Conditioned-Based Maintenance at USC - Part I: Integration of Maintenance Management Systems and Health Monitoring Systems through Historical Data Investigation

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Abstract

Maintenance Management Systems (MMS) are the core of traditional maintenance record-keeping practices and often facilitate the usage of textual descriptions of faults and actions performed on a vehicle. Recently developed Health and Usage Monitoring Systems (HUMS) are capable of directly monitoring vehicle component parameters; however, attempts to link observed MMS events to HUMS sensor measurements have been fairly limited in their approach and scalability. A new theoretical process for integrating the two disparate data types is proposed. This procedure implements a relational database which tags events from both data sets with location, severity, and rarity parameters. Metadata is extracted from the MMS textual descriptions using a natural language processor (NLP), and HUMS records are processed using simpler statistical analyses. The results and benefits of a full MMS and HUMS integration are predicted and evaluated.

Presented at the American Helicopter Society Specialists' Meeting on Condition Based Maintenance, Huntsville, AL, February 12-13, 2008.

Background

History

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 through improved logistics technology, better data management, and prompt decision making. This modern aviation maintenance transformation produces higher operational readiness using fewer, more capable resources, provides commanders with relevant maintenance-based readiness information at every level, and shifts the paradigm from preventative and reactive practices to proactive analytical maintenance processes, now commonly referred to as Conditioned-Based Maintenance (CBM). Per the Office of the Secretary of Defense (OSD), CBM is defined as "set of maintenance processes and capabilities derived, in large part, from the real-time assessment of weapon system condition obtained from embedded sensors and/or external tests and measures using portable equipment."

The Commander of AMCOM supports the unprecedented transformation from the Industrial Age to the Information Age using existing and emerging technologies that analyze near real-time aviation systems data to provide prediction and response maintenance capability. Several technological advances and initiatives by Army leaders at various levels have made a move toward CBM a reality for Army Aviation. The benefits of these technologies have already been proven for helicopter on combat missions, training, and maintenance flight conditions. Considering the long history of participation with health monitoring systems and data collection, the University of South Carolina is in a position to provide leadership, vision, and a path forward to maximize the effectiveness of these benefits across the broad spectrum of Army Aviation.

The transition to CBM requires a collaborative effort on a massive scale and is contingent on identifying and incorporating enhanced and emerging technologies into existing and future aviation systems. This will require new tools, test equipment, and embedded on-board diagnosis systems. Even more critical, the transition to CBM involves the construction of data-centric, platform-operating capabilities built around carefully developed robust algorithms. This will allow soldiers in the field, support analysts, and engineers the ability to simultaneously, and in real-time, translate aircraft conditional data and proactively respond to maintenance needs based on the actual aircraft condition.

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

Program Objectives

The research program at USC seeks to deliver results which directly contribute to CBM efforts and objectives as follows:

Link and integrate maintenance management data with onboard sensor data with test metrics 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.

Program Processes

These program goals will be accomplished through the following processes:

Qualitatively operationalize the CBM objectives through ongoing activities of surveying engineers, pilots, maintainers and crew chiefs on the non-tangible and mission benefits of the VMEP system such as safety, morale, mission capabilities, confidence on the system, and system liability.

Quantitatively operationalize the CBM objectives through our ongoing quantitative management and vibrations data that are being collected, analyzed and processed. The most obvious outcome of these activities is the cost benefits and mission benefits models.

Combine the qualitative and quantitative measures from the processes listed above to determine if the current implementation is meeting the planned CBM objectives. The combined measures will also be presented and evaluated mathematically, parametrically, and mechanistically as a diagnosis model or physical model of subsystems or components.

Create preliminary, predictive mathematical models of component, subsystem, and aircraft performance that serve to guide future CBM activities on individual aircraft. Based on available literatures on prognosis studies, this will be the first scientific step in developing accurate prognosis models of components, subsystems, and entire systems.

Interrogate and validate the historical field data through the use of component test stands. These test stands will be used to refine and improve our prognosis models by examining the process of component failures in order to correlate their observed conditions with the determined parameters.

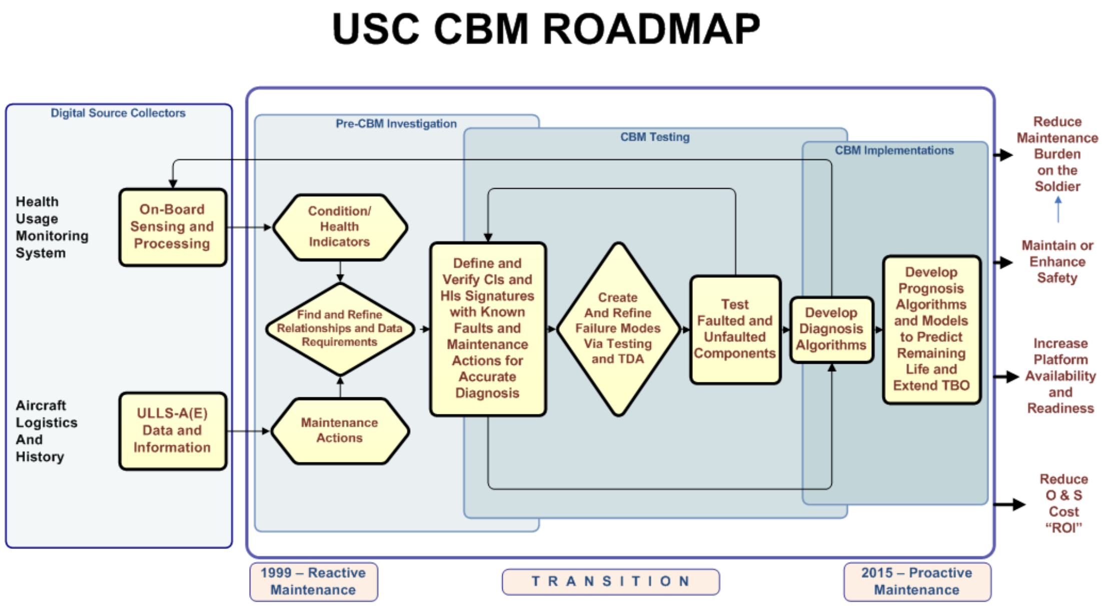


Figure 1--The procedural roadmap currently being implemented by the USC CBM research program

CBM Roadmap

As the growth and awareness of CBM develop, many ideas and technologies have arisen in efforts to improve CBM. Unfortunately without a plan or path, many of these ideas will never fully mature. There is need for a standardized methodology and roadmap for CBM to reach its full potential. In conjunction 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. This can be done in a way that will address a broad array of strategic and tactical issues so as to accomplish the CBM specific objectives. The activities of USC are being performed as a joint industry, academic, and government team.

The roadmap 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 will 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.

Introduction

Overview of CBM data collection

Maintenance Management Systems (MMS) use context-specific textual data to record information such as vehicle usage, component failures, servicing or repairs, and inventory control. Although for a given platform, there may exist several different implementations, the underlying structure is typically heavily regulated, allowing for a large base of consistently structured data. These systems are the core of traditional scheduled maintenance practices and rely on bulk observations from historical data to make modifications to regulated maintenance actions.

Health and Usage Monitoring Systems (HUMS) collect component-specific quantitative data to assist maintenance crews in the identification of failures which are imminent or have already occurred. Typically, HUMS implement a large number of electronic sensors in combination with a highly-specialized data acquisition system. Currently, there exists no standardization in the way data is collected across platforms or vendors, primarily because the technology has not been in use long enough to have fully matured. There is still much investigation and debate on what information is required for vehicle health diagnostics and how that information is used to meet CBM objectives.

Although there have been many recent efforts to collect and maintain large repositories of MMS and HUMS data, there have been relatively few studies to identify the ways these to datasets could be related. It is only logical to assume that written histories of aircraft maintenance records are linked to the measurements of onboard sensors, and it is in the interest of CBM research to develop a means by which these data sets can be consistently and reliably merged.

Description of analysis techniques to date

The most obvious obstacle in the integration of MMS and HUMS data is the disparate nature of the data types involved, and attempts to remedy this problem have been met with inconsistent implementation and limited scalability. The first such technique is to assign the mostly qualitative MMS data with quantitative indexing, allowing for HUMS data to be separated into discreet maintenance states. It is the responsibility of the maintainer to correctly insert the appropriate fault or work code into the maintenance logs, which to date has not been done with sufficient accuracy or consistency to be deemed reliable. A more recent approach is to simply embed HUMS files into MMS records or vice versa. This also has its shortcomings, namely that, the embedded files can only be opened in their original client application, providing limited opportunities for data mining or other investigations. Other attempts at linking these data types include real-time analysts and historical case study matching. Typically in the interest of HUMS manufacturers, this is done more for system validation and requires large amounts of manual investigation of the data.

Definition of Integration Process

A full integration of MMS and HUMS datasets requires a more advanced form of interfacing which more appropriately models the real-world relationships between observed maintenance and sensor data. Case studies to date have been generated by individuals who identify related events based upon their knowledge of the vehicular systems involved. For example, an abrupt change in a vibration sensor on a gearbox is assumed to be related to a recorded replacement of a nearby part. Taking an analytical approach to this decision making process is rather complex, since the determination of causality and dependence is often performed through a highly subjective process.

The overall goal of an enhanced interfacing should seek to automate the complex process of linking events from different datasets. Developing this system begins with a four-step investigation: historical data collection, importation into a single database, data abstraction, and data analysis. Using a vast wealth of historical information in combination with knowledge of system components, software agents are under development which attempt to bridge the gap between the data types by allowing for the proximity, severity, and rarity of events across datasets to be evaluated.

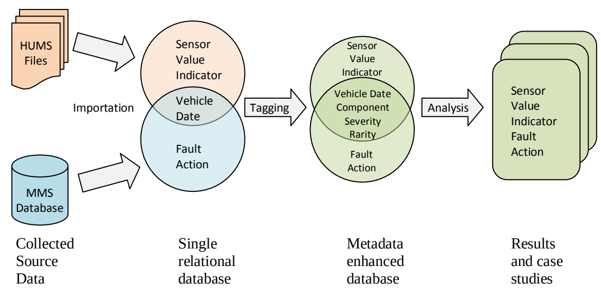


Figure 2—Depiction of the four-stage integration process

Through an integrated HUMS and MMS system, identifying instances where HUMS data is reflected by real-world events can be performed regularly. This allows for an objective determination of vehicle parts prone to failure and an evaluation of HUMS effectiveness in monitoring those regions. Based upon these evaluations feedback can be given to MMS and HUMS developers to refine the means by which the data is collected, and a strategy for the next generation of fully-integrated CBM systems can be devised.

Process Overview

Data source collection

Since the history of Maintenance Management Systems predates the information age, it has traditionally been delegated to the unit-level for implementation. Collecting data for investigation studies has required the permission of various units, thus limiting the scale of MMS research to date. Further compounding this difficulty is that MMS data contains personnel identification information and can be used to depict unit and fleet readiness levels. As a result, efforts to centralize MMS data have been slow to materialize, and for security reasons MMS warehouses are often not open to independent research groups. Therefore, data collection for early integration studies remains a small sample of the future capabilities of a centralized CBM system.

In contrast, HUMS developers have relied on automated data centralization to evaluate and validate their systems since their inception. Since HUMS data is inherently scientific and built around a mobile digital platform, developers have saved nearly all the data collected from their systems as part of an active research study. This practice will likely continue for some time until HUMS reaches full maturity. As a result, obtaining data for an integration study requires only the participation of a particular developer, allowing for vehicle fleet-wide observations to be made.

Relational data importation

Modern MMS information is stored in very large relational, or tabular, databases. This format is appropriate for an integration investigation since there are a large number of software tools available to query and investigate the tables. For the historical analysis, only certain fields are required, thus allowing for the previously mentioned sensitive data to be removed or filtered. The data subset still contains a full history of component faults and related actions, providing a comprehensive maintenance history profile while alleviating security concerns.

Importing HUMS data into a relational database is somewhat more challenging, since each type of sensor generates different data classes, sampling rates, and number of compiled indicators. Furthermore, each manufacturer stores the collected information in unique proprietary formats, requiring platform-specific importation software to be written. This software allows the HUMS data to be exported from the original interface so that it can be expanded and generalized. Once this is accomplished, the benefits are tremendous: multiple manufacturer and cross-platform data can be viewed as through generic data classes.

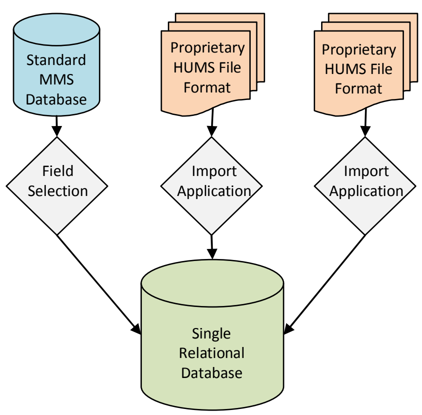


Figure 3—Graphical depiction of the importation process

Preprocessing and data abstraction

Although both the MMS and the HUMS data now co-exist within a single database where it can be queried and explored, automating the discovery of linked events requires additional processing. In their original form, the datasets only have two fields in common: vehicle identification and date. Relating a given maintenance fault or action, which is textual, to sensor data, which is some arbitrary data class type, can only be accomplished through the compilation of overlapping metadata. The fields which are generated characterize the location and significance of events, creating a quantified set of parameters by which the disparate data can be compared.

Since MMS is textual, it is processed using natural language processing (NLP). Fields are analyzed separately to create a set of interpreter agents which extract key information from the fault or action description. The NLP agent outputs which component the record is in reference to and a list of other descriptor keywords. Categorical statistical analyses are performed to characterize the rarity of a given record, and a preprogrammed scoring chart assigns each record a severity based on the available keywords.

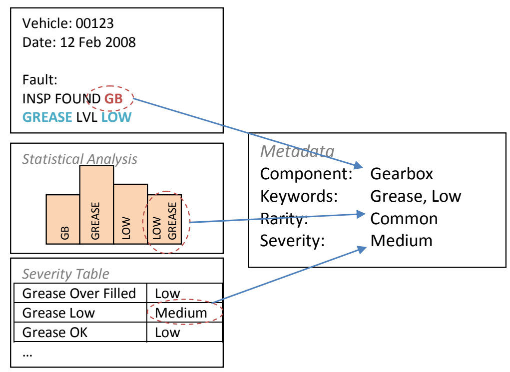


Figure 4—Representation of metadata extraction for maintenance records

Metadata for HUMS records is generated differently depending on the data class involved. One-dimensional and dimensionless quantities can be assigned rarity parameters through statistical distribution analysis, and higher dimensional data requires using neural networks to identify anomalies. Identifying which component a particular sensor or indicator is monitoring is predefined by the HUMS manufacturer.

Analysis and Correlation

The metadata is then extracted from all the available records into a single events table containing vehicle identification, component name, event time, a rarity parameter, and a severity parameter. The simplest method of determination of event-relatedness is accomplished through a proximity study of the metadata. Each component is assigned a spatial coordinate relative to a predetermined vehicle coordinate system, and in conjunction with time parameter, the space-time distance between two events can be computed. The other computed parameters of rarity and severity can also be used for ranking the results or generating a composite relatedness score.

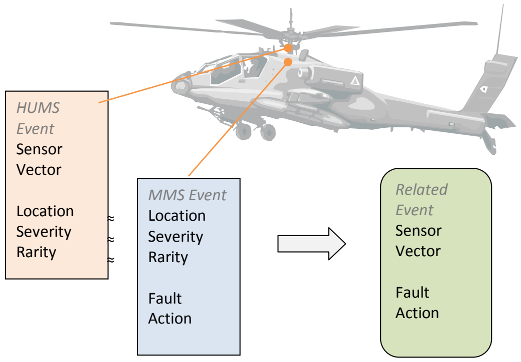


Figure 5—Event matching based upon multiple criteria

The results of this analysis could then be categorized by component and identify regions of the vehicle where HUMS devices have a high success rate in identifying component faults or reflecting maintenance actions. Known problematic regions that do not have a high count of related MMS and HUMS events indicate that revision to the sensing strategy or changes in indicator definition are needed. For these components, further analysis can be performed on the raw data to discover new algorithms for condition indicator computation.

Preprocessing Procedures

Natural Language Processing

Natural language processing (NLP) is a subfield of both artificial intelligence as well as linguistics with a very large variety of applications. It covers a many of topics ranging from machine translation to speech recognition and often focuses on a computer's ability to interpret and respond to natural human languages.

One of the most successful categories in NLP recently has been auto-summarization and information extraction. Due to a high demand for tools such as internet search engines, there remains a large amount of research into the development of increasingly accurate NLP applications.

Due to the specific context of maintenance management data, in which descriptions of vehicle faults and performed actions are stored, the lexical domain is highly restricted. Furthermore, the conciseness of individual records often leads to reduced grammatical complexity and widespread use of acronyms. Therefore, the language under study is not natural English; rather, it is a degenerate subset which is relevant to only a single vehicle type. When broken down into sub-corpora of individual vehicles and fields, the task of developing an information extraction agent becomes highly specialized and simpler to perform.

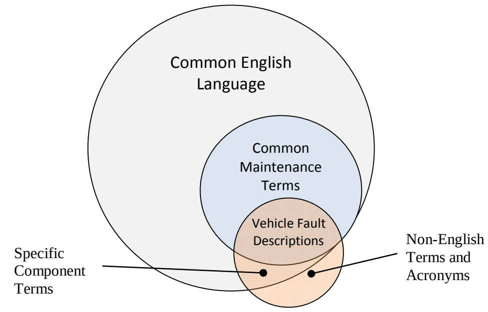


Figure 6—Relationship between common English language and maintenance fault descriptions

Despite this high degree of specialization in the NLP applications, the development process still has a high potential for being scalable. This is achieved by creating a single generic intelligence agent which is then replicated for individual platforms. The agent is then seeded with a human-guided training dataset and dictionary file which gives the agent a robust background to begin processing. Sentence structures and vocabularies found in the records which have poor retention rates are given as feedback to the human trainer, who can then adjust knowledge base of the agent until it performs at an acceptable level. This system will also be capable of withstanding top-level modifications to MMS regulations as well as minor linguistic shifts in the maintenance records over time.

HUMS Data Profiling

Methods for characterizing HUMS data are typically developed by the individual manufacturers, and are generally well-known mathematical properties of the component type being monitored. Determining rarity is often accomplished through simple single variable statistical analysis, while severity is typically derived from developers recommended threshold values. More complex domain types require more advanced, though typically well-understood analyses such as neural networks which can isolate anomalous points from multidimensional data.

It is predicted that through the integration process, more advanced metrics and indicators can be discovered which implement previously unexplored relationships in the data, such as multi-parameter trending. Ultimately, HUMS variables have a multitude of methods for event characterization, allowing for a simpler process of metadata tagging.

Conclusions and Future Work

Another benefit from this process is insight into the future establishment of HUMS data format standards. Early integration attempts will identify data structures that are most conducive and useful for long-term storage and searching. With the coordination of HUMS developers, a general set of guidelines for file formats can be established which will enhance the potential for research by the scientific community, greatly increasing the usefulness of HUMS platforms.

Following the implementation of an integrated system, the usefulness of vehicular HUMS devices will expand from mere guidance tools to automated diagnostics systems. These integrated systems will constantly compare sensor readings to the wealth of historical records and forecast likely maintenance events based upon historical precedence. This will allow for more efficient logistics and component performance evaluation. Furthermore, these systems will identify unexplained or common modes of failure directing the efforts of scientific component testing, the results of which will drive design modifications making the vehicles increasingly more reliable.

The final product will manifest itself as an automated maintenance exploration interface. Users will be able to quickly identify possible diagnoses of faults and quickly retrieve historical maintenance actions that were effective in resolving the problem. Such a system would be easily scalable across several HUMS platforms, several vehicle types, and several locations, allowing for maintainers to have information on a variety of practices being performed across the field.

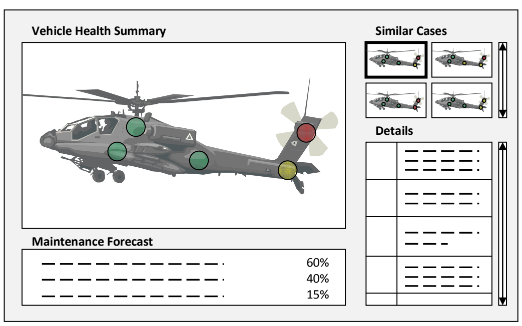


Figure 7—A possible future interface for fully integrated CBM systems

Appendix A—Common Terms

Condition Based Maintenance:

Condition-Based Maintenance (CBM) is the nomenclature assigned to a maintenance process that is based upon the electronically determined condition of a component, sub-system or system.

Condition:

Condition is based upon electronic measurements that can be related to condition without the need to disassembly and inspect through conventional means.

General CBM Objectives:

Reduce unscheduled maintenance and maintenance workload.

Decrease maintenance and logistics footprints.

Perform and integrate advanced engineering, maintenance, and information technologies.

Maintenance only upon evidence of need.

Improve diagnosis and prognosis capabilities.

Use real-time assessments of material condition obtained from embedded sensors and/or external tests and measurements using portable equipment.

Increase operational availability.

Condition Indicators (CI):

Condition indicator algorithms come in many varieties and capabilities. These condition indicators are in turn used to develop Health Indicators (HI).

Health Indicator (HI):

The Health Indicator (HI) is a non-dimensional metric that is constructed (calculated) by the manipulation of related condition indicators (the output of condition algorithms). The time history of a perfect HI would identically track (match) the time history of the CI.

Diagnosis:

Faults in bearings, gears and shafts can be detected. These detections are reported as magnitudes. Faulted shafts are the easiest to detect, and bearing faults are the most difficult.

Prognosis:

When it is possible to detect an increase in the magnitude of a detection algorithm output as a function of a tangible usage metric, it is possible to predict the useful service life remaining. This prediction is known as prognosis. A tangible usage metric is that usage metric that relates most directly to the loads and cycles causing the fault (or incipient fault) to propagate. In the case of a helicopter power train, there are many potential metrics:

Flight time

Operating time (running time)

Power spectrum

Time integral of applied power (throughput power)

Time integral of applied power normalized for the system S-N Characteristic (Normalized Throughput Power.)

Usage of Mechanical Systems:

Usage is defined as time integral of the power applied to the mechanical system. This usage is also known as generic system usage.

Flight Profile:

A flight profile is a series of ground and flight phases (or events). The simulation program is limited to the simulation of mechanical power train health during flight operations and ground operations when the rotor is turning. The analyst (user) will be able to create flight profiles or use an existing flight profiles. For the purposes of this simulation, the program needs to know the sequence of the various phases and the time spent in each phase.

Relational Database

Relational databases store information in tables and allow for efficient searching and retrieval of records in very large data sets.

Natural Language Processing (NLP)

NLP in this context is the extraction of information that is stored in a natural human language such as English

References

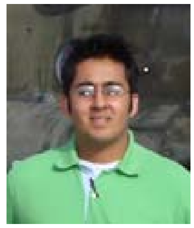
1. Adler, Matthew, Eric Posner, (1999) "Rethinking Cost-Benefit Analysis," University of Chicago Law School, "John M. Olin Law & Economics Working Paper No. 72, May 27, 1999.
2. Anon., "Reduction of Operating and Support Costs for the US Army Helicopters", AMCOM, 24 February 1995.
3. Army Regulation 11-18. (1995) "The Cost and Economic Analysis Program." January 1995.
4. Crews, Samuel T.: "Helicopter Vibration and its Effect on Operating Costs and Maintenance Requirements," AMCOM, Huntsville, AL, 1991.
5. Crews, Samuel T.: "Helicopter Vibrations for the Pilot and Maintenance Crew and use of the Army Vibration Analyzer (AVA)", 1990.
6. Dasgupta, Ajit K, D.W. Pearce. (1972) "Cost-Benefit Analysis: Theory and Practice." London, MacMillan, 1972, pp 12-13.
7. DBD (2000) "FY 2000 Defense Budget Documents," Office of the Assistant Secretary of the Army for Financial Management and Comptroller, http://www.fas.org/man/docs/fy01/topics.htm
8. Executive Order Number 12886, 3 C.F.R. 638, 639 (1993).
9. Giurgiutiu, V.; Grant, L.; Grabill, P.; Wroblewski, D. (2000) "Helicopter Health Monitoring and Failure Prevention through Vibration Management Enhancement Program," Proceedings of the 54th Meeting of the Society for Machinery Failure Prevention Technology, May 1-4, 2004, Virginia Beach, VA, pp. 593-602.
10. Grabill, P., Grant, L., 1996, "Automated Vibration Management Program for the UH-60 Blackhawk", 52nd Annual Forum of the American Helicopter Society, Washington DC, June 4-6, 1996.
11. Hein, G. F. (1976 "Cost Benefit Analysis of Space Technology," NASA, 1976.
12. Milford, M. Alex: "HUMS Cost/Benefit Analysis Model: Benefit Element Report", Booz-Allen & Hamilton, Inc., DAL Conference, September 30, 1998, Seattle, WA.
13. Milford, Sandy; McNabb, Stephen; Sanders, Tom; Phillips. Keith; "DAL-P Cost/Benefit Analysis", Booz-Allen & Hamilton, Inc., DAL Conference, September 30, 1998, Seattle, WA.
14. Nas, Tevfik (1996) "Cost Benefit Analysis: Theory and Practice," Sage Publications, 1996.
15. Noah, J. W. (1977) "Cost Benefit Analysis of the National Aviation System," FAA, 1977.
16. Parker, M. (1997) "Mission Possible. Improving design and reducing costs at Boeing Helicopter." IIE Solutions, Vol. 29, Dec. 1997, pp. 20-24.
17. Pearce, D. W.; Nash, C. A. (1981) "The social appraisal of projects: a test on cost-benefit analysis." New York, John Wiley & Sons, 1981, pp. 3-4.
18. RITA (1999) "RITA-HUMS Cost Benefits Analysis Model (CBAM) Software," Rotor Industry Technology Association, Inc., 1999.
19. Unfunded Mandates Reform Act (P.L. 104-4), 1995.
20. Unfunded Mandates - DOD – CBM Memorandum Dated: 20 November 03, Develop CBM as One of Six Future Logistics Enterprise Initiatives
21. Unfunded Mandates - DA, G4 – Army CBM Plus Plan Dated: 14 April 04, Shifts From Preventive and Reactive Maintenance to Proactive CBM
22. Unfunded Mandates - CG, AMCOM Initiative Proof of Principle for Feasibility of CBM
23. Unfunded Mandates - DA, G4 – Army Aviation White Paper CBM Plus Plan Dated: 15 December 04, Stated That Task Force Aviation One of Sixteen Army Focus Areas
24. Unfunded Mandates - Task Force Goal Achieve Full CBM Within Aviation By FY 2015
25. Unfunded Mandates CG, AMCOM Sets Initial Operating Capability Objectives FY 2011
26. Unfunded Mandates - DA, G4 – Army CBM Plus Memorandum Sets Plans for Implementation Dtd: 08-17-05

Appendix B—Biographies

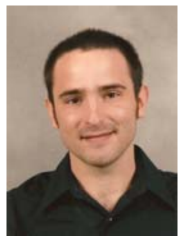
Abdel-Moez E. Bayoumi, Ph.D., has over 25 years teaching and research experience. Dr. Bayoumi is Director of the Condition-Based Maintenance Center, Director of the Biomedical Engineering and Professor of Mechanical Engineering at the University of South Carolina College of Engineering and Computing. Before joining USC, he was a Professor of Mechanical and Aerospace Engineering at North Carolina State University, a project manager at Hewlett-Packard Company, and Professor of Mechanical and Materials Engineering at Washington State University. He has been actively involved in developing strong programs in mechanical systems. His research activities have been focused in mechanical behavior of materials and design, diagnosis and prognosis of mechanical systems, and design for manufacturability. He has published over 100 papers and supervised fourteen doctoral and thirty-five masters' students.

General Lester D. Eisner is currently serving as the Deputy Adjutant General, South Carolina Army National Guard. He was commissioned into the U.S. Army in 1976. BG Eisner has held key various staff and command positions including battalion and brigade command. He has logged over 5000 hours in various U.S. Army fixed and rotary winged aircraft, including the UH-60 and AH-64. He is a graduate of the U.S. Army War College. BG Eisner has provided key leadership for many years in the development of embedded diagnostics technology for the U.S. Army helicopter fleet. He served as the Director of the Vibration Management Enhancement Program.

Chief Warrant Officer Five Lemuell Grant graduated from Georgia State University with a BS in Criminal Justice. He served over 40 years as an Army Aviator, Instructor Pilot and Maintenance Test Flight Examiner. During his career, he was twice awarded The Distinguished Flying Cross, fifty-six Air Medals and the Broken Wing Award. He was instrumental in the development of the Army Vibration Analyzer (AVA) and the Vibration Management Enhancement Program (VMEP). He continues to work in the field of Conditioned Based Maintenance.



Ronak Shah received his B.S. degree in Economics from the Moore School of Business at USC in May 2007 specializing in Applied Microeconomics with a minor in Computer Science with a focus on Database design and development. Throughout his college career, he has been involved in a number of open source projects through the Open Source Developers Network, and has developed a programming background and skills in web applications development and content management. Ronak is currently working on a M.A. in Economics at USC while working with the Condition-Based Maintenance center in conjunction with the US Army on Cost-Benefit Analysis modeling for CBM objectives.



Nicholas Goodman received his B.S. degree in Mechanical Engineering in May 2006 with a minor in Mathematics and Computer Science, specializing in Artificial Intelligence. Following a six month language study trip to East Asia, he began working towards a M.S. in Mechanical Engineering, with a specialization in Mathematics. Nicholas is also a seasoned programmer who has significant experience in working with control systems and software development. He is currently investigating the development of neural network algorithms for the analysis of rotorcraft vibrations and maintenance data in support of CBM objectives for the U.S. Army.

Dr. John Keller received his B.S. (1995) in Aerospace Engineering from Penn State University. He went on to receive his M.S. (1997) and Ph.D. (2001) in Aerospace Engineering from Penn State University, with a Fellowship from the Rotorcraft Center of Excellence. Dr. Keller has been an Aerospace Engineer with the Aeromechanics Division of the Aviation Engineering Directorate since 2001.