Imbalance Fault Detection of Direct-Drive Wind Turbines Using Generator Current Signals

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Abstract—**Imbalance faults constitute a significant portion of all faults in wind turbine generators (WTGs). WTG imbalance fault detection using generator current measurements has advantages over traditional vibration-based methods in terms of cost, implementation, and system reliability. However, there are challenges in using current signals for imbalance fault detection due to low signal-to-noise ratio of the useful information in current signals and nonstationary characteristic frequencies of imbalance faults. This paper proposes a method of using generator stator currents for imbalance fault detection of direct-drive WTGs. In the proposed method, the variable shaft rotating frequency of a WTG is estimated from one phase stator current measured from the generator terminal by using a phase-locked loop method. The estimated shaft rotating frequency is then processed by using appropriate upsampling and variable-rate downsampling algorithms. Consequently, the variable characteristic frequencies of imbalance faults in the spectrum of the estimated shaft rotating frequency are converted to constant values. Therefore, the signatures of wind turbine imbalance faults can be clearly identified from power spectral density analysis of the converted shaft rotating frequency signal. Simulation and experimental results show that the proposed method is effective to detect various imbalance faults in direct-drive WTGs.**

Index Terms—**Current signal, direct-drive wind turbine, fault detection, imbalance fault, power spectral density (PSD).**

I. INTRODUCTION

THE PENETRATION of wind power has increased greatly over the last decade in the U.S. and across the world. America's wind power industry installed 1118 MW of new capacity in the first quarter of 2011 alone and entered the second quarter with another 5600 MW under construction [1]. As the number of wind turbines continues to grow, it becomes more and more challenging for engineers to do inspection and maintenance for the wind turbines.

Imbalance faults constitute a significant portion of all faults in wind turbine generators (WTGs) [2]. A common imbalance fault in WTGs is shaft/blade imbalance. A blade imbalance can be caused by errors in manufacturing and construction, icing, deformation due to aging, or wear and fatigue during the operation of the WTG. Components tend to shift and wear in

varying degrees over time, causing imbalance on the rotating shaft/blades. Another common imbalance fault is aerodynamic asymmetry, which can be caused by several factors, including high wind shear and errors in the control mechanism. If the pitch of one blade is slightly different from the other two blades due to errors in the control mechanism, the torque on the rotating shaft will not be balanced, leading to aerodynamic asymmetry. A small imbalance fault can cause significant consequences on the towers and the WTGs. For instance, a blade imbalance caused by icing can create additional loads on the supporting tower of the wind turbine, which may lead to fractures and possible collapses [3] of the tower. Due to WTGs' delicate structure and high repairing cost [2], [4], [5], effective imbalance fault detection is of significant interest to the wind power industry.

Most existing methods for imbalance fault detection require additional mechanical sensors and data acquisition equipment to implement [6]–[9]. The most commonly used sensors are vibration sensors, such as accelerometers. These sensors are mounted on the surface of WTG components, which are situated on high towers and are difficult to access during WTG operation. Moreover, the sensors and equipment are inevitably subject to failure, which could cause additional problems with system reliability and additional operating and maintenance costs. Current-based (mechanical-sensorless) fault detection techniques use generator current measurements that have been used by the control system of the WTG; no additional sensors or data acquisition equipment is needed. Moreover, current signals are reliable and easily accessible from the ground without intruding the WTGs. Therefore, current-based fault detection techniques have great economic benefits and potential to be adopted by the wind power industry.

However, there are challenges in using current signals for imbalance fault detection. First, the characteristic frequencies of imbalance faults depend on the shaft rotating frequency, which is known as the 1P frequency [10], [11]. As mentioned in [6], since the 1P frequency of a WTG usually varies with wind speed, it is a problem to extract the imbalance fault signatures from the nonstationary stator current signals of the WTG using traditional spectrum analysis methods. Moreover, the dominant component of a current signal is its fundamental-frequency component. Therefore, the useful information in current signals for imbalance fault detection usually has a low signal-to-noise ratio, which makes the fault detection difficult.

Several signal processing techniques, e.g., the classical power spectral density (PSD) analysis [7], [8], bicoherence analysis [10], time-frequency analysis [9], [12], amplitude demodulation [13], [14], and data mining [15], have been used for imbalance fault detection of WTGs. The classical PSD analysis

and bicoherence analysis can identify imbalance faults based on their characteristic frequencies. However, this capability is only available for stationary signals. The time-frequency analysis and amplitude demodulation methods are able to extract fault signatures from nonstationary signals. However, they cannot clearly identify imbalance faults from interferences that have similar patterns as the faults in the time or frequency domain. Furthermore, these methods usually have low resolution and require high computational resources compared to the PSD analysis [13]. Data mining has been applied for wind turbine condition prediction using the records of maintenance. However, no work has been reported on WTG imbalance fault detection via data mining on current signals. Therefore, a computationally efficient, highly sensitive signal processing method is desired for current-based online imbalance fault detection for WTGs operating in nonstationary conditions.

This paper proposes a novel method of using generator stator current signals for online imbalance fault detection of direct-drive wind turbines. The proposed method first estimates the variable shaft rotating frequency of a WTG from the measured one phase stator current of the generator, and then processes the estimated shaft rotating frequency signal in a way such that the variable characteristic frequencies of imbalance faults become constant values in the PSD of the processed shaft rotating frequency signal. The proposed method is validated by simulation and experimental studies for detection of shaft/blade imbalance and aerodynamic asymmetry of direct-drive wind turbines under variable-speed operating conditions.

II. CHARACTERISTIC FREQUENCIES OF IMBALANCE FAULTS

It has been reported that the spectra of the shaft torque and the output electric power of a WTG with three blades are determined by certain events. The vibration at 3P frequency, which is three times the shaft rotating frequency of a WTG, is generated by the effect of yaw error, wind shear, or tower shadow [11], [16]. The vibration at 1P frequency is created by imbalance faults, including blade imbalance and aerodynamic asymmetry [6], [10], [17]. Moreover, these events also affect the shaft rotating frequency of the WTG and produce excitations at the corresponding frequencies in the shaft rotating frequency signals.

The shaft system of a direct-drive WTG can be represented by a one-mass model. The motion equation is given by

$$J \cdot \left[\frac{d\omega_r(t)}{dt} \right] = T_t(t) - T_e(t) - D \cdot \omega_r(t) \quad (1)$$

$$\omega_r(t) = 2\pi \cdot f_r(t) \quad (2)$$

where J is the total inertia constant of the WTG; ω_r is the angular shaft rotating speed of the WTG; f_r is the WTG shaft rotating frequency, which is equal to the 1P frequency; $d\omega_r(t)/dt$ is the angular acceleration; T_t and T_e are the torques of the turbine and the generator, respectively; and D is the damping coefficient. Since this is a linear model which presents the relationship between the shaft rotating speed and the torques of a WTG, if there is a vibration in the torques of the WTG, an excitation with the same frequency will appear in the shaft rotating speed signal.
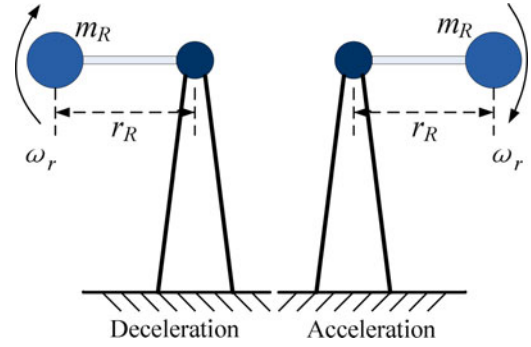

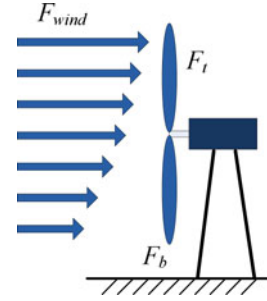Fig. 1.   Effect of blade imbalance of a wind turbine.

Fig. 2.   Effect of aerodynamic asymmetry of a wind turbine caused by wind shear.

When an imbalance fault occurs on the shaft of a WTG, an additional force will be induced in the shaft. In the case of blade imbalance where the mass distribution of one blade is different from others, a rotor mass imbalance will occur and induce vibrations in the shaft rotating speed of the WTG. This is illustrated in Fig. 1, where m_R is the equivalent imbalance mass, and r_R is the distance between the equivalent imbalance mass and the center of the shaft. When the equivalent imbalance mass rotates from the top to the bottom of the rotating plane, the power of gravity accelerates the shaft. On the other hand, when the equivalent imbalance mass rotates from the bottom to the top of the rotating plane, the power of gravity decelerates the shaft. Consequently, the shaft rotating speed vibrates at the frequency of 1P.

Aerodynamic asymmetry stands for that the force affected on one blade is different from those on other blades. Aerodynamic asymmetry along with yaw error, wind shear, or tower shadow together influences the shaft rotating speed of a WTG. For example, Fig. 2 shows the effect of an aerodynamic asymmetry caused by wind shear, where F_{wind} is the force of the wind flow affected on the blades, F_t is the force of the wind flow affected on the blade that is on the top of the rotating plane, and F_b is the force of the wind flow affected on the blade that is on the bottom of the rotating plane. The amplitude of F_t is always greater than that of F_b due to the effect of wind shear, which follows the following power law:

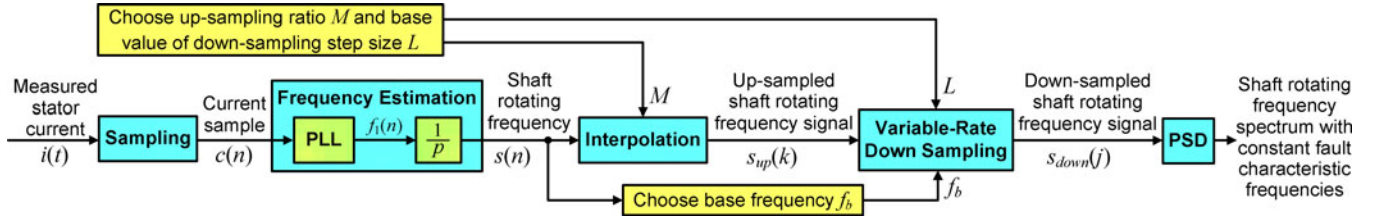$$\frac{U(z)}{U(z_r)} = \left(\frac{z}{z_r} \right)^{\alpha} \quad (3)$$

Fig. 3.   Schematic diagram of the propose method.

where $U(z)$ and $U(z_r)$ are wind velocities at height z and the reference height z_r, respectively, and α is the power law exponent [18].

Normally, a blade has the largest acceleration caused by F_t and the smallest acceleration caused by F_b. Therefore, a vibration at the 3P frequency is produced in the shaft speed by wind shear in a balanced wind turbine with three blades. In the case of an aerodynamic asymmetry, a blade of the turbine has different F_t and F_b from the other two blades. As a result, the acceleration and deceleration of the imbalanced blade produce a vibration at the 1P frequency in the shaft speed. On the other hand, the other two blades have different F_t and F_b from the imbalanced one. As a result, a vibration also appears at the 2P frequency in the shaft speed signal.

The characteristic frequencies of shaft/blade imbalance and aerodynamic asymmetry both appear at the 1P frequency in the shaft speed signal of a wind turbine. Therefore, the excitations of the shaft speed signal at the 1P frequency can be used as a signature for imbalance fault detection.

III. PROPOSED METHOD FOR FAULT SIGNATURE EXTRACTION

In the proposed method, only one phase stator current is measured for imbalance fault detection; the shaft rotating frequency is estimated from the measured current signal. In a direct-drive wind turbine, the relationship between the shaft rotating frequency f_r and the fundamental frequency f_1 of the stator current is given as follows:

$$f_1(t) = p \times f_r(t) \tag{4}$$

where p is the number of pole pairs of the generator. A phase-locked loop (PLL) model is designed in the proposed method to estimate f_1 from the stator current measurement of the WTG. Then, the shaft rotating frequency f_r is obtained from (4).

Since the imbalance fault characteristic frequency of 1P usually varies with wind speed during maximum power point tracking [19], it is difficult to extract the fault signature from the nonstationary stator current signals of a WTG using classical spectrum analysis methods [6]. However, as mentioned in [6], if a wind turbine rotates at a constant speed, the classical PSD analysis could identify an imbalance fault effectively based on its characteristic frequency. Therefore, if the estimated shaft rotating frequency signal is preprocessed in such a way that the variable 1P frequency (i.e., a characteristic frequency of imbalance faults) of the WTG is converted to a fixed value, the classical PSD analysis can then be used to detect the imbalance faults for a variable-speed wind turbine.

Define Ω_r the normalized frequency of the shaft rotating frequency or 1P frequency signal, which is estimated from the stator current signal, and define f_s the sampling frequency of the stator current. The relationship among f_r, f_s, and Ω_r can be written as

$$\frac{\Omega_r(t)}{2\pi} = \frac{f_r(t)}{f_s} \tag{5}$$

where $\Omega_r(t)$ is expected to be constant in the PSD analysis. Therefore, if the sampling frequency f_s is changed continuously with $f_r(t)$ to make the right-hand side of (5) constant, $\Omega_r(t)$ will become constant. The proposed method preprocesses the estimated shaft rotating frequency signal of a direct-drive WTG to obtain a constant $\Omega_r(t)$, which is shown in Fig. 3 and implemented in the following steps.

1) Choose an upsampling ratio M and a base value of the downsampling step size L.
2) Sample the measured nonstationary current $i(t)$ of the WTG with a fixed sampling rate; the result is $c(n)$, where $n = 1, 2, 3, \ldots, N$, and N is the length of the stator current record.
3) Estimate the variable fundamental frequency $f_1(n)$ of the nonstationary stator current signal $c(n)$ by using a PLL method.
4) Divide the estimated $f_1(n)$ by the pole pair number p to obtain the shaft rotating frequency signal $s(n)$ and choose a base frequency f_b based on $s(n)$.
5) Upsample (interpolate) $s(n)$ by an constant upsampling ratio of M; the result is $s_{\text{up}}(k)$, where $k = 1, 2, 3, \ldots, M \times N$.
6) Downsample $s_{\text{up}}(k)$ by a variable downsampling step size; the result is $s_{\text{down}}(j)$, where $j = 1, 2, 3, \ldots, J$, and J is determined by M, N, and L. In the downsampling process

$$s_{\text{down}}(1) = s_{\text{up}}(1). \tag{6}$$

If $s_{\text{down}}(j) = s_{\text{up}}(k)$, then

$$s_{\text{down}}(j+1) = s_{\text{up}}\left(k + \text{round}\left[\frac{L \cdot f_b}{s_{\text{up}}(k)}\right]\right) \tag{7}$$

where $\text{round}[L \cdot f_b / s_{\text{up}}(k)]$ is the variable downsampling step size, which depends on the upsampled shaft rotating frequency $s_{\text{up}}(k)$; and $\text{round}(\cdot)$ stands for rounding a number to the nearest integer. The downsampling process to obtain $s_{\text{down}}(j)$ is equivalent to resampling the original or upsampled shaft rotating frequency signal $[s(n)$ or $s_{\text{up}}(k)]$ with a variable sampling frequency $f_s(j)$, whose value is proportional to the value of $s_{\text{down}}(j)$. According to (5), the
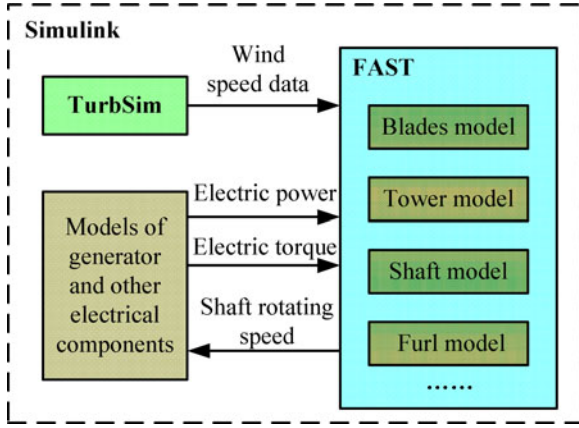
Fig. 4.   Structure of the WTG model with wind data.

normalized frequency of $s_{\text{down}}(j)$, which is $\Omega_{\text{down}}(j)$, is given by

$$\frac{\Omega_{\text{down}}(j)}{2\pi} = \frac{s_{\text{down}}(j)}{f_s(j)} \tag{8}$$

where $\Omega_{\text{down}}(j)$ is now a constant value.

7) Calculate the classical PSD of the downsampled estimated shaft rotating frequency $s_{\text{down}}(j)$ to extract the fault signature, which now has a constant characteristic frequency.

By using the proposed method, the variable characteristic frequency of 1P of imbalance faults becomes a constant value in the PSD of $s_{\text{down}}(j)$. Therefore, the resulting PSD is called the 1P-invariant PSD, and the magnitude of the excitation at the 1P frequency in the PSD of $s_{\text{down}}(j)$ can be used as a signature to clearly identify imbalance faults. In the proposed method, the constant base value of the downsampling step size L should be chosen based on two criteria. First, L should be large enough to eliminate the quantization error due to the requirement of an integral downsampling step size. Second, L should be small enough to ensure that the sampling frequency after downsampling is greater than twice the 1P frequency. Normally, L should be larger than 10. The base frequency f_b is chosen to be the mean value of the estimated shaft rotating rotating frequency $s(n)$. Furthermore, if the measured current is sampled with a sufficiently high sampling rate in Step 2 such that the sampling frequency of the downsampled signal $s_{\text{down}}(j)$ without using upsampling is greater than twice the characteristic frequency of the imbalance faults, then Step 5 is not necessary.

IV. SIMULATION STUDY OF IMBALANCE FAULT DETECTION

A. WTG Model

A dynamical model of a 10-kW direct-drive WTG system is built in a FAST (Fatigue, Aerodynamics, Structures, and Turbulence) [20] and Simulink combined environment, as illustrated in Fig. 4. FAST version 7.0 is used to simulate the dynamics of the wind turbine, while Simulink is used to simulate the generator and other electrical components of the WTG system.

FAST is an aeroelastic code developed initially by Oregon State University. It is one of the most advanced design codes for horizontal-axis wind turbines. In the simulation study, FAST works as a subroutine in Simulink. The signals of the electric power, electric torque, and shaft rotating speed are used to connect the FAST and Simulink models of the WTG system.

The model wind turbine in FAST mainly includes tower, blades, shaft, furl, and support platform. The hub height of the wind turbine is 34 m. The wind turbine has three blades with a rotor diameter of 2.9 m and an upwind configuration. A 48-pole permanent magnet synchronous machine is simulated in Simulink to convert mechanical energy from the turbine into electric energy. One phase stator current signal is recorded for shaft rotating frequency estimation.

B. Wind Speed Data

TurbSim, which is a stochastic, full-field, turbulent wind simulator developed by the National Renewable Energy Laboratory [21], is used in the simulation study to produce wind velocity vectors in a time series across the entire rotating plane of the wind turbine's rotor. An average wind speed of 12 m/s is chosen in the simulation study. The IEC Kaimal turbulence model is used to generate wind turbulence in all simulations. The cross-sectional area (8 m × 8 m) of the wind flow is divided into a 6 × 6 grid where the wind velocity and direction are calculated by TurbSim for each grid cell. The output of Turb-Sim contains a time series of wind speed, which is used for the aeroelastic simulation in FAST. The overall structure of the simulation platform is shown in Fig. 4.

C. Simulation Results

Simulations are performed for the model WTG in the healthy condition (i.e., the baseline case) as well as in two imbalance fault conditions: blade imbalance and aerodynamic asymmetry. The blade imbalance is simulated by changing the mass density of one blade, which creates an uneven distribution of mass with respect to the rotor. The aerodynamic asymmetry is simulated by adjusting the pitch of one blade, which creates an uneven torque across the rotor. One phase stator current of the WTG is recorded in the simulations to estimate the shaft rotating frequency. The proposed method is then applied to extract the signatures of the faults from the recorded data in the frequency domain.

The mass density of one blade is scaled up and down in the simulations of blade imbalance. Four scenarios are simulated with the mass density of one blade adjusted by -1%, $+2\%$, -3%, and $+4\%$, while the mass densities of the other two blades are unchanged. Here, the negative sign indicates a decrease of the mass density and the positive sign indicates an increase of the mass density. The proposed method is applied to calculate the 1P-invariant PSD of the estimated shaft rotating frequency for the baseline case and the four blade imbalance scenarios. The base frequency is chosen to be 3 Hz (i.e., 180 r/min) and the base value of the downsampling step size L is 20. Therefore, the variable characteristic frequency of 1P (2–4 Hz) of the blade imbalance faults in the estimated shaft rotating frequency signal is converted to a constant value of 3 Hz. The results are compared in Figs. 5 and 6. It is clearly shown that in the blade imbalance scenarios, excitations are evident at 1P, which is fixed at 3 Hz
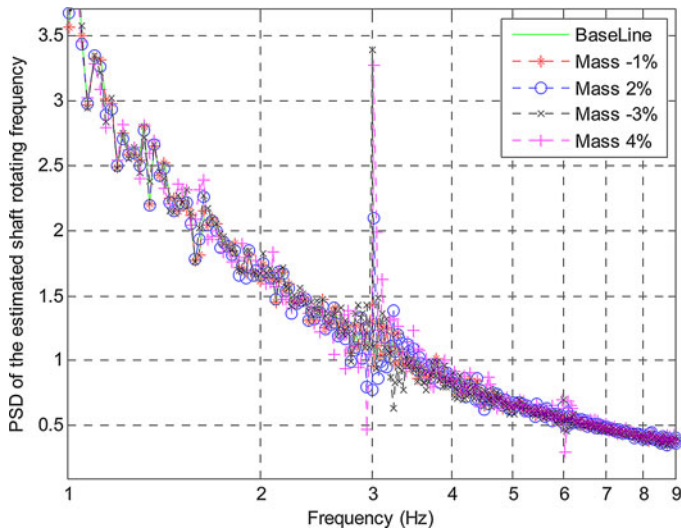
Fig. 5.   Comparison of the 1P-invariant PSD of the estimated shaft rotating frequency for the blade imbalance scenarios against the baseline case in a wide frequency range.
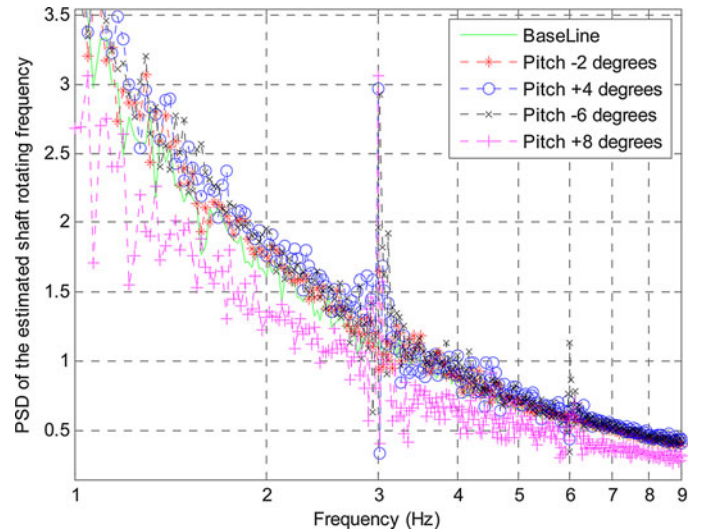

Fig. 7.   Comparison of the 1P-invariant PSD of the estimated shaft rotating frequency for the aerodynamic asymmetry scenarios against the baseline case in a wide frequency range.
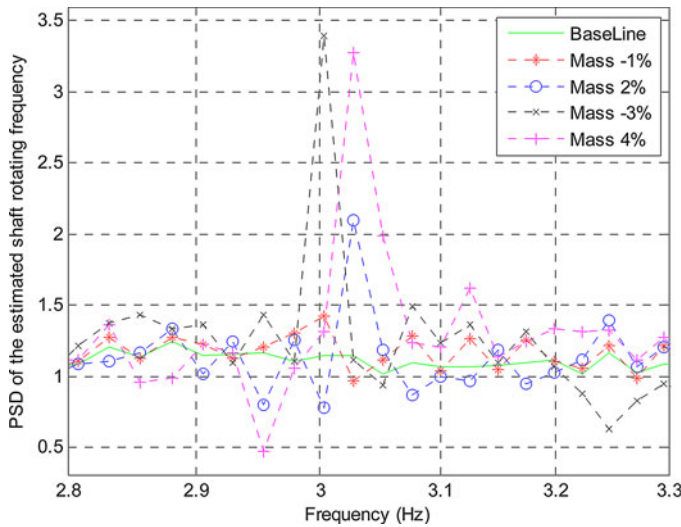

Fig. 6.   Comparison of the 1P-invariant PSD of the estimated shaft rotating frequency for the blade imbalance scenarios against the baseline case in a frequency range around 1P.
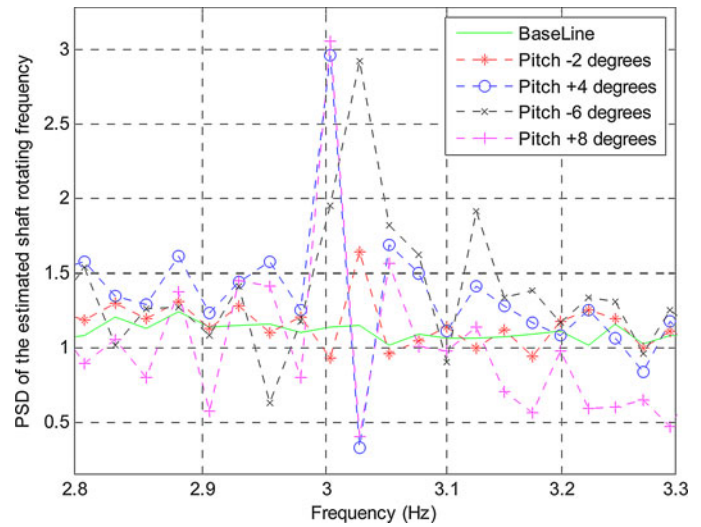

Fig. 8.   Comparison of the 1P-invariant PSD of the estimated shaft rotating frequency for the aerodynamic asymmetry scenarios against the baseline case in a frequency range around 1P.

by using the proposed method. The imbalance is caused by an eccentric mass rotating with a frequency of 1P. The shaft rotating frequency is affected by the imbalance in blades and also vibrates with a frequency of 1P. Furthermore, Fig. 6 shows that the magnitude of the excitation at 1P increases with the increase of the degree of blade imbalance. On the other hand, no excitation is observed at 1P frequency in the PSD curve for the wind turbine with healthy blades.

In order to simulate aerodynamic asymmetry faults of the wind turbine, the pitch angle of one blade is adjusted by $-2°$, $+4°$, $-6°$, and $+8°$, while the pitch angles of the other two blades are unchanged at $11.44°$. Figs. 7–9 compare the 1P-invariant PSD of the estimated shaft rotating frequency generated by the proposed method for the wind turbine in the four aerodynamic asymmetry scenarios against the baseline case. Again,

the variable 1P frequency is converted to a constant value of 3 Hz by using the proposed method. Excitations appear at both 1P and 2P frequencies in the four aerodynamic asymmetry scenarios, which agree with the theoretical analysis in Section II. Moreover, the magnitudes of the excitations at the characteristic frequencies in the PSD plot become more significant when the degree of aerodynamic asymmetry becomes greater.

V. EXPERIMENTAL STUDY OF IMBALANCE FAULT DETECTION

A. Experimental System Setup

A 160-W Southwest Windpower Air Breeze direct-drive WTG is used for experimental studies. The generator has six pole pairs. The WTG is operated in a wind tunnel, as shown in Fig. 10. The wind tunnel uses a variable-speed fan to generate
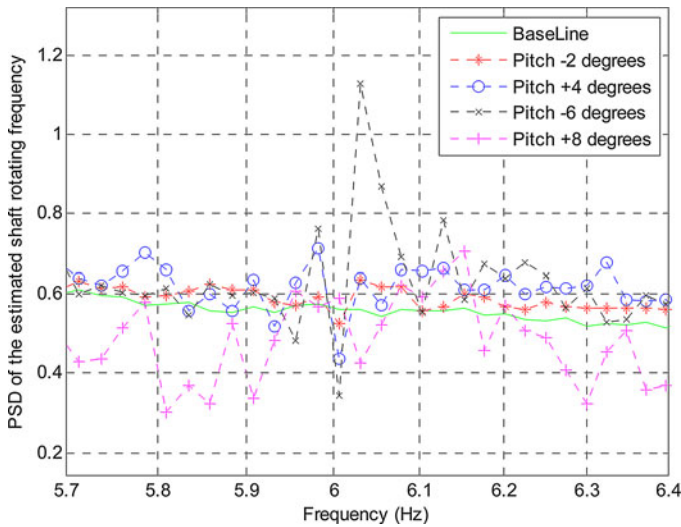
Fig. 9. Comparison of the 1P-invariant PSD of the estimated shaft rotating frequency for the aerodynamic asymmetry scenarios against the baseline case in a frequency range around 2P.
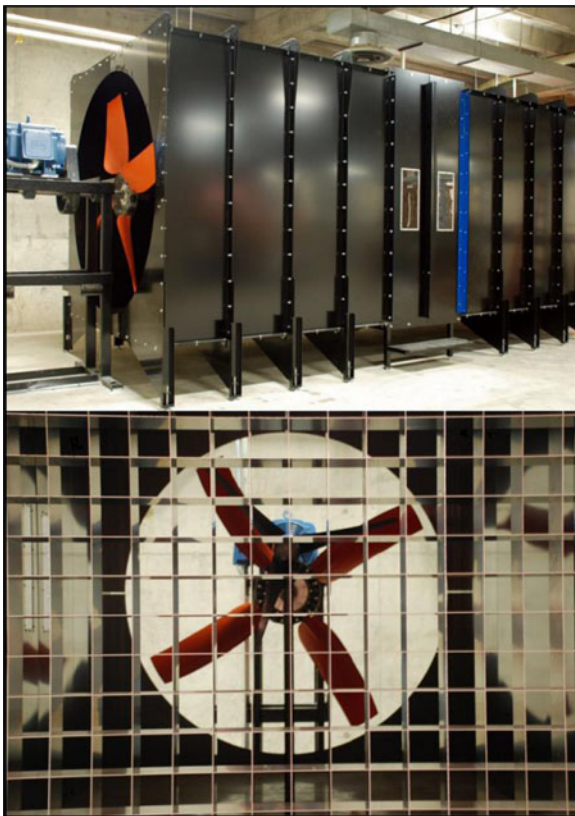

Fig. 11. Blade with an additional mass to create a blade imbalance fault.

Fig. 10. Wind tunnel with the testing WTG.

Fig. 12. Comparison of the 1P-invariant PSD of the estimated shaft rotating frequency for the blade imbalance scenarios against the baseline case in a wide frequency range.

erating on a lab computer. The length of each current record is 60 s.

B. Detection of Blade Imbalance

To create a blade imbalance, additional masses are added close to the tip of a blade of the WTG, as shown in Fig. 11. The mass of a healthy blade is measured to be 181 g. Four blade imbalance scenarios are tested by adding a mass of 2.3, 4.5, 6.8, and 9 g, respectively, to a blade. Therefore, the weight of the blade is increased by 1.25%, 2.5%, 3.75%, and 5%, respectively. During the experiments, the WTG is operated at variable speed in the range of 6–13 Hz, which is the variable 1P frequency.

The proposed method is applied to obtain the 1P-invariant PSD of the estimated shaft rotating frequency of the WTG for the four blade imbalance scenarios and the baseline case. In the proposed method, the base frequency f_b is chosen to be 10 Hz and the base value of the downsampling step size L is 100. The results are compared in Figs. 12 and 13, where excitations are clearly observed at the fixed 1P frequency of 10 Hz in the

controllable wind flows with the speed from 0 to 10 m/s. In the experiments, the rotating speed of the fan is varied to generate variable wind speed in the wind tunnel. One phase stator current of the WTG is recorded via a Fluke current clamp and National Instrument data acquisition system at a sampling rate of 10 kHz. The current samples are acquired by the LabView software op-
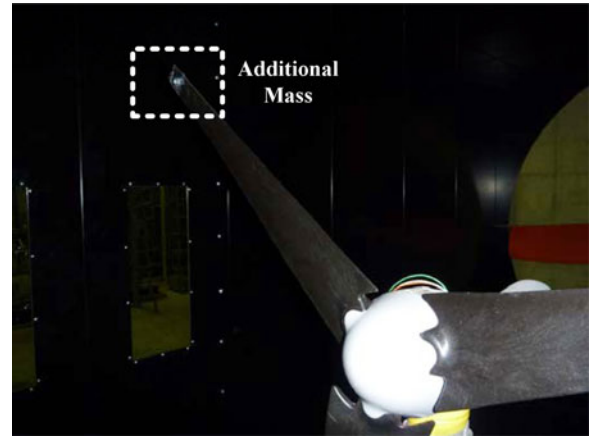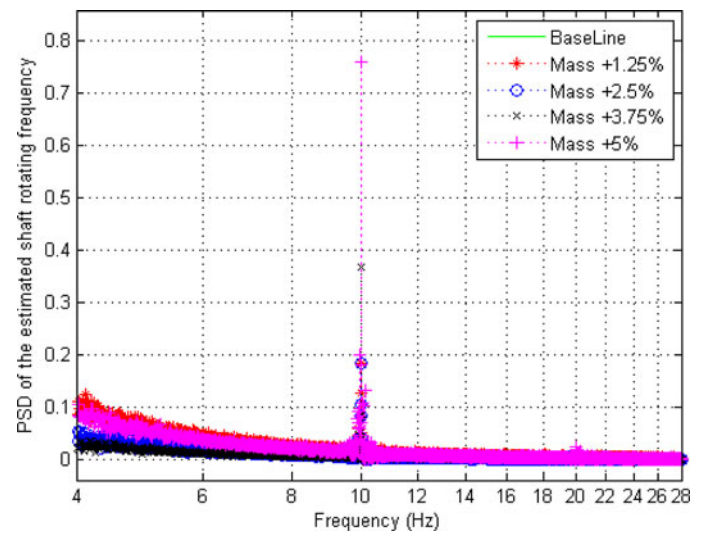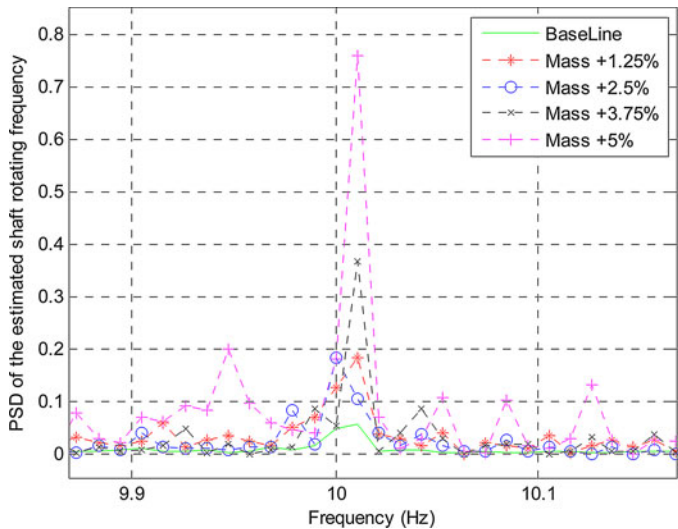
Fig. 13. Comparison of the 1P-invariant PSD of the estimated shaft rotating frequency for the blade imbalance scenarios against the baseline case in a frequency range around 1P.
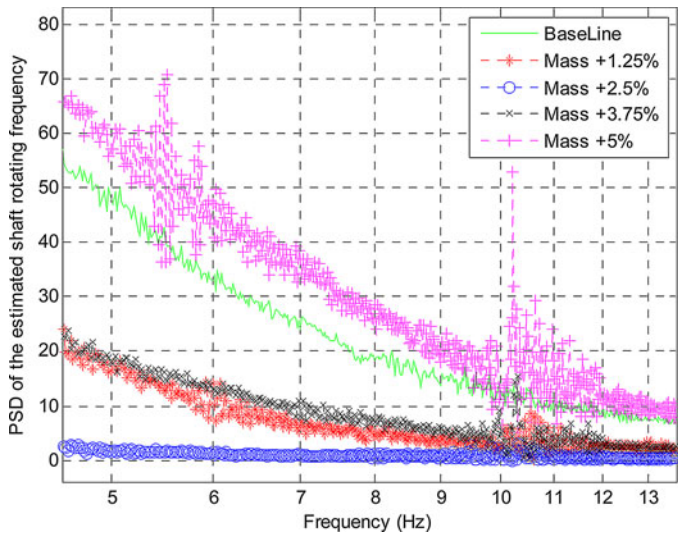

Fig. 14. Comparison of the PSD of the estimated shaft rotating frequency obtained directly from the standard PSD analysis for the blade imbalance scenarios against the baseline case.

blade imbalance scenarios. Thus, the magnitude of this excitation provides an effective index for detecting blade imbalance faults. The greater the magnitude of the excitation appears at the 1P frequency, the higher degree of the blade imbalance. Therefore, the proposed method can not only identify but can also quantify the degree of blade imbalance of the WTG.

The PSD of the estimated shaft rotating frequency is also calculated by using the standard PSD analysis directly without using the upsampling and downsampling algorithms in the proposed method. The results are compared in Fig. 14 for the blade imbalance scenarios against the baseline case. The PSD of the estimated shaft rotating frequency excites at 1P frequency in the range of 6–13 Hz in the blade imbalance scenarios. However, it is difficult to quantify and evaluate the blade imbalance faults by using these results due to the variations of the 1P frequency
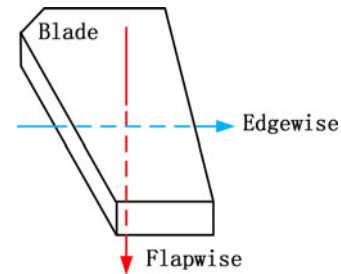

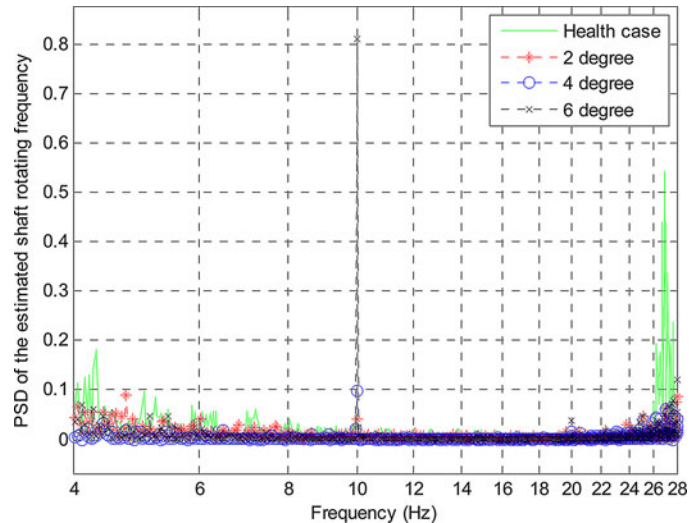Fig. 15. Blade bended flapwise or edgewise.

Fig. 16. Comparison of the 1P-invariant PSD of the estimated shaft rotating frequency for the bent blade scenarios against the baseline case in a wide frequency range.

component. Furthermore, if interferences are present near the 1P frequency, it will be difficult to identify fault signatures from the interferences by using the standard PSD analysis.

C. Detection of Bent Blade

A bent blade is a blade of a WTG that twists flapwise or edgewise, as illustrated in Fig. 15. A bent blade also generates an imbalance fault in the WTG. During the experiments, one blade of the Air Breeze wind turbine is bent edgewise at $2°$, $4°$, and $6°$, respectively.

Figs. 16 and 17 compare the 1P-invariant PSD of the estimated shaft rotating frequency of the WTG for the bent blade scenarios against the baseline case. The 1P-invariant PSD is obtained by using the proposed method with the same base frequency f_b and base value of the downsampling step size L as in the blade imbalance study. As shown in Figs. 16 and 17, an excitation appears at a fixed frequency of 1P (10 Hz) in the PSD plots of the bent blade cases. The magnitude of the 1P excitation provides an effective index for detecting and quantifying the bent blade faults.

Since the wind turbine is operated in the wind tunnel during the experiments and there is no wind shear or yaw error in the wind tunnel, as shown in Figs. 12 and 16, there is no excitation
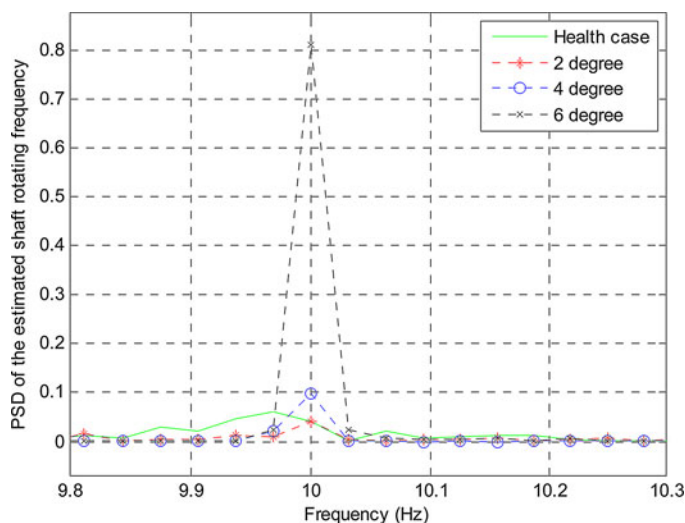
Fig. 17. Comparison of the 1P-invariant PSD of the estimated shaft rotating frequency for the bent blade scenarios against the baseline case in a frequency range around 1P.

at 2P frequency in the experimental results, which is another characteristic frequency of aerodynamic asymmetries.

VI. CONCLUSION

This paper has proposed a novel method for imbalance fault detection and quantification of direct-drive wind turbines using only one phase generator stator current signal. The proposed method firstly estimates the shaft rotating frequency of the WTG from the generator current record by using a PLL algorithm, and then processes the estimated shaft rotating frequency signal in a way such that the variable characteristic frequencies of the imbalance faults become constant values in the PSD of the processed shaft rotating frequency signal. Simulation studies have been carried out in a FAST and Simulink combined environment for blade imbalance and aerodynamic asymmetry detection of a 10-kW direct-drive WTG. Experimental studies have been performed in a wind tunnel facility for blade imbalance and bent blade detection of a 160-W direct-drive WTG. Both simulation and experimental results have confirmed that the proposed method is effective to detect and quantify various imbalance faults in a variable-speed direct-drive WTG by only using one phase current measured from the generator terminal.

The proposed method is nonintrusive, because it only uses one phase stator current signal, which has been used in existing WTG control systems; no additional sensors or data acquisition devices are needed. The proposed method is able to clearly identify excitations at the characteristic frequencies of imbalance faults. Therefore, it is sensitive to faults and is immune from interferences near fault characteristic frequencies. Compared to other signal analysis methods, such as wavelet analysis, amplitude demodulation, etc., the proposed method is less complex and has a lower computational cost and, therefore, is good for online fault detection. Furthermore, the traditional PSD analysis is a well-developed method for fault detection of rotating machines. Therefore, the proposed 1P-invariant PSD method can

be easily integrated into existing condition monitoring and fault detection systems used in the wind industry. Future work will focus on identifying the types of imbalance faults and prognosing WTG health condition by using the fault features extracted.

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