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A New Vibration Analysis Approach for Detecting Mechanical Anomalies on Power Circuit Breakers

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ABSTRACT On-line monitoring and the diagnosis of the high-voltage circuit breaker (HVCB) have been discussed and investigated significantly in the past few decades. The vibration analysis is a noninvasive and advanced diagnostic technique suitable for the detection of mechanical conditions during the HVCB operation, which plays an important role in improving the operating reliability of HVCB and reduces maintenance costs. However, due to the very complicated mechanical system and extremely short operation time of HVCB, the vibration signal has the characteristics of highly nonlinear, non-stationary, and corrupted by heavy garbage noise, which makes it very difficult to precisely extract effective features for machinery fault diagnosis. To address this issue, an energy entropy of Hilbert marginal spectrum (HMS) based on variational mode decomposition (VMD) is presented to analyze the vibration signals of HVCB in this paper. The VMD is used to decompose the vibration signal into a set of intrinsic mode functions (IMFs) reflecting its local characteristics, and then, the energy entropy of IMF's HMS, which varies from different failure modes of HVCB, is obtained by Hilbert transform and entropy-information theory. The characteristics of IMF's HMS, which reveal the variation of vibration signals, under different failure modes of HVCB, are practically analyzed and examined to illustrate the advantage of the proposed method in feature extraction. The IMF that best reflects the mechanical anomaly information of HVCB is ascertained from IMF's HMS, and its Hilbert marginal spectrum energy entropy (HMSEE), namely, IMF-HMSEE, which synthetically reflects the variations of vibration signal's amplitude, phase, and frequency, is turned out to have excellent classification performance for some mechanical anomalies of HVCB. The effectiveness of the proposed approaches is substantiated by experiments carried out in a 12-kV vacuum HVCB.

INDEX TERMS Online high voltage circuit breaker (HVCB) assessment, vibration analysis, machinery fault diagnosis, variational mode decomposition (VMD), Hilbert marginal spectrum energy entropy (HMSEE.)

I. INTRODUCTION

High voltage circuit breakers (HVCBs) are an indispensable important piece of equipment in the power system which perform the functions to break currents and protect other equipment in the grid, their reliability plays an important role in ensuring the security and stability operation of the power systems [1], [2]. Consequently, it is of great significance and attracting increasing attention in HVCB fault diagnosis to increase the reliability and decrease loss owing to HVCB faults. Vibration analysis has been verified to be an effective way for fault diagnosis of HVCB because the vibration signals from HVCB operation contain a great deal of fault-related information [3]–[8]. However, Due to the characteristics of extremely short operation time and severe impact-collision among moving parts, the vibration signal of HVCB is significantly different from these of rotating machinery: the time domain is quite short whereas the frequency domain is extremely wide, which makes it more difficult to analyze the inherently highly nonlinear and non-stationary vibration signals. Therefore, to precisely extract the fault-related features from the complex vibration signals of HVCB, a suitable signal processing method should first be adopted to analyze the vibration signals.

In the last few decades, a multitude of research efforts have been made and many techniques have been used for processing the raw vibration signals for condition monitoring, fault diagnosis, and incident prediction, which can be grouped into two major categories, namely, the classical spectral analysis method based on Fourier transform and the time-frequency analysis technology. The classic spectral analysis method based on Fourier transform, such as envelope analysis, spectrum analysis, holographic spectrum analysis, and high order spectral analysis have been widely used in the field of mechanical fault diagnosis. However, it has obvious inherent disadvantage, that is, the system being analyzed is supposed to be linear, and the signal being analyzed is required to be strictly stationary, otherwise, the spectral analysis results will lack clear physical significance. The vibration signals of HVCB, however, are non-stationary and the system is non-linear, which means it will affect the accuracy of the spectral analysis results by using these Fourier transform based classic spectral analysis methods.

Actually, the analysis of this kind of nonlinear and non-stationary signal should mainly consider its local characteristics. Therefore, the traditional frequency domain analysis method based on the global transformation of Fourier transform is obviously not suitable, while the time-frequency analysis method based on the joint time-frequency domain analysis can provide local information of the signal at the same time, which is an effective method for handling this kind of complex signal. For now, various time-frequency analysis methods have been proposed. Most of the methods are based on local transformation, which is the key to the realization of the joint analysis in the time-frequency domain. According to whether the local transformation satisfies the superposition principle or linear principle, the time-frequency analysis method can be divided into two categories: linear transformation method (such as short-time Fourier transform (STFT), wavelet transform (WT)) and nonlinear transformation method (such as the typical Cohen time-frequency distribution and ambiguity function). Considering that the theory and application of these two kinds of time-frequency analysis methods are quite mature, they are called traditional time-frequency analysis methods in this paper. These traditional time-frequency analysis methods still have some inherent defects, which affect the analysis results. For example, the STFT is actually a stationary signal analysis method, there are cross-term interference in the Cohen time-frequency distribution, and the WT lack of self-adaptability.

It is worth noting that ambiguity function (AF) plays an important role in non-stationary signal analysis and processing theory. It has been widely used in radar signal analysis and processing, optical information processing, sonar technology and other fields. For a non-stationary signal $x(t)$, the definition of the AF is as follows:

$$A_x(\eta, \tau) = \int_{-\infty}^{\infty} R_x(t, \tau) e^{j2\pi t\eta} dt \tag{1}$$

where, τ represents time delay and η represents frequency shift. $R_x(t, \tau)$ is the signal's auto-correlation function, which is defined as:

$$R_x(t, \tau) = x(t + \frac{\tau}{2}) x^*(t - \frac{\tau}{2}) \tag{2}$$

According to the above definition of AF, the relationship between AF and WVD is the two-dimensional Fourier transform. Therefore, the AF, like WVD, does not obey the principle of linear superposition, but the principle of quadratic superposition, that is, they all have the phenomenon of cross-term interference.

Different from the traditional time-frequency analysis methods, several new time-frequency analysis techniques have emerged in recent years, namely, adaptive signal processing methods, such as Hilbert-Huang Transform (HHT) [9], local mean decomposition (LMD) [10], and variational mode decomposition (VMD) [11]. These methods have been widely used in medical [12], [13], geological [14], [15], mechanical [16]–[20], electrical [21]–[25] and many other disciplines. HHT includes two processes: empirical mode decomposition (EMD) and Hilbert transform (HT). The EMD can carry out adaptive multi-resolution decomposition according to the characteristics of signals, but it is easily to generate problems such as mode mixing, IMF screening stop condition and endpoint effect in the process of decomposition [26], [27]. To overcome (to some extent) these deficiencies, LMD was proposed by Smith [10]. The LMD is an adaptive non-stationary signal analysis method proposed for more accurate analysis and processing of amplitude-frequency modulation signals. Both of EMD and LMD can decompose complex signal containing multiple components into several single-component signals with physical significance. But LMD does not have problems such as over envelope, under envelope and boundary effect, etc. Besides, LMD does not need to construct analytical signals and undergo Hilbert transformation to calculate instantaneous characteristics, but in the process of decomposing signals, corresponding instantaneous amplitude and instantaneous frequency are calculated, which makes LMD more efficient than EMD. However, in essence, the LMD suffers the same shortcomings (mode mixing, end effect, etc.) as the EMD does in decompose signals with close instantaneous frequencies cross on the time-frequency plane.

Recently, a new adaptive signal decomposition method, namely, the variational mode decomposition (VMD), was proposed by Dragomiretskiy and Zosso [11]. The VMD generalize the classic Wiener filter into multiple and adaptive bands, which can realize signal adaptive decomposition by finding the optimal solution of the constraint variational model. The center frequency and bandwidth of each IMF are updated continuously and alternately to realize the adaptive decomposition of the signal frequency band. VMD overcomes many deficiencies of EMD and LMD and greatly improves the accuracy of signal decomposition. The recent applications of the VMD method to analyze complex signals for feature extraction and fault diagnosis have been investigated in [28]–[32]. These applications testify that VMD is an effective signal processing method for complex vibration signals.

The information entropy is a measure of the disorder for a system and in this case it is an accurate measure of the complexity of the vibration signal (e.g., the amplitude, phase, frequency and energy distribution of the vibration signal changing with different fault types of HVCB). After the vibration signals from the HVCB under different fault types are decomposed by VMD, the IMF's HMS which is sensitive to the frequency spectrum and energy distribution is used to ascertain the changes in the vibration signals. Furthermore, if we define each scale feature as one information source, the IMF representing each scale feature can be regarded as a message from the information source. Therefore, the IMF's HMS energy entropy (HMSEE), called IMF-HMSEE, which is sufficiently sensitive to reflect the small changes in the vibration signal, is constructed from VMD, HMS and information entropy. Hence, in this paper, a novel method based on VMD and HMSEE, is presented to precisely extract the fault feature information of HVCB from its nonlinear and non-stationary vibration signal. The vibration signal of HVCB is firstly decomposed by the VMD to obtain a number of IMFs. Then, Hilbert transformation is performed for each IMF to obtain energy value of HMS. Finally, energy entropy of HMS, namely HMSEE, a dynamic characteristic vector reflecting the vibration signal, is obtained according to the information entropy theory.

The remainder of this paper is organized as follows. Section II introduces the implementation method of VMD and HMSEE. In section III, the experimental system for HVCB is provided. The performance of EMD, LMD, VMD, and the proposed VMD-HMS method are investigated and presented in detail in section IV. Two cases of vibration signal analysis using the proposed VMD-HMS method are conducted in section V. Section VI illustrates the application of HMSEE. Discussion and comparison are presented in section VII. Finally, conclusions and recommendations are given in section VIII.

II. THEORIES

A. VMD

The VMD decomposes the original signal $x(t)$ into K IMFs of finite bandwidth, which can be expressed as

$$u_k(t) = A_k(t)\cos(\varphi_k(t)) \tag{3}$$

where t is the time script, $u_k(t)$ is the kth IMF, $A_k(t)$ is the instantaneous amplitude, and $\varphi_k(t)$ is the instantaneous frequency.

Each IMF component $u_k(t)$ is concentrated at the center frequency ω_k, the bandwidth of each IMF can be estimated by the Gaussian smooth migration signal. The corresponding constrained variational model in the decomposition is as follows

$$\min_{\{u_k\}\{\omega_k\}} \left\{ \sum_k \left\| \partial_t[(\sigma(t) + \frac{j}{\pi t})u_k(t)]e^{-j\omega_k t} \right\|_2^2 \right\} \tag{4}$$

where ∂_t represents gradient with respect to t and $\sigma(t)$ is the Dirac function, the modes u_k subject to

$$\sum_k u_k(t) = x(t) \tag{5}$$

A quadratic penalty and Lagrangian multipliers are introduced to address the (4). The augmented Lagrangian is set using the following equation:

$$\begin{aligned} &L(\{u_k\}, \{\omega_k\}, \lambda) \\ &= \alpha \sum_k \left\| \partial_t[(\sigma(t) + \frac{j}{\pi t})u_k(t)]e^{-j\omega_k t} \right\|_2^2 \\ &\quad + \left\| x(t) - \sum_k u_k(t) \right\|_2^2 + \left\langle \lambda(t), x(t) - \sum_k u_k(t) \right\rangle \end{aligned} \tag{6}$$

where λ is the Lagrange multiplier, and α is the quadratic penalty factor to balance the data-fidelity constraint.

The saddle point of equation (6) is found using the alternate direction method of multipliers (ADMM). By iteratively updating u_k^{n+1}, ω_k^{n+1}, and λ in (7)-(9), the optimal solution of the equation (6) can be obtained.

$$u_k^{n+1}(\omega) \leftarrow \frac{x(\omega) - \sum\limits_{i=1, j<k}^{K} u_i^{n+1}(\omega) - \sum\limits_{i=1, j<k}^{K} u_i^{n}(\omega) + \frac{\lambda^n(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k^n)^2} \tag{7}$$

and

$$\omega_k^{n+1} \leftarrow \frac{\int_0^\infty \omega \left| u_k^{n+1}(\omega) \right|^2 d\omega}{\int_0^\infty \left| u_k^{n+1}(\omega) \right|^2 d\omega} \tag{8}$$

and

$$\lambda^{n+1}(\omega) \leftarrow \lambda^n(\omega) + \tau(x(t) - \sum_k u_k^{n+1}(\omega)) \tag{9}$$

The above iteration stop condition is:

$$\sum_k \frac{\left\| u_k^{n+1} - u_k^n \right\|_2^2}{\left\| u_k^n \right\|_2^2} < \varepsilon \tag{10}$$

B. HMSEE

Once the IMF components $u_k(t)$ are obtained by VMD, the HT can be applied to each individual IMF, which can be defined as follows:

$$\hat{u}_k(t) = \frac{1}{\pi} P \int_{-\infty}^{+\infty} \frac{u_k(\tau)}{t - \tau} d\tau \tag{11}$$

where P is the Cauchy principal value of the integral.

Construct an analytic signal $z_k(t)$:

$$\begin{aligned} z_k(t) &= u_k(t) + i\hat{u}_k(t) \\ &= A_k(t)e^{i\theta_k(t)} = A_k(t)e^{i\int \omega_k(t)dt} \end{aligned} \tag{12}$$

where $A_k(t)$, $\theta_k(t)$, and $\omega_k(t)$ are the kth IMF's instantaneous amplitude (namely, the envelope), instantaneous phase and instantaneous frequency, respectively, which can be determined by

$$A_k(t) = \sqrt{u_k^2(t) + \hat{u}_k^2(t)} \tag{13}$$

$$\theta_k(t) = \arctan \frac{\hat{u}_k(t)}{u_k(t)} \tag{14}$$

$$\omega_k(t) = \frac{d\theta_k(t)}{dt} \tag{15}$$

From (12) and (15), after HT, each IMF can be represented by

$$u_k = \mathrm{Re}\left[A_k(t)e^{i\int \omega_k(t)dt}\right] \tag{16}$$

and thus, the original signal $x(t)$ can be recovered as

$$x(t) = \mathrm{Re}\sum_{k=1}^{K} A_k(t)e^{i\int \omega_k(t)dt} \tag{17}$$

where K is the number of IMFs derived by VMD. The residual trend $r_k(t)$ is omitted since it is either a monotonic function or a constant.

Equation (17) gives a time-frequency distribution of the amplitude, which is called the Hilbert spectrum $H(\omega, t)$ showed as follows

$$H(\omega, t) = Re\sum_{k=1}^{K} A_k(t)e^{i\int \omega_k(t)dt} \tag{18}$$

The HMS is then obtained by integrating the Hilbert spectrum:

$$h(w) = \int_o^T H(\omega, t)dt \tag{19}$$

where T is the total length of the signal.

According to the Shannon information entropy, the energy entropy of HMS (HMSEE) for the IMF can be defined as:

$$H_k = -\sum_{k=1}^{K} (p_k \times \ln p_k) \tag{20}$$

where p_k denotes the energy ratio of the kth IMF, which can be computed as:

$$p_k = E_k / \sum_{k=1}^{K} E_k \tag{21}$$

where E_k is the energy of the kth IMF.

III. LABORATORY TESTING SYSTEM

A. DATA-ACQUISITION SYSTEM

Measurements reported in this paper were performed with a high-performance data-acquisition system. The main features of this system are: a high-voltage switchgear, HVCB (which is installed in the switchgear, the HVCB adopts spring operating mechanism (OM), rated voltage is 12 kV, rated current is 1250 A, and rated short circuit breaking current is 25 kA), power supply and vibration signal acquisition system (the system is composed of a high-sensitivity accelerometer to record vibration signals, a MDC4 (A/D converter resolution: 24 bits) to collect and preprocess the signals and an MHI or a computer to show and store the data). The vibration signal acquisition system triggered when the vibration amplitude of the breaker exceeds the preset threshold, the sampling rate is 100 kHz, and the collection time is 40 ms. The HVCB is operated by electric throughout the experiment. Fig. 1(a) shows the detail of the testing system.

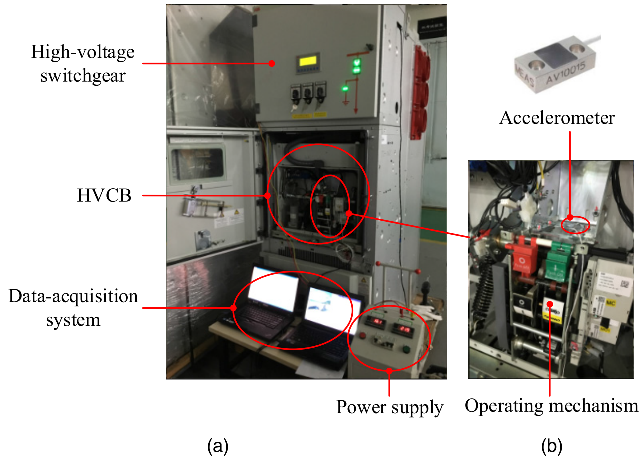

FIGURE 1. Test set-up in the laboratory for vibration data acquisition. (a) test platform and (b) placement of accelerometer.

B. ACCELEROMETER

For accurate vibration measurements on HVCBs, accelerometer performance should be selected based on the maximum vibration burst that can be expected for the breaker drive mechanism. The main parameters of the accelerometer used in this paper include: sensitivity of 0.5 mV/g; maximum range of 10000 g; frequency response of 0-50 kHz; resonant frequency of >90 kHz; and linearity of ±1%. The accelerometer is screwed [33] directly on the upper surface of the OM of HVCB to record the vibration signals, as shown in Fig. 1(b).

IV. PERFORMANCE INVESTIGATION OF EMD, LMD, VMD, AND THE PROPOSED VMD-HMS METHOD

In this section, the performances of EMD, LMD, VMD, and the proposed VMD-HMS method are studied by directly using the actual measured vibration signals (real-life signals). Fig. 2(a) shows a typical vibration waveform under normal opening operation, Fig. 2(b) shows its fast Fourier transform (FFT) spectrum. It can be observed that the vibration signal is very complex, it is composed of multiple nonlinear and non-stationary shock waves. The duration of the whole time domain is extremely short (less than 40 ms), and the frequency components are distributed over a wide range (from 0 kHz to about 30 kHz).

Using the EMD and LMD methods, we decompose the vibration signal (shown in Fig. 2(a)) into eleven IMF components and a trend, and three PF components, respectively. Since the mainly information and the energy of the vibration

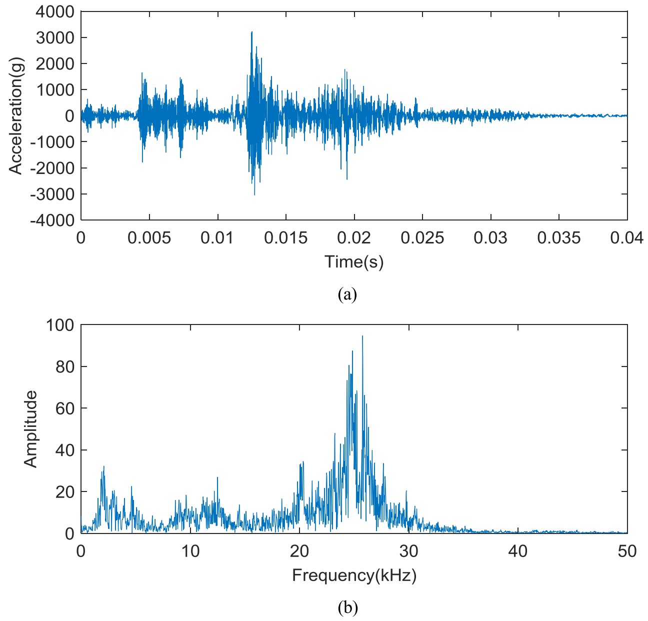

FIGURE 2. The wave of a vibration signal and its FFT spectrum under normal opening condition of HVCB. (a) time-domain waveform and (b) FFT spectrum.

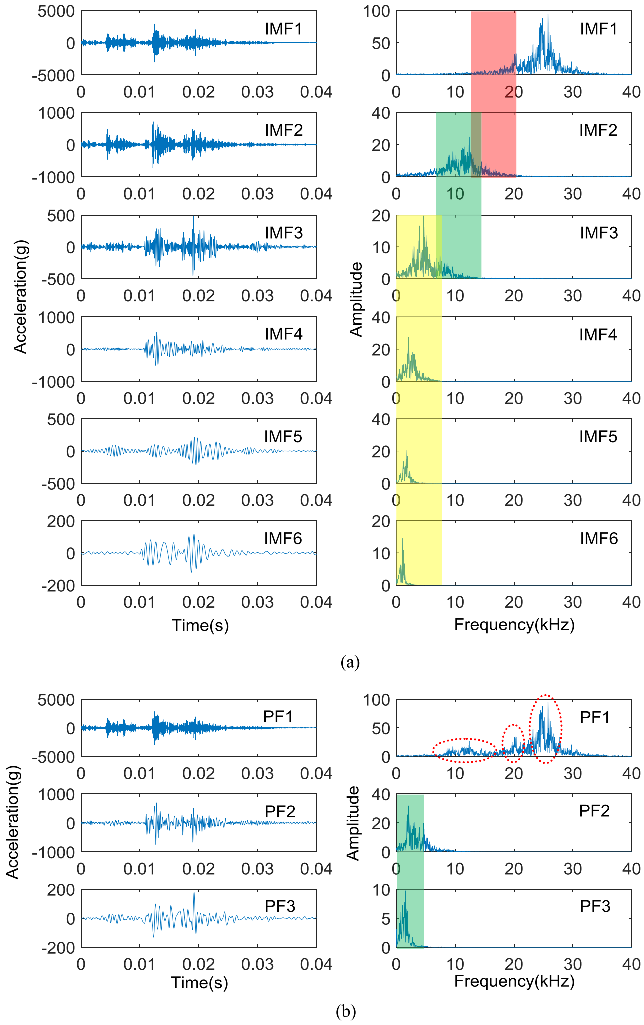

FIGURE 3. Decomposition results of the vibration signal in Fig. 2(a) by using: (a) EMD and (b) LMD.

signal processed by EMD are concentrated in the previous IMFs, hence, only the first six IMFs and their Fourier spectrum are listed in Fig. 3(a). It is evident from the figure that the mode mixing problem (also known as the frequency crossover problem) of EMD is particularly serious (denoted in colored boxes). In fact, none of the sub-modes has been decomposed successfully by EMD. Fig. 3 (b) shows the three PFs obtained from LMD. From the Fourier spectrum of the PFs, it can also be seen that LMD still exist the mode mixing phenomenon (denoted in colored boxes), and its decomposition of the original vibration signal is incomplete: there are multiple frequency components in PF1 (denoted in red color). Therefore, for the special vibration signal of HVCB, neither EMD nor LMD can effectively process it. Hence, EMD and LMD are not suitable for fault feature extraction of HVCB's nonlinear and non-stationary vibration signals.

As discussed earlier, VMD can non-recursively and concurrently decompose a complicated multi-component signal into AM-FM components adaptively. In essence, IMFs are defined as explicit AM-FM models, and they have a limited bandwidth. Fig. 4 illustrates the VMD analysis results of the vibration signal shown in Fig. 2(a). The number of IMFs and time-step are set to 6 and 1E-9, respectively. It can be clearly seen from the decomposition results that, the vibration signal is decomposed into an ensemble of IMFs that are band-limited to their respective center frequency: both frequency (energy) divergence and mode mixing phenomenon are slight. The VMD results are much better than EMD and LMD since it considers the spectral shape and takes the gravity center of spectrum as the center frequency of each IMF.

From the above comparative analysis, it can be known that EMD and LMD cannot correctly analysis the vibration signals of HVCB. VMD greatly improves the deficiencies of EMD and LMD, however, there are still existing slight mode mixing problem and the frequency aggregation is not very high, which will affect the effective extraction of fault features from HVCB's vibration signals. Therefore, in order to solve this problem, further, HT is performed for each IMF obtained by VMD to get HMS. Fig. 5(b) shows the VMD-HMS of the vibration signal (shown in Fig. 2(a)). The Fourier spectrums of the IMFs are also given in Fig. 5(a), for the convenience of comparison. As can be seen from Fig. 5, the HMS is better in frequency aggregation and has higher frequency resolution than Fourier spectrum, moreover, the effect of mode mixing is effectively reduced, thus making it more sensitive to subtle changes in vibration signals and more easily to distinguish fault feature frequencies for HVCB.

Fig. 6 summarizes the analysis results of the above methods (EMD, LMD, VMD and the proposed VMD-HMS method). As shown in Fig. 6(a), for the IMFs obtained using EMD, the frequencies of each band (IMF) overlap with each

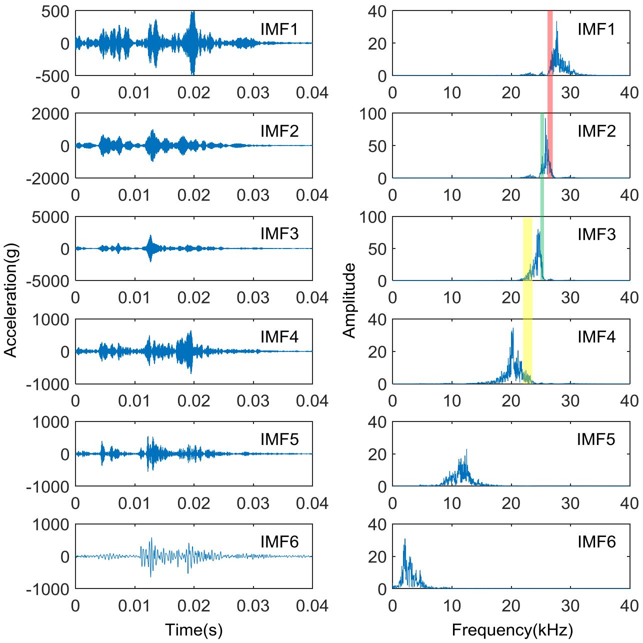

FIGURE 4. **VMD analysis results.**

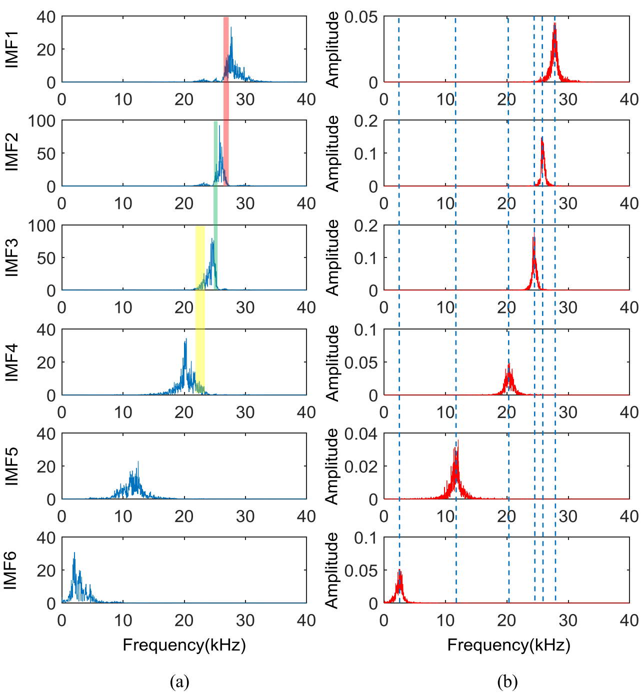

FIGURE 5. **Spectrums of IMFs derived by VMD. (a) Fourier spectrum and (b) HMS.**

other, and almost completely overlap at low frequencies, which cannot be distinguished. This problem is not solved with LMD method shown in Fig. 6(b). The behavior of all the IMFs in VMD, shown in Fig. 6(c), are greatly improved, only a fraction of their frequencies overlap, but as can be found, their frequencies are not concentrated enough. The method proposed in this paper overcomes all the above shortcomings, which is shown in Fig. 6(d), the frequency components of the vibration signal are successfully decomposed

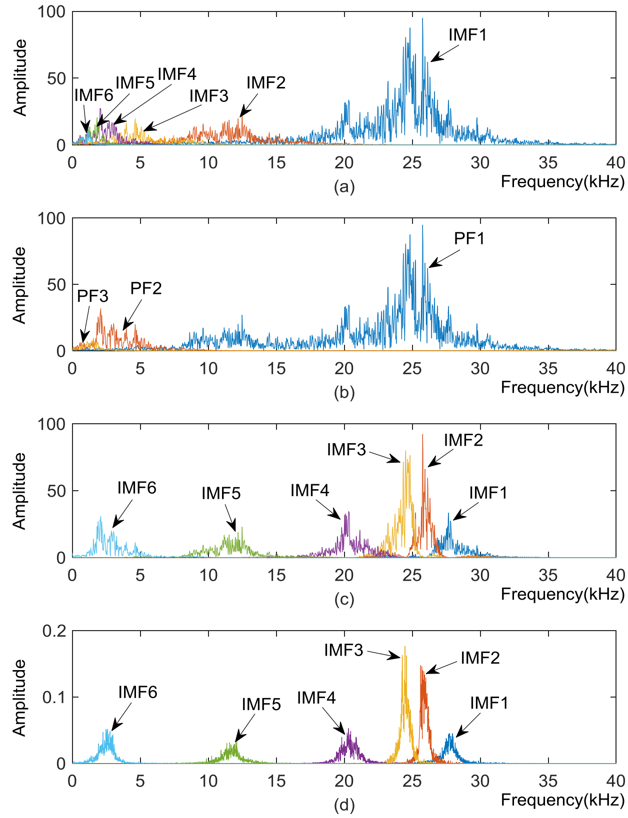

FIGURE 6. **Spectrums. (a) EMD Fourier spectrum; (b) LMD Fourier spectrum; (c) VMD Fourier spectrum; (d) VMD-HMS.**

into independent subcomponents, no frequency mixing (i.e., mode mixing), and at the same time, with high frequency concentration.

V. CASE VERIFICATIONS

A. CASE 1: OIL SHOCK ABSORBER FAILURE

The oil shock absorber [34] (shown in Fig. 7(a)) failure is one of the most common mechanical anomalies in HVCB. In the present case, the vibration signals were collected under the failure of oil shock absorber. Fig. 7(b) shows an example vibration signal during such a failure, for comparison, a normal vibration signal (the oil shock absorber works normally) is also depicted in Fig. 7(c).

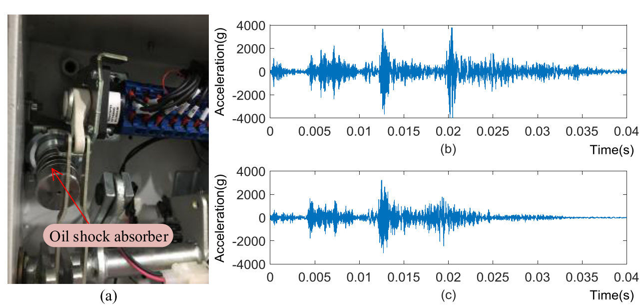

FIGURE 7. **Case 1. (a) Position of the oil shock absorber; and the waves of vibration signals under: (b) oil shock absorber failure and (c) normal condition.**

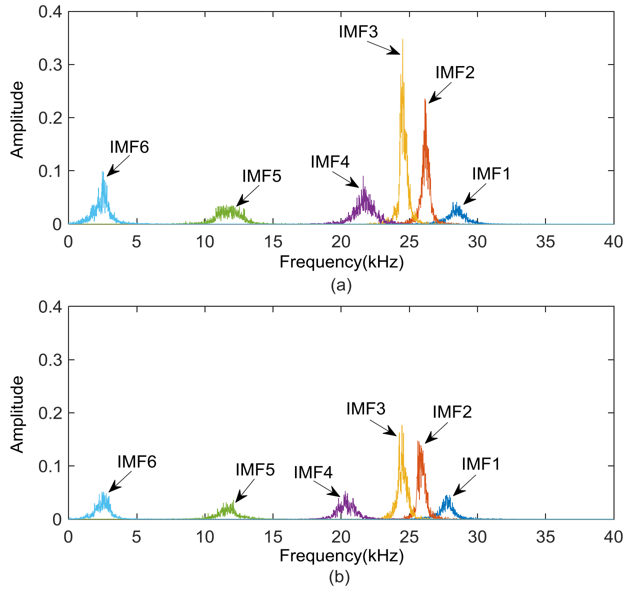

FIGURE 8. The analyzed results of the proposed VMD-HMS method for the vibration signals under: (a) oil shock absorber failure and (b) normal condition.

Fig. 8(a) shows the proposed VMD-HMS method analysis result of the vibration signal under oil shock absorber failure (Fig. 7(b)), here, the analysis result of the vibration signal under normal condition (Fig. 7(c)) is also illustrated in Fig. 8(b) for comparison. First of all, the raw vibration signal is processed by VMD (the modes number and time-step are set to 6 and 1E-9, respectively). Then, the HT is performed to obtain the IMF's Hilbert spectrum. Finally, the IMFs Hilbert spectrum are integrated to obtain the IMFs' HMS. It can be clearly seen from Fig. 8 that the vibration signals are successfully decomposed and transformed into frequencies with high resolution and without cross interference by the proposed VMD-HMS method: each frequency of the vibration signal is clearly separated without frequency mixing, and the energy concentration of each frequency is very high.

The oil shock absorber, which has the function of absorbing residual energy and reducing the impact of mechanical collision during HVCB operating. Thus, the failure of the oil shock absorber will cause the vibration of the HVCB increase to some extent. By comparing the processing results of the vibration signals under the failure of oil shock absorber (Fig. 8(a)) and normal condition (Fig. 8(b)), it can be found that, for the failure of oil shock absorber, the frequency value and frequency amplitude of all subcomponents increased, especially the first four high-frequency subcomponents, which is consistent with the increase of HVCB's vibration intensity caused by the failure of oil shock absorber. The results also indicate that a subtle alteration in the vibration signal can be clearly expressed in HMS, which demonstrates that the proposed VMD-HMS method is effective to analyze HVCB's vibration signal for fault feature extraction.

B. CASE 2: INSULATION PULL ROD ANOMALY

The insulation pull rod anomaly, which is another common mechanical anomalies occurred in HVCB. The insulation pull rod is a key component connecting the dynamic contact of arc interrupting chamber (high-voltage terminal) and the OM (ground terminal) of HVCB. It transmits the energy of the OM to the dynamic contact to perform closing and opening operation. The bolts that connecting the insulation pull rod and the main transmission linkage of the OM are subjected to various complicated forces and collisions, resulting in its frequent failures such as wear and fracture. The failure of the bolts will directly lead to abnormal motion of the insulation pull rod and seriously affect the stability performance of HVCB. Hence, in order to be able to effectively detect the motion anomaly of the insulation pull rod, here, in the present case, we simulate the insulation pull rod motion anomaly by adopting bolt (connecting the insulation pull rod and the main transmission linkage) smaller than the original size, which is shown in Fig. 9(a). The vibration signals under the insulation pull rod motion anomaly and normal condition are illustrated in Fig. 9(b) and (c), respectively.

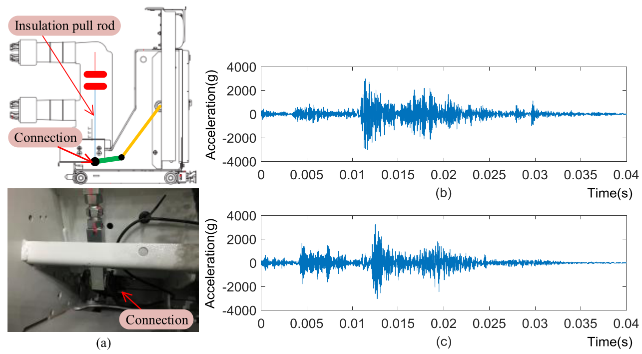

FIGURE 9. Case 2. (a) Connection position of the insulation pull rod with main transmission linkage; and the waves of vibration signals under: (b) insulation pull rod motion anomaly and (c) normal condition.

Fig. 10(a) and (b) shows the proposed VMD-HMS method analysis results of the vibration signals under the insulation pull rod motion anomaly and normal condition, respectively. From this figure, we may easily discover the changes of the IMFs' HMS due to the abnormal of insulation pull rod. It is worth noting that in the present case, the deviation of the last few low-frequency sub-components is also significant. The result of this case further demonstrate that the proposed VMD-HMS method is effective and suitable for detecting tiny variations in HVCB's vibration signal under different types of mechanical anomalies.

VI. APPLICATION OF HMSEE

When faults occur or HVCB works in abnormal state, not only the amplitude, phase and frequency of the vibration signal will change, but also the energy. That is to say, compared with those under normal state of HVCB, the vibration signals under abnormal states will have the phenomenon of amplitude, phase and frequency modulation, along with

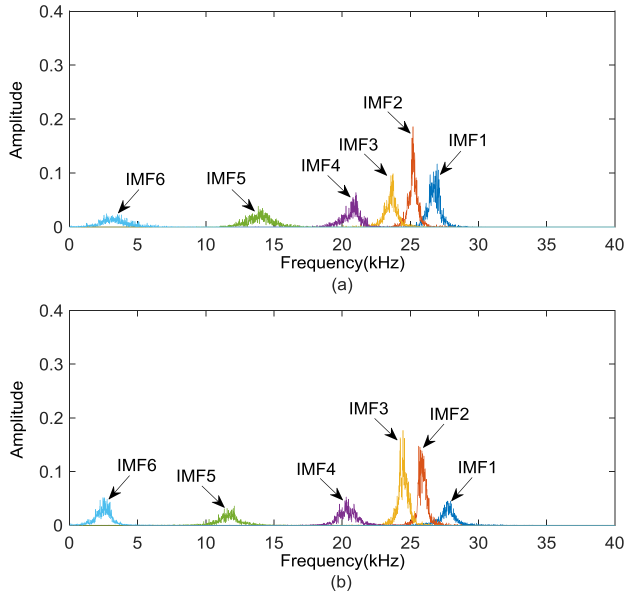

FIGURE 10. The analyzed results of the proposed VMD-HMS method for the vibration signals under: (a) insulation pull rod motion anomaly and (b) normal condition.

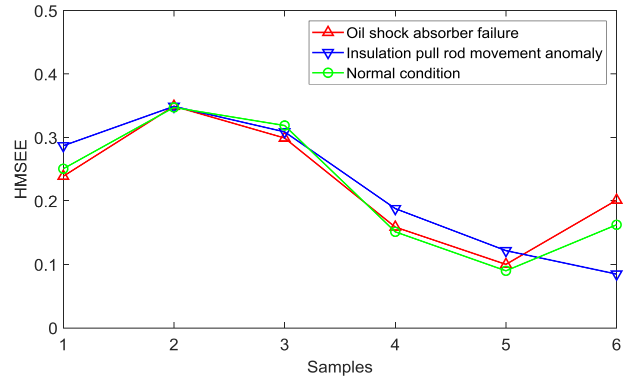

FIGURE 11. HMSEE of IMFs under three different conditions.

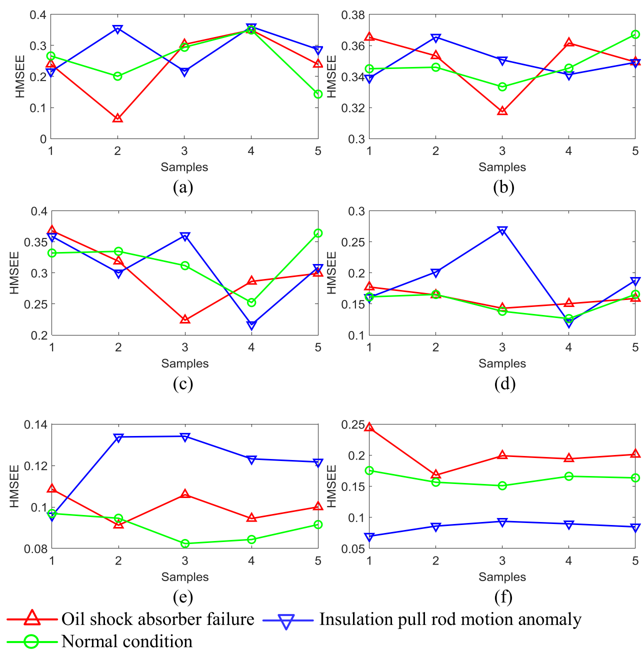

FIGURE 12. HMSEE of IMFs under three different conditions from five random samples. (a)-(f): IMF1-IMF6.

energy variation. Therefore, taking these factors into consideration, a local energy spectrum based on VMD, namely VMD-HMES (Hilbert marginal energy spectrum), is proposed here to describe the variation characteristics of the amplitude, phase, frequency and energy for the vibration signal.

In the VMD-HMES, the change of IMF's spectral line reflects the change of the fault type of HVCB, and the amplitude value of spectral line reflects the probability of the frequency feature appearing in the vibration signal. Therefore, the entire VMD-HMES can actually be regarded as a sequence of probabilities. As mentioned earlier, by referring to the definition of entropy in Information theory, the complexity of VMD-HMES can be judged intuitively by its HMSEE, which is called IMF-HMSEE in this paper. It should be noted that the IMF HMSEE must be approximately equal since the vibration signal under the same fault has similar VMD HMES, whereas for different faults' vibration signal, the IMF HMSEE will not approximately equal. Therefore, different fault types of HVCB can be classified by the IMF HMSEE.

Fig. 11 illustrates the obtained HMSEE of IMF1-IMF6 components. As can be seen, the three conditions (normal condition, oil shock absorber failure and insulation pull rod motion anomaly) can be significantly distinguished from IMF6's HMSEE, whereas the distinguishability of IMF1-IMF5 are not good in comparison with IMF6.

To make a further comparison, 5 samples with different mechanical anomalies are randomly selected from the vibration data set for VMD processing, and then IMF-HMSEE are calculated. The results of the IMF HMSEE of all samples are shown in Fig 12. It can be seen from the figure that, all the other IMFs' HMSEE show disordered and irregular phenomena except for the IMF6 which has a certain regularity in different samples: there is a clear distinction between the three types of mechanical anomalies. This suggests that the HMSEE of IMF6 appears to be useful for classifying the three types of mechanical anomalies in HVCB.

Actually, for most signals, the main information after VMD processing is contained in the first several components, that is, usually the fault characteristics should be in the first several components. However, in this paper, a series of processing results for the vibration signal of HVCB indicate that the sixth component (IMF6) is characterized by obvious separability for the HVCB's mechanical anomalies. The possible reasons and explanations for this phenomenon mainly fall into two points. The fundamental reason is that the vibration signal of HVCB is a special kind of complex signal with strong nonlinear and non-stationary, and its time duration is extremely short and frequency range is quite wide, causing that the fault characteristic information distributes over a wide frequency range. In addition, the main frequency component of HVCB's vibration signal is high frequency. However, the high-speed operation and strong collision of the mechanical system of HVCB make some mechanical abnormal signals submerged in the high frequency components, thus the performance and variation are more obvious in the low frequency components, which means the fault feature information of HVCB is mainly presented as low frequency component.

Nevertheless, the HMSEE of IMF6, which can be used to characterize the complexity of the IMF6's HMS in different scales, has been proved that its value is stable in the case of similar mechanical anomalies and has obvious difference in the case of different mechanical anomalies. Therefore, the HMSEE of IMF6 can be taken as a reference for judging the mechanical abnormal categories of the HVCB.

It is worth mentioning that there are many types of faults that can occur to circuit breakers, and different types of circuit breakers have different faults. Therefore, the feature extraction algorithm proposed in this paper is effective for the two types of typical faults (case 1 and case 2) of the breaker, while the effectiveness of other fault types and other types of circuit breakers needs to be further verified. To solve this problem, unique signatures or footprints under normal and some typical failure conditions for the individual breaker need to be pre-known before the approach is applied to practice.

VII. DISCUSSION AND COMPARISON

In order to better understand the method proposed in this paper, the relevant researches like using VMD, HMS and energy entropy for processing vibration signals of HVCB are investigated. So far, there are only 3 similar research literatures [35]–[37].

In literature [35], only VMD was used to decompose the vibration signal of circuit breaker, the key issues such as the validity and accuracy of the decomposition results of VMD were not discussed. In literature [36], particle swarm optimization algorithm was used to obtain the optimal VMD result based on the overall orthogonal coefficient, and then the spectrum of Hilbert transform of vibration signal was reasonably divided, so as to define the characteristic vector and similarity index of the vibration signal. Although there is no frequency overlap in the VMD results of the literature, the frequency clustering of each IMF is not as good as the method proposed in our study. In the literature, the fault type of HVCB is determined by calculating the similarity between the fault vibration signal and the normal vibration signal, ignoring the influence of the dispersion of vibration signal and noise on the similarity. In literature [37], VMD was used to decompose the vibration signal of HVCB firstly, then the sample entropies of all IMFs were calculated as the characteristic vector of different fault types. The literature did not make any improvement or optimization on the result of VMD. Instead, the sample entropy of VMD's result was directly calculated as a fault feature. However, it can be seen from the analysis results of our study and literature [36] that the vibration signal's VMD still has mode mixing and other problems. If left untreated for subsequent analysis, the final results obtained will have certain errors.

Based on the above comparative analysis, it is undeniable that the methods proposed in the literature [35]–[37] have certain effects, but also have some deficiencies. The method proposed in this paper can effectively eliminate the mode mixing and other defects of the VMD results, and the proposed IMF-HMSEE has a good distinction between different fault types of circuit breakers.

In this paper, firstly, the advantages and disadvantages of EMD, LMD and VMD methods in processing vibration signals of HVCB are compared, and then the VMD is improved (i.e., VMD-HMS). Finally, HMSEE is proposed based on the improved VMD method. Fig. 13 and Fig. 14 illustrate the results of EMD-HMSEE and LMD-HMSEE, respectively. As can be seen, none of these features are significantly distinguishable. The list of all the methods mentioned in this paper are summarized in Table 1.

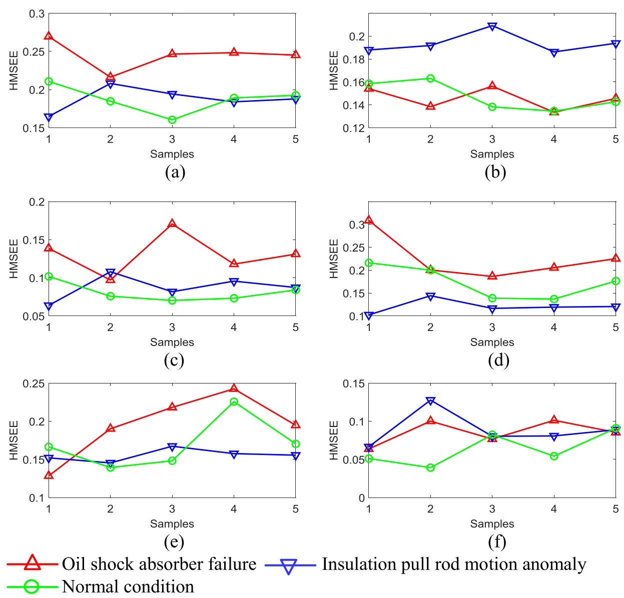

FIGURE 13. EMD-HMSEE under three different conditions from five random samples. (a)-(f): IMF1-IMF6.

TABLE 1. Performance contrast of decomposition methods and feature extraction results.

Decomposition method	Mode mixing	Frequency resolution	HMSEE feature extraction result
EMD	Yes	Low	None
LMD	Yes	Low	None
VMD	Yes	Middle	IMF6
VMD-HMS	No	High	IMF6

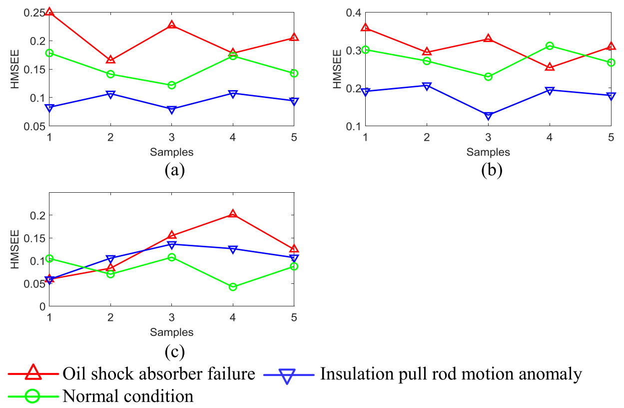

FIGURE 14. LMD-HMSEE under three different conditions from five random samples. (a)-(c): PF1-PF3.

VIII. CONCLUSION

In this paper, a novel vibration analysis approach for detecting mechanical anomalies of HVCB was presented and described. The vibration signal of HVCB is very special: the duration time is extremely short (tens of milliseconds), the frequency range is quite wide (up to 40 kHz), and it also has strong nonlinear and non-stationary characteristics. It is therefore very difficult to extract valuable information from such a complex vibration signal. The way to explore is to decompose it into several non-interference modes and look for possible patterns of changes. To explore an appropriate vibration signal decomposition method for extracting fault features used for classifying mechanical anomalies of HVCB, three existing adaptive signal analysis methods (EMD, LMD and VMD) and the proposed VMD-HMS method were compared and analyzed. Results indicate that EMD and LMD are not suitable for handling HVCB's complex vibration signal due to serious mode mixing phenomenon and poor frequency resolution. Although VMD has largely overcome the shortcomings of EMD and LMD, it still has slight mode mixing and frequency divergence. The proposed VMD-HMS method effectively reduce the effect of VMD mode mixing, and the HMS resolution (frequency concentration) of each IMF is higher than Fourier spectrum, which greatly improved the decomposition accuracy of HVCB's vibration signal. Experiment simulated two different types of mechanical anomalies for HVCB and the results show that the VMD-HMS is very sensitive to the slight changes of vibration signals under these two kinds of mechanical anomalies. The changes of VMD-HMS correspond to a specific mechanical anomaly in HVCB. In order to classify the mechanical anomalies accurately according to the changing characteristics of VMD-HMS, the IMF-based definition, HMSEE, was introduced as a changing sensitive feature. The experimental results demonstrated that the proposed VMD-HMS method described the fault frequency features in more distinguishable patterns than EMD, LMD and VMD, and the IMF-HMSEE shows a clear ability to detect mechanical anomalies for HVCB.

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