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Gear fault feature extraction and diagnosis method under different load excitation based on EMD, PSO-SVM and fractal box dimension†

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Abstract

Aiming at the problem of gear fault feature extraction and fault classification under different load excitation, we present a new fault diagnosis method that combines three methods, including empirical mode decomposition (EMD), particle swarm optimization support vector machine (PSO-SVM) and fractal box dimension. First, the non-stationary original vibration signal of gear fault is decomposed into several intrinsic mode functions (IMF) by EMD method. Then, the time, frequency, energy characteristic parameters and box dimension are calculated separately from the time domain, frequency domain, energy domain and fractal domain. And then the gear fault characteristics under different load excitation are obtained. Finally, the extracted feature parameters are input into the PSO-SVM model for gear fault classification. The experimental results show that the proposed method can effectively identify gear failure types under different load excitation.

Keywords: Gear fault diagnosis; EMD; PSO-SVM; Fractal box dimension; Different load

1. Introduction

A gearbox is an important component of rotating machinery. Gear fault diagnosis is an effective method to avoid serious failures and ensure the normal operation of machinery and equipment [1-3]. In recent years, Hong et al. studied gear fault detection with small fluctuations of the operating speed by employing fast dynamic time warping [4]. The method can characterize the local gear fault and identify the corresponding faulty gear and its position. Zhang et al. detected gearbox fault compound by the energy operator demodulation of optimal resonance components, but other types of compound faults are needed to prove the effectiveness of the proposed method [5]. Li et al. performed fault diagnosis tasks for gearboxes by a multimodal deep support vector classification method based on deep learning strategy; the results indicate that the proposed separation-fusion based deep learning strategy is effective for the gearbox fault diagnosis [6]. Xing et al. studied a novel hybrid model for gear fault diagnosis under different conditions [7]. The proposed approach can accurately diagnose and identify different fault types of gear under variable conditions. A fault diagnosis method of planetary gear based on multi-scale fractal box dimension of complementary ensemble empirical mode decomposition (CEEMD) and extreme learning machine (ELM) was studied [8]. These methods are applicable to situations where the load is constant.

Gear fault signal transmission links are more complex, while the gear box working environment is poor. The gear vibration signal not only contains background noise, but also other noise components. In addition, when the gear has a local fault, the vibration signal will produce a modulation phenomenon, the engagement frequency and frequency doubling on both sides will appear at intervals for the interval of the equal frequency band. Under normal circumstances, the type of gear failure and fault level can be found by analyzing the intensity and frequency of the modulation information. However, a different load will cause a complex vibration signal of gear fault, which is a non-linear, non-stationary signal [9-13]. With the traditional method it is difficult to extract the characteristics of gear failure under different load. The effective feature extraction method of gear fault is the key to diagnosing the operating state of the gear accurately. Empirical mode decomposition (EMD) is a new type of signal processing method that is very suitable for non-linear, non-stationary signals [14-17]. Non-stationary vibration signals can be decomposed into a number of smooth intrinsic mode functions (IMF) by EMD method. In addition, it is difficult to extract gear fault characteristics accurately from time domain and frequency domain only. As the gear fault signal has fractal

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characteristics in a certain range, fractal geometry is used to meet the complex fault signal analysis. The fractal dimension includes the Hausdorff dimension, similarity dimension and box dimension [18]. The fractal box dimension can describe the statistical self-similarity feature of the fractal boundary in the gear fault signal [19]. Fault classification is important to the gear fault diagnosis. There are some classification methods such as support vector machine (SVM), ELM, and other neural networks [20]. SVM is a data classification method that is suitable for processing small samples. For improving the classification effect, some parameter optimization algorithms such as particle swarm optimization (PSO) and genetic algorithm (GA) are combined with SVM to realize fault classification [21-23]. Though some achievements have been used in gear fault diagnosis, it is difficult to realize gear fault feature extraction and diagnosis under different load conditions.

In this study, we used the box dimension as a characteristic value of the gear running state, and the operating state of the gear is described in a simple and direct quantitative way. The irregularity and complexity of the gear vibration signal are reflected in the box dimension. The irregular and the complexity of vibration signal are different, so the box dimensions are also different. To realize the fault diagnosis of gear fault under different loads, a different load gear fault diagnosis method based on EMD and particle swarm optimization support vector machine (PSO-SVM) is proposed. In this method, the gear fault characteristic parameters of time domain, frequency domain and fractal box dimension are input into PSO-SVM under different load excitation. The experimental results show that the algorithm can effectively classify the gear faults under high load conditions.

The rest of this paper is organized as follows: Sec. 2 briefly introduces the principle of EMD decomposition algorithm. Sec. 3 presents the selection of characteristic parameters in time domain, frequency domain, energy domain and fractal domain. Sec. 4 proposes a feature extraction algorithm based on EMD and fractal box dimension, and a gear vibration data of example under different load excitation is analyzed. Sec. 5 proposes a gear fault diagnosis method based on EMD and PSO-SVM under different load excitation and a case is analyzed. Conclusions are drawn in Sec. 6.

2. The basic principles of feature extraction and diagnosis method

2.1 EMD feature extraction algorithm

The specific decomposition steps of the EMD method are as follows:

(1) The upper and lower envelope of all the data points are obtained. The average of the upper and lower envelopes is denoted as m_1, the following equation can be obtained:

$$x(t)-m_1=h_1 . \tag{1}$$

Ideally, if h_1 satisfies the IMF condition, then h_1 is the first IMF component of $x(t)$.

(2) If h_1 does not meet the IMF condition, regarding h_1 as the original data, step (1) is repeated. The upper and lower envelope of the average m_{11} are obtained, and then $h_{11}=h_1-m_{11}$ is determined whether to meet the IMF conditions or not. If not, the cycle k is repeated to obtain $h_{1(k-1)}-m_{1k}=h_{1k}$ such that h_{1k} satisfies the IMF condition. Marking $c_1=h_{1k}$, then c_1 is the first component of the signal $x(t)$ which satisfies the IMF condition.

(3) c_1 is separated from $x(t)$ to be obtained:

$$r_1=x(t)-c_1 . \tag{2}$$

Steps (1) and (2) are repeated, where r_1 is as the original data, to obtain the second component c_2 which is satisfying the IMF condition. The iteration *n* times are repeated to obtain *n* components which are satisfying the IMF condition. At last, there are:

$$\begin{cases} r_1-c_2=r_2 \\ \quad \cdots\cdots \\ r_{n-1}-c_n=r_n . \end{cases} \tag{3}$$

When r_n becomes a monotone function, the component can no longer be extracted to meet the IMF conditions, the loop ends. This is given by Eqs. (2) and (3):

$$x(t)=\sum_{i=1}^{n} c_i + r_n . \tag{4}$$

Therefore, any signal $x(t)$ can be decomposed into the sum of the *n* IMF and a residual component, and the IMF c_1, c_2, c_3, $\cdots$, c_n represent the components of the signal from high to low. The frequency components contained in each band are not the same and will vary with the change of the vibration signal $x(t)$. The residual function r_n represents the average trend of the signal.

2.2 PSO-SVM classification algorithm

2.2.1 The basic principle of support vector machine

The SVM is illustrated in Fig. 1. The distance between different support vectors is the margin. Classification line equation written as $x\cdot\omega+b=0$, which can be normalized, can make the linearly separable sample set (x_i, y_i), $i=1,\cdots,l$, $x\in R^d$, $y\in\{+1,-1\}$, satisfy

$$y_i\left[(\omega\cdot x_i)+b\right]-1\ge 0, i=1,...,l . \tag{5}$$

The classification interval is $2/\|\omega\|$ and we make the maximum interval equivalent to the minimum of $\|\omega\|^2$. The classification surface meets condition Eq. (5) and minimizing

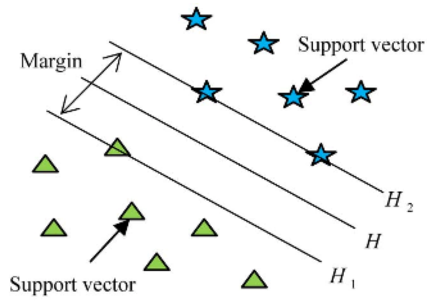

Fig. 1. Optimal classification line.

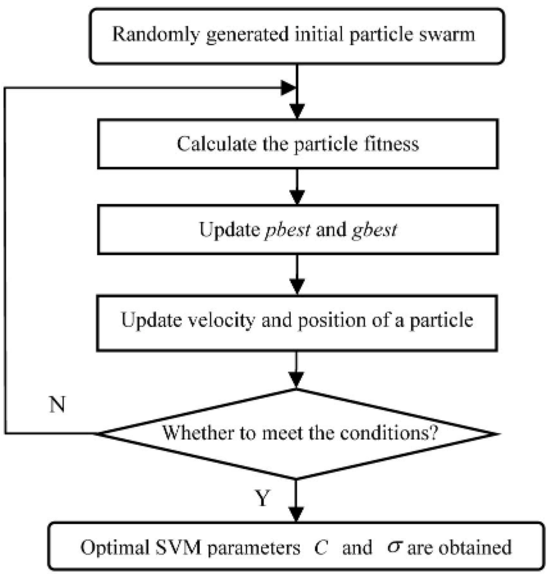

Fig. 2. Flow chart of PSO optimized SVM parameters.

$\frac{1}{2}\|\omega\|^2$ can be called optimal classification surface. Training sample points in H_1 and H_2 are called support vector.

2.2.2 Particle swarm optimization

The PSO is a population-based global optimization technique [21]. Due to its easy implementation, the PSO is used to realize the parameters selection of SVM. The standard PSO can be expressed by:

$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1 r_1 (pbest_{ij} - x_{ij}(t)) + c_2 r_2 (gbest_j(t) - x_{ij}(t)), \quad (6)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1), \quad (7)$$

where $v_i(t)$ is the i th particle's velocity at the t th iteration; $pbest_{ij}$ is the particle's best position; $gbest_{ij}$ is the best position.

2.2.3 PSO-SVM

The process of SVM parameter optimization with PSO is presented in Fig. 2.

Table 1. Dimensionless time domain feature parameters.

Time domain characteristic parameter	Dimensionless
Kurtosis	$K = \dfrac{\frac{1}{N}\sum_{i=0}^{N-1}(x_i - x_{mean})^4}{(\frac{1}{N}\sum_{i=0}^{N-1}(x_i - x_{mean})^2)^2}$
Margin indicator	$L = \dfrac{x_p}{x_r}$
Peak index	$C = \dfrac{x_p}{x_{rms}}$
Pulse index	$I = \dfrac{x_p}{x'}$
Waveform indicators	$S = \dfrac{x_{rms}}{x'}$

Description: x_i is the ith value of the signal. x and b are the total number of signal data.

3. Selection of characteristic parameter

3.1 Time domain characteristic parameter

Time domain characteristic parameter, which is simple to calculate and sensitive to the state of the gear, can be used to monitor the gear running state. The time domain feature is divided into a dimension eigenvalue and a dimensionless eigenvalue. Since the time domain feature is related to the state of the gears, the load of the gears and the working conditions, it is difficult to judge the operating state of the gears. The dimensionless time domain characteristic parameters are closely related to the gear load and operating conditions, and are particularly sensitive to the gear operating state. In this paper, we studied the gear fault data under different load excitation, so the characteristic value of the dimension does not work again. Only the dimensionless characteristic parameters can be used to extract the fault characteristics of the gear. The dimensionless eigenvalues include kurtosis, waveform index, peak index, pulse index, and margin index as shown in Table 1.

3.2 Frequency domain characteristic parameter

When the gear fails, such as gear wear, tooth root crack, broken teeth, the spectrum will change. The distribution of frequency bands in spectrum is very beneficial to extract and analyze the fault characteristic frequency. Therefore, the frequency domain parameter can be used to describe the gear fault condition. The frequency domain characteristic parameters selected in the paper are shown in Table 2.

3.3 Fractal box dimension parameter

The gear fault signal under different load excitation has non-linear and non-stationary characteristics. It is difficult to

Table 2. Frequency domain characteristic parameters.

Frequency domain characteristic parameter	Dimensionless
Spectrum center of gravity	$FC = \frac{\sum_{k=1}^{K} f_k s(k)}{\sum_{k=1}^{K} s(k)}$
Spectral average	$MeanF = \frac{\sum_{k=1}^{K} s(k)}{K}$
Root mean square frequency	$RMSF = \sqrt{\frac{\sum_{k=1}^{K} f_k^2 s(k)}{\sum_{k=1}^{K} s(k)}}$
Spectral variance	$RVF = \frac{\sum_{k=1}^{K} (s(k) - MeanF)^2}{K-1}$
Spectrum kurtosis	$FK = \frac{\sum_{k=1}^{K} (s(k) - MeanF)^4}{K \bullet RVF}$

Description: $s(k)$ is the spectrum of the signal $x(n)$, $k = 1, 2, \cdots, K$, where K is the number of lines; f_k is the frequency of the kth line; The spectral mean is the mean of the amplitude of all frequencies, and they reflect the size of the spectrum data trend.

extract gear fault characteristics accurately only from time domain and frequency domain signal. The gear fault signal has a fractal characteristic within a certain range, and the fractal geometry can be used to analyze the complex gear fault signal. We used the box dimension to analyze the characteristics of gear failure under different load excitation. The irregularity and complexity of gear fault signal are reflected in the box dimension. Suppose the time series signal $x(j) \subset X$, X is the closed set on the n -dimensional E-type space R^n. R^n is divided into fine grids as much as possible. If N_Δ is the grid count of the set X on the discrete space of the grid Δ, the box dimension of signal is defined as:

$$d_B = \lim_{\Delta \to 0} (-\lg N_\Delta / \lg \Delta) . \quad (8)$$

The sampling interval Δ is the highest resolution of the time series $x(j)$, resulting in the absence of the limit in Eq. (5) as determined by definition $\Delta \to 0$. In the actual calculation, usually using the sacrifice method, the grid Δ step by step to enlarge the grid $k\Delta$, where $k \in Z^+$. Let $N_{k\Delta}$ be the grid count of the discrete space set X with the lattice width $k\Delta$, which can also be calculated using the following equation:

$$\begin{aligned} P(\Delta) &= \left|\max(x_1, x_2) - \min(x_1, x_2)\right| \\ &+ \left|\max(x_2, x_3) - \min(x_2, x_3)\right| \\ &+ \cdots + \left|\max(x_{N_0-1}, x_{N_0}) - \min(x_{N_0-1}, x_{N_0})\right| \end{aligned} \quad (9)$$

$$\begin{aligned} P(2\Delta) &= \left|\max(x_1, x_2, x_3) - \min(x_1, x_2, x_3)\right| \\ &+ \left|\max(x_3, x_4, x_5) - \min(x_3, x_4, x_5)\right| \\ &+ \cdots + \left|\max(x_{N_0-2}, x_{N_0-1}, x_{N_0}) - \min(x_{N_0-2}, x_{N_0-1}, x_{N_0})\right| \end{aligned} \quad (10)$$

$$P(k\Delta) = \sum_{j=1}^{N_0/k-1} \left| \begin{matrix} \max(x_{k(j-1)+1}, x_{k(j-1)+2}, \ldots, x_{k(j-1)+k+1}) - \\ \min(x_{k(j-1)+1}, x_{k(j-1)+2}, \ldots, x_{k(j-1)+k+1}) \end{matrix} \right| \quad (11)$$

where $j = 1, 2, \cdots, N_0 / k$; $k = 1, 2, \cdots, K$; $K < N_0$; N_0 is the number of sampling points.

The grid of the signal $x(j)$ is counted

$$N_{k\Delta} = P(k\Delta) / k\Delta + 1 , \quad (12)$$

where $N_{k\Delta} > 1$.

The signal scale area is determined in the $\lg k\Delta - \lg N_{k\Delta}$ graph by using the genetic optimization, the three-fold line segment fitting method or the correlation coefficient test algorithm. If the start and end points of the scale-free interval are k_1 and k_2, then in this interval $\lg k\Delta$, $\lg N_{k\Delta}$ should satisfy the linear regression model:

$$\lg N_{k\Delta} = a \lg k\Delta + b \quad (k_1 \le k \le k_2). \quad (13)$$

Finally, the slope of the line is calculated by using the least squares method:

$$\hat{a} = -\frac{(k_2 - k_1 + 1)\sum \lg k \lg N_{k\Delta} - \sum \lg k \sum \lg N_{k\Delta}}{(k_2 - k_1 + 1)\sum \lg^2 k - \left(\sum \lg k\right)^2} . \quad (14)$$

Box dimension d_B is:

$$d_B = \hat{a} . \quad (15)$$

3.4 Energy domain characteristic parameter

Under different load excitation, the energy band will also have significant changes. To extract the fault characteristics more accurately, we used the IMF energy value and the total energy value ratio (called the IMF's energy band energy value) of the gear fault as the gear fault characteristic parameters under different load excitation. The IMF energy band energy value reflects the ratio of the energy value of the ith IMF component to the total energy after the signal is decomposed by EMD. The operation of the gear box can be determined under the different load excitation by comparing the IMF's energy band energy value. IMF power band energy value is expressed by:

$$P_{IMFI} = \frac{E_{IMFI}}{E} . \quad (16)$$

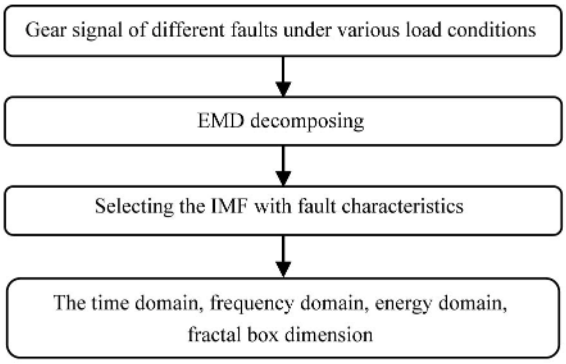

Fig. 3. Flow chart of gear fault feature extraction under different load excitation.

4. The proposed method of the paper

4.1 Feature extraction algorithm based on EMD and fractal box dimension

To extract the characteristics of gear fault under different load excitation, a feature extraction algorithm of EMD and fractal box dimension is proposed. First, the gear fault signal under different load excitation is decomposed by EMD. Second, the features of gear fault, which consist of the dimensionless time domain, the dimensionless frequency domain, the energy domain characteristic parameter and the fractal box dimension, are extracted from the modal function. The process of this method is shown in Fig. 3.

4.2 Fault diagnosis based on EMD and PSO-SVM under different load excitation

A different load gear fault diagnosis method is proposed based on EMD and particle swarm optimization support vector machine. In this method, the gear vibration signal under the different load is processed by EMD, and the gear fault feature is extracted. Finally, the extracted gear fault features are input into the PSO-SVM for different load excitation. The experimental results show that the algorithm can effectively classify the gear faults under high load conditions. First, EMD is used to decompose the gear vibration data under the different load excitation. The time domain, frequency domain, energy field and fractal box dimension are calculated separately. And then, the parameters are input to PSO-SVM for gear fault classification. The diagnostic flow is shown in Fig. 4.

5. Example analysis

5.1 Feature extraction

We collected the gear vibration data under different load excitation by the experimental platform. Fig. 5 is the gear data acquisition platform. In this experiment, the vertical measuring point data of the front axle middle gear of the gearbox are used. The gearbox has two parallel gears. The low speed gear teeth number is 90, the middle speed shaft gear teeth number is 100, the pinion teeth number is 36, and the high speed shaft gear teeth number is 29. In the middle of the test bed, the medium speed shaft pinion is faulty gear. The five types states include: normal, crack, eccentric, cutting teeth and missing teeth. In the test, the generator speed is 45 Hz (at this time, the gearbox intermediate speed is 13 Hz). The sampling frequency is 12000 Hz. The load ratio is controlled by the magnetic powder brake. The load proportions are 0 %, 20 %, 40 %, 60 %, 80 % and 100 % separately. The gear operating conditions of test bench are shown in Table 3.

Table 3. Gear load conditions.

Generator speed	Load	Working part number
45 Hz	0 %	A
45 Hz	20 %	B
45 Hz	40 %	C
45 Hz	60 %	D
45 Hz	80 %	E
45 Hz	100 %	F

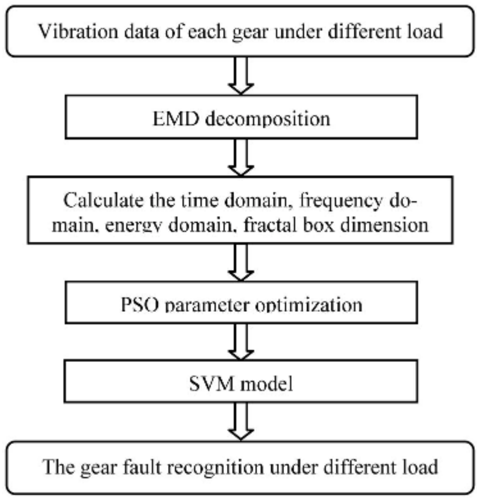

Fig. 4. Flow chart of gear fault diagnosis method under different load excitation.

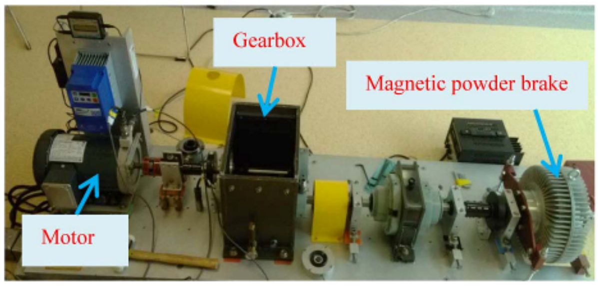

Fig. 5. Experimental platform.

By analyzing the vibration of the gear teeth under the different load excitation, it is found that the gear fault feature becomes more and more obvious as the gear load becomes larger. Therefore, a large load is beneficial to gear fault

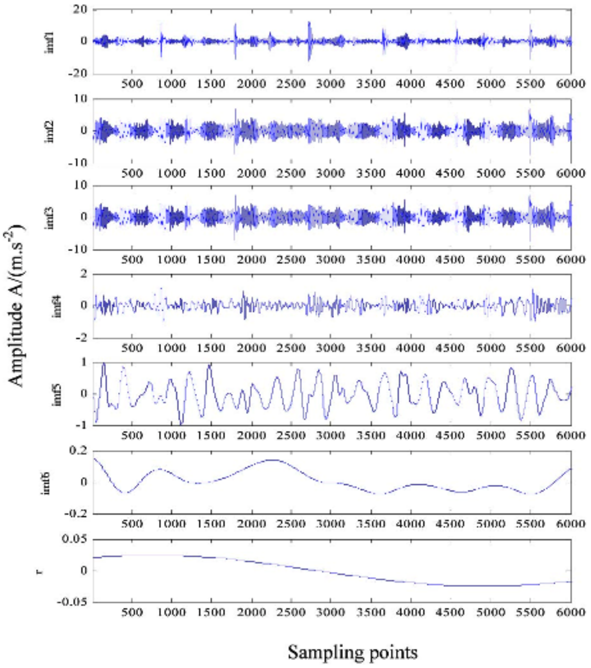

Fig. 6. Gear break fault signal EMD decomposition results.

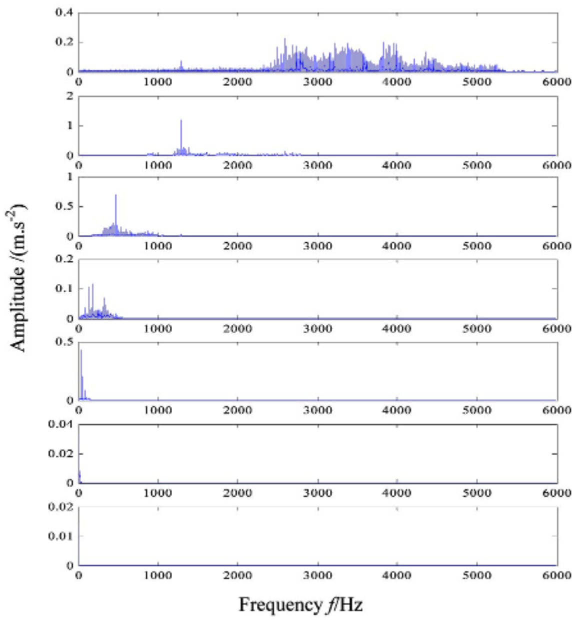

Fig. 7. Spectrum of IMF components.

diagnosis. From the results of EMD decomposition in Figs. 6 and 7, the IMF1 is mainly a high-frequency component, which is mainly between 2000 Hz and 5000 Hz, and is mainly composed of modulating the intermediate speed. IMF2 comes from the high-speed shaft gear meshing and its frequency belongs to the interference component. IMF3 is the meshing frequency of the middle speed gear and its side band. IMF4 to IMF7 is a low-frequency component, including generator frequency and some other interference frequency. Therefore, the fault characteristics of the middle speed pinion are mainly concentrated in the two signals of IMF1 and IMF3.

Table 4. The values of kurtosis index, spectrum center of gravity, fractal box dimension and margin indicator on IMF1 under different gear state.

Gear state	IMF1 kurtosis index	IMF1 spectrum center of gravity	IMF1 fractal box dimension	IMF1 margin indicator
Crack	8.45	4.32	1.66	7.62
Eccentric	50.28	5.62	1.65	20.80
Missing teeth	33.07	12.71	1.56	12.64
Cut teeth	38.11	5.44	1.68	16.93
Normal	11.26	5.78	1.64	8.79

Table 5. The values of pulse index, spectral variance and power band value on IMF1 and the power band values of IMF3 under different gear state.

Gear state	IMF1 pulse index	IMF1 spectral variance	IMF1 power band value	IMF3 power band value
Crack	6.33	3.30	0.54	0.28
Eccentric	16.11	3.60	0.52	0.40
Missing teeth	10.55	9.21	0.55	0.21
Cut teeth	13.60	3.42	0.64	0.24
Normal	7.24	1.28	0.59	0.28

It can be seen from Tables 4 and 5 that the different states of the gears correspond to the characteristic parameters of different sizes. IMF1 kurtosis index between about 8-50, the eccentricity of the gear eccentricity is the largest, reaching 50.28. For IMF1 spectrum center of gravity between about 3-13, the missing teeth of the gear is the largest, which reaches 12.71. The gear state values of IMF1 fractal box dimension and IMF1 power band value show little difference. For IMF1 margin indicator between about 6-21, the eccentricity of the gear eccentricity is the largest, reaching 20.80. For IMF1 spectral variance between about 1-10, the missing teeth of the gear is the largest which reaches 9.21. The IMF3 power band value between 0.2-0.4, and the eccentric IMF3 power band index is also the same, which reach the maximum. Although these characteristic parameters represent the state of the gears, it is not possible to determine the state of the gears only from these parameters. If these feature parameters are input to the classifier for pattern recognition, the order of magnitude of the classification of the results has a greater impact, the order of magnitude of the small parameters cannot play a role in the classification. To make all the parameters to play the same role in the classification, normalization of the parameters is needed, that is, the characteristics of the parameters are compressed to (0,1).

5.2 Case analysis

Because of the obvious characteristics of gear fault under heavy load conditions (impact, modulation edge band), the

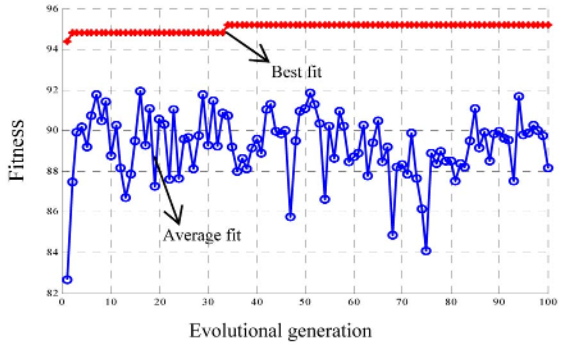

Fig. 8. Particle group suitability curve.

extracted fault features are representative. The load proportion of the experimental data is 60 %, 80 %, 100 %, the total of five states (normal, crack, eccentric, 50 sets of data were selected for each state, 50 groups of data were predicted (random load selected for each training and prediction data), and input to PSO-SVM for identification. Among them, the main parameters are set: population number N = 20, the number of iterations is set to 100, learning factor c1 = 1.9, c2 = 1.7. Through training, PSO-SVM fitness curve is shown in Fig. 8. The fitness curve in Fig. 8 is between 94 and 96. Therefore, the proposed method has a good effect on gear fault diagnosis under high load conditions.

6. Conclusion

We present a new method to extract gear fault feature under different load excitation based on EMD and fractal box dimension. The method deals with gear fault signals in the time domain, frequency domain, energy domain and fractal domain. Gear fault characteristics under different loads can be identified by integrating multiple parameter indicators that include the dimensionless time domain parameters, dimensionless frequency domain parameters, energy domain characteristic parameters and fractal box dimension. Furthermore, we propose a method to diagnose gear fault based on EMD and PSO-SVM under different load excitation. The proposed method overcomes the difficulty of traditional methods which cannot identify the fault characteristics of gear under different load excitation. Through experimental study based on the data of gear experiment plat, we proved that the method can classify gear faults under different load excitation quickly and accurately.

Acknowledgments

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