



**INTEGRATED SYSTEMS HEALTH MANAGEMENT AS AN ENABLER FOR
CONDITION BASED MAINTENANCE AND AUTONOMIC LOGISTICS**

DISSERTATION

Robert M. Vandawaker, Lieutenant Colonel, USAF

AFIT-ENV-DS-15-S-050

**DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY**

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Abstract

Health monitoring systems have demonstrated the ability to detect potential failures in components and predict how long until a critical failure is likely to occur. The decision to implement these systems on fielded structures, aircraft, or other vehicles is often a struggle due to the difficulty of demonstrating to prove cost savings or operational improvements beyond improved safety. A system architecture to identify how the health monitoring systems are integrated into fielded aircraft is developed to assess cost, operations, maintenance, and logistics trade-spaces. The efficiency of a health monitoring system is examined for impacts to the operation of a squadron of cargo aircraft revealing sensitivity to, and tolerance for, false alarms as a key factor in total system performance. The research focuses on the impacts of system-wide changes to several key metrics: materiel availability, materiel reliability, ownership cost, and mean downtime. Changes to these system-wide variables include: diagnostic and prognostic error, false alarm sensitivity, supply methods and timing, maintenance manning, and maintenance repair window. Potential cost savings in maintenance and logistics processes are identified as well as increases in operational availability. The result of this research is the development of a tool to conduct trade-space analyses regarding the effects of health monitoring techniques on system performance and operations and maintenance costs.

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Robert M. Vandawaker

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INTEGRATED SYSTEMS HEALTH MANAGEMENT AS AN ENABLER FOR CONDITION BASED MAINTENANCE AND AUTONOMIC LOGISTICS

I. Introduction

The state of health for major infrastructure and transportation systems nationally and globally is deteriorating. Aircraft, in particular, are an example where lengthening service lives and budget constraints can affect the safety of the vehicle and the occupants. Currently, more frequent inspections are required as service life increases to ensure safety of the users and the environment. The I-35W Mississippi River bridge collapse in Minneapolis in 2007, for instance, resulted in loss of life and drove a massive inspection cycle for United States highway infrastructure (Modares & Waksanski, 2012). Maintenance strategies must change to meet the extended in-service requirements and the constraints imposed by shrinking government and industry budgets.

Across many industries, systems are exceeding their intended design lives, whether they are ships, bridges or US Air Force aircraft. Structural health monitoring (SHM) research and application has the potential to lengthen the service life of a range of systems and, in some cases, predict failure modes and times. As such, funding and research are focused on researching new technologies and applications. However, the cost of large scale implementation in the case of hundreds of aircraft or approximately 70000 “structurally deficient” highway bridges is a significant hurdle to overcome in most instances (Shoup, Donohue, & Lang, 2011). The impact of shrinking budgets can also reduce inspection frequency or delay needed repairs in favor of only performing

mission critical tasks (Roach, 2009). Condition based maintenance (CBM) is an evolving maintenance concept with a goal of reducing maintenance and thus life cycle costs while increasing operational availability. It is made possible, in part, by leveraging health monitoring techniques. Integrated system health management (ISHM) incorporates health monitoring functions across a platform to provide system-wide state of health diagnostics and prognostics. The impact of ISHM and CBM on performance, cost, and supply chain as well as traditional maintenance inspections and practices is the focus of this research.

With the F-35 maintenance and logistics alone projected to cost \$1.1 trillion over the 55-year life span amid shrinking defense budgets, the need to reduce the life cycle cost (LCC) of military aircraft is paramount (Shalal-Esa, 2013). Legacy aircraft may not be fitted with the proper sensors to fully implement health assessment leading to costly inspections, in both time and maintenance dollars. The inspections result in reduced operational availability (A_O) and budget available for other needs. Figure 1 depicts the operational concept of a condition based maintenance system enabled through integrated systems health management.

One method for improving operational availability through the implementation of integrated health monitoring is by using data collected to forecast and group maintenance tasks to reduce total downtime. This reduction can be realized through the elimination of multiple set-up, tear-down, and reassembly cycles in favor of a single cycle with numerous maintenance actions accomplished during that downtime. Further efficiencies may be realized through the scheduling of maintenance personnel based on knowing when and what repairs are required prior to beginning any maintenance activity.

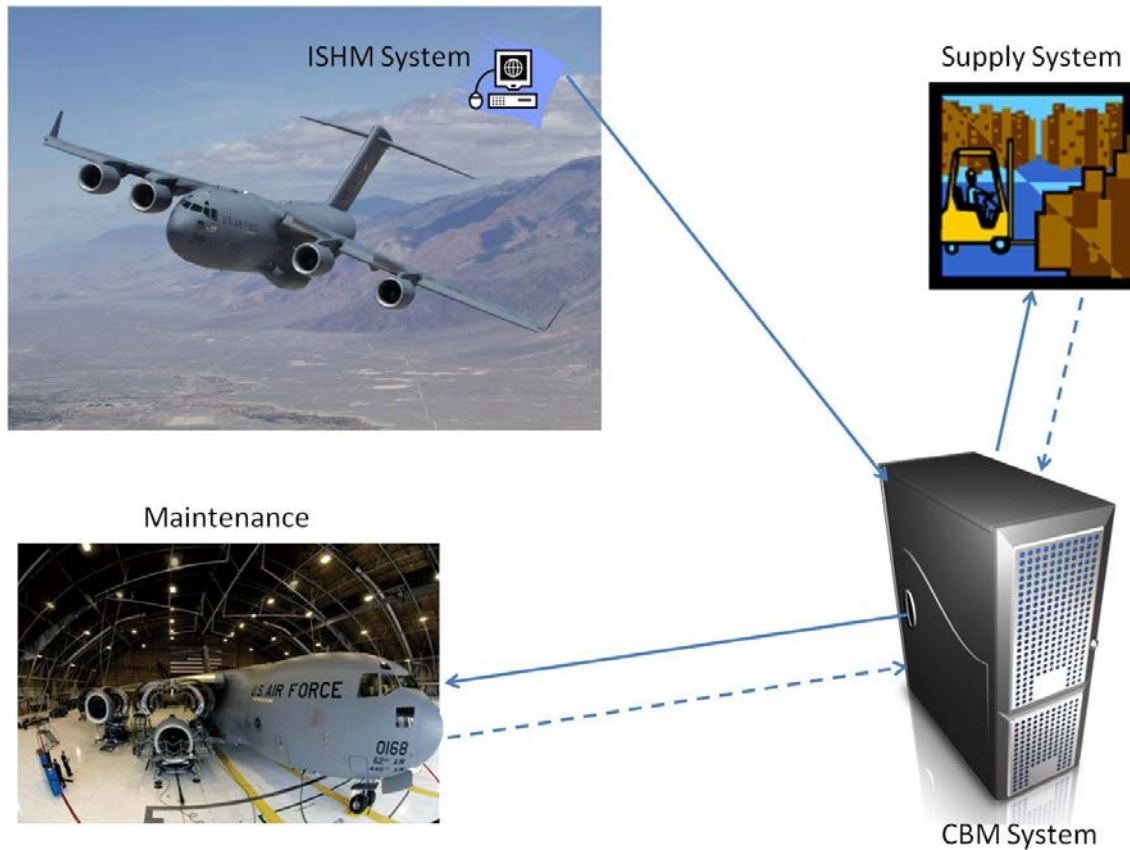


Figure 1. ISHM/CBM Operational Concept

Mean downtime (MDT) is a measure of the efficiency of maintenance and logistics processes. MDT is the total time from when the element of a system is taken out of service until it is again declared fully mission capable, as opposed to mean time to repair which is the hands-on maintenance repair portion. The DoD predicts that by implementing CBM MDT will be “significantly reduced” by performing demand versus time-driven maintenance (Under Secretary of Defense (AT&L), May 2008). Research by Derriso (2013), however, shows the MDT may actually increase as the system will only be taken down for maintenance rather than additional time-based inspections, which are

often short in duration. He also observes that total downtime is reduced for the ISHM versus the baseline time-based case.

What is missing from the mean and total downtime measures is the value of those times. Is the time being spent troubleshooting symptoms, locating a fault, or waiting on parts, as in the baseline case? If the time is spent only on repair of the system because the ISHM/CBM system predicted and isolated the failure as well as ordered parts to meet the demand, that time can be thought of as having more quality behind it. This downtime quality reflects added benefit provided by the ISHM/CBM system.

Problem Statement

While health monitoring techniques continue to evolve, the capability to study their cost and availability impacts across flight, maintenance, and logistics realms remains a difficult task.

Research Objective

Even with a policy that requires its implementation, CBM has to “buy its way” into the program. Service leadership and the program and support managers want to do the right thing for the warfighter, but a return on the investment must be identified and justified. In the long run, any Service effort to develop and deploy CBM should be leveraged by other platforms and programs (Under Secretary of Defense (AT&L), May 2008, p. 1-7).

This research seeks to determine the design and implementation processes to thoroughly integrate ISHM, CBM and logistics systems to define operational and cost trade-spaces for multiple systems with multiple subcomponents in each system.

These examinations require a comprehensive model that explores the interconnections between multiple systems each having numerous components that can provide greater detail on the impacts of changes in one area propagating throughout the remainder of the model. This research focuses on the potential benefits to A_0 and operations and maintenance (O&M) cost through the use of ISHM systems to enable CBM. This in-turn provides a detailed examination of trade-offs available to the user. Providing a means to explore A_0 and cost impact with the opportunity to improve both and reduce manpower requirements is of great interest to program managers, system operators, and financial planners

Investigative Questions

The questions posed in this dissertation include the following:

1. What are the key cost and effectiveness drivers for an ISHM enabled CBM and autonomic logistics process?
2. What is a reasonable and appropriate scope for model development to establish performance requirements for ISHM sensors and prognostics, maintenance, and logistic processes?
3. What are the operations and maintenance cost impacts of an ISHM enabled CBM system?
4. Is mean downtime a good measure of system performance for ISHM/CBM systems?
5. Does maintenance grouping based on prognostics improve operational availability, total downtime and cost?

Methodology Overview

The approach taken in this research builds upon prior work on health monitoring, condition based maintenance and logistics. An Arena[®] model is developed incorporating

systems architecture principles to analyze cost and availability impacts of proposed concepts of operation. A baseline (current) case is compared to the same aircraft with a health monitoring system implemented. Analysis of support levels, both maintenance and supply, are examined in conjunction with health monitoring techniques.

The first step in creating the model is to determine both the baseline and ISHM/CBM designs, which are found in system architectures presented in chapters 3 and 4. The inputs required and relevant for each process are identified from this architecture. Defining the reliability and maintainability of the system is next with collection and utilization methods discussed later. Next, the processes are modeled and output parameters required for the measures of effectiveness and measures of performance are evaluated. The model captures accumulated effects on system performance and aircraft life. These outputs are then analyzed to determine the impacts of ISHM/CBM on the system as a whole.

A baseline model, reflecting current maintenance and supply policies and capabilities is the first step for validation of model performance and to provide a starting point for system performance. Building upon the baseline “as-is” model, the inclusion of health monitoring and prognostics augments or replaces current maintenance inspection and preventive replacement procedures. Utilizing the prognostic capabilities of the health monitoring system, information about impending failures and system requirements is fed into the supply system to attempt to match the aircraft need with logistics capabilities. Based upon logistics, maintenance, and operational requirements, a time frame to

maintain the aircraft is projected to balance these requirements with the goal of keeping operational availability high and cost low.

The aircraft under study in this research is the C-17 Globemaster III. These aircraft are currently fully fielded in the USAF inventory and they are planned to be in the fleet for a long duration. The C-17 employs CBM techniques to an extent, with limited built in test capabilities and diagnostics (Smith, 2003). While particular aircraft subsystems represented in the model are simulated, they do not represent actual aircraft systems. Therefore, this model can also be readily applied more broadly to USAF cargo aircraft not just the C-17. Mission profiles and preflight activities utilized are representative of transport aircraft operations and yearly flying hours are comparable to the C-17. This model will process a squadron of 12 aircraft through current operational activities and compare those results to the same squadron with health monitoring, condition based maintenance and a supply system interwoven with these advanced techniques.

Assumptions/Limitations

Assumptions in this research are done in an effort to limit the scope and complexity of model. While further assumptions are contained in chapters 3-7, those relevant to the entire work are:

- A squadron of 12 aircraft is used for modeling and analysis;
- All components of interest have monitoring sensors;
- All components are non-repairable, that is, replaced versus repaired when required;

- Performance impact to the aircraft from weight and power requirements of the ISHM system and sensors is negligible;
- One subsystem comprised of 20 unique components is modeled;
- Inflation is not considered;
- Military deployments are ignored;
- Personnel are devoted to the aircraft in the model;
- Only direct maintenance actions required for the components under study are recorded.

Limitations of this work lie in that capturing costs savings may not be directly possible for military systems due to deployments, allocation of personnel across multiple systems and the mix of uniformed and contractor personnel

Implications

This research model has the potential to not only reduce aircraft O&M costs, but also to improve availability and reduce maintenance manning and/or workload. This work allows for the visualization of system processes and the impact of health monitoring techniques on overall performance. Further, the methods and techniques used herein are applicable to other vehicle types and systems.

A key impact of this work is the ability to analyze the effects of new health monitoring techniques by inputting them into the model and studying the performance outcomes. Alternatively, if a desired aircraft or logistics performance level is established, a trade study can be performed to determine health monitoring or prognostics requirements necessary to meet those demands. In general, this research provides for the analysis of ISHM enabled CBM and supply strategies for military system with emphasis on cost and availability impacts.

This work demonstrates that it is possible, based on a limited set of components, for significant savings to be realized in the maintenance and logistics direct costs and through a reduction in required personnel. Additionally, increased availability of aircraft allows for fewer aircraft to do the same mission.

Preview

This dissertation is organized as follows. Chapter 2 provides a review of literature relevant to this research and identifies gaps that this work studies. Chapter 3 establishes a system architecture and measures of effectiveness for model evaluation. Chapters 4 through 6 are drawn from manuscripts published, in review, or to be submitted. Chapter 4, titled “Prognostic Uncertainty,” addresses investigative questions #1 and #2 identified above. This chapter has been published in The International Journal of Prognostics and Health Management with the article titled *Impact of Prognostic Uncertainty in System Health Monitoring*. Chapter 5, titled “Component Supply Methods,” explores the effect of a health monitoring system on supply methodologies and addresses questions #1, #2 and #3 identified above. This chapter is drawn from a manuscript titled *Health Monitoring Impact on Non-Repairable Component Supply Methods* that will be submitted to Decision Sciences. Chapter 6, titled “Maintenance Manning Processes,” addresses research questions #1 through #4. The text is from a manuscript titled *An Examination of System Health Monitoring Impact on Non-Repairable Component Maintenance Manning* that will be submitted to the Journal of Quality in Maintenance Engineering. Chapter 7 examines investigative questions #4 and #5 with an exploration of the grouping of

component replacements. Finally, chapter 8 provides overall research conclusions and recommendations.

II. Literature Review

Chapter Overview

This chapter provides background information on key concepts and techniques within the health monitoring, maintenance and supply realms. These topics are addressed in this chapter in an effort to identify gaps in current research. Within each of the realms, technologies and policies that enable condition based maintenance are discussed with a focus on cost and system availability. The topics covered herein form the foundation for the development of an architecture for analyzing the effects of ISHM on CBM and the supply chain. Additionally, chapters 4-7 contain background and motivation specific to the topics covered therein.

Health Monitoring Concepts

Structural health monitoring (SHM), while sometimes applied as monitoring for a system at large, is a set of techniques used either individually or in conjunction with others to determine the status of structural components of a vehicle or system. SHM systems use a variety of techniques to detect the onset or growth of damage, i.e., cracks or delaminations, prior to failure. Other health monitoring sensing systems exist to monitor electrical or electronic systems as well as rotating machinery (aircraft engines) or hydraulic systems. A good review of SHM technology and application is found in (Glaser, Li, Wang, Ou, & Lynch, 2007). Integrated vehicle health management (IVHM) and integrated systems health management (ISHM), used interchangeably in published

works, seek to compile the various SHM and other sensor networks and interpret the health of the vehicle or system as a whole. This processing can be done on or off-board the system in question depending on system intent and requirements.

Prognostics and health management (PHM) is synonymous with IVHM and ISHM in most literature, emphasizing the prognostics capability to determine the remaining useful life (RUL) of a component. RUL is then used to aid in the determination of when and how to maintain the system. Examining the RUL of individual components or subsystems can assist in maintenance planning and in supply requisitions, transitioning from time-based replacement to repair or replacement based on actual material condition. The use of RUL information for mission planning, maintenance optimization and supply chain management is often referred to as autonomic logistics (AL) as the ISHM system performs these functions with little or no human interaction. Progressing from the component level sensing systems through the compilation of their data and forecasting of impending failure enables the transformation in maintenance concepts. Hess (2005) decomposes prognostics and health management (PHM) with three terms:

- ***Enhanced Diagnostics:*** *the process of determining the state of a component to perform its function(s), high degree of fault detection and fault isolation capability with very low false alarm rate;*
- ***Prognostics:*** *actual material condition assessment which includes predicting and determining the useful life and performance life remaining of components by modeling fault progression.*
- ***Health Management:*** *the capability to make intelligent, informed, appropriate decisions about maintenance and logistics actions based on*

diagnostics/prognostics information, available resources and operational demand. (p. 3)

These three terms, while broad, form the foundation for measuring the effectiveness of an ISHM/CBM system. Enhanced diagnostics encompasses probability of detection as well as false alarms, directly impacting how often the aircraft must be taken out of service for inspection and/or repair. Prognostics are the ability of the system to forecast the remaining useful life of the aircraft, safety of flight and prediction of impending failures. Health management takes the data from the previous two and determines when to order spares and when to perform maintenance.

Maintenance Concepts

Maintenance has evolved over time from a “fix it when it breaks” policy to the current focus on condition based maintenance programs. Table 1 presents a categorical breakdown of maintenance approaches and their attributes. Rising costs, longer service lives and reduced manpower have driven a proactive approach to maintaining systems. The reactive or corrective maintenance approach forces either a costly spares stockpile to prepare for all possible failures or waiting for replacement parts to arrive resulting in lower operational availability (Amari, McLaughlin, & Pham, 2006). One of the first advancements in maintenance practice was to establish regular inspection and preventive maintenance (PM) intervals. These time-based techniques analyze failure data, either anecdotal or service history, to determine appropriate timelines to inspect and replace components or systems (Walls, Thomas, & Brady, 1999). This PM approach results in reduced catastrophic failures and more predicted maintenance cycles (Deputy Under

Secretary of Defense for Logistics and Materiel Readiness, May, 2008). Unanticipated failures still occur outside the preprogrammed maintenance windows and must be taken into account.

Additionally, PM subjects the system to unnecessary “repair” based on the required schedule for the system. The unneeded repair adds extra expense to the system since the component had remaining useful life, and it increases the probability of damage resulting from the maintenance action. The diagnostic CBM approach is based on inspections, visual, automatic, non-destructive, and the like, and parts are then repaired or replaced as required. The prognostic CBM approach goes a step further than the diagnostic approach and takes the data from the inspections and forecasts when repairs or replacements are required. As Iyooob, Cassady, and Pohl (2006) point out, a majority of studies related to maintenance practices ignore limited budget, manpower or time constraints. They present logic for determining maintenance actions when the time between missions does not provide the opportunity to make all desired repairs.

Condition based maintenance and other predictive maintenance programs have further evolved from preventive strategies to analyzing system health and forecasting remaining life. Time-based inspections alone will not detect all failures, especially if the inspection timing associated with the component is such that a critical defect occurs at an unanticipated interval. The location of the defect also plays an important role in the failure detection. If the defect is located in an infrequently inspected or difficult to access area, a small amount of damage can grow to catastrophic amounts prior to detection. In

such instances, the appropriate application of SHM technology can potentially save a system from severe or catastrophic damage.

Table 1. Range of Maintenance Approaches

Maintenance Approaches				
Category	Reactive	Proactive		
Sub-Category	Run-to-fail	Preventive	Predictive	
	Fix when it breaks	Scheduled maintenance	Condition-based maintenance-diagnostic	Condition-based maintenance-prognostic
When Scheduled	No scheduled maintenance	Maintenance based on a fixed time schedule for inspect, repair and overhaul	Maintenance based on current condition	Maintenance based on forecast of remaining equipment life
Why Scheduled	N/A	Intolerable failure effect and it is possible to prevent the failure effect through a scheduled overhaul or replacement	Maintenance scheduled based on evidence of need	Maintenance need is projected as probable within mission time
How Scheduled	N/A	Based on the useful life of the component forecasted during design and updated through experience	Continuous collection of condition monitoring data	Forecasting of remaining equipment life based on actual stress loading
Kind of Prediction	None	None	On- and off-system, near-real-time trend analysis	On- and off-system, real-time trend analysis

(Deputy Under Secretary of Defense for Logistics and Materiel Readiness, May, 2008)

Why CBM?

Condition based maintenance, when appropriately applied, can reduce the life cycle cost of a system. The United States Department of Defense has implemented a program, known as condition based maintenance plus (CBM+), to encourage the implementation of processes in support of CBM across the DoD. Department of Defense

Instruction (DoDI) 4151.22 defines CBM+ as “the application and integration of appropriate processes, technologies, and knowledge-based capabilities to achieve the target availability, reliability, and operation and support costs of DoD systems and components across their life cycle” (Under Secretary of Defense (AT&L), May 2008, p. 1-1). CBM is a demand driven maintenance process based on indications of stress or impending failure of a component or system. Ellis (2008) argues that cost-effective systems monitoring allows repair actions based on system condition rather than costly time-based maintenance. The health monitoring system monitors component sensor data until a predetermined point prior to failure, then triggers maintenance to repair or replace the part. CBM can also proactively examine other systems in the vehicle or structure as well and compile this data with projected use to determine the maintenance window that optimizes downtime, manpower and spares. Additionally, interim, time-based inspections required under the baseline PM approach are forgone in lieu of continuous analysis of the aircraft via the ISHM system (Ellis, 2008).

CBM Life Cycle Cost Impacts

The real challenge is to develop valid and measurable metrics for quantifying the impact of the various prognostic technologies. The first step is to process a cost/benefit analysis using appropriate modeling tools, for each component and/or subsystem/system to evaluate the consequences of developing and supporting each component (Hess, Calvello, Frith, Engel, & Hoitsma, 2006, p. 6).

Published literature shows the cost-saving potential of condition based maintenance and health monitoring systems across the life cycle:

- 40% for vehicle maintenance (Walls, Thomas, & Brady, 1999)
- 30% to 50% for fuselage panels (Pattabhiraman, Kim, & Haftka, 2010)
- 10% electrical components (Scanff et al., 2007)
- 50-80% for the Boeing 777 (Gorinevsky, Gordon, Beard, Kumar, & Chang, 2005).

The issue in many of these studies is the failure to capture costs outside of a few components and generally restrictive assumptions. Additionally, most do not address how the prognostics of ISHM can impact supply timing and costs. Since maintenance can be forecast to match impending failures, personnel hours can be managed accordingly to meet demand.

Several authors have researched and proposed methods of considering life cycle costs (LCC) for systems, and they discuss methods for conducting cost/benefit analyses on diverse systems to determine the impact of an ISHM system on the O&M cost and LCC of a system, but fail to include logistics in their analyses. Brand and Boller (2000) use inspection times, research and development, and labor costs for higher level cost and time savings to explore inspections on commercial aircraft. Walls, Thomas and Brady (1999) examine a single critical component of hydraulic servos utilizing a decision tree to assess probability of failures and MTBF of the components, neglecting sensor inputs. Lugtigheid, Banjevic, and Jardine (2005) discuss repair or replace decisions with imperfect repair, but fail to use prognostics to inform their repair decisions, instead utilizing preventive maintenance approaches. Banks, Reichard, Crow and Nickell (2005) explore battery systems for armored vehicles using prognostics to calculate savings

through a return on investment based on replacement decisions. They discuss logistics inputs, but do not include them in the model.

Amari, McLauchlin, and Pham (2006) research CBM with manual inspections at predetermined intervals and the effect of use conditions on the wear rate of components, utilizing a Markov process to study cost savings. Pattabhiraman, Kim and Haftka (2010) compare manual versus ISHM based inspections utilizing maintenance, manufacturing and fuel costs for an aircraft. Further Pattabhiraman, et al, discuss a hybrid model of manual and ISHM inspections on a system. Gyekenyesi (2013) discusses a transitional approach for legacy systems not previously fitted with health monitoring systems and for systems with inadequate coverage by using non-destructive inspection (NDI). He further states that NDI can provide confirmation or added peace of mind for ISHM system results while the users of health monitoring systems gain trust in the prognostics. Pattabhiraman et al., (2010) also discuss a hybrid model for critical items which could be applied in a similar manner as Gyekenyesi. While these methods should produce savings, they are not addressed in this research.

Wilmering and Ramesh (2005) assessed the impact of ISHM approaches on overall system ownership costs. They argue for a system engineering approach to assess and blend requirements with technologies through the life cycle of a system to reduce cost. A seven step method is used to rank ISHM solutions on the basis of component criticality, failure modes, sensor technologies and ISHM approach to perform a cost/benefit analysis. This method is similar to the failure mode, effects, and criticality analysis (FMECA) outlined by Blanchard and Fabrycky in *Systems Engineering and*

Analysis, (2005). The aforementioned process is conducted within The Boeing Company Ownership Cost Calculator for Aerospace health Management (OCCAM) tool. The OCCAM tool captures maintenance and logistics processes, both recurring and non-recurring costs. A key item examined is what happens when a part fails, specifically the impact on the maintenance and logistics process. Labor rates, material costs, inflation and discount rates are combined to determine the cost impact of decisions. Two limiting assumptions in this model are that a fixed spares demand is assumed rather than component utilization projected by the health management system, and repairs are perfect. The tool also provides for some maintenance scheduling based in part on LCC; this neglects the impact on availability of the aircraft which can play a large role.

Modares and Waksanski (2012) state early detection of faults with health monitoring can limit repair costs and catastrophic failures. In offshore wind turbines, SHM tools, maintenance scheduling, and performance of the SHM system determine the added value of the system of systems (A. Van Horenbeek, Van Ostaeyen, Duflou, & Pintelon, 2013). Van Horenbeek et al. (2013) lay out a system of equations that includes as inputs: failure cost; component reliability; maintenance costs; and spare parts costs, to determine the added value of health monitoring for a system. This system provides a thorough examination for a single system with multiple subcomponents. It does lack, however, inventory management and the effects of multiple systems operating simultaneously.

The cost of the ISHM/CBM system must be accounted for in the LCC evaluation as well. While the long term O&M costs may be significantly reduced, the upfront cost of

development and deployment of the systems is not inconsequential. With the development cost for the F-35's ALIS system approaching half a billion dollars, the technology and training costs play a role (Butler, 2013). Degradation of the ISHM/CBM system must be taken into account as well as degradation in the overall system, in this case aircraft performance (e.g., increased weight and power requirements).

Not germane to the LCC methods discussed above is a cost benefit analysis and the translation from private, for profit frameworks, to military applications. Assigning cost impacts of downtime for a commercial aircraft is different than for a military aircraft. While maintenance and spare parts costs are counted in both, the cost of not having the plane in operation is quantifiable, at least on a broad scale, in the commercial sector. Lost revenue, penalties for occupying gates too long, transferring another aircraft to accommodate passengers, the cost of refunding or transferring passenger tickets can all be valued. On the military side, attempting to value downtime and ultimately operational availability is a much more difficult task. A thorough examination of the system capabilities, costs and infrastructure paired with the logistics, operating and maintenance requirements must be accomplished to accurately assess the viability of an ISHM system to reduce the cost of a CBM program.

By the DoD's own admission, the accuracy of current LCC figures is a rough estimate as credible means to measure it are not readily available (Under Secretary of Defense (AT&L), May 2008). In an attempt to gain a clearer picture of the true cost of a system, the DoD also proposes a Total Life Cycle Systems Management (TLCSM) metric of cost per unit of operation as what it calls "the best measure of life-cycle costs,"

(Under Secretary of Defense (AT&L), May 2008). Ryan's assessment of the DoD LCC cost accuracy echoes those above, "[d]espite the fact that DoD cost estimating practices have become increasingly sophisticated, the actual program cost estimates that are produced remain poor, at least when compared to the final, actual costs of the program" (Ryan, Schubert, Jacques, & Ritschel, 2013, p. 73). Capturing these costs in the respective baseline and ISHM models will likely also be difficult. Millar (2007) cites that the market's "invisible hand" holds back implementation and that systems engineering has thus far not demonstrated the case for use of ISHM to support system sustainment. The "invisible hand" referred to includes DoD and USG policies that direct the Air Force practices in acquisition, maintenance and supply. Additionally, while the goal is to save the taxpayers money, the DoD does not have the commercial profit requirement and pressure found in industry.

Maintenance Activity Grouping

The goals of grouping maintenance activities utilizing prognostics are reduction in cost to maintain and increased operational time. The cost savings in grouping maintenance activities comes, in general, from a reduction in set-up, tear-down and reassembly times, yielding a reduction in labor costs for multiple individual repair actions. Operational availability is increased likewise as the total downtime required for these repairs or replacements is reduced. The earlier a maintenance action is scheduled, the more useful life is wasted but, in general, the probability of failure is lower.

Prognostics, enabled through onboard sensor systems allow the useful life to be consumed up to a predetermined risk level based on uncertainties in the system.

Camci (2009) utilizes a genetic algorithm approach to optimize maintenance for the CBM case but does not examine the benefits over a PM system. The approach shows improvement in the generic cost of optimized maintenance using prognostic versus prognostics enabled CBM alone. Van Horenbeek and Pintelon (2013a; 2013b) use a heuristic search algorithm to determine the optimal maintenance time and group with results showing prognostic maintenance (CBM) superior to standard time-based maintenance policy. The approaches used by Camci and Van Horenbeek represent most of the work in this area, but do not address the impact of multiple systems with multiple components and only seek to optimize for cost with little notion of the impact to system operational availability.

Remaining Useful Life

Since achieving the theoretical limit of 100% failure avoidance is both impractical and wasteful, we are forced to accept some level of risk. (Hess et al., 2006, p. 9)

While the methods and techniques used for remaining useful life (RUL) calculations are outside the research proposed here, their use is essential for the CBM maintenance and supply processes. A good summary of RUL techniques is found in (Si, Wang, Hu, & Zhou, 2011). Risk posture and acceptance established by policy or unique mission needs help to determine when the CBM system calls for replacement of a given

component or system. This understanding is necessary because RUL calculations have inherent uncertainty as they are generally derived based upon probability distributions. After probability of detection, which is a function of the sensor type and software, remaining useful life prognostics are the most vital processes performed by the ISHM portion of the ISHM/CBM system.

RUL inference must take into account the P-F curve in Figure 2 for individual components, where P is the potential failure or point at which deterioration begins or is detected. The F is the functional failure or where the part or system actually breaks. The horizontal lines on the curve correspond to limits that are either functions of the system or prescribed by policy or directives. System detection limit is a function of the ISHM system and physical attributes of the aircraft; the point of detection (B) occurs where the failure curve of the component crosses the detection limit. Notification, a policy driven component, occurs at point C and begins the CBM supply and maintenance planning window. For components with safety limits, i.e., those that would cause a catastrophic loss, point D is where the system would be taken down for maintenance.

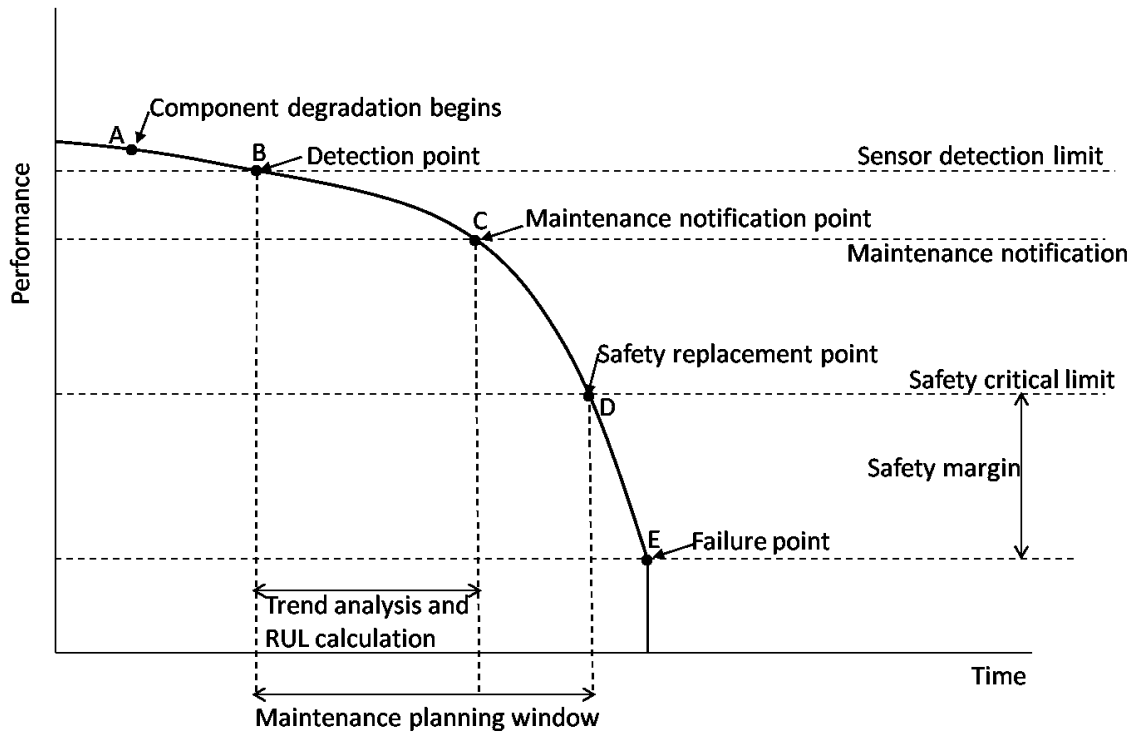


Figure 2. Remaining Useful Life Schematic (Jennions, 2011)

In the case of a time or prediction based “failure” when the part is replaced with some serviceable life remaining, policy based on observed and physics based estimates of failures dictates the appropriate time frame. The goal is that the probabilistic estimates of RUL based on real time monitoring allow increased time to accumulate on parts, thus increasing the MTBF for the ISHM aircraft and total costs associated with replacement parts.

Supply Chain Forecasting for ISHM Aided CBM Systems

ISHM systems in the US Air Force are currently limited to the F-22, which requires manual collection and analysis of sensor data, and test articles on individual

systems and limited engine monitoring systems on several other platforms. These efforts are not integrated with the logistics chain to optimize maintenance actions with supply requirements. While individual systems addressing health monitoring exist in the USAF inventory, e.g., F-22 and C-17, the future goal of Air Force ISHM/CBM integration, lies in the F-35. One of the F-35's keys to success and reduction in O&S costs is the Autonomic Logistics Information System (ALIS).

ALIS was designed to be a one-stop system to monitor aircraft systems, predict system failures, increase maintenance efficiency and streamline the supply stream by combining the range of systems currently in use for existing Air Force aircraft. The F-16, which is the standard for legacy aircraft, has separate and distinct systems for supply, maintenance, and pre and post mission inspections (Butler, 2013). These legacy systems require multiple career fields and administrative processes that increase the turn time between aircraft missions. Communication between the aircraft and ground systems by ALIS allows optimization of down-time and prepositioning of required parts, ensuring maintenance personnel maximize the availability of the aircraft. An example of maintenance time savings is the use of electronic tracking of fluid levels versus manual gauges. Additionally, Butler (2013) states that flight control maintenance on the F-35 is reduced from 8-14 hours on legacy aircraft to 5 minutes. Further details on this dramatic reduction are not provided in the article. When maintenance actions across the F-35 are compounded, the potential for large downtime savings is immense. Whether or not these savings can be realized is yet to be seen. As the F-35 approaches initial and then full

operating capability, maintenance and logistics data will be analyzed to determine the true value of the ALIS system.

Perhaps the key feature of ALIS is the prognostic capability. The prognostics and health management (PHM) system of the F-35 shifts maintenance policy from preventive time-driven routines to condition or demand driven actions. The PHM system calculates the remaining useful life of a system or component which flows into the supply pipeline to ensure lead times for part orders are met when maintenance is required. The fielding of ALIS or any similar component or vehicle-wide system on legacy aircraft will require concept of operations (CONOPs) changes for maintenance and operations. These changes, while they must be enforced and driven from higher command levels, must obtain “buy-in” at the squadron level as they are unproven and potentially unreliable. Byer, Hess, and Fila (Byer, Hess, & Fila, 2001) project that PHM’s automation capability can eliminate bureaucracy built up in military logistics and supply systems. If operational change can be affected, streamlining the maintenance, supply and operations activities proposed in the ALIS system are achievable.

The ALIS system is not without problems though, along with the rest of the F-35 program. With a development cost approaching \$448 million, ALIS is not yet proven and has security flaws (Butler, 2013). Additionally, the system is behind schedule and fails to meet maintenance and sortie generation requirements for the F-35. “To date, diagnostic system performance has failed to meet basic functional requirements, including fault detection, fault isolation, and false alarm rates,” (Director, Operational Test & Evaluation, 2013, p. 49). In the interim, manual intervention by maintainers, using legacy

aircraft techniques, and contractor support are used to keep the aircraft flying thus negating the cost savings that could be afforded by the ALIS system.

Logistics Methods

Supply chain optimization is handled in many ways across industry. Some smaller businesses manufacture all required parts in house and fix them as needed. This is seldom the case though and most businesses and industries depend on collaboration with other agencies.

In the commercial world, profit is the end goal for companies and should be the selling point for ISHM systems. As Grubic (2009) points out, PHM can shift the operating paradigm for a system but capturing the impact to potential increases in revenue is often overlooked aside from the often cited reduction in maintenance costs. The ability to foresee maintenance issues and optimize when systems are taken offline for repair is a key part of this revenue generation. Unplanned downtime drives millions of dollars in cost for organizations with unplanned maintenance costing three to ten times that of scheduled or predicted maintenance activities (Taft, 2013). This is a key difference between military and commercial activities in the logistics and maintenance area. Commercial companies are in business to make a profit, whereas military forces face no such requirement other than to be good stewards of taxpayer dollars.

In the commercial aerospace field, Boeing is an industry leader in analyzing logistics requirements for aircraft fleets. Boeing's Airplane Health Management (AHM) system takes real-time data from the aircraft to identify and diagnose faults. This data is

used to provide error identification and historical tracking to aide in fault troubleshooting to optimize operations and maintenance efficiencies (The Boeing Corp, 2013).

Additionally, Boeing developed an Arena[®] discrete event simulation model for the civil aviation sector to analyze the performance of health management options. (Williams, 2006) The AHM system performs similar functions as the ALIS system, with the commercial addition of providing a decision tool to conduct critical profit analyses. As shown with both the ALIS and AHM systems, prognostics integrated with maintenance and supply chains can enable condition based maintenance. It is this end state that the Air Force and DoD as a whole is striving to meet, not to turn a profit as in private industry, but to continue operations in a shrinking fiscal environment.

Air Force Supply Issues

The General Accountability Office conducted several audits of DoD and in particular Air Force supply systems over the past 20 years. Their findings range from lack of items to enormous on-hand stock and unneeded parts on order accounting for billions of dollars in unneeded parts and operational rates well below goals. (Government Accountability Office, 2001; Government Accountability Office, 2007) “Having spare parts available when needed to perform required maintenance is critical to the Department of Defense’s accomplishment of its missions. Shortages of spare parts are a key indicator of whether the billions of dollars annually spent on these parts are being used in an effective, efficient, and economical manner,” (Government Accountability Office, 2001, p. 1). “In January 2001, we reported on Department of Defense

management challenges and noted that the Department has had serious weaknesses in its management of logistics functions and, in particular, inventory management,” (Government Accountability Office, 2001, p. 3). These GAO reports along with several DoD initiatives to correct the findings are discussed in this section.

The spare parts shortage leads maintainers to cannibalize parts, leading to extra work to fix the aircraft they “borrowed” from. This cannibalization opens the possibility of damaging the needed part in removing it from the donor system as well as causing collateral damage in the process. The “borrowed” part will also generally not last as long as a new component, thus requiring additional maintenance (Government Accountability Office, 2001). Reasons for parts shortages range from inadequate forecasting, repair and manufacturing issues, poor replacement part reliability, and contracting problems. In one extreme example, demand for an engine bolt was projected at 828 units when actual requirements were over 12,000 in a single quarter. (Government Accountability Office, 2001) While this is an extreme example, it is indicative of problems with the forecasting models used by the Air Force to determine part requirements. This issue was still present in a 2010 review of DoD logistics citing poor requirements projections as a leading cause of inventory shortages and surpluses (Atchley et al., 2010). Implementing ISHM/CBM systems on a broad range across the service would increase the forecasting capability and provide near real time insights into requirements, both existing and in the near future. Between 2002 and 2005 Air Force spares shortages were, as seen in the Table 2 below, between 6 and 8% of total requirements averaging over \$1 billion in shortfalls. The reasons given then were the same as in 2001 and again in 2010.

Table 2. Air Force Inventory Shortages from FY 2002 through FY 2005

Dollars in billions				
Fiscal year	Value of total requirements	Shortages		
		Number of items	Value	Percent
2005	\$15.8	371,961	\$1.2	7.6%
2004	15.8	691,509	1.1	7.0
2003	14.6	356,977	0.9	6.2
2002	14.4	428,195	1.2	8.3

(Government Accountability Office, 2007)

A shortage of spares is not the only issue facing the Air Force. The GAO (2007) stated that Air Force on-order spares without projected need for future use accounted for \$1.3 billion or 52% of on-order parts. DoD and Air Force policy do not incentivize or in some cases allow for cancellation of orders without significant monetary penalties. Additionally, between 2002 and 2005 65% of on-hand inventory, amounting to \$18.7 billion, was not required for projected use rates. The additional inventory was calculated by the GAO to cost another \$15 million yearly for storage. Further compounding the unneeded on-hand inventory is that some items have a shelf life that requires disposal or refurbishment after a set amount of time. The problem does not lie entirely within the Air Force supply system control. The DoD's procurement policies drive sparing decisions to be made between 2 and 4 years prior to actual need of the part due to lead times and the DoD budgeting process (Atchley et al., 2010). This is a military issue that is not faced on the same scale in the corporate arena. A 2010 study on DoD logistics does comment on the difficulty of forecasting spares requirements stating these projections are rarely 100 percent accurate. The prognostics capability of ISHM systems can increase the reliability

of spares forecasting and, depending on projected use rates, keep sparing purchases within DoD budget timelines.

Because the military flies its aircraft beyond original service lives, B-52 and KC-135 for example, supply and maintenance issues exist. On one hand, if repairs can be made on long life items, it can save money, but when you need a new part eventually, the supplier doesn't make them anymore. An interesting dilemma arises when there is only one entity driving demand for a system such as a military aircraft. Organic military repair capabilities can drive the demand for the part so low it no longer makes financial sense for the manufacturer to support smaller components, thus when the part can no longer be repaired it cannot be purchased. Efforts to maintain industrial base through prescribed purchases can keep production lines open but do little to address over supply of some items in stock. Additionally, there is a demand driven issue for military hardware during times of conflict. Post-September 11, 2001, Air Force aircraft experienced a marked increase in sortie rates and flying hours, leaving logistics projections ineffective in determining requirements (McCoy, 2011). While an ISHM/CBM system would do little to project a wartime surge, it could provide a fleet-wide look at the remaining useful life of parts and allow decisions on purchasing priorities to be made. The ability to extend the life on systems through the prognostic capability of ISHM also allows aircraft to operate closer to the safe life limits of parts as real time condition can be obtained. The goal of ISHM enabled CBM systems is matching aircraft requirements with the supply and maintenance processes. By ensuring parts are available when needed, while keeping only

the required material on hand, supply and storage costs are reduced while maintenance downtime can be managed.

Modeling Approaches

Rebulanan models 7 elements in his JAVA model simulating the JSF ALS system: aircraft; health management system and LRUs; communication system; supply (depot, base, and flightline) and; maintenance (Rebulanan, 2000). Rebulanan uses 3 MOPs to evaluate model performance. Aircraft availability, both the number of aircraft per day and percentage available for mission (A_o), average number of sorties per day and average wait time for supply. Rebulanan's model shows sensitivity of the supply wait time to the PHM detection lead time for an impending failure, and the supply stock levels. This outcome is somewhat intuitive in that as the prognosis of an impending failure is detected earlier and with greater accuracy, the supply system can plan further in advance, ensuring parts are available when required. Malley (2001) developed a JAVA model based on Rebulanan's work with a focus on PHM intricacies. Malley examines batching to make RUL predictions, that is, processing data grouped over a set duration rather than instantaneously to dampen noise in the signal. The findings showed batch processing decreased the false alarm rate over the life of a part, but delayed detection time of impending failures.

Yager (2003) approached modeling autonomic logistics for aircraft as a queuing theory model to examine sortie generation rates. The model shows a higher sortie generation rate for the ISHM aircraft. Yager's model does have some drawbacks for

implementation on a larger and closer to realistic system in that there is no penalty for false alarms in the ISHM system and prognosis is assumed to be perfect.

Rodrigues and Yoneyama (2012; 2013) explore the effect of prognostics on spare parts inventories for both repairable and non-repairable systems compared with conventional supply processes. Both studies, simulated over 15 years each, show cost savings for the ISHM enabled system over the conventional one. For the non-repairable model a discrete event simulation is used and considers parts, storage and out of stock costs. Out of stock costs are difficult to quantify but do impact downtime for supply, which is where the impact is captured in this research model. The supply system is represented by a reorder point and an order quantity with varying levels for each. In the conventional system these are fixed, but in the ISHM model they are updated based upon system inferences. A limitation of this study is that only one item is investigated, leaving interactions of multiple components in question.

Exploring the effect of RUL inferences on repairable systems Rodrigues and Yoneyama (2013) found an improvement in fleet availability through managing when items were sent for repair. Holding, repair and out of stock costs were used again as the measure for cost. Sparing levels were varied for the systems and costs and system availability favored the ISHM scenario at each level. This model does not include maintenance costs or interactions thus the system availability cannot be considered operational availability.

Summary of Gaps

The review of current literature in this chapter highlights that most modeling efforts lack inclusion of logistics in their research. As such, the models cannot comprehensively explore the interactions between ISHM, CBM and logistics systems. Further, the inclusion of multiple systems in this research, a squadron of aircraft with multiple components is left unexplored. This gap could yield additional cost and time savings if the health monitoring, maintenance and logistics system interactions can be synchronized. Using the information above to optimize or group maintenance activities while maximizing A_0 and minimizing cost for a system of systems, is another area of research open for study. Further approaches and their associated benefits and limitations are discussed in chapters 4-7.

III. System Architecture and Metrics

Methods to Evaluate ISHM/CBM Systems

The DoD explains Condition Based Maintenance Plus (CBM+) as the use of processes and technologies to increase the reliability and maintenance effectiveness of systems (Deputy Under Secretary of Defense for Logistics and Materiel Readiness, May, 2008). Further, maintenance is performed based on need utilizing systems engineering approaches to collect and analyze data in support of the decision-making processes. The DoD Condition Based Maintenance+ Guidebook prescribes four life-cycle sustainment outcome metrics to evaluate CBM+ implementation in the Total Life Cycle Systems Management (TLCSM) process:

***Materiel availability (MA)** is a measure of the percentage of the total inventory of a system that is operationally capable (ready for tasking) of performing an assigned mission at a given time, based on materiel condition. It can be expressed mathematically as the number of operational end items [FMC] divided by the total population [fleet size]. Materiel availability also indicates the percentage of time a system is operationally capable of performing an assigned mission.*

***Materiel reliability (MR)** is a measure of the probability the system will perform without failure over a specific interval. Reliability must be sufficient to support the warfighting capability needed. Materiel reliability is generally expressed in terms of a mean time between failures (MTBF), and, once operational, can be measured by dividing actual operating hours by the number of failures experienced during a specific interval.*

***Ownership cost (OC)** balances the sustainment solution by ensuring the O&S costs associated with materiel readiness are considered when making decisions.*

Mean downtime (MDT) is the average total time required to restore an asset to its full operational capabilities. MDT includes the time from... an asset being down to the asset being given back to operations or production to operate.

(Deputy Under Secretary of Defense for Logistics and Materiel Readiness, May, 2008, p. 1-5)

The above metrics align with the Sustainment key performance parameter (KPP) spelled out in the Joint Capabilities Integration and Development System (JCIDS) manual (2015). Falling under the availability KPP, MA and A_O represent operational capability. Material reliability maps to the JCIDS reliability KSA, and OC falls under the O&S cost KSA. The combination of these high level metrics is an aggregation of the measures of effectiveness (MOEs) and measures of performance (MOPs) for the baseline and monitored systems.

Systems Architecture Approach

The foundation of an architecture for a system is the ability to map key program objectives to system performance and design. Table 3 lists the interaction between key CBM+ objectives and the aforementioned metrics where MA is materiel availability, MR is materiel reliability, OC is the ownership cost and MDT is the mean downtime. The four metrics are discussed further in the next section. These objectives are not all quantitatively measurable, but must still be considered and assessed when qualitatively evaluating the system. In mapping these objectives to the metrics, the DoD provides a conduit for candidate approaches to ensure they meet the goals for the process. The relationship between objectives and their respective metrics and subsequent

decomposition into system level measures of performance affords the opportunity to compare multiple approaches using the same upper level metrics.

Table 3. CBM+ Objectives and Metrics

OBJECTIVE	MA	MR	OC	MDT
Enhance maintenance effectiveness with integrated maintenance and logistics systems	X			X
Incorporate advanced engineering, maintenance, logistics/supply chain, configuration management, and information technologies		X		
Employ weapon system designs that use measurable, consistent, and accurate predictive parameters from embedded CBM capabilities		X		
Improve data about maintenance operations and parts/system performance	X			X
Improve advanced diagnostics, system prognostics, and health management capabilities based on current condition data	X	X	X	X
Provide more accurate item tracking capabilities				X
Reduce maintenance requirements by performing maintenance tasks only upon evidence of need (more proactive/predictive, less preventive and less corrective)	X		X	
Enable more effective maintenance training				X
Create a smaller maintenance and logistic footprint			X	
Improve maintenance capabilities, business processes, supply/maintenance planning, and responsiveness leading to optimum weapon system availability				X
Minimize unique support equipment and information systems for individual weapon systems			X	
Improve system maintainability as a part of design modification through the use of reliability analysis		X		X
Provide interoperability/jointness to the warfighter	X		X	

(Under Secretary of Defense (AT&L), May 2008)

Detailed cost comparisons, made possible by comprehensive system architecture, along with maintainability studies provide the foundation for assessing the feasibility of a

SHM system to compliment CBM. As Grubic (2009) points out, many approaches to ISHM/CBM “have been developed by engineers for engineers and therefore suffer from lack of business input. The latter brings with it a view of the customer, and the cultural and process drivers that are so important to the success” (p. 2). Byer lays out a process to evaluate an ISHM/CBM system:

1. *Define a Baseline System without PHM and the Aircraft System with PHM;*
2. *Develop Reliability and Maintainability Predictions for the Components of the Aircraft;*
3. *Define the Measures of PHM Effectiveness;*
4. *Metrics Associated with the Measures of Effectiveness;*
5. *Estimating the Impact of PHM on Reducing the Cost of Consumables;*
6. *Estimating the Impact of PHM on Reducing Maintenance manpower Costs;*
7. *Estimating the Non-recurring and Recurring Costs of Providing PHM;*
8. *Develop the Cost Benefit Results;*
9. *Estimating the Impact of PHMs on Non Dollar Denominated Benefits;*
 - a. *Sortie Generation Capability*
 - b. *Reduction in the Incidence of Major Accidents* (Byer et al., 2001, p. 3098).

In new structures and vehicles, including both CBM and ISHM in the system architecture early in the process allows for trade-offs to be made on cost, complexity and operational availability (A_O). For fielded systems, the complexity increases since most systems are deployed without health monitoring allowances and must be retrofitted which, depending on level of access, can carry significant cost and weight penalties. Sensors and their associated cables or wireless communication system and, if applicable, on-board diagnostic system have weight and power requirements also which can have

significant performance impacts in the case of aircraft. System availability is linked to the balance of sensor reliability and detectability and the capability of the system to decrease maintenance duration (Hoyle, Mehr, Turner, & Chen, 2007).

As stated previously, the benefits of ISHM are the abilities to reduce inspection length, defer maintenance and migrate to maintenance on demand or CBM (Speckmann, 2007). All of these items have the end goal to increase operational availability through reduced maintenance time. The link between the CBM program and the SHM technology is system architecture. Within sectors of industry, there are attempts to define standards or common operating practices and to persuade governments and private companies to invest in SHM technology to reduce overall maintenance costs. These will in turn enable measuring the effectiveness and cost of individual systems.

Applying ISHM enables CBM in lieu of preprogrammed periodic maintenance practices, that is, maintaining only when required instead of when prescribed by schedules, thus optimizing maintenance labor (Roach, 2009). All of the SHM technologies and resulting modified maintenance programs serve to reduce the total acquisition cost of a system with increased availability. System reliability is also cited as a reason for the lack of further adoption of the technology. Seaver et al. (2012) state that most ISHM systems lack demonstrated reliability in the field beyond estimates which, in turn, discourages program managers from investing in the technology for deployable systems. To gain user trust in predictions ISHM systems should compile and quantify uncertainty to provide some confidence interval around predictions.

Processing CBM data can prove cumbersome as well. Depending on the scope and size of the system, the ISHM platform can produce terabytes of data every month (Seaver et al., 2012). Methods to collect, process, analyze and store this data must be accounted for when developing and assessing an ISHM system (Farrar & Worden, 2007). While this is a measure to track and be aware of for a system, modeling this falls under final design for the system and will not be included in this model. The cost associated with the design, development, implementation and maintenance of these systems must be accounted for in the ISHM model in order to provide an accurate comparison of the cost benefit of the baseline system versus the ISHM/CBM system.

Model Functionality

Figure 3 lays out the process flows and functional components of for the baseline, no ISHM, aircraft through the models in this research. ISHM architecture is presented in chapter 4 and inherent ISHM processes are discussed. The models are designed to account for the processes and decisions in the appropriate flows. Following this process ensures the ability to capture the required processing times and failures for calculation of system impacts.

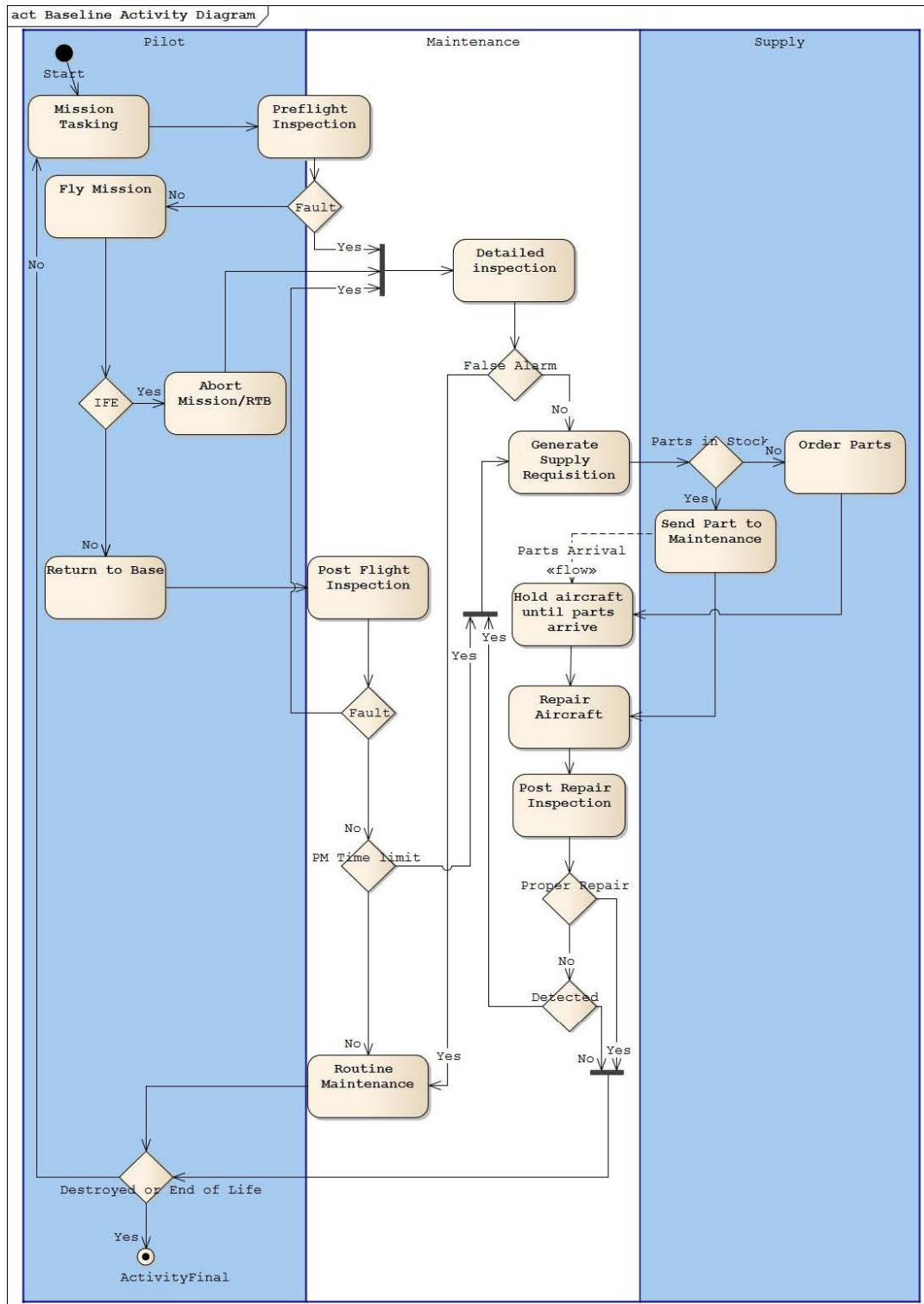


Figure 3. Baseline Activity Diagram

In the nominal baseline model in Figure 3 the aircraft are tasked for a mission and then proceed to a preflight inspection, mission execution, post flight inspection and routine maintenance before returning to the mission queue. Off-ramps can occur if inspections reveal faults that require correction or if there is an in flight emergency (IFE). Following the identification of faults, the aircraft receives a detailed inspection to isolate and locate the offending component or line replaceable unit (LRU) for repair or replacement, a supply requisition is generated and the stock level is checked. If the part(s) are in stock they are sent to maintenance to repair the aircraft. If the required items are not in stock, they must be ordered and the aircraft is down awaiting supply. Upon repair of the aircraft, the system is again checked for damage. If no damage is detected, the aircraft is sent back into service, repeating the cycle until the aircraft is retired or destroyed. The ISHM enabled CBM architecture is discussed in chapter 4.

Data Flow

The schematic outlined in Figure 4 shows the information that is transferred between the different system nodes in the ISHM model. The ISHM system updates the CBM system with systems health and RULs. This information is then processed by the CBM system, which determines maintenance and supply requirements. Supply requirements are sent to the supply system and parts statuses are returned. Likewise, maintenance windows and the subsystems to be repaired are sent from the CBM system to maintenance and maintenance updates the CBM system on status of repairs. All of this information is tracked to ensure enough aircraft are available for mission taskings.

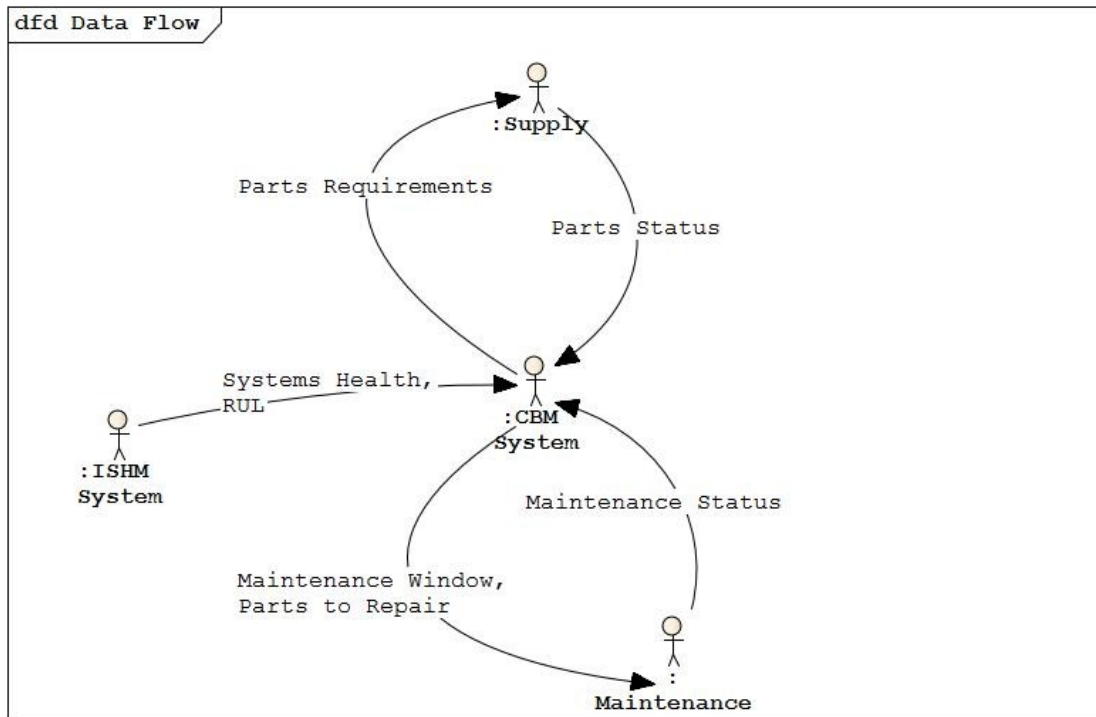


Figure 4. ISHM/CBM Data Flow

Viewed in another manner, the flow of information in Figure 4 is decomposed to show the sequence of event flows within the model. This flow, shown in Figure 5, depicts where information is transferred between model nodes and the result of data queries between nodes. Iterative items are shown in the loop boxes and continue during missions to ensure updates to system health and processing are populated throughout the system.

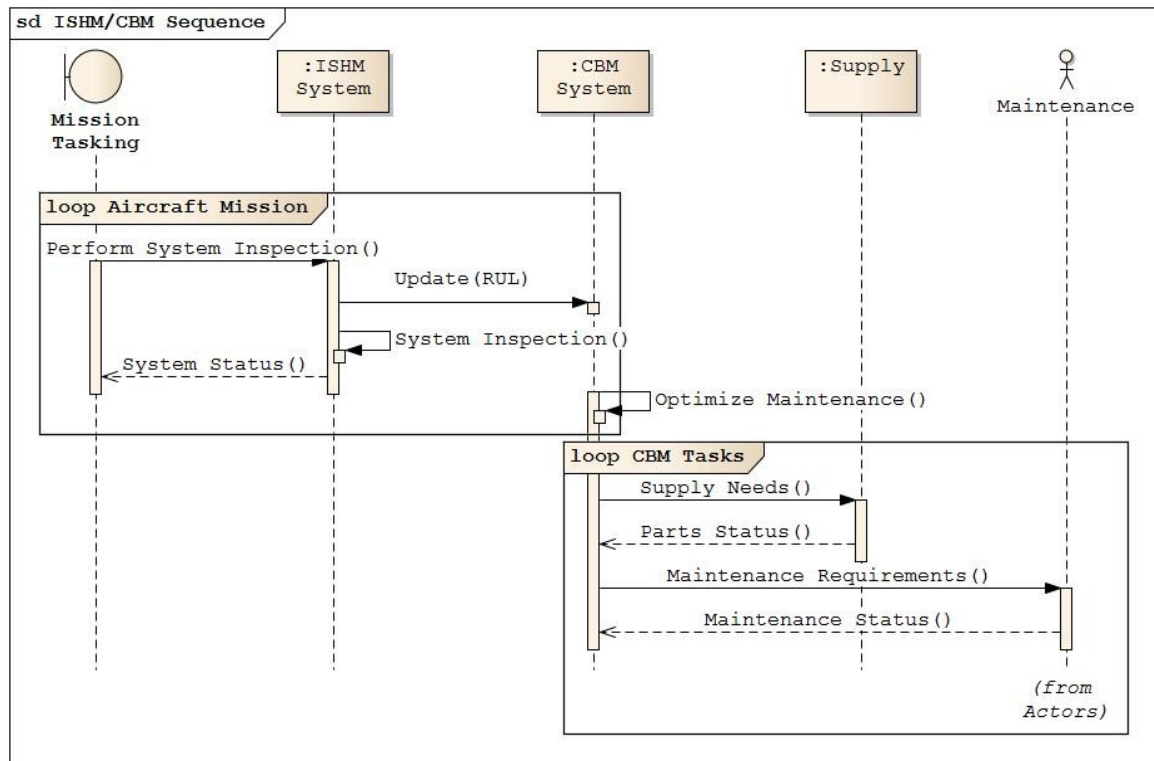


Figure 5. ISHM/CBM Sequence Diagram

Model Verification and Validation

Verification is the process of determining if the model is an accurate representation of the architecture and its processes and that those processes contain the correct information. The Arena[®] model in this work was checked against the system architectures in Figure 3 and Figure 6 to ensure proper inclusion of processes and decision points. Additionally, the data flow in Figure 4 and sequence in Figure 5 dictated model information sharing.

During model development, checks for reasonableness, i.e., inputs map to logical outputs, were conducted for individual elements and processes. Data were also output to

a spreadsheet at discrete points in the model to ensure logical behavior of the modeled parameters. In the process of conducting these checks, small errors in logic and formulas were discovered and corrected. Arena[®] has the capability to animate models, which allowed the author to follow entities throughout the model processes to ensure proper paths were followed. Further, random distributions were held as fixed values to simplify checking of timing and equations throughout the model. Verification of the finished model was conducted through checks of outputs with progressively changing inputs to verify logical shifts in outputs.

Validation is process of assurance that the data processed by the model is consistent with expected and real-world information and is performed by analyzing model simulations. In this work, validation is a difficult task as the systems are theoretical and randomly generated as are many of the processes undergone in the model. As such, there are no real-world results to compare the simulation data with for validation purposes. Therefore, what remains is to validate model assumptions and random distributions for processes to ensure their reasonableness. Distributions for model processes are meant to represent simple inspection and replacement tasks that can be conducted in a timely manner as opposed to an overhaul of an entire aircraft, which would require considerably more time. The distributions, therefore, are deemed valid for this requirement. Further, the underlying assumptions appear valid and discrepancies are annotated and discussed.

Summary

The architecture and evaluation techniques laid out in this chapter establish the processes and methods used in the remainder of this research. The establishment of a system architecture early in the design process aids in ensuring relevant processes and procedures are captured and define inputs and outputs required for successful implementation. The remaining chapters of this dissertation detail the research methods, results and conclusions relevant to the implementation of a condition based maintenance program enabled through integrated systems health management.

III. Prognostic Uncertainty

Chapter Overview

Across many industries, systems are exceeding their intended design lives, whether they are ships, bridges or military aircraft. As a result failure rates can increase and unanticipated wear or failure conditions can arise. Health monitoring research and application has the potential to more safely lengthen the service life of a range of systems through utilization of sensor data and knowledge of failure mechanisms to predict component life remaining. A further benefit of health monitoring when combined across an entire platform is system health management. System health management is an enabler of condition based maintenance, which allows repair or replacement based on material condition, not a set time. Replacement of components based on condition can enable cost savings through fewer parts being used and the associated maintenance costs. The goal of this research is to show the management of system health can provide savings in maintenance and logistics cost while increasing vehicle availability through the approach of condition based maintenance.

This work examines the impact of prediction accuracy uncertainty in remaining useful life prognostics for a squadron of 12 aircraft. The uncertainty in this research is introduced in the system through an uncertainty factor applied to the useful life prediction. An Arena[®] discrete event simulation is utilized to explore the effect of prediction error on availability, reliability, and maintenance and logistics processes. Aircraft are processed through preflight, flight, and post-flight operations, as well as

maintenance and logistics activities. A baseline case with traditional time-driven maintenance is performed for comparison to the condition based maintenance approach of this research.

This research does not consider cost or decision making processes, instead focusing on utilization parameters of both aircraft and manpower. The occurrence and impact of false alarms on system performance is examined. The results show the potential availability, reliability, and maintenance benefits of a health monitoring system and explore the diagnostic uncertainty.

Background

Across military and commercial fleets, aircraft are an example where lengthening service lives and budget constraints can adversely affect safety. As a result, more frequent inspections are required as service life increases to ensure safety of the users and the environment. However, the cost of large scale modifications or replacement in the case of hundreds of aircraft is a significant hurdle to overcome in most instances (Shoup et al., 2011). The impact of shrinking budgets can also reduce inspection frequency or delay needed repairs in favor of only performing mission critical tasks (Roach, 2009). Maintenance strategies must change to meet the extended in-service requirements and the constraints imposed by shrinking government and industry budgets.

Condition based maintenance (CBM) is an evolving maintenance concept with a goal of reducing maintenance and thus life cycle costs while increasing operational availability made possible, in part, by leveraging health monitoring techniques.

Department of Defense Instruction (DoDI) 4151.22 defines CBM as “the application and integration of appropriate processes, technologies, and knowledge-based capabilities to achieve the target availability, reliability, and operation and support costs of DoD systems and components across their life cycle,” (Under Secretary of Defense (AT&L), May 2008, p. 1-1). Integrated system health management and its impact on performance, cost, supply chain as well as traditional maintenance inspections and practices are the focus of this research. With the F-35 maintenance and logistics alone projected to cost \$1.1 trillion over the 55 year life span amid shrinking defense budgets, the need to reduce the life cycle cost (LCC) of military aircraft is paramount (Shalal-Esa, 2013). Additionally, legacy aircraft may not be fitted with the proper sensors to fully implement health assessment leading to costly inspections, in both time and maintenance dollars. This reduces operational availability (Ao) and the funds available for other needs. CBM is a demand driven maintenance process based on indications of stresses or impending failure of a component or system. When appropriately applied, CBM has the potential to reduce life cycle cost and increase mission reliability by eliminating unnecessary maintenance actions (Butcher, 2000). Ellis (2008) argues that cost-effective systems monitoring allows repair actions based on system condition rather than costly time-based maintenance. Additionally, maintenance may be forecast for completion that minimizes impact on the operational mission of the system. Secondary failures, where one component’s failure causes adverse performance or accelerated degradation of interrelated components, may also be reduced by implementing CBM as a result of prompt repair or replacement of the primary cause of fault.

CBM compares data collected from vehicle systems and their components and compares that information with a predetermined threshold prior to failure, or to failure for some non-critical components, then dictates repairs or replacement of parts. Additionally, interim time-based inspections required under the baseline preventive maintenance (PM) approach are forgone, or significantly reduced in frequency, in lieu of continuous analysis of the aircraft via the integrated systems health management (ISHM) system. CBM requires sensor or inspection data to accurately diagnose the condition of a component. Manual inspections can prove costly in terms of time to perform if the part requires disassembly or removal of other components to observe its condition. Technology exists for some, and is under development for other components, to determine wear or impending failure conditions in lieu of manual inspections (Glaser et al., 2007; Speckmann, 2007). The data from these health monitoring sensors may then be compiled to predict remaining useful life. Certainty is not 100%, be it in the interpretation of data collected on component condition or in prediction of remaining life based on that sensor data. This uncertainty has the potential to lead to poor estimation of component condition, which can result in false conclusions about safety of flight decisions and ultimately to critical failures.

Integrated Systems Health Management Enabler

The benefits of ISHM are the abilities to reduce inspection length, defer maintenance and migrate to maintenance on demand with the end goal to increase operational availability through reduced maintenance time (Speckmann, 2007). Applying ISHM enables CBM as opposed to preprogrammed periodic maintenance practices; that

is, maintaining only when required instead of when prescribed by schedules, thus optimizing maintenance labor (Roach, 2009). SHM technologies and resulting modified maintenance programs serve to reduce the total life-cycle cost of a system and increase availability. While this may drive increased acquisition cost of a weapon system or aircraft due to the inclusion of health monitoring systems, the goal is to offset the increase with reduced operations and maintenance costs over the life of the program. Published literature shows the savings potential of ISHM enabled condition based maintenance on aircraft life cycle cost:

- 40% for vehicle maintenance (Walls et al., 1999)
- 30% to 50% for fuselage panels (Pattabhiraman et al., 2010)
- 10% electrical components (Scanff et al., 2007)
- 50-80% for the Boeing 777 (Gorinevsky, Gordon, Beard, Kumar, & Chang, 2005).

In general, an application project could choose to increase the detection capability, accepting a higher acquisition cost with the goal of lowering the overall system life cycle cost through more efficient operations and maintenance. For a given detection system, however, increasing the detection capability (e.g., lowering a threshold) will come at the expense of a degraded false alarm rate; the two are competing objectives. Ultimately, the value of the prognostic system will depend on the achievable balance between detectability for safety concerns and acceptable false alarm rates to avoid unnecessary and expensive maintenance actions. Aircraft, or other vehicle, availability is linked to the balance of sensor reliability and detectability and the capability of the system to decrease maintenance duration (Hoyle et al., 2007).

It is important to understand that uncertainty will exist in the diagnosis and prognosis of system health. Numerous points of entry exist for uncertainty to work its way into remaining useful life (RUL) prediction. Component performance data is dependent on sensor health and accuracy. It is also difficult to anticipate the exact conditions, load, environment, etc, that the vehicle or machine will undergo during operation or storage. Quantifying and compiling these uncertainties is a difficult task individually and made harder by potential amplifying effects on each other.

Sankararaman and Goebel (2013) discuss factors of uncertainty in RUL prediction and lay out methods to quantify and interpret the sources. They also stress the need to accurately determine the uncertainty in the prediction for the prediction to be of use. The goal is that the probabilistic estimates of RUL based on real time monitoring allow increased time to accumulate on parts, thus increasing the MTBF for the ISHM aircraft and generating savings through fewer spares procurements or repair actions.

Determining the effectiveness of system health monitoring approaches requires a method for comparison of techniques. The remainder of this paper discusses modeling approaches, evaluation techniques and results of this research.

Modeling Approaches

Research into the effects of prognostics on integrated logistics, maintenance and aircraft systems frequently neglects the impact of uncertainty on HM model outcomes. Rebulanan utilizes a discrete event simulation to represent the F-35 autonomic logistic system (ALS) system with a health management system, LRUs, communication system, supply, and maintenance systems (Rebulanan, 2000). Rebulanan further evaluates

performance with aircraft availability, mission capable and non-mission capable rates, and mission reliability. Rebulanan's model shows sensitivity of the supply wait time to the detection lead time for an impending failure and the supply stock levels. This outcome is somewhat intuitive in that as the prognosis of an impending failure is detected earlier and with greater accuracy, the supply system can plan further in advance, ensuring parts are available when required.

Rodrigues and Yoneyama (2012; 2013) explore the effect of prognostics on spare parts inventories for both repairable and non-repairable systems compared with conventional supply processes. Both studies, simulated over 15 years each, show cost savings for the ISHM enabled system over the conventional one. In their work on non-repairable items they discuss uncertainty in failures and their impact on supply policy, but they do not include the impact of prognostic uncertainty on maintenance operations for false alarm adjudication or aircraft operational availability. Similarly, while they do address prognostic error in repairable systems they focus on the impact of sparing to account for fleet availability without addressing false alarms and how they might drive costs. Both works provide an excellent analysis of the cost impact of sparing decisions based upon health monitoring information. Out of stock costs are difficult to quantify but do impact downtime for supply, which is where the impact is captured in our research model. A limitation of the nor-repairable study is that only one item is investigated, leaving interactions of multiple components in question.

Kählert, Giljohanan, and Klingauf (2014) utilize a MATLAB discrete event simulation to analyze one Lufthansa A320 component with 100% unscheduled

replacement. They utilize process times, reliability, prognostic accuracy, and cost to evaluate PHM system performance. Additionally, the use of historic Lufthansa maintenance data provides added realism in the research. The research focus only extends for two weeks around a replacement, thus leaving out some potential for a false alarm condition to exist prematurely. One of their final conclusions is a realistic PHM system could save approximately 20% of annual fleet operation costs.

Model description

In this research, an Arena[®] discrete event simulation is utilized to represent a squadron of 12 aircraft and their associated mission, maintenance and supply processes over a 15 year duration. This model explores the impacts to this squadron in analyzing a model containing elements not addressed in the works of section 2. The authors add uncertainty not found in Rebulanan's work with an interaction of multiple components missing from Rodriques and Yoneyama.

Model Components and Architecture

The initial component failure properties were randomly generated from a uniform(250,1000) distribution for parts A-T. These times are then utilized for component replacements in the model. Each aircraft is generated and assigned 20 components with a failure time randomly sampled from an exponential distribution, with mean time between failure (MTBF) given in Table 1, and with probability density function: $f(x) = \frac{1}{\beta} e^{-x/\beta}$, for $x > 0$. The exponential distribution is chosen as a representative reliability function for the components for simplicity in model calculations

of the constant failure rate. The model can readily accept another failure distribution with other components.

Table 4. Components Failure Times

Part	MTBF (hours)
A	502
B	280
C	775
D	750
E	763
F	364
G	441
H	829
I	769
J	941
K	778
L	363
M	272
N	642
O	696
P	268
Q	822
R	585
S	996
T	842

The sampled failure times are considered “truth” in terms of component failure times. That is, if the line replaceable unit (LRU) incurs more than the associated failure time in hours without being repaired or preemptively replaced as a result of scheduled preventive maintenance, overhaul in the baseline case or ISHM indicated replacement in the prognostic case, a failure occurs. Aircraft flow through preflight processing and mission preparation prior to actually flying an assigned mission. The ISHM system performs a scan to determine if the aircraft is anticipated to have enough useful life to

complete the mission. Each component decreases its life only during engine running operations: taxi, take-off, flying, landing and parking. In this work, it is assumed that LRUs operate until failure. These processes are visually depicted in Figure 6.

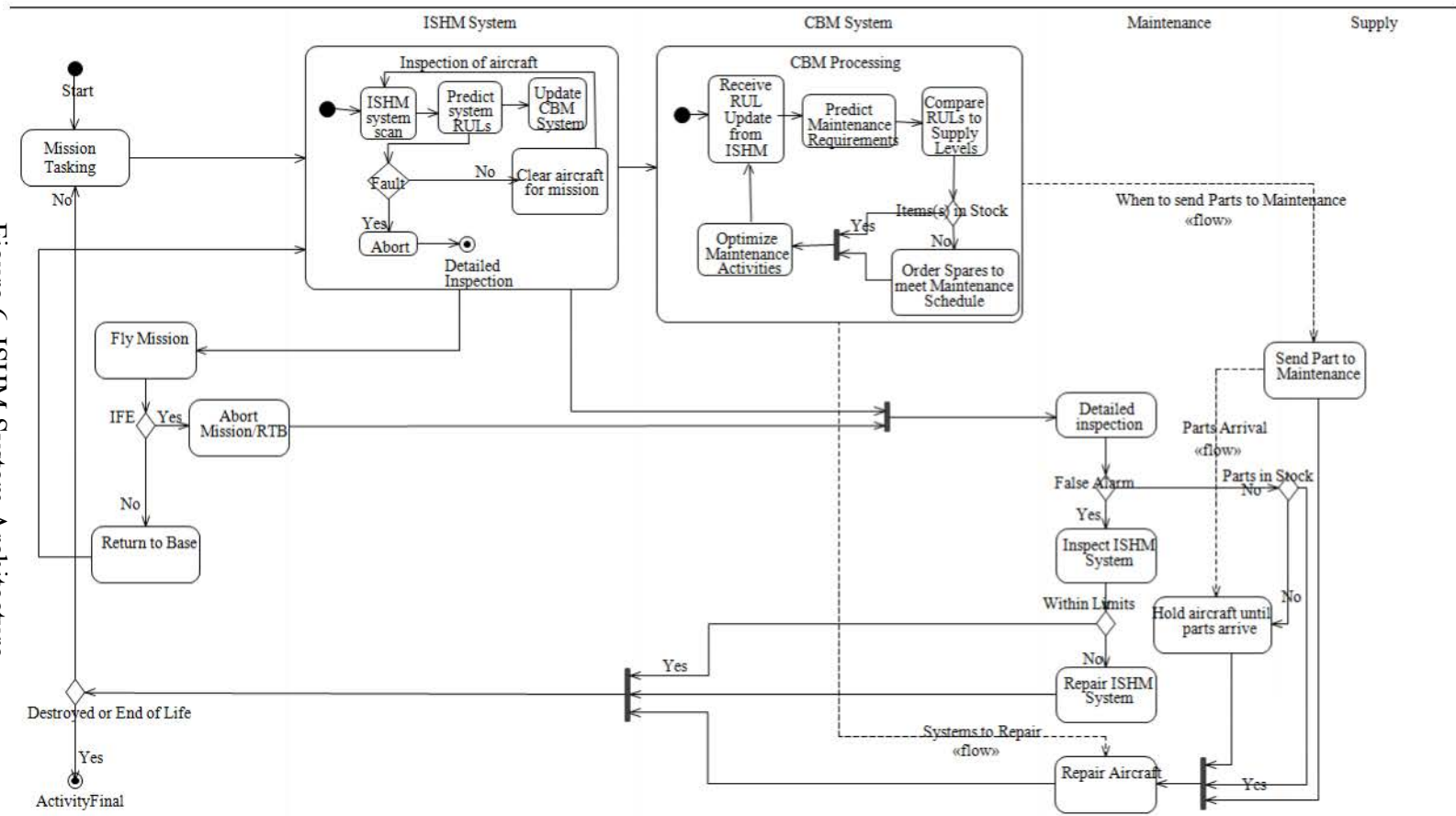
After sortie completion, diagnostics are again performed and in the baseline case, maintenance is performed as well. ISHM aircraft perform post flight scan and if acceptable are released for next flight. Baseline aircraft are inspected and checked for LRU preventive maintenance time. If PM is not required, routine maintenance and inspections are performed and the aircraft released for next mission. Aircraft are then either parked until their next mission or turned for another flight.

In the maintenance module, the number of indicated failures is recorded and the maintenance clock starts. A detailed inspection is performed for both the ISHM and baseline cases, though shorter for the ISHM case. False alarms are recorded and in the ISHM case if a false alarm threshold over the lifetime of the part is reached, the ISHM system undergoes maintenance. The model indicates a false alarm condition if the predicted component RUL is less than the “truth” remaining time minus a safety factor and the anticipated sortie duration. In the baseline case supply stock is reduced and if not in stock the aircraft is grounded until the part arrives. Parts are processed by supply (occurs simultaneously with other aircraft operations in the ISHM case) and transferred from supply to maintenance. Aircraft are maintained and LRU(s) life characteristics are resampled from the failure distribution(s) in Table 1. The aircraft repair is checked and the vehicle is routed back into the mission queue. In the ISHM case, if the standby time until the next mission is greater than the mean time to perform any outstanding

maintenance actions, the aircraft is routed to be maintained so as not to impact mission operations. In the baseline case, unless the part is scheduled for preventive maintenance the condition is not known thus the need for repair or replacement is unanticipated and the aircraft continues normal mission operations. Maintenance actions are performed serially on each aircraft, that is, only one inspection or maintenance action at a time, continuing until all required actions are complete. This assumption likely over constrains maintenance personnel actions, leading to slightly higher maintenance delays, but is done for model simplicity and has the same effect on the baseline and health monitoring cases. It is assumed that all component inspection times for indicated or actual failures are triangularly distributed (20, 30, 45) minutes and LRU replacements triangularly distributed (60, 90, 240) minutes. These times were chosen to represent a range of repairs and inspections while not portraying items which may require multiple days to maintain. Additionally, in this research required personnel for maintenance actions are always considered available. LRUs are always replaced when they are serviced.

Supplies are input into the model at an initial stock level and a reorder point. In both the baseline and ISHM cases, the stock level and reorder points are fixed for the simulation. The levels are discussed further in section 3.2. Once reorder point is reached, the difference between stock level and reorder point is ordered. Time between order and delivery is log-normally distributed (2,1) days for all parts. Additionally, a processing time upon receipt is incurred.

Figure 6. ISHM System Architecture



If RUL is within a 10 hour safety factor from failure the aircraft is routed to maintenance. If RUL is within a prescribed lead time window, a supply check is performed and if parts aren't in stock they are ordered to meet predicted maintenance activities. If RUL is within a defined maintenance window, component service can occur if parts are in stock or the aircraft can continue flying missions if there is sufficient RUL.

Sensor and Prognostics Process

The ISHM routine begins by computing the remaining useful life (RUL) of each component. The RUL prognosis has two components, the diagnosis from the HM system and the prediction uncertainty. In this research component diagnostics is taken as perfect, i.e., sensor always knows exact health. In new components sensor diagnostics can have difficulty detecting the health state, thus providing data that may not be useful. As failure becomes more imminent, sensor diagnostics can provide a more exact condition diagnosis. The resulting determination leads to component RUL being predicted as:

$$LRU\ RUL = \text{lognormal}(\textit{Diagnosis}, \textit{uncertainty}) \quad (1)$$

Where *Diagnosis* is the log mean and equivalent to the true remaining life and, *uncertainty* is the log standard deviation defined in Eq. (2).

Uncertainty is varied in this research to determine the impact of uncertain prognostics on Ao and sortie rates. Uncertainty is calculated as:

$$\textit{uncertainty} = \ln(\textit{Part\ RUL}) * \sqrt{\textit{uncertainty\ factor}} \quad (2)$$

Where *Part RUL* is the previous RUL prediction for that part and, *uncertainty factor* is a design variable.

This information is sent to the CBM module where maintenance predictions are performed. While no specific RUL prognostic technique is used, the technique above is utilized to represent compounded error or uncertainty built up in the system. Initially, RUL estimation is chiefly impacted by the uncertainty factor, but in section 4.2, additional degradation to the system is added to account for sensor diagnostic losses. Eqs. (1) and (2) are representative equations developed by the authors to portray the behavior of health monitoring systems. They are not intended to mimic the performance of a particular system, but to represent the functionality of a monitoring system. The uncertainty factor is a representation of the accumulated variability in the prognostics for remaining useful life. This work ranges the uncertainty factor from a low of 0, to represent perfect prognosis, to a high of 100, which approaches half the MTBF of some parts. Examining a range of variability between these end points allows system designers to quantify how much uncertainty is acceptable in a health monitoring system before selecting one for inclusion on an aircraft.

The system then enters a decision node where the RUL is compared to a set safety factor, which would be a policy decision based on mission requirements. If there is RUL above the safety factor and the projected sortie length does not encroach on the safety factor, the aircraft is cleared for flight. If the RUL is below the safety factor, the component(s) are flagged and sent to maintenance. If RUL is sufficient, the aircraft is cleared for the next process. In all, the aircraft is checked prior to mission preparation (fuelling and cargo loading), prior to take-off, during flight, and upon landing. If all of

these checks are satisfactory the aircraft continues through missions and standby time until a maintenance action is required.

The CBM system preorders parts to meet demands as described above. If the part is not in stock, the aircraft is placed in a non-mission capable supply hold until the part arrives. Upon maintenance completion, the ISHM equipped aircraft bypasses additional check-outs normally performed to inspect work, instead relying on the ISHM system to perform them. The aircraft is then released for the next mission tasking.

Evaluation Parameters

Establishment of useful performance measures to evaluate the model is essential. To that end, metrics currently used to determine aircraft and system performance are preferred as a means of comparison. Three categories of metrics, although interwoven, are laid out below and are used when discussing the results of this research: availability; reliability; and maintenance.

Availability

To understand operational availability and why it is a good measure of system performance for this model, it is useful to be familiar with achieved and inherent availabilities as well.

Inherent availability (A_i) is the availability of a system operating under an ideal support system. This means delays for logistics, administrative delays and preventive maintenance time are excluded, leaving only operating time and corrective maintenance.

Achieved Availability (A_a) adds preventive maintenance to A_i in addition to corrective maintenance. Logistics, supply and administrative delays are ignored and those

assets are assumed to be instantaneously available when required. Achieved availability is determined examining the mean time between maintenance, MTBM, and the mean maintenance time (MMT).

Operational availability (A_o) adds the final piece to the downtime portion of the equation. A_o includes logistics, supply and administrative delays to the PM and CM for the system resulting in the mean downtime for the system. Operational availability is the system availability the user of a system realizes, (ReliaSoft, 2007). Mathematically, operational availability is:

$$A_o = \frac{Uptime}{Uptime + Downtime} = \frac{MTBM}{MTBM + MMT + MLDT} \quad (3)$$

Where MLDT is the mean logistics delay time.

Eq. (3) is not the only way to define operational availability. Pryor (2008) discusses methods to calculate A_o seen in Eq. (4) using the uptime/(uptime + downtime) definition of Eq. (3), but the definition is slightly different.

$$A_o = \frac{OT + ST}{OT + ST + TPM + TCM + TALDT} \quad (4)$$

Where OT is the operational time, ST is the standby time, TPM is the total preventive maintenance time, TCM is the total corrective maintenance time, and TALDT is the total administrative and logistics delay time, equivalent to MLDT.

Figure 7 shows the components of up and downtimes. This is by no means an exhaustive list and further breakdowns are possible, especially in the administrative and logistics delay blocks, but for this research these components define the temporal parameters.

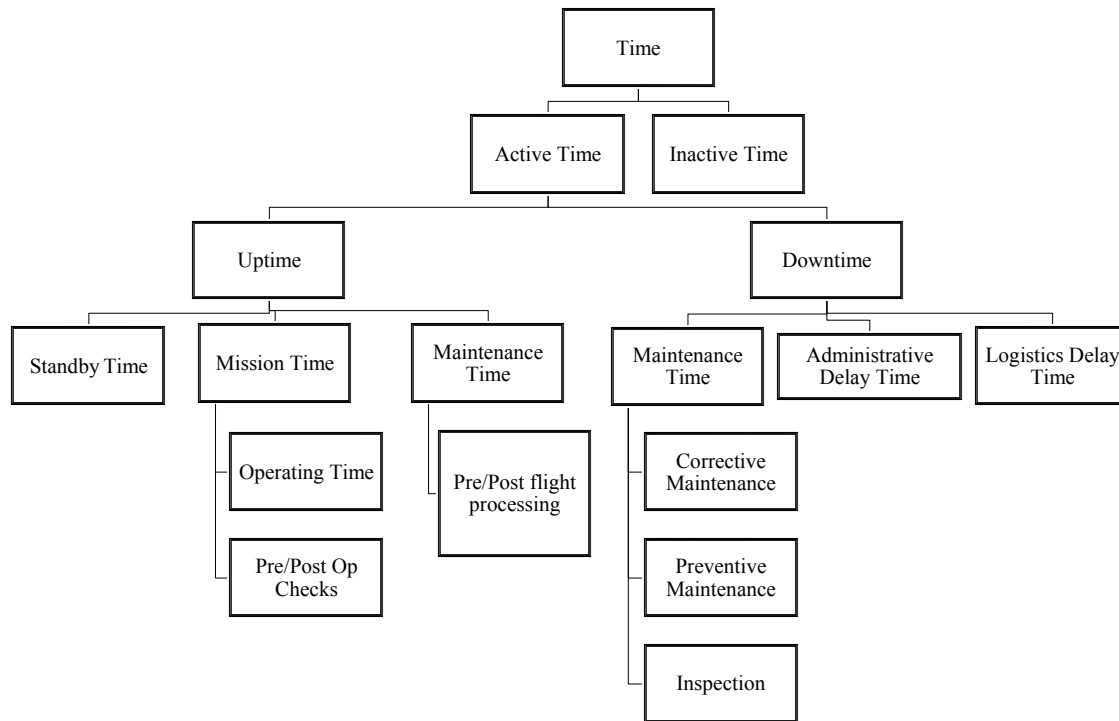


Figure 7. Components of System Usage Time (Pryor, 2008)

A function of a system's operational availability, average daily flying hours is a measurement of the ability of the squadron as a whole to perform the assigned missions. Further, the number of sorties flown per day is a function of the mission requirements, but also the performance of the aircraft as well as maintenance and logistics systems.

Reliability

In the commercial environment, up and downtimes can also be assigned costs as the systems impact revenue generation. Kählert, Giljohanan and Klingauf discuss dispatch reliability, or the “ratio of revenue departures without delay or cancellations compared to all flights,” (2014, p.1). They go on to summarize commercial aircraft cost accounting for delays and cancellations. Downtime has an associated cost beyond

maintenance labor in lost revenue. Similarly, uptime has the potential to generate revenue, when not in a standby capacity. For military systems, assigning costs to up and downtime is problematic as there is no profit to generate and supporting national security is difficult to assign a value to. In essence, military aircraft are consumptive, always operating at a loss. Policy and research can, however, strive to reduce these consumption costs.

False alarms diagnosed or predicted by the ISHM system drive unnecessary maintenance and supply actions as well as placing an otherwise mission capable aircraft into a NMC state. These maintenance and supply actions increase the overall cost impact of the ISHM system as they are not free. A key requirement for successful deployment of an ISHM architecture enabling CBM is a low false alarm rate with reliable detection (Ellis, 2008; A. Van Horenbeek et al., 2013). False alarms in the baseline model result from CND and RTOK discussed previously. Totals for each of the models will be recorded for comparison. Additionally, an increase in false alarms, above a predetermined threshold, on an aircraft with an ISHM system will trigger an inspection of the ISHM system sensors providing erroneous data and potentially of the ISHM system logic itself.

The ability to tolerate false alarms is a two-fold evaluation. First, the cost associated with each false alarm shrinks any cost benefit of the ISHM system over the baseline system. Second, too many false alarms can trigger a “cry wolf” attitude towards the system or result in wasted time maintaining, or checking the system thus decreasing the operational availability of the aircraft and the reliability of the ISHM system. For an

ISHM architecture to be effective it cannot trigger excessive false alarms which, in turn, trigger maintenance actions on the system.

Maintenance and Logistics

Inspection intervals are time-driven processes under the baseline aircraft case and are prescribed to monitor systems for indications of damage. They are generally based on historic or predicted failure data and are conducted to ensure early indications of failure are discovered before they catastrophically fail the system or adjacent components. An assumption for this research is that all systems of interest on the aircraft are monitored in the ISHM model. If that were not the case time-based, but informed through ISHM inferences, inspections would still be required. In this research, the ISHM case only requires inspection upon indication of failure or impending failure by the system. Therefore, the inspection intervals should be further apart and of shorter duration for ISHM than for time-based methods. The preprogrammed PM inspections of the baseline are defined based on operating hours.

Accounting for the required time to repair and inspect aircraft is critical in determining the impacts of system changes to downtime and manpower costs. In addition to the repair of malfunctioning components, inspections based upon fault indications, either in performance or indicated by the ISHM system, drive mission unavailability and decrease system performance metrics. A common metric is to measure the required maintenance man hours per aircraft flight hour or MMH/FH. This factor can then be utilized in forecasting manpower requirements and required downtime-based on mission requirements. Similarly, mean downtime (MDT), the average amount of time it takes to

return an aircraft to flying status once a fault is indicated, is a commonly used maintenance performance metric.

Supply delay is the time between actual part need and when the supply system delivers the part to maintenance and will impact both the baseline and ISHM/CBM cases. Non-mission capable supply (NMCS) is the common measure of this supply delay. The prognostic CBM case will anticipate failure and sparing requirements further out from maintenance demand and allow for advanced ordering if stock levels are inadequate. The current baseline process relies on anticipating failures and providing stock levels at individual bases or in some cases a central location that can be tasked to deliver spares when required. This process increases the logistic footprint by requiring storage facilities for materiel that may not be needed for upwards of a year. Managing these spares and the facility requires additional resources, manpower and money. “Logistics response time, a measure of supportability and an indirect measure of readiness,” (Deputy Under Secretary of Defense for Logistics and Materiel Readiness, May, 2008, p. 6-4), drives shorter maintenance times and as such impacts supply and maintenance downtime.

While maintenance policy and cost decisions impact LRU replacement decisions, the prognostics capability plays an important role in determining when to repair or exchange components. Confidence in the performance of the diagnostics and prognostics systems could lead to a decreasing safety factor as to when maintenance occurs. This resulting increase in useable time of each part saves money through extended service life for the components and reduces the amount of supplies consumed. Capturing the amount of useful life lost for the components can quantify the gains that may be achievable.

Model Variables

This research explores the impact of RUL prediction uncertainty on the availability, reliability, and maintenance and logistics categories above. Evaluation of the model is accomplished through simulation of 15 years of aircraft utilization. Further, two design cases are initially utilized in the simulations. The remaining useful life uncertainty factor is varied at 14 levels with two false alarm limits at 0 and 10000 and the model assessed at each increment. The levels for the FA limit is meant to indicate that at 0, the ISHM system is always maintained after a false alarm and at 10000, policy allows nearly unlimited false alarms by the ISHM system before requiring repair. These levels are found in Table 5. At each uncertainty factor 100 simulations are run to establish confidence in the results, and the means of these data are presented. Sensitivity to values of FA limit greater than 0 is presented later in this paper once sensor and prognostics degradation are considered. Additionally, two simulations of the baseline case with no prognostics are run where component stock levels are varied.

Stock levels for the ISHM case are held to 1 nominally and ordered as predicted by the system. In the baseline case, two comparisons are examined, one where the stock levels are kept the same as the ISHM case. The other stock level case holds 4 parts in stock and reorders when the level drops to 2. This variance of stock level for the baseline case makes the process comparable to minimal levels as in the ISHM case and robust levels when failure is somewhat uncertain.

Results

No ISHM Degradation Results

Daily flying hour averages for all simulation runs are located in Table 5. It is noted in these data that a decrease of 19.04 flying hours per day occurs over the range of uncertainty factors for a FA limit of 0. This decrease is smaller when the FA limit is 10000, reaching 3.45 hours. This reduction corresponds to 6949 and 1261 hours respectively in lost flying each year, the equivalent of removing more than 1 aircraft's missions from the flight taskings in the unlimited case and over 5 aircraft in the 0 FA limit case. The last two rows in Table 5 contain performance results of the baseline model where the numbers in parentheses represent the stock level and reorder point respectively. For the baseline model, the (1,0) supply case yields only 18.36 daily flying hours while the (4,2) case achieves 27.94 hours. The chief cause of this difference is attributed to the (1,0) case waiting for supplies to be delivered as they are only ordered as needed and only 1 item is held in stock. The ISHM cases all benefit from the prognostic capability of the ISHM system in ordering supplies to meet requirements.

A typical measure when examining the maintenance demand of an aircraft is maintenance man hours per flying hour. Figure 8 examines MMH/FH for the case where all false alarms trigger ISHM system maintenance and the case where FAs in the system do not incur ISHM maintenance, merely downtime to adjudicate the alarm does not require maintenance. As shown in Figure 8, the 0 FA limit case MMH/FH increases linearly as the uncertainty factor increases. This growth results from the number of maintenance actions on the ISHM system as every FA triggers ISHM maintenance.

Maintaining the ISHM system takes more time than merely adjudicating a false alarm by the ISHM system thus the increase in maintenance hours. In the case where FAs do not trigger ISHM repair, the MMH/FH grow slowly reaching a maximum of 0.268 vs. 4.198 for the 0 FA case. Inspection and maintenance times drive the maintenance hours and if inspection times were to increase significantly, the number of false alarms shown in Figure 9 could change the behavior of Figure 8. Additionally, as the uncertainty factor increases more false alarms occur as shown in Figure 9 as does the resulting downtime associated with the false alarms observed in Figure 10. For comparison, the baseline cases have MMH/FH ratios of 0.546 and 0.549 for the (1,0) and (4,2) cases respectively. In the baseline case, time-based preventive maintenance occurs at set intervals versus the condition based method employed by CBM driving extra maintenance hours.

Table 5. Average Daily Flying Hours

Uncertainty	ISHM False Alarm Limit	
	0	10000
	Mean Daily Flying Hours	
0	35.98	35.98
2	35.25	35.26
5	34.90	35.00
7	34.36	34.92
10	33.53	34.86
20	30.14	34.37
30	27.32	34.10
40	24.88	33.85
50	22.96	33.55
60	21.38	33.25
70	19.93	33.15
80	18.92	32.92
90	17.80	32.62
100	16.94	32.52
Baseline	18.36	
Baseline	27.94	

While the MMH/FH numbers are low for an entire aircraft, for a system of subcomponents when scaled up it is feasible. For example, the U.S. Air Force C-17 fleet operates around 6 MMH/FH (Nelms, 2008).

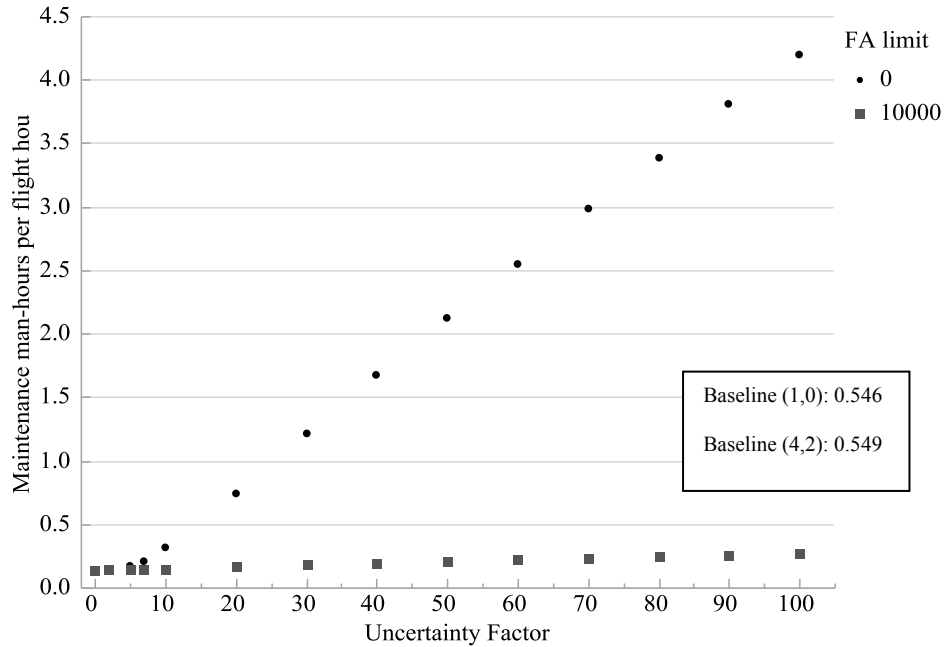


Figure 8. Maintenance Man Hours per Flight Hour

Figure 9 illustrates the average false alarms per aircraft per year. The quantity increases from 0 for the 0 uncertainty factor, perfect prognosis, case to 101.52 and 196.65 for the 0 and unlimited FA cases respectively at the 100 uncertainty factor case. As observed in the figure, since the amount of time spent in maintenance repairing the ISHM system for every FA in the 0 limit case increases as the uncertainty factor increases the number of false alarms is lower. It should be noted that this is not a reduction in the FA rate, as the prognosis accuracy is not degrading over time for this initial investigation. This mostly results from the maintenance time taking away time when the aircraft could

be flying and, as noted in Table 5, the mean daily flying hours are nearly double for the unlimited FA case.

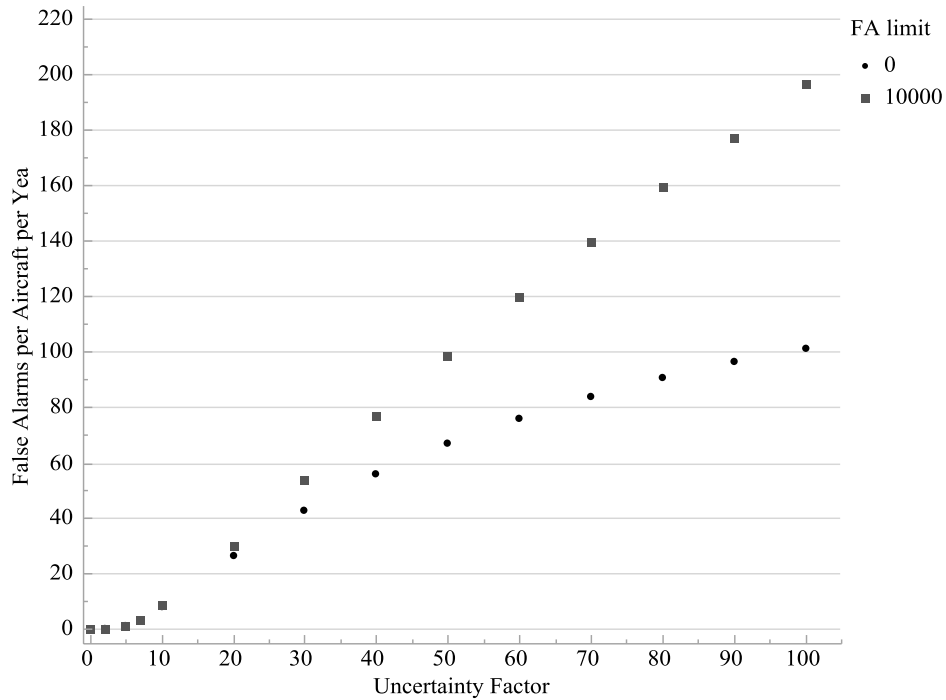


Figure 9. False Alarms per Aircraft per Year

While the number of false alarms per aircraft per year is nearly doubled in the 0 limit case versus the no limit case, FA downtime increases at a considerably higher rate. As shown in Figure 10, the average downtime each aircraft experiences per year due to FA increases from 0 for the perfect prognosis case to 111.31 hours for the unlimited FA case and over 2000 hours for the FA limit 0 case. The increase is attributed to the additional maintenance required to maintain the ISHM system at the lower FA trigger.

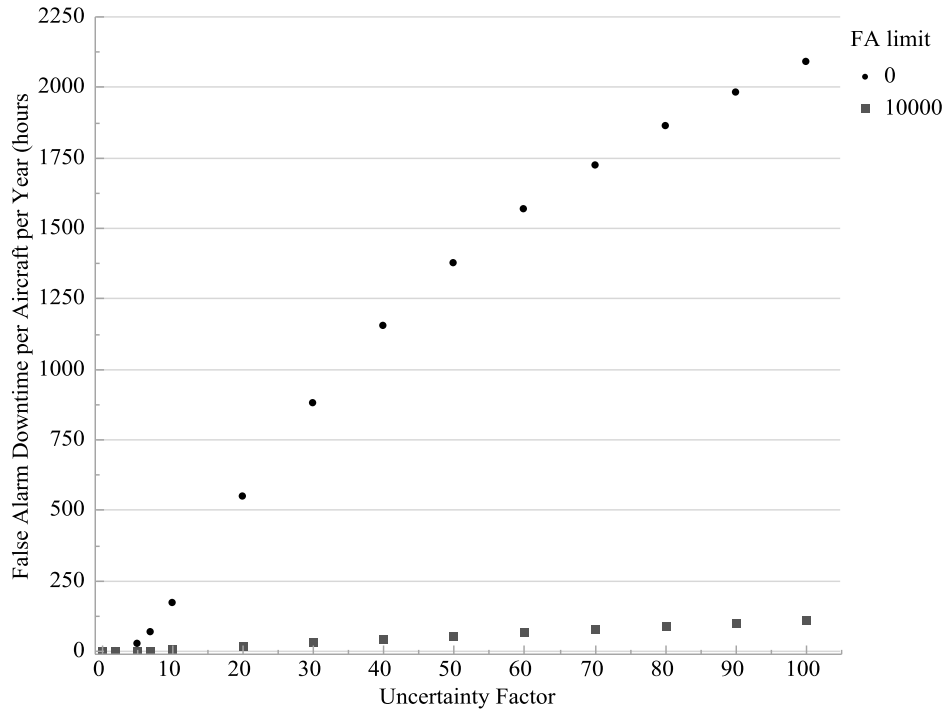


Figure 10. False Alarm Downtime per Aircraft per Year

Compiling all components of downtime and the number of times the aircraft is down for maintenance leads to the mean downtime for an occurrence. As shown in Figure 11, mean downtime decreases from 3.24 hours when the uncertainty prognosis is perfect to a low 1.09 hours when the uncertainty factor is 100 and FA limit is unlimited. This decrease is attributed to the fact that while the aircraft is being removed from service more often to adjudicate false alarms as the uncertainty factor increases, the inspections do not take as long as the aircraft is quickly returned to operation. MDT for the 0 FA limit case grows as the uncertainty factor rises, mostly due to all components requiring inspection and sensor repair for each time down. As uncertainty rises, the aircraft is brought down more frequently, but more often for a false alarm than maintenance

actions. Adjudicating a false alarm through inspection takes less time than a repair, thus the downtime is smaller. For the baseline (1,0) case, MDT is 171.82 hours, and for the (4,2) case 17.47 hours. The MDT for the (1,0) case is high mainly due to NMCS as there is only a stock level of 1 LRU and parts are ordered on demand, not schedule. The other major driver for the baseline MDT is the PM process.

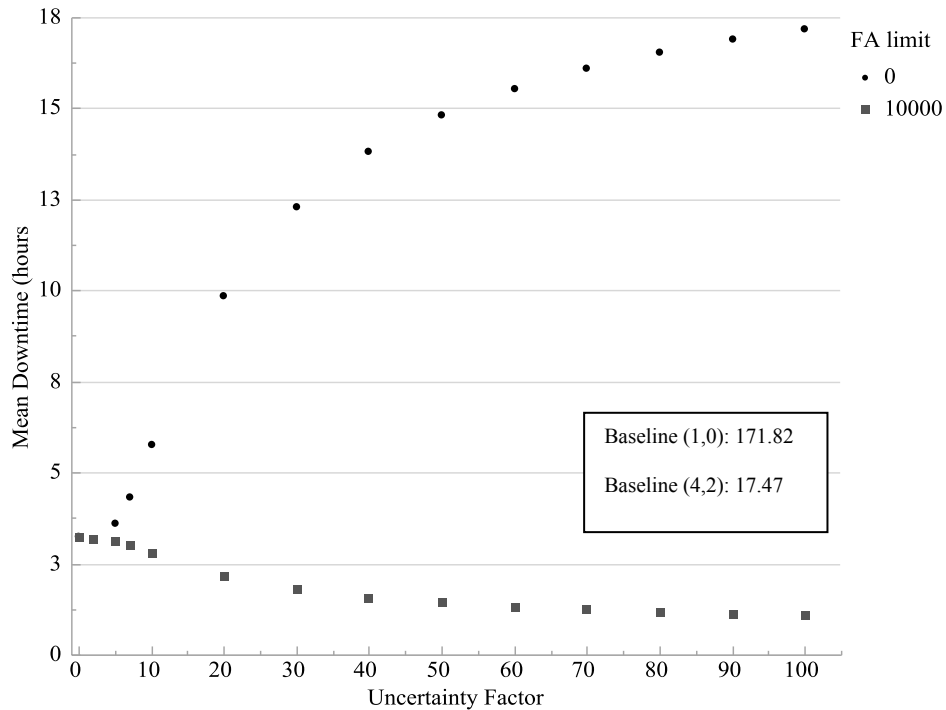


Figure 11. Mean Downtime

At the low end of the uncertainty factor range, the fixed 10 hour safety factor imposed on each part accounts for a majority of the lost life each LRU, with the remainder mostly coming from the component not being able to safely cover the projected sortie duration. As the uncertainty factor increases, the mean life lost per component increases as well due to the uncertainty in the RUL prediction necessitating

replacement before LRU failure. Additionally, the between mission maintenance window check forwards aircraft for LRU replacement or repair if the RUL prediction is within the designated maintenance window and parts are in stock. Figure 12 depicts the simulation outcome described above, growing from 15.63 hours to 35.40 hours for the uncertainty factor 100 case for each FA limit. Taken over the 15 years, the total life lost ranges from a low of 144506 hours for the perfect prognostics condition to 321236 hours for the case where uncertainty factor is 100 and FA limit is unlimited. This translates to 36.67 years of part life lost for the latter case. The mean life lost for each FA limit case is approximately equal at each point, thus they are collocated in the figure. This results from the fact that while the ISHM system may require more maintenance, the LRU components are only replaced as required. Of note is the max total life lost for the 0 FA limit case is 207901, occurring at an uncertainty factor of 20. The total life lost then continues to drop off as the uncertainty factor rises. This is due to the number of hours being flown by the aircraft declining as the uncertainty factor increases, thus not requiring LRU replacement as frequently. The lost utilization and cost implications of this figure could provide justification for system implementation. Component life lost in the baseline case is driven by the time-based preventive maintenance (PM) cycle. In this research, the PM cycle is set at 400 hours whereby all components with less than 400 hours remaining, by time accounting, are replaced, yielding a mean life lost of 376.49 and 377.06 hours for the (1,0) and (4,2) cases respectively.

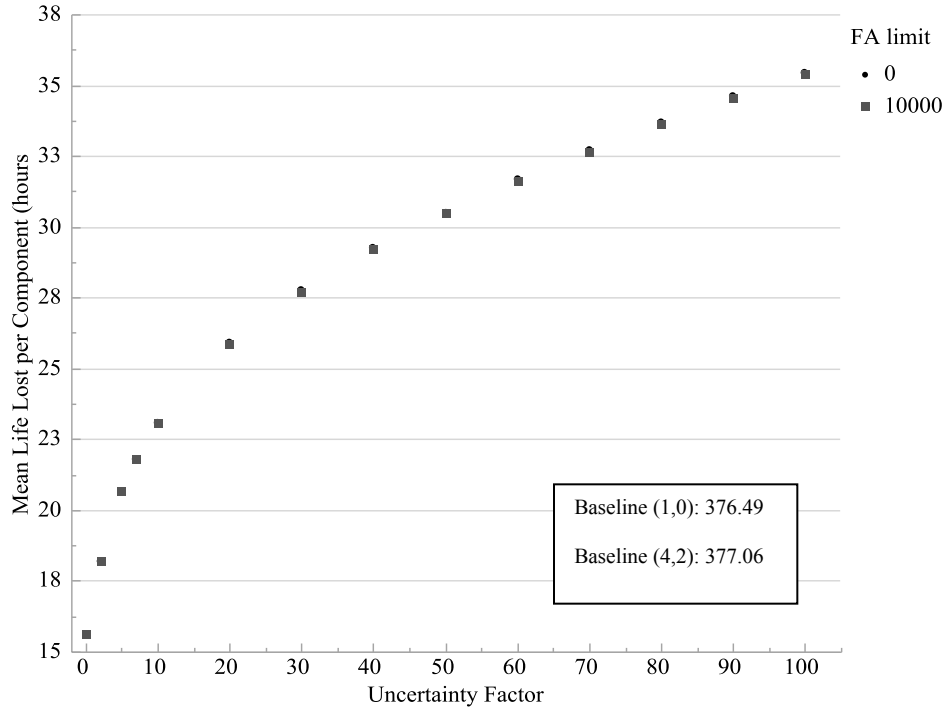


Figure 12. Mean Life Lost per Component

False alarms and maintenance hours are important when determining cost, support requirements, and system confidence, but users, whether they are military or commercial, want to know how often their aircraft are available and when tasked if they can complete the mission. Utilizing Eq. (4) to calculate Ao, Figure 13 shows the impact of uncertainty factor and FA limit. Operational availability drops from 0.983 for both FA limit levels at an uncertainty factor of 0 to 0.754 for the uncertainty factor 100, FA limit 0 case and 0.969 for the unlimited FA case. The increase in downtime to repair the ISHM system in the 0 FA limit case is the driving factor in the decrease in Ao over the uncertainty levels. In the baseline cases, Ao is 0.618 and 0.941 for the (1,0) and (4,2) cases respectively. Ao is low in the (1,0) case again for the NMCS condition.

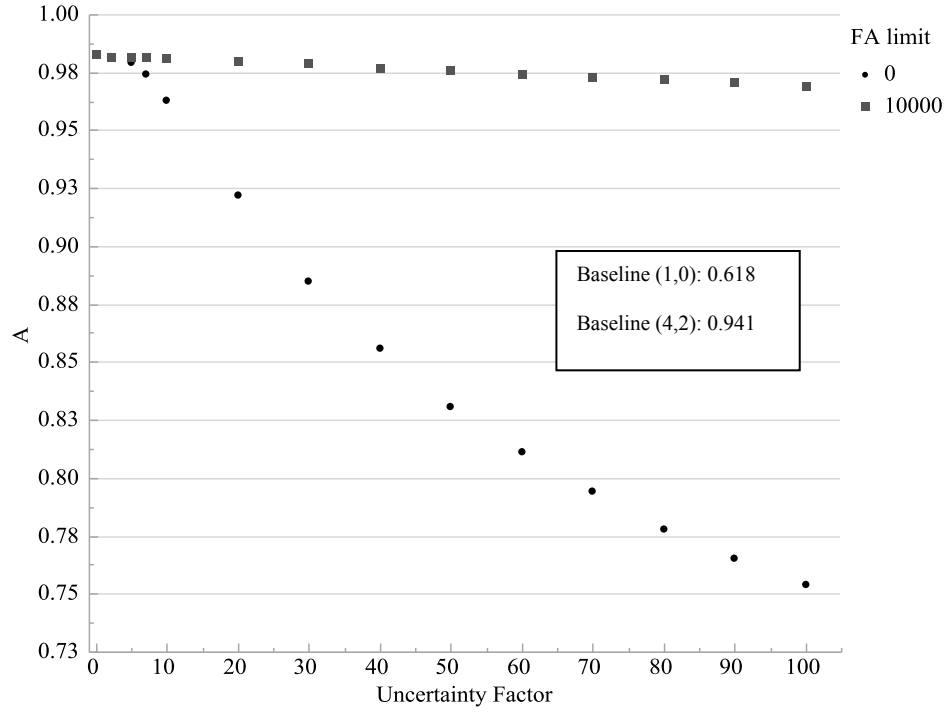


Figure 13. Operational Availability

Sensor and Prognostic Degradation Results

A further examination of the impact of a degrading prognostics capability is examined as well. Eq. (2) becomes:

$$uncertainty = degradation\ factor + \ln(Part\ RUL) * \sqrt{uncertainty\ factor} \quad (5)$$

This degradation factor places an additional uncertainty on the RUL prediction given as:

$$degradation\ factor = 10 + \left(\frac{Part\ ISHM\ timer}{growth\ factor} \right) * 10 \quad (6)$$

Where *growth factor* is either 50 or 200 to provide different rates of degradation.

Referring to Table 1, it is shown that component MTBF is bounded between 250 and

1000 hours. Therefore, the impact on RUL uncertainty could grow to nearly the component life in the case of part P if left unchecked. The Part ISHM timer is the accumulated life on the ISHM components associated with a specific component. The timer is reset upon component replacement or when a false alarm limit is reached thereby initiating maintenance on the ISHM system. Degradation factor increases as a function of the accumulated time on the Part ISHM timer. Thus, the longer the ISHM system is in operation, the higher the degradation factor becomes adding to the uncertainty in the system. As with Eqs. (1) and (2), Eqs. (5) and (6) are representative equations developed by the authors to portray the behavior of health monitoring systems.

Including the degradation factor in the model as in Eq. (5) shows a false alarm limit may be useful in actual aircraft operation. Fixing the error factor at 20, towards the lower end of the range, an exploration of the impact of false alarm limits is made. The growth factors of 50 and 200, utilized in Eq. (6), are hereafter referred to as high and low respectively. These factors correspond to a growth rate of 20 and 5 per hundred hours of accumulated time on the ISHM system respectively. The degradation factor adds additional uncertainty to the RUL prediction to examine the effect of degrading sensor or prognostics capability through use of the aircraft. In the analysis of degradation factor, FA limit is the variable of change and is varied from 0 to 100.

Examining the impact of FA limit on mean daily flying hours for the squadron shows that the 0 FA limit case, for which every false alarm triggers ISHM maintenance, dramatically reduces the flying hours. This results from the amount of maintenance required on the ISHM system depleting available hours to fly missions. These results are

shown in Figure 14 and indicate that the low degradation growth rate reduces the flying hours from 32.67 at a FA limit of 2 to 31.15 at 100. In contrast, the high growth rate drops the daily hours from 32.16 at FA limit 2 to 27.49 at FA limit 100. The difference in the magnitude of the declines lies in the fact that the high degradation rate increases uncertainty in the RUL prediction, thus driving false alarm occurrence up. That is, when the FA limit is 0 and there is a false alarm, the ISHM system is always repaired. When the FA limit increases to 2, this allows flights to continue until 2 false alarms are incurred, thus allowing increased flying hours for the aircraft. The degradation factor, slow deterioration of prognostics system, accounts for the remaining decline in daily flying hours. This results from compounded error in the system increasing as the time between service lengthens due to the FA limit being raised.

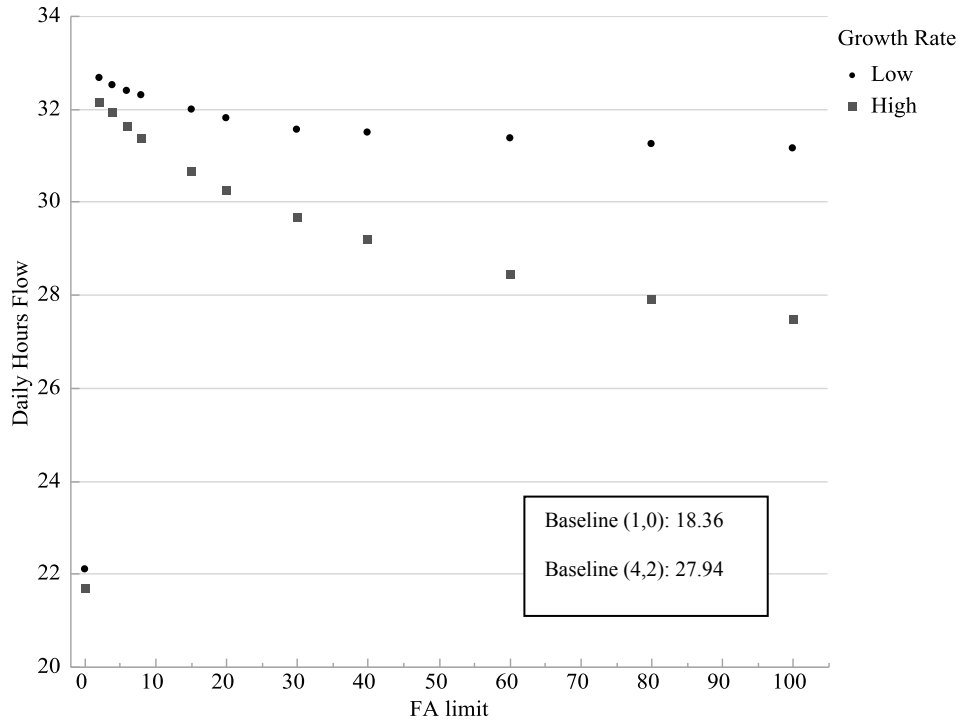


Figure 14. Daily Hours Flown

Figure 8 shows that for a static uncertainty factor of 20 the MMH/FH was 0.165 and 0.743 for the FA limit 10000 and 0 cases respectively. Figure 15 below shows that the high degradation rate reaches 0.74 at a FA limit of 100 and the low rate 0.378. The graph does not show the FA limit 0 MMH/FH data of 2.361 for the low and 2.468 for the high to allow better visualization of the remaining data. It is observed in Figure 16 that the impact of the high growth rate greatly increases the number of false alarms, thus increasing the maintenance hours required per aircraft flight hour shown in Figure 15.

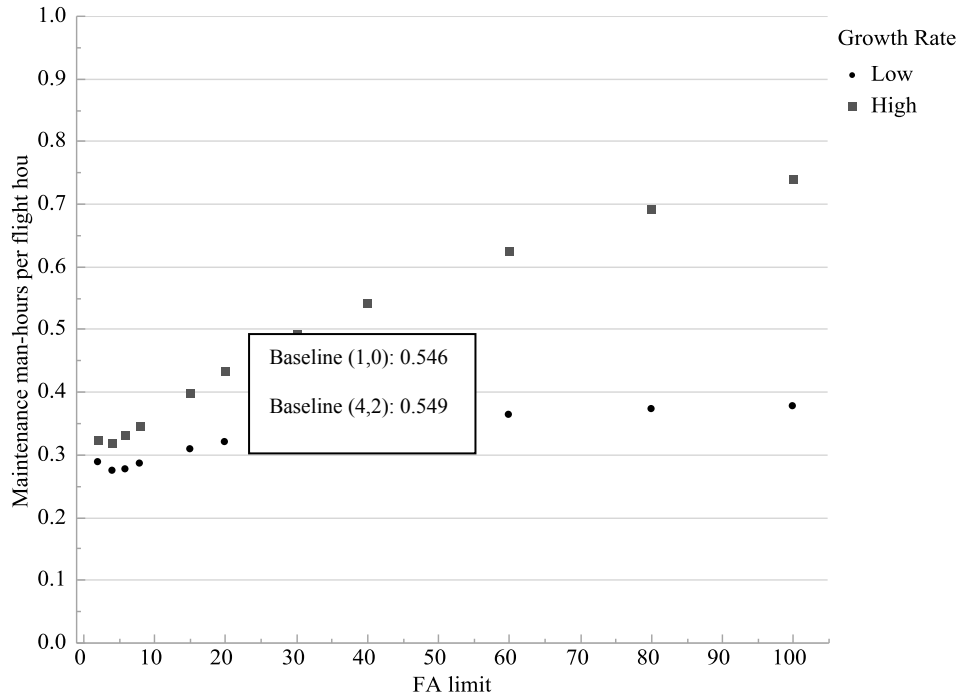


Figure 15. Maintenance Man Hours per Flight Hour

As previously mentioned, Figure 16 is perhaps the best indicator of the impact of degradation growth rates on aircraft operations. The high growth rate proves true to its name as the rate of increase in false alarms per aircraft per year remains higher than the low growth rate over the range of FA limits. The number of false alarms increases as a result of the degradation factor continually increasing as the ISHM system is not being maintained at the shorter intervals a lower FA limit brings.

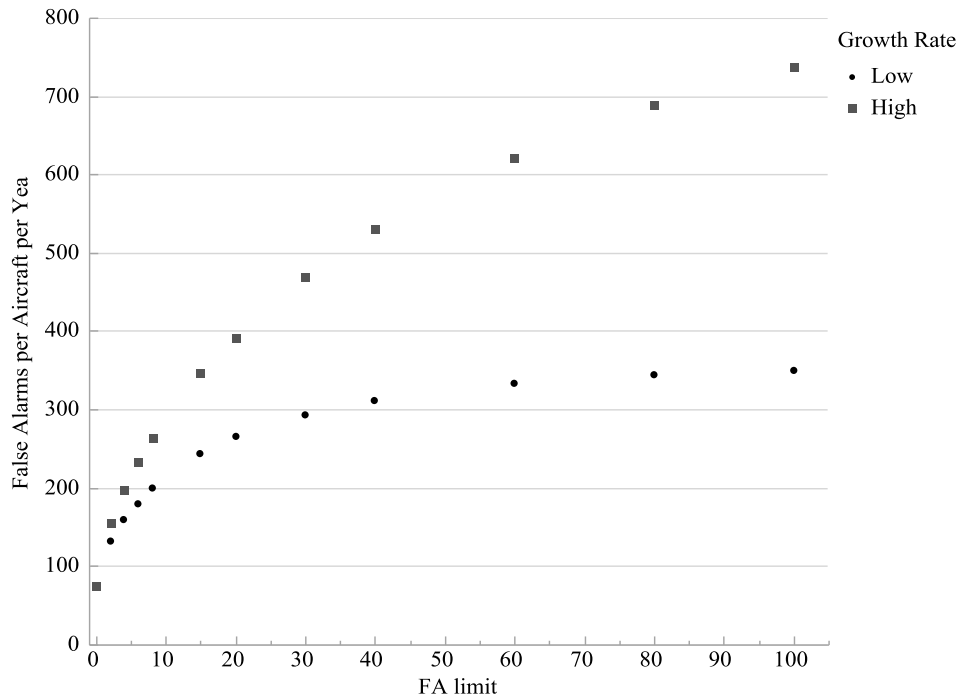


Figure 16. False Alarms per Aircraft per Year

The impact of the increase in false alarms, and thus downtime, is a decrease in operational availability, A_o , as the FA limit increases. Shown in Figure 17, the A_o trend follows that of the daily flying hours and inversely the trends of false alarms and MMH/FH. Operational availability peaks at a FA limit of 4 for both the high and low growth rates. The low growth rate levels off around 0.96 at FA limit 60 while the high rate continues a decline to 0.93 at FA limit 100 without leveling off.

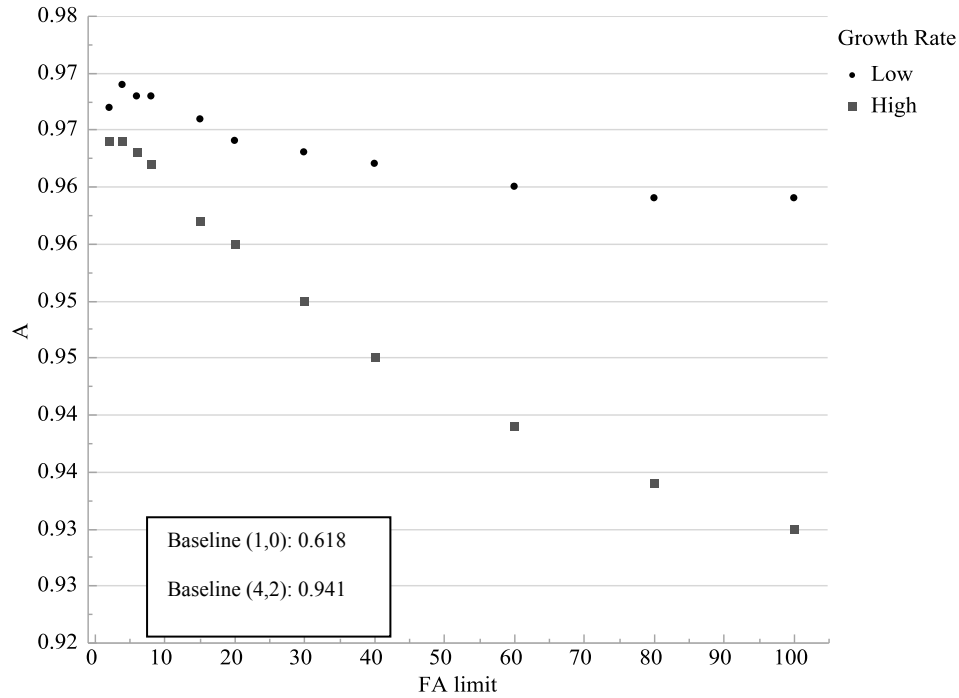


Figure 17. Operational Availability

While Figure 16 shows the increased growth in number of false alarms, the true utility of the model is in determining the “sweet spot” across the performance curves. This is the location where a peak or trough in the curves indicates performance drops off on either side and thus this set of factors should be considered for system design. In this paper, examining Figure 15 and Figure 17 show a performance drop off at a FA limit of 4. These results are specific to the set of inputs used in the model. If the time for inspection of a failure condition or to repair the ISHM system were changed, the potential for a different outcome in FA limits exists. Therein lies the utility of the model in being able to change input characteristics and policies to determine system level performance metrics.

In comparing the sensor degradation case in Figure 14 with the baseline case, daily flying hours remain higher than the baseline case across the FA limit range. The MMH/FH for the degradation case with low growth rate remains below that of the baseline cases, while the high growth rate case is higher than the baseline cases for FA limits above 40. As previously discussed, the FA limit “sweet spot” in this model is 4 thus MMH/FH would be approximately 0.3 and less than the baseline cases. Comparing Ao between the baseline and degradation models shows that around the 4 FA limit results, the degradation cases are above 0.96 while the baseline cases are 0.618 and 0.941 for the (1,0) and (4,2) cases respectively. This again shows the ISHM system to provide higher performance. Finally, the mission reliability for the baseline cases of 84.85% is higher than the ISHM cases, which are below 70% at the 4 FA limit case. Across the model metrics the ISHM case with degradation tends towards higher performance than the baseline. Depending on the desired performance levels desired for the aircraft program managers are left to weigh the performance metrics.

In the model case where degradation is present, for the uncertainty factor chosen it is generally best to set the false alarm limit low. Programmatic policy of cost, availability and reliability will drive towards the selection of a proper limit. Additionally, changes to degradation factor, i.e., ISHM sensor and prognostic characteristics, and RUL uncertainty, prediction algorithm accuracy, can change model outcomes. Cost to implement a certain health monitoring technology on the aircraft may outweigh the benefit of its inclusion if it drives too many false alarms or too much repair time.

Absent the cost impacts of manpower and component replacement, the decision as to how much uncertainty in prognostics is an easier proposition. It is shown in the model with no degradation that as the RUL uncertainty increases, most performance characteristics are adversely impacted. The comparison of baseline to ISHM cases shows the potential advantages implementation of health monitoring and condition based maintenance. The test for program managers then becomes selecting the appropriate system characteristics to meet overall aircraft fleet performance and cost metrics.

Conclusion

This research shows employment of an ISHM system supporting CBM can produce system performance greater than baseline systems. The main contribution of this effort is as a simulation tool to compare sensing options and examine their impact on desired performance factors. The ability to input ISHM system and aircraft characteristics and investigate alternative approaches to monitoring and maintenance makes this tool useful in program decisions on whether or not to implement monitoring techniques. While determining causes of system uncertainty is outside the scope of this research, quantifying the impact of the uncertainty is demonstrated. As a system designer it is important to note, as this research shows, the amount of uncertainty in your system, particularly in the prognostics. This uncertainty could be mitigated with better sensors, techniques or processing algorithms. Further, the designer should seek to minimize either the number or false alarms the prognostic system produces or set an appropriate limit on

false alarms to minimize the impact of additional inspection time to adjudicate system condition.

As cost is not included in this work making a true comparison among options is difficult. A program manager must weigh the technology costs to achieve the performance observed in the model and compare those with system objectives. This task becomes easier if these variables can be explored across a range of scenarios as this research provides.

Future work in this research will explore the impact of cost, supply factors and manpower requirements.

IV. Integrated System Health Monitoring Impact on Non-Repairable Component Supply Methods

Chapter Overview

From on-board automotive diagnostics to real-time aircraft state of health, the implementation of health monitoring and management systems are an increasing trend. This research analyzes the impact of a health monitoring system on a squadron of aircraft. Flight, maintenance and logistics operations are stochastically modeled to determine the impact of program decisions on supply metrics. An Arena[®] discrete event simulation is utilized to conduct this research on 20 components on each of the 12 aircraft modeled. Costs and availability are recorded for comparison across three sparing scenarios to include economic order quantity for baseline and health monitoring cases and a just-in-time health monitoring set of simulations. Finally, the different methodologies are compared and discussed as a trade-space for programmatic decisions.

Introduction

The development of vehicle health monitoring systems enables a focus on condition based maintenance in lieu of time-based preventive maintenance. With increased knowledge about vehicle systems gained through data collected by health monitoring systems, logistics operations too should be considered. In (Hess & Fila, 2002; Hess, Calvello, & Dabney, 2004) Hess et al. discuss the potential benefits of informed logistic systems enabled by prognostics and health management systems, in particular the

autonomic logistics information system (ALIS) of the F-35 fighter. With the development and fielding of health monitoring systems on a range of vehicles, taking full advantage of the information collected is an evolving task.

Health monitoring efforts can be integrated with the logistics chain to optimize maintenance actions with supply requirements. The future goal of integrated systems health management and condition based maintenance (ISHM/CBM) integration is to yield operations and sustainment (O&S) savings (Carnero Moya, 2004).

The General Accountability Office (GAO) has conducted several audits of the Department of Defense (DoD), with findings ranging from required items routinely missing from inventories to enormous on-hand stock. Additionally, they found unneeded parts on order accounting for billions of dollars in unneeded parts and operational rates well below goals (Government Accountability Office, 2001; Government Accountability Office, 2007). Reasons for parts shortages range from inadequate forecasting, repair and manufacturing issues, poor replacement part reliability, and contracting problems. In one extreme example, demand for an engine bolt was projected at 828 units when actual requirements were over 12,000 in a single quarter (Government Accountability Office, 2001). This issue was still present in 2010 when the Logistics Management Institute conducted a review of DoD logistics citing “inaccurate demand forecasting as a primary cause for the military services’ inability to align inventory levels with current demands” (Atchley et al., 2010, p. 2-5). Implementing ISHM/CBM systems on a broad range across the services would increase the forecasting capability and provide near real time insights into requirements, both existing and in the near future. Between 2002 and 2005, Air

Force spares shortages were between 6 and 8 percent of total requirements, averaging over \$1 billion in shortfalls (Government Accountability Office, 2007).

A shortage of spares is not the only issue facing the Air Force. As cited by the GAO, “the value of Air Force on-order inventory not needed to support required inventory levels... represent[s] an average of 52% (\$1.3 billion) of its on-order inventory” (Government Accountability Office, 2007, p. 9). Between 2002 and 2005, 65% of on-hand inventory—amounting to \$18.7 billion—was not required for projected use rates. Further compounding the unneeded on-hand inventory is that some items have a shelf life that requires disposal or refurbishment after a set amount of time. The prognostics capability of ISHM systems can increase the reliability of spares forecasting and, depending on projected use rates, keep sparing purchases within DoD budget timelines.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on health monitoring and supply and discusses supply concepts. Section 3 introduces the model formulation and measures of merit. The results for the different methodologies utilized in this research are provided in Section 4. Finally, section 5 provides a conclusion for the work and discusses future efforts.

Background

This section reviews relevant literature and discusses concepts behind model formulation.

Cost Accounting

The cost of ordering replacement parts can be decomposed into two elements, administrative cost and part cost (Sherbrooke, 2004).

$$OC = K + P * Q \quad (7)$$

where OC is the order cost, K is the fixed administrative cost per order, P is the component cost, and Q is the order quantity.

Once the ordered spares are delivered to the customer, holding costs are then accrued. These costs are related to the storage, storage buildings and upkeep, spares inventorying and maintenance, insurance, etc. These costs are generally calculated as a percentage of the per unit part cost and are determined either over discrete time periods or continuously as in Eq. (8). The cost of deterioration is also included in holding cost, but is not addressed in this research. Shah, Soni, and Patel (Shah, Soni, & Patel, 2013) propose a method to include the deteriorating spares cost in the holding cost equation.

$$HC = \int_0^T H * SL(t) dt \quad (8)$$

where HC is the holding cost, H is the part holding cost per time and SL(t) is the stock level held in inventory at time t (Rodrigues & Yoneyama, 2012).

In the commercial arena, there is a tangible cost for not having needed stock on hand when required, known as a stockout cost, such as lost revenue for a flight or halting of production. In the government or military operating environment, where revenue is not a consideration, the impact is more likely in the form of the system being labeled non-mission capable for supply (NMCS). Depending on the spare parts strategy used for the

system, a NMCS could result in contractual penalties to suppliers (Anderson, Fitzsimons, & Simester, 2006; Kennedy, Wayne Patterson, & Fredendall, 2002). Company reputations as well as relations with customers are also indirect costs of stockout conditions (Rodrigues & Yoneyama, 2012). Sustained high levels of NMCS aircraft may also require a larger fleet to meet mission requirements.

Economic Order Quantity

The concept of an optimal or economic order quantity (EOQ) was introduced by Harris in 1913 (Harris, 1990). Shown in Eq. (9), this model is concerned with a reorder point, R , and an order quantity, Q , yielding an (R, Q) model. The reorder point is determined based on the desired safety stock and order lead time. The economic order quantity is determined by,

$$Q = \sqrt{2 * D * K / H} \quad (9)$$

where Q is the quantity of spare parts to be purchased when a new order is placed, D is the average demand per unit of time, K is the administrative cost of placing an order, and H is the holding cost per unit per unit of time held in inventory (Sherbrooke, 2004).

While a traditional (R, Q) supply methodology augmented by ISHM projections could work, as shown by Rodriguez and Yoneyama (2012), a just-in-time approach may work as well.

Prior Models

Kählert, Giljohanan and Klingauf (2014) use a MATLAB discrete event simulation to analyze a single commercial component with 100% unscheduled

maintenance. They evaluate health monitoring system performance and conclude a potential annual savings of approximately 20% is possible.

Rebulanan models the F-35 ALIS system with a discrete event simulation containing LRUs, communication system, supply, and maintenance systems (Rebulanan, 2000). Rebulanan evaluates model performance with aircraft availability, mission capable and non-mission capable rates. The simulation shows sensitivity of supply lead time to the detection lead time and stock levels.

Rodrigues and Yoneyama (2012; 2013) examine the impact of ISHM prognostics on stock levels for both repairable and non-repairable systems. These models are compared with a conventional supply system. These studies both indicate potential cost savings for a prognostic system versus a conventional supply process. The non-repairable study includes only one item with a fixed supply lead time. This limitation leaves the interaction of multiple components and variable lead times in question.

Methodology

The research methodology used in this work builds upon Vandawaker, Jacques, and Freels (2015). The Arena[®] discrete event simulation processes a squadron of 12 aircraft through daily operations to include: flying, take-offs and landings, inspections, maintenance, supply and health monitoring activities. Each simulation takes the aircraft through 15 years of operation and consists of 100 runs. The architecture for the ISHM model processes is found in Figure 6. This figure depicts the flow of information and

aircraft through system operations. System processes include flight operations, ISHM diagnostics and prognostics, CBM order processing, and maintenance and supply actions.

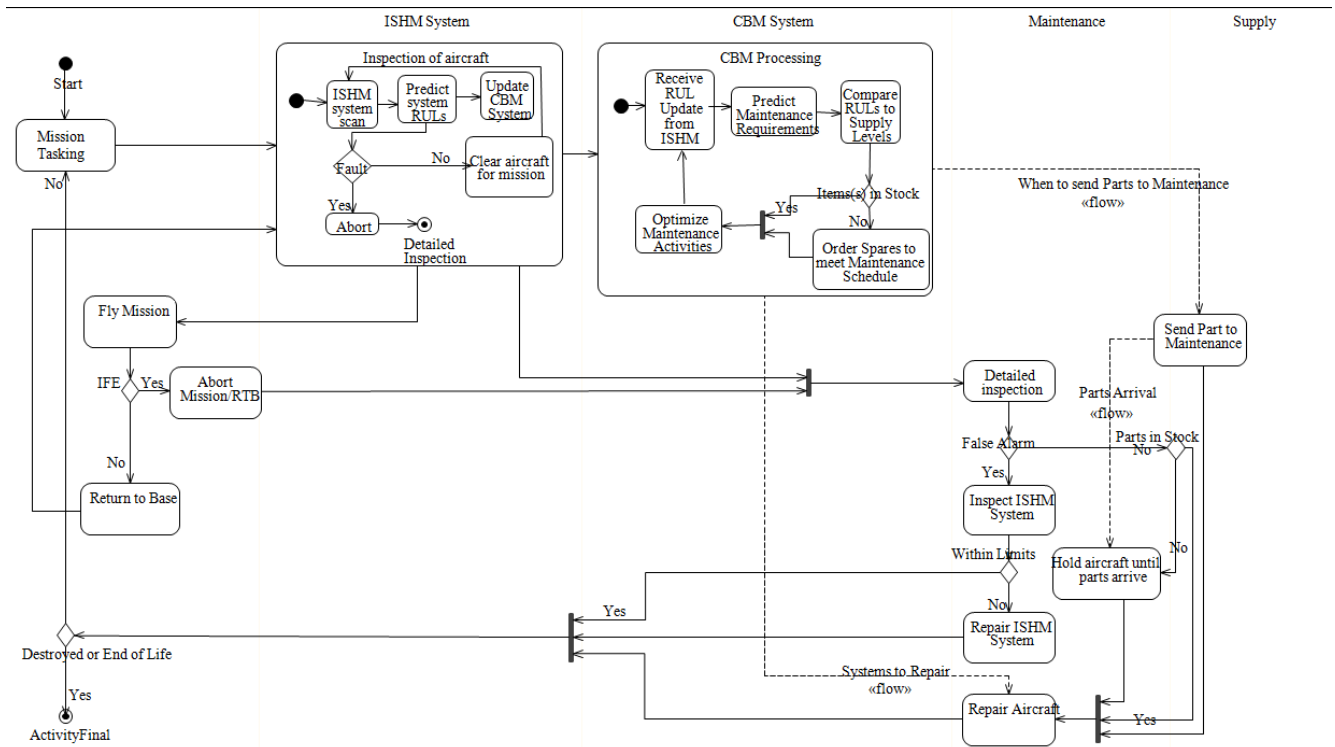


Figure 18. ISHM System Architecture

A baseline model is run as a comparison with time-based preventive maintenance and (R, Q) stocking policy. An ISHM model is also run with an (R, Q) policy based on Rodrigues and Yoneyama (2012) where the reorder point is adjusted based on need predicted by the ISHM system. These are both compared to a supply system operating nearer to a just-in-time delivery program.

Just-in-Time Logistics

Hess and Fila (2002) discuss the ability of health monitoring systems and automated logistics to enable just-in-time (JIT) inventory methods. There are, however,

conflicting views regarding the efficacy of just-in-time sparing. Bragalia, Grassi, and Montanari (2004) cite just-in-time sparing as “the most desirable approach,” but stress good integration between supplier and customer. Kennedy, Patterson, and Fredendall (2002) cite JIT sparing as a desirable option for predictable demand items, while also stating that JIT may not be a good option when demand is unpredictable. Huiskonen (2001) also suggests a strong relationship between the supplier and customer is necessary to ensure efficient and effective inventory management if JIT parts management is chosen.

In this work, ensuring adequate notification time prior to component need is accomplished through a daily analysis of projected component needs. This lead time is shown in Eq. (10) and includes factors to mitigate the risk of a stockout condition prior to component need by maintenance,

$$SF + MW + JIT \text{ factor} \geq Part_RUL \quad (10)$$

where SF is the component safety factor, MW is the maintenance window to make preemptive repairs, JIT factor accounts for supply lead time, and Part_RUL is the remaining useful life of the part in question.

This research used the methodology above for just-in-time supply with order windows of 1, 3 and 5 days across the simulation runs.

The modeling assumptions for this work are as follows:

- Components are non-repairable;
- Components do not degrade on shelf;
- Cost of money is constant across simulation time;
- No change in delivery time distribution over simulation;

- No cost penalty for backorder;
- Cost of supplies remains constant;
- There is no discount for large quantity order;
- (R, Q) model unique for each part;
- If a stockout condition occurs before order is received, aircraft is NMCS until part(s) arrive;
- Each order incurs a fixed administrative cost, K, regardless of ordering process;
- A holding cost, HC, is incurred annually for each unit in inventory;
- Enough maintenance personnel are available to complete tasks without delay.

Model Components and Architecture

Each aircraft has 20 components, denoted A-T, with failure times randomly sampled from an exponential distribution, with a given mean time between failure (MTBF), and with probability distribution function: $f(x) = \frac{1}{\beta} e^{-x/\beta}$, for $x > 0$.

In the baseline case, unless the part is scheduled for preventive maintenance, the condition is not known; thus the need for repair or replacement is unanticipated and the aircraft continues normal mission operations. Maintenance actions are performed in parallel on each aircraft. All part inspection times are in minutes and are triangularly distributed (20, 30, 45). LRU replacement times are also in minutes and triangularly distributed (60, 90, 240).

Supplies are input into the model at an initial stock level and a reorder point. In the baseline case, the reorder point and economic order quantity are fixed throughout the simulation. The baseline reorder point is two for all components, leaving a small safety stock to lessen the probability of running out of spares before the next need. In the ISHM

EOQ case, the order quantity, Q , is fixed, but the reorder point, R , varies based on predicted need from the ISHM system prognostics. In the just-in-time cases, an initial stock level of five is assigned and the ISHM prognostics decide when and what quantities of parts are ordered. The ordering system for the just-in-time cases scans all aircraft daily and determines the required number of each component over a certain lead time to need, shown in Eq. (10), and orders are made at a set interval of days to meet the demand. EOQ is not considered in the just-in-time cases. Supply lead time is log-normally distributed (5, 2) days between delivery and receipt for all parts.

The remaining useful life (RUL) prognostic technique used in this research takes into account sensor degradation and inherent uncertainty in the system as described in Vandawaker (Vandawaker, Jacques, & Freels, 2015). The health monitoring system orders spares to meet demand as described in section 2. If a component is in a stockout condition, the aircraft becomes non-mission capable for supply awaiting needed part(s).

Evaluation Parameters

Two categories of metrics are applicable to the results of this research: availability and cost.

Operational availability (A_o) includes logistics, supply and administrative delays to preventive and corrective maintenance for the system resulting in the mean downtime for the system. Operational availability is the system availability the user of a system realizes (ReliaSoft, 2007). Mathematically, operational availability is:

$$A_o = \frac{Uptime}{Uptime + Downtime} = \frac{MTBM}{MTBM + MMT + MLDT} \quad (11)$$

Where: MTBM is the mean time between maintenance, MLDT is the mean logistics delay time, and MMT is the mean maintenance time.

Non-mission capable supply (NMCS) is the time between component need by maintenance and when the part arrives in maintenance. ISHM/CBM's prognostic ability can predict impending component failure and establish sparing requirements in advance of maintenance requirements, ordering spares if stock levels are inadequate. The baseline process relies on predicted failure rates and providing stock levels to meet anticipated demands. This process increases the logistic footprint by requiring storage facilities for materiel that may not be needed for upwards of a year. Managing these spares and the facility requires additional resources, manpower, and money. Holding cost is another area of interest as it drives facility and manpower requirements.

Results

The data presented here shows the impacts of part ordering based on projected need of all aircraft over the duration in Eq. (10). Additionally, EOQ models with both ISHM and baseline architectures are provided for comparison.

Figure 19 shows the impact of the supply ordering methodology. It is observed that as the number of days between JIT orders increases, the yearly average NMCS hours per aircraft increases as well. The increase is attributed to variability in aircraft usage and supply delivery time over the period between ordering and actual receipt of the parts. The baseline case with a (R, Q) ordering scheme for spare parts yields a yearly NMCS rate per aircraft of 57 hours. This baseline result represents a 26% lower rate than ordering

parts every 5 days, but a 90% increase over the 3 day ordering schedule and an 850% increase over daily ordering. Notably, the ISHM EOQ case has the lowest annual mean NMCS time, less than 4 hours per aircraft. The high supply availability is attributed to the on-hand stock kept versus the JIT method and the forward looking capability afforded by the ISHM prognostics.

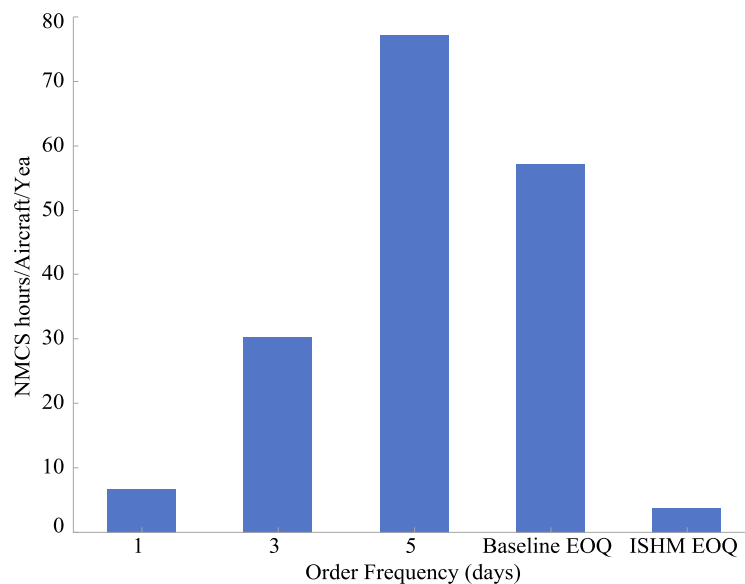


Figure 19. NMCS Hours per Aircraft per Year

While it may be desirable to choose a methodology with the lowest NMCS rate, it does not come without an accompanying cost. Shown in Figure 20 below, increased holding cost is a trade-off of a low NMCS rate. Holding cost decreases as the order frequency increases. This increase is a direct result of spares being in stock for a longer duration awaiting installation on the aircraft. In the baseline case, mean yearly holding costs are \$106K. As shown in Figure 20, this represents a 104% increase over daily ordering, a 171% increase over 3 day order frequency, and a 216% increase over 5 day

ordering. While the holding costs may not appear to be a large value in absolute terms, it must be noted that these costs are only for 20 components in a fleet of 12 aircraft at one operating location. When scaled up to thousands of parts and hundreds of aircraft, and operating at locations around the world, these costs can be sizeable.

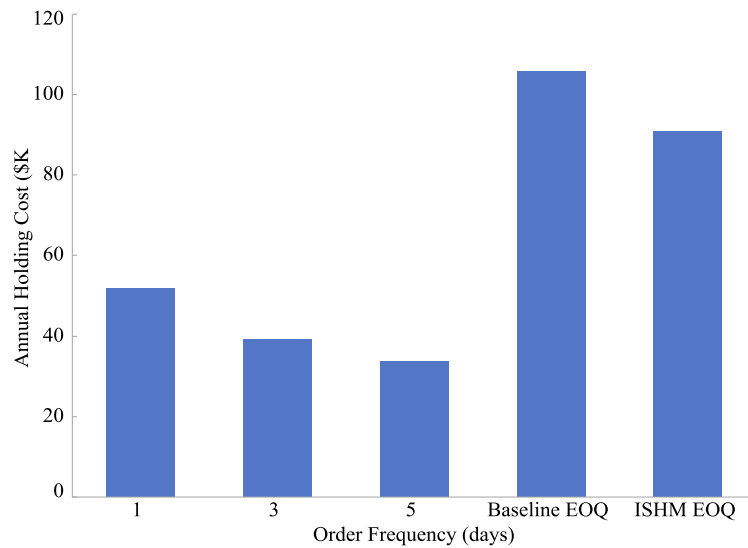


Figure 20. Holding Cost

As discussed in section 2, administrative order costs are those costs associated with the processing, shipping and handling of an order above the cost for the actual part(s). As shown in Figure 21, the administrative costs for the just-in-time delivery method are considerably higher than for the EOQ schemes for both the baseline and ISHM cases. This results from the fact that orders are being placed much more frequently to meet demand as the stock level for the JIT case is kept to only what is projected over the next several days of flying. The EOQ cases take into account economic factors of the supply process to keep overall cost low, at a higher overall holding cost and stock level.

If JIT administrative costs can be brought down through contracts or arrangements with suppliers, then the JIT system could be more competitive with the EOQ ordering scheme.

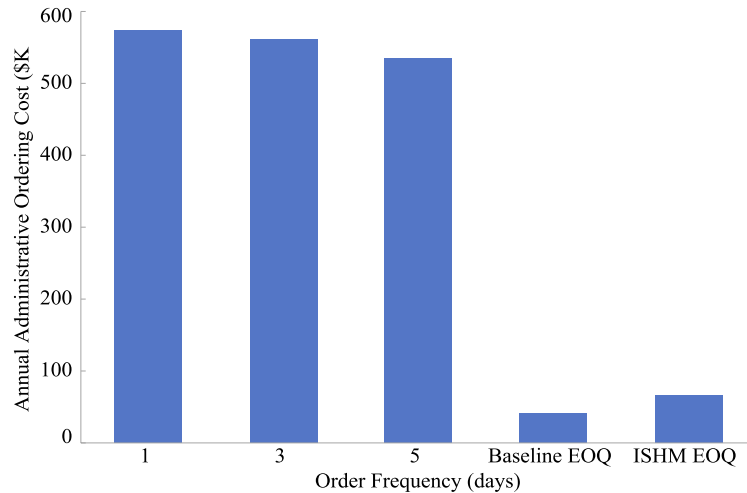


Figure 21. Administrative Cost

Figure 22 represents the total annual supply cost for each scenario; this includes, holding costs, administrative costs, and part costs. Observed in Figure 21, administrative ordering costs account for the majority of the total supply cost differences. While the baseline cost has the smallest annual cost, it is only part of the picture. When maintenance costs are included in Figure 23, the baseline case is no longer the lowest cost. Further, when considering Figure 24 and Figure 25, the baseline case has the lowest operational availability and six fewer daily flying hours across the 12 aircraft. Six flying hours per day is equivalent to requiring two fewer aircraft in the ISHM cases for comparison.

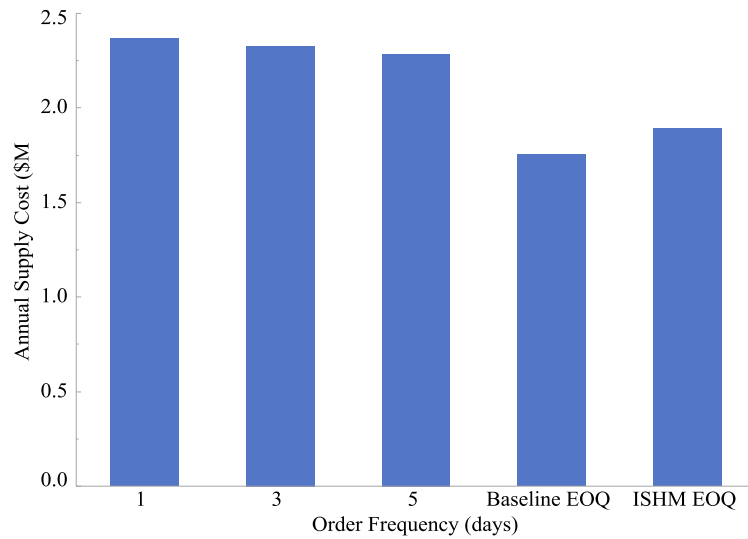


Figure 22. Total Supply Cost

Summing total supply costs along with the direct maintenance costs, actual maintenance personnel inspecting or replacing parts on aircraft, yields the total cost shown in Figure 23. This comparison shows a spread of approximately \$500,000 annually across the model cases. It is noted that the maintenance cost for the baseline case is 2.5 times higher, resulting from fixed timed based preventive replacement versus the condition based replacement under the ISHM logic.

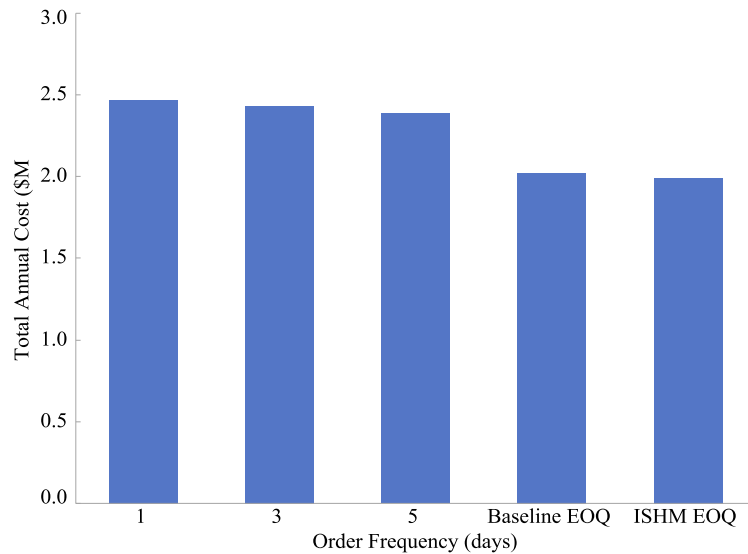


Figure 23. Total Cost

Operational availability is of concern for most systems, and aircraft are no exception, whether commercial carriers or military transports. If aircraft aren't available, the mission either doesn't get accomplished or it is delayed, costing money and/or reputation. Figure 24 shows the impact of the supply methodologies in this research. The baseline case shows the lowest operational availability resulting primarily, as mentioned above, from additional time-based maintenance and inspections. A_o for the ISHM cases remain between 0.97 and 0.98 for all the scenarios, resulting from fewer required maintenance activities. Fewer maintenance activities also means more time to conduct flying operations. Shown in Figure 25, the daily flying hours for the ISHM cases are higher than for the baseline case.

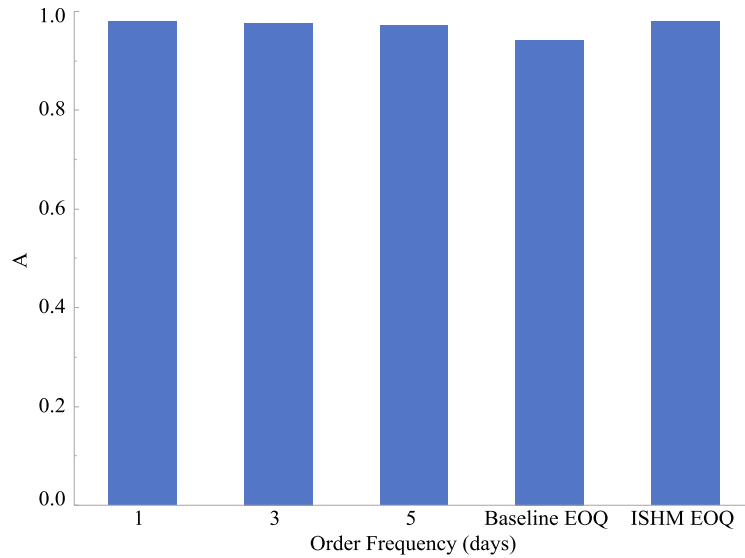


Figure 24. Operational Availability

While cost is a chief consideration of the operation of most systems, it is not the only concern or measure of merit. Selection of any system requires a balance among often competing objectives. In this research, cost and availability or flying hours are somewhat diametric parameters. While supply costs for all ISHM cases are higher than the baseline, it is not the only consideration. Management must weigh the savings potential for the supply methodology chosen with the need fewer aircraft to accomplish the same mission. So while status quo of the baseline system shows a savings of 17% annually, the ISHM cases can provide better A_0 and equivalent flying hours with two fewer aircraft. If the cost savings of removing two aircraft and the cost to instrument and implement ISHM across the remaining aircraft is less than the baseline case, the economic case is made to implement ISHM. Additionally, if the two additional aircraft

are kept as well, new missions could be accepted to increase productivity and usefulness of the systems.

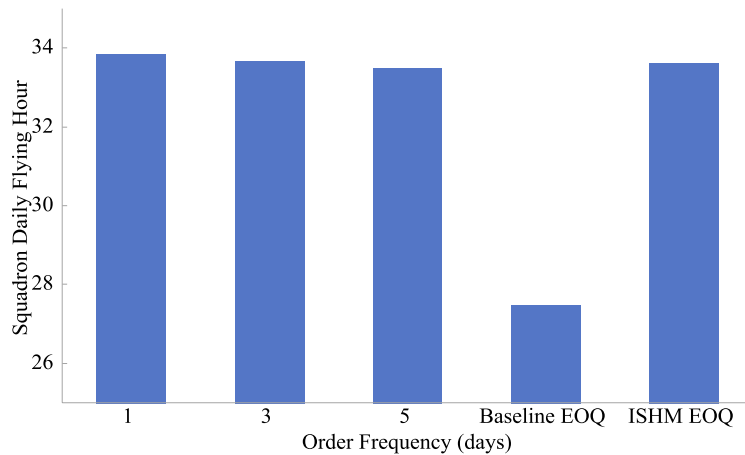


Figure 25. Daily Flying Hours

Conclusion

This model is meant as a planning and design tool to study the impact of ISHM capabilities, maintenance processes, and spares management considerations. Weighing the impacts of simulation outputs and management philosophies with cost and performance objectives is left to program managers to determine the appropriate level of service required.

The cases laid out above provide an example of the capability of integrated system health management enabling condition based maintenance to provide a competitive cost to traditional aircraft operations. The tool developed by the authors provides insight into the trade-space of health monitoring requirements, sparing decisions and maintenance operations. If the administrative cost of just-in-time sparing can be

reduced, it is possible to compete with a modified economic order quantity sparing system. Additionally, these are fictional cases and as discussed by numerous authors, the truth likely lies somewhere in between (Braglia et al., 2004; Carnero Moya, 2004; Huiskonen, 2001; Kennedy et al., 2002; Wheatley, Gzara, & Jewkes, 2015).

The results of this research show that switching from a baseline EOQ system to and ISHM EOQ system can provide cost savings, absent the initial investment of the health management system. The tool and simulation outputs are then useful in determining if the long-term performance increases of the ISHM system balance out the additional upfront cost of implementation.

The next step in this research is a study of maintenance manning decisions based on health monitoring inputs. Further study of this area of interest should also include repairable systems and their impact on the supply chain and manning.

V. An Examination of System Health Monitoring Impact Non-Repairable Component Maintenance Manning

Chapter Overview

Reductions in operating budgets are forcing many companies and militaries to consider reducing manpower, in particular maintenance personnel. Combined with longer service lives for aircraft and other systems, maintenance and operations processes must be reconsidered. One research and development method to support the above considerations is health monitoring systems. The majority of published research efforts focus on health monitoring techniques and technologies, leaving others to determine the maintenance and logistics impact on the systems. This research utilizes an Arena[®] discrete event simulation to examine a squadron of 12 military cargo aircraft, monitoring 20 components on each, equipped with health monitoring systems. The impact of health monitoring on maintenance manning decisions and system performance is studied. Data presented for numerous manning levels show potential cost and performance trade-offs. Additionally, a case study exploring the impact of two limited manning levels is presented. The value of this work is in showing the ability of health monitoring systems to affect condition based maintenance decisions. Additionally, the development of trade-spaces within operating environments is demonstrated along with the ability to conduct cost benefit analyses.

Introduction

Maintenance has evolved over time from a “fix it when it breaks” policy towards the increasingly popular condition based maintenance programs. Rising costs, longer service lives and reduced manpower has driven a proactive approach to maintaining systems. The reactive or corrective maintenance approach of many systems forces either a costly spares stockpile to prepare for all possible failures or waiting for replacement parts to arrive resulting in zero operational availability (Amari et al., 2006). One of the first advancements in maintenance practice was to establish regular inspection and preventive maintenance (PM) intervals. This technique analyzed various forms of system performance data to determine appropriate times to inspect and replace components (Walls et al., 1999). This PM approach benefits in reduced catastrophic failures at the expense of more maintenance cycles and higher maintenance cost (Deputy Under Secretary of Defense for Logistics and Materiel Readiness, May, 2008). Unanticipated failures still occur outside the preprogrammed maintenance windows and must be taken into account. Further, PM subjects the system to unnecessary “repair” based on the required schedule for the system. The unneeded maintenance adds extra expense to the system since the component may have had remaining useful life. Moreover, the probability of failure can increase as damage often occurs during maintenance actions.

Another approach to system maintenance is the concept of selective maintenance, whereby a subset of actions are performed from a group of proposed maintenance tasks (Iyoob et al., 2006). As Iyoob, Cassady, and Pohl (2006) point out, a majority of studies into maintenance practices ignore budget limitations, manpower or time constraints,

which is where selective maintenance can assist in determining what actions should be taken to maximize the available resources. They present logic for determining maintenance actions when “it may be impossible to make all possible repairs before the next mission.” The selective maintenance process can affect all maintenance approaches, but repair driven by material state afforded by condition based maintenance (CBM) allows for the management of downtime and resources. CBM and other predictive maintenance programs have further evolved from preventive strategies to actively or passively analyzing system health and forecasting remaining life.

Much research on health monitoring systems is focused on obtaining system or component states of health and predicting remaining useful life (RUL). These works generally provide estimates of savings in maintenance based upon the ability to utilize parts longer before replacement or through the elimination or reduction of inspections to determine materiel condition:

- 40% for vehicle maintenance (Walls et al., 1999)
- 30% to 50% for fuselage panels (Pattabhiraman et al., 2010)
- 10% electrical components (Scanff et al., 2007)
- 50-80% for the Boeing 777 (Gorinevsky et al., 2005).

Lacking in these studies is the impact an integrated system health management (ISHM) approach could have on maintenance manning decisions. If inspections are no longer needed or occur on a less frequent basis, are the personnel devoted to time-based inspections and repair needed at all? What needs to be addressed to fully understand the impact of these works are potential savings through a reduction or realignment of

maintenance manpower. This paper lays out a study of the implications of integrated systems health management on maintenance manning levels and the associated cost and aircraft availability impacts.

Background

Condition based maintenance, when appropriately applied, can reduce the life cycle cost of a system. Ellis (2008) argues that cost-effective systems monitoring allows repair actions based on system condition rather than costly time-based maintenance. Additionally, maintenance can be forecast for completion at a time, likely between projected flying sorties, that minimizes impact on the operational mission of the system. Under a CBM paradigm, interim time-based inspections, required under the baseline PM approach are forgone in lieu of a continuous analysis of the aircraft via the ISHM system.

Maintenance Manning

While this work does not propose a new technique to optimize maintenance manning, it does seek to utilize tools and modeling to show the impact of a health monitoring system on maintenance activities. That said a review of relevant maintenance optimization and planning literature is still insightful.

Sherif (1982) provides a good review of over 800 articles in which he defines eight aspects of reliability and maintainability that methods fall under. Additionally, Sherif surmises that system design and evaluation must consider both availability and performance criteria to meet the goal of maximizing profit and availability while minimizing cost. Most research however, deals with failing systems and neglects the

prognostics capability of ISHM based systems driving CBM (Scarf, 1997) (Huynh, Barros, & Bérenguer, 2012)(Khac Tuan Huynh, Barros, & Berenguer, 2012). Chilcott and Christer (1991) provide an examination of the impact of CBM on manning in coal operations assuming perfect diagnostic capabilities in the health monitoring system. Further, Chilcott and Christer find that even small downtime savings can provide large financial benefits. Mahulkar et al. (2009) present a study of manning based on a system of systems in a naval environment that while not specifically focused on condition based maintenance, does include the principles of actions based on component or system states. Their study showed intelligent maintenance, i.e., sensor systems, can reduce maintenance manning requirements and increase efficiency.

Dekker (1996) points out that while a number of mathematical approaches have been proposed to approach maintenance optimization, none are as straight forward as the economic order quantity methods used in supply optimization. He goes on to say that most maintenance problems require software and models to predict gains in maintenance methods and it becomes more of an art than a pure science. The key then becomes adequately and accurately measuring the model outputs to gain insight into the methodology.

Maintenance Metrics

In order to properly measure system and model performance, metrics must be established and defined across the range of model outputs. First, non-mission capable for maintenance (NMCM) is an aircraft state where the vehicle is operationally incapable due to maintenance requirements. The maintenance man-hours per flying hour (MMH/FH)

metric measures the effectiveness of maintenance personnel and the ease with which a system can be repaired. Another key metric in determining maintenance efficacy is the mean time to repair (MTTR) a system, that is, the total maintenance elapsed time divided by the number of maintenance actions (Defense Acquisition University, 2012).

$$MTTR = \frac{\text{Total Maintenance Time}}{\text{Number of Maintenance Actions}} \quad (12)$$

Operational availability (A_o) is defined as the system availability the user of a system realizes (ReliaSoft, 2007). Mathematically, operational availability is given as:

$$A_o = \frac{Uptime}{Uptime + Downtime} = \frac{MTBM}{MTBM + MMT + MLDT} \quad (13)$$

Where MTBM is the mean time between maintenance, MMT is the mean maintenance time, and MLDT is the mean logistics delay time. For the purposes of this research, MMT and MTTR are assumed to be equivalent.

Methodology

Utilizing the military aircraft model developed in (Vandawaker, Jacques, & Freels, 2015) and (Vandawaker, Jacques, Ryan, Huscroft, & Freels, 2015) by Vandawaker et al., this research explores the impact of health monitoring systems on maintenance manning. They compare a baseline squadron of aircraft, no ISHM, with the same squadron with ISHM implemented, examining false alarms and availability impacts in addition to cost. Further, they explore the impact of ISHM on economic order quantity and just-in-time supply methods. The just-in-time supply methodology from (Vandawaker, Jacques, Ryan et al., 2015) is utilized for stocking components in this

research. These works compared ISHM systems to baseline systems to show possible gains through the use of health monitoring technology. This research extends the previous modeling approach to study the impact of maintenance manning levels on a system equipped with health monitoring systems. The time-based inspections and preventive maintenance in a baseline or non-ISHM equipped aircraft are replaced with computer scans of sensor data which are then used to predict RUL and forecast maintenance.

This work does not attempt to optimize maintenance manning, but to show the impact of an ISHM equipped aircraft squadron on manning levels. The effect of maintenance personnel levels on system performance is only observed in relation to the direct maintenance on the 20 unique components modeled on each of 12 aircraft in this work. This information allows planners to determine the maintenance requirements and allocation of personnel, or fractions thereof, to the direct support of the researched parts. For each of the twenty components it is assumed that the time between successive failures follows an exponential distribution.

The ISHM system produces prognostics for RUL based upon its calculations from system diagnostics. There are two components in the RUL, diagnosis from the health monitoring system and prediction uncertainty. In this research component diagnostics is taken as perfect, i.e., sensor always knows exact health. With many health monitoring techniques, the closer a component is to failure, the better uncertainty can be quantified for the diagnosis of condition (S. Sankararaman & Goebel, 2013). This leads to the line replaceable unit (LRU) RUL given as:

$$LRU\ RUL = \text{lognormal}(Diagnosis, uncertainty) \quad (14)$$

Where *Diagnosis* is equivalent to the true remaining life and *uncertainty* is defined in Eq. (15).

$$uncertainty = degradation\ factor + \ln(Part\ RUL) * \sqrt{uncertainty\ factor} \quad (15)$$

where *Part RUL* is the previous RUL prediction for that part and, *uncertainty factor* is a design variable. The *degradation factor* places an additional uncertainty on the RUL prediction given as:

$$degradation\ factor = 10 + Part\ ISHM\ timer / 20 \quad (16)$$

Where, *Part ISHM timer* is the accumulated life on the health monitoring component associated with a specific component. The leading 10 in the equation represents a fixed initial degradation while the 20 provides a representative increase in degradation as life, or wear, incurs on each part respectively. As shown above, degradation factor increases in direct relation to the accumulated Part ISHM time. The effect of the degradation factor on RUL uncertainty is a gradual increase in the accumulated uncertainty for a particular component. When a component is replaced or reaches a limit in the number of false alarms, thus triggering ISHM maintenance, the ISHM part timer is reset (Vandawaker, Jacques, & Freels, 2015).

In this research, components are non-repairable, that is, they are replaced upon failure or an indication from the ISHM system. Upon indication of impending failure by the health monitoring system, the aircraft is brought into maintenance for inspection to adjudicate if the indication is real or a false alarm. The times to complete an inspection for all components are triangularly distributed (20, 30, 45) minutes. If the inspection

confirms the ISHM prognostics the component is then replaced along with others deemed in need of repair. The time to replace each line replaceable unit (LRU) replacements are triangularly distributed (60, 90, 240) minutes if only 1 maintainer is available for the action and triangularly distributed (40, 60, 160) minutes if 2 personnel are on the task. These parameters values were chosen to represent a range of repairs and inspections. Additionally, if multiple components require replacement or inspection, the tasks can be completed in parallel, if sufficient personnel are available.

In addition to components being replaced upon immediate need, maintenance may also occur to make use of time between missions. At the end of a mission the ISHM system scans the aircraft. If the ISHM system indicates maintenance is required within a predefined maintenance window and the projected time to complete the component replacement(s) is less than the time before the next mission, the aircraft is brought in for maintenance. Further, if an aircraft is already in for maintenance and the ISHM system indicates other components are not in need of immediate replacement, but within the maintenance window, those components can be replaced if there is adequate stock.

When maintenance actions are performed, they are arranged to take advantage of available personnel to complete all processes in the quickest manner. Depending on the number of replacements required on a particular aircraft, these tasks may be performed in parallel, serially, or some combination of the two utilizing the times discussed earlier in this section.

Maintenance personnel are assigned to one of two 12 hour shift manning levels: day, 7AM to 7PM; and night, 7PM to 7AM. Various combinations of day and night shift

manning levels are explored in this work, ranging from 1 day and 0 night shift personnel to 20 maintainers on both day and night shift. The 20 maintainer case provides enough personnel that no wait time for inspection or repair is observed.

The modeling assumptions for this work are as follows:

- Aircraft missions occur around the clock regardless of maintenance manning;
- Aircraft are either fully mission capable (FMC) or non-mission capable (NMC) with no partial mission capability (PMC).

Results

Reflected in this section are the results of manning variations across model runs. The figures herein represent the two shift manning levels from section 3. The upper row of the x-axis in the figures contains the number of personnel available for tasks on the day shift and the lower row includes those available for actions on the night shift. The results shown below are the mean of 100 model simulations at each personnel combination. The analysis for statistical significance was performed; however, confidence intervals are not presented in the figures in this work. The reason for confidence intervals not being presented is that 95% intervals shown in the figures are indistinguishable from the mean of the data, which are shown.

Model Output

Operational availability is a common measure of system performance. The A_0 's observed in Figure 20 reflect the availability of the squadron of 12 aircraft over the duration of a 15 year simulation. The addition of one maintainer to the night shift is shown to have an appreciable impact on overall system performance, as is shown further

in the remaining figures. For the condition where only 1 maintainer is available on the day shift and none on the night shift, A_O is slightly above 0.90. The addition of one person on the night shift to provide service increases the A_O to over 0.96, meaning the aircraft are available for mission tasking an additional 6% of the time. As shown in Figure 27, that 6% represents an additional 4.5 hours of flying time per day across the 12 aircraft or nearly the equivalent of adding 2 more aircraft to the squadron.

Figure 20 also shows that adding 1 additional person to the day shift for a total of 2 provides a benefit worthy of consideration by management. The addition of other personnel on both day and night shifts continues to have positive impacts on the operational availability but with smaller increase in magnitude. Beyond the inclusion of 2 personnel on the night shift, A_O gains are in the thousandths and when factoring in the remaining metrics may not sway management decisions. The largest gains noted in Figure 20 are the result of the aircraft not having to wait up to 12 hours over the night shift for maintenance which occurs in the step from 0 to 1 night shift maintainer. Other gains result from the ability to complete more component replacements simultaneously as more personnel are available.

While the A_O may appear high for many aircraft, it should be noted that these results only include the impact from 20 components on the 12 aircraft. This note should also be considered in reviewing the remainder of the data and figures presented in this research.

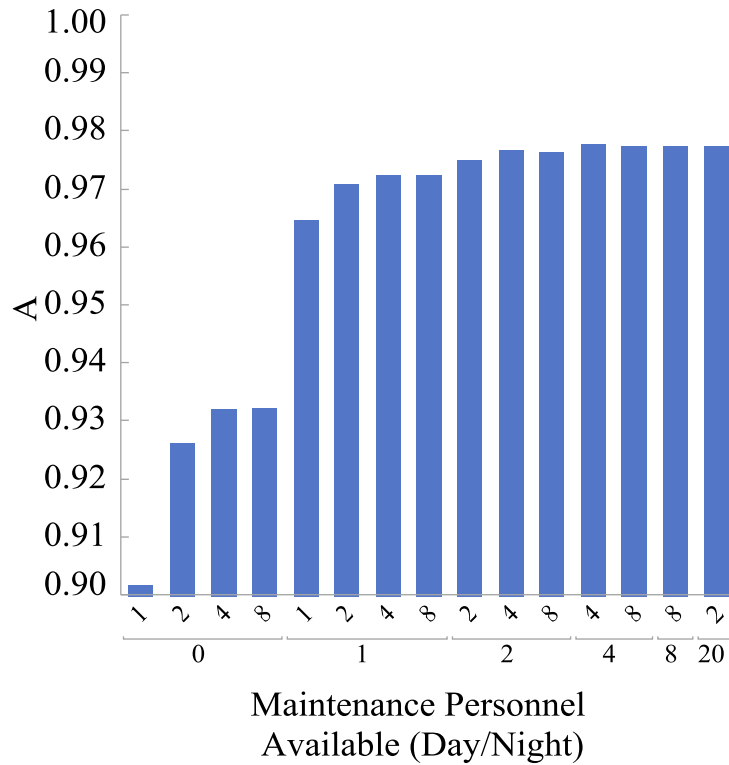


Figure 26. Operational Availability

Daily flying hours for the 12 aircraft squadron, shown in Figure 27, reflect that the inclusion of just 1 maintainer on the night shift has the effect of increasing daily output by over 3 hours. As previously mentioned, this is the equivalent of adding another mission to the daily flying schedule for the cost of one maintainer. Further gains in daily sortie production with increasing numbers of personnel, both day and night shift, are smaller and left to operations and maintenance management to determine the efficacy of including the extra manpower.

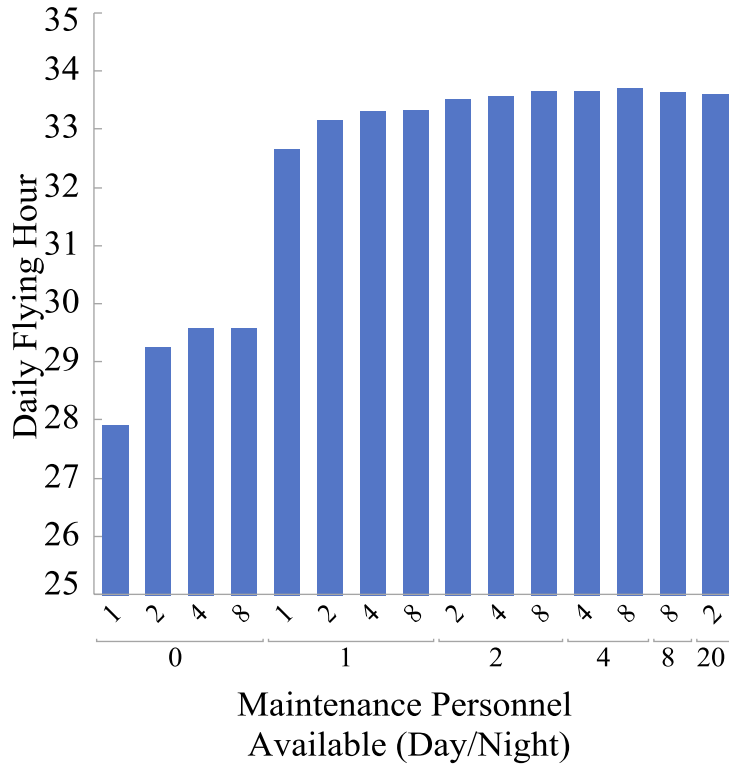


Figure 27. Daily Flying Hours

Alluded to in previous discussion, the amount of time annually the squadron is NMCM generally decreases as the number of personnel increases as observed in Figure 28. The addition of one maintainer to the night shift drops the mean NMCM from 10200 hours to 3400 for the 1 maintainer on the day shift case. The nearly 7000 hours less time down for maintenance affords increased opportunities for aircraft missions as well as lower workloads for the individual maintenance personnel. Greater gains can also be realized with the inclusion of more personnel on the day shift, but plateaus as the NMCM time becomes mostly hands-on maintenance with little to no awaiting maintenance time.

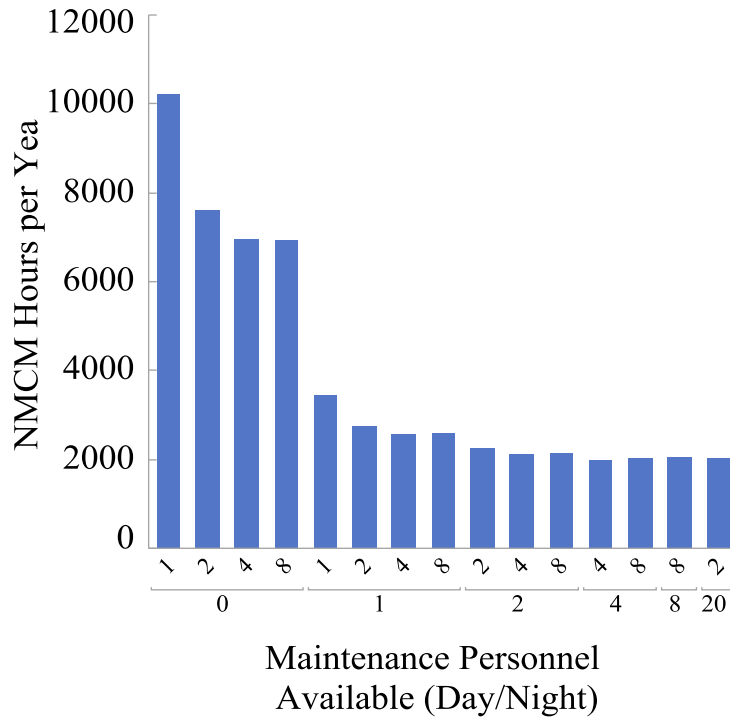


Figure 28. Annual NMCM Hours

Exploring the efficacy of maintenance manning from a different vantage than NMCM, Figure 29 shows the average time an aircraft has to wait prior to a maintenance action beginning. In other words, Figure 29 represents the responsiveness of the maintenance system to aircraft demands. If supply wait time were added to these data, the result would be the MLDT from Eq (1). The shape of Figure 29 follows that of Figure 28 with the magnitude reflecting total waiting time for all maintenance actions divided by the number of total actions. The figure clearly shows the impact of the addition of a night shift maintainer on the wait time for maintenance to begin, bringing the average wait time from over 5.5 hours to 32 minutes. Once night shift personnel are increased to 2 or more,

the average wait time is less than 6 minutes for all cases. The 8 day and 8 night case wait time is 2 seconds and 20 day, 20 night is 0.

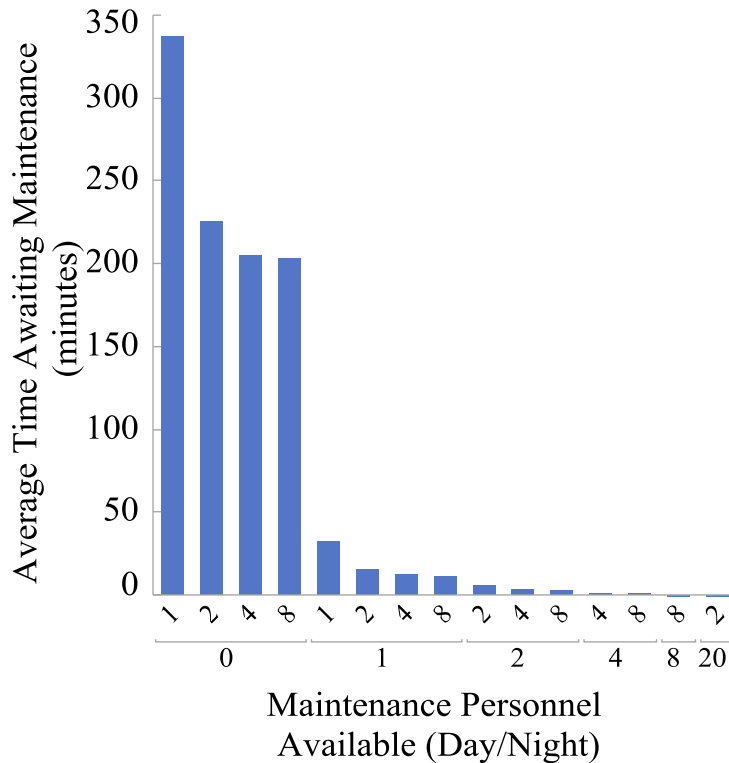


Figure 29. Mean Time Waiting for Maintenance

The addition of repair time to Figure 29 yields the maintenance metric of MTTR found in Figure 30. Again it is noted that the elimination of a 12 hour period where no personnel are available to perform maintenance is beneficial to aircraft turn-around time from maintenance. While Figure 28, Figure 29, and Figure 30 depict similar information, they each provide insight into the timeliness of the maintenance system in its ability to support aircraft operations.

As in Figure 29, Figure 30 shows an area of little variation for cases where 2 or more personnel are available on the night shift. The resulting MTTRs for these cases are predominately true labor hours as maintainers are available to perform most tasks as they arise.

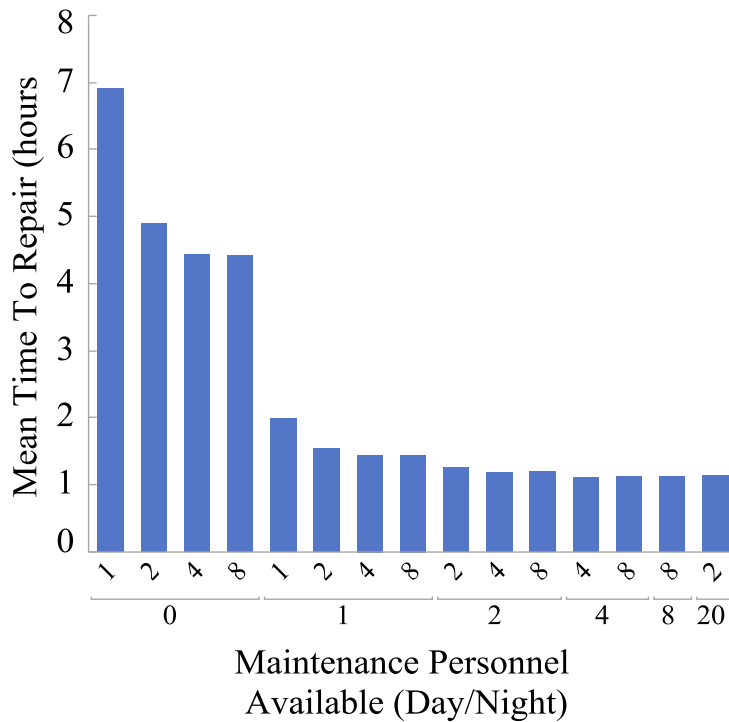


Figure 30. Mean Time to Repair

Figure 31 shows the utilization rate for the maintenance personnel assigned to each simulation. The first column shows that with only 1 person on day shift and none on the night shift, the maintainer is busy 50% of the available hours. While that may not appear to be overtaxing on the individual, that person must perform all repairs and inspections as required. While the forward looking prognostics of the ISHM system can allow for deconflicting of component replacement, failure warnings must still be

adjudicated through inspections which can lead to backups in the maintenance process, noted in Figure 29.

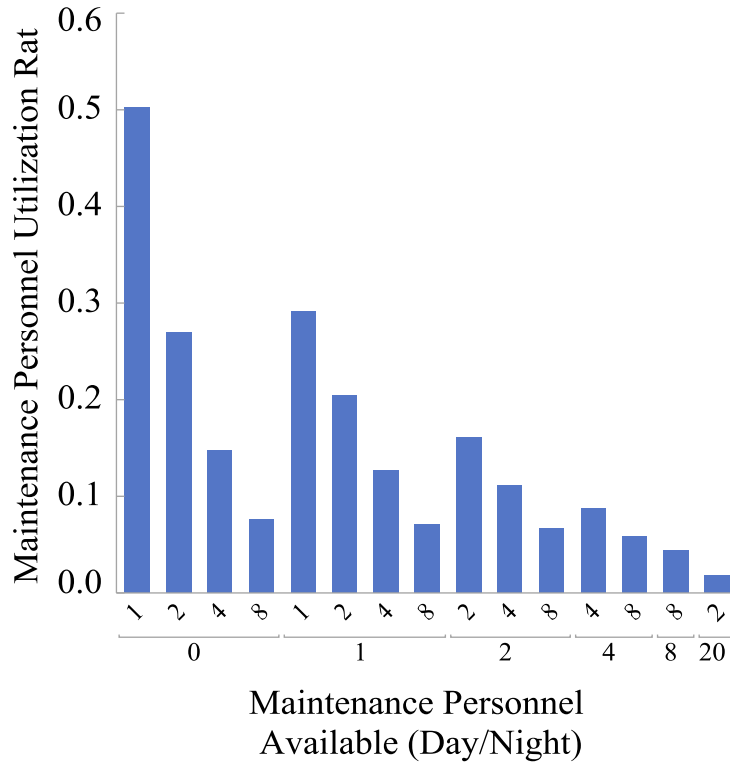


Figure 31. Personnel Utilization

The doubling of day shift personnel to 2 while keeping the night shift at 0 results in a 46% drop in utilization rate. The trend in Figure 31 shows that adding personnel on the dayshift steeply drops the utilization rate while including additional night shift personnel changes the magnitude of the group rates. Examining the 20 day and 20 night case, utilization rate drops to 0.02, leaving those personnel 98% of their time to focus on other tasks.

The usefulness of Figure 31 lies in being able to manage workload for maintenance personnel. As this model only represent 20 components there are likely other tasks maintainers are responsible for accomplishing. If it is shown that, in the case of only 1 day worker and 0 night, a maintainer will need to focus 50% of their shift, or 6 hours, to these components scheduling other work becomes more difficult.

The amount of maintenance required for a flying hour is an indication of efficiency of maintenance processes and the reparability of the aircraft. Figure 32 shows MMH/FH remains between 0.2 and 0.25. While MMH/FH doesn't show much variation, the entire picture is not clear from this one figure. Total maintenance man hours are lower for the cases with no night shift personnel, but referring to Figure 27 it is also noted that flying hours are lower as well. The driving case for a relatively stable MMH/FH results from the repair times in section 3, which do not vary across the manning scenarios. It follows then that as the cases with night shift personnel have more flying hours the maintenance hours increase accordingly, keeping the MMH/FH ratio similar. Within the night shift bands, MMH/FH variation is noted with different day shift personnel numbers. When observing Figure 20 and Figure 27 in relation to Figure 32, the incremental gains in Ao and daily hours track within the night shift bands.

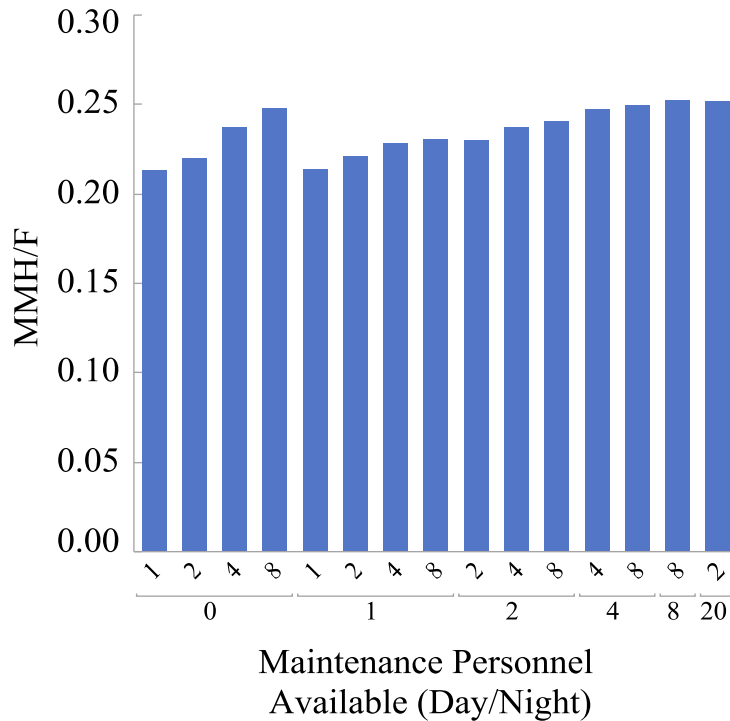


Figure 32. Maintenance Man Hours per Flying Hour

Turning to the costs associated with the maintenance of the 20 components of interest in this research, Figure 33 shows the annual cost of direct maintenance. These figures only include the time maintenance personnel are actively inspecting components to determine if failure indications are true or are in the process of replacing items on the aircraft. An hourly maintenance cost of \$50 is used for all personnel (Department of the Air Force, February 1994). The annual cost of maintenance peaks at \$155K for the 8 day, 8 night personnel case and is slightly lower for the 20, 20 case, due to the efficiency of having more personnel to complete tasks. The lower cost of the 1 day and 0 night case belies the fact that the operational output is markedly lower, as shown in Figure 20 and Figure 27.

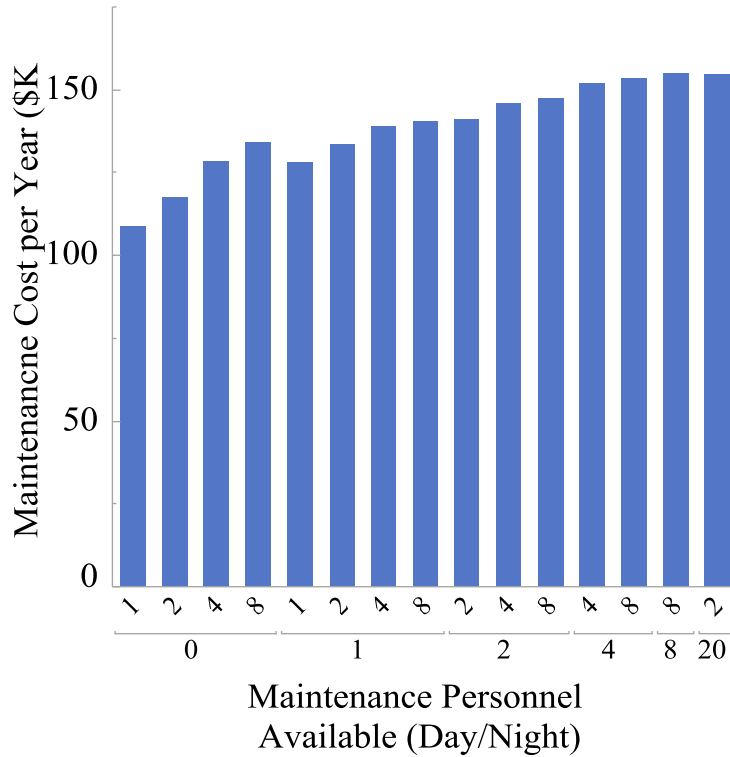


Figure 33. Annual Maintenance Cost

Shifting focus to total logistics and maintenance cost in Figure 34, it is clear that the direct maintenance costs are but a small portion of the overall price tag. Except in the cases where no night shift personnel are scheduled, maintenance costs are less than 7% of the total logistics and maintenance cost. The percentage rises to between 14% and 21% of the total cost when no night shift personnel are available. The remainder of this cost is the purchase and storage of spare parts for aircraft operation.

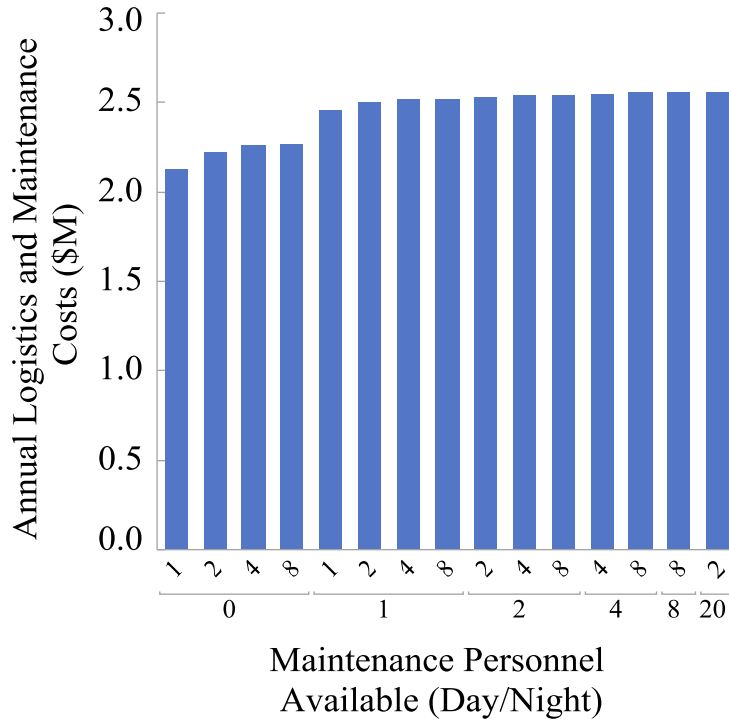


Figure 34. Annual Logistics and Maintenance Cost

Case Study

Let us explore the data in section 4.1 from a maintenance management perspective. If a decision had to be made where only 2 personnel were available for maintenance on the 20 components studied which shift combination is preferred: 2 day and 0 night; or 1 day and 1 night. We will assume that management wants the most performance, Ao and daily flying hours, for the least cost with other factors considered for comparison.

Daily flying hours for the (2, 0) case are 29.3 versus 32.7 for the (1, 1) case, with operational availabilities of 0.93 and 0.96 respectively. With only these two items considered, management would choose the (1, 1) case as better performance is achieved.

When cost is considered, annual maintenance costs are \$10000 larger for the (1, 1) case or \$150000 over the 15 year simulation time with a \$230000 total logistics and maintenance cost difference. The question for management then becomes is this cost increase justified by the higher system performance?

The likely answer to the previous question is yes as the system performance gain of the (1, 1) case over the (2, 0) case is equivalent to an additional aircraft worth of flying time each day. Thus if the cost of an aircraft is higher than \$230000 with a planned life of at least 15 years the higher support costs can be justified. Similarly, an aircraft could be removed from the (1, 1) case and still achieve performance equivalent to the (2, 0) case.

When additional factors, shown in the remaining figures, are considered, the case for choosing a (1, 1) maintenance manning scheme becomes greater: 4000 fewer NMCM hours per year; 190 minutes less wait time for maintenance; 3 hours less MTTR; and a slightly smaller MMH/FH. The personnel utilization rate of the (1, 1) case is 0.29 versus 0.27 for the (2, 0) case, which could be a positive or negative depending on other requirements placed on the personnel.

In summary, a management decision based on 2 maintainers would likely yield a 1 day and 1 night shift scheme based on the evidence presented above. Further utility in this research is offered in determining maintenance workload and the impacts of manning decisions on overall aircraft system performance. Additionally, the model parameters for health monitoring capabilities can be changed to determine the downstream effect of system design on the logistics and maintenance operations. This information can then be used to provide trade-off analyses to program management.

Conclusion

The work presented above provides a tool for managers and planners for utilization in system design and support planning. Information captured in the figures details cost and performance data that show efficiency in maintenance processes at set manning levels. The ability to define a trade-space for system parameters early in the development of an aircraft or any system affords the opportunity to explore future cost savings and weigh performance trade-offs.

Future work in this model environment should include additional study of maintenance windowing for when aircraft is already being brought in for other work. Also, the utilization of remaining useful life prognostics could be enhanced for more detailed event scheduling for further gains in downtime efficiency and aircraft utilization.

VII. Component Replacement Windowing

Chapter Overview

This chapter examines the impact of placing a maintenance opportunity timeframe (window), counting back from the projected component failure time, in the maintenance logic. This window affords the opportunity for components to be replaced if they fall within the specified time frame, and the aircraft is already in maintenance for another replacement or inspection. The data presented herein show there are potential benefits, in both cost and availability to establishing this type of maintenance window.

Model Description

The parameters used in this chapter are the same as those of chapter 6 with the addition of the maintenance opportunity introduced above. While getting all useful life out of a component is desirable, in some instances it may make sense to replace one or more components earlier than planned. The reasons can be for both availability and cost savings in the long term as maintaining several components at once is generally more efficient than replacing them individually. This grouping of maintenance actions saves on set-up time for repairs as it only has to be done once versus many times for individual components. The results below illustrate the benefits and drawbacks of a maintenance window and its effect on cost and availability.

Results

This work examines results across a range of maintenance manning scenarios initially, as in chapter 6, to show the effect on operational availability and daily flying hours. The number of maintenance personnel on the day and night shifts, and the length (lead time) of the maintenance interval will be varied to examine this effect. The remainder of the figures show only one manning scenario to focus on the impact of various levels of maintenance windowing.

Figure 1 depicts the operational availability of the twelve aircraft squadron across a range of manning scenarios and maintenance windows. It is observed in the figure that as the number of personnel available increases A_O does likewise. Within each manning band six maintenance windows are also graphed for comparison. The effect of the maintenance opportunity window on A_O shows an increase until 40 hours prior to projected failure and then a slight reduction at 50 hours. As in chapter 6, the increasing A_O trend across the manning bands is as a result of personnel available to perform repairs as required instead of aircraft sitting and waiting for inspections or component replacements. Within each manning band the operational availability increases as the window increases, until it reaches 50 hours. This A_O rise results from seizing the opportunity to perform maintenance when the aircraft is already down for another action, thus saving on inspection and set-up time to perform replacements individually. The leveling off of A_O between 30 and 50 hours results from more replacements being conducted, especially for components that have low MTBFs, which require more downtime than utilizing a smaller window.

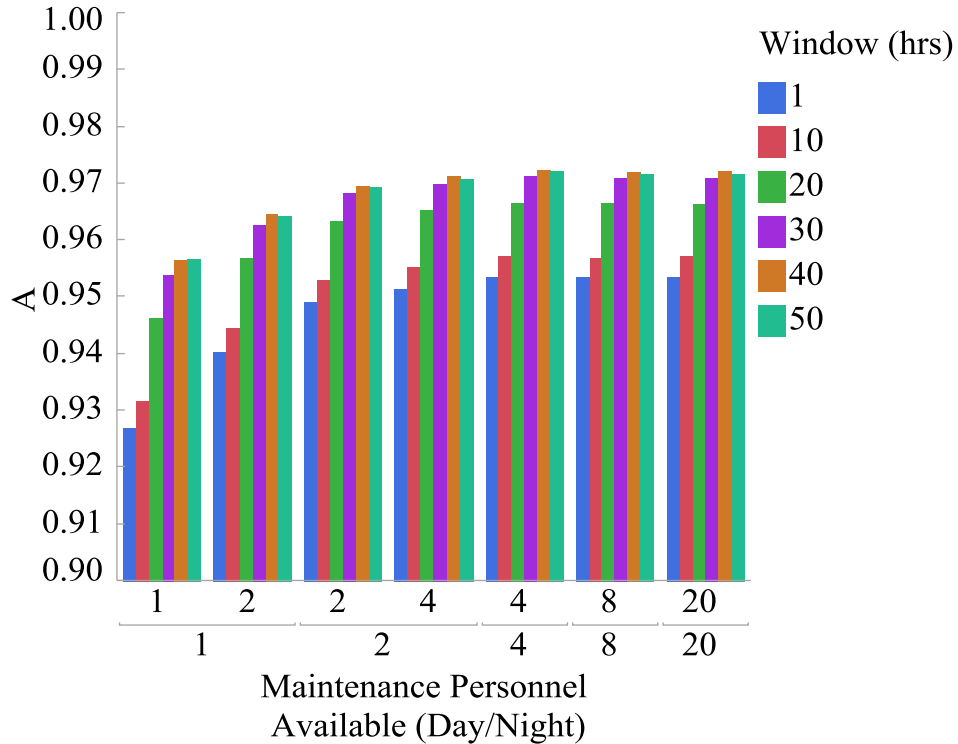


Figure 35. Maintenance Windowing Operational Availability

Mean daily squadron flying hours, shown in Figure 36, follow the general trends seen with operational availability. As in the manpower study in chapter 6, daily hours increase as more personnel are available to maintain the aircraft. Within each manning band, the effect of maintenance opportunity windowing is noted to increase as the window hours increase. The gains in daily hours associated with the different windows result from the opportunity taken to incur fewer times down to make component replacements in groups versus individually. The reason daily flying hours do not drop off at the same time operational availability does lies chiefly in the model design. When an aircraft returns to mission availability following being in maintenance it incurs a hold prior to its next mission. While this hold time is uptime in terms of A_0 , flying does not occur and thus daily hours do not accrue. Shown later in Table 6, false alarms drive the

number of times aircraft enter maintenance at lower maintenance windows. Once false alarms are cleared, the aircraft is released back to the hold status until its next mission is scheduled. Therefore, the more false alarms that occur, the more times an aircraft enters the mission hold sequence thereby reducing the number of hours the aircraft fly.

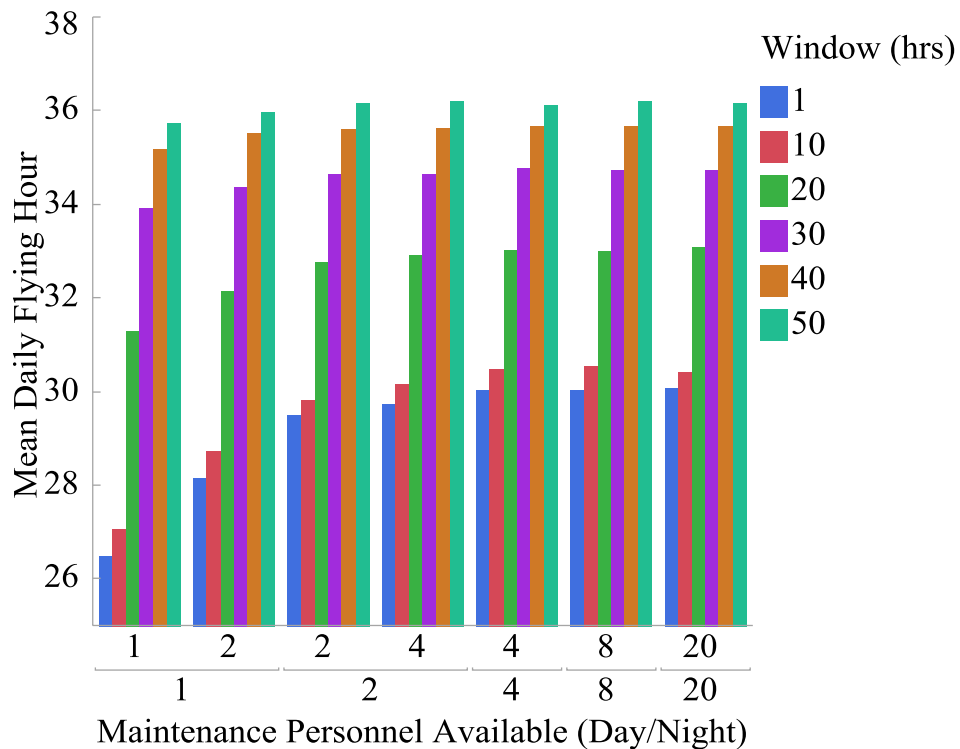


Figure 36. Mean Daily Flying Hours

From this point forward the figures and discussions examine the maintenance manning case with 4 personnel on the day shift and 2 personnel on the night shift. This case is chosen since overall gains in hours, availability, and costs are relatively low for the scenarios with additional personnel available.

One of the goals of grouping maintenance activities is to reduce the total number of hours the aircraft are down and unavailable for operations. Figure 37 shows the mean

annual NMCM time for each maintenance window. It is observed that as the window size increases, that is, a greater opportunity to replace a component before its predicted failure, NMCM hours decline. The decrease is attributed to two items. First, grouping of component replacements into a single maintenance action in lieu of several maintenance actions with only one component replaced. Second, as components are replaced more frequently as the window widens the ISHM system is reset more frequently which leads to the added benefit of fewer false alarms which require inspections to clear. From chapters 4 and 6 it is noted that as the sensors accumulate flight hours, they also degrade which leads to an increase in the number of false alarms. In this scenario, false alarms decrease from an average of 248 annually to 22 when the maintenance window widens from 1 to 50 hours. The yearly NMCM hours for a 50 hour window are 52% lower than at a 1 hour maintenance window and 50% lower than a 10 hour window. Stated another way, across the 15 year simulation the 50 hour maintenance window provides over 36000 hours more availability as the aircraft are no longer NMCM.

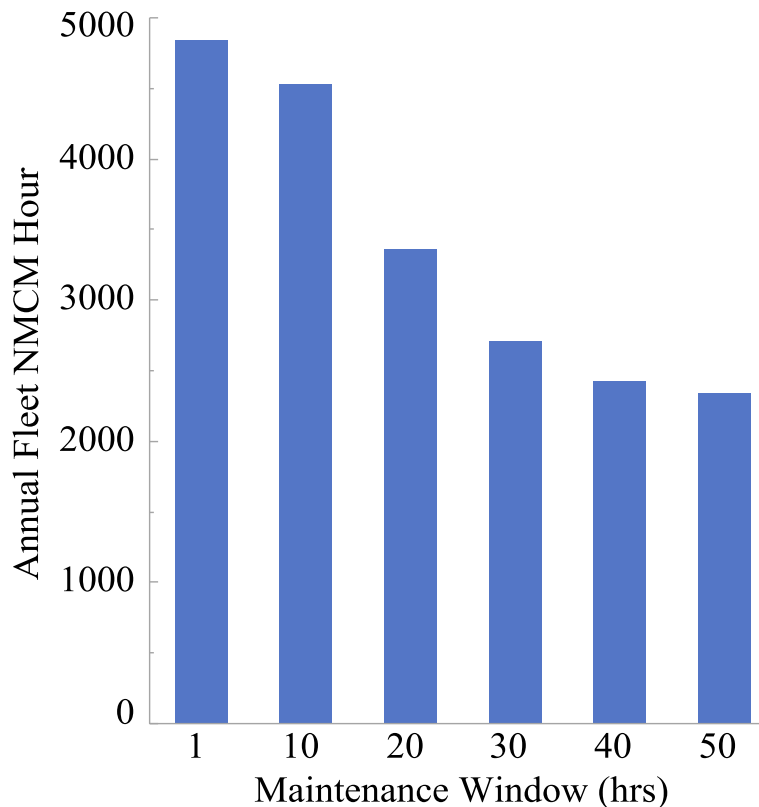


Figure 37. Mean Annual Non-Mission Capable-Maintenance Hours

The reduction in total NMCM hours with an increasing maintenance window, made possible by a grouping of maintenance tasks, has a somewhat inverse trend in mean downtime. As Figure 38 shows, mean downtime increases as the maintenance window widens. At a 50 hour window, the MDT is more than double that at either 1 or 10 hour windows. Grouping of component replacements into larger aggregate tasks versus many individual ones increases the overall time required each time down, but as Figure 37 shows the net effect is lower overall system downtime. While this stands in contrast to DoD predictions of “significantly reduced” MDTs by performing CBM versus time-based preventive maintenance it does not necessarily contradict the assertion (Under Secretary of Defense (AT&L), May 2008). Grouping takes advantage of the diagnostic

and prognostic capabilities provided by ISHM to apply CBM in a more optimal manner to reduce total aircraft downtime in lieu of many shorter downtimes enabled by the same ISHM capabilities. The net effect of the grouping of maintenance activities is to increase the mean downtime while simultaneously reducing total downtime. There is an additional increase in MDT as a result of a growth in NMCS time as the maintenance window becomes larger. The NMCS increase results from the supply ordering system, in particular the supply lead time, not keeping up with the opportunistic maintenance occurring during the grouping windows.

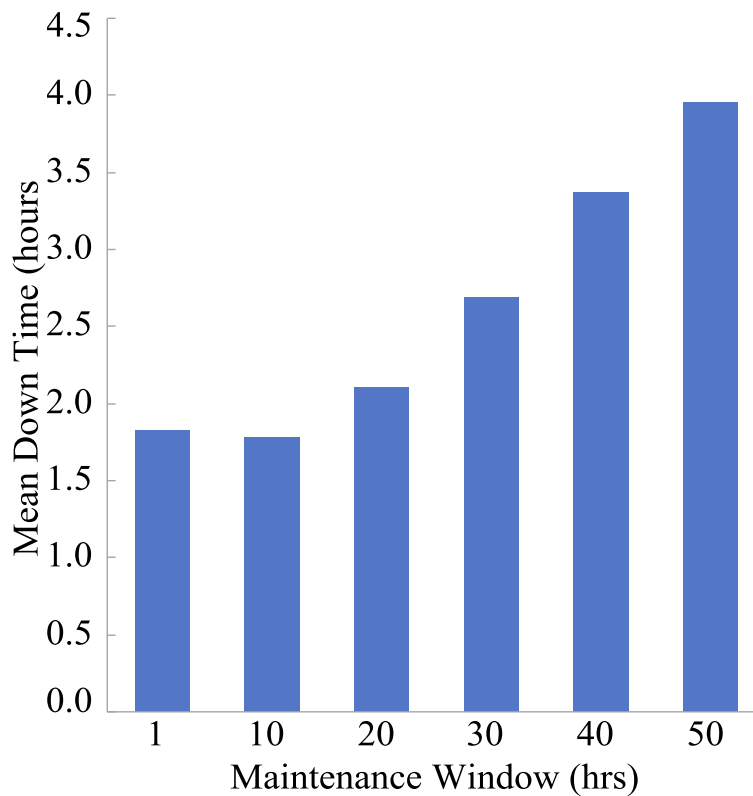


Figure 38. Mean Downtime

As the maintenance opportunity window widens, a counterpoint is developed in an increase in the unused useful life for the components. Figure 39 shows the average

useful life lost across all components. The values are determined by taking the difference between the accumulated part life at replacement and the actual (not ISHM RUL projection) failure point assigned to new parts. Major factors that contribute to life lost include the RUL prediction error, maintenance window, safety factor, projected mission duration, stock levels, and manning levels among others. Safety factor is fixed at 10 hours for all components and mission durations are LOGNORM (4, 3) hours. These two components along with error in RUL prognostics account for the majority of part life lost. The accumulation of the items above leads to the information presented in Figure 39, which shows that useful life lost increases 142% from a 1 hour window to a 50 hour window. While it may be desirable from a utility standpoint to get all the useful life available from a component, it may not be the best financial decision.

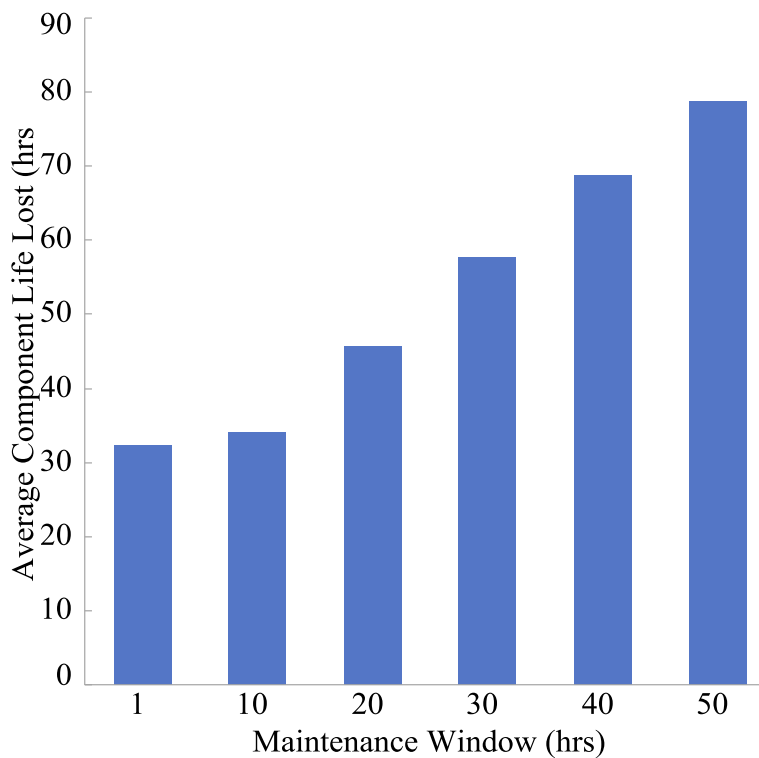


Figure 39. Average Life Lost Per Component

Examining Figure 40 shows that as the maintenance window increases, supply costs go up as well. Ideally, costs should be kept as low as possible, but a balance must be struck between cost, availability, and system performance. Following the trend from Figure 39, annual supply cost rises as maintenance window increases due to a larger demand for new components to replace those being removed from service under the maintenance opportunity window. Obviously, one would expect a correlation, and causation, between RUL and supply cost. If parts are being replaced more often, more parts will need to be purchased over the system lifetime. Further exploration of cost should be considered to develop a trade-space with the parameters discussed above.

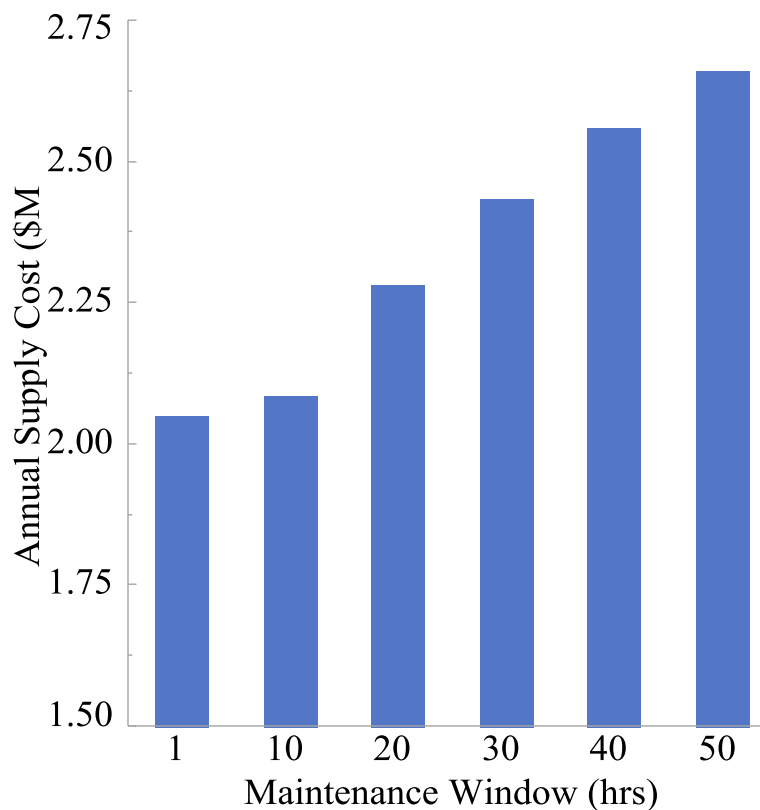


Figure 40. Annual Supply Cost

Figure 41 contains the average annual maintenance costs for the maintenance opportunity windows. It is noted that the cost of maintenance is considerably lower than that of spares. Maintenance costs captured are only those directly related to work on the aircraft performing inspections, replacements, etc. Idle costs and those associated with training and other duties are not captured in this research. Figure 41 shows that maintenance costs decrease as the maintenance window increases. This cost decrease results from the reduced set-up time for grouped maintenance actions versus individual ones.

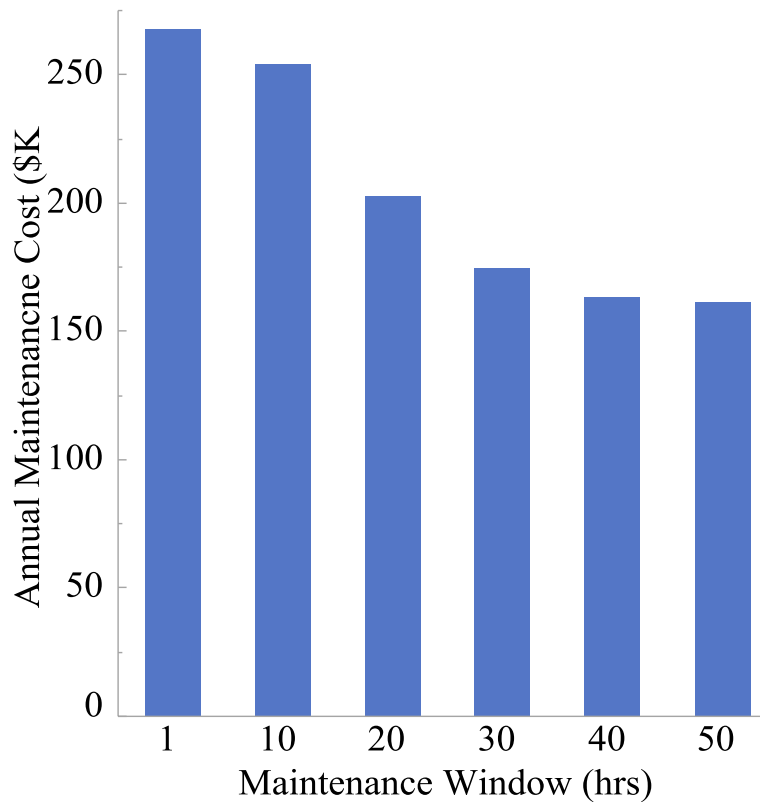


Figure 41. Annual Maintenance Cost

Combining the data from Figure 40 and Figure 41 yields the total annual cost found in Figure 42. As the maintenance costs are much lower than supply costs, total cost is dominated by the cost to procure and store parts. Over the 15 year simulation these annual costs result in a \$7.5M difference between the 1 hour maintenance window and the 50 hour window, with the 50 hour window total cost being \$42.3M. As previously mentioned these costs need to be weighed along with availability data and compared to program objectives to determine a proper maintenance window.

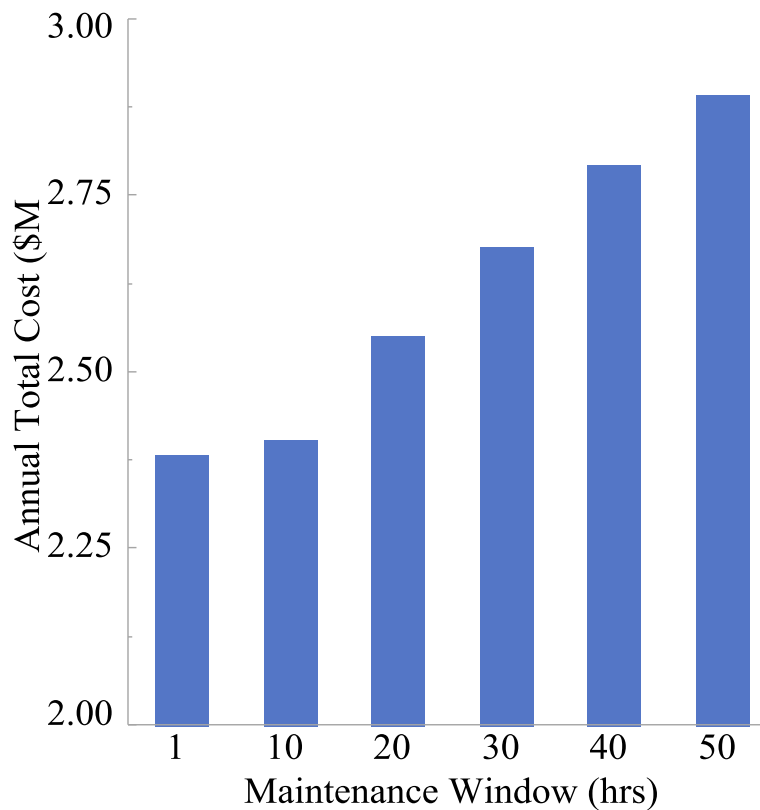


Figure 42. Total Annual Cost

An examination of the trade-space between A_O , total cost, and component life lost shows the decisions program managers face when selecting a set of maintenance

parameters. Figure 43 compares annual costs to average component lost life for the 6 maintenance windows utilized. Restating from prior discussion, it is observed that as the window increases, component life lost and total cost both rise. This figure by itself would likely drive a decision to select the smallest window, but this does not provide a complete picture of what is happening system wide.

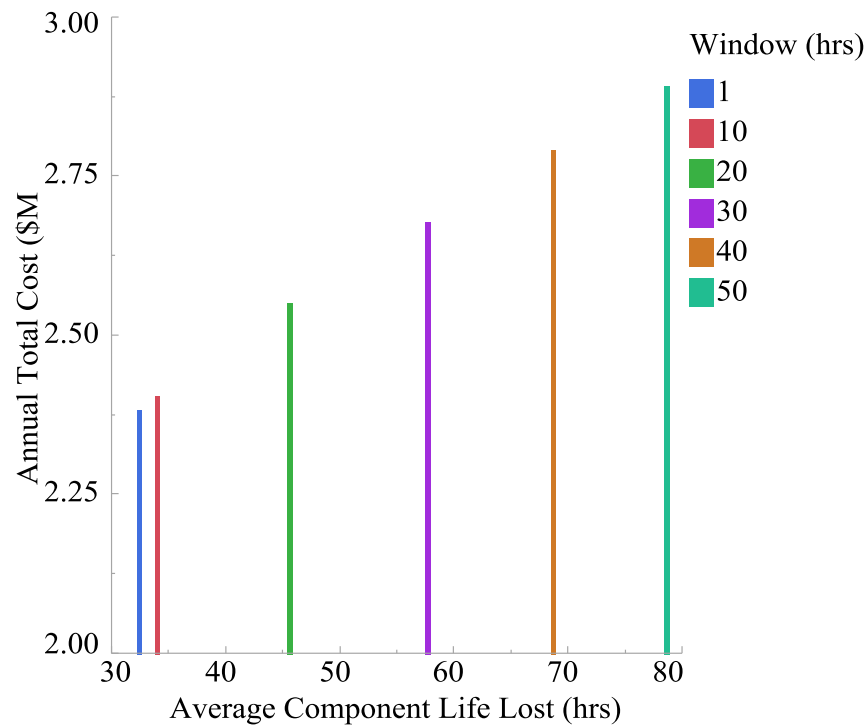


Figure 43. Annual Cost versus Component Life Lost

Figure 44 provides another component in the trade-space analysis by comparing operational availability to component life lost. While Figure 43 showed the lowest cost at the smallest maintenance window, Figure 44 shows it also produces the lowest A_O . This introduces a decision point for management to determine whether the 0.95 A_O of the 1 hour window is acceptable or if 0.97 is more desirable. It is noted that these operational

availabilities are only for the impact of the 20 components studied and not for all aircraft systems as a whole.

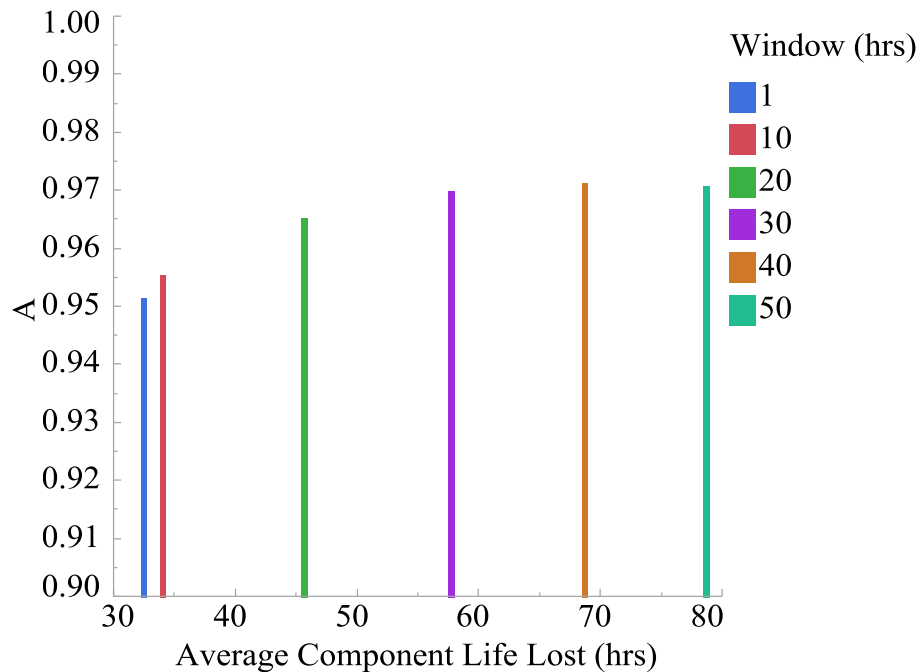


Figure 44. Operational Availability versus Component Life Lost

A final comparison, found in Figure 45, shows operational availability contrasted with total cost. Utilizing this figure, decisions can be made based upon the cost to achieve increases in A_0 for the various maintenance opportunity windows. It is observed that an increase from 0.95 at the 1 hour window to 0.97 at the 30 hour window will cost an additional \$295K annually or \$4.4 M over the 15 year simulation. It is left to management and program objectives to determine if this trade-off is beneficial to overall program goals.

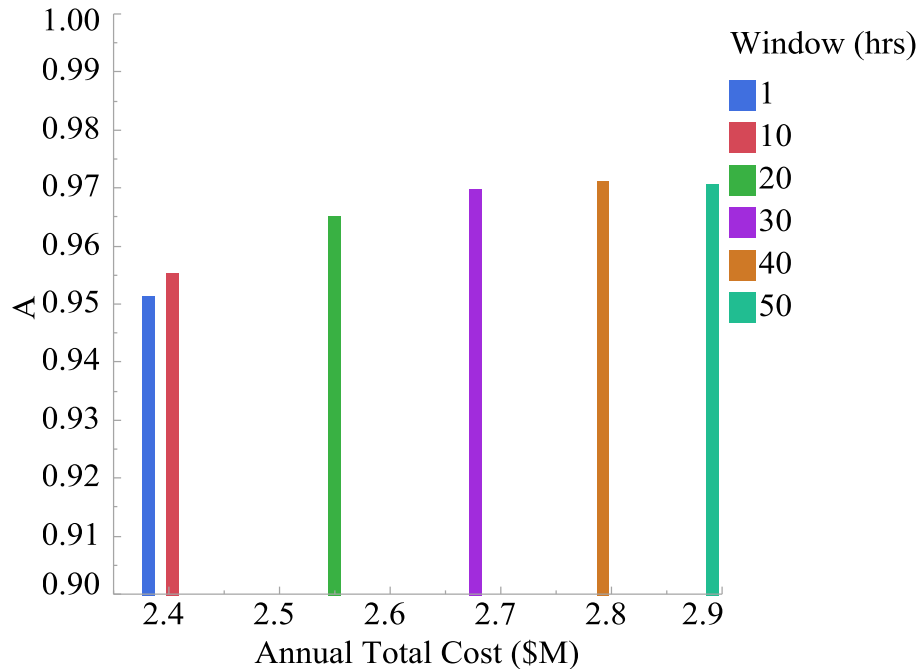


Figure 45. Operational Availability versus Annual Cost

Examining the material reliability metric of MTBF for the aircraft is not possible for this ISHM research as no component failures are recorded. The design of the ISHM monitoring logic combined with adjudication of false alarms and recalibration of true component status capture pending failures before they occur. Additionally, a 10 flight hour safety factor is included in RUL prognostics thus adding extra margin to component failure. While MTBF may not be measureable, mean time between maintenance (MTBM) and mean time between repair/replacement (MTBR) for the aircraft can be calculated.

Aircraft MTBR is determined by taking accumulated flight hours and dividing by the number of replacements or groups of replacements to find average time the aircraft as a whole are available between fixes. Figure 46 shows MTBR times for the maintenance windows utilized in this work. In this scenario a 20 hour window has the highest MTBR

by 25 minutes over the 30 hour window. Referring back to Figure 36 it is shown that as the maintenance window increases daily flying hours do as well. That information, coupled with Figure 46, must mean that more replacements are occurring since the MTBR is dropping. This is a logical inference since as more hours are flown, components will experience a corresponding increase in use thus requiring replacement more often.

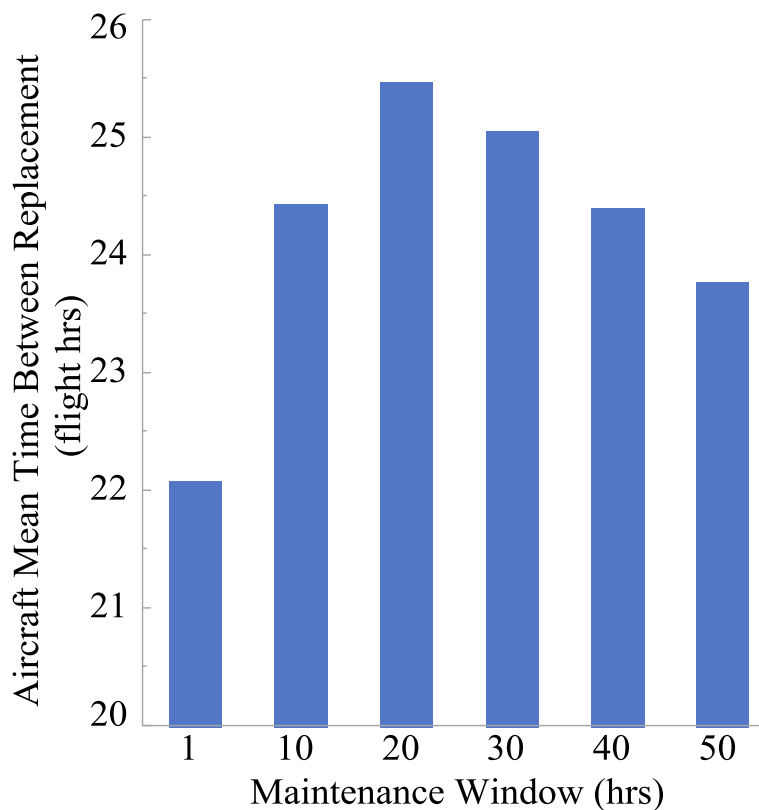


Figure 46. Aircraft Mean Time Between Replacement

Aircraft MTBM is the average of the accumulated flight time from when the aircraft leaves maintenance until it returns for any reason; inspection, false alarm, repair, etc. Figure 47 shows the aircraft MTBM which increases as the maintenance window widens. The trend tracks with the inverse of NMCM in Figure 37. As the NMCM

decreases with increasing window size due primarily to the grouping of maintenance activities, so does the number of times the aircraft enter maintenance control. This results in longer durations between inspections and replacements. The added benefit of the more frequent component replacement with an increasing maintenance window is the reduction in false alarms. False alarms, at the 1 hour window, dominate the cause of entry into maintenance, which drives the MTBM down.

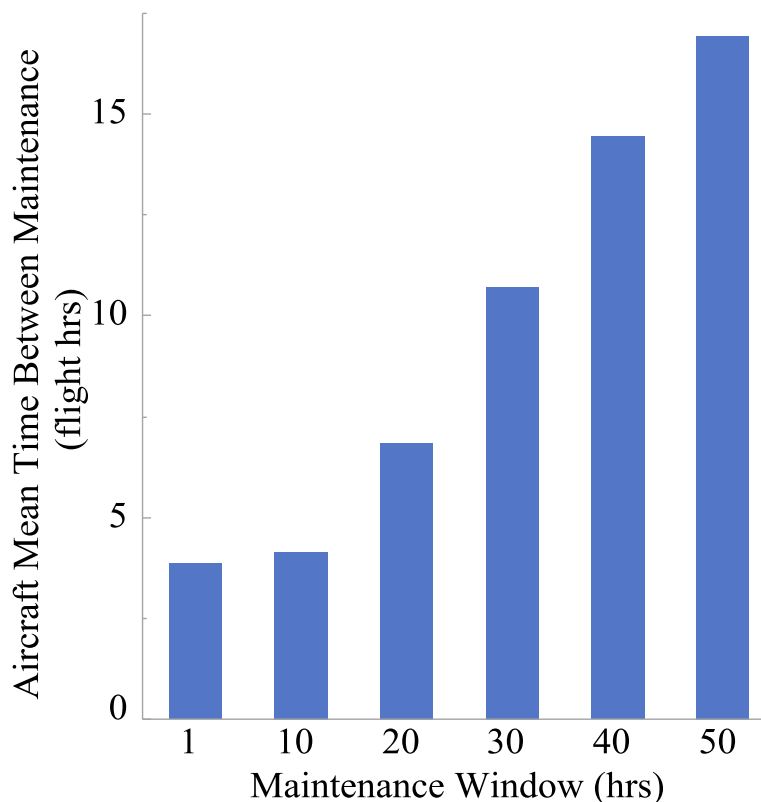


Figure 47. Aircraft Mean Time Between Maintenance Action

False alarms drive the number of times aircraft enter maintenance in the smaller maintenance windows, with the percentage decreasing as the maintenance window grows. Table 6 shows the relationship between maintenance window, number of times

entering maintenance, false alarms, and number of times components are replaced. The number of replacements counts either individual component replacements or a group of component replacements as one action. The number of replacements varies mainly as a result of the maintenance window and the impact of the window on daily flying hours shown in Figure 36. False alarms decrease because as components are replaced more frequently, and further from projected failure, the ISHM sensor and prognostic degradation does not impact the RUL projection as greatly. The difference in false alarms, along with their downtime impact on aircraft flying hours, and the effect of maintenance grouping, accounts for the difference between MTBR and MTBM.

Table 6. Maintenance Actions

Maintenance Window (hrs)	Times Aircraft Enter Maintenance	False Alarm as Cause	Number of Replacement Actions
1	42303	82.6%	7378
10	39739	83.0%	6757
20	26257	73.0%	7077
30	17713	57.2%	7576
40	13511	40.8%	7999
50	11697	28.7%	8344

As shown in Table 6 the percentage of false alarms as the sole cause of an aircraft entering maintenance is high. There are two means of entry for an aircraft into maintenance. The first entry case results from an ISHM system indication that a potential fault exists in one or more of the aircraft components that will violate the safety limit or fail within the projected flight time. If an aircraft is found to have only false alarms after inspection, the maintenance opportunity window is not checked and the aircraft is

released to perform missions. However, if one component triggers a replacement, all components on the aircraft within the maintenance window then are eligible for replacement. The second entry case for an aircraft into maintenance occurs post mission during the hold before the next scheduled flight. A maintenance window check is performed when an aircraft reaches the post mission hold. If any projected repairs can be completed prior to the next mission, the aircraft is routed to maintenance for component replacements. This between mission check provides the chance to capture maintenance actions during normal standby time for the aircraft prior to the next mission. As the maintenance window increases, this hold check for potential maintenance actions is increasingly the cause of aircraft entering maintenance.

Aircraft entering maintenance from the between mission hold check have cleared the post flight ISHM scan without any indications of potential failures within the safety window. Since the aircraft from the hold haven't been sent to maintenance as a result of immediate need for repair, only sent for opportune maintenance within the maintenance window, they forgo the inspection and false alarm check and proceed directly for replacement. This leads to components being replaced further from failure and prior to triggering most false alarms. There are, however, multiple RUL checks per mission so this hold maintenance under the maintenance window does not eliminate all false alarms. Additionally, as the uncertainty grows with sensor life (see Eq. (5)), the potential for false alarms increases as well.

A parametric analysis was performed with static prognostic uncertainty levels, without degradation, for the model confirming the increase in false alarms as uncertainty rises, regardless of maintenance window size. Further, as the uncertainty level and thus

the standard deviation of the lognormal distribution used for RUL increases, the probability that the RUL prognostic will predict less than the true remaining life increases. This shift is a function of the lognormal distribution and the impact its standard deviation has on skewing the shape of the distribution. As the standard deviation increases, the mode, or peak, of the distribution shifts to the left and decreases in magnitude while the right tail decrease more slowly, increasing the probability that the RUL prediction could be much greater than actual remaining life. Further, analysis of prognostic uncertainty shows that if the lognormal function is utilized for RUL prediction uncertainty must be held to a low level in the system. If uncertainty becomes too large, the system risks cost effectiveness resulting from too many inspections to clear false alarms and general mistrust by users.

Shown in Table 7 below are the results of the parametric analysis of prognostic uncertainty. The left two columns, uncertainty and maintenance window, are the parameters of change in the simulation. The remaining columns are model outputs related to aircraft entering maintenance and the associated reason for entering. It is noted that as the uncertainty increases, the percentage of time the only reason an aircraft enters maintenance is for a false alarm increases considerably. Above an uncertainty level of 10, the percentage of false alarms is likely unacceptable for a fielded system. Shifting focus to the maintenance window factor; it is shown in the between mission replacements column that as the maintenance window increases, the number of times the aircraft enter maintenance from the hold station increases as well. This results from the widening window capturing more components, further from actual failure, to replace during this opportunity.

Table 7. False Alarm Parametric Analysis

Static Uncertainty	Maintenance Window (hrs)	False Alarm Only Cause for Entry	Number of Times Enter Maintenance	Number of Maintenance Actions	Between Mission Replacements	False Alarm Entry Percentage
1	1	0	8083	8083	0	0.00%
1	10	0	7132	7132	0	0.00%
1	20	0	6436	6436	4578	0.00%
1	30	0	6517	6517	5744	0.00%
1	40	0	6600	6600	6056	0.00%
1	50	0	6771	6771	6280	0.00%
5	1	10	8351	8342	0	0.11%
5	10	9	7635	7626	0	0.12%
5	20	5	6841	6836	3555	0.07%
5	30	2	6659	6657	5481	0.03%
5	40	1	6798	6797	6091	0.01%
5	50	0	6968	6968	6382	0.00%
10	1	1767	10125	8358	0	17.45%
10	10	1706	9596	7891	0	17.77%
10	20	1025	8278	7253	3102	12.39%
10	30	403	7503	7100	5315	5.37%
10	40	144	7321	7177	6213	1.97%
10	50	73	7348	7275	6537	1.00%
20	1	15813	23777	7964	0	66.51%
20	10	15138	22694	7556	0	66.70%
20	20	8820	16075	7254	3338	54.87%
20	30	4202	11614	7412	5418	36.18%
20	40	1968	9537	7569	6366	20.63%
20	50	1073	8815	7742	6814	12.18%
30	1	33200	40783	7582	0	81.41%
30	10	31592	38670	7078	0	81.70%
30	20	18167	25301	7133	3582	71.81%
30	30	9377	16881	7504	5603	55.55%
30	40	4955	12733	7779	6533	38.91%
30	50	3082	11091	8009	6994	27.79%
40	1	47587	54806	7219	0	86.83%
40	10	44897	51599	6702	0	87.01%
40	20	26385	33407	7021	3653	78.98%
40	30	14280	21768	7488	5645	65.60%
40	40	8109	15949	7840	6585	50.84%
40	50	5458	13594	8136	7064	40.15%

Statistical Significance

An analysis for statistical significance was performed; however, confidence intervals are not presented in the figures in this work. The reason for confidence intervals not being presented is that 95% intervals shown in the figures are not distinguishable from the mean of the data, which are shown. This holds true for the entirety of this research. For the data presented in chapter 7, with the exception of the 10 and 40 hour maintenance windows MTBR data in Figure 46, the p-values for t-test comparisons within each figure are less than 0.0001, thus statistically significant. The data for 10 and 40 hour windows can be compared in other figures, with statistical significance, to determine which one to choose. Additionally, as each of the 100 replications run per scenario has 12 aircraft and simulates 15 years, an immense amount of data points are generated yielding the small confidence intervals.

Summary

This chapter illustrates the potential benefit of including a maintenance opportunity window to allow grouping of maintenance tasks. It is shown that grouping can improve operational availability through a reduction in total downtime. However, this performance improvement comes at the expense of increased spares costs even while maintenance costs decline. The maintenance window permits another factor to be considered in performing a trade-space analysis to determine requirements for ISHM capabilities and maintenance and logistics processes. Finally, data show that uncertainty needs to be kept low if a lognormal distribution is used for the remaining useful life prognostic.

VIII. Conclusions and Recommendations

Chapter Overview

This chapter compiles conclusions from the preceding chapters and identifies the significance of the research presented. Recommendations for action and proposed future research efforts are also discussed.

Conclusions of Research

The main contribution of this effort is a simulation tool to compare sensing and maintenance options and examine their impact on desired performance factors. The ability to input ISHM system and aircraft characteristics and investigate alternative approaches to monitoring, maintenance processes, and spares management makes this tool useful in program decisions on whether or not to implement monitoring techniques. Weighing the impacts of simulation outputs and management philosophies with cost and performance objectives is left to program managers to determine the appropriate level of service required. The ability to define a trade-space for system parameters early in the development of an aircraft or any system affords the opportunity to explore future cost savings and weigh performance trade-offs against defined system architectures and component system requirements.

Conclusions from this research and answers to the research questions from chapter 1 are as follows: Question #1 asked what the key cost and effectiveness drivers for ISHM enabled condition based maintenance and logistics processes. The research scenarios in chapters 4 through 7 show that prognostic accuracy is a driver of cost to

operate with an ISHM system in that it drives false alarms and thus unnecessary inspections and labor costs. In order to counter a set or known prognostic accuracy setting a tolerance for the number of false alarms allowed prior to ISHM system maintenance becomes a trade-off between cost and system availability. Further, maintenance personnel allocation and maintenance opportunity windows impact cost and availability and must be weighed when determining system priorities. Additionally, with ISHM prognostics, supply ordering gains efficiency over baseline processes and with careful contract negotiations a just-in-time logistics chain may be a viable alternative. Finally, cost of development, acquisition, and implementation of the ISHM/CBM system is a major driver in the deployment of a system. The model comparisons between baseline and ISHM processes can be used to develop a trade-space analysis to determine a cost difference between the two to be targeted as an ISHM development and deployment budget.

Research question #2 asked: what is a reasonable and appropriate scope for model development to establish performance requirements for ISHM sensors and prognostics, maintenance, and logistic processes? Inclusion of inspection, maintenance, supply, and health monitoring tasks along with flight operations provided reasonable depth in the model. Resources and costs associated with the aforementioned tasks were easily handled by the model as well. Scope for this research was limited mainly in the number of components modeled. One hundred simulation runs, to gain statistical significance, took approximately 1 hour to process on a standard dual-core PC. There are no indications that inclusion of additional components to the model would provide any complications other

than increased processing time, which could be mitigated with increased processing power.

The third research question posed: what are the operational and maintenance cost impacts of an ISHM enabled CBM system? In the components utilized the chief cost driver is the purchase of supplies. Total costs for like size squadrons were shown to be similar between baseline and ISHM equipped systems. The ISHM systems however had higher operational availability and daily flying hours that would allow a squadron ISHM equipped aircraft to operate with 2 fewer planes and still exceed the performance of the baseline squadron. Additionally, maintenance costs are reduced through demand versus time-driven replacements and inspections. The impact to O&M is then the ability to remove aircraft from inventory or to expand into other roles as availability and reliability increase.

It is suggested that the lognormal distribution may not be optimal for utilization in determining the remaining useful life of components. While the lognormal distribution does eliminate the potential for negative values that may occur under the left tail of the normal distribution, its skewness under increasing standard deviation, uncertainty in this research, likely drives too many false alarms for acceptance as a fielded system.

However, even with an elevated number of false alarms, the ISHM enabled aircraft provided better system performance and lower maintenance costs than a baseline system.

Research question #4 asked if mean downtime was a good measure of system performance for ISHM/CBM systems. It was shown that MDT can increase with the implementation of health monitoring particularly with maintenance grouping. This is contrary to DoD projections of significant reduction in MDT with the implementation of

condition based maintenance (Under Secretary of Defense (AT&L), May 2008).

However with a poor performing supply system MDT can actually increase due to an increase in NMCS time. Therefore, depending on the scenario an increase in MDT can be both positive and negative from a system performance perspective. This leads to the conclusion that MDT is not always a good predictor of overall system performance.

The final research question posed the question: does maintenance grouping based on prognostics improve operational availability, total downtime, and cost? The results show that maintenance grouping does increase A_O through a reduction in total downtime. While maintenance costs are reduced with grouping, supply costs increase as the maintenance window increases since more components are required due to premature replacement and loss of useful life.

Significance of Research

The significance of this research lies in the inclusion of flying, supply, and maintenance processes in a single model to study the effects of integrated systems health management. Previous research focused on these aspects individually, making limiting assumptions for those processes not of interest and leaving the interactions between systems unexplored. Additionally, proprietary systems developed in this field are not well published for competitive reasons leaving a gap between research and development and deployment. The discrete event simulation presented in this research provides a tool for new health monitoring techniques to be analyzed by inserting them into a model to determine the effect of their accuracy and prognostics capabilities on overall system performance.

The tool and simulation outputs present a capability for program management to use in determining if the long-term performance increases of the ISHM system balance out the additional upfront cost of implementation. The data are used to determine feasibility of solutions and trade-space for requirements development. Further, researchers can explore the interactions of health monitoring, supply and maintenance processes to provide more than anecdotal projections of savings. Program management can use the tool to conduct cost-benefit analyses when considering new systems or operating procedures.

Recommendations for Future Research

Several recommendations for future research efforts were identified during this research effort. Further study should include exploring repairable systems and the impact on maintenance utilization and repair versus purchase decisions. This research would add further depth and utility to the model as well as providing increased interactions between supply and maintenance decisions. Additionally, the inclusion of constraints on repair or replacement order of components would add additional realism to the work. This restriction would incur delays prior to the start of maintenance on some parts while work is conducted on others and would impact grouping decisions and outcomes. As discussed earlier in this chapter, remaining useful life prognostics could be improved over those provided by the lognormal distribution. It is suggested that other RUL formulations be studied to potentially further improve performance and cost.

A study on a fielded aircraft with proposed or deployed health monitoring systems would provide further validation of the processes and demonstrate real-world impacts to

decision makers. This research could also be applied to surface vehicles, ships or other equipment with some changes to operating procedures to determine the utility on other systems with different system interactions and constraints. Further, a cost benefit analysis of preventive maintenance, and the associated inspections, for known failure modes could be conducted against projected cost savings from ISHM. Finally, while this research discussed and provided tools for trade-space analysis, it may be possible to conduct this type of simulation as an optimization problem. Program objectives would need to be established as well as constraints on capabilities and resource allocations.

Summary

The research presented identifies the impacts of health monitoring systems on supply, maintenance and flight operations. Further, it creates a tool for management to utilize in the assessment of implementing health monitoring systems on new and legacy aircraft. As aircraft and other systems service lives are extended beyond intended design life and amid shrinking budgets and manpower, it is necessary to assess potential efficiencies afforded by ISHM. The results of the research demonstrate the potential to improve system availability, reduce cost and define a trade-space for ISHM system assessment.

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14. ABSTRACT Health monitoring systems have demonstrated the ability to detect potential failures in components and predict how long until a critical failure is likely to occur. Implementing these systems on fielded structures, aircraft, or other vehicles is often a struggle to prove cost savings or operational improvements beyond improved safety. A system architecture to identify how the health monitoring systems are integrated into fielded aircraft is developed to assess cost, operations, maintenance, and logistics trade-spaces. The efficiency of a health monitoring system is examined for impacts to the operation of a squadron of cargo aircraft revealing sensitivity to and tolerance for false alarms as a key factor in total system performance. The research focuses on the impacts of system-wide changes to several key metrics: materiel availability, materiel reliability, ownership cost, and mean downtime. Changes to theses system-wide variables include: diagnostic and prognostic error, false alarm sensitivity, supply methods and timing, maintenance manning, and maintenance repair window. Potential cost savings in maintenance and logistics processes are identified as well as increases in operational availability. The result of this research is the development of a tool to conduct trade-space analyses on the effects of health monitoring techniques on system performance and operations and maintenance costs.					
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