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Research on Fault Diagnosis of Check Valve Based on CEEMD Compound Screening and Improved SecPSO

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Abstract. In order to improve the fault diagnosis accuracy of check valve, a new method combining the complete ensemble empirical mode decomposition (CEEMD), compound screening method and improved second-order particle swarm optimization (SecPSO) is proposed. In order to select useful IMF from the intrinsic modal function (IMF) obtained by CEEMD, this paper uses the compound screening method to remove false components. In order to improve the search ability of the optimization algorithm, this paper uses the asynchronous learning factor to improve the SecPSO. Firstly, the CEEMD is used to decompose the vibration signal. Secondly, the compound screening method is used to select useful IMF and the energy features and Lempel_Ziv complexity features of these IMF are extracted. Then 10 time-domain features and 5 frequency-domain features of the IMF reconstruction signal are extracted, and all the features are combined into a mixed domain feature set. Finally, the improved SecPSO is used to optimize the parameters of least squares support vector machine (LSSVM). The proposed method is compared with various fault diagnosis methods, and the method can obtain high accuracy. The results show that the method not only removes the false components, but also improves the search ability and fault diagnosis accuracy.

Keywords: check valve, complete ensemble empirical mode decomposition, fault diagnosis, mixed-domain features, second order particle swarm optimization

1 Introduction

Slurry pipeline has the advantages of high efficiency, energy saving and environmental protection, and it plays an important role in mineral transportation [1]. High pressure diaphragm pump is the power equipment of slurry pipeline transportation, and its health condition affects the slurry transportation efficiency. The check valve is one of the most important parts of high pressure diaphragm pump, it keeps reciprocating movements [2]. In most cases, the damage of the high pressure diaphragm pump is caused by the failure of the check valve. If the failures of the check valve cannot be diagnosed in time, the diaphragm pump will be damaged, which will cause a huge economic losses. Therefore, the research on fault diagnosis of check valve is of great economic significance.

The vibration signal of check valve is non-linear non-stationary signal, and the useful signal is easily submerged by noise [3]. Therefore, the vibration signal pre-processing of the check valve is particularly important. In recent years, the time-frequency analysis method has developed rapidly, and the empirical mode decomposition (EMD) method can analyze the local characteristics of the signal adaptively. Currently, EMD there still has a lot of problems such as sifting criterion, endpoint effect, mode mixing

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and so on [4]. Chen et al. [5] use independent component analysis (ICA) to restrain mode mixing, but the uncertainty of component amplitude greatly affects the decomposition effect. Amarnath and Krishna [6] uses the ensemble empirical mode decomposition (EEMD) with white noise statistic characteristic to process signals, although the method can restrain the modal mixing, but it can't completely eliminate the modal mixing effect. Wang et al. [7] combine the CEEMD with the singular value (SVD) method to diagnose the faults of the bearing and achieve good results, the results show that CEEMD can effectively suppress the endpoint effect and the mode mixing, and the IMF obtained by this method contains more fault information. In literature [8], the author combines the CEEMD with the wavelet packet transform (WPT), which not only effectively suppresses modal mixing but also eliminates the false frequency components generated by wavelet packet transform, and the results show that the CEEMD method has good decomposition effect on the nonlinear signals. The vibration signal is easily disturbed by the noise, which is also the reason why the CEEMD method produces the false components. Therefore, many scholars use the IMF screening method to remove false components. In literature [9], the author uses the CEEMD to decompose the vibration signal, and then uses the correlation coefficient method to select the useful IMF, finally obtains the more accurate diagnosis result through the hidden Markov model. The results show that cross-correlation coefficient can effectively characterize the correlation between the IMF and the original signal. Xu et al. [10] use WPT to decompose the signal, then extract the energy features and input them into the SVM to diagnose the faults of the fan. The results show that the energy can characterize the mechanical vibration strength. In order to obtain the IMF of the useful signal, the cross correlation analysis method and the energy analysis method are combined in this paper, which is called compound screening method.

The compound screening method can obtain the IMF of useful signal, and the selection of feature parameters is particularly important when extracting fault features from these IMF. The performance of time domain feature parameters is not stable, and if only one parameter is used to evaluate the mechanical health state, the important information will be ignored. Frequency domain feature parameters can be used to analyze some related frequency components, but it is not suitable for non-stationary signals with time-varying characteristics [11]. The time-frequency domain features can effectively characterize the change of non-stationary signal over time, but the Time-frequency domain methods are constrained by the Heisenberg uncertainty principle, which leads to the poor effect of these methods on the analysis of mutation signal. In this paper, the time domain features, frequency domain features and time-frequency domain features of the useful IMF are extracted, and the improved SecPSO-LSSVM method is used to diagnose the check valve faults.

In the LSSVM model, the regularization parameter controls the penalty degree of the wrong samples, which has a great influence on the diagnostic efficiency. The kernel parameter determines the algorithm accuracy and affects the generalization ability of the diagnosis model. Therefore, the parameter optimization of the LSSVM model is particularly important [12]. At present, the particle swarm optimization (PSO) is often used to optimize the parameters of the LSSVM. Zheng et al. [13] use PSO to optimize the parameters of LSSVM model and improve the generalization ability of the algorithm by using the principle of cross verification, and diagnose the faults of the transformer effectively. Although many scholars have improved the PSO, these improved methods have defects in the local optimization accuracy and the global optimization breadth. The reason is that these improved methods only consider the current position of the particle when updating the velocity and position of the particle, without considering the change of particle position. The second-order particle swarm optimization (SecPSO) [14] can solve these problems effectively, and the method can use the particle position change information to update the particle velocity. In this paper, the improved SecPSO is used to optimize the parameters of the LSSVM model. The traditional SecPSO will lose the optimal solution because the particle velocity is too fast, and the improved SecPSO can not only solve this problem, but also ensure that the algorithm has good self-learning ability in the early iteration and has good group learning ability in the late iteration.

In the process of signal decomposition, the CEMMD often produces false components; In the process of parameter optimization of the LSSVM model, the local search effect and global search effect of the SecPSO are not good. So this paper mainly contains two key research problems. First, how to select useful IMF from the IMF obtained by the CEEMD method and remove noise and false components. Second, avoid the premature convergence of the traditional SecPSO and improve the SecPSO's search capability and fault diagnosis accuracy. Therefore, a fault diagnosis method based on CEEMD compound screening and improved SecPSO is proposed in this paper. Firstly, the vibration signal is decomposed into several IMF by using the CEEMD, the IMF of the useful signal are selected according to the compound screening method and the noise and false components are removed. Then, the energy features and Lempel_ziv complexity features of the useful IMF are extracted, and the useful IMF are used to reconstruct the signals. Secondly, the 10 time domain features and 5 frequency domain features are extracted from the reconstructed signal, and the time domain features, frequency domain features and time-frequency domain features are merged into a mixed domain feature set. Finally, the SecPSO is improved by using the asynchronous learning factor and the compression factor, and the parameters of the LSSVM model are optimized by the improved SecPSO. The LSSVM model after parameter optimization is used to diagnose the faults of the check valve, and the method is compared with BP neural network (BPNN), support vector machine (SVM) and PSO-LSSVM methods respectively. The fault diagnosis accuracy of the proposed method is 92.808%, which is far higher than that of other methods, the results show that the fault diagnosis method is very effective. On the other hand, we conducted two sets of comparative experiments. First, the proposed method is compared with the method that does not use the compound screening method. Second, the proposed method is compared with the traditional SecPSO method. The results show that the proposed method has outstanding advantages in noise suppression, parameter optimization and fault diagnosis. In summary, this paper proposes a fault diagnosis method based on CEEMD compound screening and improved SecPSO, which has two major scientific contributions. First, a compound screening method is proposed and used to select useful IMF, which effectively removed the noise and false components. Second, this paper improves the SecPSO, which not only avoids the premature convergence of the algorithm, but also improves the search capability and fault diagnosis accuracy of the algorithm.

2 The CEEMD Algorithm and Compound Screening Method

2.1 The CEEMD Algorithm

The CEEMD algorithm is often used to analyze the vibration signal, which has a prominent advantage in signal processing. If a set of vibration signal of mechanical equipment is $X_t = [x_1, x_2, \ldots, x_n]$, the decomposition process of CEEMD is introduced as follows [15]:

(1) The amplitude m and the aggregation number I are initialized;

(2) Adding white noise signals (denoted with $\pm n_i(t)$, $i = 1, 2, \cdots, n$) into the original signal $x(t)$;

$$\begin{cases} P_i(t) = x(t) + n_i(t) \\ N_i(t) = x(t) - n_i(t). \end{cases} \tag{1}$$

(3) The signals $P_i(t)$ and signals $N_i(t)$ are decomposed by EMD, and a sequence of IMF is obtained;

$$\begin{cases} P_i(t) = \sum_{j=1}^{q} c_{j,i}^1(t) \\ N_i(t) = \sum_{j=1}^{q} c_{j,i}^2(t). \end{cases} \tag{2}$$

In the formula, $c_{j,i}^1(t)$ and $c_{j,i}^2(t)$ are the jth IMF obtained by the i times decompositions, and q is the number of IMF.

(4) If the current number of decomposition is less than the maximum number of decomposition ($i < I$), then the number of decomposition increased by 1 ($i = i + 1$), after that repeat the step (2) and step (3) until all the IMF are decomposed;

(5) Calculating the average value of the IMF obtained by I-th decomposition.

$$c_j(t) = \frac{1}{2I} \sum_{i=1}^{I} (c_{j,i}^1 + c_{j,i}^2). \tag{3}$$

In the CEEMD, the author adds several pairs of Gaussian white noises into the original signal, which not only can eliminate the intermittency of the signal at various time scales, but also can avoid the decomposition error.

2.2 Compound Screening Method

The CEEMD method decomposes the vibration signal of the check valve into the IMF of useful signals, the IMF of mixed signals consisting of useful signals and noise signals, and the IMF of noise signals. The purpose of the IMF screening is to remove most of the IMF that contains noise. In literature [16], the IMFs obtained by CEEMD are screened by cross-correlation coefficient method, which effectively removed the vibration noise and achieved good fault detection results. In literature [17], the author uses the energy threshold method to analyze the IMF, and the results show that the energy levels of different types of IMF vary widely. Therefore, we first calculate the energy coefficient of each IMF and set an energy threshold. If the energy coefficient of an IMF is greater than the energy threshold, the IMF is judged as an useful IMF, otherwise it is judged as a noise component and removed. In this paper, the energy threshold method is combined with cross-correlation method to screen the useful IMF. The energy and its normalized formula are as follows:

$$M_i = \sum_{i=1}^{I} c_j(t)^2. \tag{4}$$

$$e_i = M_i / \max(M). \tag{5}$$

The CEEMD method often has problems such as over decomposition, difference error, which can lead to the generation of false IMF components. In general, the correlation between the original signal and the false IMF component is very weak. Therefore, in this paper, we first calculate the cross correlation coefficient between the original signal and each IMF, and set a cross-correlation threshold. If the correlation coefficient of an IMF is greater than the cross correlation threshold, the IMF is judged as an useful IMF, otherwise it is judged as a false component and removed. The cross-correlation coefficient ρ_{xy} is used to describe the linear correlation between signal $x(t)$ and signal $y(t)$ in statistics:

$$\rho_{xy} = \frac{E[(x-m_x)(y-m_y)]}{\{E[(x-m_x)^2]E[(y-m_y)^2]\}^{1/2}}. \tag{6}$$

In the formula, E represents the mathematical expectation, m_x represents the mean of the original signal x, and m_y represents the mean of components $c_j(t)$ obtained by decomposition. The value of the cross correlation coefficient is between negative one and positive one ($\rho_{xy} \in [-1,1]$). If the signal x is completely linearly correlation with the signal y, their cross correlation coefficient is equal to 1 ($|\rho_{xy}| = 1$). If the correlation between the signal x and the signal y is weak, their cross correlation coefficient is less than 1 ($|\rho_{xy}| < 1$). If the signal x is not associated with the signal y, their cross correlation coefficient is equal to 0 ($|\rho_{xy}| = 0$).

In this paper, the IMFs are arranged in descending order of energy coefficient e_i and cross-correlation coefficient ρ_{xy}. Then, the cross correlation threshold is set to 0.15 ($\rho_\lambda = 0.15$) and the energy threshold is 0.1 ($e_\lambda = 0.1$). Finally, the IMFs of useful signals are obtained according to the compound screening method, and the time-frequency domain characteristics are extracted from the IMF of the useful signals.

3 Mixed-domain Feature Extraction

3.1 Energy Features and Lempel_Ziv Complexity Features

Aiming at the defects of time domain features and frequency domain features, the authors extract the energy features and Lempel_Ziv complexity features of signals, and combine these two features with time domain features and frequency domain features for fault diagnosis. The energy feature can characterize the mechanical vibration strength, and its calculation method is shown in formula (5). The

Lempel_Ziv complexity can not only characterize the complexity of the time series, but also reflect the dynamic characteristics of the mechanical equipment. In literature [18], the author extracts the Lempel_ziv complexity as the fault features and compares they complexity difference, and finally obtains a higher diagnostic accuracy. When the fault states of the check valve changes, the time-frequency characteristic of the IMF becomes complex, so the Lempel_Ziv complexity is used to characterize these complex features. The computational process of the Lempel_ziv complexity of the IMF sequence $X=(x_1,x_2,\cdots,x_N)$ is shown in Fig. 1.

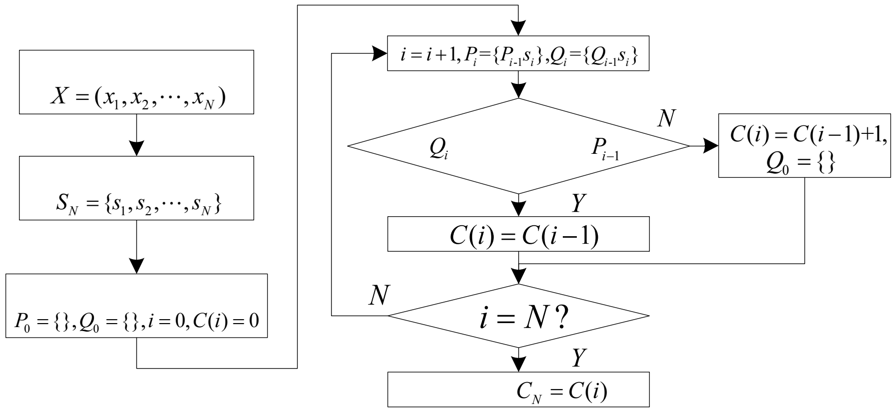

Fig. 1. Flow chart of Lempel-ziv complexity algorithm

(1) First, the average value of the IMF series is calculated, so that the data point greater than the average is equal to 1, the data point less than or equal to the average is 0, and a set of digital sequence $S_N=\{s_1,s_2,\cdots,s_N\}$ composed of 0 and 1 is obtained. The temporary character variables P_0 and Q_0 are then initialized to null characters ($P_0=\{\}$, $Q_0=\{\}$), and the complexity is initialized to 0 ($C(i)=0$) when i is equal to 0 ($i=0$);

(2) Then the values of the complexity are calculated through the N cycles. In the calculation, $P_i=\{P_{i-1}s_i\}$ represents a string formed by concatenating the string P_i and the string s_i , and $Q_i=\{Q_{i-1}s_i\}$ represents a string formed by concatenating the string Q_i and the string s_i . In each loop, it is necessary to determine whether the string Q_i is a substring of the string P_{i-1} . If the string Q_i is a substring of the string P_{i-1} , it indicates that the sequence does not have a new pattern and the complexity $C(i)$ does not change. Otherwise, it indicates that a new pattern has appeared and the complexity $C(i)$ is added by 1. Through N cycles, the algorithm can judge all the values in the sequence X and find the corresponding complexity.

Lempel and Ziv also proposed the normalized formula of Lempel-ziv complexity, which makes the Lempel-ziv complexity range between 0 and 1 ($C_N\in[0,1]$).

$$0\le C_{nN}=\frac{C_N(N)}{C_{UL,N}}\le 1. \tag{7}$$

$$C_{UL,N}=\lim_{x\to\infty}C_N(N)=\lim_{x\to\infty}\frac{N}{(1-\beta)\log_k N}\approx\frac{N}{\log_k N.} \tag{8}$$

In the formula, k represents the number of elements in the symbol sequence S_N , and the experience shows that the upper formula is valid when the signal length N is greater than 3600. The Lempel_Ziv complexity can characterize the complexity of time series, so it can be used for fault feature extraction.

3.2 Time Domain Features and Frequency Domain Features

Although the energy features and Lempel_Ziv complexity features can characterize the fault information of the mechanical equipment, many fault information is still included in the time domain features and frequency domain features. Therefore, we can obtain more state information of mechanical equipment by extracting time domain features and frequency domain features. Wang et al. [19] take the time domain features, frequency domain features and IMF energy features of bearing vibration signals as fault features, and then uses the improved logistic model to obtain the reliability of the rolling bearing and diagnoses the bearing fault accurately. Zhang et al. [20] take the time domain features, frequency domain features and wavelet energy entropy of the bearing signal as the fault features. First, principal component analysis (PCA) method is applied to reduce the dimension of the features, and then the hidden Markov model is used to diagnose the faults and obtain good results. The vibration signal of the check valve is a nonlinear and non-stationary signal, and the results of fault diagnosis based on single-domain fault features is often unreliable. The change of the running state of the check valve will cause the change of the time domain parameters and the frequency domain parameters of the vibration signal, so the information of the running state of the check valve can be obtained by extracting the time Domain features and frequency domain features. In this paper, the time domain features, frequency domain features, energy feature and Lempel_ziv complexity feature of vibration signal are extracted to diagnose the faults.

3.3 Mixed Domain Feature Extraction

Firstly, the energy features and Lempel_Ziv complexity features of the useful IMF are extracted, and if there are N useful IMF, then the $2N$ feature parameters can be obtained. Then, the IMFs of the useful signal are reconstructed, and the 10 time-domain features and 5 frequency domain features of the reconstructed signal are extracted. In this paper, the extracted fault feature parameters are shown in Table 1.

Table 1. Mixed domain feature set

Mixed domain	Count	Characteristic parameters
Time domain	10	Peak value, Mean value, Root-mean-square value, Variance, Standard deviation, Peak factor, Waveform factor, Pulse factor, Margin, Kurtosis
Frequency domain	5	Frequency Mean, Frequency center, Root Mean Square frequency, Frequency standard deviation, Frequency variance
Time-frequency domain	$2N$	Energy features, Lempel_Ziv complexity features

In summary, a total of 15+$2N$ features are extracted from time domain, frequency domain and time-frequency domain, which are sequentially arranged in the order of the time domain features, the frequency domain features and the time-frequency domain features to form a mixed domain feature matrix. This mixed domain feature matrix is used as sample set $X_i = \{X_i(k) \mid k = 1 \sim n\}$. In this sample set, i denotes the i-th sample ($i \in [1, m]$), m denotes the number of samples, n denotes the number of feature parameters ($n = 15 + 2N$), and N denotes the number of useful IMF. The matrix is normalized as follows, in which X_i represents the i-th data point, and $X_{\min}$ and $X_{\max}$ represent the minimum and maximum value of the data sequence respectively.

$$X = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}. \tag{9}$$

The construction of the mixed domain feature set is shown in Fig. 2.

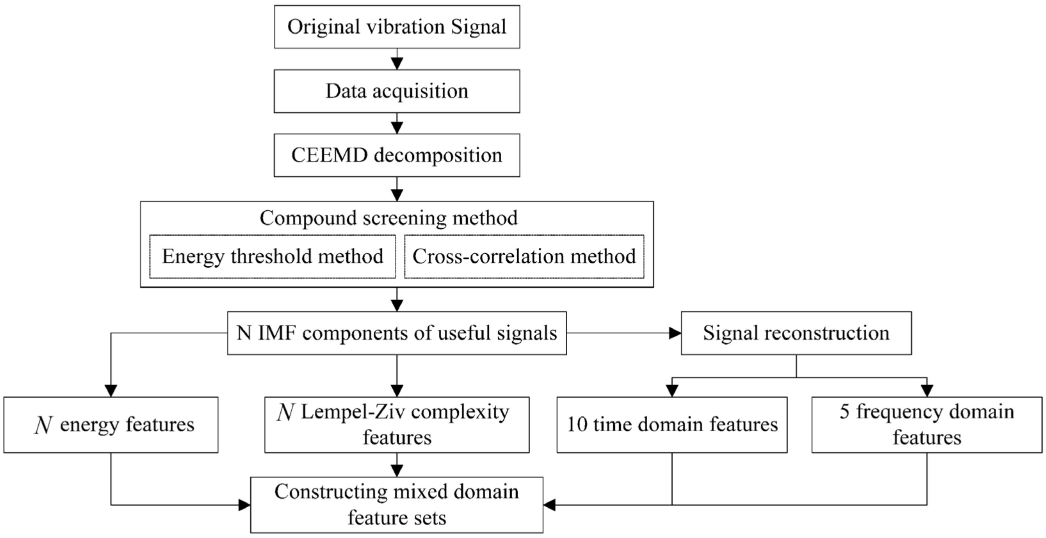

Fig. 2. Construction of the mixed domain feature set

4 Improved Second Order Particle Swarm Optimization Algorithm

4.1 LSSVM Model and Its Parameters Optimization

The mixed domain feature matrix obtained above is input to the LSSVM for fault diagnosis. According to the model in literature [21], the mixed-domain feature set and the category label are used as training set $\{(x_1,y_1),(x_2,y_2),\cdots,(x_l,y_l)\}$, in which the sample $x_i (i=1,2,\cdots l)$ corresponds to the class $y_i \in \{-1,1\}$, then the optimal separating hyperplane satisfies the following constraint conditions.

$$\begin{cases} \omega^T x_i + \beta \geq 1, y_i = 1 \\ \omega^T x_i + \beta \leq -1, y_i = -1. \end{cases} \tag{10}$$

In the formula, ω is the hyperplane normal vector and β is the offset. The decision function is as follows:

$$f(x_i) = \mathrm{sgn}(\omega^T x_i + \beta). \tag{11}$$

The solution of LSSVM model can be transformed to solve the following optimization functions:

$$\Phi_{\min}(\omega, e_i) = \frac{1}{2}\|\omega\|^2 + \frac{1}{2}C\sum_{i=1}^{l} e_i^2. \tag{12}$$

In the formula, C is the regularization parameter and e_i is the error variable. Considering the error rate allowed by the algorithm, the tradeoff between the maximum classification interval and the fewest misclassification samples should be considered. Therefore, the formula (12) must satisfy the following equality constraint:

$$y_i(\omega^T \varphi(x_i) + \beta) = 1 - e_i. \tag{13}$$

In the formula, $\varphi(x_i)$ represents the nonlinear mapping of sample x_i, which maps the sample set from the input space to the high-dimensional space. The classification decision function of LSSVM can be obtained by constructing and solving the Lagrange equation, as follows:

$$f(x) = \mathrm{sgn}(\sum_{i=1}^{l} \alpha_i y_i K(x, x_i) + \beta). \tag{14}$$

In the formula, the kernel function $K(x_i, x_j)$ includes polynomial function, radial basis function and sigmoid kernel function, etc. In this paper, we use radial basis function, the formula is as follows:

$$K(x, x_i)=\exp(-\|x - x_i\|^2 /(2\sigma^2)). \quad \textbf{(15)}$$

The radial basis kernel parameter σ controls the complexity of sample distribution in high-dimensional space, which affects the learning ability of the model. The regularization parameter C affects the generalization ability of the training model to be applied to the new samples. Therefore, optimization of parameters is particularly important.

The classical parameter optimization methods include trial-and-error method, grid search method and cross validation method, etc. Trial-and-error method has a large randomness, which is not only calculates time consuming but also has great computational error. Jiang et al. [22] diagnose blast furnace failure by combining the rough sets with LSSVM, and optimize the parameters through grid search method. However, the classification accuracy of most parameter groups is very low, and the classification accuracy is high only in the small interval. In literature [23], the improved LSSVM is used to diagnose the faults of aero engine sensors, and the parameters are evaluated by cross validation, but the results are greatly affected by the sample set. In this paper, an improved SecPSO method is used to optimize the parameters of LSSVM model, which can solve many problems in traditional optimization methods.

4.2 Improved Second Order Particle Swarm Optimization Algorithm

Particle swarm optimization (PSO) is an evolution computing method based on the predatory behavior of birds, which seeks the optimal solution through individual information transmission in the particle swarm. The position updating algorithm of PSO is as follows:

$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1 r_{1j}(t)(p_{ij}(t) - x_{ij}(t)) + c_2 r_{2j}(t)(p_{gj}(t) - x_{ij}(t)). \quad \textbf{(16)}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1). \quad \textbf{(17)}$$

In the formula, i represents the i th particle, $i \in [1, M]$, and j represents the j th dimension of the particles; t is the number of iterations; c_1 represents a learning factor for a single particle; c_2 represents a learning factor for a particle swarm, r_{1j} and r_{2j} are the random initial values; $p_{ij}(t)$ represents the optimal solution of the particle i in j-dimensional space ; $p_{gj}(t)$ represents the optimal solution of the particle swarm in j-dimensional space; $x_{ij}(t)$ and $v_{ij}(t)$ are the position and velocity of the i th particle at time t respectively.

In view of the fact that PSO is very easy to get into local optimum, the researchers are improving the learning factor, flight speed and weight coefficient. Be sure, there are some classical improved algorithms, such as synchronous and asynchronous learning factor method, compression factor method, decreasing weight method, adaptive weighting method, etc. on this basis, various better algorithms are proposed, Sha and Song [24] use different acceleration factors for different particle swarms in each iteration. Although the method can enlarge the search interval of particles effectively, the particle swarms are divided in the each iteration, which increases the complexity of the algorithm. Zhao et al. [25] utilize the dynamic linear adjustment, diversity variation, adaptive inertia weight and other methods to make PSO algorithm better. As a result, these scholars get a higher-precision model for classification. But the dynamic change of particle position is neglected when the updating of particle velocity, which leads to error in location updating. As a matter of fact, the SecPSO method can effectively avoid the problem. And besides, the improvement of SecPSO has not been reported.

Wang [26] put forward a new method of predicting the age of converter by combining SecPSO with SVM, which has a high predictive accuracy. The SecPSO takes full account of the dynamic changes of the particle position when updating the particle velocity. After several iterations, the optimal solution of the algorithm can be obtained. Assuming that the personal best P_{Best} is the optimal solution found by the particle, the global best g_{Best} is the optimal solution found by the particle swarm and the formula $x_{ij}(t) - x_{ij}(t-1)$ denotes the change of particle position. In each iteration, the particle updates its position according to the personal best P_{Best}, the global best g_{Best} and the change of particle position $x_{ij}(t)-x_{ij}(t-1)$. The rules are as follows:

$$v_{ij}(t+1)=v_{ij}(t)+c_1r_{1j}(t)(p_{ij}(t)-2x_{ij}(t)+x_{ij}(t-1))+c_2r_{2j}(t)(p_{gj}(t)-2x_{ij}(t)+x_{ij}(t-1)). \quad \textbf{(18)}$$

$$x_{ij}(t+1)=x_{ij}(t)+v_{ij}(t+1). \quad \textbf{(19)}$$

In the above rules, the learning factor $c1$ determines the ability of particles to use the individual experience information, and learning factor $c2$ determines the ability of the particle to use the group experience information, and both values affect the information exchange and experience sharing of the particle swarm. Therefore, this paper uses asynchronous learning factor to balance the global searching ability and local search capability, so that the particles have a greater self-learning ability in the early stage, widening the scope of the global search, and make it have a larger group learning ability in the later stage, which is beneficial to converge to the global optimum quickly. The asynchronous learning factor is as follows:

$$\begin{cases} c_1=c_{1,ini}+[(c_{1,fin}-c_{1,ini})/t_{\max}]*t \\ c_2=c_{2,ini}+[(c_{2,fin}-c_{2,ini})/t_{\max}]*t. \end{cases} \quad \textbf{(20)}$$

In the formula, $c_{1,ini}$ and $c_{2,ini}$ are the initial values of c_1 and c_2 respectively, $c_{1,fin}$ and $c_{2,fin}$ are the iteration terminal values of c_1 and c_2 respectively, and these values are $c_{1,ini}=c_{2,fin}=2.5$ and $c_{2,ini}=c_{1,fin}=0.5$ respectively.

Firstly, the asynchronous method is used in the algorithm, which makes the learning factor changes with the number of iteration t. At the beginning of the algorithm, the learning factor c_1 is relatively large, but it decreases with the increase of iteration t, and the self-learning ability gradually weakened. In the latter part of algorithm, c_2 is relatively small, it increases with the increase of iteration t, and the group search capabilities gradually increased. Secondly, the compressibility factor φ is introduced in formula (18). When the particle's flight speed is updated, the compressibility factor φ changes with the learning factors c_1 and c_2, but it always satisfies the condition $\varphi\in[0,1]$. This method can not only effectively control the flying speed of particles, but also have good global detection ability and local mining ability. The improved particle flying speed is as follows:

$$v_{ij}(t+1)=\varphi\{v_{ij}(t)+c_1r_{1j}(t)[p_{ij}(t)-2x_{ij}(t)+x_{ij}(t-1)]+c_2r_{2j}(t)[p_{gj}(t)-2x_{ij}(t)+x_{ij}(t-1)]\}. \quad \textbf{(21)}$$

In the formula, the formula for the compression factor φ is $\varphi=2/(|2\text{-}C\text{-}\sqrt{C^2\text{-}4C}|)$, where C satisfies the condition $C=c_1+c_2>4$. In the iteration, the algorithm calculates the fitness according to the objective function, and determines the best position $p_{ij}(t)$ of the particles and the best position $p_{gj}(t)$ of the swarm according to the fitness. Then, the algorithm updates the velocity and position of the particle according to the formula (21) and the formula (19). When the number of iterations reaches the maximum value or the optimal position found by the swarm satisfies the operation precision, the iteration of the algorithm is terminated.

4.3 Optimization of LSSVM Model

According to the above analysis, the steps to optimize the parameters of the LSSVM model with the improved SecPSO algorithm are as follows:

(1) The training sets and the test sets are selected from the normalized mixed domain feature set and the parameters of the improved SecPSO are initialized;

(2) In order to effectively evaluate the effect of parameter optimization, the average classification accuracy is used as the fitness $F(u_i)$;

$$F(u_i) = (1/p)\sum_{q=1}^{p}[(l_{Tq}/l_q)\times 100\%]. \quad \textbf{(22)}$$

In the formula, l_{Tq} represents the number of samples that are correctly classified in the q th test set; and l_q represents the total number of samples in the test set.

(3) Comparing the current position fitness $F(u_i)$ of the particle with the optimum position fitness $F(p_{besti})$, if the current position fitness of the particle is greater than the optimal position fitness ($F(u_i) > F(p_{besti})$), the optimal position of the particle is updated to the current position ($p_{besti} = u_i$). Comparing the current position fitness $F(u_i)$ of the group with the optimal position fitness $F(g_{besti})$, if the current position fitness of the group is greater than the optimal position fitness ($F(u_i) > F(g_{besti})$), the optimal position of the group is updated to the current position ($g_{besti} = u_i$).

(4) If the algorithm reaches the iterative termination condition, the iteration is terminated, otherwise, the iteration number is added by 1 and the Step (2) is executed.

(5) The learning factor and the compression factor are updated asynchronously according to the formula (20), and then the velocity and position of the particle are updated according to the formula (21) and the formula (19).

(6) The algorithm continues to execute until the best kernel parameter σ and the regularization parameter C are found and the two parameters are entered into the LSSVM model for fault diagnosis. The flow chart is shown in Fig. 3.

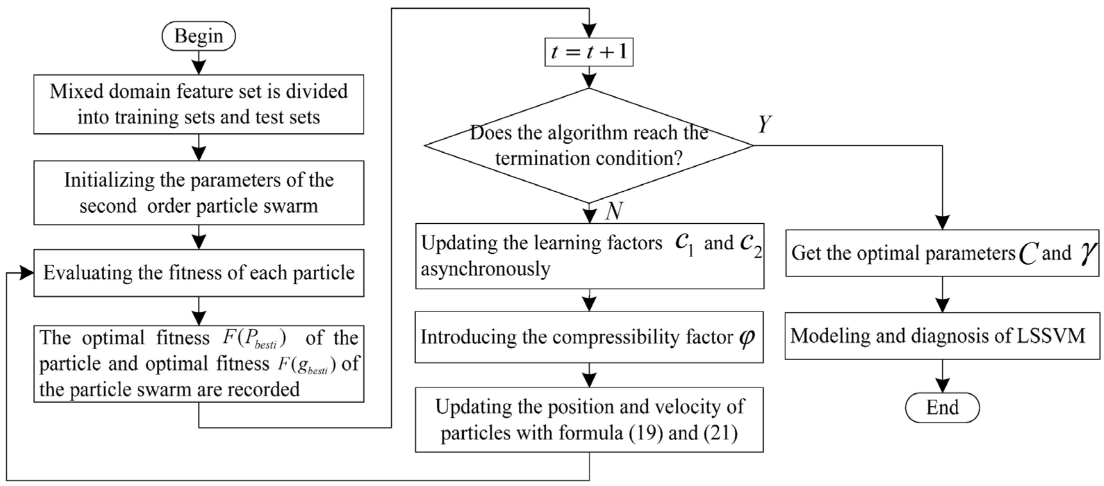

Fig. 3. Optimization of LSSVM model

5 Experimental Research

5.1 Experimental Analysis

The experimental data of this paper comes from the No. 3rd high-pressure diaphragm pumping station of the Yunnan Dahongshan Pipeline, which contains the signals of normal state, stuck valve fault and wear fault. And the sampling frequency of the vibration signal is 2560 Hz ($fs = 2560Hz$), and the sampling data length is 10240. Fig. 4 is the time domain diagram and the frequency domain diagram of the wear fault signal, so it can be seen that there are too many burrs and irregular variations in the signal, and the frequency characteristics are not obvious.

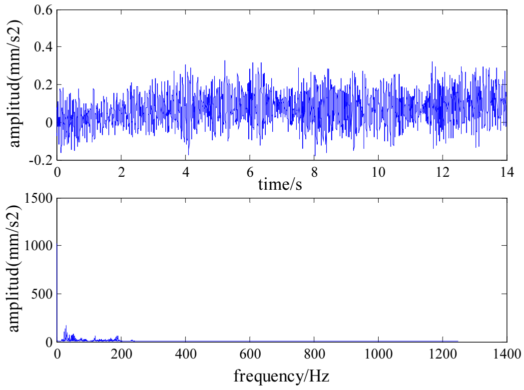

Fig. 4. The time domain diagram and frequency domain diagram of the wear fault signal

In the first step, 60 pairs of Gaussian white noise with the standard deviation of 0.35 are added to the signals, and the signals are decomposed by CEEMD. The mixed signal is decomposed into 8 IMF, and the result is shown in Fig. 5. Then, we calculate the cross correlation coefficients between each IMF and the original signal, and calculate the energy coefficient of each IMF at the same time, the result is shown in Table 2.

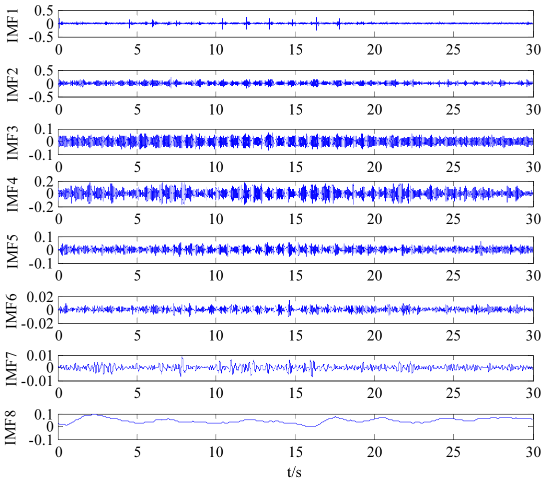

Fig. 5. The CEEMD decomposition of the wear fault signal

Table 2. Cross correlation coefficients and energy coefficients

Parameter	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8
Cross correlation coefficient	0.085	0.175	0.081	0.644	0.117	0.008	0.002	0.330
energy coefficient	0.035	0.168	0.058	0.429	0.044	0.006	0.001	0.262

From Table 2, it is known that the cross correlation coefficients and the energy coefficients of these IMF have the same change tendency, so the IMF are sorted in order of energy coefficients from large to small, the result is shown in Fig. 6. According to the cross correlation threshold (ρ_λ=0.15) and the energy threshold (e_λ=0.1), those IMF with weaker correlation with the original signal and the IMF with smaller energy are removed. The IMF of the useful signal are obtained by the compound screening method, these IMF include IMF4, IMF8, and IMF2, and then the energy features and Lempel_Ziv complexity features of these IMF are extracted.

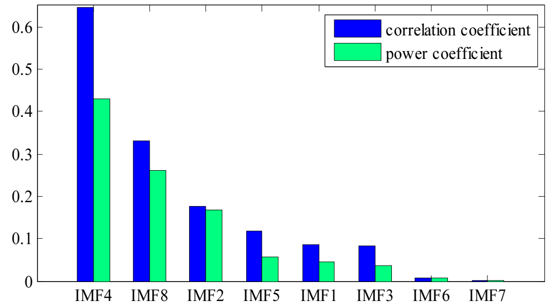

Fig. 6. The sorting of IMF components

In the experiment, 50 samples are taken for each state, and the time-frequency feature matrix with the size of 150 * 6 is obtained in three states. As shown in Fig. 8, the 16th to 21st features are the energy features and the Lempel_Ziv complexity features in the time-frequency domain.

The IMFs of the useful signal obtained by the compound screening method are reconstructed, and the reconstructed signal is shown in Fig. 7. A lot of glitch noises and false signals are removed, which makes the signal more regular, and the frequency characteristics are more prominent. 10 time domain features and 5 frequency domain features of the reconstructed signal are extracted to obtain the time domain feature set and the frequency domain feature set. The time-frequency domain feature set obtained above is combined with the time domain feature set and the frequency domain feature set to form a mixed domain feature set matrix. Because the dimension of each feature in the mixed domain is inconsistent, normalization is required. Figure 8 shows the normalized mixed-domain feature set, where the first to tenth features are time-domain features, the eleventh to fifteenth features are frequency-domain features, and the sixteenth to twenty-first features are time-frequency domain features. Each fault state contains 50 sets of samples, and then the feature set matrix of 50 * 21 is obtained through feature extraction. The three fault states contain 150 sets of samples, and the feature set matrix of 150 * 21 is obtained through feature extraction.

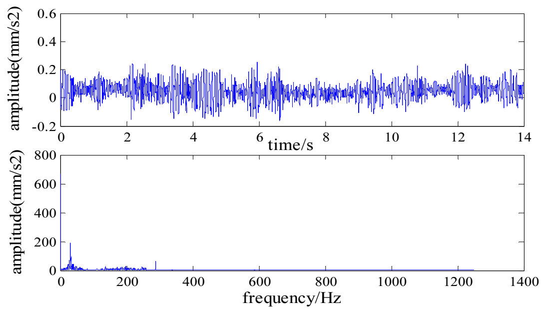

Fig. 7. The waveform of the reconstructed signal

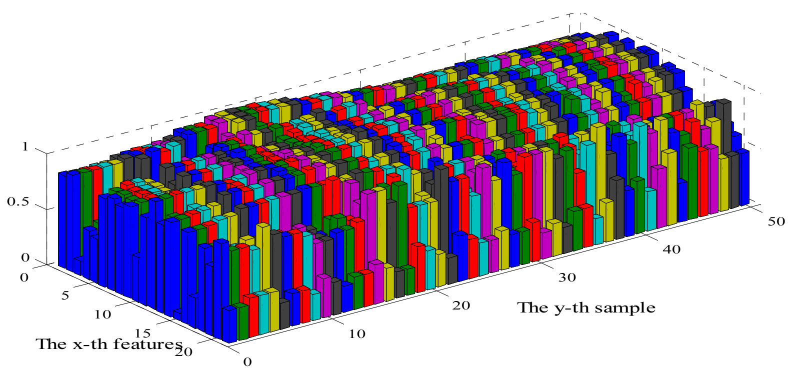

Fig. 8. The mixed domain feature set of wear fault

In the second step, the mixed domain feature sets (150 * 21) of the three fault states are subdivided into training samples and test samples, and the improved SecPSO-LSSVM model is used to diagnose the faults. As shown in Table 3, the first 30 groups of samples in each fault state are selected as training samples, and the latter 20 groups of samples in each state are selected as test samples, and the corresponding category labels are marked. The 150 sets of samples are divided into 90 groups of training sets, 60 groups of test sets, and these samples are input into the improved SecPSO method to optimize the parameters.

Table 3. Training samples and test samples

Fault category	Training sample	Test sample	label
Normal	30	20	1
Stuck valve	30	20	2
Wear failure	30	20	3

Before the parameter optimization, the parameters of the algorithm need to be set up. The search scope of the nuclear parameters is $\sigma \in [0,100]$, the search scope of the regularization parameter is $C \in [0.1,10]$, the number of evolution is 300, the number of particle swarm is 5, and the CV folding number is 3 and ω_1=0.9 , ω_2=0.1 , $c_{1,ini}$=$c_{2,fin}$ = 2.5 , $c_{2,ini}$=$c_{1,fin}$ = 0.5 . The velocity and position of particles are updated according to formula (21) and formula (19) in the each iteration, and the fitness convergence curve of parameter optimization is obtained, as shown in Fig. 9. The average fitness in the graph refers to the average fitness of all particles in each generation, and the best fitness refers to the maximum fitness of all particles in each generation. In the first 60 iterations, the convergence rate of fitness curve is very fast, after that, its convergence rate is flattened, and the final fitness curve converges to the best fitness and the parameter optimization of LSSVM is realized. The best kernel parameter and the best regularization parameter obtained by the improved SecPSO method are σ^2=1.4416 and C=8.8608 .

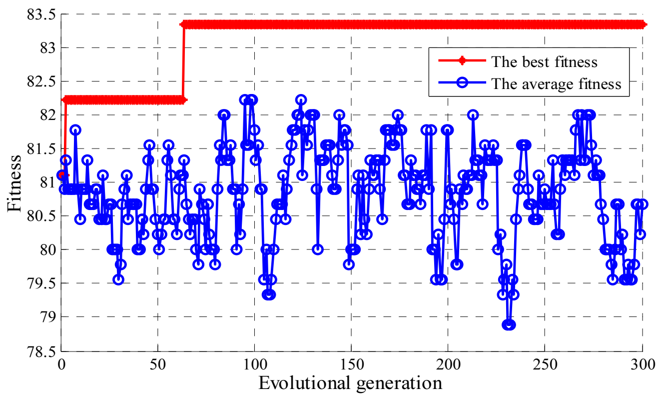

Fig. 9. Parameter optimization of the improved SecPSO

The optimal parameters obtained by the improved SecPSO method are input into the LSSVM model, and the fault diagnosis results of the check valve can be obtained. As shown in Fig. 10, 7 groups of training samples are misclassified, and the classification accuracy of the training samples is 92.232%, and 4 groups of test samples are misclassified, and the classification accuracy of the test samples is 93.385%, and the wear fault is incorrectly diagnosed as a stuck valve fault.

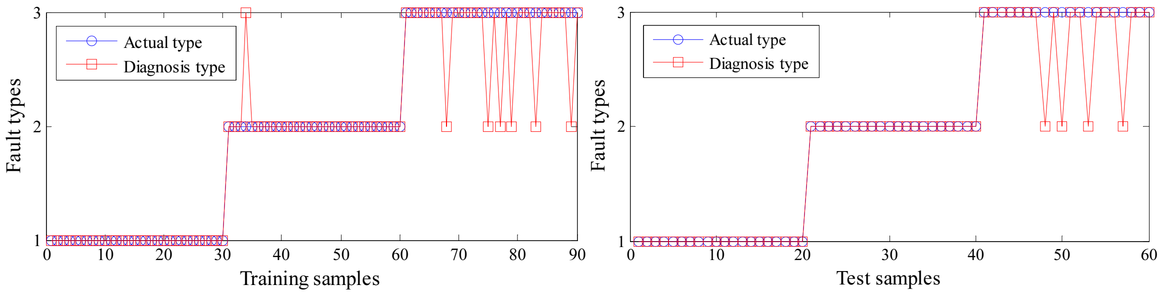

Fig. 10. Fault diagnosis result of check valve

5.2 Result Comparison

In order to verify the effectiveness of the fault diagnosis method proposed in this paper, the method is compared with BPNN, SVM and PSO-LSSVM. All four methods have mixed domain feature set as sample set, and the division of training samples and test samples are the same as above. The BPNN method adopts the double hidden layer neural network and selects the log-sigmoid and tangent-sigmoid transfer functions. The SVM model uses the radial basis function, and obtains the kernel parameter σ^2=0.53 and the penalty factor C=16.64 with higher diagnostic accuracy through 20 independent experiments. The radial basis function is also used in the PSO-LSSVM method, and the initialization of the parameters is the same as that of the improved SecPSO-LSSVM method. The results of parameter optimization are shown in Fig. 11, and the optimized kernel parameter σ^2=1.0346 and regularization parameter C=12.5408 can be obtained. After 10 iterations, the optimal fitness of the algorithm is about 81%, and the average fitness fluctuates within the range of 55%~80%. Comparing figure 9 and figure 11, we can see that the improved SecPSO method is not easy to fall into local optimum. It converges fast in the first 60 iterations, and then converges at a gentle rate. Finally, the best fitness tends to be 83.5% and average fitness ranged from 78.5% to 82.5%. Comparing with the PSO method, the local search ability and global search ability of the improved SecPSO method are greatly improved.

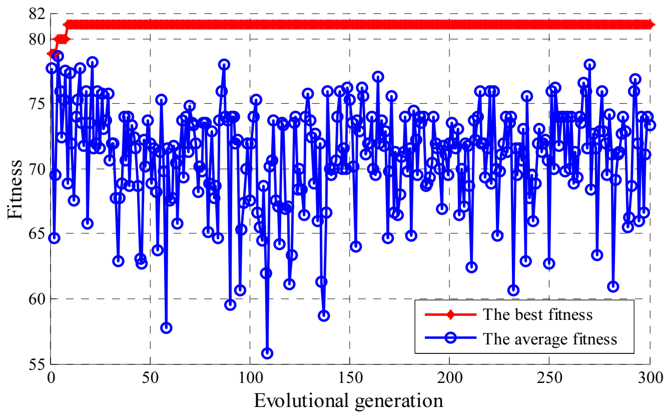

Fig. 11. Parameter optimization of the PSO

As shown in Table 4, the diagnostic accuracy of the above four methods is obtained through experiments. The results show that the classification accuracy of the BPNN method for training samples and test samples are 62.5414% and 65% respectively. The results are related to the characteristics of the BPNN method, and the neural network algorithm needs a large number of training samples to achieve higher diagnostic accuracy, while the mixed-domain feature set belongs to the small sample data. After 20 independent experiments, the classification accuracy of SVM model for training samples and test samples are 81.7381% and 80.230% respectively, which shows that SVM method has good performance in small sample, nonlinear and high dimensional pattern recognition. The experiment shows that the PSO algorithm avoids the blindness of parameter selection in LSSVM model, and the classification accuracy of training samples and test samples are 83.3817% and 86.9302% respectively. But the traditional PSO algorithm converges quickly and tends to be trapped in local optima in parameter optimization. In this paper, a fault diagnosis method based on improved SecPSO method and LSSVM is proposed, and the diagnostic accuracy of the method for the training samples and the test samples are 92.232% and 93.385% respectively, and the classification accuracy of the samples is significantly improved.

Table 4. Comparison of different classification methods

Method	Training sample	Test sample
BPNN	62.5414%	65%
SVM	81.7381%	80.230%
PSO-LSSVM	83.3817%	86.9302%
Improved SecPSO-LSSVM	92.232%	93.385%

In order to prove that the compound screening method can remove the false components and noise produced by the CEEMD algorithm, in the first group of contrast experiments, we directly extract the mixed domain features of IMF1, which includes 10 time-domain features, 5 frequency domain features, 1 energy feature and 1 Lempel_ziv complexity feature. The mixed domain features are applied to parameter optimization of LSSVM model, and the kernel parameter and regularization parameter obtained by the traditional SecPSO algorithm are 14.9161 and 8.765 respectively, and the fault diagnosis accuracy is 81.6667%. In order to prove that the improved SecPSO algorithm can improve the global optimization ability and local optimization ability, in the second group of contrast experiment, we use the traditional SecPSO algorithm to optimize the parameters of the LSSVM model. The kernel parameter and regularization parameter obtained by the traditional SecPSO algorithm are 1.2783 and 9.2319 respectively, and the accuracy of fault diagnosis is 88.3333%. The experimental results are shown in Table 5. It can be seen from the number of fault features that the compound screening method avoids the blindness in the selection of IMF components. From the optimized parameters, it can be seen that the optimal parameters of different feature sets have great difference. Although the SecPSO algorithm can achieve good optimization results, the parameters obtained by the improved SecPSO algorithm are closer to the global optimum. It can be seen from the diagnosis accuracy that the compound screening method improves the diagnostic accuracy significantly. The improved SecPSO algorithm not only improves the diagnostic accuracy, but also avoids premature convergence of the parameters.

Table 5. Comparison of fault diagnosis methods

Method	Features	Kernel parameter σ^2	Regularization parameter C	Convergence point	Accuracy
CEEMD+Mixed domain features +SecPSO+LSSVM	15+1*2	14.9161	8.765	1	81.666%
CEEMD+IMF selection +Mixed domain features +SecPSO +LSSVM	15+3*2	1.2783	9.2319	24	88.333%
The proposed method	15+3*2	1.4416	8.8608	80	92.808%

6 Conclusion

In this paper, a fault diagnosis method based on CEEMD compound screening and improved SecPSO is proposed. In order to remove the false components and noise produced by the CEEMD algorithm, this paper proposes a compound screening method and compares it with the method of selecting IMF1. The fault diagnosis method based on the compound screening method has achieved a higher diagnostic accuracy. In order to characterize the fault characteristics of the check valve, the mixed domain features are extracted for analysis, where the time-frequency domain features include energy features and Lempel_Ziv complexity features. In order to avoid the premature convergence of parameters, the SecPSO algorithm is improved and compared with the traditional SecPSO method. The improved method has a larger convergence point and higher diagnostic accuracy. Under the condition of the same mixed domain features, the method proposed in this paper is compared with BPNN, SVM, PSO-LSSVM methods, and the proposed method has the highest fault diagnosis accuracy. Through the above comparative analysis, there are two representative conclusions which are as follows:

(1) The compound screening method proposed in this paper not only avoids the blindness of IMF selection, but also effectively removes false components and noise components, and improves the accuracy of fault diagnosis.

(2) The improved SecPSO algorithm can not only avoid premature convergence of the algorithm, but also improve the search capability and fault diagnosis accuracy of the algorithm.

The method proposed in this paper has high fault diagnosis accuracy, which provides a reference for fault diagnosis of complex mechanical equipment. However, mechanical fault types are mostly composite fault modes in the actual production process, which are needed to analysis and research further.

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