A Training and Educational Demonstration for Improving Maintenance Practices

Travis Edwards
Research Engineer
University of South Carolina
Columbia, SC, U.S.

Rhea McCaslin
Grad. Research Assistant
University of South Carolina
Columbia, SC, U.S.

Edward Bell
Research Engineer
University of South Carolina
Columbia, SC, U.S.

Dr. Abdel E. Bayoumi
CPM Program Director
University of South Carolina
Columbia, SC, U.S.

Lester Eisner MG (USA Ret.)
Deputy Director, Office of Economic Engagement
University of South Carolina
Columbia, SC, U.S.

ABSTRACT

Improper and unnecessary maintenance actions can result in a waste of resources, time, and money. Training and education play a vital role in maintenance implementation and can be used to prevent improper maintenance procedures. The Center for Predictive Maintenance (CPM) has developed a demonstration framework and tool that can be used to educate and train users extending from maintainers to leadership on the maintenance process from fault to maintenance action. This demonstration tool will walk an audience through the maintenance process starting with the collection of sensor and historical data, and how it is then integrated to create predictive models. Finally, the data and results are displayed in unique dashboards that provide personnel with the information needed to make educated decisions on the condition and maintenance of their system.

INTRODUCTION

Predictive maintenance (PM) is a maintenance process in which tasks are performed based on evidence of need, integrating reliability, availability, and maintainability (RAM), reliability-centered maintenance (RCM), and condition-based maintenance (CBM) analyses. These processes, technologies, and capabilities enhance the readiness and maintenance effectiveness of systems and components. PM uses a systems engineering approach to collect data, enable analysis, and support the decision-making processes. The main objectives of PM are to reduce maintenance burden, prevent unnecessary maintenance actions, increase safety, increase system readiness, refine the maintenance process, and ultimately improve component design. Analysis and predictions include, but are not limited to, predicting remaining useful life (RUL), determining failure points, assessment of component design, materials behavior, tribological properties, and design and manufacturing properties.

An optimal maintenance practice logically starts with robust data collection and storage infrastructure. This enhances current health monitoring systems by providing controlled fault conditions for diagnostics development and condition indicator (CI) threshold level adjustment[10, 11, 12, 13].

Presented at the AHS 72nd Annual Forum, West Palm Beach, Florida, USA, May 17-19, 2016.

This paper focuses on the usage of these techniques in rotorcraft systems. A maintenance demonstration framework was established based on diverse data collection, statistical modeling, and user interfaces. These tools were utilized to develop a tool to help educate users and prevent unnecessary maintenance procedures.

BACKGROUND

For nearly 20 years the University of South Carolina (USC) has been collaborating with the South Carolina Army National Guard (SCARNG), Army, and DoD to help fully develop the needed capabilities pertaining to condition-based maintenance (CBM) and now PM. This effort has resulted in the CPM within the USC Department of Mechanical Engineering which hosts several aircraft component test stands in support of PM objectives. Since its inception, the center has strived to take on new tasks and responsibilities in order to satisfy the needs of defense aviation. Activities at the center include, but are not limited to, researching and testing aircraft components for the U.S. Army in order to increase time between overhauls, increase mission availability and readiness, create new diagnosis and prognosis algorithms in order to improve the operations of various aircraft (Apache (AH-64), Osprey (V-22), Black Hawk (UH-60) and Chinook (CH-47)), improving and/or creating new sensors to advance the onboard HUMS. These new enhancements also reduce improper and unnecessary maintenance tasks which can account for 33% of total maintenance costs. Since the US industry spends over $260 billion each year on maintenance, improper maintenance results in a loss of over $85 billion annually [15]. Other benefits include, improved safety, increased morale, and eventually save lives. To enable this practice, a high priority should be placed upon current sensor data as well as historical data including those coming from digital source collectors (DSC) and maintenance records.

Sensor Data Collection

Sensor signals are the starting points to any PM program. Optimal placement of the sensor on the component (gearbox, rotor blade, transmission, etc.) is necessary to provide the highest quality of collected data. The next challenge is to determine the rate of data collection to ensure no faults go undetected. After collection from the component, all data should be properly stored for easy readability. By properly implementing this framework, data originating from multiple sensors on the component can be integrated using tools like data fusion. This allows the health of the entire structure to be determined and monitored (Figure 1). After the health of the component has been determined, sensor data needs to be evaluated to ensure that the correct parameters are being collected. When integrated with historical data, the PM process can be used to its fullest capacity to determine items such as remaining useful life and the proper maintenance action to repair a fault.

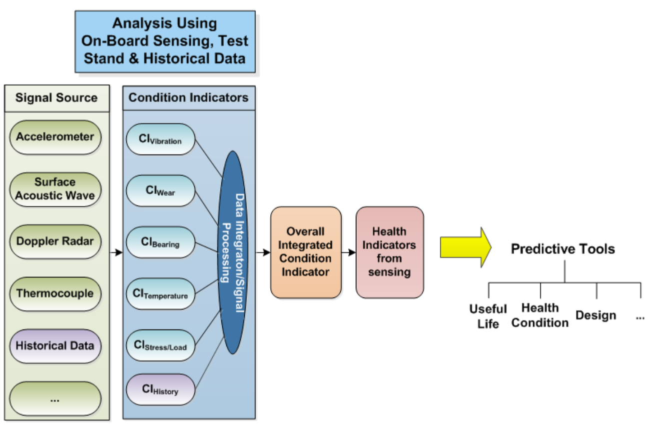

Figure 1. A PM concept based on measurement

Historical Data Collection

Historical data plays a critical role in PM by allowing a program to capture the human factor, including operational experience from working on the component and knowledge of how a component will react when a certain maintenance practice is performed. Historical data can come from a variety of different sources in the form of maintenance records and OEM technical manuals. Historical data can also include collected sensor data during previous operation hours. Data collected should be regularly reviewed to ensure that all parameters being recorded are being utilized. If certain parameters are deemed unnecessary, the recording scheme should be adjusted accordingly. Effective capturing of this knowledge could provide a novice maintainer access to the wisdom of a multi-year veteran.

Data Integration

Data can be integrated from multiple sources to gain a better understanding of how a component operates and behaves in the field. Better predictions can be made by utilizing all data sources possible, including multiple sensor signals and historical data. Differing sensor signals will be processed through appropriate feature mapping tools and analyzed to create sets of CIs. These CIs will then be integrated through fault and diagnosis classifiers that correspond to specific faults or fault classifiers for specific components (spall, cracks, etc.). This process is known as diagnosis fault classifying. These classifiers will then be fused for prognosis and prediction purposes: health indicators, failure modes, remaining useful life, etc. (Figure 2). The results from this data fusion will be used to 1) find the optimal combination of sensors to give the best results, 2) to detect new faults that they could not individually, and 3) educate personnel how to respond in the case of a sensor failure and what course of action to take.

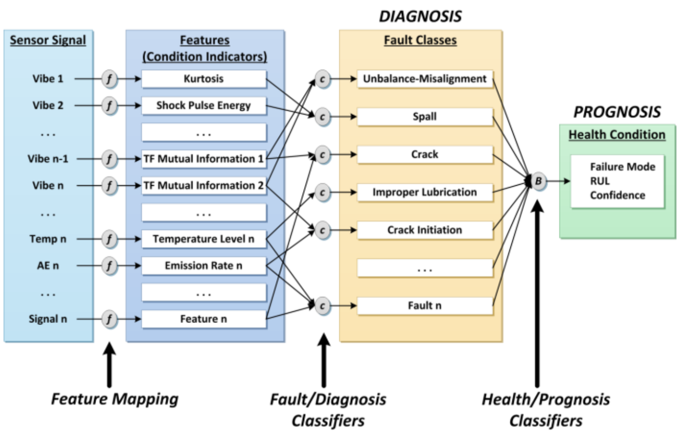

Figure 2. Fault detection with data fusion

Figure 3 shows collection of sensor data from a component, integration with historical data, comparison with models, the predicted state of the component, and then how it is presented in a dashboard for the user to then make a decision based on the status of the component.

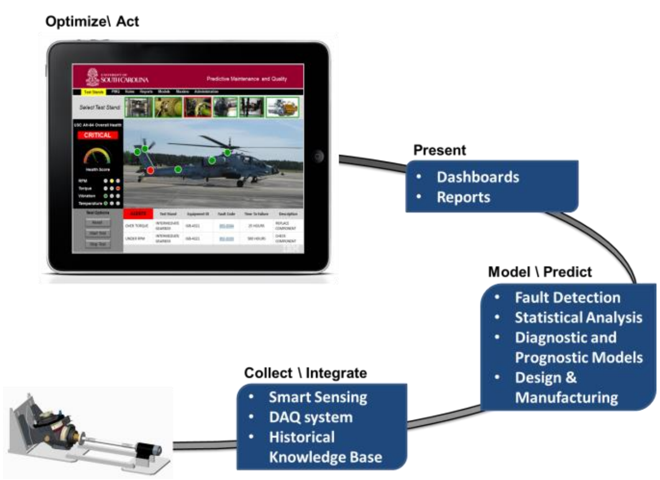

Figure 3. Demonstration of data flow

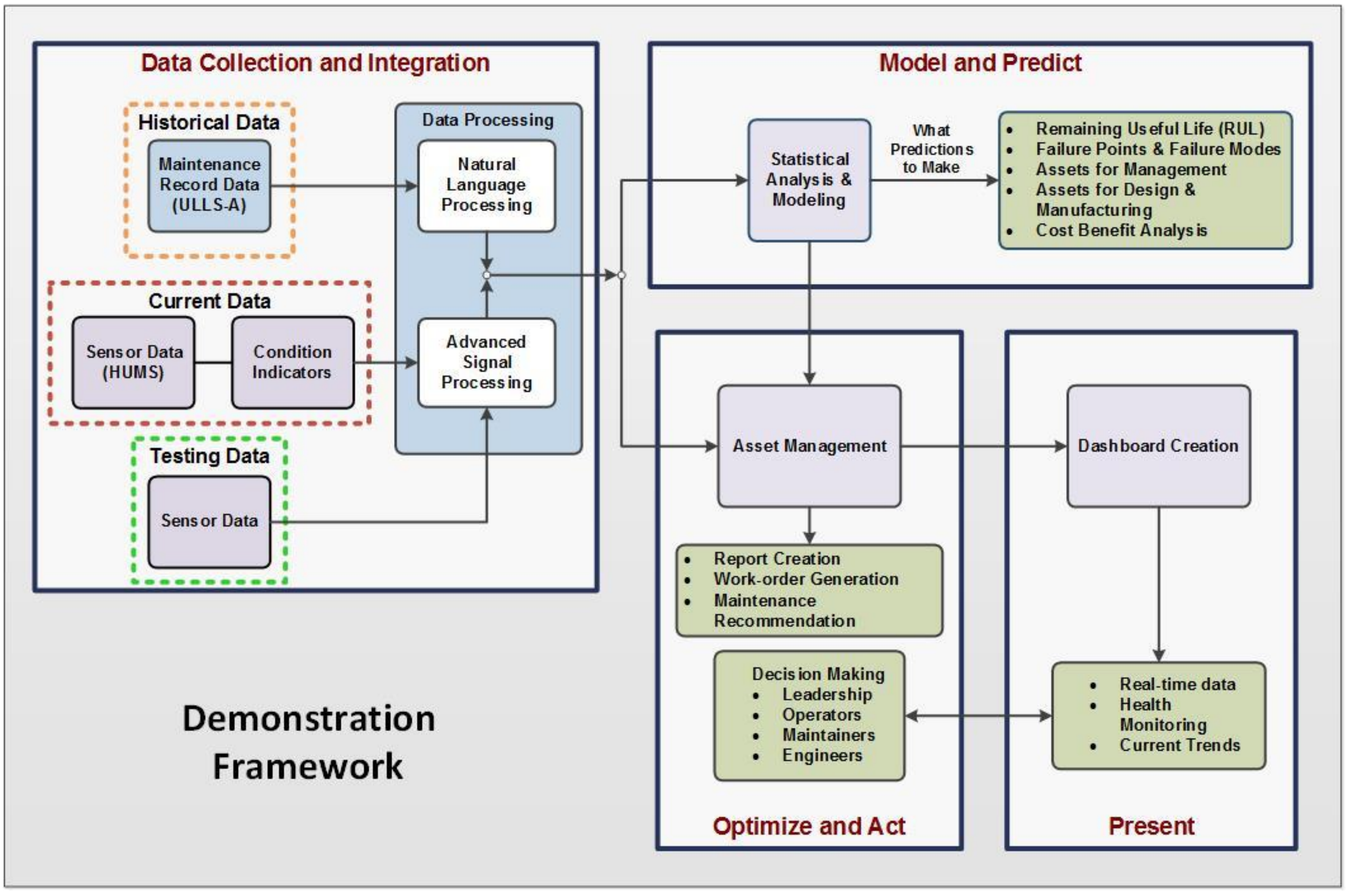

Figure 4. A simplified predictive maintenance demonstration framework

Figure 4 shows a simplified representation of the PM demonstration framework which can be divided into four main steps. These steps include collecting and integrating data from a different of sources, creating models for various types of data analysis, predicting critical factors, presenting results in dashboards, and optimizing and acting based on the results of data analysis.

DEMONSTRATION FRAMEWORK

Currently, new maintainers are expected to obtain their knowledge about current maintenance procedures from the flight line while their peers may not have been properly trained on the subject. Personnel may also have different viewpoints on the status and operation of PM practices based on their assignment and rank. If personnel, at all levels including management, are not properly trained and educated on how to utilize new tools and technologies then the full benefits of using PM will not be realized. Improper training can result in a piece of equipment designed to improve readiness being considered a failure only because it wasn't used properly. This lack of education could be helped by more tools being taught like this demonstration. This will require an upfront investment, but if properly implemented, would have a positive long-term effect on maintenance culture.

Users not only need to be trained on how to implement these maintenance actions but also need to be educated on it. If a maintainer does not fully understand the purpose of a requested action or how it positively impacts their maintenance routine, then he or she may be less likely to perform that action. This results in the neglect of simple tasks such as downloading HUMS data and sending it in for evaluation. Routine neglect of this action greatly hinders the development process of condition indicators (CIs) because engineers cannot validate the theoretical models on which they are based. Like maintainers, other groups of users may not be fully educated on how PM can improve their decision-making. Leadership can utilize this process to determine an aircraft's mission profile and supply chain personnel can determine whether to replace a component, dependent on its condition, before its time before overhaul (TBO) [4].

The objective is to address these problems of training and education by utilizing the demonstration presented in the previous sections. This tool can be used as an enabler to promote the advancement of technology in aviation. It can also be used to help the Army move forward in implementing PM by furthering the understanding of how all items work together to help improve maintenance practices in aviation.

Approach

The overall goal is to construct a demonstration based on this framework for educating users on the practice of PM from fault to maintenance actions. The development of the demonstration tool has been divided into three phases, each phase building on the phase before it. These are:

- Phase I – Develop and implement demonstration framework from fault to action on a single component
- Phase II – Demonstrate signal source diversity from sensors or historical data by utilizing data integration techniques and tools
- Phase III – Develop and implement the demonstration framework on a complete system

Phase I: Phase I is the development and implementation of the demonstration framework on a single component, starting with a fault and ending with an action. For this purpose a component would be a single part of a system (i.e. gearbox, hanger bearing, driveshaft etc.). The goal of this phase is to establish the basic hardware and software fundamentals needed to demonstrate PM on a single component, outlined in Figure 5. In this phase, the component is fitted with a native sensor and tested in near real conditions. Sensor data is collected and integrated with historical sensor data from the component and compared against a model. This model then makes a prediction of the current state of the component is displayed on a dashboard. The necessary software is developed for data collection, integration, and analysis. These include a set of preliminary tools and algorithms that include statistical models, health predictions, and dashboards.

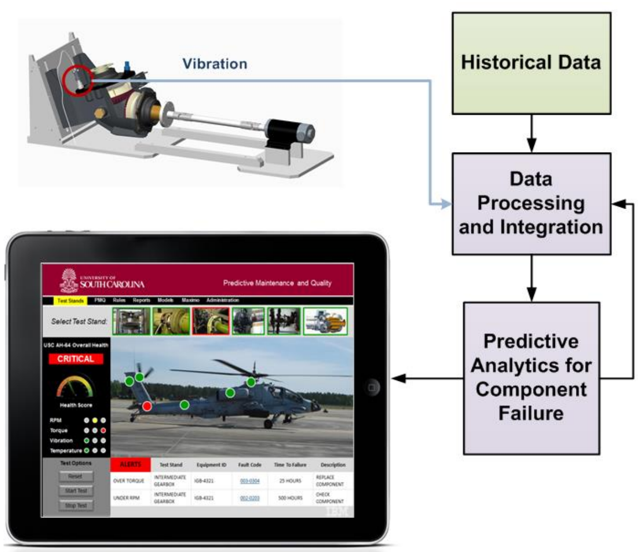

Figure 5. Phase I data flow

Phase II: Phase II is a demonstration of multiple faults on a single component by introducing a full suite of sensors and technologies (Figure 6). This includes exploring the viability of new sensors that are currently not installed on the component. Data integration is used to analyze the signals from multiple sensors to determine the overall health of the component. Figure 4 shows this process of combining information gained from different sensors to detect faults that they could not detect individually. Building upon Phase I, where a single sensor was used to make a prediction of component health, Phase II uses multiple sensors to determine possible system faults. Sensor data is collected and integrated with historical sensor data from the component. Like Phase I, this is compared against a model. The software developed for Phase I remains the same, with the exception of expanding the data collection and integration interface to allow for the addition of more sensors to the demonstration.

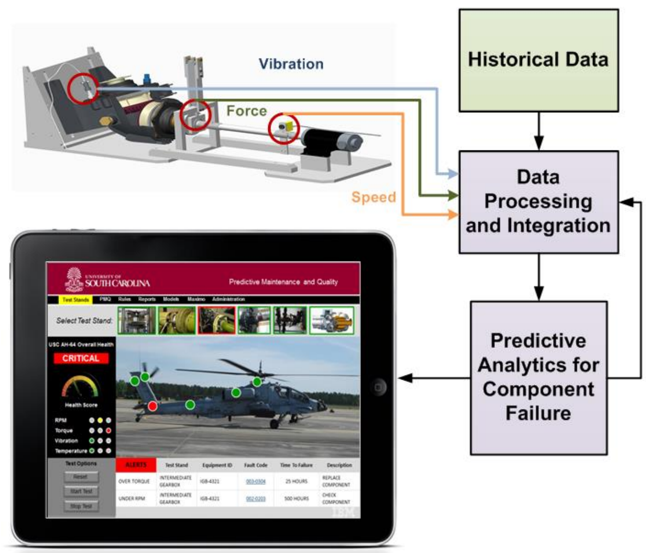

Figure 6. Phase II data flow

Phase III: Phase III is a development and implementation of the demonstration framework on a system (Figure 7). The definition of a system for this demonstration would be a drivetrain, consisting of hanger bearings, drive shafts, and gearboxes. This phase builds on the demonstration from Phase II and moves from a single component to multi-component system. Tools developed in Phase II are used to apply a systems-level approach to data collection and analysis**.** Data integration, using data fusion, in this phase is performed at both the sensor data level and at the component data level in order to predict the overall health of the system by taking advantage of historical data.

Figure 8 shows a representation of the demonstration setup consisting of an intermediate gearbox (IGB) instrumented with multiple sensors and a data acquisition (DAQ) system. The data collected by the DAQ system is transferred to a device that processes and pushes the data to cloud storage. There are various subscribers that have access to the cloud storage, including a server for offline analysis and backup storage, and different end-users for data analysis and decision-making. The offline analysis is performed using historical data to create predictive health models. A statistical modeler retrieves new data and runs them against previously built models to detect if a fault exists. Other end users will be able to retrieve the data and send critical information to other dashboards about maintenance actions, fleet management, supply chain, etc.

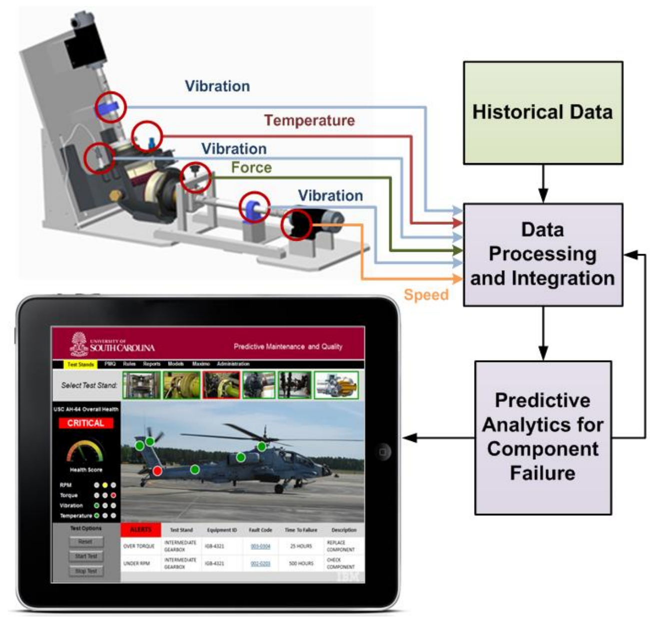

Figure 7. Phase III data flow

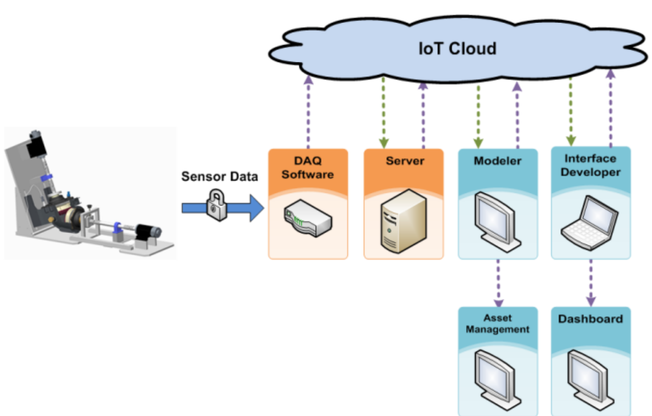

Figure 8. The completed demo data accessibility

This tool will be a multi-component system capable of simulating and detecting a variety of faults, providing logistics information, and creating maintenance decisions based on historical trends. The demonstration is an easy to use platform that demonstrates how maintenance data and predictions can be analyzed and applied to the strategic, tactical, and operational management of an aircraft.

Ultimately, the outcomes of this demonstration are to help leadership, decision-makers, and users achieve their PM objectives. These objectives include: reducing maintenance burden on the solider, educating and training users on PM, reducing supply costs, improving safety, and changing the status quo of the maintenance process and culture.

IMPLEMENTATION – PHASE I

Demonstration Hardware

The component chosen for the demonstration was an AH-64 intermediate gearbox (IGB). The IGB (Figure 9) is an important component of the aircraft that requires frequent maintenance actions. Some sensors monitoring the article are native to the aircraft's IGB, including thermocouples, an accelerometer, and a tachometer. The thermocouples are used to measure temperature and are placed in the same locations where they would be on the aircraft. The accelerometer is used on the aircraft to measure vibration in a single axis and the tachometer is used to measure the rotational speed of the gearbox. In order to replicate the data coming from a DSC the sensors used for USC's DAQ system are placed in close proximity and orientation as the military devices.

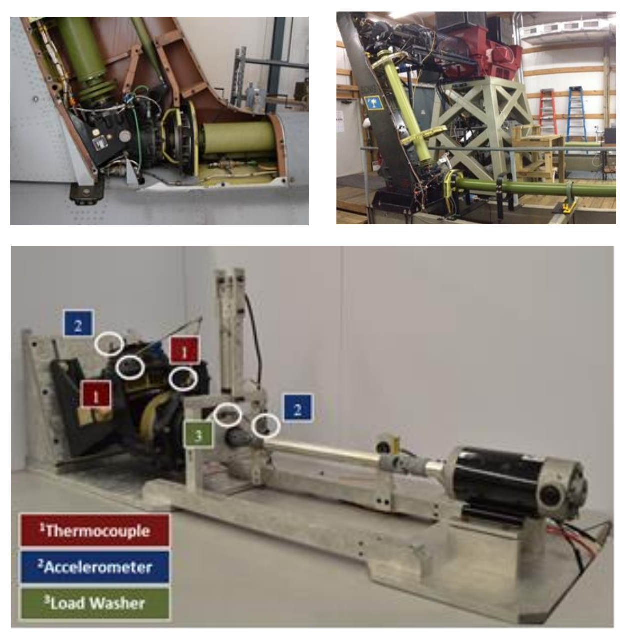

Figure 9. Picture of the IGB installed on the aircraft (top-left), CPM test stand (top-right), and demonstration (bottom)

Additionally, a load washer was installed to accurately measure the amount of force being introduced on the system. Electrical power consumed by the demonstration is also monitored to ensure normal operation of the motor supporting the IGB (Figure 9). This allows for the system to be shut down in the case of an emergency through the data collection interface.

Three unique faults have been created to simulate a real-world problem to show the user the potential utilization of each sensor. The effectiveness of a thermocouple is shown by using heat tape. This heat tape, when triggered, results in an increase in temperature simulating a thermal fault within the gearbox. Another fault shown during the demonstration is a small motor with an imbalance to induce abnormal vibration in the component housing. This fault displays the capability of an accelerometer and how it can be fully utilized to detect an abnormality. A linear actuator was also installed to apply force on the input spline to simulate an over torque condition on the driveshaft and shows the effectiveness of accelerometers, amperage monitoring, and load cells. These three sensor signals can be used together through data fusion and allow the operator to exploit data streaming from multiple sensors in case one of them fails during collection.

Data Collection and Integration

Previously collected data, sensor readings, are stored in a database located on a server. The database is periodically updated with new data coming from the demonstration. This data storage is done at a separate location from the demonstration, but houses all of the information collected and allows it to be accessed by users with the proper credentials. The data being collected comes in multiple forms from different sources. In order to integrate the data together, data processing tools are used including advanced signal processing. Security is a high priority therefore the information associated with this demonstration will not contain any sensitive information. After the data is processed and scrubbed of sensitive information, it is then integrated together using data fusion and stored in the database.

During the demonstration, the operator collects data from the test stand using a DAQ with the proper modules for the different sensors. The data collection program has been written to retrieve data from the sensors and publish it to cloud storage. The collected data points are visualized on the front panel of the visual interface (VI) (Figure 10). This screen is similar to what an engineer might see when collecting data from a component that could later be analyzed to determine the validity of CIs and further improve the reliability of the component. The program also writes the sensor data to an output text file that can be accessed by other devices that have been granted permission.

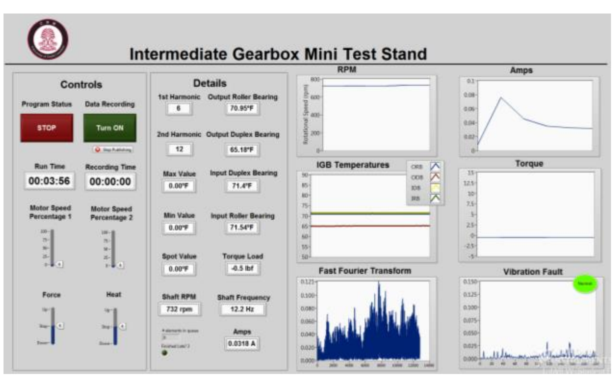

Figure 10. The data collection interface used for the demonstration

Model and Predict

There are different types of analysis that can be performed using the collected data including cost-benefit analysis, diagnosis and prognosis, life predictions, and failure mode and effects. Before starting the analysis the problem being solved needs to be defined. Once the problem is defined the type of analysis and data to be used can be assigned.

The demonstration uses predictive modeling to assess the health of the component in order to diagnosis if a fault is occurring. For this type of analysis, models representing different faults were created. Figure 11 shows process for creating the model. Historical data containing baseline sensor readings and sensor readings from a component are collected and processed. The data is then analyzed using a statistical modeling program. This analysis establishes different models that represent the component at a baseline state and at the different fault states. The models are then stored to be used later for scoring new data.

During the demonstration, the sensor data being collected is then scored against the premade models and the model that scores the highest is the output. The output of the program is the predicted fault state of the component. The newly created data is also stored to be used to refine the models at set increments.

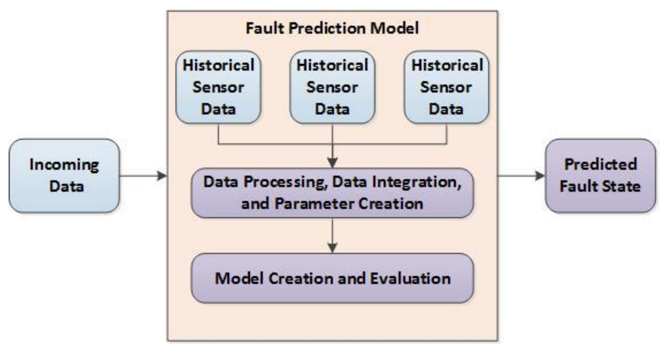

Figure 11. Data processing done by modeler

Present

After the analysis has been completed, the results need to be presented to the users. Each user will have different needs and can include personnel in leadership, engineers, maintainers, and operators. In order to address the needs of different users, the information displayed can be tailored to fit these needs. The data can also be displayed in different forms including dashboards and reports. To display the data coming from the modeler in a user friendly interface that everyone involved in the operation of the component can use a proper dashboard needs to be created (Figure 12). Depending on the user, this dashboard can have access to fleet data, temperature data, component replacement information, etc. The figure below shows different dashboard states during the demonstration.

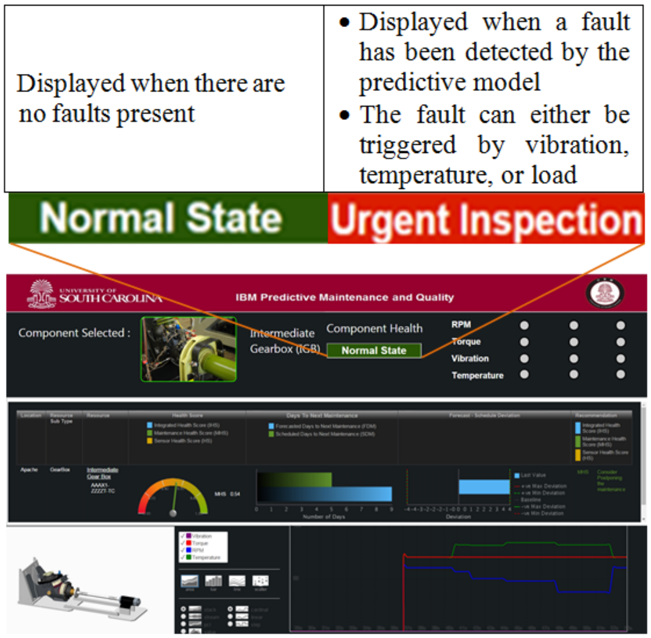

Figure 12. The dashboard interface showing a normal state

During the baseline (normal) portion of the demonstration, all indicators are green and there are no actions that need to be taken. When a fault is initiated by the operator the screen with then transition from a normal state to an urgent inspection based on the incoming data. The audience can view the sensor readings on a graph at the bottom right-hand portion of the screen used to predict when a fault will occur. There they can see temperature, vibration, rpm, and other valuable readings. When a measurement trends towards a threshold, the component health will change and the status of the gearbox will be adjusted.

Optimize and Act

After a user is presented with the results from the analysis, they will need to use this information to perform an action as suggested by leadership. These actions can include maintenance recommendations, report creation, and work-order generation. These actions need to be backed up with reliable data and analysis so leadership can feel confident with their decisions. Historical data, combined with the data currently coming from the component in the demonstration, can be easily displayed so that those in a leadership role can make timely decisions about a faulted component.

To create a maintenance action for a crew chief or maintainer, a work order needs to be completed to notify the user that a component needs to be changed out at a desired interval. Once it has been determined by the modeler that a work order is be created, a program will fill in the proper fields and send it to the designated maintainer.

HIGHLIGHTS – PHASE I

Since its creation, this demonstration has been shown to different groups of people who would like to gain a greater understanding of PM. Breaking the stigma that PM is nothing more than a sensor collecting data and educating personnel properly from the beginning of life to the end of life for a component can result in a cost-avoidance on Army rotorcraft. This benefit will be seen if implemented with the proper technology along with proper use by soldiers that understand the power of the system and how to leverage the data coming from it. Through the utilization of data by properly collecting it, integration with historical data, inputting it into predictive models, and displaying these actions in user friendly dashboards, this educational tool can ultimately help progress the maintenance culture in Army aviation to PM.

CONCLUSIONS AND FUTURE WORK

There is still more work to be done on this demonstration in order to complete all three phases. In its current state, only Phase I and some portions of Phase II have been completed. To finish Phase II, a wider variety of sensors need to be installed to allow data integration between signals. Phase III would take this framework one step further and apply it to multiple components to show users its implementation at a systems-level. A dashboard for this phase can be seen below in Figure 13. The different stages are structured by no fault present as green, 10-100 hours till failure as yellow, and 10 hours or less left to failure as red.

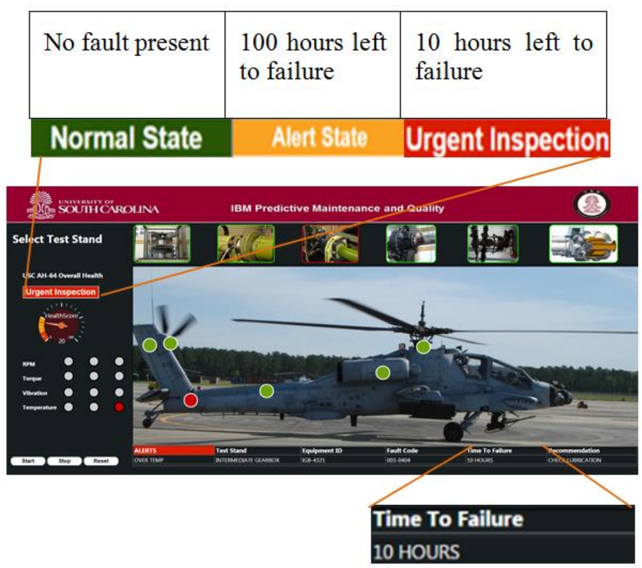

Figure 13. A screen showing the health of multiple components on the airframe

These distinctions are based on the Aviation Engineering Directorate's Propulsion Division assigned color codes [2]. The predictions made in this stage will become more refined over time because of the various types of data being used to create the models. The more data that is input into the system, the more reliable the level and threshold between predicted states can become. The dashboard for Phase III would include another level above the interface seen in Figure 12. In Figure 13, all components on the aircraft are displayed and the user could click on the individual item to obtain further information about a faulted article. Further phases show an additional layer up displaying the fleet view to inform leadership which aircraft are available to conduct certain missions.

ACKNOWLEDGEMENTS

This work is being done in collaboration with QMT LLC.

Author contact: Travis Edwards edwardt2@email.sc.edu
Rhea McCaslin mccaslir@email.sc.edu
Edward Bell beller2@cec.sc.edu
Dr. Abdel E. Bayoumi bayoumi@sc.edu
Lester Eisner eisnerl@mailbox.sc.edu

REFERENCES

[1] AR 750-1, *Army Material Maintenance Policy*, September 20, 2013.

[2] Allen, Jamie. "*CBM Vibration Monitoring Lessons Learned from the Apache MSPU Program.*" Huntsville, AL, 2015.

[3] "Aviation & Missile Command (AMCOM) Condition Based Maintenance+ Strategic Plan," December 1, 2011.

[4] AVNIK Defense Solutions, Inc., and Valu-Lytics, Inc. "*Connecting CBM+ to the Supply Chain Presentation*."

[5] Eisner, Lester, and Abdel Bayoumi. *"'Road-Ahead' Army Aviation Implementation of Conditioned Based Maintenance,*" June 18, 2006.

[7] DoD Instruction 4151.22, Condition Based Maintenance Plus (CBM+) for Materiel Maintenance, December 2, 2007

[8] National Research Council of the National Academies. "*Force Multiplying Technologies for Logistics Support to Military Operations,*" 2014.

[9] Parlier, Greg. "*Transforming U.S. Army Supply Chains: Strategies for Management Innovation,*" February 2015.

[10] Nicholas Goodman, Abdel Bayoumi, Vytautas Blechertas, Ronak Shah, and Yong-June Shin. "*CBM Component Testing at the University of South Carolina: AH-64 Tail Rotor Gearbox Studies*".American Helicopter Society Technical Specialists' Meeting on Condition Based Maintenance conference proceedings. 2009.

[11] N. Goodman, "*Application of data mining algorithms for the improvement and synthesis of diagnostic metrics for rotating machinery*". PhD dissertation, University of South Carolina, 2011.

[12] Abdel Bayoumi, Amber McKenzie, Kareem Gouda, Jacob McVay and Damian Carr "*Impact of Lubrication Analysis on the Improvement of AH-64D Helicopter Component Performance*," Proceedings of the AHS 68th Annual Forum, Ft. worth, TX, May 1-3, 2012.

[13] Abdel Bayoumi, Nicholas Goodman, Ronak Shah, Trevor Roebuck, Andrew Jarvie, Les Eisner, Lem Grant, Jonathan Keller, "*CBM at USC - Part III: Aircraft Components Mapping and Testing for CBM*", in Proceedings of the AHS International Specialists' Meeting on Condition Based Maintenance, Huntsville, AL, 2008.

[14] Bayoumi, Abdel, Nicholas Goodman, Ronak Shah, Les Eisner, Lem Grant, and Jonathan Keller. *"Conditioned-Based Maintenance at USC - Part IV: Examination and Cost-Benefit Analysis of the CBM Process."* AHS International Specialists' Meeting on Condition Based Maintenance, Huntsville, AL, 2008.

[15] R. Keith Mobley, An Introduction to Predictive Maintenance. Second Edition, Elsevier, 2002.