

Internet of Things – A Complete Solution for Aviation's Predictive Maintenance

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Abstract

The University of South Carolina has been involved in research for the US military for helicopters and rotary aircraft for over 18 years. Majority of this work has been focused on optimizing aircraft uptime and flight readiness by leveraging condition-based maintenance (CBM), more commonly known as predictive maintenance (PM). This type of maintenance differs from other classical styles (reactive and preventive) in that it has a high reliability and a low cost. The foundation of PM in any application is data collection and storage. It begins with applying tools such as natural language processing (NLP) to historical maintenance records to determine the most critical components on the aircraft. Data mining of previously collected sensor data is then used to establish the most reliable types of condition indicators (CIs) that monitor the critical components. These thresholds from the CIs can be modified over time as more data is collected. Once a data collection scheme is in place, prognostics can be used to determine the remaining useful life of a component. Using this process, along with an optimized maintenance schedule through the maintenance steering group (MSG-3) program, helps to eliminate unnecessary maintenance actions on the aircraft, as well as, reduce the inventory of components needed for the aircraft to operate. After this maintenance scheme has been set up, the Internet of Things (IoT) can be leveraged to allow the entire process to operate within a single environment. This further develops the solution, and allows actions to be executed more quickly than if they were performed individually. The expected benefits and future development of these practices will never come to fruition unless personnel are properly educated and trained. Developing a culture of predictive maintenance practices in an aviation environment is necessary to ensure success of this solution.

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1. Introduction

The Internet of Things (IoT) is the connection of any device to another entity with the ability to transfer data between one another. It has recently gained popularity due to the realization of the benefits that it can have while being used to monitor a multitude of devices, including expensive machinery, cars, and even our own activity levels. With this knowledge, it should come as no surprise that this technology is currently being implemented to enhance the current predictive maintenance (PM) practices of the Army aviation fleet to help reduce maintenance burden, prevent unnecessary maintenance actions, increase safety, increase system readiness, refine the maintenance process, and improve component design.

Traditional maintenance practices, like reactive (failure-based) and preventive (time-based), are becoming less popular due to the amount of overall cost associated with having to repair components that are either not broken, or have failed unexpectedly and are now costly due to unforeseen downtime. Optimized scheduled maintenance through the MSG-3 program allows the user to better understand the failure modes of component that is being monitored, however it still has untapped potential. PM has become a popular cost-effective alternative driven by the increased affordability of computing equipment and electronics. PM is a process in which tasks are performed on a component based on evidence of need, which integrates reliability, availability, and maintainability (RAM), reliability-centered maintenance (RCM), and 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. 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 (Edwards et al., 2016, Goodman et al., 2009, Goodman, 2011, Bayoumi et al., 2012, 2013).

2. 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 CBM and now PM. This effort has resulted in the Center for Predictive (CPM) within the USC Department of Mechanical Engineering. CPM 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, increasing mission availability and readiness, creating 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)), and 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. The US industry spends over \$260 billion each year on maintenance, and, because of improper maintenance, 85 billion of these dollars are lost annually (Mobely, 2002). Other benefits include improved safety, reduced casualties, and increased morale. 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 (Goodman et al., 2009, Edwards et al., 2013).

3. Predictive Maintenance Methodology

The PM methodology starts with various data sources, including historical, current, and testing data, to create the parameter that needs to be monitored on a particular component. These data sources can then be formatted using tools such as NLP and data fusion to create and be used in a predictive model. This model can determine expected outcomes like RUL, failure points, and how to improve asset management. The transformed data can then be sent to individual users and decisions about how to maintain the component can be made automatically. This process reduces maintenance burden on leadership, operators, maintainers, and engineers. All of this information will also be available in dashboards to inform all users on current trends with the fleet.

3.1. Data Collection, Processing, and Analysis

For a component or a process to be connected to IoT it needs to collect data via a sensor. So it is a natural fit between PM and IoT since the foundation which it bases all of its reasoning off of is a sensor. Selecting the

proper sensor(s) to monitor a particular component is critical to being able to collect the highest quality data. Just as important as the sensor is the rate at which data is acquired. The collection frequency needs to be a balance between having too much data that it is no longer useful and collecting such a small amount that those important characteristics cannot be interpreted. Different sensors can monitor aspects of a component's health, but data from multiple sensors can also be integrated together to create new condition indicators (CIs) that can give an entirely new perspective on the piece of equipment. By utilizing tools like advanced signal processing and data fusion an aircraft can become more reliable. The usefulness of the on-board sensors is optimized without the cost or weight of new components. It is also important to audit sensor readings periodically so that it can be confirmed that the proper parameters are still being collected, and have not changed over time.

Historical data is valuable when trying to establish and adjust procedures that occur when a component needs to be repaired. It allows an engineer to alter CIs thresholds that were once purely based on theoretical work and can now be backed up with reliable data from the field. This makes the predictions upon which they are based more accurate and ensure that the component being removed is actually faulted. Historical data does not only include health usage monitoring system (HUMS) data. It can also utilize standards, regulations, manuals, and historical logs to capture the human factor of maintenance. This creates a reliable prediction that is based on maintainers' past experiences. Capturing this knowledge and effectively relaying it to a maintainer, gives someone who may have relatively little experience the same amount of wisdom that a seasoned veteran would have. Reviewing this data can also help determine common failure modes and establish methods for how they can be fixed or deterred. Periodic review will also help confirm that the appropriate type and amount of data is being collected to accurately identify faults.

3.2. Statistical Analysis and Modeling

Proper implementation of a new prognostics system is critical for ensuring that maintenance procedures are carried out at the correct intervals. Improper maintenance intervals could lead to failure of a component even shortly after an aircraft has been serviced. To assure this step is completed fully, the decision needs to be based on solid models as well the current sensor readings coming from the aircraft. Once these rules and standards are established for determining when a component is faulted, a statistical algorithm is used to assess when a safe removal time will occur. To complete this there are a few criteria that need to be established to better understand the type of prognostic tool to be used: 1.) Has the type of fault been determined? 2.) How long has the fault been active for? 3.) What is the severity of the fault? Justification for which statistical algorithm that is used is dependent upon these criteria. The goal of determining RUL is to output a reliable time interval and to minimize the number of false alarms which is a key part of decision making for leadership.

3.3. Asset Management and Dashboard Creation

After the analysis has been completed, the results must 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 requirements. The data can also be displayed in different forms including dashboards and reports. 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. This makes sure that no unnecessary repairs are conducted and the maintainer knows exactly what needs to be repaired and how to complete the action. 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.

4. Leveraging IoT to Improve Aviation Maintenance

4.1. Native Environment

The major advantage of conducting PM in an IoT environment is that all of the processing, storage, and calculations are conducted in a single place. This creates an edge when trying to complete a task in an industry that has as many regulations as aviation does. With all processes connected it adds accountability to each user. They have to get input from everyone involved so that an individual cannot skip steps to make an action go faster or try and hide the work being done. By leveraging IoT, the maintenance process can run more efficiently and faster. Leadership is now aware of all decisions being made due to the connectivity of all the processes to one centralized place. The decisions will be more knowledgeable and can yield better results.

The single environment of IoT also allows for better management of parts tracking and the historical data of these parts. It is always a concern about how secure a database is when dealing with a defense entity, especially in an IoT environment. Security of the data needs to be a high priority to make sure that everything is being done to keep the integrity of the data while not detracting from the efficiency of the process. Data being collected from the HUMS unit on the aircraft should be downloaded and added to server as securely as possible. Since the inventory of components, sensor data, and historical maintenance records are now hosted together more information can be gathered about a particular component that is going to be used on an aircraft. Personnel can know exactly when a component was overhauled, and how long it has been in storage, which aircraft it has flown on and for how long. CIs associated with the component can also be captured, making it easier to isolate faults in an individual component rather than the entire aircraft. Diagnosis capabilities become stronger as a result of having complete information for an article. By tracking parts and associating individual records with one component, changes in the maintenance of that article, whether it is a design change, tooling change, or procedural change, can now happen faster.

4.2. Automation

Since all of the processes are connected it requires less human interaction for a maintenance work order to be processed. By having prognostic algorithms, the system can determine the best time to complete a maintenance action. RUL should be considered with the routine maintenance schedule in mind so that if the component is predicted to fail in 530 hours, and there is scheduled maintenance occurring in 500 hours, then the component should not be removed until the scheduled interval. This reduces the burden on the maintainer and assures it does not become a risk to the operator on a future mission.

Automated work-orders reduce the burden on leadership and increase maintenance productivity. Due to the automation of this process because of IoT environment, it now benefits other departments such as supply chain. It is known when a part is going to be removed so a smaller inventory of parts can be kept on hand and the component can be shipped only when necessary. When the maintainer is scheduled to do the repair the component is already at the facility, and does not spend time somewhere it is not needed.

Having a process that is self-sustaining also allows for it to become “smarter” as more data is added to the database. By using cognitive features like machine learning to improve condition indicators without additional user input, the thresholds can change overtime, as well as the maintenance recommendations. This also makes it easier to find an imperfection in the process.

5. Optimized Scheduled Maintenance

5.1. MSG-3 Methodology

The ultimate goal in creating an optimized scheduled maintenance plan through MSG-3 is to be able to adequately use all of your resources to create the best result. This includes being able to produce a good product while making use of resources, including cost and time, and not affecting the morale and safety of the personnel that are involved in the maintenance process. The maintenance steering group (MSG) process was originally created to form a standardized decision making process that could be used for scheduled maintenance on fixed wing aircraft. Over the years different iterations have been established, slowly including PM attributes as they became more valuable throughout the industry. The advantage of a task oriented program is that it is based on specific functional failures and the reliability of each piece of equipment being monitored. Tasks are selected depending on the amount of cost, difficulty, and the safety effects on the crew. A general list of tasks includes lubrication, visual check, inspection, restoration, and discarding the component. These functions are found in each of the maintenance program groupings: zonal, systems and power plant, structures, and lighting and high intensity radiated field (Ackert, 2010).

Working groups (WG) are created from the four areas (Zonal, Structural, Systems, and L/HIRF) to develop minimum scheduled tasking intervals consisting of operators, maintainer, engineers from industry, and other relevant positions. These working groups are overseen by multiple entities to ensure that their recommendations are sufficient to be included in the maintenance plan. The maintenance steering committee (MSC) is made up of various representatives to define the systems to be analyzed, direct activities of the WG, and to remain in contact with all of the necessary partners. The OEM and a contracting organization will work together to achieve a balanced recommendation and provide data, models, reliability metrics, and any other significant items to the WG.

Before WG activities can start there are critical pieces that need to be setup so that their job can be done efficiently and yield the best results. A contractor will prepare and provide each WG with necessary documentation including technical description of the aircraft configurations, data, results, models/algorithms, presentation overview slides, and other training materials. They will also prepare and provide data, results, models, and technical manuals that are needed. All of these files need to have a central location in the form of a secure interactive web-based environment so that file exchange and user interaction can occur easily.

5.2. Combining Optimized Scheduled Maintenance with HUMS data

Although there are many benefits to an optimized scheduled maintenance plan, it still does not take full advantage of the on-board HUMS system and IoT. This is because most tasks are based on time metrics like calendar time or flight hours, and not based on the actual degradation of the component that is being monitored. This way of scheduling tasks is also disadvantageous when accounting for the wide variety of operating conditions of the aircraft. Since mission profiles can change drastically from one aircraft to another, the failure time can also vary greatly. Due to this variation the worst case scenario has to be accounted for causing more part replacements to occur well before they are needed.

By using PM on an individual aircraft through the HUMS system and monitoring the historical data a better prediction can be made about component replacement. The chances of a component failing greatly increase after maintenance is performed due to human error during the installation. Using HUMS also gives another opinion to the health of the aircraft because it can detect degradation that might not be seen during a visual inspection. It is also a more exact way of measuring a fault because trends in the data give you a quantifiable number to measure against versus a visual inspection which might determine that the fault has not grown by a considerable amount. Being able to leverage PM through HUMS data and connecting it with the proper scheduled interval with MSG-3 allows for more inputs that can be taken into IoT. Having all of this

impactful data in one location, connected to all necessary personnel, allowing real-time decision making about an aircraft's maintenance needs, is an asset to all users involved.

5.3. Benefits and Training

The benefits an optimized scheduled maintenance combined with PM can include a reduction of maintenance burden, high reliability, increased safety, increased cost avoidance, and improved morale. These benefits will increase as the process continues and users become more familiar with how to use it. CPM at the University of South Carolina has experience at creating these demonstrations and has recently created one using the AH-64 intermediate gearbox. This demonstration shows a user how a fault on a gearbox can be detected by a sensor, analyzed using PM techniques and then displayed and processed into a work order quickly using IoT. This demonstration adds to the list of components that are able to be tested at the facility.

6. Center for Predictive Maintenance Capabilities and Outcomes

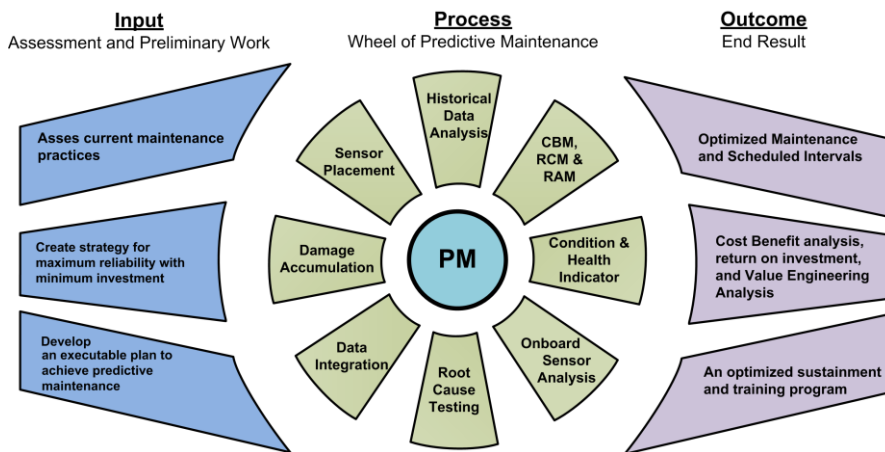


Fig. 1. Three steps are used to create an effective PM program

CPM at the University of South Carolina has been working on improving this process over the years. Flight data and testing data are important for improving and disproving the validity of CIs (Allen, 2015). Once optimal thresholds are determined for these values it will ultimately reduce the amount of false positives and increase the amount of true positives (Cao, 2013). CPM has been focused on component testing to improve condition indicators and independent projects to better the entire PM program. As seen in Figure 1, there are three major steps to implementing a successful program in industry. The first step is assessing current procedures, creating a strategy to maximize reliability while using minimum investment, and developing and easily executable plan. The next step is analyzing the different needs in the program, which has been the focus of CPM's different research projects. The final step is the outcome, which should be an optimized scheduled maintenance plan that is based on sound engineering and will have a high return on investment.

6.1. CPM Testing Facility

CPM currently operates several test stands that have helped support PM objectives for aviation. The main objective for testing is to improve aircraft reliability through the testing of naturally-occurring and seeded-fault testing. Other benefits from testing also include development of new sensors and improved CI

algorithms that can be created using data. These test stands include an auxiliary power unit (APU), a main rotor swashplate (MRSP), and a tail rotor drive train (TRDT). Each test stand emulates the normal flight conditions experienced by the components. Structure, instrumentation, data acquisition systems, and supporting hardware are installed according to military standards. The test stands are designed and built to accommodate the use of various HUMS. USC's own data acquisition results have been validated with data obtained from actual airframes. The testing facility is capable of being modified to test new and existing drivetrain components of military and civilian aircraft, including the ARH-70, CH-47, and UH-60 drivetrains (Bayoumi et al., 2008, Goodman et al., 2009, Edwards et al., 2013).

6.2. Project Results

Multiple faults have been examined using the TRDT test stand. One fault was of the tail rotor gearbox leaking grease through its input and output seals. An experiment was designed to create a worst-case scenario for a leaking output seal on three different high-life gearboxes, which were to be run for 500 hours in a seeded fault condition. Although previously considered impossible, during the study it became evident that grease freely moves from the main gear compartment into the static mast. The three gearboxes tested survived 490, 487, and 573 hours after fault seeding, and numerous vibration and thermal observations were recorded as the gearboxes approached failure. Benefits seen from this project were a return on investment of 20.2:1, increased readiness, and fewer maintenance actions needed (Goodman et al., 2009).

Another set of components studied were the hanger bearings on the AH-64. The objective of the seeded fault test was to examine whether existing CIs would respond to failure modes simulated by seeded faults (Prinzinger et al., 2012). The faults were tested for over 8000 hours with no substantial evidence that the CI values were responding as expected. As a result CBM credit was sought and approved for extending the time between overhaul (TBO) for the hanger bearing from 2750 to 3250 hours leading to a new airworthiness release for hanger bearings (Cao, 2013)

An Advanced Vibration Sensing Radar (ADVISER) for condition monitoring experiment tested Honeywell's ADVISER sensor and its potential diagnostic and prognostic capabilities. The sensor measures the phase change between input and output signals caused by the target displacement. The ADVISER sensor has a wide field-of-view giving it the capability to monitor more than one component at a time. As a result from this testing, a new, platform independent, non-contact sensor was validated for CBM use. This could lead to a reduction in the required number of sensors and consequently overall weight (Bharadwaj et al., 2013)

Another effort was to apply NLP techniques to improve reliability and reduce costs of V-22 aircraft. The program had three main objectives. First, research and develop methods to align maintenance actions, based on what was reported in the free text fields with entries in the aircraft's technical manual. Second, trim the unwieldy technical manual of redundant entries, for which entries that are semantically similar but syntactically different needed to be recognized. Third, research the suitability of current ontology technologies for creation of a maintenance "reasoner" knowledge base. Value-added results included: creation of a new text pre-processor specific to maintenance records, that improves the performance of baseline NLP part-of-speech tagging and entity extraction methods, and a program to identify similar text entries amongst large textual data stores and categorize them by degree of differentiation (Bokinsky et al., 2013).

7. Conclusion

There are many advantages that can be gained, in comparison to standard maintenance practices, by having a proper understanding of the PM process and applying it in an IoT environment. The failure points of the aircraft should first be established by creating an optimized maintenance plan through input of the industry community and regulatory bodies. This scheduled maintenance should be based on safety, reliability, and the

cost repairing the aircraft. It can be further enhanced by HUMS capability on the aircraft. PM through the use of historical records, testing, and technical documents allow the user to advance their knowledge of the health of components further than basic inspections could yield. When PM is based in an IoT environment it creates a streamline process that leads to less downtime and more informed decisions on the maintenance that needs to be performed on the aircraft. Proper implementation will help reduce maintenance burden, prevent unnecessary maintenance actions, increase safety, increase system readiness, refine the maintenance process, and ultimately improve component design.

CPM has been heavily involved in this effort in many projects to make sure that PM is advancing to its full capability in the field. The philosophy has worked well for the center and lead to an increase in cost avoidance for the Army on rotor blades, tail rotor gearboxes, and hanger bearings. This also resulted in: an increased time on wing for tail rotor gearboxes and hanger bearings and increased health monitoring capability through tachometer clearance, enhanced natural language processing techniques, sensor development, and increased diagnostic algorithms. This solution has already shown results and will continue to do so, not just on aircraft, but to any system to which it is applied.

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