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A short-term power load forecasting model based on the generalized regression neural network with decreasing step fruit fly optimization algorithm

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ABSTRACT

Short term power load forecasting plays an important role in the security of power system. In the past few years, application of artificial neural network (ANN) for short-term load forecasting (STLF) has become a research hotspots. Generalized regression neural network (GRNN) has been proved to be suitable for solving the non-linear problems. And according to the historical load curve, it can be known that STLF is a non-linear problem. Thus, the GRNN was used for STLF in this paper. However, the value of spread parameter σ determines the performance of the GRNN. The fruit fly optimization algorithm with decreasing step size (SFOA) is introduced to select an appropriate spread parameter σ. Combined with the weather factors and the periodicity of short-term load, an effective STLF model based on the GRNN with decreasing step FOA was proposed. Performance of the proposed SFOA-GRNN model is compared with other ANN on the basis of prediction error.

1. Introduction

With the development of agriculture, industry and the improvement of living standards, the quality of power supply has been putting forward higher requirements. Power system consists of power grid and power users, its role is to provide an economical and reliable electric energy for all kinds of users. The generating capacity and electricity consumption are changing all the time, however, electricity is not easy to store, the generating capacity must follow the change of the electricity consumption, thus dynamic balance can be achieved, otherwise it will affect the quality of power supply, and even endanger the safety and stability of the power system.

Short term load forecasting, mainly refers to the power load forecasting for the next few hours, one day to several days. According to the load forecasting, the system can optimize operation time of generating units, determine the start and stop time of the generating units and its output. Accurate load forecasting can minimize the total consumption of the whole generating units. Therefore, short term load forecasting plays an important role in power system. The accuracy of prediction has a direct impact on the security, economy and quality of the power system. To improve the accuracy has become an important research field in the operation and management of the modern power system [1].

The research on short term load forecasting has a long history. It has been studied since 1950s. Classical methods include regression analysis, time series method, Kalman filter method and other traditional mathematical statistics method [2–8]. In early 1990s, with the development of artificial intelligence technology, artificial intelligence has been gradually introduced into the short-term load forecasting, such as expert system approach, fuzzy prediction method, wavelet analysis method, chaos theory method and SVM method [9–13]. But there are still shortcomings among them, such as complex procedures, low precision, slow convergence speed, poor stability and so on.

So far, the neural network theory has gradually become mature [14–19], application of artificial neural network (ANN) for short-term load forecasting has emerged, and many papers have reported successful experiments and practical tests with ANN [20]. Classical BP neural network can fit the high dimension and nonlinear mapping between the input and output from the complex sampled data, thus it can make forecast with high precision. But the method can not clearly distinguish the impact factors on the load data, the network structure is not able to be determined automatically, and the forecasting results are easy to fall into the local optimum [21].

The generalized regression neural network (GRNN) which was developed by Specht [22] is a kind of radial basis function neural network. Due to its good nonlinear approximation ability, excellent

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performance of anti-interference, the ability of autonomous learning and fast convergence speed, it is widely used in various disciplines and engineering fields [23]. There are several applications of short term load forecasting as well [24–26]. GRNN does not need to set the model form, but there is spread parameter in the kernel function of the implicit regression unit, and its value has a great influence on the prediction performance of the generalized neural network. It is significant to select an appropriate spread parameter. So the parameter optimization algorithm is needed, paper [27] used differential evolution algorithm (DE), paper [28] used genetic algorithm (GA) and paper [29] used particle swarm optimization algorithm (PSO) to achieve better forecasting performance.

Fruit fly optimization algorithm is a kind of swarm intelligence algorithm proposed by Taiwan scholar Wenchao Pan [30]. Compared with ant colony algorithm, particle swarm optimization algorithm (PSO) and other swarm intelligence algorithms, its program is simple, easy to understand, with fast convergence speed and not easy to fall into local optimum [31]. The performance of FOA mainly depends on the size of the population, the number of iterations, the initial position and the value of the iteration step. Among them, to optimize the step size is more feasible and significant, which affects the search ability of the fruit fly group. Using the appropriate step value can greatly increase the search ability of the FOA [32]. Therefore, the fruit fly algorithm with decreasing step (SFOA) is used to optimize the propagation parameter σ of GRNN, in order to improve the accuracy of GRNN for short term power load forecasting.

The rest of the paper is organized as follows: In Section 2, the network structure and theoretical basis of GRNN are introduced. In Section 3, the paper introduces the FOA, and puts forward FOA with decreasing step size. In Section 4, the model of GRNN optimized by SFOA is proposed. In Section 5, simulation and analysis are carried out, performance of the proposed SFOA-GRNN model is compared with other ANN on the basis of prediction error. Finally, conclusions are drawn in Section 6.

2. Generalized regression neural network

The generalized regression neural network, which was proposed by Dr. D.F. Specht in 1991, is a form of deformation of the radial basis function (RBF) neural network. Based on non-parametric regression, GRNN is established on the basis of sampled data, executes the Parzen non-parameter estimation, and the network output is calculated based on the maximum probability principle. So it has a good ability of nonlinear approximation. Compared with the radial basis function neural network, GRNN training is more convenient, and it is with advantages in the approximation ability and learning speed. The network finally converges to the optimal regression surface, which is the most accumulation of samples. GRNN can be used to deal with the unstable data as well [33]. Generalized regression neural network is especially suitable for solving the non-linear problems, such as STLF.

The generalized regression neural network consists of four layers, the input layer, the pattern layer, the summation layer and the output layer [34,35], shown as in Fig. 1.

Different from the transfer neural network like BP neural network, the generalized regression neural network does not need to repeat the iterative training process and initialize the network connection weights, the main purpose of learning is to find the best smoothing parameter, which is the value of Spread in Matlab neural network toolbox. Assuming that $f(x, y)$ is the joint density of random variables x and y, then the observed value of x is x_0, the regression of y with respect to x as follows

$$E(y|x_0) = y(x_0) = \frac{\int_{-\infty}^{0} yf(x_0, y)dy}{\int_{-\infty}^{0} f(x_0, y)dy}, \tag{1}$$

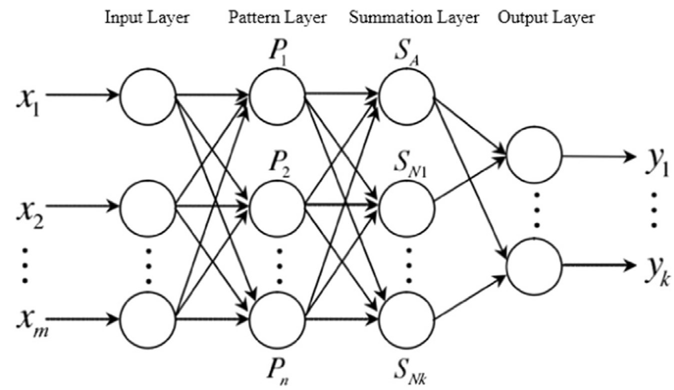

Fig. 1. The structure of generalized regression neural network.

where $y(x_0)$, that is the predictive output of y under the input for X_0. Using Parzen non-parametric estimation, the density function $f(x_0, y)$ can be estimated from the sampled data set $\{x_i, y_i\}_{i=1}^{n}$ according to the following formula:

$$f(x_0, y) = \frac{1}{\sigma^{p+1} n (2\pi)^{\frac{p+1}{2}}} \sum_{i=1}^{n} e^{-d(x_0, x_i)} e^{-d(y, y_i)}, \tag{2}$$

$$d(x_0, y) = \sum_{j=1}^{p} \left[\frac{x_{0j} - x_{ij}}{\sigma}\right]^2, \tag{3}$$

$$d(y, y_i) = [y - y_i]^2, \tag{4}$$

where n is the size of sample, and p is the dimension of the random variable x. σ is called smooth factor, is actually the standard deviation of Gauss function. Considering with the above formula, exchange the order of integration and summation, we obtain

$$psy(x_0) = \frac{\sum_{i=1}^{n} (e^{-d(x_0, x_i)} \int_{-\infty}^{+\infty} ye^{-d(y, y_i)}dy)}{\sum_{i=1}^{n} e^{-d(x_0, x_i)} \int_{-\infty}^{+\infty} e^{-d(y, y_i)}dy)}. \tag{5}$$

Due to $\int_{-\infty}^{+\infty} xe^{-x^2}dx = 0$, the above formula can be simplified as follows:

$$y(x_0) = \frac{\sum_{i=1}^{n} ye^{-d(x_0, x_i)}}{\sum_{i=1}^{n} e^{-d(x_0, x_i)}}. \tag{6}$$

Obviously, in the above formula, the molecule is the weighted sum of the y_i values of all training samples, the weights are $e^{-d(x_0, x_i)}$. It should be noted that the value of the spread parameter σ. If the spread parameter is very large, $d(x_0, x_i)$ approaches 0, $y(x_0)$ is similar to the average of all the sample dependent variables. If the spread parameter approaches to zero, then $y(x_0)$ is very close to the value of the training samples. When the data is predicted in the training sample, the predicted values are very close to the expectation in the sample. But once the new input was considered, the forecasting performance will become worse, the loss of network generalization ability is named overfitting phenomenon.

Therefore, it is required to determine a suitable spread parameter value, for what all samples of the dependent variables can be taken into account. Taking into account the distance of different training samples from testing input sample, the test samples in the training samples will be given greater weight. And training samples close to the testing samples will be given a greater weight.

3. Fruit fly optimization algorithm and its improvement

3.1. Standard fruit fly optimization algorithm (FOA)

The fruit fly optimization algorithm is a new method to search for global optimization, it is based on the foraging behavior of the fruit fly.

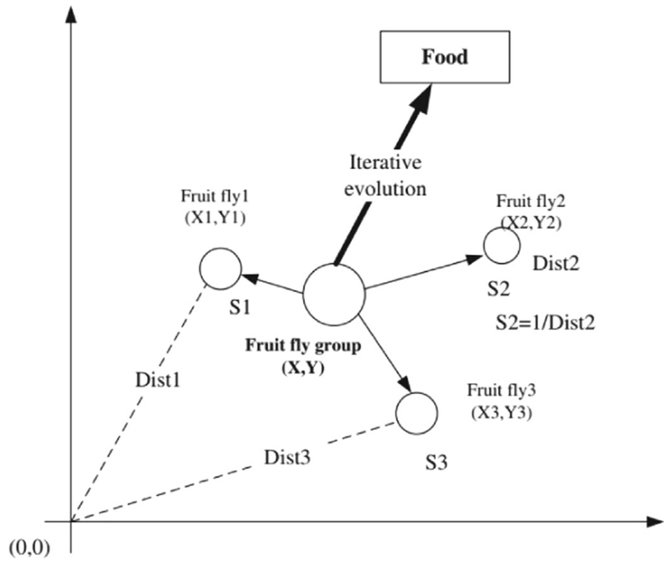

Fig. 2. Food finding iterative process of fruit fly swarm.

The algorithm is proposed by Taiwan scholar Wenchao Pan in 2011 [21].

Like the ant colony algorithm and particle swarm optimization algorithm, which are all developed from the foraging behavior of the animal population, FOA belongs to swarm intelligence algorithm. The sense of smell, sight and other senses of fruit flies are superior to other species. Olfactory organ makes fruit fly easy to collect all kinds of smell that float in the air. After flying close to the food, the fruit fly can use sharp vision to find the location of food and other fruit flies, then fly to the direction of them. As a new global optimization method, the fruit fly optimization algorithm has the advantages of simple operation, convenient application, fast convergence and so on. The characteristic of fruit flies searching for food is shown as in Fig. 2.

Standard fruit fly optimization algorithm steps are presented as follows:

Step 1 Initialize position (x_0, y_0) of the fruit fly swarm randomly

$$x_0 = \text{random}(), \tag{7}$$

$$y_0 = \text{random}(). \tag{8}$$

Step 2 Initialize step size L. Set the random direction and distance of the fruit fly individual to search for food through the sense of smell

$$x_i = x_0 + L, \tag{9}$$

$$y_i = y_0 + L. \tag{10}$$

Step 3 Unable to know the location of the food, so firstly estimate the distance between the location and the origin (Dist_i), then calculate the value (S_i) of smell concentration, which is the reciprocal of the distance

$$\text{Dist}_i = \sqrt{x_i^2 + y_i^2}, \tag{11}$$

$$S_i = \frac{1}{\text{Dist}_i}. \tag{12}$$

Step 4 Take smell concentration determination value (S_i) into the smell concentration detection function, in order to get the smell concentration of the fruit fly's individual location (Smell_i)

$$\text{Smell}_i = \text{Function}(S_i). \tag{13}$$

Step 5 Find out the fruit fly with the highest smell concentration in the fruit fly swarm

$$[\text{bestSmell bestIndex}] = \max(\text{Smell}). \tag{14}$$

Step 6 Retain the best smell concentration and coordinate. Then the fruit fly swarm uses vision to fly to the position (x_b, y_b)

$$\text{Smellbest} = \text{bestSmell}, \tag{15}$$

$$x_b = x(\text{bestIndex}), \tag{16}$$

$$y_b = y(\text{bestIndex}). \tag{17}$$

Step 7 Enter the iterative optimization, repeat steps 2–5. And determine whether the smell concentration is better than the previous iteration of the smell concentration. If it is, then perform step 6.

3.2. Fruit fly optimization algorithm with decreasing step (SFOA)

The performance of FOA mainly depends on the size of the population, the number of iterations, the initial position and the value of the iteration step. Among them, the greater the population size and the number of iterations, the better the effect of convergence will be, but will increase the system's memory consumption and the running time of the program, especially in the case of a huge amount of data is more obvious. Among them, to optimize the step size is more feasible and significant, which affects the search ability of the fruit fly group. Using the appropriate step value can greatly increase the search ability of the FOA.

In Step 2 of FOA, the step size L is a fixed value. The larger the L is, the stronger the global optimization ability is, the weaker the local search ability is and vice versa. Meanwhile, when L is small, FOA is easily trapped in the local optimum. Through experiments, it is found that the dynamic step size is better than the fixed value. It can make the algorithm have stronger global searching ability to avoid falling into local optimum and have better ability of local optimization as well, thus it is able to improve the accuracy of the search.

Fruit fly optimization algorithm with decreasing steps is based on FOA. However, the fixed step size is changed to be the decreasing step size. To get better performance, the formula of step value refers to the *sigmoid* function, it is as follows

$$L_i = L_0 - \frac{L_0}{1 + e^{\left(6 - \frac{12G_i}{G_{max}}\right)}}, \tag{18}$$

where L_0 is the initial step size; G_{max} is the maximum number of iterations; G_i is the current iteration number.

Decreasing step size makes FOA have the largest search step in the initial stage of iteration. At this point, the search space is large, the global optimization ability is the most powerful. Thus, in the early stage of foraging, there is a great probability to find the global optimal solution. This prevents SFOA from falling into the local optimum problem. With the increase of the number of iterations, the step size is decreasing, the local optimization ability is enhanced. At the end of the iteration, the accuracy of the algorithm becomes the highest, as shown in picture Fig. 3.

With decreasing step size, the balance between the global optimization ability and the local optimization ability can be achieved. Thus, using decreasing step size greatly improves the performance of the fruit fly algorithm.

4. Network structure of SFOA-GRNN

Due to the value of σ directly affects the performance of the generalized regression neural network, now σ can be optimized through optimization ability of SFOA. Firstly, use the olfactory and visual of fruit fly to find out the location with the most strongest smell. Then calculate the root mean square error (*RMSE*) between the output value and the actual value of the network. *RMSE* will be minimized by iterative optimization. Retain the smell value at this time, which is the value of σ. Specific steps are presented as follows:

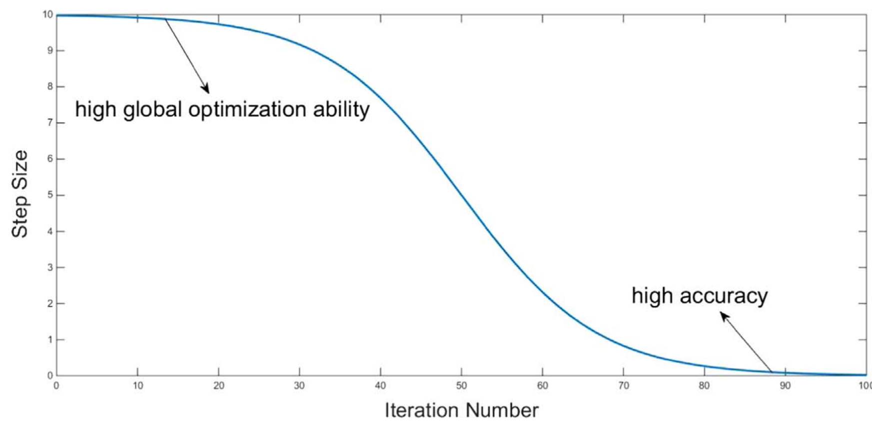

Fig. 3. Decreasing step size.

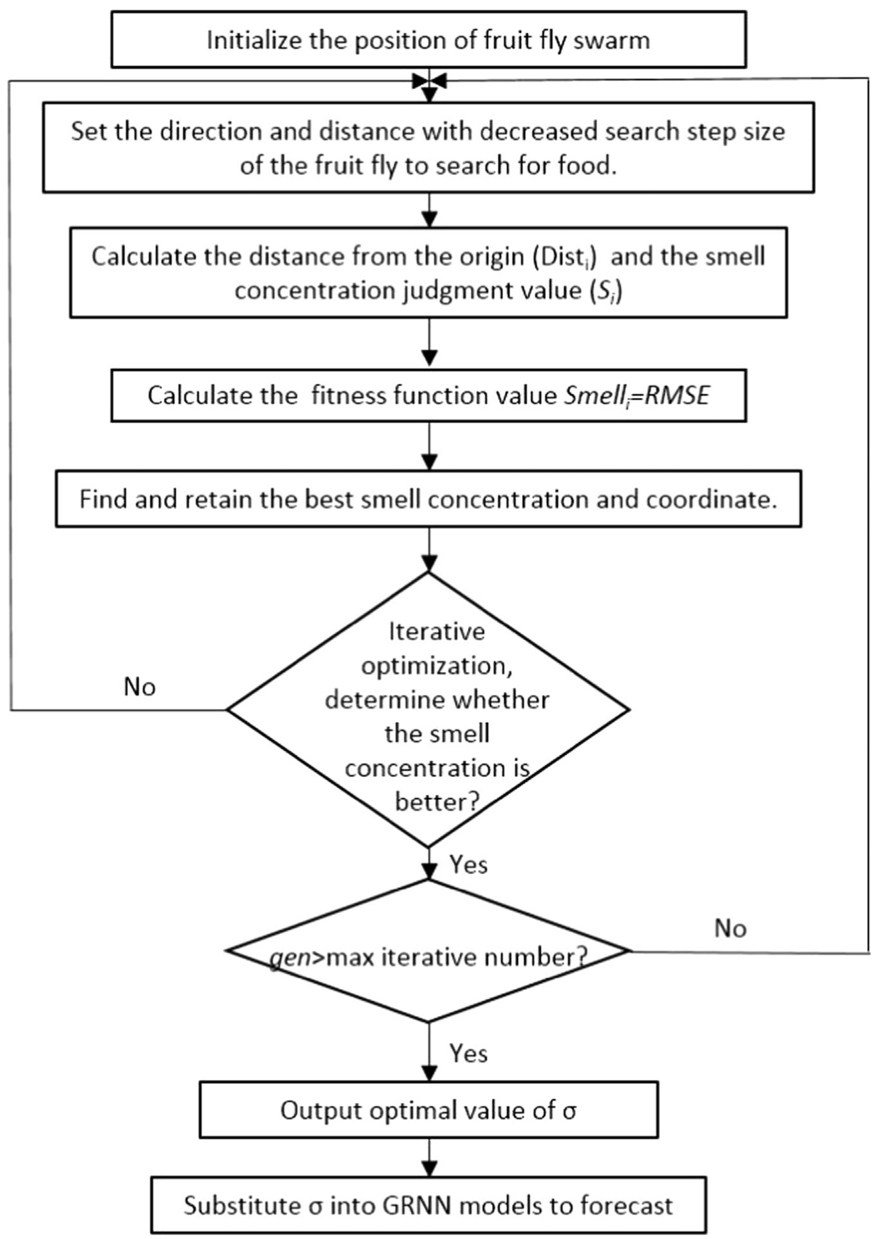

Fig. 4. The flowchart of SFOA-GRNN model.

Table 1
A part of the normalized data.

Data	06/11	06/13	06/13	06/14
01:00	0.5513	0.6360	0.6487	0.6371
02:00	0.5341	0.6122	0.6249	0.6142
.	.	.	.	.
.	.	.	.	.
22:00	0.7641	0.7928	0.7618	0.7657
23:00	0.7374	0.7515	0.7312	0.7303
00:00	0.6754	0.6796	0.6659	0.6560
Maximum temperature	0.0023	0.0031	0.0028	0.0020
Minimum temperature	0.0000	0.0003	0.0006	0.0003
Weather characteristic	0.7000	0.9000	0.9000	0.3000

Step 1 Random initial population location (x_0, y_0) in the range of [0, 1]. Set the number of Population individual quantity and the maximum number of iterations: sizepop = 10, maxgen = 100.
Step 2 Using the sense of smell to search for food, determine the direction and distance of the fly, in which the flight distance is L_i with decreased search step size

$$L_i = L_0 - \frac{L_0}{1 + e^{(6-\frac{12G_i}{G_{max}})}}, \tag{19}$$

$$x_i = x_0 + L_i, \tag{20}$$

$$y_i = y_0 + L_i. \tag{21}$$

Step 3 Estimate the distance between the location and the origin (Dist_i), then calculate the value (S_i) of smell concentration, and take S_i as smooth factor σ of GRNN

$$\mathrm{Dist}_i = \sqrt{x_i^2 + y_i^2}, \tag{22}$$

$$S_i = \frac{1}{\mathrm{Dist}_i}, \tag{23}$$

$$\sigma = S_i. \tag{24}$$

Step 4 Take smell concentration determination value (S_i) into the smell concentration detection function, in order to get the smell concentration of the fruit fly's individual location (Smell_i). The root mean square error (RMSE) in the GRNN model is determined as a function of smell concentration, as follows

$$\mathrm{Smell}_i = \mathrm{RMSE}_i = \left[\frac{1}{n}\sum_{i=1}^{n}(y_c - t)^2\right]^{0.5}, \tag{25}$$

where y_c is the network output value, t is the target value.
Step 5 Find out the fruit fly with the best smell concentration in the fruit fly swarm, which is the minimum value of RMSE.
Step 6 Retain the best smell concentration and coordinate. Then the fruit fly group uses vision to fly to the position (x_b, y_b)

$$\mathrm{Smellbest} = \mathrm{bestSmell}, \tag{26}$$

$$x_b = x(\mathrm{bestIndex}), \tag{27}$$

$$y_b = y(\mathrm{bestIndex}). \tag{28}$$

Step 7 Enter the iterative optimization, repeat steps 2 to 5. And determine whether the smell concentration is better than the previous iteration of the smell concentration. If it is, then perform step 6.
Step 8 Determine whether the maximum number of iterations is reacceded, substitute the optimal value of σ into GRNN models to forecast.

The flowchart of SFOA-GRNN model is shown as in Fig. 4.

5. Simulation and analysis

5.1. Selection of prediction index and data processing

Short term power load is affected by many factors, such as economic factors, time factors, meteorological factors and Emergent events. However, meteorological factors determine the use of air conditioning and lighting device, thus the impact of meteorological factors is particularly evident for power load. In this paper, meteorological factors are quantifiable on weather characteristics and environmental temperature, they are served as an important parameter for short-term load forecasting.

In order to realize the unified analysis of different kinds of sampled data and improve the accuracy, firstly, the original data needs to be processed by normalization. In this paper, the linear transformation method is used to deal with the data, shown as follows:

$$X^n = \frac{X^i - X_{min}}{X_{max} - X_{min}} \quad (i = 1, 2, \ldots, n), \tag{29}$$

where X^i is the original sampled data matrix, X_{max} and X_{min} are the maximum and minimum values of the matrix, and the X^n is the matrix vector with the same characteristic after the normalization process.

The processed sampled data is converted to a matrix within the [0,1], shown as in Table 1.

5.2. Experimental analysis and comparison

Historical load curve of a week is shown in Fig. 5. It can be seen that short term load has obvious daily periodicity. Thus, power load data of

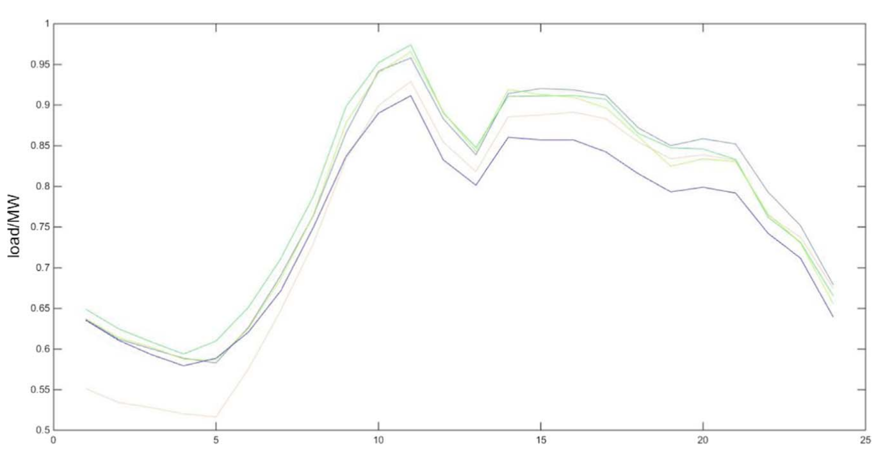

Fig. 5. Historical load curve of a week.

Table 2
Input of network training sample.

Serial number	Network input variables
1	Load value at t o'clock on day $(d-1)$
2	Load value at $(t-1)$ o'clock on day $(d-1)$
3	Load value at t o'clock on day $(d-2)$
4	Load value at $(t-1)$ o'clock on day $(d-2)$
5	Maximum temperature on day $(d-1)$
6	Minimum temperature on day $(d-1)$
7	Weather characteristic a value on day $(d-1)$
8	Maximum temperature on day $(d-2)$
9	Minimum temperature on day $(d-2)$
10	Weather characteristic a value on day $(d-2)$
11	Maximum temperature on day d
12	Minimum temperature on day d
13	Weather characteristic a value on day d

the past two days is regarded as an important reference. In addition, combined with the meteorological characteristics mentioned above, the daily load of electric power, weather characteristics and the environment temperature are selected out to be three types of indicators.

In this paper, the load data and meteorological characteristics of Dalian area in June 2012 are used as an example to build the SFOA-GRNN model for short term electric load forecasting. The original data from June 4th, 2012 to June 23rd are regarded as the training data. The data on June 24th are regarded as a testing data. Set d as the forecast date. The output is the electric load at t o'clock on the forecast day d, then the sampled input includes 13 indicators, as shown in Table 2.

After the simulation is completed, the optimization trajectory of fruit fly is depicted in Fig. 6. It can be known, the location of population of fruit fly group is $(-0.4719, 0.4683)$ at this time. Thus, the best value of σ is 1.5413. After 100 iterations of the SFOA-GRNN model, the value of *RMSE* is shown in Fig. 7. *RMSE* begins to converge in the eighty-fifth generation, and the minimum error value is 0.0018.

The trained SFOA-GRNN short-term power load forecasting model was used to predict the load of 24 hours in June 24th. The convergence speed of the network is very fast, and the simulation results are shown in Fig. 8. It can be seen that the proposed model is able to realize the power load forecasting with good performance, both in accuracy and convergence rate.

In order to highlight the superiority of the proposed model, the BP model is applied to the same example. The BP network with three layer

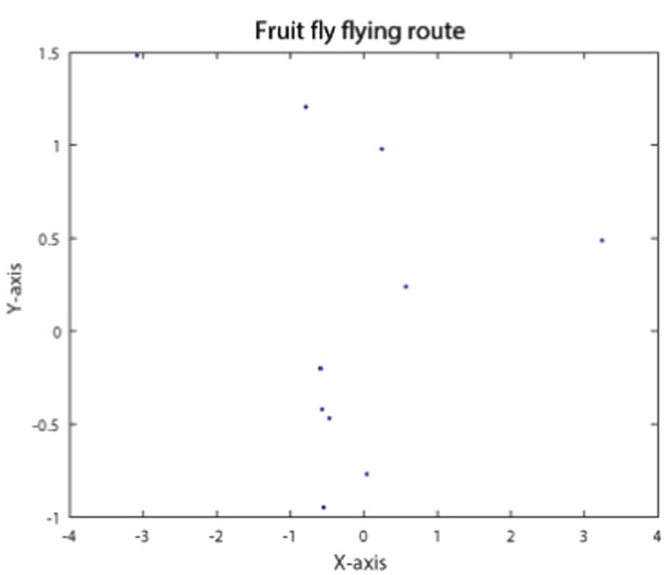

Fig. 6. Fruit fly flying route.

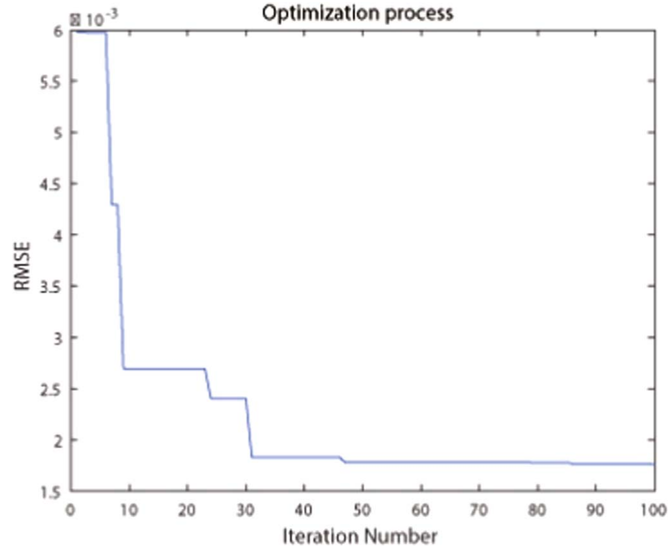

Fig. 7. Optimization process.

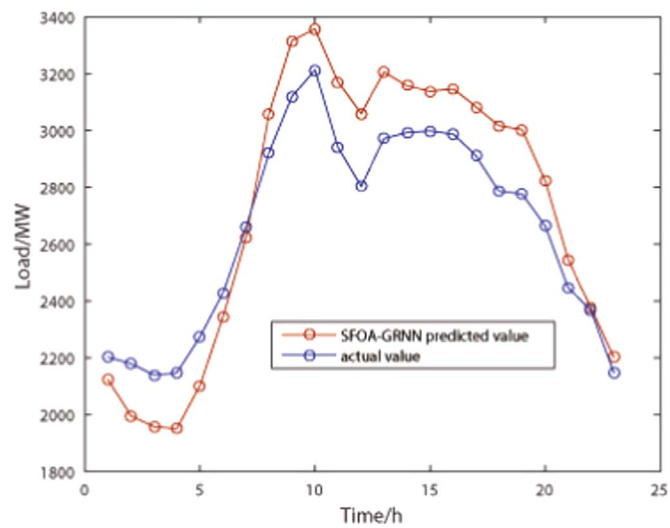

Fig. 8. Actual and predicted load curves of June24.

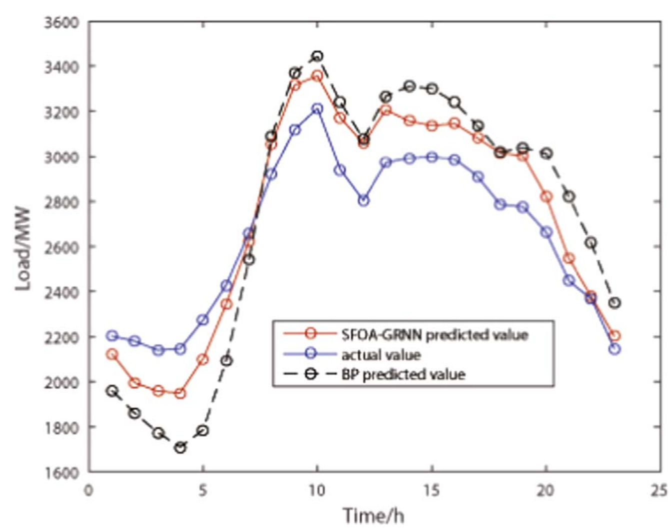

Fig. 9. The comparison of BP neural network and SFOA-GRNN.

is established, the input layer node number is 13, the output layer node number is 1, the hidden layer node number is 10, the training function is LM algorithm, the comparison of BP neural network and SFOA-GRNN model is shown in Fig. 9.

Through calculation, the *RMSE* of the BP neural network for STLF is 0.024, while the *RMSE* of the SFOA-GRNN model is 0.0018. It is clear that the accuracy of the proposed model is higher. Meanwhile, in the process of simulation, it is found that the stability of BP neural network is very weak, for the predicting outcomes of BP neural network is without reproducibility. This problem is mainly due to the following three reasons: (i) BP neural network needs to set many parameters, such as number of hidden layer nodes, learning rate and iteration number, while there is no effective way to select these parameters; (ii) it is easy to fall into local optimum; (iii) it is very sensitive to the initial weight, but the initial weights are given randomly, thus BP neural network does not have reproducibility. However, the proposed model needs fewer parameters to set, it is easy to be trained and with reproducibility. In addition, BP neural network needs to calculate the gradient and update weights, while GRNN only needs to calculate pseudo inverse matrix without updating weights, therefore the proposed model has advantages in convergence speed. In a word, the forecasting performance of the proposed model is much better than the BP neural network.

6. Conclusion

In this paper, the short-term power load forecasting model was based on the GRNN which was optimized by decreasing step fruit fly optimization algorithm. The search capabilities of FOA with decreasing step size made it possible to select the appropriate spread parameter σ of GRNN. The simulation was based on the historical load data of Dalian area. During establishing the SFOA-GRNN short term load forecasting model, the daily periodicity of short-term power load and the influence of meteorological factors were considered. Through the simulation results, it can be known that the proposed model was able to achieve short-term load forecasting, it owned good performance in stability and stability. A new approach was provided for the effective prediction of short-term power load.

However, due to the lack of data and the defects of learning style, compared with FOA-GRNN model, the advantages of SFOA-GRNN model did not reflected greatly in this case. It is still needed to be studied and perfected.

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