initialize various parameters of the artificial bee colony optimization algorithm. Including the total number of worker bees (N_S), the number of bee (N_e), the number of solutions (SN), the number is the number of honey sources is equal to the number of bees, the number of followers (N_O), the maximum number of cycles (MCN), the maximum limit (limit), and produces the initial solution of the D dimensionX_i (i = 1, 2, …, N_S). Here, the initial solution X_i (i = 1, 2, …, N_S)of the D dimension is the weight and threshold of the BP neural network in step 1, and the dimension D satisfies the following formula:

$$D = N_{input} \times N_{hidden} + N_{hidden} + N_{hidden} \times N_{output} + N_{output} \tag{1}$$

Among them: N_{input}, N_{hidden}, N_{output} are the number of neurons in the input layer, the hidden layer, and the output layer, respectively. $N_{input} \times N_{hidden} + N_{hidden}$ represents the threshold and weight of the input layer to the hidden layer. $N_{hidden} \times N_{output} + N_{output}$ represents the threshold and weight of the hidden layer to the output layer.

When the honey source is initialized, SN feasible solutions (equal to the number of hired bees) are randomly generated and the fitness function value is calculated. The formula for randomly generating a feasible solution is as follows:

$$x_{ij} = x_{min,j} + rand(0,1)(x_{max,j} - x_{min,j}) \tag{2}$$

Where (x_i,i=1,2,…,SN)is the randomly generated initial solution, which is a D-dimensional vector, D is the dimension of the problem is the number of optimization parameters, j∈{1, 2, ... , D}.

Step 3, the fitness value of each initial solution is calculated and evaluated. The formula is as follows:

$$f(X_i) = \begin{cases} 1 & MSE_i = 0 \\ \frac{1}{MSE_i + 1} & MSE_i > 0 \end{cases} \tag{3}$$

Where i =1, 2, …, N_S, MSE_i represents the BP neural network mean square error of the ith solution. It can be known from the formula that when the value of MSE _i is 0, the fitness value is 1 is the optimal solution.

Step 4, lead the bee to search for a new honey source, E_i a new solution, according to formula (4). When a new solution is found, the bee is led to calculate the fitness value of the new solution and compare it with the fitness value of the old solution. The lead bee is selected by the greedy algorithm. When the fitness value of the new solution is larger, the honey source information is updated, otherwise the number of failures is increased by one.

The formula for searching for a new honey source is:

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \tag{4}$$

Where j∈{1,2, … ,D}, k∈ {1,2, …,SN} ,and k is a random number generated randomly and k≠i, φ_{ij} is [-1, 1].

Step 5, the following bee follows the formula (5) to calculate the probability and selects the lead bee. Follow the bee according to the honey source information of the bee to carry out the probability calculation, select the honey source with large fitness value to collect the honey, and continue to search for the new honey source through the formula (4) near the honey source, that is, search for a new one in the neighborhood of the original solution. solution.

Follow the bee selection probability:

$$P_i = \frac{fit(x_i)}{\sum_{n=1}^{SN} fit(x_n)} \tag{5}$$

Where $fit(x_i)$is the fitness value of the solution, and the fitness value of the solution represents the pros and cons of the honey source? The better the honey source, the larger the fit value, which means the probability of following the bee selection is greater. The easier it is to find the optimal solution.

Step 6: If the number of failed failures of a certain honey source is greater than a preset limit value, indicating that the honey source is in a local optimum, the honey source is abandoned and the corresponding lead bee is turned into a scout bee, and a new formula (2) is generated. The source of honey.

Step 7. Save the optimal honey source, that is, the optimal solution.

Step 8, it is determined whether the number of iterations is greater than a preset maximum number of loops (MCN). If it is greater than, the training is ended. Otherwise, the process returns to step 4 to continue the iteration.

2.2 Improvement of Artificial Bee Colony Algorithm

Through the above simple description of the artificial bee colony algorithm, it can be seen that in the later stage of the algorithm, after the reconnaissance bee is repeatedly iterated, it is converted into the bee of the extreme point, which leads to weak search ability and even falls into local optimum. Therefore, this paper uses the simulated annealing algorithm to optimize the artificial bee colony algorithm. The simulated annealing algorithm is derived from the principle of solid annealing. Its main advantage lies in the ability to utilize the disorder of particles at high temperatures and effectively avoid falling into local optimal solutions. This paper introduces this mechanism into the artificial bee colony algorithm, that is, when the new food source yield is lower than the current food source, it still accepts the new food source with a certain probability. The annealing temperature T in simulated annealing determines the probability that the bee accepts a low-yield food source. The higher the temperature, the larger the food source receives the low-yield food, and the lower the temperature, the smaller the temperature. Therefore, the annealing temperature should be large at the beginning of the algorithm iteration. In turn, the algorithm tends to global search. In the later stage of the iteration, the temperature should be smaller and smaller, which in turn makes the algorithm tend to focus on local search and speed up the convergence of the algorithm. The specific operation is as follows.

The bee-keeping stage and the observation bee stage are judged using a simulated annealing mechanism when selecting a new honey source.

(1) Calculate the fitness difference between the new honey source and the old honey source $\Delta f = f_{x'} - f_x$;

(2) If$\Delta f > 0$, accept the new honey source, otherwise when $\exp((f_{x'} - f_x)/t_k) > random[0,1)$ accept the new honey source;

(3) An annealing operation is performed using the annealing public $t_{k+1} = \lambda t_k$.

The improved wolf group algorithm is called ABC-SA algorithm, and the algorithm flow chart is shown in Fig 1.

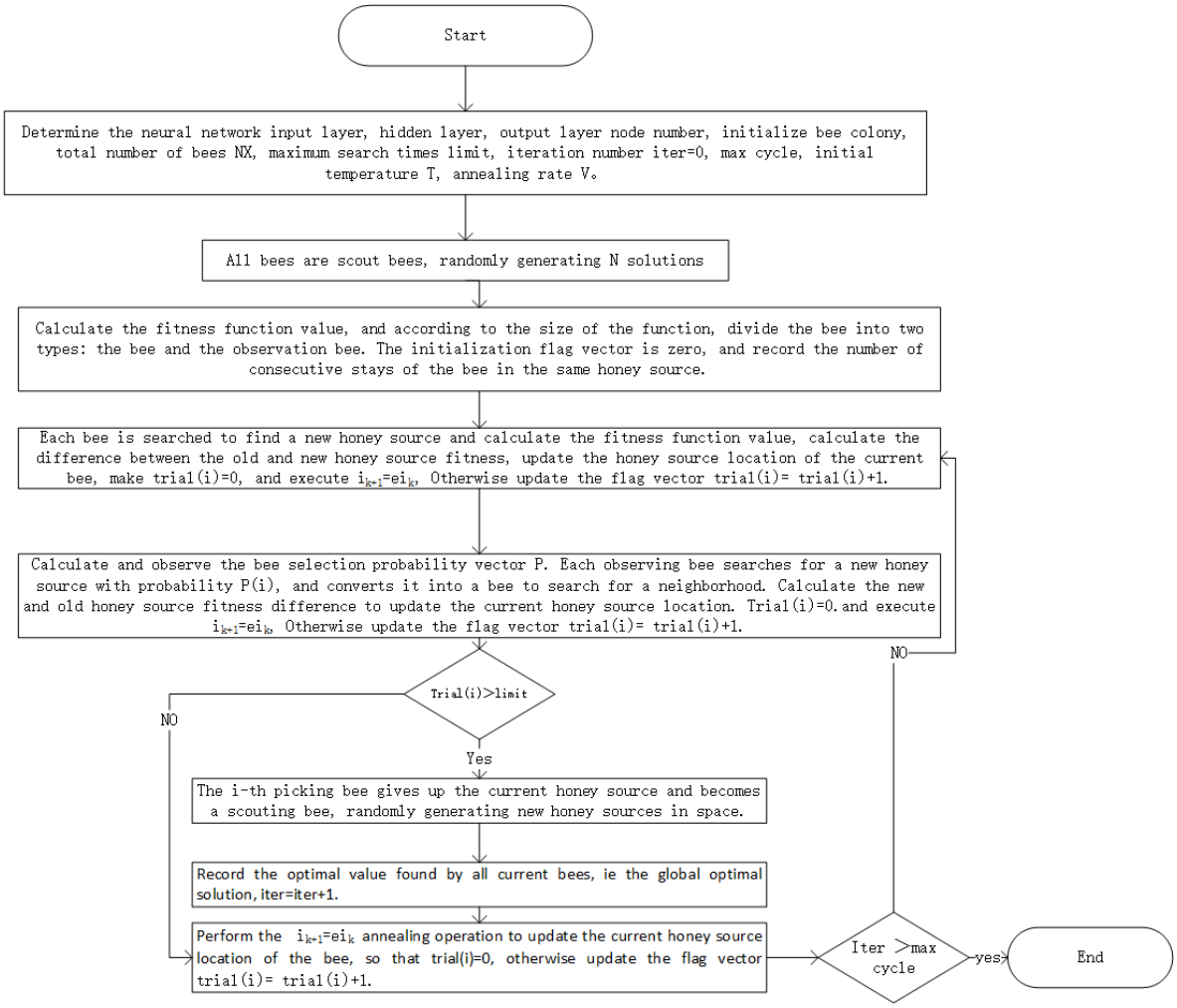

Fig 1. Algorithm flow chart

3. ABC-SA Load Forecasting Model

The multi-layer neural network has strong nonlinear learning ability and is widely used in power load forecasting, but it also has many shortcomings. In this paper, based on the shortcomings of BPNN, the artificial bee colony algorithm and simulated annealing algorithm are combined to optimize the relevant parameters of BP neural network, that is, the ABC-SA load forecasting model is used to improve the prediction accuracy. The process of artificial bee colony and simulated annealing to optimize BP neural network is as follows.

(1) Initialize the BP network. Including determining the number of network layers, the number of nodes in each layer, etc.; initializing the ABC-SA algorithm parameters, initializing the bee population and setting parameters: ① total number of bees Nx; number of honey sources 1/2Nx; ②maximum

number of iterations max Cycle; ③ maximum number of searches limit, initial Temperature T and annealing rate λ;

(2) The bee is searched for a new honey source, the fitness value is calculated, and a simulated annealing mechanism is used to determine whether to select a new honey source.

(3) Observe that the bee is converted to seal, search for the honey source, and judge whether to retain the honey source according to the simulated annealing mechanism.

(4) Determine the number of iterations in the scouting stage. If the number of iterations has been reached and the honey source is not updated, the honey source is discarded and the new honey source is randomly searched, otherwise the iteration is continued.

4. Simulation Experiment

The experiment selected the maximum power load per day for a whole year in a city as a training sample and predicted the maximum daily load for the 31st day of July of the second year. Each prediction uses the true value of the day before the forecast to replace the predicted value. BP neural network and ABC-SA neural network were used for training and prediction, respectively. Figure 2 is a comparison of predicted and real values in July.

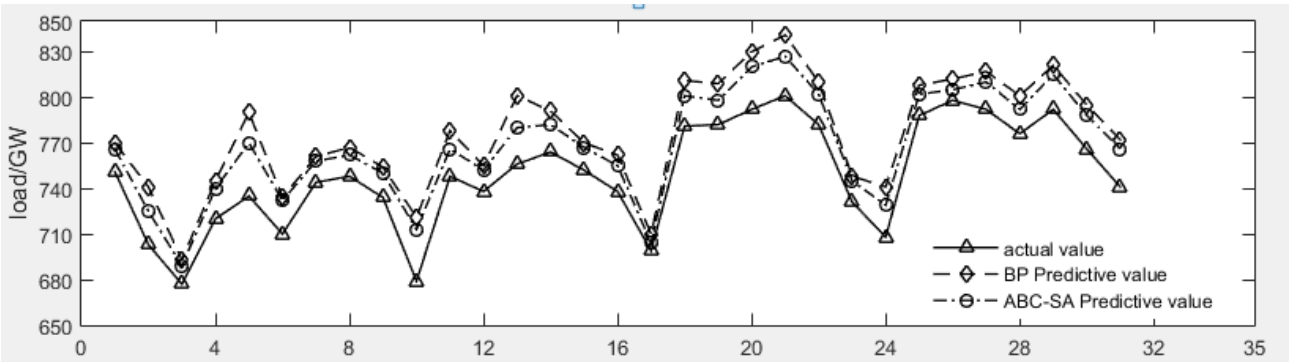

Fig 2. Comparison of two model load prediction values

Table 1 shows the load prediction results and relative errors of the classical BP model and the ABC-SA model. Table 2 gives a comparative error comparison analysis table for the two models.

It can be seen from the comparison table of prediction results and prediction results that the average relative error of the classical BP model prediction is 3.59%, and the prediction result of the ABC-SA model is 2.11%. Therefore, the improved artificial bee colony algorithm is applied to the BP neural network. Optimization is carried out, the load prediction results are gradually reduced, and the prediction accuracy is also improved accordingly. It is proved that the ABC-SA model can predict the electric load more accurately.

Tab 1. Comparison table of prediction results of two prediction models

Date	Actual value(MW)	BP model		ABC-SA model	
		Predictive value (MW)	Relative error (%)	Predictive value (MW)	Relative error (%)
1	751	770	2.3	766	2.0
2	703	741	5.4	725	3.1
3	677	693	2.4	689	1.8
4	720	745	3.5	740	2.8
5	735	790	7.5	770	4.8
6	710	734	3.4	732	3.1
7	744	761	2.3	758	1.9
8	748	767	2.6	762	1.9

9	734	754	2.7	750	2.2
10	679	721	6.1	713	5.0
11	748	778	4.0	766	2.4
12	738	755	2.3	752	1.9
13	756	801	6.0	780	3.2
14	764	791	3.5	782	2.4
15	752	770	2.4	767	2.0
16	738	762	3.3	755	2.3
17	699	710	1.6	704	0.7
18	781	811	3.8	801	2.6
19	782	809	3.5	798	2.0
20	792	830	4.8	820	3.5
21	801	841	5.0	827	3.2
22	782	810	3.6	802	2.6
23	731	748	2.3	745	2.0
24	708	741	4.7	729	3.0
25	788	808	2.5	802	1.8
26	798	812	1.8	805	0.9
27	792	817	3.2	810	2.3
28	776	801	3.2	792	2.0
29	792	821	3.7	815	2.9
30	766	795	3.8	788	2.9
31	741	772	4.1	766	3.4

Tab 2. Comparison of two prediction model errors

Predictive model	Minimum relative error (%)	Maximum relative error (%)	Average relative error (%)
BP model	1.6	7.5	3.59
ABC-SA model	0.7	5.0	2.11

5. Conclusion

Because the artificial bee colony algorithm is easy to fall into the local optimal solution, this paper uses the simulated annealing algorithm to improve it, and then becomes the ABC-SA algorithm, and applies the ABC-SA algorithm to optimize the parameters of the BP neural network. Simulation experiments show that the ABC-SA model can effectively predict the highest power load on a certain day. Comparing with the prediction results of the classical BP model, the prediction accuracy is greatly improved, and the short-term prediction of the electric load can be completed well, and the electric load forecasting system with higher accuracy requirements can be satisfied.

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