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Health status assessment of axial piston pump under variable speed①

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Abstract

The axial piston pump usually works under variable speed conditions. It is important to evaluate the health status of the axial piston pump under the variable speed condition. Aiming at the characteristic signals obtained under different wear levels of the port plate, a feature signal extraction method under variable speed conditions is proposed. Firstly, the combination of complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) energy spectrum and fast spectral kurtosis principle is used to accurately extract the intrinsic mode function (IMF) component containing the sensitive information of the degraded feature. Then, the aspect ratio analysis method of the angle domain variational mode decomposition (VMD) is used to process the feature index containing the sensitive information of the degraded feature. In order to evaluate the health status of the axial piston pump under variable speed, the vibration reliability analysis method for axial piston pump based on Weibull proportional failure rate model is proposed. The experimental results show that the proposed method can accurately evaluate the health status of the axial piston pump.

Key words: axial piston pump, variable speed condition, order ratio variational mode decomposition (VMD) in angle domain, health status assessment

0 Introduction

The axial piston pump is suitable for high pressure, large flow, high power and flow regulation needs, and has been widely used in modern industry. The port plate is one of the most critical friction sub-assemblies of the axial piston pump. It must not only function as a port but also support the cylinder to maintain the force balance of the cylinder[1]. The health of the port plate can have a major impact on the life of the plunger pump and the reliability of the entire hydraulic system. Therefore, it is very important to evaluate the reliability of the axial piston pump port plate.

The prognostic and health management (PHM) technology has become a hot topic in research, and there is also some research progress in the field of hydraulic power components. Tian et al.[2] established a prediction model combining wavelet packet decomposition and support vector machine (SVM), and effective fault prediction for axial piston pump. Lin et al.[3] proposed a piston pump fault prediction method based on fuzzy comprehensive evaluation and analytic hierarchy process for the problem that the axial piston pump fault was difficult to predict accurately. Li et al.[4] carried out time domain analysis and wavelet packet analysis of the vibration signal of the axial piston pump, extracted the characteristic parameters used for fault prediction, and established the fault prediction model. Du et al.[5] proposed a fault diagnosis method for the vibration signal of axial piston pump, and verified the effectiveness and accuracy of the method. Tang et al.[6] fused the vibration signal and the pressure signal to obtain a more accurate fault diagnosis method than using a single signal. Kou et al.[7] proposed a fault diagnosis method based on cosine neighboring co-

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efficients (CNC) noise reduction and ensemble empirical mode decomposition (EMMD) for the vibration signal of axial piston pump casing. Jiang et al.[8,9] proposed an evaluation method based on kurtosis, power and standard deviation to diagnose the fault of the axial piston pump. Aiming at the difficulty in extracting fault signature signals under variable speed conditions, a diagnostic method based on order tracking technology was proposed. He et al.[10] used the time-varying state transition hidden semi-Markov model to predict the remaining service life of the axial piston pump.

In recent years, modal decomposition technology has been applied in many fields. Tang et al.[11] used the variational mode decomposition (VMD) method to process the bearing fault data and extracted the characteristic frequency to make the result more accurate. Xie et al.[12] adaptively decomposed the rolling bearing by complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) method, obtained fault feature information, and introduced SVM classification algorithm to realize intelligent diagnosis. Ren et al.[13] combined the CEEMDAN algorithm with the Teager energy operator, and the accuracy of the calculation results was improved compared with the EEMD algorithm.

Axial piston pumps are often in a variable speed condition. It is very important to find an effective vibration signal analysis method under this condition. Aiming at the difficulty of selecting the intrinsic mode function (IMF) component of the vibration signal degradation characteristic sensitivity information, a method based on CEEMDAN fast spectrum kurtosis diagram and energy spectrum is proposed. Aiming at the VMD method which is not suitable for dealing with large-scale fluctuation of the rotational speed, the method of extracting the degraded feature of the angular domain signal by VMD is proposed, and the characteristic index containing the sensitive information of the degraded feature is accurately extracted. The hydraulic pump with Weibull port as the reference port actively monitors the proportional failure rate model, which provides a new idea for the evaluation of the health status of the axial piston pump.

1 Algorithm introduction and theoretical analysis

1.1 Order ratio analysis method based on angle domain

The order ratio analysis is an effective method to analyze the rotating mechanical signals under variable speed conditions. The key of the order ratio analysis is to find out the relationship between the original vibration signal and the speed signal, realize the equal angle sampling, eliminate the influence of the speed, and convert the unsteady signal in the time domain into the angular stationary signal.

The essence of VMD is the process of solving the variational problem[14], and the VMD algorithm is as follows.

(1) First, initialize $\{\hat{u}_k^1\}$, $\{\omega_k^1\}$, $\{\hat{\lambda}_k^1\}$ and n;

(2) According to $\hat{u}_k^{n+1}$ and ω_k^{n+1} update u_k and ω_k;

$$\hat{u}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i\neq k}\hat{u}_i(\omega) + \dfrac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k)^2} \tag{1}$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega\,|\,\hat{u}_k(\omega)\,|^2 \mathrm{d}\omega}{\int_0^\infty |\,\hat{u}_k(\omega)\,|^2 \mathrm{d}\omega} \tag{2}$$

(3) Update λ;

$$\hat{\lambda}^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega) + \tau[\hat{f}(\omega) - \sum_k \hat{u}_k^{n+1}(\omega)] \tag{3}$$

(4) For a given discriminant accuracy, the loop ends until the stop iteration condition (Eq. (4)) is met, resulting in a narrowband IMF component, otherwise returning to Step (2) continues.

$$\sum_k \|\hat{u}_k^{n+1} - \hat{u}_k^n\|_2^2 / \|\hat{u}_k^n\|_2^2 \tag{4}$$

in the above formulas, u_k is each modal function; ω_k is each center frequency; λ_t is a Lagrangian multiplier; α is a quadratic penalty factor; $\hat{u}_k^{n+1}(\omega)$ is a Wiener filter of $\hat{f}(\omega) - \sum_{i\neq k}\hat{u}_i(\omega)$, ω_k^{n+1} is the center of gravity of the power spectrum; e is accuracy.

1.2 Establishment of Weibull proportional failure rate model

The proportional failure rate model establishes the relationship between the state indicator and the reliability, and can effectively use the data that has not completely failed, obtain the degradation rate of the current state, and then evaluate the reliability. This model has been widely used in the field of mechanical equipment reliability analysis[15], which is defined as follows.

$$h(t:Z) = h_0(t)\exp(\gamma Z) \tag{5}$$

where, $h_0(t)$ is the rate of time-dependent basic failure; Z is the covariate and affects the factor variable; γ is the regression coefficient vector and is affected by the failure rate caused by the factor variables.

The Weibull proportional failure rate model is an effective model in practical applications, enabling accurate analysis of product reliability[16]. The Weibull proportional failure rate reliability model is

$$R(t:Z) = \exp(-H(t:Z)) = \exp[-\int_0^t \frac{\beta}{\eta}(\frac{t}{\eta})^{\beta-1}\exp(\gamma Z)\,dt] \quad (6)$$

The kurtosis and peak indicators are effective indicators for analyzing vibration signals. As the degree of wear increases, the kurtosis value will increase accordingly, and the peak indicators will rise to a certain peak and then show a downward trend. In this paper, the kurtosis and peak indicators of the hydraulic pump angle domain signal are used. To reflect the covariate Z_{1k}, Z_{2CF} of its operating state and apply it to the Weibull proportional failure rate model, the above equation can be expressed as

$$R(t:Z) = \exp(-H(t:Z)) = \exp[-\int_0^t \frac{\beta}{\eta}(\frac{t}{\eta})^{\beta-1}\exp(\gamma_1 z_{1K} + \gamma_2 z_{2CF})\,dt] \quad (7)$$

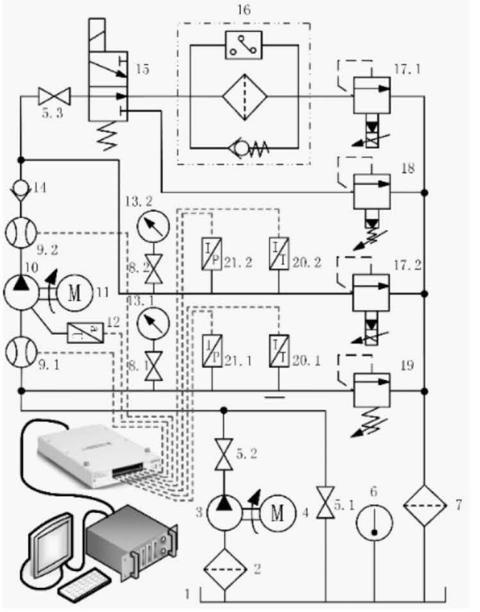
2 Simulation experiment and signal processing of the health state of the port plate under variable speed

2.1 Construction and data acquisition of simulated vibration signal test bench

The experiment will simulate 5 working health states of the hydraulic pump port plate, which are normal state ($\delta = 0$ mm), wear state 1 ($\delta = 0.0432$ mm), wear state 2 ($\delta = 0.00477$ mm), wear state 3 ($\delta = 0.1248$ mm), wear state 4 ($\delta = 0.4661$ mm).

The calculation of the volumetric efficiency is used to analyze whether the hydraulic pump fails during its design life, and the durability parameters of the pump are obtained. The volumetric efficiency of the pump in the 5 cases is 91.95%, 89.83%, 88.44%, 87.68%, and 84.11%, respectively. According to the volumetric efficiency value, the degree of wear of the port plate is classified into normal state, slight wear, moderate wear, heavy wear, and complete failure.

The schematic diagram of the experimental system is shown in Fig. 1. The test bench can collect vibration signal data during the acceleration and deceleration of the hydraulic pump. Manually adjust the working pressure of the relief valve to 10 MPa, run the control program, when the pressure is stable at 10 MPa, click the data acquisition button, adjust the potentiometer at the same time, change the parameters of the inverter, and then change the speed of the motor from 1 500 r/min to 900 r/min (50 – 30 Hz), the data acquisition card monitors the change of the speed through the panel of the speed monitor, and collects the characteristic signals in the process. Fig. 2 is a site photograph of the test platform.



1. Fuel tank 2. Suction filter 3. Vane pump 4. Oil supply motor 5. Globe valve 6. Liquid temperature gauge 7. Return oil filter 8. Pressure gauge switch 9. Flowmeter 10. Pump to be tested 11. Drive motor 12. Vibration sensor 13. Pressure gauge 14. Check valve 15. Two-position three-way electromagnetic reversing valve 16. High pressure filter 17. Pilot proportional relief valve 18. Pilot operated relief valve 19. Direct acting relief valve

Fig. 1 Schematic diagram of hydraulic system

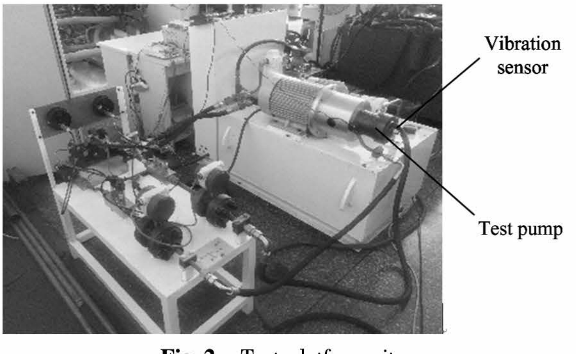
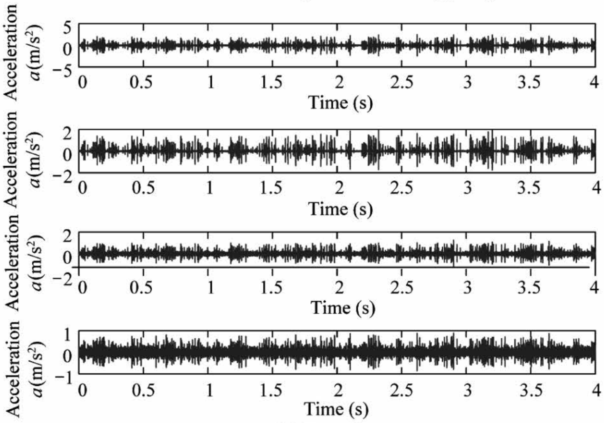


Fig. 2 Test platform site

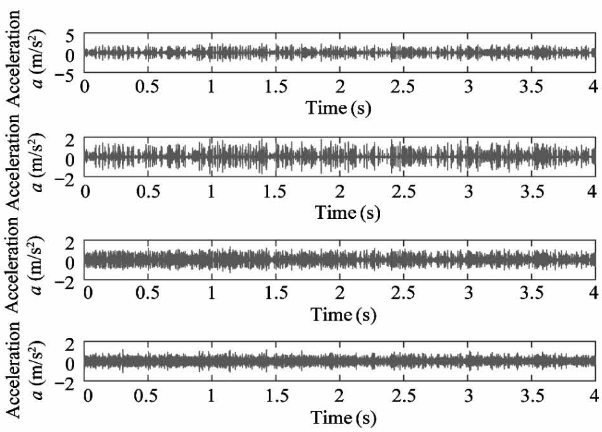
2.2 Signal processing analysis of vibration test of different health status of hydraulic pump port plate

In this work, the CY-type axial piston pump is taken as the research object, and the rated speed of the motor is 1 500 r/min. Set the sampling frequency to 20 kHz and collect the vibration signal of the pump cover. The initial pressure of the test is set to 10 MPa, and the data of the 4 s time period is selected for analysis. The main goal is to determine the degree of damage of the port parts of the key components of the hydraulic pump. Therefore, the peak and kurtosis values are selected as diagnostic indicators. Perform CEEMDAN decomposition to obtain a series of IMF components, as shown in Fig. 3 (only the first 4 orders are listed).

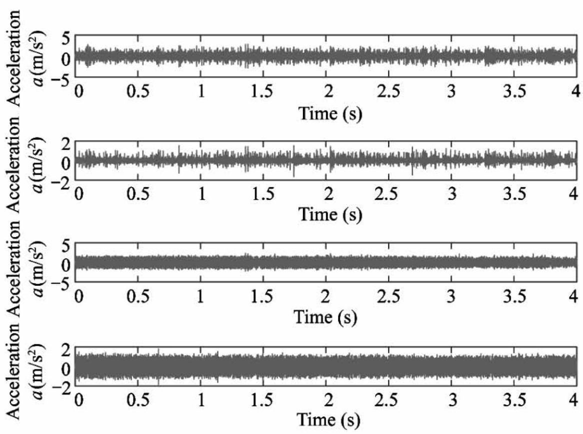
Taking the original signal in the normal state of the port plate as an example, using the fast spectral kurtosis principle and the energy spectrum principle, the energy values of the first 4 order IMF components and the fast spectral kurtosis diagrams of the original signal and the first 4 order IMF components are calculated. The fast spectrum kurtosis diagram and the first 4 orders of IMF component energy spectrum in normal state are shown in Fig. 4. And the fast spectral kurtosis parameters under normal conditions are shown in Table 1. The frequency band at which the maximum spectral kurtosis is located is a rectangular area (6 667, 10 000) Hz pointed by the arrow, and the frequency band range of the fast spectrum kurtosis diagram under the original signal of the normal state of the port plate is selected. According to the figure, where, only the maximum amplitude of the IMF1 spectral kurtosis is (6 667, 10 000) Hz, the characteristic frequency band interval is subordinate to the original signal band interval of the port plate normal state, and is in the same as the original signal. The decomposition level is $k = 1.5$, and the maximum amplitude of the other IMF component spectral kurtosis is not in the entire frequency band. Therefore, IMF1 is the sensitive IMF, and the energy value of IMF1 is the largest in the energy spectrum. IMF1 is selected as the sensitive factor. In the same way, according to the above method, without reference, sensitive IMF screening for mild wear state, moderate wear state, severe wear state, and complete failure state are all IMF1 components.



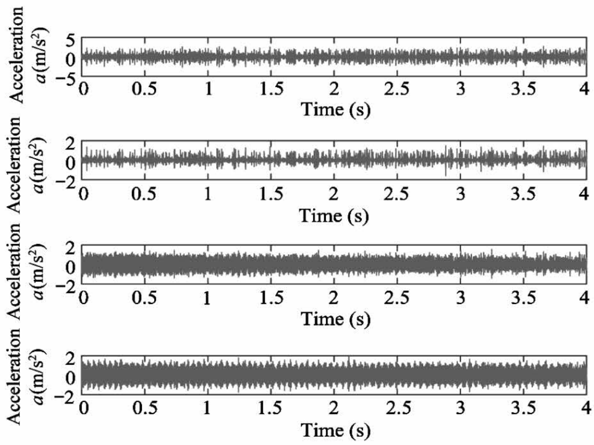
(a) Normal state



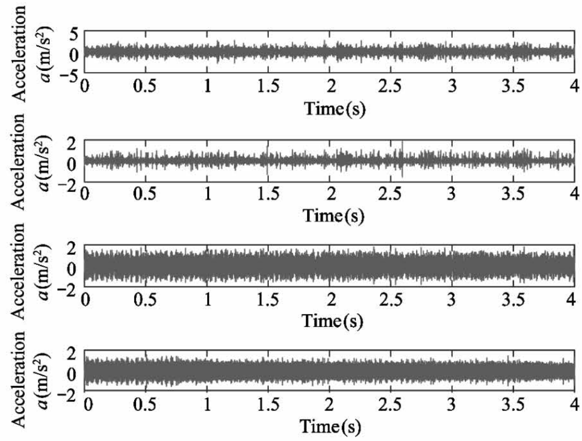
(b) Minor state



(c) Moderate wear



(d) Severe wear



(e) Complete failure

Fig. 3 The first 4 order IMF components of CEEMDAN decomposition of 5 healthy states of the port plate

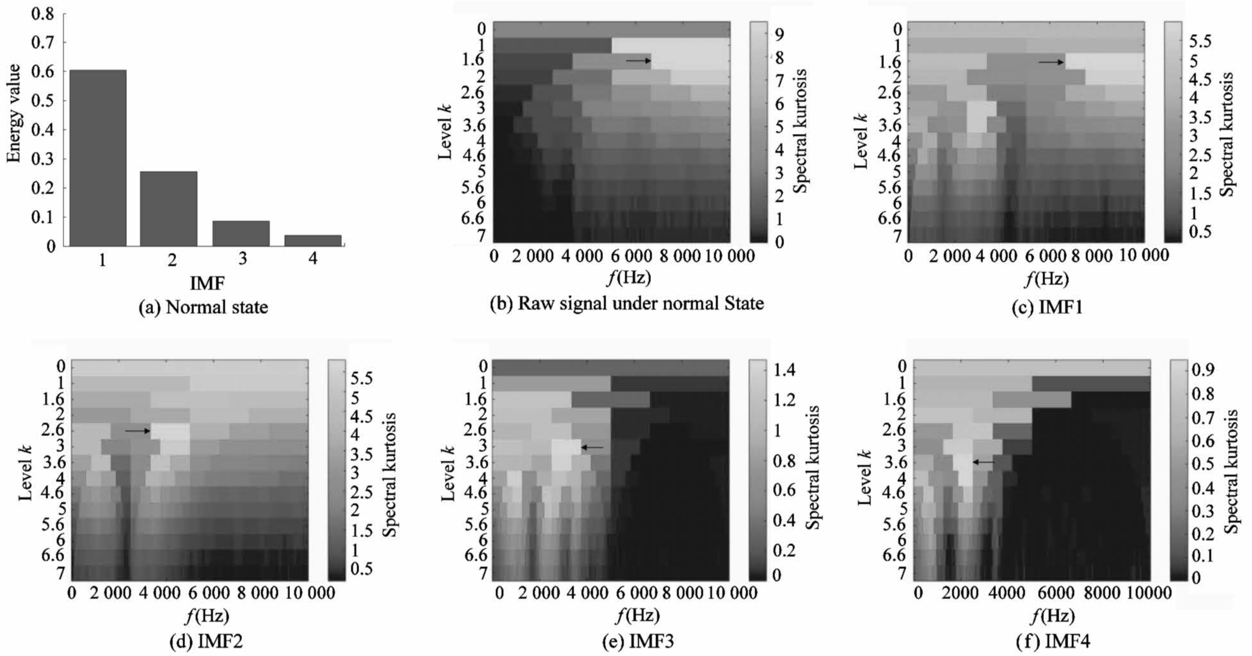


Fig. 4 Fast spectrum kurtosis diagram and energy spectrum diagram of the first 4 orders of IMF component under normal conditions

Table 1 Fast spectral kurtosis parameters under normal conditions

The sequence	Maximum kurtosis	Bandwidth (Hz)	Center frequency (Hz)	Decomposition level	Characteristic band interval
The original data	9.5	3 333	8 333	1.5	(6 667, 10 000)
IMF1	6.0	3 333	8 333	1.5	(6 667, 10 000)
IMF2	5.8	1 666	4 166	2.5	(3 333, 5 000)
IMF3	1.5	1 250	3 125	3.0	(2 500, 3 750)
IMF4	0.9	625	2 187	4.0	(1 875, 2 500)

The Hilbert envelope demodulation is performed on the IMF1 order components of the 6 states of the port plate to obtain the corresponding envelope demodulation signal. The sampling frequency of the envelope demodulated signal is reduced to 2 kHz, and then the instantaneous frequency is obtained by performing wavelet cluster band pass filtering on the down sampled signal. Set the sampling frequency to 100 Hz to perform angular equal-angle resampling of the signal, where $\Delta\theta = 2\pi/100$ is obtained. Obtaining an equal-angle resampled phase-detection time-scale sequence and resampling the signal to obtain a resampled signal, and obtaining a resampled angle domain signal. The VMD decomposition is performed on the angle domain signal, and the first-order component is selected as the degenerated feature component of the feature extraction, as shown in Fig. 5.

3 Hydraulic pump health status assessment based on Weibull proportional failure rate model

The average data of the first-order characteristic sensitive component of the obtained angular domain signal VMD is divided into 75 segments, the average value of each small segment is calculated, and the discrete point fitting is performed to obtain a smooth straight line, which is convenient for observing the trend. The kurtosis index is obtained, as shown in Fig. 6.

It can be seen from Fig. 6 that in each of the wear state kurtosis value decomposition maps, as the hydraulic pump speed gradually decreases, the kurtosis value also shows an overall downward trend. In the normal state, the kurtosis index of more than 50% of the 75 time series values is around 3. When it is slightly worn, most of the indicators are around 4. As the degree deepens, the overall value of the kurtosis becomes larger and larger. A maximum of 5.2 is reached when it fails completely.

The peak index of the first-order characteristic sensitive component of the angle domain signal VMD is obtained, as shown in Fig. 7. It can be seen from Fig. 7 that in each wear state peak factorization diagram, as the hydraulic pump speed is gradually decreased, the peak factor also shows an overall downward trend. As the damage degree of the port plate is deepened, the peak factor tends to increase gradually. In the case of heavy wear, the peak factor value is greater than 4, reaching a maximum of 4.2, but it drops to 3.65 when it fails completely. In order to verify the effect of the proposed Weibull proportional failure model, the health status is evaluated from the data collection collected in the hydraulic pump port plate failure simulation experiment system. Under the condition that the other parts of the pump are kept in a normal state and the only variable of the port plate, the data of the hydraulic pump port plate is collected in 5 different degrees of damage. The Weibull proportional failure rate model is constructed by combining 2 indicators of kurtosis and crest factor, and the reliability value is calculated. The discrete reliability curve and fitting reliability are shown in Fig. 8. The reliability value is also sequentially decreased, which indicates that the health state also shows a downward trend.

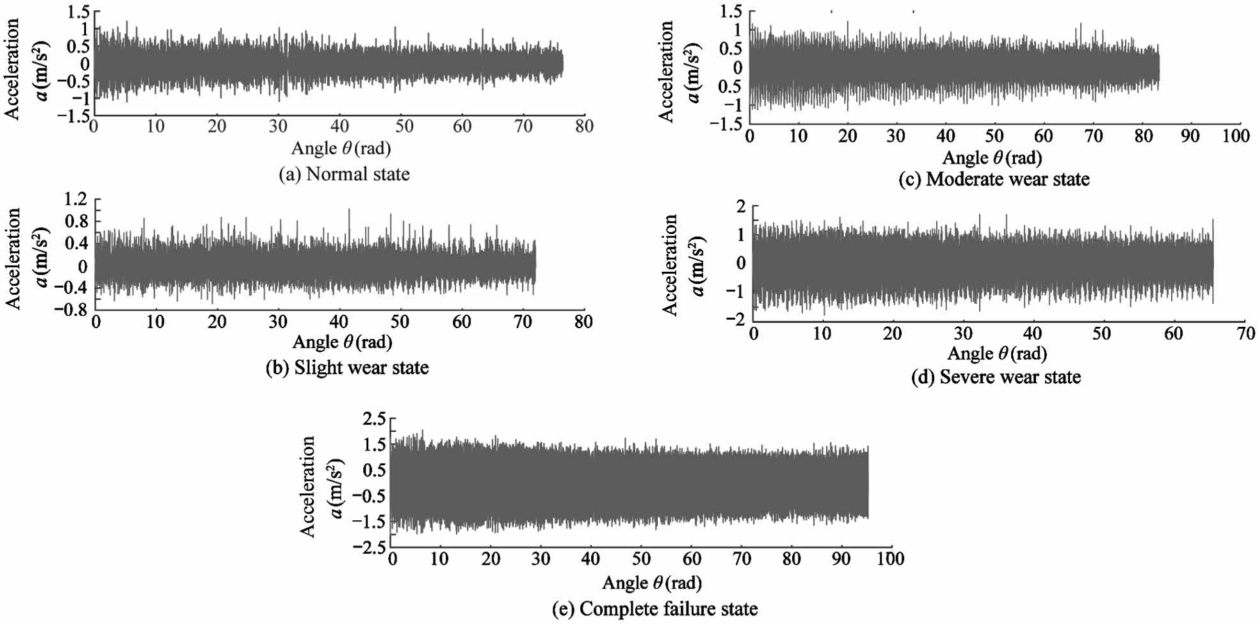


Fig. 5 Angle domain signal VMD processing first-order sensitive component

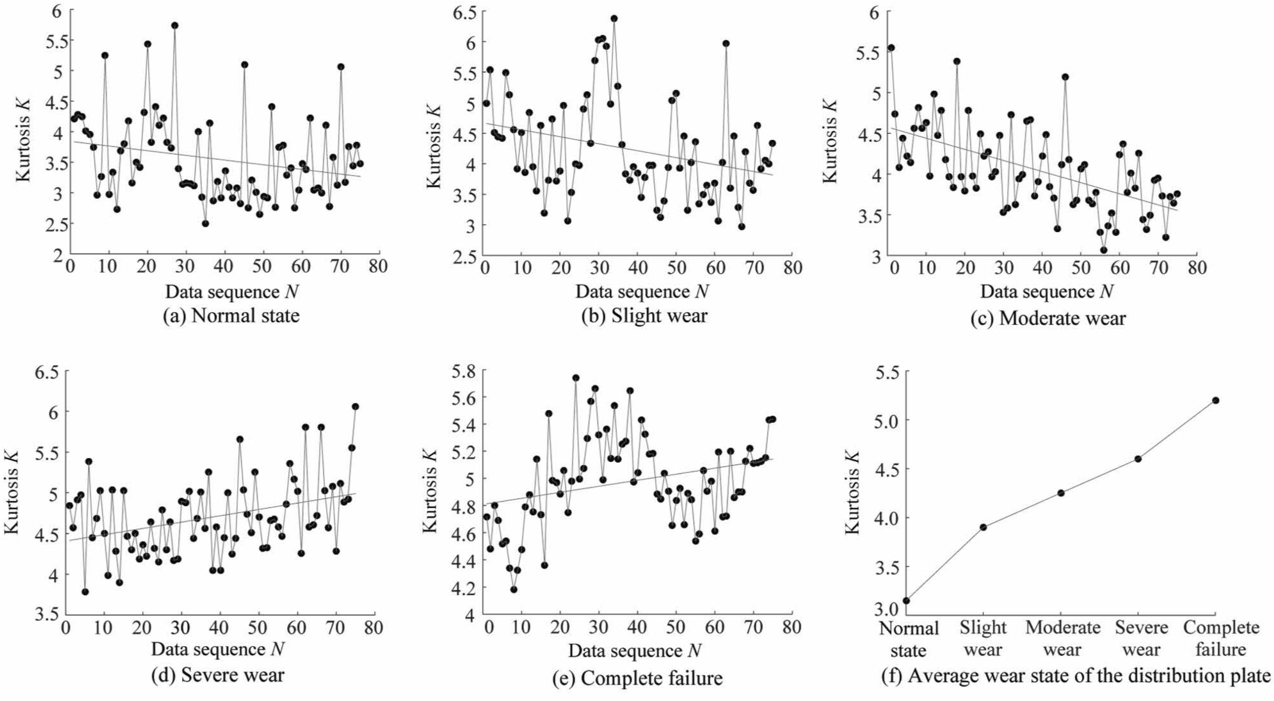


Fig. 6 Kurtosis value index of different wear degree of the port plate

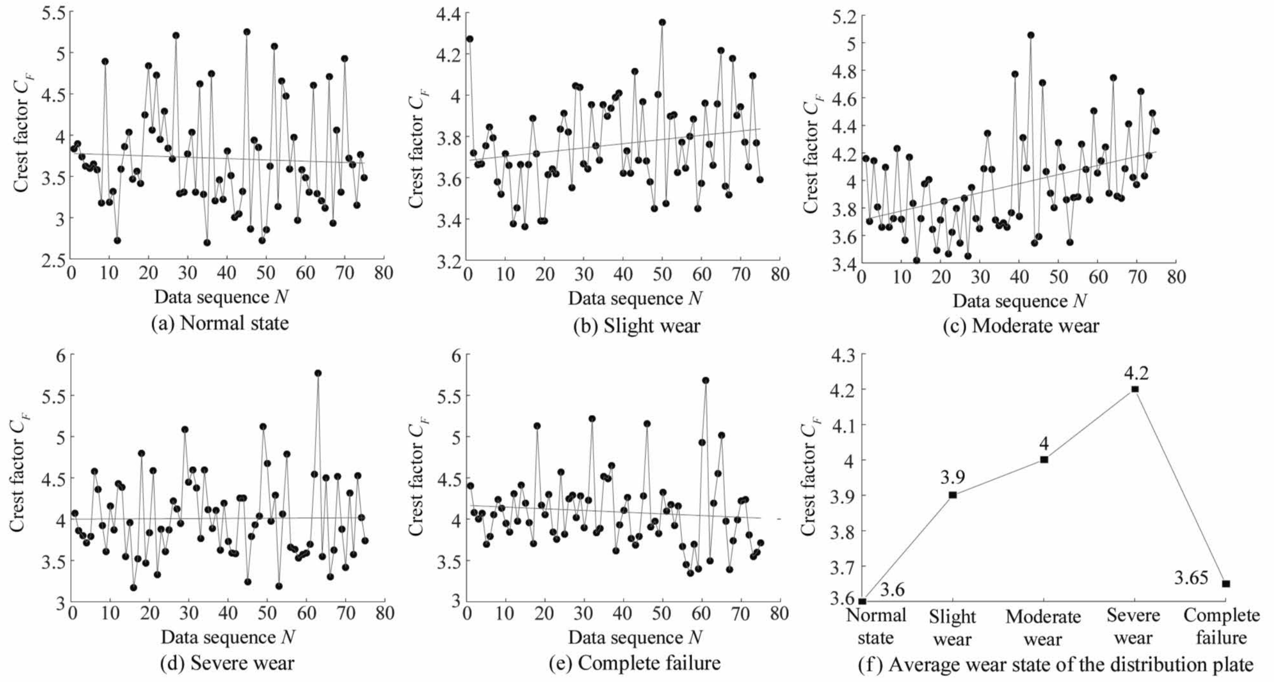


Fig. 7 Pivot factor indicator of different wear degree of the port plate

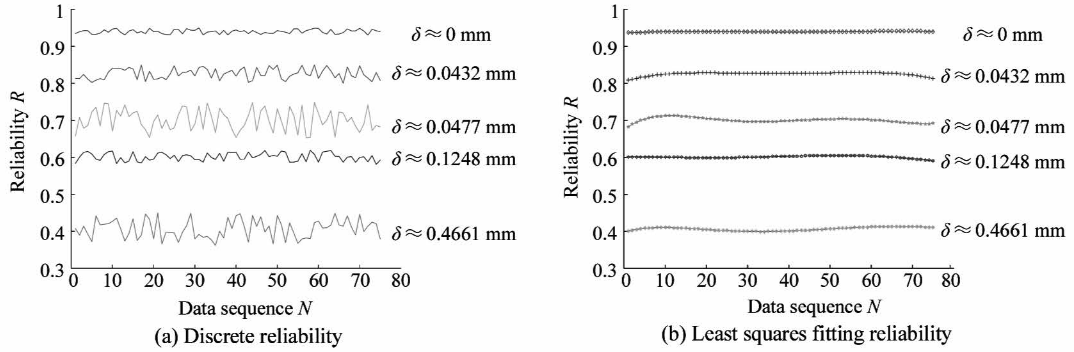


Fig. 8 Discrete reliability curve and fitting reliability curve for different wear levels of the port plate

The degree of reliability is shown in Table 2. Calculate the reliability of the equipment, quantitatively analyze the current operational health status of the equipment according to the reliability division in the table, so as to master the operation status, determine whether to repair in advance, and prevent serious failures.

Table 2 Reliability classification table

Mechanical reliability	Operating status
$0.91 < R < 1$	Good
$0.75 < R < 0.85$	Satisfied
$0.36 < R < 0.61$	Not satisfied
0	Not allowed

When the failure value is completely fluctuated, the reliability value fluctuates around 0.4. According to Table 2, it is known that it is in an unsatisfactory category, which is consistent with the actual health state of the axial piston pump, thus verifying the validity of the proportional model.

4 Conclusion

Using the combination of CEEMDAN energy spectrum and fast spectral kurtosis principle, the signals of various working states of hydraulic pump port plate under variable speed are processed to accurately extract the IMF component containing the sensitive information of degraded features.

Using the angular domain signal VMD degeneration feature extraction method, the influence of the rotational speed fluctuation caused by the variable rotation speed on the vibration signal can be effectively eliminated, and the characteristic index containing the degraded characteristic sensitive information can be accurately extracted.

Combining the Weibull proportional failure rate model with the sensitive feature extraction of the real-time degraded vibration signal of the hydraulic pump provides a new idea for effectively solving the problem of hydraulic pump health assessment.

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