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INDICATIVE BEARING FAULT ANALYSIS USING WIND TURBINE TOWER VIBRATION

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In case of major large-scale wind turbine generator bearing faults, it has been reported that sound of vibration and shock can be heard from the bottom of the wind turbine. That motivated the authors to perform a feasibility study by which vibration is measured at the bottom of the tower. Then, vibration analysis using empirical mode decomposition are implemented to identify whether the collected data can be related to drive-train fault features. This simple method could be implemented on wind turbines which do not have sophisticated tower-top monitoring.

Keywords: wind turbine, bearing, fault analysis, condition monitoring, Wind turbine tower vibration

1. Introduction

In case of major generator bearing fault, it has been reported that sound of vibration and shock can be heard from the bottom of the wind turbine. The purpose of this paper is to identify whether vibration signals taken from the bottom of the turbine are correlated to the vibration data collected by the accelerometers attached to the generator bearing housing. Investigating this phenomena is crucial since this type of analysis could benefit the wind farm operators to identify if there is any fault in the generator bearings, before performing any relatively complicated vibration analysis. The experiment was to be as simple as possible since it is not intended to be a full replacement of vibration analysis at this stage. It was planned to have the sensors located inside and at the bottom of the tower.

To the authors' knowledge there have been no similar studies reported in the literature, so the analysis in this article can open a new window for extension and more research.

1.1 Wind Turbine Drive-train Operation Monitoring

In order to make the generated wind energy more profitable comparing to fossil fuels, cost per kilowatt needs to be minimized. "Cost" in general refers to manufacturing and installation costs, and operation and maintenance costs. In terms of operation and maintenance cost control, there are three main strategies: Reactive, Preventive and Predictive maintenances [1]. Reactive strategy [2] means to run until a component is damaged and causes the wind turbine to shut down. Then, the repair is performed and operation resumes until the next incident. This strategy is not economical; the reason being, sudden component repairs and replacements could cost much more than planned maintenance, and also the break down of a component in the drive-train could damage other components, which itself is an additional cost.

Preventive maintenance [3] is a planned maintenance strategy (time-based) which is triggered and scheduled based on events. It relies heavily on operator experience, age of the machine, and manufactures recommendations. The fundamental assumption is that an operating component has a certain life and is to be replaced or repaired at specific time frames. The main problem with preventive maintenance is that the intervals between inspections in most cases are too long to detect a defect at its early stage.

Predictive maintenance [4], which is also called condition-based strategy, is the cost-optimal strategy. It is performed by monitoring the status of the machine, based on several sets of data (such as vibration, oil, temperature, etc.). By analyzing the online data, the operator can potentially detect the issues as early as possible and schedule applicable economical remedies. For example, wind farm operators in Canada do not tend to schedule any maintenance in winter time due to the harsh weather and the cost. If they follow the reactive or preventive maintenance strategies, a sudden breakdown of a component might happen in winter and they do not have any other option other than shutting down the turbine and replace the part. However, if they detect the defect early enough by data analysis, they could effectively apply some temporary remedies to delay the breakdown and have the part replaced in warmer seasons. Through this strategy, wind farm operators can also repair and replace a group of parts at the same time, as one of the major costs of wind turbine repair is the daily cost of crane rental. Instead of renting a crane for a few days to change only one part, they can replace a group of damaged components on several wind turbines in the farm.

A survey of over a thousand failed wind turbine generators showed that bearing failure is the dominant cause of wind turbine generator failure [5]. Predictive maintenance costs a fraction of the total cost of replacement and required man-hours and most importantly the indirect cost of the turbine shut down. In some cases, the total revenue loss due to generator bearing failure can reach \$20,000-\$30,000 for each wind turbine, according to a large wind farm operator in Canada.

Although bearing design and material selection have improved to operate under harsher condition such as high speed, high load, there are still a significant number of root causes of bearing failures. The most common bearing damage are due to excessive load, overheating, brinelling, fatigue, contamination, improper lubrication, corrosion, and shaft misalignment [6]. Fault diagnosis is the main part of the predictive maintenance approach, which is done before root causes analysis and prognosis. There are three main techniques to detect bearing faults used by Wind energy industry; oil analysis, temperature analysis, and vibration analysis. Vibration analysis is perhaps the most efficient type of bearing defect detection method [7]. An undamaged bearing generates a steady state vibration, however a fault in any elements of it can change the condition and produce noticeable vibration impulses. In other words, fault(s) on bearing element amplify the vibration, therefore vibration analysis is a great tool to detect these type of changes. Vibration analysis (including time domain, frequency domain and combination of time and frequency domains) of bearings has been used for a long time in both academia and industry, and has been significantly improved during almost the last two decades. In terms of wind turbine application, the very old turbines did not benefit from online vibration monitoring, but today's installed turbines are typically fully equipped with vibration sensors on different parts of the drive-train including main bearing, gearbox, gearbox bearing, and generator bearings, and an operation centre monitors the status of the drive-train [8]. For a typical 1.5 MW wind turbine, eight to eleven vibration sensors are installed [9]. Vibration from the wind turbine drive-train unlike oil samples can be monitored remotely, from the diagnosis center. There are several communication configurations, but typically a group of wind turbines are connected locally to a small server, which itself is connected to wind farm server via wireless connection. The wind farm server is then connected to the diagnosis server via a local-area network (LAN) and can be controlled and monitored remotely.

1.2 Bearing Fault Characteristics and Modulation

Bearings in wind turbines are rolling element bearings, and there are typically five main bearings in the drive-train; main shaft bearing, two bearings for the gearbox, and two bearings for the generator. Each of them could generate five defect frequencies (outer race pass, inner race pass, cage

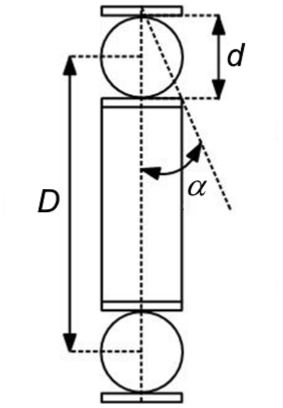

Figure 1: Geometric parameters of a bearing- side view

or fundamental train, rolling element spin, and twice rolling element spin). It is easy to see that the combination of the gearbox mesh frequencies, harmonics, and bearing defect frequencies can make frequency analysis a difficult task. In addition, the shaft speed varies with the wind speed therefore characteristic frequencies of the bearing and gearbox change with speed.

When a rolling element passes over a fault, the temporary loss of contact causes a slight deflection on the element. When the element hits the far side of the defect, regaining the contact can produces an impact to the bearing structure [10]. It is believed that these impacts excite the bearing structure at the natural frequency, called the carrier frequency. This happens each time an rolling element hits the defect, so an impulse waveform is produced. This produces a series of impulse events that repeat at the bearing defect frequency. The described situation leads to a series of amplitude modulated impulses, where the content appears as changes in the amplitude (modulation) of the carrier signal. In wind turbine generator bearings, the carrier frequency is typically in the range of 4 to 10 kHz.

The generation frequency related to the period of the pulses is called the characteristic frequency. Depending on the location of the fault, these frequencies can be formulated as [11]:

- Ballpass frequency, outer race:

$$BPFO = \frac{nf_r}{2}(1 - \frac{d}{D}cos\alpha) \tag{1}$$

- Ballpass frequency, inner race:

$$BPFI = \frac{nf_r}{2}(1 + \frac{d}{D}cos\alpha) \tag{2}$$

- Fundamental train frequency (Cage speed):

$$FTF = \frac{f_r}{2}(1 - \frac{d}{D}cos\alpha) \tag{3}$$

- Ball spin frequency:

$$BSF = \frac{Df_r}{2d}(1 - (\frac{d}{D}cos\alpha)^2) \tag{4}$$

In the above equations, d is the diameter of balls, D is the pitch diameter, α is the contact angle between the ball and the race, f_r is shaft rotational frequency, and n is the number of balls, as shown in Fig.1. Amplitude modulation of a signal by a single frequency results in pairs of sidebands in the spectrum, spaced around each modulated frequency component by an amount equal to the modulation frequency.

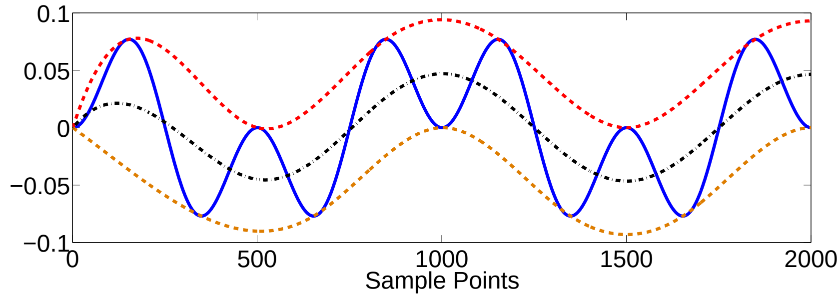

Figure 2: EMS decomposition (sifting)- blue line is the signal, red line is the upper envelope, orange is lower envelope, and black line is the mean envelope

1.3 Order Analysis

Order analysis is a technique for analyzing noise and vibration signals in rotating or reciprocating machinery which typically has a variety of mechanical parts such as a shaft, bearing, gearbox, blade, coupling, etc. Each mechanical part generates unique noise and vibration patterns as the machine operates. When performing vibration analysis, many sound and vibration signal features are directly related to the running speed of a motor or machine, such as imbalance, misalignment, gear mesh, and bearing defects. Order analysis is geared specifically towards the analysis of rotating machinery and how frequencies change as the rotational speed of the machine changes. It resamples raw signals from the time domain into the angular domain, aligning the signal with the angular position of the machine. This removes the effect of changing frequencies on the FFT algorithm, which normally cannot handle such phenomena. An order, referring to a frequency which is a certain multiple of the rotational speed, is defined as:

$$O = \frac{f}{f_r} \tag{5}$$

where f and f_r are observed frequency and shaft rotation frequency (Hz), respectively [12]. For example, vibration signal with a frequency equal to twice the shaft frequency corresponds to the order of two. Order analysis synchronizes the sampling of input signal to the instantaneous angular position of the shaft using a resampling technique. Rather than a constant number of samples per time, it represents in a constant number of samples per revolution and converts the analysis to the order domain rather than the frequency domain.

2. Empirical Mode Decomposition

Empirical Mode Decomposition is an iterative adaptive decomposition technique for non-stationary and nonlinear signals [13], without leaving the time domain. The overall concept is similar to other decomposing techniques such as Short time Fourier transform or Wavelet decomposition. It starts decomposing the signal from a local oscillation level. This technique is a practical technique rather than having a robust theoretical foundation. The decomposed modes unlike other methods (e.g. DWT) are not necessarily orthogonal, and decomposed modes themselves are sufficient to describe the original signal, as there is no external windowing function. Decomposed modes are in the time domain with same length as the original signal, therefore varying frequency in time is preserved. The key in EMD is to determine the oscillatory modes existing in time scales defined by the interval between local extrema. Local extremum points are any points where the derivative with respect to time is zero, and its second derivative non-zero. The term "local" is used to distinguish it from global extremum points. The decomposed modes are called Intrinsic Mode Functions (IMF) which have the following conditions:

- Each IMF has only one extremum between zero crossings,

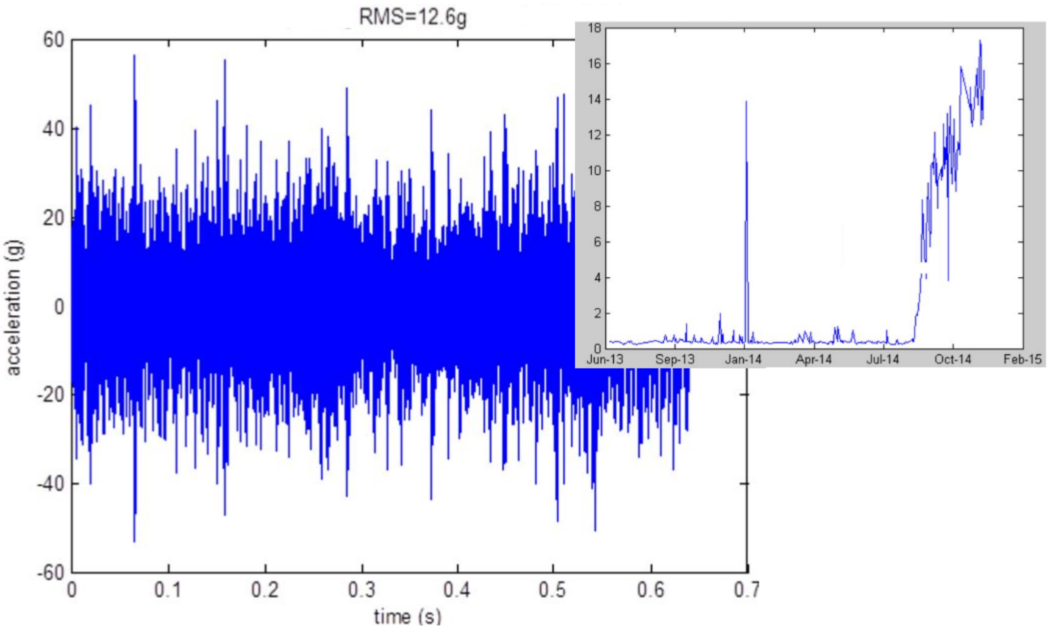

Figure 3: 1.5 MW wind turbine generator bearing vibration and RMS level development with time

- Each IMF has a mean value of zero

An IMF represents a simple oscillatory mode. IMF can have a variable amplitude and frequency as function of time [14]. Therefore in order to start decomposing, one can identify all local extrema of the signal, $x(t)$, to create the upper envelope. Similarly, the lower envelope is created by identifying all local minima [15]. Their mean envelope is called m_1. The first detail, $h_1(t)$, is then defined as:

$$h_1(t) = x(t) - m_1(t) \tag{6}$$

It is illustrated in Fig.2 where blue line is the signal, red line is the upper envelope, dark orange is the lower envelope, and black line is the mean envelope. If $h(t)$ does not satisfy the above two conditions, the iteration continues and the previous steps are repeated. This procedure is called sifting, which continues until $h(t)$ meets the condition and can be considered as an IMF. The subsequent modes, IMF$_i$, are generated by repetition of the same algorithm. The signal, then, can be represented as:

$$x(t) = \sum_{i=1}^{N} IMF_i + r(t) \tag{7}$$

where $r(t)$ is the residue. IMFs start from the highest frequency band to the lowest frequency band which is called a residue of the signal.

As useful as EMD has proved to be, it has some numerical problems, which need to be addressed. The major drawbacks of EMD is the appearance of mode mixing (which means that different modes of oscillations coexist in a single IMF) due to signal intermittency [14], and end effects. Therefore, Huang et. al. [14] proposed a noise-assisted data analysis, which is called Ensemble Empirical Mode Decomposition (EEMD), "which defines the true IMF components as the mean of an ensemble of trials, each consisting of the signal plus a white noise of finite amplitude" [16]. In other words, based on the ensemble number (N), different white noise with the same amplitude is added N times to the original signal to generate N modified signals. Then, EMD is applied on each modified signal to create sets of IMF$_i$. As a result, each final IMF is calculated by averaging the N IMF included in one set. White noise in a time space ensemble mean cancels each other out; and only the signal in the final noise-added signal ensemble mean comes out. The additional white noise populate the time-frequency space uniformly.

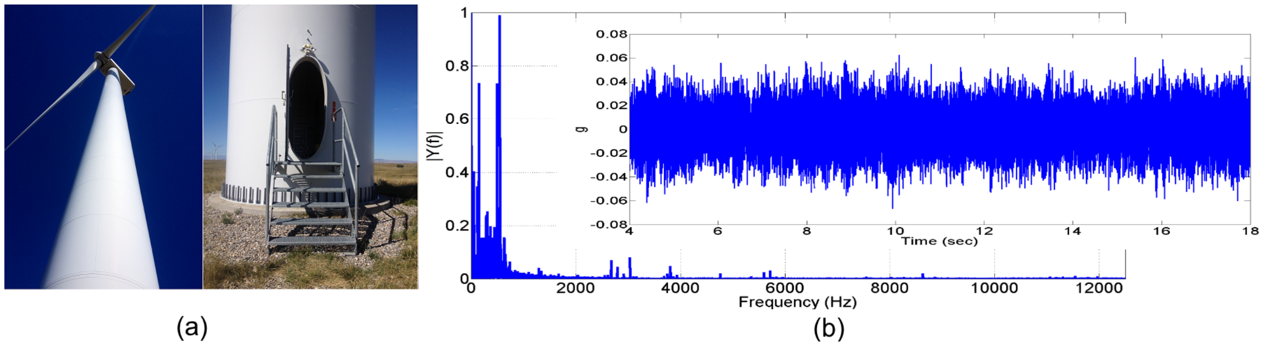

Figure 4: a) 1.5 MW wind turbine tower b) Tower vibration signal and its spectrum- taken September 2015

3. Wind Turbine Tower Vibration Analysis

As mentioned, in case of major generator bearing fault, it has been reported that sound of vibration and shock can be heard from the bottom of the wind turbine. The purpose of this section is to identify whether vibration signals taken from the bottom of the turbine are correlated to the vibration data collected by the accelerometers attached to the generator bearing housing. Investigating this phenomena is crucial since this type of analysis could benefit the wind farm operators to identify if there is any fault in the generator bearings, before performing any relatively complicated vibration analysis. The experiment was to be as simple as possible since it is not intended to be a full replacement of vibration analysis at this stage. It was planned to have the sensors located inside and at the bottom of the tower.

Root mean square (RMS) of the bearing vibration signals is typically the first indicator for wind turbine operators to identify the state change of running bearings. This value started to increase significantly over the time, and went up to "extreme" level according to the diagnosis centre of the wind farm operator, as shown in Fig.3. The increasing RMS trend is not a transient incident similar to what occurred in Jan 2014 (same figure- top right), therefore there is definitely some type of abnormality with this specific generator bearing. Other rotating components such as main bearing, gearbox, gearbox bearings have their vibration RMS level in "satisfactory" level, thus the chance of them having generating fault frequencies were low, again according to the operator's diagnosis centre. Figure 4 shows a few pictures of the wind turbine tower from outside of it. The vibration signals directly from the generator bearings were collected with the sampling frequency of 25.6 kHz. The wind turbine is a 1.5 MW with 80 m tower. The vibration data from the tower were collected at the very bottom of the tower by two accelerometers attached orthogonally inside of the tower, with sampling frequency of 25.6 kHz. Since bearing fault frequencies tend to be carried by a carrier frequency, the idea was to use two accelerometers, thus tower structural frequencies in both directions are acquired, and the chance of collecting bearing vibration transmitted through the tower is increased. Figure 4 shows a sample of the tower vibration, after DC offset component removed. The vibration level is less than 0.1 g, yet small impulses are observable. In the spectrum, the majority of high peaks are located in lower frequency range, which most likely correspond to tower resonance frequencies. The other observation is that there are small peaks spaced at exactly 60 Hz, which is generated electricity frequency.

EEMD is used to decompose the signal into IMFs, as shown in Fig.5 with normalized spectrums. Spectrums suggest that excited frequencies after IMF 3 are in lower frequency bands, which probably relate to tower characteristic frequencies and low frequency excitation from wind and drive-train components. Looking at the correlation between the tower vibration IMFs and the vibration from the generator bearing, the highest value is linked to IMF 2. Figure 5d shows the order diagram of the second IMF where the order of 3.6 and the next two harmonics are excited (having bearing parameters of: d= 4.5 cm, D= 23.5 cm, $\alpha = 0$, and n=9). Although the magnitude is very low, in the range of 10^{-4}, it is an indication of the BPFO on the generator bearing.

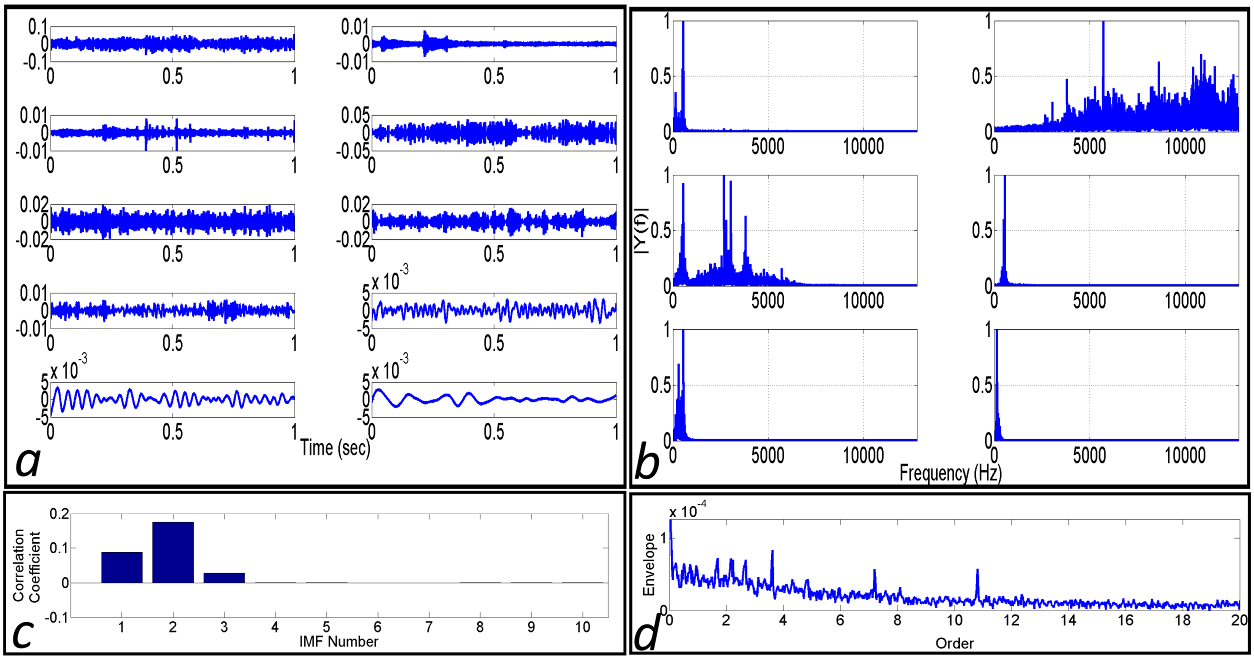

Figure 5: a) First 10 IMFs of the tower vibration, b) First 6 spectrums of IMFs, c) First 10 Correlation with gen bearing vibration, d) Ordergram of the second IMF

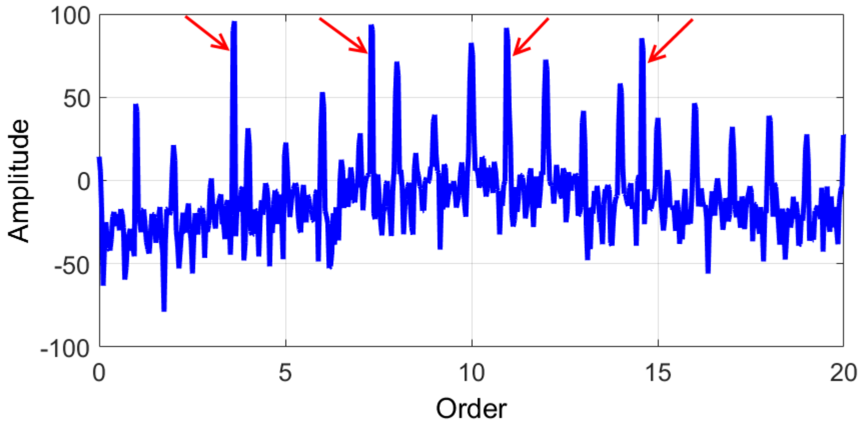

Figure 6: Order analysis of the generator bearing suggesting outer race fault frequency order excitation

As mentioned, vibration data collected from the bearing housing was also available. Figure 6 shows the order tracked results using the the denoising algorithm and estimated instantaneous phase (details not explained due to the paper limitation). The 3.6 shaft order and its harmonics are excited which is the outer race fault order, which is consistent with the tower vibration analysis results. The integer orders refer to the shaft speed orders.

4. Conclusion

The idea of indicative fault diagnosis scheme based on wind turbine tower vibration was described in this article. When there is a major fault on the generator bearing, shock and noise can be heard from the bottom of the tower. Therefore, two accelerometers were attached orthogonally inside of the tower to collect tower vibration. Vibration analysis using EEMD and Correlation factor suggest evidence of the bearing fault frequency/order on the tower vibration. Vibration collected from the generator bearing housing suggested the same result. This idea can be investigated more for potential establishment of indicative fault detection scheme.

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