Smart Wind Turbine: Artificial Intelligence based Condition Monitoring System

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Abstract: This project is motivated by the importance of wind energy and reducing the financial and operational impact of faults in wind turbine generator using artificial intelligence based condition monitoring system. It is to classify the fault alarms and diagnose smart solutions at level zero to resolve the faults without service expert's intervention. Big data analysis of the large historical data pool results in the intelligent algorithms that can power the diagnostic models. For maximum efficiency, wind turbines tend to be located in remote locations such as on offshore platforms. However, this remoteness leads to high maintenance costs and high downtime when faults occur. These factors highlight the importance of early fault detection and fast resolution in great extent. The aim of the project has been to have smart wind turbines integrated with artificial intelligence. The condition monitoring system should have the capability to detect, identify, and locate a fault in a wind turbine and remotely reset the turbines whenever possible.

1 INTRODUCTION

Wind turbine generator (WTG) condition monitoring systems are an example of predictive diagnostic tools using big data and Artificial Intelligence (AI) that allow automatic fault detection in the rotor and stator of WTGs with substantial time before a critical fault occurs.

The installation of such systems is developing at a fast pace in industry with the current increasing popularity of offshore wind projects and the problems that are derived from their O&M such as high downtime, often a result of complex repair procedures in remote locations.

The main motivation is to avoid reduced efficiency and production of WTGs as wells as an increase in the overall costs as, when a fault occurs and there is not predictive maintenance in place, WTG supervisors must first send the maintenance crew to the turbine to identify the fault's location. This would imply repairs which may involve using specialist equipment (cranes and support vessels) increasing the risk of potential delays caused by unfavourable weather or wave conditions (Crabtree, 2010). During these steps it is likely that no energy will be produced as without knowledge of the fault type the risk to operate cannot be taken.

Condition Monitoring systems perform an early fault detection, location and identification which, under some circumstances, would not be possible otherwise. Electrical faults are a clear example, as protection relays cannot be attached to all the parallel paths of the windings individually and the generator could keep operating if a small fault happening in a path of one of the windings goes undetected due to the small unbalance. The fault will eventually erode the parallel path winding and cause a catastrophic fault. Small electrical faults can also create pulsating torque in the machines and, with time, this can lead to machine failures. This is also the reason why these type of systems aim for very fast operation; which implies strong design requirements and high tech equipment selection.

These are situations where condition monitoring (CM) systems come into effect to detect and locate the electrical fault using big data analysis and AI to prevent severe damages in wind turbines.

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2 METHODS

2.1 Fault Detection

Electrical and mechanical (bearing or gearbox) faults are the most frequent damaging and expensive type of faults in wind turbine generators. Vibration analysis of the machine has been used in industry for many years as a way of identifying both types of fault; but lately industrial companies and research organizations have started to look and analyze the current output of the generator in the search for fault indicators. In this way, current is used to detect electrical and mechanical faults, and vibration used as a second way to look for mechanical faults.

CM systems use different techniques for fault detection and analysis, being spectral (frequency) analysis one of the most popular mainly due to the accuracy and speed of its predictive technology.

This method for fault detection relies on the principle that the spectral magnitude of specific fault frequencies of the electrical or mechanical signal's spectrum, increase when the particular fault related to such frequency occurs.

The working sequence of CM systems using spectral analysis involves:

1. obtaining information from the sensors, as well as from the power measurement equipment present on WTG,
2. processing this data to transform it to its frequency domain,
3. check for particular fault frequencies present on them.

Lastly, fault detection algorithms will check the spectral magnitudes of the fault frequencies, within an error margin. A threshold magnitude, set on automatic tests performed on the WTG, will determine if specific fault frequencies' magnitudes are high enough to be taken into consideration and reported to the control center. The latter will be performed using big data to maintain active inspection on particular fault frequencies for long periods (over a year) and AI to send fault severity warnings and details to remote control centers.

2.1.1 Electrical Faults

Research at The University of Manchester (Djurovic, 2009) has defined a set of frequency characteristic equations (Figure 1) for each possible type of electrical fault in both Doubly-Fed Induction Generators (DFIGs) and Squirrel Cage Generators. These equations are the core of the CM fault detection software.

WINDINGS		SUPPLY		INDUCED DFIG STATOR CURRENT FREQUENCIES
STATOR	ROTOR	STATOR	ROTOR	
BALANCED	BALANCED	BALANCED	BALANCED	$f_{ind}^{k} = \lvert 6k(1-s) \pm 1 \rvert f$
BALANCED	BALANCED	BALANCED	UNBALANCED	$f_{ind}^{k} = \lvert 6k(1-s) \pm 1 \rvert f$ $f_{ind}^{k} = \lvert 6k(1-s) \pm (1-2s) \rvert f$
BALANCED	UNBALANCED	BALANCED	BALANCED	$f_{ind}^{k} = \left\lvert \frac{2k}{p}(1-s) \pm \left[s + \frac{1-s}{p} \right] \right\rvert f$
BALANCED	BALANCED	UNBALANCED	BALANCED	$f_{ind}^{k} = \lvert 6k(1-s) \pm 1 \rvert f$
UNBALANCED	BALANCED	BALANCED	BALANCED	$f_{ind}^{k} = \left\lvert \frac{2k}{p}(1-s) \pm 1 \right\rvert f$

Figure 1: Fault Frequencies Characteristic Equations.

k = 0 → Stator excitation frequency; k > 0 → Speed-dependent high frequency components
p = number of pole pairs; f = supply frequency; s = generator slip
(Synchronous speed assumed to be 1500rpm for the generators used in the project)

2.1.2 Mechanical Bearing Faults

Bearing faults are the most common faults in a generator. They can be categorised in single-point defects and distributed faults. This report focuses on single-point defects.

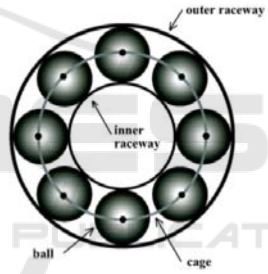

Figure 2: Diagram of bearing (Blodt, 2008).

The following equations have been identified (Stack, 2003) as the fault frequency characteristic equations for different bearing defects:

Cage Fault

$$F_{cf} = \frac{1}{2} F_r \left[1 - \frac{B_d}{P_d} \cos\beta \right] \tag{1}$$

Outer Raceway Fault

$$F_{orf} = \frac{N_b}{2} F_r \left[1 - \frac{B_d}{P_d} \cos\beta \right] \tag{2}$$

Inner Raceway Fault

$$F_{irf} = \frac{N_b}{2} F_r \left[1 + \frac{B_d}{P_d} \cos\beta \right] \tag{3}$$

Ball Fault

$$F_{bf} = \frac{D_p}{2D_b} F_r \left[1 - \frac{{B_d}^2}{{P_d}^2} \cos^2\beta \right] \tag{4}$$

F_r=speed of rotor, N_b=number of balls,
B_d=diameter of ball, P_d=ball pitch diameter,
β=ball contact angle

Mechanical faults can also be identified by analysis of the stator current as vibrations cause air-gap eccentricities that cause disturbances in the air-gap flux density of the generator which changes induction affecting, therefore, stator current.

2.2 Spectral Analysis

To account for the non-periocity of signals such as the current and vibration signals obtained from a generator, whose output and condition changes with the wind and the electrical supply, the Short Term Fourier Transform (STFT) is one of the methods identified for signal processing and fault detection software (Dudek, 2011).

The STFT analyzes real time data in predefined periods of time, called windows, where the speed of the rotor and the supply frequencies are assumed constant and applies Fast Fourier analysis for such window length. Other methods of fault detection (Empirical Mode Decomposition or Wavelets) have been researched to be commercially applied but Fourier analysis was one of the methods that provided higher frequency resolution.

The STFT relies on the assumption that during a single time window, the signals that it processes are periodic.

$$\mathrm{STFT}\{x(t)\}(\tau,\omega) \equiv X(\tau,\omega) = \int_{-\infty}^{\infty} x(t)\omega(t-\tau)e^{-j\omega t}dt \quad (5)$$

w(t) = Window function; x(t) = Signal to be transformed; X(τ,ω) = Fourier Transform;
x(t)w(t-τ) = Function representing the magnitude and phase of the signal; ω = Frequency; τ = time

The STFT truncates the given window with specific functions to obtain better resolutions when processing the signal. These functions are defined window types mathematical defined and used for many applications. Some examples are: Hann, Rectangular, Hamming, Blackman window types (LDS, 2003).

2.2.1 Frequency and Time Resolutions

Heisenberg's uncertainty principle applies here: the more it is known about the frequency resolution of a signal (width of the window), the less precisely it is known about the time resolution of the signal (narrow window). A balance is necessary in the system for good quality results.

(A) (B)

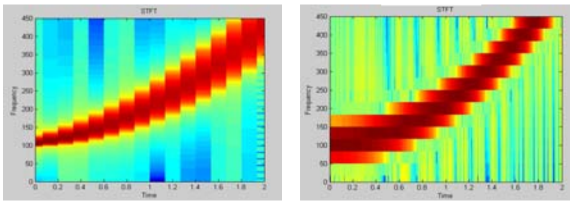

Figure 2: (A) Good frequency resolution but high spectral leakage; (B) Good time resolution but low frequency resolution.

2.2.2 Envelope Analysis - Hilbert Transform

In vibration spectral analysis, envelope analysis acts like a filter (Wavemetrics, 2012). It eliminates the signal originated from the initial vibration of the machine, facilitating the fault detection after the spectral analysis has taken place.

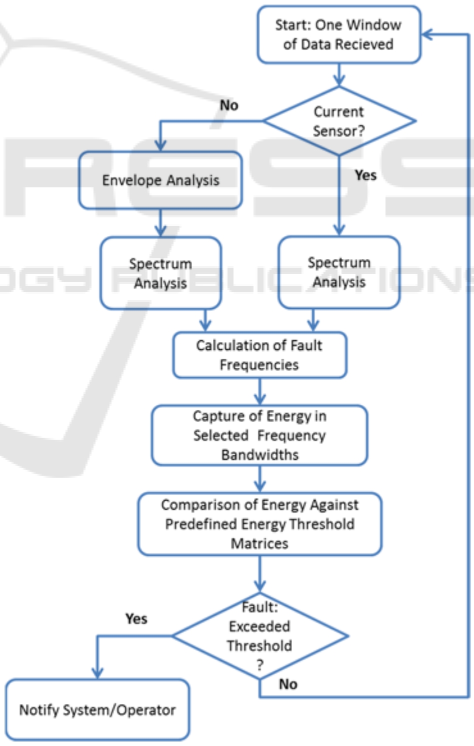

Figure 3: Overall Process Diagram.

2.3 CM System's Fault Alarms

CM systems monitor each of the fault frequencies' spectral magnitude and their harmonics in order to check for an increase through time.

A fault in the system inevitably increases the energy of the fault frequencies given by the characteristic equations by a value between 7 to 10 times the energy of the selected frequencies under normal, healthy, operation in the case of electrical faults. This value would depend on the severity and type of fault. When such a change in energy occurs, the fault detection algorithm gives notice of the fault to the operator, including the location and the severity of the fault.

In this respect, AI algorithms are also able to identify the severity of each fault according to the evolution of the spectral energy content of the monitored fault frequencies in comparison to energy threshold levels tuned up previously. This allows CM systems to send different alarms, and required corrective actions, depending on the severity of the fault to the remote control centers of the system operators.

Alarms could range from level zero, indicating that a particular fault is starting to develop and that it might be required to reset the WTG or send an O&M operator in the mid-term (weeks) while in the meantime the WTG can be kept running, to level one which requires expert judgment to decide if the WTG can be kept running while O&M operators would need to be sent in the short term (days), or to level two were the WTG is required to be stopped for safety reasons and O&M operators need to be sent as soon as possible.

3 RESULTS

The following examples show electrical and mechanical faults that CM systems are able to detect thanks to big data processing and energy threshold algorithms.

3.1 Electrical Fault Detection by Current Spectral Analysis

The following example shows the current spectrum of a turn to turn fault in the stator windings of a squirrel cage generator which happens around the sixth second and how the spectral energy content of such frequency band increases with the fault.

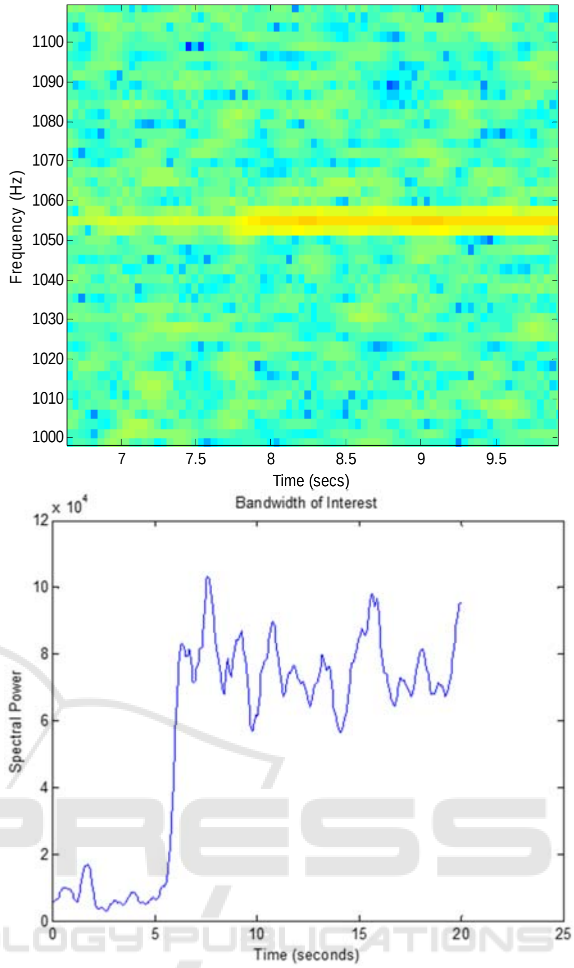

Figure 4: (A) MarelliMotori current spectrum; (B) Spectral energy increase with fault.

3.2 Bearing Fault Detection by Vibration Spectral Analysis

The following example shows an inner race bearing fault simulated in a squirrel cage generator where the energy increase in the whole spectrum is clearly visible (Figure 5(A) below) while the energy summation of all the calculated fault frequencies in the first 8 time harmonics is shown in Figure 5(B). This case differentiates itself from the electrical faults because looking at the 8 checked individual harmonics is no longer necessary. The energy increase is present in all of them.

4 CONCLUSIONS

The use of big data and data processing algorithms in CM systems becomes key for the detection of

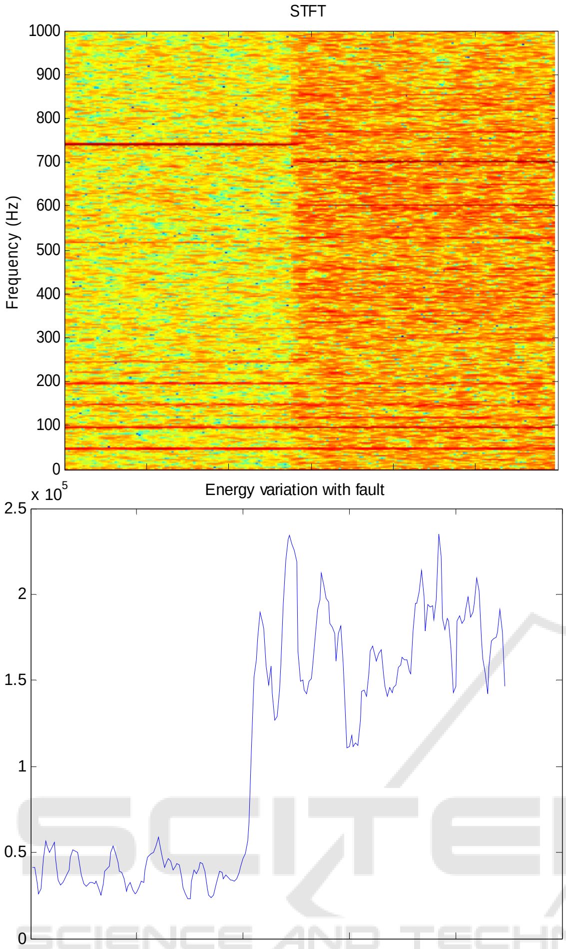

Figure 5: (A) Vibration spectrum with inner race bearing fault; (B) Energy variation in calculated fault frequencies.

electrical and mechanical faults as many faults slowly develop, increasing their fault's frequencies spectral energy, through time.

Big data is required to store real and processed operation data from electrical and vibration sensors in the WTG for at least one year. AI would require algorithms to tune up the fault thresholds for each machine automatically, as well as to identify which should be the normal, healthy, energy levels taking into consideration variables such as rotor speed.

The solutions provided in this paper will provide a competitive advantage to the organization since many tasks done previously by the operators can now be executed by the computers. This will leave more time for the operators to review complex alarm diagnostics and have them focus on more delicate services. Another advantage is the speed and more diagnostics that were not possible without computer interventions.

The idea is to implement the collective intelligence where the CMS system can do the level zero diagnostics and filter the difficult tasks that is hard for computers to be done by operator experts.

This collaboration will also lead to more accurate and precise predictions and save a lot of time and money in the offshore business.

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