Emerging Challenges and Technologies in Signal Processing for Prognostics and Health Management in Wind Energy

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ABSTRACT

The use of condition monitoring (CM) in wind energy machines continues to evolve as wind energy machines grow in size and move offshore. Early and smaller wind generation machines offered little financial incentives for condition monitoring, justifying only simple and inexpensive health monitoring technologies. Today, multi-megawatt wind machines are more complex, more difficult to physically reach, and generate more revenue than previous models. This paper reviews challenges and candidate technologies for next generation condition monitoring in Wind Energy.

Larger wind turbines typically employ Doubly-Fed induction generators with gearbox based drive trains or direct drive generators with multi pole rotors and fixed stators. Both configurations employ variable speed wind driven rotors, variable due to wind speed. Fixed rotor speed signal processing techniques no longer work in a variable speed environment. Synchronous sampling, order analysis, wavelet filters, Cepstrum and related frequency analysis of sensor waveforms are examples of advanced feature extraction tools now available for up-tower condition monitoring systems to address the variable speed nature of modern wind turbines. These signal processing tools operate to reduce and preprocess sensory data producing and extracting signal features. With extracted features, performance prediction and health diagnostics are then able to produce machine degradation rate and degradation levels.

This paper provides a tutorial of signal processing techniques for analysis of sensory information from variable speed rotary machines. The paper concludes with a discussion of prediction and diagnostics techniques which consume the analysis results of previously mentioned signal processing techniques. *

1 INTRODUCTION

As wind energy machines grow in size and move offshore, reaching the machines to conduct routine maintenance and repairs becomes extremely difficult. As wind turbines evolve to higher MW ratings, reliability is more critical. In off shore environments limited human access and poor weather often lengthen the time to repair. To reduce the burden of maintenance activities, improved reliability of wind energy machines becomes paramount.

Reliability of the wind turbine generator drive train, for example, depends on several factors including design, manufacturing quality, acceptance testing, and monitoring (Tan 2010). We often think of design and manufacturing as fundamental to reliability of the drive train. However, reliability of any system is increased with monitoring and supervision. Monitoring technologies coupled with mathematics (that indicate failures) allow for operations personnel to respond to drive train health degradation on a convenient schedule by using failure indications from monitoring technology. Reliability is then improved by avoiding surprise failures and by scheduling resources at the most cost and risk effective time. When action is taken to prevent failures, the wind turbine is more reliable.

There are many variables to consider in choosing a monitoring strategy. These include identification of typical failure modes of the drive train, the generator, driving forces, and key machine performance indicators. A holistic approach to monitoring incorporates all system parameters to provide a complete picture of the health of the wind turbine. On the other hand, an extreme volume of data from monitoring instruments is burdensome to evaluate and act upon. Due to this burden, evaluations are set aside and maintenance decisions to act are made without the benefit of failure indications hidden in the data. Operational decisions then suffer from data overload.

In order to benefit from a holistic monitoring approach and to avoid data overload, smart monitors analyze and reduce at the point of data acquisition. The combination of sensor and monitoring technologies can create a smart sensor to analyze incoming sensory information and reduce it to actionable items. Measured signals, such as vibration and temperature, carry feature information describing a physical aspect of the electromechanical component where the sensor is placed. Time domain and frequency domain analysis reduces the digitized sensor signal into key features. However, the wind turbine is subjected to variable excitation forces (wind) and operates at variable rotational speeds. The variability of excitation force and rotational speeds creates challenges for traditional signal processing techniques.

To compensate for variability of excitation forces wavelet and order analysis are two base signal processing technologies used to reduce errors from traditional signal processing analysis techniques.

2 CHALLENGES WITH TRADITIONAL SIGNAL PROCESSING TECHNIQUES

Traditional signal processing techniques for rotating machinery signal evaluation assume the machine speed remains constant. As noted above, wind energy machines are subjected to varying aerodynamic forces which result in speed variations significant enough to cause significant errors in signal processing results.

2.1 Limitations of the Fast Fourier Transform

The Fast Fourier Transform (FFT) is the basic operation in frequency analysis of vibration response of wind turbine excitation forces. However, frequency analysis produces frequency, amplitude, and phase information from the vibration signal. However, the FFT does not indicate when in time the feature occurred. Frequency analysis is useful for analyzing stationary signals where frequency content does not change over time, such as unbalance in a constant speed machine. Figure 1 shows an example of shaft unbalance time waveform and the corresponding frequency analysis as produced by the power spectrum FFT. In a tenth of a second, the 3600 RPM (60 Hz) machine's shaft wobbles back and forth 6 times. The FFT indicates a vibration frequency component at 60 Hz, which is the rotational speed of the machine. We know from machine vibration texts, that machine unbalance features exist at the rotational speed of the machine.

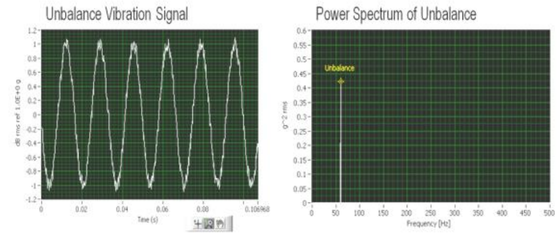

Figure 1: 3600 RPM machine with unbalance shown in time waveform and power spectrum analysis.

However, as the speed changes, the standard FFT is unable to isolate the core frequency. For example, a high speed pump increasing in speed from 1000 RPM to 3600 RPM with unbalance and mechanical looseness offers vibration measurements as shown in Figure 2. Here the unbalance and mechanical looseness are hard to isolate with an FFT alone.

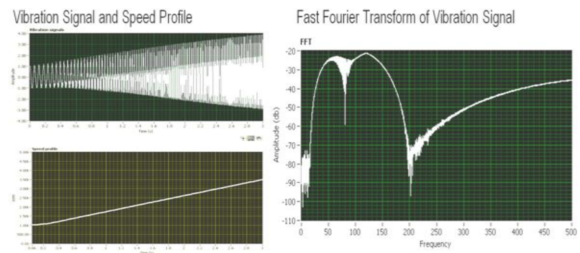

Figure 2: Machine run-up vibration measurement, speed profile and FFT of vibration measurements.

The increasing speed of the machine causes frequency variations in the time record. The FFT "sees" all of these frequencies and reports the existence of many frequencies and amplitudes. Therefore, it is nearly impossible to isolate the mechanical fault vibrations that change with changes in speed. While some machines may change speed rapidly as shown here, wind turbines do change speed, yet not as quickly. Even so, changes in speed reduce the accuracy of the FFT if the signal processing sequence is not adapted for changes in speed (Zhang 2008).

2.2 Using Resampling Order Analysis to Compensate for Machine Speed Variations

In order to correctly isolate the individual unbalance and mechanical looseness measurements, it is necessary to track the running speed of the machine and remap the time series data to the angular position of the shaft. This is accomplished by a technique called resampling. Resampling combines the speed measurements taken from a tachometer with the vibration measurements and interpolates the vibration measurements into a data point per fraction of angular rotation. The vibration measurements are now in the angular domain as compared to the time domain. Once in the angular domain, an FFT can be performed on the angular domain vibration measurement to produce what is known as an order spectrum. This analysis is often referred to as order analysis. Taking the same vibration measurements shown in Figure 2, and performing order analysis, the out of balance signature and the mechanical looseness signature of the pump are easier to separate, detect, and quantify. Figure 3 shows the same vibration and speed information along with an order spectrum.

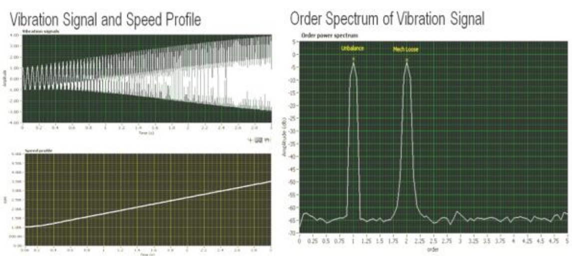

Figure 3: Machine run-up vibration measurement, speed profile, and order spectrum of vibration measurements.

With order analysis then, we are able to isolate repetitive vibrations from mechanical components even as the speed of the machine changes.

2.3 Resampling Process Defined

Resampling from time domain to angular domain is a signal processing step, when correctly done, aligns data with the angular position of the shaft and inhibits aliasing of high frequency signals into the measured time waveform. Historically synchronous sampling (resampling) has been accomplished with an encoder and an externally clocked analog to digital converter. However, this technique does not inherently provide alias protection. Modern vibration monitoring systems employ 24 bit delta sigma analog to digital converters that provide excellent anti-aliasing filters and a wide dynamic range over 100dB. A central element of this 24 bit technology is an internal precision oscillator that clocks the internal filters of the converter. Since the delta sigma converters rely on their internal oscillator, they cannot be externally clocked.

Using resampling, data is digitized with a 24 bit (delta sigma) analog to digital converter at a high rate, sampling well above the highest frequency of interest. The delta sigma converter includes the anti-aliasing filter as it digitizes sensory information in the time domain. Simultaneously, an encoder or tachometer signal is digitized to indentify the angular position of the rotating shaft. Next, software determines the desired angular position where a process or vibration signal is desired and an interpolation algorithm generates a angular series data point from the existing time record that exactly aligns with the desired angular position. A second stage low pass filter is then applied based on the desired samples per revolution. Finally, the angular position waveform may be decimated to the desired number of samples per revolution of the rotating shaft (National Instruments 2009, Sound and Vibration). Figure 4 graphically depicts the process.

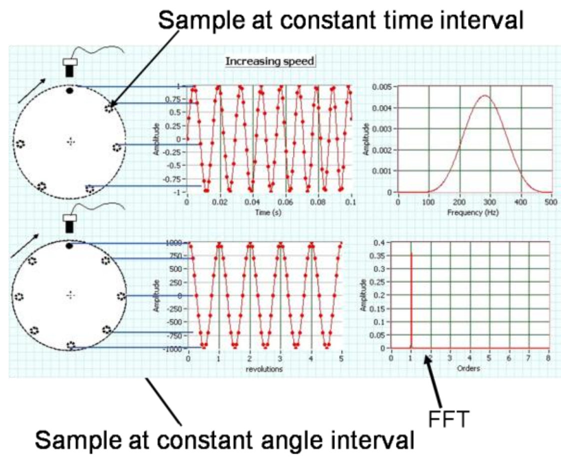

Figure 4: Resampling Method

As a result, both original time series time waveforms as well as angular position angular base waveforms are available for signal processing. For example, the FFT of angular base waveform sensory signals produces Order Analysis results as described in section 2.2.

All mathematical algorithms that are typically used for fault detection and diagnosis can work on either time waveforms or angular waveforms. Mathematical algorithms expect a constant uniform increment between units of time, or angle. With the original time waveform, and now the angular domain waveform, the unit of measure increment (time or angle) is constant. Further, the data blocks when acquired correctly are continuous from block to block.

Again, the new angular waveform has removed the variability of speed from the data samples and now allows advanced signal processing to correctly identified desired metrics (as shown with the FFT in order analysis).

3 ANALYSIS TECHNIQUES FOR IMPACT DETECTION IN MECHANICAL SYSTEMS

Gear and bearing defects in rotating machinery are often associated with impacting between metal components such as roller balls and race or between teeth of pinion and output gears. Impacting creates a high frequency transient signal in the time waveform. Because the impact is transient in nature, and not periodic, the FFT does not adequately represent the transient in its frequency, or order domain.

3.1 Transient Signals and the FFT

Transients are sudden events lasting for only a short time in measurement. Transients usually have low energy and a wide frequency band. When transformed into the frequency domain or the order domain by a Fourier transform, the transient energy is spread over a wide frequency range. Because of the transient's low energy per frequency, it is difficult to recognize their existence in the frequency domain. Figure 5 shows an unbalance vibration measurement from a 1800 RPM machine (30 Hz) with and without a transient impact.

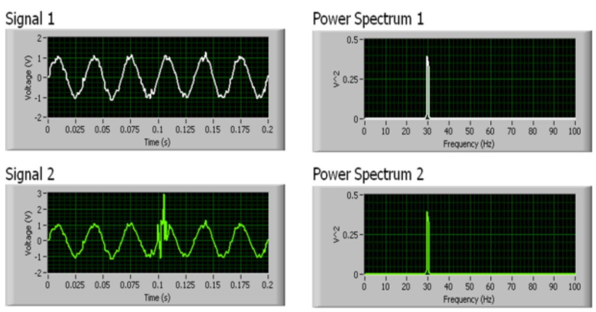

Figure 5: Machine unbalance vibration measurement with and without a transient impact.

3.2 Using Wavelets to Detect Impacts

Wavelets, the reference used in wavelet analysis, are defined as signals with two properties: admissibility and regularity. Admissibility means that a wavelet reference or mother wavelet must have a band-pass-limited spectrum. Admissibility also means that wavelets must have a zero average in the time domain. A zero average implies that wavelets must be oscillatory. Regularity means that wavelets have some smoothness and concentration in both the time and frequency domains. Regularity then means that wavelets are oscillatory and compact signals (Qian 2002).

As comparison, sine waves oscillate along the time axis forever in time without any decay, which means they are not compact. In other words, sine waves do not have any concentration in the time domain. On the other hand, sine waves have extreme concentration in frequency domain. Sine waves have maximum resolution in frequency domain but no resolution in time domain.

Wavelets have limited bandwidth in the frequency domain and compact bandwidth in the time domain. So, wavelets have a good concentration and resolution trade-off between the time and frequency domain. Figure 6 depicts the differences between a sine wave and a wavelet in both time and frequency domains.

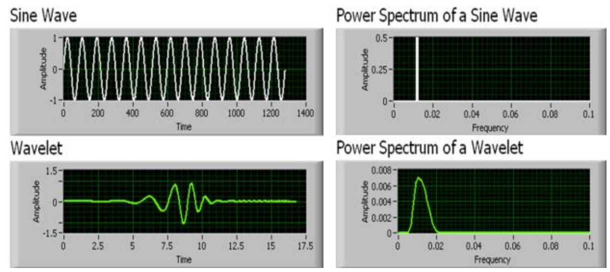

Figure 6: Comparison of a sine pattern and a wavelet pattern

The use of wavelets can be referred to as the application of wavelet filters. In other words, the filtering process removes sensory signal components that do not "match" the wavelet pattern. Figure 7 offers and additional example of wavelet analysis of a motor with internal impacting. It is noted that the vibration time waveform in Figure 7 is more complex than that of Figure 5.

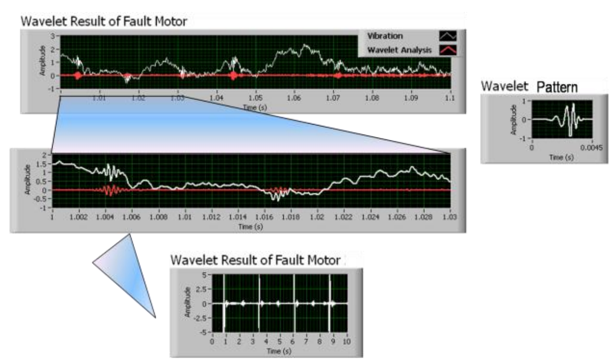

Figure 7: Wavelet filter analysis of motor with internal impacting fault.

In Figure 7, the white vibration trace contains both imbalance vibratory signatures as well as impacting. With wavelet "analysis", only the signal components that match the characteristic pattern of the wavelet are passed to the resulting waveform, the red trace. In addition, wavelet analysis results in wavelet coefficients that indicate the strength of the match along the same time instances. The third or bottom graph in Figure 7 shows the wavelet coefficients and the strength of the match along a proportional time line.

In effect, wavelets offer a method to detect bearing defect and gear mesh faults by extracting characteristic impacts from the time or angular waveform.

3.3 Using Cepstrum to Automatically Detect Harmonics in the FFT Result

Traditional spectrum analysis of machinery vibration faults results in an FFT indicating excited mechanical forces such as imbalance, mechanical looseness, misalignment, bearing faults, and gear mesh faults. When the data acquisition is set-up per common rules of thumb, the frequency span of the FFT is ten times that of calculated or expected fault frequencies. Impacting in mechanical looseness, bearing faults, and gear-mesh creates harmonics of these fault frequencies that are visible in the frequency domain. The vibration analyst typically uses harmonic cursors to manually identify these harmonics. Identify of harmonics is an important aid in correct diagnosis of detected mechanical component degradation.

However, the detection of harmonics as a manual human process step is time consuming and requires human intervention in the process. Fortunately, there is a mathematical frequency analysis tool that can assist, the Cepstrum.

A Cepstrum, which is an anagram of the word spectrum, is the Fourier transform of the natural logarithm of a spectrum (the original time waveform FFT). The estimated Cepstrum is used to identify echoes or periodic components in a time series. A Cepstrum also is useful for separating homomorphic or convolved components in a time series by transforming the time series into a domain where the convolution becomes a simple summation operation. Cepstrum estimation methods treat frequency-domain data as time-domain data. The domain of a Cepstrum is called quefrency, which is an anagram of the word frequency (National Instruments 2009, Advanced Signal Processing).

Figures 8 and 9 provide an illustration and comparison of the FFT and Cepstrum in analysis of roller bearing fault frequencies.

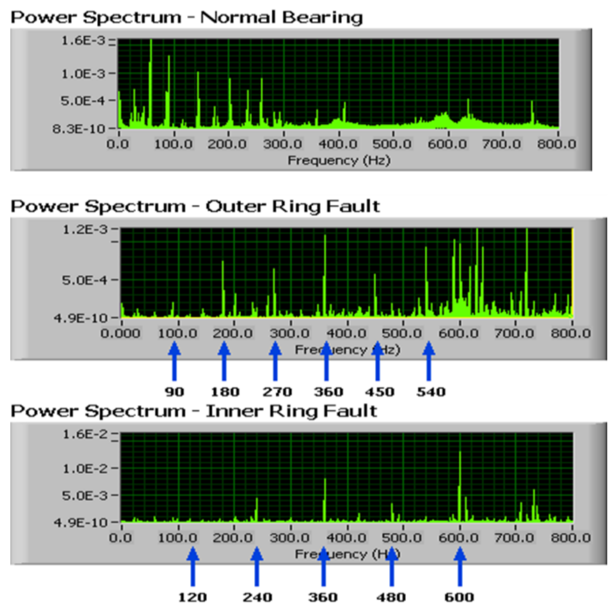

Figure 8: FFT (Power Spectrum) of bearing vibration signature.

In Figure 8, the ball pass frequency outer race (BPFO) is 90 Hz. Harmonics of 90 Hz are clearly visible in the Power Spectrum at 180, 270, 360, 450, and 540 Hz. Also, in Figure 8, the ball pass frequency inner race (BPFI) is 120Hz. Harmonics of 120Hz are visible at 240, 360, 480, and 600Hz. However, a trained eye experienced in identification of bearing fault harmonics is often required to identify these harmonics.

With Cepstrum, there is just one peak in the resulting Cepstrum graphic as shown in Figure 9. Recall, from the definition above, that the X-axis in Figure 9 is quefrency as compared to frequency.

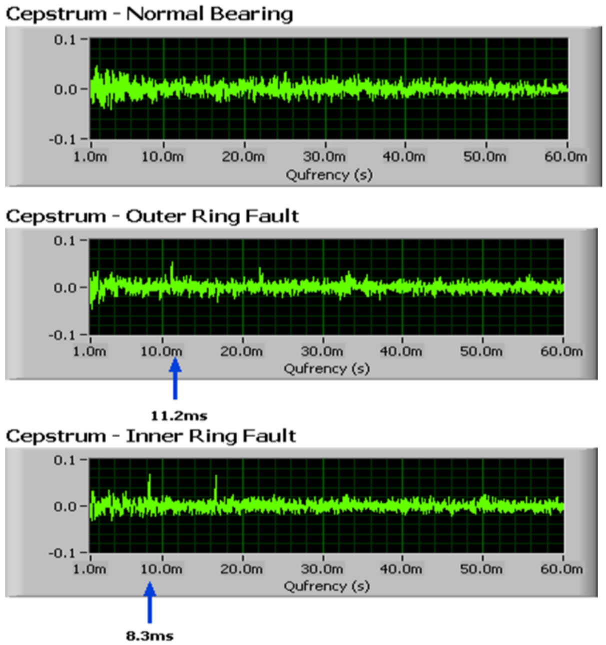

Figure 9: Cepstrum of bearing vibration signature.

In Figure 9, harmonics of BPFO and BPFI are noted in a single location, quefrency of 11.2ms and 8.3ms respectively. If we take the inverse of each of these quefrency, we get the base frequency of the harmonic series, 90Hz and 120Hz respectively.

With the resulting series (Cepstrum) simplified, it is now possible to automate the detection of harmonics related to impacting mechanical faults including mechanical looseness, bearing faults, and gear mesh faults. To carry this further, when using the angular waveform as the basis for the original spectrum, it is possible to remove spectral leakage skewing resulting from speed variations in the machine.

3.4 Time Synchronous Averaging for Noise Reduction.

In vibration fault frequency analysis, it is often desired to remove non periodic signal or noise from the initial time series waveform. A proven technique is time synchronous averaging (TSA). Here, the data acquisition of sensory information is synchronized to shaft position and each rotation's data block is averaged with data blocks from other rotations. By averaging the data blocks from individual machine rotations, any signal that is not an integer harmonic of rotational speed is averaged out of the time waveform. This technique is often used to enhance analysis of high frequency faults such as gear mesh, blade pass, looseness, and mechanical rotation of poles in a generator. Several studies of TSA algorithms and noise reduction results are available. One in particular cites the improvement of condition indicator calculations (in particular time domain statistics) with the use of TSA for gear applications (Bechhoefer 2009).

Unfortunately, TSA also averages away bearing fault signatures as these are not exact integer harmonics of rotational frequency or speed. However, early work suggests a synthesized reference tachometer (derived from the relationship of the shaft rotational speed and bearing cage rotational speed) can produce similar results for roller bearing signature analysis (McFadden 2000).

TSA is a widely used technique in predictive maintenance to assist in early detection of mechanical faults. An illustration of TSA is provided in Figure 11.

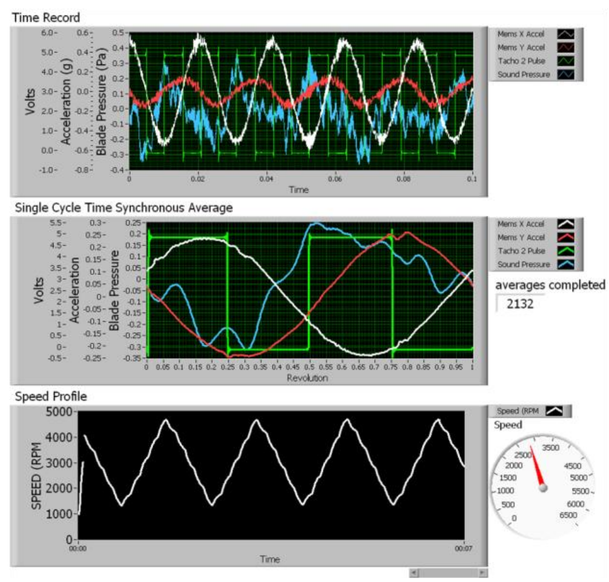

Figure 11: Time Synchronous Averaging

In Figure 11, the original time waveform is shown in the top time waveform plot. The mechanical system exhibiting vibration is an unbalanced fan. The red and white traces are acceleration in the vertical and horizontal direction. A pressure sensor (microphone) measures pressure pulsation from seven blades and is shown in the blue trace. The green trace is an encoder producing two pulses per revolution. Visual inspection of the time waveform indicates noise in the sensor signals.

The fan is not operating at a constant speed. The bottom time series graph shows the speed profile over a seven second time period. The speed of the fan during the acquisition and averaging process varies between 1500 RPM and just over 4000 RPM.

To compensate for speed variations, the signals are resampled into the angular waveform and multiple revolutions are averaged together. The middle graphic in Figure 11 depicts the TSA of the angular waveform after more than 2000 averages. The mechanical signatures are clearer now that noise has been removed. In fact, on close visual inspection, the blade pass of the seven blades is visible in the blue trace. The once per revolution triangular shape of the trace is a result of a missing blade. The blade pass following the missing blade is absent the wake of the previous blade and hence produces a large pressure pulsation that decays over the rotation until the missing blade appears.

With TSA of the angular waveform, it is now possible to identify the angular position of the missing blade, which is the third blade from top dead center of the fan shaft.

There are two areas in TSA which will benefit from additional research. The first area is research and development of embedded versions of time synchronous averaging that are able to execute on the up tower data acquisition system. Given, the ability of the initial data acquisition system to filter and reduce sensory data with TSA, bearing and gear health information is readily available to transmit to the control system and the maintenance engineer's desk. The second area is the development of additional case studies. With additional data sets and installation in wind turbines, the application of TSA can be tuned more closely for specific turbine classes and applications.

4 COMBINE SIGNAL PROCESSING WITH PERFORMANCE AND OTHER MECHANICAL MEASURES

Vibration is not the only sensory measure used to evaluate the mechanical health of a wind turbine generator. Metrics calculated from vibration measures should be integrated with performance and structural measures to create a more holistic view of the machine. Additional measures of choice include stress and strain forces on wind turbine blades, wind turbine rotational speed, turbine control functions including pitch and yaw, wind speed, temperature, electrical power output and others.

4.1 Wind Turbine Blade Stress and Strain

New developments in stress and strain measures are available to wind energy. In particular, fiber optic sensors provide a means to monitor multiple stress points along the blade within a single fiber optic cable that is immune from electromagnetic noise, including lightning. Figure 12 depicts a typical strain measurement layout for the blade roots in a wind turbine.

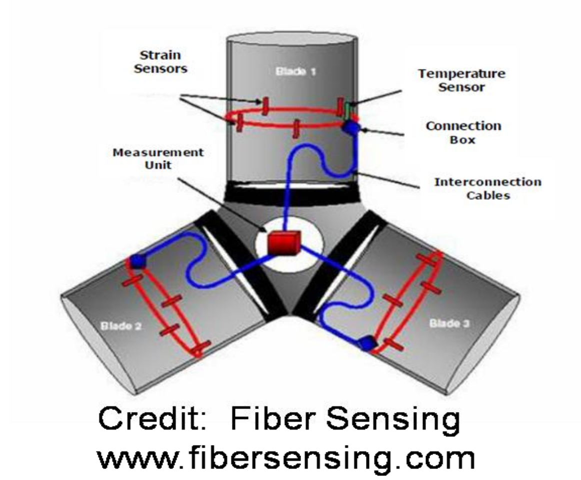

Figure 12: Fiber optic strain gauge sensor map of blade root.

Fiber optic sensors and the associated light wavelength interrogator provide a noise immune sensor measure of stress and strain of blade roots. Typical strain measurements are made approximately 10 times per second. A common analytic technique used in evaluation of a material damage or degradation is fatigue analysis. Fatigue analysis is the identification of a load or stress cycle and an accumulation measure of these cycles. The accumulation is compared to an S-N curve for the material of the structure. The S-N curve indicates the number of stress cycles a material can sustain before fatigue occurs (National Instruments, 2010). In the case of dynamic strain, frequency analysis may also be used to characterize core cyclical components and compare to the resonant frequency of the blade.

This time waveform may also be resampled into an angular waveform for easy correlation with the vibration measurements described earlier. With time synchronized data acquisition devices, it is possible to correlate stress and strain on wind turbine blades with rotational speed and position of the wind turbine shaft as well as with vibration signatures.

4.2 Other Measures in Wind Turbines

There are many additional measures that enhance the operational performance and health of the wind turbine generator. These include speed, pitch and yaw position, wind speed and direction, generator power output, oil particulate and viscosity measurements, temperature, and many others. By integrating many of these measurements, a more holistic view of the wind turbine is developed. This holistic view offers the opportunity for development of additional cause and effect relationships.

To make sense of these additional parameters, a data organizational scheme can be used.

5 SORTING AND REPORTING

Monitoring this wide range of sensory data without sorting, filtering, prioritizing, analyzing and correlating the data only produces more data than the human expert is able to utilize.

5.1 Regime Sorting

Now that measurements and important metrics are in place, the next step is to sort data into similar machine operational parameters. In the case of a wind turbine, shaft rotational speed, wind speed, and power output are often key measures for organizing data. The Center for Intelligent Maintenance Systems (IMS), www.imscenter.net, illustrates this process in Figure 13.

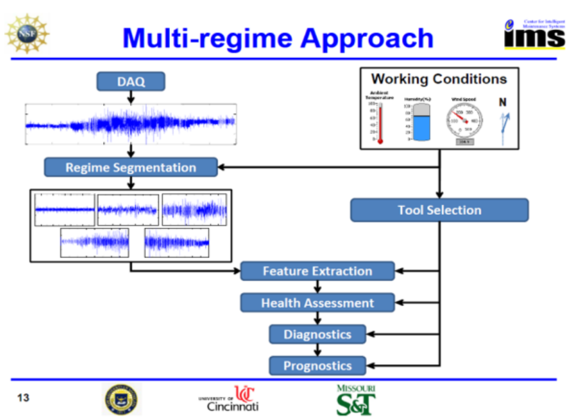

Figure 13: IMS Center multi-regime sorting approach

Example operating conditions include low, medium, and high load on the electrical power output side of the generator. Other examples include low, medium, and high wind speeds. Within these two external condition categories, turbine turning speed further separates data sets. Finally, sensory output levels such as low, medium, or high vibration levels in each of these conditions adds to the number of conditions. For example, a single data set might have the label including high load, high wind speed, high turbine speed, and medium vibration level.

Once data is sorted into like operating conditions, comparing signal processing results from similar classified data sets produces more accurate maintenance information. In fact, this regime sorting method played a key role in the IMS Center's win of the 2009 PHM Data Challenge in October, 2009 (IMS Center 2009). With sorted data, typical signal processing metrics were computed on like data to determine gearbox faults including cracks, missing teeth, bearing faults, and overall gear fatigue.

In other words, it is important to organize data into similar operating conditions. It is common practice in the field of vibration analysis to ensure time waveforms and associated analysis results are only compared with time waveforms of the same or like machines under the same operating conditions.

A smart embedded data logging system for wind turbines will not only calculate key metrics, it will also record machine operating condition and other performance metrics along with high fidelity information such as frequency analysis metrics. By recording operating conditions along with high fidelity metrics, it becomes possible to sort data. Once data is sorted into like operating conditions, comparing signal processing results from data sets produces more accurate maintenance information.

5.2 Pattern Matching to Identify Faults in Sorted Data Sets

Now that data is sorted into like operating conditions, a range of statistical and model based pattern matching can be performed. The IMS center has determined the applicability of several statistical and model based approaches to pattern matching in machinery health assessment applications (Lee, 2009). These approaches are listed in Figure 14.

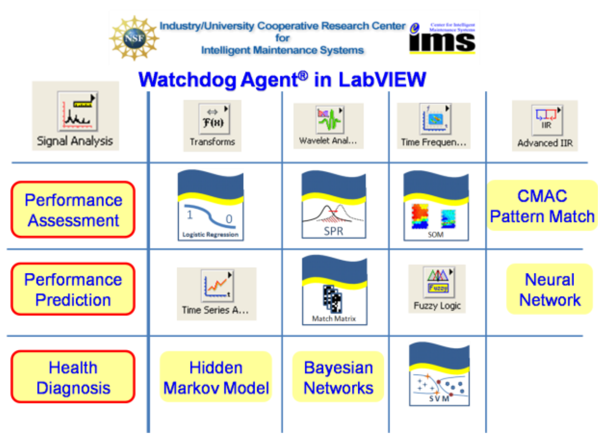

Figure 14: Statistical and model based tools for assessing performance and health of industrial machinery.

Similar to recognizing harmonics in the FFT, as discussed earlier, these pattern matching and classification tools are able to automatically organize operational signatures into both operating and mechanical health categories. In fact, these tools were used to facilitate the Academic and commercial wins of the PHM Society 2009 Data Challenge (IMS Center 2009).

Two examples in the performance assessment row of Figure 14 are Logic Regression and Statistical Pattern Matching (SPR). Logic regression allows the prediction of group membership such as faulty bearing under speed and load, or normal behavior. Logic regression is useful when the number of extracted features used is 5 or less. Statistical Pattern Matching compares the distribution of features for the current state to the distribution of features in a known normal state and/or a faulty state. Additional details of the Watchdog Agent^{TM} tools are provided in the toolbox documentation (Intelligent Maintenance Systems, 2007)

It is important to recognize the advantage of automatic analysis, correlation, and sorting of wind turbine measurements. Much of this work can be accomplished in the data recording device installed at the wind turbine.

With recorded data and metrics that are sorted or tagged with specific operating conditions, a wind farm site data server can then begin making a wider range of correlations. Statistical and model based pattern matching can be performed on the data server which pulls date from multiple wind turbines. Now it is possible to compare like wind turbine behavior to determine best operating procedures, best performing mechanical components, and common failure modes. With this additional knowledge or information, the wind farm asset health monitoring information system can learn new data relationships and apply these relationships to future data sets.

5.3 Creating Reports to Facilitate Action

With sorted and pattern identified data sets, data visualization in terms of reporting is a key next step. To accompany the pattern and operating regime information, the IMS center has developed a series of graphics to assist operations management in determining the risk of failure and scheduling maintenance activities. These graphical reports are shown in Figure 15.

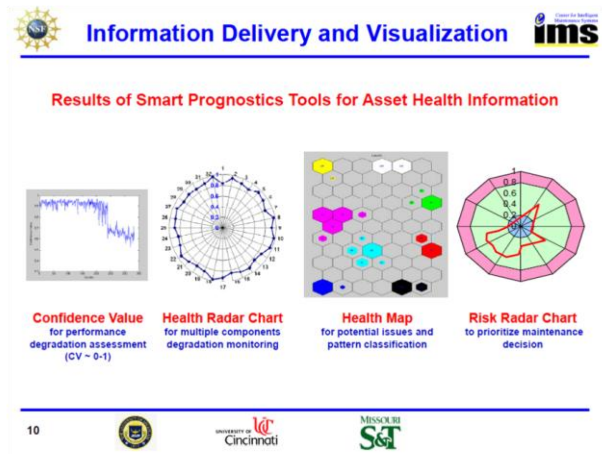

Figure 15: Smart Prognostic Graphics for Reporting

These graphics provide visual display of health information. The Confidence Value trend chart shows the mechanical health of a specific machine component using a measure of 1 (very healthy) to 0 (badly damaged). The confidence value is commonly calculated using statistical pattern matching described earlier. The Health Radar Chart shows the confidence value of multiple components on a single chart. For example a wide circle shape indicates a healthy machine. When one angular direction of the circle begins to collapse, a specific machine component is showing signs of degradation.

The Health Map combines machine operational states with machine failure modes. The Health Map is based on a self-organizing map concept which organizes clusters of data points into machine states. For example, electrical load, wind speed, and turbine turning speed provide operational states. These are coupled with bearing and gear degradation states to produce a health map with machine health states combined with operational states. The health map provides a high level view of the wind turbines' current operational and health states as well as other empirical operational and health states.

The Risk Radar Chart combines machine state and health indicators along with safety and financial parameters to indicate an element of risk. A health risk radar chart, similar to the health radar chart, indicates high plant operational health when the circular circumference is along the outer boundary of the chart. Mechanical health problems are magnified or diminished based on the financial or safety impact of a failure. For example, detected bearing health degradation on a lower power wind turbine with easy access and spare parts availability will not impact the risk radar chart. However, a high power off-shore wind turbine gearbox degradation indication will be magnified by challenging access and higher cost of revenue.

Armed with these reports, operations and maintenance teams are best prepared to make operational and maintenance decisions. Of course these end reports depend on solid data collection and signal processing techniques described earlier. Without solid data and informational metrics, the pattern matching and reporting process will not be effective.

6 CONCLUSION

Advanced signal processing techniques including resampling, order analysis, wavelets, Cepstrum analysis and time synchronous averaging work to address the challenges of wind turbine generators. These techniques compensate for variable speed and load conditions which the wind energy generator is subjected to. By combining the results of these techniques with time correlated performance and operational information, signal processing results are sorted, matched with similar data sets, and organized in reports which improve operations and maintenance actions. The end result is improvements in reliability of individual wind turbines, wind farm operations, and a promise of reduced power generation costs.

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