Journal of Computers Vol. 35 No. 4, August 2024, pp. 31-38
doi: 10.53106/199115992024083504003

Degradation Evaluation of Hydropower Equipment Based on Variational Modal Decomposition

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Received 3 April 2023; Revised 3 April 2023; Accepted 19 April 2023

Abstract. Hydropower is the green energy with the most significant comprehensive emission reduction benefits in the whole life cycle. The signals of hydropower equipment include fault information, and it can assist the fault diagnosis of hydropower units. However, most of the existing methods lack the quantitative evaluation of the equipment degradation. A quantitative evaluation method of degradation for hydropower equipment is proposed. Variable modal decomposition (VMD) is employed to obtain decomposed simple signal. The singular values and sample entropy of the intrinsic mode functions are obtained and combined into a feature vector. Jenson-Shannon divergence is adopted to evaluate the degradation of hydropower equipment by comparing the current feature vector with the normal state feature vector. Experimental results show that this method can provide degradation evaluation information. The proposed method can provide not only quantitative indicators of equipment degradation, but also early warning of equipment degradation than the usual anomaly detection methods.

Keywords: degradation evaluation, hydropower equipment, variational modal decomposition

1 Introduction

Hydropower is recognized as the green energy with the most significant comprehensive emission reduction benefits in the whole life cycle. As a kind of new clean and renewable energy, it has become a hot topic in clean energy research because of its significant comprehensive utilization benefits and many other advantages [1]. Compared with coal and other energy sources, the development of hydropower is conducive to environmental protection and ecological construction, and it achieves the goal of all-round and high-quality development of economic and social environment [2].

With the continuous expansion of hydropower energy development scale, the construction volume of hydropower stations is also increasing. As the core equipment of hydropower station to convert electric energy by using water flow drop, the working state of hydropower unit can directly affect the operation of hydropower station. If the abnormal or faulty operation state of hydropower unit itself occurs, it will endanger the safety and stability of hydropower unit and hydropower station's operation. In the actual operation process of hydropower stations, problems and incidents of hydropower mechanical equipment operation failures caused by mechanical equipment aging, external influences and human factors also occur from time to time, which makes people realize the importance of timely maintenance of hydropower units [3]. Therefore, it is important to monitor the operational status of hydropower units in real time and to find out abnormal situations and timely maintain them, as this can ensure the normal operation of hydropower units and hydropower stations.

There are two maintenance modes for large-scale mechanical equipment: maintenance of damaged equipment after an accident and maintenance of mechanical equipment according to a scheduled maintenance plan. However, these two kinds of troubleshooting methods have their own shortcomings. After the accident, the troubleshooting is to make an after-the-fact troubleshooting and emergency repair of the mechanical components that have already failed, but the accident has occurrence for a long time, and there is no way to remedy the possible

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device injury and economic loss. Overhauling the mechanical equipment according to the scheduled overhaul plan may lead to over-overhaul of some components that do not need to be overhauled, resulting in waste of manpower and financial resources, or failure to overhaul the faulty equipment. This can also result in emergency repair after unit failure that aggravated the production cost. To meet the current situation of increasing emphasis on production safety and the pursuit of benefits, it is necessary to improve the previous maintenance methods. When the real-time running states of hydropower units are monitored, and the running state information is collected and analysed, the running state and the fault diagnosis of the units according to the processing results can be judged to plan maintenance in time. These developing techniques can ensure the long-term stable operation of mechanical components. The stable operation of hydropower units is the guarantee for hydropower stations to achieve their optimal power generation capacities. It has important application value to take effective fault diagnosis methods to analyse the operational status of hydropower units and arrange maintenance in time to ensure the safe operation of their mechanical components and prevent accidents.

The researches and developments of working condition detection and fault diagnosis technology of hydropower units are relatively early, and many research results have been obtained [4-8]. These studies focus on fault diagnosis, anomaly detection, and trend prediction of hydropower equipment based on machine learning. In recent years, deep learning techniques have not only achieved success in areas such as images and vision, but also in the monitoring and prediction of hydropower equipment [9-15]. Time-frequency analysis method is widely used in fault diagnosis and anomaly detection for hydropower equipment. As more and more hydropower equipment signals are used for monitoring, adaptive decomposition algorithms are beginning to be adopted due to their excellent processing capabilities for nonlinear and nonstationary signals. Among these adaptive decomposition methods, empirical mode decomposition (EMD) and empirical wavelet transform (EWT) methods were proposed earlier, but these methods cannot automatically determine the frequency bandwidth of each mode after decomposition [16]. The variational modal decomposition (VMD) method has achieved good results in signal processing and has been used in fault diagnosis or anomaly detection [17, 18]. VMD determines the frequency center and bandwidth of each component by iteratively searching for the optimal solution of variational model, so as to adaptively realize the frequency domain division of the signal and the effective separation of each component. VMD decomposes the input signal into a number of sub-signals that have specific sparsity in reproducing the input signal. The VMD method has recently been applied to the processing of signals from hydropower equipment to enable anomaly detection or prediction [14, 19-21].

The state signal of hydropower units can reflect most of the fault information, and it has strong non-stationary and nonlinear characteristics. By analysing the state information of hydropower units and extracting its characteristics by using time-frequency analysis method, it can assist the fault diagnosis of hydropower units. However, most of the existing methods are to detect the abnormality or fault, and they stop the operation after finding the fault or abnormality, lacking the quantitative evaluation of the abnormal state of the hydropower unit equipment. The main contribution of this paper is that based on the VMD analysis of time-frequency signals, a quantitative evaluation method of abnormal state of hydropower equipment is proposed. This research allows anomalies to be detected early in their occurrence, which is beneficial to health management and early warning of hydroelectric equipment and systems.

2 Degradation Evaluation of Hydropower Equipment

2.1 Variable Modal Decomposition

Variable modal decomposition can divide the signal data to a set of intrinsic mode functions (IMF) with limited bandwidth, it can automatically and adaptively change the optimal center frequency and bandwidth among different IMF [17, 18]. In VMD decomposition, it can be assumed that the original signal

$$u_k(t) = A_k(t)\cos(\phi_k(t)) \quad , \tag{1}$$

$$\omega_k = \frac{d\phi_k(t)}{dt} \quad , \tag{2}$$

where A_k is the instantaneous amplitude and ω_k is the instantaneous frequency. Here, the intrinsic mode number of limited bandwidth with stricter constraints is redefined.

Variable modal decomposition is a process to solve variational problems, and the core of VMD is to solve variational problems through construction. If a modal fraction of a given channel is displayed on the intermediate frequency spectrum and the limited bandwidth, the original signal is divided into *K* fractions, and the variational problem can be regarded as calculating *K* modal fractions u_k. To make the estimated values of broadband and central spectrum of each modal fraction more accurate, there are the following processes [17].

(1) Hilbert transform is employed to obtain the corresponding unilateral frequency $[\sigma(t)+\frac{j}{\pi t}]u_k(t)$. Hilbert transform can transform signals in real number domain into analytical signals, and project 1D signals onto 2D plane.

(2) The complex exponents of each mode and center frequency are estimated simultaneously. The exponents $e^{-j\omega_k(t)}$ are used to correct the signal and move its frequency spectrum to the corresponding base frequency band $\{[\sigma(t)+\frac{j}{\pi t}]*u_{k(t)}\}e^{-j\omega_k(t)}$.

(3) When the demodulated signal is used to calculate L_2 norm, bandwidth of every decomposed mode is estimated. This problem is described as

$$\begin{aligned}&\min_{\{v_k\}\{w_k\}}\left\{\sum_k\left\|\partial_t\left[\left(\sigma(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|^2\right\}\\&s.t.\quad \sum_k u_k = s\end{aligned}, \tag{3}$$

$\{u_k\}=\{u_1,...,u_k\}$ represents IMF components, and their center frequency is $\{\omega_k\}=\{\omega_1,...,\omega_k\}$.

To solve the variational constraint problem, Lagrange multiplier $\tau(t)$ and second-order penalty factor α are employed. So a variational unconstrained problem can be obtained. Lagrange multiplier can guarantee the strictness of constraints, and second-order penalty factor can make signal reconstruction more accurate under Gaussian noise. Lagrange function is as follows

$$\begin{aligned}&L\left(\{u_k\},\{\omega_k\},\tau\right)=\alpha\sum_k\left\|\partial_t\left[\left(\sigma(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|^2\\&+\left\|s(t)-\sum_k u_k(t)\right\|^2+.....+\left\langle\tau(t),s(t)-\sum_k u_k(t)\right\rangle\end{aligned}, \tag{4}$$

Through the iterative calculation of the process (2) and (3), the central frequency spectrum and width of each mode can be calculated and updated. So, the sum of bandwidth is minimized, and the optimal value of the original signal can be obtained.

VMD decomposition can analyze the spectrum of aperiodic signal and decompose complex signal into multiple harmonic signals. In the actual application, VMD analysis mainly needs to set the variational modal decomposition modulus *K* and bandwidth limiting parameter, namely penalty factor α, both of which have great influence on the actual processing results of VMD analysis.

VMD decomposition has good anti-noise ability, which can overcome the overlapping frequency characteristics that may occur when empirical mode decomposition is used. The most common problem that empirical mode decomposition may encounter when processing and analyzing signals is frequency aliasing. If the frequency of an eigenmode function is reasonable, it should be in a relatively concentrated and narrow frequency range, but frequency aliasing will make the frequency components of an eigenmode function distribute in different eigenmodes, and VMD can avoid this problem.

2.2 Degradation Evaluation Method

Each component after VMD decomposition forms a matrix. The matrix can be decomposed by singular value. That means, a group of pairwise orthogonal unit vector sequences can be found, so that the new vector sequences obtained after the matrix acts on this vector sequence can be pairwise orthogonal. The decomposed singular values are arranged in a row as features to form a singular value vector.

Sample entropy is one of the commonly used complexity characteristic indexes, and it is an improved form of approximate entropy. It measures the probability of new patterns by measuring the complexity of time series. The smaller the entropy, the smaller the complexity of signal. The sample entropy is calculated for every component of VMD, and it is regarded as a feature, and these feature values are merged into the singular value vector to obtain the feature vector which is composed of singular value and sample entropy.

To evaluate the degradation of hydropower equipment, Jenson-Shannon (JS) divergence is adopted in this paper. JS divergence measures the distance of two probability distributions. It is different from Kullback-Leibler (KL) divergence, especially it is asymmetry, but KL divergence is not [22-24].

KL divergence is defined as

$$D_{KL}(P \mid Q) = \sum_{i} P(i) \log \frac{P(i)}{Q(i)} \ , \tag{5}$$

It represents the difference between two probability distributions of P and Q. Moreover, if the two distributions are so far apart that there is no overlap, KL divergence cannot be calculated, while JS divergence is a constant. JS divergence is defined as

$$D_{JS}(P \mid Q) = \frac{1}{2} D_{KL}(P \mid \frac{P+Q}{2}) + \frac{1}{2} D_{KL}(Q \mid \frac{P+Q}{2}) \ , \tag{6}$$

By calculating JS divergence of different feature vectors composed of singular values and sample entropy, we can quantify the distance between these feature vectors and reflect the difference. When in the normal supervisor state, these feature vectors are very close, and the JS divergence is close to zero. With the degradation of equipment performance, the distance from the normal state eigenvector is getting bigger and bigger, and the JS divergence is far away from zero. Therefore, this measure can reflect the degree of equipment performance degradation and is an effective measure of equipment performance degradation.

3 Experimental Results and Discussion

The sensor data of hydropower equipment used in the experiment is obtained by monitoring the unit at the same acquisition time [14]. The sensor data include oil level in the oil leakage tank and oil pressing device, et al. The data is complicated, nonlinear and unstable, and their characteristics are not obvious.

The normal signal of oil level in the oil leakage tank is shown in Fig. 1. The variational modal number K of VMD is 8, and the penalty factor is 2717.04. The VMD decomposition results are shown in Fig. 2 and Fig. 3. The IMF components processed by VMD are added and compared with the initial signal data, and the residual value is 0.0089. To determine the variational modal number K and the penalty factor, particle swarm optimization algorithm [25-27] is employed to obtain the optimal value of the two parameters. The minimum value of the envelope entropy is used as object function, as the envelope entropy represents the sparseness of signal. When IMF component noise is less and feature information is enough, the envelope entropy is smaller. The envelope entropy E_p of the signal $x(i)$ can be calculated as

$$E_p = -\sum_{j=1}^{N} p_j \lg p_j \ , \tag{7}$$

$$p_j = \frac{a(j)}{\sum_{j=1}^{N} a(j)} \ , \tag{8}$$

where $a(j)$ is the envelope of modal components, and p_j is the probability distribution sequence obtained by normalization of $a(j)$. N is the number of sampling points. The envelope entropy E_p is obtained by calculating the entropy value of p_j.

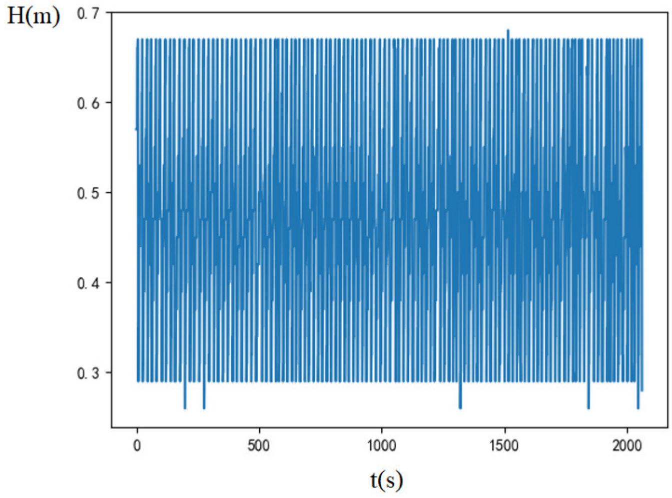

Fig. 1. Oil level in the oil leakage tank

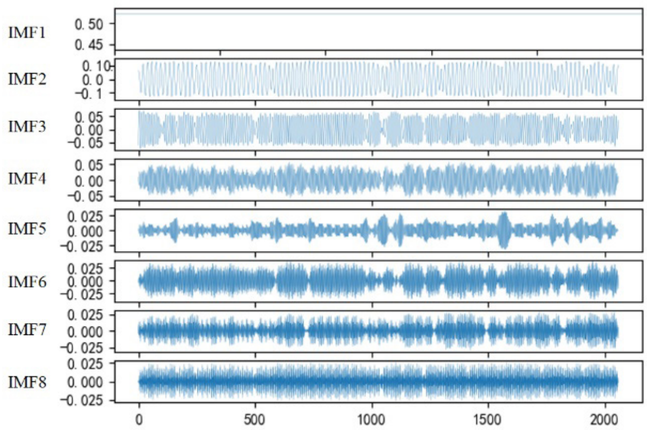

Fig. 2. VMD result of oil level signal

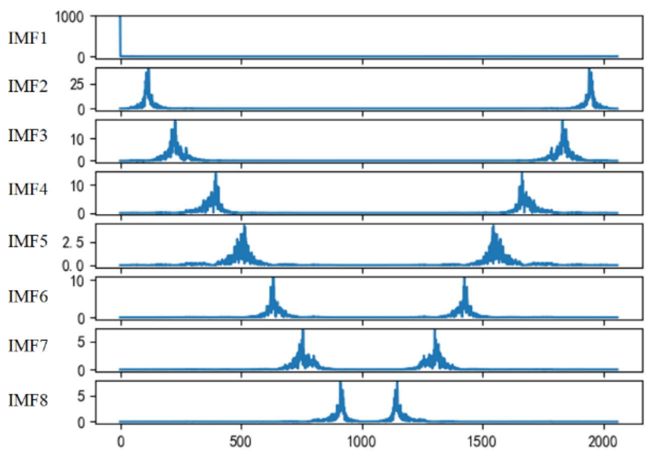

Fig. 3. Frequency diagram of VMD result of oil level signal

According to the degradation evaluation method proposed in section 2.2, the feature vector composed of singular value and sample entropy is calculated for the normal signal. Under certain operating conditions, normal signal of oil level is acquired to calculate feature vector. A total of 720 non-anomalous data pieces under the same operating conditions are collected and their feature vectors are calculated.

After the degraded data are collected, VMD decomposition is performed respectively, and the feature vectors are calculated. JS divergence is used to quantify the distance between degraded feature vectors and normal feature vectors. The JS divergences of these data are calculated and their distribution is plotted in Fig. 4. The distribution of JS divergence is roughly normal. The mean, variance and standard deviation of the JS divergence were 0.29957, 0.000047 and 0.006859, respectively. The minimum and maximum values in this distribution are 0.018 and 0.041, respectively, and the distance from the mean of this distribution is -0.012 and 0.011, respectively. These distances are 1.743 times the standard deviation. Therefore, it is more reasonable to choose the position of 6 standard deviations as the threshold for anomalies, that is, the threshold of JS divergence is 0.03024.

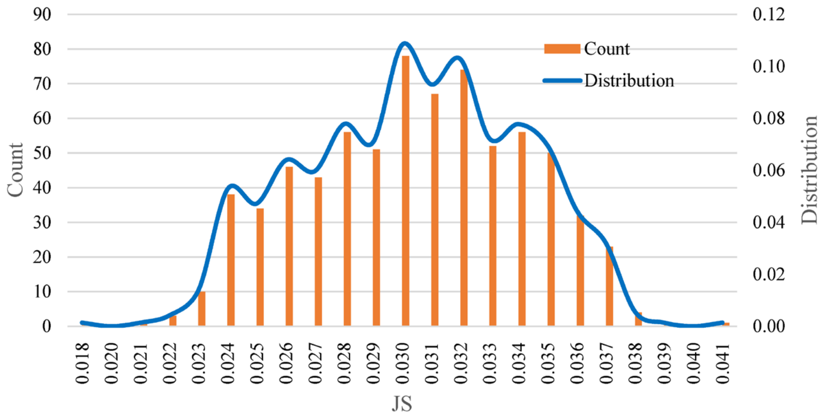

Fig. 4. JS divergence distribution of non-anomalous oil level signals

The JS divergence results of degraded oil level signal are shown in Fig. 5. The marked point A is the time of the 16th minute. The hydropower equipment is in the normal state before A, and it begins to degrade after A. When the abnormality detection method [14] is applied to the degradation process, the abnormality can be detected after the 102th minute, marked as B. If the threshold value of JS divergence is set to 0.3024, an abnormal alarm can be generated in the 67th minute, which is obviously earlier than the normal abnormal detection method.

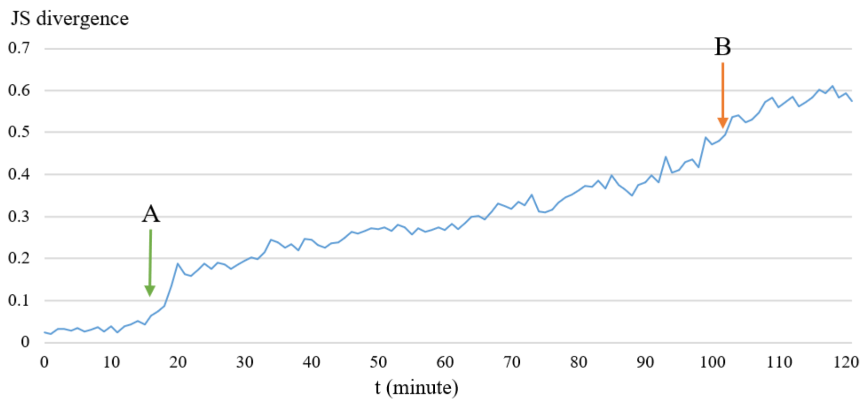

Fig. 5. JS divergence of degradated oil level signal

4 Conclusion

After some modal signals are obtained from a hydropower equipment signal through VMD, singular value and sample entropy features are extracted from the modal signals of signals. And these features are measured by JS divergence to evaluate the degradation of hydropower equipment. The usual anomaly detection and fault diagnosis methods can only be detected when the equipment is abnormal or the fault reaches a certain degree. The proposed method provides a complete quantitative evaluation of the degradation process from normal to abnormal. By setting a reasonable threshold, the proposed method can be used for early warning of anomalies. This is very useful for the complete monitoring of the health status of hydropower equipment. In the future, the method will combine the state prediction of hydropower equipment to provide quantitative prediction of the degree of abnormality of hydropower equipment.

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