Advanced Algorithms for Wind Turbine Condition Monitoring and Fault Diagnosis

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***Abstract*—The work undertaken in this research focuses on advanced condition monitoring and fault detection methods for wind turbines (WTs). Fourier Transform (FFT) and Short Time Fourier transform (STFT) algorithms are proposed to effectively extract fault signatures in generator current signals (GCS) for WT fault diagnosis. With this aim, a WT model has been implemented in the MATLAB/Simulink environment to validate the effectiveness of the proposed algorithms. The results obtained with this model are validated with experimental data measured from a physical test rig. The detection of rotor eccentricity is discussed and conclusions drawn on the applicability of frequency tracking algorithms. The newly developed algorithms are compared with a published method to establish their advantages and limitations.**

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

I. INTRODUCTION

Most components in wind turbines (WTs) are subjected to different sorts of failures during the operation, including blades, yaw systems, gearboxes rotor and shaft, bearings, generators, etc. The faulty component in WTs might change the main characteristics in the monitored signal. Traditionally, WTs condition monitoring system (CMS) is supervised using vibration signals 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 [1]. For example, accelerometers need to be mounted near to each possible faulty component of the WT. To overcome this problem, the detection could be based on the measurement of stator currents which are already available for control purposes which means no additional sensors or data acquisition devices are needed [2]. However, there are challenges in using current measurements for WT CMS 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. 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.

CMS can be used to help schedule maintenance and reduce downtime [3]. However, many of these techniques evaluate WT state of health in terms of a binary state, i.e. either faulty or not. They provide technical insights and detect early abnormalities, but cannot forecast the expected degree of deterioration over a particular time frame [4]. For example, a gearbox is either broken and needs replacement or fixing, or it is fine until the next scheduled maintenance operation. CMS are carried out based using knowledge of the characteristics of signals obtained from a turbine. These signals are often non-stationary signals whose characteristics change over time due to the time-varying nature of machine operations and fault effects [5]. To date, the majority of signal processing techniques used in the condition monitoring of rotating machinery have been developed based on stationary signals and cannot reveal the time information of any frequency changes. To enable the benefits of a truly condition-based maintenance philosophy to be realized, robust, accurate and reliable algorithms, which provide maintenance personnel with the necessary information to make informed maintenance decisions, will be key. The work undertaken in this research focuses on advanced signal processing and statistical analysis techniques to lead to better remaining useful life prediction which will results in a much optimized maintenance schedule and less unscheduled maintenance events. The proposed method is based on time-frequency analysis to capture the fault frequencies from the measured signal and monitor the fault frequencies over time. This will provide the capability to potentially take historical and current data to create long-term forecasts of future asset conditions.

The following approach was taken in this paper:

- The data used in this work is recorded from a physical test rig at Durham University. Details of the data and test rig are presented in [4]. During the tests, rotor unbalance fault levels were implemented on the test rig by successively adding two additional external resistances to phase A of the rotor circuit through an external load bank. They correspond to two levels of rotor unbalance of 21% and 43%, respectively, given as a percentage of the rotor balanced phase resistance;
- A WT generator simulation model was also developed and validated with the experimental data in order to demonstrate the kind of results expected under a range of operating conditions. The model allows for certain nonlinear and time-varying characteristics and takes into account varying wind speeds similar to those experienced by WTs;
- Other aspects of this work are related to the use of the Gabor transform for time- frequency analysis. Another aspect is the observation of the change of the fault signature for different wind speed and fault level cases. This observation was connected theoretically with what is known as fault prognostics process;
- Finally, the Gabor transform for time- frequency analysis was proposed as a potential method for detecting early anomalies in WT generator operation;

II. FAULT SIGNATURE ANALYSIS IN WIND TURBINE CURRENT SIGNALS

Mechanical faults such as unbalanced load and shaft misalignments essentially create a rotor eccentricity inside the motor [6]. These types of faults introduce sideband harmonics around the fundamental frequency in the motor current spectrum. Potentially, these fault signatures could be used to detect incipient failure if they can be clearly detected during the early stages of a developing fault. It has been reported that during a rotor eccentricity event, the sideband currents are given by [7]

$$f_{ecc,d} = \left(1 \pm \frac{k(1-s)}{p}\right).f \tag{1}$$

Where $f_{ecc,d}$ and f are the rotor fault and fundamental frequency components for a doubly fed induction generator (DFIG), respectively, k is an integer (k=1, 2, 3, ...) and p the number of pole pairs.

III. SIGNAL PROCESSING TECHNIQUES FOR FAULT DETECTION

Signal processing is used in WT fault studies and is becoming an important class of tools to facilitate the extraction of fault-related features in the monitored signals, and then, the fault detection can be automated via threshold comparison or probability analysis. The fault level and location can then be identified by a classification method, such as artificial neural networks, fuzzy logic, support vector machines, etc. A key aspect of a reliable and efficient condition monitoring technique in WTs is determining which parameters should be measured and to what accuracy, as well as which signal processing methods provide the best characterization and analysis of the signals to be investigated.

A. Fast Fourier Transform

The Fast Fourier Transform (FFT) is one of the most well-known methods in the area of signal processing and has been widely used in fault diagnosis for Motors. The FFT algorithm is used to convert the time domain signal into a frequency domain signal in order to extract features related with characteristic defects. Fig. 1 shows a Fourier Transform of the stator current from the Durham test generator operating in a normal healthy state.

The upper plot is actual measured data and the lower plot is the WT generator simulation model set up using similar parameters to the test rig. The generator was driven close to a fixed rotational speed corresponding to a fixed wind speed, but with a degree of variation corresponding to a certain simulated level of wind turbulence.

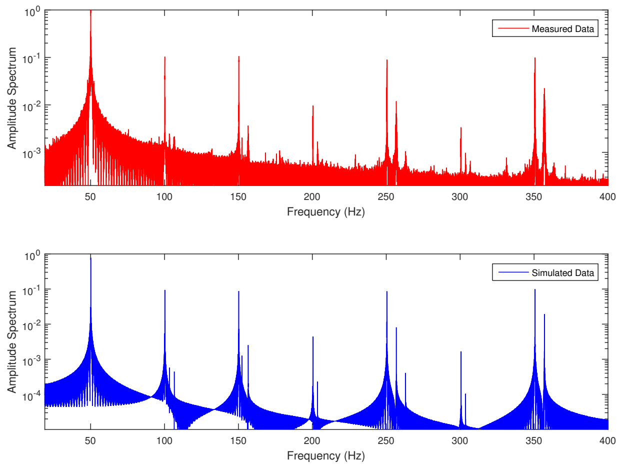

Fig. 1: The FFT of GCSs for the healthy case.

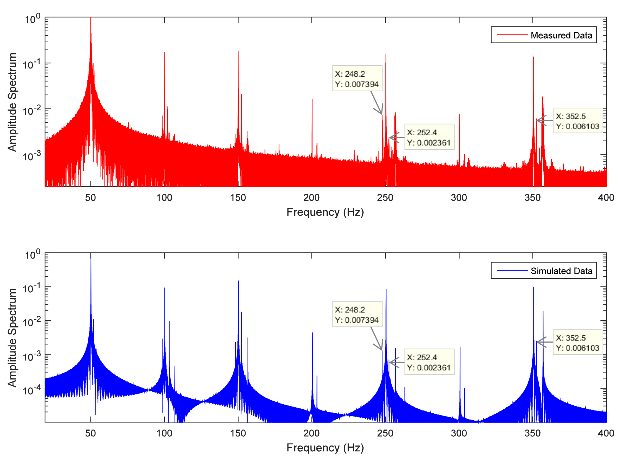

Fig. 2: The FFT of GCSs for the rotor unbalance case.

As can be seen in Fig. 1, there are unexpected harmonics around the even and odd harmonics even when operating in a healthy state (no unbalance). This might be caused by manufacturing and installation errors or might be frequency components that are apparent when the generator is first turned on. Fig. 2 shows a similar spectrum, but this time the rotor is subject to a degree of unbalance. Although the amplitudes of those frequency components in the rotor unbalance case shown in Fig. 2 are different from those in Fig. 1, it is difficult to distinguish the two cases. The fault signature frequencies are defined and labelled in Fig. 2 according to Equation (1).

B. Short Time Fourier Transform (STFT)

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. The Hungarian electrical engineer and physicist Gabor Denes (Physics Nobel Prize in 1971 for the discovery of holography in 1947) was the first person to propose a formal method for localizing both time and frequency [8]. His method is known as the short-time Fourier transform (STFT), STFT of a continuous-time signal $x(t)$ is defined as:

$$STFT(f,\tau) = \int_{-\infty}^{\infty} x(t)g(t-\tau)e^{-j2\pi ft}\,dt \qquad (2)$$

where $g(t-\tau)$ is the window function whose position is translated in time by τ. The integration over the parameter τ slides the time-filtering window along the entire signal in order to pick out the frequency information at each instant of time. Fig. 3 gives a clear illustration of how the time filtering scheme of STFT works. In this figure, the time filtering window is centered at with a width a. Thus the frequency content of a window of time is extracted and is modified to extract the frequencies of another window. The definition of the STFT captures the entire time-frequency content of the signal. Indeed, the STFT is a function of the two variables time and frequency.

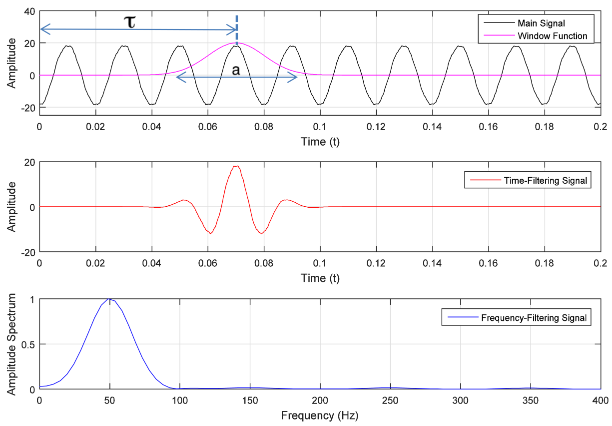

Fig. 3: Graphical illustration of the STFT for extracting the time-frequency content of a measured signal.

The key now for the STFT is to multiply the time filter function with the original signal in order to produce a windowed section of the signal. The Fourier transform of the windowed section then gives the local frequency content in time. Fig. 4 shows the generated spectrogram for the measured stator current signal for the healthy test rig generator. It is clearly seen that the measured time signal is comprised of various frequency components that are seen throughout the entire time.

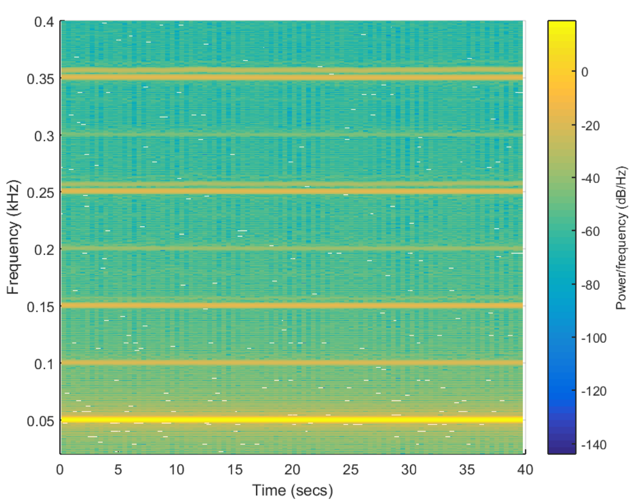

Fig. 4: The STFT of GCSs for the healthy case.

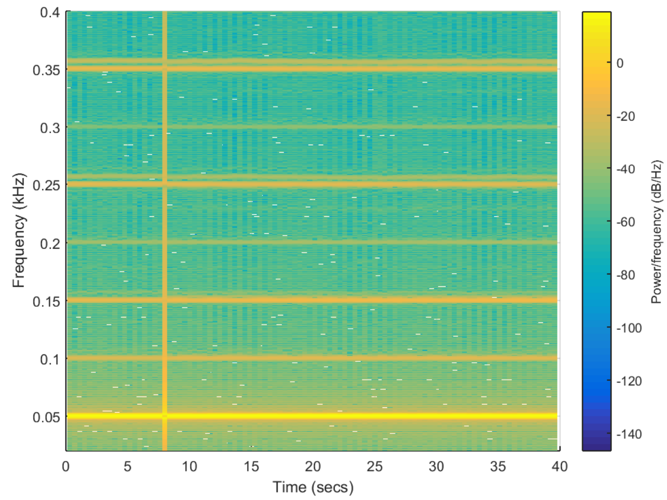

Fig. 5: The FFT of GCSs for the rotor unbalance case.

Figure 5 shows the stator current spectrogram after rotor unbalance conditions were applied. Although the fault characteristic frequency components are combined and buried in other dominant frequency components of the current signal that are irrelevant to the fault, the STFT captures the moment in time when the fault actually occurs at t=8 sec. This is clearly the main disadvantage of the STFT, and their capability to localize the frequency components of the measured signal in time domain, when compared to the Fourier transform. One could admit that this is a very apparent indication of the fault presence using this simple approach. In order to have a clear understanding of how we could use the STFT for faults prognosis, the same datasets are used again in the next example (Figure 6), this time after applying transient rotor unbalance fault from t=20sec to t=30 sec to see if we can still forecast the fault over time. What is shown here is that the fault signature frequencies are seen only during the time between (20-30 sec). So it is clear from this simulation, that the proposed method can be used to provide the capability to take historical and current data to create highly accurate long-term forecasts of future asset conditions.

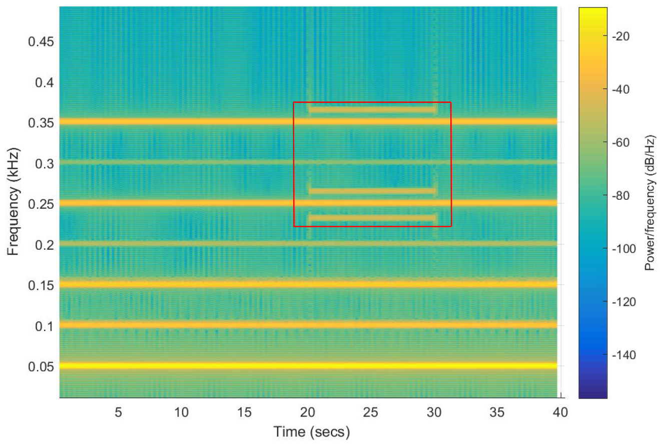

Fig. 6: The STFT of simulated GCSs for the transient fault.

IV. CONCLUSION

A new approach based on time-frequency analysis of signals has been proposed, for fault diagnosis WTs to lead to better remaining useful life prediction which will result in a much optimized maintenance schedule and less unscheduled maintenance events. The simplest novelty in this work that the use of STFT for time- frequency analysis as a potential method for detecting and forecasting early abnormalities over a substantial time. Preliminary simulation results presented highlight its advantages over the conventional Fourier transform approach, and go on to indicate its potential and suitability.

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