Research on fault diagnosis of mechanical system based on mechanical vibration signal identification

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Abstract: The research of mechanical system fault diagnosis has become one of the key enabling technologies of intelligent manufacturing. With the increase of the application fields of rotating machinery, many countries actively carry out research on the theory and application technology of mechanical fault diagnosis. The fault diagnosis technology of mechanical system in this paper is based on PNN(Probabilistic neural network) and GA(genetic algorithm), which realizes the collection, processing and analysis of vibration signals of rotating machinery. Firstly, GA is used to search the global optimal values of PNN weights and thresholds, and then it is input into PNN to replace the randomly generated weights and thresholds. Finally, network training is carried out. The simulation results show that the correct rate of fault state classification and identification of the test sample bearing is 99.06%, and the recognition rate is high, which can meet the needs of engineering application. The GA_PNN model proposed in this paper is superior to BPNN(Back propagation neural network) in reducing the loss function value, which proves the feasibility of GA_PNN model. The feasibility of extracting fault characteristics of bearing vibration signals with different scales by the model is verified.

1. Introduction

With the rapid development of modern science and technology and modern industry, rotating machinery is becoming more and more integrated, high-speed and automatic. The higher the level of intelligence, the more complex the structure and the closer the connection between components. Once a component fails, it will have a chain reaction and cause equipment damage. As an important technical support for preventive maintenance, mechanical system fault diagnosis of mechanical equipment is of great significance for reasonably prolonging the service life of mechanical equipment, reducing periodic maintenance costs and ensuring the safety of equipment operation [1-2]. The research of mechanical system fault diagnosis has become one of the key enabling technologies of intelligent manufacturing. Combined with the latest research results of artificial intelligence and signal processing technology, it has gradually become an independent emerging discipline, which represents the development level of national manufacturing industry to some extent [3]. With the increasing application fields of rotating machinery, many countries actively carry out research on the theory and application technology of mechanical fault diagnosis [4-5]. After decades of development, fault diagnosis of rotating machinery is no longer a simple technology, but has now developed into an interdisciplinary subject, which involves detection technology, process control, artificial intelligence and computers and many other disciplines [6]. The fault diagnosis technology of mechanical system in this paper is based on PNN(Probabilistic neural network) and GA(genetic algorithm), which realizes the collection, processing and analysis of vibration signals of rotating machinery.

2. Research method

2.1. Vibration signal analysis of rotating machinery

Because of the complex structure, changeable operating conditions and long cycle, the rotating

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machinery equipment has a high probability of failure, and the characteristics of its fault signals are weak. It is difficult for conventional detection methods to obtain the characteristics of fault signals efficiently and accurately, which requires analysis based on its operating mechanism and the characteristics and types of faults. How to reduce the dimension of high-dimensional feature information is also one of the problems to be solved.

Because the signal features are related to the running state of key parts of mechanical equipment, nonlinear supervised learning classification methods, such as BPNN (Back Propagation Neural Network) and HMM(Hidden Markov model), can be used to classify the extracted features, so as to realize the identification of running state [7-8].

In the process of gear meshing, due to the fluctuation of load, speed and other factors, the amplitude and frequency will change to varying degrees, resulting in amplitude modulation, frequency modulation or amplitude modulation and frequency modulation, including:

$$X_c(t) = \sum_{m=0}^{M} A_m(1 + a_m(t))\cos(2\pi mft + \phi_m + b_m(t)) \tag{1}$$

Where $a_m(t)$ is an amplitude modulation signal and $b_m(t)$ is a frequency modulation signal. Different faults have different modulation methods, if it is amplitude change, it is amplitude modulation, if it is frequency or phase change, it is frequency modulation.

Static eccentricity of the motor means that the centerline of the rotor shaft and the centerline of the rotating shaft coincide, but they have a constant offset to the centerline of the stator. The uneven air gap between the rotor and the stator will not change with time, while dynamic eccentricity means that the centerline of the stator coincides with the centerline of the rotating shaft, but the length of the air gap will change dynamically with the rotation of the rotor. Therefore, the surface vibration signal will contain frequency components with static and dynamic eccentricity characteristics [9].

The distribution $\sigma(\theta,t)$ of radial force σ in time t and space angle θ is calculated as follows:

$$\sigma(\theta,t) = \frac{B^2(\theta,t)}{2\mu_0} \tag{2}$$

Where $B\ (\theta,t)$ represents the distribution of magnetic flux density B in time t and space θ.

As a key component of rotating machinery, the rotor has a complicated structure. In general, the common vibration forms of rotating machinery include free vibration, self-excited vibration, forced vibration and parametric vibration. Among them, free vibration generally appears in the start-up stage of rotating machinery, and it will gradually weaken when the rotating machinery runs to a stable state. In the running process of rotating machinery, rubbing between static and dynamic parts is a fault with high frequency [10]. When local rub-impact occurs, if it is not repaired in time, it will gradually evolve into full-circle rub-impact, causing the rotor to always contact with the stator parts when rotating, and then causing severe vibration that makes the rotating machinery unable to work normally.

Static and dynamic rubbing can usually be divided into three stages: no rubbing, initial rubbing stage, static and dynamic interaction stage and static and dynamic separation stage. The vibration characteristics of each stage are different. In practice, the rubbing between static and dynamic parts is a rather complicated problem. In order to facilitate the research, the actual rotor system of dynamic and static rubbing is simplified here. The schematic diagram of rubbing force is shown in Figure 1.

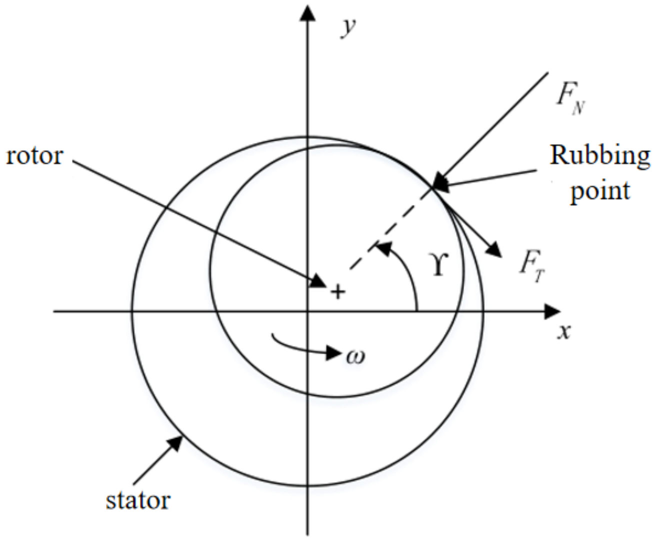

Figure 1 Schematic diagram of rubbing force

Because of the short time interval between static and dynamic rubbing, it is assumed that the deformation of the stator is elastic when static and dynamic rubbing occurs. Assuming that the average gap between the rotor and the stator at rest is δ, and F_N is the normal force of the rubbing force when static and dynamic rubbing occurs, then the normal force F_N and the tangential force F_T can be expressed as:

$$\begin{cases} F_N = (e-\delta)k_c, (e \geq \delta) \\ F_T = fF_N \end{cases} \tag{3}$$

In the above formula, f represents the friction coefficient between the rotor and the stator, and k_c represents the stiffness of the stator; e is the displacement of the rotor.

In the actual process of bearing fault diagnosis, people usually choose the best position to place the sensor, but the sensor can only be placed on the bearing seat, so the collected vibration signal contains many noise signals. How to separate the vibration signal caused by bearing fault from these noisy signals is the key to fault diagnosis, because only by finding the fault vibration signal can we accurately process and analyze the signal and find out the cause of equipment fault. It may even be because the sensors we install to collect signals will also produce vibrations, which are mixed together to form a complex signal source.

2.2. Fault diagnosis of mechanical system

Signal processing method is a common method of fault diagnosis, and it is also the premise and theoretical basis of diagnosis. If you can't correctly extract the fault features, you can't correctly diagnose the mechanical operation state. Therefore, in the diagnosis process based on vibration signal analysis, extract different fault features to eliminate other interference as much as possible and get the correct diagnosis results. There is no comparability between the dimensional indexes of different gears, and the dimensionless eigenvalues have nothing to do with the operation of the equipment itself, so in the diagnosis process, dimensionless indexes are used as the basis besides the dimensional indexes.

In this paper, GA is chosen as the optimization algorithm of PNN. Firstly, GA is used to search the global optimal values of PNN weights and thresholds, and then it is input into PNN to replace the randomly generated weights and thresholds. Finally, network training is carried out. Relevant theories show that GA can also improve the convergence speed of PNN and get the diagnosis results faster.

PNN overcomes the shortage that BPNN needs to calculate the reverse error, and will not fall into the local optimal extreme value. Because of its advantages of small calculation, stable results, strong fault tolerance and fast convergence, PNN has good classification ability for nonlinear problems, and has been widely used in intelligent traffic monitoring system, chart type identification, mechanical fault diagnosis and so on.

GA is a search algorithm that simulates natural selection and inheritance in the biological world, and obtains new characteristics to meet the needs according to the rules of survival of the fittest. It simulates the biological evolution in nature, establishes a continuous iterative process, and makes every individual in the evolutionary process run according to the principle of survival of the fittest like a biological group until we get the best result we need. GA is not only a computational model, but also an effective search method for solving optimization problems in many practical engineering applications.

PNN uses Parzen window function to calculate the conditional probability density function of the sample to be identified, and then completes the pattern classification and recognition by Bayes classification criterion. The function of the pattern layer is to match the nonlinear relationship between the transmitted sample vectors and the pattern categories. The number of neurons in the pattern layer is the same as the total number of training samples, and the output expression of the neurons is:

$$f(X,W_i)=\exp\frac{-(-W_i)^T(X-W_i)}{2^2} \tag{4}$$

Where, X represents the samples transmitted to the mode layer, σ represents the smoothing factor, and W_i represents the weights from the input layer to the mode layer.

The evaluation function is a key step in GA operation. We also solved the evaluation function when identifying the initial characteristic parameters, and calculated the fitness of the characteristic parameters according to the following method.

Assuming that two states, state 1 and state 2, are identified by a certain characteristic parameter x, the recognition rate P_0 can be calculated by the following formula:

$$P_0=\int R_i^{f_i(x)dx(i=1,2)} \tag{5}$$

$f_i(x)$ is that probability density function of x measure in the state i.

Because GA is the repeated operation of the population, it is necessary to establish an initial iterative population, and the size of the population should be determined according to the actual problems. When the optimization problem is small, it may be about 10 to 20, and when it is large, it may be about 50 to 100. We can get the individuals in the initial population by random method, and the genetic operators of two mating can choose λ_i according to the following formula:

$$\lambda_i=\frac{q_i}{q_{\max}},q_j=\left[\frac{DI_j}{\sum_{j=1}^{c}\frac{DI_j}{G}}\right] \tag{6}$$

G is the total number of genetic operators, and DI_j is the fitness of the i th genetic operator.

The specific process of establishing GA_PNN model is shown in Figure 2:

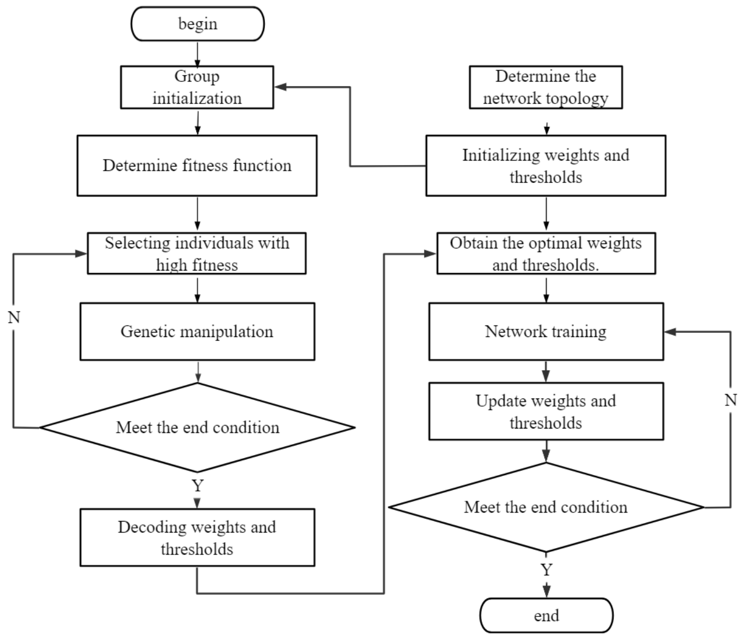

Figure 2 GA_PNN process

3. Simulation experiment and analysis

The experimental platform used in this experiment is IntelR Core™2 Duo CPU E7400 2.8GHz, RAM 2.00GB, and the operating system is Win 10. The vibration data of rolling bearing fault comes from the electrical engineering laboratory of a university, the actual shaft speed is 1572r/min, and the sampling frequency is 12000Hz. 1064 data points are selected as a data sample for each fault, and 100 samples are randomly selected for each fault type without overlapping. Then randomly select 20 groups as training samples to extract fault feature vectors to train PNN, and 80 groups as test samples to extract fault feature vectors for fault pattern recognition.

The GA of the training sample and the test sample are respectively constructed as feature vectors, and the input of the classifier is set as the GA feature vector of the sample, and the output is the corresponding seven bearing states. Firstly, PNN is trained with training samples, and then the GA eigenvector of the test samples is used as input, and the bearing state is identified by PNN. The output result is shown in Figure 3.

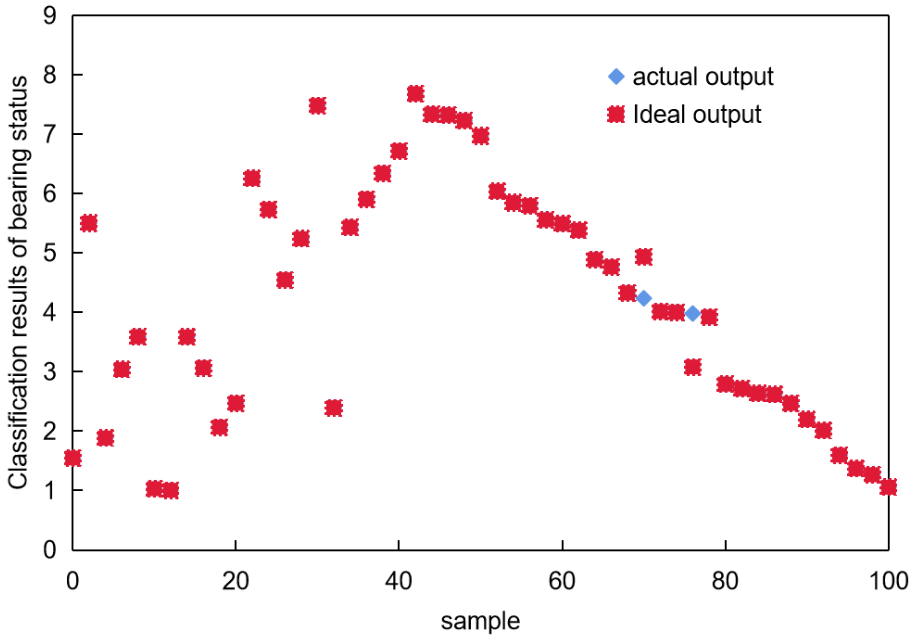

Figure 3 Output result of PNN classifier

Judging from the classification results of bearing fault states of test samples, the correct recognition rate is 99.06%, and the recognition rate is high, which can meet the needs of engineering application.

Among them, there are two sample identification errors, one is to identify the minor fault of the rolling element as the minor fault of the inner ring, and the other is to identify the minor fault of the rolling element as the serious fault of the rolling element. This is because the sensor is closest to the outer ring in the measurement process, and the vibration signal measured by the slight or serious fault of the outer ring can be accurately measured, analyzed and identified. However, the fault shock signals of inner ring and rolling element are complex and far away from the sensor, and their slight fault state is easily confused with the slight fault signals of bearing inner ring, which leads to the identification error.

In order to measure the ability of the BPNN model designed in this paper in bearing fault diagnosis, the model GA_PNN designed in this paper is compared with the BPNN model, and both models are trained with data under 3hp load. The setting of relevant training parameters is the same as above, and the change of loss function under this training set is obtained. The comparison results are shown in Figure 4.

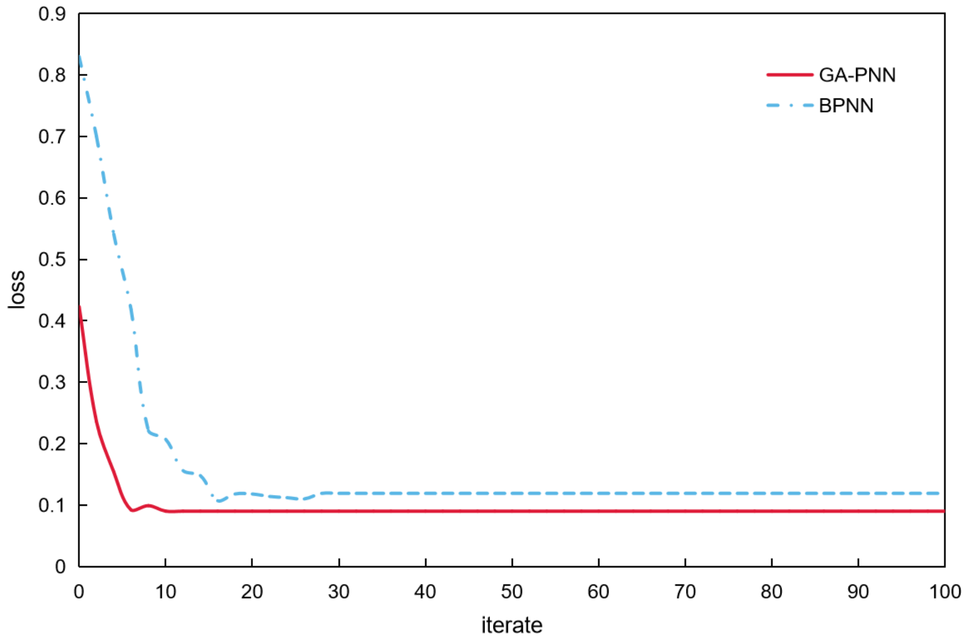

Figure 4 Comparison of loss function values between two models

By comparison, it is found that the GA_PNN model proposed in this paper is superior to BPNN in reducing the loss function value, which proves the feasibility of GA_PNN model. The feasibility of extracting fault characteristics of bearing vibration signals with different scales by the model is verified.

4. Conclusions

As an important technical support of preventive maintenance, mechanical system fault diagnosis of mechanical equipment is of great significance to reasonably prolong the service life of mechanical equipment, reduce the periodic maintenance cost and ensure the safety of equipment operation. The fault diagnosis technology of mechanical system in this paper is based on PNN and GA, which realizes the collection, processing and analysis of vibration signals of rotating machinery. The simulation results show that the correct classification and identification rate of bearing fault state of test samples is 99.06%, and the recognition rate is high, which can meet the needs of engineering application. The GA_PNN model proposed in this paper is superior to BPNN in reducing the loss function value, which proves the feasibility of GA_PNN model. The feasibility of extracting fault characteristics of bearing vibration signals with different scales by the model is verified.

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