The Investigation of Fault Diagnosis Based on GA-HPSO-NN

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Abstract—**At present, although most fault diagnosis methods of rotating machinery is qualitatively used, it is gravely lacking in quantitative accuracy. So a novel algorithm GA-HPSO combining with the advantages of genetic algorithm (GA), simulated annealing (SA) and particle swarm optimization (PSO) was provided to train neural network (NN). The proportion and blend methods were applied to the novel algorithm. Information entropy was used to take fault signals. Four kinds of spectral entropies and six kinds of typical rotor faults were used as input and output data. NN classifier based on GA-HPSO was set up. The simulation results indicate that GA-HPSO has a better ability to escape from a local minimum and is more effective than the conventional single algorithm. It can rapidly and accurately realize fault data classification. It provides a new method for fault diagnosis.**

Index Terms—**Information Entropy; GA-HPSO-NN; Fault Diagnosis**

I. INTRODUCTION

With the development of modern industry, the large rotating machines are developing toward high speed and high efficiency increasingly. The relationship of fault and sign is unclear which hampers operator's ability to diagnose and eliminate equipment failures before faults happen [1]. With the prevalence of computer technology, the intelligence monitoring system is more important. Fault diagnosis is the main embodiment of intellectual monitoring system, so the level of diagnose technology influences the function of intellectual monitoring system. It also has important meaning to keep normal running, reduce product cost, raise product efficiency and ensure product safety for whole system.

The coupling weights that distributed in NN are used to express the diagnosis knowledge. It can realize the complex non-linear mapping relation of fault and sign through associative memory, pattern matching and similar induction. It is widely used in fault diagnosis of rotor system, especially for pattern recognition of multiple faults and many signs.

Back propagation algorithm (BP) based on gradient learning is the most common training method for NN, but it is easy to fall in the local best solution. GA, PSO and SA are some of the well-known meta-heuristic algorithms. GA shows unique advantages in establishing system structure and global optimization. PSO is an evolutionary computational method, which may be conveniently employed to execute random and global search. SA is a generic probabilistic metaheuristic for the global optimization problem. It accepts the current optimal solution at a probability after searching, so it can overcome local minimum point. There are some scholars and many experts who used different algorithms to train NN and solve different problems. Ya-xiang Xu et al. adopted adaptive PSO to optimize NN [2]. K. Premalatha et al. proved that GA-PSO had advantages over standard PSO [3]. Chang-cai Cui et al. put forward a novel heuristic method GA-PSO to optimize engineering problem [4]. Wen-yi Wang et al. proposed a effective optimization method GA-PSO [5]. Jun Liu et al. adopted improved PSO to train NN [6].

In order to avoid the shortcoming of the standard single algorithm, a novel algorithm GA-HPSO-NN combining with the advantages of GA, PSO, SA and NN was put forward based on previous research. Fault vibration signals were evaluated from the time, frequency and time-frequency domains in extraction sample. Multi-angle characteristics of rotor fault signals are the input variables of NN. The output values are six kinds of typical fault. GA was used for coarse search of weights and threshold under optimized NN structure, then HPSO with cross factor was used for exact search. In order to improve the ability of the new algorithm to escape from a

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local optimum, SA was used to modify GA. The final weights and bias of NN were gotten through GA-HPSO. Computer simulation results are provided to compare the performance of GA, PSO and GA-HPSO. The results show that the fault diagnosis accuracy is effectively improved using GA-HPSO [7].

II. GA-HPSO-NN

A. Fault Feature Extraction

There is much relevant information with actual condition in the original signal detection. The extracted characteristic should be able to reflect the regularity and sensitivity of actual condition, contain regularity fault characteristic and have better fault separability. So the fault feature extraction and processing is the key to realize NN classification. The information entropy expresses statistical characterization of the whole signal which is used to measure the overall uncertainty of information source. The value is smaller, then the information is more certain and unordered degree is smaller. Singular value spectral entropy of time domain, power spectral entropy of frequency domain, wavelet energy and space spectrum entropy of time-frequency domain are used to measure rotor fault signal index [8].

The information entropy can be defined as follows:

$X=\{x_1,x_2,\cdots,x_n\}$ expresses a whole set of rotor vibration signal. Probability x_i of every component is $P=(x_i)$ and $\sum_{i=1}^{n}P(x_i)=1$. The information entropy $H(X)$ of X is:

$$H(X)=-\sum_{i=1}^{n}P(x_i)\log P(x_i)=-\sum_{i=1}^{n}P_i\log P_i \qquad (1)$$

Four kinds of spectral entropy can be gotten through formula (1).

B. GA

GA is stochastic search technique. It first proposed by Holland, is inspired by the mechanism of natural selection and natural genetics. GA represents a highly parallel adaptive search process. GA has received considerable attention regarding their potential as a class of stochastic searching algorithms for complex problems and has been successfully applied in the area of industrial engineering. GA can avoid the problems inherent in more traditional approaches. Restrictions on the range of the parameter-space are imposed only by observations and by the physics of the model. Although the parameter-space so-defined is often quite large, the GA provides a relatively efficient means of searching globally for the best-fit model. While it is difficult for GA to find precise values for the set of best-fit parameters, they are well suited to search for the region of parameter-space that contains the global minimum. In this sense, the GA is an objective means of obtaining a good first guess for a more traditional method which can narrow in on the precise values and uncertainties of the best-fit.

The following list shows the general procedure of GA as described by Mitsuo Gen and RunWei Cheng.

Procedure of GA

start
  initialize X(t);
  t=0;
  while (not termination condition)
  do
    Evaluate fitness of X(t) of each individual;
    Selection operation to X(t);
    Crossover operation to X(t);
    Mutation operation X(t);
    X(t+1)=X(t);
  end while
end

GA starts from a population of randomly generated individuals and happens in generations called population. Each individual in the population is called a chromosome, representing a solution to the problem at hand. A chromosome is a string of symbols; it is usually, but not necessarily, a binary bit string. The chromosomes evolve through successive iterations, called generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. Fitter chromosomes have higher probabilities of being selected. The new population is then used in the next iteration of the algorithm. Some of the parents are rejected and an equal number of offsprings are accepted as the replacement of these parents so as to keep the population size constant. After several generations the algorithms converge to the best chromosome, which hopefully represents the optimum, or at least suboptimal, solution to the problem [9-10].

C. SA

SA is a well-known algorithm used to solve discrete optimization problems. SA is based on the annealing of metals. If a metal is cooled slowly, it forms into a smooth piece because its molecules have entered a crystal structure. This crystal structure represents the minimum energy state, or the optimal solution, for an optimization problem. If a metal is cooled too fast, the metal will form a jagged piece that is rough and covered with bumps. These bumps and jagged edges represent the local minimums and maximums. Kirkpatrick originally thought of using SA on computer related problems. He did this in 1983 and applied SA to various optimization problems. From there, many other people have worked on it and have applied it to many optimization problems. The algorithm borrows the annealing analogy from Statistical Mechanics. In the search process, the SA accepts not only better but also worse neighboring solutions with a certain probability. Such mechanism can be regarded as a trial to explore new space for new solutions, either better or worse. The probability of accepting a worse solution is larger at higher initial temperature. As the temperature decreases, the probability of accepting worse solutions gradually approaches zero. This feature means that the SA technique makes it possible to jump out of a local optimum to search for the global optimum. So SA is a good algorithm because it is relatively general and tends to not get stuck in local minimum [11-12].

D. PSO

PSO is an evolutionary computation technique and simulates the behavior of birds flocking developed by Dr. Eberhart and Dr. Kennedy in 1995. Individuals in the community have the ability to control their own behavior based on certain internal and external information. It means that each individual has certain sensory ability and can perceive the local best and global best position of the individual. The particle takes its next action according to the current condition and obtained information. So the whole community displays a certain intelligence. When solving an optimization question, each individual position is correspondingly regarded as a latent solution. According to the above rules, the global optimal solution can be obtained through repeatedly adjusting these latent solutions. For the nth iteration, the particles of PSO change according to the following two formulas:

$$x_{id}^{n+1} = x_{id}^{n} + v_{id}^{n+1} \tag{2}$$

$$v_{id}^{n+1} = \begin{cases} w \cdot v_{id}^{n} + c_1 \cdot rand() \cdot (p_{id} - x_{id}^{n}) + \\ c_2 \cdot rand() \cdot (p_{gd} - x_{id}^{n}) \end{cases} \tag{3}$$

$$i = 1, 2, \ldots, M$$

Where M is the particle sum; v_{id}^{n} is the dth weight of flight velocity vector for the nth iteration for particle i; x_{id}^{n} is the dth weight of position vector for the nth iteration for particle i; p_{id} is the dth weight of *Pbest* for particle i; p_{gd} is the dth weight of *Gbest* for particle i; *Pbest* is the best of a particle; *Gbest* is the best of all particles; c_1 and c_2 are learning factors; rand() is a random number between 0-1; w is an inertia weight function. The new velocity of particle i is computed using the formula (2) through three parts:

(1) The first is the previous time velocity of particle i. It shows the present condition and can balance global and local search ability.

(2) The second is the recognition part. It indicates the particle thought, enables the particle have the strong global search ability and avoid a local minimum,

(3) The third is the social part. It realizes information sharing between particles.

Under the influence of the three parts, the particles adjust their positions based on experience and information sharing. Finally the globe best solution can be obtained [13-14].

E. NN

NN is an information processing paradigm that is inspired by the way biological nervous systems. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (nodes) working in unison to solve specific problems. NN is configured for a specific application, such as data classification or pattern recognition, through a learning process. Learning in biological systems involves adjustments to the connection strengths that exist between the nodes.

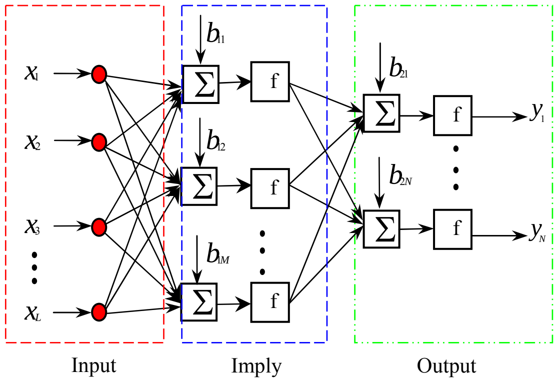

Fig.1 Standard BPNN

Fig.1 is the standard BPNN. It is made up of input layer, imply layer and output layer. If there are L inputs and N outputs, there is a nonlinearity mapping from input to output. Much research displayed that enough imply layer nodes can approach any continuous function. Relational coefficient was applied to simplify the number of the hidden layer nodes. It can be realized as follows:

O_{pi} is the output of imply layer node i under studying sample p. O_{pj} is the output of imply layer node j under studying sample p. N is learning samples total.

So $$\overline{O_i} = \frac{1}{N}\sum_{p=1}^{N} O_{pi} \tag{4}$$

$$\overline{O_j} = \frac{1}{N}\sum_{p=1}^{N} O_{pi} \tag{5}$$

$$X_p = \overline{O_{pi}} - \frac{1}{N}\sum_{p=1}^{N} O_{pi} = O_{pi} - \overline{O_i} \tag{6}$$

$$Y_p = \overline{O_{pj}} - \frac{1}{N}\sum_{p=1}^{N} O_{pj} = O_{pj} - \overline{O_j} \tag{7}$$

So relational coefficient of O_{pi} and O_{pj} is:

$$\rho_{ij} = \frac{\sum_{p=1}^{N} X_p \times Y_p}{\sqrt{\sum_{p=1}^{N} X_p^{\ 2}} \times \sqrt{\sum_{p=1}^{N} Y_p^{\ 2}}} \tag{8}$$

Where $\rho_{ij} \leq 1$, it reflects function repetition rate of node i and j. If $\rho_{ij} \geq 0.9$, node i and j are incorporated.

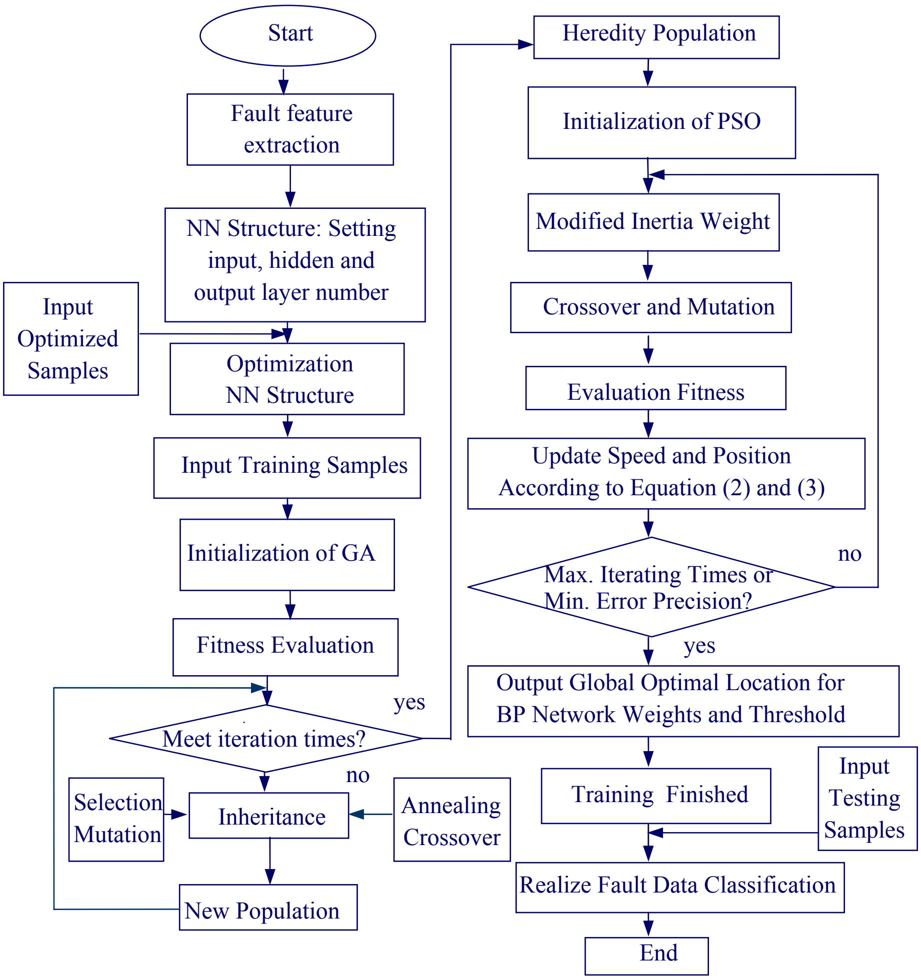

Fig.2 Rotor fault diagnosis flow chart based on GA-HPSO-NN

F. GA-HPSO-NN

There are many approaches to train NN using GA and PSO combination. The most common way is order and embedded combination. For order combination way, GA is used only for position vector of the particle. Particle velocity vector is difficult to track particle, so the effect is not good. While embedded method was too simple, the final effect is also not very ideal. So a novel GA-HPSO-NN combining GA, SA, PSO and NN, was proposed. After running M generations GA, then N generations HPSO was run. M and N value was selected according to the certain proportion. At the same time SA, selection, mutation and crossover were used to GA, and mutation and crossover were used to PSO. Fig.2 is the proposed rotor fault diagnosis flow chart based on GA-HPSO-NN. The weights and biases optimization of NN was divided into two stages: GA-SA-NN and HPSO-NN.

The article is a small sample problem. The sample size was selected 60 according to convergence time and precision. Every individual of population is chromosome including weight and threshold of NN.

Dimension of population can be defined as follows:

$$D = r \times S_1 + S_1 \times S_2 + S_1 + S_2 \tag{9}$$

Where r is input layer number of NN. S_1 is hidden node number of NN. S_2 is output layer number of NN.

In order to simplify coding and avoid inhomogeneity of initialized weights and threshold, real number coding and grid distribution method was applied [15-16].

GA-SA-NN

Step 1 Start.

Step 2 Fault Feature Extraction.

Step 3 NN Structure.

Four kinds of spectral entropy of fault diagnosis are the input variable of NN. The output values are six kinds of typical faults of rotor: rotor misalignment, mass unbalanced, contact rubbing, loose, oil film whirl and oil whip. In order to speed up the training speed, improve anti-noise ability, and avoid NN into local optimal, noise samples were added to the original data. In order to avoid excessive input value produce saturation state, the input data was normalized from 0.4 to 0.9, and interval is 0.1.

Step 4 Optimization NN Structure and Input Training Samples.

Rotor test-bed is shown in Fig.3. 13 eddy current sensors are arranged in different position in test-bed. Number 1 to 12 are rotor vibration signal. Number 13 is speed signal. Testing data of speed=3200r/s are selected as calculated data. 5000 data samples of one of the channels are selected to calculate four types of spectral entropy. 15 sets of data are selected to optimize hidden layer nodes of NN. 60 sets of data are selected to train NN. 10 sets of data are used to test NN. Learning rate of NN is 0.05.

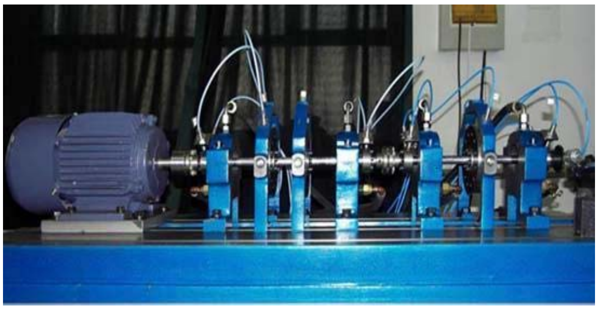

Fig.3 A test bench for rotor

Step 5 Initialization of GA.

Crossover rate P_c is 0.6. Matation rate P_m is 0.1, and iterations are 100 in GA.

Step 6 Fitness Evaluation.

Fitness function of GA is F=1/E. Output error E of NN is:

$$E = \frac{1}{N}\sum_{j=1}^{N}\sum_{i=1}^{C}(y_{ij} - O_{ij})^2 \tag{10}$$

Where N is number of test samples. y_{ij} is i output node ideal value of sample j.

If meet iteration times, new population will be moved to HPSO-NN. If not, the program will execute step 7.

Step 7 Inheritance.

Roulette and random selection was applied to individual fitness. Elitism is used to reserve optimal individuals. It makes the evolution process to high probability converge to the global optimal solution. In order to prevent premature, SA and crossover operator was used to individual $X_i(t)$ and $X_j(t)$:

$$\begin{cases} X_i(t+1) = aX_i(t) + (1-a)X_j(t) \\ X_j(t+1) = aX_j(t) + (1-a)X_i(t) \end{cases} \tag{11}$$

Where a is the random number in range (0,1) uniformly. t is iterations.

For results of crossover, fitness of $X_i(t)$ and $X_i(t+1)$ was compared according to Metropolis acceptance criteria. If fitness $X_i(t+1)$ is the optimal. $X_i(t)$ is replaced. Or for the random number r in range (0,1). If the under formula is workable.

$$e^{\frac{F_i(t+1)-F_i(t)}{T}} > r \tag{12}$$

$X_i(t+1)$ was accepted. Where $F_i(t+1)$ is fitness of $X_i(t+1)$. $F_i(t)$ is fitness of $X_i(t)$. T is SA temperature. SA temperature function is $T = T_0 \times \alpha^M$. T_0 is initial temperature of SA. α is temperature attenuation coefficient. M is the operation execution number of crossover. Initial temperature of SA T_0 is 100000. Temperature attenuation coefficient α is 0.95.

The same principle was applied to selection of $X_j(t)$ and $X_j(t+1)$. Some individuals are selected randomly to change gene value of using mutation probability P_m. Multipoint random mutations was used in this paper.

The final population as HPSO initial position vector was gotten when training reached iteration of terminate evolution.

HPSO-NN

Step 8 Initialization of PSO.

Learning factor C_1 and C_2 of HPSO are 1.4962. w_0 is 0.9. Max. speed of particle is 0.2, iterations are 200.

Step 9 Modified Inertia Weight.

Inertia weight was calculated using the following formula [13]:

$$w = w_0 + r_1 \times e + r_2 \times a \tag{13}$$

Step 10 Crossover and Mutation, Evaluation Fitness, and Update Speed and Position.

Fitness function and population size selection of HPSO are same with GA. Particle fitness of PSO was sorted according to the current position fitness of every particle. Half outstanding particle fitness is chosen directly into the next generation. Same with GA, a crossover position is randomly generated for particle position vector through crossover of other half particles. Same number of offspring is gotten. Update is conducted after crossover finished. The fitness of calculated offspring was compare with corresponding father generation. Half outstanding particle fitness of offspring and parent was kept. Half outstanding particle in the kept particle and the original half particle was selected according to fitness sequence in order to keep populations number. Individual optimal value and global population optimal value of every particle was calculated. Speed and position of particle was updated according to formula (2) and (3).

Step 11 Max. Iterating Times or Min. Error Precision?

If training reached Max. iterating times or minimum error precision. The training process finished. If not,the program will move to step 9. [17-18].

III. Numerical Simulation

Fig. 4 is iteration error of the three algorithms. Green dashed, blue dotted lines and red solid line respectively represent training process of GA, PSO and GA-HPSO. Before 70 times, GA and GA-HPSO are of obvious advantage. As the iterations As the increase of iteration times, GA-HPSO has an obvious superiority over GA and small advantage over PSO. Overall, PSO and GA have better convergence than GA-HPSO.

Testing samples are used to test the trained NN. Table 1 is the fault data classfication results. Calculation formula of relative error is:

$$E_i = \frac{|O_i - y_i|}{|y_i|} \times 100\% \tag{14}$$

Where O_i and y_i are classification result and ideal output of testing sample i. Four kinds of algorithms are used to train NN. The trained NN is used to predict six kinds of typical fault of rotor. The forecasting results are compared with idea output. The results show that GA-HPSO can rapidly and efficiently realize NN training. The novel algorithm shows high diagnostic accuracy and good classification effect in fault prediction.

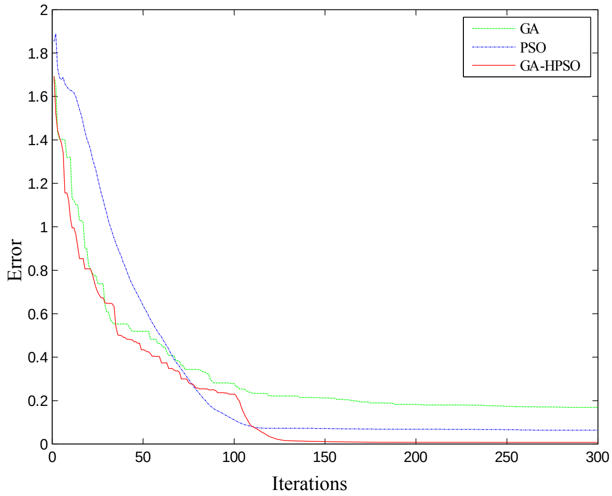

Fig.4 Iteration error of three kinds of algorithmic

TABLE I.
THE FAULT DATA CLASSFICATION RESULTS

No.	Ideal Output	GA-HPSO Output	Relative error(%)	GA-BP Output	Relative error(%)	PSO-BP Output	Relative error(%)	BP Output	Relative error (%)	Fault Types
1	0.5	0.5228	4.56	0.5240	4.80	0.5246	4.92	0.5107	2.14	mass unbalanced
2	0.6	0.6130	2.16	0.6253	4.22	0.6262	4.37	0.6406	6.78	contact rubbing
3	0.4	0.3975	0.63	0.3998	0.05	0.4015	0.38	0.4096	2.40	rotor misalignment
4	0.7	0.7101	1.44	0.7090	1.29	0.7085	1.21	0.7162	2.31	loose
5	0.5	0.5246	4.92	0.5248	4.96	0.5254	5.08	0.5051	1.02	mass unbalanced
6	0.8	0.7980	0.25	0.8031	0.39	0.8054	0.68	0.8167	2.09	oil film whirl
7	0.8	0.7986	0.18	0.8055	0.69	0.8075	0.71	0.8097	1.21	oil film whirl
8	0.4	0.3984	0.40	0.3999	0.03	0.4017	0.43	0.4081	2.03	rotor misalignment
9	0.9	0.8945	0.61	0.9130	1.44	0.9175	1.94	0.8987	0.14	oil whip
10	0.4	0.3891	2.53	0.3867	3.33	0.3863	3.43	0.4008	0.20	rotor misalignment

IV. Conclusion

Four kinds of spectral entropy of fault diagnosis are the input variable of NN. The output values are six kinds typical fault of rotor. GA-HPSO are used to optimize weight and threshold of NN and compared with GA and PSO. The testing results show that the novel algorithm can realize quicker and more accurate fault diagnosis of rotor system than PSO and GA. GA-HPSO can give idea output results for multiple-diagnosis symptom. It shows that the novel algorithm is feasible and superior and supplies a new way and method for fault diagnosis.

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