Research on Vibration Fault Diagnosis Technology of Steam Turbine Unit in Power Plant Based on Wavelet Theory

Yu Sun1, *, Xuhui Han2

1 Huadian Electric Power Research Institute Co., Ltd., Hangzhou 310030, Zhejiang, China
2 Harbin No.3 Power Plant, Huadian Energy Company Limited, Harbin 150024, China

*Corresponding author e-mail: yu-sun@chder.com

Abstract. Aiming at the frequency spectrum characteristics of the vibration of steam turbine generator sets, a fault diagnosis method of steam turbine rotor vibration based on wavelet packet transform is proposed, which can better reflect the spectral components and energy contained in vibration signals than general wavelet transform. Experimental analysis shows that the fault feature extraction method based on wavelet packet analysis and signal energy decomposition can obtain the fault status of steam turbine rotor vibration; according to the frequency spectrum characteristics of different faults, different faults can be identified, so as to perform steam turbine rotor vibration fault diagnosis. This method is more effective than the fault feature extraction method based on Fourier transform and is suitable for mechanical fault diagnosis.

Key words: Wavelet theory, power plant steam turbine unit, vibration fault, fault diagnosis.

1. Introduction

The steam turbine is the main equipment of a power plant, and its safe operation directly affects the economic benefits of the entire power plant. In order to improve the efficiency of power plants, the power of steam turbines has continued to increase, and the equipment has gradually developed in the direction of large-scale development. The factors affecting the safe operation of steam turbine generator sets have gradually increased. Rotor imbalance, rotor misalignment, and friction between moving and static parts are common faults in turbo-generator units. These faults will cause unit vibration. Excessive vibration will cause the unit to be unable to continue operation and need to be forced to shut down for maintenance, which will bring huge economic losses to the power plant. Therefore, we need to monitor the vibration of the steam turbine generator unit, predict the potential failure of the unit in advance, and control the failure to continue to expand. By collecting vibration signals and extracting fault characteristics from them, the types of faults can be predicted, and measures can be taken in time to reduce the possibility of faults. For a long time, the analysis of vibration signals has always relied on Fourier transform to realize it, but Fourier transform can only extract frequency information and lose time information. Fourier transform can only analyse stationary and periodic signals, while steam turbine vibration signals are usually non-stationary and abrupt. Because wavelet analysis has localized
characteristics in time and frequency domains, wavelet analysis technology can be used to determine the singularity of abrupt signals Location and distribution in space [1].

2. Basic theory of wavelet analysis

Wavelet transform is an advanced signal processing method. Compared with Fourier transform and window Fourier transform, wavelet transform can analyse and study a certain position of the signal, so that we can get the signal contained in a certain period of time information. Wavelet analysis is a multi-resolution signal analysis method. It has low time resolution and high frequency resolution for slow-changing signals. It can well describe the characteristics of the signal. Using wavelet transform for denoising can achieve very Good denoising effect [2].

Local analysis capabilities, such as distant targets in the air, fingerprints, speech signals, sonar signals, etc., are identified. The insignificant zero component of these signals only appears for a short time, and then quickly decays to zero. We are only interested in signals within a limited time interval, and there is no need to analyse the signals within an infinite time range in the past, present, and future. Therefore, we need to find an analysis method with both time resolution and frequency domain resolution. The basic idea is: take a smooth function \( g(t) \) as the window function, which is always equal to 0 or quickly tends to 0 outside the finite interval. The image of the window function is shown in Figure 1.

\[
\begin{align*}
g(t) &= \text{the function obtained after } g(t) \text{ is translated by } \delta \text{ units. Multiplying by } \ g(t−\delta) \text{ and the function to be analysed, its effect is equivalent to opening a window at } t = \delta. \text{ In this way, the signal } f(t) \text{ is effective after multiplying by the translational sliding window } g(t−\delta). \text{ Signals other than } t = \delta \text{ are suppressed. Therefore, the window Fourier transform overcomes to a certain extent the defect that the Fourier transform does not have the ability to analyse signals in a certain period of time.}
\end{align*}
\]

Let \( g(t) \) be the time window function, the centre of the time window can be expressed as Equation 1, and the radius of the time window can be expressed as Equation 2.

\[
\begin{align*}
t^* &= \int_{-\infty}^{\infty} |g(t)|^2 \, dt \\
\Delta t &= \sqrt{\int_{-\infty}^{\infty} (t-t^*)^2 |g(t)|^2 \, dt}
\end{align*}
\]

Then \( G(w) \) is the frequency window function, the time window centre can be expressed as Equation 3, and the time window radius can be expressed as Equation 4.

\[
\begin{align*}
w^* &= \int_{-\infty}^{\infty} w |G(w)|^2 \, dw / \int_{-\infty}^{\infty} |G(w)|^2 \, dw \\
\Delta w &= \sqrt{\int_{-\infty}^{\infty} (w-w^*)^2 |G(w)|^2 \, dw / \int_{-\infty}^{\infty} |G(w)|^2 \, dw}
\end{align*}
\]
It can be seen that after $g(t)$ is determined, the width of the time-frequency window $\Delta t$ and $\Delta w$ are all constants. In terms of time-frequency localization, the Fourier change of the window has made substantial progress. Window Fourier analysis signals can be used to observe the signal in the local range of the time-frequency window. The area of the time-frequency window reflects the accuracy of the time-frequency localization. The smaller the window, the higher the accuracy. So, can a certain window function be selected to make its area sufficiently small? But $\Delta t$ and $\Delta w$ are mutually restricted, and they cannot be arbitrarily small at the same time. In practical applications, the low-frequency signal changes slowly in amplitude over a relatively long period of time and the frequency range is narrow. Therefore, the time window width of the time-frequency window used to analyse the low-frequency signal should be relatively wide, and the frequency window width should be relatively narrow. The time window width of the time-frequency window of the frequency signal should be relatively narrow. 

CWT (Definition of Continuous Wavelet Transform): After shifting a function $\psi(t)$ called basic wavelet to $\tau$, it is inner product with the signal to be analysed at different scales $a$:

$$WT_{\psi}(a, \tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^* \left( \frac{t - \tau}{a} \right) dt$$

(5)

3. Denoising of vibration signal of steam turbine unit based on wavelet transform

3.1. Wavelet threshold denoising
First, perform wavelet decomposition on the signal (such as three-layer decomposition, the decomposition process is shown in Figure 1), $c_{D1}$, $c_{D2}$, $c_{D3}$ are the wavelet coefficients of the first, second, and third layers obtained after decomposition, $c_{A1}$, $c_{A2}$, $c_{A3}$ are the three-layer high-frequency coefficients obtained from the decomposition, keep the low-frequency coefficients $c_{D1}$, $c_{D2}$, $c_{D3}$ unchanged, and noise is usually mainly contained in the high-frequency coefficient $c_{A1}$, $c_{A2}$, $c_{A3}$ So you can set the threshold function, limit the threshold to process the high-frequency coefficients $c_{A1}$, $c_{A2}$, $c_{A3}$ and then reconstruct the signal with the low-frequency coefficients $c_{D1}$, $c_{D2}$, $c_{D3}$ to achieve the purpose of denoising [3].

Figure 2. Wavelet denoising process

3.2. Threshold function and threshold selection
The most commonly used are two threshold functions: hard threshold function and soft threshold function. The mathematical expressions of these two threshold functions are as follows, the hard threshold function:
In equations 6 and 7, $w$ is the wavelet coefficient and the threshold, and $\sigma(w)$ is the estimated value of the wavelet coefficient of the pure signal. Fig. 3 uses MATLAB software as the simulation platform, selects the threshold value to be 0.4, uses the hard threshold value function and the soft threshold value function to process a straight line.

**Figure 3.** Simulation results of the hard and soft threshold functions acting on a straight line

It can be seen from Figure 3 (a) that between the y-axis and the original line has an obvious breakpoint, but the other points are described correctly, just like the original line. It can be seen from Figure 3 (b) that after the soft threshold function is applied, the image has no breakpoints, but each point is slightly different from the original image. These analyses show that soft thresholds usually smooth the signal after denoising, but some features are also lost; hard thresholds can retain the characteristics of the signal, but it is slightly insufficient in terms of smoothing. Therefore, in practical applications, we have to compare the denoising effects of specific signals. Whether to use hard threshold denoising or soft threshold denoising can get the best denoising effect. In threshold denoising, the selection of threshold $\lambda$ is directly related to the quality of signal denoising [4]. This article selects the most commonly used threshold selection form, minimax and Stein unbiased likelihood estimation. The specific selection rules are as follows:

1. Minimum maximum variance threshold: This is a fixed threshold selection form, which makes the selected threshold produce the smallest maximum variance. The calculation formula is:

$$\lambda = \begin{cases} \sigma \
0.3936 + 0.1829 \left( \frac{\ln N}{\ln 2} \right), & N > 32 \\
0, & N \leq 32
\end{cases}$$

(8)

Among them, $\sigma$ is the noise intensity of the original signal, and $N$ is the signal length.

2. Based on Stein unbiased likelihood estimation, also called adaptive threshold (rig sure): take the absolute value of each element of the signal $f(n)$, and then sort from small to large, and then square each element to obtain a new signal sequence as follows:

$$sx2(k) = (\text{sort}(|f(k)|))^2, k = 0, 1, \ldots, N - 1$$

(9)
3.2.1. Comparison of denoising effects of hard threshold and soft threshold functions. Select the collected vibration signals of the noisy steam turbine unit, select db3 wavelet for 5-layer decomposition, uniformly adopt the rig sure threshold, keep the wavelet basis function and threshold selection form unchanged, use the hard threshold function and soft threshold function to denoise the signal respectively. Figure 4 is a comparison of the denoising waveforms of the vibration signal of the steam turbine unit by the hard threshold and soft threshold functions. According to the calculated signal-to-noise ratio in Table 1, the denoising effect of the hard threshold function is better than that of the soft threshold function. Theoretically, the edge characteristic of the vibration signal of the steam turbine unit is more important than the smooth characteristic, so the hard threshold denoising effect is better [5].

![Figure 4. Comparison of denoising effects of hard threshold and soft threshold functions](image)

Table 1. The signal-to-noise ratio of the signal after the two threshold functions are denoised

| Method                              | SNR (db) |
|-------------------------------------|----------|
| Original signal                     | -5.3189  |
| Signal denoised by the hard threshold function method | 5.1824   |
| Signal denoised by soft threshold function method | 4.6248   |

It can be seen from Figure 4 that the signal distortion after soft threshold denoising will be more serious, but the signal will have fewer glitches, and the signal waveform will be smoother after denoising; the signal feature points after hard threshold denoising are more obvious, and the signal can be retained. Characteristic, but will produce additional shock. For example, at about 300, 700, and 1100 sampling points, it can be seen that some features of the signal after denoising by the soft threshold function are lost, but the signal integrity is better.

3.2.2. Comparison of denoising effects of different wavelet forms. The hard threshold function is used to denoise, and the threshold selection rule based on Stein unbiased likelihood estimation (SURE) is used, and Haar/db3/coif2 wavelet basis functions are used to denoise the original signal in five layers. Figure 5 is a comparison of the effect pictures after denoising. From the noise ratio calculated in Table 2, it can be seen that the signal-to-noise ratio after denoising using coif2 wavelet is the largest and the denoising effect is the best.
Table 2. Signal-to-noise ratio of four different wavelet basis functions after denoising

| Method                                    | SNR (db) |
|-------------------------------------------|----------|
| Original signal                           | -5.3189  |
| Signal denoised using Haar wavelet basis function | 3.9637   |
| Signal after denoising using db3 wavelet basis function | 4.6248   |
| Signal denoised using coif2 wavelet basis function | 11.205   |

From the waveform of Haar wavelet denoising in Figure 5 (b), it can be seen that the waveform after denoising at sampling points 300 and 700 shows a stepped shape. The continuity of the waveform after denoising using db3 wavelet is better than that of Haar wavelet. some. The coifN wavelet is developed from the dbN wavelet, which overcomes its shortcomings of asymmetry and improves its smoothness.

3.2.3. **Comparison of the denoising effects of the two threshold selection forms.** Choose the coif2 wavelet for five-layer decomposition, keep the wavelet basis function and threshold function form unchanged, change the threshold selection form, use the minimum maximum variance threshold and the threshold estimation based on Stein unbiased likelihood to denoise the original signal. Figure 6 is a comparison of the denoising results of two different threshold selection forms. Calculating the signal-to-noise ratio from Table 3 can also know that the signal-to-noise ratio of the minimax threshold selection form after denoising is larger than the rig sure threshold selection form. For the vibration signal of the steam turbine unit, the minimax threshold selection form has a better denoising effect [6].
Figure 6. Comparison of denoising effects of two threshold selection forms

Table 3. The signal-to-noise ratio of the signal after denoising in the two threshold selection forms

| Method                                         | SNR (db) |
|------------------------------------------------|----------|
| Original signal                                | -5.3189  |
| Rig sure threshold selection form denoised signal | 11.532   |
| Minimax threshold selection form denoised signal | 15.4     |

It can be seen from Figure 6 that the two types of threshold selection are better to remove noise. The signal glitches after rig sure denoising are more obvious, such as 700 and 1000 points. This is due to the rig sure threshold selection form after denoising the continuity of the signal waveform is generally better, without obvious breakpoints, but the smoothness is poor [7]. The minimax threshold selection form focuses on the edge characteristics of the signal. By using the control variable method to control the factors that affect the threshold denoising, convert multiple factors into a single factor, and change only one of the factors that affect the denoising effect each time, we can get the threshold function and wavelet basis function. The best denoising effect can be obtained in the selection form of sum threshold.

4. Conclusion

The application of wavelet analysis technology to the shaft vibration monitoring of steam turbine generator sets is of great significance to the safe operation of the unit. The wavelet analysis technology has flexible time-frequency resolution. It can not only diagnose the faults of the steam turbine unit represented by the smooth signal, but also it can detect sudden failures during the operation of the unit, which can effectively reduce the failure rate and false alarm rate. In this paper, the problem of fault feature extraction in the application of wavelet analysis technology in steam turbine fault diagnosis is deeply studied, and a fault feature extraction method based on wavelet energy distribution is proposed. A large number of experiments on the rotor test bench show that this method can fully meet the requirements of vibration signal analysis, and it is a very effective and practical feature extraction method. The above research has good reference value for the practical engineering application of wavelet analysis technology.

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