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A Feature Extraction Method Based on LMD and its Application for Fault Diagnosis of Reciprocating Compressor Annular Valve

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ABSTRACT

Taking the reciprocating compressor annular valve as the research object, the vibration signal of the reciprocating compressor ring valve was tested by the accelerometer vibration sensor. Through local mean decomposition (LMD), several *PF* (Product Function) components corresponding to the signal were obtained. Three characteristic parameter factors of these *PF* components are extracted, including the skewness coefficient (g_i), kurtosis coefficient (q_i) and total energy ratio (E_i/E). Then the valve is damaged to various degrees, including sawing the valve plate, removing some springs from the valve and drilling the valve plate. The same analysis on the operating vibration signal of the damaged valve plate was carried out to obtain the corresponding parameter factors, and compared with the corresponding parameter factors of the normal valve. The results show that under the circumstances of valve sawing and part spring removing, the valve vibration signal obtained by the corresponding characteristic parameter factor will reflect the abnormal value of the fault, but the valve disc perforated state is not obvious. The above shows that although the LMD method has some limitations, it can accurately and effectively evaluate the vibration signals of reciprocating compressor valves, and classify the working status and the fault type of the valve, so it is a practical method to study the diagnosis of valve failure.

1. INTRODUCTION

Reciprocating compressor is one of the most commonly used machines in the chemical production process of the oil and gas industry. With the increasing requirements of high performance and high security, the operational safety has become an important research topic [1-3]. Vibration-based measurement and analysis techniques have been proven to be very effective in mechanical health monitoring and fault diagnosis, because the vibration signals [4-6] can reflect a large amount of operating state information when the equipment is in operation, and can be successfully analyzed using some analysis methods. Vibration signals detects the faults in rotating machineries such as gearboxes and bearings under certain conditions [7-9]. However, because of the factors such as the gap, the nonlinear stiffness of the bearing, and the unbalanced and time-varying forces of the multi-component coupling components, the vibration signal of the reciprocating compressor has the characteristics of non-linearity and non-stationarity, using traditional analysis techniques, such as time domain statistics, Fourier transform may not be able to extract effective signal characteristics from the vibration signals of reciprocating compressor [10, 11].
Local mean decomposition (LMD) is a new adaptive time-frequency analysis method proposed by Smith [12]. It can adaptively decompose complex multi-component signals into multiple sets of PF components. It is the product of the envelope signal and the pure frequency-modulated signal and has real physical meaning. The time-frequency distribution result can be clearly and accurately reflected. The signal energy distributes at various spatial scales. Therefore, LMD is a suitable method to deal with non-stationary, nonlinear and multi-component problems, especially suitable for the coupled vibration signal of rotary reciprocating machinery. Recently, many scholars have studied the fault signal feature extraction method based on LMD. Wang et al. [13] proposed a demodulation method based on LMD, and extracted the characteristics of a gas turbine system to successfully identify its friction impact fault from the actual vibration signal. Tian et al. [14] used the LMD to diagnose bearing

and gear failures and achieved good results.
The valve is the most critical part in a reciprocating compressor because it has a crucial influence on the efficiency, power, displacement and reliability of the compressor. According to the statistics data, about 60% of failures of reciprocating compressors are caused by gas valves. Therefore, the research on fault diagnoses of gas valves is of practical significance. However, till now there is no perfect fault diagnosis method for the valve vibration signal. The LMD method was used by many scholars to study the rotor components of fluid machineries. In this paper, the LMD method is used to decompose and analyze the vibration signal of the valve of the reciprocating compressor, and the characteristic parameters reflecting the failure state of the valve are obtained so as to realize the fault diagnosis of the valve of the reciprocating compressor.

2. LMD METHOD THEORY

The LMD method is actually to decompose the signal into envelope signals and pure frequency modulation signals of different scales. By multiplying the envelope signal and the pure frequency modulation signal, one can obtain the *PF* component with instantaneous physical meaning, and then obtain the time-frequency distribution of the signal. For any signal $x(t)$, the *PF* component can be obtained as follows:
1) Determine all local extreme points n_i of the signal $x(t)$, including all local maximum and minimum points in the signal;
2) Calculate the mean value m_i and the estimated envelope value a_i of the two extreme points n_i and n_{i+1} from the obtained extreme points n_i. The calculation method is as Equation (1);

$$m_i = \frac{n_i + n_{i+1}}{2}, \quad a_i = \frac{|n_i - n_{i+1}|}{2} \tag{1}$$

3) Connect each adjacent local mean m_i with a straight line and obtain the local mean function $m_{11}(t)$ of the signal $x(t)$ by linear interpolation. Connect the envelope estimate a_i also with a straight line and envelope the estimation function with linear interpolation $a_{11}(t)$;
4) Separate the local mean function $m_{11}(t)$ from the original signal to obtain the stripping function $h_{11}(t)$, as Equation (2);

$$h_{11}(t) = x(t) - m_{11}(t) \tag{2}$$

5) The stripping function $h_{11}(t)$ is demodulated by the envelope estimation function $a_{11}(t)$ to obtain the frequency-modulated signal $s_{11}(t)$. The calculation formula is shown as Equation (3);

$$s_{11}(t) = h_{11}(t) / a_{11}(t) \tag{3}$$

6) Determine if $s_{11}(t)$ is a pure FM signal. The judgement method is to consider $s_{11}(t)$ as the original signal, and then calculate the envelope estimation function $a_{12}(t)$ of $s_{11}(t)$ according to the steps 1) to 3) above. It is determined whether $a_{12}(t)=1$ is satisfied. If the condition is not satisfied, the above steps 1) to 5) are repeated as the original signal with $s_{11}(t)$ until the pure frequency modulation signal $s_{1n}(t)$ is obtained. The iterative termination condition of the loop is shown as Equation (4);

$$\lim_{n\to\infty} a_{1n}(t) = 1 \tag{4}$$

In practical applications, in order to reduce the number of iterations and reduce the operation time, a variable Δ may be set. Δ may be selected according to the calculated accuracy requirement, and is generally selected between 10^{-5} and 10^{-9}. When the condition $1-\Delta \leqslant a_{1n}(t) \leqslant 1+\Delta$ is satisfied, the above iterative process terminates;
7) Multiply all the envelope estimation functions produced during the iteration to obtain the envelope signal $a_1(t)$ (also called the instantaneous amplitude function), as Equation (5);

$$a_1(t) = a_{11}(t)a_{12}(t)\cdots a_{1n}(t) = \prod_{i=1}^{n} a_{1i}(t) \tag{5}$$

8) Multiply the envelope signal $a_1(t)$ and the resulting pure frequency-modulated signal $s_{1n}(t)$ to obtain the *PF* component $PF_1(t)$, as Equation (6);

$$PF_1(t) = a_1(t)s_{1n}(t) \tag{6}$$

$PF_1(t)$ is called the first *PF* component of signal $x(t)$ and contains the highest frequency component of the original signal, which is a single-component AM-FM signal;
9) The first *PF* component $PF_1(t)$ is separated from the original signal $x(t)$ to obtain the remaining signal $u_1(t)$, as Equation (7);

$$u_1(t) = x(t) - PF_1(t) \tag{7}$$

10) Since the remaining signal $u_1(t)$ also contains more frequency components, $u_1(t)$ is then repeated as

the original data in steps 1) to 8) to decompose it to obtain the second *PF* component $PF_2(t)$ and the second remaining signal $u_2(t)$. Then repeat this process with $u_2(t)$ as the original signal until $u_k(t)$ is a monotonic function, so that a certain amount of *PF* components can be obtained. The final signal $x(t)$ can be expressed as the sum of the k *PF* components and the margin $u_k(t)$, as Equation

$$x(t)=\sum_{i=1}^{k} PF_i(t)+u_k(t) \tag{8}$$

It shows that this method does not cause the original signal to be lost, $u_k(t)$ is a residual function, which represents the average trend of the signal.

11) After obtaining the *PF* components of the original signal decomposition, characteristic parameters of each *PF* component $PF_i(t)$ are extracted, the *PF* component skewness coefficient g_i, the kurtosis coefficient q_i, and the total energy ratio E_i/E are obtained, and the skewness coefficient g_i is normalized. The third-order center moment is calculated and the kurtosis coefficient q_i is calculated using the normalized fourth-order center moment. The total energy ratio E_i/E is obtained by performing the full-wave integral of the square values of the *PF* components. The specific formula is as Equation (9) to Equation (11).

$$g_i=\frac{1}{N}\sum_{k=1}^{N}\left[\frac{x_k-u}{\sigma}\right]^3=\frac{E\left[x-u\right]^3}{\sigma^3} \tag{9}$$

$$q_i=\frac{1}{N}\sum_{k=1}^{N}\left[\frac{x_k-u}{\sigma}\right]^4=\frac{E\left[x-u\right]^4}{\sigma^4} \tag{10}$$

$$E_i/E=\frac{\int_{-\infty}^{+\infty}\left|PF_i(t)\right|^2 \mathrm{d}t}{\int_{-\infty}^{+\infty}\left|x(t)\right|^2 \mathrm{d}t} \tag{11}$$

Where N denotes the total number of signal points in the *PF* component, u denotes the average of the *PF* component signals, σ denotes the standard deviation of each *PF* component signal, and operator $E[x]$ denotes the averaging operation for x.

The skewness coefficient is a characteristic number that describes the degree of deviation from the symmetry of the distribution. When the distribution is symmetrical, the coefficient of skewness is zero. When the skewness coefficient is greater than 0, ie, the heavy tail is on the right side, the distribution is right-biased. When the skewness coefficient is less than 0, that is, when the heavy tail is on the left, the distribution is left-biased; the kurtosis index reflects the statistical value of the random variable distribution characteristics and is a dimensionless parameter because it has nothing to do with bearing speed, size, load, etc. It is particularly sensitive to impact signals and is particularly suitable for the diagnosis of surface-damage faults, especially early failures. The energy ratio is an optimal design method. Can be used as one of the criteria for function optimization. The ratio of the main lobe energy to the total spectral energy under the condition of the width of the main lobe of the given frequency spectrum is called the energy ratio of the function. Through the analysis of the above three kinds of characteristic parameters, the judgment of the *PF* component is more specific, and the effective characteristic parameters corresponding to different faults can be more clearly and intuitively judged, which is more accurate than the existing method that only uses the correlation coefficient as the determination index. higher.

Through the above analysis methods, comparing the characteristic parameters of the normal state and different fault states, the corresponding characteristic parameters reflecting different faults are obtained, and the fault diagnosis of the annular gas valve of the reciprocating compressor is realized.

The beneficial effects of this method are:

1) The method can use linear interpolation mean decomposition method to analyze the valve vibration signal with nonlinear and non-stationary characteristics. At present, there is no perfect universal fault diagnosis method for the valve vibration signal. Scholars use similar methods to study the rotating parts of fluid machinery.

2) This method extracts the characteristic parameters from the *PF* component that is decomposed from the valve vibration signal, which serves as a basis for fault diagnosis and warning of the valve. At present, there is no intuitive and reasonable trade-off parameter for fault diagnosis and warning of gas valve in the project.

3. LMD ANALYSIS OF VIBRATION SIGNAL OF RECIPROCATING COMPRESSOR VALVE

3.1 Reciprocating compressor and its valve vibration signal

In order to study the fault diagnosis method of the reciprocating compressor, a reciprocating compressor fault diagnosis experiment platform is established in the State Key Laboratory of Compressor Technology of Hefei General Machinery Research Institute. The reciprocating compressor studied in this experiment is shown in the Figure 1. The reciprocating compressor is a DW-8/10 two-stage air compressor manufactured by Sichuan Venus Compressor Co., Ltd. with a volumetric flow of 8 m^3, an air supply of 480 Nm^3/h, and an exhaust pressure of 1.0 Mpa.

Figure 1: Reciprocating compressor fault diagnosis platform

The gas valve used in this compressor is a three-ring annular gas valve, which mainly consists of valve cover, valve seat, valve plate and spring. The valve plate is divided into the outer ring, middle ring and inner ring, as shown in Figure 2.

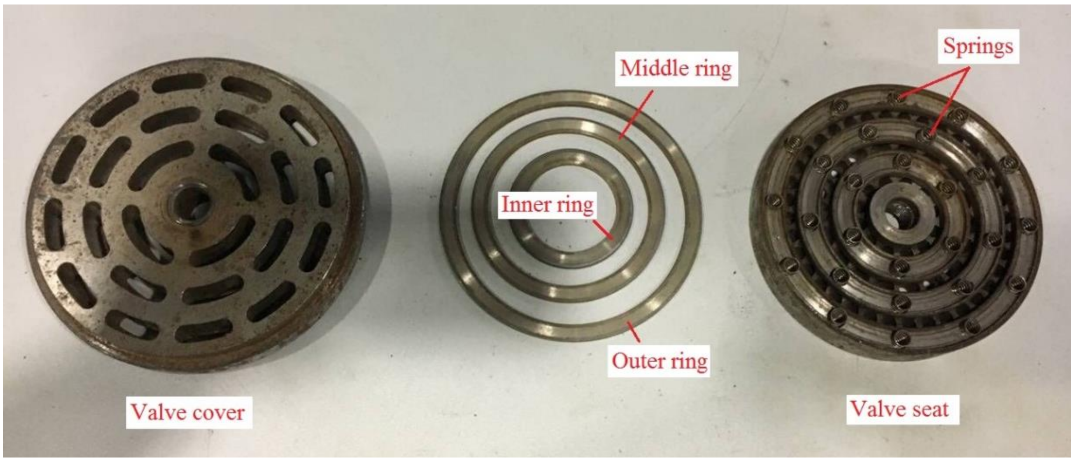

Figure 2: Reciprocating compressor circular air valve structure

The experimental study of the gas valve is a two-stage exhaust gas valve, and its vibration signal is collected by the PCB EXM 608A11 and the NI 9234 board. The *P-θ* diagram of the secondary cylinder of the compressor and the vibration acceleration signal of the valve cap of the valve are shown in Figure 3 .

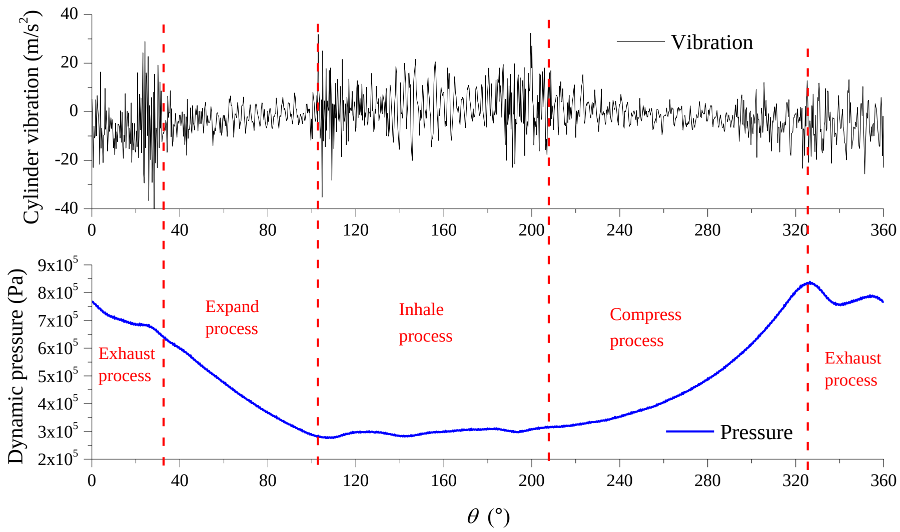

Figure 3: *P-θ* diagram of cylinder pressure and vibration signal of exhaust valve in normal operation

It is shown in Figure 3 that the vibration signal of the exhaust valve reflects the operating status of the compressor intuitively, and the operating status of the compressor in different processes can be visually seen from the vibration signal.

3.2 Valve vibration signal in different failure states

To discover the difference between the vibration signals of the valve under different faults, and to simulate different fault signal classifications, including: a) valve fracture; b) valve spring failure; c) valve leakage, we did all these different damages on exhaust valves respectively. The valve plate has been damaged to various degrees. The failure mode corresponds to the type of failure, including: a) sawing off the valve plate; b) removing part of the spring; c) machining open holes on the valve plate. Among them, a) The effect chart after the saw blade is broken, as shown in the Figure 4(a), the three rings are sawed at the same time to obtain better vibration analysis data. For b), the 1/3 spring in the valve is removed. For c) Four holes were drilled on the inner ring valve of the valve, as shown in the Figure 4(b), to simulate the effect of valve leakage. The comparison of the vibration signals of the valve under the three different faults is shown in the Figure 5.

(a) three rings fracture

(b) inner ring leakage

Figure 4: Different types of valve fault simulation

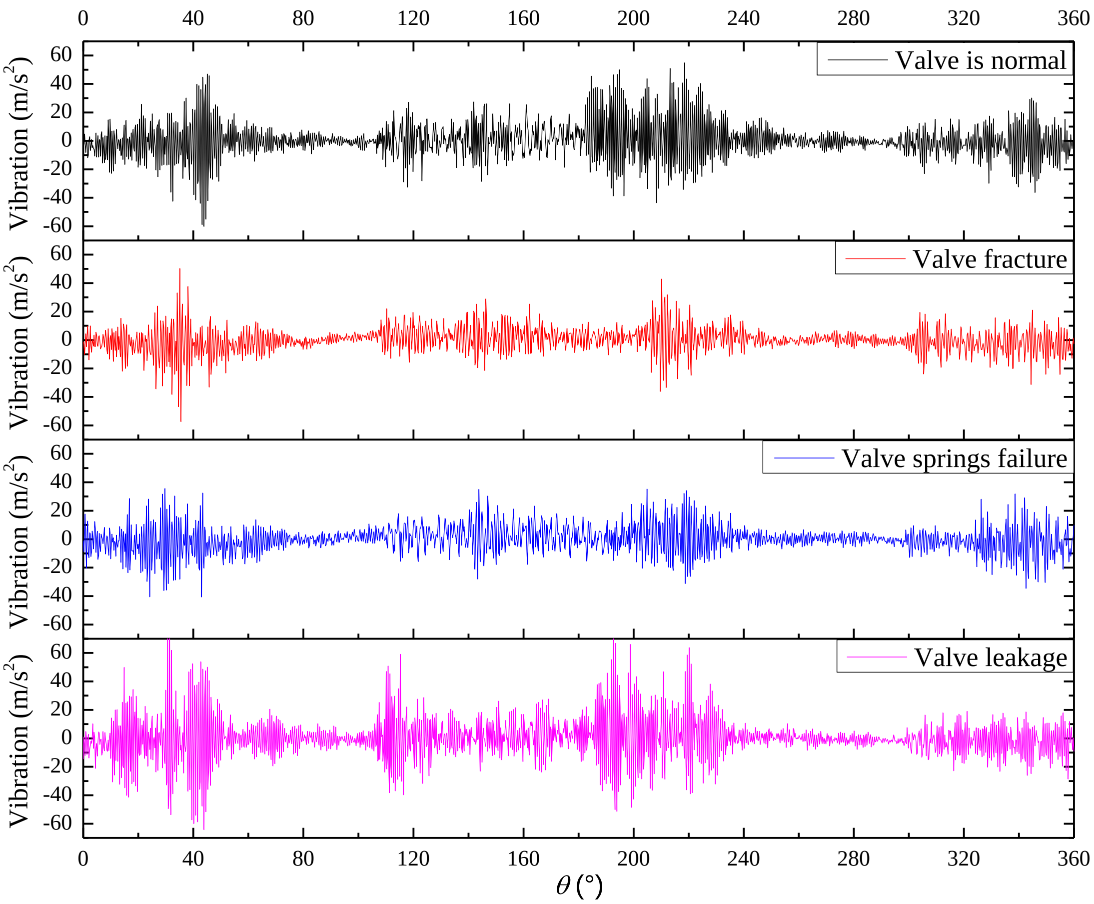

Figure 5: Different valve fault vibration signals

Although we can see some differences in the vibration signal from Figure 5, it is difficult to directly distinguish the characteristics of each group of signal, and it is also hard to identify the fault type directly through the fault vibration signal, so we need to use the LMD method to analyze different fault signals, by decomposition to find out the characteristic parameter values corresponding to different faults.

3.3 Feature parameter extraction of different fault signals by LMD method

In order to obtain more characteristic parameter values, we performed three experiments on the normal operating mode of the compressor and each group of failure modes. The LMD method was performed on all measured valve vibration data in one cycle. Each group of vibration data for four PF components are obtained, as shown in the Figure 6 to Figure 9 (Only one LMD method figure is shown in the same normal or failure mode).

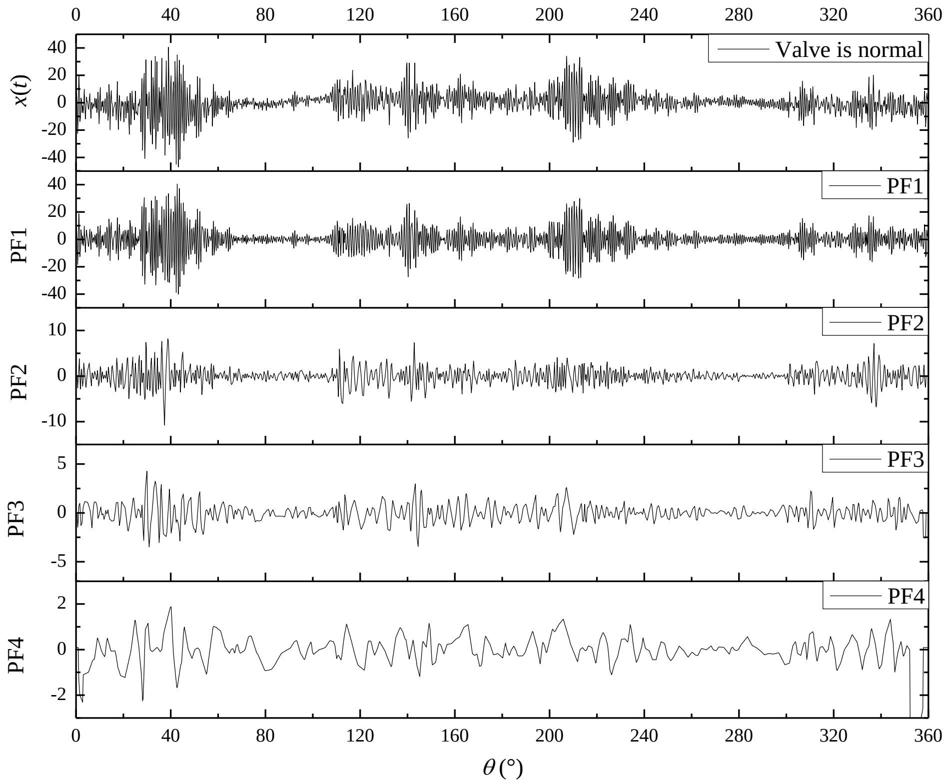

Figure 6: Decomposition of valve normal vibration signal by LMD method

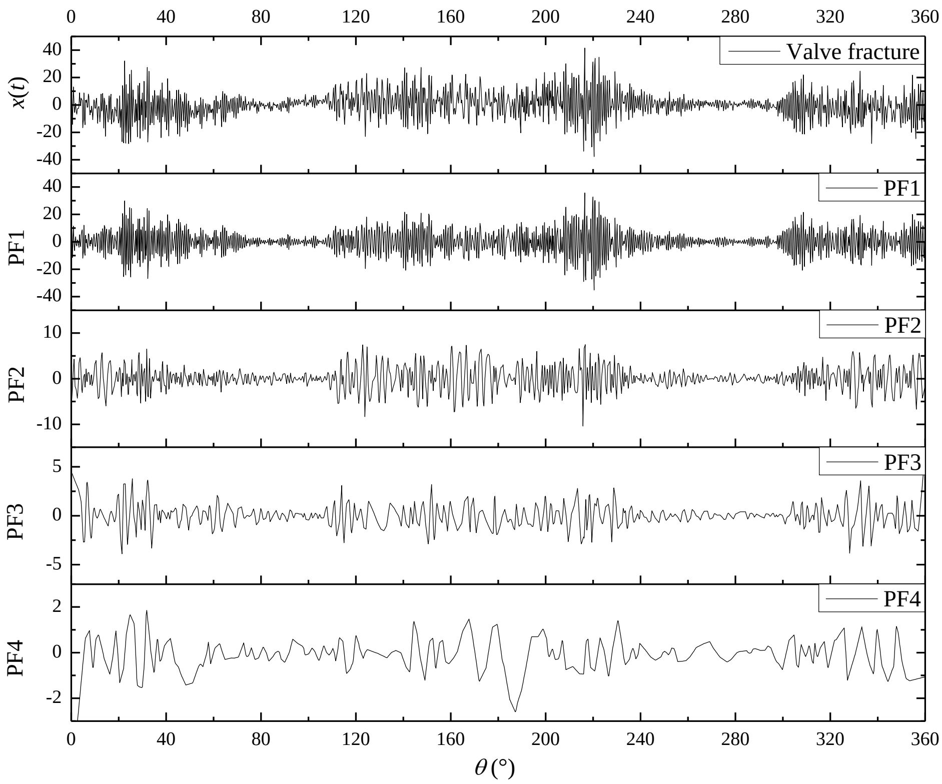

Figure 7: Decomposition of valve fracture vibration signal by LMD method

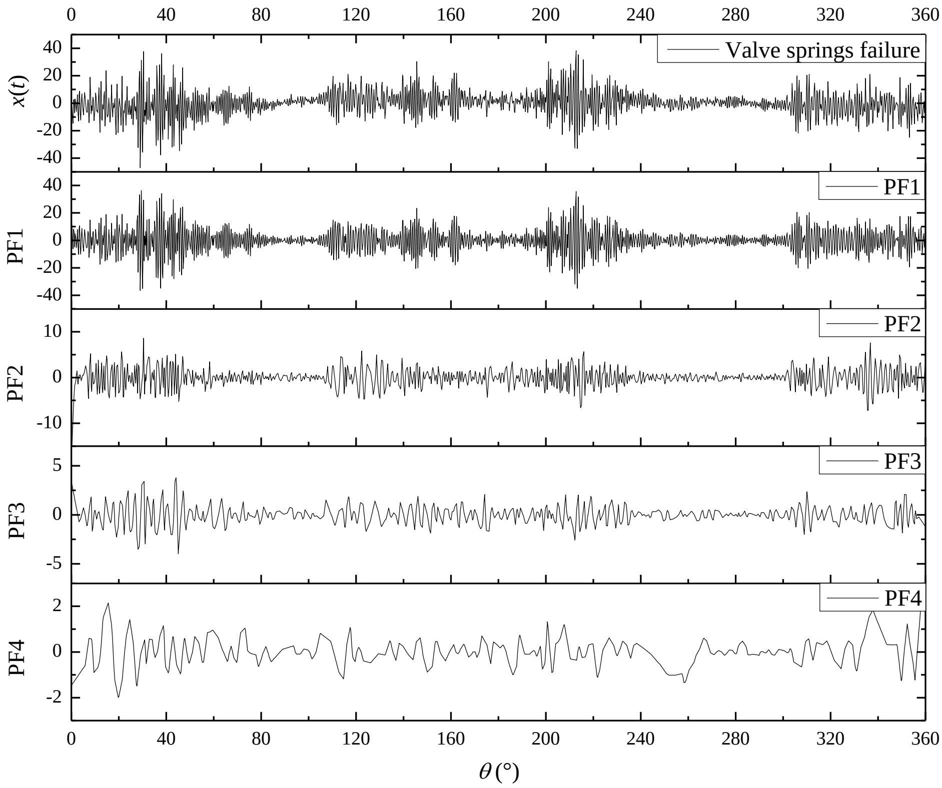

Figure 8: Decomposition of valve springs failure vibration signal by LMD method

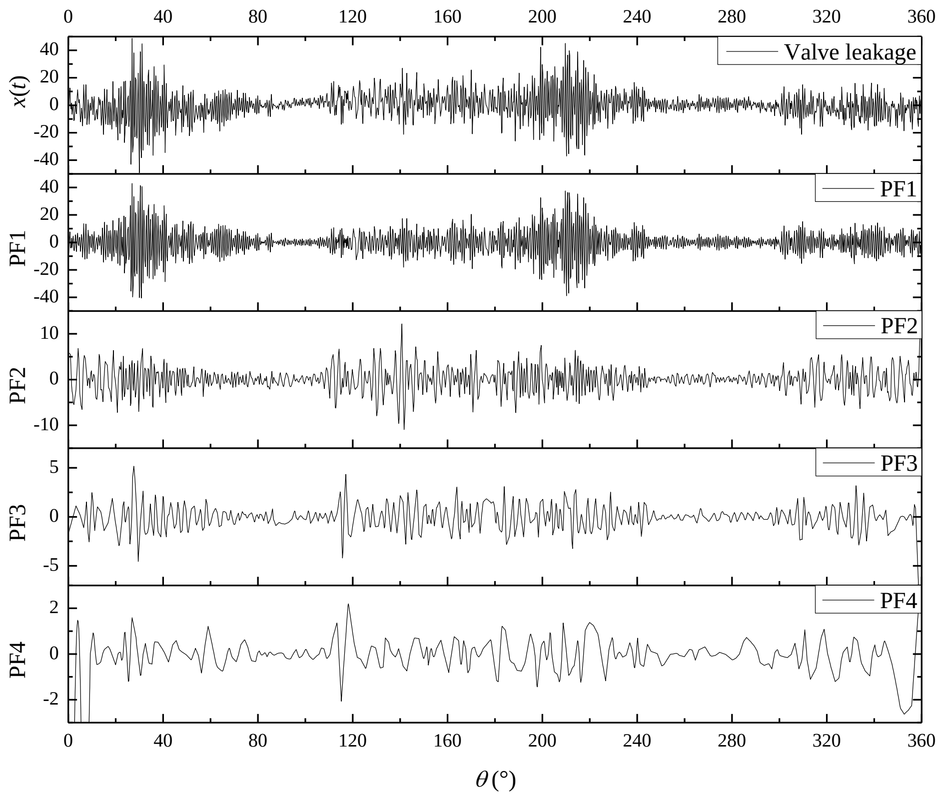

Figure 9: Decomposition of valve leakage vibration signal by LMD method

After obtaining the vibration data of *PF* components, we calculated the characteristic parameter values of all *PF* components in each fault state, including the skewness coefficient g_i, the kurtosis coefficient q_i, and the total energy ratio E_i/E. By the calculation method, described in Equation (9) to Equation (11), all calculation results are summarized in Table 1, and each figure in the calculation result retains 5 effective numbers.

Table 1: Characteristic parameter values of all *PF* components in each normal and fault state

	valve is normal	**valve is normal**	**valve is normal**	**valve fracture**	**valve fracture**	**valve fracture**
g_1	0.0122	0.0415	-0.0427	-0.1209	-0.0053	-0.0078
g_2	0.2184	-0.9808	-0.0538	-0.0923	-0.2816	-0.1478
g_3	-0.8368	0.1880	0.0535	0.3555	-0.0502	0.1412
g_4	-0.0712	0.9755	-1.8392	-1.0685	-0.3517	-0.9173
q_1	3.8665	2.3252	3.6788	2.1019	1.4087	1.8317
q_2	2.6889	8.7673	3.7378	1.7736	1.5793	1.7006
q_3	17.101	2.3736	2.1511	2.6448	4.6720	2.9811
q_4	1.1366	5.5864	8.1470	3.8599	1.9925	3.4101
E_1/E	0.8765	0.8856	0.8758	***0.4532***	***0.4697***	***0.4599***
E_2/E	0.0460	0.0460	0.0369	***0.1659***	***0.1293***	***0.1474***
E_3/E	0.0085	0.0091	0.0091	0.0277	0.0452	0.0354
E_4/E	0.0022	0.0050	0.0058	0.0206	0.0127	0.0178
	valve springs failure	**valve springs failure**	**valve springs failure**	**valve leakage**	**valve leakage**	**valve leakage**
g_1	0.0290	-0.0020	0.0546	0.0345	0.0545	0.0427
g_2	0.1752	0.7818	-0.0179	0.5224	-0.7785	0.3856
g_3	***-5.1740***	***-3.1199***	***-7.6801***	0.3677	-0.2678	0.1258
g_4	***5.6622***	***-11.409***	***-8.8161***	0.8820	-0.7455	-0.6589
q_1	3.3598	3.3736	1.3960	3.0512	2.7824	2.9586
q_2	10.466	7.3383	1.1058	5.2723	7.1474	6.3358
q_3	***37.964***	***31.567***	***33.156***	8.3297	3.1468	7.3654
q_4	***39.912***	***165.24***	***29.517***	6.3158	3.3245	4.0024
E_1/E	0.9125	0.8452	0.8280	0.8728	0.8827	0.8801
E_2/E	***0.0781***	***0.0649***	***0.0757***	0.0485	0.0378	0.0417
E_3/E	***0.0526***	***0.0169***	***0.0447***	0.0088	0.0107	0.0101
E_4/E	***0.0383***	***0.0398***	***0.0074***	0.0068	0.0065	0.0066

From Table 1, it can be seen that compared with the characteristic parameters of the *PF* component extracted by the LMD decomposition of the normal signal, there are obvious differences in several parameters of the sawing-off signal characteristics, mainly focusing on the characteristics of the high-order decomposition *PF*3 and *PF*4. In the parameters, these characteristic parameters are generally much higher than those of the normal signal. Therefore, among the *PF* components obtained after the valve vibration signal is decomposed, *PF*3 and *PF*4 can be used as important discriminating indexes for whether the valve is broken or not. As a means of fault identification and diagnosis. The E_1/E characteristic parameter extracted from the vibration signal of some valve springs are significantly lower than that of the normal signal, while the E_2/E values are much higher. These two criteria can be used in the valve spring failure identification and diagnosis method. However, for the valve opening vibration signal, it is difficult to find the characteristic parameters that are particularly different from each other. This shows that in the case of valve opening, although the valve leaks, the vibration signal does not change too much, which is a very reasonable phenomenon in this failure mode. The observation of the reciprocating compressor intake and exhaust pressure, PV diagram and valve cover temperature rise and other parameters should identify the fault more effective and reasonable.

4. Conclusion

This paper presents a vibration signal feature extraction method based on the LMD method, which is applied to the fault diagnosis of the reciprocating compressor valve.
1) In the proposed method, the LMD is used to decompose the signal into four groups of *PF*

components, and the terms of the skewness coefficient g_i, the kurtosis coefficient q_i, and the total energy ratio E_i/E are used as the basis for extracting the characteristic parameters of the *PF* component.
2) Among the characteristic parameters of the extracted *PF* components, the characteristic parameters of *PF*3 and *PF*4 can be used as the diagnosis indexes for the rupture of the valve disc, and E_1/E and E_2/E can be used as the diagnosis indexs for the failure of the valve spring.
3) This method is suitable for the fault diagnosis, and is sensitive to the vibration signal of the reciprocating compressor. If the influence of the valve vibration caused by the fault is not significant, the fault cannot be identified. Therefore, this method still has a certain limitation for the fault diagnosis of the valve.

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