



APPLICATION OF MORLET WAVELET IN THE DIAGNOSIS OF NOISE SIGNAL CHARACTERISTICS OF A WIND TURBINE BLADE IN ABNORMAL OPERATION

Chao-Nan Wang

Department of Engineering Science and Ocean Engineering, National Taiwan University, Taipei City, Taiwan, R.O.C.

Yao-Chi Tang

Department of Engineering Science and Ocean Engineering, National Taiwan University, Taipei City, Taiwan, R.O.C., tom8908@yahoo.com.tw

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Acknowledgements

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Key words: Morlet wavelet, marginal spectrum, regression analysis, feature extraction.

ABSTRACT

This study developed an estimation model for noise signal characteristic diagnosis based on the time-frequency analysis technique. The time-frequency analysis theory uses the relatively mature and extensively used wavelet method as the basis of signal analysis, but wavelet analysis generates wavelet theories different from other mother wavelet methods. This study used the Morlet Transform, which is a type of wavelet transform using a mother wavelet for wavelet analysis of signals. The time axis was integrated according to the result of time-frequency analysis in order to obtain the marginal spectrum value of the frequency domain. Finally, statistical regression analysis was used as the estimation method of feature extraction. This study determined and validated the behavior estimation functional equation of a wind turbine blade in normal operation versus the signal of a wind turbine blade in abnormal operation. The proposed model can be used as a diagnostic method of early warning and health management of a wind turbine.

I. INTRODUCTION

Frequency analysis is presently an important tool for vibration and noise analyses, with spectral analysis being the most extensively used in recent years. However, spectral analysis cannot show the variation of frequency with time. The variation of frequency with time reveals whether an abnormal rotational frequency of a machine is continuous or intermittent, which significantly influences the judgment of the mechanical anomaly. (Chian, 2011). Therefore, the variation of frequency with time is of great importance (Pan, 2015). The present analysis modes

for time-frequency analysis include the approximate wavelet analysis method (Meyer, 1993), HHT (Huang et al., 1998), and STFT (Qian and Chen, 1996). This study uses the wavelet method as the theoretical method for time-frequency analysis.

In recent years the wavelet method has been used extensively in speech processing, image processing, computer vision, biomedicine, and vibration noise analysis. The wavelet transform evolved from wavelet analysis, as first proposed by Haar in 1910 (cited in He (2003)). The Haar wavelet is the easiest orthogonal wavelet and is the basic dyadic wavelet transform. In 1984, French geophysicist Jean Morlet applied the concept of the wavelet method to signal analysis (Goupillaud et al., 1984). The most frequently used signal analysis at present is Fourier transform. When the time-domain signal is converted via Fourier transform, the signal distribution in the frequency domain will be obtained and the main frequency of the signal will be found. However, the disadvantage of Fourier transform is that the time of the occurrence of the main frequency cannot be identified. Morlet wavelet is preferred over Fourier transform because it simultaneously converts the time sequence for each frequency of occurrence. In addition, the Morlet wavelet uses finite or quickly attenuated mother wavelet oscillation waveforms to represent signals. This waveform and matched input signal are processed by scaling or translation. However, the defect of the Morlet Transform is that the high frequency diverges as the frequency resolution decreases. Therefore, the Enhanced Morlet Transform (Cheng et al., 2005; Jeng et al., 2005) is processed by the Gauss function in advance, in order to solve the energy spread in the high frequency parts and to meet the primitive character of the original signal.

Regression analysis is a convenient and rapid method for statistical analyses, which helps to build a statistical model of the relationship between dependent variables and independent variables. The trend of dependent variables can be predicted by the appropriate selected independent variable. It is most frequently used as a statistical analysis tool. The regression analysis of one dependent variable for one or multiple independent variables is called univariate regression analysis. The regression analysis of multiple dependent variables for one or multiple in-

dependent variables is called multivariate regression analysis. The univariate regression analysis has both linear regression (Neter et al., 1996) and nonlinear regression methods (Seber and Wild, 2006). This paper will use regression analysis to calculate the estimation functional equation of feature extraction.

The research on the abnormal operation of wind turbine blades is relatively sparse. The research method adopted generally centers on vibration signal analyses, with diagnoses on feature noise signals relatively rare. Therefore, this study utilizes noise analyses to diagnose the abnormal operation of a wind turbine blade.

II. INTRODUCTION TO THEORY

The calculation methods of the Morlet wavelet theory, the Enhanced Morlet Transform, and the linear regression are briefly described as follows.

1. Wavelet Analysis

The wavelet transform is roughly divided into continuous wavelet transform (CWT) and discrete wavelet transform (DWT). The continuous transform operates on all probable scaling and translation, while the discrete transform uses the specific subset of all scaling and translation values (Li, 2011). CWT decomposes the continuous signal of a time in order to decompose the time sequence into several wavelets. The function $x(t)$ with continuous time and integrability processed by CWT can be expressed as Eq. (1).

$$X_w(a, b) = \frac{1}{\sqrt{|(a)|}} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t-b}{a}\right) dt, \quad (1)$$

where $\psi(t)$ is called the mother wavelet, which is a continuous waveform in the time and frequency domains, b is the translation parameter for translating the wavelet function, and a is the compressed and amplified wavelet parameter. The a value is converted into frequency. The mother wavelet is defined as

$\psi(t) = \frac{1}{\sqrt{|(a)|}} \psi\left(\frac{t-b}{a}\right)$; however, the mother wavelet must

meet the following conditions:

$$(I) \int_{-\infty}^{\infty} |\psi(t)|^2 dt = 1$$

$$(II) \int_{-\infty}^{\infty} |\psi(t)| dt < \infty$$

$$(III) \int_{-\infty}^{\infty} \psi(t) dt = 0.$$

The Morlet wavelet in this paper is a method using Gabor Functions (Mallat, 1999; Jeng et al., 2005) to convert signals to a complex plane. According to the uncertainty principle, the

temporal resolution must be poor when the frequency resolution is high, and the frequency resolution must be poor when the temporal resolution is high. The main defect of the Morlet Transform at high frequency is the poor frequency resolution; thus, the calculated time-frequency chart will have an energy spread in the high frequency region. Therefore, another Enhanced Morlet Transform is used.

The Gabor Function is multiplied before wavelet transform, and the marginal and low amplitude signals are removed, in order that the high frequency resolution is increased. Eq. (2) of this transform is below.

$$X_w(a, b) = \frac{1}{\sqrt{|(a)|}} \int_{-\infty}^{\infty} x(t) \psi\left[\frac{t-b}{a}\right] G(\sigma, b, t) dt, \quad (2)$$

where $G(\sigma, b, t)$ is the Gaussian function expressed as $\left[\frac{1}{4\pi} \cdot \frac{1}{\sigma}\right]^{1/2} \cdot e^{-\frac{1}{4\sigma}(t-b)^2}$ due to the high frequency section, the scale parameter a of the Morlet wavelet decreases, and the high frequency resolution worsens as a result. Hence, the Morlet wavelet is multiplied by a Gaussian Window $G(\sigma, b, t)$ to increase the frequency resolution before the wavelet transform. The computing time is relatively prolonged; however, the divergence resulting from a lack of high frequency resolution can be solved.

2. Marginal Spectrum

After time-frequency analysis of a signal, The $H(t, \omega)$ is obtained after time-frequency analysis of a signal, and the frequency axis is integrated to get obtain the distribution of time as a parameter. It is mathematically expressed as Eq. (3).

$$h(t) = \int_{-\infty}^{\infty} H(t, \omega) d\omega, \quad (3)$$

where $H(t, \omega)$ is the time domain distribution of the time-frequency two-dimensional array, i.e., Marginal Time. The distribution of frequency as a parameter can be obtained by integrating the time axis. The mathematical expression is Eq. (4).

$$h(\omega) = \int_{-\infty}^{\infty} H(t, \omega) dt \quad (4)$$

where, $h(\omega)$ is the frequency domain distribution, i.e., Marginal Frequency. The marginal spectrum measures the total amplitude or total energy of each frequency.

3. Regression Analysis

Researchers can judge the model of this mathematical formula according to past experience or theory. There are 5 main basic classes: linear, logarithmic, polynomial, power, and exponential. It is expected to be linear in calculation, as the general

linear model provides simple and intelligible ways and uses samples to better approach the parent.

When K independent variables are imported, the generalized multivariate regression model is:

$$Y = A_0 + A_1X_1 + A_2X_2 + \dots + A_kX_k + \varepsilon$$

The matrix is expressed as Eq. (5).

$$[Y] = [X] \times [A] + [\varepsilon] \tag{5}$$

$$[Y] = \begin{bmatrix} Y_1 \\ Y_2 \\ \bullet \\ \bullet \\ \bullet \\ Y_n \end{bmatrix}, [X] = \begin{bmatrix} 1 & X_{1l} & \dots & \dots & X_{1k} \\ 1 & X_{2l} & \dots & \dots & X_{2k} \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ 1 & X_{nl} & \dots & \dots & X_{nk} \end{bmatrix}$$

$$[A] = \begin{bmatrix} A_0 \\ A_1 \\ \bullet \\ \bullet \\ \bullet \\ A_K \end{bmatrix}, [\varepsilon] = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \bullet \\ \bullet \\ \bullet \\ \varepsilon_n \end{bmatrix}$$

where, $Y = A_0 + A_1X_1 + A_2X_2 + \dots + A_kX_k + \varepsilon$ uses the Least Square Regression Formula to export the estimates $a_0, a_1, a_2 \dots a_K$ of parameters $A_0, A_1, A_2 \dots A_K$ in the regression equation. The estimation equation of the corresponding regression line can be expressed as:

$$y = a_0 + a_1X_1 + a_2X_2 + \dots + a_kX_k + \varepsilon$$

The least square method is selected for the general multivariate regression model, and the estimated regression line $y = a_0 + a_1X_1 + a_2X_2 + \dots + a_kX_k + \varepsilon$ can minimize the sum squared error $\sum(Y_i - y_i)^2$ of all sample points. The sum squared error is expressed as follows:

$$SSE = \sum(Y_i - y_i)^2 = (Y_i - a_0 - a_1X_1 - a_2X_2 - \dots - a_kX_k)^2$$

$$\frac{\delta SSE}{\delta a_0} = \frac{\delta SSE}{\delta a_1} = \dots = \frac{\delta SSE}{\delta a_k} = 0,$$

where $a_0, a_1, a_2 \dots a_k$ can be worked out.

There are two main standards for determining the feasibility of the regression equation: rationality of data and conformance of data. Rationality means the regression equation shall be reasonable, it can be combined with theory, and it is intelligible. In terms of data conformance, the regression equation should fully interpret and match data. Data conformance is judged on the residual. The residual value (Ei) is the observed value minus

the predicted value, where the larger the residual is, the more ideal the regression line is. All residual values are squared and summed up to obtain the sum of the squares of residuals SSE . The total sum of squares (SS_t) is all numerals minus the mean, which are squared and added up.

Let Y denote the observed value of data, where \hat{Y} represents the predicted value generated by this regression line, and \bar{Y} is the mean:

$$SSE = \sum(Y - \hat{Y})^2, SS_t = \sum(Y - \bar{Y})^2$$

After conversion, SS_t minus SSE leaves the sum of squares of regression (SS_{reg}), i.e.:

$$SS_t - SSE = \sum(\bar{Y} - \hat{Y})^2 = SS_{reg}$$

The sum of the squares of regression is SS_{reg} , where each prediction value, minus the mean, is squared and added up. The percentage of SS_{reg} to SS_t is the part of this regression line conforming to data, which is known as R^2 , as well as the coefficient of determination. It is expressed as Eq. (6).

$$R^2 = \frac{SS_{reg}}{SS_t} = \frac{\sum(\bar{Y} - \hat{Y})^2}{\sum(Y - \bar{Y})^2} \tag{6}$$

The value of R^2 is 0 to 1. If the interpretation of this line of data equals the guess on mean, then R^2 equals 0. If this line completely conforms to the data without any residual, then R^2 equals 1. In fact, the R^2 value does not equal 0 or 1, but is between them. The larger R^2 is, the better the regression line conforms to the data, i.e., better conformance.

If R^2 of two regression lines is almost identical, then the rationality is almost identical, and as the regression line is the simpler the better, problems can be simplified. For example, the regression equation can be used to estimate the error value, and this estimated error value cannot be completely accurate. Therefore, the calculation of standard deviation (SD) must be imported. SD is used to measure the difference between the observed data and the mean and can be one of the standards for judging the feasibility of this estimation model.

The technique of regression analysis is like order number and nonlinear terms and is free of criteria. The advantage is that the regression equation is not complex, and it can be calculated by a microprocessor. As it is reliable to some extent in estimating data, it is a noncomplex and feasible method.

III. RESEARCH STRUCTURE AND DESIGN

1. Research Structure

This study developed a noise characteristic estimation model for wind turbine blades in rotation and applied it to estimate

Table 1. Operating conditions.

Noise value calculation conditions	
Common operating conditions	
1. Wind turbine 3 blades	1. Wind turbine 3 blades
2. Vinlet = 11.4 (m/s)	2. Vinlet = 11.4 (m/s)
3. Rotation speed is 12.1 rpm	3. Rotation speed is 12.1 rpm
4. TI value is 0.01%	4. TI value is 0.01%
Normal operation	Abnormal operation
1. $\beta = 0^\circ$	1. $\beta = 0^\circ$
2. $\alpha = 0^\circ$	2. $\alpha = 5^\circ$

TI: Turbulence intensity
 β : Angle of wind inflow direction
 α : Pitch angle of top blade
 Vinlet: Inlet velocity of wind

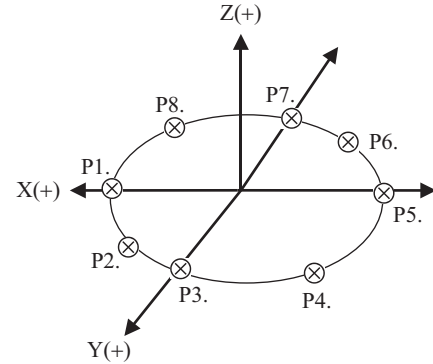


Fig. 2. Noise value calculated positions.

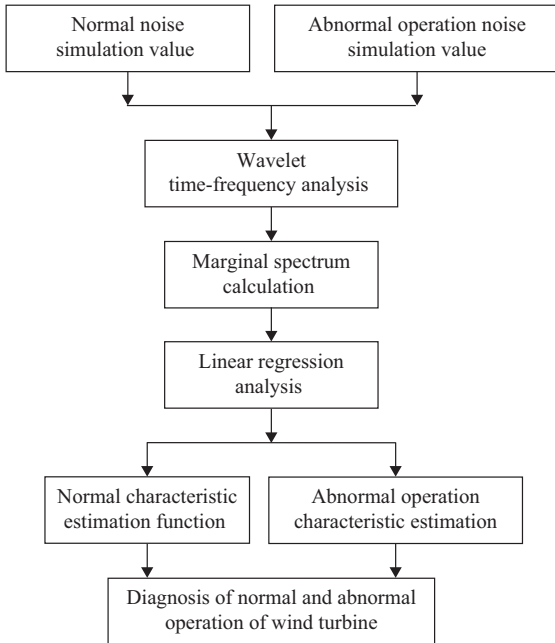


Fig. 1. Noise characteristic estimation model analysis process.

the service behavior of this wind turbine. This study refers to abnormal operation as changes in the pitch angle of the top blade. The noise data of wind turbines are derived from numerical analysis of noise simulation. The analysis process is shown in Fig. 1.

2. Research Design

The positions of this project’s calculated noise data are shown in the following figure, where the calculated position is on the ground within a radius of 125 m from the wind turbine center, and the precalculated positions are at intervals of 45°, as shown in Fig. 2. Table 1 lists the operating conditions.

IV. ANALYSIS COMPARISON

1. Creation of Feature Estimation Functional Equation in Normal Operation

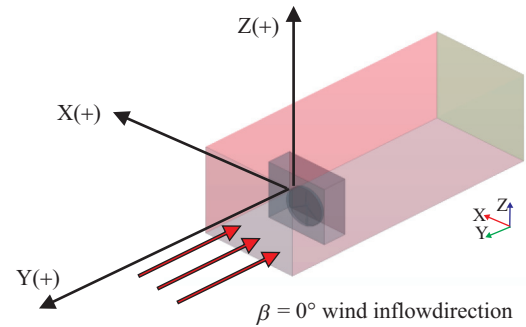


Fig. 3. Wind inflow direction.

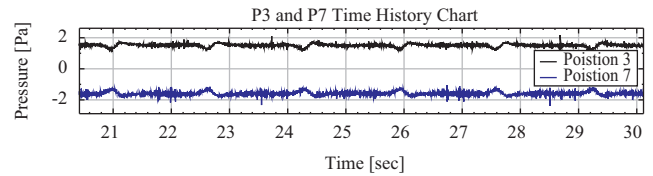


Fig. 4. Position 3 and Position 7 time series.

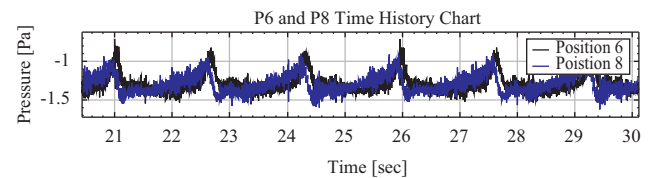


Fig. 5. Position 6 and Position 8 time series.

The noise signal analyzed is from the numerical calculation simulation result of this study. The wind turbine has three blades, and the calculated positions are shown in Fig. 2. The rotation speed is 12.1 rpm, and the wind inflow is normal to blades, as shown in Fig. 3. The noise signal of the time series of normal operation is extracted, as shown in Figs. 4. and 5. The black curve symbolizes positions 3 and 6. The blue curve symbolizes positions 7 and 8.

To develop a wind turbine blade feature estimation model

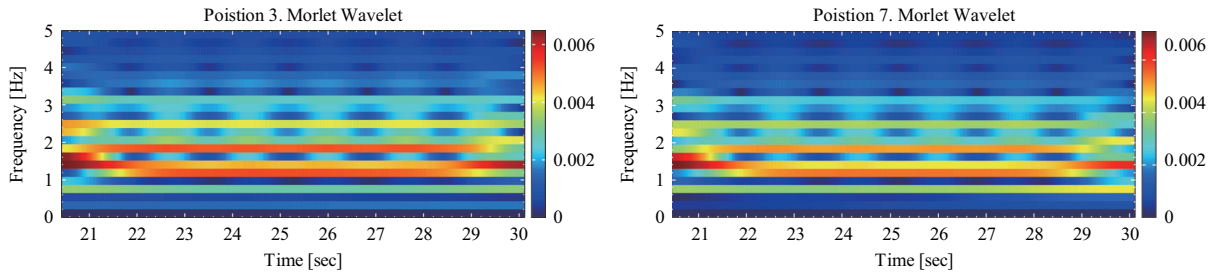


Fig. 6. Position 3 and Position 7 time-frequency analysis.

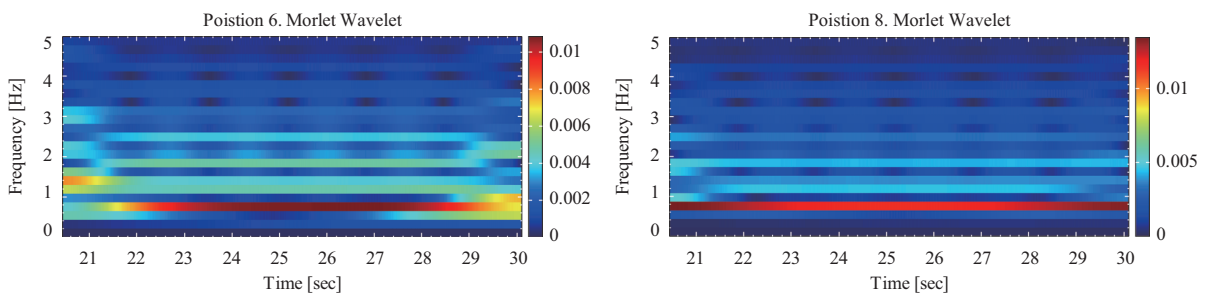


Fig. 7. Position 6 and Position 8 time-frequency analysis.

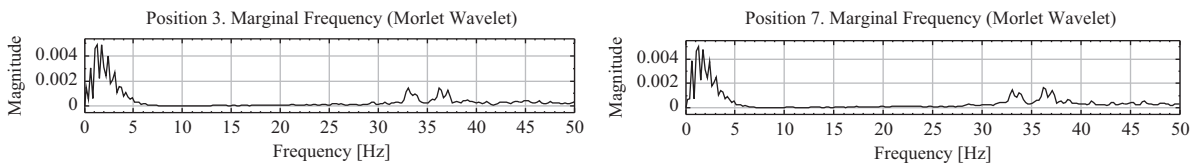


Fig. 8. Position 3 and Position 7 marginal frequency analysis.

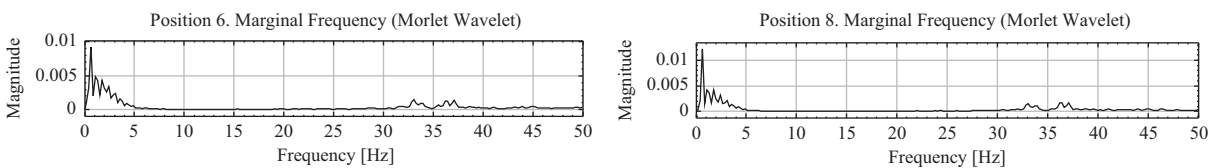


Fig. 9. Position 6 and Position 8 marginal frequency analysis.

and diagnostic capability, the symmetrical positions of P3 and P7 and of P6 and P8 are taken as examples to analyze normal operation feature estimation. First, the wavelet method is used for time-frequency analysis of the two groups of position signals, as shown in Figs. 6. and 7. From the time-frequency chart, the apparent frequency occurs at the dominant frequency and double frequency of the blades and continues with time. In addition, the wind inflow is positive zero, and so the energy in front of and behind the wind turbine is greater than that on the sides, which adhere to the physical phenomenon.

In order to know the sum of amplitude or energy corresponding to each frequency, the marginal spectrum of the time-frequency signal is made to obtain the marginal frequency, as shown in

Figs. 8. and 9. According to this analysis, 1.22 Hz-3.1 Hz is most apparent at the dominant frequency 0.61 Hz and 2-5 double frequency; thus, the linear regression independent variable frequency characteristic range is 3 Hz.

2. Time-Frequency Analysis and Marginal Spectrum Calculation in Abnormal Operation

The noise signal analyzed is derived from the numerical calculation simulation result of this project. This wind turbine has three blades, and the top blade is turned 5° as an abnormal operating condition. The time-frequency chart, as obtained by the wavelet method, is shown in Figs. 10. and 11. The marginal spectrum of the time-frequency signal is made to obtain the

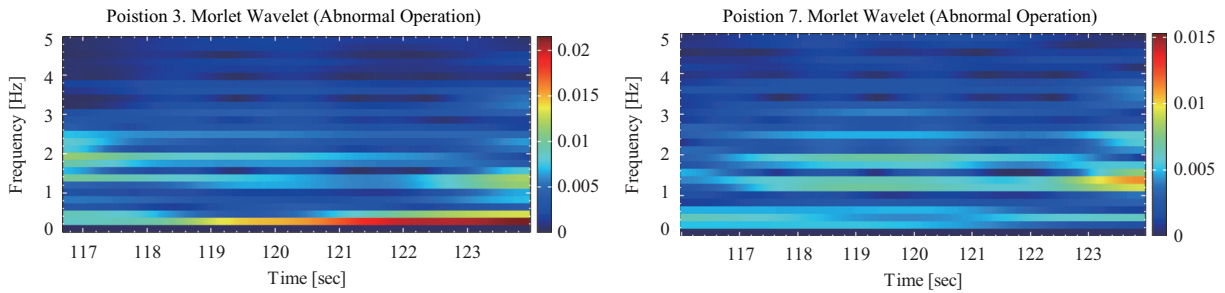


Fig. 10. Position 3 and Position 7 time-frequency analysis in abnormal operation.

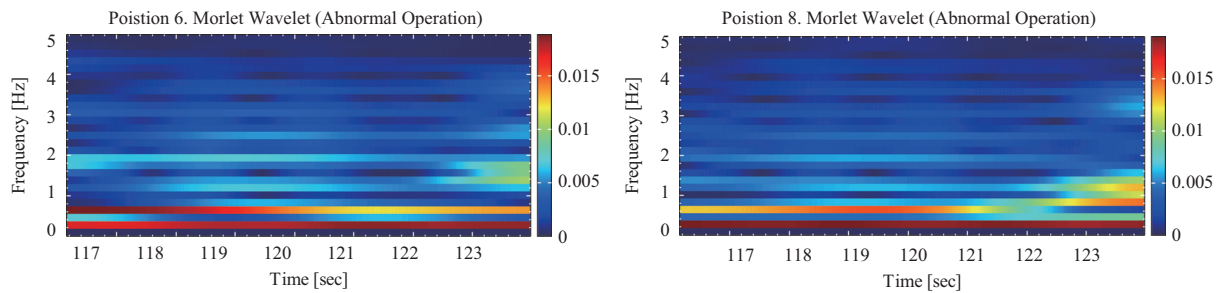


Fig. 11. Position 6 and Position 8 time-frequency analysis in abnormal operation.

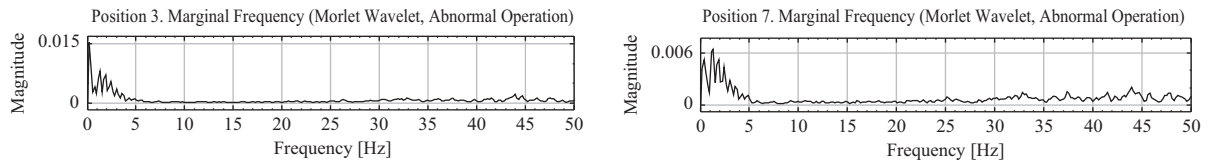


Fig. 12. Marginal frequency analysis of Position 3 and Position 7 in abnormal operation.

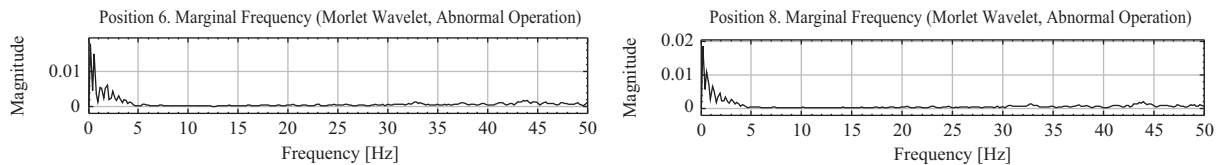


Fig. 13. Marginal frequency analysis of Position 6 and Position 8 in abnormal operation.

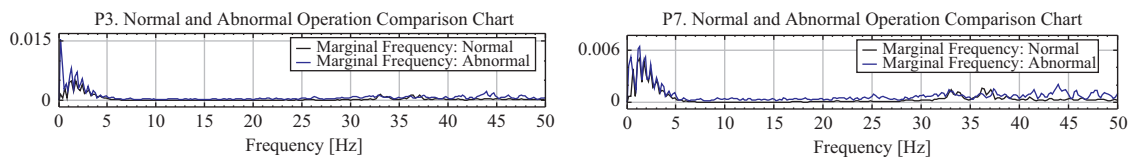


Fig. 14. Marginal spectrum analysis of Position 3 and Position 7 in normal and abnormal operation.

marginal frequency, as shown in Figs. 12. and 13.

3. Noise signal Diagnosis in Normal and Abnormal Operations

The wavelet time-frequency is calculated in normal and abnormal operations and converted into marginal spectrum. The two signals in the same position are combined and compared in Figs. 14. and 15. According to this result, the frequency 0-5

Hz is the most apparent extracted feature. Thus, the marginal frequency distribution in four positions in normal operation is averaged to calculate the estimated trend curve of 6-order linear regression and to create the feature estimation function in normal operation, as shown in Figs. 16 and 17.

$$\text{Index 1} = \frac{\text{Se in abnormal operation} - \text{Se in normal operation}}{\text{Se in normal operation}}$$

Table 2. Abnormal noise feature extraction judgment criteria.

Abnormal noise feature extraction judgment criteria (at radius of 125 m from wind turbine center point)							
P	Sum of residuals (Se)			SD of estimated value and measured value			
	Nor	Abnor	Inde × 1	Nor	Abnor	Inde × 2	Model
3	0.022	0.118	4.4	0.002	0.009	3.5	0.845
7	0.021	0.116	4.5	0.002	0.005	1.5	0.828
6	0.017	0.142	7.4	0.002	0.008	3.0	0.914
8	0.028	0.127	3.5	0.003	0.007	1.3	0.875

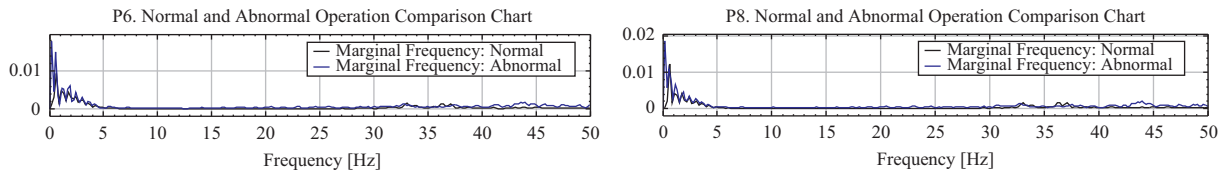


Fig. 15. Marginal spectrum analysis of Position 6 and Position 8 in normal and abnormal operation.

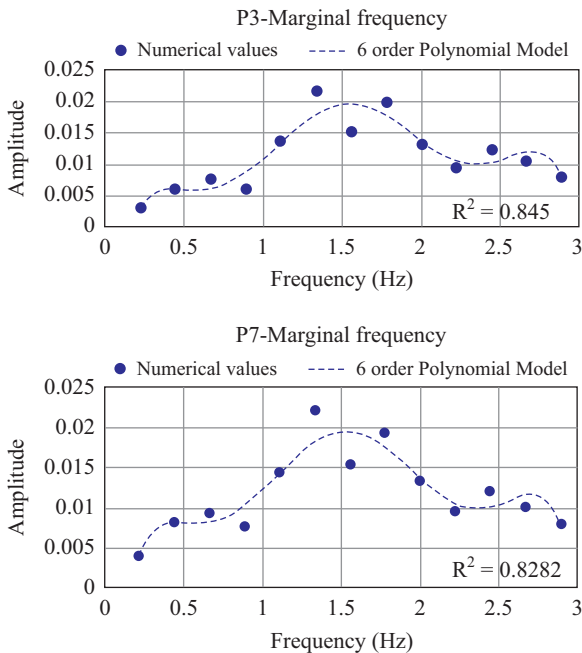


Fig. 16. Position 3 and Position 7 linear regression estimated curve.

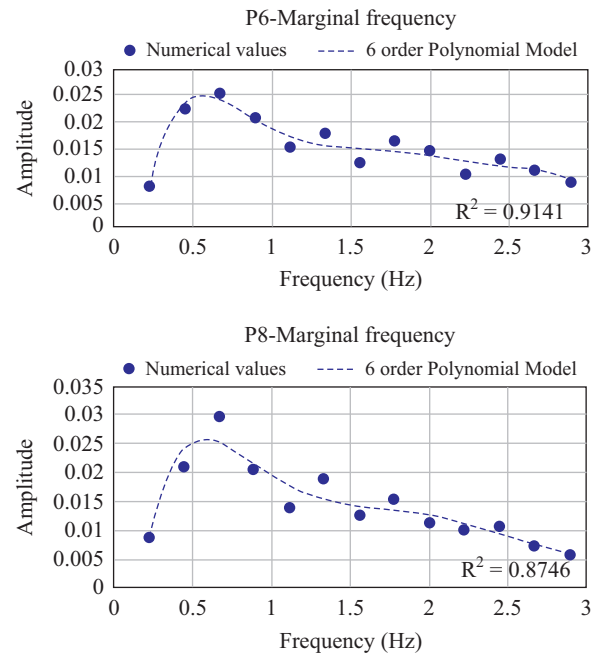


Fig. 17. Position 6 and Position 8 linear regression estimated curve.

$$\text{Index 2} = \frac{\text{SD in abnormal operation} - \text{SD in normal operation}}{\text{SD in normal operation}}$$

- Se: Absolute values of all residuals are taken and added up, i.e., the sum of residuals
- P: Position
- Nor: Normal operation
- Abnor: Abnormal operation
- Model: Model (coefficient of determination)

The smaller the sum of residuals (Se) is, the more accurate the estimation of the regression equation; standard deviation (SD) represents the amount of dispersion of the regression equation and the values measured. Thus, this study utilizes the two indices, Se and SD, to distinguish between normal operation and abnormal operation.

tion and abnormal operation.

According to the above figures and Table 2, positions P3 and P7 have the same curve distribution trend, where the coefficient of determination of 6-order regression analysis is higher than 0.7, and Se is lower than 0.002. In addition, positions P6 and P8 have closer curve distribution trends, the coefficient determination of 6-order regression analysis is higher than 0.9, and Se is lower than 0.002. Therefore, the 6-order curvilinear equation obtained in the four positions conforms to the consistency of statistical indices and the accuracy of estimation, which is applicable to creating the functional equation of the estimation model in the future. The measurement or calculation result will be converted by the estimation program, and the values are substituted in related estimation equations, in order to know the usability of the blades as reference and eigenfunction for judging

the abnormal sound of blades.

V. CONCLUSION

This study used time-frequency analysis, marginal spectrum transform, and a linear regression estimation curve to build a noise estimation model. According to the above analysis, Position 3 and Position 7, or Position 6 and Position 8, have a certain symmetry in regression statistics, data synchronism, and rationality. The coefficient of determination (R^2) of the prediction function of regression analysis is 0.85 on average, meaning the prediction curve matches the actual data. Therefore, the 6-order polynomial regression analysis estimated equation has certain accuracy. The mathematical model for normal operation is determined by this noise feature extraction estimation model.

The data in abnormal operation (top blade 5°), as calculated in this study, are calculated by the feature extraction of the marginal spectrum, and the obtained values are substituted in the regression analysis feature model in normal operation, with the result shown in Table 2. When Se (index 1) and SD (index 2) are analyzed, index 1 and index 2 in abnormal operation are obviously different from that in normal operation and are even change multiple times.

Provided that the system noise value is substituted in this estimation model, the service behavior of this wind turbine blade can be easily determined. It should be noted that when this feature estimation system is used, the model must be rebuilt for different forms of wind turbines in order to ensure the accuracy of the mathematical model. In the same way, for the same form of wind turbine, the model is built only once for mass production and can even adjust relevant parameters. The feature extraction estimation procedure can be used as a health evaluation result of predictive diagnosis and health control and can provide a decision reference for wind farms to operate and repair wind turbines in the future.

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