Proceedings of GT2007
ASME Turbo Expo 2007: Power for Land, Sea and Air
May 14-17, 2007, Montreal, Canada

GT2007-27660

A COMPREHENSIVE HIGH FREQUENCY VIBRATION MONITORING SYSTEM FOR INCIPIENT FAULT DETECTION AND ISOLATION OF GEARS, BEARINGS AND SHAFTS/COUPLINGS IN TURBINE ENGINES AND ACCESSORIES

Matt Watson, Jeremy Sheldon, Sanket Amin, Hyungdae Lee, Ph.D, and Carl Byington
Impact Technologies, LLC
2571 Park Center Blvd. State College, PA 16801
Matthew.Watson@impact-tek.com

Michael Begin
NAVAIR, Code 4.4.2
Patuxent River, MD 20670
Michael.Begin@jsf.mil

ABSTRACT

The authors have developed a comprehensive, high frequency (1-100 kHz) vibration monitoring system for incipient fault detection of critical rotating components within engines, drive trains, and generators. The high frequency system collects and analyzes vibration data to estimate the current condition of rotary components; detects and isolates anomalous behavior to a particular bearing, gear, shaft or coupling; and assesses the severity of the fault in the isolated faulty component. The system uses either single/multiple accelerometers, mounted on externally accessible locations, or non-contact vibration monitoring sensors to collect data. While there are published instances of vibration monitoring algorithms for bearing or gear fault detection, there are no comprehensive techniques that provide incipient fault detection and isolation in complex machinery with multiple rotary and drive train components. The author's techniques provide an algorithm-driven system that fulfills this need.

The concept at the core of high frequency vibration monitoring for incipient fault detection is the ability of high frequency regions of the signal to transmit information related to component failures during the fault inception stage. Unlike high frequency regions, the lower frequency regions of vibration data have a high machinery noise floor that often masks the incipient fault signature. The low frequency signal reacts to the fault only when fault levels are high enough for the signal to rise over the machinery noise floor.

The developed vibration monitoring system therefore utilizes high frequency vibration data to provide a quantitative assessment of the current health of each component. The system sequentially ascertains sensor validity, extracts multiple statistical, time, and frequency domain features from broadband data, fuses these features, and acts upon this information to isolate faults in a particular gear, bearing, or shaft. The techniques are based on concepts like mechanical transmissibility of structures and sensors, statistical signal processing, demodulation, time synchronous averaging, artificial intelligence, failure modes, and faulty vs. healthy vibration behavior for rotating components. The system exploits common aspects of vibration monitoring algorithms, as applicable to all of the monitored components, to reduce algorithm complexity and computational cost. To isolate anomalous behavior to a particular gear, bearing, shaft, or coupling, the system uses design information and knowledge of the degradation process in these components.

This system can function with Commercial Off-The-Shelf (COTS) data acquisition and processing systems or can be adapted to aircraft on-board hardware. The authors have successfully tested this system on a wide variety of test stands and aircraft engine test cells through seeded fault and fault progression tests, as described herein. Verification and Validation (V&V) of the algorithms is also addressed.

NOMENCLATURE

A/D	Analog-to-Digital Converter
AE	Acoustic Emission
AM	Amplitude Modulation
AMT	Accelerated Mission Test
DC	Direct Current
FM	Frequency Modulation
kHz	Kilohertz
MDTB	Mechanical Diagnostic Test Bed
PHM	Prognostics and Health Management
PSD	Power Spectral Density
RMS	Root Mean Squared
RPM	Revolutions Per Minute
TSA	Time Synchronous Average
UAV	Unmanned Autonomous Vehicle

INTRODUCTION

The ability to successfully detect and isolate faults is critical to the performance of diagnostic algorithms and the implementation of Prognostics and Health Management (PHM). Prognostics rely on incipient (early) fault detection and isolation to provide reliable and timely predictions. A well-designed PHM system seeks to extend the detection horizon as far as possible. Detection horizon is the elapsed time between the initial detection of a fault and the resultant mechanical failure. Figure 1 shows a timeline representation of several diagnostic approaches and their detection horizons. Incorporating features that increase detection horizon is key in the design of a high performance PHM system.

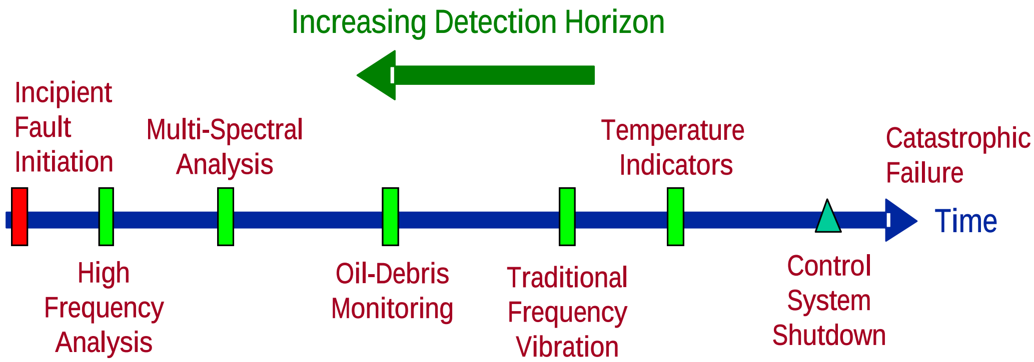

Figure 1 – Typical Turbo Machinery Diagnostics Detection Horizon Comparison

Vibro-acoustic data continues to provide some of the most quantitative and reliable indicators of bearing, gear, and rotating member fatigue for detection and diagnosis. These indicators are typically spread throughout the vibro-acoustic regime. Figure 2 illustrates the regions of response and health management uses of vibro-acoustic data, as well as the detection horizon provided. As shown, healthy machine vibration energy for a gas turbine engine dominates the frequency region from DC through approximately 50 kHz. This region is also appropriate for rotordynamic fault detection, such as misalignment and imbalance. However, the use of high frequency measurements is required for effective prognostic-enabling incipient fault detection and fault isolation.

The typical utility of high frequency measurements in diagnostics and prognostics is documented in several studies [1-3]. Research has shown that early material distress and incipient faults are most detectable at higher frequencies; thus an indication at this point will provide the greatest detection horizon. For instance, the earliest indications of bearing problems appear in ultrasonic frequencies (>30 kHz). As wear increases, component noise drops in the frequency range.

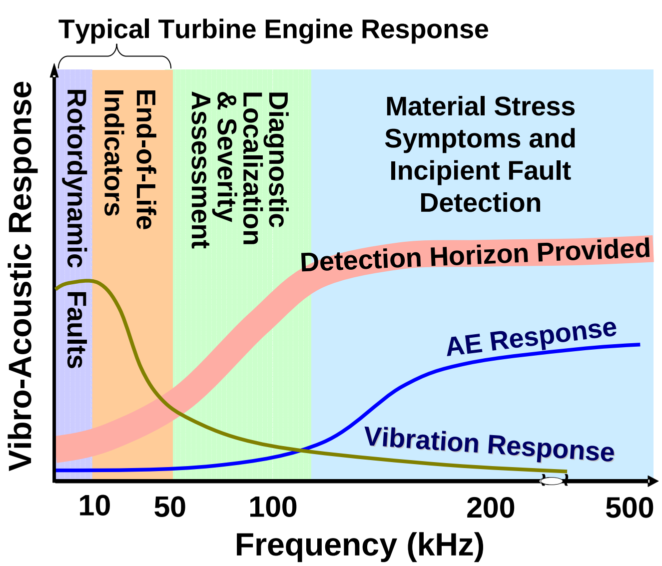

Figure 2 – Vibro-Acoustic Spectrum and PHM Uses

During fault progression, slight defects begin to ring the bearing at natural frequencies and overall high frequency energy and demodulated spectra values increase. Further in the progression, bearing defect frequencies and harmonics appear in the conventional spectrum analysis (if the overall machinery noise is not too high). High frequency demodulation and enveloping confirms this progression of damage. At the very end of life, the magnitudes of 1 times RPM are affected and more harmonics appear in the frequency analysis. Defect frequencies start to disappear and are replaced by high frequency random noise as the damage induces more random, chaotic vibration. Just prior to failure, spectrum energy will usually grow by excessive amounts.

This paper describes a comprehensive turbine engine and accessory vibration monitoring system that has been developed to take advantage of the changes in high frequency vibration that occur during the incipient stages of a fault. The approach, shown in Figure 3, uses component-specific PHM modules that extract information from high frequency vibration sensors to detect incipient faults. As seen, the system addresses each of the critical rotating components of a turbine engine, including the gears, bearings, shafts, and couplings. In addition, the validity of data from the vibration sensors is also evaluated prior to data processing to ensure that false alarms are not triggered by anomalous data. The PHM modules also consider the operational mode of the system and appropriately normalize the results to further reduce false alarms. The results from the component-specific PHM modules are then interpreted by a system-level reasoner that accounts for functional interaction and dependency between elements. This approach reduces the complexities associated with tracking competing failure modes because all information is presented to a single point for interpretation. The system-level reasoner interprets the results from the PHM modules and produces an overall assessment that detects and isolates system faults and predicts future health through the application of prognostic algorithms. Operation/usage statistics, visual inspection, experience-based data, user input, etc., can also be incorporated into the analysis. This hierarchal approach to system/subsystem health monitoring produces an overall assessment of health that considers all relevant Prognostics and Health Management (PHM) information.

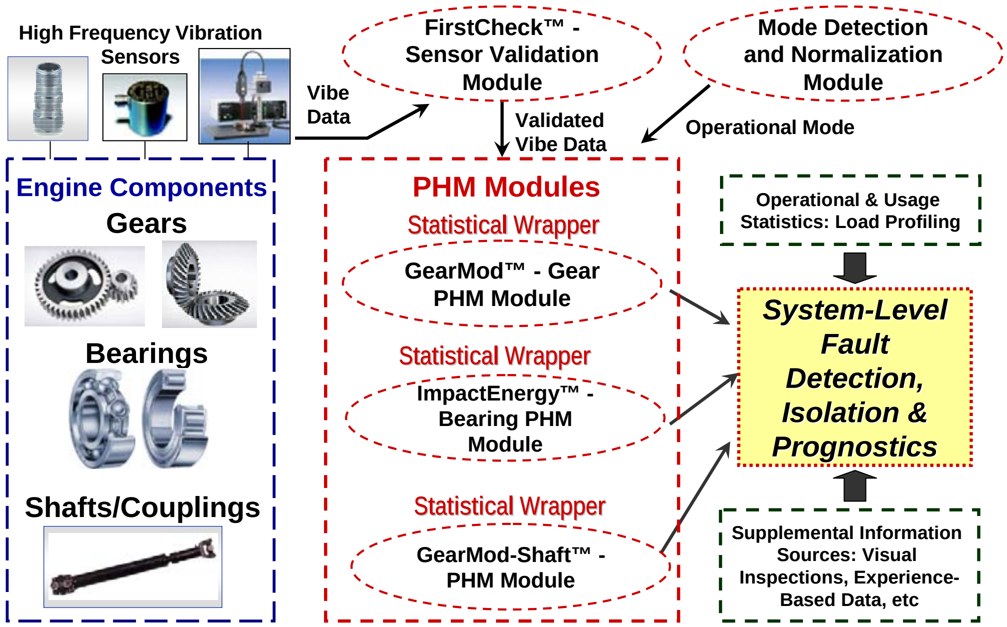

Figure 3 - A Comprehensive Turbine Engine and Accessory Vibration Monitoring System

This paper describes the key elements of the PHM architecture shown in Figure 3 and highlights its successful application in a number of military and industrial test cell applications. These successes clearly demonstrate the system's ability to detect and isolate incipient faults in complex machinery with multiple rotary and drive train components, including gears, bearings, shafts, and couplings.

FIRSTCHECK™: SENSOR VALIDATION

An important assumption in the deployment of an automated PHM system is that the data used by the system is accurate and valid. However, there are various factors associated with sensor hardware degradation and inadequate data collection methods that can compromise the integrity of vibration data. For example, accelerometers can be damaged by exposure to excessive shock or temperature or by improper handling by maintenance personnel. Other factors are more insidious and arise from loose electrical connections, poor solder joints, loose mounts, ground loops, electromagnetic interference (EMI) and Radio Frequency Interference (RFI) noise, or degradation of sensing instrumentation due to thermal effects. Data acquisition effects, such as A/D clipping and insufficient dynamic range, can also alter the dynamic characteristics of the signal. These issues can be very problematic and lead to significant safety concerns (i.e., onboard) and cost increases (i.e., during development or validation testing, where lost data means that a test may have to be repeated). In addition, changes in the dynamics of a vibration signal characteristic due to sensor faults can be deceptively similar to those due to mechanical failures (or vice versa), which will inevitably result in false alarms. Rigorous and automated analysis of the integrity of vibration data is therefore critical to providing accurate health assessments.

Based on the authors' experience, vibration monitoring algorithms can be impeded by faulty accelerometer data. Figure 4 shows the result of the authors' analysis of a gear pinion failure that occurred on the test stand of a high-speed (thousands of RPMs), high-power (tens of thousands of horsepower) military fighter aircraft drive train. As seen, several vibration features react simultaneously, indicating that a potential fault is present in the system. Information gathered solely from this sensor would confidently indicate a fault. However, upon further investigation of the raw sensor data (shown in the top plot of Figure 4), one can see that this reaction was caused by faulty (intermittent) data and, therefore, should not be trusted.

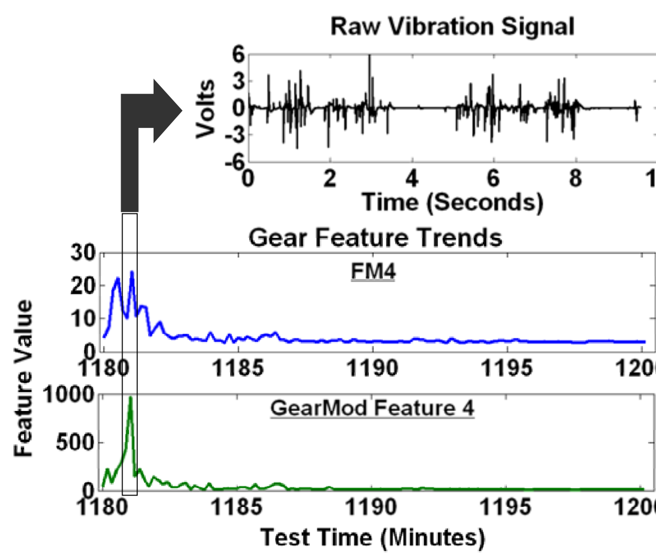

Figure 4 – False Alarm Caused by Faulty Sensor

In order to address this potential source of false alarms and validate the integrity of the signal, the developed approach first evaluates the high frequency vibration signal using a technique termed FirstCheck™. This technique tracks specific signal characteristics and statistical-based features to identify basic sensor failures, such as clipping, weak signal, over-amplification, and DC-bias, as well as other forms of corrupt data. This approach is more effective than traditional energy measures (i.e., peak-to-peak strength), which cannot detect a corrupt vibration signal when its values are within normal range but lacking in frequency content. Similar to mechanical fault detection algorithms, the developed approach uses a baseline of healthy sensor values to ensure that the algorithm does not disregard a valid signal.

Figure 5 shows an example of the algorithm's ability to detect anomalous vibration data. This data was collected from a small engine used to power a military UAV. As seen, the feature response varied significantly over the course of the test (left plot). In the early part of the test, the high feature response was indicative of a loose sensor connection. This is evident in the raw, time-series waveform (top right plot) and was confirmed through inspection. This problem was corrected and normal response resumed (see right, middle plot). As the test continued, the feature intermittently returned a value close to zero. This was a result of the data collection system being left on when the engine was not operating. This evidence is supported by the time waveform shown in the bottom right plot of Figure 5.

These results clearly demonstrate the algorithm's ability to autonomously detect a vibration sensor that has been disconnected or damaged. In addition to the examples presented, the algorithm has been rigorously developed and validated in many fielded and test cell applications, including Navy shipboard propulsion systems, helicopter engine FADECs, aircraft engine test cells, and onboard military ground and aircraft propulsion/drive train systems.

IMPACTENERGY™: BEARING FAULT DETECTION AND ISOLATION

Within the developed approach, bearing fault detection and isolation is performed using a set of algorithms termed ImpactEnergy™. Although bearing characteristic frequencies are easily calculated, they are not always easily detected by conventional frequency domain analysis. Incipient bearing damage is most often characterized by short-burst impulses in the vibration signature. Vibration amplitudes at these frequencies due to incipient faults (and sometimes more developed faults) are often indistinguishable from background noise or obscured by much higher amplitude vibration from other sources, including engine rotors, blade passing, and gear meshing. Similarly, time domain energy features, such as RMS and Kurtosis, are not significantly affected by such short bursts of low intensity vibrations. Therefore, traditional time domain or frequency domain analyses often encounter problems in detecting the early stages of bearing failure.

The developed algorithms integrate traditional time-domain statistical analysis and frequency-based spectral analysis techniques with high-frequency demodulation and advanced feature extraction algorithms to provide a more effective PHM solution. The advantages of using the high frequency response to identify and track bearing damage is well documented [2, 4] and proven to be effective. Demodulation (or enveloping) allows the broadband energy caused by failure effects to be differentiated from normal system noise. This approach provides the ability to detect defect impulse events much easier than traditional analysis techniques. A key consideration is selecting the bandpass filter that is centered on the expected carrier frequencies. Through proprietary knowledge and field-application experience, the authors have developed a process to identify key carrier frequencies [5, 6].

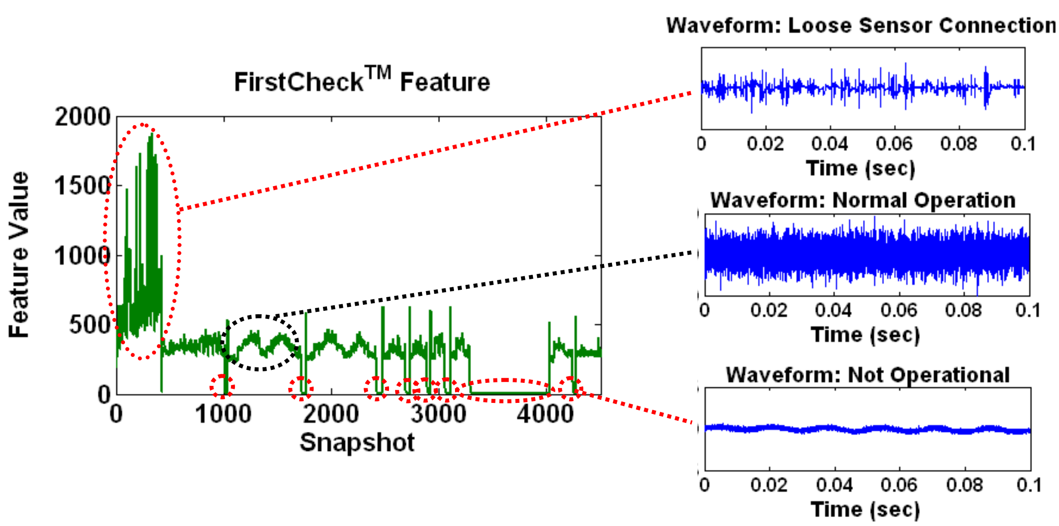

Figure 5 – Sensor Validation Feature and Corresponding Time Waveforms from a Military UAV Engine

For complete characterization of bearing health from incipient fault to failure, the algorithms include processing to extract an extensive set of time and frequency domain features from both the raw (unprocessed) and demodulated vibration signals. This extensive feature set provides an effective fault isolation capability. Time domain features include traditional statistical measures, such as RMS, Kurtosis, and Crest Factor. Frequency domain features include the power levels of specific bearing defect frequencies, which are compared against known, healthy baseline thresholds. These features can be very useful in diagnosing a fault [7]. In addition, observing the magnitude of the rate of change of these features can also provide a prognostic benefit.

The developed algorithms have been applied in numerous industrial and military platforms, including power generation equipment and several gas turbine engines. Figure 6 shows an example using vibration data that was collected from a multi-stage military fighter aircraft drive train with multiple bearings (more than ten) and a sophisticated, high-power gearbox. The advantage of using the developed algorithm is clear in this example, which compares the power spectral density of the raw, unprocessed, conventional vibration signal against the ImpactEnergy™ processed signal. The results obtained using the developed approach clearly demonstrate an increase in bearing defect frequency identification and the advantage of applying the preprocessing. These results were confirmed by teardown inspections, which revealed a single bearing with significant raceway damage.

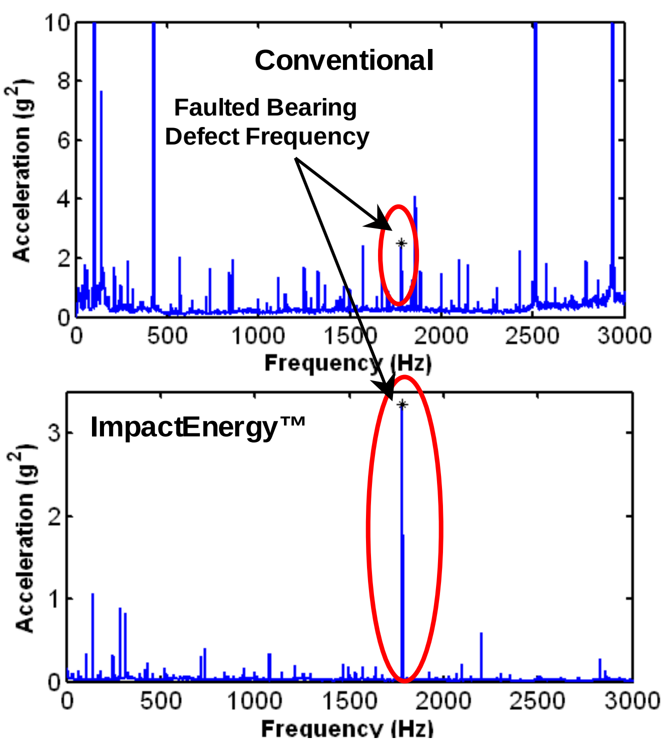

Figure 6 - Traditional Vs. ImpactEnergy™ Power Spectrum Density Estimates

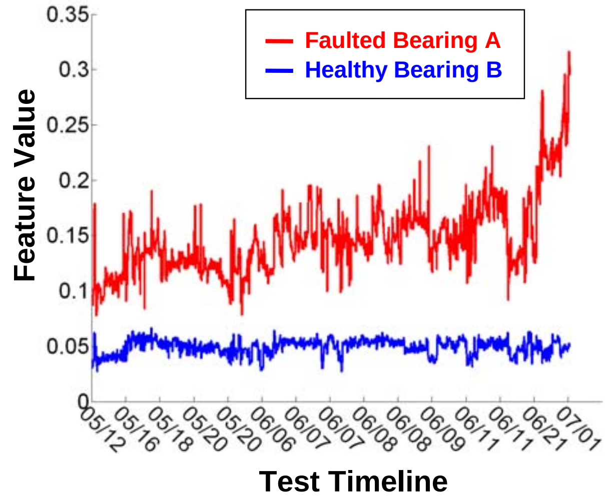

Figure 7 – Feature Trend of Faulted Bearing vs. Nearby Healthy Bearing from a Military Fighter Aircraft Drive Train

The algorithms also provide increased fault isolation capability. This is demonstrated in Figure 7, which compares the respective defect frequency feature trends of two bearings (one healthy and one faulted) from the example aircraft drive train system just described. As seen, the defective bearing feature is larger in magnitude than the healthy bearing feature and shows a gradual upward trend and variance increase, which is representative of the progression of a fault. The trend for the healthy bearing, on the other hand, remains constant with minimal variance.

Figure 8 (below) provides an additional example of the algorithm in a high performance test stand used for researching the failure propagation patterns of full-scale aircraft ceramic hybrid bearings. The test stand includes a 150 HP electric motor that drives two identical ceramic hybrid bearings, one of which was seeded with a spall on the surface of a single rolling element partly through the test (after approximately 575 hours). The test cycle contained three stages of operation, with load and speed conditions simulating military accelerated mission tests (AMTs). Data was sampled at 200 kS/s, allowing for high-frequency analysis.

The left plot in Figure 8 provides results for one of the energy features. As seen, the feature behaved statically up to approximately 575 hours of testing. At this point, the feature began to distinctively increase in magnitude and variance on all three accelerometers, indicating that fault inception had occurred. In addition to the fault detection performance of the energy feature, a feature specifically developed to detect outer raceway defects provided good fault isolation performance, as shown in the right plot of Figure 8. Similar to the energy feature trend, a dramatic increase in magnitude occurred approximately 575 hours into testing. Furthermore, the magnitude and variance of the outer race feature significantly increased after 774 hours, indicating that the fault had progressed to a severe state. These results were supported by periodic teardown inspections.

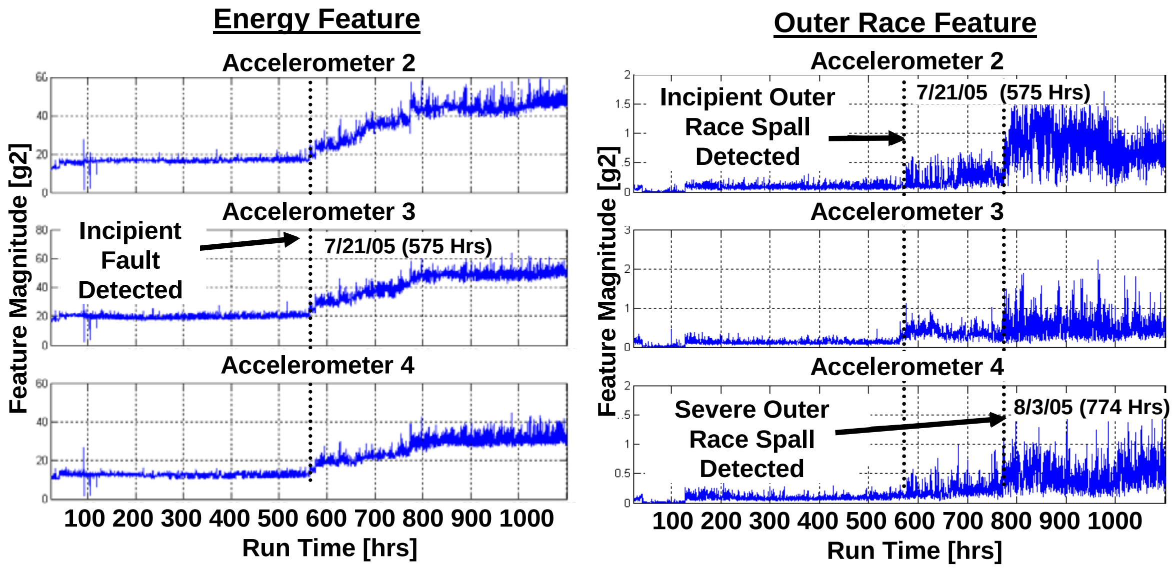

Figure 8 - Fault Detection (left) and Isolation (right) Capability of Developed Bearing PHM Approach

GEARMOD™: GEAR FAULT DETECTION AND ISOLATION

The authors have developed a set of algorithms, termed GearMod™, that are used to extract diagnostic features that can be employed for gear fault detection and isolation. These algorithms contains a broad range of statistical methods based on time synchronous averaged (TSA) and other processed signals. The time synchronous averaging technique is a very useful noise reduction tool that reduces random noise levels and disturbances from events unrelated to the gear of interest. TSA has been extensively used to preprocess gear vibration signals [8, 9]. The fundamental principal of TSA is that the vibration signals related to shaft and gear rotation will repeat periodically with each rotation. Therefore, TSA divides the vibration signal into contiguous segments (with each segment representing one shaft rotation) and calculates the average of the segments. This process reinforces vibration components that are synchronous to the shaft rotation and cancels out others that are out of phase in consecutive rotations. The algorithms calculate time-domain features, such as RMS, Skewness, Kurtosis, Energy Operator Kurtosis, and Crest Factor, as well as features from the spectrum of the averaged signal, including FM0, Sideband Index, and Sideband Level Factor. Additional features are also calculated using proprietary methods [10, 11].

These algorithms have been successfully applied in numerous military and research applications, including gear fault progression test data acquired from a Mechanical Diagnostic Test Bed (MDTB) at the Pennsylvania State University Applied Research Lab. Figure 9 shows an example trend of a diagnostic feature that was extracted from the MDTB data. The circles in black (on the left side of vertical dotted line, which is coincident with crack initiation) represent the gear in good condition and the circles in blue (on the right side of the dotted line) represent the gear in faulty condition. As seen, the developed feature accurately represents the health of the gearbox. Figure 10 shows another successful application of the algorithms, as applied to a high performance military fighter aircraft gearbox. In this case, the fault was not detected by the test cell monitoring system, which resulted in a catastrophic failure that destroyed the test stand. However, subsequent offline analysis of the data using the developed approach showed significant feature response more than five minutes before the failure occurred. This result means that real-time application of the developed module would have detected the fault in sufficient time to save the test stand.

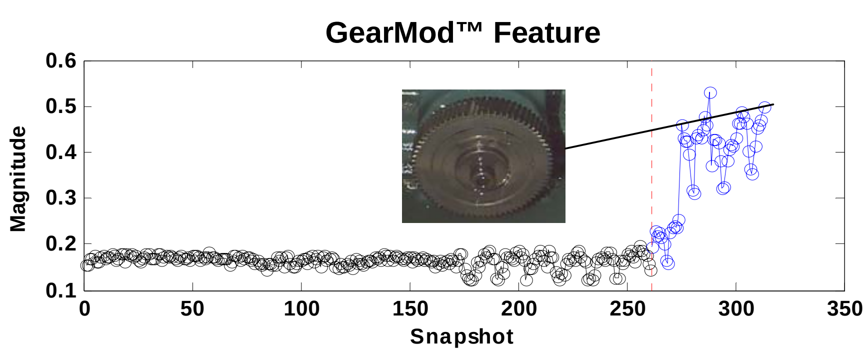

Figure 9 – Gear Feature Results from MDTB Fault Progression Test

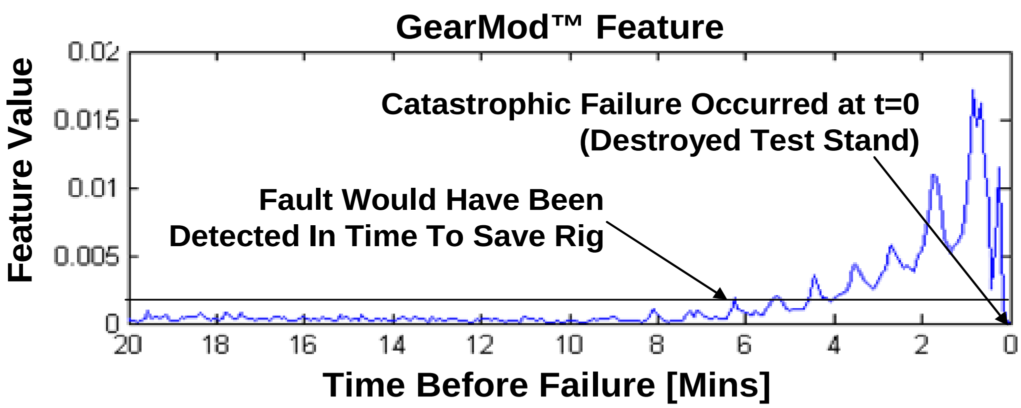

Figure 10 - Gear Fault Detection of Catastrophic Military Fighter Aircraft Gearbox Failure

GEARMOD-SHAFT™ AND COUPLING OVERVIEW

The authors have developed a set of algorithms, termed GearMod-Shaft™, that combines traditional shaft harmonic inspection methods, TSA analysis, and a Nonlinear Energy (NLE) estimation algorithm to identify frequency variations related to a failing shaft or coupling. These algorithms have also proven useful in identifying shaft misalignment. Unlike a bearing fault, which is small and induces an impulse response each time it rolls over another element, shaft and coupling vibration energy is primarily limited to the dominant forcing frequencies (i.e., the shaft RPM and its exact multiples). Sabnavis et al [12] conducted a literature review of cracked shaft diagnostics and cited several case studies that support looking at the trend of 1x and 2x orders of the shaft. Furthermore, a direct advantage is gained when performing this type of traditional analysis using the TSA signal, since non-cyclic events and random noise are diminished through the TSA signal calculation process. Example results of the developed approach are captured in Figure 11. In this example, a shaft failure occurred on a full-scale aircraft bearing test stand approximately 8 hours and 50 minutes after testing began.

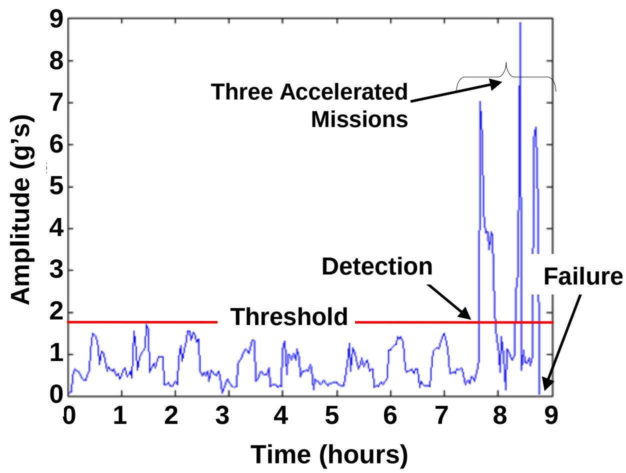

Figure 11 - Shaft Feature from a Full-Scale Aircraft Bearing Test Stand Failure

Figure 11 trends a TSA-based feature throughout the progression of the test. The plot in Figure 11 shows the dynamic behavior of the feature throughout the progression of testing and reveals a drastic increase in amplitude at approximately 7.5 hours into testing, resulting in a detection horizon of approximately 1.5 hours (a maintenance lead time of approximately 3 accelerated missions in this scenario). It is worth noting that the dynamic variation of the feature is a result of the testing's cyclic load and speed conditions, which simulate military accelerated mission test profiles.

The Nonlinear Energy (NLE) algorithm enhances the traditional approach by tracking the energy in resonant systems and accentuating characteristic modes while diminishing random noise and events. The process is termed 'nonlinear' because it uses a nonlinear operator. Nonlinear energy operators have been successfully applied to signal envelope detection, AM and FM demodulation in audio signals, and voice recognition [13]. Figure 12 illustrates the detection advantage gained when the nonlinear energy algorithm is used to identify a shaft coupling fault. The vibration data in this example was collected from a test stand dedicated to the research of coupling failure detection. The test setup included a motor coupled to a generator using a disc-type coupling. Vibration data was collected and processed for various types of coupling faults. Figure 12 compares a healthy, no-fault coupling with one that contained a seeded incipient crack. As seen, analysis of the frequency spectrum from the TSA signal alone (top plots) makes it difficult to discern between the healthy and faulted couplings. However, as seen in the lower plots, applying the nonlinear energy estimation process to the TSA signal makes the fault detectable through an increase in the shaft harmonic content. It is clear from this example that the NLE approach employed by the developed module significantly enhances coupling fault detection capability.

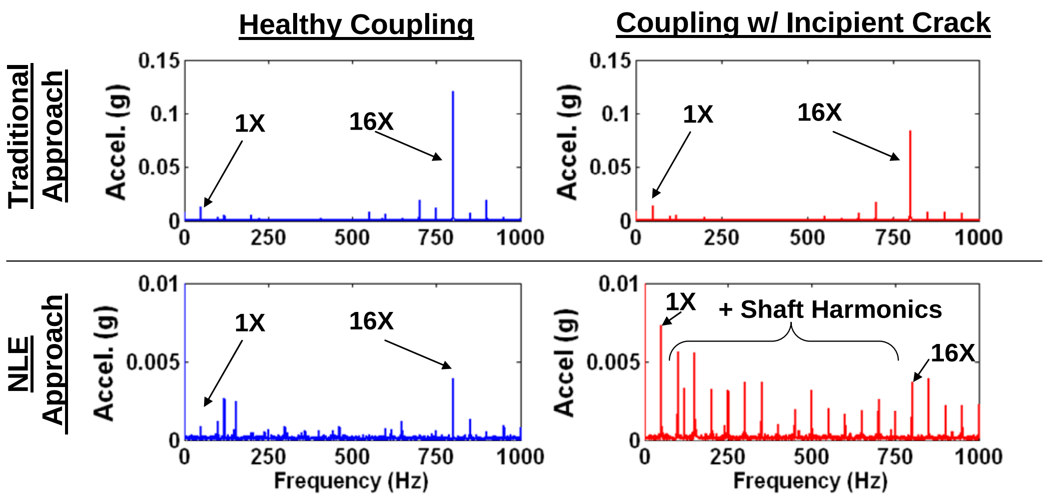

Figure 12 - Traditional vs. Nonlinear Energy (NLE) Approach to Identify Coupling Faults

SYSTEM-LEVEL FAULT REASONER OVERVIEW

The comprehensive approach of the developed system results in many diagnostic features that are individually useful in fault detection. However, the intelligent fusion of these complimentary features provides a more accurate and robust indicator of overall component health. As a result, the authors have developed a system-level reasoner that is capable of combining various component-level features into a single assessment of the targeted component's health. In addition, the various component health states are used to evaluate overall system health. A flowchart representation of the system-level reasoner is shown in Figure 13. Depending on whether or not baseline/healthy data is available, the reasoner operates in one of two modes. If baseline data is available, the reasoner will use historical feature values to estimate the fault severity predicted by each feature. Unlike many diagnostic fusion techniques, the fault severity estimate accounts for both abnormally high feature values and high rates of change in feature values. The reasoner also compares the baseline data to the respective fault feature threshold, which is statistically determined from baseline data, to calculate its confidence in the fault estimate.

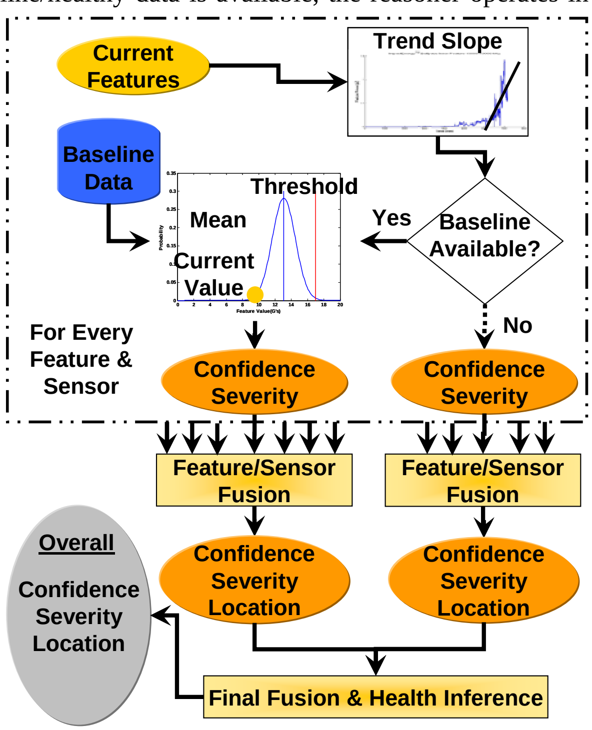

Figure 13 – Inference Engine Process Flow

If there is no baseline data, the reasoner will only use information derived from the trends of the features to estimate fault severity and calculate fault confidence. After fault severity and confidence have been calculated for each feature and sensor in the system, the individual features are fused to provide a more robust health indicator. In either mode of operation, feature fusion uses a sequential combination of knowledge fusion techniques (i.e., Bayesian Inference and Dempster-Shafer Combination) and voted weighting schemes. In the later case, unique feature weights are a determined from the feature's fault prediction capability, the fault transmissibility to each sensor, previous experience, and the availability of baseline data and operating condition information. Finally, overall fault severity and confidence are calculated using a final fusion and health inference engine. The health inference engine uses a combination of implicit and explicit approaches, such as Bayesian Belief Networks (BBN), Fuzzy Logic, or Neural Networks, to name a few.

The developed fault reasoning approach was validated using vibration data from a high speed military helicopter gas turbine engine. The data was collected in a test cell while the engine was operating under load conditions simulating an actual flight. Validation was performed using data from a healthy bearing (for baseline) and a bearing seeded fault progression test (a small dent was created on the inner raceway in the load zone of the running bearing using a hardness testing machine and allowed to progress). The seeded fault data was evaluated by the reasoner to determine fault confidence (Figure 14, left plot) and fault severity (right plot).

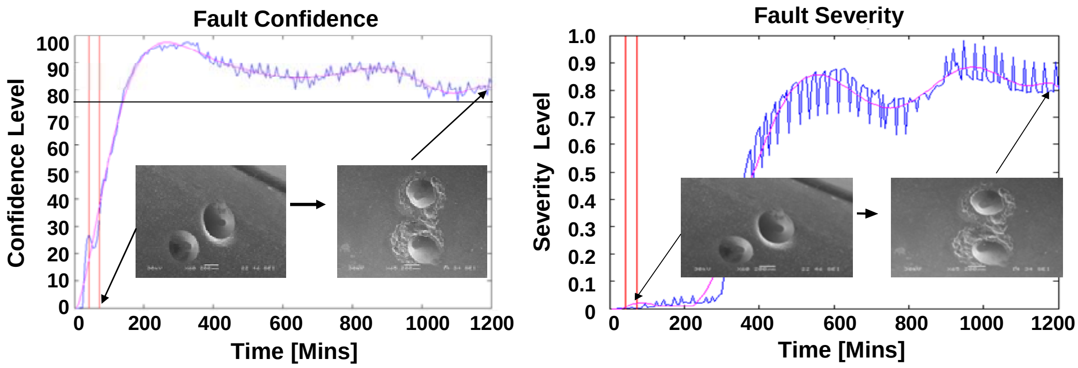

Figure 14 – Fault Severity Assessment and Confidence for a Dented Bearing in a Military Helicopter Engine

As expected, the reasoner was less confident that an incipient fault existed at the beginning of the test. However, the reasoner's confidence quickly increased as its results were reinforced by new features indicating a fault. The reasoner was also able to accurately predict and track bearing fault severity as it progressed from the incipient level (at the beginning of the test) to a much more severe state. It is worth noting that the fluctuations in the severity assessment were caused by varying speeds and loads of the engine during testing. However, even with these fluctuations, the reasoner was very sensitive and correlated well with the increase in bearing damage. These results were confirmed with tear down inspections and pictures taken using a scanning electron microscope.

VERIFICATION & VALIDATION

Verification and Validation (V&V) of incipient fault detection systems can be accomplished using statistical analysis. This analysis is based on the separability of features between the no-fault ("healthy") and faulted conditions. Figure 15 shows the probability density function (PDF) of feature values for a no-fault condition (the PDF on the left) and a component with a fault (the right PDF). These distributions are fairly typical of most features that are designed for fault detection purposes; however, the concepts can be applied regardless of whether the faulted feature increases or decreases as a result of component damage.

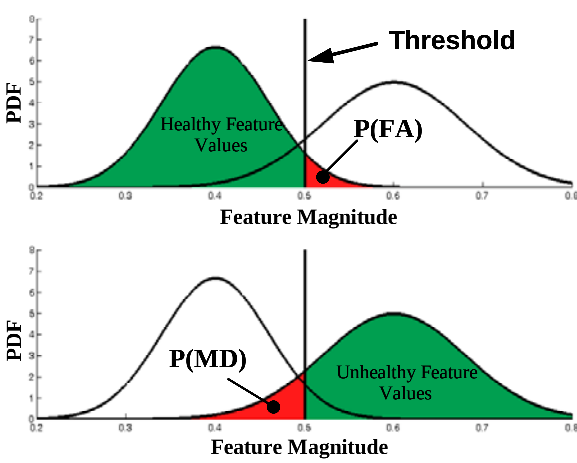

Figure 15 –Statistical Detection Metrics

The upper plot of Figure 15 emphasizes the no-fault distribution. As seen, the Probability of False Alarm, P(FA), is represented in red on the right side of the threshold. This represents the feature values that would incorrectly indicate that a fault existed. The lower plot of Figure 15 emphasizes the "unhealthy" distribution. The Probability of Missed Detection, P(MD), is the red area below the threshold and represents feature values that (incorrectly) would not have indicated a fault given the threshold set-point. It is worth noting that the Probability of Correct Rejection, P(CR), and Probability of Detection, P(D), are the conjugates of P(FA) and P(MD), respectively.

As seen, P(FA) and P(MD) are interdependent due to their measurement with respect to a particular threshold. If the threshold is raised to decrease the P(FA), P(MD) is consequently increased. Therefore, once sensors are positioned, data is collected, and features are extracted, a threshold choice must be made to either minimize P(FA) or P(MD). Assuming the computed feature is sensitive to changes brought about by a damage mechanism, the system designer's goal is to maximize that sensitivity, thus separating the mean values while minimizing the variance to decrease the spread and resultant overlap of the distributions. Additional details on this analysis can be found in [14] and [15].

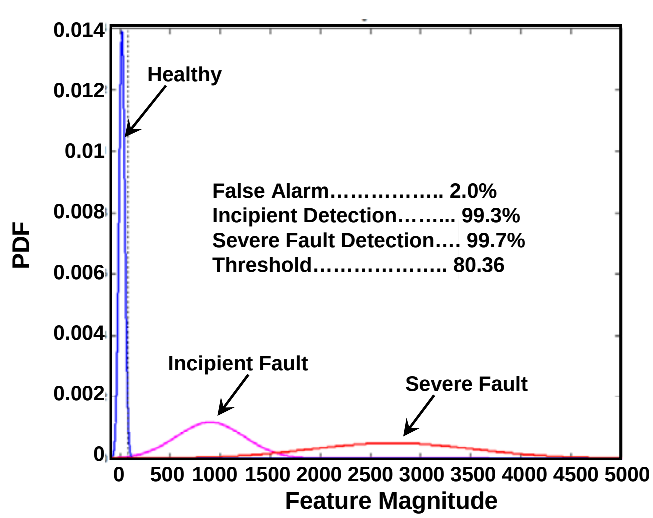

Figure 16 – V&V of a Military Test Stand Bearing Fault

Figure 16 shows an example of the statistical analysis performed on the ImpactEnergy™ algorithm using data from a seeded fault on a military test stand. In this case, a threshold was set to achieve a 2% probability of false alarm. As seen, this threshold produced a very good detection rate for both the incipient and severe faults that were evaluated.

CONCLUSIONS & FUTURE WORK

The authors have developed a comprehensive high frequency (1-100 kHz) vibration monitoring system for incipient fault detection of critical rotating components within engines, drive trains, and generators. This comprehensive approach begins with validation of vibration sensor data to reduce the occurrence of false alarms. Component-specific PHM modules are then applied to individually detect and isolate incipient faults in gears, bearings, and shafts. Component-specific information is then interpreted by a system-level reasoner that considers component interaction and other operational factors to produce a confident analysis of overall system health. As described herein, this PHM system has been successfully applied to several industrial and military systems (in the field or currently under development) for the detection and isolation of faults in gears, bearings, and shafts. The developed vibration monitoring system represents significant technology maturation from traditional demonstrations, which are performed in controlled, sub-scale test environments, to actual applications in real, complex systems with multiple rotary components that operate under dynamic conditions.

ACKNOWLEDGMENTS

This work has significantly benefited from the invaluable support and technical consult of Andy Hess, Doug Gass, Bill Hardman, and Eric Carney of the Naval Air Warfare Center (NAVAIR) and Joint Strike Fighter program office, along with Dr. Al Behbahani, Ken Semega, Christopher Klenke, and Matthew Wagner of the Wright-Patterson Air Force Research Laboratory (AFRL). Financial support for this work, provided through multiple contracts from both the NAVAIR and Air Force Small Business Innovative Research (SBIR) program offices, is also gratefully acknowledged. The authors would also like to thank DARPA for proving Phase III funding for test cell evaluation of the previously developed ImpactEnergy™ techniques. Finally, the authors would like to acknowledge the contributions of countless others at Impact Technologies, including Dr. Michael Roemer, Patrick Kalgren, Rolf Orsagh, Dr. Kallappa Pattada, and the numerous others who have helped make these efforts successful.

REFERENCES

[1] Lebold, M., McClintic, K., Campbell, R., Byington, C., and Maynard, K., 2000, "Review of Vibration Analysis Methods for Gearbox Diagnostics and Prognostics," *Proc. 54th Meeting of the Society for MFPT*, May 1-4, 2000, pp. 623-625.

[2] Bagnoli, S., Capitani, R., and Citti, P., 1988, "Comparison of Accelerometer and Acoustic Emission Signals as Diagnostic Tools in Assessing Bearing Damage," *Proc. of the 2nd International Conference on Condition Monitoring*, London, pp. 117-125.

[3] Campbell, R.L, Byington, C.S, and Lebold, M.S, 2000, "Generation of HUMS Diagnostic Estimates Using Transitional Data," *Proc. 13th International Congress and Exhibition on Condition Monitoring and Diagnostic Engineering Management*, The Society for Machinery Prevention Technology (MFPT), Haymarket, VA, pp. 587-595.

[4] Braun, S., and Datner, B., 1979, "Analysis of Roller/Ball Bearing Vibrations," J. of Mechanical Design, **101**, pp. 118-25.

[5] Kallappa, P., Byington, C., Kalgren, P., and DeChristopher, M., 2005, "High Frequency Incipient Fault Detection for Engine Bearing Components," *Proc. ASME Turbo Expo 2005: Power for Land, Sea, and Air*, Paper No. GT2005-068516, Reno-Tahoe, NV.

[6] Kalgren, P., Byington, C., and Kallappa, P., 2004, "An Intelligent Ultra High Frequency Vibration Monitoring System for Turbomachinery Bearings," *Proc. 2004 ASME/STLE International Joint Tribology Conference*, Paper No. TRIB2004-64317, Long Beach, CA.

[7] Harris, T.A., 2001, *Rolling Bearing Analysis*, John Wiley & Sons, Inc., New York, pp. 993-1000.

[8] Braun, S.G., and Seth., B.B., 1979, "On the Extraction and Filtering of Signals Acquired from Rotating Machines," J. of Sound and Vibration, **65**(1), pp. 37-50.

[9] Decker, H.J., and Zakrajsek, J.J., 1999, "Comparison of Interpolation Methods as Applied to Time Synchronous Averaging," Technical Memorandum, NASA/TM-1999-209086, ARL-TR-1960, Army Research Lab, Cleveland, OH.

[10] Orsagh, R., and Lee, H., 2006, "An Enhancement to TSA and Filtering Techniques for Rotating Machinery Monitoring and Diagnostics," *60th Meeting of the Society for MFPT*, Virginia Beach, VA, pp. 339-349.

[11] Orsagh, R., Lee, H., Watson, M., Byington, C., and Powers, J., 2005, "Application of Health and Usage Monitoring System (HUMS) Technologies to Wind Turbine Drive Trains," *WindPower 2005*, Denver, CO, May 15-18, 2005.

[12] Sabnavis, G., Kirk, R., Kasarda, M., and Quinn, D., 2004, "Cracked Shaft Detection and Diagnostics: A Literature Review," Shock and Vibration Digest, **36**(4), pp. 287-296.

[13] Maragos, P., Stokes, V., and Handel, P., 1993, "On Amplitude and Frequency Demodulation Using Energy Operators," IEEE Transactions on Signal Processing, **41**(2), pp. 506-7.

[14] Byington, C., Safa-Bakhsh, R., Watson, M., Kalgren, P., 2003, "Metrics Evaluation and Tool Development for Health and Usage Monitoring System Technology," AHS Annual Forum 59, Phoenix, AZ, May 6-8, 2003.

[15] Roemer, M., Dzakowic, J., Orsagh, R., Byington, C., Vachtsevanos, G., 2005, "Validation and Verification of Prognostic and Health Management Technologies," Proc. 2005 IEEE Aerospace Conference, Big Sky, MT, pp. 3941-3947.