Journal of Information Hiding and Multimedia Signal Processing ©2018 ISSN 2073-4212
Ubiquitous International Volume **9**, Number **1**, January **2018**

An Improved FOA to Optimize GRNN Method for Wind Turbine Fault Diagnosis

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Received July, 2016; revised September, 2017

Abstract. *To improve poor performance of GRNN which can not reach better accurate rate of wind turbine fault diagnosis. An improved FOA to optimize GRNN method for wind turbine fault diagnosis is proposed in this paper. By adjusting the evolution direction of fruit fly, FOA can get rid of local optima and speed up convergence speed. In addition, flying route of fruit fly add to three-dimensional. Then the improved FOA is used to optimize GRNN model. Finally the fault of wind turbine is detected by optimal GRNN model. Simulation experiments have shown that the improved FOA in favor of selecting better smooth factor of GRNN, and this method of wind turbine vibration fault diagnosis is more feasible and more effective than those of the existing ones. The data size is lager, the accuracy is better.*
Keywords: Wind turbines, FOA, GRNN, Fault diagnosis

1. **Introduction.** In the last few years, renewable energy concern such as wind energy and solar energy have raised as one of the most important issues in the world. Among these renewable energies, wind energy is considered as the most practical substitute energy to replace the traditional fossil fuel, due to its competitive cost of electricity and maturity of technology. Wind energy is a renewable power source that produces no known significant atmospheric pollution. As the size of wind farms continues to increase, business economics dictate the need for effective condition monitoring systems that allow for careful asset management to minimize downtime and maximize availability and profits. Under this background, the condition monitoring and fault diagnosis in wind turbine system are important for avoiding serious damages [1].

Due to the wind turbine working environment is strict and poor, which makes the vibration signals be non-stationary and non-Gaussian characteristic. So that it increases the difficulty of fault diagnosis and error diagnostics [2]. In recent decades, some approaches have been proposed to solve these problems. In [3], the Generalized Regression Neural Network (GRNN) model used for diagnosis of aerogegines' gas path faults was built. In [4], a method based on Particle Swarm Optimization algorithm and Generalized Regression Neural Network (PSO-GRNN) was proposed in order to build the optimal model of wind turbine fault diagnosis. The method for wind turbine fault diagnosis based on artificial neural network and expert system hybrid model was developed in [5]. The fault diagnosis scheme of Genetic Algorithm (GA) to optimize the BP neural network was designed in [6]. The Fruit Fly Optimization Algorithm (FOA) to optimize artificial neural network for wind turbine fault diagnosis was explored in [7]. The FOA to optimize generalized regression neural network for studying on business performance was presented in [8].

According to all kinds of applications mentioned above, the methods seem to be excellent. However there is still insufficiency in all the strategies. Though GRNN has obvious advantages to fault diagnosis of wind turbines, the best smooth factor which is the only adjustable parameter is difficult to get. So that there are many optimization algorithms to optimize the smooth factor, however, the common disadvantages of these algorithms are complicated computational processes, difficult of understanding for beginners and there are very many parameters in these methods. FOA has fewer parameters than other optimization algorithms, but its search strategy is defective, so that it may trap into the local optimum.

In order to overcome the lack of these mechanisms leading to poor quality of wind turbine fault diagnosis, in this paper, a method for wind turbine fault diagnosis based on an improved FOA to optimize GRNN model is proposed. Firstly an improved FOA algorithm is used to choice the optimal smooth factor of GRNN. Secondly the optimal smooth factor is used to build GRNN model. Finally wind turbine fault diagnosis is finished by the GRNN model.

The remainder of this paper is organized as follows. In section 2, we briefly describe the preliminaries theory of our scheme. In section 3, we introduce procedures of our algorithm in detail. In section 4, the simulation performance analysis is presented. Finally, in section 5, we summarize our main works.

2. The Preliminaries Theory.

2.1. Generalized Regression Neural Network (GRNN).

The GRNN is a kind of Radical Basis Function(RBF) neural networks, which is a feed-forward neural network model based on non-linear regression theory. The GRNN not only has a very good non-linear mapping performance and a flexible network structure, but also has strong fault tolerance and robustness, so that it is very appropriate for solving the non-linear problem [9]. The GRNN has strong advantages in approximation quantity, classification quantity and learning speed compared with RBF network, and network finally converges to optimization regression surface which accumulates a lot of samples. What is more, the prediction effect is good when lacking in sample datas, too. In addition, the GRNN network also can handle the instable datas [10].

The GRNN is relatively similar to RBF network in structure. It can be specifically divided into four layers: input layer, pattern layer, summation layer and output layer, as shown in Fig.1. The input of the network is $X = [x_1, x_2, \ldots, x_n]^T$, and the output is $Y = [y_1, y_2, \ldots, y_k]^T$.

(1) Input layer

The number of neurons of input layer is equal to the dimension of input vectors of training samples. The input layer directly delivers the various elements of the input vector to the pattern layer [11].

(2) Pattern layer

The pattern layer is also hidden layer. The number of neurons of pattern layer is equal to the quantity n of learning samples. Each neuron corresponds to different sample. The transfer function of pattern layer can be presented as follows:

$$p_i = \exp\left[-\frac{(X - X_i)^T(X - X_i)}{2\sigma^2}\right] \quad i = 1, 2, \ldots, n \tag{1}$$

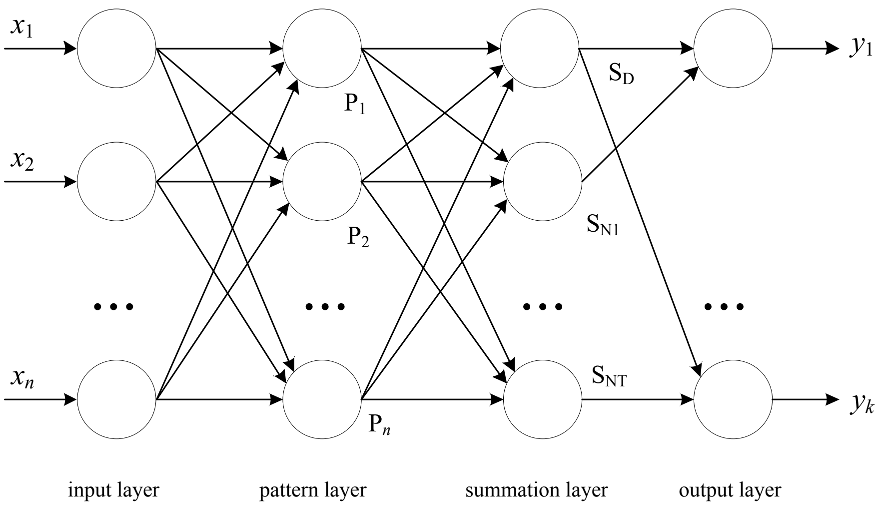

Figure 1. Topology of GRNN network

Where X is input variables of the network; X_i is the learning sample corresponding to the neuron i; σ is smoothing parameter. The output of neuron i is the exponential form of the squared Euclidean distance between input variable and relevant sample X.

(3) Summation layer

The summation layer consists of two types of neurons. One of them does an arithmetic summation of the output of all neurons in pattern layer, and its computational formula is $\sum_{i=1}^{n} \exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right]$. The connectional weight values of the neuron and all other neurons in pattern layer are 1. The transfer function of this neuron is

$$S_D = \sum_{i=1}^{n} P_i \tag{2}$$

The other one does a weighted summation of the output of all neurons in pattern layer, and its computational formula is $\sum_{i=1}^{n} Y_i \exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right]$. The connectional weight value of the ith neuron in pattern layer and the jth neuron is the jth element y_{ij} in the ith sample Y_i. The transfer function of the jth neuron of summation layer is

$$S_{Nj} = \sum_{i=1}^{n} y_{ij} P_i \quad j = 1, 2, \ldots, k \tag{3}$$

(4) output layer

The number of neurons of output layer is equal to the dimension of the output variables of learning samples. Each neuron does an arithmetic quotient of output of summation layer. The final output value of the jth neuron of output layer is the jth element in the estimation result $Y(X)$. The basic equation is defined as follows:

$$y_j = \frac{S_{Nj}}{S_D} \quad j = 1, 2, \ldots, k \tag{4}$$

Smooth factor has a huge impact on the fault diagnosis of GRNN. Theoretically the smaller smooth factor is, the better approximation quantity is, but the less smooth process of the approximation is. In other words, the bigger smooth factor is ,the better smooth process of the approximation is, but the greater the approximation error is [12]. So that the appropriate smooth factor value is difficult to determine just by network training process. We use an improved FOA algorithm to optimize the smooth factor, which can improve the behavior of the model.

2.2. **Fruit Fly Optimization Algorithm (FOA).** The FOA is a new swarm intelligent method based on fruit fly's foraging behaviors, and it belongs to a kind of interactive evolutionary computation [13]. Fruit flies have visual and olfactory senses better than other species. They can easily make good search of various odors floating in the air with their olfactory organ or even smell the food sources 40 km away from them [14]. Then, after it gets close to the food location, it can also use its sensitive vision to find food and the company's flocking location, and fly towards that direction too, which is as shown in Fig.2.

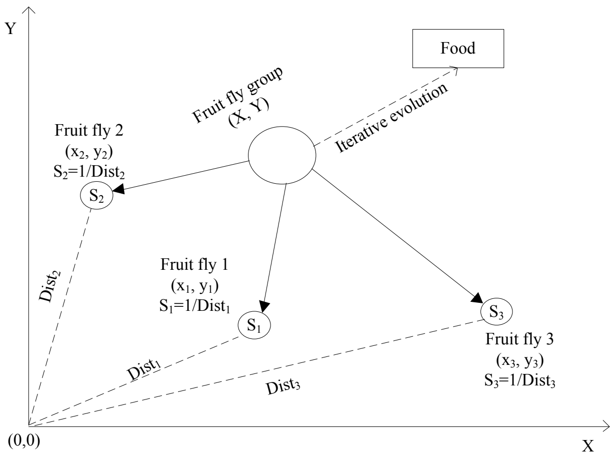

FIGURE 2. Food searching iterative process of fruit fly

According to the food finding characteristics of fruit fly, the FOA can be divided into several necessary steps as follows.

Step 1. Parameters initialization: the main parameters of the FOA are the total evolution number, the population size pop,and the initial fruit fly swarm location.

$$\text{maxgen; sizepop; lnit } X\_axis\text{; lnit } Y\_axis$$

Step 2. Give the random direction and distance for the search of food using osphresis by an individual fruit fly.

$$\begin{aligned} X_i &= X\_axis + Random\ Value \\ Y_i &= Y\_axis + Random\ Value \end{aligned} \tag{5}$$

Step 3. The distance to the origin is thus estimated first ($Dist$), then the smell concentration judgment value (S) is calculated, and this value is the reciprocal of distance.

$$Dist_i = \sqrt{X_i^2 + Y_i^2}; \quad S_i = \frac{1}{Dist_i} \tag{6}$$

Step 4. Substitute smell concentration judgment value (S) into smell concentration judgment function (or called fitness function) so as to find the smell concentration ($Smell_i$) of the individual location of the fruit fly.

$$Smell_i = Function(S_i) \tag{7}$$

Step 5. Find out the fruit fly with minimal smell concentration (finding the minimal value) among the fruit fly swarm.

$$[bestSmell\ bestindex] = min(Smell) \tag{8}$$

Step 6. Selection operation: keep the best fitness function value and coordinates. Then, the fruit fly swarm flies towards that location with the best fitness function value by using vision.

$$Smellbest = bestSmell;\ X\_axis = X(bestindex);\ Y\_axis = Y(bestindex) \tag{9}$$

Step 7. Judge if the stopping condition is satisfied. If not, go to *step 2*; otherwise, stop the circulation.

Due to the original FOA is prone to fall into the local optima in evolution so that it can not search the global optimum. And this phenomenon is mainly caused by the fitness function [15]. So we should modify the fitness function, that is to say S_i must be modified. In practice, fruit fly living area is a three-dimensional space, which is different from the search space of the original FOA.

2.3. **Improved Fruit Fly Optimization Algorithm.** On account of the fruit fly swarm just flies towards the optimal individual in iterative process, if the optimal is the local extreme value, so that it will cause premature convergence. On the other hand, search direction is random in iterative process, which will cause slow convergence speed. This paper will adjust the evolution direction, this operation can get rid of local optima and increase convergence speed [16]. This paper will adjust the evolution direction, this operation can get rid of local optima and increase convergence speed. In addition, this paper will adopt three-dimensional search space to search the optimum spread value.

The main modified places of the improved FOA as follows in detail: parameters initialization add lnit Z_axis, so the distance to the origin is became to:

$$Dist_i = \sqrt{X_i^2 + Y_i^2 + Z_i^2};\quad S_i = \frac{1}{Dist_i} \tag{10}$$

The fruit fly swarm flies towards to the individual fitness value by using vision in iterative process. So we adjust the fly direction and distance with adaptive factor $c(i)$, which is defined as follows:

$$c(i) = \frac{c_{\max} - i(c_{\max} - c_{\min})}{i_{\max}} \tag{11}$$

Where c_{max} is the biggest flight direction; c_{min} stands for the smallest flight direction; i_{max} is the largest number of iterations. So the coordinates of fruit fly in iterative process can be presented as follows:

$$\begin{aligned} X(i) &= X\_axis + c(i) * (X\_axis - X(i-1)) \\ Y(i) &= Y\_axis + c(i) * (Y\_axis - Y(i-1)) \\ Z(i) &= Z\_axis + c(i) * (Z\_axis - Z(i-1)) \end{aligned} \tag{12}$$

3. **Procedures of Algorithm.** The flow chart of diagnosis method is shown in Fig.3.

Overall segmentation scheme is described as follows:

Step 1: Parameters initialization: maxgen; sizepop; lnit X_axis; lnit Y_axis; lnit Z_axis.

Step 2: Give the random direction and distance for the search of food.

Step 3: Calculate the Dist and S using formula (10).

Step 4: Calculate fitness function MSE (Mean Squared Error).

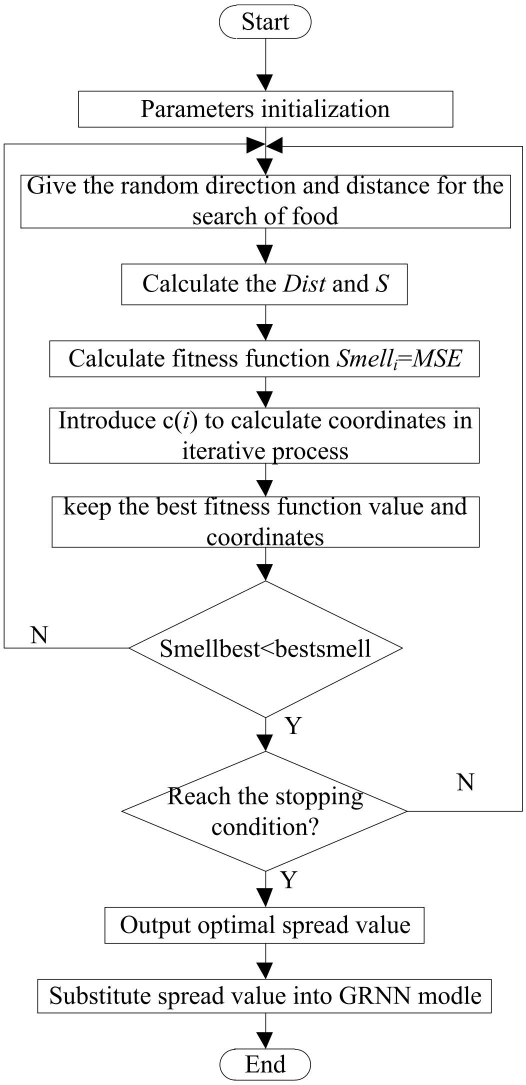

FIGURE 3. The flow chart of diagnosis method

Step 5: Introduce $c(i)$ to calculate coordinates using formulas (11) and (12).
Step 6: Find out the optimal individual, that is to say, the minimum of the MSE.
Step 7: Keep the best fitness function value and coordinates.
Step 8: If $smellbest > bestsmell$, return *step 2*. Otherwise execute *step 9*.
Step 9: Judge if the stopping condition is satisfied. If not, go to *step 2*; otherwise, execute *step 10*.
Step 10: Keep the optimal spread value.
Step 11: Substitute the optimal spread value into GRNN model and conduct fault diagnosis.

4. **Simulation Performance Analysis.** The parameters are set initially as the population size of fruit fly swarm, sizepop=10; the maximal iteration numbers, maxgen=100. We have used MATLAB version 12.0 to simulate the proposed method and compared it to other algorithms.

4.1. **Verify the Efficiency of the Proposed Method.** In experiment, we select GW50-750 wind turbines which belong to the same region of Buerjin wind farm as experimental subject. As for the noise of the collected datas, it is eliminated by means of the soft threshold wavelet de-noising. The normalized function is premnmx, and the anti-normalized function is postmnmx. In order to avoid network overtraining, we use the method of cross validation while training network. Number of the cross validation is 4 when we train the GRNN. Fig.4 shows the cross validation process of the GRNN. It can be seen that the MSE is increased with increase of the spread value, which is in accordance with theory except the second cross validation. The optimum spread value of GRNN output is 0.1. But the error diagnostics of wind turbine fault diagnosis is 0.3245. So we should optimize the factor to build the better model.

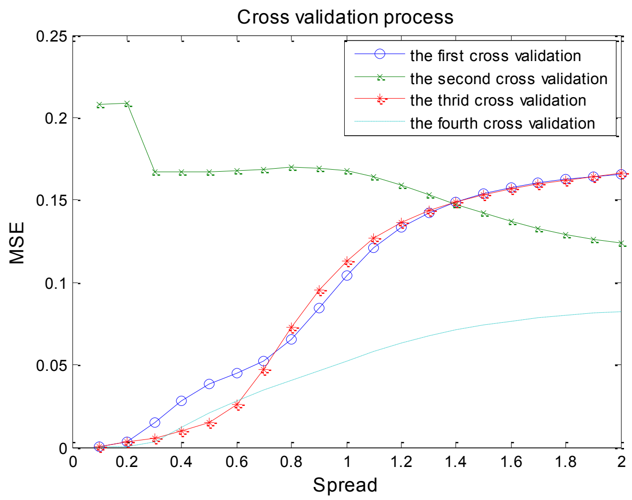

FIGURE 4. The cross validation process

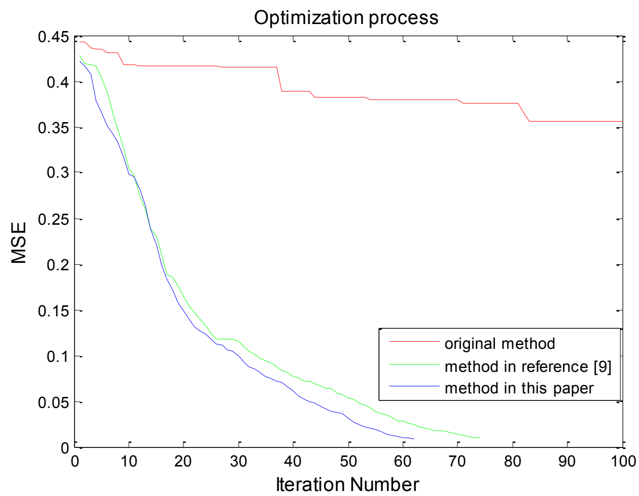

FIGURE 5. Optimization process of three method

Fruit fly optimization algorithm and its related methods are used to optimize the smooth factor of GRNN. In order to avoid excessive network, the limit value of MSE sets as 0.01. Compared with the original method of FOA, method in reference [9] and the improved FOA method in this paper, it can be seen that optimization process of these three method in Fig.5. MSE of original method has no obvious change when iteration number is increased, and the value of MSE is about 0.36. However MSEs of the other two methods drop rapidly and the value can fall below 0.05. It shows that the original method of FOA is worst. It also can be seen that terminal condition is satisfied of the proposed method in 62th generation, but that is 74th generation about method in reference [9]. So that convergence speed of improved FOA is faster than that of the original method and the method in reference [9].

Fruit fly flying route of two-dimensional space and three-dimensional space are shown in Fig.6 and Fig.7 respectively. It can be seen that fruit fly flying route in Fig.7 is more actual and compact than that in Fig.6.

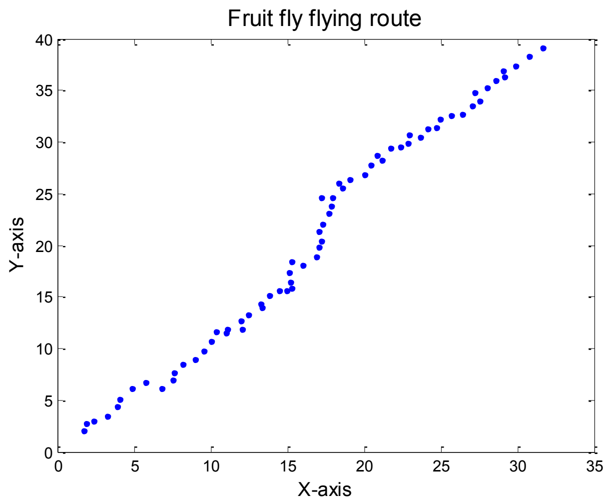

Figure 6. Fruit fly flying route of two-dimensional

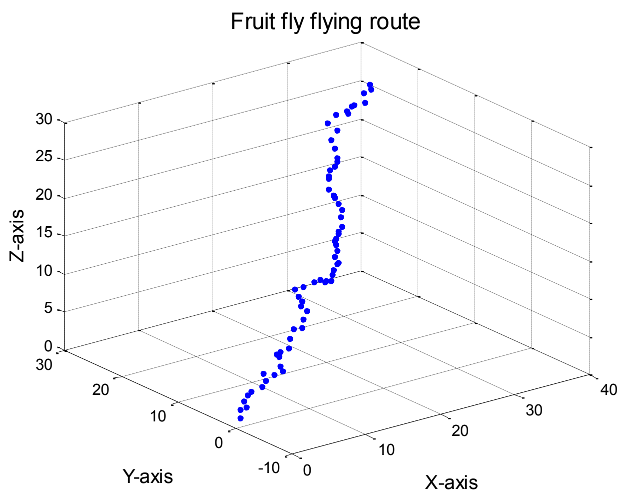

Figure 7. Fruit fly flying route of three-dimensional

4.2. **Further Analysis.** Accuracy of fault diagnosis is one of the most important performance indexes in fault diagnosis schemes. In order to further verify the effectiveness of the proposed algorithm, experiments are carried out by choosing 10 groups, 50 groups, 100 groups, 500 groups and 1000 groups sample datas. We compare the performance with

GRNN, FOA-GRNN and method in this paper for wind turbine fault diagnosis respectively, through contrasting the MSE of wind turbine fault diagnosis, which is as shown in Fig.8. It can be seen that the MSE is shrinking as number of samples increased, that is to say, the accuracy is increased when training samples is increased. There is not major difference of these three method when number of samples is less than 100. It also can be found that method in this paper has a better superior than the other methods when number of samples is large. When the sample arrived in 1000, the MSE can reduce to 0.2 below. And the data size is larger, the superiority is better.

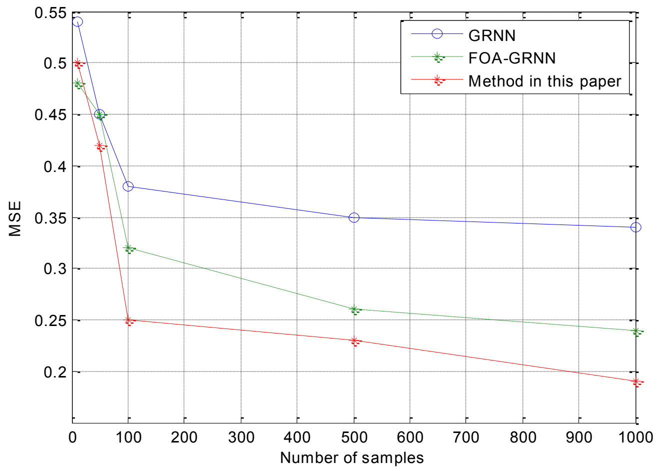

FIGURE 8. The performance of three methods

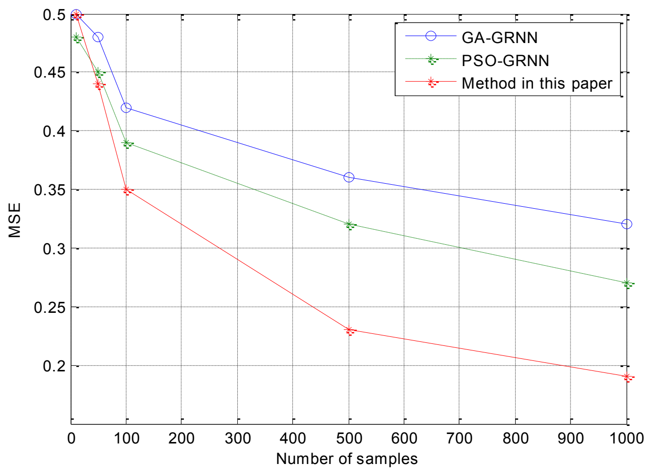

FIGURE 9. The MSE of the three methods

In order to improve the wind turbine fault diagnosis, there are many optimization algorithms to optimize the smooth factor at home and abroad, we should ensure that the proposed method is better than others. Simulation is executed by comparing MSE of GA-GRNN, PSO-GRNN and method in this paper for wind turbine fault diagnosis, as shown in Fig.9. It can be found that method in this paper has lower MSE than the other two methods when number of samples is increased. MSE of method in this paper can probably 0.1 lower than MSE of PSO-GRNN for wind turbine fault diagnosis, 0.2 lower than MSE of GA-GRNN for wind turbine fault diagnosis. So that the improved FOA has better superiority than other optimization algorithms.

5. **Conclusions.** In this paper, we have proposed a novel method for wind turbine fault diagnosis based on improved FOA to optimize GRNN. By building optimal GRNN model which is optimized by improved FOA, we improve the wind turbine fault diagnosis. In experimental function, the performance of this model was compared with many other methods. Simulation results show that the method can achieve higher accuracy rate, and especially when number of samples is large. And the data size is lager, the accuracy is better by comparison.

Acknowledgment. This work is partially supported by the National Natural Science Foundation of China (61501107). The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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