Title: ONLINE NONINTRUSIVE CONDITION MONITORING AND FAULT PROGNOSIS FOR WIND TURBINES

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Introduction: Wind turbine (WT) condition monitoring techniques (CMT) can be used to help schedule maintenance and reduce downtime [1]. 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 [2]. For example, a gearbox is either broken and needs replacement or fixing, or it is fine until the next scheduled maintenance operation.

CMT 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 [3]. 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.

Approach: The following approach was taken in this paper:

1. 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.
2. 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.
3. Other aspects of this work are related to the use of the *Gábor 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.
4. Finally, the *Gábor transform* for time- frequency analysis was proposed as a potential method for detecting early anomalies in WT generator operation.

Main Body of Abstract: The Fourier transform is one of the most well-known methods in the area of signal processing and has been widely used in CMT and fault diagnosis for WTs. The Fourier transform is used to convert the time domain signal into a frequency domain signal in order to extract features related with characteristic defects.

Djurovic et al. [4] looked at the effectiveness of stator current spectra for detecting rotor unbalance in a WT driven doubly-fed induction generator. Their simulation results showed that the frequency signature of rotor unbalance could be well identified using a Fourier transform. Although the Fourier transform based method can be used to detect faults before they turn into failures, it does not forecast the expected level of deterioration over a given time frame. This is mainly because when a measured time signal is transformed to the frequency domain, the frequency content of the signal can be captured with the transform, but the transform fails to capture the moment in time when various frequencies actually occur.

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. 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 [4].

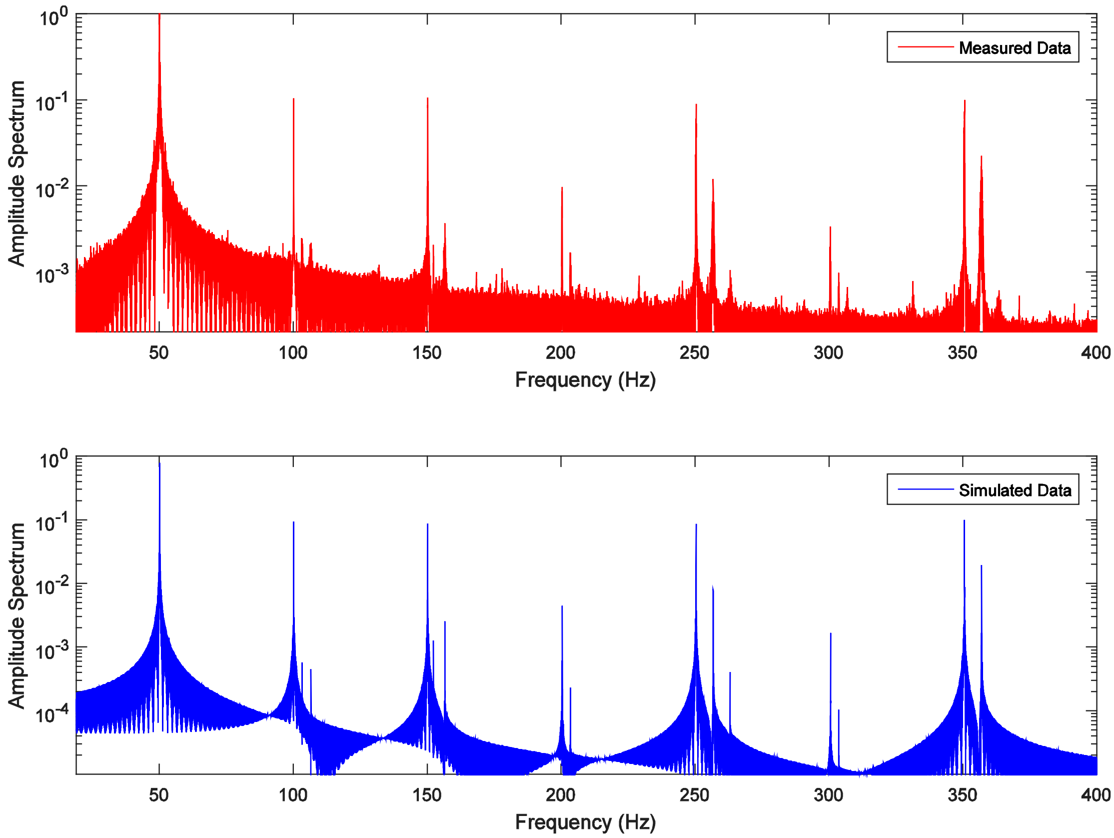

Figure 1: The Fourier transform of generator current signals for the healthy case.

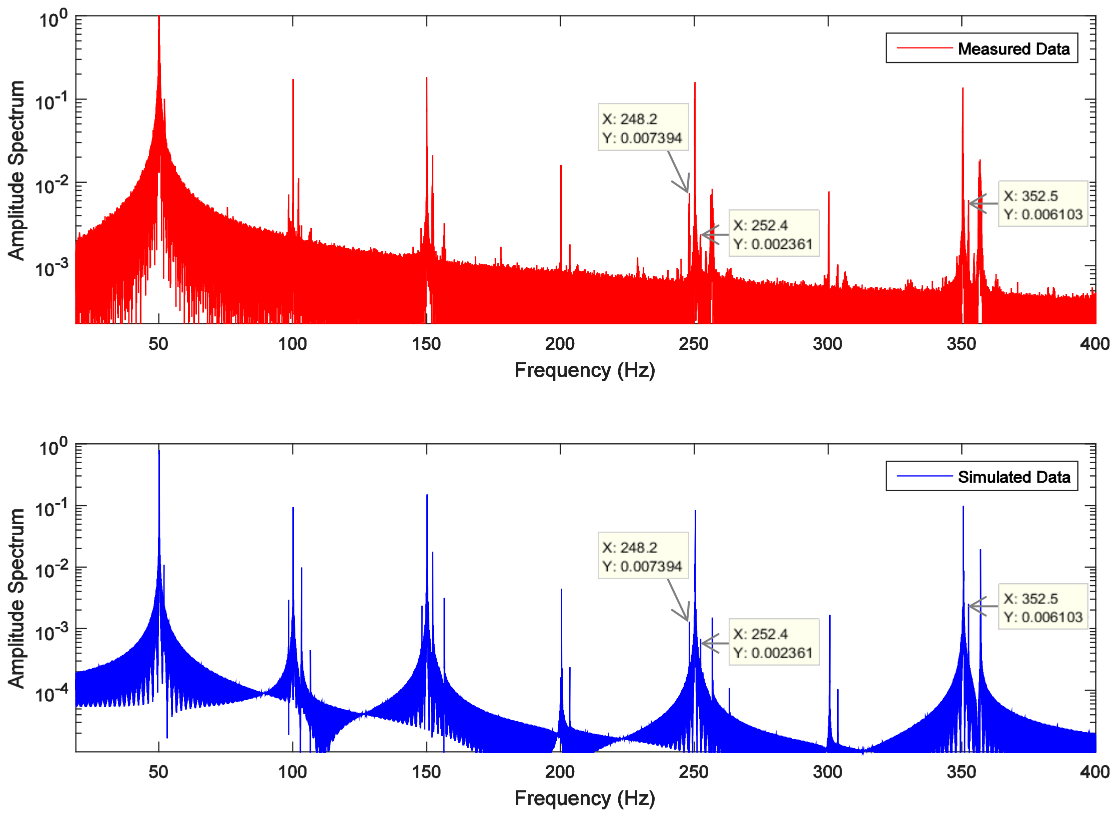

Figure 2: The Fourier transform of generator current signals for the rotor unbalance case.

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 Gábor Dénes (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 [5]. His method involved a simple modification of the Fourier transform kernel:

$$g_{t,\omega}(\tau) = e^{i\omega\tau} g(\tau - t) \tag{1}$$

where the new term incorporated into the Fourier kernel $g(\tau - t)$ was introduced with the aim of localizing both time and frequency. The Gâbor transform, also known as the short-time Fourier transform (STFT) is then defined as the following:

$$\mathcal{G}[f](t,\omega) = \tilde{f}_g(t,\omega) = \int_{-\infty}^{\infty} f(\tau)\bar{g}(\tau - t)e^{-i\omega\tau} d\tau = (f, \bar{g}_{t,\omega}) \tag{2}$$

where $g(\tau - t)$ 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 Gábor works. In this figure, the time filtering window is centered at τ with a width a. Thus the frequency content of a window of time is extracted and τ is modified to extract the frequencies of another window. The definition of the Gábor transform captures the entire time-frequency content of the signal. Indeed, the Gábor transform is a function of the two variables time and frequency.

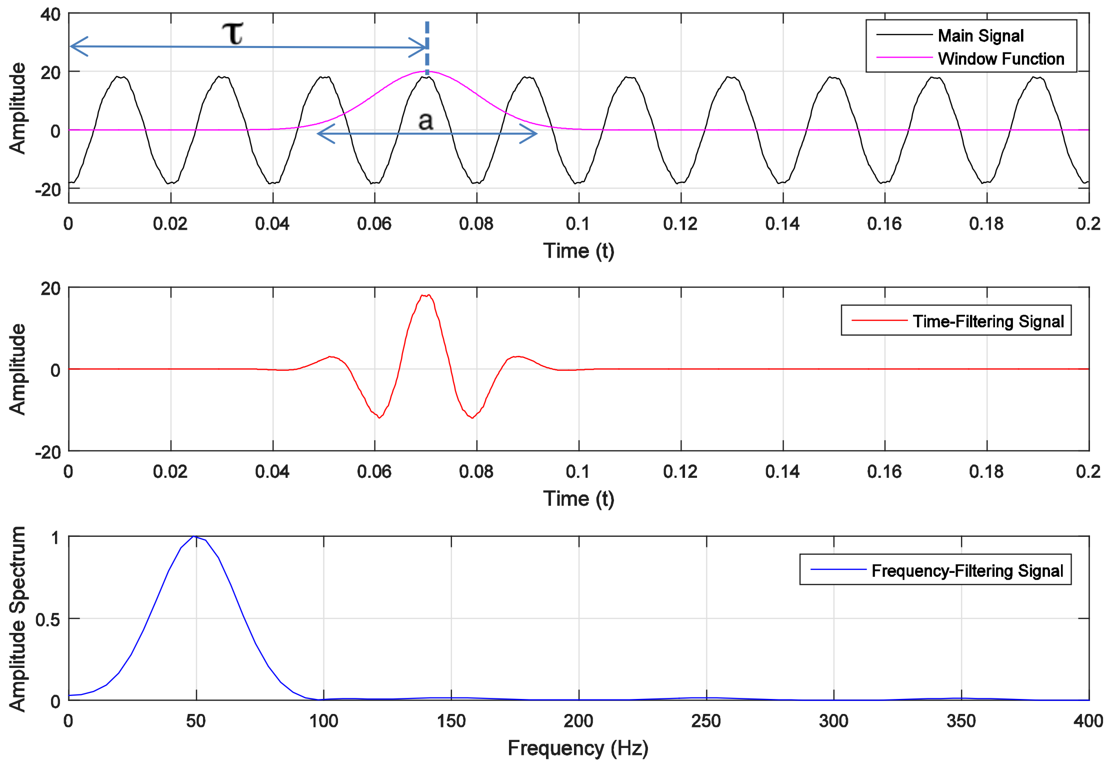

Figure 3: Graphical illustration of the Gábor transform for extracting the time-frequency content of a measured signal. The time filtering window $g(\tau - t)$ is centered at τ with width a.

The key now for the Gábor transform is to multiply the time filter Gábor function $g(t)$ 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.

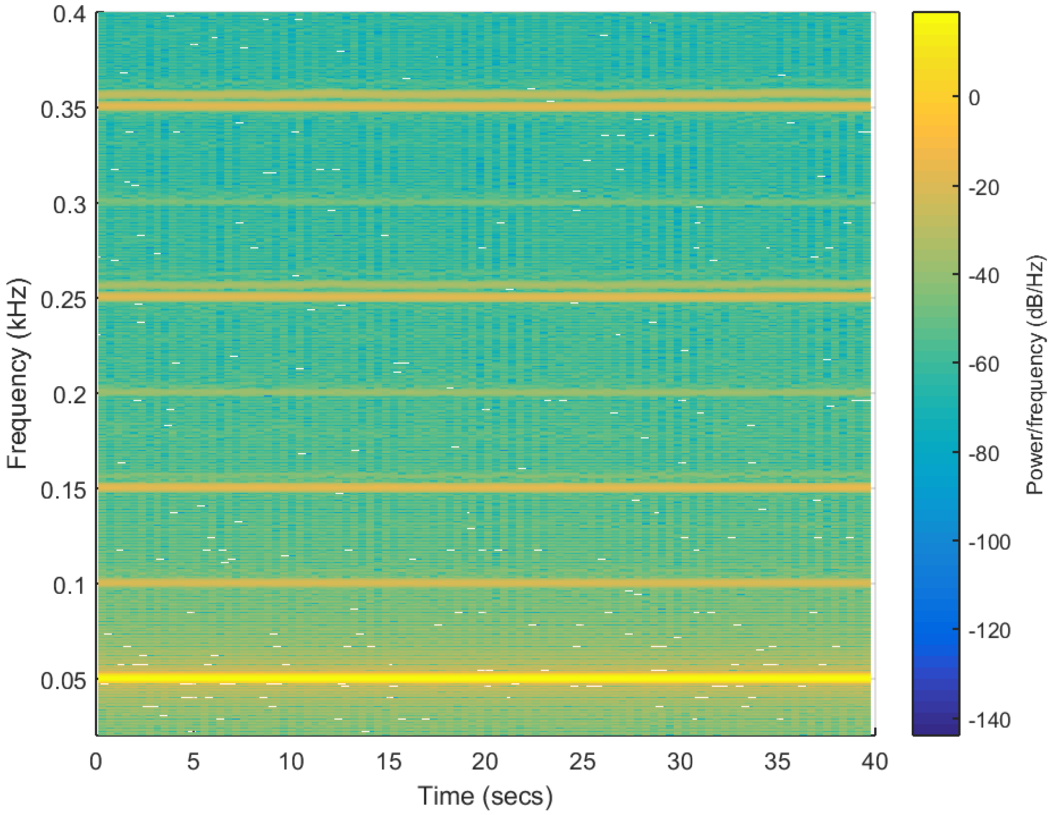

Figure 4: The Gábor transform of measured generator current signals for the healthy case.

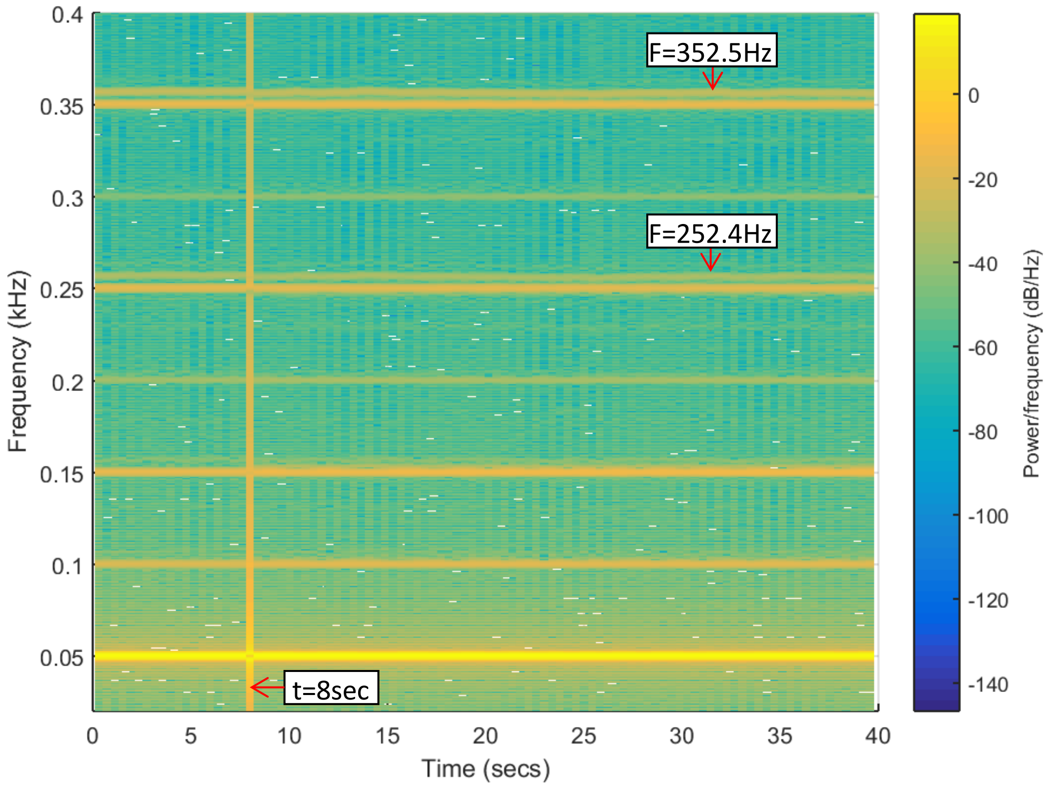

Figure 5: The Gábor transform of measured generator current signals for the rotor unbalance case.

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 Gábor transform captures the moment in time when the fault actually occurs at t=8 sec. This is clearly the main disadvantage of the Gábor transform, 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 Gábor transform 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.

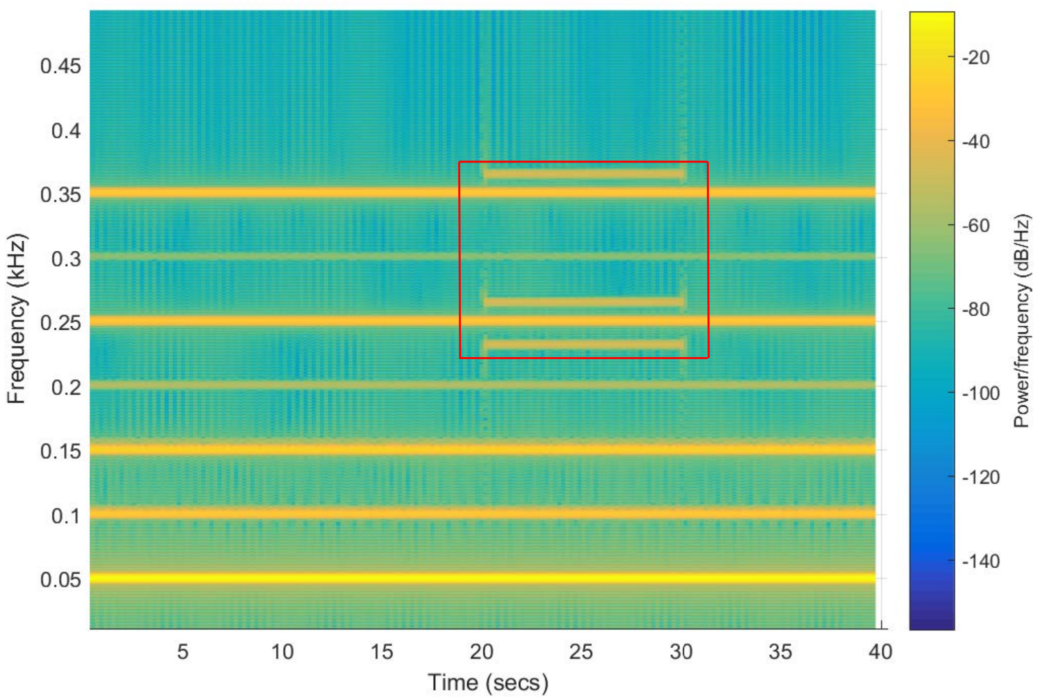

Figure 6: The Gábor transform of simulated current signals for the transient fault.

Conclusion: This paper presents an online nonintrusive condition monitoring and fault prognosis for WTs to lead to better remaining useful life prediction which will results in a much optimized maintenance schedule and less unscheduled maintenance events. The simplest novelty in this work that the use of Gábor for time- frequency analysis as a potential method for detecting and forecasting early abnormalities over a substantial time. This is a novel concept for fault prognostics applications in WTs. The submitted paper will show further analysis to provide the capabilities of the proposed prognostic solution for addressing the uncertainty challenges in predicting the remaining useful life of abatement systems, subject to uncertain future operating loads and conditions.

Learning Objectives: Learning objectives include:

1. Novel prognostic applications for existing WT condition data.
2. Compare and understand WT condition monitoring, diagnostic and prognostic methods.
3. Show the need for WT nonintrusive condition monitoring and fault prognosis.
4. Identify fault trends with time for minor repairs, major repairs and major replacements.
5. Use the proposed method for further work, such as O&M and Cost of Energy modelling.

References:

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