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Sensor Fault Detection and Isolation for a Wireless Sensor Network-Based Remote Wind Turbine Condition Monitoring System

Mrs.C.Rajeswari, S.Siva, S.Pasupathi, G.Vijay , T.Prakash

Abstract **—**To improve the reliability of wind turbines, various condition monitoring systems (CMSs) have been developed and most of them transmit data using wired communication channels. Recently, wireless sensor networks (WSNs) have been used to transmit data in wind turbine CMS due to the low cost and easy deployment feature of WSNs. However, since wind turbines are installed in harsh environments, the sensors and sensor nodes used in the WSN-based wind turbines CMSs are easily subject to faults, leading to corruption of the signals used for condition monitoring, which decreases the reliability of the CMS. This paper proposes a three-stage method for detection and isolation of three most common sensor faults, i.e., SHORT fault, CONSTANT fault, and NOISE fault, in WSN-based wind turbine CMS. The proposed sensor fault detection and isolation (SFDI) greatly increases the accuracy and reliability of wind turbine CMSs. Data collected from wind turbines in the field are used to validate the effectiveness of the proposed method.

Index Terms—Condition monitoring system (CMS), cross-correlation, dynamic time warping (DTW), fault diagnosis, sensor fault, wavelet transform, wind turbine, wireless sensor network (WSN).

Mrs.C.Rajeswari Assistant Professor, Department of Electrical and Electronics Engineering, Excel College of Engineering and Technology, Namakkal, India, (Email: chandranrajes@gmail.com)
S.Siva, UG Student, Department of Electrical and Electronics Engineering, Excel College of Engineering and Technology, Namakkal, India, (Email: siva10999@gmail.com)
S.Pasupathi, UG Student, Department of Electrical and Electronics Engineering, Excel College of Engineering and Technology, Namakkal, India, (Email: pasupathirockstar800@gmail.com)
G.Vijay , UG Student, Department of Electrical and Electronics Engineering, Excel College of Engineering and Technology, Namakkal, India, (Email: vijayeeegpp@gmail.com)
T.Prakash, UG Student, Department of Electrical and Electronics Engineering, Excel College of Engineering and Technology, Namakkal, India, (Email: prakashpmk1999@gmail.com)

I. INTRODUCTION

WIND turbine condition monitoring technologies have been widely adopted in recent years to provide diagnostic information on the health condition of various wind turbine components and subsystems, which allows maintenance to be scheduled and taken before a failure or a critical malfunction occurs. Compared with offline condition monitoring techniques which require the wind turbine to be taken out of service to allow inspection by maintenance personnel, online condition monitoring enjoys the benefit of no interruption on the wind turbine operation and provides a deeper insight into the condition of wind turbine components and subsystems [1].

The online condition monitoring systems (CMSs) can be classified according to the type of sensors used (e.g., vibration, acoustic, temperature, etc.) or the method of data transmission (e.g., wired or wireless). Most commercially available wind turbine drivetrain CMSs use vibration signals because most drivetrain faults and defects will excite new vibration modes or change the existing vibration modes of the drivetrains.

A disadvantage of the vibration-based CMS is that vibration sensors and the associated data acquisition equipment have high costs. Moreover, the performance of vibration-based CMS depends on the locations of vibration sensors. The diagnosis accuracy will reduce if the sensors are placed far away from the vibration source.

Recently, wind turbine generator current signals have been used successfully for fault diagnosis of wind turbine blades, shaft, bearings, and gearboxes [2]-[5]. Compared to vibration signals, the use of generator current signals for drivetrain condition monitoring has the advantage of lower cost, nonintrusive, and independence of sensor locations. In [6], a comparative study on vibration- and current-based approaches was conducted; the effectiveness of a current-based method for wind turbine gearbox fault diagnosis was validated;

and it concluded that current signals were less sensitive to environment noise. However, sensors are subject to failures. It has been reported that sensor failures account for more than 14% of failures in wind turbines [7].

In the traditional CMSs for electric power system assets, condition monitoring data are mostly transmitted through wired communication channels. This requires installation of dedicated communication cables and regular maintenance. Compared to wired communication systems, wireless communication systems, such as wireless sensor network (WSN), have the advantages of easier installation and lower capital, installation, and maintenance costs [8] and, therefore, provide an alternative and promising technology for transmitting condition monitoring data to enhance the reliability of the electric power system assets. In this paper, WSN is adopted for collecting and transmitting generator stator current signals for wind turbine health condition monitoring and fault diagnosis.

However, the data received from a WSN can be corrupted due to malfunctions of sensors or sensor nodes or interference in the communication channels, which will reduce the accuracy of condition monitoring and fault diagnosis or even lead to false fault diagnosis. Fault-tolerant protocols have been used to verify and correct corrupted data due to interference in communication channels [9]. Therefore, only data corruptions caused by malfunctions of sensors and sensor nodes are considered in this paper and they are both called sensor faults in this paper.

This paper proposes a sensor fault detection and isolation (SFDI) method for the wind turbine condition monitoring data received from the WSN. After the SFDI, only the data from healthy sensors will be used for health condition monitoring; while the data from faulty sensors will be restored or discarded depending on the fault types. In this paper, the sensor faults are defined from a “data-centric” point of view. Three types of faults have been observed in the data of real-world applications: single-sample spikes (called a SHORT fault), anomalous constant offset (called a CONSTANT fault), and long duration noise (called a NOISE fault) [10].

These faults can be caused by malfunctions of hardware and/or software. Typical hardware-caused sensor faults include sensor damage, short circuits, low battery, and calibration errors. Software faults typically influence the data logging process and result in abnormal data, such as a SHORT fault. Several sensor fault detection methods have been proposed, which, in general, fall into four categories: rule-based method, estimation-based method, time-series-analysis-based method, and learning-based method [11]. For example, the reference [12] used multiple model adaptive estimation methods for sensor fault detection in a mobile robot. The work [13] developed a cross-validation-based technique for online detection of sensor faults. Reference [14] detected sensor faults based on the residuals calculated from observed and measured signals. Most of these methods required either historical data or a model of the system being monitored. Moreover, little work has been reported on SFDI of wind turbines [1].

According to the fault characteristics, this paper proposes different methods for detection and isolation of different types of sensor faults [15]. Specifically, a wavelet transform-based method is proposed for SHORT fault detection and isolation; a cross-correlation-based method is proposed for CONSTANT fault detection and isolation; and a dynamic time warping (DTW) based method is proposed for NOISE fault detection and isolation. None of these methods requires a model of the wind turbine and all of them can be applied online for SFDI. The proposed SFDI methods are applied to the WSN-based wind turbine CMS to improve its reliability.

The rest of this paper is organized as follows. Section II describes the proposed SFDI methods for a WSN-based wind turbine condition monitoring system. Section III presents experiment validation of the proposed method for SFDI of wind turbines equipped with a WSN-based condition monitoring system. Concluding remarks are provided in Section IV.

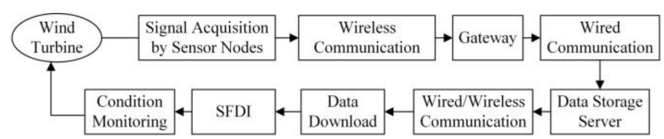


Fig. 1. Framework of a WSN-based wind turbine CMS.

II. PROPOSED SFDI METHODS FOR A WSN-BASED WIND TURBINE CONDITION MONITORING SYSTEM

The framework of the proposed WSN-based wind turbine condition monitoring system is shown in Fig. 1. First, condition monitoring signals, such as three-phase generator stator current signals, are acquired by the sensor node(s) installed in the wind turbine. Then, the data are transmitted wirelessly and received by the gateway located in the control center or substation of the wind turbine or wind farm.

Then, the data are transmitted to a server through wired communication such as Ethernet and stored on a server. Next, the data are downloaded from the server through wired or wireless communication. The signals received might be corrupted due to sensor faults. To solve this problem, SFDI is implemented for the data downloaded from the server. After the SFDI, only the healthy signals are used for condition monitoring of the wind turbine to ensure the accuracy and reliability of the CMS.

The framework of the proposed SFDI is shown in Fig. 2, which consists of three stages. The first stage uses a wavelet-transform-based method to decompose the signal into detail coefficients and approximation coefficients for the detection of SHORT faults. Once a SHORT fault is detected, the corrupted data is restored by an interpolation method. The second stage is the detection of CONSTANT faults using a cross-correlation-based method. When there is no fault in the three-phase current signals, they are highly correlated with each other. However, when a CONSTANT fault occurs, the correlation between the corrupted signal and the healthy signal will become weaker.

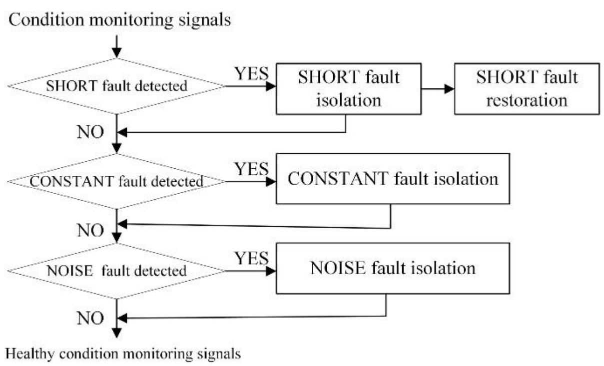


Fig. 2. Framework of the proposed SFDI method.

This information will be used for CONSTANT fault detection and isolation and only the healthy signal(s) will be used for condition monitoring. The third stage uses a DTW-based method to detect NOISE faults. The DTW-based method measures the similarity of the signals. If a signal is corrupted by a NOISE fault and the others do not, the similarity between the corrupted and healthy signals will decrease.

This information will also be used for NOISE fault isolation. By detecting and isolating the corrupted signal(s), only the healthy signal(s) are used for condition monitoring and fault diagnosis. Therefore, the reliability and accuracy of the CMS is improved. Diagnosis of sensor faults has rarely been discussed in the literature on wind turbine condition monitoring. In fact, the quality of collected condition monitoring data affects the accuracy and reliability of the fault diagnosis result; and corrupted data may even lead to a false fault diagnostic result [15].

A. Wavelet Transform-Based SHORT Fault Detection and Isolation

A SHORT fault refers to the occurrence of single-sample spikes in sensor readings. It was reported that a short circuit in a sensor node may cause a SHORT fault [11]. Therefore, detecting this type of fault is important to evaluating the health condition of the sensor node. If a SHORT fault is detected multiple times during a specified period, it indicates that maintenance is needed; otherwise, the sensor node will be damaged. The diagnosis of a SHORT fault requires a time-domain localized analysis for the signal. Wavelet transform, which decomposes a signal into elementary building blocks that are well localized in both time and frequency, can characterize the local regularity of the signal [16] and, therefore, is adopted for SHORT fault detection. A function $\psi(t)$ is said to be a wavelet if and only if its Fourier transform $\hat{\psi}(\omega)$ satisfies the following condition [16]:

$$\int_0^{+\infty} \frac{|\hat{\psi}(\omega)|^2}{\omega} d\omega = \int_{-\infty}^{0} \frac{|\hat{\psi}(\omega)|^2}{|\omega|} d\omega = c_\psi < +\infty \quad (1)$$

where c_ψ is a constant and depends on the wavelet used.

A set of template wavelets can be obtained by scaling and shifting the base wavelet $\psi(t)$ as follows:

$$\psi_{s,u}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \quad (2)$$

where $s>0$ represents the scaling parameter, which determines

the time and frequency resolutions of the wavelet $\psi\left(\frac{t-u}{s}\right)$ obtained from the scale operation. The specific values of s are inversely proportional to the frequency. The symbol u is the shifting parameter, which translates the scaled wavelet along the time axis [17].

The wavelet transform of a signal $x(t)$ is defined by:

$$wt_x(s,u) = \int_{-\infty}^{+\infty} x(t)\psi^*_{s,u}(t)\,dt \quad (3)$$

When the scaling and shifting parameters are discretized, the corresponding wavelet transform is called discrete wavelet transform (DWT). The DWT uses a pair of low-pass and high-pass wavelet filters, denoted as $h(k)$ and $g(k) = (-1)^k h(1-k)$, respectively, to decompose the signal. These filters, also known as Quadrature Mirror Filters, are constructed from a selected base wavelet function and scaling function [17] and a detailed discussion was provided in [18].

To detect a SHORT fault, the discrete signal $x[n]$ is decomposed into low frequency approximation coefficients $y_{\text{low}}[n]$ and high frequency detail coefficients $y_{high}[n]$. The one level decomposition of $x[n]$ is done by convolution of $x[n]$ with $g[n]$ and $h[n]$ expressed as follows.

$$y_{high}[n] = x[n] * g[n] \quad (4)$$

$$y_{low}[n] = x[n] * h[n] \quad (5)$$

A SHORT fault appears as abrupt changes (i.e., spikes) of one or multiple data samples in each specific period. The high frequency component of the abrupt changes appears as spikes in the detail coefficients, and the locations of the spikes in the detail coefficients indicate the locations of the corrupted data samples in the original signal caused by the SHORT fault. Therefore, the SHORT fault can be detected and isolated from the detail coefficients of the signal. When a SHORT fault is detected and isolated, the corrupted data samples of the signal can be restored by an interpolation method, such as replacing them using the average values of the data samples before and after them.

B. Cross-Correlation-Based CONSTANT Fault Detection and Isolation

A CONSTANT fault is also called a "stuck-at" fault. When it occurs, the values of data samples experience a zero or near-zero variation in a period of time longer than expected. This type of fault is often caused by a sensor hardware malfunction [11]. The traditional method of detecting this type of fault is judging whether the variation is zero for a certain period. However, it is hard to determine the length of the period. To solve this problem, a cross-correlation-based method is proposed to detect this type of fault. The cross-correlation function $R_{12}(\tau)$ between two different signals $x_1(t)$ and $x_2(t)$ is a measure of similarity between one signal and the time delayed version of another signal and is defined by:

$$R_{12}(\tau) = \int_{-\infty}^{+\infty} x_1(t)\, x_2(t-\tau)\, dt \quad (6)$$

where τ is the delay parameter or searching parameter, which is the time shift of one of the two signals [19]. For any three-phase signals, when τ is equal to the time delay between any two of them, $R_{12}(\tau)$ will reach the maximum value r_{12}, which is denoted by:

$$r_{12} = \max(R_{12}(\tau)) \quad (7)$$

When three-phase current signals are in a healthy condition, they are correlated with each other with a phase delay. If a CONSTANT fault occurs in a signal, the cross-correlations between the faulty signal and the healthy signals will decrease. Therefore, a CONSTANT fault can be detected and isolated according to the summation r_i of the cross-correlations between each signal and other signals.

$$r_i = \sum_{j=1,\, j\neq i}^{n} r_{ij} \quad (8)$$

where i and j are indices of signals and n the is total number of signals. If the ith signal has a CONSTANT fault, it will have a smaller r_i value than the other healthy signals. Unlike a SHORT fault in which only a single or a few data samples are corrupted, in a CONSTANT fault, more data samples are corrupted and some important information of the signal is lost. Therefore, once a CONSTANT fault is detected and isolated, the faulty signal is discarded and maintenance is needed for the faulty sensor if the faulty signal is critical to the control and operation of the wind turbine.

C. DTW-Based NOISE Fault Detection and Isolation

While noise is commonly present in sensor data, if the noise level is unusually high, there might be a sensor problem. An unusually high level noise may be due to a hardware failure or low battery [20]. When a NOISE fault occurs, the cross-correlations between the three-phase signals may not reduce. Therefore, the cross-correlation method is not sensitive to NOISE faults. Another commonly used method of measuring the similarity between two signals is Euclidean distance. However, Euclidean distance is effective only when the signals are in phase, but will produce a poor result if the signals are out of phase, which is the case of three-phase current signals. This paper proposes to use DTW distance to solve the problem of measuring the similarity between signals that are out of phase.

The DTW distance of two signals is computed by finding the best alignment between them. Suppose that the lengths of two signals x_1 and x_2 are n and m, respectively. To align these two signals, an $n \times m$ matrix is constructed. The element (i, j) ($i = 1, 2, \cdots, n$ and $j = 1, 2, \cdots, m$) of the matrix is equal to $(x_1[i]-x_2[j])^2$, which represents the cost to align the point $x_1[i]$ with the point $x_2[j]$. An alignment between the two signals is represented by a warping path $\mathbf{W} = [w_1, w_2, \cdots, w_k, \cdots, w_K]$, where K is the length of the warping path satisfying $\max(m, n) \le K < (m+n-1)$. The kth element of $\mathbf{W}$ is $w_k = (i, j)_k$, which represents the ith and jth data samples of x_1 and x_2, respectively. There are many warping paths in the matrix, e.g., $x_1[i]$ can be aligned with $x_2[j]$ or $x_2[j+1]$, $x_2[j+2]$, $\cdots$. The best alignment is then given by a warping path that minimizes the total cost of aligning the data samples of x_1 and x_2, and the corresponding minimum total cost is called DTW distance $DTW(x_1,x_2)$ expressed as follows [21]-[24].

$$DTW(x_1, x_2) = \arg\min_{\mathbf{W}} \sqrt{\sum_{k=1,\, w_k=(i,j)_k}^{K} (x_1[i]-x_2[j])^2} \quad (9)$$

The three-phase current signals collected from a wind turbine are out of phase and the DTW distance can be used to measure their similarity. In the case of more than two signals, the similarity between one signal x_i and the other signals can be measured by the total DTW distance D_i between the signal x_i and the other signals expressed as follows.

$$D_i = \sum_{j=1, j \neq i}^{n} DTW(x_i, x_j) \quad (10)$$

where i and j are indices of the signals and n the is total number of the signals. If the ith signal is corrupted by a NOISE fault, its D_i value will be larger than those of other healthy signals. In this way, the NOISE fault can be detected and isolated.

III.EXPERIMENTAL VALIDATION

A. Experiment Setup

Experimental studies are carried out for wind turbines equipped with WSN-based condition monitoring systems, as shown in Fig. 3 for one wind turbine used in the studies. The WSN consists of one or multiple wireless sensor nodes at the sending end and one gateway at the receiving end. One wireless sensor node (Model: V-Link®-LXRS®) is installed in the wind turbine to collect three-phase generator stator current signals at a sampling frequency of 1,000 Hz for 15 seconds as a data record.

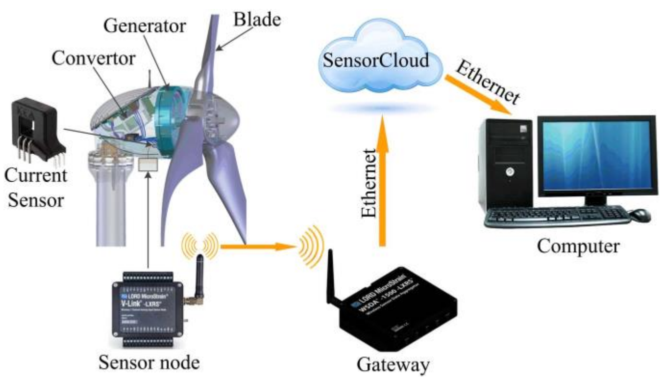


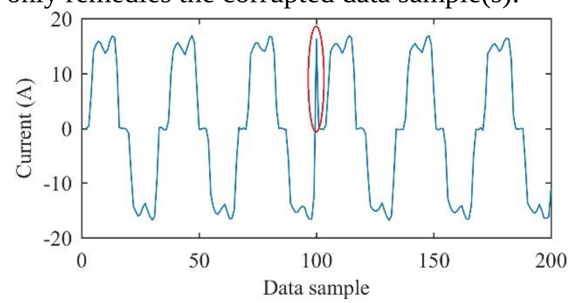
Fig. 3. Experiment Setup.

Thus, each data record contains 15,000 data samples. The data records are collected continuously with certain time intervals, such as four hours. The gateway (Model: WSDA®-1500-LXRS®) receives data from the wireless sensor node(s) and uploads the data to SensorCloud™ through Ethernet. SensorCloud™ is a network server for storing data, which can be downloaded to a terminal computer through Ethernet. The data downloaded are then used by the fault diagnostic algorithms implemented on the computer for SFDI and other wind turbine fault diagnosis.

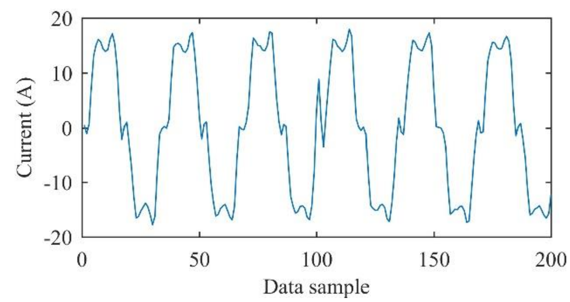
B. SHORT Fault Detection, Isolation, and Restoration

A SHORT fault causes an abrupt change (i.e., spike) in the signal. When the amplitude of the spike is much higher than the amplitude of the signal, the spike can be easily detected by comparing the maximum of the signal with a threshold. The purpose of the proposed method is to detect the SHORT fault where the magnitude(s) of the spike(s) are comparable to the signal amplitude and, therefore, are difficult to detect from the signal. To solve this problem, the proposed DWT-based method decomposes the signal into the high frequency detail coefficients and low frequency approximation coefficients. Fig. 4 shows a stator phase current signal with a SHORT fault and the one layer decomposition of the corrupted current signal by the DWT, where the SHORT fault appears clearly as an abrupt change in the detail coefficient of the signal and, therefore, can be easily detected by the proposed method; and the corrupted data sample can be easily isolated.

Each corrupted data sample is restored by replacing it with the average value of the data samples before and after it. Fig. 5 shows the restored signal. Compared with the traditional method using a low-pass filter to filter out the spikes from the signal, the proposed method does not filter out useful information from the signal, but only remedies the corrupted data sample(s).



(a)



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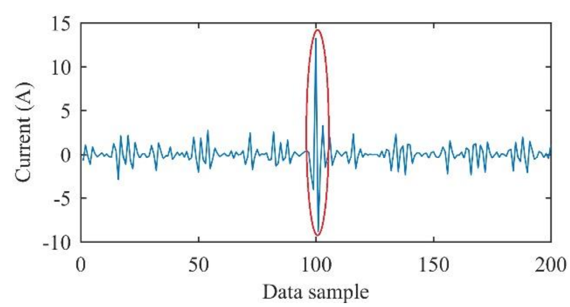


(c)

Fig. 4. Detection and isolation of a SHORT fault: (a) the corrupted stator phase current signal, (b) the approximation coefficients of the signal; and (c) the detail coefficients of the signal.

D. CONSTANT Fault Detection and Isolation

A CONSTANT fault is shown in Fig. 6 where phase-A current is “stuck” at ±11 A periodically. However, simply judging whether the variation is zero during a certain period is not a persuasive method because it is hard to determine the length of the period. Moreover, in a time interval of each switching period when the power converter is not conducting, the variation of the corresponding current signal may also be zero.

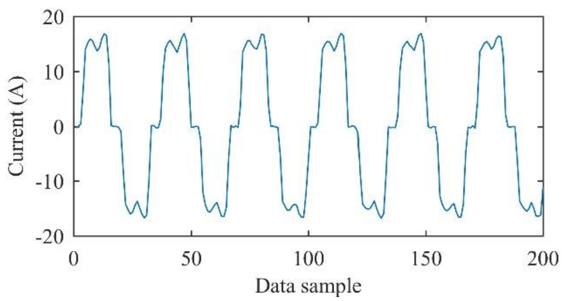


Fig. 5. Stator phase current signal after fault restoration.

Since a CONSTANT fault causes a decrease in the cross- correlation between the faulty signal and the healthy signals,

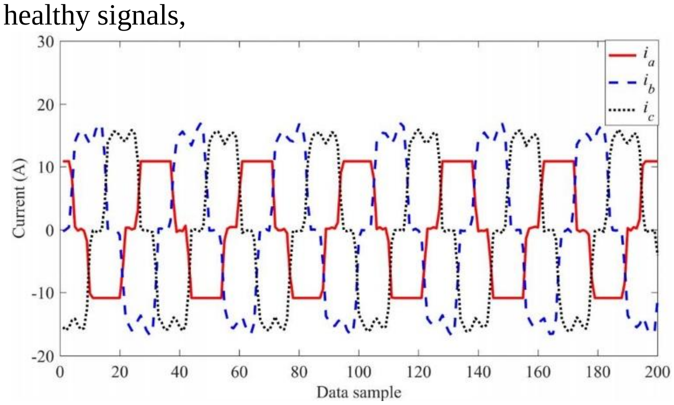


Fig. 6. Three-phase stator current signals with a CONSTANT fault in i_a.

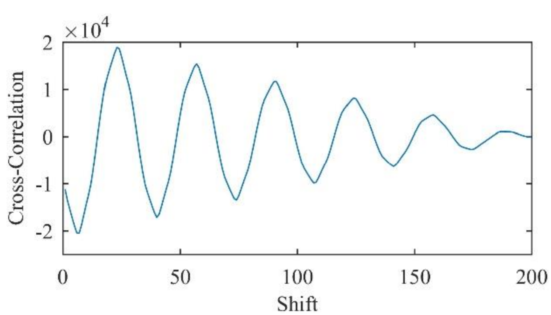


Fig. 7. Cross-correlation between i_a and i_b.

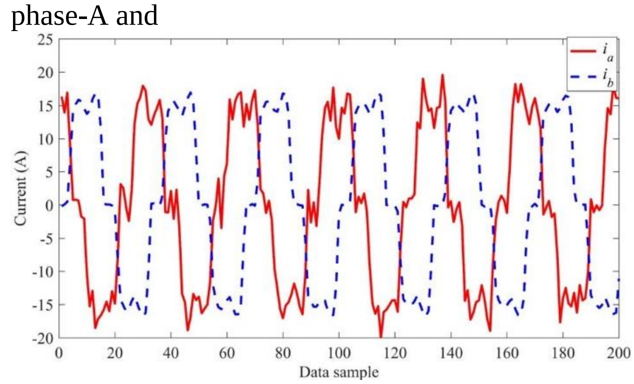
TABLE I
CROSS-CORRELATIONS BETWEEN CURRENT SIGNALS

rab	r_{bc}	r_{ac}	r_{ac}	r_{ac}	r_{ac}	r_a	r_b	r_c
2.04 ◊10^4	2.67 ◊10^4	2.01 ◊10^4	2.01 ◊10^4	2.01 ◊10^4	2.01 ◊10^4	4.05 ◊10^4	4.71 ◊10^4	4.68 ◊10^4

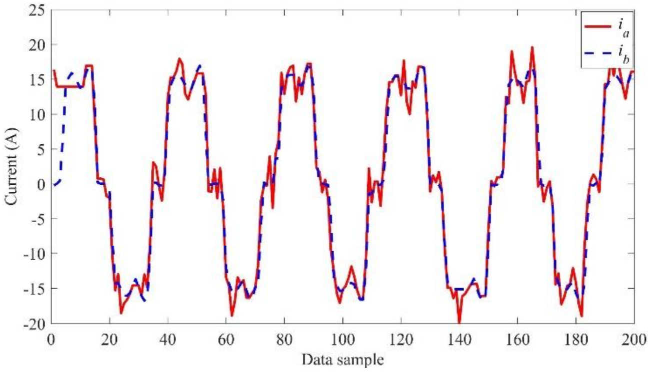
this type of fault. Fig. 7 shows the cross-correlation between phase-A and phase-B current signals. The cross-correlation reaches the maximum value when the data sample shift is 23. The method is also applied to calculate the cross-correlations between phase-B and phase-C and between phase-A and phase-C current signals. The maximum cross-correlations between the three-phase current signals are shown in Table I. It is obvious that phase-A current signal is less correlated with either phase-B or-phase C current signal and the summations of the cross-correlations of the phases A, B, and C with the other two phases, r_a, is smaller than r_b and r_c. Thus, a CONSTANT fault occurs in the phase-A current signal. When a CONSTANT fault is detected and isolated, the faulty signal will be discarded and not be used for condition monitoring of the wind turbine.

E.*NOISE Fault Detection and Isolation*

The DTW aligns two current signals and measures the distance between the aligned signals. Noise will increase the DTW distance between two signals. Assume that the phase-A current signal is corrupted by injecting artificial noise in the signal, as shown in Fig. 8(a). The amplitude of the noise is 10% of that of the signal. The resulting aligned phase-A and phase-B current signals are shown in Fig. 8(b). The method is also applied on the phase-B and phase-C as well as phase-A and



(a)



(b)

Fig. 8. A NOISE fault in the phase-A current signal: (a) original phase-A and phase-B current signals and (b) aligned current signals.

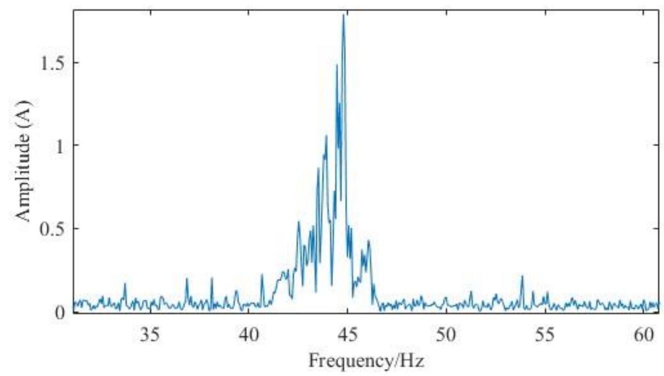


Fig. 9. Frequency spectrum of the original generator stator phase current signal around the fundamental frequency.

TABLE II
DTW DISTANCE BETWEEN ALIGNED CURRENT SIGNALS

DTW (i_a, i_b)	DTW (i_a, i_c)	DTW (i_b, i_c)	*Da*	*Db*	*Dc*
587	575	360	1162	947	935

phase-C current signals. The DTW distances between any two of the three-phase current signals are compared in Table II. The DTW distances between phases A and B and between phases A and C are larger than that between phases B and C. As a result, D_a is larger than D_b and D_c. Therefore, the faulty phase-A signal is detected and isolated and should not be used for wind turbine condition monitoring.

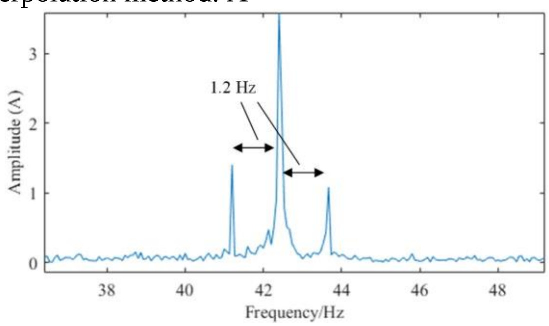
F. Wind Turbine Fault Diagnosis Results

A fault in a wind turbine drivetrain will typically excite a torsional vibration, which will modulate generator current signals. By detecting the fault characteristic frequency or frequencies in the sidebands of a current signal, the fault type in the drivetrain can be identified [25]. The corrupted or faulty signal(s) will reduce the accuracy of condition monitoring and fault diagnosis. Therefore, after the SFDI, only the healthy signal(s) or the signal(s) remedied from SHORT fault(s) are used for wind turbine fault diagnosis. To study the effect of different sensor faults on wind turbine fault diagnosis, a healthy generator stator phase current signal is first used as the baseline case. Fig. 9 shows the frequency spectrum around the fundamental frequency of the generator stator current signal. Due to the varying shaft rotating speed of the wind turbine, the collected current signals are nonstationary because the fundamental frequency and fault characteristic frequencies are proportional to the varying shaft rotating speed, causing a spectrum smearing problem. As a result, the sidebands of the fundamental frequency, which are the characteristic frequency components related to faults, cannot be easily detected.

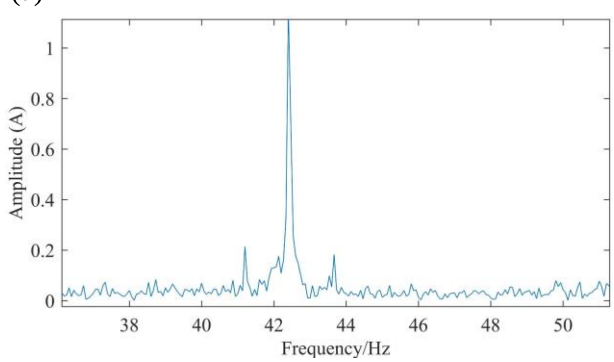
To solve the spectrum smearing problem and facilitate fault characteristic frequency identification, the synchronous resampling method proposed in [26] is used to resample the current signal with a constant phase increment in the angle domain. The resampled current signal becomes stationary, namely, the fundamental frequency and its sidebands become constant in the spectrum of the synchronously resampled current signal and, therefore, are easily detectable, as shown in Fig. 10(a). Two sidebands are visible, indicating that the current signal is modulated with the fault characteristic frequency. Therefore, the sidebands contain the information on the fault type. The sidebands in Fig. 10(a) are 1.2 Hz from the fundamental frequency, meaning that the fault characteristic frequency is 1.2 Hz, which is the characteristic frequency f_{FTFI} of the main bearing cage fault of the wind turbine. Therefore, it can be inferred that the wind turbine has a cage fault in the main bearing. Fig. 10(b) shows the frequency spectrum of the synchronously resampled current signal that has a CONSTANT fault, in which the current amplitude is clamped at ±5 A. The CONSTANT fault decreased the amplitudes of the fundamental frequency component and its sidebands, thus making the fault diagnosis difficult. Fig. 10(c) shows the frequency spectrum of the synchronously resampled current signal with a NOISE fault. As a result, the sidebands are submerged in heavy noise, which again makes the fault diagnosis difficult.

IV. CONCLUSION

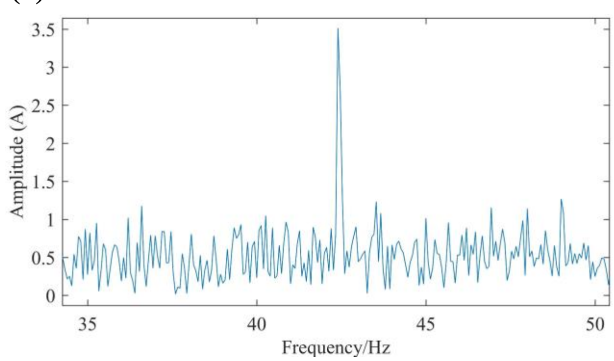
In a WSN-based CMS, the sensor data can be corrupted due to sensor faults. This paper proposed three different methods implemented sequentially to detect and isolate three common sensor faults in the WSN-based wind turbine CMS, which are SHORT fault, CONSTANT fault, and NOISE fault. For a SHORT fault, the proposed wavelet transform based method could accurately detect and isolate the corrupted data sample(s), which could be restored by an interpolation method. A



(a)



(b)



(c)

Fig. 10. Frequency spectrum of synchronously resampled current signal: (a) no sensor fault, (b) with a CONSTANT fault, and (c) with a NOISE fault.

cross-correlation-based method was proposed to detect and isolate CONSTANT faults because they would cause a decrease in the cross-correlations between the corrupted and uncorrupted signals. Moreover, a DTW-based method was proposed for detection and isolation of NOISE faults according to the similarity measured by the DTW distance between signals that are not in phase. After the SFDI, the synchronous resampling method was applied on the healthy current signal(s) for the wind turbine drivetrain fault diagnosis. The proposed method has been validated using the three-phase generator stator current data collected from wind turbines in the field in the cases of no sensor fault as well as CONSTANT and NOISE sensor faults, respectively. The results showed that the proposed method successfully detected and isolated all the sensor faults so that the wind turbine drivetrain fault diagnosis was performed successfully by using the signals from healthy sensors. Therefore, the proposed method improved the reliability of the wind turbine CMS.

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