Wavelet Denoising for the Vibration Signals of Wind Turbines Based on Variational Mode Decomposition and Multiscale Permutation Entropy

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ABSTRACT The vibration signals of wind turbines are often disturbed by strong noise and will be annihilated when exhibiting fault or strong instability. Denoising is required prior to facilitating an analysis of vibration fault characteristics. A wavelet denoising method based on variational mode decomposition (VMD) and multiscale permutation entropy (MPE) is proposed. The characteristics of VMD are analyzed, and the randomness and complexity of noise are evaluated by MPE. If the MPE of the modal component after VMD is larger than the evaluation value, then it is denoised by wavelet, and the signal is reconstructed with other modal components without wavelet denoising to achieve the denoising effect. The db1, sym8, EMD and EWT denoising methods and the proposed method are compared using the same simulation signal. Simulation results show that the denoising effect of the proposed method is better than the other four methods, and the two quantitative evaluation indexes of relative error and root mean square error obtain desirable values. The shaft vibration signals of the Case Western Reserve University and wind turbine are used to verify the effectiveness of the proposed method, and the denoising effect is also better than the other four methods. The proposed method eliminates most of the noise components while retaining the effective information of the signal. Therefore, this method can provide a good foundation for the research and analysis of the characteristics of late vibration signal.

INDEX TERMS Variational mode decomposition, permutation entropy, vibration signal, wind turbine, denoising.

I. INTRODUCTION

In recent years, wind energy has received increasing attention as a clean and renewable energy source; thus, wind turbines have developed rapidly around the world. How to ensure the stable and efficient operation of wind turbines has become a key technology. Vibration signals can reflect the internal information of machineries. The analysis of vibration signals is widely used in early fault diagnosis of rotating machineries [1]–[4].

However, the actual acquired vibration signal often contains a large amount of interference signals for various reasons. In order to avoid the inaccurate fault diagnosis caused by the heavy noise, the interference signal must first be filtered in the preprocessing of the vibration signal [5].

In terms of signal noise processing, numerous methods have been studied and applied. The traditional filtering method can achieve good filtering effect for continuous stationary signals; however, it cannot achieve the same effect for nonstationary and nonlinear signals and even causes signal distortion after filtering. To this end, many scholars have proposed particle, Bayesian, Kalman, adaptive,
mathematical morphology, wavelet, enhanced stochastic resonance, local mean decomposition (LMD), empirical wavelet transform (EWT) and independence-oriented variational mode decomposition filtering methods [6]–[15].

Particle filter is an approximate recursive algorithm for Bayesian filter based on Monte Carlo simulation. Because of its non-parameterization, it can solve the problem of nonlinear non-Gaussian system, and estimate the fault vibration signal. The estimated signal is the noise reduction signal, but it has the problem of weight coefficient degradation.

Kalman filtering has a good filtering effect for linear dynamic systems that satisfy Gaussian noise. However, for nonlinear non-Gaussian models, it is difficult to obtain a complete analytical expression of the probability density function, and only a few approximation algorithms can be used to obtain the optimal Bayesian estimation. Moreover, it could only obtain optimal filtering when the statistical characteristics of the signal and noise were known. In practical engineering applications, these statistical characteristics are often unavailable; thus, true optimal filtering is difficult to achieve [16].

The mathematical morphology was also applied to the vibration signal of a rotating machinery, and good experimental results were achieved through simulation [17]; however, there are still many problems to be solved, such as how to select the optimal estimation structure elements and morphological transformation.

The adaptive filtering method does not need prior knowledge such as signal frequency, and has the characteristics of being suitable for processing non-stationary signals and adapting to the change of background noise. The filtering accuracy is high. However, as the number of iterations increases, the result of the rounding error accumulation will be unstable in some cases.

Various filtering methods based on wavelet analysis are used for signal filtering, and the effect is significantly better than other nonlinear and linear filtering methods, such as enhanced stochastic resonance method and EWT method [13], [14]. However, some wavelet filtering methods can only be effective for some signals. For example, wavelet threshold denoising has obvious effects on suppressing high-frequency signal, and can effectively filter out random noise, but the filtering effect on pulse interference is not good. And wavelet functions are not unique, often unavailable; thus, true optimal filtering is difficult to achieve [16].

The vibration signal of a wind turbine with noise is a typical nonstationary mixed signal. In this study, a denoising method that combines VMD and MPE is used to decompose the vibration signal into several band limited modal components, and then the MPE of each modal component is calculated. According to the MPE of each modality, the value indicates the greater randomness of the signal. Then, combined with wavelet denoising, the modal components are reconstructed to complete the signal denoising.

II. DENOISING METHODS

A. VMD

The essence of VMD is to construct and solve variational problems based on classical Wiener filtering, Hilbert transform, and frequency mixing. By searching the optimal solution of the constrained variational model, the signals are decomposed into a series of modal components with sparse characteristics. Each modal is based on the center frequency and limited bandwidth. The construction and steps in solving concrete variational problems are as follows [24], [27], [28].

1) Suppose that the original signal $f(t)$ is a multi-component signal and consists of $K$ ($k$ is the preset scale) eigenmode function components $u_k(t)$ with finite bandwidth, and each $u_k(t)$ has a center frequency of $\omega_k(t)$.

Definition $u_k(t)$ is an amplitude-modulated signal, which can be expressed as follows:

$$u_k(t) = A_k(t)\cos(\phi_k(t))$$  \hspace{1cm} (1)

where $A_k(t)$ is the instantaneous amplitude of $u_k(t)$, and $\omega_k(t) = \phi_k'(t)$ is the instantaneous frequency of $u_k(t)$. VMD seeks the modal function $u_k(t)$, which is the smallest sum of $K$ estimated bandwidths.

2) Estimate the frequency bandwidth of each modal function $u_k(t)$. First, for the amplitude-modulated signal $u_k(t)$, the analytical signal is obtained by Hilbert transform, and its unilateral spectrum is also obtained. Second, the exponential term is added to move the spectrum of the modal function to the respective estimated central frequency and transfer the spectrum to the baseband. Third, the Gaussian smooth
demodulation signal is used to obtain the width of each segment, that is, the square root of the $L^2$ norm gradient. The variable constraint problem function can then be obtained as follows:

$$
\min_{\{u_k\}, \{\omega_k\}, \lambda} \left\{ \sum_k \left\| \partial_t \left[ \left( \delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|^2_2 \right\} \\
\text{s.t.} \quad \sum_k u_k = f
$$

(2)

where $\{u_k\} := \{u_1, \ldots, u_K\}$, $\{\omega_k\} := \{\omega_1, \ldots, \omega_K\}$, $\sum_k := \sum_{k=1}^{K}$, and $\delta(t)$ is a unit pulse signal.

3) To obtain the optimal solution of the constrained variational problem in Step 2, the Lagrangian multiplication operator $\lambda(t)$ and the second penalty factor are introduced; $\alpha$ can ensure the reconstruction accuracy of the signal in the presence of Gaussian noise, and $\lambda(t)$ maintains the strictness of the constraints. The augmented Lagrange expression is

$$
L(\{u_k\}, \{\omega_k\}, \lambda) :
= \alpha \sum_k \left\| \partial_t \left[ \left( \delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|^2_2 \\
+ \left\| f(t) - \sum_k u_k(t) \right\|^2_2
+ \left( \lambda(t), f(t) - \sum_k u_k(t) \right)
$$

(3)

The iteration terms $\hat{u}^{n+1}_k, \hat{\omega}^{n+1}_k$, and $\lambda^{n+1}$ in Equation (3) are solved by alternating the direction multiplier method to determine the saddle point of the Lagrange function. The number of iterations $K$ of the convergence conditions are

$$
\sum_n \left\| \hat{u}^{n+1}_k - \hat{u}^n_k \right\|^2_2 < \varepsilon
$$

(4)

4) The Fourier isometric transform is used to transform the iterated result into the frequency domain for updating, and the optimal solution is

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

(5)

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

(6)

Thus, the original signal $f(t)$ is decomposed into $K$ narrowband modal components $u_k(t)$, as shown as follows:

$$
f(t) = \sum_{k=1}^{K} u_k(t)
$$

(7)

Through the construction and solution process of the above variational modal problem, the steps of the VMD algorithm can be obtained as follows.

1) Initialize: $\{\hat{u}_k\}, \{\omega_k\}, \{\hat{\lambda}\}, n \leftarrow 0$;
2) $n = n + 1$;
3) Update $\hat{u}_k$ and $\hat{\omega}_k$ using Equations (5) and (6);
4) The updated step size is indicated in Equation (8), and $\tau$ is set as the noise margin parameter. When the signal contains strong noise, $\tau = 0$ can be set to achieve a good denoising effect.

$$
\hat{\lambda}^{n+1}(\omega) = \hat{\lambda}^{n}(\omega) + \tau \left( \hat{f}(\omega) - \sum_k \hat{u}^{n+1}_k(\omega) \right)
$$

(8)

5) If the convergence condition is satisfied, then the iteration is stopped and the $K$ modal components $u_k(t)$ become the output; otherwise, return to Step 2.

B. MPE

The MPE is improved based on the PE to improve the anti-interference capability. First, the time series is multi-scale coarse-grained, and the entropy of the coarse-grained sequences at different scales is then calculated [29]–[31].

Let a time series $X = \{x_t, i = 1, 2, \cdots, N\}$ of the sequence length $N$ be processed by coarse graining to obtain the following sequence:

$$
y^s_j = \frac{1}{s} \sum_{i=(j-1)s+1}^{js} x_i, j = 1, 2, \cdots, [N/s]
$$

(9)

where $s$ is a scale factor, $s = 1, 2, \cdots$; and $[N/s]$ is an integer to $N/s$. When $s = 1$, the coarse-grained sequence becomes the original time series, and the entropy of computation becomes the entropy of arrangement.

First, the coarse granulation sequence $y^s_j$ is time reconstructed as follows:

$$
Y^s_l = \left\{ y^s_{l+1}, y^s_{l+2}, \cdots, y^s_{l+q} \right\}
$$

(10)

where $l$ is the $l$th reconstructed component, $l = 1, 2, \cdots, N - (m - 1)\tau; m$ is the embedded dimension; and $\tau$ is the delay time. The time reconstruction sequence $Y^s_l$ is arranged in ascending order as follows:

$$
y^s_l = \left\{ y^s_{l+(r_1-1)\tau}, y^s_{l+(r_2-1)\tau}, \cdots, y^s_{l+(r_m-1)\tau} \right\}
$$

(11)

where $r_1, r_2, \cdots, r_m$ represents the original position index of each element in the reconstruction time series. If equal values exist in the reconstructed components, then they are arranged in order. A set of symbol sequences can be obtained for any reconstructed sequence $Y^s_l$, as shown as follows:

$$
\beta_q = \{r_1, r_2, \cdots, r_m\}
$$

(12)

where $q = 1, 2, \cdots, k, k \leq m!$. A time-reconstructed sequence with an embedding dimension of $m$ has a total of $m!$ permutations, and $\beta_q$ is one of the permutations. Assuming the probability $P_q$ of each symbol sequence, the PE of the defined time series at multiple scales is

$$
H_p(m) = -\sum_{q=1}^{k} P_q \ln P_q
$$

(13)

When $P_q = 1/m!$, the maximum value of $H_p(m)$ is $\ln(m!)$. Normalizing $H_p(m)$ yields

$$
H_p = H_p(m)/\ln(m!)
$$

(14)
The value of $H_p$ represents the complexity and randomness of the time series. A larger $H_p$ denotes a more random time series, whereas a smaller $H_p$ implies a more regular time series.

C. DENOISING METHOD BASED ON VMD AND MPE

Wind turbines usually have serious environmental noise interference, and the fault characteristics of the vibration signal are weak. The VMD algorithm can only completely decompose the signal; however, sometimes it cannot highlight the weak fault signal. In view of the wavelet denoising method, most of the noise in the fault signal can be eliminated; however, some useful information is also lost. To preserve the useful information in the signal while removing the fault signal noise, a wavelet denoising method based on VMD and MPE is proposed in this study.

First, the vibration signal of the wind turbine is decomposed into a set of modal components $u_k(t)$ using VMD. Then, the multiscale entropy values of each modal component $u_k(t)$ are calculated, and the random noise contained therein is evaluated on the basis of the multiscale entropy value. For some modal components $u_k(t)$ with more noise, the wavelet filter $w$ is used, and the 8th-order Symlet wavelet is selected to adjust the unbiased estimation according to the noise level of the first layer wavelet decomposition, and the noise is adaptively denoised according to the soft threshold.

Finally, the results of wavelet denoising are combined with other modal components $u_k(t)$ that have not been subjected to noise reduction to perform VMD reconstruction to obtain the denoised vibration signal. The denoising method process is shown in Fig. 1.

III. DENOISING ANALYSIS OF SIMULATION SIGNAL

Because the actual vibration signal of the wind turbine contains more unpredictable interference noise, it is difficult to verify the effect of the VMD denoising method. Thus, a vibration simulation signal is designed to verify the effectiveness of the proposed method without loss of generality.

The simulated signal $x(t)$ consists of three sinusoidal exponential decay signals, that is, $x_1(t)$, $x_2(t)$, and $x_3(t)$, and noise with different amplitudes and frequencies, as shown in Equation (15). The noise of $x(t)$ is a random number signal with a mean value of 0, standard variance of 1, and amplitude of 1.3; and the $x_3(t)$ is completely annihilated by noise. Fig. 2 shows the mixed simulation signal.

$$
\begin{align*}
    x_1(t) &= 4e^{-5t} \cdot \sin(100\pi t) \\
    x_2(t) &= 3e^{-2t} \cdot \sin(500\pi t) \\
    x_3(t) &= e^{-2t} \cdot \sin(800\pi t) \\
    x(t) &= x_1(t) + x_2(t) + x_3(t) + 1.3 \cdot \text{rand}(n)
\end{align*}
$$

Fig. 3(a) shows the resolution modal components of the signal $x(t)$ in Fig. 2 after being decomposed via VMD. Similar to EMD, the signal $x(t)$ is decomposed into four modal components, namely, $V_1$, $V_2$, $V_3$, and $V_4$. The random noise is also decomposed into modal components $u_k(t)$ via VMD; however, most of the noise is decomposed into high-frequency modal components.

After EMD, the simulated signal is decomposed into eighth-order modal function components and first-order residuals, as shown in Fig. 3(b). From the figure, the simulation signal is decomposed via EMD, and the noise is nearly in the high-frequency modal components. Similar to VMD decomposition, the same simulation signal $x(t)$ is decomposed by EWT. The signal $x(t)$ is decomposed into four modal components $f_0, f_1, f_2$ and $f_3$, as shown in Fig. 3(c). Different from Fig. 3(a), a lower frequency component $f_0$ is decomposed and a higher frequency component is missing; random noise is mainly decomposed into high frequency modal components.

The comparison of Figs. 3(a), (b) and (c) shows that VMD, EMD and EWT can decompose the same simulation signal adaptively and clearly reflect the components of the signal without losing signal energy. However, the methods differ in the number of decomposition layers. VMD and EWT have fewer decomposition layers, and a smaller running time of simulation signal decomposition in comparison with EMD.

For each modal component $u_k(t)$ in Fig. 3(a) decomposed via VMD, a multiscale coarse-grained sequence is constructed, and the MPE is then calculated. If the value is greater than 3, the modal component is strongly disturbed by noise. The modal components are denoised by wavelet transform and reconstructed with other modal components without wavelet denoising. The denoised signals are shown in Fig. 4(a).

In comparison with the original signal in Fig. 2, the random noise is eliminated, especially in the latter half of the time-domain waveform. When the $x_1(t)$, $x_2(t)$, and $x_3(t)$ exponential decay to an extremely small amplitude, the noise is nearly completely denoised and annihiliated. The noise burr elimination effect is remarkable.

Similarly, the classical wavelet db1 is selected on the basis of threshold denoising, and the denoised signal is obtained, as shown in Fig. 4(b). The heursure heuristic threshold, the soft threshold mode, and the five-layer decomposition number are used on the basis of the sym8 wavelet basis function. The denoised signal is shown in Fig. 4(c). Similar to the VMD-based denoising method, the multiscale
entropy values are constructed and calculated after EMD and EWT; the modal components with values greater than 3 are also selected for wavelet denoising, and signal the signal is then reconstructed with other modal components without wavelet denoising. The denoised signals are shown in Fig. 4(d) and (e), respectively.

By analyzing and comparing the signal denoised by the five methods and the original simulation signal, the denoising effect in Fig. 4(a) is better than that in Fig. 4(d) and (e), especially in the latter half of the time-domain waveform where the amplitude of strong noise is nearly eliminated. Although Fig. 4(d) has noise cancellation relative to Fig. 2, the visual changes from the waveform are relatively small. In Fig. 4(e), there are also some notable noise burrs. The waveform in Fig. 4(b) is nearly distorted, and the original signal is partially lost in energy. The waveform in Fig. 4(c) shows the cleanest noise cancellation; however, some features of the original signal are eliminated, especially in the latter half of the time domain where all the signals are eliminated as noise.

To evaluate the five denoising effects quantitatively, the signal-to-noise ratio (SNR) and root mean square error (RMSE) are introduced as evaluation indicators to measure the difference in filtering and denoising effect on the original simulation signal. Table 1 shows the calculation results of the denoising evaluation indexes of the five methods after experimental denoising.

As shown in Table 1, the SNR of the signal after VMD denoising is the largest, and the RMSE value is the smallest. This result indicates that the VMD denoising method is the best effect. After the same method, the SNR after EWT denoising is second only to VMD denoising method, and the RMSE is larger than the VMD method, and smaller than the EMD denoising method, indicating that the denoising effect.
FIGURE 4. Waveform of simulated signal after denoising: (a) VMD denoising, (b) db1 denoising, (c) sym8 denoising, (d) EMD denoising, (e) EWT denoising.

by EWT is better than the EMD method and lower than the VMD method; the SNR based on EMD denoising method is larger than sym8 method but less than the EWT method. The RMSE value is also between the sym8 and EWT, which indicates that the noise cancellation effect is somewhere in between. The SNR based on db1 denoising is small and the RMSE value is the largest, which indicates that the noise canceling effect is the worst. After numerous experiments, the five denoising methods change the results of the denoising analysis of different simulation signals; however, the effect is still better based on the VMD denoising method.

IV. DENOISING ANALYSIS OF THE VIBRATION SIGNAL OF WIND TURBINES

In different environments, the vibration signal of wind turbines is generally disturbed by different degrees; thus, the denoising methods used in other studies are incomparable. Given the small difference in motor vibration signal types, the bearing vibration experimental data of the Case Western Reserve University of the United States is used in this study for comparison to verify the proposed denoising method based on VMD and MPE.

The experimental platform is shown in Fig. 5. It consists mainly of a 2 Hp three-phase induction motor (left), a torque transducer/encoder (center), a dynamometer (right), and control electronics. The various fault vibrations of the experimental database are single point damage by electrical discharge machining (EDM). The fault location is set in the inner ring, outer ring and ball of the bearing. It is collected by three acceleration sensors installed on the motor drive end, fan end and base under different loads, different speeds and different fault levels.

The test bearing is a 6205-2RS JEM SKF deep groove ball bearing with a single point of failure on the bearing using EDM technology. First, the fault point is selected on the outer ring of the fan end bearing, and the fault diameter is 7 mils. The vibration acceleration signal is collected by an acceleration sensor installed in the six o’clock direction of the bearing housing of the motor drive end. The motor load is 1 Hp, the motor speed is 1772 rpm, the sampling frequency is 12 kHz, and the data sample length is 2160. Fig. 6 shows the diagram of the time-domain signal where the vibration signal contains strong noise. A periodic fault shock signal appears in the vibration signal.

Similar to the aforementioned analysis of the noise simulation signal, the vibration signal in Fig. 6 is also

| Method | SNR (dB) | RMSE |
|--------|---------|------|
| db1    | 0.6898  | 0.0425 |
| sym8   | 1.4191  | 0.0391 |
| EMD    | 1.7670  | 0.0376 |
| EWT    | 3.1413  | 0.0321 |
| VMD    | 5.6651  | 0.0240 |

FIGURE 5. Experiment platform.
denoised based on the proposed denoising method, EMD, sym8, db1, and EWT. The resulting waveforms are shown in Figs. 7(a)–7(e).

The ideal noise-free original vibration signal cannot be obtained because the signal is the measured bearing fault vibration signal. Therefore, the previous SNR and RMSE cannot be used to quantitatively analyze and compare the effects of the two methods.

However, as shown in Fig. 7, the waveform in Fig. 7(a) has no burrs in the time domain with no fault impact signal in relation to Fig. 6, and the noise canceling effect is remarkable. Although Fig. 7(b) partially eliminates noise with respect to Fig. 6, the waveform does not change considerably, and the effect is not evident. The waveform in Fig. 7(c) is excessively denoised in relation to Fig. 6; thus, the part of the vibration signal is lost, which results in severe signal distortion. However, the waveform in Fig. 7(d) has nearly no burrs in the time domain without the distribution of fault impact signals, the noise reduction effect is better, and some weak vibration signals in the time-domain segment are eliminated; thus, the original vibration signal loses its characteristic energy. Although Fig. 7(e) shows that some noise signals are eliminated, there are still more noise signals in the time domain of the faultless impulse signal distribution, and the effect of noise reduction is not as good as that of Fig. 7(a).

In order to further analyze the denoising effect of the actual vibration signal, the vibration signal of different fault parts of the bearing is selected for noise elimination comparison. For this reason, the ball with the fault point at the drive end is also selected, and the fault diameter is also 7 mils. Vibration acceleration signals are collected by an acceleration sensor installed at the motor driving end. The motor speed is 1750 rpm, the sampling frequency is 12 kHz and the sample length is 2160 under the load of 2Hp. The signal time domain diagram is shown in Fig. 8. It can be seen from Fig. 8 that the vibration signal is weak and contains strong noise, so that the vibration signal is almost annihilated by the noise.

Similarly, the ball vibration signal of Fig. 8 is denoised by VMD, EMD, Sym8, db1 and EWT. The results are shown in Fig. 9 (a), (b), (c), (d) and (e), respectively.

Fig. 9 (a) has significantly fewer burrs in the whole time domain than in Fig. 8. The vibration characteristics are highlighted in some time periods, and the effect of noise reduction is remarkable. Similar to the denoising effect of the outer ring vibration signal of Fig. 7(a), the vibration characteristic signal is retained, and the purpose of eliminating noise can be achieved.
weakened, resulting in no denoising effect. As in Fig. 7 (e), the denoising effect of ball vibration signal based on EWT is not as good as that based on VMD method.

In order to test the denoising effect of the proposed method for the vibration signal of wind turbine, a wind power plant in Fujian Province of China is taken as an example. A wind turbine vibration online monitoring system of SKF Group is adopted in the wind power plant. A low-frequency acceleration sensor (WT135-1D, made in Connection Technology Center, Inc., USA) is installed on the fan side and the motor side of the wind turbine main shaft bearing area in the vertical direction respectively. Here, the vibration signals collected by the low-frequency acceleration sensor on the fan side of the main shaft for a period of time are analyzed and verified. The signal is shown in Fig.10. It can be seen that the vibration signal contains noise.

Similarly, the vibration signal of Fig. 10 is denoised by VMD, EMD, Sym8, db1 and EWT. The result waveforms are shown in Fig. 11 (a), (b), (c), (d) and (e), respectively.

Fig. 11 (a) is obviously free of burrs in the full time domain compared to Fig. 10, and the vibration characteristics are also prominent. This is the same as that of Figs. 7 and 9 (a), which not only preserves the vibration characteristic signal, but also eliminates the noise. Compared with Fig. 10, noise elimination in Fig. 11 (b) is not obvious, and the waveform is almost unchanged. The effect is the same as that in
Figs. 7 and 9 (b). Fig. 11 (c) eliminates part of the noise and vibration signals at the same time compared to Fig. 10, which is the same as Fig. 7 and Fig. 9 (c), resulting in signal distortion. In Fig. 11 (d), as in Figs. 7 and 9 (d), the weak vibration signal is eliminated and the vibration signal energy is lost. Fig. 11 (e) completely eliminates some noise signals, but some vibration signals are also weakened equally, and some burrs are obvious, so the denoising effect is not as good as VMD method.

Although the effect of the vibration signal using the VMD algorithm for denoising has changed, it is the best when the effect is combined with the denoised signals of the simulation signal, fault vibration signals of outer ring and ball, and vibration signal of wind turbine. Most of the noise components are eliminated while preserving the effective information of the signal. Although the denoising algorithm has different effects on the denoising of various signals, the performance of eliminating noise remains unchanged.

V. CONCLUSION
The vibration signal of wind turbines often contains strong noise, which is disadvantageous to feature extraction and fault diagnosis of vibration signal. A wavelet denoising method based on VMD and MPE for vibration signals of wind turbines is proposed in this study. In signal decomposition, the proposed method has the advantages of avoiding over-decomposition and anti-mode aliasing in comparison with the EMD method. This method has the best denoising effect in comparison with db1, sym8, EMD and EWT denoising methods. It not only eliminates most of the noise components but also preserves the effective information of signals.

The proposed method has good modal identification and denoising capability, which is beneficial to real-time analysis and provides a new idea for the vibration signal denoising of wind turbines. However, the proposed denoising algorithm has certain defects. For example, the K value of the VMD must be initially determined and is not adaptable. The determination or range of other parameters of the VMD and the MPE is still lacking in theoretical basis and must be further improved. These limitations are the next research direction of this study. And other methods, such as envelope spectrum, will be used to analyze the denoising effect and extract fault features.

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