Research on Denoising Method of Fan Blade Fault Signal Based on Variational Mode Decomposition

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Abstract

Wind power is an important clean energy source in the future, and the fan blade has a high failure rate and is difficult to detect. At present, the main methods used for fault signal detection include spindle vibration signal detection and acoustic emission signal detection, but the operating environment of the fan equipment will result in a low signal-to-noise ratio of the collected signal. How to remove the higher noise content becomes detection The key to technology. In recent years, there have been few related studies on the detection of aerodynamic noise generated by blades. Based on the aerodynamic noise of the blade, this paper proposes the VMD variational mode decomposition for the high frequency noise signal emitted by the blade, which effectively avoids the modal aliasing and end effect of the traditional EMD empirical mode decomposition, and can be more flexible. Decomposing the number and component demarcation points improves efficiency compared to the transmission empirical mode decomposition.

Keywords

Fan blades, aerodynamic noise, VMD.

1. Introduction

As a high-cleanness and high-efficiency power generation method, wind power generation has experienced tremendous development in the past decade. According to statistics, the installed capacity of wind power in China has ranked first in the world. The basic function of the existence of wind turbines is to convert the wind energy into mechanical energy, use the transmission system for energy transmission, and finally convert the mechanical energy into electrical energy through the generator.

For wind turbines, the blades are the key components for wind energy. Constrained by the manufacturing conditions, the blade often has defects such as matrix cracking, delamination, fiber breakage, edge damage, etc. [1], in the harsh external environment and complex stress state, the blade with such defects is more susceptible to damage. Therefore, the early detection of blade defects is of great significance to ensure long-term reliable operation of the blade. However, the blade size is large, the shape is irregular, and the structure is complex. The conventional non-destructive testing method is difficult to achieve effective detection of large areas of the blade, and it is impossible to detect the key parts of the in-service blade in real time.

The aerodynamic noise of the blade is a nonlinear non-stationary signal. Denoising filtering of such signals often uses wavelet denoising or empirical mode decomposition to denoise. Wavelet denoising involves the selection of the basis function and the number of decomposition layers, as well as the threshold uncertainty. The EMD mode decomposition algorithm can autonomously decompose the input signal. It is adaptive and requires no prior knowledge. Determine the eigenmode function (IMF) component dominated by the useful signal and reconstruct it. In [3], the correlation between the IMF component and the denoising signal is used to judge the IMF component dominated by the useful signal and the IMF component dominated by the noise, but it is too absolute in the selection of the IMF; the literature [4] proposes to decompose the EMD with The KL divergence combined denoising method screens useful IMF components, but there is a selection problem of screening thresholds, and the threshold setting is not flexible enough.

In this paper, the method of wind turbine blade defect detection based on aerodynamic noise signal is studied. Based on the aerodynamic noise of wind turbine blade, the VMD decomposition and the improved continuous mean square error algorithm are used to process the aerodynamic noise. The feasibility of the method is demonstrated by simulation experiments.

2. Fan blade common fault type

2.1 wear

When the fan is running, the fan blades are exposed to the harsh natural environment such as sand, rain, snow and temperature difference. The surface is corroded and peeled off due to the friction of sand, rain, snow and frost. The blade will become weaker, plasticity is reduced, and brittleness Increased, while the vibration of the work further accelerates the process of corrosion, causing further damage.

2.2 Cracks and cracking

Low temperature and mechanical vibration are likely to cause cracking defects in the fan blades. The vibration of the blade and the bending and torsion force during the excitation cause the original crack to be deepened and lengthened and expanded continuously. At the same time, the dirt and sand in the air continuously enter the crack, so that the crack is further deepened, widened and expanded, and the crack is further deteriorated. After the crack is expanded, the blade may be cracked, and the transverse crack may cause the blade to break to a certain extent. At the same time, the wind wheel operation and the tower system are easy to generate mutual excitation, and under the influence of the excitation effect, the resistance of the fan operation is increased, so that the system becomes unstable in the coupled vibration, and the force acting on the blade also makes the blade A fracture occurred.

2.3 Material carbonization and breakdown

Another type of damage to the blade is mainly from the natural environment. For example, long-term sun exposure and high temperature can easily lead to carbonization on the surface of the blade. In addition, lightning strikes are also likely to cause carbonization of the surface material of the blade. According to statistics, about 1% to 2% of the blades of the wind turbines in the world are damaged by lightning strikes. When the lightning damage is not serious, most of the damage at the tip of the blade is easy to repair. In the case of a few lightning strikes, the entire blade is replaced. After a slight lightning strike on the blade, the surface will generally be carbonized, and a severe lightning strike will cause the blade to break down.

3. Blade aerodynamic noise distribution

3.1 Mechanical noise

Mechanical noise mainly includes friction and vibration between various mechanical structures of wind turbines. The mechanical structure of the interaction mainly includes: gearbox, gearbox, cooling fan, bearing and generator. The main working principle of wind power generators is to convert wind energy into mechanical energy and then convert mechanical energy into electrical energy. The generation of mechanical noise is mainly caused by the gear occlusion and the relative motion of the gear during the conversion of mechanical energy into electrical energy, and is also the main source of mechanical noise.

In mechanical noise, there are mainly two modes of propagation. The first is the propagation of air as a medium, followed by the propagation through the fixed structure of the fan, which radiates mechanical noise into the air through a series of solid structures. With the development of domestic and foreign technology, we can achieve physical noise reduction by reducing bearing mass imbalance, improving balance accuracy and adding lubricant to various components.

3.2 Pneumatic noise

The blades rub against the air during the rotation, creating a flow of air in each state. The noise emitted by these air streams is called aerodynamic noise. Among them, different airflow movements lead to different types of noise. Research at home and abroad shows that the main types of aerodynamic noise are as follows:

1) Low frequency noise: It includes constant load noise generated by the rotation of the blade or the lifting surface and unsteady load noise generated by the blade through the local loss zone or wake region of the flow.

2) The incoming turbulent interference noise, which is the broadband noise generated by the turbulent flow and the blade interference, is difficult to quantify due to the instability of the incoming air.

3) Blade self-excitation noise, which is generated by the flow of air along the surface of the blade. This noise has typical broadband characteristics, but the blunt trailing edge, slit and small hole of the blade also produce pure tone components.

Blade self-excitation noise mainly includes:

1) Turbulent boundary layer trailing edge noise: It is generated by the interaction of turbulent boundary layer and trailing edge. This part of the noise is mainly broadband, and the frequency is mainly concentrated between 750HZ-5000HZ, which is the main sound source of wind turbine.

2) Tip noise: It is generated by the tip turbulence and the tip surface. This noise is generally smaller than the trailing edge noise of the turbulent boundary layer, but it increases the high frequency noise, so it is also a major component of aerodynamic noise.

3) Air separation noise: the angle of attack increases, and the gas flow velocity at the specific position of the blade increases. The larger the flow velocity, the unstable the airflow, the stall phenomenon of the airflow separation, the interaction between the turbulence and the blade, and the noise is broadband. the Lord.

4) Laminar boundary layer shedding noise: generated by the nonlinear interaction between the boundary layer and the blade. This part of the noise is essentially a kind of harmonic. Because the fluid state around the fan blade is turbulent, such noise is pneumatic. The proportion of noise is not large.

5) Blunt trailing edge noise: generated by the vortex shedding of the blunt trailing edge, which is related to the thickness of the trailing edge and the thickness of the boundary layer.

6) Noise generated by small holes and gaps: generated by unsteady shear flow through small holes and gaps.

3.3 Research on the location of the collection point of aerodynamic noise

The two major components of aerodynamic noise are tip noise and turbulent boundary layer trailing edge noise. These two kinds of noise are mainly distributed at the tip and trailing edge of the blade. To determine the best orientation for the acquisition, it needs to be determined based on the distribution of noise generation.

In reference [17], the main sound source locations of different frequency bands are measured experimentally. LEE GS, CHEONG C et al. use the model to calculate the aerodynamic noise when the angle between the blade tip and the ground connection line and the ground is 139°. The highest decibel value.

The experiment is proposed to measure the decibel level on the windward side, the leeward side, and the side wind surface with a blade angle of 139°, and compare the decibel size to determine the position of the aerodynamic noise of the collected blade.

4. Research on Pneumatic Noise Treatment Scheme and Experimental Feasibility Theory

4.1 Variational mode decomposition

Variational mode decomposition (VMD) enables multiple sets of signals f(t).In this sub-frame, the signal is decomposed into a series of modal functions IMF through the adaptive principle, where the IMF has the following definition:

$$\mathrm{u}_k(t) = A_k(t)\cos(\phi_k(t)) \tag{1}$$

Where, $A_k(t)$ representing the instantaneous amplitude of the IMF component $u_{\mathrm{k}}(t)$, we introduce the instantaneous frequency of the IMF component $f_{\mathrm{k}}(t)$, defined as follows：

$$f_{\mathrm{k}}(t) = \frac{d\phi_k(t)}{dt} \tag{2}$$

Through VMD decomposition, the signal will be fixed in the variational framework. By decomposing, the center frequency and bandwidth of the IMF can be updated continuously. The adaptive solution is used to obtain the optimal solution of the constrained variational model.

Since each eigenmode function has a finite bandwidth of center frequency, the problem is transformed into a constrained variation problem of k eigenmode function IMF. The model is designed as follows:

$$\min_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \partial_t \left[(\sigma(t) + \frac{j}{\pi t}) u_k(t) \right] \times e^{-j\omega_k(t)} \right\| \right\} \quad s.t. \sum_k u_k = f \tag{3}$$

$\{\mathrm{u}_{\mathrm{k}}\}$ represents a set of individual IMF components $\{\omega_k\}$ representing a set of center frequencies for each IMF component.

The quadratic penalty factor α and the Lagrangian multiplication operator λ （t） are introduced to guarantee the reconstruction precision and the strictness of the constraint under Gaussian noise. Equation (1) can be extended as follows:

$$\begin{aligned} & L(\{u_k\},\{\omega_k\},\lambda) := \\ & \partial \sum_k \| \partial_t [(\delta(t) + \frac{j}{\pi t}) * u_k(t)] e^{-j\omega_k t} \|^2 + \\ & \| f(t) - \sum_k u_k(t) \|_2^2 + (\lambda(t), f(t) - \sum_k u_k(t)) \end{aligned} \tag{4}$$

Using the multiplicative operator alternating direction method, constantly updating μ_k^{n+1}, ω_k^{n+1}, λ^{n+1} and finding the saddle point, the solution of the intrinsic mode can be obtained as:

$$\hat{\mu}_k^{n+1}(\omega) = \frac{\hat{f}(\omega) - \sum_{i=k} \hat{\mu}_k^n(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_k)^2} \tag{5}$$

The solution for the center frequency is:

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega |\hat{\mu}_k^n(\omega)| d\omega}{\int_0^\infty |\hat{\mu}_k^n(\omega)| d\omega} \tag{6}$$

4.2 Energy entropy

During blade service, defects such as cracks and air interact to produce various types of sound signals. The acquired signal is decomposed by VMD into a finite number of intrinsic modal functions IMF. At this time, the defect feature information exists in several IMF components. However, due to the narrow frequency range of the IMF component, it is prone to frequency domain overlap and feature extraction difficulties. In order to better realize the signal identification, it can be characterized by calculating the energy distribution. Therefore, information entropy can be introduced into the VMD to define the VMD energy entropy.

The VMD is used to decompose the acoustic emission signals f(t) of different defects to obtain k intrinsic mode functions: IMF1(t), IMF2(t), ⋯, IMFk(t). The energy of the k IMF components is E1, E2, ⋯, Ek. Since the results of the VMD decomposition are orthogonal, there are:

$$E = \sum_{i=1}^{\mathrm{k}} E_{\mathrm{i}} \tag{7}$$

Where: E the total energy of the singal m^2

The energy of the IMF component after being decomposed by

The k IMF components respectively contain different frequency components of the original signal. Therefore, the energy E1, E2, ⋯, Ek of each IMF component form the characteristic energy distribution of the acoustic emission signal energy in the frequency domain, and the corresponding VMD energy entropy Can be defined as follows:

$$H_{EN} = -\sum_{i=1}^{k} p_i \lg p_i \tag{8}$$

among them:

$$\mathrm{p}_i = \frac{E_{\mathrm{i}}}{E} \tag{9}$$

The ratio of the energy of the i-th intrinsic IMF component to the total energy.

4.3 Experiment and result analysis

In this paper, VMD decomposition experiments are performed on random signals. In the specific operation process of the experiment, apart from the difference of the algorithm itself, the difference mainly exists in the determination of the K value of the component number in the decomposition process of the two methods. In the EMD decomposition, we do not need to set the specific value of K. The algorithm will decompose according to the characteristics of the signal and terminate the iteration. The VMD needs to choose the K value.

Modal aliasing and endpoint effects occur during EMD decomposition, and aliasing modal problems are first discovered in signal decomposition with discontinuities. A discontinuous signal can be understood as a small amplitude high frequency signal occurring at a certain time or within a small time interval. When the aliasing mode occurs, the resulting eigenmode function IMF is meaningless. EMD and VMD decomposition were performed using three cosine signals and random signal superposition.

The empirical mode decomposition using EMD is shown in the figure:

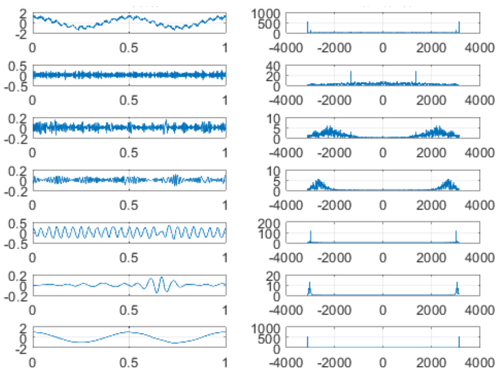

Fig. 1 EMD

Use VMD variational modal decomposition as shown:

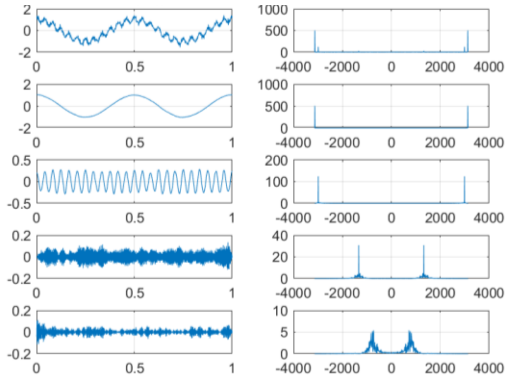

Fig. 2 VMD

Next, the collected aerodynamic noise signal is decomposed by using the VMD, and the number of IMFs that are decomposed is set to 12, and the original signal and the 1st to 12th IMFs and the corresponding spectrum are from top to bottom, and the decomposition result is:

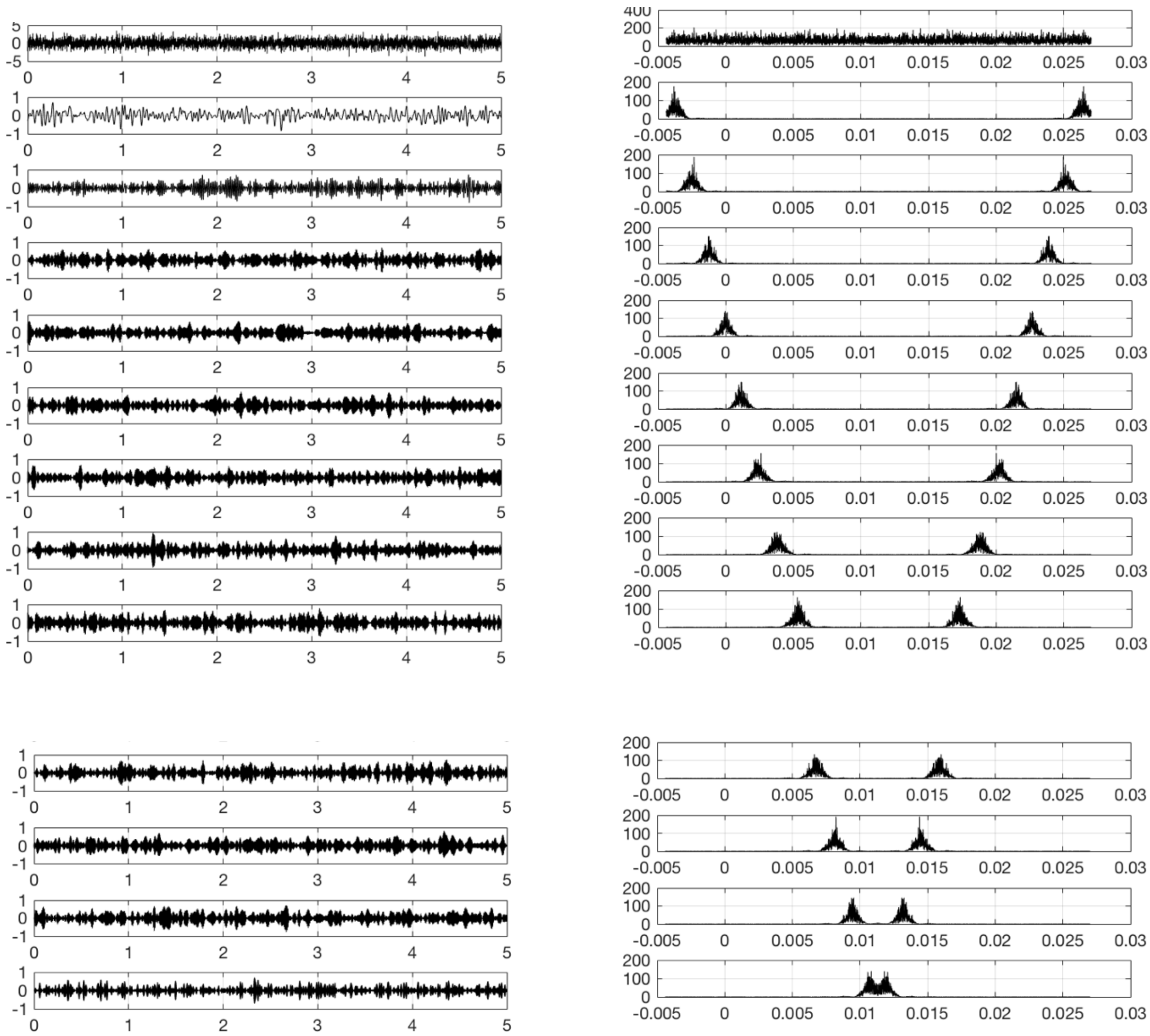

Fig. 3 VMD decomposition result

4.4 Continuous mean square error

The conventional CMSE is to arrange the IMF component energy from small to large according to the IMF scale. The small-scale IMF component noise dominates, the large-scale IMF component dominates the signal, and the first minimum value of the IMF component energy is useful. The demarcation point of the IMF component and the noise IMF component, the IMF component after reconstructing this point can obtain the denoised signal; since the useful signal is concentrated in the high frequency band relative to the noise, that is, concentrated in the small-scale IMF component, it is needed Improvements have been made to conventional continuous mean square error criteria.

The first 8 IMF component energies are arranged from large to small according to the IMF scale, and the last local minimum value of the IMF component energy is the demarcation point, and the IMF component after the demarcation point is reconstructed. Since the useful signal energy is mainly concentrated in IMF1~IMF4, if the scale of the boundary point is greater than 5, it is determined that the boundary point is a false demarcation point, that is, there is no effective demarcation point.

Except that the demarcation point scale is greater than 5, it is determined that there is no effective demarcation point in the IMF component energy curve. If the signal to noise ratio is too small, the demarcation point will not exist. In these two cases, the IMF component needs to be supplemented by the VMD decomposition. Randomly arrange-reconstruction-accumulate-average algorithm to improve the signal-to-noise ratio of the signal. The noise signal n(t) is randomly arranged i times, and the arranged signal and the original signal are accumulated and averaged to obtain a new noise signal, and the power of the noise signal is greatly reduced, thereby achieving the purpose of improving the signal to noise ratio. Referring to this theory, a cyclic random permutation-reconstruction-accumulation-average algorithm for improving the signal-to-noise ratio of the fan blade audio signal is proposed. The steps are as follows.

$$\bar{x}(t) = \frac{x_{cumulate}(t)}{P+1} \tag{10}$$

Perform VMD decomposition on the noisy signal x(t) to obtain N IMF components. The first 8 IMF components are processed in this paper;

1) $x_1(t) = IMF_8(t)$, $x_2(t) = \sum_{i=1}^{7} IMF(t)$ $x_{cumulate}(t) = x(t)$

For random arrangement $x1(t)$, reconstruct the randomly arranged signals $x2(t)$ together $x'_k(t)$ and add them to the top $x_{cumulate}(t)$, and $x_{cumulate}(t) = x_{cumulate}(t) + x'_k(t)$;

Step 3 is repeated P times to obtain the final cumulative amount, $x_{cumulate}(t)$ and the average is worth $\bar{x}(t)$ $\bar{x}(t)$ As the original noisy signal, repeat steps 1) to 4) Q times to obtain a signal with enhanced signal $\bar{X}(t)$ to noise ratio;

For $\bar{X}(t)$ the VMD decomposition, a series of eigenmode functions are obtained. According to the continuous mean square error criterion improved in this paper, the IMF component energy is arranged according to the scale from large to small, and the boundary point of the IMF component energy is found, and the corresponding IMF component is obtained. Refactoring. According to experience, P generally takes 3 to 7, and Q generally takes 2 to 5. In order to obtain a suitable random arrangement number P and repetition number Q, a simulation experiment was performed on aerodynamic noise with low frequency noise. According to the above steps, the relationship between the signal-to-noise ratio of the reconstructed signal and the number of random alignments P is obtained.

5. Conclusion

This paper mainly summarizes the damage classification of the blade and the type of aerodynamic noise emitted by the blade, and analyzes the generation of various noises and the impact on the defects. Next, the effective information extraction of the aerodynamic noise generated by the blade is proposed by using VMD variational mode decomposition. For the required high frequency effective IMF component, the IMF component required in this paper is mainly high frequency component, mainly concentrated on small scale. The IMF component is proposed to reconstruct the decomposed IMF component using an improved continuous mean square error algorithm. For the discontinuity and non-stationary of the signal, and the generated burst high-frequency signal, the modal aliasing and endpoint effects are effectively avoided on the basis of the traditional EMD. The improved continuous mean square error algorithm can be more flexible. Select the number of components and the demarcation point of the selected component, and apply to high frequency signals.

Among the signals that are discarded, there are a small number of useful signals. Studying how to extract these effective signals and judging their effects on the results is the next research content and direction.

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