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Research on Prediction Model for Icing Thickness of Transmission Lines Based on BP Neural Network Optimized with Improved Fruit Fly Algorithm

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Abstract

Icing of transmission line has seriously impacted on the safe operation of power grid. Therefore, after analyzing meteorological factors which influence icing thickness, we proposed to construct an icing thickness prediction model based on a 3-layer BP neural network in this article. In order to solve problems that BP neural network converges slowly and is prone to local minimum values, the prediction speed and accuracy have been increased by using improved fruit fly algorithm to optimize BP neural network. Taking icing historical data on 500kV transmission line of Shenxin Line I in China as an example, the rationality and accuracy of this model have been proved, and the analyzing results could be provided to instruct the operation and maintenance of transmission lines.

Key words

Transmission lines, icing, BP neural network, fruit fly algorithm

1. Introduction

With the global climate changes in recent years, the air temperature is frequently getting instable in most areas in China, which has tremendously impacted the high-voltage transmission lines erected in field, and especially resulted in icing phenomena on transmission lines in winter, and further threatened the safe operation of power grid and lowered the reliability of power supply. When the icing thickness exceeds a specific value, serious accidents like tripping, line breaking, tower base tilting or breaking, and electricity interrupting will possibly occur, which will cause enormous losses on both national economy and people's life. Therefore, research on how to predict icing thickness of overhead transmission lines is profound.

The growing of icing on transmission lines is a very complicated non-linear process that is influenced by several factors with characters of dynamic, mutability and uncertainty [1]. In this article, firstly several factors as air temperature, wind speed, wind direction, humidity, and air pressure have been considered. Then a prediction model has been constructed based on a BP neural network algorithm which uses the most common single-hidden layer and feed-forward network, i.e., a 3-layer topological structure includes input layer, output layer and single hidden layer. However, there are two obvious defects for a BP neural network based prediction model: it converges slowly and is prone to local minimum values. Therefore, we introduce an improved fruit fly algorithm to optimized BP neural network so to establish a transmission lines' icing prediction model with the inputs of meteorological factors and the output of icing thickness. After analyzing and processing amount of historical data on transmission lines' icing, a transmission lines' icing prediction model has been finally constructed, and further analysis on early warnings has been conducted.

2. Prediction model based on a BP neural network optimized with an improved fruit fly algorithm

2.1 BP neural network

BP (short for Back Propagation) neural network is a kind of multi-layer feed-forward neural network using the error back propagation, and is simple, feasible, and characterized with small computing volume and strong parallelism. It is one of the most perfect and most applied neural network training algorithms [2]. A BP neural network mainly comprises 3 layers of input layer, hidden layer and output layer as shown in Figure 1.

Via training, BP neural network could acquire capabilities of associative memory and prediction. However, since BP neural network usually has multi-nodes on hidden layer, the training time increasing and convergence slowing are both inevitable and the model tends to be optimized locally but not globally. Besides, parameters like the number of hidden layer and so on, depend on empirical formula or need debugging so that self-learning load of BP network is heavy and self-learning is also not stable. When new sample is added in training, old one tends to vanish [3]. In order to enlarge searching space, to speed convergence and to improve accuracy to search for optimal values, external algorithm should be introduced to optimize parameters of BP neural network. In this article, fruit fly algorithm is applied to optimize BP neural network.

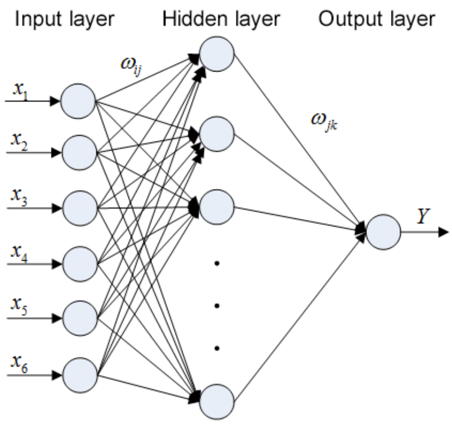


Fig.1. Network topological structure of prediction model

2.2 Fruit fly algorithm and its improvement

FOA (short for Fruit Fly Optimization Algorithm) is a new method to search the global optimal solution and is deduced according to foraging behavior of fruit fly. It is a new branch evolving from swarm intelligence, which is widely applied in fields of management, engineering, and military. It can be used with other intelligent algorithms like neural network, grey system, fuzzy theory and so on [4, 5]. It is with characters of quick optimization, high stability, and high accuracy to search for optimal solution without the problem of being prone to local optimal value [6- 8].

Firstly, by random initializing the site of fruit fly swarm, each fruit fly will search for the direction of and the distance from food depending on its sense of taste. Then it will estimate the distance from itself to origin point in case of unknowing the site of food. After that, the reciprocal of this distance is taken as the judgment value of taste concentration for each fruit fly, and put into the judgment formula to find out the fruit fly with the largest value of taste concentration in swarm. Finally, its site of this fruit fly will be located and the other fruit flies will fly to it depending on their visual sense. Repeat the above steps until flies find the optimal site of food [9].

The process to optimize FOA is exactly to continuously learn from the optimal fruit fly and to make swarm get together on the site of this fruit fly. However, there are two problems: one is locally optimal value, and the other one is that fixed step impact the searching efficiency. If this optimal fruit fly does not locate at the global optimal site, the algorithm will be prone to the local optimal value with the problem of premature convergence. In order to keep algorithm from local optimization, a mechanism should be provided so that individual fruit fly can enter other region in solution space to continuously search for the global optimal solution [10]. Meanwhile, the fixed step length of FOA will also significantly impact on the efficiency of searching. When step length of searching is fixed as L and the number of fruit fly swarms is also fixed, the value of L is larger, the searching space of individual is larger, and the capability to search for the global solution is stronger. On the contrary, the value of L is smaller, the searching space of individual is smaller, and the capability to search for the local optimal solution is stronger so to be prone to the local optimum value. It can be seen that proper step length can balance the capacity to search for optimal solution globally and locally so to improve the searching accuracy of the algorithm [11]. Therefore, fruit fly algorithm has been improved to optimize parameters of BP neural network regarding to the two problems mentioned above.

(1) Introducing mutation operation of genetic algorithm into FOA

Judgment on whether FOA is in status of local convergence or not shall be made according to the variance of taste concentration, that is, when $\sigma^2 \leq \delta$（hereof σ^2 is the variance of taste concentration, and δ is the threshold of taste concentration) and the optimal taste concentration is greater than the theoretical optimal or target one, the algorithm is judged as in the status of local optimization. In this case, the number of optimal flies will be added up to M by copying the original optimal fruit fly at first，then mutation operation will be done with a probability P_m. After that, the mutated flies will be searched for the optimal solution for second time, i.e., the site of each mutated fruit fly will be initialized again. The searching space of each fruit fly will be expanded again so that some flies that have been at the site of optimal taste concentration can move to other site and search in a larger space. In this way, not only the diversity of flies will be remained, but also the possibility that FOA searches for the optimal value will increase.

The selection of mutation probability P_m significantly impact on the performance of algorithm. When P_m is too small, new individual is not easy to generate. When P_m is too large, the algorithm is prone to a pure random search. Therefore, mutation operation as a selection algorithm has been introduced into FOA to select the self-adaptive mutation probability [12], the formula is shown below:

$$P_m = \begin{cases} p_{m1} - \left| \dfrac{(p_{m1} - p_{m2})(T - T_{avg})}{T_{best} - T_{avg}} \right| & T \geq T_{avg} \\ P_{m1} & T \leq T_{avg} \end{cases} \tag{1}$$

Here, T_{best}——the optimal taste concentration among flies

T_{avg}——the average taste concentration of flies

T——the taste concentration of fruit flies before mutation

p_{m1}, p_{m2}——parameters，their values vary in the interval of (0,1). They will be adjusted during optimization. In this article, p_{m1}=0.1, and p_{m2}=0.1.

(2) Dynamically adjusting the searching step length L

In order to acquire better capability to search, in this article, it is proposed that the linearly-decreasing searching step method will be used to dynamically adjust the searching step length L, that is:

$$L(k) = L_{start} - {(L_{start} - L_{end})(G_{\max} - k)}\big/{G_{\max}} \tag{2}$$

Here, L_{start}——the initial searching step length

L_{end}——the searching step length with the maximum iterations

k——the current iterations

G_{max}——the maximum iterations

When first generation flies are foraging, Let L=L_{start} and the largest value is L_{start}. When number of iterations increases by 1 at each time, the step length will decrease by (L_{start}-L_{end})/G_{max} until it goes down to 0.

Obviously, at the beginning of searching for optimal solution, the searching step length of algorithm is the largest with a large searching space and high capability to search for optimal solution globally. With the increasing of iterations to forage, the capability to search for optimal solution locally will enhance. In this way, it can be ensured that global optimal solution will be found out most probably at beginning of searching without being prone to the optimal solution. Meanwhile, the optimal searching accuracy can be reached at the end of searching to realize the balance between global and local searching for optimal solution.

2.3 Prediction model based on BP neural network optimized with improved FOA

By using 3-layer BP neural network optimized with improved FOA in this article, firstly weights of input layer to hidden layer and of hidden layer to output layer, thresholds of hidden layer and of output layer in BP neural network will be treated as individual fruit flies, and the direction and the distance for each swarm of flies will be set randomly [3]. Secondly, the searching step length will be dynamically adjusted according to the improvement method above, and specific flies will be picked out to initialize again. Thirdly, iteration algorithm will be conducted to search for the optimal value of fitness function.

Then the optimized weights and thresholds will be entered into BP neural network, and BP neural network will be trained with excitation function and study sample. Finally, the trained BP neural network will be validated by entering a test sample. The procedures of optimization are shown below [13, 14]:

1) Initializing BP neural network. Determine number of neurons on input layer, output layer and hidden layer, and calculate the specific number of weights and thresholds.

2) Take all weights and thresholds as individual fruit flies, and initialize their site, that is:

$$\begin{cases} x = x_0 \\ y = y_0 \end{cases} \tag{3}$$

3) Set the direction and the distance for each fly swarm randomly. In formula (2), L is the searching step length adjusted dynamically.

$$\begin{cases} x_i = x_0 + L \\ y_i = y_0 + L \end{cases} \tag{4}$$

4) While unknowing the site of food, estimate the distance D from individual fly to origin point, and then calculate the judgment value S of taste concentration, that is:

$$D_i = \sqrt{x_i^2 + y_i^2} \tag{5}$$

$$S_i = 1 \big/ D_i \tag{6}$$

5) Put the judgment value S_i of taste concentration in the fitness function T and then the taste concentration of individual fly is shown as below:

$$T_i = f\left(S_i\right) \tag{7}$$

6) Search for the fruit fly with the optimal taste concentration in this swarm, and record the optimal value and its site on coordinate as (x_{best}, y_{best}). Then visually guide other flies to this site:

$$T_{best} = \min\left(T_i\right) \tag{8}$$

$$\begin{cases} x = x_{best} \\ y = y_{best} \end{cases} \tag{9}$$

Repeat steps from 3) to 6). When the new value of fitness function is more optimal than the old one, step 7) will be conducted, otherwise, searching will continue.

7) Calculate the average taste concentration T_{avg} of flies and the taste concentration variance σ^2 of fruit fly swarm:

$$T_{avg} = \sum_{i=1}^{G_{\max}} T_i / G_{\max} \tag{10}$$

$$\sigma^2 = \sum_{i=1}^{G_{\max}} \left(T_i - T_{avg}\right)^2 \tag{11}$$

8) If $\sigma^2 \leq \delta$ and T_{best}> the theoretical optimal value or the target accuracy, make M copies of the optimal fruit fly, and let individual flies mutate evenly based on mutation probability formula (1). Update the site of the optimal fruit fly after copying. Here, j=1, 2,…, M, r is a random number within the specific range and conforms to the uniform distribution:

$$\begin{cases} x_j = x_{best} \\ y_j = y_{best} \end{cases} \tag{12}$$

$$\begin{cases} x_j^{'} = x_{best} + r\left(U_{\max}^k - U_{\min}^k\right) \\ y_j^{'} = y_{best} + r\left(U_{\max}^k - U_{\min}^k\right) \end{cases} \tag{13}$$

9) Repeat steps from 3) to 6). Estimate the distance D' from the site of new fruit fly to the origin point and the judgment value S' of new fruit fly once more. Then put the above estimated value in the judgment function of taste concentration to calculate the taste concentration T' of new fruit fly.

If $T' < T_{best}$， then：

$$T_{best} = T' \tag{14}$$

$$\begin{cases} x = x'_{best} \\ y = y'_{best} \end{cases} \tag{15}$$

10) Update coordinates of weights and thresholds for new optimal fitness function

Repeat steps from 7) to 10).Until the current iterations equal the maximum iterations G_{max} or the target accuracy is reached, stop searching for optimal solution.

11) Put the optimal value in BP neural network, and then train the network with study sample. Finally, validate the trained BP neural network with test sample.

3. Study on cases

In this article, 1000 sets of meteorological data and icing thickness data, which were collected by icing monitoring system on 500KV transmission lines of Shenxin Line I from 9th to 20th, 11, 2014, have been used as training and validating data. Among them, wind speed, wind direction, temperature, humidity and air pressure are basic data as indexes, and their changing trends are shown respectively in Figure 2.

In the above changing trend chart drawn based on meteorological index data, it can be seen that the order of magnitude for each input sample data is greatly different from others, and the difference among data for single index is also large. The excitation function of neuron nodes on each layer of BP neural network mostly adapts function Sigmoid. Output value will be greatly impacted if Input value is too small or too large. To avoid output values in saturation area of this function as possible, to enhance input value’s impact on output value, and to decrease data difference’s impact on the error of model, data normalization should be done at first. In this article, function Premnmx of the software MATLAB will be called to normalize the five indexes mentioned above, and make them distribute in the interval of [-1,1].

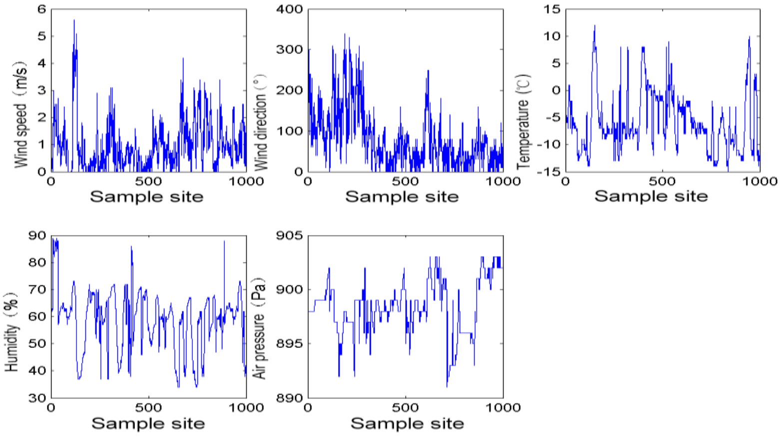


Fig.2. Changing trends of meteorological factors impacting on icing thickness

To validate the accuracy of trained model, maximum relative error δ_{max} and average absolute percentage error δ_{mape} are applied in this article, and their definitions are below:

$$\delta_{\max} = \max\left(\frac{100\times\left|p_i-\hat{p}_i\right|}{p_i}\right) \tag{16}$$

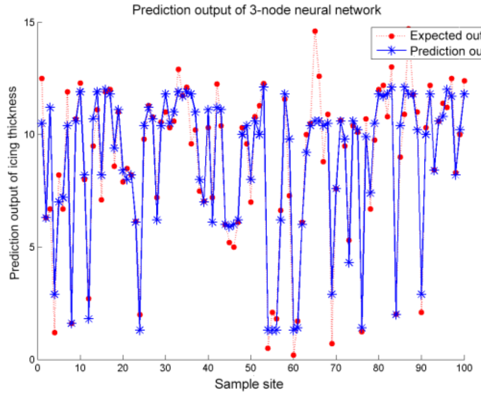
$$\delta_{\text{mape}} = \frac{100}{N}\sum_{i=1}^{N}\frac{\left|p_i-\hat{p}_i\right|}{\bar{p}}, \bar{p} = \frac{1}{N}\sum_{i=1}^{N}P_i \tag{17}$$

Here, $\hat{p}_i$—— predicted icing thickness

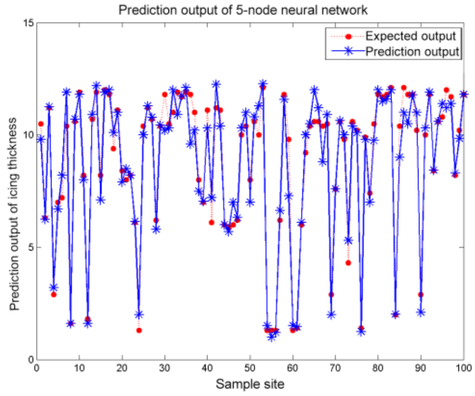
p_i——actual icing thickness

N ——number of predicted icing thickness

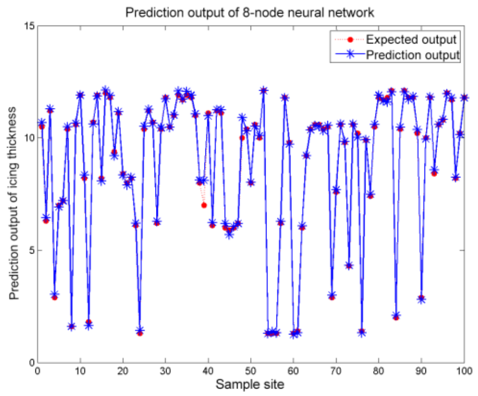
3-layer BP neural network is selected in this article, which includes input layer, output layer and hidden layer. On input layer, there are 5 nodes of meteorological factors as wind direction, wind speed, temperature, humidity and air pressure. On Output layer, there is 1 node, icing thickness. The number of nodes on hidden layer is uncertain, and will be adjusted during training. Set the display frequency as *freq*=10, the maximum training times as max=1000, the target error as err=0.01, and the study speed as 0.1. With regard to BP neural network, the number of nodes on hidden layer will significantly impact on model generalization. Therefore, in this article, the number of nodes on hidden layer has been gradually increased from 3 to 13 so to search for the optimal number of nodes on hidden layer. While the number of nodes on hidden layer is 3, 5, 8, and 13 respectively, icing thickness prediction curve based on BP neural network is shown from Figure 3(a) to Figure 3(d).



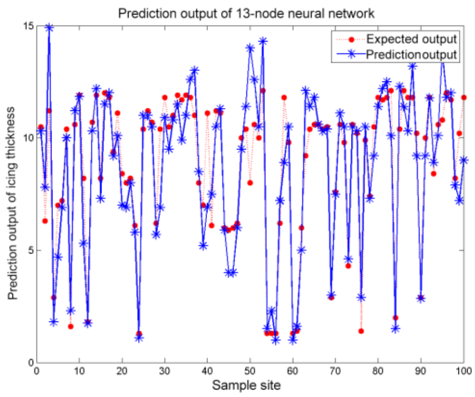
a) Prediction simulation curve of 3-node BP neural network



b) Prediction simulation curve of 5-node BP neural network



c) Prediction simulation curve of 8-node BP neural network



d) Prediction simulation curve of 13-node BP neural network

Fig.3. Prediction simulation of BP neural network for various number of nodes

From the above simulation results, it can be seen that the curve of training error is the smoothest and fitting curve is the most ideal when the number of nodes on hidden layer is 8. Therefore, the following analysis will focus on 8-node BP neural network. Firstly, let the number of fruit fly swarm equal 30, and iterations equal 100. Then the optimized path via BP neural network which is optimized by improved FOA is shown in Figure 4. When iterations reach 15, the algorithm has found the local optimal solution. When iterations reach 37, fitness function has mostly acquired the optimal solution with the value of fitness function as 0.092. Now, the optimal weights and thresholds searched via FOA can be put in BP neural network to get a trained and optimized BP neural network [3].

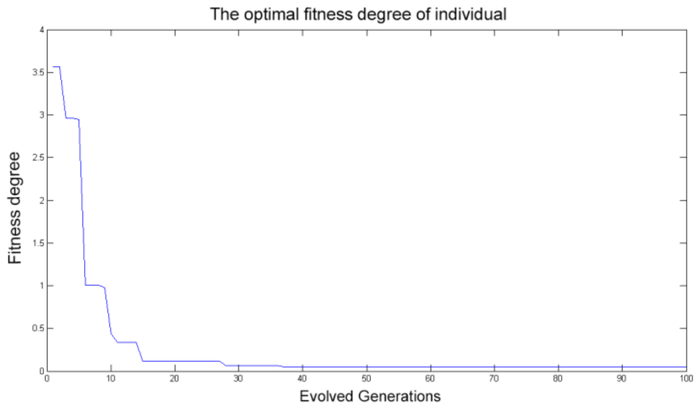
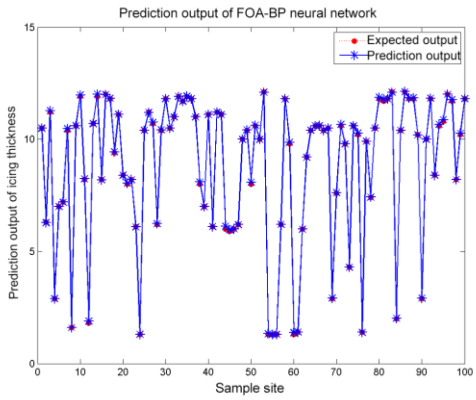
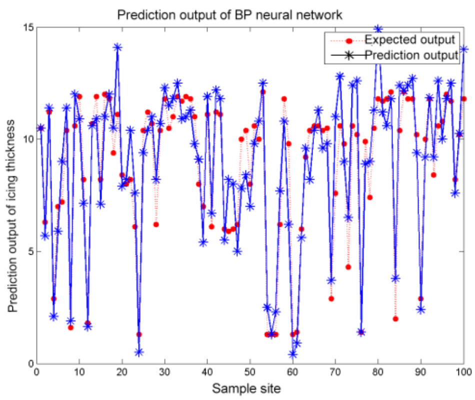


Fig.4. Optimization path of BP neural network based on fruit fly optimization algorithm (FOA)

In this article, we choose a common BP neural network and a BP neural network optimized with FOA (FOA-BP) to individually predict icing thickness on 500KV transmission lines of Shenxin Line I, Shanxi province, China. 900 sets of data are picked out from 1000 sets of data as the training set, and the left 100 sets of data are treated as the test set. Icing thickness prediction figures as for two models are compared below. It can be seen in Figure 5 that the prediction result via FOA-BP approaches to the practical situation more closely than that one via BP neural network. See Figure 5, 6, and 7.



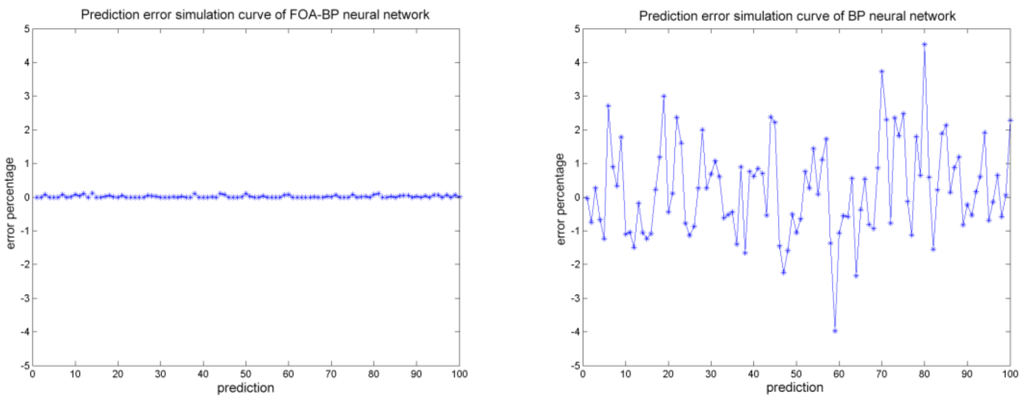
a) Prediction simulation curve of FOA-BP neural network



b) Prediction simulation curve of BP neural network

Fig.5. Comparison in prediction results between improved FOA-BP network and BP network

Comparison in prediction error between improved FOA-BP neural network and BP neural network is shown in Figure 6. The maximum error of BP neural network prediction model is about 5.0, and the one of FOA-BP neural network prediction model is about 0.1 with the obviously improved prediction accuracy.



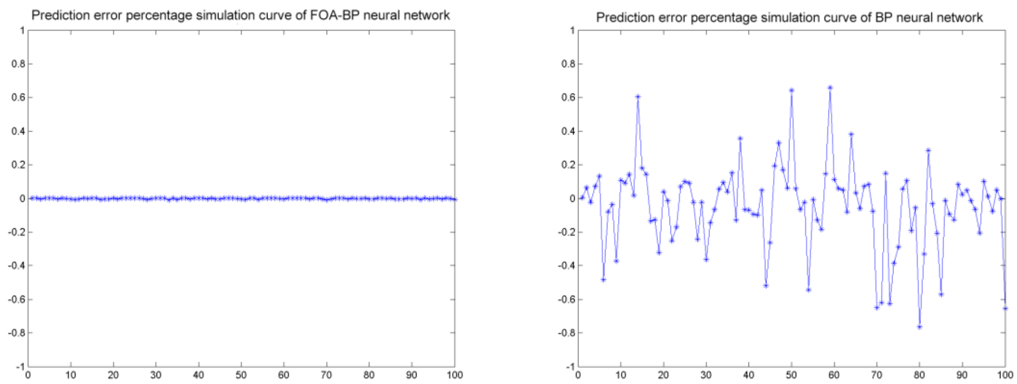
a) Prediction error simulation curve of FOA-BP neural network

b) Prediction error simulation curve of BP neural network

Fig.6. Comparison in prediction errors between improved FOA-BP network and BP network

Comparison in prediction error percentage between improved FOA-BP neural network and BP neural network is shown in Figure 7. The error percentage of FOA-BP neural network model is around 0, but the one of BP neural network model varies in a wide range.

After analyzing, it can be seen that the fitting degree between prediction curve of test sample and the practical curve for FOA-BP model is higher with a better simulation effect than that one for BP model.



a) Prediction error percentage simulation curve of FOA-BP neural network

b) Prediction error percentage simulation curve of BP neural network

Fig.7. Comparison in prediction percentage error between improved FOA-BP neural network and BP neural network

4. Discussion

In order to compare testing results of two prediction models, training and testing for both BP and FOA-BP neural networks could be carried out for several times. Since the prediction accuracy in training will vary a little each time, we have selected the best set of data from the testing results to compare and analyze. Each performance index is shown in Table 1.

Table 1. Testing results of two prediction models

Performance index	BP neural network	Improved FOA-BP neural network
Training error	0.47	0.023
Average absolute percentage error	0.374%	0.0017%
Maximum relative error	0.852%	0.015%
Running time	22.753s	16.072s

From Table 1, it can be seen that with maximum relative error of 0.015 and average absolute percentage error of 0.0017, improved FOA-BP neural network has higher prediction accuracy than BP neural network has with maximum relative error of 0.852 and average absolute percentage error of 0.374. From the aspect of running time, it can be seen that improved FOA-BP neural network model with running time of 16.072s runs more quickly than BP neural network model with running time of 22.753s.

5. Conclusion

To sum up, via comparisons in various aspects, it is concluded that improved FOA-BP neural network prediction model is more accurate to predict, and more effective and quicker to run than BP neural network prediction model.

In decision support system, by collecting meteorological parameters and applying icing prediction model, icing thickness could be predicted as warnings on icing status based on icing warning standards. Meanwhile, prediction results could also be reference for decisions on how to respond to transmission line icing disaster. This model is worth to be applied extensively.

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