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Damage Recognition of Gearbox and Blade for Wind Generation System Using Frequency Spectrum Analysis

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Abstract: This paper presents a novel approach based on the frequency spectrum analysis for the gearbox and blade damage recognition of wind generation system. The proposed approach utilizes a back-propagation neural network (BPNN) to extend the end of the frequency spectrum to overcome the end effect problem of the Hilbert-Huang transform (HHT), which consists of empirical mode decomposition (EMD) and Hilbert transform (HT). The extension of the two ends obtained by the proposed approach forms a new frequency spectrum to improve the end effect problem which can distort Hilbert spectrum. The proposed approach is successfully applied to analyze the generator currents of a wind generation system. Simulated results reveal the new frequency spectrum obtained by the proposed approach can substantially improve the recognition accuracy of gearbox and blade damage.

Keywords: Frequency Spectrum Analysis, Hilbert-Huang Transform, Empirical Mode Decomposition, Back-Propagation Neural Network

1 Introduction

The maintenance cost of gearbox and blades becomes a major expense of a wind generation system. Damage of each component of wind turbines should be detected on the earliest time to avoid cascade damage to all turbines. Gearbox and blades of wind turbines are the two important components which are easily neglected. A common damage of gearbox and blades is caused by collision and non-lubrication friction. Recently, damage inspection of blades employs the ultrasonic, shearography, thermography and X-ray CT techniques, etc, but the generator operation needs interrupting during the inspection. Although the methods can offer a sophisticated report for the status of the blade, it costs and is time-consuming. To solve the problem, accelerometers are the alternatives.

The vibration signals obtained from accelerometers are applied in recognizing the characteristics of the gearbox damage [1]. However, aging and inaccurate adjustment of accelerometers might not be available in measurement. The generator system is always in danger to an unreliable recognition alarm system. Therefore, new methods for the gearbox damage recognition without extra measurement apparatus should be researched. It is important to develop a new approach that can efficiently detect damage of a wind generator by only using current signals of a gearbox without accelerometers. In recent literatures [2,3], accelerometers are also used for damage recognition of the blade. The aging and adjustment problem still exist. Thus, the current analysis might be a good method to recognize the status of blade even when a wind turbine is on operation.

Many studies discussed the analytic methods of the signals. For example, fast Fourier transform (FFT) is used to recognize the generator damage [4] but it fails to obtain instantaneous frequency. Therefore, the short-time Fourier transform (STFT) or wavelet transform (WT) is adopted instead [5,6]. Liao Wei et al. applied the multi-resolution of wavelet transform to monitor the vibration signal and detect the fault of wind turbines [7]. The vibration signals analysis of generators is a rather practical technique that many similar researches discuss the issue [8]. For instance, W. Yang et al. applied wavelet transform in the current of wind turbines to monitor operation condition and detect faults [6]. The

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aforementioned methods are mainly based on fast Fourier transform and wavelet transform, but the spectrum is not clear due to the limitation of conversion base. Traditional methods such as fast Fourier transform and wavelet transform are unsuitable for recognizing the faults of wind turbines. To improve the resolution of spectrum, the Hilbert-Huang transform is applied in this paper and a tailor made gearbox and blade are used in the experimental systems. The measured current signals of the damaged gearbox and blade were analyzed for the patterns of the spectrum obtained by using the Hilbert-Huang transform. The result shows that it is feasible recognizing the status of gearbox and blades by using generator currents.

This paper measures and analyzes the currents of wind generators to identify the possibility of the proposed approaches for damage recognition of gearbox and blades of wind turbines. In this paper, a tailor-made gearbox and blade are used in the experimental systems, the current signals of the damaged gearbox and blade were measured and the signals were analyzed to discover the patterns of the spectrum obtained by using the Hilbert-Huang transform analysis. The results show that recognizing the status of the gearbox and blade by the generator currents could be possible and alternative.

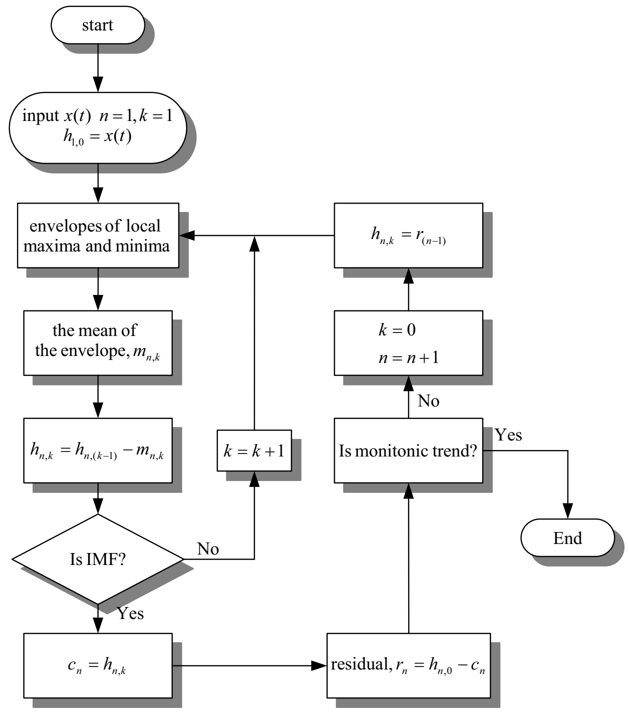


Fig. 1: The procedure of empirical mode decomposition.

2 Hilbert-Huang Transform

Traditional time-frequency techniques cannot precisely analyze the energy-frequency spectrum of non-stationary and nonlinear signals. The Hilbert-Huang transform composed of empirical mode decomposition and Hilbert transform is advantageous to the analysis problem [9,10,11]. A signal can be decomposed into several intrinsic mode functions (IMFs) by using Hilbert-Huang transform and the instantaneous amplitude and frequency can be observed from intrinsic mode functions through Hilbert transform. Subsequently, the corresponding distributions of time, frequency and energy can also be obtained. The procedures are detailed as below.

2.1 Empirical Mode Decomposition

Hilbert transform analyzes stationary and linear signals efficiently instead of non-stationary and nonlinear ones. The empirical mode decomposition is a solution to the problem [9,10,11]. In the signal analysis, the empirical mode decomposition can extract different frequency components from a complex signal which the flowchart is shown in Figure 1 and the calculating steps are as blows.

Step 1. Find local maxima and local minima of original signal $x(t)$. Connect them to produce the upper and lower envelopes. The original signal $x(t)$ can be decomposed by empirical mode decomposition to obtain several intrinsic mode functions and a monotonic trend, as shown in equation (1).

$$x(t)=\sum_{j=1}^{n} c_j + r_n \tag{1}$$

Step 2. Compute the mean of envelopes $m_{1,k}$ to be the average of the upper and lower envelopes.

Step 3. Compute $h_{1,k}=x(t)-m_{1,k}$.

Step 4. Repeat **Step 1** to **Step 4** until $h_{1,k}$ satisfies the definition of IMF, and save as $c_n=h_{n,k}$.

Step 5. Compute the residue: $r_n=h_{n,0}-c_n$.

Step 6. If the residue r_n is a monotonic trend, stop the procedures. Otherwise, repeat the above **Step 1** to **Step 4** to obtain residue intrinsic mode functions.

2.2 Hilbert Transform

The $y_j(t)$ can be obtained from IMF $c_j(t)$ by using Hilbert transform, as shown in equation (2), where PV is the Cauchy principal value.

$$y_j(t)=\frac{1}{\pi}PV\int_{-\infty}^{\infty}\frac{c_j(\tau)}{t-\tau}d\tau \tag{2}$$

The analytic signal $z(t)$ can be expressed as a complex conjugate pair of real part $c_j(t)$ and imaginary part $y_j(t)$, as shown in equation (3).

$$z(t)=c_j(t)+iy_j(t)=a_j(t)e^{i\theta_j(t)} \tag{3}$$

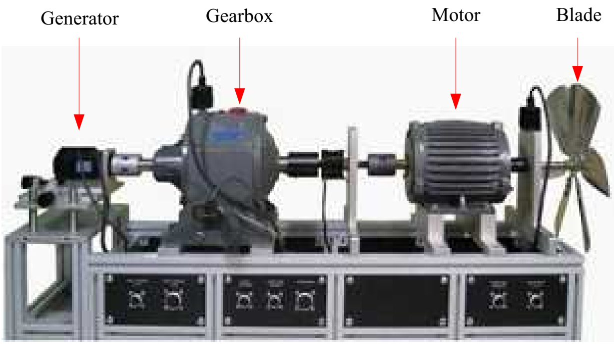


Fig. 2: Test platform of wind generation system.

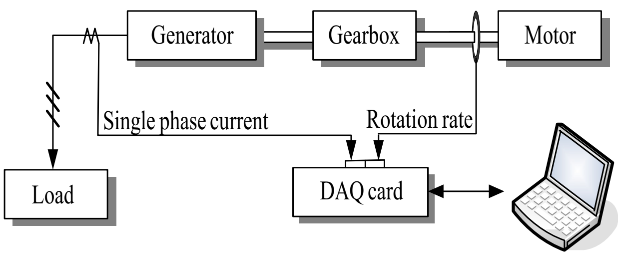


Fig. 3: Structure of test platform.

The instantaneous amplitude $a_j(t)$ and the instantaneous phase $\theta_j(t)$ are shown in equations (4) and (5), respectively.

$$a_j(t) = \sqrt{c_j^2(t) + y_j^2(t)} \tag{4}$$

$$\theta_j(t) = \tan^{-1}\frac{y_j(t)}{c_j(t)} \tag{5}$$

Then, the instantaneous frequency $\omega_j(t)$ can be obtained by computing the derivatives for the instantaneous phase $\theta_j(t)$, as shown in equation (6).

$$\omega_j(t) = \frac{d\theta_j(t)}{dt} \tag{6}$$

The results of Hilbert spectrum offer the information about the energy distribution over time and frequency. The ability can capture time-frequency localization to make the concept of instantaneous frequency and time relevant [9].

3 Damage Measurement for Gearbox and Blade

The test platform consists of a motor, a gearbox, a generator and six blades, as shown in Figure 2. The motor is used for simulating the wind source to drive the gearbox and generator, and the blades are used for the simulation of rotation. We used a DAQ card to obtain the current signals of the generator and the speed of the rotation in the experimental test, as shown in Figure 3.

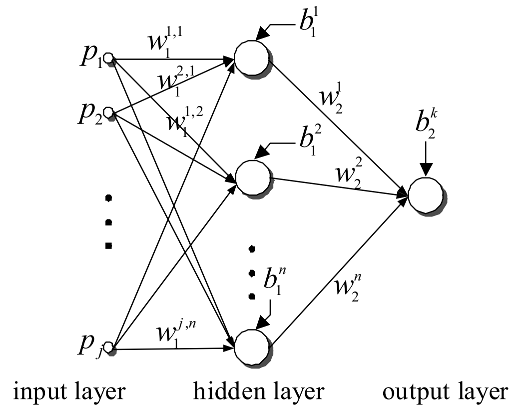


Fig. 4: Back propagation neural network topology.

The tailor-made damaged samples of gearbox and blades were used for the measurements which are representative of a loss-of-lubrication gearbox and a damaged blade. The type of six-fold blades is employed in this paper. We damaged one of the blades and measured the current signals when the blades were rotating.

We took out all the lubrication oil from the gearbox as a damaged sample and then measured the current signals after 1 hour. The new gearbox with full lubrication is a normal sample, and the current signals were measured after 1 hour. By using equations (2)-(6), the Hilbert spectrums of the damaged sample can be compared with normal samples.

4 BPNN Solution Methodology

Back propagation neural network(BPNN), a supervised learning network consisted of an input layer, an output layer, and a hidden layer, is one of the most widespread methods applied to categorization and prediction as shown in Figure 4. The principle of back propagation neural network is gradient steepest descent method. By repeatedly transmitting the gradient error to update weight value w and bias b, the output achieves the target value. The procedure of back propagation neural network can be divided into two parts: 1) the feed-forward phase and 2) the back propagation phase. Network starts output computation during feed-forward phase, and amends weights and biases backwards during back propagation phase, as shown in Figure 5.

Establish the relevance between the input and output of a network is a necessary task for constructing a neural network model. The data base is composed of a training set data and a test set data, where the former is for network training to construct a network model and the

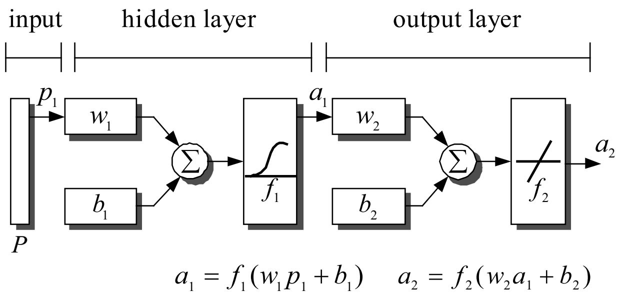


Fig. 5: Back propagation neural network solution structure.

latter is for testing the accuracy of network. When not achieving the target value, the accuracy will process network training again or increase the data of the training set to achieve the goal. The network procedures are explicitly explained as below.

4.1 Feed-Forward Phase

Step 1. Assume P is the input. Calculate the output of the hidden layer, a_1, using the formula as shown in equation (7) where w_1, b_1, and f_1 represent the weight value, bias, and activation function, respectively.

$$a_1 = f_1(w_1 p + b_1) \tag{7}$$

Step 2. The output of the hidden layer, a_1, acts as the input of the output layer. Then, calculate the formula as shown in equation (8) to obtain the output a_2. In equation (8), w_2, b_2, and f_2 represent the weight value, bias, and activation function, respectively.

$$a_2 = f_2(w_2 a_1 + b_2) \tag{8}$$

4.2 Back Propagation Phase

Step 1. Amend weight and bias based on mean square error. Calculate the mean square error of output a_2 and target value d, as shown in equation (9).

$$E(t) = [d(t) - a_2(t)]^2 \tag{9}$$

Step 2. Calculate the gradient error of each weight and each bias affected by mean square error using equations (10) to (13).

$$\frac{\partial E(t)}{\partial w_2(t)} = -\left[e(t) f_2'(w_2(t)a_1(t) + b_2(t))\right] a_1(t) \tag{10}$$

$$\frac{\partial E(t)}{\partial b_2(t)} = -e(t)\, f_2'[w_2(t)a_1(t) + b_2(t)] \tag{11}$$

$$\frac{\partial E(t)}{\partial w_1(t)} = -\left[\sum_k e(t) f_2'(w_2(t)a_1(t) + b_2(t)w_2(t))\right] f_1'(w_1(t)p(t) + b_1(t)p(t)) \tag{12}$$

$$\frac{\partial E(t)}{\partial b_1(t)} = -\left[\sum_k e(t) f_2'(w_2(t)a_1(t) + b_2(t)w_2(t))\right] f_1'(w_1(t)p(t) + b_1(t)) \tag{13}$$

Step 3. Suppose learning rate is α and adjust each weight and each bias, as shown in equations (14) to (17).

$$w_2(t+1) = w_2(t) - \alpha \frac{\partial E(t)}{\partial w_2(t)} \tag{14}$$

$$b_2(t+1) = b_2(t) - \alpha \frac{\partial E(t)}{\partial b_2(t)} \tag{15}$$

$$w_1(t+1) = w_1(t) - \alpha \frac{\partial E(t)}{\partial w_1(t)} \tag{16}$$

$$b_1(t+1) = b_1(t) - \alpha \frac{\partial E(t)}{\partial b_1(t)} \tag{17}$$

5 Experimental Results

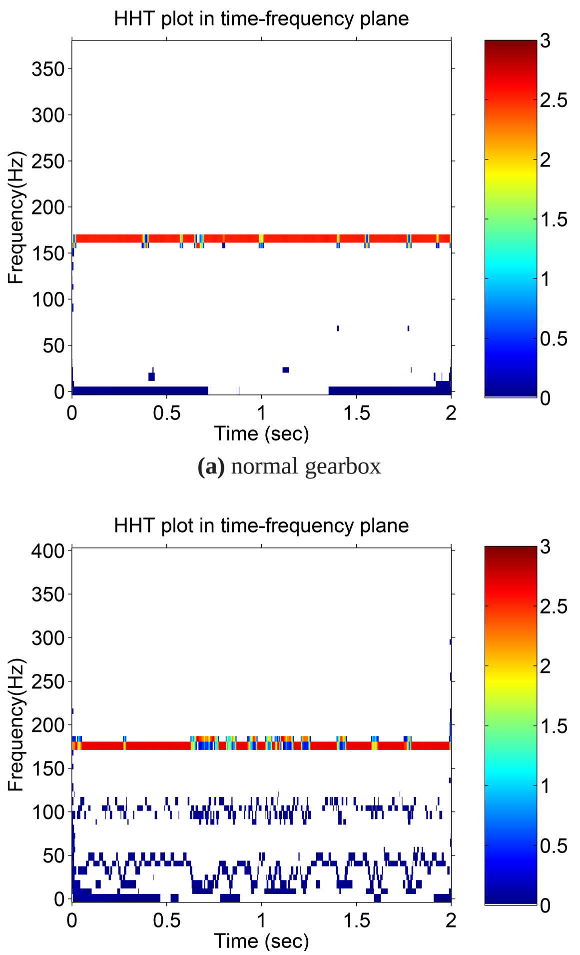
It is difficult to distinguish the difference between output current signals of a normal gearbox and output current signals of a damaged gearbox. The Hilbert spectrum obtained by using the Hilbert-Huang transform is employed in this work. Differences between both normal and damaged gearboxes can be observed from the instantaneous frequency and amplitude of the spectrum.

5.1 Gearbox Damage

The output current signals of both normal and damaged gearboxes are measured. The Hilbert spectrums of the output currents of both normal and damaged gearboxes are illustrated in Figures 6(a) and 6(b). In the Figure 6(a), the spectrum is clear with a stable frequency component and a measurement noise. However, the disturbance phenomena exit within 10 to 50 Hz and 100 to 130 Hz in the spectrum of Figure 6(b). The results show that the Hilbert spectrum can recognize the damage of a gearbox.

5.2 Blade Damage

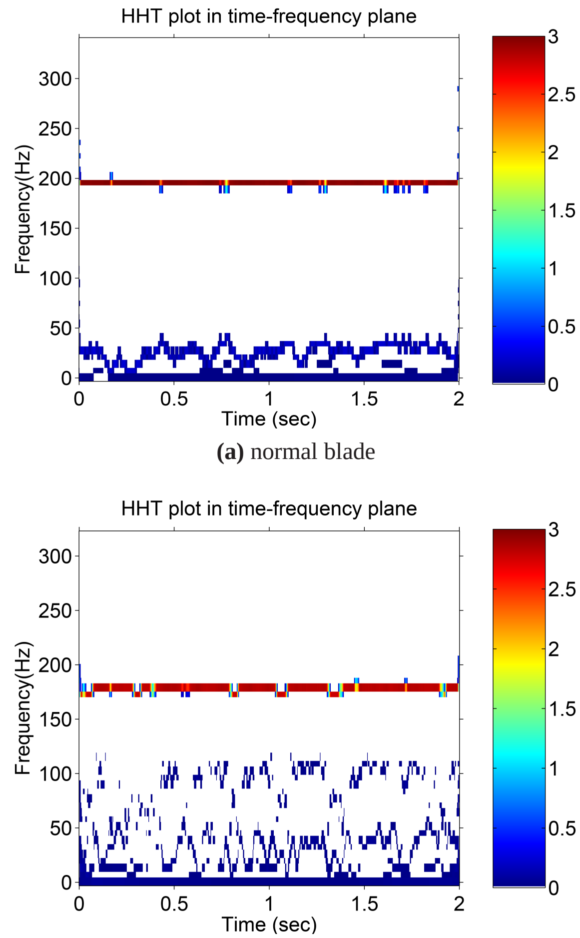
The output current signals of normal and damaged blades are measured. The Hilbert spectrums of the output currents of both normal and damaged blades are illustrated in Figures 7(a) and 7(b). In the Figure 7(a), the spectrum is clear and with a stable frequency component and a measurement noise of about 40 Hz. However, the



(a) normal gearbox

(b) damaged gearbox

Fig. 6: Hilbert spectrum of generator currents.



(a) normal blade

(b) damaged blade

Fig. 7: Hilbert spectrum of generator currents.

disturbance phenomena are chaotically distributed within 0 to 100 Hz in the spectrum of Figure 7(b). The results show that the Hilbert spectrum can recognize the damage of a blade.

6 Conclusions

This paper presents a novel recognition approach to the damaged gearbox and blade of wind generation system. The Hilbert-Huang transform is mainly applied to obtain the Hilbert spectrums of the generator currents to recognize the damage of gearbox and blades. The results show that the Hilbert-Huang transform is advantageous to the recognition of the damage through the current of generator. The experimental test can be regarded as a successful reference to encourage researchers who can have an alternative way of using the currents to recognize the status of the gearbox and blades of wind generation system.

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