Research on Turbine Rotor Fault Diagnosis Based on CPSO-BBO Optimization SVM

Zhibiao Shi and Wenzhuo Dong*
School of Mechanical Engineering, Northeast Electric Power University, Jilin, China, 132012
*2274971760@qq.com

Abstract: In order to improve the recognition accuracy and efficiency of the turbine rotor fault diagnosis, a fault diagnosis method based on CPSO-BBO (chaos particle swarm optimization biogeography based optimization) algorithm was proposed to optimize SVM (support vector machine). Firstly, four common faults states of turbine rotors were simulated by ZT-3 rotor test-bench to obtain fault data. Secondly, CEEMD (complementary ensemble empirical mode decomposition) is used to decompose the rotor vibration signal, and the more effective intrinsic mode function (IMF) is screened by combining the variance contribution rate, and the corresponding PE (permutation entropy) is calculated as the fault characteristic value. After that, chaos theory and PSO (particle swarm optimization) algorithm are combined into the theory of BBO (biogeography based optimization) to obtain CPSO-BBO algorithm, which is used to optimize SVM to obtain the optimal parameters of the diagnostic model. Finally, the fault identification is studied by using the acquired fault data.

1. Introduction
Since the turbine rotor running environment is complex and the fault features are easy to be submerged in the noise, the fault diagnosis results are affected and the fault occurrence is difficult to be predicted. Therefore, it is very important to study the fault diagnosis of turbine rotor accurately and quickly [1].

SVM by using structural risk minimization criterion instead of empirical risk minimization criterion, has the ideal generalization ability, can solve high dimensional and nonlinear problems [2]. In the process of SVM application, the SVM parameters optimization is important, which will directly affect the learning and generalization ability [3]. At present, some commonly used algorithms are deficient to varying degrees. The ant colony algorithm has slow convergence speed, easy to fall into local optimal and easy to appear stagnation phenomenon. The grid search method needs to be set according to human experience, while the simulated annealing algorithm is easy to fall into local optimal [4]. PSO algorithm has outstanding advantages such as fast convergence and adaptability to dynamic environment, and can effectively solve global optimization problems [5]. The BBO algorithm has strong adaptive ability, high search accuracy, few parameters and easy implementation.

In order to avoid the defects of single algorithm in search ability and robustness, and improve the fault recognition rate and efficiency of SVM, CPSO-BBO algorithm is proposed by combining chaos theory with PSO algorithm and BBO algorithm. CPSO-BBO algorithm is used to optimize the parameters of SVM, penalty factor c and kernel function σ to obtain the optimal diagnosis model, meanwhile, compared with the SVM model optimized by BBO algorithm.
2. Basic principle

2.1 CPSO algorithm principle

Firstly, particle swarm is used to initialize a group of particles, \( X = \{x_1, x_2, \ldots, x_n\} \), each particle has a random position, and the position in the \( d \) dimensional space, which is \( x_i = (x_{i1}, x_{i2}, \ldots, x_{id}) \), and the velocity is \( v_i = (v_{i1}, v_{i2}, \ldots, v_{id}) \). Each particle is evaluated by a uniform fitness function \( f(x_i) \). The optimal position experienced in the successive evolution is called the individual extreme value \( P_{\text{best}_i} \), and the optimal position experienced by all particles in the population is called the global extreme value \( g_{\text{best}} \). In the process of each iterative evolution, the particle adjusts its speed and position according to the individual optimal position \( P_{\text{best}_j} \) and the global optimal position \( g_{\text{best}} \) [6,7],
\[
\begin{align*}
\dot{v}_i(t+1) &= \omega \dot{v}_i(t) + c_1 r_1 (P_{\text{best}_i} - x_i(t)) + c_2 r_2 (g_{\text{best}} - x_i(t)) \\
\dot{x}_i(t+1) &= x_i(t) + v_i(t+1)
\end{align*}
\]

where \( \omega \) is the weight of inertia, \( t \) is the number of iterations, \( r_1 \) and \( r_2 \) are random numbers between \([0,1]\), and \( c_1 \) and \( c_2 \) are the learning factors.

In order to avoid falling into local optimum in particle search, logistic mapping was introduced into the population to form chaotic PSO. The global optimal value in the population \( g_{\text{best}} \) is mapped to the chaotic variable of \([0,1]\) according to the following formula [8,9],
\[
c^{(t)}_x = \frac{g_{\text{best}}(t) - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}
\]  
where \( x_{\text{min}} \) and \( x_{\text{max}} \) represent upper and lower bounds of position vectors respectively. Substitute the obtained chaotic variables \( c^{(t)}_x \) into the logistic mapping formula.
\[
c^{(t+1)}_x = 4c^{(t)}_x(1-c^{(t)}_x)
\]  

M iterations were carried out by logistic mapping formula and the new optimal particle sequence was obtained through the mapping of formula (3).
\[
g_{\text{best}}(t+1) = x_{\text{min}} + c^{(t+1)}_x(x_{\text{max}} - x_{\text{min}})
\]  

That is the new optimal population \( X_{\text{best}} \), which is merged and updated with the original population \( X \) to get the new population \( X' \).

2.2 Principle of biogeography algorithm

2.2.1 Migration operation. In this paper, the cosine mobility model closest to the natural law is used to simulate the migration process of species in the biogeographic environment, as shown in figure 1.

![Figure 1 Cosine migration rate model](image)

In the figure, \( I \) is the maximum migration rate; \( E \) is the maximum removal rate; \( S_{\text{max}} \) is the maximum number of species in the habitat; \( \lambda \) is the rate of immigration; \( \mu \) is the removal rate; and \( S_0 \) is the equilibrium point. When \( S_{\text{max}} = n \), the number of species in the habitat is \( S = k \), the migration rate
\[
\lambda_k = \frac{I}{2} \left[ \cos \left( \frac{k\pi}{n} \right) + 1 \right]
\]  
and migration rate
\[
\mu_k = \frac{E}{2} \left[ \cos \left( \frac{k\pi}{n} \right) + 1 \right].
\]

2
BBO with suitable habitat index (HSI) is used to evaluate habitat suitability function, where the characteristic factors related to HSI are expressed by the suitable index vector (SIV), so the optimal solution problem is transformed into the fitness optimization problem.

When carrying out the migration operation, the HSI value of the habitat should be calculated first and arranged in order from large to small. \( \lambda \) is then determined by the rate of immigration to the habitat, and \( \mu \) is determined according to the removal rate to determine how to exchange with the adjacent habitat. A SIV was randomly selected from the adjacent habitat to replace one SIV in the habitat. Finally, the HSI value of each habitat was calculated in order, where the highest HSI point corresponds to the optimal solution.

2.2.2 Mutation operation. BBO algorithm improves species diversity through mutation operation. The rate of habitat variation is inversely proportional to the number of species,

\[
m_s = m_{\text{max}} \left[ 1 - \frac{P_s}{P_{\text{max}}} \right]
\]

where \( m_{\text{max}} \) is the maximum variation rate; \( P_s \) is the probability that the number of species in the habitat corresponds to \( S_1 \); \( P_{\text{max}} \) is the maximum value of \( P_s \). The relationship of \( P_s \) to inflow rate \( \lambda \) or outflow rate \( \mu \) is as follows.

\[
P_s = \begin{cases} 
- (\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_sP_s & S = 0 \\
- (\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_sP_s & 1 \leq S \leq S_{\text{max}} - 1 \\
- (\lambda_s + \mu_s)P_s + \lambda_{s-1}P_{s-1} + \mu_sP_s & S = S_{\text{max}} 
\end{cases}
\]

In BBO, if the variation probability of a certain habitat \( m_s \) is non-zero, a SIV is generated randomly according to the mutation operation to replace the existing SIV in the habitat, so as to increase the species diversity, improve the solution set of the habitat and obtain the optimal solution.

2.3 Principle of CPSO-BBO algorithm

CPSO-BBO can effectively prevent all individuals of the population from falling into local optimum by means of molecular grouping. That is, CPSO population is divided into several sub-populations at the beginning of each iteration, and CPSO optimization is conducted for each sub-population. A certain number of optimal individuals are generated in each sub-population to form “elite population”. Then, BBO is used to optimize the “elite population”. At the end of the operation, the “elite population” is put back into their subpopulations to continue the next iteration cycle. This algorithm avoids the defects of single algorithm in search ability and robustness and effectively coordinates the search ability between the two algorithms.

2.4 Typical function tests

To verify the optimization performance of this algorithm, use Schaffer function and Sphere function to calculate and compare the minimization problem of BBO algorithm and CPSO-BBO algorithm. The iterative optimization process of the two test functions is shown in figure 2.

CPSO-BBO algorithm has a fast convergence rate, fewer iterations, is not easy to get into local optimization and can quickly enter into the optimal solution interval.
2.5 SVM parameter optimization of CPSO-BBO algorithm

In order to improve classification accuracy and recognition efficiency of SVM, CPSO-BBO algorithm is used to optimize RBF kernel function parameter $\sigma$ and support vector machine parameter $c$. Moreover, CPSO-BBO algorithm is used to optimize SVM classification accuracy of training set as fitness function,

$$\psi = \frac{1}{m} \sum_{n=1}^{m} \left( \frac{x_m}{x_n} \times 100\% \right)$$

(7)

where $x_m$ is the correct number of categories in the $m^{th}$ test set; and $x_n$ is the number of samples in the step test set.

The steps for CPSO-BBO to optimize SVM model parameters are as follows.

Step1: Determine the suitability function, initialize the population and set initial parameters, including chaos search times $T$, maximum migration rate $I_{max}$, maximum migration rate $E_{max}$, maximum number of species that can be accommodated in the habitat $S_{max}$, and iteration times, etc.

Step2: Initialize a group of habitats with chaotic mapping. Set the initial fitness vector to be $X_i$ and $X_j$ include the $\sigma$ and $c$ parameters of SVM.

Step3: Divide the population into $m$ sub-populations.

Step4: CPSO algorithm optimizes the divided population and calculates the fitness value to complete the mapping of each species. Take the one with high fitness value as the local optimal solution.

Step5: Use BBO algorithm to conduct global search for the local optimal solution obtained.

Step6: Get the global optimal solution.

Step7: Judge whether the termination condition has been reached. If so, output optimization results; Otherwise, continue repeating Step3–Step7 until the termination condition is satisfied.

The optimal penalty factor $c$ and kernel parameter $\sigma$ are obtained through the algorithm steps above, and then the diagnosis model of CPSO-BBO optimization SVM is constructed.

3. Experimental study on rotor fault diagnosis

3.1 Failure data acquisition

ZT-3 rotor test bed was used to simulate four different states of turbine rotor (normal state, action touch ground, imbalance, mismatched). Parameters of the test were set as follows: rotor speed was 3 000 r/min and sampling frequency was 5000 Hz, and the software platform is matlab 2014a.

3.2 Singular value denoising

In order to avoid the appearance of singular sample data, first of all, the vibration signal collected is normalized, so that the input sample set conforms to the standard normal distribution. Then, the phase space reconstruction of its time series is carried out by using c-c algorithm [10] to determine the optimal embedding dimension of phase space reconstruction $m$ and best delay time $\tau$. Finally, the singular value denoising of reconstructed phase space is carried out [11].

To evaluate the effect of noise reduction, vibration signal to select amount of improving SNR, $\Delta$SNR (signal noise thewire, SNR) [12]. To test its noise reduction effect. The improvement of SNR is shown in table 1, and the noise reduction effect is obvious.

Table 1. Improvement of SNR before and after noise reduction

| Type            | Normal | Action touch ground | Mismatched | Unbalanced |
|-----------------|--------|---------------------|------------|------------|
| SNR(dB)         | 19.1325| 21.9834             | 16.1566    | 20.7293    |

3.3 Feature extraction

CEEMD can not only solve the modal aliasing problem of EMD decomposition process, but also effectively eliminate the influence of residual white noise. IMF components obtained after CEEMD
decomposition of mismatched states are shown in figure 3.

![Image](image_url)

**Figure 3** Misaligned state noise CEEMD decomposition results

It can be seen that CEEMD can obtain a clear waveform. According to the principle of variance contribution rate, fault feature sensitive components are selected to calculate their entropy values, and fault feature vectors are constructed as input components of SVM classifier.

To eliminate the influence of endpoint effect and false component, the first three IMF components were selected and their permutation entropy was calculated. To test the effect of arrangement entropy as the characteristic vector of four states, the boxplot of arrangement entropy was used to verify the degree of differentiation. This paper selects IMF1 for example, the boxplot of entropy values of four states is shown in figure 4.

![Image](image_url)

**Figure 4** Permutation entropy boxplot of 4 states rotor

It can be seen that the selection of entropy of arrangement as the eigenvalue to construct the feature vector has an obvious distinction effect, so it can be used as the feature vector of pattern recognition.

3.4 Fault identification results and analysis

In order to verify the feasibility of CPSO-BBO algorithm to optimize SVM diagnosis model, the BBO algorithm were compared. Four simulated states were used as experimental data on ZT-3 test bench.

Figure 5 shows the classification diagram.

According to figure 5, CPSO-BBO optimized SVM diagnostic model after training, among the 60 test samples, there are 2 groups of sample identification errors. After testing 60 groups of test samples in the BBO-SVM diagnostic model, 6 groups of sample identification errors were found.
4. Conclusion

(1) Using chaotic particle swarm optimization biogeography algorithm to improve the convergence speed and optimization accuracy of the algorithm.

(2) CPSO-BBO algorithm can quickly and effectively determine the penalty factor and kernel parameters of SVM, thus improving the learning ability and generalization ability of SVM.

(3) Under the same test samples, the recognition accuracy of CPSO-BBO optimized SVM diagnostic model is 96.67%, 6.7% higher than that of the BBO-SVM diagnostic model, and the running time is 21.837s, 12.5 s shorter than that of BBO. The advantages of CPSO-BBO optimization SVM algorithm in turbine rotor fault diagnosis are fully verified.

Reference

[1] He Qing, Xie Fangfang, Li Hong, et al. Vibration feature extraction of steam turbine units based on manifold learning method [J]. Vibration, test and diagnosis, 2014, 34 (4) : 705-708.

[2] Jiang Jiliang, Liu Wenyi, Hou Yujie, et al. Research on bearing fault diagnosis method based on inner product extension LMD and SVM [J]. Vibration and impact, 2016, 35(6): 104-108.

[3] Zhao Chongchong, Liao Mingfu, Yu Xiao. Application of Support Vector Machine to Fault Diagnosis of Rotating Machinery [J]. Journal of Vibration, Measurement & Diagnosis, 2006, 26(01): 53-57.

[4] Feng Zonghui, Peng Dan, Yuan Rongli. Engine fault diagnosis based on PSO-SVM [J]. Computer measurement and control, 2014, 22(2): 355-360.

[5] Xiong Qing, Zhang Weihua. Fault diagnosis method of rolling bearing based on mf-dfa and PSO optimized LSSVM [J]. Vibration and impact, 2015, 34(11): 188-193.

[6] Sun Shuguang, Yu han, Du Taihang, et al. Fault vibration and acoustic diagnosis method of universal circuit breaker based on multi-feature fusion and improvement of QPSO-SVM [J]. Journal of electrical technology, 2017, 32 (19) : 107-117.

[7] ZHAO F Q, LI G Q, YANG C, et al. A human computer cooperative particle swarm optimization based immune algorithm for layout design[J]. Neuro computing, 2014, (132) : 68-78.

[8] MOJTAB S, BAMAKAN H, WANG H D, et al. An effective intrusion detection framework based on MCLP /SVM optimized by time-varying chaos particle swarm optimization [J]. Neurocomputing, 2016 (199) :

[9] QIN Q D, CHENG S, CHU X H, et al. The Solving nonconvex/non - smooth economic load dispatch problems via an enhanced particle swarm optimization [J]. Applied Soft Computing, 2017 (59) : 229-242.

[10] Xu Zili, Wang Yiyang, Zhou Jiliu. C-C average method for estimating the embedding delay time and delay time window of nonlinear time series [J]. Journal of SiChuan university: engineering science, 2007, 39(1): 151-155.

[11] Walton J, Fairley n. Noise Reduction in X - ray Photoelectron Spectromicroscopy by A Singular Value Decomposition Sorting Procedure [J]. Journal of Electron Spectroscopy and Related Phenomena, 2005.

[12] Hou Pingkui, Gong Yunfan, Yang Yuying, et al. Nonlinear noise reduction for underwater target radiated noise time series [J]. Acta acustica sinica, 2001, 26(3): 207-211.