Condition Monitoring of a Wind Turbine Gearbox Using the Empirical Mode Decomposition Method and Outlier Analysis

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ABSTRACT

Wind turbines are subject to variable aerodynamic loads and extreme environmental conditions. Wind turbine components fail frequently, resulting in high maintenance costs. For this reason, gearbox condition monitoring becomes important since gearboxes are among the wind turbine components with the most frequent failure observations. The major challenge here is the detection of faults under the time varying operating conditions prevailing in wind turbine systems.

This paper analyses wind turbine gearbox vibration data using the empirical mode decomposition method and the statistical discipline of outlier analysis for the damage detection of gearbox tooth faults. The instantaneous characteristics of the signals are obtained with the application of the Hilbert transform. The lowest level of fault detection, the threshold value, is considered and Mahalanobis squared-distance is calculated for the novelty detection problem.

INTRODUCTION

Statistics show that the most frequent damages observed in wind turbine systems are in electrical control, blades and gearboxes and that the most responsible component for downtime is the gearbox [1]. This means that condition monitoring of wind turbine gearboxes is a necessary practice. Vibration analysis is a commonly used method for condition monitoring, and is based on the idea that the rotating machinery have a specific vibration signature for their standard condition that changes with the development of damage.

Several scientific fields, such as signal processing, statistics and neural networks have been used for structural health monitoring in general and condition monitoring more particularly. A review of such methods was written by Doebling *et al.*[2]. In the early studies, some of the conventional techniques used were the probability distribution characteristics of the vibration signals such as skewness and kurtosis [3],

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Fourier analysis and modulation sidebands [4, 5], and Cepstrum analysis [6]. However, as research in the signal processing area developed, the drawback of the assumption of stationarity and linearity of the vibration signals by these methods became more evident. To deal with nonstationary signals, attention was given to time-frequency analysis methods, such as the Wigner-Ville distribution [7], the wavelet analysis [8], Cyclostationary analysis and Spectral correlation. Wavelet analysis is probably the most popular technique [9], but has the drawback that the basic functions of the decompositions are fixed and do not necessarily match the varying nature of the signals. Relatively recently, in the quest for accurate time and frequency resolution, Huang *et al*. [10] proposed the Empirical Mode Decomposition method (EMD). Since then, attention was gained in applying the EMD in the damage detection of gears [11, 12]. This technique decomposes the signal into intrinsic mode functions and the instantaneous frequency and amplitude of each intrinsic mode function can be then obtained by applying the Hilbert Transform.

DATA DESCRIPTION

The gearbox vibration data analysed in this study come from an NEG Micon NM 1000/60 wind turbine in Poland. The gearbox is described by the following kinematic scheme:

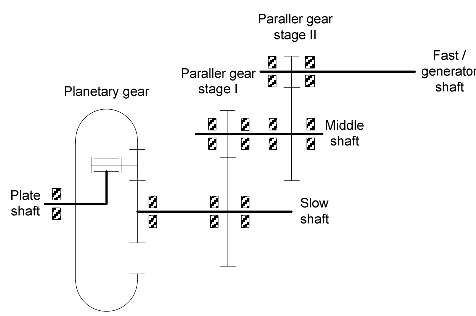

Figure 1. Kinematic scheme of the wind turbine gearbox.

Acceleration signals from this gearbox were obtained at three different dates: 31/10/2009, 11/2/2010 and 4/4/2010. The first dataset was described as the one to be used as a reference, meaning that no damage was identified up to that date. The second dataset was considered to be the one describing an early damage of the gearbox and the third one was the dataset of the vibration signal with confirmed tooth loss in the gearbox.

When a gearbox has two or more mesh stages, signal processing of its vibration signals becomes more challenging because there are multiple shaft speeds and meshing frequencies apart from noise. This means, for the case of gear tooth damage, that one should examine the specific frequencies associated with the meshing frequencies of the damaged gears. Figure 2 shows 12300 points of the time domain signal of the dataset obtained at 31/10/2009. The gearbox examined has a 28-tooth gear (smaller wheel) rotating at 1500 rpm that meshes with an 86-tooth gear (bigger wheel) at the parallel gear stage II. The parallel gear stage II is the one at which damage was observed. The rotating frequency of the smaller wheel gear is therefore, (28/86)*1500 = 488,372 rpm = 8.139 Hz. Taking into consideration that the sampling frequency of the vibration signals is 25 kHz one can estimate the points of the vibration signal corresponding to one gear rotation: in this case 3072 points. Tooth faults appearing at this specific gear should be shown in the signal periodically, at every 3072 points. Now concerning the frequency spectrum of the signal, shown in Figure 3, noise has been removed and the frequency components (meshing frequencies and their harmonics) of it are the following:

- 2.3 Hz: relative meshing frequency of the planetary gear,
- 14.3 Hz: relative meshing frequency of the 1st gear stage,
- 28, 56, 112, 168, 224 Hz: relative meshing frequency and harmonics of the 2nd gear stage.

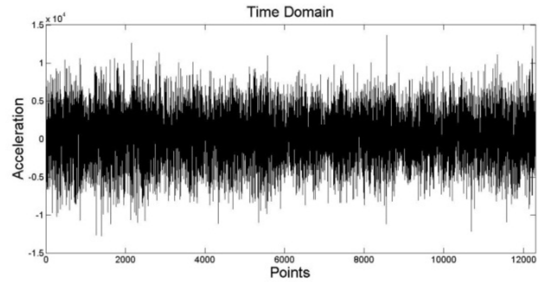

Figure 2. Time domain of the gearbox vibration signal at the first state examined (31/10/2009).

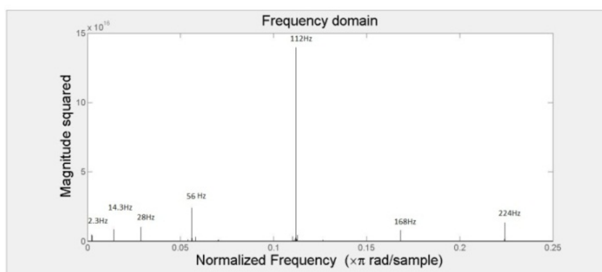

Figure 3. Frequency domain representation of the signal shown in Figure 2.

THE EMPIRICAL MODE DECOMPOSITION

The Empirical Mode Decomposition method (EMD) decomposes the time-domain signal into a set of oscillatory functions in the time-domain, called intrinsic mode functions (IMF). An IMF should satisfy the following conditions [10]: (a) the number of extrema and the number of zero crossings over the entire length of the IMF must be equal or differ at most by one, (b) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The non-stationary signal is decomposed into IMFs using the EMD algorithm. The final step in analyzing the signal is based on the Hilbert transform and finally the original signal $x(t)$ can be expressed as:

$$x(t) = Re\,\{\sum_{j=1}^{N} A_j(t) e^{i\int \omega_j(t)dt}\}. \quad (1)$$

The above equation enables one to represent the instantaneous amplitude and instantaneous frequency of the signal in a three-dimensional plot. This time-frequency distribution is designated as the Hilbert spectrum. So in the final step of the EMD, the Hilbert transform is applied on each IMF and the Hilbert spectrum and the instantaneous features of each IMF are obtained and studied.

OUTLIER ANALYSIS

Outlier analysis is a technique from multivariate statistics which has recently been used for damage detection purposes [13]. Briefly, the approach is described by the following. A discordant outlier in a data set is an observation that appears to be inconsistent with the rest of the data. The detection of outliers involves the use of a discordancy test. The simplest one is based on deviation statistics and is given by:

$$z_\zeta = \frac{|x_\zeta - \bar{x}|}{s}, \tag{2}$$

where is x_ζ the measurement corresponding to the potential outlier and $\bar{x}$ and s the mean and standard deviation of the undamaged sample respectively. In the case of multivariate data, damage detection is more difficult than the univariate situation. The discordancy test, equivalent of equation (2), is in this case the Mahalanobis squared-distance measure, given by:

$$D_\zeta = (x_\zeta - \bar{x})^T S^{-1} (x_\zeta - \bar{x}), \tag{3}$$

where x_ζ is the potential outlier, $\bar{x}$ is the mean vector of the sample observations and S the sample covariance matrix. The discordancy test calculated value has to be compared to a threshold value, which is calculated by a Monte Carlo procedure.

RESULTS AND DISCUSSION

The EMD is basically a method that decomposes the signal into a series of signals, the IMFs, each one of which represents a bandwidth of frequencies. So it can be seen as a "bank of filters". Each IMF can then be analysed separately. Finally, by applying the Hilbert transform, on the IMF of one's interest, one can obtain the instantaneous frequency and instantaneous amplitude of it. The Figures 4, 5 and 6, display the results of the EMD. The diagrams represent four gear revolutions. Only the first five intrinsic mode functions of each signal are presented, because they are the ones that contain the highest signal frequencies, therefore, they are more suitable for damage identification. More particularly, the first IMF is related to the noise of the signal, the second to part of the second harmonic of the meshing frequency of the parallel gear stage II, the third to a second part of the same harmonic, the fourth to the meshing frequency of the same stage and the rest of the IMFs to meshing frequencies and harmonics of the other two stages (lower frequencies).

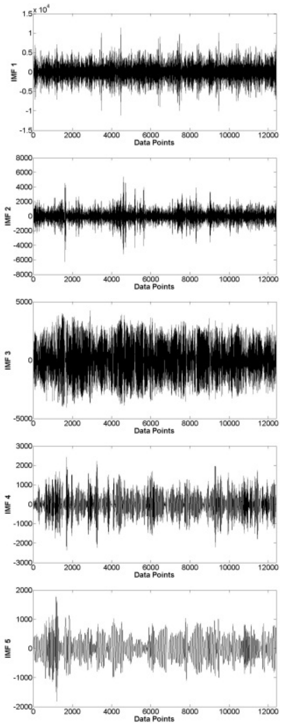

Figure 4. The first five IMFs for signal 31/10/2009.

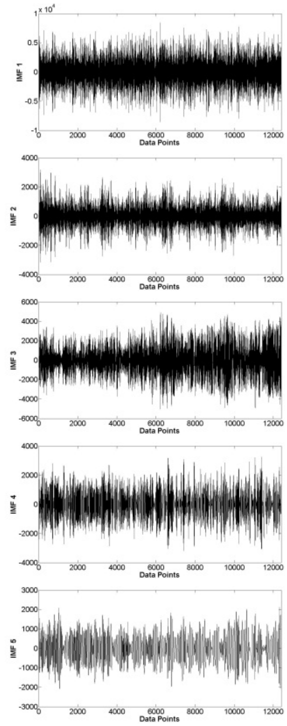

Figure 5. The first five IMFs for signal 11/2/2010.

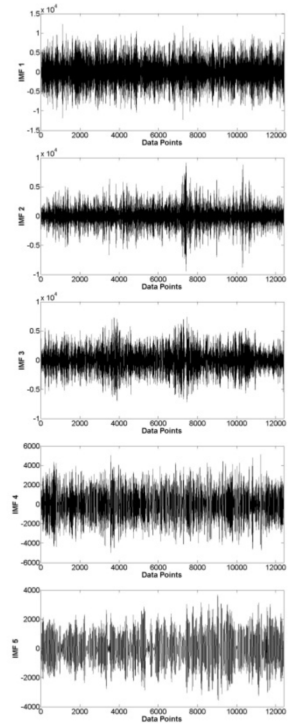

Figure 6. The first five IMFs for signal 4/4/2010.

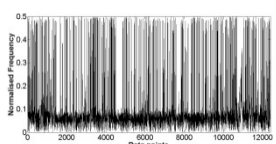

Figure 7. The instantaneous frequency of the signal resulting from the sum the 2nd and 3rd IMFs (31/10/2009).

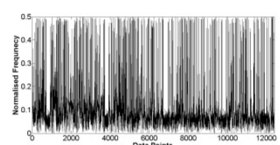

Figure 8. The instantaneous frequency of the signal resulting from the sum the 2nd and 3rd IMFs (11/2/2010).

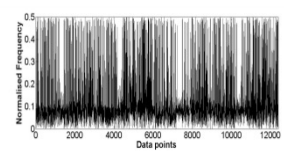

Figure 9. The instantaneous frequency of the signal resulting from the sum the 2nd and 3rd IMFs (4/4/2010).

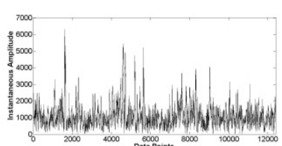

Figure 10. The instantaneous amplitude of the 2nd IMF.

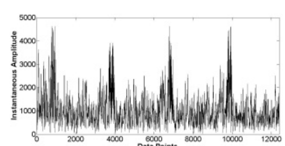

Figure 11. The instantaneous amplitude of the 2nd IMF.

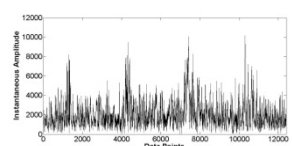

Figure 12. The instantaneous amplitude of the 2nd IMF.

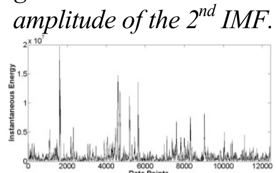

Figure 13. The instantaneous energy of the 2nd IMF (31/10/2009).

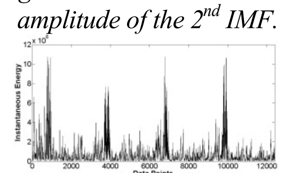

Figure 14. The instantaneous energy of the 2nd IMF (11/2/2010).

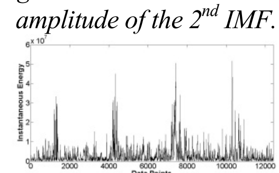

Figure 15. The instantaneous energy of the 2nd IMF (4/4/2009).

The tooth fault is vaguely depicted in the second IMF (Figures 4, 5 and 6), taking the form of periodic pulses with the period of the pinion revolution. The analysis presented in the figures, shows that the harmonics of the meshing are dependent upon the damage severity level. Moreover, the instantaneous amplitude of the second IMF seems to be the one more dependent on the evolution of damage.

The feature examined in this case was the instantaneous energy of the signal simply described by the equation:

$$E_2 = \frac{1}{2} A_{inst_2}^2(t)$$

where $A_{inst_2}(t)$ is the instantaneous amplitude of the second IMF. The presence of damage results in a sudden increase of the vibration energy described by the specific mode. As can be seen by the instantaneous energy diagrams (Figures 13, 14 and 15) and by the outlier analysis results (Figures 16, 17 and 18) the dataset obtained at 31/10/2009 shows some presence of damage at its early stage, since the energy levels of the fault are significantly lower. The instantaneous frequency diagrams of the sum of the second and third IMFs (Figures 7, 8 and 9) show that frequency is also lowered in this case periodically every 3072 points something that confirms this speculation. The fact that there wasn't recognised any damage at that date by the condition monitoring systems of the specific gearbox, probably using conventional signal processing techniques such as Fourier Transform, proves that the EMD method improves the analysis. Concerning the outlier analysis results and the way features were selected, in the instantaneous energy diagrams a 20-dimensional feature was defined as a 20-point window. One series of 100 features was defined as reference and used for the training data. In this way whenever a fault appears, the outlier statistics diagram shows a peak that is distinct from the normal condition data.

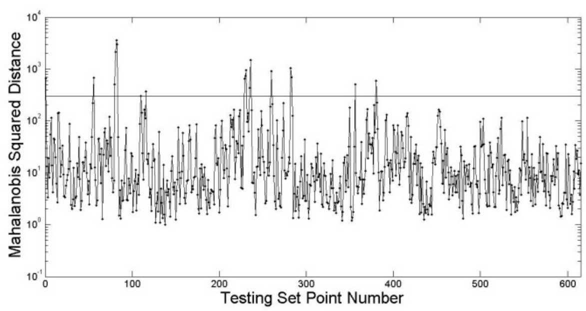

Figure 16. Outlier statistics for the instantaneous energy of the 2nd IMF for the 31/10/2009 dataset.

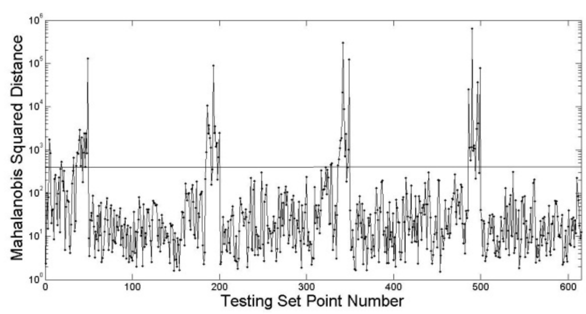

Figure 17. Outlier statistics for the instantaneous energy of the 2nd IMF for the 11/2/2010 dataset.

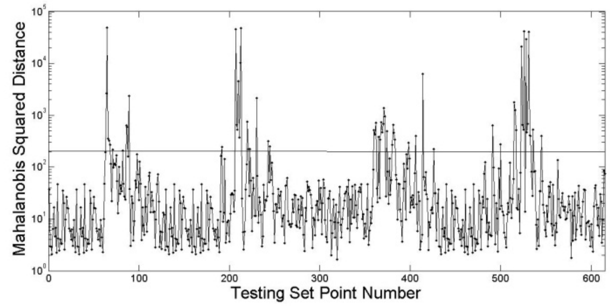

Figure 18. Outlier statistics for the instantaneous energy of the 2^{nd} IMF for the 4/4/2009 dataset.

CONCLUSIONS

In this paper the EMD method in combination with Outlier analysis was used for the condition monitoring of a wind turbine gearbox. From the original signals, the IMFs, the instantaneous amplitudes and frequencies were calculated and examined. The instantaneous energy of the mode identified as the most sensitive to damage was used as a feature and it was proved that the EMD method can improve the results. Further study on the features that could be used for damage detection with the EMD method is considered important by the authors.

Acknowledgements

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