

Condition-Based Maintenance at the University of South Carolina: A Smart Predictive System

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ABSTRACT

Condition-based maintenance (CBM) is a valuable tool to any industry looking to improve productivity, product quality and overall effectiveness of critical systems. Based on the University of South Carolina's (USC) experience and research partnerships, USC's vision of a smart predictive system involves a comprehensive integrated methodology that involves a two prong approach: i) CBM analysis involving gathering experimental data from mechanical systems on test stands; ii) theoretical analysis involving modeling and simulation. A theoretical framework based on component, subsystem, and integrated system models is presented to understand the physics of the failure modes. The two approaches provide complementary information that can be used to enhance CBM. The correlation of these two data fusion approaches will allow the implementation of predictive tools to capture the condition of a component, subsystem and system to maximize useful life and minimize cost and risk. In addition, the predictive tools can be used to inform the next generation of system design.

INTRODUCTION

Condition-based maintenance (CBM) is a valuable instrument in improving productivity, product quality and overall effectiveness of critical systems for any industry. Since 1998 the University of South Carolina (USC) and the South Carolina Army National Guard have participated in a number of important projects that were directed at reducing the Army aviation costs and increasing operational readiness (Ref. 1-9). This joint effort succeeded in higher operational readiness using fewer, more capable resources, provided commanders with relevant maintenance-based readiness information at every level, demonstrated millions of dollars in operational costs savings, and shifted the paradigm from preventative and reactive practices to proactive analytical maintenance processes, now commonly known as CBM.

The transition to CBM requires a set of maintenance processes and capabilities derived primarily from real-time

assessment of component, subsystem or system condition obtained from embedded sensors and external test and measurements. Even more critical, the transition to CBM involves the construction of data-centric, platform-operating capabilities built around robust algorithms. This will give soldiers in the field, support analysts, and engineers the ability to simultaneously, and in real-time, translate aircraft sensor data and proactively respond to maintenance needs based on the actual aircraft condition.

USC 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 CBM. The research program at USC seeks to deliver tangible results which directly contribute to CBM efforts and objectives such as: link and integrate maintenance management data with on-board sensor data and 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, subsystems and systems; explore the development of models for early detection of incipient faults; develop models to

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predict remaining life of components, subsystems and systems.

USC has continued to refine its CBM roadmap and vision and has arrived at what is now referred to as a *smart predictive system*. This vision incorporates the integration of mechanical systems with that of simulation suites to produce a set of predictive tools that will enable the pro-active planning of future maintenance schedules and actions needed to maximize component life while minimizing risk and cost. It will also inform the design of future components by eliminating the root causes found in current systems. This integration of mechanical systems and simulation suites will transform CBM into a smart predictive system.

BACKGROUND

Condition-based maintenance is an information-driven process used to better maintain systems. CBM uses data from the actual operating condition of system components to determine maintenance needs. This is accomplished by optimizing system operation by maximizing the interval between repairs and minimizing the frequency and costs of unscheduled repairs and downtime. This allows the transformation from reactive maintenance procedures to proactive ones. CBM also advances the design of new and/or existing components and subsystems.

Two typical maintenance strategies are run-to-failure management and preventive maintenance practices. Run-to-failure management entails waiting to perform maintenance actions after the component has failed. An example would be a stereotypical teenager with their first car who chooses to ignore maintenance needs until something breaks down that makes the car undriveable. While possibly saving money in the short-term, it always turns out to be more expensive in the long-term with higher repair costs and longer downtimes. Preventive maintenance is a time-based or a usage-based scheduled maintenance. Engine oil is a good example of both time-based and usage-based since recommendations for scheduled maintenance is based on either the time since the last oil change (time-based) or mileage (usage-based); whichever event occurs first. Preventive maintenance can be more costly if the scheduled maintenance takes place before it is actually needed resulting in additional unnecessary maintenance actions and costs.

RATIONALE FOR A CBM SYSTEM (PRODUCT)

CBM is typically viewed only as a maintenance management tool used to prevent unscheduled downtime and catastrophic failures. However, it can also be utilized as a system optimization tool. CBM can be used to significantly improve maintenance procedures and practices for all critical systems. Moreover, it can act as a reliability improvement

tool to measure deviations from nominal operating parameters allowing personnel to plan and schedule minor modifications to prevent further degradation of the component or system thus eliminating the need for major repairs and downtime in the future. Used correctly, CBM can eliminate unnecessary downtime, both scheduled and unscheduled; eliminate unnecessary corrective and preventive maintenance actions; extend the useful life of critical systems; and reduce the total life-cycle costs of these systems (Ref. 10).

IMPLEMENTING CONDITION-BASED MAINTENANCE METHODOLOGY

CBM is dependent on the collection of sensor data, and the processing, analysis and correlation of that data to maintenance actions. The initial investigation phase involves gathering historical data from maintenance records and Health Usage Monitoring System (HUMS) units to correlate the two disparate data sources. Maintenance records contain qualitative data such as maintainers' observations of components, diagnosis of component health, any necessary corrective actions taken and (sometimes) the degree of success of these maintenance actions. This information is unique in nature and is not measureable by any sensor. HUMS contain quantitative data such as condition/health indicator values calculated from sensor readings taken during flight. Combining qualitative and quantitative data together into an analytical form for data mining is a non-trivial process. Manual processing would be time-consuming and cost-prohibitive for any large data source and be susceptible to transcription errors. Tools such as natural language processing are needed to process and transform maintenance records into a data format that can easily be processed by data mining algorithms (Ref. 11). This will enable the development of relationships between the condition/health indicators and maintenance actions to help identify failure modes, symptoms of known faults and root causes (Figure 1 - background investigation stage).

Smart Predictive System

USC's vision of integrating mechanical systems with that of simulation suites leads to the creation of a comprehensive integrated methodology that utilizes a smart suite of sensing, control and data fusion for the next generation of A Smart Predictive System or "CBM+" (Figure 2). It involves a two prong approach including i) CBM analysis involving gathering experimental data from mechanical systems on test stands; ii) theoretical analysis involving modeling and simulation. The following sections discuss the two approaches in more detail.

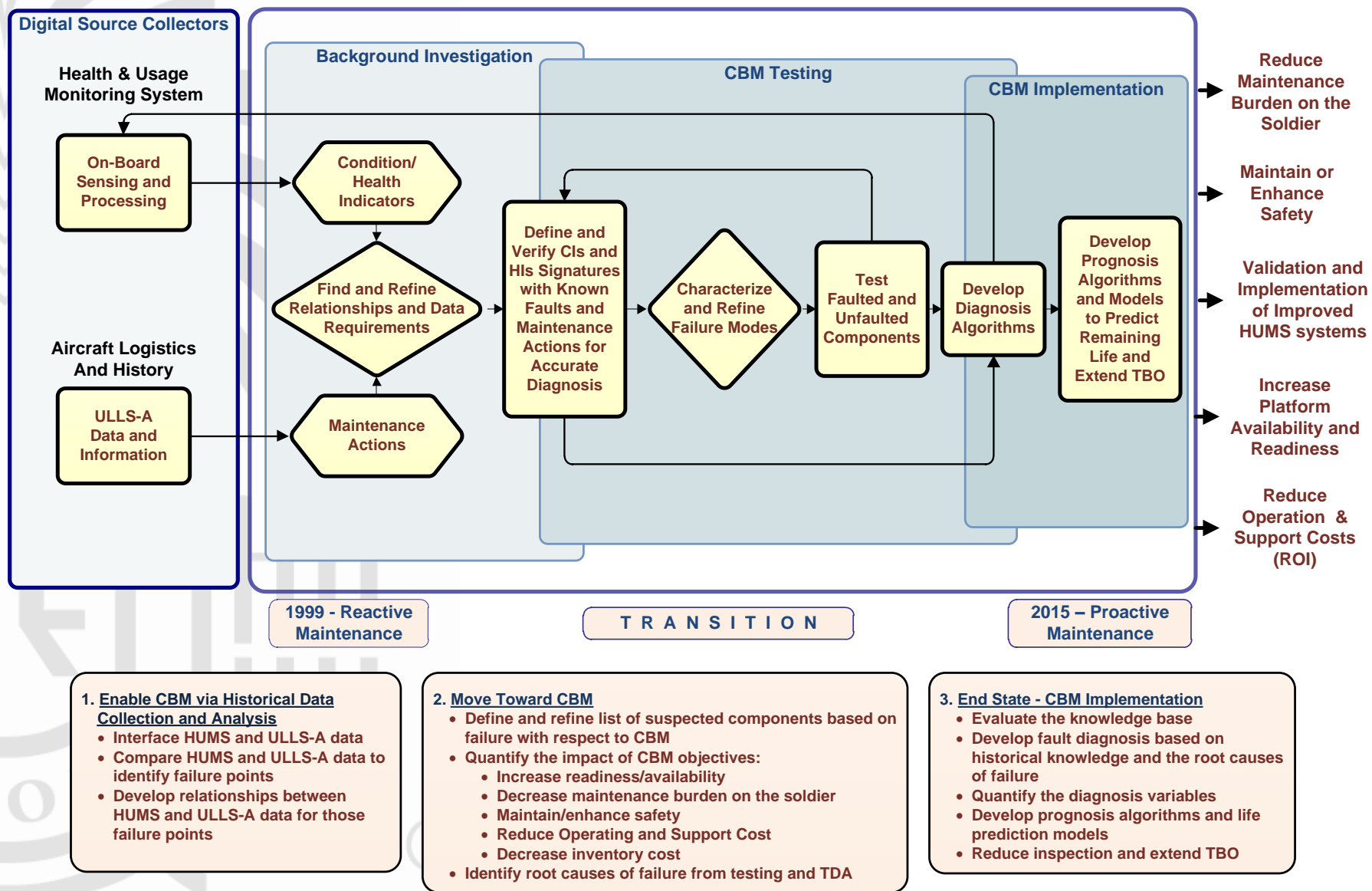


Figure 1. Roadmap for Condition-Based Maintenance at the University of South Carolina

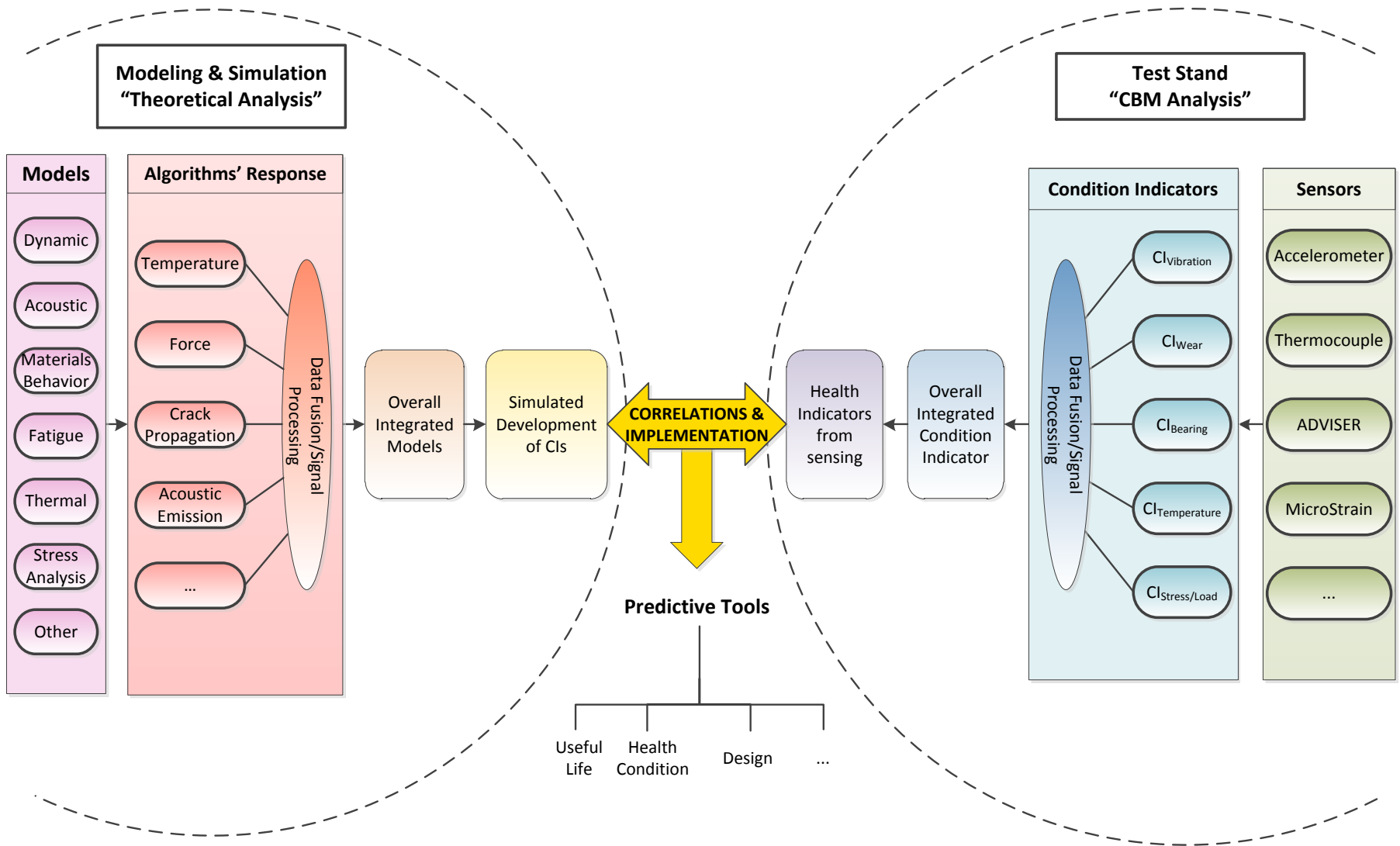


Figure 2. USC's vision of integrating mechanical systems with that of simulation suites

CBM Analysis

The testing phase is an iterative process that involves using the failure modes identified from the initial investigation phase. The failure modes are used to create new or verify existing condition/health indicator signatures. Testing is used, in turn, to characterize or refine these CIs. The testing of faulted versus unfaulted components allows the definition of boundaries separating nominal operating condition with abnormal conditions (Figure 1 - CBM testing stage). Moreover, fault testing allows validation and refinement of existing CIs. More specifically, seeded fault testing allows the examination of possible fault progression and severity in a controlled reproducible environment. Test data from fault testing and failures, along with the qualitative data gained from inspections or tear down analysis is used to correlate the CIs with faults and degree of severity for diagnostic purposes. This enhances understanding of the underlying problem and relates CIs to physical parameters (e.g. bearing failure). This iterative process produces fault-correlated condition indicators based on historical knowledge and failure modes.

In addition, during the CI development phase, the CIs can in turn be combined using data fusion/signal processing techniques to create an overall integrated condition indicator (Figure 2 – Condition Indicators block). The benefits include a potentially richer source of information from an integrated sensor suite that a single sensor/condition indicator could not provide by itself. This data-fused CI would lead to a health indicator based on an integrated sensor suite.

The aeronautical design standard recommends that the seeding of faults concentrate on the actual failure modes regardless of the root cause. Test articles should be chosen based solely on the expected failure modes (Ref. 12). However, determining the root cause of failures can prove difficult. The actual failure modes can be informed from system models and simulations to address this deficiency by

examining both experimental and model based simulation of root causes and failure modes.

Theoretical Analysis

To monitor the health of components and detect failures requires an understanding of the physics of the failure mechanisms. This understanding requires that data collected from the system be correlated with specific component condition-based usage. Historically, these correlations were developed based on costly instrumentation, physical tests and empirical relationships.

Using a theoretical framework based on component, subsystem, and integrated system models can be used to understand the physics of the failure modes (Figure 3). This helps determine root causes of failure, the type of sensor to measure data and where to strategically place the sensor. The data from the model's responses from energy inputs is used for the algorithm development of condition indicators that are sensitive to specific faults and failure modes. Model inputs can be velocity, forces, heat source, cracks etc. The model's response would be in terms of stress, strain, temperature etc. The simulated system models would be used for data fusion where virtual sensors are used to sense and monitor system health in cases where a single sensor is not able to provide adequate information (Figure 2 – Algorithms' Response block). The models would encapsulate the dynamic, acoustic, material (stress, strain), and thermal response of component and subsystem models and relate them to the overall system model (Figure 2 – Models block). The utilization of component, subsystem and system models allows for the identification and classification of fault and failure mechanisms that might not be possible or practical to create in a field or test environment.

The integrated system model will be efficient through its use of data fusion and signal processing through the creation of

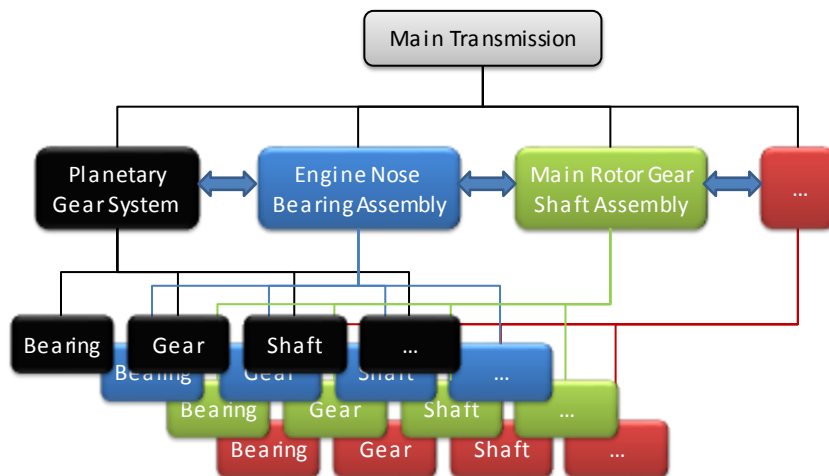


Figure 3. Theoretical framework based on component, subsystem, and integrated system models using a main transmission as an example.

additional CIs without the need for additional sensors. In addition, data fusion of different simulation models would take into account potential model interaction yielding a richer source of information than a single model by itself. An integrated model can ascertain the effect that a fault has on the functionality of the various elements of the system.

This integrated system model will greatly accelerate the development of new condition indicators and algorithms while also helping to support and inform testing of the system (Figure 2 – Double Arrow connecting two analyses section). Also, assessing the CBM data to determine gaps in the data can provide insight into any additional modeling and simulation required to support algorithm development. Data gaps can be defined as missing information or data that, if existed, would significantly increase knowledge about the algorithm. This is where models and simulations can play an important role by filling in data gaps in testing data. Simulations will allow us to track the virtual condition indicators values as faults progress with time. The reliability and robustness of the modeling and simulation capability of the proposed algorithm can be demonstrated with sensor data from a test stand.

In summary, the models and simulations can be used to determine strategic sensor resource utilization, develop new condition indicators, and capture the health of the complete system.

Predictive Tools

CIs from the simulation models can be correlated with existing CIs and sensor data. With the implementation of data fusion of CBM and theoretical analysis (Figure 2 – Predictive Tools section), predictive tools can be developed based on the current status of component and fault progression models from the analyses. Such tools can be used for predicting remaining useful life (RUL), predicting current and future health status of components under various flight conditions and to inform the design of future components by eliminating the root causes found in current systems. Prognosticating RUL will enable the pro-active planning of future maintenance schedules and actions needed to maximize component life while minimizing risk and cost. The data fusions of these integrated analyses are used to transform CBM into a smart predictive system or CBM+.

University of South Carolina

USC's implementation of CBM has resulted in a reduced maintenance burden on personnel. This was achieved through a reduction in both corrective maintenance actions and required number of inspections and/or overhauls. Consequently, this increased system availability and operational readiness allows for a higher throughput. Supply chain efficiency was increased by decreasing the need to stock a large variety and/or number of parts since there were

fewer unscheduled repairs. Future required maintenance actions will be predictable. Overall, the aforementioned items reduced operations and support costs while maintaining or enhancing safety. This leads to increased morale from the end user and increased confidence in the system (Figure 1 – Outcomes of CBM Implementation stage). These methodologies and techniques by themselves are necessary but not sufficient for an effective CBM program. It also requires extensive training and dedicated personnel with the support of management.

Several cases of value added have been seen from the USC's implementation of CBM. One case study is the cost-benefit analysis of an on-board vibration monitoring system that reduced costs of maintenance test flights by 80% over an 8-year span. This cost-benefit analysis also helped to significantly reduce the incidence of unscheduled maintenance actions as a percentage of total maintenance actions (Ref. 13). Another case study is the component testing of the AH-64 tail rotor gearbox assembly which was frequently leaking grease (Ref. 14). Through seeded fault testing, USC managed to change the maintenance schedule of the tail rotor gearbox to reduce operation and support costs. As a result, several new maintenance awareness releases were issued changing future maintenance procedures

CONCLUDING REMARKS

USC's vision of a smart predictive system involves the integration of CBM analysis and theoretical analysis with the use of data fusion. Models and simulations can be used to determine strategic sensor resource utilization, develop new condition indicators, and capture the health of the complete system. Data fusion of CIs and models creates a richer source of information from an integrated sensor suite and system model that a single CI or simulation could not provide by itself. The correlation of these two data-fused approaches will allow the implementation of predictive tools to capture the condition of a component, subsystem and system to maximize useful life and minimize cost and risk. Moreover, predictive tools can be used to inform the next generation of system design.

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