BP Network for Diagnosing Rotor Broken Fault Based on a New PSO

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Abstract— **A new BP neural network is proposed in this paper, the weights and thresholds of the network are optimized by an improved PSO algorithm instead of gradient descent method. The strategy of the algorithm is that at each iteration loop, on every dimension of particle swarm, choose the particle whose acceleration is biggest and the velocity is small enough to mutate its velocity according to some probability. The strategy could improve the global exploring ability of the particle, and could avoid the particle sticking to the local minimum. Also the improved PSO algorithm could effectively improve the convergence performance of conventional BP neural network. The new BP network is applied to diagnosing the rotor broken fault of motor in this paper. Experiment results show that the new algorithm enhance the diagnosis accuracy and improve the performance of network effectively.**

***Index Terms*—rotor broken, PSO, fault diagnosis, BP neural network**

I. INTRODUCTION

In industrial processes, where motors are playing a key role as a prime-mover or energy conversion device, and a sudden machine failure will likely result in an overall process failure. Moreover, a severe fault such as rotor broken may lead to irreversible damage. In other words, early stage fault detection will enable orderly process shutdown, thereby avoiding expensive repairs and minimizing lost production time. Motor fault diagnosis is a hot research field all the time [1]-[4]. This paper would introduce a new rotor broken detecting method by BP network based on Particle Swarm Optimization. Though the new method is simple, it's very effective to detect the anomalous condition of motor quickly and accurately.

Artificial neural networks (ANN) have been widely used in fault diagnosis systems due to their good inner adaptability. Among the various ANN, the back-propagation (BP) algorithm is one of the most important and widely used algorithms and has been successfully applied in many fields [5]-[9]. However, the conventional BP algorithm suffers from some shortcomings, such as slow convergence rate and easily sticking to a local minimum. Hence, the researching on improving the BP algorithm is always hot.

This paper presents a new BP network which is based on the Particle Swarm Optimization algorithm. The method can improve the convergence performance of BP network obviously.

II. THE PARTICLE SWARM ALGORITHM

A. Conventional PSO

Particle Swarm Optimization was first proposed by Kenney and Eberhart [10][11] based on the metaphor of social behavior of birds flocking and fish schooling in search for food. PSO is a relatively novel approach for global stochastic optimization. PSO is conceptually very simple, and is strong robust and excellent ability of global exploration. Using PSO to optimize the parameters of the BP neural network can effectively improve the convergence performance of the BP neural network, and overcome shortcomings of BP neural network mentioned above.

Many researches indicate that PSO has a good convergence, however it could easily stick to local minimum and converge too early when the algorithm is searching at the end age.

B. Improved PSO

Aiming at the fact that conventional PSO (CPSO) algorithm can easily stick to local minimum and converge too early, scholars have proposed some different improved PSO (IPSO) algorithms to enhance the global optimization performance of PSO algorithm[12]-[16]. Reference [12] added an inertial weight ω in CPSO velocity iteration equation. Researching on ω finds that a big ω can be benefit to global exploring for particle and harmful to local exploring for particle. However a small ω is benefit to local exploring for particle and harmful to global exploring for particle. So the author proposed a self-adaptive adjusting ω method to improve the performance of PSO. Reference [13] proposed a new PSO algorithm, which is based on the velocity mutation. The mutation strategy is that in each iteration loop, on every dimension d of particle swam containing n particles, find the smallest velocity $|v_{T,d}|$,

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then mutate it according to some probability, and make $v_{T,d}$ distribute on $\left|-v_{\max}, v_{\max}\right|$ stochastically, evenly. Reference [16] improved velocity mutation PSO algorithm based on the acceleration of particle. The method is that mutate the velocity of the particle whose acceleration is biggest, on every dimension d of particle swam containing n particles at each iteration. But the method only considered the acceleration and didn't take into account the velocity factor of the particle when operated the mutating algorithm. The biggest acceleration of particle is one of the necessary conditions for illustrating that the particle is flying to the local minimum, however another necessary condition is that the velocity should be very small even be zero, only in this case they can sufficiently indicates that the particle is flying to the local minimum.

Based on the method mentioned in reference [16], this paper furthermore presents a velocity mutating rule by considering both acceleration and velocity to supplement the strategy for mutating the velocity of particle more reasonably.

The new strategy can be described as:

Step 1, calculate the acceleration of each particle on dimension d .

$$a_{i,d} = -\frac{v^{k}{}_{i,d} - v^{k-\Delta k}{}_{i,d}}{\Delta k} \tag{1}$$

Where $i = 1,2,...n$, $d = 1,2,...D$, Δk is the number of variational iteration, $v^{k}{}_{i,d}$ is the velocity of particle i on dimension d at iteration k , $v^{k-\Delta k}{}_{i,d}$ is the velocity of particle i on dimension d at iteration $k - \Delta k$.

Step 2, define $a_{I,d} = \max\{a_{1,d}, a_{2,d}, ..., a_{n,d}\}$, $I \in [1, n]$.

Step 3, set a velocity threshold $v_T \in [-v_{\max}, v_{\max}]$, and v_T is close to zero.

Step 4, find the particle I whose acceleration is $a_{I,d}$, if $\left|v^{k}{}_{I,d}\right| < \left|v_T\right|$, then mutate the velocity $v_{I,d}$ (particle I , dimension d), and distribute the $v_{I,d}$ on $\left|-v_{\max}, v_{\max}\right|$ stochastically. Otherwise, find out another particle I' whose acceleration is biggest except particle I , and repeat step 4.

When particle converges close to the local minimum or global minimum, and the velocity of particle could even decrease to zero, so the acceleration could vary greatly. The acceleration of particle indicates the varying trend of particle velocity. If the acceleration of a particle is biggest, the same time, the velocity is small enough, that can foretell that the particle is flying to the local minimum and it may be converge too early. So choosing the particle to mutate its velocity can make it explore in more extended space and avoid it sticking to local minimum. The convergence performance can be improved obviously.

This paper uses two classical test functions, one is Rosenbrock function and the other is Rastrigin fuction, to compare the convergence performance of the IPSO algorithm proposed by this paper with the convergence performance of the CPSO algorithm.

Rosenbrock is a function of one peak value, when $x = (1,1,...,1)$ it gets to its global minimum: $f(x) = 0$.

$$f(x) = \sum_{i=1}^{n} (100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2) ,$$
$$-10 < x_i < 10 \tag{2}$$

Rastrigin is a function of multiple peak values, when $x = (0,0,...,0)$ it gets to its global minimum: $f(x) = 0$.

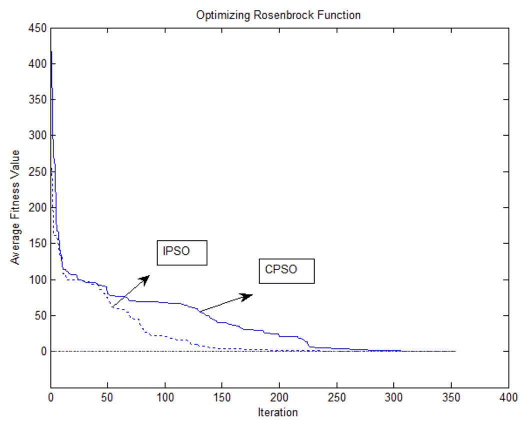
$$f(x) = \sum_{i=1}^{n} (x^2{}_i - 10\cos(2\pi x_i) + 10) ,$$
$$-5.12 < x_i < 5.12 \tag{3}$$

In the test, swarm size is set to 50; dimension is set to 8; $v_{\max}$ is set to the initial upper limits according to the two test functions; c_1 and c_2 are both set to 2. Additionally, in the new algorithm, v_T is set to 0.1, Δk is set to 30.

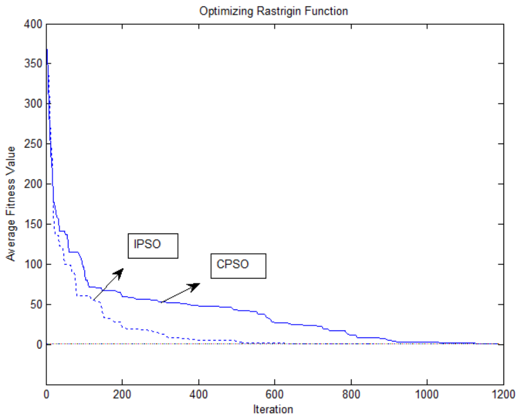
Define $\left|F_{best} - \bar{F}\right| = E$, F_{best} is the fitness value of the algorithm, $\bar{F}$ is the global minimum. E is the error. The precision is set to 0.1. The two test functions are used to test every algorithm for 30 times, and the average iteration times according to the two test functions respectively can be indicated in Table I , also the convergence performance can be illustrated by Fig.1.

TABLE I .
COMPARISON RUSULTS BETWEEN THE IPSO ALGORITHM AND THE CPSO ALGORITHM.

Function	IPSO	CPSO
Rosenbrock	275(times)	330(times)
Rastrigin	733(times)	1117(times)



(a)



(b)

Figure 1. Convergence performance comparison between the CPSO and the IPSO. (a) The curves of optimizing Rosenbrock function. (b) The curves of optimizing Rastrigin function

Table 1 and fig.1 show that, for the function Rosenbrock, the two algorithms have the equivalent convergence performance, and both the two algorithm has the fast convergence speed. So both the two methods have the good ability of local exploring for the function has only one peak value, also the convergence performance of IPSO is better a bit. However, for the function Rastrigin, the IPSO has a much better convergence performance than the CPSO obviously, namely, the IPSO has a better global exploring performance than the CPSO. The test indicates that the IPSO has a perfect performance in both global exploring and local exploring, and the IPSO can avoid the particle from sticking to local minimum effectively.

III. BP Neural Network Based on PSO Algorithm

BP neural network has the excellent abilities of self-adaptive and self-learning, and the researchers' attentions are always attracted by it in fault diagnosis field. However BP neural network has its inner shortcomings, such as, easily sticking to local minimum, slow convergence rate, sensitivity to original weights and thresholds in algorithm training process. This paper presents a new BP learning method based on PSO algorithm to overcome the shortcomings above. The algorithm uses PSO instead of gradient descent to optimize the parameters of neural network, and it has the better performance of learning rate and convergence than conventional BP algorithm.

This paper utilizes PSO algorithm to optimize the weights and thresholds of BP neural network, and the optimizing process can be indicated as follows:

Step1: Initialization. n_i is the number of input nerve cells, n_h is the number of hidden nerve cells, n_o is the number of output nerve cells.

$$D = n_h + n_o + n_i \times n_h + n_h \times n_o \tag{4}$$

Where D is the number of dimensions in the swarm.

Step2: Set fitness function of the particle, this paper chooses mean square error as fitness function in BP network,

$$E = \frac{1}{M}\sum_{k}^{M}\sum_{j=1}^{n_o}(y_{k,j} - \bar{y}_{k,j})^2 \tag{5}$$

Where $y_{k,j}$ is the theoretic output j of sample k in the neural network, $\bar{y}_{k,j}$ is the real output j of sample k of neural network, M is the sample number of the network.

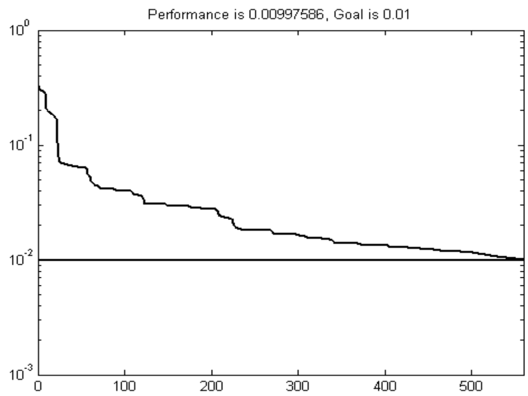
Step3: Optimize the weights and thresholds of BP network using the IPSO algorithm.

Step4: Obtain the optimized weights and thresholds according to (6).

$$g_{best} = [h_1, h_2, \ldots h_{n_h}, o_1, o_2, \ldots o_{n_o}, ih_1, ih_2, \ldots ih_{n_i \times n_h}, ho_1, ho_2, \ldots ho_{n_h \times n_o}] \tag{6}$$

Where h_i ($i = 1, 2, \ldots n_h$)is the threshold i of the hidden layer, o_i ($i = 1, 2, \ldots n_o$) is the threshold i of the output layer, ih_i ($i = 1, 2, \ldots n_i \times n_h$) is the weight i between input layer and hidden layer, ho_i ($i = 1, 2, \ldots n_h \times n_o$) is the weight i between hidden layer and output layer.

According to the algorithm mentioned above, this paper trains the BP network using a set of fault data from rotor broken motor, and compares the convergence performance between the BP network based on IPSO and conventional BP network which used the same fault data. Both the two neural networks included 4 neural cells in input layer, 10 neural cells in hidden layer and 8 neural cells in output layer. The error is 0.01. Additionally, in network based on IPSO algorithm, swarm size is set to 20, dimension is set to 138, $v_{\max}$ is set to 5, c_1 and c_2 are both set to 2, v_T is set to 0.1, Δk is set to 50.



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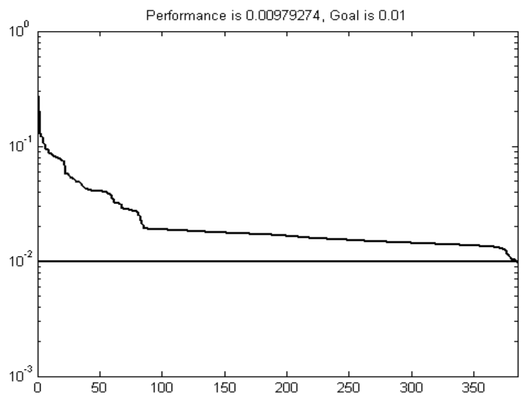


(b)

Figure 2. The convergence curves of the two algorithms. (a) The convergence curve of conventional BP network. (b) The convergence curve of BP network based on IPSO algorithm.

Fig.2 includes two convergence curves of the two methods respectively. (a) shows that conventional BP algorithm converged after 560 iterations with the error 0.01. (b) shows that BP neural network based on IPSO algorithm converged after 385 iterations with the error 0.01. These figures indicate that BP neural network based on IPSO has a faster convergence velocity than the conventional BP neural network, so the BP neural network based on IPSO has a perfect convergence performance.

Ⅳ. Faut Diagnosis of Motor Based on The New BP Network

Rotor broken is a common fault in inductive motor. The rotor broken fault diagnosis of inductive motor is realized in this paper through symbolic time series analysis of stator current signal of motor. A healthy motor and a rotor broken motor are selected in the experiment, and the parameters of the two motors are same, the power is $3\,KW$, $2p=4$, $s=0.04$. Sample the signal 2048 times (frequency is 2k/s). The test bed is shown in Fig.3.

Figure 3. Test bed of Motor

A. Preparatory Data Processing

This paper applied BP neural network based on the IPSO algorithm to recognize the rotor broken fault of motor. The weights and thresholds of BP neural network are optimized by the IPSO. The inputs of BP neural network are the symbol occurrence probabilities of the stator current which is mentioned in [17], and the outputs of the network are the recognizing results, namely the classification of fault.

The fault diagnosis test is executed as follow steps:

First, acquire stator current signal and process the signal. Wavelet can perfectly analyze the signal characteristics in both local time domain and frequency domain, and using wavelet to analyze the characteristic frequency of typical fault can detect the fault signal effectively. Thus, the anomaly condition can be effectively detected by analyzing the wavelet coefficients after wavelet transformation. For every wavelet, there exists a certain frequency called the center frequency F_c that has the maximum modulus in the Fourier transform of wavelet. The pseudo-frequency f_p of the wavelet at a particular scale α is given by the following (7).

$$f_p = \frac{F_c}{\alpha \Delta t} \tag{7}$$

The wavelet coefficients of a signal have the maximum magnitude at the scale corresponding to the pseudo-frequency. Hence, it would be appropriate to choose such scales which the pseudo-frequency corresponds to the frequency of interest. Thus the change of fault signal can be detected more effectively and more shrewdly by focus on fault property frequency.

The sideband components around the fundamental of the line current spectrum are usually measured to detect broken bar faults, where the sideband is $f_b = (1 \pm 2s) f$. These fault signatures naturally will also appear in the line current signals. The phase current signals can be written as:

$$i_A = i_f \cos(\omega t - \alpha_0) + i_l \cos((1-2s)\omega t - \beta_l) + i_r \cos((1+2s)\omega t - \beta_r) \tag{8}$$

$$i_B = i_f \cos(\omega t - \alpha_0 - \frac{2\pi}{3}) + i_l \cos((1-2s)\omega t - \beta_l - \frac{2\pi}{3}) + i_r \cos((1+2s)\omega t - \beta_r - \frac{2\pi}{3}) \tag{9}$$

$$i_C = i_f \cos(\omega t - \alpha_0 + \frac{2\pi}{3}) + i_l \cos((1-2s)\omega t - \beta_l + \frac{2\pi}{3}) + i_r \cos((1+2s)\omega t - \beta_r + \frac{2\pi}{3}) \tag{10}$$

Where i_l and i_r are the peak values of the fundamental supply phase current respectively, namely the lower sideband component at frequency $(1\text{-}2s)f$, and the upper sideband component at frequency $(1\text{+}2s)f$. Three angles α_0 , β_l and β_r denote the initial phase angle respectively, for the fundamental component, the lower sideband component and the upper sideband component. Here again the Parks vector modulus is computed:

$$\left|i_d + j i_q\right|^2 = \frac{2}{3}(i_f^2 + i_l^2 + i_r^2) + 3 i_f i_l \cos(2s\omega t - \alpha_0 + \beta_l) + 3 i_f i_r \cos(2s\omega t + \alpha_0 - \beta_r) + 3 i_r i_l \cos(4s\omega t + \beta_r + \beta_l) \tag{11}$$

The fault frequencies are clearly concentrated at frequencies of $2sf$ and $4sf$, with no component at the fundamental supply frequency. Although there are bound to be variations in speed and consequently changes in the slip; but if the rough operating point is known, wavelet analysis can be used to zoom in and extract the fault information. Need to explain, the frequencies $(1 \pm 2s) f$ would appear together only the speed of motor are fluctuant. Most of motors operate with the constant speed, so only the frequency $(1\text{-}2s)f$ is left, and (11) should be :

$$\left|i_d + ji_q\right|^2 = \frac{2}{3}(i_f^2 + i_l^2) + 3i_f i_l \cos(2s\omega t - \alpha_0 + \beta_l) \quad (12)$$

Equation 12 indicates that the fault component would appear at $2sf$ frequency range, so the fault information can obtain through the way that decomposes the fault signal at $2sf$ frequency by wavelet.

Second, the wavelet coefficients are assigned to several symbols, the assigning rule is introduced in [17]. In this paper, the symbol number is eight, namely, the coefficients are assigned to eight regions.

Third, calculate the occurrence probabilities $P\{p_1, p_2 ... p_n\}$ of every symbol for the occurrence probabilities can contain much fault information.

$$p_i = m_i / N\ ,\ \ i = 1, 2 ... n \quad (13)$$

Where, p_i is the occurrence probability of symbol i in symbol series, N is the number of all the symbols.

Fourth, train the BP network using the similar data.

Then, take the occurrence probabilities as the inputs of the BP neural network.

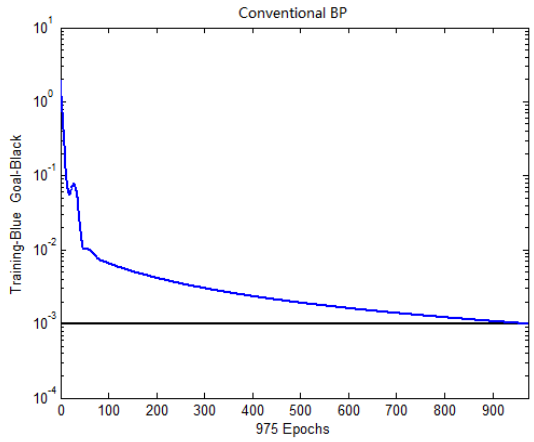
Finally, get the recognizing results from the trained BP neural network based on the new IPSO.

B. Experiment Verification

This paper applies the BP neural network based on IPSO algorithm and the conventional BP neural network respectively to diagnosing motor fault. In addition to the IPSO, CPSO are also adopted to optimize the BP network in order to contrast the diagnosis results. So there are three BP networks applied in the test. The configurations of the three BP networks are the same with what mentioned in chapter 3. Fig.4 show the convergence speed of the three trained network. In each network, chose 8 symbol occurrence probabilities of fault current as inputs, and chose four kinds of fault as outputs.

The test chooses 50 sets of fault samples for every fault type individually (the four kinds of fault are health, one broken bar, three broken bar and five broken bar), and the sample sum for all the 4 types is 200. 30 samples of each type are used to train the three BP neural networks, and the others are used to test the outputs of the three trained BP networks.

Fig.4 shows that the BP network based on IPSO has the fastest convergence speed with 581 epochs, and the BP network based on CPSO has a convergence speed with 717 epochs. Conventional BP network has the most slow convergence speed with 975 epochs among the three networks. So the new BP network has a better convergence. The same time, table Ⅱ indicates that the BP network based on IPSO also has a smallest convergence error among the three networks. The BP network based on IPSO has a good performance from figure 4 and table Ⅱ, and it is satisfied.



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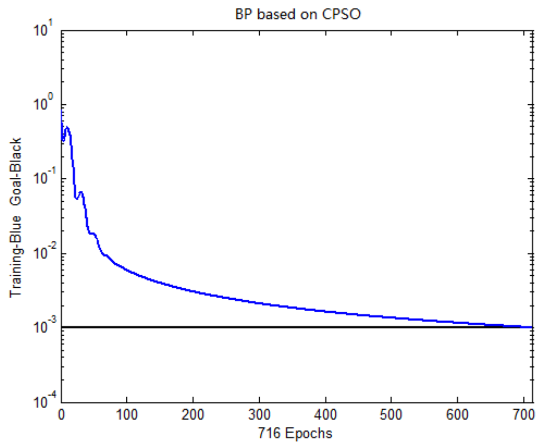

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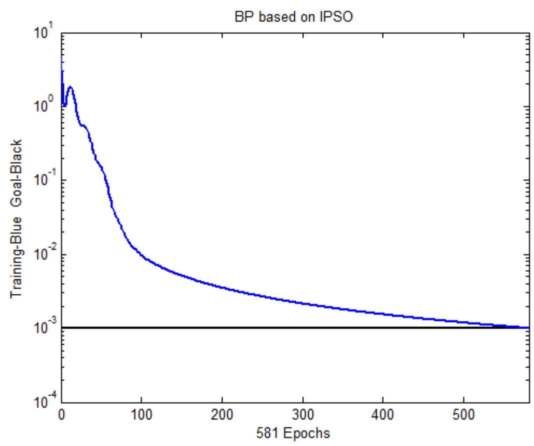

(c)

Figure 4. Convergence curves of the three network.(a)Conventional BP Network (b) BP based on CPSO.(c)BP based on IPSO

TABLE II.
THE AVERAGE CONVERGENCE ERRORS OF THE THREE NETWORK

	Conventional BP	BP based on CPSO	BP based on IPSO
Average convergence errors	0.00053	0.00026	0.00012

The average outputs of the three networks are shown in fig.5-fig.8.

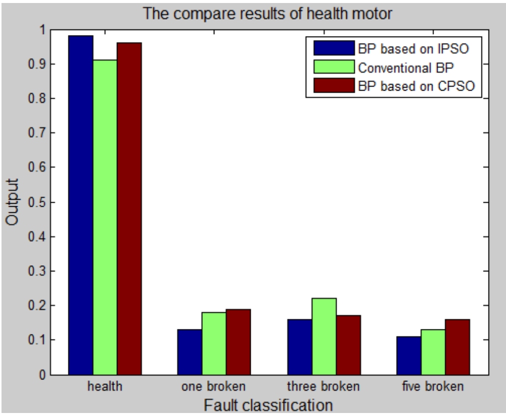

Figure 5. The compare results of health motor

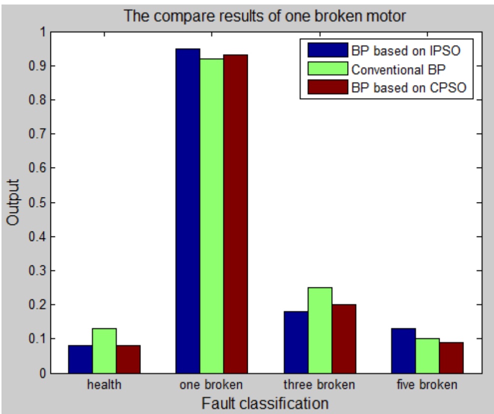

Figure 6. The compare results of one broken motor

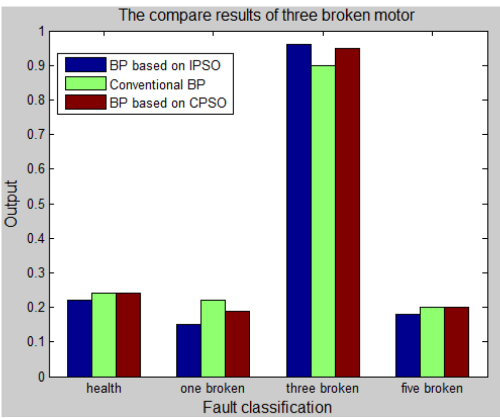

Figure7. The compare results of three broken motor

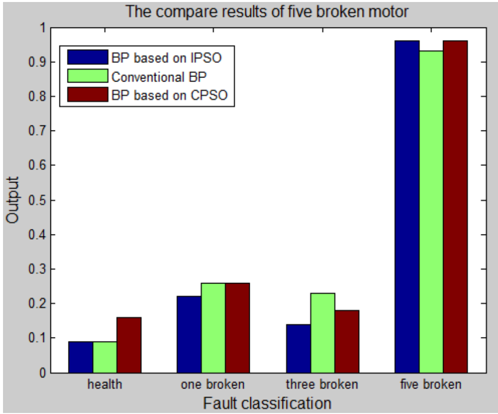

Figure 8.The compare results of five broken motor

Fig. 5- Fig. 8 indicate that the average of 20 outputs in each BP network under the different conditions of motor. The bar of BP network based on IPSO is the most high, and the bar of conventional BP network is the most low. The height of the bars represents the accuracy of the output. The figures indicate that the outputs of BP network based IPSO are the most satisfied among the three networks, and the results of the conventional BP network are the most unsatisfying.

Except that, the correct recognition number and wrong number are listed in tableIII- tableV. So tableIII-tableV represent the average diagnosis accuracy of each network. The results of the three tables indicate that the BP network based on IPSO algorithm has a best diagnosis performance in all the three networks with the diagnosis average accuracy being 98.75%, and the conventional BP network has the worst performance with the diagnosis average accuracy being 96.25%.

TABLE III.
AVERAGE DIAGNOSIS ACCURACY OF THE BP NETWORK BASED ON IPSO ALGORITHM

	Health	One broken	Three broken	Five broken
Sample number	20	20	20	20
Correct number	20	19	20	20
Wrong number	0	1	0	0
Accuracy (%)	100	95	100	100

TABLE IV.
AVERAGE DIAGNOSIS ACCURACY OF THE BP NETWORK BASED ON CPSO ALGORITHM

	Health	One broken	Three broken	Five broken
Sample number	20	20	20	20
Correct number	19	19	20	20
Wrong number	1	1	0	0
Accuracy (%)	95	95	100	100

TABLE Ⅴ
AVERAGE DIAGNOSIS ACCURACY OF THE CONVENTIONAL BP NETWORK

	Health	One broken	Three broken	Five broken
Sample number	20	20	20	20
Correct number	19	19	19	20
Wrong number	1	1	1	0
Accuracy (%)	95	95	95	100

TableⅢ- tableⅤ show that the average diagnosis accuracy for the four kinds of fault using the BP network based on IPSO is higher than the other two networks. This indicates that the IPSO has a better optimal performance, and it can offer the more accurate parameters for BP network. So it has better diagnosis accuracy in the test of rotor broken fault diagnosis.

Ⅴ. CONCLUSION

This paper introduces a new BP network which based on IPSO algorithm and applies it to rotor broken fault diagnosis. In the method a conventional PSO algorithm is improved, and this paper proposes the velocity mutation algorithm based on both particle acceleration and particle velocity. The method can effectively avoid the particle sticking to the local minimum; also it can enhance the global exploring ability for the particle. Applying the method to optimizing weights and thresholds of BP neural network can enhance the convergence performance of BP network, and utilizing the optimized BP network to diagnose the rotor broken fault of motor can obtain a satisfied diagnosis result.

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