2015

A Survey on Wind Turbine Condition Monitoring and Fault Diagnosis–Part II: Signals and Signal Processing Methods

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This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIE.2015.2422394, IEEE Transactions on Industrial Electronics

Year: 2015, Volume: PP, Issue: 99

Pages: 1 - 1, DOI: 10.1109/TIE.2015.2422394

A Survey on Wind Turbine Condition Monitoring and Fault Diagnosis−Part II: Signals and Signal Processing Methods

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***Abstract*--This paper provides a comprehensive survey on the state-of-the-art condition monitoring and fault diagnostic technologies for wind turbines. The Part II of this survey focuses on the signals and signal processing methods used for wind turbine condition monitoring and fault diagnosis.**

***Index Terms*—Condition monitoring, fault diagnosis, survey, wind turbine (WT)**

I. Introduction

This paper is the continuation of the Part I of the survey on condition monitoring and fault diagnosis (CMFD) for horizontal-axis wind turbines (WTs). Fig. 1 illustrates a typical WT CMFD system, which consists of several functional modules, including a sensing and data acquisition module, a signal processing module for signal conditioning, fault feature extraction and fault diagnosis, an alarm management module, an equipment management module, and a diagnostic record management module. The most important components of the WT CMFD system are the signals and the signal processing methods. Therefore, the Part II of this survey will focus on signals and signal processing methods for WT CMFD. The functions, capabilities, and limitations of the major signals and signal processing methods that have been applied or studied for WT CMFD will reviewed and compared.

II. Signals for WT CMFD

The signals used for WT CMFD mainly include vibration, acoustic emission (AE), strain, torque, temperature, lubrication oil parameter, electrical, and supervisory control and data acquisition (SCADA) system signals. They are acquired using appropriate sensors installed in various WT components. Table I provides a comprehensive comparison of using these signals for WT CMFD, where Std, Temp and Com stand for Standardized, Temperature and commercial, respectively.

Manuscript received September 3, 2014; revised January 15, 2015; accepted February 15, 2015.

The work presented herein was funded in part by the U.S. National Science Foundation under Grant ECCS-1308045 and in part by the Office of Energy Efficiency and Renewable Energy (EERE), U.S. Department of Energy, under Award Number DE-EE0006802.

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A. Vibration

Many WT faults induce vibrations of the corresponding WT subsystems, which can be detected by using the signals acquired from vibration sensors. Vibration monitoring is the dominant technique used in almost all commercially available WT condition monitoring systems (CMSs), in which the vibration sensors are usually installed on the casing of the gearbox, generator, main shaft and bearing, and blade surface.

The major types of vibration sensors include accelerometers, velocity sensors, and displacement sensors. Accelerometers have the widest working frequency range from 1Hz to 30 kHz, In contrast, velocity sensors have a working frequency range from 10 Hz to 1 kHz and displacement sensors have a working frequency range of 1-100 Hz. Accelerometers are the most widely used vibration sensors in CMFD of WTs for their wide working frequency range. The signals acquired from accelerometers contain the information of accelerations of WT components caused by faults [1]. Displacement sensors have also been used in WT CMFD systems for diagnosing the faults leading to low-frequency vibrations of WT components. Vibration monitoring has been used for CMFD of WT gearbox [2], [3], bearing [4], rotor and blade [5], generator, tower, main shaft, etc. The amplitude of the vibration signal can indicate the severity of a fault [6]. For example, the amplitude of the 1P frequency components in vibration signals provides a measure of rotor asymmetries [5].

Through years of applications, the vibration-based CMFD technologies have been mature and standardized by ISO10816. However, this approach requires the installation of

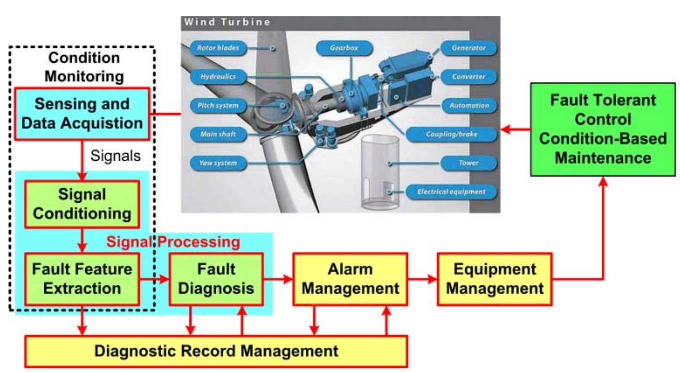

Fig. 1. A typical CMFD system for WTs.

vibration sensors and data acquisition devices, which increases the capital cost and wiring complexity of the WT system. The vibration sensors are usually mounted on the surface or are buried in the body of WT components, making them difficult to access during WT operation. Moreover, the sensors and data acquisition devices are also inevitably subject to failure. Sensor failure may further cause the failure of WT control, mechanical, and electrical subsystems. These could cause additional problems with system reliability and additional operation and maintenance (O&M) costs. In addition, vibration signals usually have a low signal-to-noise ratio (SNR) when used to diagnose an incipient fault.

B. AE

Materials that are subjected to stress or strain may emit sound waves, which is called AE [7]. The sources of AE can be located to detect possible defects of a structure using one or more AE sensors. The AE monitoring technology has been used for CMFD of WT blades [1], gearboxes [8], [9], and bearings [10]. As a blade is usually made of various materials and components, damages often grow over critical areas and the interfaces of different internal components inside the blade. Therefore, AE sensors were usually mounted on the critical areas and interfaces of the blade surface [1].

Since AE signals can be excited by tiny structural changes, they can be used to detect an incipient structure defect or damage and monitor its development to a failure [10]. The work of Bonno [7] Schulz [11] showed that the changes of the AE waveforms obtained from AE sensors installed on WT blades could be used to detect the incipient blade faults, such as fatigue, reduced stiffness, crack, and increased surface roughness. Moreover, it was effective to use AE waveform characteristics (e.g., amplitude, rise-time, etc.) of the detected AE events to predict when and where a damage would occur, identify the location of the damage, and monitor and predict how the damage would develop and result in a failure [12].

AE signals have high SNRs for CMFD and, therefore, can be used in high-noise environments. Compared to vibration signals, AE signals have much higher frequencies and, therefore, are more effective for the diagnosis of incipient defects or faults before damages or failures occur. A shortcoming of this technique is that it usually requires the installation of a large number of AE sensors, which are difficult to access during WT operation. Moreover, each AE sensor needs a dedicated data acquisition system for signal sensing, processing and transfer, which are more complicated than other sensing technologies. For example, high sampling rates are needed to process AE signals for CMFD, which makes the signal processing complex and expensive. These requirements could significantly increase the capital cost and wiring complexity of the WT system.

C. Strain

Fiber optic strain sensors have been used in several commercially available CMSs for condition monitoring of WT blades [13]. The strain sensors are usually mounted on the surface or embedded in the layers of a blade. The measured strain signals can be used to detect structural defects or damages in the blade [1], [14]-[17], blade icing, mass unbalance, or lighting strikes [13].

There are several advantages of using strain measurements for WT CMFD. First, strain measurements are sensitive to small structural changes and, therefore, are effective for incipient fault detection of WT blades [16]. Second, compared to vibration-, AE-, and electrical signals-based monitoring techniques, the strain-based CMSs can be operated at lower sampling rates as they are looking to observe changes in the time domain [13]. Third, the measurements from fiber optic strain sensors do not degrade with time or long transmitting distance [15], [16]. Fourth, fiber optic strain sensors are passive sensors, which do not require external power sources. However, there are still challenges in using fiber optic strain sensors for CMFD of WT blades. First, strain sensors should always be attached to the materials being monitored (i.e., intrusive); otherwise, the measurements are not accurate [17]. However, the deformation of the materials may lead to the separation of the sensors and the materials. Moreover, the deformation level of the materials should not exceed the physical limitation of the sensors; otherwise, the sensors will not provide accurate measurements or even be damaged [1]. Furthermore, similar to the vibration and AE monitoring, the implementation of the strain monitoring requires additional capital costs, increases WT system complexity, and is subject to problems of sensor reliability.

D. Torque and Bending Moment

Generally, torque tends to be used when there is an axle or pivot to be turned around; while bending moment tends to be used in nonrotational situations, such as stress on a beam. Torque measurements can be obtained using rotary torque sensors, while bending moment measurements can be obtained using reaction torque sensors. Torque sensors are usually installed on the mechanical components of a WT, such as rotor, gearbox, generator, etc. Torque can be also calculated from the electrical outputs of a generator. Thus, it is possible to perform torque signal-based WT CMFD without using torque transducers, which is an advantage of this method.

The defects in WT mechanical components usually have signatures in torque signals and, therefore, can be diagnosed by using torque signals. Different forms of aerodynamic asymmetries can be distinguished by analyzing the torque experienced by the tower of a WT [18]. For example, the surface roughness of one blade of a WT operating in skew wind can lead to changes at the 1P and 2P frequencies of the tower's torque spectra. Therefore, the P-amplitudes can be used as an indicator of rotor defects. Torque can also be used to detect faults in drivetrains. Based on Wilkinson's experiments [19], variations in wind speed excited an array of harmonics in the signal acquired from a torque sensor installed on the drivetrain, which could be used to detect generator faults in a WT. Moreover, Caselitz found that rotor imbalance and aerodynamic asymmetries could lead to a significant increase of the 2P amplitude in the frequency spectrum of the edgewise bending moment of the tower of a WT [18].

The limitations and shortcomings of torque and bending moment signals-based CMFD techniques are similar to those

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of the vibration signal-based methods, e.g., requiring additional space to mount sensors (intruding to the systems being monitored), needing additional capital and O&M costs, increasing WT system complexity, problems of sensor reliability. Compared to vibration sensors which measure the displacement, velocity, or acceleration of a component, torque sensors measure the strain within a component for CMFD. Moreover, when a fault occurs, a relevant torque signal is a fault information modulated signal with the dominant components related to load. In this case, using torque signals for fault diagnosis will require more complicated signal processing techniques than using vibration signals. Thus, torque sensors are not used as commonly as vibration sensors in WTs for the purpose of fault diagnosis.

E. Temperature

The temperatures of all components or subsystems in a WT should not exceed certain values during normal operating conditions. An abnormal temperature can be caused by a degradation of gearing, generator winding short circuits, rotor over speed, etc. Therefore, temperature measurements can provide useful information on the WT health condition.

Temperature-based techniques have mainly been applied for fault diagnosis of gearboxes, generators, bearings, and power converters. Zaher and McArthur [20] proposed a FDS for CMFD of gearboxes and generators through temperature anomaly detection using the temperature data of gearbox oil, gearbox bearings, and generator windings with the aid of electrical power and wind data. In [21], a WT generator thermal model was constructed using a nonlinear state estimation technique, from which generator incipient failures could be detected when the residuals between model-estimated and measured generator temperatures become significant. In addition to vibration signals, Lekou [22] used temperature signals of a gearbox to help with condition monitoring of the gearbox and bearings. Power converters are usually monitored by using coolant temperature, case and junction temperatures of semiconductor modules, etc.

As a mature technique, the temperature-based CMFD is considered cost effective and reliable. Particularly, the IEEE Standards 1310-2012 [23] and 1718-2012 [24] and the ISO Standard 17359-2006 [25] have standardized the use of temperature for CMFD. However, a temperature rise in a WT can be caused by many factors. It may be difficult to identify the source and root cause of the temperature variation. For example, if a thermal sensor is mounted on a WT component, a fault in a nearby component may also cause a temperature rise in that component. Therefore, a temperature rise can only indicate a possible fault within the WT but may not indicate which component has the fault. In addition, the temperature-based methods require the installation of embedded thermal sensors, which are intrusive to the system being monitored and are quite fragile in a harsh environment.

F. Lubrication Oil Parameters

Lubrication oil condition monitoring has been commonly used for WT rotating subsystems and components, such as gearbox, generator, and bearing. The current practice in the wind industry is to monitor oil parameters, such as viscosity, water content, level, particle counting and identification, temperature, and pressure [26]. By analyzing these parameters, the oil contamination and degradation process can be monitored to reveal the health condition of the WT components containing the oil and detect defects of the components at an early stage.

The available lubrication oil condition monitoring techniques for WTs can be classified into offline and online techniques [26]. The offline oil condition monitoring, which is currently the dominant approach in the wind industry, is based on offline oil sample analysis using the parameters measured by instruments, such as viscometer and optical emission spectrometer. Since the oil is usually sampled periodically, e.g., every 6 months [27], the faults that occurred between two sampling operations cannot be detected timely. Moreover, it is difficult to access the WT components to take oil samples when the WT is in operation.

The online oil condition monitoring overcame the drawbacks of the offline monitoring by using oil sensors, such as viscometer, level sensor, particle counter, and thermometer, to monitor the oil condition in real time [27], [28]. However, the use of additional sensors increased the costs of the WTs. In addition, not all of the oil parameters can be monitored in real time using the oil sensors [26]. Moreover, it is not easy to correctly interpret the real-time measurements for online oil condition monitoring, as the operational condition of the WT has various impacts on the oil conditions.

G. Electrical Signals

Voltage and current are electrical signals acquired from the terminals of the generator and motors in a WT. Electrical signal-based methods have been widely applied for diagnosis of generator electrical faults [2]. For example, the amplitudes of certain harmonics in electrical signals can be used to detect electrical faults at an early stage. Popa [29] used stator and rotor currents and stator voltages to monitor the induction generator in a WT. Three failure modes, i.e., stator phase unbalance, rotor phase unbalance, and stator turn-to-turn faults, were detected by using stator and rotor currents. It was also found that the rotor line current spectrum offered more information of the rotor phase unbalance than the stator line current spectrum. To verify whether a fault has occurred in a doubly-fed induction generator (DFIG) WT, Bennouna et al. [30] proposed a stator and rotor current-based data recondition technique using the equations of a model representing the DFIG WT. The detection of rotor electrical imbalance of an induction generator using power signals (calculated using voltage and current signals) was studied in [31]. The detection of stator open-circuit faults of DFIGs using current and power spectra was studied in [32].

A mechanical fault or structural defect in a WT component usually induces vibration of the component. Due to electromechanical coupling between the generator and the faulty component, the fault-induced vibration will modulate generator electrical signals. Consequently, the electrical signals will contain fault-related information and, therefore, are effective for diagnosis of the mechanical fault or structural

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defect of the WT [33]-[38]. For example, the mechanical faults in WT generators, such as rotor mass imbalance of a synchronous generator [31], [39], could be detected by monitoring the changes in the harmonics of electrical signals. It was proven that generator electrical power signals carried the information of surface condition of WT blades [5]. The P-amplitudes of generator electrical signals were indicators of rotor imbalance caused by the increased surface roughness of one blade or yaw misalignment [18], [40]. Moreover, both a reduction in the stiffness of one blade and an equal reduction in the stiffness of all blades can be detected through monitoring the changes of the power spectral density of the WT electrical power [41].

Another typical mechanical fault in a WT is bearing failure, whose feature can be extracted from the WT generator current signals for fault diagnosis. Analyzing the amplitude and phase spectra of generator current signals can reveal the development of bearing failures from an early stage [37], [38], [42]. Electrical signals can also be used for CMFD of WT gearboxes [33]-[36]. CMFD of power electronics mainly used electrical signals [43].

Electrical signal-based WT CMFD has gained more and more attention in the last decade owing to its distinctive advantages. First, electrical signals are already used in existing WT control and protection systems, no additional sensors or data acquisition devices are needed. Therefore, the electrical signal-based WT CMFD requires almost no additional capital expenditure and is easy to implement. Moreover, electrical signals are reliable and easily accessible without intruding the WTs. Therefore, compared to CMFD based on other signals, such as vibration and AE, the electrical signal-based CMFD has significant advantages in terms of cost, hardware complexity, implementation, and reliability and will have great potential for the wind industry.

The downsides of electrical signals include the following. First, they have low SNRs for WT CMFD. Moreover, the fault-related components in an electrical signal are modulated with its fundamental and harmonic components, which are proportional to the nonstationary WT shaft rotating speeds. Therefore, the signatures of WT faults in electrical signals are usually nonstationary and identification of the fault signatures for CMFD will require complex signal processing algorithms.

I. SCADA Signals

SCADA systems have been installed in many WTs produced by major manufacturers, such as Vestas, GE, and Siemens, to monitor the operational performance of the WTs. A typical SCADA system keeps a record of data with an interval of a few seconds to 10 minutes. The SCADA data are typically statistical features (e.g., mean, maximum and minimum values, and standard deviation) of the signals (e.g., temperature, current, voltage, power, rotor speed, wind speed, etc.) collected from various sensors in the WT during each interval [44], [45]. SCADA signals provide rich information on WT performance. With appropriate algorithms, SCADA signals can be used effectively for CMFD, prognostics, and remaining useful life (RUL) prediction of WTs [45]. Since no additional sensors or data acquisition devices are needed [46], it is cost-effective to use SCADA signals for WT CMFD.

However, since SCADA signals are recorded with a long interval, which was initially not for the purpose of CMFD [44], most dynamical features of WT faults which are useful for CMFD are lost. Therefore, the detailed information (e.g., location and mode) of most WT faults cannot be diagnosed by using SCADA signals via frequency or time-frequency analysis. Currently, SCADA signals have been mainly used by model-based methods and prediction methods for WT CMFD and prognosis [44], [47]-[51].

J. Nondestructive Testing (NDT) Techniques

The NDT techniques, such as ultrasonic scanning, infrared thermography, X-ray inspection, and tap test, are useful for detecting hidden damages in composite materials. Thus, they

TABLE I
COMPARISON OF DIFFERENT SIGNALS FOR WT CMFD.

Signal	**Monitored components**	**Intrusive**	**Complexity**		**Capability**					**SNR/ Sampling frequency**	**Cost**	**Std**	**Used in Com CMS**
			Install	**Signal process**	**Online/ Offline**	**Incipient fault detection**	**Fault detection**	**Fault location**	**Fault identify**				
Vibration	Bearing, blade, gearbox, generator, shaft, tower	Yes	High	Medium	Online	Yes	Yes	Yes	Yes	High/ Medium	High	Yes	Yes
AE	Bearing, blade, gearbox	Yes	High	High	Online	Yes	Yes	Yes	Yes	High/High	High	Yes	Yes
Strain	Blade	Yes	High	Medium	Online	Yes	Yes	Yes	Yes	High/low	High	No	Yes
Torque	Blade, gearbox, generator, shaft	Yes	High	Medium	Online	Yes	Yes	Yes	Yes	High/ Medium	High	No	No
Temp	Gearbox, generator, bearing, power converter	Yes	Medium	Low	Online	Possible	Yes	Possible	No	High/Low	Medium	Yes	Yes
Oil parameters	Bearing, gearbox, generator	Yes	Medium	Low	Both	Possible	Yes	Possible	Possible	High/Low	Medium or high	No	Yes
Electrical signals	Bearing, blade, gearbox, generator, motor, power converter, sensor, shaft, tower	No	Low	High/ medium	Online	Possible	Yes	Yes	Yes	Low/ Medium	Low	No	Yes
SCADA signals	Blade pitch, control system, generator, hydraulic system, power converter, sensor, overall system	No	–	Medium	Online	Possible	Yes	Possible	Possible	Low/Low	Low	No	No
NDTs	Blade	Yes	Low	Low	Both	Possible	Yes	Yes	Yes	High/–	High	No	No

have been mainly used for fault diagnosis of WT blades [15].

Ultrasonic scanning is the most frequently used NDT technique in industry [14]. It can be carried out to investigate whether damages (e.g., delamination) are present in the inner structures of a WT blade [1], [17]. Infrared thermography is the measurement of heat distribution of a surface. It can be used to examine the condition of a blade by monitoring the temperature difference in different areas caused by material changes in the laminate and adhesive joints which are critical points in blade structures [52]. X-rays can penetrate a large number of materials including composite materials [1], [16], [17]. The shadows of X-ray images can reveal structural variations of the materials and, therefore, can be used to detect faults in the structures of WT components. A radiographic system based on the X-ray technique was demonstrated to be effective for fault diagnosis of WT blades [1]. The tap test is based on the fact that sonic waves will emit when a blade is tapped. It can be used to diagnose a disbond between the skin laminate and the main spar of a blade [53].

The NDT techniques have the capability of detecting incipient faults and monitoring the propagation of the faults. However, their implementation usually requires expensive instruments. Moreover, most NDTs are intrusive and offline techniques which require interrupting the operation of the WT and need specialists to operate the instruments to take measurements.

III. Signal Processing Methods for WT CMFD

The signal processing methods used for WT CMFD mainly include classical time-domain analysis methods (e.g., statistical analysis, Hilbert transform, and envelope analysis), classical frequency analysis methods (e.g., fast Fourier transform (FFT)), classical time-frequency analysis methods (e.g., short-term Fourier transform (STFT) and wavelet transform), model-based methods, probability-based methods (e.g., Bayesian methods), artificial intelligence (AI) methods, etc. Fig. 2 illustrates the logic flow on how these methods are used to perform different functions (i.e., signal conditioning, feature extraction, fault diagnosis, and fault prognosis) for WT CMFD. Signal conditioning is usually applied to raw signals to facilitate the extraction of fault-related features in the signals. Then the faults can be detected via threshold comparison or probability analysis, e.g., analyzing the probability of failure (PoF) using various features extracted. In the threshold comparison, if the values of the extracted fault features exceed their thresholds, it indicates that some fault(s) occurs. The fault mode and location can then be identified by a classification method, such as artificial neural networks (ANNs), support vector machines (SVMs), etc. Table II compares different methods.

A. Synchronous Sampling

Since most WTs usually operate with varying rotating speeds, the signals (e.g., vibration and electrical signals) collected from the WTs are nonstationary. Therefore, the information of a WT fault hidden in a nonstationary signal acquired from the WT cannot be revealed by using the classic

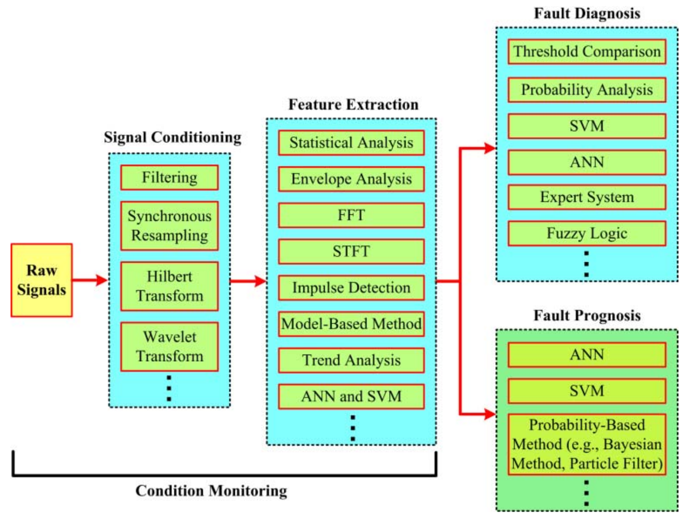

Fig. 2. Signal processing methods for WT CMFD and prognosis.

frequency analysis for the signal. To solve this problem, several synchronous sampling algorithms were developed in [33]-[38], [40], [54], [55] to process the nonstationary electrical signals collected from WT generator terminals in a way such that the varying characteristic frequencies of WT faults in the frequency spectra of the signals were converted to constant values. Then, the classic FFT could be applied to the processed signals to obtain their frequency spectra for WT CMFD. The synchronous sampling-based frequency analysis methods have higher frequency-domain resolutions than the time-frequency analysis methods, such as STFT and wavelet transform, for processing nonstationary signals and are computational efficient. Therefore, they are promising for signal conditioning in online CMFD of variable-speed WTs.

B. Hilbert Transform

The Hilbert transform is a classical method to compute the instantaneous amplitude $C(t)$ and phase $\phi(t)$ of a signal $x(t)$ by (1) and (2), respectively:

$$C(t) = \sqrt{x(t)^2 + H(x(t))^2} \tag{1}$$

$$\phi(t) = -\arctan\frac{x(t)}{H(x(t))} \tag{2}$$

where $H(\cdot)$ represent the Hilbert transform of the signal:

$$H(x(t)) = \int_{-\infty}^{\infty} \frac{x(\tau)}{\tau - t} d\tau \tag{3}$$

If a fault in a WT component induces a vibration of the component, the vibration will modulate the signals (e.g., vibration, electrical or torque signals) acquired from the sensors installed on the faulty component or other components of the WT. Although the modulated signals contain fault-related information, it is difficult to extract fault signatures from the signals directly for fault diagnosis due to the modulation. To solve the problem, demodulation is usually performed for the signals to facilitate the fault signature extraction. The Hilbert transform has been primarily used for the signal demodulation in the fault diagnosis of important WT mechanical components, such as bearings and gearboxes

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TABLE II
COMPARISON OF SIGNAL PROCESSING METHODS FOR WT CMFD AND PROGNOSIS.

Signal processing method	Domain	Function	Resolution		Complexity/ computational cost	Handling nonstationary signal	Signal sampling rate	Used in Com CMS
			Time domain	Frequency domain				
Synchronous sampling	Time	Signal conditioning	High	–	Low/medium	Yes	High/medium	No
Hilbert transform	Time	Signal conditioning	High	–	Medium	Yes	High/medium	Yes
Envelope analysis	Time	Feature extraction	High	–	Low/medium	Possible	High/medium	Yes
Statistical analysis	Time/frequency	Feature extraction	Rely on input	Rely on input	Low	Possible	Any	Yes
FFT	Frequency	Feature extraction	–	High	Medium	No	High/medium	Yes
STFT	Time-frequency	Feature extraction	Medium	Medium	High	Yes	High/medium	No
Wavelet transform	Time-frequency	Signal conditioning	Medium	Medium	Low/medium	Yes	High/medium	Yes
Model-based methods	Time/frequency	Feature extraction	Rely on input	Rely on input	Medium/high	Possible	Medium/low	Yes
ANN	Time/frequency	Feature extraction, diagnosis, prognosis	Rely on input	Rely on input	Medium/high	Possible	Medium/low	No
SVM	Time/frequency	Feature extraction, diagnosis, prognosis	Rely on input	Rely on input	Medium/high	Possible	Medium/low	No
Expert system	Time/frequency	Diagnosis	Rely on input	Rely on input	Medium	Possible	Medium/low	No
Fuzzy logic	Time/frequency	Diagnosis	Rely on input	Rely on input	Medium	Possible	Medium/low	No
Bayesian methods	Time/frequency	Prognosis	Rely on input	Rely on input	High	Possible	Medium/low	No

[33]-[35], [55]. For example, (1) is amplitude demodulation of the signal.

The Hilbert transform is also usually combined with other methods, such as empirical mode decomposition (EMD) and Fourier transform, to generate spectra in the frequency or time-frequency domain for WT fault diagnosis. For example, in [56], the EMD was firstly applied to decompose a vibration signal into components in different frequency ranges. The Hilbert spectra were then generated for the obtained signal components in different frequency ranges to reveal the characteristic frequencies of a bearing pedestal looseness fault in a WT.

C. Envelope Analysis

The envelope of a signal is a smooth function outlining the extremes of the signal, such as $C(t)$ in (1), which is also called the amplitude modulating component of the signal. In addition to the Hilbert transform, the envelope of a signal can be obtained by other amplitude demodulation methods, such as a band-pass filter.

The envelope of a signal usually contains the signatures of WT faults explicitly. For example, the envelopes of the vibration signals collected from a WT contain valuable information for most bearing-related fault detection [57]. From the envelope of a signal, fault signatures can be extracted directly using appropriate feature extraction methods. For example, the characteristic frequencies of bearing faults can be revealed from the frequency spectrum of the envelope of a vibration signal for bearing fault diagnosis. This method is valid for detecting not only inner and outer race bearing faults but also fretting corrosion and assembly damage of bearings. It was reported that the envelopes of vibration signals can reveal bearing faults in their early stages of development before detectable by other methods [58]. A wavelet-envelope method has also been developed for bearing outer race fault diagnosis of a gearbox, where vibration signals were interfered by gear meshing frequencies and had low SNRs. The envelope analysis is a simple and efficient method and has been used in many commercial WT CMSs. The envelope of a signal is a time-domain signal and usually needs to be further processed by other signal processing methods, such as FFT, for WT CMFD.

D. Statistical Analysis

In the statistical analysis methods [4], [5], [59]-[63], appropriate statistical features, such as mean value, root-mean-square (RMS) value, variance, crest factor, kurtosis, skewness, etc., of time-domain signals acquired from a healthy WT were first recorded as the base values for various operating conditions. Then, the same statistical features of the signals were monitored online during the WT operation. If the deviations of some monitored features from their base values exceeded predetermined thresholds, it would indicate that a fault occurred in the WT. For example, in [5], the mean output active power of a WT in the healthy condition as well as the upper and lower alarm limits of the WT output active power as functions of mean wind speed were established according to the requirements of the CMS. A fault alarm will be triggered when more than a certain number of the mean output active power samples exceed the alarm limits during the WT operation. The advantage of using statistical mean values is that random influences of incoherent wind fields are damped in the calculated mean wind speed and power signals. RMS values have been proven a better choice than mean values for WT CMFD [4] and are especially useful when the signal is alternating, e.g., a sinusoidal signal. Other statistical features, such as crest factor, kurtosis, and skewness, represent statistical variances of a signal and have also been used for WT CMFD [59]-[63].

The statistical analysis methods are mature techniques and easy to implement. They have been widely used in commercial WT CMSs. However, these methods usually can

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only indicate the occurrence of a fault in a WT or a WT subsystem, but can rarely reveal the detailed information of the fault, such as fault location or mode. This is because many faults in the WT will cause similar changes in the same statistical features. Moreover, the statistical methods are sensitive to noise and, therefore, are not effective in high-noise environments. Furthermore, the application of statistical methods for WT CMFD may require large data sets.

E. FFT

Fourier analysis is probably the most frequently used frequency analysis techniques. In real-world applications, the FFT is usually applied in a digital system to obtain the frequency spectrum of a signal. The variations of certain harmonic components in the frequency spectrum of a signal acquired from a WT can be related to a specific fault and, therefore, can be used as the fault signature for fault diagnosis of the WT [7], [22], [29], [32], [41]. For example, in [7], the changes of the frequency spectrum of an AE signal in a specific frequency range were used as a fiduciary point for diagnosis of blade failures. It was found that the harmonic contents in the frequency spectra of the current and power signals of a WT generator were directly related to winding unbalance of the generator [32]. The FFT analysis showed that there was a correlation between the recorded AE levels and health conditions of WT gearboxes [22].

The classic FFT is capable of frequency analysis for stationary signals but cannot indicate how the frequency content of a nonstationary signal changes over time [38]. Therefore, the information of a WT fault hidden in a nonstationary signal acquired from the WT cannot be revealed by the FFT spectrum of the signal. Several techniques have been developed to overcome this challenge [5], [42]. Caselitz and Giebhardt [5] proposed an order spectrum analysis method based on the samples recorded at equidistant rotational angles of the WT rotor. The frequency components in the resultant order spectrum of the recorded vibration signal have constant frequencies and, therefore, are usable for fault diagnosis of WTs operating in variable-speed conditions. In [42], the nonstationary power signal was first processed using a continuous wavelet transform (CWT); the resulting wavelet coefficients were then analyzed by using the FFT. The spectra of the wavelet coefficients in specific frequency ranges contain the features closely related to certain faults. This method has been used successfully to detect generator misalignments and bearing failures in WTs. In [33]-[38], [40], [54], [55], synchronous resampling were first performed to process the nonstationary electrical signals collected from WT generator terminals. The classic FFT were then applied to the synchronously resampled signals to generate their frequency spectra, from which the fault features could be extracted by the impulse detection method [55] for effective WT CMFD.

F. STFT

The STFT provides a means for analyzing the time-varying frequency response of a nonstationary signal. The STFT of a signal offers a three-dimensional representation (i.e., time, frequency, and amplitude) of the frequency response of the signal [19]. This method has been successfully applied to detect a variety of faults in variable-speed WTs, such as rotor unbalance, open-circuit and short-circuit faults in generators [19], [32], gear tooth defects in gearboxes [64], [65], and structure damage in blades [66].

However, since the STFT is a window-base method, both the time and frequency resolutions are limited. In fact, high time resolution and high frequency resolution are complementary in the STFT and cannot be achieved simultaneously. Therefore, this method cannot be applied to the frequency analysis of nonstationary signals which requires high frequency resolutions.

G. Wavelet Transform

The basic principle of the wavelet transform is hierarchically decomposing a signal into a set of frequency channels having the same bandwidth on a logarithmic scale [3]. In this way, the wavelet transform is capably of grasping both the time and frequency information of a signal [42], [67], [68] and resolving signal denoising problems effectively [6]. Therefore, wavelet transform is a useful technique for analyzing a nonstationary signal to extract the features in the signal that vary in time [69]. Wavelet transform has been widely used in CMFD of WTs. For example, it has been applied to AE signals to detect bearing [69] and blade faults [67], to vibration signals to detect mechanical faults in gearboxes [2], [3], [6], and to electrical signals for diagnosing generator electrical and mechanical faults [2], [31], [39], [42].

Two forms of wavelet transform have been used for WT CMFD: CWT and discrete wavelet transform (DWT). In [2], the features charactering electrical faults in a WT generator were correctly identified from current and power signals using a CWT, even though the electrical signals are harmonic-rich due to the variable-speed operation and stochastic aerodynamic load of the WT. The CWT was also proven to be a promising and effective technique for diagnosing drivetrain bearing faults in WTs [37], [70]. Unlike the CWT, the DWT uses a discrete scale factor and a discrete time shift, which yields a faster computation than the CWT. The DWT has been applied to vibration signals to detect gear faults in WTs [71] and to generator stator/rotor currents to detect unbalance stator winding fault and load anomaly of WTs [72], [73]. Another application of the DWT is for noise cancellation. The noise in low SNR signals is rich and difficult to be removed using conventional filters with fixed cut-off frequencies [2]. The use of the DWT can reduce the noise in nonstationary signals and to facilitate the use of the signals for WT CMFD. However, wavelet transform suffers from the same problems of the STFT, such as limited time and frequency resolutions.

H. Model-Based Methods

In the model-based CMFD, accurate mathematical models were constructed to simulate the dynamic behaviors of a WT and its critical subsystems and components [30], [74]-[76] or extract the trend of a signal acquired from the WT [21] using physical principles or data-driven approaches. For example, in [77], [78], WT models were built based on the stochastic recordings of the structural responses of the WTs in the healthy conditions described by vibration, AE, and other signals. Once an accurate model was built for a healthy WT, possible failures in the WT could be diagnosed by analyzing the residual between the actual WT output and the model estimated output for the same input [1], as shown in Fig. 3, where the input and output of the WT are signals acquired from the WT. By predicting the trend of the residual signal using an appropriate trend analysis method, the development of the fault and the RUL of the WT component having the fault could be predicted. The trend analysis method has been used in some commercial WT CMSs.

Compared to the aforementioned signal processing methods for WT CMFD, the model-based methods do not need high-resolution signals (e.g., signals with high sampling rates). For example, the low-resolution, low-sampling-rate SCADA signals of a WT can be used effectively by model-based methods for WT CMFD [44]-[48]. This removes the need of installing additional sensors and data acquisition hardware to obtain high-resolution signals, such as vibration and AE signals. In addition, the complex and costly computations in the aforementioned methods to extract fault features from signals are not needed in the model-based methods. Moreover, in many cases a relatively small damage in a WT component can cause nonnegligible changes in the model output or parameters. Therefore, the model-based methods are often effective for diagnosis of faults in an early stage and monitoring or even predicting the development of the faults. However, the effectiveness of model-based methods critically depends on the accuracy of the models, which is usually difficult to obtain in real-world applications. Moreover, the model-based methods usually can only indicate the occurrence of a fault in a WT or a WT subsystem, but have a limited capability in revealing the detailed information of the fault, such as fault location and mode.

I. AI Methods

AI techniques, including ANNs, SVMs, expert systems, and fuzzy logic systems, have been applied for fault diagnosis of WTs. ANNs have been used for fault diagnosis of different WT components, such as gearboxes [3], [6], [79], bearings [22], generators [77], and power electronics [43], [80], primarily for two functions: behavior prediction and classification. In the behavior prediction, an ANN learns the dynamics of a WT or a WT subsystem from the patterns of input and output collected from a dataset. The trained ANN is then used to predict the behavior of the WT or its subsystem from new input data. By comparing the ANN-predicated behavior and the measured actual behavior of the WT [77], possible faults can be detected from the changes in the WT behaviors. In this case, the function of the ANN is similar to that of the model in Fig. 3. In the classification, an ANN is trained to recognize the patterns (e.g., mode, location, and severity) of different WT faults from the input signals containing the information of the faults, which can be raw signals [77], [80], [81], conditioned signals [6], [82], or features extracted from raw and conditioned signals [3], [83]. The trained ANN is then able to diagnose the faults (i.e., identify fault modes, locations, and severities) according to the

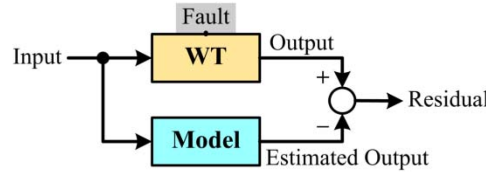

Fig. 3. Model-based CMFD by analyzing the residual signal.

new input features collected during the WT operation, as illustrated in Fig. 4.

The ANN-based methods are data-driven techniques which require little or even no knowledge of the dynamics of the WTs being monitored. Another advantage of the ANN-based methods is that they are robust to signal noise, making them useful in noisy environments. However, training ANNs can be time consuming and requires a large amount of data that cover all possible conditions of the WT, which may be difficult to obtain in practice. In addition, since ANNs are a heuristic technique, it is often difficult to prove the convergence and reliability of the ANN-based methods.

SVMs have been be used for fault diagnosis of WTs and their components, such as rotor [84], gearbox [36], [85], [86], bearing [85], generator [85], and sensors [76]. Similar to ANNs, SVMs have two main functions in WT fault diagnosis: behavior prediction [84] and fault classification [85]. SVMs have better generalization performance than ANNs. Therefore, training SVMs requires fewer data samples than training ANNs and the trained SVMs can have higher accuracy and reliability in fault diagnosis of WTs [87]. However, SVMs are also a data-driven heuristic technique and, therefore, have similar shortcomings of ANNs.

The expert systems are rule-based techniques and have been used for fault diagnosis of WTs, such as gearbox [78], [88]. Based on the operational history of a WT, an expert system constructs a mapping that correlates the measurements to the corresponding health conditions of the WT. The expert system constructed can then diagnose faults by reasoning with new measurements. In addition to having the same shortcomings of other heuristic methods, a main shortcoming of an expert system is that its size will increase exponentially with the number of the fault modes in a WT, making the expert system computationally expensive.

Fuzzy logic systems have been used for fault diagnosis of WT generator [89] and pitch system [90], [91]. A fuzzy logic system is designed to perform certain rules to deal with reasoning based on fuzzy sets of linguistic variables. Fuzzified features of faults are fed into the fuzzy logic system designed,

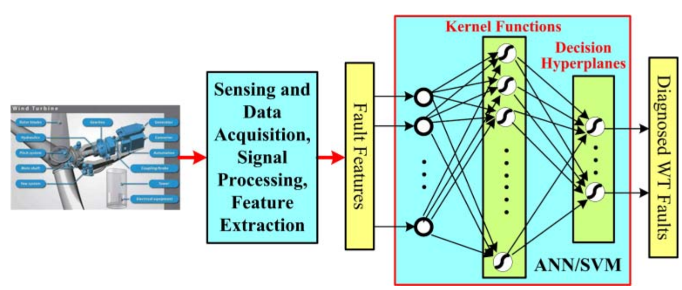

Fig. 4. Illustration of an ANN- or SVM-based WT fault diagnostic method.

which diagnoses the faults based on the predesigned rules. Obviously, designing the rules requires the full knowledge of the failure mechanisms of the WT being monitored, which is usually unavailable in practice. If the rules are not robust, it can cause false diagnostic results. Moreover, similar to expert systems, the size of a fuzzy logic system will increase exponentially with the number of the fault modes in the WT, making it computationally expensive.

J. Bayesian Methods

Bayesian methods are probability-based techniques suitable for solving real-time state prediction problems. A Bayesian prediction is achieved with two operations recursively: propagation and update, as illustrated in Fig. 5. In the propagation operation, the prior probability density function (PDF) of the state is obtained through the Chapman Kolmogorov equation:

$$p(x_k \mid z_{1:k-1}) = \int p(x_k \mid x_{k-1}) p(x_{k-1} \mid z_{1:k-1}) dx_{k-1} \tag{4}$$

where k is the time index, z is the measurement, $p(x_k \mid z_{1:k-1})$ is the prior conditional PDF of the state x_k at time k given that the measurements in the previous $k-1$ time steps are known, $p(x_k \mid x_{k-1})$ is the probability of the system state transition, which can be modeled as a Markov process of order one, $p(x_{k-1} \mid z_{1:k-1})$ is the posterior state PDF at time $k-1$. When a new measurement becomes available, the update operation is carried out, in which the posterior state PDF is calculated by

$$p(x_k \mid z_{1:k}) = \frac{p(z_k \mid x_k)}{p(z_k \mid z_{1:k-1})} p(x_k \mid z_{1:k-1}) \tag{5}$$

where

$$p(z_k \mid z_{1:k-1}) = \int p(z_k \mid x_k) p(x_k \mid z_{1:k-1}) dx_k \tag{6}$$

and the PDF $p(z_k \mid x_k)$ is defined upon the following function h_k that models the nonlinear relationship between the state and the noisy measurement.

$$z_k = h_k(x_k, v_k) \tag{7}$$

where v_k is the measurement noise. In the fault diagnosis and prognosis, (7) is commonly in the following form:

$$z_k = x_k + v_k \tag{8}$$

Based on the concept of sequential importance sampling and the Bayesian theorem, a recursive Bayesian algorithm called particle filtering was proposed. It is suitable for the system observed with non-Gaussian noise [92]. This feature makes the particle filtering a promising technique for CMFD and RUL prediction of WTs. The Bayesian method or particle filtering technique has been used for blade fault diagnosis [93], [94], bearing fault diagnosis and RUL prediction [95], condition monitoring and RUL prediction of lubrication oil [27], [28], and reliability evaluation [96] of WTs.

The accuracy of Bayesian methods highly depends on the number of prior tests and the size of data samples. This limits their capability in real-world applications due to the lack of prior data samples. Compared to the traditional Bayesian methods, the particle filtering technique avoids the problem of massive data storage and recalculation, but has a high computational complexity since it is a recursive algorithm.

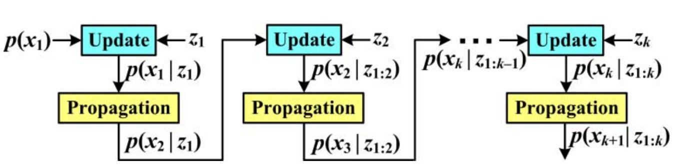

Fig. 5. Illustration of the Bayesian prediction method.

IV. Summary and Discussion

This paper has surveyed the signals and signal processing methods used for WT CMFD. The functions, capabilities, and limitations of these signals and signal processing techniques for WT CMFD have been discussed and compared. Table III summarizes the survey, where Syn. stands for Synchronous.

WT CMFD has received more and more attention in the past decade. Most major WT manufacturers and many CMS original equipment manufacturers (OEMs) have developed commercial WT CMSs, such as the ADAPT Wind of GE Company, the TCM Turbine Condition Monitoring System of Siemens, and the WindCon System of SKF [13]. Therefore, most modern WTs are equipped with some integrated CMSs interfaced with the operators via SCADA systems. The majority of the commercially available CMSs mainly use vibration signals measured from WT rotor blades and key drivetrain components, such as gearbox, main bearing, and generator. Several CMSs solely use oil debris monitoring. The vibration signals are usually processed with the envelope analysis, FFT frequency analysis, and time-domain analysis methods for WT CMFD. Other methods, such as wavelet analysis and Hilbert transform, are also used some commercially available CMSs. Furthermore, all of the commercially available CMSs have either very limited or no fault prognosis capability. In fact, with appropriate modification or improvement, many CMFD and prognostic techniques used in other industries [97], [98] can be adopted in the wind industry. In addition, the use of no- or low-additional-cost signals, such as electrical signals and SCADA signals, for WT CMFD and prognosis has attracted more and more attention and has great potential to be adopted by the wind industry. Furthermore, a fault in a WT may have signatures in multiple signals of the same or different types available in the WT and may have different signatures in a signal processed by different signal processing methods. Therefore, it will be beneficial to use different signals and different signal processing methods jointly to improve the fault diagnostic and prognostic accuracy and reliability and reduce the false alarm rate. However, significant effort is still needed to develop these technologies to achieve cost-effective, reliable CMFD and prognosis for WTs [20] particularly for the high-risk components, to improve WT reliability.

References

[1] B. F. Sorensen, L. Lading, P. Sendrup, M. McGugan, C. P. Debel, O. J. D. Krinstensen, G. Larsen, A. M. Hansen, J. Rheinlander, J. Rusborg, and J. D. Vestergaard, "Fundamentals for remote structural health monitoring of wind turbine blades−A preproject," Tech. Rep. Risø-R-1336(EN), May 2002.

[2] W. Yang, P. J. Tavner, and M. R. Wilkinson, "Condition monitoring and fault diagnosis of a wind turbine synchronous generator drive train," *IET Renew. Power Generation,* vol. 3, no. 1, pp. 1-11, Mar. 2009.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIE.2015.2422394, IEEE Transactions on Industrial Electronics

TABLE III
SUMMARY OF THE SURVEY FOR WT CMFD.

WT subsystems	Fault modes	Signals used for CMFD	Signal processing methods
Rotor hub and blade	• Rotor asymmetries • Blade: Fatigue Reduced stiffness Cracks Surface roughness Deformation	• Vibration • AE • Strain • Torque • Electrical signals • SCADA signals • NDT	• Syn. sampling • Hilbert • FFT • Wavelet • Model • Threshold • AI, etc.
Gearbox	• Bearing faults • Gear tooth abrasion • Gear surface fatigue • Gear or tooth crack • Gear tooth breakage • Gear tooth fracturing	• Vibration • AE • Torque • Temperature • Oil parameters • Electrical signals • SCADA signals	• Syn. sampling • Hilbert • Envelope • Statistical • FFT • Model • AI, etc.
Bearing	• Wear or surface roughness • Fatigue, crack, or breakage of outer race, inner race, ball, or cage	• Vibration • AE • Temperature • Oil parameters • Electrical signals	• Syn. Sampling • Envelope • Hilbert • FFT • Model • AI, etc.
Main shaft	• Corrosion • Crack • Misalignment • Coupling failure	• Vibration • Torque • Electrical signals • SCADA signals	• Syn. sampling • Hilbert • FFT, etc.
Hydraulic system	• Oil leakage • Sliding valve blockage	• Pressure • Level	• Threshold comparison
Mechanical brake	• Disc/caliper wear • Disc crack or failure • Hydraulic section failure • Motor failure	• Vibration • Temperature • Electrical signals	• Statistical • FFT • Model • Threshold comparison
Tower	• Structure damage • Corrosion and crack	• Vibration	• FFT • Model, etc.
Electric machine (generator and motor)	• Electrical faults: Stator/rotor insulation damage or open circuit Electrical imbalance • Mechanical faults: Broken rotor bar Bearing failure Bent shaft Air-gap eccentricity Rotor mass imbalance Magnets failure	• Vibration • Torque • Temperature • Oil parameters • Electrical signals • SCADA signals	• Synchronous sampling • Hilbert • Envelope • Statistical • FFT • STFT • Wavelet • Model • Threshold • AI, etc.
Power converter	• Capacitor failure • PCB failure • Semiconductor failure	• Temperature • Electrical signals • SCADA signals	• Statistical • Model • Threshold • AI, etc.
Sensors	• Sensor failure • Failure of data processing hardware • Communication failure • Software malfunction	• All related signals	• Wavelet • Model • Threshold comparison • AI, etc.
Control subsystem	• Hardware failures: Sensor fault Actuator fault Controller failure Communication failure • Software malfunction	• All related signals	• Statistical • Model • AI, etc.

[3] Q. Huang, D. Jiang, L. Hong, and Y. Ding, “Application of wavelet neural networks on vibration fault diagnosis for wind turbine gearbox,” in *Proc. 5th Int. Symp. Neural Netw.: Advances in Neural Netw., Part II*, Sept. 2008, pp. 313-320.

[4] J. J. Christensen, C. Andersson, and S. Gutt, “Remote condition monitoring of Vestas turbines,” in *Proc. European Wind Energy Conf.*, Mar. 2009, pp. 1-10.

[5] P. Caselitz and J. Giebhardt, “Rotor condition monitoring for improved operational safety of offshore wind energy converters,” *J. Solar Energy Eng.*, vol. 127, no. 2, pp. 253-261, Sept. 2005.

[6] S. Yang, W. Li, and C. Wang, “The intelligent fault diagnosis of wind turbine gearbox based on artificial neural network,” in *Proc. Int. Conf. Condition Monitoring and Diagnosis*, Apr. 2008, pp. 1327-1330.

[7] T. Bouno, T. Yuji, T. Hamada, and T. Hideaki, “Failure forecast diagnosis of small wind turbine using acoustic emission sensor,” *KIEE Int. Trans. Elect. Machinery and Energy Convers. Syst.*, vol. 5-B, no. 1, pp. 78-83, Jun. 2005.

[8] Y. Qu, E. Bechhoefer, D. He, and J. Zhu, “A new acoustic emission sensor based gear fault detection approach,” *International Journa. Prognosis and Health Management,* vol. 4, pp. 1-14, Jul. 2013.

[9] L. Ruoyu, S. U. Seckiner, D. He, E. Bechhoefer, and P. Menon, “Gear fault location detection for split torque gearbox using ae sensors,” *IEEE Trans. Systems, Man, and Cybernetics, Part C: Applications and Reviews,* vol. 42, no. 6, pp. 1308-1317, Feb. 2012.

[10] A. Widodo, E. Y. Kim, J. Son, B. Yang, A. Tan, D. Gu, B. Choi, and J. Mathew, “Fault diagnosis of low speed bearing based on relevance vector machine and support vector machine,” *Expert Systems with Applications,* vol. 36, no. 3, Part 2, pp. 7252-7261, Apr. 2009.

[11] M. J. Schulz and M. J. Sundaresan, “Smart sensor system for structural condition monitoring of wind turbines,” Tech. Rep. NREL/SR-500-40089, Aug. 2006.

[12] K. K. Borum, M. McGugan, and P. Brondsted, “Condition monitoring of wind turbine blades,” in *Proc. 27th Risø Int. Symp. Mater. Sci.: Polymer Composite Mater. for Wind Power Turbines*, Sept. 2006, pp. 139-145.

[13] C.J. Crabtree, D. Zappala, and P.J. Tavner, “Survey of commercially available condition monitoring systems for wind turbines,” Technical Report, Durham University School of Engineering and Computing Sciences and the SUPERGEN Wind Energy Technologies Consortium, May 2014.

[14] L. G. Hansen and L. Lading, “Fundamentals for remote structural health monitoring of wind turbine blades−A preproject: Annex A−Cost-benefit for embedded sensors in large wind turbine blades,” Tech. Rep. Risø-R-1340(EN), May 2002.

[15] L. Lading, M. McGugan, P. Sendrup, J. Rheinlander, and J. Rusborg, “Fundamentals for remote structural health monitoring of wind turbine blades−A preproject: Annex B−Sensors and non-destructive testing methods for damage detection in wind turbine blades,” Tech. Rep. Risø-R-1341(EN), May 2002.

[16] P. Sendrup, “Fundamentals for remote structural health monitoring of wind turbine blades−A preproject: Annex C−Fiber transducer for damage detection in adhesive layers of wind turbine blades,” Tech. Rep. Risø-R-1342(EN), May 2002.

[17] J. D. Kristensen, M. McGugan, P. Sendrup, J. Rheinlander, J. Rusborg, A. M. Hansen, C. P. Debel, and B. F. Sorensen, “Fundamentals for remote structural health monitoring of wind turbine blades−A preproject: Annex E−Full-scale test of wind turbine blade, using sensors and NDT,” Tech. Rep. Risø-R-1333 (EN), May 2002.

[18] P. Caselitz, J. Giebhardt, T. Krüger, and M. Mevenkamp, “Development of a fault detection system for wind energy converters,” in *Proc. European Union Wind Energy Conference*, May 1996, pp. 1004-1007.

[19] M. R. Wilkinson, F. Spinato, and P. J. Tavner, “Condition monitoring of generators and other subassemblies in wind turbine drive trains,” in *Proc. IEEE Int. Symp. Diagnostics for Electric Mach., Power Electron. Drives*, Sept. 2007, pp. 388-392.

[20] S. Zaher and S. D. J. McArthur, “A multi-agent fault detection system for wind turbine defect recognition and diagnosis,” in *Proc. IEEE Lausanne Power Tech.*, Jul. 2007, pp. 22-27.

[21] P. Guo, D. Infield, and X. Yang, “Wind turbine generator condition-monitoring using temperature trend analysis,” *IEEE Trans. Sustain. Energy,* vol. 3, no. 1, pp. 124-133, Jan. 2012.

[22] D. J. Lekou, F. Mouzakis, A. A. Anastasopoulos, and D. Kourousis, “Emerging techniques for health monitoring of wind turbine gearboxes and bearings,” in *Proc. European Wind Energy Conference: Scientific Track-Operation and Maintenance*, Mar. 2009.

[23] IEEE Recommended Practice for Thermal Cycle Testing of Form-Wound Stator Bars and Coils for Large Rotating Machines - Redline, IEEE Std 1310, 2012.

[24] IEEE Guide for Temperature Monitoring of Cable Systems, IEEE Standard 1718, 2012.

[25] L. Hitchcock, "ISO Standards for Condition Monitoring," in *Proc. 1st World Congress on Engineering Asset Management*, Jul. 2006, pp. 606-613.

[26] S. Sheng, "Investigation of oil conditioning, real-time monitoring and oil sample analysis for wind turbine gearboxes," presented at the *AWEA Project Performance and Reliability Workshop*, Jan. 2011.

[27] J. Zhu, J. M. Yoon, D. He, and E. Bechhoefer, "Online particle-contaminated lubrication oil condition monitoring and remaining useful life prediction for wind turbines," *Wind Energy,* Mar. 2014.

[28] J. Zhu, J. M. Yoon, D. He, Y. Qu, and E. Bechhoefer, "Lubrication oil condition monitoring and remaining useful life prediction with particle filtering," *International Journal Prognosis and Health Management,* vol. 4, pp. 2-6, Jul. 2013.

[29] L. M. Popa, B. B. Jensen, E. Ritchie, and I. Boldea, "Condition monitoring of wind generators," in *Proc. 38th IEEE IAS Annu. Meeting*, Oct. 2003, pp. 1839-1846.

[30] O. Bennouna, N. Heraud, H. Camblong, and M. Rodriguez, "Diagnosis of the doubly-fed induction generator of a wind turbine," *Wind Eng.,* vol. 29, no. 5, pp. 431-447, Sept. 2005.

[31] W. Yang, P. J. Tavner, C. J. Crabtree, and M. Wilkinson, "Research on a simple, cheap but globally effective condition monitoring technique for wind turbines," in *Proc. Int. Conf. Elect. Mach.*, Sept. 2008, pp. 1-5.

[32] S. Djurovic, S. Williamson, W. Yang, and P. Tavner, "Condition monitoring artifacts for detecting winding faults in wind turbine DFIGs," in *Proc. European Wind Energy Conference*, Mar. 2009.

[33] D. Lu, X. Gong, and W. Qiao, "Current-based diagnosis for gear tooth breaks in wind turbine gearboxes," in *Proc. IEEE Energy Convers. Congr. Expo.*, Sept. 2012, pp. 3780-3786.

[34] D. Lu and W. Qiao, "Frequency demodulation-aided condition monitoring for drivetrain gearboxes," in *Proc. IEEE Transportation Electrification Conf. Expo.*, Jun. 2013, pp. 1-6.

[35] D. Lu and W. Qiao, "Current-based fault detection for wind turbine systems via Hilbert-Huang transform," in *Proc. IEEE PES General Meeting*, Jul. 2013, pp. 1-5.

[36] D. Lu and W. Qiao, "Adaptive feature extraction and SVM classification for real-time fault diagnosis of drivetrain gearboxes," in *Proc. IEEE Energy Convers. Congr. Expo.*, Sept. 2013, pp. 3934-3940.

[37] X. Gong, W. Qiao, and W. Zhou, "Incipient bearing fault detection via wind generator stator current and wavelet filter," in *Proc. 36th Annu. Conf. IEEE Ind. Electron. Soc.*, Nov. 2010, pp. 2615-2620.

[38] X. Gong and W. Qiao, "Bearing fault diagnosis for direct-drive wind turbines via current-demodulated signals," *IEEE Trans. Ind. Electron.,* vol. 60, no. 8, pp. 3419-3428, Aug. 2013.

[39] W. Yang, P. J. Tavner, C. J. Crabtree, and M. Wilkinson, "Cost-effective condition monitoring for wind turbines," *IEEE Trans. Ind. Electron.*, vol. 57, no. 1, pp. 263-271, Jan. 2010.

[40] X. Gong and W. Qiao, "Simulation investigation of wind turbine imbalance faults," in *Proc. Int. Conf. Power Syst. Technol.*, Oct. 2010.

[41] W. Q. Jeffries, J. A. Chambers, and D. G. Infield, "Experience with bicoherence of electrical power for condition monitoring of wind turbine blades," *IEE Proc. Vision, Image and Signal Process.,* vol. 145, no. 3, pp. 141-148, Jun. 1998.

[42] S. Watson and J. Xiang, "Real-time condition monitoring of offshore wind turbines," in *Proc. European Wind Energy Conf.*, Feb. 2006, pp. 647-654.

[43] Z. Wang and Q. Guo, "The diagnosis method for converter fault of the variable speed wind turbine based on the neural networks," in *Proc. 2nd International Conference on Innovative Computing, Information and Control*, Sept. 2007, pp. 615-615.

[44] M. Schlechtingen, I. F. Santos, and S. Achiche, "Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 1: System description," *Applied Soft Computing*, vol. 13, no. 1, pp. 259-270, Jan. 2013.

[45] Y. Zhai, D. Wang, J. Zhang, and Y. Han, "Research on early fault diagnostic method of wind turbines," *TELKOMNIKA Indonesian Journal of Electrical Engineering,* vol. 11, no. 5, pp. 2330-2341, May 2013.

[46] Y. Qiu, Y. Feng, P. Tavner, P. Richardson, G. Erdos, and B. Chen, "Wind turbine SCADA alarm analysis for improving reliability," *Wind Energy,* vol. 15, no. 8, pp. 951-966, Nov. 2012.

[47] W. Yang, R. Court, and J. Jiang, "Wind turbine condition monitoring by the approach of SCADA data analysis," *Renewable Energy,* vol. 53, pp. 365-376, May 2013.

[48] M. Schlechtingen and I. F. Santos, "Wind turbine condition monitoring based on SCADA data using normal behavior models. Part 2: Application examples," *Applied Soft Computing,* vol. 14, Part C, pp. 447-460, Jan. 2014.

[49] S. Gill, B. Stephen, and S. Galloway, "Wind turbine condition assessment through power curve copula modeling," *IEEE Trans. Sustainable Energy*, vo. 3, no. 1, pp. 94-101, Jan. 2012.

[50] A. Kusiak and A. Verma, "A data-driven approach for monitoring blade pitch faults in wind turbines," *IEEE Trans. Sustainable Energy*, vo. 2, no. 1, pp. 87-96, Jan. 2011.

[51] A. Kusiak and A. Verma, "A data-mining approach to monitoring wind turbines," *IEEE Trans. Sustainable Energy*, vo. 3, no. 1, pp. 150-157, Jan. 2011.

[52] P. Meinlschmidt and J. Aderhold, "Thermographic inspection of rotor blades." in *Proc. European Conference on Non Destructive Testing*, Sept. 2006.

[53] W. Liu, B. Tang, and Y. Jiang, "Status and problems of wind turbine structural health monitoring techniques in China," *Renewable Energy,* vol. 35, no. 7, pp. 1414-1418, Jul. 2010.

[54] X. Gong and W. Qiao, "Imbalance fault detection of direct-drive wind turbines using generator current signals," *IEEE Trans. Energy Convers.,* vol. 27, no. 2, pp. 468-476, Jun. 2012.

[55] X. Gong and W. Qiao, "Current-based mechanical fault detection for direct-drive wind turbines via synchronous sampling and impulse detection," *IEEE Trans. Industrial Electronics,* vol. 62, no. 3, pp. 1693-1702, Mar. 2015.

[56] X. An, D. Jiang, S. Li, and M. Zhao, "Application of the ensemble empirical mode decomposition and Hilbert transform to pedestal looseness study of direct-drive wind turbine," *Energy,* vol. 36, no. 9, pp. 5508-5520, Sept. 2011.

[57] N. Weller, "Acceleration enveloping-Higher sensitivity, earlier detection," *Orbit,* pp. 10-19, 2004.

[58] R. M. Jones, "Enveloping for bearing analysis," *Sound and Vibration,* vol. 30, pp. 10-15, Feb. 1996.

[59] P. Guo and N. Bai, "Wind turbine gearbox condition monitoring with AAKR and moving window statistic methods," *Energies,* vol. 4, no. 11, pp. 2077-2093, Oct. 2011.

[60] I. Antoniadou, G. Manson, N. Dervilis, T. Barszcz, W. Staszewski, and K. Worden, "Condition monitoring of a wind turbine gearbox using the empirical mode decomposition method and outlier analysis," in *Proc. 6th European Workshop on Structural Health Monitoring*, Jul. 2012, pp 1-8.

[61] Y. Amirat, V. Choqueuse, and M. E. H. Benbouzid, "Wind turbines condition monitoring and fault diagnosis using generator current amplitude demodulation," in *Proc. IEEE Int. Energy Conf. Exhibition*, Dec. 2010, pp. 310-315.

[62] P. Santos, P. Santos, L. F. Villa, A. Renones, A. Bustillo, and J. Maudes, "Wind turbines fault diagnosis using ensemble classifiers," in *Proc. 12th Ind. Conf. Advances in Data Mining. Appl. Theoretical Aspects*, Jan. 2012, pp. 67-76.

[63] F. P. G. Márquez, A. M. Tobias, J. M. P. Perez, and M. Papaelias, "Condition monitoring of wind turbines: Techniques and methods," *Renewable Energy,* vol. 46, no. 0, pp. 169-178, Oct. 2012.

[64] T. Barszcz and R. B. Randall, "Application of spectral kurtosis for detection of a tooth crack in the planetary gear of a wind turbine," *Mech. Syst. and Signal Process.*, vol. 23, no. 4, pp. 1352-1365, May 2009.

[65] R. Zimroz, J. Urbanek, T. Barszca, W. Bartelmus, F. Millioz, and N. Martin, "Measurement of instantaneous shaft speed by advanced vibration signal processing−Application to wind turbine gearbox," *Metrology Meass Syst.*, vol. 18, no. 4, pp. 701-712, Dec. 2010.

[66] C. Tsai, S. Huang, and C. Hsieh, "Inspection enhancement of wind turbine blades using novel signal-processing approaches," in *Proc. IEEE PES Power Syst. Conf. Expo.*, Mar. 2009, pp. 1-7.

[67] C. Tsai, C. Hsieh, and S. Huang, "Enhancement of damage-detection of wind turbine blades via CWT-based approaches," *IEEE Trans. Energy Convers.,* vol. 21, no. 3, pp. 776-781, Sept. 2006.

[68] S. G. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation," *IEEE Trans. Pattern Analysis and Machine Intelligence,* vol. 11, no. 7, pp. 674-693, Jul. 1989.

[69] C. Chen, C. Chen, C. Sun, Y. Zhang, and N. Wang, "Fault diagnosis for large-scale wind turbine rolling bearing using stress wave and wavelet

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIE.2015.2422394, IEEE Transactions on Industrial Electronics

analysis," in *Proc. 8th Int. Conf. Elect. Mach. Syst.*, Sept. 2005, pp. 2239-2244.

[70] S. J. Watson, B. Xiang, W. Yang, P. J. Tavner, and C. J. Crabtree, "Condition monitoring of the power output of wind turbine generators using wavelets," *IEEE Trans. Energy Convers.,* vol. 25, no. 3, pp. 715-721, Sept. 2010.

[71] Y. Guo, W. Yan, and Z. Bao, "Gear fault diagnosis of wind turbine based on discrete wavelet transform," in *Proc. 8th World Congress on Intelligent Control and Automation*, Jul. 2010, pp. 5804-5808.

[72] Y. Gritli, A. Stefani, F. Filippetti, and A. Chatti, "Stator fault analysis based on wavelet technique for wind turbines equipped with DFIG," in *Proc. International Conference on Clean Electrical Power*, Jun. 2009, pp. 485-491.

[73] E. Al-Ahmar, M. E. H. Benbouzid, Y. Amirat, and S. E. Ben Elghali, "DFIG-based wind turbine fault diagnosis using a specific discrete wavelet transform," in *Proc. 18th International Conference on Electrical Machines*, Sept. 2008, pp. 1-6.

[74] C. S. Gray and S. J. Watson, "Physics of failure approach to wind turbine condition based maintenance," *Wind Energy,* vol. 13, no. 5, p. 395-405, Jul. 2010.

[75] E. Echavarria, T. Tomiyama, and G. J. W. v. Bussel, "Fault diagnosis approach based on a model-based reasoner and a functional designer for a wind turbine: An approach towards self-maintenance," *Journal of Physics: Conference Series,* vol. 75, no. 9, p. 012078, Aug. 2007.

[76] J. Zeng, D. Lu, Y. Zhao, Z. Zhang, W. Qiao, and X. Gong, "Wind turbine fault detection and isolation using support vector machines and residual-based method," in *Proc. Amer. Control Conf.*, Jun. 2013, pp. 3661-3666.

[77] A. Zaher, S. D. J. McArthur, D. G. Infield, and Y. Patel, "Online wind turbine fault detection through automated SCADA data analysis," *Wind Energy,* vol. 12, no. 6, pp. 574-593, Sept. 2009.

[78] M. C. Garcia, M. A. Sanz-Bobi, and J. del Pico, "SIMAP: Intelligent System for Predictive Maintenance: Application to the health condition monitoring of a windturbine gearbox," *Computers in Industry,* vol. 57, no. 6, pp. 552-568, Aug. 2006.

[79] Y. Wang and D. G. Infield, "Neural network modelling with autoregressive inputs for wind turbine condition monitoring," in *Proc. International Conference on Sustainable Power Generation and Supply*, Sept. 2012, pp. 1-6.

[80] G. Hou, P. Jiang, Z. Wang, and J. Zhang, "Research on fault diagnosis of wind turbine control system based on Artificial Neural Network," in *Proc. 8th World Congress on Intelligent Control and Automation*, Jul. 2010, pp. 4875-4879.

[81] L. Ju, D. Song, B. Shi, and Q. Zhao, "Fault predictive diagnosis of wind turbine based on LM arithmetic of Artificial Neural Network theory," in *Proc. 7th International Conference on Natural Computation*, Jul. 2011, pp. 575-579.

[82] M. An, S. Park, J. Shin, H. Lim, and D. Kang, "Implementation of automatic failure diagnosis for wind turbine monitoring system based on neural network," *Multimedia and Ubiquitous Eng.,* vol. 240, no. 5, pp. 1181-1188, Jan. 2013.

[83] X. An, D. Jiang, and S. Li, "Application of back propagation neural network to fault diagnosis of direct-drive wind turbine," in *Proc. World Non-Grid-Connected Wind Power and Energy Conference*, Nov. 2010, pp. 1-5.

[84] N. Yampikulsakul, E Byon, S. Huang, S. Sheng, and M. You, "Condition monitoring of wind power system with nonparametric regression analysis," *IEEE Trans. Energy Conversion,* vol. 29, no. 2, pp. 288-299, May 2014.

[85] B. Tang, T. Song, F. Li, and L. Deng, "Fault diagnosis for a wind turbine transmission system based on manifold learning and Shannon wavelet support vector machine," *Renewable Energy,* vol. 62, pp. 1-9, Feb. 2014.

[86] D. Martinez-Rego, O. Fontenla-Romero, and A. Alonso-Betanzos, "Power wind mill fault detection via one-class v-SVM vibration signal analysis," in Proc. *2011 International Joint Conference on Neural Networks*, Jul. 2011, pp. 511-518.

[87] M. Schlechtingen and I. F. Santos, "Comparative analysis of neural network and regression based condition monitoring approaches for wind turbine fault detection," *Mech. Syst. Signal Process.,* vol. 25, no. 5, pp. 1849-1875, Jul. 2011.

[88] Z. Yang, W. Bin, X. Dong, and L. Hao, "Expert system of fault diagnosis for gear box in wind turbine," *Systems Engineering Procedia,* vol. 4, pp. 189-195, 2012.

[89] H. Li, Y. G. Hu, C. Yang, Z. Chen. H. T. Ji, and B. Zhao, "An improved fuzzy synthetic condition assessment of a wind turbine generator system," *International Journal of Electrical Power & Energy Systems,* vol. 45, no. 1, pp. 468-476, Feb. 2013.

[90] H. Liu, X. Dong, Z. Yang, and K. Zheng, "The application of intelligent fuzzy inference to the fault diagnosis in pitch-controlled system," *Energy Procedia,* vol. 16, Part C, pp. 1839-1844, May 2012.

[91] B. Chen, P. C. Matthews, and P. J. Tavner, "Wind turbine pitch faults prognosis using a-priori knowledge-based ANFIS," *Expert Systems with Applications,* vol. 40, no. 17, pp. 6863-6876, Jun. 2013.

[92] C. Chen, B. Zhang, and G. Vachtsevanos, "Prediction of machine health condition using neuro-fuzzy and Bayesian algorithms," *IEEE Trans. Instrumentation and Measurement*, vol. 61, no. 2, pp. 297-306, Feb. 2012.

[93] M. E. Orchard, "A particle filtering-based framework for on-line fault diagnosis and failure prognosis," Ph. D. disseration, Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, Georgia, Nov. 2007.

[94] M. E. Orchard and G. J. Vachtsevanos, "A particle-filtering approach for on-line fault diagnosis and failure prognosis," *Transactions of the Institute of Measurement and Control*, vol. 3, no. 3/4, pp. 221 -246, Jun. 2009.

[95] S. Sharma and D. Mahto, "Condition monitoring of wind turbine gear box," *International Journal of Research Studies in Science, Engineering and Technology*, vol. 1, no. 5, pp. 33-51, Aug. 2014

[96] G. Li and J. Shi, "Applications of Bayesian methods in wind energy conversion systems," *Renewable Energy,* vol. 43, no. 0, pp. 1-8, Jul. 2012.

[97] D. He, R. Li, and J. Zhu, "Plastic bearing fault diagnosis based on a two-step data mining approach," *IEEE Trans. Ind. Electron.*, vol. 60, no. 8, pp. 3429-3440, Apr. 2013.

[98] G. H. B. Foo, X. Zhang, and D. M. Vilathgamuwa, "A sensor fault detection and isolation method in interior permanent-magnet synchronous motor drives based on an extended Kalman filter," *IEEE Trans. Ind. Electron.*, vol. 60, no. 8, pp. 3485-3495, Apr. 2013.

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