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Properties on Bearing Fault Diagnosis of Water Injection Motor

Jianguo Jiang, Zepeng Zhang

School of Electrical Engineering and Information Technology, Northeast Petroleum University, Daqing 163318, China

Abstract

Water injection motor in western Daqing Oilfield is the key equipment of water injection to the oil field. Due to the great pressure of water injection to the oil field, the water injection motor is often overloaded and runs at high speed, so that the rolling bearing of the motor is worn, deformed and other faults. In order to detect the small faults that are not easy to detect in the early stage of the motor bearing, this paper proposes a method combining variational mode decomposition (VMD) and fast spectral kurtosis. The optimal number of modes is determined by correlation and energy ratio. The fast spectral kurtosis operation is carried out on the modes with large kurtosis. The fault signal is enveloped and decomposed by the optimal filter parameters. The experimental results show that the algorithm can successfully identify the rolling bearing fault of water injection motor and determine the fault location.

Keywords

Fault Diagnosis; Variational Mode Decomposition; Fast Spectral Kurtosis; Rolling Bearing of Water Injection Motor.

1. Introduction

At present, more than 80 % of oil fields in China need water injection to ensure stable and efficient production. The commonly used water injection pumps are high-pressure centrifugal pump, piston pump and horizontal electric pump[1]. EMD is the mode of different frequency bands (IMFs) decomposed from the signal to be processed, and then denoising and filtering are carried out according to the amount of energy contained in each mode. However, for the mode mixing phenomenon in EMD decomposition, Dragomiretskiy et al.[3] proposed the variational mode decomposition according to the principle of empirical mode and related experience in 2013, which can solve this problem well. In the actual strong noise environment, VMD has better anti-noise performance. In 1983, Dwyer[4] used the spectral kurtosis as the detection statistic for the first time in view of the poor filtering effect of power spectral density on non-stationary signals, and successfully converted the sinusoidal and narrow bandwidth Gaussian signals into non-Gaussian signals according to the frequency domain kurtosis estimation. Liu Zerui in China used the optimal filter parameters of fast spectral kurtosis to envelope the modal with the maximum energy after the variational mode decomposition, which effectively improved the success rate of fault diagnosis of rolling bearings[5].

2. Related Algorithms

2.1. VMD Algorithm

In the decomposition process of the variational modal decomposition method, a new meaning of the modal function is given, that is, the AM-FM signal[6]. In the decomposition process, the bandwidth value and marginal spectrum of each modal component can be calculated by transferring the spectrum of modal component to their respective fundamental frequency bands.

$$\begin{cases} \min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\} \\ s.t. \sum_{k=1}^{K} u_k = f(t) \end{cases} \tag{1}$$

where $f(t)$ is the signal to be processed, $u_k(t)$ is the corresponding intrinsic mode function, and the central frequency of the signal to be processed after modal decomposition is ω_k.

After constructing the VMD model, the Lagrange multiplier λ, which is the same as the equality constraint, is introduced into the upper formula, and the constraint problem is transformed into the unconstrained problem. Then the unconstrained problem is constrained as a penalty term by the penalty factor α, and the upper formula is transformed into the saddle point problem. Therefore, the expression of the new modal function $u_k^{n+1}(t)$ is :

$$u_k^{n+1} = \arg\min_{u_k \in X} \left\{ \alpha \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) \sum_i u_i(t) + \frac{\lambda(t)}{2} \right\|_2^2 \right\} \tag{2}$$

After getting the time domain solution of VMD, it is necessary to convert the upper expression to frequency domain by Fourier transform :

$$\hat{u}_k^{n+1} = \arg\min_{\hat{u}_k, u_k \in X} \left\{ \alpha \left\| j(\omega - \omega_k) \left[1 + \operatorname{sgn}(\omega) \hat{u}_k(\omega) \right] \right\|_2^2 + \left\| \hat{f}(\omega) \sum_i \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2} \right\|_2^2 \right\} \tag{3}$$

From this, the frequency domain solution of each mode on the quadratic optimization problem can be obtained :

$$\hat{u}_k^{n+1}(\omega) = \left(\hat{f}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega) + \frac{\hat{\lambda}(\omega)}{2} \right) \frac{1}{1 + 2\alpha(\omega - \omega_k)^2} \tag{4}$$

The calculation of central frequency ω_k is similar to that of Eq. (5), which is the solution of central frequency after quadratic optimization :

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega \left| \hat{u}_k(\omega) \right|^2 d\omega}{\int_0^\infty \left| \hat{u}(\omega) \right|^2 d\omega} \tag{5}$$

2.2. Fast Spectral Kurtosis

Spectral kurtosis algorithm is an algorithm that transforms the signal in time-frequency domain and calculates the optimal filtering parameters, such as center frequency and bandwidth, through short-time Fourier transform, and then filters the signal[7]. The emergence of fast spectral kurtosis algorithm further improves the spectral kurtosis algorithm. By calculating the spectral kurtosis values in different frequency bands, the calculation time is greatly shortened, and the efficiency of feature extraction is effectively improved[8]. In the actual fault diagnosis of rolling bearings, the difficulty of fast spectral kurtosis is how to obtain the maximum spectral kurtosis value at the frequency resolution Δf by frequency f to form a fast spectral kurtosis map. The spectral kurtosis formula is as follows :

$$K(f_i, \Delta f) = \frac{\left\langle \left(\left| c_k^i(n) \right| - \left\langle \left| c_k^i(n) \right| \right\rangle \right)^4 \right\rangle}{\left\langle \left(\left| c_k^i(n) \right| - \left\langle \left| c_k^i(n) \right|^2 \right\rangle \right)^2 \right\rangle} - 2 \tag{6}$$

In the formula, $c_k^i(n)$ is the filter coefficient.

3. VMD Decomposition Parameter Selection

3.1. Bearing Fault Simulation Signal

When the roller bearing raceway or other structures of the motor have wear or other faults, due to the continuous high-speed rotation of the motor, the repeated impact of various forces will cause the high-frequency vibration of the water injection pump[9]. The frequency of the vibration signal generated by this reason remains unchanged when filtering, but it is not proportional to the motor speed. In order to study this signal, this paper first obtains the fault frequency of the rolling bearing of the water injection motor according to the specific parameters of the bearing shown in Table 1.

Table 1. Rolling Bearing Parameters

Ball diameter d(mm)	Pitch diameter D(mm)	Ball number Z	Contact angle α
22.2	95.8	8	0

Fault frequency f_i for rolling bearing inner ring with defects:

$$f_i = \frac{Z}{2} f_s \left(1 + \frac{d}{D}\cos\alpha\right) = 143.7HZ \tag{7}$$

Fault frequency f_o for rolling bearing outer ring with defects:

$$f_o = \frac{Z}{2} f_s \left(1 - \frac{d}{D}\cos\alpha\right) = 89.68HZ \tag{8}$$

When the rolling element has defects, the fault frequency f_r is:

$$f_r = \frac{D}{2d} f_s \left[1 - \left(\frac{d}{D}\cos\alpha\right)^2\right] = 59.56HZ \tag{9}$$

When the cage has defects, the fault frequency f_c is:

$$f_c = \frac{f_s}{2}_s \left(1 - \frac{d}{D}\cos\alpha\right) = 11.21HZ \tag{10}$$

The following experiments verify the filtering effect of VMD decomposition. First set the simulation signal of bearing fault in MATLAB, set rated speed $N_r = 1800$ and initial signal x_1 as:

$$x_1 = s_1 \cdot e^{-A \cdot t_0} \cos\left(2\pi \cdot f_r \cdot t_0 + \pi / 3\right) \tag{11}$$

The superimposed sine signal x_2 is:

$$x_2 = x_1 \cdot 0.5\sin\left(2\pi \cdot f_r \cdot t_0 + \pi / 6\right) \tag{12}$$

Finally, Gaussian white noise is added to obtain the bearing simulation signal x_n as follows:

$$x_n = x_2 + wgn(m,n,p) \tag{13}$$

In the formula, x_n is the final output simulation signal. A is the attenuation coefficient, take 300 ; f_r is the relative rotation frequency of the inner and outer ring. Because of the assumption that the outer ring speed is constant, it is equal to the inner ring rotation frequency : $f_r = N_r / 60 = 30$ Hz ; t_0 is the discrete sampling step of a single pulse period ; $wgn(m,n,p)$ is superimposed noise parameters, where m is 1, p is 5, n is the total number of sampling points, set to 8192.

3.2. Selection Rules of Modal Component Number

Before VMD decomposition, the most critical step is to select the number of decomposition modes K. In this process, if the value of K is too small, the IMF component obtained by decomposition may contain multiple signal components, otherwise, the same signal component may exist in multiple IMF components, resulting in modal aliasing.

For the number of modal components, researchers usually use the central frequency observation method, that is, to determine the K value based on the principle of whether the central frequencies of the adjacent IMF components have similar terms. However, due to the lack of discriminant threshold, the selection of K value has great subjectivity. The correlation coefficient is used as the discriminant threshold to decompose the VMD, and the modal component will have different eigenvalues. The mode similar to the eigenvalues of the original signal is selected for analysis. Ignoring those signals with large difference from the original signal will greatly improve the filtering accuracy. In addition, the energy can also be used as a criterion for modal analysis. The larger ratio of modal energy to initial signal can also improve the filtering accuracy. Based on the above analysis, this paper adopts a method to select the number of modal decomposition K based on correlation and energy ratio.

Correlation can be expressed as :

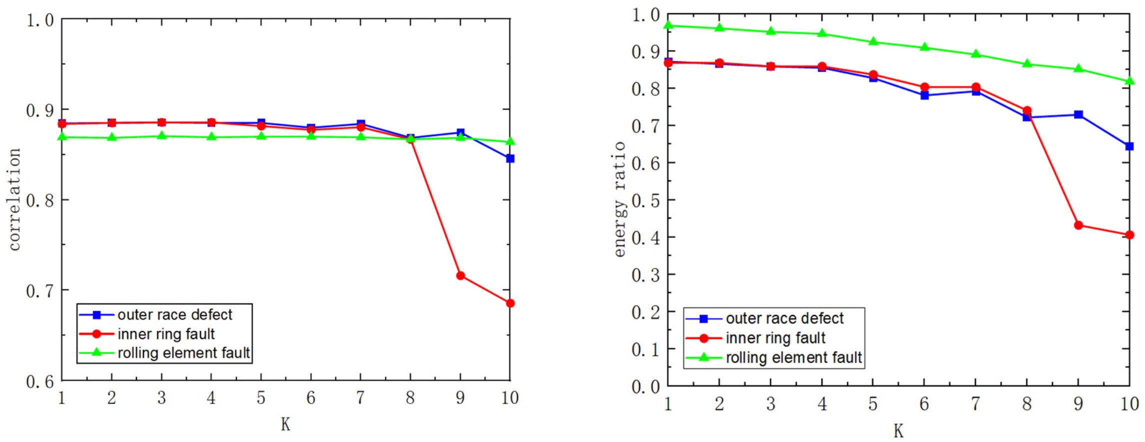
$$r_{xy} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i}^{n}(Y_i - \bar{Y})^2}} \tag{14}$$

In the formula, $\bar{X} = \frac{1}{n}\sum_{i=1}^{n} X_i$, $\bar{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$;

Energy ratio can be expressed as :

$$e_{xy} = \frac{\sum_{i=1}^{n}(X_i)^2}{\sum_{i=1}^{n}(Y_i)^2} \tag{15}$$

Through the experimental analysis of the bearing fault, the correlation ratio and energy of each part of the bearing fault are shown in Fig. 1.



(a) Correlation (b) Energy ratio

Fig 1. Correlation and energy ratio after VMD decomposition

In VMD decomposition mode, the main mode is the maximum energy mode. Obviously, when $K=1$, the correlation and energy ratio are the largest. When $K=5$, the correlation is basically the same, and the energy ratio decreases slightly. In order to ensure the fidelity of the main mode obtained by VMD and retain the energy of the original signal as much as possible, the number of modal decomposition K is 5.

3.3. Selection Rules of Penalty Factor

The penalty factor α mainly affects the bandwidth and convergence speed of each mode after decomposition. The smaller the penalty factor α is, the smaller the constraint on the input signal is, the worse the filtering effect of VMD decomposition is, and the more prone to modal aliasing. On the contrary, if the penalty factor α is too large, it will cause VMD decomposition to filter out the bearing fault information as the interference noise error, so that the information contained in the modal component is insufficient. In the bearing fault diagnosis, the penalty factor α is generally taken as 2000.

3.4. Modal Selection Rule based on Kurtosis Value

Mechanical equipment will be impacted to different degrees in the long-term operation process, resulting in impact signals. Kurtosis is positively correlated with the impact signal of mechanical equipment, and increases with the aggravation of the impact received by mechanical equipment. Due to this feature, kurtosis is very effective for the fault diagnosis of rolling bearing damage, and sensitive to the nonlinear and unstable impact signal. Moreover, kurtosis, as an dimensionless statistical value, does not need the relevant parameters of rolling bearing, and only needs to calculate the kurtosis value to determine the severity of the fault.

In this paper, the kurtosis is used to select the mode. The kurtosis is the normalized fourth-order center distance, which is a mathematical statistical unit. It can calculate the distribution characteristics of random variables and count their peak signals.

$$K=\frac{E(x-\mu)^4}{\sigma^4}=\frac{1}{N}\sum_{i=1}^{N}\left[\frac{x_i-\mu}{\sigma}\right]^4 \tag{16}$$

In the above formula, K is the kurtosis index of signal x ; μ is the average value of the signal ; N is the sampling length of the signal ; σ is the standard deviation of the signal.

4. Experimental Verification

4.1. Experimental Process

In this experiment, the optimal number of modal decomposition and penalty factor are selected through the calculation of correlation and energy ratio, and the fault signal is decomposed by VMD to generate five modal components with different frequencies. Then according to the kurtosis value of five modal components, several modes with the highest fault energy are selected for fast spectral kurtosis calculation. The signal at this time has filtered out a large number of interference information, so the optimal filter parameters can be selected for fault feature extraction according to the calculated fast spectral kurtosis map, and the characteristic frequency of bearing fault can be obtained. The specific process is shown in Fig. 2.

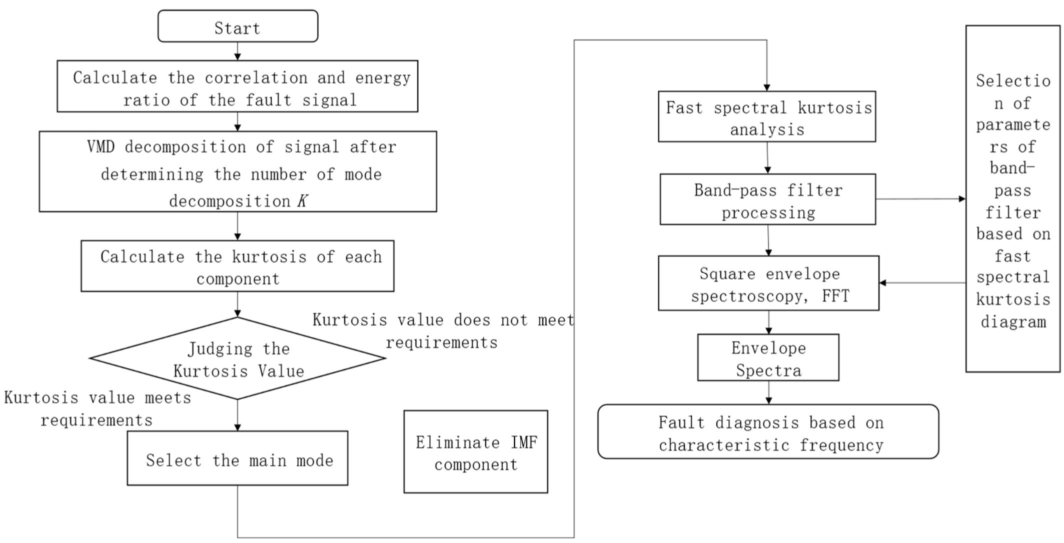
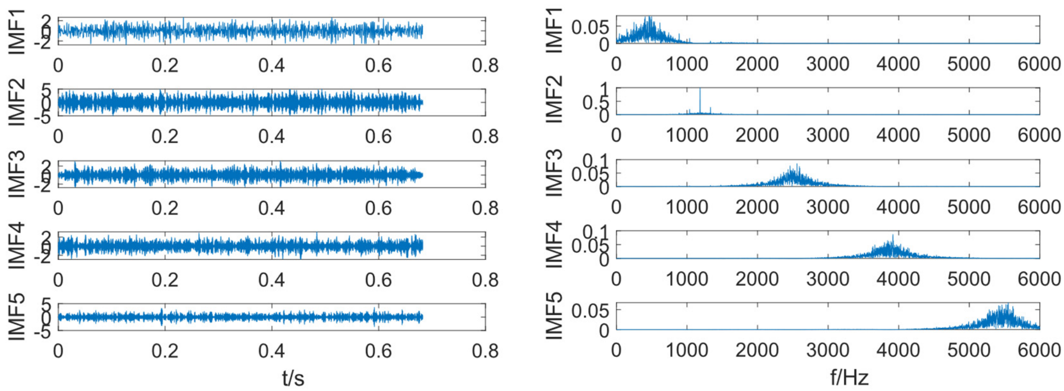


Fig 2. Fault diagnosis process

4.2. Case Analysis

VMD decomposition method can effectively filter the useless shock components and noise existing in the measured signal, and the fault data required for feature extraction are shown in the figure. The input signal is decomposed by VMD with $K = 5$, $\alpha = 2000$ as the specific decomposition parameter, and five independent modal components are obtained. The decomposition results are shown in Fig 3.



(a)Time domain diagram (b)frequency domain

Fig 3. VMD Decomposition Diagram of Bearing Fault

Due to the various noise generated by bearing signal during operation and the limitation of VMD decomposition principle, each decomposed mode does not contain the characteristic frequency of bearing fault. In order to select the mode with high bearing characteristic frequency for calculation, the kurtosis value mentioned above is needed. The calculation results of the five modal components are shown in Fig. 4. The kurtosis values of modal components in Fig. 4 are used to measure the main modes with bearing fault frequency, and the first three main modes with the largest kurtosis values are taken for fast spectral kurtosis calculation to obtain the fast spectral kurtosis diagram as shown in Fig. 5. According to the main filter parameters of the optimal band-pass filter in the fast spectral kurtosis map, such as the center frequency is 1500Hz, the bandwidth is 3000Hz. Based on these parameters, the main modal signals can be further filtered, and the characteristic frequency of the bearing fault signal can be extracted in the form of square envelope spectrum shown in Fig. 6.

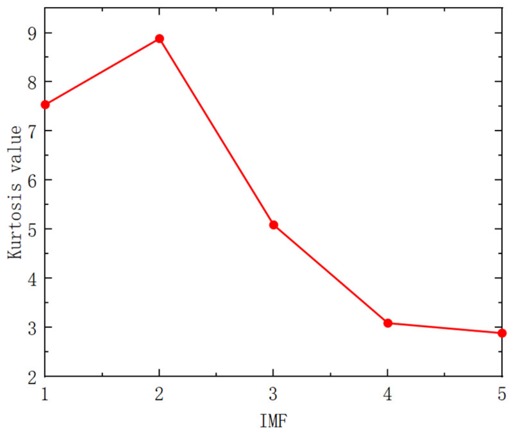


Fig 4. Kurtosis value of modal component

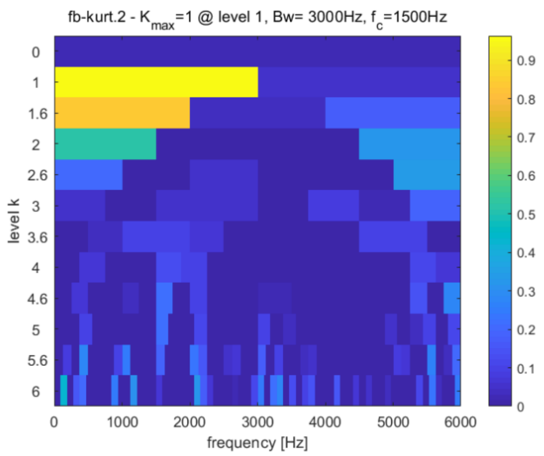


Fig 5. Fast Spectral Kurtosis Diagram of Bearing Fault

After the input signal of bearing fault is processed by VMD algorithm and spectral kurtosis algorithm, the interference noise has been basically eliminated. From Figure 6, various impact frequencies of bearing inner ring fault can be clearly observed, and the highest is the double characteristic frequency of bearing inner ring fault, which is 144.3 Hz. By comparing with the theoretical value of 144.3 Hz of the bearing inner ring fault, the maintenance personnel can determine the fault.

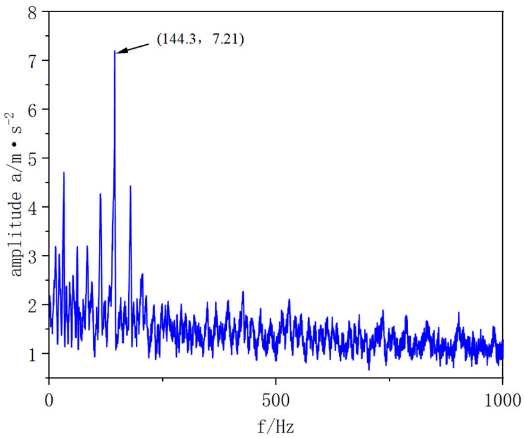


Fig 6. Square envelope spectrum of bearing fault

5. Conclusion

In order to verify the superiority of VMD decomposition and fast spectral kurtosis in signal filtering and good denoising effect. In this paper, the simulation signal of the bearing fault of the water injection motor is constructed. The number of modes and the penalty factor required in the decomposition process are determined by the correlation and energy ratio. The kurtosis index is selected to analyze the decomposed modes again, and the main modes containing the bearing fault information are calculated. Because the bearing contains a lot of interference noise in operation, so this paper carries out fast spectral kurtosis operation on the main modes, and obtains the optimal filter parameters in the result diagram for envelope spectrum decomposition. By comparing the characteristic frequency of the bearing in the envelope spectrum diagram, the fault of the bearing of the water injection motor is judged.

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