Survey of Condition Indicators for Condition Monitoring Systems

Junda Zhu, Tom Nostrand, Cody Spiegel, and Brogan Morton

Renewable NRG Systems, *Hinesburg, Vermont, 05461, USA*

jz@renewablenrgsystems.com

ABSTRACT

Currently, the wind energy industry is swiftly changing its maintenance strategy from schedule based maintenance to predictive based maintenance. Condition monitoring systems (CMS) play an important role in the predictive maintenance cycle. As condition monitoring systems are being adopted by more and more OEM and O&M service providers from the wind energy industry, it is crucial to effectively interpret the data generated by the CMS and initiate proactive processes to efficiently reduce the risk of potential component or system failure which often leads to down tower repair or gearbox replacement. The majority of CMS are designed and constructed based on vibration analysis which has been refined over the years by researchers and scientists. This paper provides detailed description and mathematical interpretation of a comprehensive selection of condition indicators for gears, bearings and shafts. Since different condition indicators are sensitive to different kind of failure modes, the application for each condition indicators were also discussed. The Time Synchronous Averaging (TSA) algorithm was applied as the signal processing method before the extraction of condition indicators for gears and shafts. Time Synchronous Resampling algorithm was applied to stabilize the shaft speed before the extraction of bearing condition indicators. Several case studies of real world wind turbine component failure detection using condition indicators were presented to demonstrate the effectiveness of certain condition indicators.

1. INTRODUCTION

As the global market of wind energy continuously grows over the recent years, the maintenance strategy of wind farms is evolving from schedule base maintenance to condition based maintenance. Scientists, researcher and engineers specialized in condition based monitoring techniques designed and utilized condition indicators to monitor and track the health status of the assets of interest. Condition indicators can be extracted from various signal sources including tradition vibration based signal from accelerometers, acoustic emission signal, oil condition signal and signal collected from SCADA systems. Different condition indicators were designed for different applications. Ideally, vibration based condition based monitoring techniques are very capable of detecting component fault signatures at high speed or intermediate sections of the wind turbine while acoustic emission based techniques are more capable of low speed or planetary section component fault detection.

Previously, Vecer et al (2005) summarized a comprehensive selection of condition indicators for gears along with some typical vibration signal analysis algorithms. Also, the National Renewable Energy Laboratory (NREL) published a document named 'Wind Turbine Gearbox Condition Monitoring Round Robin Study – Vibration Analysis' in 2012 covered detailed information regarding lots of the common condition indicators. This paper summarized a great amount of the information from the above mentioned two reports. And the authors provided an industry perspective on how to utilize different CIs including those not only for gears but also for bearings and shafts on machine health status monitoring.

In general, the definition of condition indicators consists of two parts, the analysis algorithm and the statistical features. Analysis algorithm can be narrowband analysis, residual analysis and frequency/amplitude modulation analysis and so on. Statistical features include root mean square (RMS), kurtosis, crest factor, skewness, peak, peak to peak etc. A typical condition indicator can be expressed as narrowband kurtosis or residual RMS. Therefore, as a matter of fact, condition indicators are designed to describe the time or frequency domain signal waveform or analysis result from specific analysis algorithm in a statistical manner. Typical condition monitoring system data processing flowchart for gears is presented in Figure 1. In Figure 1, the incoming raw vibration signal were collected from the accelerometers and then goes into the Time Synchronous Averaging Algorithm (TSA) to remove noises that were not synchronous with the shaft rotating frequency. Time synchronous average signal

is calculated by dividing the vibration signal into one revolution sections (based on the once-per-revolution tachometer signal). Each single revolution section is resampled into a common length to eliminate variations in speed. Then all the equal length sections are combined and averaged. TSA is a vibration signal processing algorithm that calculates the average vibration caused by one revolution of the shaft under analysis. It converts the vibration from the time domain into the revolution (or order) domain and significantly reduces all vibration that is not synchronous with the shaft. Bechhoefer explained the algorithm and its derivation (Bechhoefer and Kingsley, 2009). The signal then goes through residual analysis algorithm. After that, statistical features are extracted from the residual analyzed vibration signal. Similarly, the raw vibration signal goes through narrowband analysis, energy operator analysis, Amplitude Modulation (AM) analysis and Frequency Modulation (FM) analysis. Accordingly, statistical features are extracted from the analyzed signals which are defined as condition indicators.
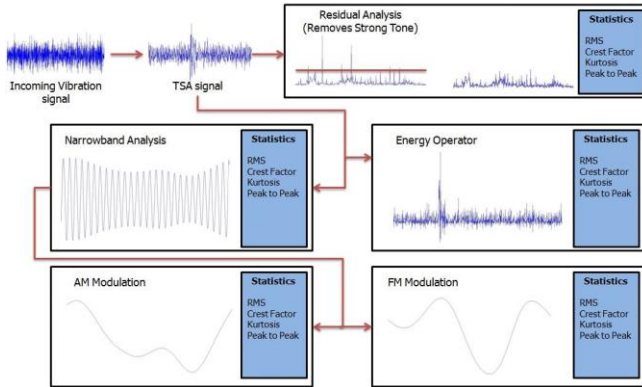

Figure 1. Vibration signal processing flow chart.

The first section of this paper gave an introduction to the techniques. The second section of this paper covered the definition of the statistical features, their definitions and applications. Then, the third section went over the analysis algorithms for different components including gears, bearing and shafts. The general descriptions of the analysis algorithm along with their applications were discussed. After that, the 4th session covered several case studies of real world wind turbine component failure detection using condition indicators to demonstrate the effectiveness of some of the described condition indicators. The last section summarized this paper.

2. STATISTICAL FEATURES

In general, statistical features were designed to describe the result of a specific vibration signal analysis algorithm. Common statistical features include Root Mean Square (RMS), Delta RMS, Peak, Peak to Peak, Kurtosis, Crest Factor, and Skewness, which were shown in the following respectively.

2.1. Root Mean Square (RMS)

RMS describes the energy content of the signal. RMS is used to evaluate the overall condition of the components. Therefore, it is not very sensitive to incipient fault but used to track general fault progression (Vecer et al, 2005).

$$s_{rms} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (s_i)^2} \qquad (1)$$

s_{rms} is the root mean square value of dataset s

s_i is the i-th member of points in dataset s.

N is the number of data points in dataset s.

2.2. Delta RMS

Delta RMS is the difference between two consequent RMS values.

$$Delta\ RMS = RMS(T) - RMS(T-1) \qquad (2)$$

If the gear damage occurs, the vibration level will be increased more rapidly than in a normal case without gear damage (Vecer et al, 2005).

2.3. Peak

Peak value is the maximum amplitude of the signals within a certain time interval.

$$s_{peak} = max(s_1, s_2, s_3 \dots s_N) \qquad (3)$$

Peak value is usually not used very often compared to peak to peak value.

2.4. Peak to Peak

Peak to peak value is the distance between the maximum amplitude and the minimum amplitude of the signal. Peak to peak is a measurement of spread in the signal.

$$s_{peak-peak} = s_{max} - s_{min} \qquad (4)$$

2.5. Kurtosis

The shape of the amplitude distribution is often used as a data descriptor. Kurtosis describes how peaked or flat the distribution is. A kurtosis value close to 3 indicates a Gaussian-like signal. Signals with relatively sharp peaks have kurtosis greater than 3. Signals with relatively flat peaks have kurtosis less than 3. The following equation calculates the kurtosis (Vecer et al, 2005).

$$kurtosis = \frac{N \cdot \sum_{i=1}^{N} (s_i - \bar{s})^4}{\{\sum_{i=1}^{N} (s_i - \bar{s})^2\}^2} \qquad (5)$$

N is the number of points in the history of signal s

s_i is the i-th point in the time history of signal s

Kurtosis provides a measure of size of the tails of distribution and is used as an indicator of major peaks in a set of data. As a gear wears and breaks, this feature should signal an error due to the increased level of vibration.

2.6. Crest Factor

Crest factor is the ratio of the single side peak value of the input signal to the RMS level (Vecer et al, 2005).

$$CF = \frac{S_{peak}}{S_{rms}} \qquad (6)$$

CF is the crest factor

$S_{peak-peak}$ is the single side peak of the signal

S_{rms} is the root mean square value of the vibration signal

This value is normally between 2 to 6. Crest factor value over 6 indicates possible machine failure. There are certain variations on the definition of crest factor. The numerator could be the single side peak value (maximum or minimum) or a mean of the maximum and minimum of the signal of interest. Crest factor can be used to indicate faults in an early stage. This feature is used to detect changes in the signal pattern due to impulsive vibration sources such as tooth breakage on a gear.

2.7. Skewness

Skewness indicates the symmetry of the probability density function (PDF) of the amplitude of a time series. A time series with an equal number of large and small amplitude values has a skewness of zero. The following equation calculates skewness (Vecer et al, 2005).

$$Skewness = \frac{N \cdot \sum_{i=1}^{N}(s_i - \bar{s})^3}{\left\{\sqrt{\sum_{i=1}^{N}(s_i - \bar{s})^2}\right\}^3} \qquad (7)$$

N is the number of points in the history of signal s

s_i is the i-th point in the time history of signal s

A time series with many small values and few large values is positively skewed (right tail), and the skewness value is positive. A time series with many large values and few small values is negatively skewed (left tail), and the skewness value is negative.

3. ANALYSIS ALGORITHMS

Analysis algorithms were applied before the extraction of statistical features. These algorithms were developed to enhance the component fault signatures. The statistical features extracted from the result of the algorithm are called condition indicators. Different condition indicators were developed to detect various faults on different components. This section categorizes them into three categories including bearing, shaft and gear. The typical analysis algorithm for

different components were listed and explained along with the extracted condition indicators.

3.1. Bearings

Time Synchronous Resampling algorithm was applied to stabilize the shaft speed before the extraction of bearing condition indicators. In the CMS industry, it is common to have a hard threshold over certain shaft speed that triggers the data collection. Combined with TSR, the shaft speed can be controlled to a maximum extend in terms of speed fluctuation. In general, bearing fault characteristic frequencies are used to diagnose and localize the bearing fault induced by pitting, spall, cracking and etc. The specific bearing fault characteristic frequency of different components can be obtained from the bearing kinematic information. There are 4 common condition indicators for bearings which are ball energy, cage energy, inner race energy and outer race energy, respectively. A window of observation is usually set around the fault frequency of the bearings. This is designed to ensure even if the shaft speed is somewhat inaccurate, the amplitude of the bearing fault frequency can still be captured.

3.1.1. Ball Energy

Ball energy represents the energy of the bearing vibration signal at/around the rolling element fault frequency.

$$Energy_{ball} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_b \pm N)^2} \qquad (8)$$

f_b is the fault frequency of the rolling element

N is half of the window of observation

3.1.2. Cage Energy

Cage energy represents the energy of the bearing vibration signal at/around the cage precession frequency.

$$Energy_{cage} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_c \pm N)^2} \qquad (9)$$

f_c is the fault frequency of the cage

N is half of the window of observation

3.1.3. Inner Race Energy

Inner race energy represents the energy of the bearing vibration signal at/around the inner race fault frequency.

$$Energy_{Inner\ race} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i \pm N)^2} \qquad (10)$$

f_i is the fault frequency of the inner race

N is half of the window of observation

3.1.4. Outer Race Energy

Outer race energy represents the energy of the bearing vibration signal at/around the outer race fault frequency.

$$Energy_{outer\ race} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_o \pm N)^2} \qquad (11)$$

f_o is the fault frequency of the outer race

N is half of the window of observation

3.2. Shafts

All the condition indicators mentioned in this section were extracted after the original signal was processed through TSA algorithm. Typical condition indicator for shafts includes shaft order 1, shaft order 2, shaft order 3 and so on. Shaft condition indictors are used to detect shaft faults including shaft imbalance, misalignment etc.

3.2.1. RPM

Number of shaft revolution per minute. RPM is measurement of shaft speed. The 1/rev derivative of the RPM is a measurement of rated change of RPM at the 1/rev frequency. This measurement is capable of rotor shaft imbalance indication.

3.2.2. Shaft Order 1 (SO1)

Shaft Order 1 represents the magnitude of the first harmonics of the shaft of interest in frequency domain. SO1 is an indicator of mass imbalance or a bent shaft.

3.2.3. Shaft Order 2 (SO2)

Shaft Order 2 represents the magnitude of the second harmonics of the shaft of interest in the frequency domain. SO2 is sensitive to coupling failures (misalignment) or bent shaft.

3.2.4. Shaft Order 3 (SO3)

Shaft Order 3 represents the magnitude of the third harmonics of the shaft of interest in the frequency domain. SO3 is sensitive to coupling failures. For the main rotor, SO3 is driven by combined effect of tower shadow and wind shear.

3.2.5. TSA RMS

The root mean square value of the TSA signal

3.2.6. TSA Peak to Peak

The peak to peak value of the TSA signal

3.2.7. Shaft Order 1 Phase Angle

Phase angle can be calculated as four-quadrant inverse tangent of the complex conjugate FFT transform of the raw vibration signal. The phase angle of the shaft order 1. SO1 Phase Angle is an indication of imbalance.

3.2.8. 1/Rev Derivative of RPM

Rated shaft RPM change per revolution.

3.3. Gears

Among the condition indicators used on different components, condition indicators for gears normally involves a specific signal processing algorithm and a statistical feature. This section shows the common signal processing algorithm for gears and the condition indicators extracted from the analysis result that are often used.

3.3.1. Residual Analysis

The residual signal for a gear can be calculated by removing the shaft harmonics and the gear mesh frequency and harmonics from the time synchronous average signal. But the residual analysis algorithm can vary depends on the information the researchers trying to acquire or remove. Residual Signal is effective for detecting gear scuffing, tooth pitting and tooth crack faults. Periodic faults like tooth breakage normally can have impact of 1 per rev show up in the TSA signal. The residual analysis allows fault impact signatures to become prominent in the time domain.

Combined with the above mentioned statistical features, common condition indicators extracted from residual analysis are residual RMS, residual peak to peak, residual kurtosis, and residual crest factor.

3.3.2. Energy Ratio

Energy ratio is the ratio between the energy of the difference signal and the energy of the original meshing component (Vecer et al, 2005).

$$ER = \frac{\sigma(d)}{\sigma(r)} \qquad (12)$$

$\sigma(d)$ is the standard deviation of the difference signal

$\sigma(r)$ is the standard deviation of the original signal

Energy ratio is very good indicator for heavy wear, where more than one tooth on the gear is damaged. The energy ratio will trend towards 1 as a fault progresses.

3.3.3. Energy Operator

Energy operator is computed as the normalized kurtosis from the signal where each point is computed as the difference of two squared neighborhood points of the original signal (Vecer et al, 2005).

$$EO = \frac{N^2 \sum_{i=1}^{N}(\Delta x_i - \Delta \bar{x})^4}{\{\sum_{i=1}^{N}(\Delta x_i - \Delta \bar{x})^2\}^2} \qquad (13)$$

$\Delta \bar{x}$ is the mean value of signal Δx

$\Delta x_i = s_{i+1}^2 - s_i^2$

N is the number of data point in the dataset x

Energy Operator is a type of residual of the autocorrelation function. It is designed to reveal the amplitude modulations and phase modulations of the signal of interest. For a nominal gear, the predominant vibration is gear mesh. Surface disturbances and scuffing generate small higher frequency values, which are not removed by autocorrelation. Large energy operator indicates server pitting or scuffing.

Combined with statistical features, common condition indicators extracted from energy operator analysis are EO RMS, EO peak to peak, EO kurtosis, and EO crest factor.

3.3.4. FM0

FM0 is defined as the peak to peak level of the TSA signal divided by the sum of the amplitude at the gear mesh frequency and its corresponding harmonics (Vecer et al, 2005; Lebold et al, 2000).

$$FM0 = \frac{s_{peak-peak}}{\sum_{i=1}^{N} A(i)} \qquad (14)$$

FM0 is the zero-order figure of merit

$s_{peak-peak}$ is the peak to peak value of the TSA signal.

$A(i)$ is the amplitude of the ith mesh frequency harmonics

FM 0 is a statistic used to detect major changes in the meshing pattern. For heavy wear, the peak to peak value remains constant while the meshing frequency decreases, causing the FM0 parameter to increase. FM0 is a generalized gear fault indicator, sensitive to gear wear/scuffing/pitting and tooth bending due to crack root. However, FM0 is not a good indicator for minor tooth damage.

3.3.5. Sideband Modulation Lifting Factor (SMLF)

Sideband modulation lifting factor (SMLF) or sideband level factor (SLF) is defined as the sum of the first order side band about the fundamental gear mesh frequency

divided by the standard deviation of the signal of interest (Vecer et al, 2005).

$$SMLF = \frac{\sum_{i=1}^{n} si_{gear\ mesh \pm i}}{s_{std}} \qquad (15)$$

si is the amplitude of the ith sideband around fundamental gear meshing frequency

s_{std} is the standard deviation of the time signal average.

This parameter is based on the idea that tooth damage will produce amplitude modulation of the vibration signal. This CI is designed to detect gear misalignment.

3.3.6. G2

G2 is defined as the amplitude of the 2nd harmonics of gear meshing frequency over the amplitude of the gear meshing frequency in the frequency domain.

3.3.7. Narrowband (NB) Analysis

Narrowband analysis operates the TSA signal (or other time domain signal of interest) by filtering out all the tones except that of the gear mesh and with a given bandwidth. Narrowband signal is calculated by zeroing the bins in the Fourier transform of the TSA except the gear mesh. Statistics features of the narrowband signal can be calculated to enhance the fault feature. Narrowband represents the vibration associate with the primary gear mesh frequency. Narrowband analysis can capture sideband modulation of the gear mesh due to misalignment, or detect a cracker/soft/broken tooth.

Combined with statistical features, common condition indicators extracted from narrowband analysis are NB RMS, NB peak to peak, NB kurtosis, and NB crest factor.

3.3.8. Amplitude Modulation (AM) Analysis

Amplitude Modulation (AM) analysis is the absolute value of the Hilbert transform of the narrowband signal (Bechhoefer, 2012), since primary gear meshing characteristics extracted from narrowband analysis is the subject of interest. However, AM analysis is not limited to narrowband signal.

Modulation is a non-linear effect in which several signals interact with one another to produce new signals with frequencies not present in the original signals. Amplitude modulation is defined as the multiplication of one time-domain signal by another time-domain signal. For a gear with minimum transmission error, the AM analysis feature should be a constant value of gear tooth displacement. Gear defects or faults can increase the kurtosis of the signal significantly. AM is sensitive to eccentric gears and broken or soft tooth faults.

Combined with statistical features, common condition indicators extracted from AM analysis are AM RMS, AM peak to peak, AM kurtosis, and AM crest factor.

3.3.9. DAM

DAM is defined as the derivative of the amplitude modulation (AM) signal. DAM is sensitive to both soft and broken gear tooth faults.

Combined with statistical features, common condition indicators extracted from DAM analysis are DAM RMS, DAM peak to peak, DAM kurtosis, and DAM crest factor.

3.3.10. Frequency Modulation (FM) Analysis

Frequency Modulation (FM) is the derivative of the angle of the Hilbert transform of narrowband signal (Bechhoefer, 2012), since primary gear meshing characteristics extracted from narrowband analysis is the subject of interest. However, FM analysis is not limited to narrowband signal.

Modulation is a non-linear effect in which several signals interact with one another to produce new signals with frequencies not present in the original signals. Frequency modulation (FM) is the varying in frequency of one signal by the influence of another signal, usually of lower frequency. The frequency being modulated is called the carrier. Frequency Modulation analysis is in radians. Frequency modulation (FM) analysis is a powerful tool capable of detecting changes of phase due to uneven tooth loading, characteristics of a number of fault types. For certain gear architectures, FM analysis is more sensitive to fault than either the narrowband or amplitude modulation analysis.

Combined with statistical features, common condition indicators extracted from FM analysis are FM RMS, FM peak to peak, FM kurtosis, and FM crest factor.

3.3.11. FM4

FM4 is a simple measure if the amplitude distribution of the difference signal is peaked or flat. The mathematical representation is shown below. NA4 is determined by dividing the fourth statistical moment of the residual signal by the current run time averaged variance of the residual signal, raised to the second power (Vecer et al, 2005; Lebold et al, 2000).

$$FM4 = \frac{N \times \sum_{i=1}^{N}(d_i - \bar{d})^4}{\left\{\sum_{i=1}^{N}(d_i - \bar{d})^2\right\}^2} \tag{16}$$

d_i is the i-th point of the differential signal in the time record

N is the total number of points in the time record

The parameter assumes that a gearbox in good condition has a difference signal with a Gaussian amplitude distribution (kurtosis of 3), whereas a gearbox with a major peak or a series of major peaks results in a less peaked amplitude distribution (kurtosis greater than 3). For single tooth defect fault progression, the data distribution becomes peaky and the kurtosis increases. For multiple teeth fault progression, the data distribution becomes flat and the kurtosis value decreases.

3.3.12. NB4

NB4 is designed from the NA4 parameter.NA4 is calculated from the residual signal while NB4 uses the envelop of a band-passed segment of the time synchronous averaged signal.NB4 is determined by dividing the 4th statistical moments of the envelop signal, raised to the 2nd power. (Lebold et al, 2000; Lebold et al, 2000).

$$NB4 = \frac{N \times \sum_{i=1}^{N}(E_i - \bar{E})^4}{\left\{\frac{1}{M}\sum_{j=1}^{M}\sum_{i=1}^{N}(E_{ij} - \bar{E}_j)^2\right\}^2} \tag{17}$$

E is the envelop of the band passed signal

$\bar{E}$ is the mean value of the enveloped signal.

N is the total data points in time record.

M is the current time record in the run ensemble.

$$E = |\bar{s}(t)| = \sqrt{s^2(t) + \tilde{s}^2(t)} \tag{18}$$

$|\bar{s}(t)|$ is the envelope of the analytic signal

$s(t)$ is an input analog signal

$\tilde{s}(t)$Is the Hilbert transform of the input signal

A few damaged gear teeth will cause transient load fluctuations that are different from normal tooth load fluctuations. The theory suggests these fluctuations will be manifested in the envelop of a signal which is band-pass filtered about the dominant meshing frequency.

3.3.13. NA4

NA4 is determined by dividing the fourth statistical moment of the residual signal by the current run time averaged variance of the residual signal, raised to the second power (Vecer et al, 2005; Lebold et al, 2000).

$$NA4 = \frac{N \times \sum_{i=1}^{N}(r_i - \bar{r})^4}{\left\{\frac{1}{M}\sum_{j=1}^{M}\sum_{i=1}^{N}(r_{ij} - \bar{r}_j)^2\right\}^2} \tag{19}$$

r_i is the i-th point in the time record of the residual signal.

r_{ij} is the i-th point in the j-th time record of the residual signal.

j is the current time record

i is the data point number per reading

M is the current time record in the run ensemble

N is the number of points in the time record

3.3.14. NA4*

NA4* is an enhanced version of NA4. The improvement is achieved by normalizing the fourth statistical moment with the residual signal variance for a gearbox in good condition instead of the running variance, which is used for NA4 (Vecer et al, 2005; Lebold et al, 2000).

$$NA4^* = \frac{N \times \sum_{i=1}^{N}(r_i - \bar{r})^4}{(var(r_{OK}))^2} \qquad (20)$$

$var(r_{OK})$ is the variance of the residual signal for a gearbox in good condition (obtained from a well-functioning gearbox)

When gear damage progresses, the averaged variance value increases rapidly which results in the decrease of the $NA4^*$ parameter. To overcome this problem $NA4^*$ is developed to be more robust when progressive damage occurs.

4. CASE STUDIES

This section presents three case studies covering gear, bearing and shaft. All the case studies are from the wind energy industry where there is a pressing need for condition monitoring systems. For the next three case studies, all data was collected and processed by TurbinePhD system.

4.1. Wind Turbine High Speed Pinion

The purpose of installing a condition monitoring systems is to help mitigate the high financial risk of unplanned maintenance and establish the framework for a new predictive maintenance program. A well developed condition monitoring systems should be capable of monitoring every bearing, gear and shaft in the gearbox as well as the generator and main bearing.

A condition monitoring system is designed to detect faults early on so that wind farm operators have the longest possible time to plan a maintenance action. This early detection is critical in avoiding secondary damage from catastrophic failure and the subsequent additional financial cost. Additionally, the system uses numerous complex algorithms to track the condition of a component, which in turn are then normalized and combined to estimate the overall health of the component. The result is excellent fault discrimination, which is arguably one of the most important aspects of a condition monitoring system. Fault discrimination is the ability to separate out a faulted component from good components. If the fault discrimination is good, then the alarms the system provides are trustworthy and actionable. On the other hand, if the fault discrimination is poor, then the likelihood of false alarms and missed detections increases. Finally, the system uses a patented automated diagnostic capability to provide the user with an easy to read display of which turbines need attention all through a cloud-based client interface. Thus, eliminating the need for complex data processing and interpretation before a maintenance decision can be made.

After installation, the condition monitoring systems gathered wind turbine fleet vibration data for two weeks at which point alarm and warning thresholds were generated. These thresholds are data driven values obtained by statistically eliminating the outlying abnormal components on each turbine that define if a component is damaged. Once the thresholds were established, an alarm was triggered for the High Speed Pinion (the last gear in the gearbox before the generator) on one of the turbines. Alarms are triggered when one or more Condition Indicators or CIs were elevated over the generated thresholds. In this case, several CIs were elevated while others were not. Since different CIs are sensitive to different fault modes, the type of fault can be estimated solely based on which CIs are elevated and which are not. From the list of CIs that responded to this fault, there was strong evidence that the alarm was triggered by a broken tooth. The wind farm operators were notified and an up tower visual inspection revealed the cracked tooth.

One of the Condition Indicators that is very sensitive to gear tooth pitting, scuffing and bending is called the FM0. It compares the general vibration level with the amplitude of gear meshing. A high FM0 value indicates the general vibration level is higher than normal and the gear meshing characteristic frequency is submerged in the high noise floor. In this case, FM0 was elevated to the point where the fault discrimination was perfect, meaning there were absolutely no overlapping values between the FM0 tracking the broken pinion and the FM0 tracking normal pinions on other turbines as seen in the following Figure 2. This means the probability of a false alarm or missed detection was extremely low.
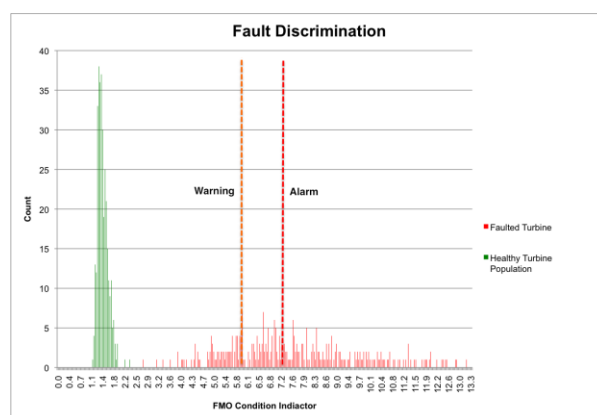

Figure 2. Fault discrimination based on FM0

While the FM0 Condition Indicator contributed to the triggered the alarm, other condition indicators were less sensitive to the fault. As explained previously, a condition monitoring system should offer clients the capability of

determining not only which component is not operating at a nominal condition but also performing diagnostics. This is critical information when it comes to cost savings, as different fault modes require different maintenance actions. In this case, the AM Kurtosis CI, which is a sensitive indicator of eccentric gears but less so at capturing tooth damage, remained at the nominal level as seen in the following Figure 3.
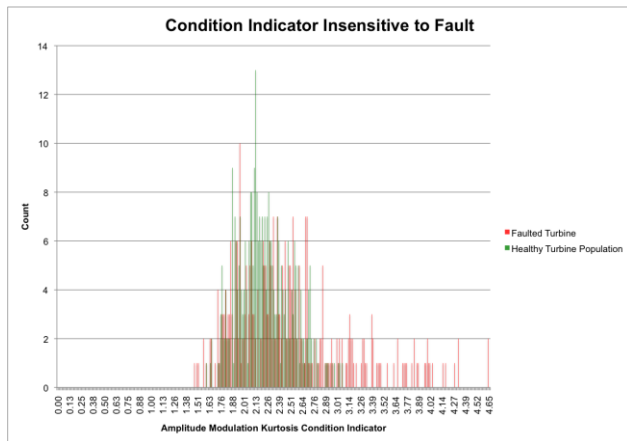

Figure 3. Fault discrimination based on AM Kurtosis

This specific turbine was shut down and inspected, the initial inspection found tooth damage on the high speed pinion as shown in the following Figure 4.

Figure 4. High speed pinion inspection result

Detecting this broken tooth early is critical for maintenance cost savings. When a gear loses a tooth, the remaining meshing teeth experience significant increases in load and subsequent stress and strain. This can cause cascading damage on the gear, which in turn will fill the gearbox with metal debris. Before long, other components are damaged and the gearbox potentially needs to be removed from the tower and rebuilt. A full gearbox rebuild, which requires the mobilization of a crane, can cost upwards of $150,000 and results in significant downtime, especially when climate can affect the ability to get a crane to the turbine. Additionally, a gear with a broken tooth, if left to run, will transfer damage to any gear that it is mated with. When this

happens, both gears must be replaced. In this case, by implementing a well developed condition monitoring system, the wind farm operators obtained actionable information that left them with the option of performing an up-tower repair of just the High-Speed Pinion. The cost differential between performing this up-tower repair and a gearbox rebuild is estimated at $250,000. This proves that condition monitoring systems are valuable as a crucial part of the wind turbine maintenance cycle.

4.2. Wind Turbine High Speed Bearing

As mentioned earlier, the purpose of implementing a condition monitoring system is to help the wind farm operators to maximize the fleet availability by means of detecting the early damage of the drive train assembly before secondary damage occurs. Most retrofit condition monitoring systems need a certain period of time to gather data and thresholding, a process that defines the data characteristics of healthy components. Following the system thresholding, the Health Indicator (HI) of a "High Speed Bearing" (The bearing that holds the high speed generator shaft) started trending in March. The HI exceeded the warning and alarm limit around May.

The recommendation is when the HI exceeds the threshold of 1, an inspection should be performed on this component. The wind farm O&M team confirmed the bearing inner race fault and replaced the HS bearing. When the turbine started up and condition monitoring recommenced, the HI value dropped to below 0.2 indicating a nominal component.
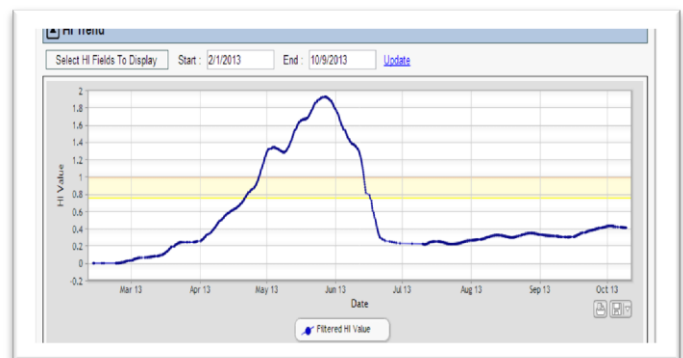

Figure 5. High speed bearing health indicator

The High speed bearing detail components CIs are also listed in the client interface as shown in Figure 6. From the pattern of the CI data log, the outer race, cage and rolling element energy showed no signs of degradation except the energy of the inner race. The inner race energy started increasing at March. Around May, the at the same time high speed bearing HI exceeds alarm limit, the inner race CI also exceed its own alarm threshold. This confirms that the HS bearing inner race cased the failure. The inner race fault had been located in March. The TurbinePHD systems tracked the fault progressing over a 2 month period. After HS

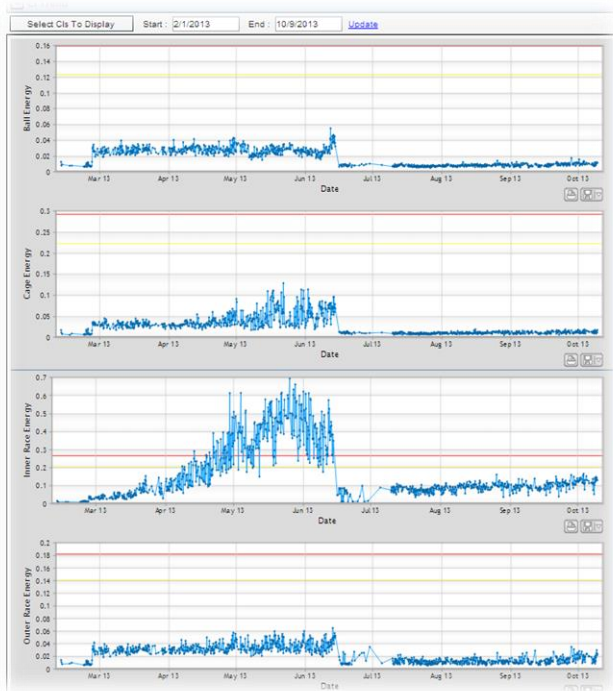shaft/bearing replacement, the inner race energy dropped back to nominal.

Figure 6. High speed bearing component trend

Based on the inner race details presented in Figure 3 and 4, which is available using the client web interface of TurbinePHD. One can observe that the condition indicator has pick up the inner race fault and starts trending 2 month before the condition indicator exceeded the alarm threshold. In the component detail page of the Web interface (Figure 4) the spectral information is displayed in the frequency domain. A high magnitude peak around the inner race fault frequency with characteristic sidebands that are a product of the shaft modulation can be seen.

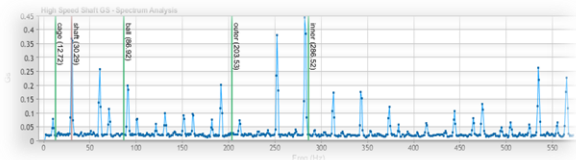Figure 7. A detail look at the inner race condition indicator

Figure 8. Spectrum analysis showed a high magnitude peak around the inner race fault frequency

After the O&M bore scope inspection, a large crack was found on the inner race which confirms the TurbinePHD diagnostics as shown in Figure 9.

Figure 9. Bore scope inspection of the inner race

4.3. Wind Turbine Rotor Imbalance

There can be many reasons behind a imbalanced rotor. In general, wind turbine rotor imbalance can be differentiating in the 2 types, Mass imbalance and aerodynamic imbalances. The imbalance can be induced by main reasons and some of them are listed as follow.

• Improper component manufacturing.

• Uneven buildup of debris on rotors, vanes or blades (ice, etc.).

• The addition of shaft fittings without an appropriate counter balancing procedure.

• Vane/blade erosion, crack or thrown balance weights. Fluid inclusion in the rotor blades.

• Rotor division error.

• Blade bearing jammed.

• Gearbox support structure excessive wear and tear.

• Generator alignment loss and coupler damage.

• Support structure and main frame damage.

• Yaw system/yaw breaks excessive wear and tear.

• Door frame damage, cracks at welds top and bottom, steps.

• Foundation bolt failure.

The effects of rotor imbalance include the following.

• 35% of all wind turbines have rotor caused vibrations which exceed the designed specifications. These vibrations cause unusual structure loads, an increased

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wear, adverse startup conditions and often vibration causing emergency turn off.

- Rotational excitations cause higher dynamic load beyond design specification on bearing which leads to bearing failure from early fatigue. Fatigue, in a bearing, is the result of stresses applied immediately below the load carrying surfaces and is observed as appalling away of surface material.

- A wind turbine with an unbalanced rotor will lose some of its low wind production capability.

- High level of rotor vibration that appear as high magnitude of 1st harmonics of shaft rotating frequency.

- High levels of vibration caused by rotor imbalance results in turbine efficiency loss.

Rotor unbalance is a leading contributor to the need for frequent and costly maintenance action on yaw systems and fastening hardware. The unbalanced force on the rotor causes a reaction on the yaw system twice per revolution, accelerating the wear on the yaw gear teeth through impact loading and adding to the fatigue loading of the tower shell and mounting bolts.

A Leading wind energy operator asked Renewable NRG Systems to instrument their MW class turbine fleets with the TurbinePHD Condition Monitoring System to help them maximize the turbine availability by means of detecting the early damage of the drive train assembly before any secondary damage occurs. Following the standard commissioning procedure, the system ran for two weeks gathering data and was then thresholded, a process that establishes data driven definitions of when a component is no longer nominal. Following the system thresholding it was immediately apparent that "Nacelle X" (a component that watches the sway of the turbine tower) was not "nominal".
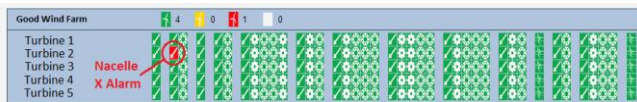

Figure 10. TurbinePHD Cloud Based Client Interface

A quick click on the red component revealed the Health Indicator (HI) value was elevated because the tower was swaying at the rotational frequency of the main rotor. This condition is a typical characteristic of a heavy blade and the subsequent imbalance (once per revolution imbalance). The recommendation is that when the HI exceeds the threshold of 1 an inspection needs to be performed on these component/components. In this case the HI value was floating around 1 between March 12th and June 13th. The wind farm O&M team inspected the blades and found that a heavy blade was causing the imbalance. The other turbine blades had a weight adjustment and subsequently the HI value dropped to nominal. After the 13th there was no data

for a month because the turbine was down for maintenance. When the turbine started up and condition monitoring recommenced, the HI value had dropped to below .2 indicating a nominal component.

Figure 11. Health Indicator Trend

The Health Condition (HI) represents the data fusing result of all the Condition Indicators (CI). In TurbinePHD The shaft condition indicators includes shaft order 1 (SO1), shaft order 2 (SO2), shaft order 3 (SO3), 1 per revolution delta RPM and etc.

In this case, compared to SO2 and SO3, SO1 is trending along with the HI. The trending pattern correlates well between SO1 and component HI. The trending of SO1 confirmed the reason behind the high HI is because of the imbalance of the Rotor. Meanwhile, the CI on the Tach component, 1/rev dRPM, showed the same patter between March and October.
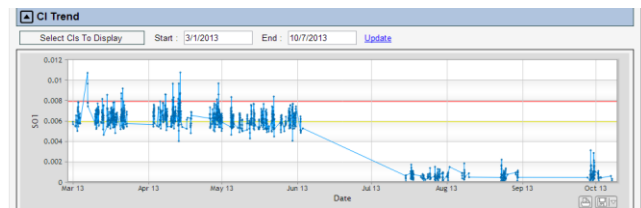

Figure 12. 1st shaft order (SO1), a measurement of the energy associated with the rotational frequency of the rotor. SO1 is one of several Condition Indicators (CIs) that are used to calculate the HI.
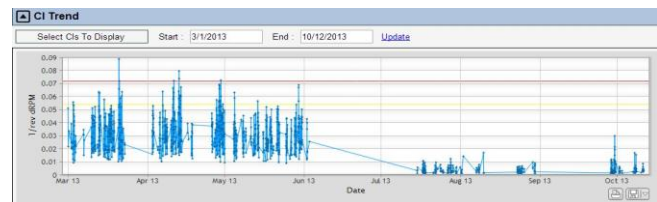

Figure 13. 1/rev dRPM, a measurement of rated change of RPM at the 1/rev frequency. 1/rev dRPM is one of the several Condition Indicators that are used to calculate Component HI of the Tach.

5. CONCLUSION

Condition indicators play a significant role in machine health status monitoring and tracking. Over the years, scientists and researchers have developed a great selection

of condition indicator for various components and applications. These condition indicators provides insights of the components condition and increase the signal storage and transmitting efficiency at the same time. Therefore, condition indicators are widely accepted by researchers and engineers for vibration signal analysis, acoustic emission signal analysis and sometimes oil debris and oil condition analysis as well.

This paper provided a detailed description and mathematical interpretation of a comprehensive selection of condition indicators developed for gears, bearings and shafts. Since different condition indicators are sensitive to different kind of failure modes, the application for each condition indicators were explained and discussed. The Time Synchronous Averaging (TSA) and Time Synchronous Resampling (TSR) algorithm was applied as the signal processing method before the extraction of condition indicators by the authors. Several case studies of real world wind turbine component failure detection using condition indicators were presented to demonstrate the effectiveness of certain condition indicators.

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BIOGRAPHIES

Junda Zhu received his B.S. degree in Mechanical Engineering from Northeastern University, Shenyang,

China, and M.S. degree in Mechanical Engineering from The University of Illinois at Chicago in 2009, and Ph.D. degree in Industrial Engineering and Operational Research from The University of Illinois at Chicago in 2013. Dr. Junda Zhu is a Systems Engineer in the Turbine Health Monitoring Group in Renewable NRG Systems. His current research interests include rotational machinery health monitoring, diagnosis and prognosis with vibration or acoustic emission based signal processing techniques, lubrication oil condition monitoring and degradation simulation and analysis, physics/data driven based machine failure modeling.

Tom Nostrand received his BS in Engineering from the University of New Hampshire. He is currently an Engineering Manager at Renewable NRG Systems, Turbine Products Group. He has been working in the wind power industry for 6 years. Prior to this he spent 20 years in the aerospace electronics field working on many different commercial aircraft platforms and systems.

Cody Spiegel received his B.S. in Mechanical Engineering from The University of Vermont in 2013. He began a

mechanical engineering internship at Renewable NRG Systems in 2011 and is now an Associate Mechanical Engineer working in the Turbine Health Monitoring Group. His current work includes condition monitoring diagnostics and support as well as R&D of new condition monitoring systems.

Brogan Morton received his B.S. and M.S. in Mechanical Engineering from The University of New Hampshire in 2000 and 2002 major in estimation and controls. He received MBA from the Idaho State University major in technology development and deployment. Brogan is currently the product manager for the TurbinePHD condition monitoring system in Renewable NRG Systems. He is responsible for the full product life cycle of several technologically advanced products in the wind energy industry.