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INTEGRATING OIL HEALTH AND VIBRATION DIAGNOSTICS FOR RELIABLE WIND TURBINE HEALTH PREDICTIONS

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ABSTRACT

The Department of Energy's (DOE) goal for wind energy is that it comprise 20% of the nation's energy by 2030. For this to be achieved, so called "distributed wind" and off-shore wind farms will be required. However, to date, operating & maintenance and unscheduled outage costs make such applications risky [1]. A potential risk mitigation strategy is implementation of Prognostics and Health Management (PHM). Prognostics promise great benefits to parts order/handling, logistic planning, maintenance scheduling, which ultimately reduces the cost of ownership/operation. Successful prognostics require that faults be detected at the earliest possible stage. However, to fully realize the benefit of the investment, PHM systems must provide early detection of precursors for failure modes. Incipient fault detection is critical to increasing reliability and lowering Operation and Maintenance (O&M) costs for wind turbine gearboxes. The combination of this critical incipient fault detection capability with prognostics will allow wind turbine owners to reap the promised PHM benefits.

It is possible to generalize gearbox faults into two areas: mechanical and lubricant related faults. To provide adequate coverage to both generalized areas, the authors will show how two primary sensing technologies can be combined to provide the necessary detection horizon for wind turbine gearboxes. The authors will introduce a generalized PHM architecture that can be adapted for a broad range of mechanical systems, especially wind turbine gearboxes. Various sensors and diagnostic techniques that can be integrated into the architecture will be discussed. Finally, the authors will show how the architecture, sensors, and techniques can be applied to a subscale test, including example results.

NOMENCLATURE

*	denotes complex conjugate,
a	scale factor of wavelet coefficient
b	position factor of wavelet coefficient
c	material constant
CCDF	Cohen's Class Distribution Function
CWD	Choi-Williams Distribution
CWT	Continuous Wavelet Transform
da	Incremental crack growth
dN	Incremental cycle count
DOE	Department of Energy
FA	False Alarm
Fa	pseudo frequency
Fc	center frequency of a mother wavelet in Hz
Fc/a	center frequency of the baby wavelet
FFT	Fast Fourier Transform
Fe	Ferrous
FTIR	Fourier transform infrared
FN	Frobenious Norm Feature
GMM	Gaussian Mixture Model
g(a,b)(t)	baby wavelet
g(t)	mother wavelet
JTFA	joint time-frequency analysis
kHz	kiloHertz
ΔK	Stress Intensity Factor
µm	micron
lbf	pound force
L/min	liters per minute
m	material constant
NP4	Nondimensional feature
O&M	Operation and Maintenance
PPM	parts per million
P(MD)	Probability of Miss Detection
PDF	Probability Density Function
PHM	Prognostics and Health Management
RH	relative humidity
RPM	Revolutions Per Minute
STFT	Short-time Fourier Transform
t	time
x(t)	Vibration Signal

INTRODUCTION

A potential risk mitigation strategy for off-shore wind farms is the utilization of an integrated PHM approach. PHM technologies are designed to predict the current and future conditions of critical systems by actively monitoring available data from the targeted system. PHM can be applied to a wide variety of systems; for wind turbines, they are most applicable to the gearbox due to documented reliability concerns [2].

For a wind turbine operator, knowing the current and future health of an asset (in this case, a gearbox) promises several benefits. First, current health state can be used to help determine how best to achieve load requests and unit downtime (if specific units can be brought on/off line). Second, accurate future health predictions that provide advance warning of system failures would greatly decrease costs associated with maintenance, spares ordering, and logistics (crane and crew) by allowing optimal scheduling and planning. Third, robust diagnostics with proven incipient fault detection would ensure that any system faults are detected with enough time to allow for a *planned* reaction, even without sophisticated prognostics. Ultimately, PHM benefits offer to reduce the cost of ownership/operation and maintain operational time. Achieving these objectives is key to achieving the aforementioned DOE goal.

Several factors affect a PHM system's effectiveness, therefore affecting potential cost benefits. The system's reliability, sensor suite, fault detection/isolation capability, and prognostic accuracy are some of the primary influencing factors. Various reliability effects can influence the results of the PHM system; for instance, faulty sensors can cause erratic readings and erroneous diagnoses. Obviously, the sensors themselves strongly influence the PHM system's capabilities. Inadequate range, sensitivity, incorrect location, and many other factors can cause missed or incorrectly diagnosed faults. Even the best sensors will not reliably detect or isolate mechanical faults in a poorly designed diagnostic system.

Therefore, the authors' approach to PHM system definition begins with careful selection of data sensors and evaluation of various signal processing and feature extraction/interpretation techniques. This approach generates high level, reliable, accurate, and actionable diagnostic/prognostic information. Within this method, detection and prediction of gearbox failures results from the fusion of diagnostic/prognostic algorithms with reliable sensed data that is focused on critical failure modes.

Sensor-based health assessments of gearbox components can detect failures at various phases, from incipient to near-failure. This is often referred to as the detection horizon. The authors have generated a notional graphic, see Figure 1, of common gearbox failure root cases, sensor-based readings (observables), and the approximate detection horizon provided. In this figure, detection horizon observables are to the left, with gearbox functional failure to the extreme right. In addition, the approximate range of each sensor's maximum effectiveness is provided. Although notional, the authors have developed this overview based on a thorough literature review and their own experience with multiple gearbox failures. One of the goals of any diagnostic system should be to provide the earliest possible confident indication of a fault - in other words, the longest detection horizon. This is especially true for wind turbine applications, in which early indications of future faults can allow for spares ordering and optimal scheduling of downtime and maintenance.

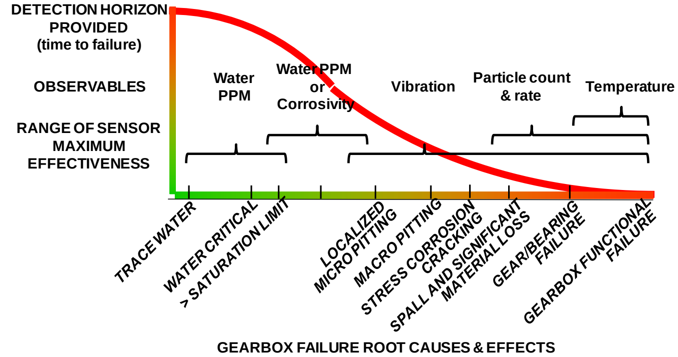

Figure 1 – Gearbox Failure Mode Observables (Notional)

As with any mechanical system, gearboxes are prone to particular failure modes/types. For a wind turbine system with many subcomponents, multiple potential failure modes exist. A succinct list by Mark Barnes summarizes the most prevalent gearbox failure types: shaft misalignment, wrong oil, low oil level, age-induced fatigue, lubricant degradation, and contamination (water or particles) [3].

As mentioned above and in Figure 1, many (if not most) gearbox failures can be diagnosed with two primary sensing technologies: lubricant (oil) monitoring and vibration. In the case of most gearbox components, vibration analysis has proven to provide some of the most quantitative and reliable indicators of rotating member fatigue. Furthermore, the utility of using high frequency measurements (sampling rates greater than 100 kHz) for diagnostics and prognostics of these components is well documented in numerous studies [4,5,6]. Prognostics play an important role in any PHM system; however, it is only through robust, accurate information about current health (diagnostics) that future system health (prognostics) can be predicted. For this reason and for the sake of brevity, this paper focuses on diagnostics; prognostics will be evaluated in future work.

APPROACH

The purpose of any diagnostic algorithm is to provide an assessment of the current health state of a monitored system given a set of observations (e.g., monitored variables, features, condition indicators, etc.). Typically, a diagnostic algorithm will indicate whether the assessed state has reached a specified value or threshold. However, to realize the full benefit of a PHM system, it is necessary to integrate diagnostics with prognostics by quantifying the health state rather than merely indicating whether its condition indicators have reached a certain threshold. Diagnostic results should include an estimate of the assessed state and its uncertainty (since the health state is inferred from analysis and interpretation of indirect measurements). Uncertainty information can be provided by assigning probabilities to a series of estimated health conditions. These probabilities and their corresponding condition values will generate a probability density function (PDF), as seen in Figure 2. Obviously, the more uncertainty a PHM system's result has, the less beneficial the system is. Therefore, a diagnostic or PHM system should mitigate the uncertainty in the current (and future) health in order to be as beneficial as possible.

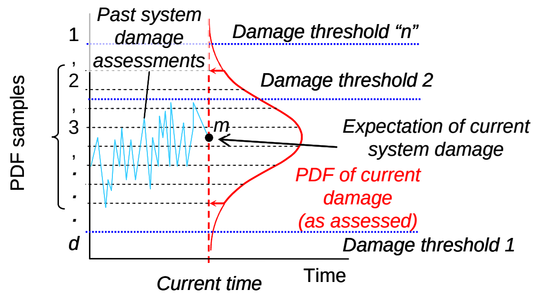

Figure 2 – Statistical Diagnostic Output

The intelligent use of oil and vibration sensing technologies is crucial in decreasing uncertainty levels in wind turbine gearbox diagnostics and thereby increasing PHM performance. For instance, an oil sensor may give an indication of wear (and even amount of wear) in the gearbox, but it cannot isolate the damage to a specific component. In contrast, a vibration sensor can isolate damage to a specific degraded component, but may not be able to correlate it to a wear level with an acceptable amount of uncertainty. Both of these sensors provide information that is critical to PHM. The generic approach shown in Figure 3 is a potential method for combining these oil and vibration measurements to create more accurate diagnostics (and eventually PHM) of wind turbine gearboxes.

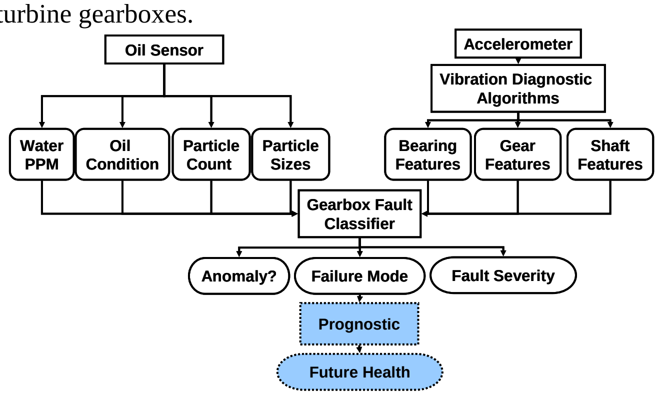

Figure 3 – Generic Gearbox PHM Approach Integrating Oil and Vibration Monitoring

Within this approach, the accelerometer data (vibration) and available oil sensor data are used to diagnose the appropriate gearbox failure modes:

- Accelerometer: age-induced fatigue (normal wear) and shaft misalignment.
- Oil sensor: incorrect oil, low oil, level lubricant degradation, contamination (water or particles).

In addition, appropriate information from both sensors is combined (or fused) to form a better, less uncertain diagnostic/prognostic. For example, since vibration data needs more interpretation and analysis for correlation to mechanical system health when compared to measurements like oil debris, it is inherently more uncertain. Therefore, the authors propose development of a fault classifier that utilizes the two separate sensing techniques to isolate and describe current system faults/health. Combining measurements from the two sensors will generate a more accurate overall classification since the two methods address each other's limitations.

In addition, by integrating on-line oil quality/debris measurements with vibration measurements, gearbox failure mode indicators can be fused to produce fault classification, maintenance action recommendations, and component replacement recommendations. This on-line predictive capability will improve asset reliability and availability.

OIL MONITORING

Oil monitoring is usually more straightforward than vibration analysis since oil sensors typically measure the appropriate data for a particular failure mode directly, which minimizes the need for additional processing. (As discussed later, vibration sensing requires determination of the appropriate signal processing and feature extraction methods based on the failure modes of interest.) There are three leading modes of degradation for wind turbine gearbox oil:

- **Water** – water contamination can lead to corrosion as well as accelerated breakdown of the lubricant's additive package, ultimately leading to micro-pitting (on bearings and/or gears) and consequently lowered fatigue life [7].
- **Wrong/Aged Lubricant** – oil degradation by-products and depleted additive molecules can lead to loss of operating clearance or loss of heat transfer capability [8]; incorrect oil can cause similar detrimental heat and clearance effects as well as accelerated wear.
- **Contamination (particles or water)** - metallic particles can be both indicators of wear and initiators of collateral damage through debris "dents" acting as stress risers or blocking fine clearances, causing oil starvation [7]. Water in even trace amounts can greatly reduce gearbox component life.

Detection of these lubricant faults is discussed briefly in the following sections.

Detecting Water Contamination

Water is one of the most detrimental contaminants within a lubricating system. Depending on its state, water can not only reduce oil's lubricating ability but also increase oxidation, leading eventually to rust and/or corrosion induced fatigue. By itself, dissolved water poses a reduced threat to lubricant performance. However, emulsified and free water will greatly reduce the operating life of the system. Emulsified water droplets can travel through the lubricating system, attaching to steel surfaces and, in time, forming rust and/or embrittling those surfaces. It has been shown that 1% water in a lubricating system can cause a 90% reduction in the life of a journal bearing [9] and 0.1% water can reduce ball bearing life by 70% [10], as illustrated in Figure 4.

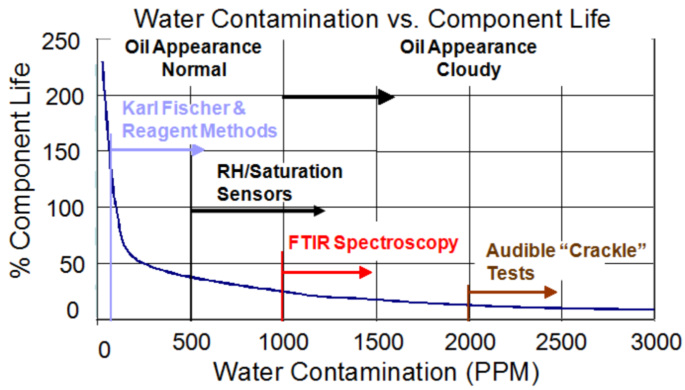

Figure 4 – Water Contamination's Effect on Bearing Life [11]

Traditionally, water content is measured using offline laboratory type testing, such as Crackle or Karl Fisher testing. These types of tests are less than ideal for distributed or off-shore wind turbine applications since they involve large, fragile laboratory equipment and dedicated trained personnel. Therefore, to accurately track water contamination, the authors have developed an online/inline sensing element that detects moisture in oil in a similar fashion as a humidity sensor detects moisture in air (refer to [12] for further sensor details). The sensor measures the relative humidity (RH) of the oil, correlates that to parts per million (PPM), and outputs the PPM of water directly.

Figure 5 shows the benefit that can be provided through real-time monitoring of water contamination using the above-mentioned sensor. In this example, a dehydrator stalled, causing a steady increase in contamination. Without real-time monitoring, several weeks or even months would have passed before an oil analysis report would have identified the problem. Even then, maintainers would have likely waited to receive a second report to confirm the problem before taking action due to the lack of repeatability in lab analyses. However, with real-time monitoring via the inline RH sensor, corrective action was taken before the contamination could reach a level that would threaten the health of the system.

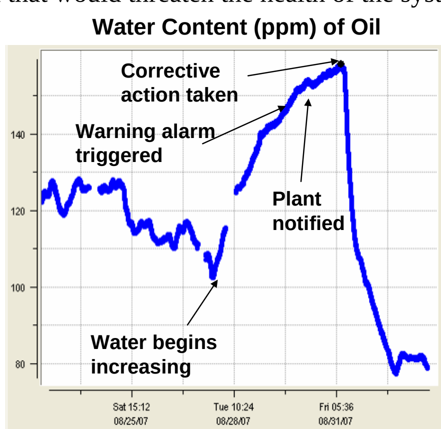

Figure 5 – Example Gearbox Water Contamination, Detected Via On Line RH Measurement

Detecting Wrong/Aged Lubricant

Incorrect or aged lubrication can lead to premature wear of oil-wetted components. Again, this is traditionally detected using periodic (every 100 – 300 hours [2]) oil sample methods, such as Fourier transform infrared (FTIR) (condition and contamination), viscometer (viscosity), and flashpoint (contamination). Although these tests can be very accurate, they are also offline and costly, limiting their usefulness within an integrated and practical wind turbine diagnostic system.

Some online quality sensors are available, typically using electrochemical impedance or conductivity meters. Unlike some sensors, the authors' sensor interrogates the oil with a wide range of frequencies to extract more information from the oil than other sensors. Changes in the measured impedance spectrum correlate with changes in oil condition and contamination levels. An example impedance spectrum is shown on a Nyquist plot in Figure 6. Data summarized in this figure was collected during a degradation test (according to ASTM D2272) of wind turbine gearbox oil. As shown by the shifting Nyquist curves, the sensor's response clearly trends with the oil's degradation level.

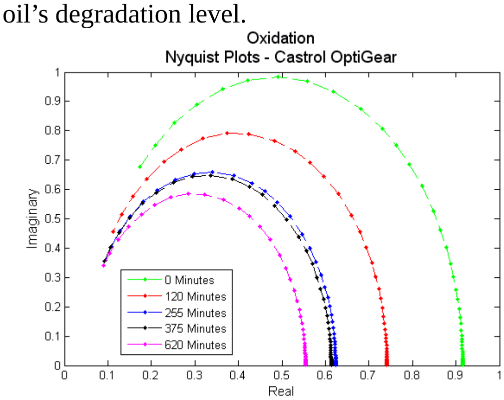

Figure 6 –Example Oil Quality Results from Degradation Testing

Detecting Metallic Debris

Oil debris monitoring technology can be employed to identify a failure in its early stages before it can propagate to other components. While some level of particulate is anticipated in any system, a sudden increase in particle detection rates can be attributed to an impending component failure.

Several technologies exist for online/inline debris detection, including atomic emission spectroscopy (wear debris and dirt) [8], LaserNetFines (silhouette of particle, plus size and shape), ferrography (particle size, shape, ferrous/non-ferrous), and magnetic chip collector/detectors (ferrous quantity/rate) [such as the sensor in reference 13].

Another technology used for debris sensing is based on an inductive sensor. Such a sensor is created by winding one or more wire coils around a non-conductive tube. As metallic particles entrained in an oil stream within the tube pass through the energized coils of wire, they cause the impedance properties of the coils to change. These changes can be measured through appropriate signal conditioning and acquisition electronics (built into sensor) and the resulting signal can be assessed to determine attributes of the particle. Because ferrous material impacts the coil in a different manner than non-ferrous material, particle type can be determined in addition to size.

An inductive sensor in development by the authors was tested in a lubrication loop (MIL-23699 oil at 3 L/min) similar to those found on wind turbines. During testing, ~30 [100-200 µm] ferrous particles were added at approximately 21:14, followed by and additional ~15 [400-500 µm] ferrous particles at 21:17. Note that an exact count of particles was not performed and that the particles were sorted by a mesh screen, thus *exact* counts and sizes of the inserted particles are not known. These sensor readings during the test are shown in Figure 7 and the final totals for the various size bins are shown in Figure 8.

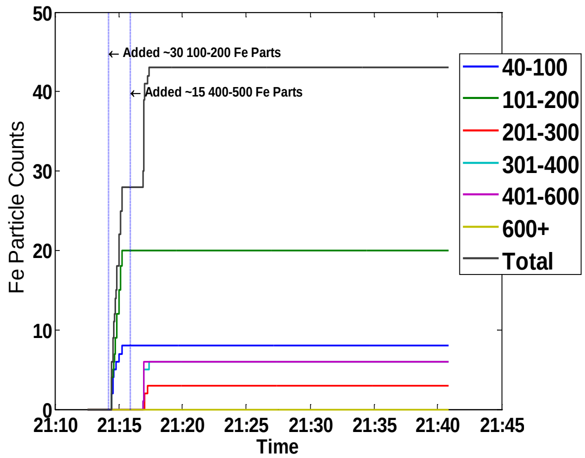

Figure 7 – Lubricant Loop Test, Ferrous Particle Count Trends

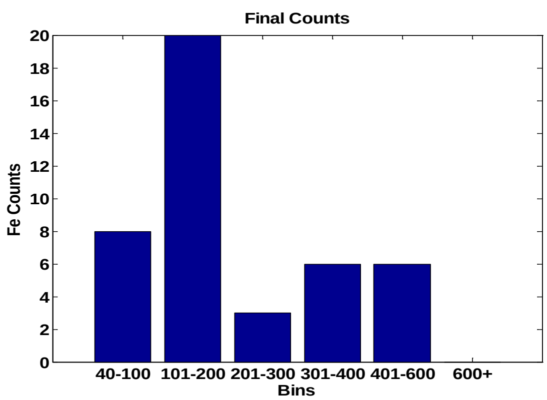

Figure 8 – Lubricant Loop Test, Ferrous Particle Count Totals

VIBRATION-BASED ANALYSIS METHODS

As previously mentioned, many common gearbox diagnostic methodologies use vibration based algorithms to infer or estimate gearbox health states. Although commonly used, one cannot directly use a reading from an accelerometer like the above mentioned oil sensors. In order to turn the raw vibration signal into something useful, complicated analysis often needs to be performed.

Vibration based diagnostic methods typically involve various signal processing techniques to manipulate the raw vibration data before health indicative features are extracted. Gearbox vibration diagnostics are often based on frequency domain analysis, which assumes the monitored signal is "stationary" during the analysis period. However, because operating conditions are often non-stationary and evolving, this assumption leads to spectral smearing and erroneous analysis that creates uncertainty in the health assessment.

Spectral smearing, in which energy from an evolving characteristic frequency (i.e., shaft frequency, bearing fault frequency, gear mesh frequency, etc.) gets spread across multiple frequency bins, can reduce the efficacy of traditional frequency domain analysis, including Fourier transforms. Typically, this is avoided by defining steady state operating conditions in which to perform the analysis. Although this may be acceptable for some systems, most wind turbines have constantly varying shaft speeds. In addition, certain component faults and their progressions can also lead to non-stationary signals that could be missed by traditional techniques. As a result, the authors have developed a novel vibration diagnostics methodology that is applicable during non-steady operation through application of joint time-frequency analysis (JTFA) [refer to 14 for more details].

These methods use various techniques to transform the two dimensional time domain signal into a three dimensional time-frequency domain signal to increase feature extraction accuracy. Various features are then extracted from the three dimensional signals for fault detection. The following sections provide a brief description of the joint time-frequency analysis methods considered by the authors for gearbox monitoring applications.

Wavelet Analysis

Wavelet decomposition is a commonly used signal processing technique that can localize the exact time of specific vibration events [15]. Wavelets can reveal amplitude and phase modulation within their frequency band. From these modulations, algorithms can be applied to detect specific fault signatures. For gearbox monitoring, the authors employ a Continuous Wavelet Transform (CWT) for decomposing the time domain signal into the time-frequency domain. For a signal x(t), the CWT of the signal is defined as:

$$Wx(a,b)=\int g^*(a,b)(t)x(t)dt \qquad \textbf{(1)}$$

where * denotes complex conjugate, g(t) represents the mother wavelet, and g(a,b)(t) is a baby wavelet, and a and b represent the scale (dilation factor) and position (translation factor) at which the wavelet coefficient is calculated. The pseudo frequency (Fa) corresponding to the scale (a) can be defined in Equation 2.

$$Fa=Fc/(a\ \Delta) \qquad \textbf{(2)}$$

where Fc is the center frequency of a mother wavelet in Hz and Δ is the sampling period. Fc/a is the center frequency of the baby wavelet. By carefully selecting the Fc and Fa (equating them with gear mesh, bearing, and shaft frequencies) used during the decomposition, the approach can be tailored to gearbox analysis. In addition, the authors decompose the raw time domain vibration data, time synchronized signal, and demodulated signal for general anomaly, gears/shaft, and bearing fault detection, respectively.

Short-Time Fourier Transform

The authors have developed a Short-time Fourier Transform (STFT) method, commonly used in speech, sonar, and radar processing, that segments a time domain signal, applies a weighting window to each overlapping segment, and computes the discrete-time Fourier transform of each segment. An estimate of the short-term frequency content of the signal is estimated and assumed to be stationary since sufficiently short time spans are used. However, the method still uses a typical Fast Fourier Transform (FFT), so the segment sizes must be set such that any shaft acceleration over the small time slice is negligible. A balance also must be struck between frequency and time resolution as dictated by the targeted fault detection needs. Small time slices result in high time resolution but low frequency resolution, affecting the resulting feature extraction. This approach is illustrated in Figure 9.

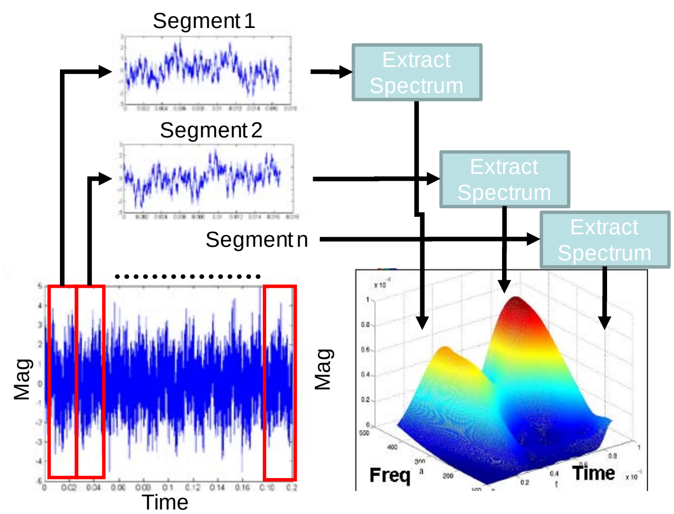

Figure 9 – Example Short-time Fourier Transform Analysis

Cohen's Class Distribution Function

Cohen's Class Distribution Function (CCDF) is a generalized time-frequency analysis method that utilizes bilinear transformations through the use of a kernel function [16]. There are many available kernel functions, including Choi-Williams (commonly used in speech analysis and ultra wideband signal analysis) [17], Wigner-Ville (commonly used in biometrics), and Zhao-Atlas-Marks (evaluated for bearing diagnostics [18] and motor diagnostics [19]). CCDF offers two primary advantages. First, CCDF analysis can be used to analyze vibration data collected during transient conditions. Second, a CCDF approach can result in both good frequency resolution and good time resolution, as opposed to the STFT approach, which trades time resolution for frequency resolution.

However, one of the commonly cited drawbacks of the CCDF approach is the influence of so-called cross term artifacts [19]. These cross terms are interferences caused by the linear combination of both auto and cross terms that result in increased signal redundancy [17, 19]. The resulting artifacts often obfuscate the frequencies necessary for fault isolation. To reduce the cross term effects, multiple methods having been implemented, including changing parameters of the kernel, utilizing different kernels, applying a filter, and using the analytic signal. In this paper, the authors chose a well-known kernel function, Choi-Williams, as described next.

The Choi-Williams Distribution (CWD), also called the Exponential Distribution, is a derivative of CCDF that uses an exponential kernel (Equation 3) to suppress the cross terms. However, it also reduces the time-frequency resolution. This tradeoff can be adjusted using the factor σ (controls cross terms) in Equation 3 to provide the optimal time-frequency resolution needed for a particular application [16, 17]. ξ is related to the time window used during CWD calculation and τ determines frequency resolution.

$$CWD(\xi,\tau)=e^{\frac{-\xi^2\tau^2}{\sigma}} \quad \textbf{(3)}$$

Vibration Features

Once calculated, the various JTFA signals still cannot be directly used to infer the health of a mechanical system. The signals need to be further analyzed for characteristics linked to gearbox failure phenomena. Most frequently, these characteristics are captured by features of the signals. From these various processed signals, several features (condition indicators) can be calculated that have been shown to relate to damaged gearboxes. Three primary features are extracted: NP4, FNP, and CWT variance. NP4 is a non-dimensional parameter related to the normalized kurtosis of signal power that depends only on the shape of the power distribution and is invariant to scale transformation [20]. The scale invariance property of this fault detection parameter can greatly simplify its application. The Frobenious Norm Feature (FN) describes the energy distribution of a vibration signal. Typically, the energy distribution is symmetrical under healthy conditions, but becomes asymmetric while the relative magnitude of the energy increases as faults occur and progress. These features can calculated for on any time domain signal, though the authors calculated each from the above mentioned transformed signals, the conventional (unprocessed or raw) signal, and finally the demodulated enveloped signal.

EXAMPLE APPLICATION OF METHODS

Although development of the oil and vibration analysis methods can be performed individually, a much more robust and accurate gearbox health assessment can be achieved by combing them. Therefore, data collected from a subscale bearing test rig was used to test this hypothesis and the above-mentioned approaches. Due to the proprietary nature of the test rig used, the authors will introduce only generalized information about the testing. As part of a series of tests run on the rig a damaged bearing was installed and ran for a period of time. Over the duration of this seeded fault test, vibration and oil debris data was acquired and saved for further analysis.

An inner raceway fault was seeded by means of a small hardness indentation (diameter <5% of circumference) made within the bearing's wear path. The bearing was then loaded (>3000 lbf radial load, >150% of bearing's maximum static load rating) and ran at a constant speed (>10,000 RPM). A radially mounted accelerometer (sampled at 200 kHz, 10 seconds every minute) was used to collect the vibration. Within approximately 3.5 hours of accelerated life testing, the fault progressed from a small indent into a large spall that completely covered 20-30% of the inner race circumference. Note that only the initial and final spall sizes were directly measured; there were no intermediate damage measurements.

Although the above-mentioned inductive sensor was not available for this testing, the quantity of debris was measured using a commercial magnetic chip collector. As the purpose of this test was to generate accelerated fatigue caused by high Hertzian stress (>400 kpsi), no other faults were seeded.

Therefore, only vibration and oil debris sensing are of interest for these results.

Based on the test rig's design/use (only a single test bearing) and the install sensor suite (a single accelerometer and chip collector), the authors adapted the generic approach introduced in Figure 3 to a form applicable for this test system. As shown in Figure 10, the generic vibration diagnostic algorithms block was replaced with the above-mentioned signal processing methods and the generic bearing features replaced with the 2-3 features extracted for each technique. Finally, a specific Gaussian Mixture Model (GMM) classifier routine was applied, which is discussed below.

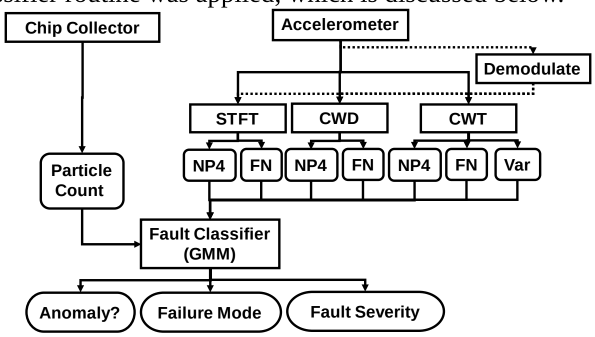

Figure 10 – Customized Vibration and Oil Diagnostic Approach

The STFT and CWD features for the conventional (raw) and demodulated signals are shown in Figure 11. The y-axis of these plots is the normalized feature magnitude and the x-axis is the time. There was a change in bearing health state over the duration of the test, as evidenced by the dramatic increase in feature magnitudes, particularly in the Frobenius Norm. The NP4 feature did react; however, it did not trend like FN.

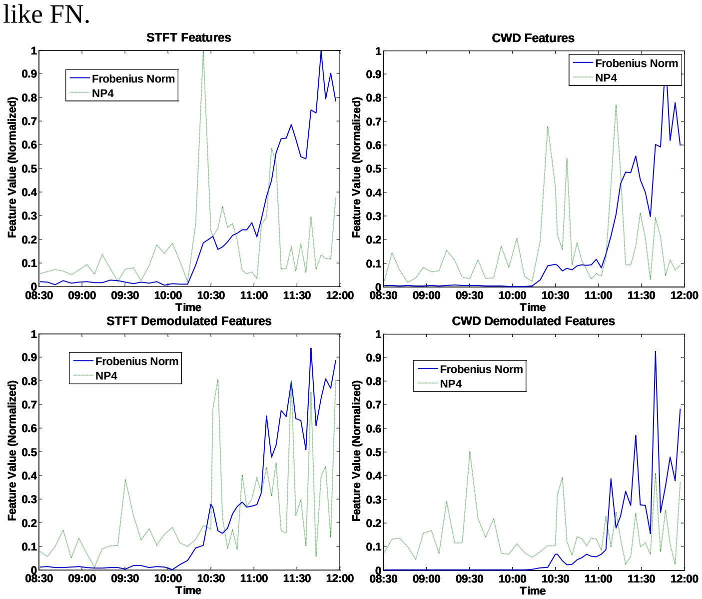

Figure 11 – STFT (Left) and CWD (Right) Feature Trends, Conventional Signal (top), Demodulated Signal (bottom)

The CWT features are shown in Figure 12. The axes are the same as Figure 11. Again, FN features trended with the degrading bearing. However, the trends in Figure 11 and Figure 12 alone do not indicate the exact level of damage; only that something is occurring and progressing.

These feature responses let us know there is a defect in the bearing and that the anomaly is evolving. However, for the accurate robust diagnostics required to provide the most diagnostic benefit, the amount of damage needs to be quantified. Unfortunately, vibration features are difficult to correlate directly to damage level. In contrast, oil debris can be directly correlated to damage. The normalized oil quantity trend shown in Figure 13 clearly depicts an increasing particle generation rate.

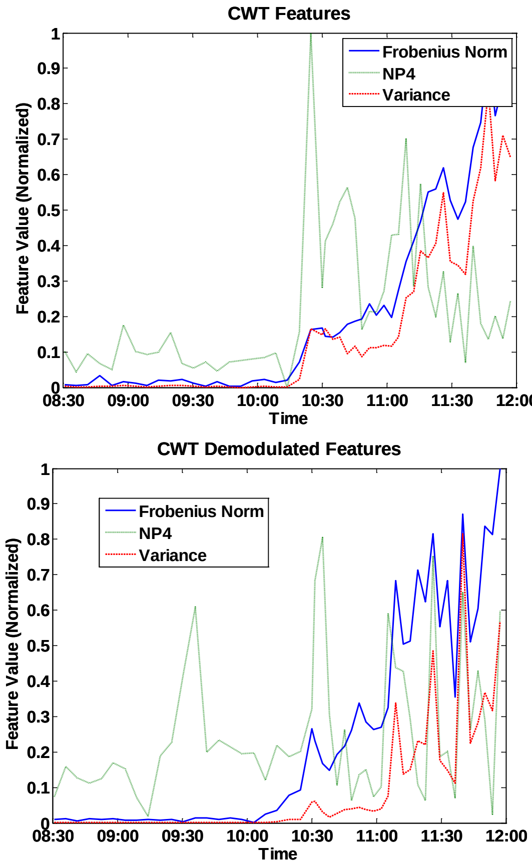

Figure 12 – CWT Feature Trends, Conventional Signal (top), Demodulated Signal (bottom)

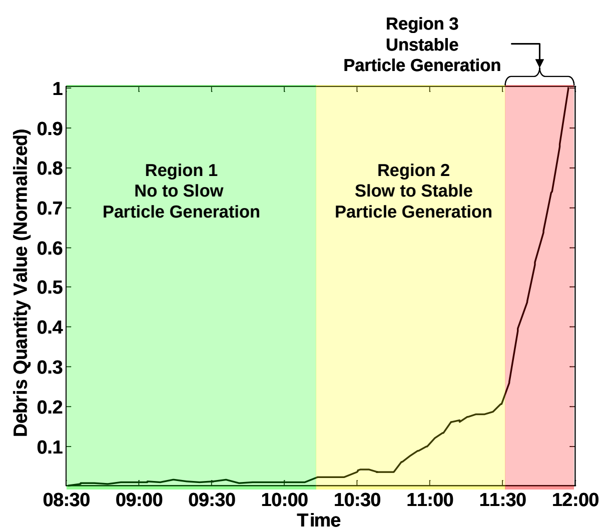

Figure 13 – Oil Debris Quantity Trend

In fact, drawing a comparison to crack growth phases, the authors identified three distinct regions of particle generation:

Region 1 (0-2 particles per minute), Region 2 (2-5 particles per minute), and Region 3 (>5 particles per minute). Notionally, these Regions correlate to the typical 3 phases of fatigue crack growth often described by the Paris Law (da/dN = $c\Delta K^{m}$)[21]. For this discussion, one could assume that any diagnostics that can characterize the defect size to one of these regions adequately meets the fault's size assessment criteria. In addition, by characterizing the defect size to one of these zones, there is inherently a characterization of the risk of failure.

- Slow Growth: incipient fault state (Region 1) [low risk of immediate failure]
- Stable Growth: moderate fault state (Region 2) [medium risk of immediate failure]
- Unstable Rapid Growth: severe fault severities fault state (Region 3) [high risk of immediate failure].

One could certainly apply a typical statistical analysis to the individual features and achieve some sort of diagnostic performance. Within the process, thresholds are set on the individual feature magnitudes by optimizing the balance between probability of false alarm (P(FA)) and the probability of miss detection (P(MD) = 1-probability of detection P(D)), as illustrated in Figure 14, which is provided solely for reference.

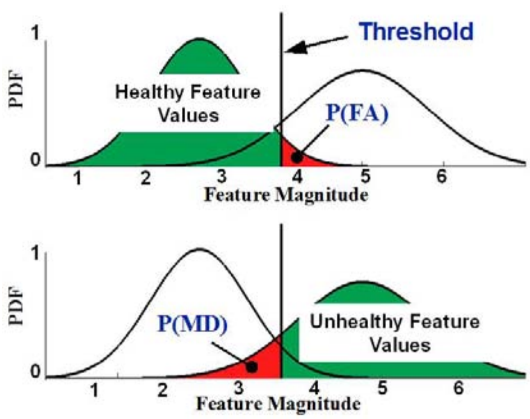

Figure 14 – Illustrations of Probability of False Alarm and Probability of Detection

Assume that only the single "best" vibration feature was used, for this analysis that would be CWT Demodulated FN (based on P(D)). Setting a theoretically acceptable P(FA)=2%, leads to a normalized threshold of 0.025 and P(D)~=100% and a detection of a bearing anomaly at ~10:19 (the earliest time a feature crosses the threshold). All of the diagnostic information is there, except for the fault severity assessment. Conversely, if we used only the oil debris sensor with the same process, the threshold would be 0.0654 and P(D)~=81% and the detection of an anomaly would occur at ~10:40. All of the diagnostic information is there except the fault isolation (debris cannot be readily correlated to specific component).

However, if the sensors and their features are combined, or fused, the resulting diagnostic would contain all necessary information. To address this fusion, the authors developed a cluster based classification method by generating a Gaussian Mixture Model (GMM) [22]. Many other techniques are available, but the GMM is a convenient method for this work. In the GMM process, also known as unsupervised learning modeling, clustering is performed using convex combination of probability distributions (similar to weighted sum). Clustering methods can be thought of as separating groups (or clusters) of features in multidimensional space. Unique to the GMM approach described herein, a model was defined that was capable of grouping the various features into classes associated with the oil debris regions shown in Figure 13. That is, the classifier was constructed in a manner to allow the sensor features to be assigned to one of the regions and thereby correlated to damage severity.

Like most clustering based techniques, developing the GM models requires both healthy and faulted data. The authors developed the model using 30% of the collected data (the remainder was used to test its performance). The resulting classification routine used several vibration features and oil debris data to provide an estimate on the fault severity (incipient, moderate, and severe). As shown in Figure 15, the estimated fault level is the blue line and is a direct output of the GMM classifier. The damage severity estimates were correlated well to the ground truth, in this case, the oil debris (green line, more detailed in Figure 13). Note that since the information is fused, the resultant time for anomaly detection from the fused is ~10:24, a bit later than vibration only and a bit sooner than oil only.

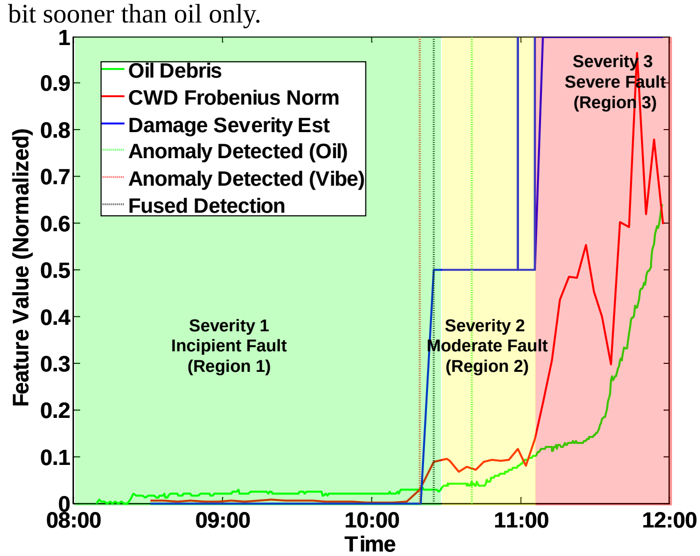

Figure 15 – Damage Assessment Based on Final Fused Diagnostics

Although the resulting damage assessment does not predict a discrete defect size (in this case, spall size), it provides the necessary diagnostic information required by a robust diagnostic approach, and ultimately by a complete PHM approach. The classification of severity level and risk of rapid fault progression, offered by correlating oil debris to known mechanical degradation phenomenon, would provide the wind turbine user with actionable information to make confident decisions on the current and future health of their gearboxes.

CONCLUSION & FUTURE WORK

In this paper, the authors briefly introduced the requirements needed by a wind turbine gearbox PHM system, focusing on the diagnostics. A methodology was provided that allows optimization of failure mode coverage with a minimal set of sensor technologies. Within this methodology, the anomaly detection, fault isolation capabilities, and detection horizons provided by the potential sensors and diagnostic techniques are considered.

New and innovative vibration analysis techniques were introduced. These JTFA methods have been shown in previous work to provide excellent fault detection/isolation capabilities, even in cases of unsteady operation like wind turbine gearboxes. In addition, several potential oil sensing methods were provided including their benefit to gearbox monitoring.

Finally, a potential method for fusing vibration features and oil debris results was developed and applied to a bearing run-to-failure test. From the vibration data collected during this test, the JTFA vibration features clearly detected and isolated the fault. Using the information from the oil debris sensor as ground truth, an automatic health classification scheme was developed. By combining the oil debris and vibration data with a GMM-based classifier, the authors were able to categorize the fault severity over the duration of the testing.

The authors believe this process described herein highlights some of the potential benefits of fusing oil sensing with vibration for wind turbine gearbox monitoring. Although only debris and bearing vibration data was available, this type of approach could be applied to any combination of oil sensing and mechanical component specific vibration diagnostics. The work presented in this paper is the first step in developing a complete gearbox PHM system. Additional oil sensing and vibration techniques would increase the fault mode coverage and increase its benefits.

An accurate, robust diagnostic system that can reliably assess the current gearbox health, such as the one presented herein, would readily enable prognostics to autonomously predict future health. The authors intend to build upon these results by integrating appropriate prognostic techniques. In addition, the authors are working to identify a more comprehensive set of data to refine and verify the approaches. Once combined with accurate prognostics, the integrated PHM approach would enable wind turbine operators to fully realize the benefits of their PHM investment.

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