A Study on Fault Diagnosis of Rotating Machinery Combined Wavelet Transform with VMD

Huan Zhou and Hao Wang*
Machinery and Energy Engineering College, Shanghai University of Electric Power
Shanghai 200090

*Corresponding author email: whouco@163.com

Abstract. Effective diagnosis of rotating machinery is difficult in view of the complex structure, weak early fault signals, non-stationary and non-linear vibration signals, and low signal-to-noise ratio. In this paper, a fault diagnosis method is proposed based on particle swarm optimization (PSO) and variational modal decomposition (VMD). Firstly, wavelet packet threshold is denoised on the signal, VMD is decomposed on the reconstructed signal, and PSO is optimized on the inherent mode function (IMF) obtained from decomposition so as to determine the best IMF function. Then Hilbert transform and envelope spectrum analysis are carried out on the IMF function, and the envelope spectrum analysis result is compared with theoretical calculation frequency to finally determine the fault type. The results indicate that this method can effectively reduce noise components in signals, extract weak fault information and realize fault diagnosis.

Keywords: Wavelet packet denoising; VMD; IMF; Particle swarm optimization algorithm; Rotating machinery.

1. Introduction
Wavelet transform has been widely used in signal analysis in recent years, which shows the time-frequency localization characteristics well according to changeable window functions [1-2]. However, there is a disadvantage of poor adaptability to processed signals, as the analysis results of this method are interfered by wavelet basis functions and are irreversible during the whole analysis process [3]. Variational mode decomposition (VMD) not only has the advantage of avoiding mode aliasing with integrated set of empirical mode decomposition, but also can realize the adaptive separation of required modal components. The main principle is to minimize the sum of the estimated bandwidth of modal variables according to the transformation of integration. Then the iterative search variational model is applied to calculate and infer the parameter values of each component, and the optimal solution [4-5] is calculated with this model.

Based on the study on several common fault diagnosis methods, it is found in this thesis that a single fault analysis method is not effective enough for weak signal extraction and is prone to signal leakage, and cannot accurately extract fault signals, thus unable to identify the cause of the fault. Therefore, it is feasible to extract fault signals by combining two methods, namely wavelet denoising and VMD decomposition. The final study results show that this method can achieve good results and greatly improve the accuracy of early weak signal fault analysis.
2. Fault Diagnosis Method

2.1. Principle of Variational Modal Decomposition (VMD)
VMD is a completely non-recursive adaptive modal variation and signal processing method \[^{6-9}\]. In terms of self-adaptability, it is mainly embodied in that it can accurately define the number of modal decomposition of a given sequence from the actual situation. In the subsequent search and solution process, it can adaptively match the optimal centre frequency and limited bandwidth of each mode, and realize effective separation of inherent modal components (IMF) without aliasing.

2.2. Particle Swarm Optimization Algorithm
When applying VMD method to decompose signals, two parameters shall be initialized, i.e. the number of modes and the centre frequency. The two parameters have different settings and thus different analysis results. Unreasonable settings may generate erroneous decomposition signals. Therefore, how to select the decomposition parameters reasonably is the most critical step for VMD to decompose signals. In this thesis, particle swarm optimization algorithm is used to select the optimal modal number and centre frequency for VMD decomposition.

After the signal is decomposed by VMD, the signal-to-noise ratio is relatively small if there is much noise in the IMF, and the corresponding sparse characteristic is also relatively weak, while its envelope entropy value will be relatively large. On the contrary, it will be relatively small \[^{10-14}\]. When the \(i\)-th particle is at a certain position \(X_i\), where \(X_i\) represents the combination vector of two parameters, the IMF component envelope entropy value is obtained by calculating decomposition. Among the envelope entropy values, the minimum value is the local minimum entropy value (\(min \ E_p\)), the minimum value is taken as the fitness value, and its global minimization is taken as the ultimate optimization target. The two parameter values determined by this method are taken as the optimal decomposition parameters.

2.3. New Diagnosis Method
To sum up, this thesis combines variational modal decomposition method, particle swarm optimization algorithm, wavelet packet transform and envelope entropy to analyse fault signals.

3. Fault Diagnosis Algorithm Flow
In this thesis, wavelet packet denoising and VMD are combined to diagnose the early weak fault signals of rotating machinery. Firstly, the original signal is denoised by wavelet packet, and then the original signal is reconstructed. The reconstructed signal is optimized by PSO algorithm to determine the optimal modal number and centre frequency parameters. Then VMD decomposition is carried out again with the parameters to calculate the optimal IMF component. Hilbert transform and envelope spectrum analysis of the obtained component are carried out, and then comparative analysis of envelope spectrum characteristic signal frequency and theoretical calculation of fault frequency is made to accurately find out the fault of rotating machinery.

The algorithm flow chart is as follows:

![Flow chart of fault diagnosis algorithm](image)

**Figure 1.** Flow chart of fault diagnosis algorithm.
In order to verify the accuracy of the method in this thesis, two methods are added to compare the diagnosis results. Scheme 1: The fault signal is subjected to wavelet transform and Hilbert transform, and the envelope spectrum analysis operation is performed to observe its diagnosis analysis diagram. Scheme 2: The fault signal is subjected to wavelet transform and EMD decomposition, double noise reduction is carried out, Hilbert transform is made, and envelope spectrum analysis is finally carried out to obtain a result analysis diagram for extracting effective signals from the fault signal. The purpose is to compare and analyse the two schemes with the fault diagnosis analysis method extracted in this thesis to verify the proposed method. See the following figure for the fault diagnosis flow charts of the two schemes.

4. Experimental Data

4.1. Bearing Test Settings and Data Acquisition

In this experiment, the selected fault bearing is a single-point fault bearing. The inner ring of the bearing is set with a fault point through electric spark technology, and the diameter of the fault point is set to be 0.1778mm (0.007 in) (the early fault characteristics of the bearing is met due to the small diameter of the fault point). The signal acquisition system attached to the rotating machinery fault diagnosis test bench is used to extract signals, and the vibration acceleration sensor is placed on the bearing seat. The sampling frequency is set to 12,000 Hz and the bearing speed is set to 1,730rpm. In order to avoid the interference of high-frequency noise, the input of the data collector is set as a low-pass filter.

4.2 Theoretical Frequency of Bearing Inner Ring Failure

When the bearing inner ring fails, the corresponding failure frequency is:

$$f = \frac{N}{2} \times \frac{n}{60} \times (1 + \frac{d}{D} \cos a)$$

(1)

In the above formula, $D$ represents the diameter of the rolling elements, $D$ represents the pitch diameter of the bearing, where $D=(d_1+d_2)/2$, $N$ represents the rotational speed of the bearing, $n$ represents the total number of rolling elements in the rolling bearing, $d_1$ and $d_2$ sequentially represent the inner ring diameter and the outer ring diameter of the bearing, and $a$ is the contact angle.

| Fault Diameter | Revolving Speed | Fault Frequency |
|----------------|-----------------|----------------|
| 0.1778mm       | 1730r/min       | 156.48HZ       |

5. Fault Diagnosis Results Analysis

5.1. Fault Diagnosis of Inner Ring Obtained by New Diagnosis Method

Firstly, the inner ring fault data collected by the test bench is decomposed and reconstructed by wavelet, and then optimized by particle swarm optimization algorithm. See Fig. 3 below for the iteration curve. In the sixth iteration step, the envelope entropy value is basically convergent, when the
centre frequency is 210, and the number of modes is 4. This parameter is decomposed by VMD, and Hilbert transform is performed to calculate the IMF component envelope spectrum as shown in Fig. 3.

As shown in Fig. 4, the curve has peaks at 309.8Hz and 155.3Hz (the fault is weak at the initial stage and the signal amplitude is small), which is basically the same as the fault frequency calculated theoretically, indicating that the fault signal frequency is successfully separated by the method.

5.2. Fault Diagnosis of Inner Ring Obtained from Two Schemes

Fig. 5 directly performs Hilbert transform and envelope spectrum analysis for this signal after wavelet transform is completed. Although peaks are also generated at corresponding frequencies, their peaks are not obvious. Fig. 6 shows the EMD decomposition and Hilbert envelope spectrum analysis of the signal after wavelet transformation. Although the peak value also appears at the corresponding frequency, its peak value is small and not obvious, which is hidden by the peak values of other spectral lines around, bringing troubles for identifying fault characteristic signals.
6. Conclusion
(1) Although some of the high-frequency noise can be eliminated after wavelet transform and reconstruction of the signal, the peak value of spectral line at the fault characteristic frequency is not obvious if Hilbert envelope spectrum analysis is directly performed on the signal.
(2) After wavelet transform and reconstruction of the signal, EMD decomposition and Hilbert envelope spectrum analysis are carried out to obtain that the peak value of the spectral line corresponding to the fault characteristic frequency is not obvious and there are many miscellaneous frequencies.
(3) After wavelet transform and reconstruction, VMD decomposition and Hilbert envelope spectrum analysis can be made to effectively and fully identify the fault characteristic frequency, and the peak value of spectral line is obvious, which has certain advantages over wavelet analysis and EMD analysis. This provides a new method for early fault diagnosis of rotating machinery.

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References
[1] Jun Pan, Jinglong Chen, Yanyang Zi, Yueming Li, Zhengjia He. Mono-component feature extraction for mechanical fault diagnosis using modified empirical wavelet transform via data-driven adaptive Fourier spectrum segment [J]. Mechanical Systems and Signal Processing, 2016, 72-73.
[2] Weiye Xu. Fast operation of long signal convolution and its application in speech processing. [J]. Computer Engineering, 2004, (01): 110-113.
[3] Chuang Ding, Pengcheng Jiang, Bingzhi Zhang, Fuzhou Feng. Application of LMD and time-frequency entropy in condition monitoring of planetary gearbox. [J]. Noise and Vibration Control, 2016, 36 (06): 154-157+185.
[4] Jiandong Wang, Mengqi Wang, Yanzhong Li, Jianqiang Ma. A new morphological filtering method for adaptively adjusting parameters [J]. Journal of Shijiazhuang Tiedao University (Natural Science Edition), 2018, 31 (01): 100-104.
[5] Jianguo Wang, Jian Li, Xudong Wan. Rolling bearing fault feature extraction method based on singular value decomposition and local mean decomposition [J]. Journal of Mechanical Engineering, 2015, 51(03): 104-110.
[6] Aihua Xu, Junquan Yan, Xucan Wu, Lei Ge. Fault feature extraction of rotating machinery based on VMD and MP algorithm [J]. Foreign Electronic Measurement Technology, 2017, 36 (08): 11-17.
[7] Meng Yang, Jin Wang, Xifeng Zhou, Qiangang Guo. Research on denoising method based on CEEMD and wavelet packet [J]. Journal of Nanjing University of Posts and Telecommunications (Natural Science Edition), 2018, 38(02): 41-47.
[8] Yan Zhao, Junchao Zhu, Baofeng Zhang, Lei Shao, Ji Li, Yu Dai. Rubbing fault diagnosis
method of rotating machinery based on VMD and Hilbert spectrum [J]. Journal of Vibration. Measurement and Diagnosis, 2018, 38 (02): 381-386+425.

[9] Youren Wang, Jun Wang, Haian Huang. Fault diagnosis of variable speed planetary gearbox based on nonlinear short time Fourier transform order tracking [J]. China Mechanical Engineering, 2018, 29 (14): 1688-1695.

[10] Zhe Wu, Shaopu Yang, Jianchao Zhang. Application of LMD adaptive multiscale morphology and teager energy operator method in bearing fault diagnosis [J]. Journal of Vibration and Shock, 2016,35 (03): 7-13.

[11] Yin Yu, R. Ajit Shenoi, Hangbin Zhu, Lijuan Xia. Using wavelet transforms to analyse nonlinear ship rolling and heave-roll coupling. Ocean Engineering 2006,33: 912-926.

[12] S. C. Phillips, R. J. Gledhill, J.W Essex, and C. M. Edge. Application of the Hilbert-Huang transform to the analysis of molecular dynamic simulations. J. Phys. Chem, A(107), pp: 4869-4876, 2003.

[13] Morlet J,Arens C,Fourgeau E et al. Wave Propagation and Sampling Theory-part2: Sampling Theory and Complex Waves. Geophysics,1982,47(2):222-236

[14] SHI Shichen. Research of time-frequency method based on EEMD and simulation system design[D]. Shanghai: East China Normal University, 2010.