

## Research Article

# Research on the Noise Reduction Method of the Vibration Signal of the Hydrogenerator Unit Based on ITD-PE-SVD

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Received 4 August 2021; Accepted 25 August 2021; Published 8 September 2021

Academic Editor: Xian-Bo Wang

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Aiming at the problem that the vibration signals of the hydrogenerator unit are nonlinear and nonstationary and it is difficult to extract the signal features due to strong background noise and complex electromagnetic interference, this paper proposes a dual noise reduction method based on intrinsic time-scale decomposition (ITD) and permutation entropy (PE) combined with singular value decomposition (SVD). Firstly, the vibration signals are decomposed by ITD to obtain a series of PRC components, and the permutation entropy of each component is calculated. Secondly, according to the set permutation entropy threshold, the PRC components are selected for reconstruction to achieve a noise reduction effect. On this basis, SVD is carried out, and the appropriate reconstruction order is selected according to the position of the singular value difference spectrum mutation point for reconstruction, so as to achieve the secondary noise reduction effect. The proposed method is compared with the LMD-PE-SVD and EMD-PE-SVD dual noise reduction method by simulation, taking the correlation coefficient and signal-to-noise ratio to evaluate the noise reduction performance and finding that the ITD-PE-SVD noise reduction has good noise reduction and pulse effect. Furthermore, this method is applied to the analysis of the upper guide swing data in the *X*-direction and *Y*-direction of a unit in a hydropower station in China, and it is found that this method can effectively reduce noise and accurately extract signal features, thus determining the vibration cause, which is helpful to improve the turbine fault recognition rate.

## 1. Introduction

As a clean and renewable energy, hydropower has mature development technology, which meets the needs of China's energy strategic development. As the core equipment of hydropower energy conversion, the operation state of hydropower units directly affects the efficiency of energy conversion. If an abnormality or failure occurs, it will lead to the reduction of power transmission quality and the disturbance of power grid frequency, endangering the safety and stability of units and power plants. In severe cases, it will cause huge economic losses and casualties. Therefore, the stability of its operation has always been the focus of research. Due to the nonlinearity and nonstationarity of the

signal are more intense when the hydropower unit is in unsteady operation, and at the same time, due to the influence of strong background noise and complex electromagnetic interference, the collected signal contains larger noise components, thus affecting the accurate extraction of vibration signal features. In the practical engineering application of unit condition monitoring and fault diagnosis, in order to extract the most representative fault features and improve the accuracy of diagnosis and analysis, the key first step is to process vibration signals. Therefore, the effective noise reduction of the collected vibration signals is of great significance to accurately judge the fault function of the unit.

At present, there are many methods for nonstationary signal processing, such as short-time Fourier transform

(STFT) [1], wavelet transform (WT) [2], empirical mode decomposition (EMD) [3], and local mean decomposition (LMD) [4]. The basic idea of short-time Fourier transform is to realize the quasi-stationary performance of nonstationary signal through time window function and then obtain the time-varying law of signal frequency domain characteristics. As a generalization of Fourier transform, this method retains the characteristics of linear transformation and has good effect in processing quasi-stationary signals, but it is not ideal for processing nonstationary signals [5–7]. Wavelet transform inherits and expands the localization idea of STFT, effectively overcomes the defect of fixed window area, and can focus on arbitrary details of signals, which is a real multiresolution analysis and is widely used. However, its noise reduction performance is greatly affected by the selection of wavelet bases, and there is no unified standard for selecting wavelet bases at present [8–10]. Aiming at the shortcomings of wavelet transform, the scholars have proposed EMD analysis methods [11, 12], which can adaptively decompose the signal into a series of IMF components with definite frequency amplitude according to the time domain characteristics of the signal itself. However, the EMD decomposition can easily lead to modal aliasing and large iterative computation [12, 13]. The adaptive signal decomposition method of local mean decomposition proposed in [4] can overcome the defects of EMD method after improvement, and the iteration times and operation speed are better than EMD, but the problem of modal aliasing has not been fundamentally solved [14–16]. In addition, considering the complexity of the real signal and its application in practical engineering, it is more effective to extract the useful signals from strong interference by using the hybrid method than by using one method alone [17–19].

Based on the above analysis, aiming at the problem that it is difficult to extract the vibration signal characteristics of hydrogenerator units under the background of strong noise and complex electromagnetic interference, combined with the advantages of inherent time-scale decomposition, permutation entropy and singular value, a dual noise reduction method based on ITD-PE-SVD is proposed. Intrinsic time-scale decomposition (ITD) is an adaptive signal time-frequency analysis method proposed by Frei et al. in 2007 [20, 21]. This method decomposes the nonstationary complex signal into a series of intrinsic rotation components (PRC) and a residual trend component (RTC), which overcomes the edge effect of EMD and weakens the mode mixing and other phenomena. The calculation speed is significantly improved compared with EMD and LMD, and the feature information of nonstationary can be extracted more accurately and efficiently [22, 23]. The permutation entropy (PE) is an algorithm for measuring the complexity of time series. Compared with sample entropy and approximate entropy, it has the advantages of simple calculation process, prominent anti-interference ability, and more sensitive to mutation signals. It can be used to deal with the problems of complex vibration signal components and weak fault signal of hydropower units [24–26]. Singular value decomposition (SVD) is based on matrix decomposition and transformation; it decomposes the signal into the

superposition of a series of linear components and has the advantages that the waveform is not easy to be distorted, and the zero-phase shift is small. It can effectively detect the weak information mutation in the signal under complex background and has outstanding effect in feature information extraction and noise reduction [27–29].

Therefore, the ITD-PE-SVD proposed in this paper combines the advantages of the above three algorithms, so as to realize the dual noise reduction of the vibration signal of the unit under the background of strong noise and complex electromagnetic interference and accurately extract the weak fault feature information of the unit, so as to accurately determine the vibration reason of the unit and provide theoretical basis for the subsequent fault diagnosis.

The first part of this paper describes the principle of this noise reduction method, the second part uses this method to carry out simulation and comparative analysis, and the third part selects the upper guide swing data in  $X$ -direction and  $Y$ -direction of a hydropower station in China for example verification. Finally, the application of this method in vibration signal feature extraction of hydrogenerator units under strong noise background is summarized and prospected.

## 2. Principle of the ITD-PE-SVD Method

*2.1. Principle of Inherent Time-Scale Decomposition.* The ITD adaptively decomposes nonlinear nonstationary signals into multiple proper rotation components (PRC) and a residual trend component (RTC). The main idea of constructing the baseline signal is to perform linear transformation between any two adjacent maximum or minimum signal segments [20–22].

Suppose the fault signal  $X_t$ ,  $t = 0, 1, 2, L$  is defined as the baseline extraction operator and the decomposition process is expressed as follows:

$$X_t = LX_t + (1 - L)X_t = L_t + H_t. \quad (1)$$

$L_t$  is the baseline component and contains local relatively low frequency information in the fault signal;  $H_t$  is the appropriate rotational component and contains the local relative high-frequency information in the fault signal.

Remove the high-frequency rotating component after one decomposition, then take the baseline component signal as the next signal to be decomposed, and finally iterate the above decomposition process until the monotone trend component signal shows trouble signal  $X_t$ . The whole decomposition process of  $X_t$  is defined as follows:

$$\begin{aligned} X_t &= HX_t + LX_t = HX_t + (H + L)LX_t \\ &= \left( H \sum_{k=0}^{N-1} L^k + L^N \right) X_t. \end{aligned} \quad (2)$$

$LX_t$  is the linear baseline extraction operator,  $HX_t$  is the intrinsic rotation component extraction operator,  $HL^k X_t$  is the  $k + 1$  rotation component, and  $L^N X_t$  is the monotone trend component.

**2.2. Principle of Permutation Entropy.** Permutation entropy is sensitive to mutated signals, and it is an algorithm to describe the complexity of time series [23, 24]. The principle is as follows:

Given sequence  $\{X(K), K = 1, 2, \dots, N\}$ , and the phase space reconstruction is performed:

$$Z = \begin{pmatrix} x(1) & x(1 + \tau) & \dots & x(1 + (d-1)\tau) \\ x(2) & x(2 + \tau) & \dots & x(2 + (d-1)\tau) \\ \vdots & \vdots & \ddots & \vdots \\ x(K) & x(K + \tau) & \dots & x(K + (d-1)\tau) \end{pmatrix}. \quad (3)$$

$d$  is the embedded dimension,  $\tau$  is the delay time, and  $k$  is the reconstructed component.

Put the matrix  $Z$  each row in the sequence is arranged in ascending order:

$$x(t + R_1\tau) \leq x(t + R_2\tau) \leq \dots \leq x(t + R_d\tau). \quad (4)$$

$t$  is the number of columns indexed, and  $R_1, R_2, \dots, R_d$  is the location of each element in the  $X(K)$ .

Define  $x_i^d$  as any set of reconstructed sequences,  $0 \leq R \leq d!$ . For the  $d$ -dimensional phase space mapping, there are the possibility of  $d!$  arrangement and the possibility  $P_1, P_2, \dots, P_i$  of each sequence calculated. For the time series  $X(K)$ , there are  $i$  arrangement modes of  $H_p$ :

$$H_p(d) = - \sum P_i \ln(P_i). \quad (5)$$

When  $P = m!$ ,  $H_p(d)$  will reach the maximum value of  $\ln(m!)$ ; in order to facilitate the comparison, the permutation entropy is often normalized:

$$H_p = \frac{H_p(d)}{\ln(m!)}. \quad (6)$$

The size of  $H_p$  represents the random degree of time series. The smaller  $H_p$  is, the more regular the corresponding time series is, and vice versa.

It should be noted that when the permutation entropy algorithm is carried out, the time delay  $\tau$  has little effect on the time series, while the insertion dimension  $d$  is too small or too large, which will affect the construction accuracy of the reconstruction matrix. Bandt [30, 31] suggested that the dimension should be selected from 3 to 7; the results of the sample entropy obtained by calculation are highly reasonable in statistical theory. Therefore, the insertion dimension  $d = 5$ , and the time delay  $\tau = 1$ .

**2.3. Principle of Singular Value Decomposition.** As a non-linear filtering method, SVD decomposes the matrix containing signal information into a series of singular values and time-frequency subspaces corresponding to singular value vectors from the perspective of matrix, which can eliminate noise to the maximum extent and retain useful information with fault signals, and has been widely used in the field of signal analysis [27, 28].

Suppose there is a signal to be decomposed  $Y = (y(1), y(2), \dots, y(n))$ ; an  $m \times n$ -order Hankel matrix is constructed for this signal:

$$H = \begin{bmatrix} y(1) & y(2) & \dots & y(n) \\ y(2) & y(3) & \dots & y(n+1) \\ \vdots & \vdots & \ddots & \vdots \\ y(N-n+1) & y(N-n+2) & \dots & y(N) \end{bmatrix}. \quad (7)$$

$N$  is the length of the signal to be decomposed,  $1 < n < N$ ;  $m = N - n + 1$ ;  $H \in R^{m \times n}$ .

SVD decomposes the resulting matrix as follows:

$$H = USV^T. \quad (8)$$

$$S = \begin{cases} (\text{diag}(\sigma_1, \sigma_2, \dots, \sigma_q), 0), & m \leq n, \\ (\text{diag}(\sigma_1, \sigma_2, \dots, \sigma_q), 0)^T, & m > n. \end{cases} \quad (9)$$

$U = (u_1, u_2, \dots, u_m) \in R^{m \times m}$  and  $V = (v_1, v_2, \dots, v_n) \in R^{n \times n}$  are two orthogonal matrices;  $S \in R^{m \times n}$ , determined by the relationship between  $m$  and  $n$ , 0 stands for zero matrix,  $q = \min(m, n)$ , and then the singular value of matrix  $H$  is  $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_q \geq 0$ ,  $\sigma_i = (i = 1, 2, \dots, q)$ .

It should be noted that when creating a signal through the Hankel matrix, the number of rows  $m$  and columns  $n$  can be determined according to the following principles [27, 28]; when the signal length  $N$  is even, take  $m = (N + 1)/2$ ,  $n = N/2$ ;  $q$  takes the maximum value  $q = N/2$ . When the signal length  $N$  is odd, take  $m = (N + 1)/2$ ,  $n = (N + 1)/2$ ;  $q$  takes the maximum value  $q = (N + 1)/2$ .

The sequence formed by the singular value of the descending order is set as  $\delta_i = (i = 0, 1, 2, \dots, q)$ ; then the former singular values are subtracted from the latter singular values; that is,  $b_i = \delta_i - \delta_{i+1} = 0, 1, 2, \dots, q - 1$ ; then, the new sequence composed of  $b_i$  is the singular value difference spectrum. It can automatically select the effective order according to the difference of contribution of useful signal and noise signal to singular value energy. If the maximum mutation occurs at the position of the  $S$  point, the noise reduction can be realized when the reconstruction order is selected before the  $S$  point [28, 29].

#### 2.4. Steps of the Signal Noise Reduction Method for ITD-PE-SVD

- (1) Firstly, carry out ITD decomposition on collected vibration signals to obtain a series of PRC components
- (2) According to formulas (4)–(6), calculate the arrangement entropy of PRC components
- (3) According to the results of many simulation experiments and the principle of permutation entropy calculation, the threshold value of permutation entropy is set to 2, and the appropriate PRC component is selected for reconstruction, so as to achieve a noise reduction effect
- (4) Perform SVD decomposition on the reconstructed signal again according to formula (8), and select suitable singular values to reconstruct the characteristic signal again according to the decomposed singular value differential spectrogram, so as to

achieve the secondary noise reduction effect and obtain the final denoised signal

- (5) Analyze the characteristic frequency of the final denoised signal to judge the fault reason of the unit

The technical route is shown in Figure 1.

### 3. Simulation Signal and Analysis

In order to preliminarily judge the rationality of this method, the simulation signal is constructed according to the frequency characteristics of the hydraulic turbine under actual operating conditions.

Assuming that the unit frequency is 2 Hz and the sampling frequency is 500 Hz, the simulation signal without noise  $x_1$  contains four characteristic frequencies, namely, 1 Hz, 2 Hz, 4 Hz, and 7.5 Hz. The simulated noiseless waveform and spectrum diagram are shown in Figure 2. Consider adding a random white Gaussian noise  $x_2$  and a pulse signal  $x_3$ ; the signal after noise addition is  $x$ , and the waveform and spectrum after noise addition are shown in Figure 3. The formula for setting the simulation waveform is shown in the following:

$$\begin{aligned} x_1 &= 6 \sin(4\pi t) + 1.5 \sin(15\pi t) + 4.5 \sin(8\pi t) + 1.8 \sin(2\pi t), \\ x_2 &= 20\text{randn}(1: 5000), \\ x_3 &= 35 * \text{pulstran}(T, D, \text{'tripuls'}, 0.0000001, 0), \\ x &= x_1 + x_2 + x_3. \end{aligned} \quad (10)$$

$T$  is the time axis, generally a one-dimensional array, and  $D$  is the sampling interval.

It can be seen from the figures that when the simulated signal contains noise and abnormal pulse, the waveform is abnormally disorderly, and there are many interference frequencies in the spectrum diagram. Because of the existence of interference frequencies, the fault features are difficult to extract in the spectrum diagram, which may lead to misjudgment of the actual unit fault.

The proposed ITD-PE-SVD denoising method is used to process the noised signal. At the same time, in order to verify the effectiveness and superiority of the proposed method, the LMD-PE-SVD and EMD-PE-SVD are used to process the noised signal. The waveform and spectrum diagram of the three methods are shown in Figures 4–6.

It can be seen from Figures 4–6 that the simulated frequencies of 1 Hz, 2 Hz, 4 Hz, and 7.5 Hz are all extracted after being processed by four methods. However, after being processed by LMD-PE-SVD and EMD-PE-SVD, there are many interference frequencies around the signal, and the overall information is not fully reflected. After EMD-PE-SVD method, due to the presence of modal aliasing in the EMD decomposition process, the waveform is distorted.

After the ITD-PE-SVD denoising processing, not only the characteristic frequency can be clearly observed, but also the waveform diagram is almost completely close to Figure 2 (simulation without noise waveform and spectrum diagram), with smaller error, less surrounding

interference, and better signal integrity, which fully demonstrates the effectiveness of the ITD-PE-SVD noise reduction method.

In order to quantitatively analyze the noise reduction performance, correlation coefficient ( $R$ ) and signal-to-noise ratio (SNR) are taken as quantitative analysis indexes. The correlation coefficient refers to the correlation degree between the original signal and the denoised signal. The closer the value is to 1, the better the fitting degree between the denoised signal and the original signal is, and the more useful information of the original signal is retained [32–34]. The signal-to-noise ratio refers to the ratio of the original signal energy to the noise energy. The higher the signal-to-noise ratio, the better the denoising effect is [34–36]. The formula is as follows:

$$R = \frac{\sum_{i=1}^N v_i \hat{v}_i}{\sqrt{\sum_{i=1}^N v_i^2 \sum_{i=1}^N \hat{v}_i^2}} \quad (11)$$

$$\text{SNR} = 10 \lg \frac{\sum_{i=1}^N v_i^2}{\sum_{i=1}^N (v_i - \hat{v}_i)^2}$$

$N$  is the number of signal sampling points,  $v_i$  is the original signal,  $\hat{v}_i$  is the estimation of  $v_i$ , and  $\lg$  is the logarithm based on 10.

The noise reduction performance indexes of each method are shown in Table 1. It can be seen that after ITD-PE-SVD denoising method is used to process the data containing noise and pulse, the data correlation is as high as 0.9956 and the signal-to-noise ratio is larger, and the comprehensive performance index is better than LMD-PE-SVD and EMD-PE-SVD, which shows the effectiveness of this method. At the same time, it also shows that the method maximizes the elimination of noise and retains useful information with fault signals and has a good effect on the data containing noise and pulse.

### 4. Engineering Examples

In order to verify the feasibility and effectiveness of this method in practical engineering application, the  $X$ -direction and  $Y$ -direction swing vibration data at the rated output of a hydropower station in China are selected to collect. The turbine model is HL220-LJ-410, the unit speed is 136r/min, and the acquisition frequency is 500 Hz. Some continuous data are selected and processed by ITD-PE-SVD.

The waveform and spectrum are shown in Figures 7–10. Among them, Figures 7 and 8 are the upper guide  $X$ -direction swing data waveform, spectrum diagram, and the upper guide  $X$ -direction swing waveform and spectrum diagram after the ITD-PE-SVD noise reduction. Figures 9 and 10 are the upper guide  $Y$ -direction swing data waveform, spectrum diagram, and the upper guide  $Y$ -direction swing waveform and spectrum diagram after the ITD-PE-SVD noise reduction.

It can be seen from the figures that the swing signal of the unit contains a large amount of background noise, and the noise distribution is uneven. After the denoising processing

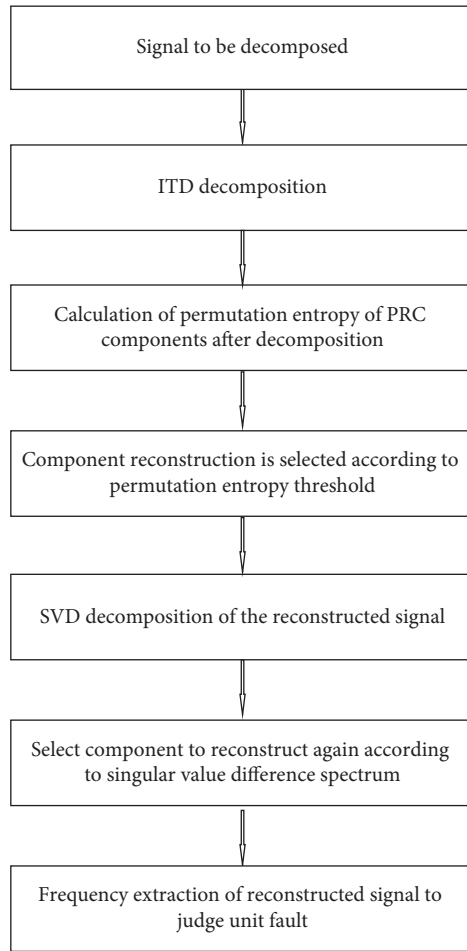


FIGURE 1: Denoising flowchart.

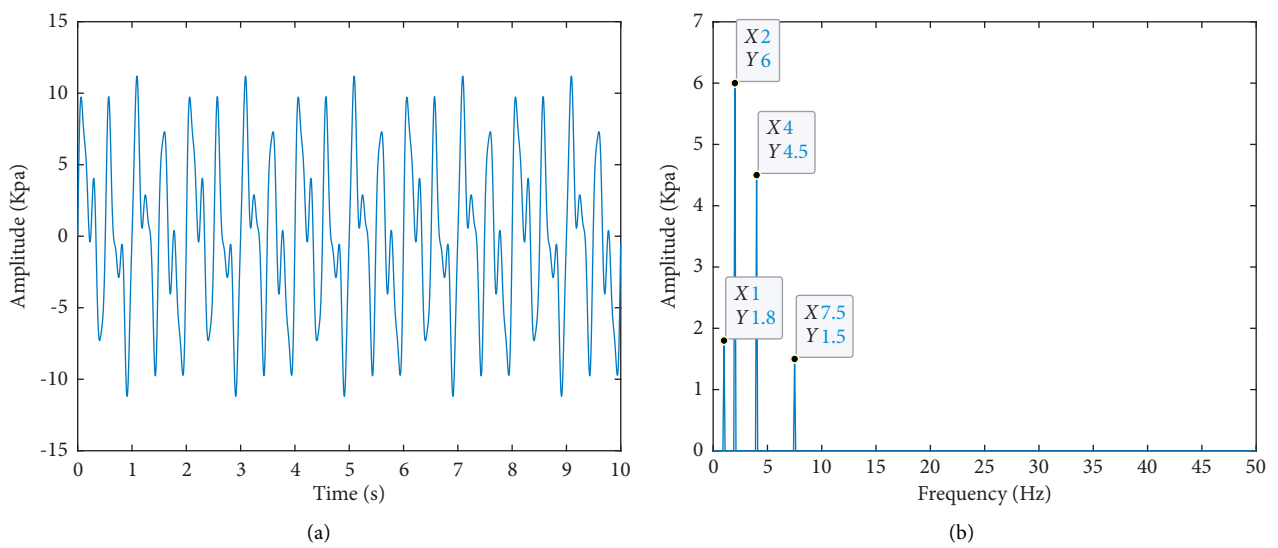


FIGURE 2: Simulation without noise waveform and spectrum diagram. (a) Waveform diagram. (b) Spectrogram.

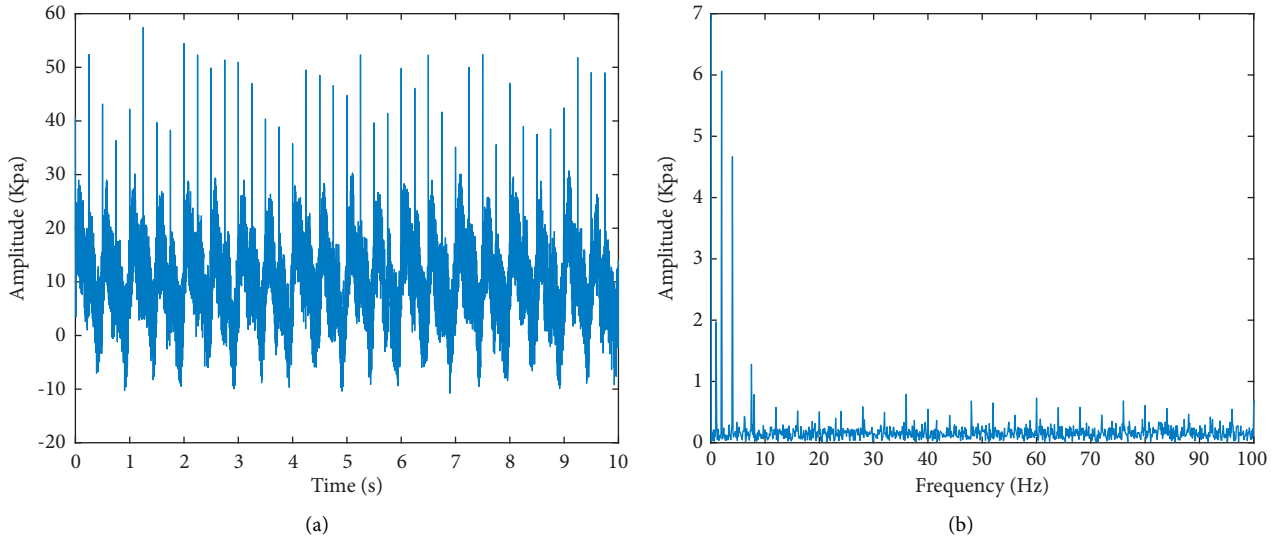


FIGURE 3: Simulation of noise addition waveform and spectrum diagram. (a) Waveform diagram. (b) Spectrogram.

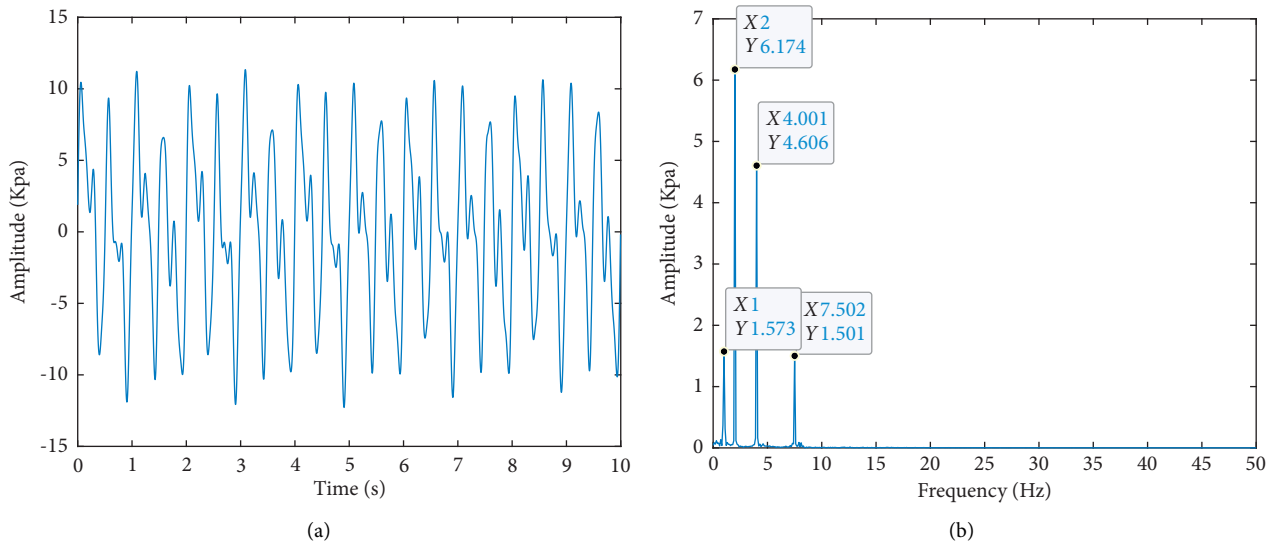


FIGURE 4: (a) Waveform diagram and (b) spectrogram after LMD-PE-SVD noise reduction.

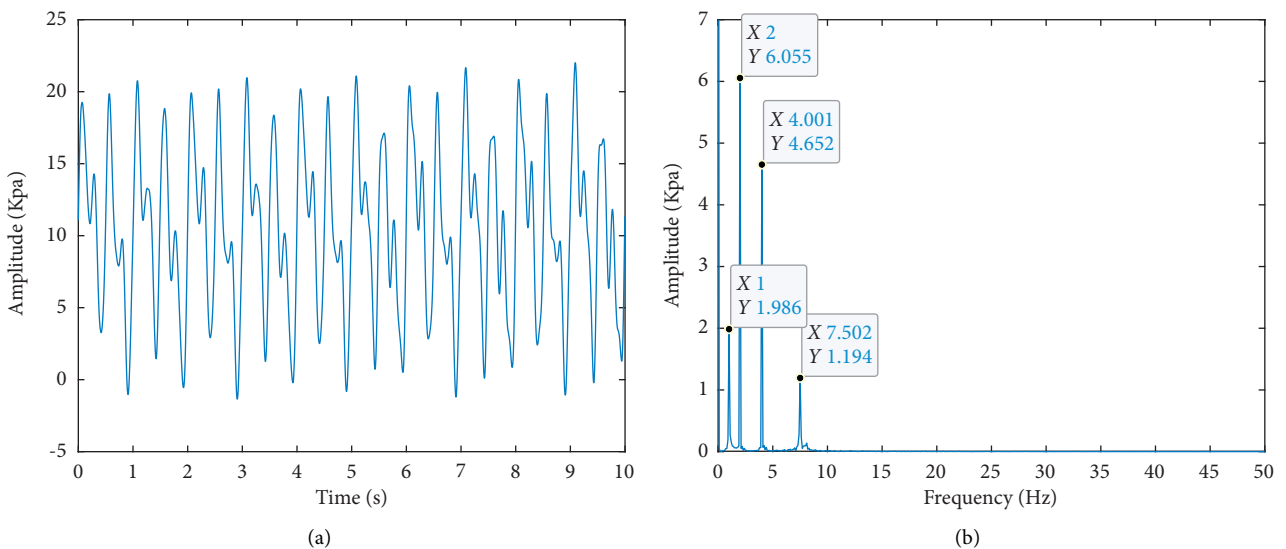


FIGURE 5: (a) Waveform diagram and (b) spectrogram after EMD-PE-SVD noise reduction.

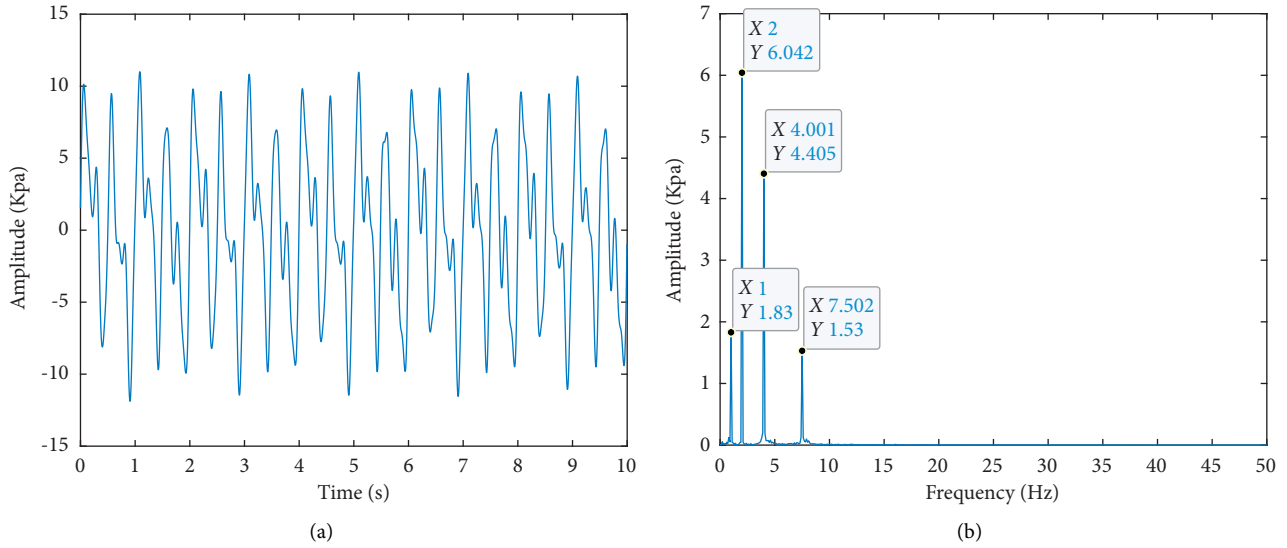


FIGURE 6: (a) Waveform diagram and (b) spectrogram after ITD-PE-SVD noise reduction.

TABLE 1: Related index values.

|            | Correlation coefficient | Signal-to-noise ratio |
|------------|-------------------------|-----------------------|
| LMD-PE-SVD | 0.9906                  | 17.2549               |
| EMD-PE-SVD | 0.9910                  | 18.2341               |
| ITD-PE-SVD | 0.9956                  | 20.5502               |

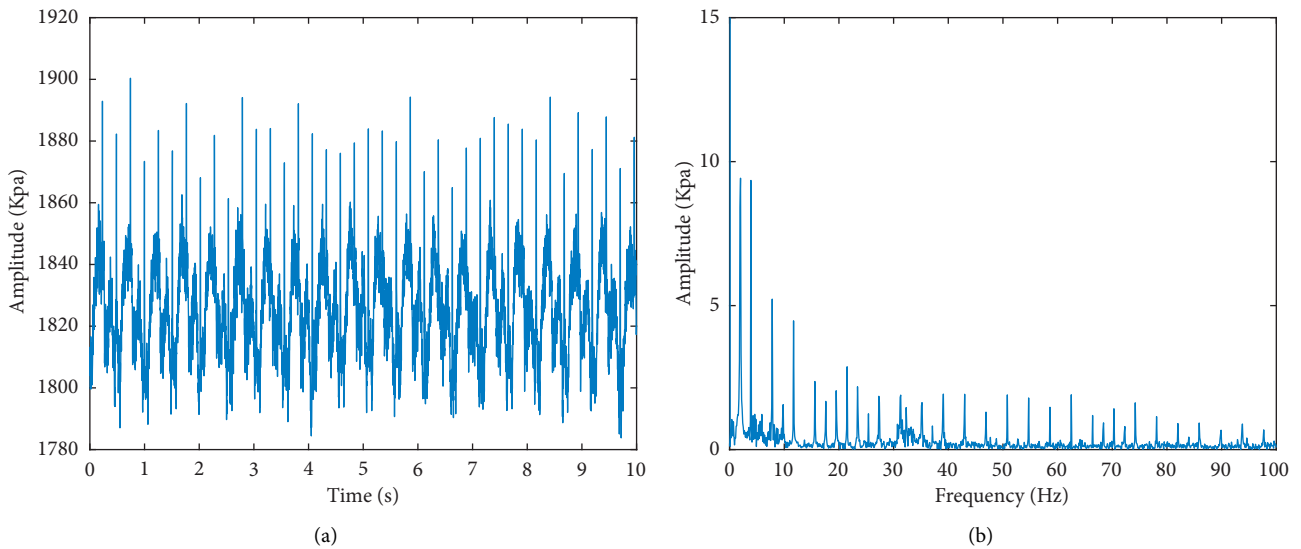


FIGURE 7: (a) Waveform diagram and (b) spectrogram of the upper guide X-direction swing data.

of the ITD-PE-SVD method proposed in this paper, the background noise is well filtered, and the waveform diagram is very clear, which further verifies the effectiveness of the method in engineering.

According to the frequency spectrum analysis of the denoised data of the unit, the frequency characteristics are

1, 2, 4, and 6 times of the frequency conversion of the unit, and there is no influence of other interference frequencies. According to [37], it can be seen that the vibration amplitude of the unit exceeds the specified standard due to mechanical factors, and the reason may be caused by the asymmetry or mass imbalance of the unit.

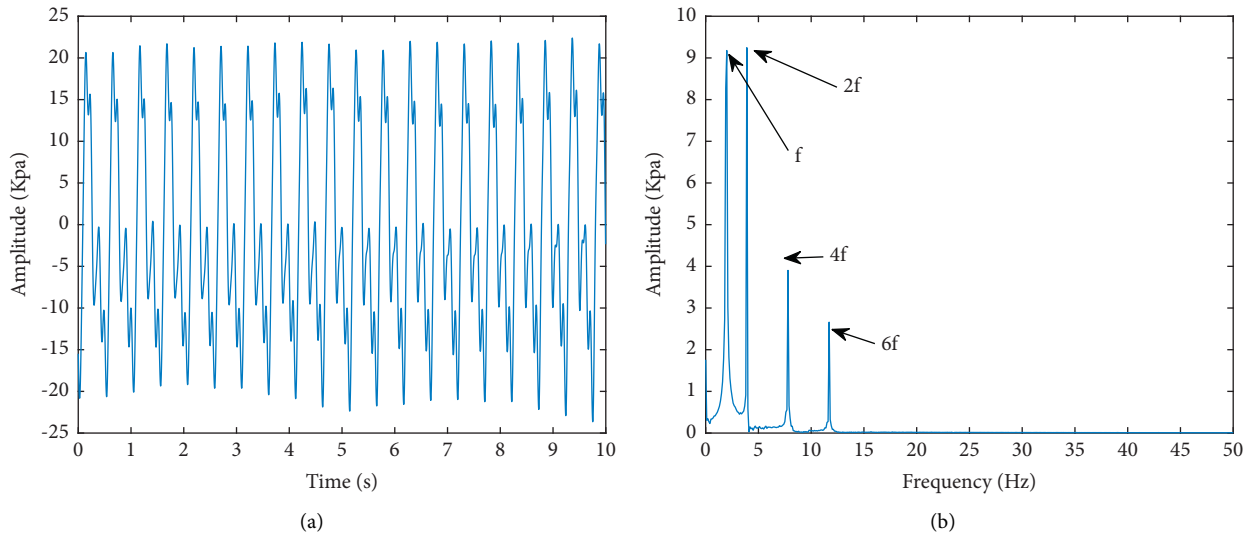


FIGURE 8: (a) Waveform diagram and (b) spectrogram of the upper guide X-direction swing data after ITD-PE-SVD noise reduction.

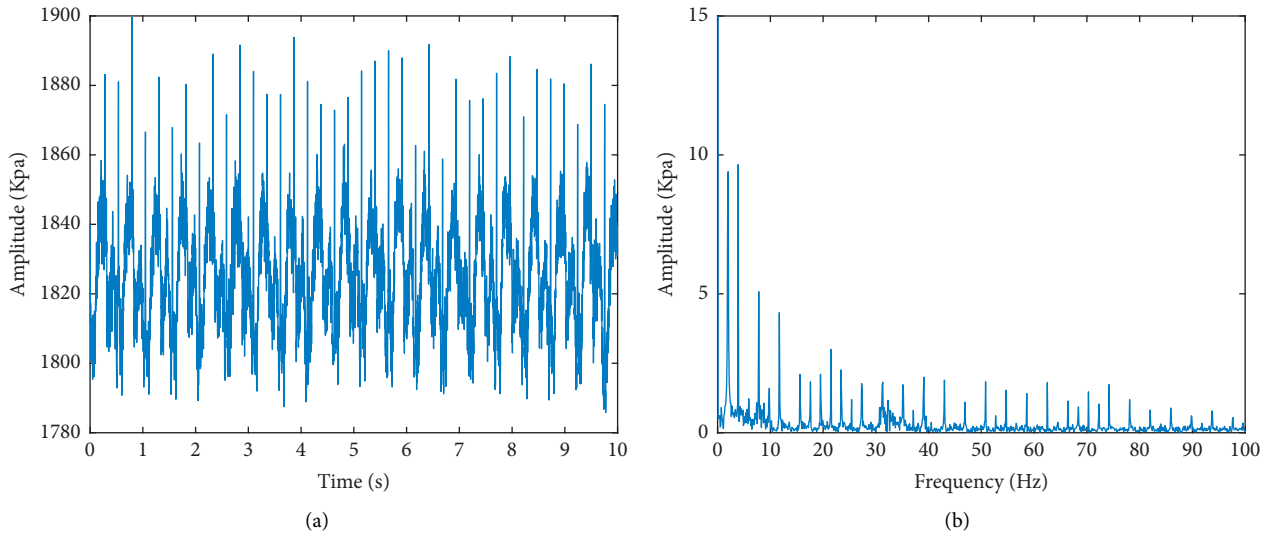


FIGURE 9: (a) Waveform diagram and (b) spectrogram of the upper guide Y-direction swing data.

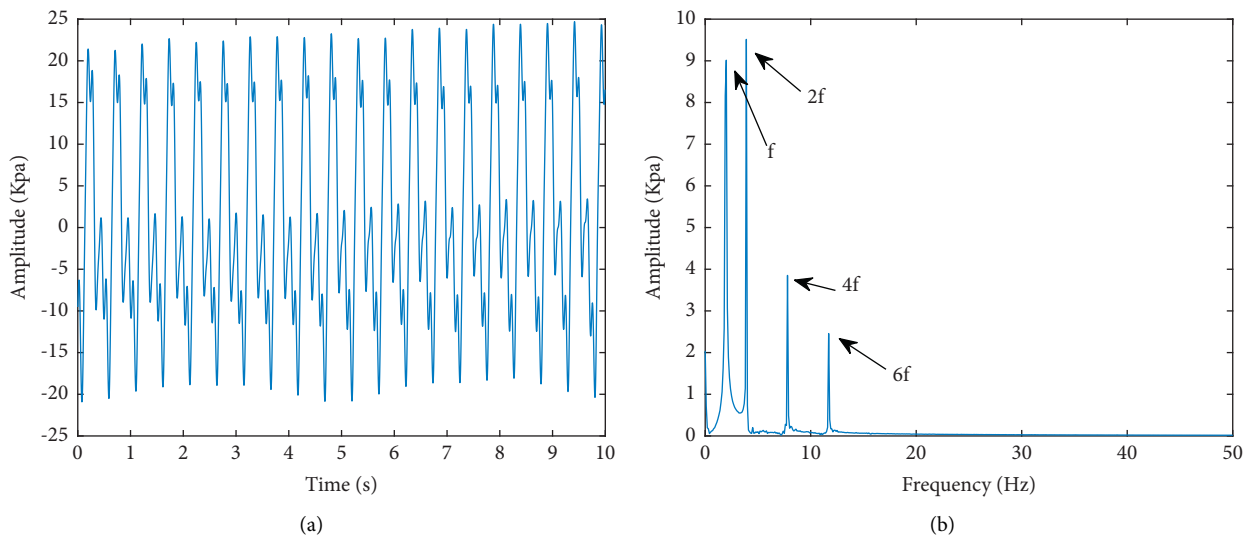


FIGURE 10: (a) Waveform diagram and (b) spectrogram of the upper guide Y-direction swing data after ITD-PE-SVD noise reduction.



## 5. Conclusion

In this paper, by combining the advantages of inherent time-scale decomposition, permutation entropy, and singular value decomposition, a denoising method based on ITD-PE-SVD is proposed to solve the problem that it is difficult to extract the vibration signal features of hydrogenerator unit under the background of strong background noise and complex electromagnetic interference.

- (1) The ITD-PE-SVD denoising method is compared with LMD-PE-SVD and EMD-PE-SVD denoising methods through simulation experiments. At the same time, the correlation coefficient and signal-to-noise ratio are taken as quantitative indicators to analyze the noise reduction performance. It is found that after signal noise reduction processing by this method, data with correlation coefficient as high as 0.9956 and larger signal-to-noise ratio can be obtained, which can eliminate noise to the maximum extent while retaining useful information with fault signals. It has good noise reduction and pulse effect and avoids the modal aliasing in the EMD decomposition process.
- (2) Through the analysis of the measured  $X$ - and  $Y$ -direction swing data of the upper guide of the hydrogenerator unit, it is found that this method can effectively reduce the noise of the measured unit data and accurately extract the characteristic frequency of the vibration signal, so as to determine the vibration reason of the unit through the frequency.
- (3) The ITD-PE-SVD denoising method proposed in this paper can effectively extract the vibration signal characteristics of hydrogenerator units under the background of strong background noise and complex electromagnetic interference and provide a theoretical basis for subsequent fault diagnosis. It is convenient scientific and reasonable formulation of condition-based maintenance plans, greatly reduces the diagnosis time of power plants for complex hydraulic faults in actual operation, and thus improves the power generation efficiency and promotes the safety and stability of units and power grids.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Acknowledgments

The study was supported by the following fund projects: (1) Henan Province Key R & D and Promotion Project (Science and Technology Research) in 2021 (212102311054); (2) Training Program for Young Key Teachers in Colleges and Universities of Henan Province in 2019 (2019GGJS097); (3)

Hunan Key Laboratory of Renewable Energy Power Technology (Changsha University of Technology) Open Fund Project (2016ZNDL001).

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