

REAL-TIME CONDITION MONITORING OF OFFSHORE WIND TURBINES

Simon Watson' Jianping Xiang

Centre for Renewable Energy Systems Technology (CREST), Department of Electronic and Electrical Engineering, Loughborough University, Loughborough, LE11 3TU, UK, Tel: +44 1509 222421, Fax: +44 1509 610031, email: s.j.watson@lboro.ac.uk, j.xiang@lboro.ac.uk

Abstract: Condition monitoring has been used extensively in the power industry to monitor the performance of conventional power generators. Such generators are frequently run for long periods at constant loading and spotting changes due to potential failure modes is relatively straightforward using standard signal processing techniques. The application of condition monitoring to wind turbines is relatively new and relies on the setting of relatively crude alarm levels above which a shut-down may be instigated with little information about the failure mode or possible time to failure with sufficient warning. The variable speed operation of many modern wind turbines represents both a challenge and an opportunity to the application of an 'intelligent' condition monitoring system. On the one hand a variable loading means that it can be difficult to spot a potential failure mode within a frequency spectrum. On the other hand, a variable load can excite a range of modes within a wind turbine and potentially elucidate significant information about the health of the turbine. The need for effective condition monitoring with more precise information about a particular failure mode and accurate prediction of mean time to failure becomes ever more acute within the offshore environment. In this paper, the authors present a new method that utilises the advantages of both fast fourier transforms (FFTs) and wavelets and illustrate their application to the detection of a generator bearing fault in a 1.5MW pitch-regulated variable speed wind turbine.

1 Introduction

Due to their location, offshore wind farms inevitable incur increased operation and maintenance costs compared with wind farms onshore. Indeed, it has been estimated that operations and maintenance could contribute 30% of the total energy costs for offshore wind farms [1]. These costs must be reduced in order to increase the economic competitiveness of offshore wind power. At present, research into early failure detection and diagnosis of wind turbines (and wind farms) has become an important area. However, the techniques for condition monitoring are rather new in wind power engineering and the added value for wind farm operators has not yet been demonstrated. Condition monitoring of offshore wind turbines is not an area which is yet fully established. Therefore, research work in this area is vital if pro-active condition monitoring of offshore wind farms is to become a reality. To help further this field of research, this paper describes a technique for diagnostic condition monitoring of offshore wind turbines using the power signal from a 1.5MW pitch-regulated variable speed wind turbine as part of an ongoing EU-funded project 'Condition Monitoring of Offshore Wind Turbines (CONMOW)'.

The method described in the paper is based on the spectral analysis of the power output of a wind turbine, which employs both wavelets and fast fourier transforms (FFTs) to analyse a potentially complex signal.

The output from a wind turbine generator is generally more complex than that of a conventional generator due to the continually varying driving torque from turbulent. When turbines are placed out in the field, particularly offshore, it is difficult to simulate ideal test conditions. Also, since the wind speed varies in time, the speed of the turbine rotor and the generator rotor also vary in time, changing the vibration frequencies of some components and producing large fluctuations in the power output. This means that the signals generated by potential faults in the turbines tend to be non-stationary.

Wavelets are useful for providing frequency and time information about a non-stationary signal, but precisely identifying the amplitude of the frequency component in time is more problematic. On the other hand, FFTs are difficult to apply in non-stationary situations but do give a clearly defined amplitude for a frequency component in a stationary signal. We have chosen to combine the benefits of both to find the signal amplitude and phase spectrum of a non-stationary signal. In fact, if the time range of certain signals in a non-stationary time series is identified by wavelet analysis, the amplitude and phase spectrum of the identified signals can be obtained by FFT of that certain time range. It is shown that the Morlet Wavelet transform of a signal extracts the required information. An algorithm describing how to extract the harmonic spectrum information is also described in the paper.

The method proposed is then demonstrated in the identification of a generator bearing fault that developed in a 1.5MW wind turbine.

2 Amplitude and phase spectrum calculation

First, assume that a continuous signal $x(t)$ can be described in time t by a Fourier series given by:

$$x(t) = \frac{a_0}{2} + \sum_{n=1}^{N-1} a_n \cos(n\omega t) + b_n \sin(n\omega t) \quad (1)$$

Which consists of $N-1$ multiples of the angular frequency ω where a_n and b_n are the amplitudes of each frequency component. For convenience, as we are more interested in the amplitude and phase information of the signal, we rewrite the above equation using the amplitude component A_n and phase component φ_n :

$$\begin{aligned} x(t) &= \frac{a_0}{2} + \sum_{n=1}^{N-1} \{A_n \sin \varphi_n \cos(n\omega t) + A_n \cos \varphi_n \sin(n\omega t)\} \\ &= A_0 + \sum_{n=1}^{N-1} \{A_n \sin(n\omega t + \varphi_n)\} \\ &= \sum_{n=0}^{N-1} \{A_n \sin(n\omega t + \varphi_n)\} \end{aligned} \quad (2)$$

Where:

$$a_n = A_n \sin \varphi_n \quad (3a)$$

$$b_n = A_n \cos \varphi_n \quad (4b)$$

The amplitude component A_n and phase component φ_n can be obtain from Eq. 4 thus:

$$A_n = \sqrt{a_n^2 + b_n^2} \quad (4a)$$

$$\varphi_n = \arctan\left(\frac{a_n}{b_n}\right) \quad (4b)$$

To find the amplitude component A_n and phase component φ_n , we use the Discrete Fourier Transform (DFT). Let $x[n]$ denote the discretised version of the continuous time signal $x(t)$. The DFT of $x[n]$ is given in terms of wave number k by:

$$X[k] = \sum_{n=0}^{N-1} x[n] \{ \cos(2\pi kn / N) - j \sin(2\pi kn / N) \} \quad (5)$$

The inverse DFT that recovers the signal from its spectrum is given by:

$$x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k] \{ \cos(2\pi kn / N) + j \sin(2\pi kn / N) \} \quad (6)$$

Assume the continuous signal $x(t)$ has been converted with sampling frequency f to the discrete signal $x[n]$ without aliasing. The statement $y = \text{fft}(x)$ in Matlab gives a series of spectral coefficients $X(k)$ in terms of real parts and imaginary parts [2]:

$$a(k) + ib(k) = [\text{real}(y(i))] + i[\text{imag}(y(i))] \quad k = 1, 2, \dots, N. \quad (7)$$

The amplitude component and phase component are given by:

$$A(k) = \frac{2}{N} \sqrt{a^2(k) + b^2(k)} \quad (8a)$$

$$\varphi(k) = a \tan\left(\frac{a(k)}{b(k)}\right) \quad (8b)$$

where $0 \leq |\varphi(k)| \leq \pi$.

The frequency of other harmonics is given by $f(k) = kf$, $k = 2, 3, 4, \dots, N/2$.

The program for the calculation of signal amplitude and phase spectrum has been designed using Matlab to create an algorithm that is used to detect failure harmonics.

3 Fourier transforms of continuous wavelets

A Fourier transform quantitatively describes the harmonic components of a signal, while wavelet analysis distinguishes components through an image map. The Fourier transform has been widely used in signal processing and up until now has been more acceptable than the inexplicit wavelet image method. However, the FFT is not easy to use in the case of non-stationary signals. On the contrary, wavelet analysis can extract information from non-stationary signals in both the frequency and time domains, but the amplitude spectrum of the signal is not well defined. The question then arises as to whether there is a method that can accurately detect the amplitudes of the harmonics of a non-stationary signal. To answer this question, we use a Morlet wavelet as an example in this section.

It is well known that the convolution of two sequences is equal to the product of those sequences in Fourier space. As the amplitude spectrum of a Morlet wavelet has a peak at its central frequency, the peak value of the amplitude spectrum of Morlet wavelet coefficients (resulting from a the continuous wavelet transform) can be used to find the harmonics amplitude of the signal that is convolved with the Morlet wavelet. Next we give the proof of this statement.

The wavelet transform of a signal $s(t)$ is denoted by $W_s(a, b)$ given by:

$$W_s(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(t) \psi^*\left(\frac{t-b}{a}\right) dt \quad (9)$$

The superscript * in Eq. 9 refers to the complex conjugate. Wavelet $\psi(t)$ is in general called the mother wavelet which can be transformed by scaling using the value a and time shifting using the value b . and its Fourier transform is $\psi(\omega)$.

Rewriting Eq. 9 using the variable t instead of b and the variable τ instead of t , we have:

$$W_s(a, t) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(\tau) \psi^*\left(\frac{\tau-t}{a}\right) d\tau \quad (10)$$

Eq. 10 is the convolution of the signal $s(t)$ with the time reversed wavelet $\frac{1}{\sqrt{a}} \psi\left(-\frac{t}{a}\right)$ given by [3]:

$$W_s(a, t) = s(t) * \psi_a^*(-t) \quad (11)$$

The function $\psi_a(t)$ is given by

$$\psi_a(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t}{a}\right) \quad (12)$$

The Fourier transform of the mother wavelet $\psi_a(t)$ can be derived as follows:

$$\begin{aligned}
\psi_a(\omega) &= FT[\psi_a(t)] = \int_{-\infty}^{\infty} \frac{1}{\sqrt{a}} \psi\left(\frac{t}{a}\right) e^{-j\omega t} dt \\
&= \int_{-\infty}^{\infty} [\sqrt{a} \psi\left(\frac{t}{a}\right) e^{-ja\omega\left(\frac{t}{a}\right)}] d\left(\frac{t}{a}\right) \\
&= \sqrt{a} \psi(a\omega)
\end{aligned} \tag{13}$$

According to convolution theorem, the Fourier transform of $W_s(a, t)$ is [4]:

$$W_s(a, \omega) = FT[W_s(a, t)] = S(\omega)H_a(\omega) \tag{14}$$

Now we take the Morlet wavelet as an example. The Morlet mother wavelet is [5]:

$$\psi(t) = e^{-t^2/2} \cos(5t) \tag{15}$$

The Fourier Transform is then given by:

$$\psi(\omega) = FT[\psi(t)] = \sqrt{2\pi} \{ e^{-(\omega+5)^2/2} + e^{-(\omega-5)^2/2} \} \tag{16}$$

The scaled Morlet wavelet function is:

$$\psi_a(t) = \frac{1}{\sqrt{a}} e^{-(t/a)^2/2} \cos\left(5\frac{t}{a}\right) \tag{17}$$

According to Eq. 13, the Fourier Transform of the scaled Morlet wavelet is:

$$\psi_a(\omega) = \sqrt{2\pi a} \{ e^{-(a\omega-5)^2/2} + e^{-(a\omega+5)^2/2} \} \tag{18}$$

The peak value $\max\{\psi_a(\omega)\}$ is at the central frequency $f = \frac{\omega}{2\pi} = \frac{5/2\pi}{a}$.

The ratio of the peak value to the factor \sqrt{a} is nearly a constant given by

$$\max\left\{\frac{\psi_a(\omega)}{\sqrt{a}}\right\} \approx \sqrt{2\pi} \tag{19}$$

By combining Eq. 14 and Eq. 18, we obtain the Fourier transform of $W_s(a, t)$ as:

$$W_s(a, \omega) = S(\omega)\psi_a(\omega) = S(\omega)\sqrt{2\pi a} \{ e^{-(a\omega-5)^2/2} + e^{-(a\omega+5)^2/2} \} \tag{20}$$

The top plot in Figure 1 shows the ratio of the spectrum of the Morlet wavelet to the factor \sqrt{a} at central frequencies 2.5, 2.6, 2.7, 2.8, 2.9 and 3Hz. The middle plot in Figure 1 shows the amplitude spectrum of sinusoidal signals at these central frequencies obtained by an FFT. The bottom plot in Figure 1 shows the ratio of the Fourier Transform of $W_s(a, t)$ to the factor \sqrt{a} . It is evident from Figure 1 that the amplitude spectrum of a signal can be obtained from the peak amplitude spectrum of its wavelet coefficients, *i.e.* $\max\{W_s(a, \omega)\}$.

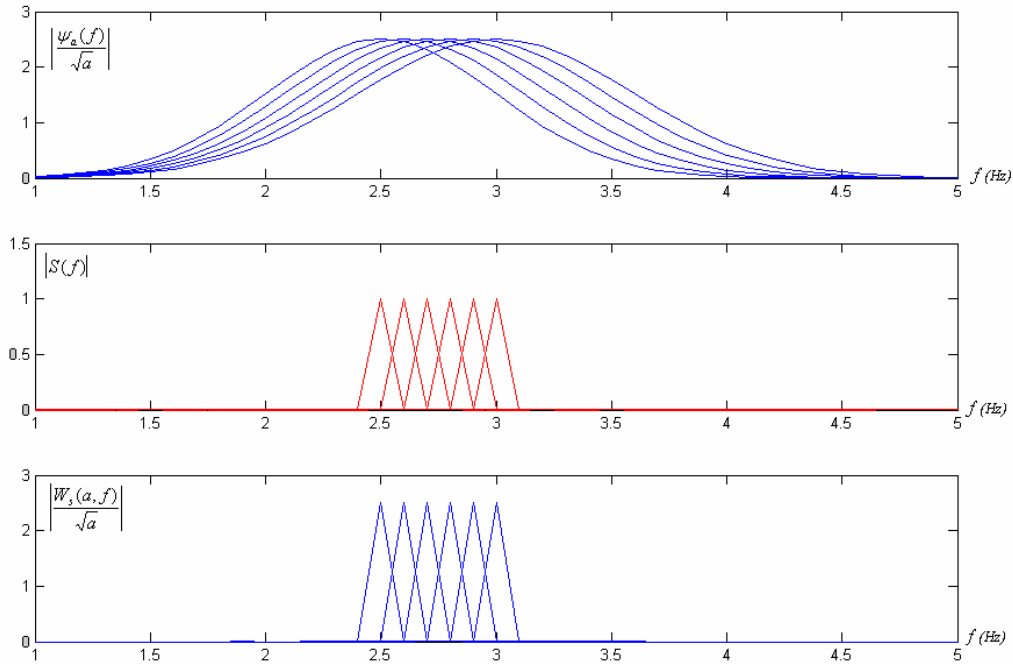


Figure 1: Top=the ratio of the spectrum of the Morlet wavelet to the factor \sqrt{a} at central frequencies 2.5, 2.6, 2.7, 2.8, 2.9 and 3Hz; Middle=the amplitude spectrum of sinusoidal signals at the central frequencies obtained by an FFT; Bottom=the ratio of the Fourier Transform of $W_s(a, t)$ to the factor \sqrt{a} .

4 Identification of frequency components from stationary signals from f wind turbines

The signals from variable speed wind turbines are complex due to the varying wind speed and the response of the controller. For example, many of the frequency components that indicate faults in the generator are related to the rotor speed, which is related to the variable speed wind. Therefore, the frequencies related to the faults are variable, which makes fault detection more difficult [6, 7]. Figure 2 shows a typical set-point controller to optimise the tip speed ratio for a variable speed wind turbine [8]. It can be seen that by selecting a narrow band of rotor speed, this corresponds to a narrow band of power. The generator signal input is the low-pass – filtered generator rotor speed in rpm, which is controlled according to the wind speed. By the use of a look-up table, the power and the rotor speed have an approximately linear relationship between the set-points. As the controlled low-pass – filtered generator rotor speed varies very slowly, the resulting vibration harmonics from the impacts of damaged elements can be detected from the power signal [9]. Figure 3 shows the the instantaneous power vs. rotor speed curve obtained from a the 1.5MW variable speed wind turbine used in this study. It can be seen that the relationship follows a series a series of set-points similar to Figure 2 though there is significant scatter as the data have not been filtered using a low-pass filter at this stage.

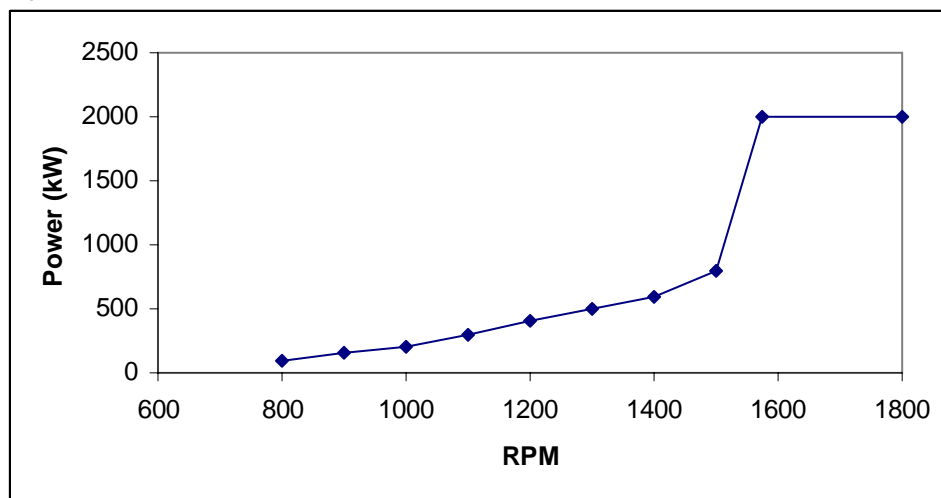


Figure 2: A typical series of set-points for the controller of a 2MW variable speed wind turbine.

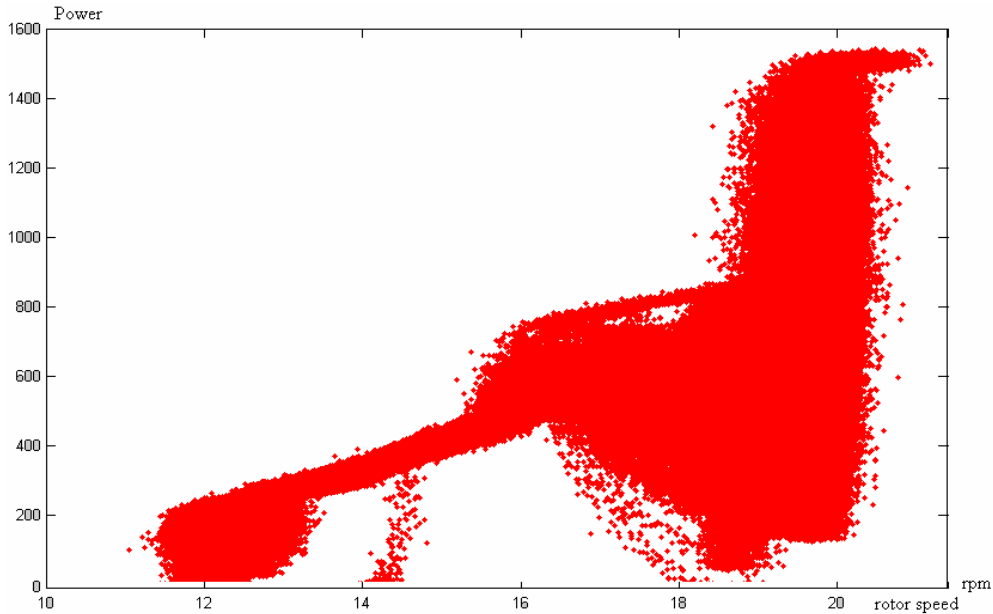


Figure 3: The instantaneous measured power (kW) against rotor speed (rpm) relationship for the 1.5MW variable speed wind turbine in this study.

For failure analysis of variable speed wind turbines, one possible method is to choose the a time period when the rotor speed and power vary in a specified range, for example, the low-pass-filtered rotor speed around 12rpm and power around 230kW. Figure 4 (a) the power signal, and (b) the related rotor speed signal measured over the period of a day on the 1.5M wind turbine used in this study.

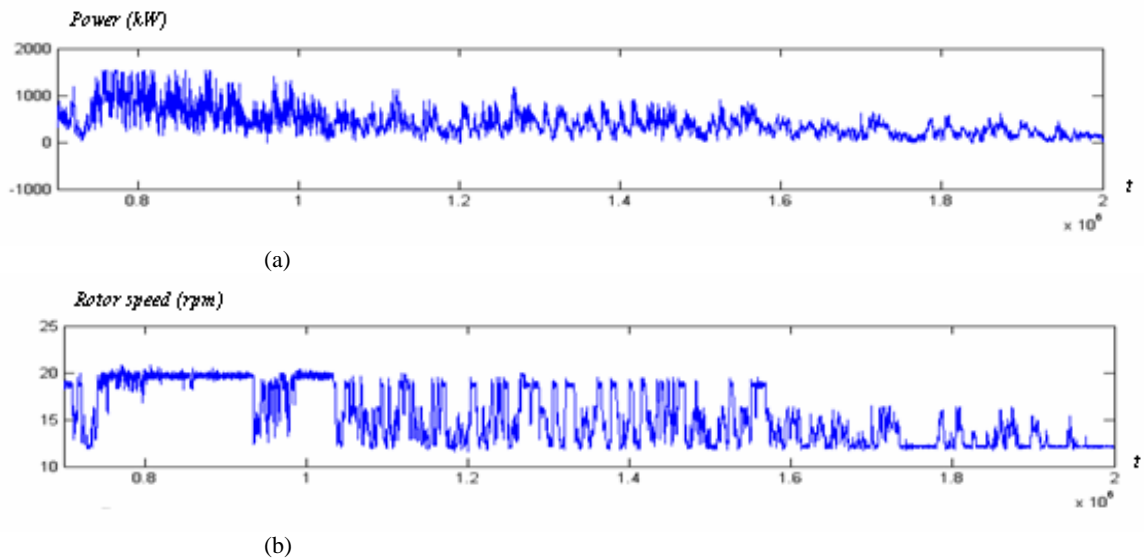


Figure 4: Variation over a day in the power output (a) and rotor speed (b) of the 1.5MW variable speed wind turbine used in this study.

Figure 5 shows the Morlet wavelet transform of a fifteen-second power signal from the 1.5MW wind turbine, with the low-pass-filtered rotor speed around 12rpm and power around 20-40kW. Its central frequency is 2.89 Hz. It is evident that the wavelet transform produces a time-frequency representation (TFR) of non-stationary signals. As mentioned above, a Fourier transform can more accurately determine the amplitude of the harmonic components and so we use the Fourier transform to find the peak amplitude spectrum of the wavelet coefficients during the given time period and hence obtain the amplitude spectrum of the power signal at a central frequency where the power signal may show mechanical faults. The analysis in Section 3 has indicated that the signal harmonic components can be obtained from the central frequency component of the Morlet wavelet transform, calculated by an FFT.

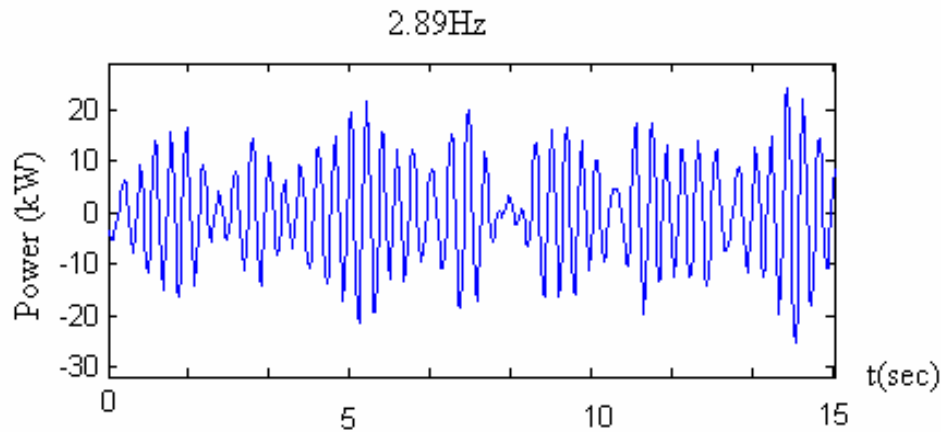


Figure 5: The Morlet wavelet transform of a fifteen-second power signal from the 1.5MW turbine, with the low-pass-filtered rotor speed around 12rpm and power around 20-40kW.

5 Example of fault detection of a wind turbine generator

During the running of AC machines, one problem is excessive noise and vibrations, which can be caused by various magnetic and electrical asymmetries (eccentricity, short-circuited stator or rotor coils, etc), bearing faults, loose stator laminations, etc. The signals such as speed, torque, vibration and power can be analysed in order to calculate the frequency component of different types of faults [10, 11].

In this section, we use the electrical power data from the 1.5MW wind turbine to verify the method proposed in this paper. Two faults were known to have occurred within the period of monitoring over a year. Software was developed to handle the large data set sampled at 30Hz, including data loading operation from binary format to Matlab data format, data limiting for setting the data range of interest, discrete Wavelet transform (DWT) digital filter to get the fault related details and Fourier transforms of wavelets transform to get a quantitative description of the harmonics. The algorithm is shown schematically in Figure 6 whereby the power signal from the wind turbine is firstly selected for a narrow range by sub-setting on the filtered rotor speed. This sub-set of values is then wavelet transformed using a Morlet wavelet and the resulting transformed data is then transformed again using a Fourier transform.. Figure 7 is the final result showing the maximum amplitude of the Fourier transformed frequency components in the range 2.5 to 3.5 Hz taken from a large data set sampled at 30 Hz.

Two failures between August 2003 to June 2004 are indicated in Figure 7, namely rotor misalignment and bearing failure. It is evident that, in general, the amplitudes of the harmonics in the frequency range of 2.5-3.0Hz are much higher before the repair of damaged components than after the repairs. It is suggested that these harmonic components are due to an asymmetrical rotor of the induction machine caused by bearing failure and misalignment. We suggest this as when the rotor of an induction machine is asymmetrical, the vibration will contain a twice slip frequency sideband ($2sf$) on the shaft frequency f_s . For the rotor speed range selected for this analysis, the predicted slip modulation would be within the range 2.2 to 3.0Hz which is consistent with our results.

The result shows the amplitude of the harmonics would seem to indicate early stage of failures, around two months before the final failure and shows that the method described based on a Fourier transform of a wavelet transform can be effective in detecting this failure.

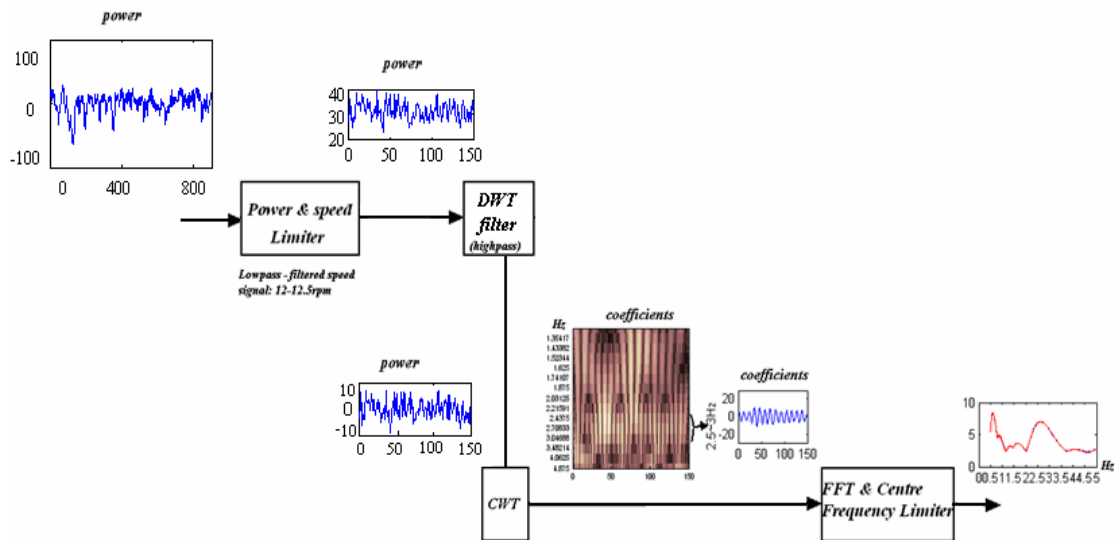


Figure 6: Schematic representation of the algorithm consisting of a wavelet transform of the filtered power data followed by a Fourier transform.

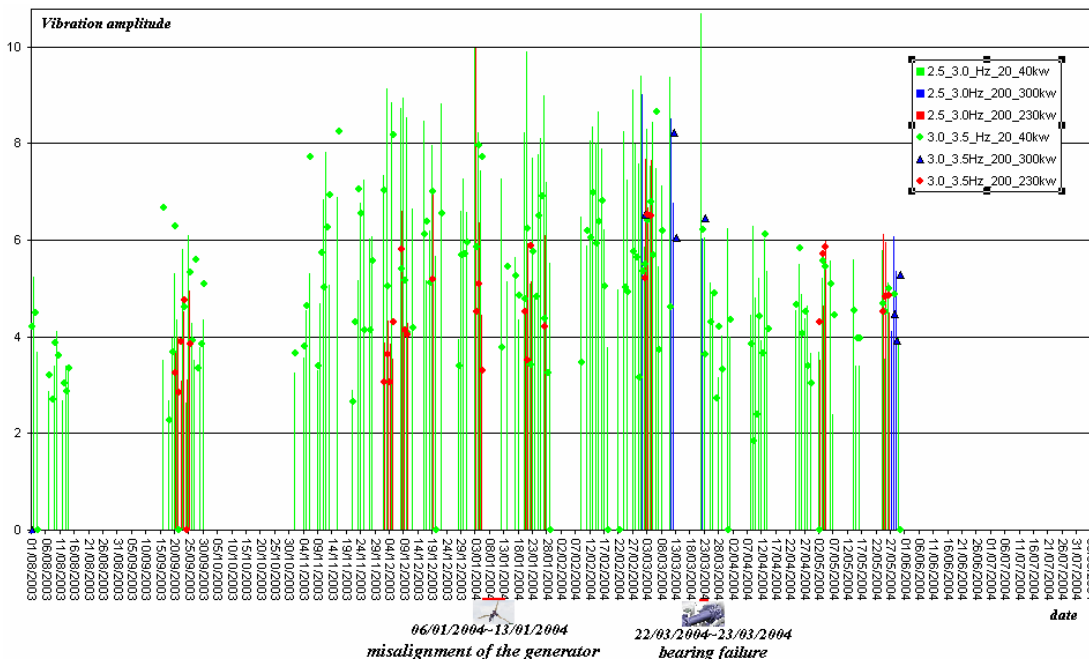


Figure 7: The maximum amplitude of the Fourier transformed frequency components in the range 2.5 to 3.5 Hz taken from a large data set sampled at 30 Hz.

6 Conclusions

The new method described in this paper based on the Fourier transform of a Wavelet transform has some advantages over other methods used for fault diagnosis of electro-mechanical devices, because this method provides not only the time and frequency information, but also the amplitude and phase information of non-stationary signals.

The paper has described an algorithm indicating the time and frequency information flow and demonstrated the application of a hybrid method for condition monitoring of a wind turbine generator. Wind turbines include many components, so different harmonic components may suggest different types of faults. The paper suggests that the Fourier analysis of wavelet coefficients according to specific frequency ranges, which are related to specific types of faults, could be important for failure detection. Furthermore, because it can be effective to observe the changes of vibration amplitude in specific frequency ranges to detect the existence of wind turbine faults, the vibration amplitude information in the range of 2.5~3.0Hz is presented in Figure 7, to demonstrate the detection of a specific fault namely rotor misalignment through bearing failure.

Finally, we have presented a relatively simple method which can be coded with appropriate software using well established transforms and can be used automatically for machine fault detection. In this study we have shown that we can detect relative levels of damage. The challenge which remains is to relate the magnitude of the signature frequency components to *absolute* levels of damage.

7 Acknowledgments

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8 References

- [1] Bussel van, G J W, Schöntag C. Operation and Maintenance Aspects of Large Offshore Windfarms. Proceedings of the 1997 European Wind Energy Conference, Dublin.
- [2] Xiang J, Mueller M A, Baker N J, Signal Processing and Modelling of a Linear Vernier Hybrid Permanent Magnet Machine, ISCP'04 (7th International Conference on Signal Processing), 2004; Beijing, China.
- [3] Abbate A., DeCusatis C M, Pank, *Wavelets and sub bands: fundamentals and applications*, 2001; Boston: Birkhauser.
- [4] Wavelet Toolbox User's Guide, http://www.mathworks.com/access/helpdesk/help/pdf_doc/wavelet/wavelet_ug.pdf, last accessed: 26/2/06.
- [5] Phillips W J. Wavelets and Filter Banks Course Notes, 2003, <http://www.engmath.dal.ca/courses/engm6610/notes/notes.html>, last accessed: 26/2/06.
- [6] Tavner P, J and Penman J. *Condition monitoring of Electrical machines*. 1987; Research Studies Press: Letchworth, UK.
- [7] Vas P. *Parameter estimation, condition monitoring, and diagnosis of electrical machines*. 1993; Clarendon Press: Oxford.
- [8] Hansen M H, Hansen A, Larsen T J, Øye S, Sørensen P and Fuglsang P, Control design for a pitch-regulated, variable speed wind turbine, Risø National Laboratory, January 2005, 84 p., ISBN 87-550-3409-8.
- [9] Legowski SF et al., Instantaneous power as a medium for the signature. analysis of induction motors., *IEEE Trans. Ind, Applicat.*, 1996; **32**: 904-909.
- [10] Nandi S, Toliyat H A. Condition monitoring and fault diagnosis of electrical machines – a review, Proc. IEEE-IEMDC Conference, 1999; Seattle: WA.
- [11] Tse P, Peng Y H, Yam R. Wavelet analysis and envelope detection for rolling element bearing fault diagnosis – their effectiveness and flexibility. *Trans ASME J Vib Acoust*; 2001: 303–310.