International Journal of Structural Stability and Dynamics
Vol. 19, No. 1 (2019) 1940008 (16 pages)

DOI: 10.1142/S021945541940008X

Experimental Verification of the Statistical Time-Series Methods for Diagnosing Wind Turbine Blades Damage

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Received 25 December 2017
Accepted 2 May 2018
Published 3 July 2018

This paper presents an experimental verification of the statistical time-series methods, which utilize adapted frequency response ratio (FRR), autoregressive (AR) model parameter and AR model residual as performance characteristics, for diagnosing the damage of wind turbine blades. Specifically, the statistical decision-making techniques are used to identify the status patterns from turbine vibration data. For experiments, a small-size, laboratory-used operating wind turbine structure is used. The performance of each method in diagnosing damages simulated by saw cut in three critical positions in the blade are assessed and compared. The experimental results show that these methods yielded a promising damage diagnosis capability in the condition monitoring of wind turbine.

Keywords: Damage diagnosis; time series; wind turbine; statistical decision; experimental verification.

1. Introduction

With the growth of energy demand and the development and utilization of renewable energy, wind power, as a renewable clean energy, is undergoing expansion. Despite the rapid development of wind turbines, operation and maintenance costs remain high. This is because wind power plants are usually in the remote sites and offshore locations, and failures occur in wind turbine components such as gearboxes and blades frequently due to harsh operating environment. In particular, the blades are the most crucial and costly part among wind turbine components,[1] and they are easily damaged and failed.[2] Thus, there is a great need to monitor the performance of wind turbine blades.

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Various diagnosis methods were used to identify the damage of wind turbine blades. Poozesh *et al.*[3] applied the acoustic microphone array method for blades damage detection. Tang *et al.*[4] used the unsupervised pattern recognition methods to characterize different acoustic emission (AE) activities corresponding to different fracture mechanisms. These studies are conducted on isolated wind turbine blades, and the AE methods are not appropriate for online detection. Schroeder *et al.*[5] and Tian *et al.*[6] applied fiber Bragg grating (FBG) sensors to detect the damage of wind turbine according to the measured strain distribution. Park *et al.*[7] presented a real-time strain response monitoring system for wind turbine blades using FBG sensors. However, the health monitor system based on dense FBG sensor network is expensive and very complex. There has been a considerable research effort focused on applying the frequency domain techniques by measuring the vibration response on detecting the fault modes of wind turbines.[8,9] This is based on the fact that the various faults of wind turbines will make the resonance frequencies of the running wind turbines to shift. However, due to the complexity and uncertainties of the wind turbines system and the operation environment, traditional frequency domain techniques are facing great challenges.[10] The time-series response of a wind turbine system not only represents the physical properties of the system, but also contains various uncertainties (such as measurement, environmental, operational, excitation, and structural uncertainties) of the system. Light-Marquez *et al.*[11] found that time-series method is more effective and reliable comparing with the Lamb wave methods and frequency domain techniques. Hoell *et al.*[12] presented a time-series method using output-only vibration data to detect damage in wind turbine blades. Among these methods, they treat structural damage diagnosis as a statistical pattern recognition problem, that is, each concerned data are assigned to one of the given set of classes (in our case, given structure vibration data are determined as "undamaged" or "damaged"). The input data and physical model are not required, and the natural uncertainties of wind turbine system, including measurement, environmental, operational, excitation, and structural are considered inherently. The time-series methods can be classified as non-parametric and parametric. Non-parametric methods generally use frequency domain information to characterize the obtained data.[13–16] Park *et al.*[16] used frequency response ratio (FRR), which is the ratio of cross-spectral and auto-spectral density functions, to detect global damage. The control chart analysis is used to cope with experimental and environmental uncertainties. Among the parametric methods, autoregressive (AR) time-series method receives considerable attention.[17–19] Fassois *et al.*[20] proposed a statistical AR time series with statistical decision-making method to diagnose damage. This method does not depend on the physical model and only uses the output-only vibration data.

Among the various damages of wind turbine blades, someone makes the statistical performance characteristics of the time-series representations of wind turbine shifted. Thus, the analysis and measurement of the shifted statistical performance characteristics of the time series representations of dynamic responses could be an effective method to detect the damage in wind turbine blades. There are various ways based on the time-series representations which can be used to diagnose the condition of wind turbine blades. Data mining of time-series representations of the wind turbine provides an easy yet robust approach to damage diagnosis. In this paper, the non-parametric and parametric representations of time series with statistical decision-making methods (adapted FRR performance characteristics, AR model parameter performance characteristics, and AR model residual performance characteristics) are discussed in order to find useful information/patterns from turbine vibration data.

An experimental verification of the proposed methods for diagnosing wind turbine blade damage is presented. Various lengths of saw cut in three critical positions in the blade are made to simulate various damage cases on a small-size, laboratory-used operating wind turbine structure. The experimental results validated the validity and feasibility of the proposed methods for the online damage diagnosis in the field of wind turbine blades.

2. Statistical Time-Series Method

The statistical time-series method consists of model construction and statistical decision-making. In the construction of the model, a non-parametric or parametric time-series model will be constructed from the output-only available random vibration data Y^N (N, the length of Y) that describes their time evolution and part of the structural dynamics. The objective is to extract the performance characteristic, designated as $Q = Q(Y^N)$ (a function of Y^N), which is influential in the following part, from each dataset. In the statistical decision-making part, decisions are made by "comparing" the current performance characteristic Q_u to its counterparts $Q_o, Q_A, \ldots, Q_D$ through formal statistical hypothesis testing. The subscript index represents the various possible structural state (subscript "u" for unknown, "O" for undamaged, and "A" for damage type A, "D" for damage type D).

2.1. *Non-parametric modeling*

Frequency response function is the most efficient non-parametric model to characterize the obtained data. When the input and output data are available, the frequency response functions can be generated by the cross-spectral and auto-spectral density functions of these data. Kim[16] proposed an FRR method that uses two outputs at separate locations to generate an FRR function while only output data are available. The form of FRR is defined as follows:

$$\mathrm{FRR}_{i,i+1}(\omega) = \frac{S_{i,i+1}(\omega)}{S_{i+1,i+1}(\omega)} = \frac{H_i(\omega)}{H_{i+1}(\omega)}, \tag{1}$$

where $H_i(\omega)$ and $H_{i+1}(\omega)$ are frequency response functions measured at locations i and $i+1$, respectively; $S_{i,i+1}(\omega)$ and $S_{i+1,i+1}(\omega)$ are cross-spectral and auto-spectral density functions, respectively; and ω is the frequency.

In this paper, an adapted FRR method is used to acquire an appropriate test statistic in the subsequent procedure. The adapted FRR method uses the performance characteristic $Q = R(\omega)$. $R(\omega)$ is defined as follows:

$$Q = R(\omega) = \left| \frac{1}{\mathrm{FRR}_{i,i+1}(\omega)} \right| = \left| \frac{S_{i,i+1}(\omega)}{S_{i+1,i+1}(\omega)} \right|. \tag{2}$$

2.2. *Parametric modeling*

The most frequently used and efficient parametric time-series model is AR time-series model. Its form can be written as

$$y[t] = -\sum_{k=1}^{n_a} a_k y[t-k] + e[t], \quad e[t] \sim NID(0, \sigma_e^2), \tag{3}$$

where $y[t]$ is the vibration time series, t is the discrete time, a_k is the AR model parameter, n_a is the corresponding model orders, and $e[t]$ is the residual error series with zero mean and variance σ_e^2. Model order selection is conducted by a discrete search to provide the model that minimizes a proper criterion, such as the model's Akaike information criterion (AIC) and Bayesian information criterion (BIC). This study uses the Burg method to estimate the model parameters.

Two types of performance characteristics are normally used in AR statistical time-series method. One is based on AR model parameters and the other is based on model residual sequence. From each type, a typical performance characteristic Q is selected (model parameters vector $Q = \theta = [a_1\, a_2 \cdots a_{na}]$ for the former and the variance of residual series $Q = \sigma^2 = \mathrm{var}(e[t])$ for the latter).

2.3. *Statistical-based damage identification*

In this paper, the damage diagnosis criteria are combined with hypothesis testing. In the case of damage detection, the hypothesis testing problem can be stated as follows:

$$H_0\colon Q_u = Q_o \quad \text{(null-undamaged hypothesis)},$$

$$H_1\colon Q_u \neq Q_o \quad \text{(alternative-damaged hypothesis)},$$

where Q represents the performance characteristic extracted in the analysis part. The subscript index o represents the baseline vibration data, and u represents the inspection vibration data.

The statistical decision-making depends on the test statistic which is calculated by these two performer characteristics being tested. The form of test statistic should be carefully selected so that its probability distribution is given under the null hypothesis. If the test statistic is less than the distribution threshold at the specified significance level, then the null hypothesis is accepted, that is, the structure is not damaged. The calculation method of the test statistic is related to the type of performance characteristics, which will be described as follows.

2.3.1. *Adapted FRR method*

If the null hypothesis is true, then $\delta\hat{R}(\omega) = \hat{R}_o(\omega) - \hat{R}_u(\omega) \sim N(0, 2\hat{\sigma}_o^2(\omega))$ (the performance characteristic $R(\omega)$ may be shown to follow a distribution approximated as Gaussian[21]), where $\hat{\sigma}_o^2(\omega)$ represents the variance of $\hat{R}_o(\omega)$. Therefore, test statistic $Z(\omega)$, which follows standard normal distribution can be formulated as

$$Z(\omega) = \frac{|\delta\hat{R}(\omega)|}{\sqrt{2\hat{\sigma}_o^2(\omega)}} \sim N(0,1). \tag{4}$$

The following test is constructed at significance level α:

$$Z(\omega) \le Z_{1-\alpha 2} \to H_0 \text{ is accepted (null hypothesis, undamaged)}$$
$$\text{Otherwise} \to H_1 \text{ is accepted (alternative hypothesis, damaged).}$$

with $Z_{1-\alpha/2}$ designating the corresponding standard normal distribution's $1-\alpha/2$ critical point.

2.3.2. *AR model parameters method*

If the null hypothesis is true, then $\delta\hat{\theta} = \hat{\theta}_o - \hat{\theta}_u \sim N(0, 2P_o)$, where P represents the covariance matrix. Therefore, test statistic X, which follows chi-square distribution with d degrees of freedom (because it is the sum of squares of independent standardized Gaussian variables[21,22]) can be formulated as follows:

$$X = \delta\hat{\theta}^T \cdot \delta P_\theta^{-1} \cdot \delta\hat{\theta} \sim \chi^2(d), \tag{5}$$

where $\delta P_\theta = 2P_o$, d is the length of the parameter vector. The following test is constructed at the significance level α:

$$X \le \chi^2_{1-\alpha}(d) \to H_0 \text{ is accepted (null hypothesis, undamaged).}$$
$$\text{Otherwise } \to H_1 \text{ is accepted (alternative hypothesis, damaged)}$$

with $\chi^2_{1-\propto}(d)$ designating the corresponding chi-square distribution's $1-\alpha$ critical point.

2.3.3. *AR model residual method*

If the null hypothesis is true, the model residual $e_{uo}[t]$ are IDD Gaussian with zero mean and variance σ_{oo}^2. Hence the quantities $(N-d)\hat{\sigma}_{uo}^2/\sigma_{oo}^2$ and $(N-d)\hat{\sigma}_{oo}^2/\sigma_{oo}^2$ follow chi-square distribution with $(N-d)$ degrees of freedom, respectively (as each is the sum of squares of independent standardized Gaussian random variables; see Ref. 21). N is the length of time series. Consequently, the test statistic F which follows F distribution with $(N-d)$ degrees of freedom can be formulated as follows:

$$F = \frac{\frac{(N-d)\hat{\sigma}_{uo}^2}{\sigma_{oo}^2(N-d)}}{\frac{(N-d)\hat{\sigma}_{oo}^2}{\sigma_{oo}^2(N-d)}} = \frac{\hat{\sigma}_{uo}^2}{\hat{\sigma}_{oo}^2} \sim F(N-d, N-d). \tag{6}$$

The following test is constructed at the significance level α:

$$F \leq f_{1-\alpha}(N-d, N-d) \rightarrow H_0 \text{ is accepted (null hypothesis, undamaged).}$$
$$\text{Otherwise} \rightarrow H_1 \text{ is accepted (alternative hypothesis, damaged)}$$

with $f_{1-\alpha}(N-d, N-d)$ designating the corresponding F distribution's $1-\alpha$ critical point.

Statistical-based damage detection uses the hypothesis test to examine whether two sets of response data are consistent in the statistical sense. One set is pre-collected, undamaged structure response data (baseline data); the other group is the data collected under unknown health status (unknown data). If the response data of different damage types can be obtained as baseline data in advance and the aforementioned process is repeated, then the identification of damage type can be achieved.

3. Experimental Studies

3.1. *Experimental setup*

Figure 1 shows the small wind turbine used for the experiment. The small wind turbine consists of a 100 W permanent magnet three-phase generator, three 55-cm-long blades, and a 1.5-m-tall steel pole. The total weight of the wind turbine is 3.5 kg. The frame of the generator is made from aluminum alloys. The blades are made from fiber–nylon composites. The generator is connected to the pole by flange and the pole is fixed to a concrete base by expansion bolts.

According to the study of wind turbine blades damage,[1,10,23] the damage generally occurs at the points of trisection and the root of the blades. Thus, various lengths of saw cut in three critical positions in the blade are made to simulate various damage cases, as shown in Fig. 3.

Artificial wind made by electric fans instead of natural wind is used to ensure that the wind turbine operates efficiently during the experiment. In order to avoid cables entanglement, the direction of the wind keeps a very small angle change in all experiments. In each experiment, the vibration acceleration is collected via acceleration sensors (PCB33B32) placed on the wind turbine body after the rotation of the blades becomes steady. Figure 2 shows the layout of the sensors, including three sensors placed on the case of the generator and one under the flange. The data are collected via LabVIEW SignalExpress3.0. The data are measured twice in each experiment, hence, 14 sets of data are collected in total, as presented in Table 1.

The initial sampling frequency is 1 652 Hz, and data preprocessing is conducted as follows: First, a low-pass filter with 80 Hz cut-off point is performed. Second, the sampling frequency is down to 160 Hz. Third, 14 sets of time series with a length of 4 800 are cut. Finally, each time series is standardized. After comparative analysis and considering the influence of noise, the data collected via sensors 1 and 4 are used in the adapted FRR method, and the data collected via sensor 3 are used in the AR model parameter and AR model residual methods.

Fig. 1. Laboratory test wind turbine structure.

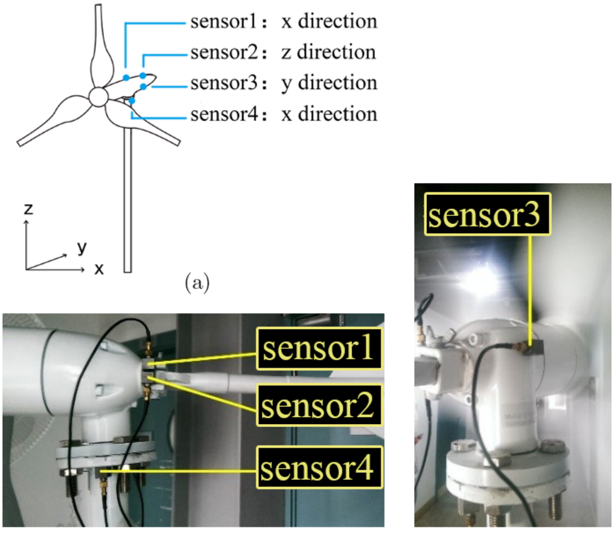

Fig. 2. Sensor layout.

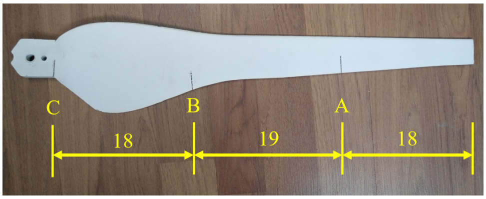

Fig. 3. Saw cut damage.

Table 1. Damage case.

Baseline data	Inspection data	Damage case
to0	tu0	Undamaged
to1	tu1	1 cm saw cut at A
to2	tu2	2 cm saw cut at A
to3	tu3	2 cm saw cut at A and 1 cm saw cut at B
to4	tu4	2 cm saw cut at A and 2 cm saw cut at B
to5	tu5	2 cm saw cut at A, 2 cm saw cut at B, and 1 cm saw cut at C
to6	tu6	2 cm saw cut at A, 2 cm saw cut at B, and 2 cm saw cut at C

3.2. *Model construction*

3.2.1. *Non-parametric modeling*

The welch method is used in the estimation of cross-spectral and auto-spectral density functions. The window length is 500 with 80% overlap, and the Nodes of Fast Fourier Transformation (nfft) is 512. Figure 4 presents the power spectrum density of typical time series in undamaged and damaged conditions. It shows that the first four vibration frequencies of undamaged wind turbine are 0.156, 3.438, 4.219, and 10.469 Hz.

3.2.2. *Parametric modeling*

The Burg method is used to estimate the AR model parameter. The model order must be selected before completing the construction process of the AR model. The proper model order is determined by a compromise between the accuracy and

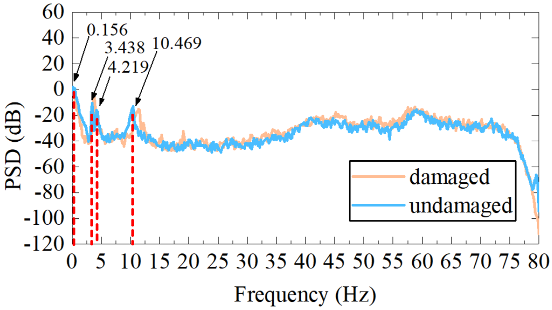

Fig. 4. Power spectrum density function.

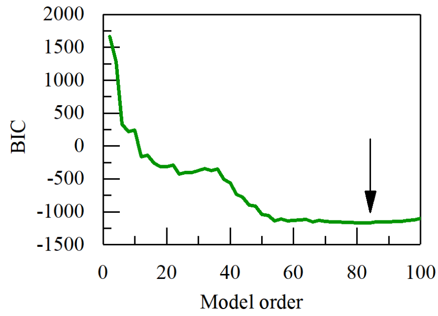

Fig. 5. Model order selection based on BIC.

complexity of the model. Moreover, a high-order model might cause over fitting. Therefore, BIC is used.

Figure 5 shows the model order selection using a time series measured in undamaged condition. Hence, 84 is selected as the model order. The whiteness of the model residuals is examined through auto correlation function (ACF). The ACF of a typical model residual (with 95% confidence) is presented in Fig. 6.

3.3. *Damage diagnosis*

A total of 14 sets of time series are collected. Seven of them are regarded as baseline data, and the rest are inspection data, as shown in Table 1. The damage diagnosis consists of damage detection and damage identification. The former detects the occurrence of damage, and the latter identifies the type of damage. Three methods are validated through these procedures.

3.3.1. *Adapted FRR method*

Performance characteristics $\hat{R}_{o0}(\omega), \ldots, \hat{R}_{o6}(\omega)$ and $\hat{R}_{u0}(\omega), \ldots, \hat{R}_{u6}(\omega)$ are acquired after the construction of the model. Subsequently, test statistic $Z(\omega)$ can be calculated by using Eq. (4).

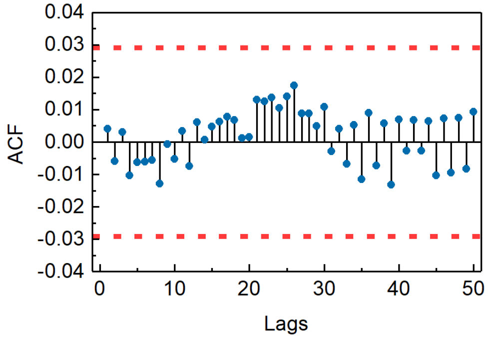

Fig. 6. ACF of a typical model residual (with 95% confidence).

The damage detection procedure is performed by comparing the inspection data tu0, tu1,. . ., tu6 to0 with the baseline data to0. The results are presented in Fig. 7, in which the specified significance level is $\alpha = 10^{-5}$. The distribution threshold is 4.417, and only Z_{06} (the test statistic $Z(\omega)$ calculated by the baseline data to0 and inspection data tu0) exceeds it. According to the results, inspection data tu0, tu1,. . ., tu5 are undamaged and tu6 is damaged. Damage cases 1 to 5 are missed. Hence, the adapted FRR method failed in damage detection.

3.3.2. *AR model parameters method*

The model parameters of the baseline and inspection data are required for the calculation of test statistic X. As a result, the AR model construction process is required for all 14 sets of time series. After all, the 14 AR (84) models are constructed, 14 parameter vectors are acquired ($\theta_{o0}, \theta_{o1}, \ldots, \theta_{o6}$; θ_{u0}, $\theta_{u1}, \ldots, \theta_{u6}$). Subsequently, test statistic X can be calculated by using Eq. (5).

The damage detection results are presented in Fig. 8, at the specified significance level $\alpha = 10^{-8}$. The distribution threshold is 178.07, and only X_{00} is lower than the distribution threshold whereas the others are higher than it. Therefore, the damage diagnosis result of inspection data tu0 is undamaged and the others are damaged. The health state of all inspection data is detected successfully.

After detecting the occurrence of damage, the AR model parameters method is validated in the damage identification procedure. The damaged inspection data should be compared with the damaged baseline data to find out the exact damage cases. For example, the inspection data tu3 should be compared with baseline data to1, to2,. . .,to6. The results are presented in Fig. 9. Only $X_{33} = 142.69$ is lower than the distribution threshold whereas the others are higher than it. Therefore, the damage identification result of tu3 is damage case 3. The other damage cases of the rest of the inspection data are also identified correctly. The damage identification is accomplished successfully via AR model parameter method.

3.3.3. *AR model residual method*

In this method, the AR model construction process is needed only for the baseline data. The residual sequence e_{oo} is acquired in the construction process. The inspection data are taken into the AR model constructed from the baseline data to acquire the residual sequence e_{uo}. Subsequently, the test statistic F can be calculated by Eq. (6).

The damage detection results at the specified significance level $\alpha = 10^{-8}$ are presented in Fig. 10. The distribution threshold for F distribution at the specified significance level $\alpha = 10^{-8}$ is 1.18, and only F_{00} is lower than the distribution threshold whereas the others are higher than it. Therefore, the damage diagnosis result of inspection data tu0 is undamaged whereas the others are damaged. The health state of all inspection data is detected successfully.

In the damage identification procedure, the method is validated by finding out the correct type of the damaged inspection data. Take the inspection data tu3 for

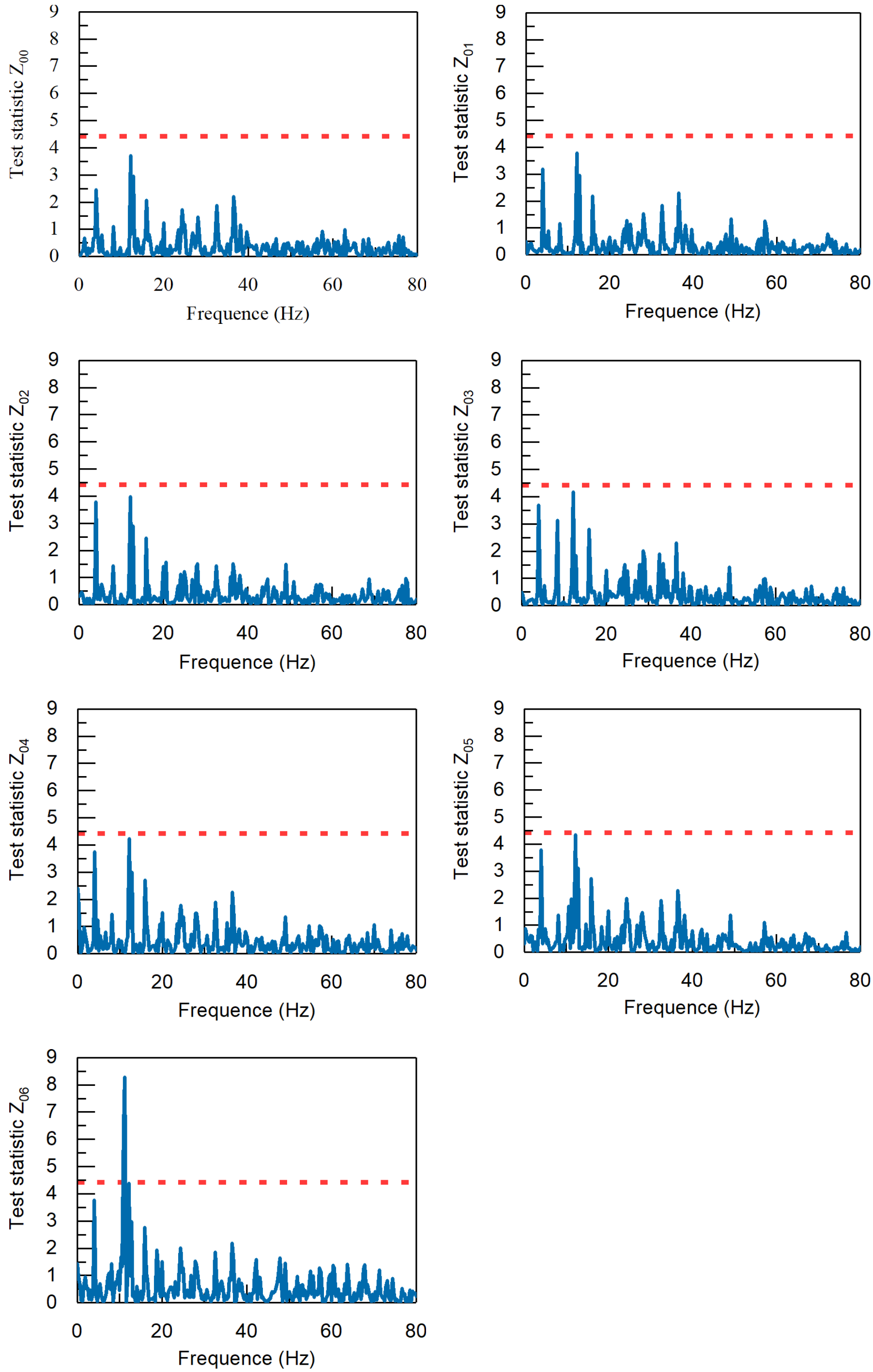

Fig. 7. Test statistic $Z(\omega)$ for damage detection.

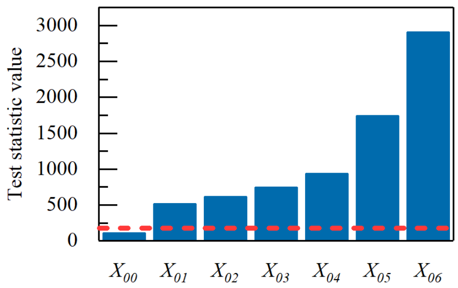

Fig. 8. Test statistic X for damage detection.

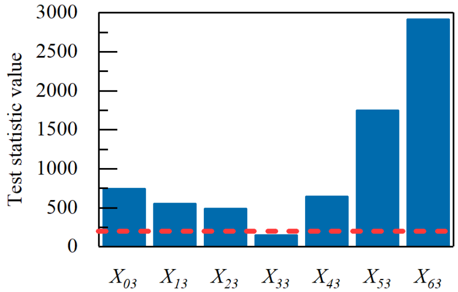

Fig. 9. Test statistic X for damage identification (taking tu3 for example).

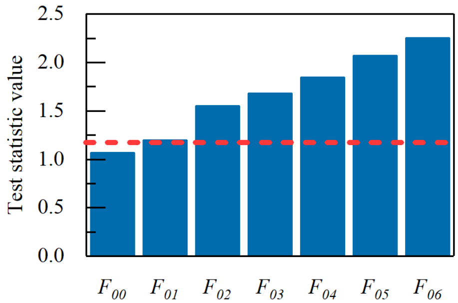

Fig. 10. Test statistic F for damage detection.

example, and the results are presented in Fig. 11. Only $F_{33} = 0.97$ is lower than the distribution threshold whereas the others are higher than it. Therefore, the damage identification result of tu3 is damage case 3. The other damage cases of the rest inspection data are also identified correctly. The damage identification via AR model residual method is accomplished successfully.

3.3.4. *Results discussion*

According to the test results, the AR model parameters method and the AR model residual method achieve damage detection successfully, whereas the adapted FRR

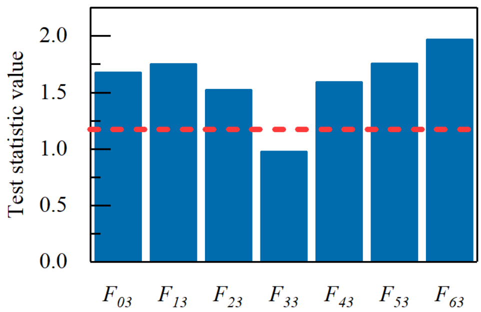

Fig. 11. Test statistic F for damage identification (taking tu3 for example).

method failed. It can be seen from Fig. 7 that no significant difference is found from inspection data tu1 to tu5. These findings may indicate that the adapted FRR method is not capable of detecting the condition of blades, while the other two methods perform well in contrast. In the damage identification procedure, both parametric methods identify the exact damage case successfully.

The following findings should be noted:

(1) Physics-based or finite element (FE) models are not required. The damage detection procedure using the statistical time-series method avoids the estimation of structural modal parameters. Therefore, the physics-based or FE models, which are very difficult to obtain in the case of wind turbine damage detection, are no longer the fundamental factor.
(2) Uncertainty is considered inherently. The method treats damage detection as a statistical pattern recognition problem based on the collected vibration data, which contains all the uncertain factors. The overall uncertainty is dealt in a theoretical basis.
(3) The damage diagnosis criteria are based on the statistical decision-making with the specified performance characteristics. The AR time-series method is not only used as a statistical analysis tool, but also it is combined with the most critical part of the damage detection procedure.
(4) Natural random vibration data records are used effectively. Compared with the input signal, the vibration data are easy to collect without interrupting the normal operation. This feature makes it possible for the method to achieve online damage diagnosis.
(5) It should be noted that coupled oscillations among various components of the wind turbine have significant impact on the overall vibration responses.[1,10] There is a surprising fact that most of the existing works for diagnosing blades damage are conducted on isolated wind turbine blades. Thus, a further study in the overall operation of wind turbines in the future should be considered.
(6) The significant level is a critical factor that indicates the severity of the damaged decision-making whereas its selection highly depends on the experience of the

researchers. The determination of the significance level should refer to the previous study and make sure it is higher than the test statistic calculated by two undamaged data. Hence, the statistical time-series methods require experience of user and it is a drawback indeed. Further research may be required for the practical application in the future.

4. Conclusion

This study presented an experimental verification for diagnosing wind turbine blade damage using the statistical time-series methods. Numerous experiments are conducted on operate–simulate small-size, laboratory-used wind turbine structure, and various damage cases are made in these experiments. The effectiveness for damage diagnosis using the statistical time-series method was assessed subsequently from the output-only available random vibration data. The statistical decision-making is based on the statistical test with three different methods (adapted FRR performance characteristics, AR model parameter performance characteristics, and AR model residual performance characteristics). The test results show that both parametric methods, namely, AR model parameter method and AR model residual method, achieve successful damage detection and damage identification, respectively, whereas the non-parametric method (adapted FRR method) fails in damage detection. The non-parametric modeling method seems to be insufficient in describing the time evolution of vibration data and the structural dynamics due to the uncertainties.

The experiments prove that the statistical time-series method using AR modeling method is feasible for online damage diagnosis in the field of wind turbine blades. It shows the following advantages over alternatives: (1) Physics-based or FE models are not required. (2) Uncertainty is considered inherently. (3) The damage diagnosis criteria are based on the statistical decision-making with specified performance characteristics. (4) Natural random vibration data records are used effectively. The disadvantage is that experience of user is required for the determination of significance level. The efficacy and usefulness of statistical time-series techniques discussed here have an empirical background, and so getting useful information/patterns from the turbine vibration data is a promising tool for condition monitoring and fault diagnosis of wind turbine operation.

Acknowledgments

This study was supported by the Ministry of Science and Technology of China (Grant No. SLDRCE14-B-03), the National Natural Science Foundation of China (Grant Nos. 51578140 and 51178337), and Natural Science Foundation of Shanghai (Grant No. 17ZR1431900).

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