

Case Study of a Faulted Planet Bearing

Eric Bechhoefer¹ and Dave He²

¹*GPMS Inc., Cornwall, VT, 05753, USA*
eric@gpms-vt.com

²*Dept. of Mechanical and Industrial Engineering, UIC, Chicago, IL, 6-612, USA*
davidhe@uic.edu

ABSTRACT

Fault detection in planet bearings is difficult. This is particularly true in wind turbines, where the main rotor shaft is under 20 rpm, such that the planet fault frequency can be sub 1 Hz. This paper analyzes a missed fault on a wind turbine planet bearing, and discusses how changes in the analysis configuration then allowed this type of fault to be detected. Raw data from ten machines was collected. From this, a strategy for fault feature identification was developed, to include: the evaluation of window selection, biasing of the data set with faulted components, and the use of improved analysis techniques. This allowed meaningful and appropriate thresholds to be set.

1. THE WIND TURBINE MARKET

There are over 1000 utility scale wind energy projects, representing 74,000 megawatts of power production in the United States. This comprises over 52,000 installed wind turbines, most of them less than 10 years old (AWEA Fact Check, 2016). The vast majority of these machines do not have condition monitoring equipment installed. Because of higher than expected failure rate of these machines, the number of condition monitoring retrofit opportunities is increasing.

While condition monitoring does not affect the overall reliability of the wind turbine, monitoring gives the operator improved information into the balance of plant operations. Improved information allows the operator to better marshal logistic assets, resulting in reduced unscheduled maintenance. Additionally, condition monitoring allows the operator to have the right personnel and replacement parts needed for a repair, reduce the time needed for the repair. In many cases, replacing a damaged component, such as a

bearing in the high-speed section when indicated by a condition monitoring system (CMS), can greatly reduce the cost of maintenance. These type of actions are performed “up tower” vs. a “down tower”. Any “down tower” event will require marshaling a crane, and replacing the entire gearbox (perhaps \$450,000 per event). This is compared to replacing a bearing up tower, which might cost \$50,000.

Recently, a number of 2.0 MW machines were retrofitted with a CMS. These machines had five years of operations and were assumed to be in a nominal state. Once every 10 minutes data was collected by the CMS using a commercial system. The data was processed locally (on the wind turbine) and condition indicators (CIs) were sent to a central server. Configuration data was then used to map the CIs into a component health indicator (HI), (Figure 1).

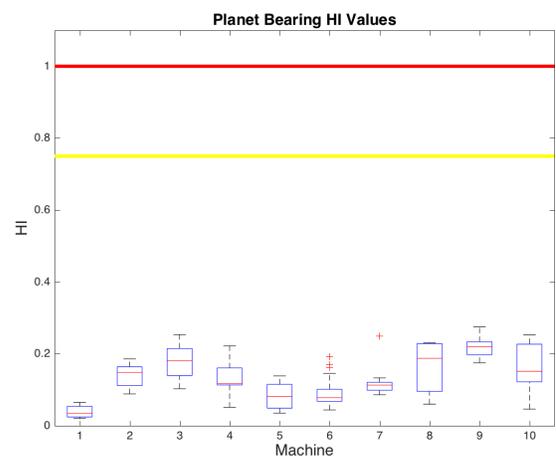


Figure 1. Planet Bearing Health on Ten Machines, Initial Thresholds

Using the CI data from all of the machines, the initial thresholds suggested that all 10 machines were nominal. This was not unexpected, as these machines had only operated for five years.

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2. CALCULATION OF THE PLANET BEARING HEALTH INDICATOR

Because no single CI has been identified that works with all fault modes, the concept of fusing n number of CIs into a bearing HI was presented in (Bechhoefer, He, 2012). The HI provide decision-making tool for the end user on the status of the systems' health. The HI consists of the integration of several CIs into one value that provides the health status of the component to the end user.

Highlighted in (Bechhoefer et. al., 2007) are a number of advantages of the HI over CIs, such as: controlling false alarm rate, improved detection, and simplification of user display. This approach uses a well established statistical method. Further, it is a generalized process for threshold setting, where the HI is a function of distribution of CIs, regardless of the correlation between the CIs.

To simplify presentation and knowledge creation for a user, a uniform meaning (e.g. a nomenclature) across all components in the monitored machine was developed. The measured CI statistics (e.g. PDFs) will be unique for each component type (due to different rates, materials, loads, etc.). This means that the critical values (thresholds) will be different for each monitored component. By using the HI one can normalize the CIs, such that the HI is independent of the component and have a common meaning across all components.

The HI can be designed such that there are two alert levels: warning and alarm. This paradigm also provides a common nomenclature for the HI, such that:

- The HI ranges from 0 to 1, where the probability of exceeding an HI of 0.5 for a nominal component (e.g. no damage) is the probability of false alarm (PFA). The nominal PFA is set to $10e-6$.
- A warning alert is generated when the HI is greater than or equal to 0.75.
- An alarm alert is generated when the HI is greater than or equal to 1.0. Continued operations could cause collateral damage.

Note that this nomenclature does not define a probability of failure for the component, or that the component fails when the HI is 1.0. Rather, it suggests a change in operator behavior to a proactive maintenance policy: perform maintenance opportunistically to reduce down time.

2.1. Controlling for the Correlation Between CIs

All CIs have a probability distribution function (PDF). Any operation on the CI to form a health indicator (HI) is then a function of distributions. For the CMS, the HI function is taken as the norm of n CIs (energy). In general, the correlation between CIs is non-zero. This correlation implies that for a given function of distributions to have a

threshold that operationally meets the design PFA, the CIs must be whitened (e.g. de-correlated). Fukunaga presented a whitening transform using the Eigenvector matrix multiplied by the square root of the Eigenvalues (diagonal matrix) of the covariance of the CIs:

$$A = \Lambda^{1/2} \Phi^T \quad (1)$$

where Φ^T is the transpose of the Eigenvector matrix and Λ is the Eigenvalue matrix. The transform is not orthonormal as the Euclidean distances are not preserved in the transform. While ideal for maximizing the distance (separation) between classes (such as in a Bayesian classifier), the distribution of the original CI is not preserved. This property of the transform makes it inappropriate for threshold setting.

If the CIs represented a metric, such as bearing energy, then a HI can be constructed which is the square of the normalized power (e.g. square root of the squared acceleration). A generalized whitening solution can be found using Cholesky decomposition (Bechhoefer, 2011). The Cholesky decomposition of a Hermitian, positive definite matrix results in $A = LL^*$, where L is a lower triangular, and L^* is its conjugate transpose. By definition, the inverse covariance is a positive definite Hermitian. By construction:

$$LL^* = \Sigma^{-1} \quad (2)$$

and

$$Y = L \times CI^T \quad (3)$$

The vector CI is the correlated CIs used for the HI calculation, and Y is 1 to n independent CIs with unit variance (one CI representing the trivial case). The Cholesky decomposition, in effect, creates the square root of the inverse covariance. This in turn is analogous to dividing the CIs by their standard deviations (the trivial case of one CI). This creates the necessary independent and identical distributions required to calculate the critical values for a function of distributions.

2.2. HI Based on the Rayleigh PDF

The CIs for bearing energy (assuming nominal bearings) have Rayleigh like PDFs (e.g. heavily tailed). Consequently, the HI function was designed using the Rayleigh distribution. The PDF for the Rayleigh distribution uses a single parameter, β , defining the mean:

$$\mu = \beta(\pi/2)^{1/2} \quad (4)$$

and variance

$$\sigma^2 = (2 - \pi/2)\beta^2 \quad (5)$$

When applying (3) as a whitening process, the PDF of the CIs are independent and identical (CIs are IID), with variance of 1. The value β reduces to:

$$\beta = 1/(2 - \pi/2)^{1/2} \quad (6)$$

The HI function using the norm of n CIs can be shown to define a Nakagami PDF (Bechhoefer, 2007). The statistics for the Nakagami are $\eta = n$, and $\omega = \beta^2 * 2 * n$, where n is the number CIs used in the calculation of Y . The critical value for the HI, given 4 CIs where used (cage, ball, inner and outer race energy), such that: $\eta = 4$, and $\omega = 18.64$. For a PFA of 10^{-6} , the threshold 9.97, with the HI function calculated as:

$$HI = \frac{0.5}{9.97} \sqrt{YY^T} \quad (7)$$

The 0.5 value normalized the HI, such that the probability of a HI being greater than 0.5 for a nominal bearing is $10e-6$, as defined by the HI nomenclature.

3. THE MISSED DETECTION

Subsequently, oil debris analysis suggested that machine 8 had a damaged bearing. A borescope confirmed damaged planet bearings (Figures 2 and 3). Clearly, there is a large amount of inner and outer race spalling. The damage is heavily distributed. As an aside, many researchers have noted that the fault frequency energy can drop one the bearing fault becomes distributed.



Figure 2. Borecope view of planet bearing

This level of damage, and the fact the health of machine 8 was 0.22, indicates failure of the threshold setting process and the need to determine a strategy to set appropriate thresholds: Machine 8 health should be > 1 , as the bearing is heavily damage. The CMS should have indicated an alarm state.



Figure 3. Borecope of Damaged Bearings

3.1. Background Configuration

The gearbox was a typical, 3 stage gearbox with:

- Ring Gear: 87 teeth
- Planet Gear: 33 teeth
- Sun Gear: 18 teeth
- Intermediate Gear: 74 teeth (the notation is that a gear drives a pinion)
- Intermediate Pinion: 18 teeth
- High Speed Gear: 99 teeth and a
- High Speed Pinion: 20 teeth

The tachometer was on the output of the high speed shaft, typically with a shaft rate of 30.4 Hz. The overall gearbox ratio is 118.7:1, or $(1+87/18) \times (74/18) \times (99/20)$. The planet shaft rate was calculated as: $87/33$ or 2.64 from the main shaft. Note: the planet shaft is affixed to the carrier. The apparent rate of the planet shaft to the bearing is 3.64, as there is one extra “turn” of the shaft relative to the bearing because of the rotating carrier. The bearing fault rates were given as:

- Cage, 0.316
- Ball, 4.89
- Inner Race, 8.69 and
- Outer Race, 6.54.

Given the 30.4 Hz output shaft rate, the planetary shaft rate relative to the bearings is: $30.4/118.71 \times 3.64 = .935$ Hz. The shaft rate multiplied by the bearing fault rates, give the bearing bearing fault frequencies: $.935 \times [0.326 \ 4.89 \ 8.69 \ 6.54]$ of 0.29, 4.56, 8.1 and 6.1 Hz, respectively: The low frequency of the cage will be important.

4. BEARING ANALYSIS TECHNIQUES

The bearing fault signal is characterized by signals whose statistical properties change periodically with time (Antoni, 2009). While quasi-periodic and random in nature, these signals are the result of a periodic phenomenon. In the time domain, these signals exhibit periodic variation of statistical descriptors, such as the instantaneous power, or auto-correlation.

By defining a cyclostationary signal (CS) $X[n]$ with n as the temporal index, the signal will have a joint probability density function which is quasi periodic function of time. This implies that the ensemble statistics are stationary and ergodic. For the purposes of bearing analysis, one can model the CS as periodically modulated white noise:

$$X[n] = p[n] \cdot W[n] \quad (8)$$

Where $p[n] = p[n + N]$ is a N periodic function and $W[n]$ is strictly Gaussian noise. This model accounts for random process including slippage of the bearing elements (e.g. no Hertzian contact of the roller element with the inner/outer race, see [8]).

The second order statistics, which of the instantaneous auto correlation function (as per [7]) is:

$$\mathcal{R}_{2X}[n, \tau] = E\{X[n + \beta\tau]X[n - \bar{\beta}\tau]^*\} \quad (9)$$

where $\beta + \bar{\beta} = 1$, with $\beta = 1/2$ for the symmetric instantaneous auto-correlation function. The random signal from the bearing impact will then have a periodic instantaneous auto-correlation function of:

$$\mathcal{R}_{2X}[n, \tau] = \mathcal{R}_{2X}[n + N, \tau] \quad (10)$$

This defines the signal as a second order CS.

By definition, the instantaneous auto-correlation function of CS has a Fourier representation

$$\mathcal{R}_{2X}[n, \tau] = \sum_{\alpha_i \in \mathcal{A}} \mathcal{R}_{2X}[\tau; \alpha_i] e^{j2\pi\alpha_i n \Delta} \quad (11)$$

over the spectrum $\mathcal{A} = \{\alpha_i\}$ of cyclic frequencies α_i , where Δ denotes the sampling period.

As noted, the instantaneous autocorrelation function $\mathcal{R}_{2X}[n, \tau]$ is a function of the time variables n and τ . For analysis, the frequency domain representation allows the identification of α , the cyclic frequency (e.g. the bearing material response) and f , the bearing fault frequency (0.29, 4.56, 8.1 and 6.1 Hz). The frequency domain is a 2D Fourier transform of the two frequency variables α and f :

$$\mathfrak{R}_{2X}(\alpha, f) = \Delta^2 \sum_{n=-\infty}^{\infty} \sum_{\tau=-\infty}^{\infty} \mathcal{R}_{2X}[\tau; \alpha_i] e^{-j2\pi\alpha n \Delta} e^{-j2\pi f \tau \Delta} \quad (12)$$

This is the spectral correlation of the power distribution of the signal with respects to the spectral frequency f (the bearing fault rate) and the cyclic frequency α (the cyclic evolution of the waveform as a result of the bearing material

response to f). For a more detailed analysis (Antoni, 2009). Figure 4 is the spectral correlation of the planet bearing for machine 8. There is structural resonance (α) at 600 and 1200 Hz (the sample rate was 3052 sps: there may be higher harmonics above Nyquist). A number of spectral frequencies are seen below 2 Hz (cage and 1/rev ‘‘tick’’) and at 6.5Hz, associated with the outer race.

4.1. Envelope Analysis vs. Cyclostationarity

The spectral correlation is the 2D Fourier transform of spectral frequency f (the bearing fault rate) and the cyclic frequency α . Fixing α to a given frequency, the spectrum is the envelope analysis of the signal. Defining the envelope for a signal instance of α greatly reduces the computational burden and allows for more automated/embedded diagnostics. The implementation of the embedded diagnostic system then requires proper window selection (Ganeriawala, 2006), which holds constant the cyclic frequency α .

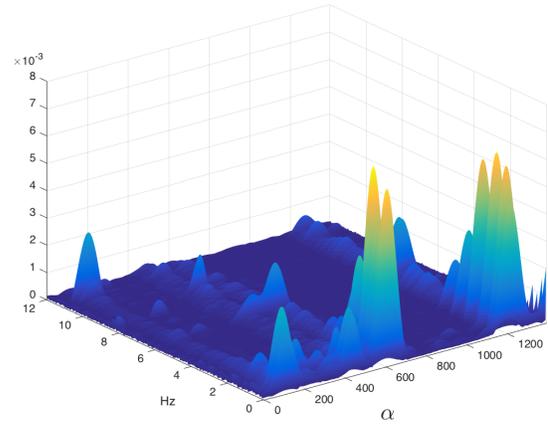


Figure 4. Cyclostationary Signal of Machine 8 Planet Bearing

Then for each fault frequency (Eq 1 – Eq 4, 0.29, 4.56, 8.1 and 6.1 Hz), the energy associated with the frequency spectrum is the fault condition indicator. Eq 8 then reduces to:

$$\mathfrak{R}_{2X}(f) = \Delta^2 \sum_{\tau=-\infty}^{\infty} \mathcal{R}_{2X}[\tau] e^{-j2\pi\alpha n \Delta} e^{-j2\pi f \tau \Delta} \quad (13)$$

The pseudo code for this is simply:

$$y = y \times \exp(-i2\pi\alpha t)$$

$$Y = \mathfrak{F}(y)$$

$$\text{Spectrum}(f) = Y \times Y^* \quad (14)$$

as per definition $t = n\Delta$.

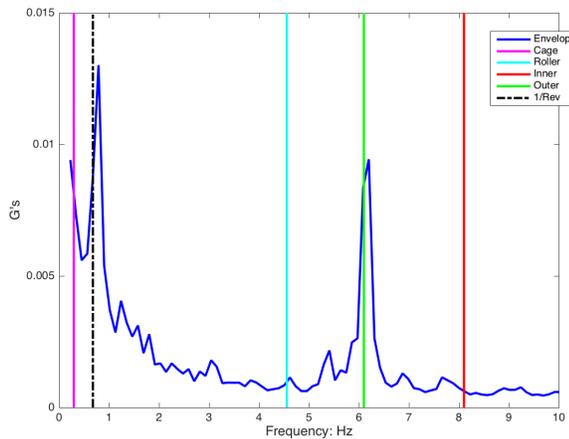


Figure 5. Envelope Analysis of the Planet Bearing, Machine 8

Window selection (e.g. α) greatly affects the performance of analysis. The initial analysis configuration set α to 1325 Hz, and with a bandwidth 225 Hz. The spectrum window length was 8192 point. The data was resample using the tachometer data (Bechhoefer, 2010) to control for changes in shaft speed over the 2 minute acquisition at 3052 sps. The resolution of the analysis is 0.113 Hz, Figure 5.

Clearly, the envelope identifies an outer race and 1/Rev issue. A 6.2 Hz outer race features is easily detected: why did the initial analysis fail?

5. STRATEGY OF CORRECTED ANALYSIS

The missed detection suggests that some of the entering assumptions are incorrect. With the initial threshold setting, it was assumed that all the machines are nominal. Additionally, one needs to identify a feature present in the faulted machine that is not present in the nominal machines. In an examination of the 10 machines, it was found that there were bearing/shaft artifacts in the envelope for all machines.

All lines after the first line of each entry should be indented one-quarter inch from the left margin. This is called hanging indentation.

Its evident that there is low frequency content associated with Cage and 1/Rev and Outer Race. Recall that the Cage frequency is 0.29 Hz, and the bin width was 0.11 Hz: the bin resolution is not fine enough to resolve the low frequency content below 1 Hz. In order to resolve these lower frequencies, the analysis needs more resolution. Further, from cyclostationary analysis, it is seen that the gearbox resonance (α) is closer to 1200 Hz than 1325 Hz. By increasing the spectrum window length to 16384 and reducing the envelope bandwidth to 100 (which better matches the bandwidth of α , see Figure 4), the spectrum bin bandwidth is reduced to 0.026 Hz.

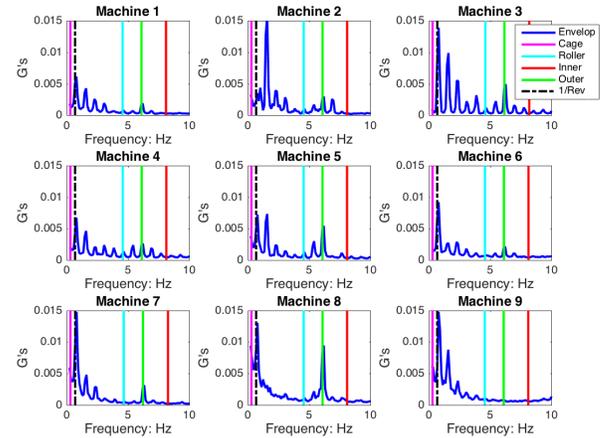


Figure 6. Envelope Features for Planet Bearings on nine machines

From Figure 6 it is seen that every machine exhibited a 1/Rev impact at 0.68 Hz. This is sometime associated with a gear failure, although there were nothing to indicate gear fault. Also, for almost every machine there is an indication of an outer race feature. This may be due to actually damage, but it should not be ruled out that this is a design issue. For example, it is usual practice in gearbox design that: $2 \times$ the planet gear teeth + the sun gear teeth are equal to the number of ring gear teeth. For a standard gearbox design the ring gear would be 84 teeth. In this gearbox, the ring gear has 87 teeth. This design, as a result, may have mechanical looseness, which is the cause of the 1/Rev impact.

Updating configuration, the envelope analysis for all ten machines was run. Each machine had from eight to twelve acquisitions, which at gives some idea of the distribution of the CIs for the Cage, Ball, Inner ant Outer race energy. For the damage machine, 8, the improved resolution shows multiple Cage frequency harmonics, Figure 7.

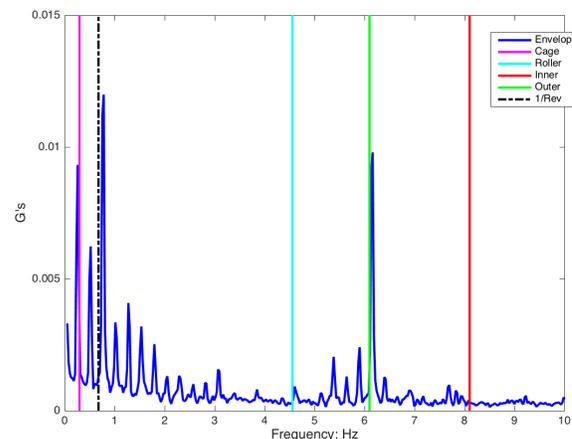


Figure 7. Envelope analysis after updating configuration

The boxplot of the bearing CIs gives further insight into the features that are indicative of bearing fault for this machine, Figure 8.

The cage, inner race, and outer race energies are all elevated for machine 8. The most prominent feature is the cage. The boxplot also gives a good indication as which machines are best: 1, 3, 4, 6 and 10. Warning (Yellow) and Alarm (Red) thresholds for each individual CI have been shown as a reference. These thresholds are calculated as part of the output of the HI threshold seeing process.

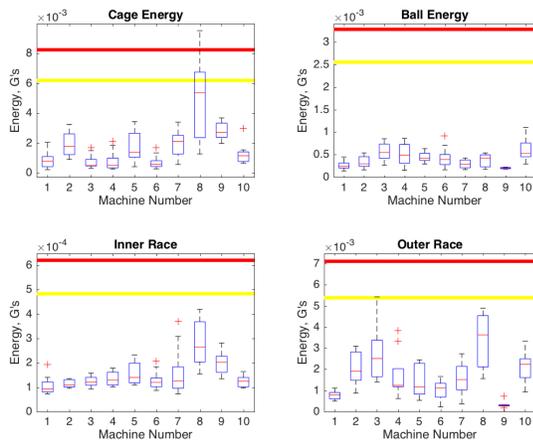


Figure 8. Boxplot for Bearing CIs for machine 1 through 10

Observe that when fusing the CIs into an HI, there is an improvement in the ability of the system to detect the fault (e.g. machine 8 cage energy is in warning, but the HI is > 1). The new thresholds were based on the covariance calculated from machines 1, 3, 4, 6 and 10. The machine HIs are now calculated using equation 3, in Figure 9.

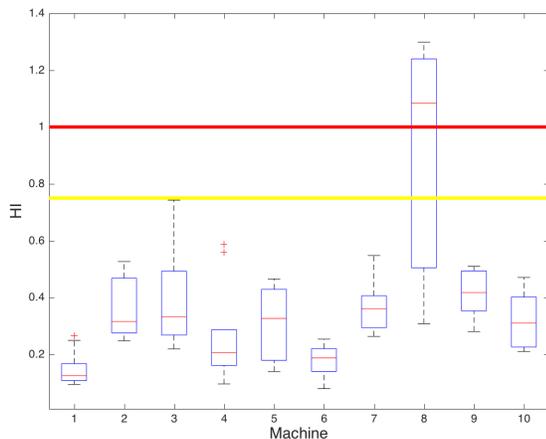


Figure 9. Planet bearing Health Index, Machine 8 is bad

Machine 8 now had a median HI of 1.05, and is in Alarm.

6. CONCLUSION

After retrofitting ten, five year old machines with a CMS and setting the threshold, it was found that one machine had a bad planet bearing. Machine 8 was verified via borescope (Figure 2 and 3) that the planet bearing was damage. This is a problem for the asset owner, as they want to be assured that the thresholds on the monitored machines are set appropriately. The question is, what failure in process occurred such so that the bearing fault was missed?

Upon investigation, a number of relatively minor errors can be attributed to the incorrect thresholds to include:

- Poor frequency resolution: 0.11 Hz bin for analysis of a 0.29 Hz feature, which was resolved by
 - Improving the selection of the analysis envelope frequency and bandwidth
 - Increasing the length of the window spectrum
- Assuming that all the machines were health/nominal.

By reviewing the distribution of the machine condition indicators for Cage, Ball, Inner and Outer Race energy, it was apparent that some machines were better than others. Reprocessing the vibration data with the new envelope window and spectral length, and removing the CI data from those machines that were deemed in poor health, more appropriate thresholds were developed. These new threshold allowed the identification of machine 8 of having damaged planet bearing.

The wind site will be continued to be monitoring, and over time it will be made clear if the current thresholds are appropriate.

NOMENCLATURE

- CI*s condition indicators
- CMS* condition monitoring system
- CS* cyclostationary signal
- HI* health indicator
- PDF* probability density function
- PFA* probability of false alarm

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Eric Bechhoefer received his B.S. in Biology from the University of Michigan, his M.S. in Operations Research from the Naval Postgraduate School, and a Ph.D. in General Engineering from Kennedy Western University. A former Naval Aviator, Dr. Bechhoefer who has worked extensively on condition based maintenance, rotor track and balance, vibration analysis of rotating machinery and fault detection in electronic systems. Dr. Bechhoefer is a board member of the Prognostics Health Management Society, and a member of the IEEE Reliability Society.

David He received his B.S. degree in metallurgical engineering from Shanghai University of Technology, China, MBA degree from The University of Northern Iowa, and Ph.D. degree in industrial engineering from The University of Iowa in 1994. Dr. He is a Professor and Director of the Intelligent Systems Modeling & Development Laboratory in the Department of Mechanical and Industrial Engineering at The University of Illinois-Chicago. Dr. He's research areas include: machinery health monitoring, diagnosis and prognosis, complex systems failure analysis, quality and reliability engineering, and manufacturing systems design, modeling, scheduling and planning.

BIOGRAPHIES