Adaptive Fault Detection and Tracking for a Wind Turbine Generator using Kalman Filter

Adaptive Fault Detection and Tracking for a Wind Turbine Generator using Kalman Filter

Raed Khalaf Ibrahim, Abdullahi Daniyan and Simon Watson
Wolfson School of Mechanical, Electrical and Manufacturing Engineering,
Loughborough University, UK.
R.Ibrahim@lboro.ac.uk, A.Daniyan@lboro.ac.uk, S.J.Watson@lboro.ac.uk

***Abstract*—This paper describes a wind turbine (WT) condition monitoring technique that uses the measurement of stator current and rotational speed to derive a fault detection signal. The detection algorithm uses a Kalman filter (KF) to extract and track the strength of particular frequency components, characteristic of faults in the stator current signal. This has been done by an extensive simulation studies to develop an on-line detection and monitoring of mechanical faults in permanent magnet synchronous generators (PMSGs), recentlly used in modern variable-speed WTs. The model is developed and validated with operational data of five 2.5MW turbines were recorded by the supervisory control and data acquisition (SCADA) system over the period of 1 year. The simulation results show that the KF algorithm can provide a reliable indication of the presence of a fault with low computational times, from director indirect-drive fixed- or variable-speed WTs. The proposed algorithm can indicate the severity of the fault, where in contrast with traditional methods, they failed to extract the fault features from non-stationary current measurements, due to variable-speed operating conditions of WTs.**

***Index Terms*—Wind turbine, Generator, Condition monitoring, Current Signature, Fault signature, Fault detection, Diagnosis.**

I. Introduction

Wind energy has been one of the fastest growing power sources in the world over the last two decades. The worldwide wind capacity reached 392.927 GW by the end of June 2015, out of which 21.678 GW were added in the first six months of 2015 [1]. The cost of operations and maintenance (OM) has been shown to be anything between 15% and 35% of the cost of energy from wind [2], and there is a great demand to reduce OM cost. The goal can be reached by detecting and identifying the fault of WTs in early stage which gives the operator sufficient time to make more informed maintenance decision. Traditionally, WTs condition monitoring method is supervised using vibration analysis but measuring such mechanical quantities is often expensive. Indeed, vibration sensors such as piezoelectric accelerometers and associated load amplifier are often expensive. Moreover, the ability of a clear detection of mechanical faults by vibration measurements potentially depends in the sensor locations [3]. For example, accelerometers need to be mounted near to each possible faulty component of the WT. The technique is also not ideally suited to all WT types and faults [4]. It has been reported in a recent reliability survey [5] that WT electrical components have a higher failure rate than the mechanical components. As the measurement of stator currents are already available for control purposes which means no additional sensors or data acquisition devices are needed [6], so the detection based on the measurement of stator currents would be beneficial and could be more comprehensive, simpler, and cheaper than other techniques. However, there are challenges in using current measurements for WT condition monitoring and fault detection. First, it is a challenge to extract WT fault signatures from non-stationary current measurements, due to variable-speed operating conditions of WTs [7]. Moreover, the useful information in current measurements for WT usually has a low signal to noise ratio, and thus very difficult to extract without a dedicated signal processing [8].

Generally, the majority of WT condition monitoring and fault diagnosis techniques have employed the Fourier Transform (FT) to detect a fault from the stator current [9]. The limitations of the direct application of the Fourier transform methods, and their inability to localize a signal in both the time and frequency domains, was realized very early on in the development of radar and sonar detection. Thus, a number of more advanced time-frequency analysis techniques were developed in recent years in order to extract fault signatures from the monitored signal. Among these newly developed methods, the short time Fourier transform (STFT) also known as windowed Fourier transform which has been widely used to compute the spectrogram from time signal which shows the spectral density of a signal varying with time [10]. Although the STFT can be used for analyzing transient signals using a time-frequency representation, it fails to give detailed information of the fault level because the STFT can only analyze the signal with a fixed sized window for all frequencies, which leads to poor frequency resolution. Wavelet transform is another well-known method for feature extraction in the area of fault detection and diagnosis [11]. Unlike the STFT with a fixed window function, the wavelet transform involves a varied time-frequency window and can provide good localization property in both the time and frequency domain, but it suffers from inevitable issues of low resolution, interference terms, border distortion, and energy leakage [12].

The KF algorithm is a relatively new method for time-frequency analysis that is able to track the instantaneous amplitude and frequency of nonlinear and non-stationary signals [13]. Unlike, short-time Fourier transform and wavelet transform, the KF is based on an adaptive algorithm and does not use any windowing technique. Therefore, no prior knowledge of the signal is required to implement the KF. Consequently, the trade-off between time and frequency resolutions is less controversial and can be used for real-time frequency tracking. Recently, the KF has been found to be powerful and successful in condition monitoring of permanent magnet synchronous machines operating under various speed and load conditions [14], and in detection of half- as well as full broken single rotor bar fault of a squirrel-cage induction machine under various loading conditions and speeds using stator current data [15].

This paper is a continuation of the preliminary investigation into the protection of PMSG-based WTs presented in [7]. The current work investigates the application of the KF to detect mechanical failures in WTs using generator stator current signals. Successful utilization of stator currents represents a cost-effective, non-intrusive condition monitoring and fault diagnosis technique for retrofitting existing condition monitoring methods for WTs. To verify the effectiveness of the proposed algorithm, a WT simulation model is developed and validated with operational data of five 2.5MW turbines were recorded by the SCADA system over the period of 1 year. The simulation results demonstrate that the proposed method is effective in detecting mechanical faults in a variable speed machine.

II. Kalman Filter for Fault Detection and Tracking

A system whose physical process can be mathematically modelled as it changes or evolves over time is known as a dynamical system. In making inference for such a system, two models are usually considered, a state model and a measurement model. The problem of fault detection and tracking using electrical signals from a WT can be related to dynamical systems. This is so due to the fact that the operating state of a WT changes or evolves over time depending on whether the machine is operating at below the rated wind speed or above the rated, whether a fault occurs or not, whether the fault is transient or permanent and so on. The two dynamical system models mentioned above are used with the KF and applied to our problem.

The Kalman filter (KF) can be thought of as a sequential minimum mean square error (MMSE) estimator of a given signal (for example, electrical signals from a WT that is embedded in noise, where the signal is characterized by a state model [16]. The state and measurement models used in our problem are described next.

A. State Model

The state model is otherwise known as the state evolution model. In our problem, it describes the motion model of a given frequency profile, i.e. how the amplitude of a frequency changes from an observation time k to next $k+1$.

$$\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \mathbf{v}_k \tag{1}$$

where $\mathbf{x}_k$ denote a normal state with dimension $\mathbf{dx}_1$ and $\mathbf{x}_k = [f, A]^T$, where f and A denote frequency and amplitude respectively. k = 1,2,... is the time instant of the discrete model. $\mathbf{F}$ is a $\mathbf{dx}_d$ matrix that define the linear function and is known as state transition matrix. $\mathbf{v}_k$ is a $\mathbf{dx}_1$ zero mean and an independent and identically distributed (i.i.d.) process noise vector with a $\mathbf{dx}_d$ covariance matrix $\mathbf{Q}_k$.

B. Measurement Model

The measurement model maps the normal state from the state space onto the observation space. In our problem, it is given as:

$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{n}_k \tag{2}$$

where $\mathbf{z}_k$ denote the measurement received at time k, $\mathbf{H}$ is a matrix that define the transformation function and is known as the transformation matrix. $\mathbf{n}_k$ is a zero mean and an i.i.d. measurement noise vector with covariance matrix $\mathbf{C}_k$.

In order to implement the KF in our fault detection and tracking problem, we assume that both the state and measurement models are linear and Gaussian as evident from (1) and (2). Following this assumption, we formulate the KF algorithm for our problem thus:

$$\mathbf{x}_{k|k-1} = \mathbf{F}\mathbf{x}_{k-1|k-1} \tag{3}$$

$$\mathbf{M}_{k|k-1} = \mathbf{Q}_k + \mathbf{F}\mathbf{M}_{k-1|k-1}\mathbf{F}^T \tag{4}$$

$$\mathbf{x}_{k|k} = \mathbf{x}_{k|k-1} + \mathbf{K}_k(-\epsilon_k) \tag{5}$$

$$\mathbf{x}_{k-1|k-1} = \mathbf{x}_k \tag{6}$$

$$\mathbf{M}_{k|k} = \mathbf{M}_{k|k-1} - \mathbf{K}_k\mathbf{H}\mathbf{M}_{k|k-1} \tag{7}$$

where

$$\epsilon_k = \mathbf{x}_k - \mathbf{z}_k \tag{8}$$

$$\mathbf{P}_k = \mathbf{H}\mathbf{M}_{k|k-1}\mathbf{H}^T + \mathbf{C}_k \tag{9}$$

$$\mathbf{K}_k = \mathbf{M}_{k|k-1}\mathbf{H}^T\mathbf{P}_k^{-1} \tag{10}$$

where $\mathbf{z}_k$ is the signal from the WT, and $\mathbf{x}_k$ is the expected normal state. ϵ_k denote the measurement innovation and $\mathbf{P}_k$ is covariance of the innovation term ϵ_k, with $\mathbf{K}_k$ being the Kalman gain. For a matrix $\mathbf{B}$, $\mathbf{B}^T$ is its transpose. Equations (3) and (4) are the KF prediction equations and (5) and (7) are the update equations.

Notice in (5) that the Kalman gain, $\mathbf{K}_k$ is multiplied by the negative of the innovation term, ϵ_k. This is because in our approach, we are interested in detecting whether a given normal state, $\mathbf{x}_k = [f, A]^T$ changes due to fault by tracking $\mathbf{x}_k$. When a fault occurs, it will be captured by the KF algorithm and both the fault frequency, f and amplitude, A as well as the time k of the fault can be observed. The Implementation of the KF algorithm for fault detection and tracking is discussed next.

C. Implementation

At time k, observed time series electrical signals obtained from the WT are converted to the frequency domain through Fourier transform. Various known and expected fault frequencies are selected along with their acceptable normal operating amplitudes to form the normal state vector, $\mathbf{x}_k^n = [f_n, A_n]^T$, where $n = 1, \cdots, N$ and N is the number of frequency-amplitude pair selected for monitoring. N banks of KF algorithms using (3) to (7) are deployed to perform the fault detection and tracking.

The fault detection and tracking for the n-th frequency-amplitude pair is captured in $\mathbf{x}^n_{k|k}$ of eqn. (5). A 2D plot of the amplitude, A_n of the n-th frequency-amplitude pair against time, (i.e. k) from the tracked normal state, $\mathbf{x}^n_{k|k}$ can easily be used to visualize the fault profile of the n-th frequency-amplitude pair having frequency, f_n. A rise in amplitude from the normal state indicates the occurrence of a fault (of which the fault frequency, amplitude and time of occurrence are contained in $\mathbf{x}^n_{k|k}$). If this fault is transient, the observed rise will eventually fall and if the fault is permanent or fixed, the rise will remain constant or increase further depending on the severity of the fault.

III. Simulation

In order to verify the performance of the fault detection and tracking algorithm, a general model for representation of variable speed WTs was implemented in MATLAB/Simulink, including wind speed, rotor, pitch control system, drivetrain and generator model [7]. The model has been developed to facilitate the investigation of condition monitoring and effective algorithm development for fault detection. The measured wind speed data recorded by 2.5MW WT SCADA system has been used as model input to validate the response of the WT model. Figure 1 shows the response of the model to measured generator speed. It is clear the model is in good agreement with the measured data.

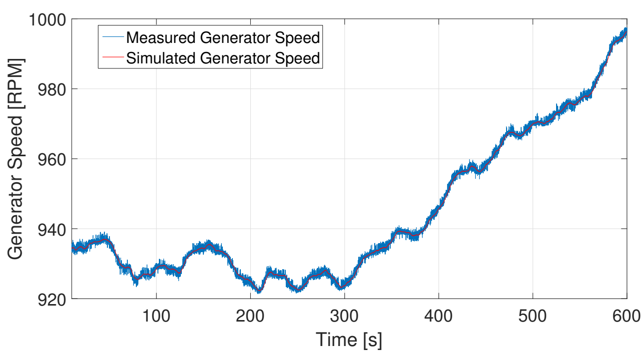
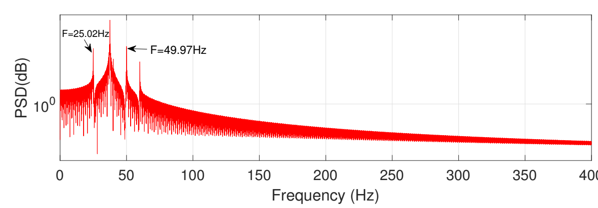


Fig. 1: Example of model validation considering generator speed.

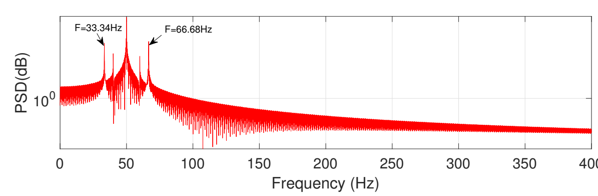
Rotor eccentricity in a variable speed WT with a permanent magnet synchronous generator (PMSG) is used as an illustrative example to investigate the use of the KF algorithm with the aim of developing knowledge based fault detection method for performing online fault detection in variable speed WTs. During rotor eccentricity, certain sideband harmonics around the fundamental frequency in the machine current signal occur and their amplitude increases proportionally with the fault level. It was experimentally proven [6] that rotor eccentricity faults actually give rise to a sequence of such sidebands given by:

$$f_c = \left(1 \pm \frac{2k_p - 1}{p}\right).f_f \tag{11}$$

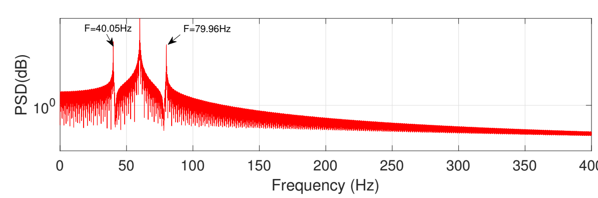
Where f_c and f_f are the rotor fault and fundamental frequency components, respectively, k_p is an integer (k_p=1, 2, 3, ...) and p is the number of pole pairs. In order to observe the excitation of sideband harmonics, known as fault signature frequencies, due to the fault, the model was run at constant sub-synchronous, synchronous and super-synchronous speeds, respectively. Figure 2 shows the stator current spectra for the faulty machine operating at three operational points under faulty rotor conditions. One can notice components with frequencies at 60 Hz and 40 Hz, which are intentionally simulated to be present in the spectra as a dynamic eccentricity. Other spectral components given by the Equation (11) are generated by the fault. However, it is clear that the fault signature frequencies are not consistent across the results. This is mainly because the fundamental frequency in PMSGs is proportional to the rotational speed so that the fault signature frequencies are shifted respect to the rotational speed value, which means that the current signals acquired from the generator terminals of the WTs are always non-stationary.



(a) constant sub-synchronous speed



(b) constant synchronous speed



(c) constant super-synchronous speed

Fig. 2: Stator current spectra for the healthy PMSG at three operational points.

Generally, WTs based PMSGs operate in variable-speed conditions owing to varying wind speeds. As a consequence, the fault signature frequencies are buried in wide-band dominant frequency components (i.e. harmonics due to variable rotational speeds) of the current signal that are irrelevant to the fault as shown in Figure 3. To solve this problem, the Kf algorithm is employed to track the magnitude of the lower fault signature frequency (LFSF) and upper fault signature frequency (UFSF),given by the Equation (11), over time form the non-stationary generator current signal.

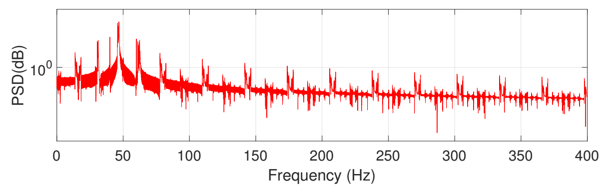


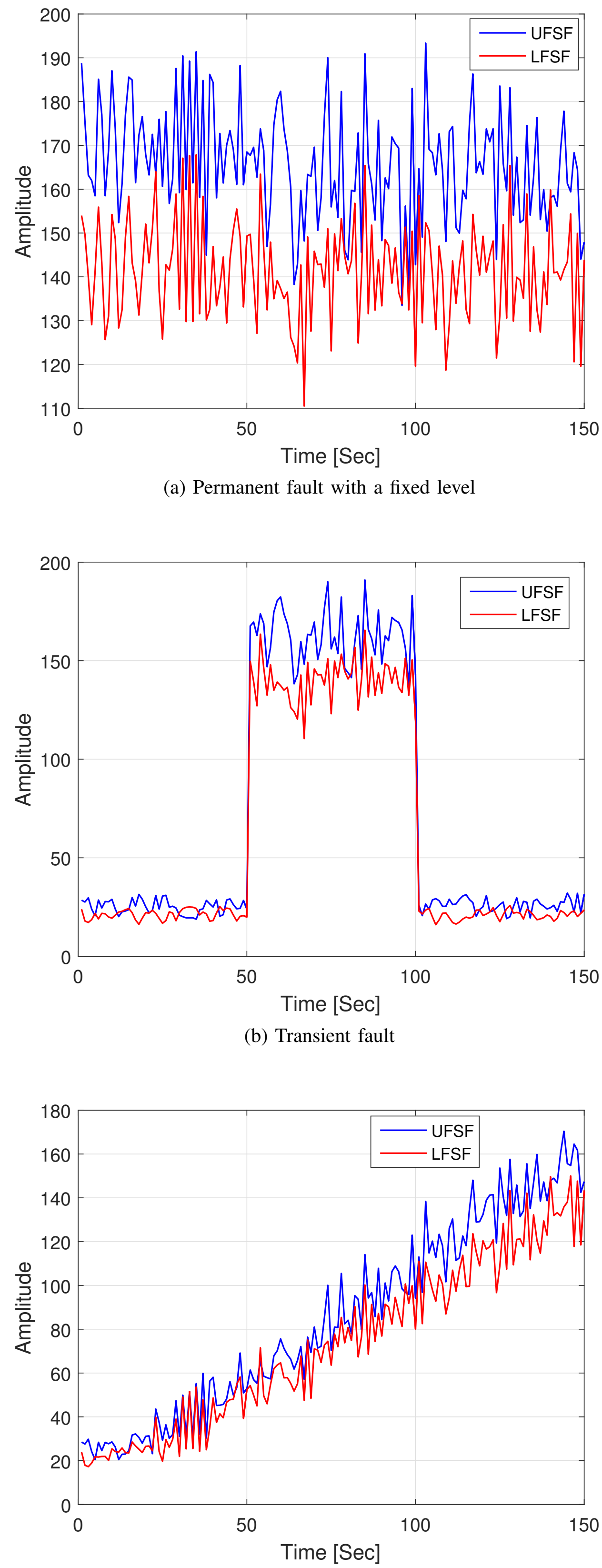
Fig. 3: Stator current spectra for the faulty PMSG at variable speed.

IV. Fault Feature Extraction

A novel algorithm is developed to employ the KF for extracting the fault features among other wide-band dominant frequency components of the current signal that are irrelevant to the fault due to variable rotational speeds. To solve this problem, a non-stationary current signal which recorded for 300 seconds is firstly splitted into 2 second intervals leading to 150 data sets. The data sets are transformed to frequency domain using the Fast Fourier Transform (FFT) algorithm. The period of two seconds is chosen as the shortest possible interval with a sufficient resolution frequency domain to capture all frequency components of interest. Secondly, the fault-related features are then extracted from the FFT spectrum of the converted stationary current signal to reconstruct a new signal for quantitative health condition evaluation of the WT. After completing the previous steps, the 150 data sets have been applied to the KF algorithm at variable speeds at different fault conditions as follow:

- Permanent fault with a fixed level during the entire time simulation,
- Transient fault during the time period from 50sec to 100 sec,
- Variable fault level increasing linearly and proportionally with time simulation,

A process is developed to extract the maximum magnitude of particular frequency among fault signature frequencies for each data set. Then the magnitude of the frequencies of interest has been tracked over time as shown in Figure 5. By doing so, it is possible to create simple graphs tracking the fault signature frequencies over time as shown in Figure 5. The results can be visually inspected to verify the presence of the fault in question as well as to identify its severity. The KF algorithm innovatively explores the impacts of faults on stator current signatures, in the sense of variations in time domain over frequency ranges, rather than the changes at a specific frequency or several specific frequencies. The proposed algorithm is especially useful for cases where no specific frequency components are available in the measured signals, or when the characteristic frequencies are non-stationary, and thus not directly observable.

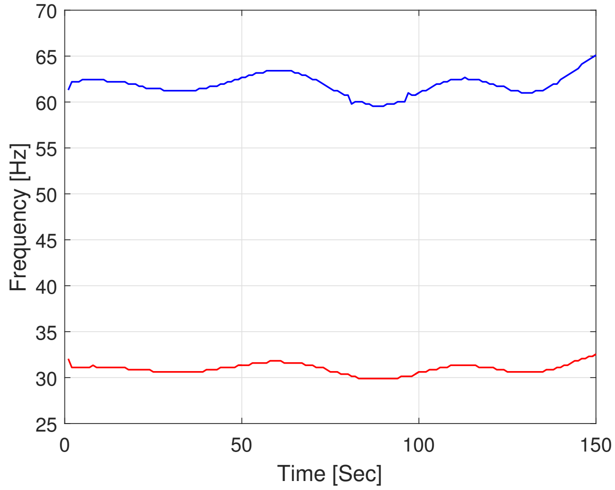


(a) Permanent fault with a fixed level

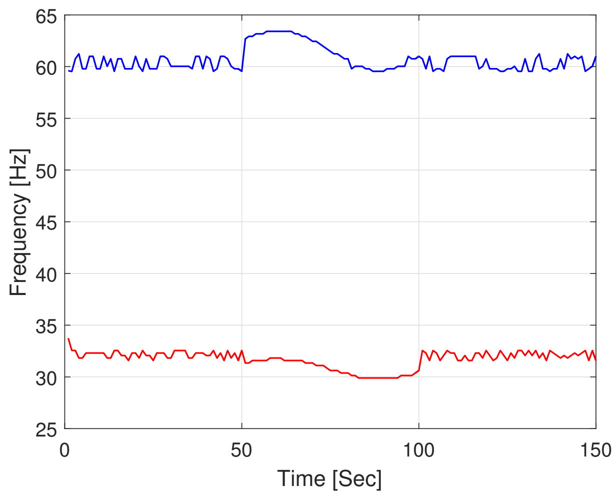
(b) Transient fault

(c) Variable fault level

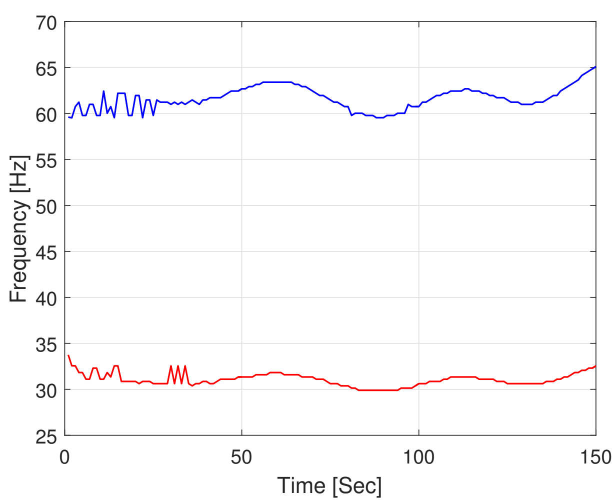
Fig. 4: Extracting the magnitude of the fault signature frequencies over time at different fault conditions.



(a) Permanent fault with a fixed level



(b) Transient fault



(c) Variable fault level

Fig. 5: Tracking the fault signature frequencies over time at different fault conditions.

V. Conclusion

The KF-based algorithm is capable of detecting mechanical faults based on time-frequency analysis by tracking the instantaneous amplitude and frequency from the current signal. It can be directly applied to the nonlinear and non-stationary signals, without prepossessing to convert the characteristics frequencies to corresponding constant values. It overcomes the drawbacks of traditional frequency-based fault detection techniques that particular characteristic frequencies related to the faults should be pre-acquired.

References

[1] The World Wind Energy Association, WWEA BULLETIN SPECIAL ISSUE 2015, [Online]: http://www.wwindea.org/wwea-bulletin-special-issue-2015/.

[2] E. Wiggelinkhuizen, T. Verbruggen, H. Braam, L. Rademakers, J. Xiang, and S. Watson, "Assessment of condition monitoring techniques for offshore wind farms," *Journal of solar energy engineering*, vol. 130, no. 3, p. 031004, 2008.

[3] Y. Amirat, M. Benbouzid, B. Bensaker, and R. Wamkeue, "Condition monitoring and ault diagnosis in wind energy conversion systems: a review," in *Electric Machines & Drives Conference, 2007. IEMDC'07. IEEE International*, vol. 2, pp. 1434–1439, IEEE, 2007.

[4] W. Yang, P. Tavner, C. Crabtree, and M. Wilkinson, "Cost-effective condition monitoring for wind turbines," *Industrial Electronics, IEEE Transactions on*, vol. 57, pp. 263–271, Jan 2010.

[5] C. Crabtree, Y. Feng, and P. Tavner, "Detecting incipient wind turbine gearbox failure: a signal analysis method for on-line condition monitoring," in *Proceedings of European Wind Energy Conference (EWEC 2010), Warsaw, Poland*, pp. 20–23, 2010.

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

[7] R. K. Ibrahim and S. Watson, "Wind turbine simulation model for the study of combined mechanical and electrical faults," in *Scientific Track Proceedings of European Wind Energy Association. EWEA*, 2015.

[8] R. K. Ibrahim and S. Watson, "Effect of power converter on condition monitoring and fault detection for wind turbine," in *Power Electronics, Machines and Drives, 2016. PEMD 2016. 8th IET Conference on*, IET, 2016.

[9] W. Jeffries, J. Chambers, and D. Infield, "Experience with bicoherence of electrical power for condition monitoring of wind turbine blades," *IEE Proceedings-Vision, Image and Signal Processing*, vol. 145, no. 3, pp. 141–148, 1998.

[10] B. Yazici and G. B. Kliman, "An adaptive statistical time-frequency method for detection of broken bars and bearing faults in motors using stator current," *IEEE Transactions on Industry Applications*, vol. 35, no. 2, pp. 442–452, 1999.

[11] S. J. Watson, B. J. Xiang, W. Yang, P. J. Tavner, and C. J. Crabtree, "Condition monitoring of the power output of wind turbine generators using wavelets," *Energy Conversion, IEEE Transactions on*, vol. 25, no. 3, pp. 715–721, 2010.

[12] Z. Peng, W. T. Peter, and F. Chu, "An improved hilbert–huang transform and its application in vibration signal analysis," *Journal of sound and vibration*, vol. 286, no. 1, pp. 187–205, 2005.

[13] H. Hajimolahoseini, R. Amirfattahi, H. Soltanian-Zadeh, and S. Gazor, "Instantaneous fundamental frequency estimation of non-stationary periodic signals using non-linear recursive filters," *IET Signal Processing*, vol. 9, no. 2, pp. 143–153, 2015.

[14] C. Wang, M. Delgado, L. Romeral, Z. Chen, F. Blaabjerg, and X. Liu, "Detection of partial demagnetization fault in pmsms operating under nonstationary conditions," 2016.

[15] F. Gu, T. Wang, A. Alwodai, X. Tian, Y. Shao, and A. Ball, "A new method of accurate broken rotor bar diagnosis based on modulation signal bispectrum analysis of motor current signals," *Mechanical Systems and Signal Processing*, vol. 50, pp. 400–413, 2015.

[16] S. Kay, *Fundamentals of Statistical Signal Processing: Estimation Theory*, vol. 1. Prentice-Hall PTR, 1993.