

An Intelligent Approach to the Condition Monitoring of Large Scale Wind Turbines

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Abstract

In view of the limitations of the condition monitoring (CM) techniques nowadays available for wind turbines (WTs), a fully intelligent condition monitoring technique has been developed in this paper using Empirical Mode Decomposition (EMD). The EMD method is characterized by its powerful capability in processing non-stationary and nonlinear signals and by being an efficient sifting algorithm. The effectiveness and the merits of the proposed technique in wind turbine condition monitoring have been experimentally validated on a Wind Turbine Condition Monitoring Test Rig.

Keywords: wind turbine, condition monitoring, empirical mode decomposition.

1 Introduction

A cost-effective condition monitoring (CM) technique is essential to raise the availability of large WTs, whether onshore or offshore for the following reasons [1][2]:

- The high construction costs of large WTs increasing the need to improve payback;
- Large WTs are prone to failure from extreme environments, such as rain, sand, lightning, typhoon, tornado, snow and ice, and subject to constantly variable load;
- Large WTs breaking down have long downtimes due to access difficulties;
- Furthermore, in most large WTs subassemblies are installed in the space-limited nacelle on the tower at a height over 60m making replacement difficult.

The use of a reliable CM system will enhance the maintenance and prevent critical WT subassemblies from being fatally damaged. Many commercially available WT CM systems have been developed to meet this need [3]. However, experience has shown that to date, a cost-effective WT CM system has not yet been achieved. Commercial available CM systems can give frequent false alarms, whilst sometimes not giving alarms when real faults

occur. The reasons for these disappointing results are various, but one of the main causes is the lack of an ideal technique to analyze WT monitoring signals [4].

The WT is driven by constantly varying wind. Therefore, the monitoring signals collected are non-stationary and nonlinear, both in time and frequency. However, the majority of commercially available WT CM systems employ Fourier transform (FT)-based techniques to process WT signals as FT is considered possessing an efficient algorithm, although its limitations in dealing with non-stationary signals have been widely recognized. The inaccurate analysis of WT signals leads to frequent false alarms, which not only devalue the WT CM systems, but also are very dangerous once a fault really occurs.

Some efforts have been made recently to improve the situation. Among the contributions, the wavelet transform seems one of the most promising methods [5][6]. However, the wavelet transform still has a limitation because of its intensive calculation and consequent inefficiency in dealing with lengthy data [7] such as WT signals. In view of this, a new EMD-based WT CM technique is developed by the authors and some preliminary research results have been reported in [8], in which the advantages of using the EMD in WT CM have been discussed in detail. However in [8], only the effectiveness of the EMD in detecting WT electrical/mechanical faults is investigated, whereas no more details about the EMD-based CM strategy are developed. In this paper, a deeper research on this subject is conducted and finally, a feasible new EMD-based WT CM technique is achieved. The proposed technique has been experimentally validated on a specially designed WT drive train test rig.

2 Information reconstruction by the EMD

As described in many references [9][10], the EMD decomposes a signal into a finite number

of independent intrinsic mode functions (IMFs) without any energy leakage in an intelligent manner. Each IMF represents a basic oscillatory mode of the signal and satisfies the following two conditions:

- The numbers of extrema and zero-crossings are identical or differ at most by 1;
- The upper and lower envelopes are symmetric with respect to zero.

The dominant frequencies of the IMFs are in descending order, although they are not strictly single frequency component functions. This allows us to reconstruct the signal using those IMFs with the frequencies of interest [8]. The procedure for signal reconstruction is shown in Fig.1.

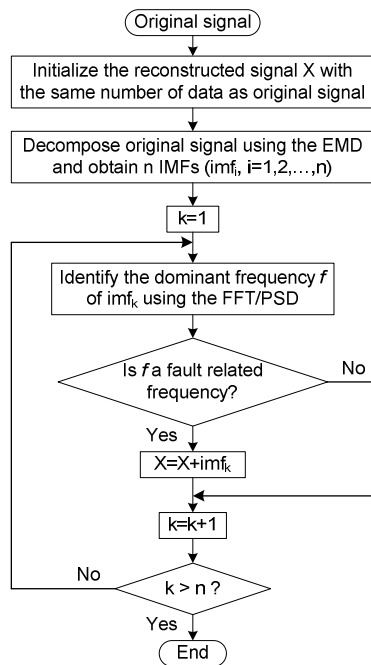


Fig.1 Procedure for information reconstruction

In Fig.1, the fault-related frequencies are defined in advance. The details of them are discussed in the following Section.

3 Fault-related frequencies in WT drive train signals

The schematic diagram of the drive train of a large scale geared WT is shown in Fig.2. From the figure, it is known that in the WT drive train, WT blades, main bearing, shaft, gearbox teeth and bearings, generator bearing, generator rotor and stator are prone to failure in the operation. This has been confirmed by long-

term experience in wind farms [1][2][11]. Moreover, references have already concluded the characteristic frequencies for detecting the faults occurring in these components [12].

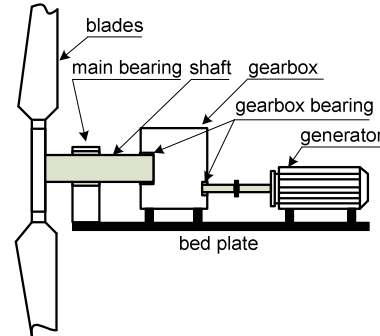


Fig.2 Schematic diagram of a geared WT

A number of advantages are attributed to the use of the generator total power signal for WT CM rather than using traditional line current analysis [4][5][6], therefore only generator total power signal is considered in this paper. For simplifying the calculation, fault-related frequencies, as defined in [12], are classified into roughly four groups, as shown in Table 1. It is assumed that the WT generator is a two pole-pair induction machine with a synchronous speed of 1500 rev/min and operates at a variable speed from 1500 to 1950 rev/min. The frequency of the mains is 50Hz.

Table 1. Frequencies characterizing WT defects

No.	Range of frequency	WT Defects being indicated
1	100±1Hz	Generator stator and grid imbalance faults
2	50±1Hz	Faults occurring in the whole WT drive train
3	25-32.5 Hz	Mechanical faults caused by or unbalanced blades and shaft
4	5-30Hz	Electrical faults caused by a generator rotor winding fault or rotor eccentricity

4 Condition monitoring criteria

Long-term CM experience shows that a well designed CM criterion is helpful for assessing machine running condition correctly. Two CM criteria will be used to evaluate the reconstructed WT power signals. One is instantaneous amplitude (IA); the other is instantaneous frequency (IF) and either deviating from recorded normal values will indicate a change in the machine condition. Previously, the signal IA and IF have been estimated by using the Hilbert Transform (HT) approach [13]. However, the HT is a linear

operator, which is good at estimating IA and IF single frequency component signals, but does not work satisfactorily when dealing with amplitude and frequency modulated (AM-FM) signals, especially non-stationary and nonlinear multi frequency component signals [14]. The IMFs obtained using the EMD are similar single component frequency signals, but are not strictly so. This is why the Hilbert-Huang Transform (HHT) usually presents previously unidentified information in its results [10]. Moreover, the sum of a few IMFs is certainly an AM-FM signal, whose IA and IF cannot be correctly extracted using the standard HT-based approach. In this paper, the energy operator (EO) designed by Maragos et al. [15] is adopted to estimate the IA and IF of a reconstructed power signal. In comparison with the HT-based method, the EO approach has many attractive features such as simplicity and efficiency. But its major advantage is that it is a nonlinear operator, hence it can be adaptive to instantaneous signal variations, which guarantees excellent time resolution [14]. Its algorithm is simply depicted as follows:

For a continuous AM-FM signal $x(t)$, the operator is defined as

$$\psi_c [x(t)] \square [\dot{x}(t)]^2 - x(t)\ddot{x}(t) \quad (1)$$

where $\dot{x}(t) = dx(t)/dt$, $\ddot{x}(t) = d\dot{x}(t)/dt$.

Then, the IA and IF of the signal can be estimated respectively by the equations

$$|a(t)| \approx \psi_c [x(t)] / \psi_c [\dot{x}(t)] \quad (2)$$

and

$$\omega(t) \approx \sqrt{\psi_c [\dot{x}(t)] / \psi_c [x(t)]} \quad (3)$$

The counterpart EO for a discrete time series signal $x(k)$ ($k = 1, 2, \dots, N$) can be written as

$$\psi_d [x(k)] \square [x(k)]^2 - x(k-1)x(k+1) \quad (4)$$

Applying function $\psi_d [\cdot]$ to both $x(k)$ and its backward difference $y(k)$

$$y(k) = x(k) - x(k-1) \quad (1 < k \leq N) \quad (5)$$

Then, have

$$|a(k)| \approx \sqrt{\frac{\psi_d [x(k)]}{1 - [1 - \xi(k)]^2}} \quad (6)$$

$$\omega(k) \approx \arccos(1 - \xi(k)) \quad (7)$$

where

$$\xi(k) = \frac{\psi_d [y(k)] + \psi_d [y(k+1)]}{4\psi_d [x(k)]} \quad (8)$$

Detailed derivations are not repeated further, to keep the text concise. the interested reader may refer to [14] and [15].

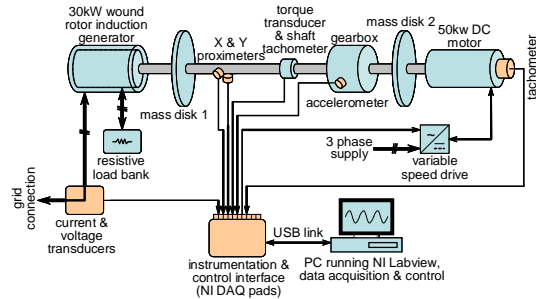
5 Verification experiments

To verify the efficacy of the proposed WT CM strategy, mechanical and electrical faults were emulated on a specially designed WT drive train test rig. The details of are as follows.

5.1 Test rig and experiments on it

As Fig.3 shows, the test rig comprising a 50kW DC variable speed-driven controlled motor and a three-stage gearbox, instrumented and controlled using NI Labview. In the experiments a variety of drive shaft speed inputs were applied to the test rig via the DC motor controlled by an external model, incorporating the properties of natural wind and the mechanical behavior of a large 2 MW WT operating under closed-loop conditions. Relevant signals were collected from the terminals of the generator and the drive train.

Fig.3 Schematic diagram of the test rig



The generator was a 30kW, 3-phase, 4 pole, wound rotor induction machine, the rotor circuit was coupled via slip rings to an adjustable 3-phase resistance load bank, so that rotor electrical imbalance could be emulated, and the stator fed the 3-phase mains.

Two experimental balance planes were installed respectively on the low and high speed shafts of the test rig to allow the emulation of mechanical unbalance faults occurring in real WTs.

The faults emulated on the test rig were:

- Mechanical unbalance on the high speed shaft, by installing a 92g mass on the disk at different radius distances from disk centre, which could represent degrees of

mechanical unbalance on the WT high speed shaft.

- Electrical imbalance on the generator rotor, by adjusting the phase resistances of the load bank connected to the generator rotor, which could represent the effect of electrical imbalance caused by a winding fault or air gap eccentricity in the WT generator due to bearing wear.

5.2 Experimental results

It is important to note that the following CM results were based solely on the analysis of generator power signal, based on the advantages cited in [4][5][6], shaft vibration and torque signals were collected in the experiments only for verification purposes.

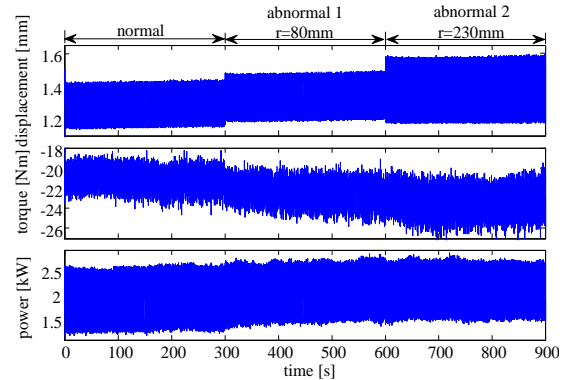
5.2.1 Mechanical shaft unbalance

When a 92g unbalance mass is attached to the experimental unbalance plane 1 in the angular location but at respectively radii, 80mm and 230mm, the shaft displacement, mechanical torque and the generator total power signals were collected using a sampling frequency of 1kHz. The time-waveforms of the signals and the corresponding experimental results are shown in Fig.4, in which the signals and their analysis results, obtained with the machine running under constant speed conditions, are shown for comparison.

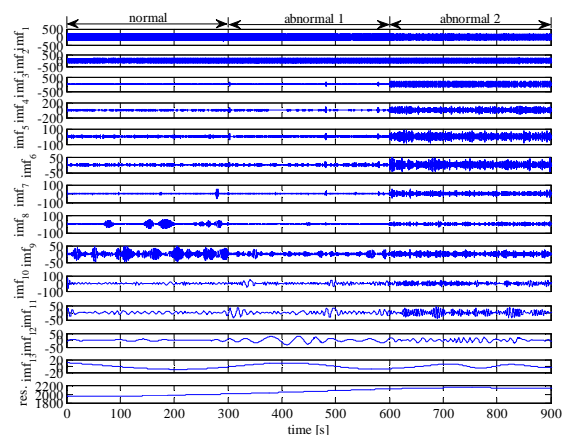
From Fig.4a, it is observed that both shaft displacement and mechanical torque respond to the shaft unbalance. The generator power signal changes as well but does not respond significantly to the fault.

The computational procedure shown in Fig.1 was applied to the generator power signal. The IMFs obtained by the EMD are shown in Fig.4b. The signal reconstructed using the IMFs with the frequencies of interest is shown in Fig.4c, upper plots of which are the IA and IF calculated using (6) and (7) from the reconstructed signal.

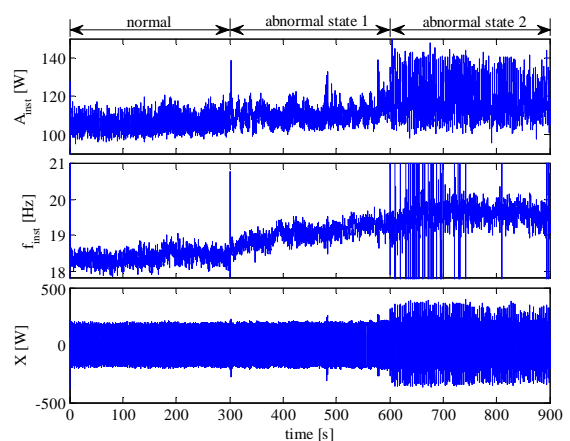
From Fig.4b, it can be seen that the functions $IMF_3 \sim IMF_7$ give a clear indication of the presence of the final shaft unbalance, whereas they not give an indication when the initial shaft unbalance occurs. The amplitudes of the functions IMF_{11} and IMF_{12} change a little when the initial shaft unbalance occurs, but the variation is small.



(a) time-waveforms of the original signals



(b) IMFs derived from power signal



(c) reconstructed power signal and its IA and IF

Fig.4 The detection of different severity of shaft mechanical unbalance faults

From Fig.4c the reconstructed power signal shows similar results. However, the IA and IF extracted from it not only give a sensitive response to the presence of shaft unbalance, but also give a significant response to the severity of the fault.

5.2.2 Electrical rotor imbalance

An electrical imbalance fault was emulated on the generator rotor by adjusting the phase resistances of the external load bank connected to the induction generator. The same fault but with different severities was periodically applied to the machine for testing the fault detection capability of the proposed technique. The shaft displacement, mechanical torque and generator total power signals were obtained with the machine running under constant speed conditions. These are shown for comparison in Fig.5 and the generator power signal was analyzed using the procedure shown in Fig.1.

From Fig.5a, it is seen that the shaft vibration, mechanical torque and the shaft rotational speed do not respond to the electrical rotor modification. However, the generator power signal responds to the presence of the fault, but is affected by the variable speed of the shaft, so the fault cannot be clearly observed from the signal waveform.

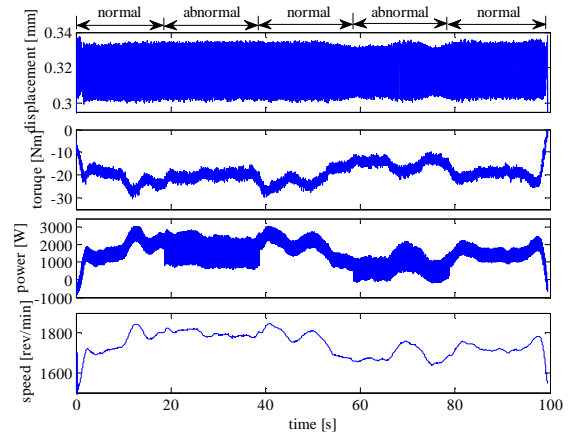
From Fig.5b, it is seen that the faulty symptom created by the electrically imbalanced generator rotor can be clearly observed in the functions IMF₂ and IMF₃.

The presence of the fault is also correctly indicated by the reconstructed power signal shown in Fig.5c. In particular, the IA and IF derived from the reconstructed power signal not only successfully detect the fault, but also correctly indicate its severity.

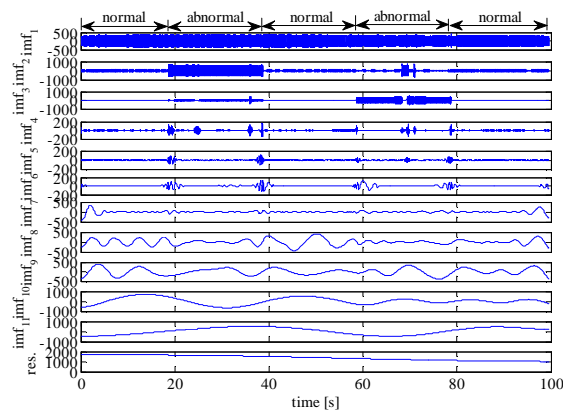
Through both experiments described above, it can be concluded that the WT CM technique developed in this work does detect both shaft mechanical unbalance and generator electrical imbalance faults.

6 Conclusions

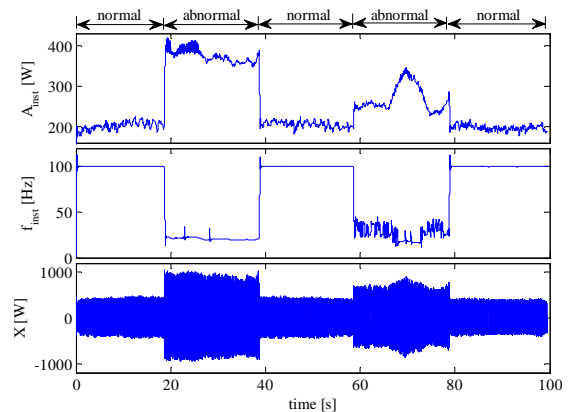
A new wind turbine condition monitoring approach was designed in this paper with the aid of the EMD and taking its advantages in dealing with non-stationary, nonlinear signals. Two experiments, performed on a specially designed drive train test rig, verified the efficacy of the technique proposed in detecting both the mechanical and electrical faults known to occur in real WTs. From the work described above, the following conclusions can be reached:



(a) time-waveforms of the original signals



(b) IMFs derived from power signal



(c) reconstructed power signal and its IA and IF

Fig.5 The detection of electrical imbalance fault occurring on generator rotor

- The EMD is an effective method for decomposing non-stationary and nonlinear WT signals into a number of IMFs with frequencies in descending order;
- The IMFs derived from the WT generator total power signal are able to reveal the

presence of WT drive train faults both mechanical and electrical;

- The symptoms of the faults can be observed more clearly from the generator power signal reconstructed using the IMFs for the frequencies of interest;
- The IA and IF of the reconstructed power signal respond sensitively not only to the presence of the fault, but also to its severity.

The proposed technique could be applied to detecting other electrical and mechanical faults probably occurring in WT drive train. But further efforts and more extensive experiments are needed in the future for verification.

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