CBM Fundamental Research at the University of South Carolina: A Systematic Approach to U.S. Army Rotorcraft CBM and the Resulting Tangible Benefits

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The present paper addresses systematic approach to Condition-Based Maintenance, and research results at the University of South Carolina Condition-Based Maintenance Research Center, directly related to U.S. Army rotorcraft Vibration Management Enhancement Program. The paper gives an analysis of the CBM concept and its functional layers, such as condition monitoring, diagnostics, prognostics and health management systems, followed by diagnosis and prognosis enabling technologies and concepts; followed by research and development of Health and Usage Monitoring Systems enhancing technologies, such as expansion of military aircraft condition sensing technologies through integration of multi-sensor data fusion, and exploration of new signal analysis techniques. The paper is concluded by Tail Rotor Gearbox case studies, and results of cost benefit analysis of the rotorcraft Condition-Based Maintenance program implemented at the South Carolina Army National Guard.

Introduction

Since 1998 the University of South Carolina (USC) and the South Carolina Army National Guard (SCARNG) have participated in a number of important projects that were directed at reducing the Army aviation costs and increasing operational readiness [1-8, 43]. This joint effort succeeded in higher operational readiness using fewer, more capable resources, provided commanders with relevant maintenance-based readiness information at every level, showed and enabled millions of dollars in operational costs savings, and shifted the paradigm from preventative and reactive practices to proactive analytical maintenance processes, now commonly referred to as Condition-Based Maintenance. The benefits of these technologies have already been proven for helicopters on combat missions, training, and maintenance flight conditions.

The transition to CBM requires a collaborative joint effort of an Industry, Academia, and Government team, and is contingent on identifying and incorporating enhanced and emerging technologies into existing and future aviation systems. This requires new tools, test equipment, sensors, and embedded on-board diagnosis systems.

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The University of South Carolina has supported the U.S. Army by conducting research to enable timely and cost-effective aircraft maintenance program enhancements. Research emphasis has been to collect and analyze data and to formulate requirements assisting in the transition toward Condition-Based Maintenance for the U.S. Armed Forces.

The research program at USC seeks to deliver tangible results which directly contribute to CBM efforts and objectives as: link and integrate maintenance management data with onboard sensor data and test metrics [5-7], and to quantify the importance of each data field relative to CBM; understand the physics and the root causes of faults of components or systems; explore the development of models for early detection of faults; develop models to predict remaining life of components and systems.

Concept of Condition Based Maintenance

Condition Based Maintenance (CBM) (sometimes called Predictive Maintenance) is an approach to equipment maintenance, where actions are performed based on part's condition, which is found through observation and analysis rather than on event of failure (Corrective Maintenance) or by following a strict maintenance time schedule (Preventive Maintenance). CBM is looked upon as an efficient way of asset maintenance, which, if properly established and implemented, could significantly reduce the number or extent of maintenance operations, eliminate scheduled inspections, reduce false alarms, detect incipient faults, enable autonomic diagnostics, predict useful remaining life, enhance reliability, enable information management, enable autonomic logistics, and consequently reduced life cycle costs.

The approach of CBM to asset management is not new and over the last seventy years dramatic improvements have occurred in the technology, equipment and practices used for machinery vibration measurement, condition monitoring and analysis [12]. Rapid technological progress in semiconductor and information technologies over the last two decades has made data acquisition and computation hardware much more compact, robust and less expensive, enabling implementation in reliability critical machinery like civilian and military rotorcraft vehicles, and in industrial, medical, automotive, electronics, energy, oil and gas production industries. Currently, still due to relatively high CBM implementation costs, traditional maintenance approaches of Corrective Maintenance, Preventive Maintenance and CBM techniques are being used in parallel.

A full CBM system consists of several functional layers. According to Open Systems Architecture for Condition-based Maintenance (OSA-CBM) standard [10] and Condition Monitoring and Diagnostics of Machines ISO-13374 standard [11] these are:

Data Acquisition: converts an output from a sensor measurement to a digital parameter, representing a physical quantity and related information such as the time, velocity, acceleration, sensor configuration.

Data Manipulation: performs signal analysis, computes meaningful descriptors, and derives virtual sensor readings from the raw measurements.

State Detection: facilitates the creation and maintenance of normal operation baselines, searches for abnormalities whenever new data is acquired, and determines in which abnormality zone, if any, the data belongs (e.g. alert or alarm).

Health Assessment (Diagnosis): diagnoses any faults and rates the current health of the equipment or process, considering all state information.

Prognostics Assessment (Prognosis): determines future health states and failure modes based on the current health assessment and projected usage loads on the equipment and/or process, as well as remaining useful life.

Advisory Generation: provides actionable information regarding maintenance or operational changes required to optimize the life of the process and/or equipment based on diagnostics/prognostics information and available resources.

Data Acquisition	Condition Monitoring	CBM
Data Manipulation		
State Detection		
Health Assessment	Diagnostics	
Prognostics Assessment	Prognostics and Health Management	
Advisory Generation		

Fig. 1. Functional layers of CBM.

Data Acquisition, Data Manipulation and State Detection layers comprise Condition Monitoring system, and make a foundation of a general CBM program (Fig. 1). Further growth of more efficient CBM program involves realization of Diagnosis, Prognosis, and Advisory Generation layers, which incorporates a broader range of new technologies.

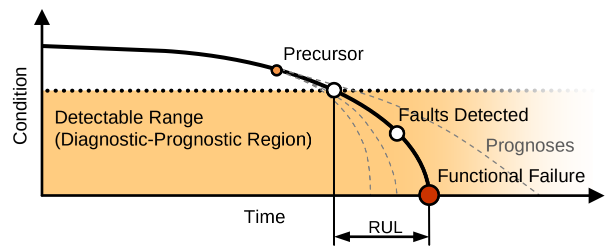

Fig. 2. Schematic of a component lifetime curve, relating to its condition diagnosis and prognosis.

Diagnostics focus on identification of individual components' condition, which include early fault detection, isolation and identification (like current crack location and size). Prognostics is a general term that describes a process to predicting the remaining useful life (RUL) of a component and system (how, how fast and to what extent the diagnosed fault will progress) (Fig. 2)[13, 28-32]. Prognostics are critical in order to further improve reliability, minimize life cycle costs and realize automated logistics. Then Health Management is a procedure to handle the information gathered through condition monitoring, diagnostics and prognostics, in order to present an accurate report of the current condition of the system, and recommend maintenance actions, schedule operations, order supplies, aid technicians in making the repairs, or suggest how to temporarily extend the life of the component by maintenance actions or adaptive control. These technologies require integration and automation across the subsystems, systems and logistics management system levels in holistic approach [9], since most of them are focusing on fault diagnosis and prognosis within individual components. Currently CBM is

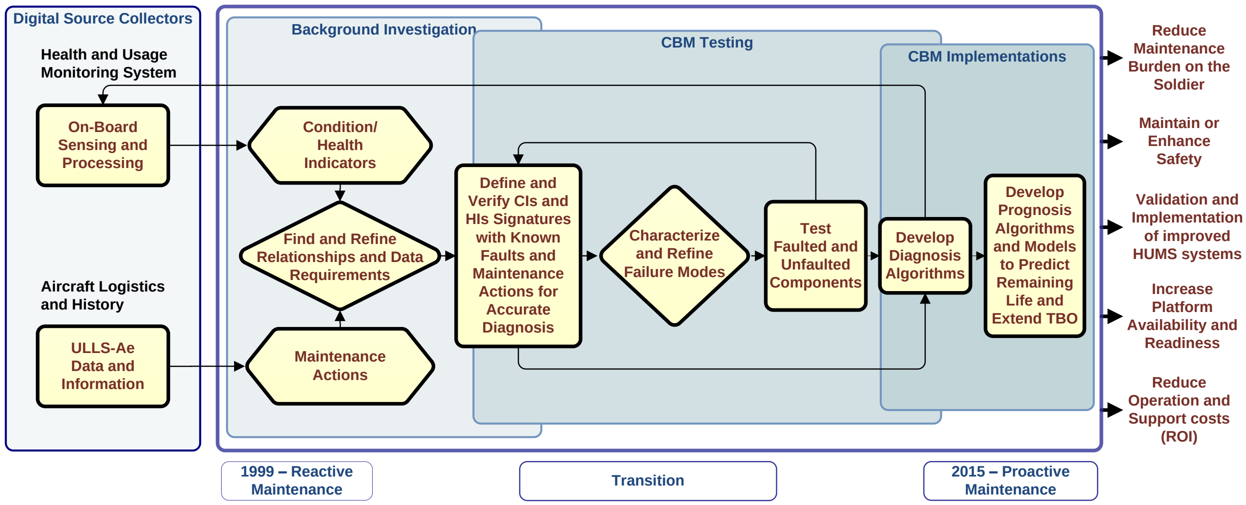

Fig. 3. Procedural roadmap of USC CBM research program.

dominantly diagnostic, since machine condition prognosis is relatively new and by its definition has a high level of uncertainty and complexity with many remaining challenges.

Research and Development for Military Rotorcraft CBM at the University of South Carolina CBM Research Center

As the growth and awareness of CBM develop, many ideas and technologies have arisen in efforts to improve it. There is need for a standardized methodology and roadmap for the currently implemented CBM of military rotorcraft to reach its full potential. In cooperation with the South Carolina Army National Guard, the University of South Carolina has the resources and channels to develop a roadmap to investigate the transformation of CBM. The activities of USC are being performed as a joint Industry, Academia, and Government team.

The research roadmap (Fig. 6) consists of three phases: initial investigation, component and system testing and the implementation of a fully-capable CBM system. This roadmap is driven by the currently available digital source collectors, which through integration and linking direct the needs of laboratory testing. The results of this self-refining process will ultimately lead to the development of diagnosis and prognosis algorithms which will facilitate proactive CBM practices.

The research program at USC seeks to deliver additional results which directly contribute to CBM efforts and objectives as: link and integrate maintenance management data with onboard sensor data and test metrics [5-7], and to quantify the importance of each data field relative to CBM; understand the physics and the root causes of faults of components or systems; explore the development of models for early detection of faults; develop models to predict remaining life of components and systems.

Component Testing and Data Collection

One of the most expensive and time consuming tasks relating to CBM involves testing of mechanical components. The goal of testing is to identify the root causes of components' failure, failure modes, identification of ways to improve serviceability of aircraft components, and research and development of alternative sensing, diagnostic and maintenance technologies.

USC CBM Research Center has been active in the vibration diagnostics area both through internally funded research and contracted research. In the last ten years, USC has been working closely with the S.C. Army National Guard, U.S. Army Aviation Engineering Directorate (AED) and Intelligent Automation Corporation (IAC) on the implementation of VMEP (Vibration Management Enhancement Program), which resulted in on-board Modern Signal Processing Unit (MSPU) (vibration data acquisition and signal-processing equipment for the health monitoring of critical mechanical components) for the AH-64 (Apache), UH-60 (Blackhawk) and CH-47 (Chinook) fleets. The CBM Center at the USC is one of the key players on the U.S. Army CBM team. USC has focused on defining and developing a long-term roadmap of methodologies and processes that reinforce CBM activities and objectives. State-of-the-art indoor helicopter test stands have been designed and built, and are being used to test rotating mechanical components. The Tail Rotor Drive Train (TRDT) and Main Rotor

Swashplate (MRSP) test stands shown in Fig. 4 are capable of testing AH-64 drive train components (bearings, gearboxes, swash-plates, oil coolers and shafts), AH-64 hydraulic pumps, and AH-64 main rotor swash-plate bearing assemblies.

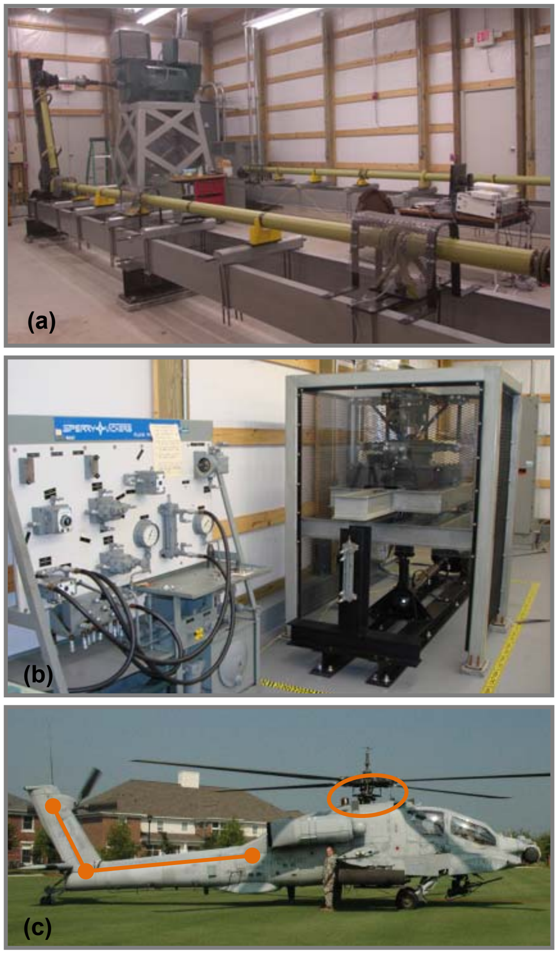

Fig. 4. USC Tail Rotor Drive Train (a) Test Stand, Main Rotor Swashplate Assembly (b) Test Stand, and Their Correspondence on the Actual AH-64 Helicopter (c).

All test stands utilize several data acquisition systems, including current in-flight MSPU health monitoring system, as well as a specialized laboratory data acquisition system, recording torque, speed, temperature, vibration, and capable of electrical signature, and acoustic emission monitoring. They are controlled based on measures of speeds, torques, and temperatures, which are collected throughout the experiment. The testing capabilities are structured to test new and existing drive train components of military and civilian aircraft, with particular emphasis on AH-64, ARH-70, CH-47 and UH-60. Aircraft components' testing also supports data requirements necessary for accurate diagnosis and proper maintenance of aging aircraft. All of the measurement data is constantly collected and migrated to a secure in-house file server which is also readily accessible to Army personnel.

The test facility is designed to be flexible and practical for multiple purposes, while facilitating the ability to scientifically understand and interrogate the actual condition of components as they relate to Army Maintenance Management System for Aviation (TAMMS-A) inspections, vibration signals, health and usage monitoring systems output, and other data sources. This data is needed for the development of comprehensive and accurate diagnosis algorithms and prognosis models.

MSPU Technology Advancement for Diagnostics and Prognostics

The Army-developed Modern Signal Processing Unit (MSPU) grew out of the Vibration Management Enhancement Program (VMEP) and is currently in use on a significant part of the Army helicopter fleet including AH-64D, UH-60, and CH-47. The MSPU acquires data and calculates the Condition Indicators (CIs) used to determine the health of the drive system mechanical components. The next generation of the MSPU system will utilize the ongoing test and in-flight data, together with historical maintenance data, and research in sensor data fusion, new signal analysis techniques, and maintenance techniques, for developing and demonstrating advanced diagnostic capabilities for this technological area.

General Approach to Diagnostic and Prognostic Techniques

Generally solutions to the diagnostics and prognostics problems can be classified into data-driven and physics-based model techniques [44-47].

Data-driven approaches are based on monitored system's current, historical and expert knowledge data. These approaches rely on the assumption that measured statistical characteristics of a healthy system are relatively similar to the previously known healthy state of the same or similar system. When considerable deviations in measured data are detected, it is assumed that a certain fault was initiated and diagnosis is attempted through comparison to historical faults progression data. Thus data-driven approaches are based on statistical and machine learning techniques from the theory of pattern recognition [43]. The data-driven approaches are applicable to systems, where understanding of the first principles of system operation is not comprehensive or where sufficient historical/test data is available that maps out the damage space. The advantage of data-driven techniques is that often they can be deployed quicker and cheaper, while providing a system-wide coverage (physics-based model techniques can be more limited).

Physics-based model techniques are potentially more accurate since they use damage propagation physical models along with actual health information of the system to predict the condition or remaining useful life of a component once fault initiation has been detected. The models usually consist of a healthy component model that simulates operation under normal conditions and a series of models that simulate various failure modes. Then signals from an actual system in operation are employed to match the situation in the physical model in order to calculate/find the fault and its condition. The physics-based model techniques are more robust since they can deal with fault scenarios that are missing from the historical data, because mathematical models can analytically account for a wider range of system behaviors. Because of this ability, physics-based model techniques do not require extensive training and need much less historical data, compared to data-driven techniques [29]. However, very robust and accurate mathematical models are needed. Thus, accurate modeling and simulation of the physical systems is an essential task in applying model-based techniques for CBM. Data-driven and physics-based model techniques have their own advantages and disadvantages (Fig. 5 [49]) and consequently should be used together.

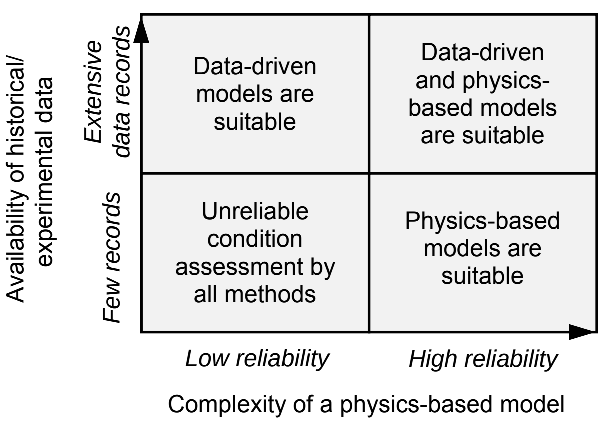

Fig. 5. Applicability of data-driven and physics-based model techniques for diagnosis and prognosis.

In case of prognostics, physics-based model techniques differ from data-driven by the fact that they can make remaining useful life predictions in the absence of real-time measurements, by calculations based on previous diagnosis data and usage changes (operation time, load, environment changes etc. since last diagnosis). If/when updated diagnostic information is available the model can be recalibrated and remaining useful life reassessed. Therefore a combination of the data-driven and physics-based model techniques can provide full prognostic ability over the entire life of the component (Fig. 2).

Historical and Test Data Analysis for the Rotorcraft CBM

The U.S. Army CBM program has led to a significant amount of historical data for use in diagnosis and prognosis on the currently operating helicopter fleet. Also a considerable amount of data is being collected at the USC AH-64 tail rotor drive-train (TRDT) test facility, through seeded fault component testing. Currently the USC CBM Research Center has access to 35,000 flight-hour records that include records from UH-60A, UH-60L, AH-64A, AH-64D, and CH-47D aircraft, collected by the U.S. Army CBM program. Also from the test facility, USC has the advantage of being able to generate new data by implementing capabilities such as thermal, acoustic, electrical signature, and oil debris analysis. In such case there is a significant amount of historical vibration data and maintenance records database, allowing for data-driven diagnostic/prognostic models application.

In order to achieve the goal of the rotorcraft diagnosis-prognosis, we have established a research that can be summarized in Fig. 6 as: (1) the process of multi-sensor data acquisition, (2) development of new diagnostic features/CIs and refinement of available CIs, (3) establishing fault classifiers through historical and experimental data analysis, (4) condition diagnosis through statistical/expert methods for classifying and fusing CIs into fault classes, (5) establishing health classifiers through historical and experimental data analysis, (6) health prognosis through statistical inference classification methods, which all are covered in the following paragraphs.

The major components of the procedure are sensors data collection and historical data analysis in building of a feature/CI vector that contains enough information about the current machine operating condition to allow for fault classification and identification. In order to address the issue of more effective and informative diagnostic measure, we have proposed a new method/function of CI mapping in the form of mutual information measure [4]. So the feature vector will contain data obtained by signal processing techniques that are already implemented in the MSPU, and by proposed signal analysis technique, applied on the historical and experimental multi-sensor data. The research investigates the efficiency of the advanced time-frequency techniques in order to extract the health state information from a variety of observations. The research is featured by considering multiple physical dimensions of the systems, including mechanical vibrations, acoustic emission, electrical signatures and temperatures as some of the available diagnostic data sources.

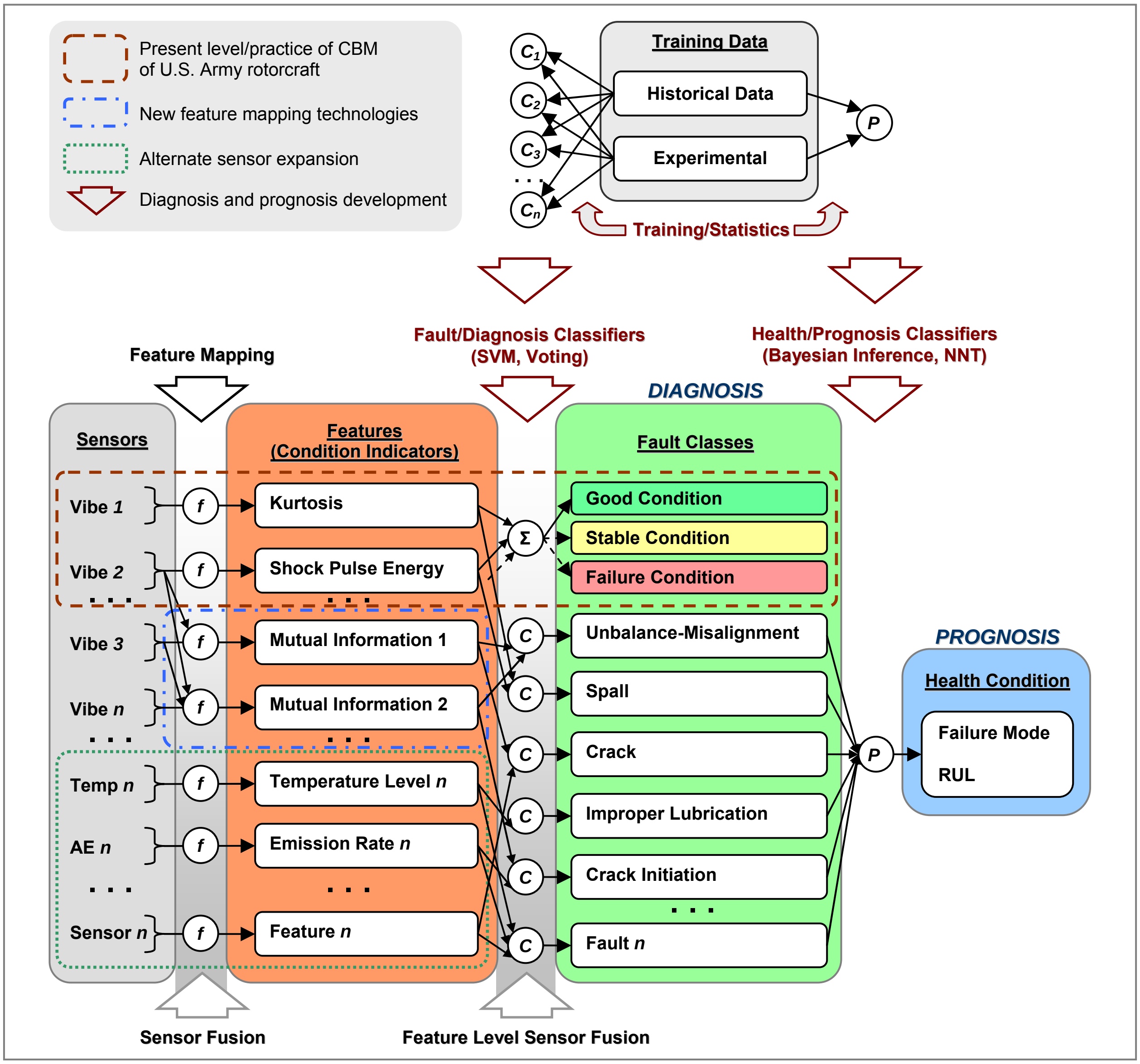

Fig. 6. Flowchart to data fusion/diagnosis/prognosis, followed by USC CBM Research Center.

Multi-sensor data fusion

In the research, multi-sensor data fusion (here it is fusion of features/CIs from multiple sensors) is reasoned by the fact that many measurement techniques can be used to monitor the same failure mode. A mechanical problem identified by vibration analysis can also be cross-checked with an oil debris analysis, Electrical Signature Analysis (ESA), or thermography (Table 1). Electro-mechanical problem identified by ESA can be confirmed through vibration or ultrasound analysis techniques. Hence, a confirmation of the diagnosis is possible through the use of the different measurement techniques. A single data type will rarely provide evidence of a particular malfunction that is as conclusive as when multiple data types can be compared. It is always desirable to have multiple sensor data in agreement when performing machinery diagnostics, in order to support a conclusion with a higher confidence level. This makes CBM more convincing, especially when critical machinery is involved. This way another perspective to producing more reliable machinery diagnostic and prognostic system lies in the fusion of data and information at different levels. Fusion of information across multiple sensors offers potentially significant improvements in robustness and accuracy in fault detection and isolation.

Also fusion should help to reduce the occurrence of false alarms. Diagnostic performance is improved by allowing detection of unique fault patterns seen on sets of signals and information instead of a single signal (as in the proposed mutual information measure). Information is integrated across a variety of sensors, so potential faults can be detected earlier. For example, several case studies at the USC CBM Research Center [43, 50] show that in case of improper gear lubrication, direct temperature measurement can be an earlier indicator of an impending problem in comparison to vibration measurement.

Non-Destructive Measurement Techniques Investigation

USC CBM Center has investigated several sensors for non-destructive testing/measurement (NDT) and their applicability for rotating machinery fault detection. There is a variety of sensors (piezoelectric, eddy current, thermal imaging, optical) that have been designed for non-destructive in-situ temperature, vibration, acoustic emission (AE), oil analysis, electrical signature analysis (ESA), ultrasound and other measurements. Among these vibration monitoring and analysis is the most recognized, informative and applicable technique in rotating machinery condition monitoring and is used in combination with all the mentioned measurements, since no single measurement technique can capture all failure precursors:

Vibration: Numerous studies of roller bearings condition monitoring have shown that vibration, temperature or other measurement is not always the best and only solution to the problem. For example roller bearings vibration monitoring was proven successful only where the vibration energy from other components (shaft, gears, etc.) does not overwhelm the lower energy content from the defective bearing. In case of fatigue failure, the bearing develops microscopic cracks or spalls below the surface of the race, that usually stay undetected by vibration analysis techniques. Usually it is only when failure progresses the bearing produces audible sound and the temperature rise (in such case temperature measurements can be effective only at the late failure stages). Some studies show that only 3 to 20% of a bearing's useful life remains after spall initiation [15, 16].

If a bearing is correctly chosen and installed, the main reason for premature damage usually is improper lubrication or contamination of the lubricant. In such case vibrations are non-periodic and difficult to detect and interpret by vibration analysis techniques. Also when machinery speeds are very low, the bearings generate low energy signals which again may be difficult to detect.

Similarly vibration analysis of gears could detect damage after 30% of contact area is already pitted.

Temperature: Bearings temperature monitoring is of limited value in case of a physical damage, since a noticeable temperature rise does not occur until there is a significant damage. But in case of improper lubrication, installation, misalignment or overload - temperature rise can be an early sign of an impending fault, because in such case there will be no significant change in vibration levels. So bearing temperature monitoring may be useful in applications where loss of lubrication, rather than contact fatigue is the primary failure mechanism, such as rotorcraft hanger bearings. Monitoring of a lubricant temperature is also important, since thickness, quality and lifetime of the lubricating film greatly depend on the lubricant’s nominal operational temperature ranges.

Electrical Signature Analysis: Electrical Signature Analysis (ESA) in CBM is mainly referred to as Motor Electrical Signature Analysis (MESA) or Current Signature Analysis (CSA). Electrical motor/generator/tachometer current can act as a sensor for detecting electro-mechanical faults in the motor. This way through motor’s current and voltage signals analysis we can detect various mechanical faults of the motor or drive-train. Main applications of ESA are for electrical motor electro-mechanical diagnostics: rotor bar damage, foundation looseness, static eccentricity, dynamic eccentricity, stator mechanical faults, stator electrical faults, defective bearings. But ESA has also been found applicable for the motor mechanical drive train diagnostics (gears, bearings, belts, shafts, valves and other components), since all key mechanical events that are measurable by accelerometer also can be measured by a motor [22-27]. Though its sensitivity in comparison to seismic sensor (accelerometer) remains uncertain [22].

Oil debris and condition analysis: Oil analysis has been a prime condition monitoring technique for gearboxes, often able to detect gearbox wear before vibration analysis.

On-line oil debris monitoring uses mainly two types of sensors: magnetic chip detector or electric chip detector. The magnetic chip detector requires scheduled inspection, while the electric chip detector provides immediate indication in the cockpit without the need for scheduled inspection. Newer generation inductive electric chip detectors can collect and count ferromagnetic particles, especially for rolling-contact-fatigue failures; some of them even count nonferrous metals [13]. Debris particles are typically analyzed off-line with an energy-dispersive scanning electron microscope or X-ray fluorescence instrument to determine the material and isolate the origin of the particles.

Currently main limitations of on-line oil debris monitoring are insensitivity to fine debris and inability to detect non-metallic particles.

Acoustic Emission: Stress waves inside materials occur due to collective motion of a group of atoms during a crack nucleation and growth, dislocations, phase transformations and other processes. These processes can be monitored by the means of Acoustic Emission (AE) measurement in the range of 100 kHz to 300 kHz. AE signal has its origin in the material itself, not in external geometrical discontinuities, so generation and propagation of cracks associated with plastic deformation are among the primary sources of acoustic emission. Main problems in interpretation of AE signal and application of the technology are related to parallel sources of AE and temperature variations, causing a noisy signal [33]. The advantage of AE monitoring over vibration monitoring and other techniques is that it can detect the growth of subsurface cracks, while other techniques can detect defects only when they appear on the surface [34]. High frequency vibration energy attenuates very rapidly with increasing distance from a source. This leads to a limitation that a sensor needs to be very close to the source of vibration. From another perspective - the advantage is that the localized nature of the vibration can be used to isolate the source of a problem. Again, in case of roller bearings, vibration energy from other components does not affect the AE signal released in the higher frequency range. Also high frequency measurements proved to be very sensitive to lubrication conditions in grease lubricated roller bearings [37]. This way AE can be considered as a solution to the previously mentioned late fault detection problems. Other applications of high frequency measurements include: detecting and monitoring of leaks, cavitation, monitoring chemical reactions and material phase transformations. Despite numerous studies in the field of AE application for gear diagnostics, it is still facing challenges, but still can be considered as a complementary tool [33-37].

All of the measurement techniques try to detect the smallest possible fault as early as possible with minimal investment. Thus, industry research is continuing into new sensor and implementation technologies such as sensor arrays, fiber optic sensors, power harvesting/self powered sensors, MicroElectroMechanical sensors (MEMS), wireless sensors, - enabling telemetric monitoring, component integration, minimization, and providing new methods for fault monitoring and detection.

Vibration, temperature, AE, ESA measurements and oil analysis are some of the more widely practiced condition monitoring techniques. Choosing between the measurements mainly depends on the monitored component and system. Problem of measurement technique selection for CBM can be addressed with the following roadmap [14]: Define system boundaries › Establish equipment criticality › Conduct failure modes and effects analysis › Evaluate regulatory requirements › Establish failure modes to be addressed by NDT › Define information required from NDT technique › Evaluate safety and access constraints › Evaluate cost per point › Determine skills required › Select NDT based on information, access, cost and skills required › Establish sampling locations › Establish sampling intervals › Document and formalize the program.

In the Table 1 we have tried to compare different NDT measurement methods in respect to their application field, diagnostics potential and width of faults coverage for rotating machinery component monitoring.

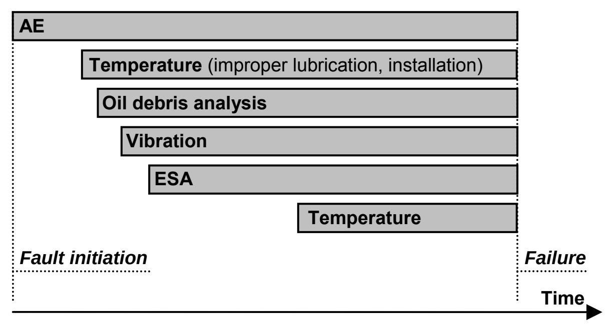

Fig. 7. Relative comparison of predictive capabilities of the studied measurement methods.

MSPU and VMEP enhancement by temperature monitoring (in parallel to current vibration monitoring) seems the most feasible, and, as shown by the research and case studies, enhancing option. One of the supporting factors is that it requires minimal investment in MSPU and helicopter hardware modifications - AH-64 already has OEM installed thermistors on the most critical components like gearboxes.

Mechanical Vibrations Data Processing with Application for Mechanical Fault Detection

Currently MSPU is equipped only with accelerometers that measure one physical dimension. Mechanical vibrations data collected from the accelerometers is processed in MSPU independently by direct feature/CI mapping functions: Kurtosis, Shock Pulse Energy, Root Mean Square, Amplitude Demodulation, FM0, FM4, Sideband Level Factor, Sideband Index, Energy Ratio. Though full list is even longer, it does not mean that it is sufficient/efficient – it states that diagnosing mechanical failure modes of rotating components is very complex and needs further

Table 1. Comparison of vibration, temperature, acoustic emission, electrical signature analysis, and oil/oil debris analysis non-destructive testing techniques.

	Vibration	Temperature	AE	ESA*	Oil debris
Fields of application:					
Science/R&D	●	●	●	●	●
Civil engineering structures	●	●	●		
Electrical distribution systems	●	●		●	
Mechanical systems	●	●	●	●	●
Electronics	●	●	●	●	
Chemical processes		●	●		
Usability:					
Non-destructive	●	●	●	●	●
Non-intrusive (■ – thermal imaging)	●	■		●	
Online monitoring	●	●	●	●	●
Diagnostics potential:					
Proven real life applications	●	●	●	●	●
Fault detection	●	●	●	●	●
Fault isolation	●	●	●	●	●
Fault identification	●	■	●	●	●
Early fault detection (1 – best)	2	4	1	3	2
Monitoring of low frequency (< 0.1Hz) processes		●	●		●
Sensitivity to mechanical interference	●		●	●	
Complexity of data analysis (1 – highest)	1	3	1	1	2
Hardware cost	1	4	2	3	1
Faults coverage (○ - low sensitivity):					
Crack initiation or propagation	●		●		
Gear defects	●	○	○	○	●
Roller bearing defects	●	○	●	○	
Friction/lubrication	○	●	●		●
Unbalance	●			●	
Misalignment	●	○		●	
Belt drive problems	●	●		●	
Cavitation	○		●		
* – In context of ESA measurements made on generator or tachometer connected to mechanical drive train.					

	Vibration	Temperature	AE	ESA*
Typical measurement ranges	10 Hz – 20kHz	50 F (10 C) – 300 F (150 C)	100 kHz – 300 kHz	20 Hz – 20 kHz
Sensor ranges	0.1 Hz – 100 kHz	-328 F (-200 C) – 2282 F (1250 C)	20 Hz – 5 MHz	0 Hz – 100 kHz

research and refinement. The importance of the statement and the research is highlighted by recent studies at the CBM Center, where MSPU CIs have showed inadequate response to severe failure modes resulting from insufficient gear lubrication [43, 50].

As there is no single sensor that is sensitive to all failure precursors or faults - there is no single data processing technique that can extract all the features/CIs from vibration, AE, ESA or other raw measurement data. That is why there are numerous data processing methods and algorithms that are used in parallel, in order to extract all the available CIs, required for its condition analysis and diagnosis of a mechanical component/system.

Currently Practiced Vibration Analysis Techniques

First step in data processing is data conditioning in order to filter noisy/erroneous sensor or manually entered data. The next step is data analysis. In CBM case data analysis deals with time-domain, frequency-domain and time–frequency domain analysis methods that are applicable for fault monitoring and diagnosis.

Time-domain analysis mainly deals with waveform statistics like Root Mean Square (RMS), Crest Factor, Kurtosis [15-21]:

The crest factor is equal to the ratio of a peak value to RMS value of a waveform. The purpose of the crest factor calculation is to give an analyst a quick idea of how much impacting is occurring in a waveform, since impacting is often associated with gear tooth wear, roller bearing wear, or cavitation. In such case it can be more informative method than FFT frequency-domain analysis (discussed further), since impacts and random noise appear the same in the FFT spectrum, although they mean different things in the context of machinery vibration.

Kurtosis can be defined as a degree of peakedness of a probability distribution of a waveform. Its application in bearing diagnostics is attractive by the fact that no prior baseline data is needed - kurtosis value greater than 3 is assumed to be an indication of impending failure itself. However, kurtosis value drops down to the acceptable level as damage advances.

Frequency-domain analysis is based on the analysis of transformed signal in respect to frequency. This is normally displayed as a spectrum (plot of frequency against amplitude). The advantage of frequency-domain analysis over time-domain analysis is its ability to easily identify and isolate certain frequency components of interest. The most widely used and known frequency-domain analysis method is spectrum analysis by means of FFT (fast Fourier transform) [4]. The overall vibration signal of a machine is contributed from many of its components, surrounding machinery and structures. However mechanical faults excite characteristic vibrations at different frequencies related to specific fault conditions. By analyzing the spectrums, both the nature and severity of the defect can be identified. Though FFT is very popular and indispensible tool in vibration analysis it has a few limitations. It was mentioned that by definition FFT is intended for stationary/harmonic signals analysis, so impacts and random noise appear the same in the spectrum. Another limitation of the spectrum is that time information is totally lost - it is unknown if the signal of certain frequency was present all the time during the data acquisition or it appeared only at certain times or time periods. These limitations are addresses in Time-frequency domain analysis of the signal.

Cepstrum is another frequency-domain technique that has the ability to detect harmonics and sideband patterns in the FFT spectrum. For example one characteristic common to most vibration signatures of rolling element bearings is that there exist a harmonic series not-synchronized with the shaft speed. These series are fundamental bearing frequencies or rotation rate sidebands that are important in bearing failure diagnosis and are difficult to identify in the spectrum. Because cepstrum has peaks corresponding mainly to the harmonics and sidebands in the signal, they can be more easily identified. This way it is even possible to detect bearing fault without knowing its geometrical parameters by looking for a series of harmonics that are not synchronized with the shaft speed.

In order to improve the signal-to-noise ratio and make the spectral analysis more effective in mechanical diagnosis, there are specialized techniques like: averaging technique, adaptive noise cancellation technique, envelope detection or the high-frequency resonance technique. Envelope technique [20] is primarily used for early detection of faults in rolling element bearings and gearboxes, because the over-rolling of a defect shows up in the vibration signal as a high frequency periodic impulsive action that can be easily extracted from a noisy signal by a band-pass filter, rectified and analyzed in frequency-domain. It is an early fault detection technique that can reveal faults in their earliest stages of development, before they are detectable by other vibration analysis techniques.

Time-frequency domain analysis investigates non-stationary waveforms in both time and frequency domains, because frequency-domain analysis is unable to handle non-stationary waveform signals, which are very common when machinery faults occur. STFT (short time Fourier transform), Wigner-Ville distribution and Wavelet transform are the most popular time-frequency analysis methods [4, 17, 26]. The Short-Time Fourier Transform is an effective tool that overcomes the FFT non-stationary waveform limitations, but, again, it analyzes all the frequencies in a signal with the same window that limits frequency resolution. The wavelet transform is another time-frequency domain method that preserves the time information of the original signal and can overcome the resolution problems encountered when analyzing transient signals using Fourier analysis. Wavelet transform has been suggested for analysis of very weak signals, where FFT becomes ineffective, and also has been applied for fault diagnostics of gears, bearings and other mechanical systems [26].

The field is continuing to grow as the potential of new data processing techniques is being introduced for the early fault detection, which is shown by the example of the following paragraph.

Advanced Time-Frequency Analysis Technique

As it was said, there is a need for more efficient CI functions that are more sensitive in extracting relevant vibration or transient measurements data, as there are great challenges and opportunities in the field.

Consequently, USC CBM Research Center is developing and exploring a new information measure metric for time and frequency domain [4, 38]. Inspired by traditional information theory, this technique considers self- and mutual-information of the time-frequency distribution and it provides measure of in-phase and quadrature components of a pair of non-stationary signals. This idea is unique and an innovative approach for time-frequency analysis which is investigated in the research.

The presently accepted practice of vibration analysis for mechanical component diagnosis and prognosis is performed in time and frequency domain, while time-frequency domain analysis is performed in a large time scale for vibration level trending or order analysis by professional human experts. The major difference in the ongoing work is that time-frequency analysis is performed on very short time scale signals, representing all the transients of the time signal. As a result, it is possible to extract meaningful parameters such as instantaneous frequency, group delay, and Rényi information [39], which is a key factor for a quantitative description of transient signal. Thus, one can take great advantage of time-frequency analysis for the scientific investigations of transient/non-stationary signals.

The mutual information measure is comprised of a quadrature component and an in phase component which seem to indicate differences in the actual physics of the system. Fig. 8 shows the scatter plot distribution of the in phase component of the measure on the x-axis and the quadrature component of the measure on the y-axis for cases of: (1) balanced and aligned shaft (baseline), (2) unbalanced and aligned shaft, (3) balanced and misaligned shaft, (4, 5): unbalanced and misaligned shaft. In the condition of system unbalance, as seen in Fig. 8 (a), (c), and (d), the in phase component trend is toward a greater amount of information bits. Similarly, misalignment can be observed to increase the number of information bits contained in the quadrature component (Fig. 8 (b) and (d)). As a distribution these values can be seen to shift along the x-y plane indicating a shift in part or system status. Differences in this mutual information measure could be further developed into an increased precision statistical indicator of part or system health status.

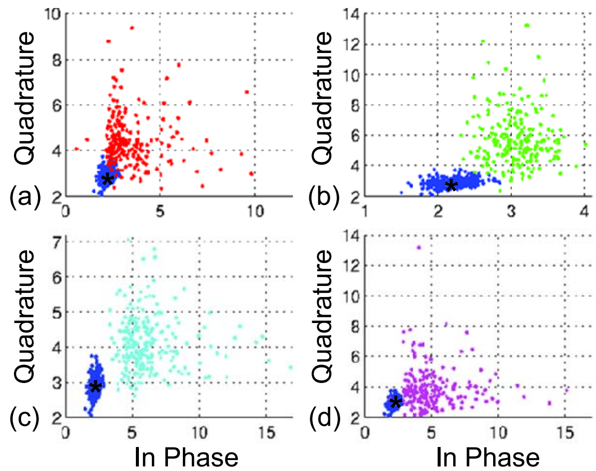

Fig. 8. Baseline comparisons of the mutual information measure where the baseline distribution (*) is compared to various states of misalignment and unbalance.

The proposed signal analysis technique is applicable on the historical and experimental multi-sensor data, since by investigation of drive-train component failures [4, 43, 50] we have found that additional sensors, as acoustic and electrical, exhibit their unique features in the given time-frequency analysis technique. Thus, in the proposed research we will investigate the efficiency of the advanced time-frequency technique in order to extract the health state information from a variety of multi-physical dimensions of the systems including mechanical vibrations, acoustic emission, electrical signatures and temperatures as some of the available diagnostic observations.

Condition Diagnosis and Prognosis

In order to conduct fault prognosis and maximize uptime of a failing component through CBM, first we seek to determine impending or incipient failure conditions. The stage of diagnosis (Fig. 6) requires classification of calculated diagnostic features/CIs to currently MSPU employed condition classes as good/stable/failure condition, or to enhanced localized fault classes like unbalance, spall, crack (to enable further prognosis). In order to classify the feature vector, first we need to establish proper classifiers (library of fault patterns and alarm thresholds). This process involves analysis of historical MSPU (and HUMS) and Unit Level Logistics Support – Aviation (ULLS–A) data, USC historical and ongoing experimental data, in order to set threshold limits and establish probability distributions for enabling methods like weighted voting, Bayesian inference or Support Vector Machine (for the clustered mutual information data classification). There is no ultimate solution or answer to which diagnostic or prognostic classifier performs the best for a given scenario, - different tools and methods are investigated in the research:

As shown in Fig. 8, the proposed mutual time-frequency information measure provides clear clustering signatures of baseline, unbalanced load, and misaligned shaft in terms of in-phase and quadrature information components. The first task in utilizing this data for diagnosis (Fig. 6) should be statistical study of the signature clustering in order to determine bounds of baseline, unbalanced load, and misaligned shaft so that one can assess current health condition of the drive shaft. One of the enabling techniques for clustered data classification is Support Vector Machine (SVM):

The SVM [40] is based on statistical learning theory and is extensively used for classification, regression, and density estimation. SVM maps the input patterns into a higher dimensional feature space through nonlinear mapping chosen a priori. A linear classification surface is then constructed in this high-dimensional feature space (basically a hyperplane is defined that separates two clustered data sets). Thus, SVM is a linear classifier in the parameter space, but it becomes a nonlinear classifier as a result of the nonlinear mapping of the space of the input patterns into the high-dimensional feature space. Training the SVM is a quadratic optimization problem. The construction of a hyperplane $\mathbf{w}^T\mathbf{x}+b = 0$ ($\mathbf{w}$ is the vector of hyperplane coefficients and b is a bias term), so that the margin between the hyperplane and the nearest point is maximized, can be posed as the quadratic optimization problem. SVM has been shown to provide high generalization ability [41].

For the two-class problem, assuming the optimal hyperplane in the feature space is generated, the classification decision of an unknown pattern $\mathbf{y}$ will be made based on:

$$f(y) = \operatorname{sgn}\left(\sum_{i=1}^{N} \alpha_i y_i K(\mathbf{x}_i, \mathbf{y}) + b\right), \qquad (1)$$

where $\alpha_i \geq 0$, $i = 1, 2, \ldots, N$ are nonnegative Lagrange multipliers that satisfy $\sum_{i=1}^{N} \alpha_i y_i = 0$, $\{y_i | y_i \in \{-1,+1\}\}_{i=1}^{N}$ are class labels of training patterns $\{\mathbf{x}_i | \mathbf{x}_i \in R^N\}_{i=1}^{N}$, and $K(\mathbf{x}_i,\mathbf{y})$ for $i = 1, 2, \ldots, N$ represents a symmetric positive definite kernel function that defines an inner product in the feature space. This way $f(\mathbf{y})$ is a linear combination of the inner products or kernels. The kernel function enables the operations to be carried out in the input space rather than in the high-dimensional feature space. Some typical kernel functions are $K(\mathbf{u},\mathbf{v}) = \mathbf{v}^T\mathbf{u}$ (linear SVM); $K(\mathbf{u},\mathbf{v}) = (\mathbf{v}^T\mathbf{u}+1)^n$ (polynomial SVM of degree n); $K(\mathbf{u},\mathbf{v}) = \exp(-\mathbf{x}\|\mathbf{u}-\mathbf{v}\|^2 / 2\sigma^2)$ (radial basis function SVM); $K(\mathbf{u},\mathbf{v}) = \tanh(\kappa\mathbf{v}^T\mathbf{y}+\theta)$ (two layer neural SVM), where σ, κ, θ are constants [40].

One of the following tools for the classified data fusion is the rule-based fusion method, which is a superset of voting fusion method and can approximate all other data fusion methods [42, 46, 47]. Voting and weighted voting decision fusion techniques can be implemented by assigning weights to sensors/CIs based on their a priori reliability models at detecting a certain fault (Table 1) or their correlation (Table 1). Similarly some sensors can be ignored or assigned a low credibility based on their performance in time (Fig. 7) or fault being diagnosed. If all weights are set equal, weighted voting is reduced to voting. For the feature/CI fusion by weighted voting, each sensor, i, outputs a binary vector, x_i, with n binary CI values corresponding to given faults. The classification vector, $x_{i,}$ from sensor i becomes the i^{th} row of the weighting matrix A. Each row of the matrix is weighted using the a priori assumption of the sensor liability W_i. Subsequently the elements of the array are summed along each column:

$$D(j) = \sum_{i=1}^{m} W_i(t) A[i, j], \qquad (2)$$

where $D(j)$ is a fused decision on fault j, m – number of sensors, W – weighting factor, t – time.

Other approach to the method could be suggested, where normalized CI values are input parameters for previous equation, so fault severity is represented [48]. Normalization could be applied by min-max function:

$$A[i,j] = (CI_{i,j} - CI_{\min})/(CI_{\max} - CI_{\min}), \qquad (3)$$

where CI is condition indicator, $CI_{\min}$ and $CI_{\max}$ are minimum and maximum CI threshold values.

This way, a parallel fusion approach to Bayesian inference, which is discussed further, can be taken.

Other statistical methods, such as Bayesian inference, are supposed to yield an “inverse probability”, or probability of the “cause” F (a fault), on the basis of the observed “effect” S (sensor reading/feature). Whereas $P(F)$ is the a priori, $P(F|S)$ is the a posteriori conditional probability of the cause F. Bayes’ theorem serves as the basis for the Bayesian inference technique for identity fusion. Bayesian inference assumes that a set of S mutually exclusive (and exhaustive) hypotheses or outcomes exists to explain a given situation. In the decision-level fusion problem Bayesian inference is implemented as follows: a system exists with N sensors that provide decisions on membership to one of S possible classes. The Bayesian fusion structure uses a priori information on the probability that a particular hypothesis exists and the likelihood that a particular sensor is able to classify the data to the correct hypothesis. The inputs to the structure are $P(F_j)$ – the a priori probabilities that object j exists (or equivalently that a fault condition exists), $P(S_{k,i}|F_j)$ - the likelihood that each sensor k will classify the data as belonging to any one of the S hypotheses, and S_k the input decisions from the K sensors [46]:

$$P\left(F_j \middle| S_1,\dots,S_K\right)=\frac{P(F_j)\prod_{k=1}^{K}P\left(S_k \middle| F_j\right)}{\sum_{i=1}^{N}P(F_j)\prod_{k=1}^{K}P\left(S_k \middle| F_j\right)}. \qquad (4)$$

The output is a vector with element j representing the a posteriori probability that the data belong to hypothesis j. The fused decision is made based on the maximum a posteriori probability criteria given in following equation:

$$d(k)=\arg\max_j\left[P\left(F_j \middle| S_1,\dots,S_K\right)\right]. \qquad (5)$$

A basic issue with the use of Bayesian inference techniques involves the selection of the a priori probabilities and the likelihood values. The choice of this information has a significant impact on performance. In our case there is an advantage in extensive historical HUMS and USC CBM Center data and expert knowledge that can be used to determine the probability distributions [49].

Only after successful implementation of previous steps we can go to the final step of prognosis. Here from historical and experimental data we need to identify a statistical aging model that describes migration time of given state to reach the safety condition limit. This aging model should be experimentally verified by the proposed research. Same diagnostic algorithms and intelligent data-fusion architectures will be extended to optimally combine extracted data with probabilistic component models to achieve the best decisions on the overall health of components (Fig. 6).

AH-64 Tail Rotor Gear Box Case Study

One of the latest test articles at the USC test facility was a Tail Rotor Gearbox (TGB) (Fig. 9) that was tested for durability under critical lubrication conditions [50]. That is a bevel spiral tooth gear, having a 22:57 transmission ratio, operating at approximately 3700 rpm input shaft speed, at 330 hp load.

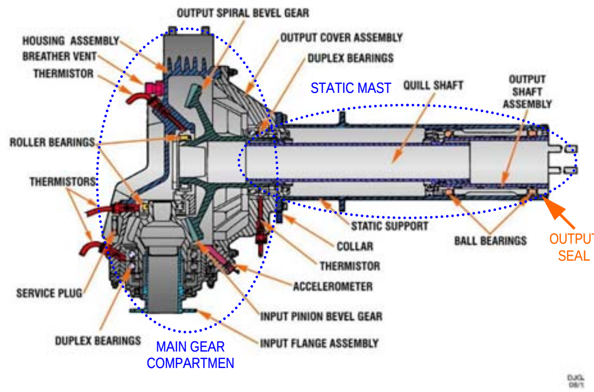

Fig. 9. AH-64 Tail Rotor Gearbox cross section.

The reasoning behind the experiment was that output seal (Fig. 9) on the static mast of the gearbox often starts leaking grease and it cannot be replaced without servicing the static mast. Also the procedure requires grounding of the helicopter and fixing the seal immediately after the leak is detected. It cannot be accomplished without removing the entire gearbox and tail swash-plate, which is a time consuming process and keeps helicopter grounded in case of a mission. So the intent was to test performance and durability of the gearbox in case it is kept as is with the output seal leaking and see if it can last 250 hours till its scheduled maintenance date or end of a mission.

The experiment was set up so the gearbox would gradually leak all of its grease during the first 150 hours of operation, resulting in accelerated wear, measured vibrations increase and deceiving temperature drop due to heat transferring medium loss and heat localization.

When the gearbox is fully serviced, the grease acts as a heat sink/mediating medium that helps to efficiently dissipate localized heat, generated at the gear-mesh and initially as the lubricant in the friction pair. Also it is the transfer medium that distributes heat to thermocouples installed inside the gearbox (thermistors, which are originally installed on the gearbox, were replaced by thermocouples at the USC test facility). That is the way a gearbox is designed and expected to operate. When the lubricant is lost, it leaves air as the mediator, leading to heat localization and thermal gradient/bias that shows up as a misleading lower temperature inside the gearbox.

In addition to automated sensor data logging, optical tooth wear observations were made manually with digital borescope between the test runs. Testing was concluded after significant teeth deterioration and tooth fracture.

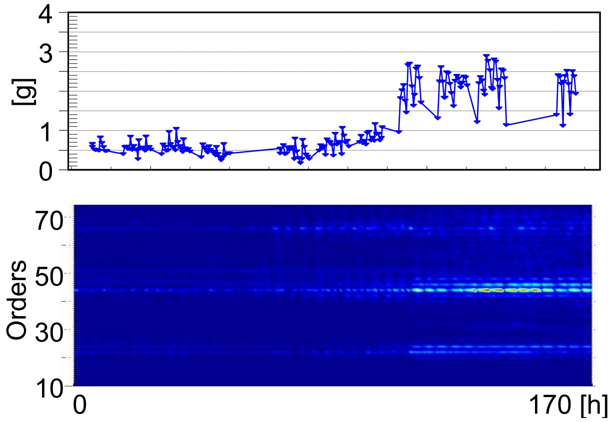

Fig. 10. TGB Sideband Index CI and vibration order trends over time.

Testing fully proved its expectations by providing valuable MSPU calibration data and supporting the importance/necessity of component testing for CBM program development. This conclusion is based on the discovery that some thresholds for CIs, that are most informative and critical in gear-mesh diagnosis, were set too low in attempt to minimize false alarm rates due to an absence of statistical failure propagation data to that extent. For example, Sideband Index's (sum of largest gear-mesh frequency sidebands divided by the number of sidebands) vibration acceleration value was set well above 4 g (Fig. 10)); Diagnostic Algorithm 1 (RMS of Signal Average) also did not show warning signs due to inadequate diagnostic threshold levels.

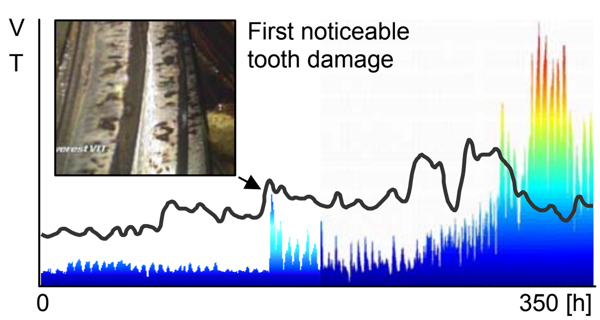

Fig. 11. Relative maximum vibration level over monitored frequency band, and temperature plots over time.

Similarly it was shown that temperature might be a better indicator of an impending problem in case of poor lubrication (Fig. 11), showing clear deviations from nominal operation temperature, while vibration levels and tooth wear remained relatively low in order to cause concern.

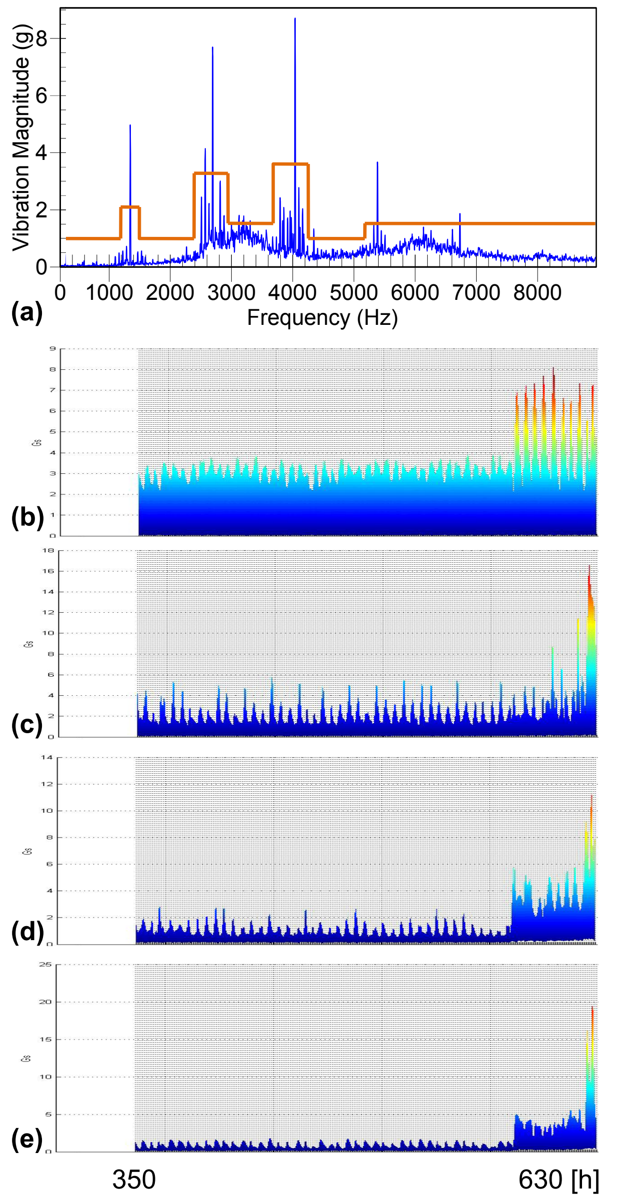

Fig. 12. Lateral vibrations spectrum over 0-9 kHz frequency band, and its threshold envelope (a); vibration magnitudes at the gear-mesh frequency (1345 Hz) (b), its second (2690 Hz) (c), third (4035 Hz) (e) and fourth (5380 Hz) (d) harmonics, measured at the gearbox duplex input bearing.

Such findings give support for MSPU modernization by additional sensing capabilities and data fusion implementation in order to enable earlier identification and diagnosis of an impending fault.

Other finding, that might lead to development of a new CIs for friction pair damage diagnosis, is that overall vibration magnitude of the gearbox (Fig. 11), and vibration magnitudes at gear-mesh frequency and its separate harmonics (fourth harmonic in particular) (Fig. 12) show clear response to the friction pair damage, with signal to noise ratio higher than in available condition indicators embedded in MSPU. This allows consideration of direct vibration magnitude monitoring as the means for new CIs, and diagnosis of severe friction pair damage in the gearboxes of the U.S. Army helicopters (Fig. 12 (a)).

Cost Benefit Analysis of CBM and VMEP for SCARNG

USC is receiving desensitized VMEP mechanical vibrations data and TAMMS-A flight and maintenance related data since 1999 for AH-64, AH-60 and CH-47 aircraft. This data is stored on USC data server, enabling USC to update the Cost Benefit Analysis (CBA) records, investigate the operating and support (O&S) analysis, safety and benefits. The deliverables make an outcome of an ongoing USC Cost Benefit Analysis of the VMEP Program.

In order to provide a timely and sufficient cost and economic analysis to support the effective allocation and management of resources for the Army programs, custom CBA model has been developed by USC CBM Center. The goal is to develop and maintain cost and economic analyses as effective and efficient tools for decision-making, while supporting management decisions by quantifying the resource impact of alternative options. In our model, as in any good cost model, the cost analysis grows in complexity and detail as the program matures and more information becomes available.

In developing the model other models such as the Galorath SEER-H and the Cost Analysis Strategy Assessment (CASA) model for O&S cost assessment were investigated.

The intuitive model utilizes flight and maintenance data from the TAMMS-A database DA 2408-12, DA 2408-13, and DCR records, in order to estimate cost savings and recovery of the initial costs of the hardware installation and future cost savings for the Apache and Blackhawk helicopters. The model includes cost variables such as: maintenance test flight hours, cost per maintenance flight hour, VMEP investment, number of VMEP helicopters, unscheduled maintenance hours, installed parts costs.

The Cost Benefits Analysis has been executed in a 3-step procedure:

<u>Define the CBA Objectives</u>: The CBA initially focused on the AH-64 platform, and the investment efforts were focused mainly at the Unit-Level and below, because the costs and benefits were most quantifiable at these levels.

<u>Develop CBA Framework</u>: The Vibration Management Enhancement Program was considered as investment opportunity. The investment was analyzed in terms of primary and secondary benefits. For each presumed benefit, a definition and a metric were developed.

<u>Cost Estimations, and Benefits Analysis</u>: The analysis initially targeted the operating and support costs. The O&S costs are a subset of life cycle costs (LCC). Intent was to address every aspect of O&S costs in search of major cost drivers. Pursuit of O&S costs reduction is particularly complex because problem areas and potential solutions involve multiple dependent variables. The O&S analysis was guided by the AMCOM document “Reduction of Operating and Support Costs for the US Army Helicopters” as of 24 February 1995. In this activity, O&S estimates were developed, benefits were characterized, and impacts were organized. This activity had three levels of depth depending on assignment requirements. The analysis focused on selected ares that had the potential to show investment cost returns. Cost savings and cost avoidances from any source were considered as returns. A project would be successful if the benefits and returns exceed the investment costs. This factor was determined using return-on-investment (ROI) metrics, i.e., the ratio of savings to investment. Savings were represented by returns that are quantified in financial terms.

As of today the U.S. Army CBM program and the joint team activities have been highlighted by:

- $33.4 million savings in parts costs.
- $38.3 million savings in parts cost and operation support.
- Increased mission capability through a reduction in maintenance test flights and unscheduled maintenance - increase in mission flight time.
- Improved safety, sense of safety, morale, and performance.
- Meeting CBM objectives.

The above benefits and results are extracted from a series of analyses, based on the SCARNG AH-64 fleet data, which is the most consistent over the years. The results are graphically presented in Fig. 13 through Fig. 15. Actual costs data has been collected for estimation of the costs and savings of each of the two project alternatives (baseline and VMEP) for each year of analysis. Maintenance costs for VMEP non-equipped fleet were assessed, based on the data from between

October of 2000 and September of 2001. They were used as a baseline in comparison to VMEP equipped fleets for the following years.

The CBA model also includes non-tangible benefits such as: mission availability, morale, safety, operational flight hours' gain, premature parts failure, mission aborts, and unscheduled maintenance occurrences. In our case, benefits take the form of tangible and non-tangible benefits. Therefore, we first analyze the savings of the VMEP alternative by comparing the tangible costs in the two cases.

Maintenance Test Flights (MTFs) are highly time demanding operations of active helicopters, which are performed after maintenance actions, in order to determine if all elements of the helicopter are performing accordingly. Results in Fig. 13 indicate that the ability of maintenance crews to use the VMEP system is improving with time, and the average number of maintenance flight hours for each aircraft at SCARNG is decreasing. This data is based on TAMMS-A DA 2408-12 records, which contain flight logs for every aircraft. Based on the data and costs of maintenance test flights, we can find the total annual cost savings on MTFs, which make a total of $4.8M over the five years of CBM program implementation.

The law of diminishing returns suggests that the VMEP program will reach an equilibrium number of MTFs after few years. Based on the logarithmic regression model applied to the MTF data, we can project the system equilibrium at the annual savings of $37.6k per aircraft.

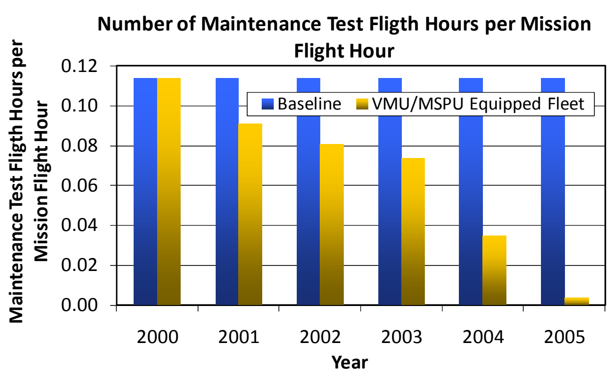

Fig. 13. Decrease in maintenance test flight hours for Apache fleet at the SCARNG, due to CBM practice.

Reduction in Unscheduled Maintenance actions is another strong indicator of mission readiness increase. It is reflected in Fig. 14 as the reduction in unscheduled maintenance hours over the data collection period, as a percentage of total maintenance actions. There is a clear reduction in unscheduled maintenance actions to less than 4% of total maintenance actions, and to less than one fourth of levels prior to CBM program, leading to significant increase in mission readiness and savings. The use of the VMEP system allows maintenance crews more opportunities to spot minor faults, that otherwise would lead to a chain of more serious failures, and provide adequate time to schedule these maintenance actions.

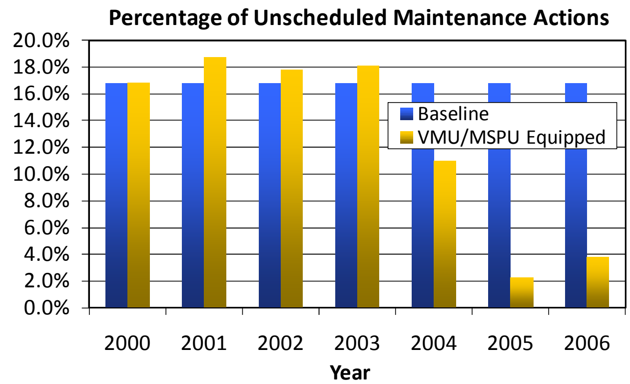

Fig. 14. Decrease in unscheduled maintenance operations for Apache fleet at the SCARNG, due to CBM practice.

Parts Costs consume the greatest part of the aircraft maintenance related budget. Data in the Fig. 15 shows that implementation of the CBM program allows to fix minor impending faults and this way prevents more serious and expensive failures, saving millions of dollars in spare parts and maintenance man hours. According to the data this accounts for $33.4M in part costs savings over the five years period. In the following years we would expect annual savings of $270.6k per aircraft from the baseline levels.

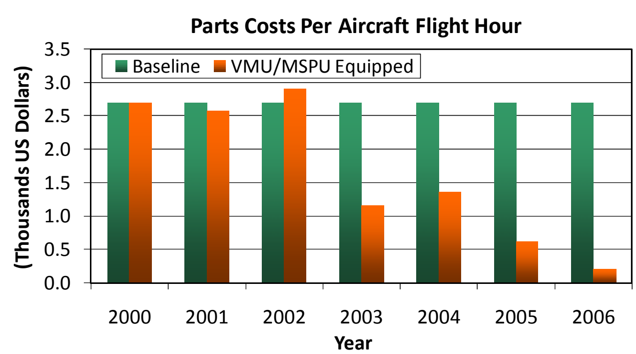

Fig. 15. Decrease in replaced mechanical components costs for Apache fleet at the SCARNG, due to CBM practice.

Non-tangible benefits analysis model is based on information and surveys from the McEntire Joint National Guard Base and is used to show the non-tangible benefits that arise from the use of VMEP.

Again, the idea is to determine, with the implementation of the VMEP program, whether or not the fleet will see an increase in aircraft availability, safety, and operational flight hours along with a decrease in premature parts failure, mission aborts, and unscheduled maintenance occurrences.

Brainstorming sessions identified two categories of benefits, - basic and mission, which are important areas to "measure" VMEP outcomes in a comprehensive cost and benefit model. Mission benefits, the "soft" benefit area, were conceived to comprise four areas: operational readiness, morale, performance, and safety. Our research team, crew chiefs, and pilots reviewed various iterations of a set of questions designed to address aspects of operational readiness, morale, performance and safety as they related to operating and maintaining Apache and Blackhawk helicopters. Numerous questions and items were suggested, and through a series of review, discussion and reaction iterations, narrowed down to four items that addressed each of the four non-tangible mission benefit areas. Anchor points for each were created using a seven-point Likert` Scale. The results were summarized as:

- Safety – 16 % improvement
- Sense of Safety – 30% improvement
- Performance – 21% improvement
- Mission – 13% improvement
- Confidence – 20% improvement
- Morale – 35% improvement
- Ease of Troubleshooting – 32% improvement

Tangible benefits resulting from the direct USC research and the joint team activities can be highlighted by the facts that USC and the United States Army have identified types of aircraft components to be tested for MSPU and CBM enhancement based on their return value within a short time for implementation of CBM. Some of the chosen components that are tested at USC and other Army test facilities, include AH-64 tail drive-train, Auxiliary Power Unit clutch (APU), and main rotor swash-plate assembly.

Testing of these components has already allowed the Army to eliminate the APU clutch vibration check and the special inspection on the main rotor swashplate. In addition, it has allowed extension of the APU mount inspection times, 16% increase in Time Between Overhaul of APU clutch; deferred replacements of the leaking tail rotor hanger bearings until 250 hour inspection cycle (moved an unscheduled 5.5 Maintenance Man-Hour (MMH) task to a scheduled task). This results in a 5.2% increase in aircraft readiness and annual savings of $9.3M.

Also the recent TGB study at the USC CBM Research Center [43, 50] is leading to a Maintenance Information Message, which will provide the authority and procedures to perform in-field maintenance on AH-64 Tail Rotor Gearboxes. It enables in-field replacement of leaking output seal on TGB static mast, and moves an unscheduled 28 MMH task to a scheduled 10 MMH task, saving $35k a part. Over 50% of tail gearboxes were removed for this reason, totaling 80 in year 2006 alone.

Including additional components into CBM, and CBA model will allow for further increases in aircraft availability and annual cost savings.

Conclusions

1. The transition of the U.S. Army rotorcraft fleet maintenance practices to CBM requires a systematic collaborative joint industry, academic, and government team effort.
2. If critical operation conditions of a component are not estimated in initial design process of the component and system, it may lead to misleading sensor and diagnostic system output.
3. Aircraft component durability testing is an essential tool in CBM program development, supplying necessary calibration data for condition monitoring and diagnostic systems, giving insights to design flaws and improvement possibilities.
4. Multi-sensor implementation and data fusion give an opportunity to enhance and accelerate impending problem diagnosis and CBM system development. Fusion of information across vibration and temperature sensors offers potentially significant improvements in robustness and accuracy in fault detection and isolation with relatively simple hardware and software modifications of MSPU and Army helicopters.
5. Based on the data collected so far, MSPU condition indicators "Sideband Index", "Diagnostic Algorithm 1", and USC custom installed thermocouples show good correlation with critical gear mesh conditions and show potential in diagnosis of inadequately lubricated gears through adjustment of MSPU threshold levels for the given CIs.
6. Alternative time-frequency vibration signal analysis technique is proposed in effort to reveal short duration transients in vibration signal, enabling new diagnosis techniques.
7. Monitoring of overall vibration magnitude, and vibration magnitude of separate gear-mesh frequency harmonics, show clear response to gear friction pair damage, with signal to noise ratio higher than in available condition indicators embedded in MSPU. This allows consideration of direct vibration magnitude monitoring as the means for diagnosis of severe friction pair damage in the gearboxes of the U.S. Army helicopters.

8. The U.S. Army CBM program is constantly evolving and gaining millions of U.S. dollars in tangible benefits through its implementation. Some of the cost reduction factors include maintenance test flight hours, unscheduled maintenance and maintenance man-hours, replacement parts costs, and time between overhauls extension.

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