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Structural Health Monitoring System Trade Space Analysis Tool with Consideration for Crack Growth, Sensor Degradation and a Variable Detection Threshold

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DISSERTATION

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**DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY**

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

STRUCTURAL HEALTH MONITORING SYSTEM TRADE SPACE ANALYSIS TOOL WITH CONSIDERATION FOR CRACK GROWTH, SENSOR DEGRADATION AND A VARIABLE DETECTION THRESHOLD

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Abstract

Structural Health Monitoring (SHM) systems face many obstacles and gaps that have resulted in the slow implementation in real-world applications. These obstacles include technology performance, implementation issues and a solid business case that justifies the investment in a SHM system. The presentation of a solid business case for the SHM system is a great challenge and arguably is the main factor contributing to the slow implementation of this technology. The research intent of this dissertation is to focus on the business case by providing a tool to aid decision makers. Simulated aging aircraft flight data are used in this effort due to the fact that many aging military aircraft will be flying beyond their initially intended design life. An analytical model was developed to address the business case and the integration of the SHM system into Condition Based Maintenance (CBM). The model aids the calculation of the cost of Life Cycle (LC) events resulting from the implementation of the SHM system on an aging aircraft. In addition, the model captures the events and effect on aircraft availability due to different SHM detection threshold settings and replacement of degraded sensors. The model captures false alarm rates, crack growth, probability of detection, and sensor degradation amongst other parameters. The proposed analytical model is a useful tool that provides the decision makers the confidence to either implement the SHM system on an aging military aircraft or not. Two models were developed; one was the SHM system model with no degradation and the second was the SHM system model with simulated degrading sensors. Three major subcomponents of the SHM model will be the sensor detection component, the crack growth component and the sensor degradation component (second model only). Linking these three components where the main parameters of interest (crack length, sensor degradation/detection) are not static and accounting for

senor replacement will provide useful data of LC cost estimation that have not been

accomplished before.

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I. Introduction

Motivation

Aircraft (Structural Health Monitoring) SHM is a research area that will lead to a major change in the way we manage the health of our fleet in the future. Relatively few SHM systems are in operation on aircraft today. A review and a gap analysis of some of the relevant SHM literature led us to identify the current challenges facing the implementation of an SHM system. Some of the main SHM system's challenges are the technology performance, implementation issues and a solid business case. The presentation of a solid business case for such a system is considered very important as this challenge has a great impact on the decision to implement an SHM on an operational aircraft.

A perspective of the structural mechanics program of the Air Force Office of Scientific Research on structural health monitoring (SHM) and non-destructive evaluation (NDE) was presented by (Giurgiutiu, 2008). NDE and SHM have an essential role in the operational readiness and safety of the Air Force fleet; however, considerable challenges face the operators and the maintainers due to aging aircraft. NDE techniques have proven to be reliable in detecting damage during phase inspections. SHM has great potential due to its on board sensors and systems that provide structural health assessment

on demand. This study concludes that considerable applied and fundamental research is needed to develop, integrate and implement SHM technology.

Research Problem Statement

Develop a decision support model to explore the tradespace associated with implementation of an SHM system on aging aircraft.

Features of the model should include:

- Capture representative crack propagation with respect to accumulated flight hours;

- Capture representative performance of SHM sensors as influenced by SHM detection thresholds and acceptable crack lengths;

- Capture representative change in detection of SHM sensors due to degradation as a result of accumulated flight hours;

- Capture representative events and aircraft unavailability encountered due to sensor maintenance/replacement during SHM system scheduled and unscheduled maintenance;

- Capture representative events and aircraft unavailability encountered due to aircraft scheduled and unscheduled maintenance associated with SHM alarm verification inspection and inspect/repair of aircraft;

- Capture catastrophic failure events due to miss detection and a crack reaching the critical length.

Assumptions and limitations of this model are as follows:

- The SHM system monitors a hot spot on an aging military aircraft;

- Initially a single hot spot will be assumed; while not demonstrated in this research, the approach herein is readily extensible to monitoring multiple hot spots;

- Degradation of sensors is due to loads exerted due to flight maneuvers;

- While the model will capture event data, for purposes of this research notional event parameters will be utilized;

- While maintenance events are captured by the model, a cost per event is not assumed or modeled.

The model can be utilized for informing decisions associated with implementation of an SHM system on aging aircraft. This will be attained through the more realistic modeling of crack growth, sensor detection/degradation, cost and SHM system maintenance procedures associated with a particular aircraft.

The outline of the dissertation is as follows: Chapter II will discuss the current state of aircraft SHM research and will build the case for what is proposed through this research effort. This is accomplished by identifying the gaps in previous SHM studies and will help support why this research effort is needed. Chapter III is a journal article demonstrating a trade space analysis of an aircraft equipped with a SHM system. This trade space analysis considers the effect of setting the SHM system detection threshold on the LC events. Chapter IV is a journal article that demonstrates the effect of the SHM system sensor degradation on the LC events that an aircraft might encounter. Chapter V discusses results, conclusions, future work and recommendations.

II. Literature Review

Technology Performance

Much research in the field of structural health monitoring (SHM) for aircraft has been conducted with performance objectives of reduced life cycle cost and increased availability. Yet there are still gaps that slow the implementation of SHM systems. The performance of SHM technology has been and is still being investigated. Many believe that available technology did not reach the maturity level for what we want to accomplish. In research on SHM by (Derriso et al., 2007) technical feasibility is described as facing three fundamental challenges: 1) small-scale damage must be detected in relatively large-scale structures, 2) SHM systems must work in an unsupervised learning mode, and 3) the redundancy and robustness of a SHM system must be reliable. Reliability and durability are a major technological concern for SHM systems.

Reliability

False alarms that could be produced from the SHM system cause more maintenance actions than are necessary. A simulation model of a prognostics and health management (PHM) system used as an autonomic logistics system (ALS) for the joint strike fighter (JSF) was developed and used by (Miller et al., 2007). Their simulation captured a large number of commonly used flight line measures of performance for aircraft availability and mission effectiveness. Multivariate statistical analysis of these measures provided ways to analyze the positive impact of a PHM system on aircraft sortie generation. On the other hand, their analysis showed a great sensitivity to false

alarms. This great sensitivity implies that more research effort should be devoted to investigating and trying to minimize false alarms which cause's excessive downtime and cost without significantly degrading detection performance.

Another experiment was conducted on a fast military jet by (Read et al., 2008) to try to test a SHM system in near real-world applications. A BAE Hawk jet carrying an experimental test pod with specimens that had crack initiators was used to test the effect of flight maneuvers on the SHM system detection capability and the possibility of detecting crack growth during flight. The conclusion was that this system was effective in detecting a crack and the growth of the crack during flight especially if false alarms can be avoided. The tests were run throughout the flight envelope in the presence of acoustic noise levels in excess of 135 decibels and considerable electromagnetic interference. With this experiment, one still can argue that the system was not attached to a real structure.

Many reliability models are developed in the general area of structural monitoring. For example, a Reliability-Based System Assessment was used by Hosser et al. (2004) for monitoring building structures with sensors.

For reasons of economy, structural monitoring currently has to be concentrated on the weak spots critical for the structural behavior and the corresponding uncertainties. In order to accomplish this, methods for the identification of such weak points and uncertainties are used for the definition of optimal monitoring measures as well as assessment and decision criteria. These methods are based on recognized procedures of reliability and system theory.

In order to make the application possible to building engineers without special training in reliability theory, the methods were summarized in the knowledge-based system PROBILAS (PRObabilistic Building Inspection and Life ASsessment). This computer code consists of a data base module, a computation module and a statistics and updating module, which are linked by graphical user interface and server for the optimization of the building assessment cycle. An essential component of the assessment is the illustration of the building as a system and its integration into the data base and the computation module of PROBILAS. Since the logical models of real structures, e.g. bridges, needed as elements of the system reliability computation can be very complex, methods are developed to identify and integrate the possible failure mechanisms. In their article, the building assessment cycle with the knowledge-based system PROBILAS is illustrated first. The continuous reevaluation of the system and the focusing of both the stochastic and the physical models on the failure-relevant parts of the system, limit states and parameters are characteristics of this cycle. A main focus of this article is on the methods of system integration. Some steps of the system generation run more or less automatically, e.g. the creation of response surfaces for the limit-state functions of system components. In other domains the monitoring engineer is consciously involved in the process while PROBILAS offers the necessary assessment and decision criteria. The different methods are described and demonstrated using an example of a bridge construction.

The large amount of data produced from monitoring needs improved statistical tools to clearly identify defects. A synopsis review conducted by (Sohn and Los Alamos National Laboratory, 2004) identified that in general there is not yet tools that are well

developed and implemented for statistical pattern recognition. Many damage detection methods try to identify damage by solving an inverse problem, which requires the construction of analytical models. An inverse problem can be described as a general framework that is used to convert observed measurements (i.e., monitoring data) into information about a physical object or system (i.e., defect) of interest. A neural network approach can be used to map the inverse relationship between the parameter of interest and the measured response. The main drawback for this approach is that a large amount of data is needed for the damaged and undamaged component and this is not available in the real world (Sohn and Los Alamos National Laboratory, 2004). Analysis of hypotheses approaches includes outlier analysis, statistical process control charts and simple hypothesis testing as indicated by this review. These approaches are demonstrated to be very effective for identifying the onset of damage growth, and they are identified as one of the most significant improvements (Sohn and Los Alamos National Laboratory, 2004).

Durability and Robustness

Many studies show degradation of SHM sensors over time due to static loads, cyclic loads, temperature and corrosion. Durability and robustness are additional technology performance issues for an SHM system.

An investigation on the effect of cyclic loads on sensor performance was conducted by Kuhn (2009) which will be discussed in more detail in Chapter III. In his research, degradation was identified in sensor performance as having a direct relationship with cyclic strain which was estimated by using a power law model. A probability of detection (POD) degradation model was also developed to show the overall performance of a SHM system. Research by Achenbach (2007) indicated that some of the technical

challenges for sensors are that they should be small, autonomous, cheap, robust, repairable, accurate, densely distributed, measure local and system level responses, and designed to measure relevant damage parameters. Beard et al. (2005) found that environmental conditions such as temperature can affect the signal obtained from sensors. This research used calibration to compensate for temperature variation based on the structure and application. A sensor diagnostics and validation process was presented by Park et al. (2006). It performs in situ monitoring of the operational status of a piezoelectric (PZT) active-sensor in SHM applications. Both degradation of the mechanical/electrical properties of a PZT transducer and the bonding defects between a PZT patch and a host structure could be identified by the proposed process in Park et al. (2006). The proposed process can provide a metric that can be used to determine the sensor functionality over a long period of service time or after an extreme loading event. More research is needed to understand all environmental factors that could degrade the sensing of an SHM system such as corrosion. Moreover, the maintenance action needed to bring the degraded SHM system back to its original condition needs to be investigated.

Implementation Issues

Design of an SHM system should be part of a system engineering framework that integrates health monitoring and maintenance with all other requirements for the system. For a new aircraft design, this would begin with the conceptual design of the system and would affect decisions regarding levels of maintenance and inspection intervals, among others. Less extensive implementations are being proposed for aging aircraft. A framework for SHM system design was presented which could be applied to aging aircraft through hot spot monitoring (Malkin et al., 2007). Understanding the structure of

interest and establishing requirements could start the framework flow. This flow ends with comparing requirements to specific SHM system designs. The data needed from an identified requirement for an SHM system can be obtained by focusing on the following points: 1) benefits and drawbacks of the SHM system, 2) requirements for the SHM system, 3) available SHM technologies, 4) detail design of the SHM systems, and 5) identifying the SHM design that meets the requirements and the cost of the SHM system that meets the requirements. Although this framework is developed for hot spot monitoring it could be modified for other applications. It would be useful if this framework could be modified to include the effect of sensor degradation.

Research by Millar (2007) identifies that the barriers that have slowed acceptance and use of PHM tools in military propulsion systems over the past two decades were the product of incomplete total life cycle systems engineering management (TLCSM). The US Department of Defense Acquisition Guidebook states in Section 4.1.3 TLCSM in Systems Engineering: "It is fundamental to systems engineering to take a total life cycle, total systems approach to system planning, development, and implementation." (Defense Acquisition Guidebook, 2004:Ch 4, 80). It is also important to implement TLCSM not only on new systems but also on legacy systems currently operating to control the high maintenance cost as the systems continue to operate beyond their design life. Further, the research describes up and down periods in the engine condition monitoring which are time phases. The up periods are triggered by the cost benefits that could be gained by successful monitoring and the down period is when the demanded monitoring technology is not available for the monitoring system. This study concludes that using TLCSM

through the systems engineering process is the right tool to close the gaps that held the large scale applications and implementation of integrated monitoring systems.

Advanced integrated vehicle health monitoring systems (IVHM) are expected to formulate a decision response based on the extent of the damage unlike a pure monitoring system that only reports damage (Price et al., 2003). Price et al. sub-divided the problem to achieve the requirements of this system as follows: 1) Detection of damage events requires some knowledge of the environment in which the vehicle will operate and threats it will face, 2) The development of sensors will depend on the time required for the system to respond, 3) For events requiring a rapid response the use of passive embedded sensors is the best solution, 4) Characterization of damage may be accomplished during detection of damage or separately by using different sensors or using a sensor in different ways, 5) Active sensors could be employed to accomplish characterization of damage by being embedded in the structure, 6) Prioritization of the seriousness of damage and how it can compromise the mission of the vehicle is needed to give the level of urgency to the response, 7) Identification of the cause of the damage can be accomplished using an intelligent system, 8) Large number of sensors can provide information on the vehicle as a whole, 9) Formulation of a response of an intelligent system is dependent on the extent of the damage and could be a panic response for major damage requiring the isolation of a whole section of the vehicle, 10) Execution of a response could be a maintenance action or could be a more immediate action of limiting the flight maneuvers of the vehicle. This approach will be hard to implement on an aging aircraft where embedding sensors on the existing structure might be hard or infeasible.

The integration process of SHM on aging aircraft is a challenge. In the near future, an SHM system could be integrated on aging aircraft to monitor known failure modes as a starting step in the integration process. Aging aircraft face challenges on how to integrate an SHM system with Condition Based Maintenance (CBM) because design choices are limited by the existing system architecture. A number of integration issues were researched by Buderath (2004) and concluded the following: 1) There should be a clear process for integration to ensure the right selection of an SHM system, data analysis, and sensor location, 2) Integration technology should be researched in order to reach acceptance on all system levels, 3) An integrated process is needed during the development phase of an SHM system to be able to fully integrate with CBM, 4) Research should be extended to include the integration technologies, 5) When a successful SHM system and CBM integration is achieved we can improve safety and trigger maintenance action only when needed.

Business Case

The presentation of a solid business case for the SHM system is a great challenge and arguably is the main factor contributing to the slow implementation of this technology. Factors that could help create a business case are the understanding of the customer needs and requirements and performing a credible cost and risk analysis (Perez et al., 2010).

Quantifying cost reduction

Quantification of cost reduction in the total life cycle of a system by using SHM needs to be presented. There are few research attempts to quantify the cost benefit of

SHM found in literature. In one study, implementation of SHM on a commercial transport aircraft could result in an estimated 30% to 40% reduction in maintenance requirements. This would result in a recovery of the initial implementation costs in only two to three years (Kent et al., 2000). Another research effort (Schmidt et al., 2004) shows only a one percent reduction of the maintenance by using SHM systems on an AIRBUS aircraft, but it did not include the increased availability due to reduced inspection times. Another finding of this study is a reduced panel weight up to 15 percent by using SHM which impacts cost in many ways such as less fuel consumption and longer operating range. In the case of reusable launch vehicles a study has shown that the benefits of implementing a SHM system outweigh the cost (Derriso et al., 2007). Further, research on aging military aircraft show cost benefits of using SHM on some hot spots of the structure of a Tornado fighter as long as the hot spots with real payoff are identified (Boller, 2001).

Systems level cost model

A unique cost-benefit analysis for the allocation and cost justification of an Integrated System Health Management (ISHM) at the conceptual design level was presented by Hoyle et al. (2007). An optimization framework was used to determine the optimal allocation of ISHM to maximize profit. This was calculated using the following profit function (Π):

$$\Pi = A_S \cdot R - C = \prod_{i=1}^{M+N} A_{F,i} \cdot R - \sum_{i=1}^{N}(C_R + C_D)_i \qquad (1)$$

The objective function, referred to as Profit, Π, is expressed as the product of System Availability (A_S) and Revenue per unit Availability (R), minus Cost (C), which is a summation of Cost of Detection (C_D) and Cost of Risk (C_R) over the total number of system functions N. The system availability is determined as the product of the availabilities of the N system functions and the M allocated ISHM sensor suites; the models function availability will differ for functions with and without ISHM. This framework can also determine the optimal detection/false alarm threshold and inspection interval. When this framework was applied to an aerospace system it was shown that applying ISHM increased profit by 11%, reduced cost by a factor of 2.4 and lengthened the inspection intervals by a factor of 1.5. It would be interesting to try to modify and use this framework for a system that does not have a clear identification for revenue, such as military systems which can benefit by a reduction in the total life cycle cost (LCC). Further it would also be interesting to modify this approach to include sensor degradation and its effect on the aircraft life cycle.

Esperon-Miguez et al. (2012) studied a methodology that takes advantage of the historical maintenance data available for legacy platforms to determine the performance requirements for diagnostic and prognostic tools to achieve a certain reduction in maintenance costs and time. The effect of these tools on the maintenance process is studied using Event Tree Analysis, from which the equations are derived. However, many of the parameters included in the formulas are in reality not constant and tend to vary randomly around a mean value (e.g.: shipping costs of parts, repair times), introducing uncertainties in the results. As a consequence, the equations are modified to take into account the variance of all variables. Additionally, the reliability of the

information generated using diagnostic and prognostic tools can be affected by multiple characteristics of the fault, which are never exactly the same, meaning the performance of these tools might not be constant either. To tackle this issue, formulas to determine the acceptable variance in the performance of a health monitoring tool are derived under the assumption that the variables considered follow Gaussian distributions.

Leao et al. (2008) proposed a cost benefit analysis methodology. This study presents a methodology to perform cost-benefit analysis on the application of PHM for existing (legacy) commercial aircraft. The methodology takes into account the characteristics of the commercial aircraft operation business to yield conclusions on the economic feasibility of the application of the technology to these platforms. The study presented guidelines to develop such calculations and the tools that may be used to analyze the results. The final product of the methodology is a cost benefit model which provides insight to the aircraft's original equipment manufacturer (OEM) and to the aircraft operator on how PHM technologies should be applied in order to maximize their bottom lines. One of the draw backs of this model is that it treats false alarm rate as a constant value provided by the PHM technology manufacturer.

Another cost model was presented by Hou-bo and Jian-min (2011). When they considered adopting and selecting a PHM technology, the first important step is to conduct the cost-benefit analysis. The purpose of implementing a PHM technology is to reduce failure rates and reduce cost needed for repair action. They proposed a Cost-Benefit Model for PHM to identify the main factors of implementing PHM which can provide costs benefits. Obviously, none of the presented benefits come for free. Both the manufacturer and the operator must invest money in order to implement PHM. The costs

associated with development and operation, training costs of maintenance people and operations were taken into consideration. The model can be a useful tool for decision-making and maintenance planning. On the other hand, for a SHM system, a different approach is needed because the structure is not designed and treated like a component that fails abruptly as considered in their study. The approach would need to be augmented to include sensors that are continuously monitoring a crack growth.

Another approach by Kacprzynski et al. (2002) involves the developments associated with a PHM system design tool that integrates a model-based Failure Mode, Effects and Criticality Analysis (FMECA) methodology with state-of-the-art system simulation directly linked to downstream Life Cycle Costs (LCC). This design tool will seek out recommended PHM system designs based on a cost function that accurately represents key LCC variables such as system availability, maintainability, reliability, and failure mode observability. The tool will be capable of assessing PHM sensor requirement specifications at the component and subsystem levels, and will then allow for integration into a broader integrated system model. Tradeoff, sensitivity and "what if" analysis will then allow the designer/user to examine the cost/benefit relationship of either adding or removing sensor and algorithms under consideration for the PHM design. This study is different from that proposed in this dissertation since it does not focus on the effect of degradation on the sensors. Further, it does not investigate the interaction between component degradation and sensor degradation and how it affects resulting events and availability of the aircraft.

Optimization and simulation models

The number of sensors needs to be optimized to provide the desired effectiveness within cost and weight constraints as well as a balance between detection sensitivity, false alarms and the number of sensors.

 A promising area for optimization is the use of genetic algorithms, which allows the determination of the optimal number and location of sensors for damage locations (Boller, 2000). Optimization and simulation of a maintenance phase with SHM technology was used by Kapoor et al. (2008) to quantify benefits when applied to commercial aircraft. The effect of using SHM technologies to reduce maintenance downtime was provided. The concept of this approach was to identify the critical paths along the maintenance process. After a critical maintenance path was identified it was substituted with a SHM alternative. After optimization and simulation, a reduction factor of 6 to 100 hrs was found. This study indicates that further work for a better estimate of savings should involve employing the method proposed to a Maintenance Planning Document (MPD) with defined maintenance phases. Also this study did not include the effect of false alarms by SHM system.

Williams (2006) suggested that the performance improvement on a system by implementing Integrated Vehicle Health Management (IVHM) can be evaluated before design dollars are ever committed or contracts signed. By identifying the processes, measures of effectiveness (MOE), and input drivers, a discrete event simulation can be applied to assess the first order requirements for IVHM implementation on systems. Williams (2006) discusses the benefits to 5 different categories of operators: 1) the Original Equipment Manufacturers (OEMs), 2) the mission operators, 3)

command/control elements, 4) fleet management, 5) and maintenance operators. These

five categories may overlap in organizational structure and personnel, but they have

clearly identifiable processes and performance that can be analyzed and measured. The

paper then goes on to discuss how IVHM technologies impact events in the field and how

the effects on individual events affect the MOEs of the larger system. Finally, an example

is illustrated of the impacts IVHM has on the field performance of a notional system from

a simulation run using a notional system and scenario data. This type of analysis enables

a larger business case to be developed to aid designers and planners in their decisions of

how to implement IVHM. It will be of great value to extend this study to include the

IVHM system's change of performance over time due to degradation in the IVHM

sensors.

Standardization

      Standardization of SHM systems across different platforms should help in

reducing the ownership cost as well. In the automobile industry, SHM has great potential

and has seen more aggressive application than the aircraft industry (e.g. On-Star System).

Integrated system health monitoring in an automobile typically monitors important

features such as Oil pressure, Engine Temperature, Tire pressure etc. (You, Krage, &

Jalics, 2005) in which it was shown that standardization of remote diagnostics and

maintenance systems between different automobile models will reduce cost

tremendously.

Structural health monitoring cost models

In a study by Pattabhiraman et al. (2010), the cost effectiveness of progressive inspection over scheduled inspection is analyzed. The lifecycle of an airplane was modeled as blocks of damage propagation interspersed with inspection. The Paris model (Beden et al., 2009) with random parameters is used to model damage growth and detection probability during inspections and it is modeled by Palmberg's expression (Palmberg et al., 1986). SHM based progressive inspection were found to be 50% more cost effective than schedule-based preventive inspections. The sensitivity of the lifecycle cost to the inspection parameters has been studied. To accommodate critical panels which must be manually inspected, a hybrid model of inspection is also proposed. The hybrid model is found to have sufficient cost savings over a scheduled inspection model. In this model false alarms and SHM operation cost were neglected.

Another study by Aldrin et al. (2007) presented a software package for integrating NDE and SHM design with product life cycle management models. Hybrid life management strategies for new and aging aircraft were proposed that combine traditional nondestructive evaluation (NDE) methods and recently developed SHM technologies. In recent times, a usual aim for managing the life of aircraft components that are critical or that are subject to fatigue or corrosion damage is to attempt development of in situ damage detection systems that can indicate when more detailed inspection is necessary. This creates a need for decisions about the type and settings of sensors and signal processing algorithms for the health monitoring system, and system type, settings, and scheduling for NDE. How well these systems are matched will have great influence on overall maintenance cost, aircraft availability and system reliability.

A study conducted by Wilmering and Ramesh (2005) focused on the means for assessing the impact of potential health management approaches on LCC as implemented within a system-engineering framework. A disciplined approach to selecting appropriate health management solutions to satisfy design and operational requirements was presented, and a software tool for performing trade studies of alternate approaches' impact on life cycle cost was discussed. A primary goal was to allow domain experts and health management specialists to perform thorough life cycle cost analyses without requiring the services of specialized cost analysts.

Summarization of gaps

There are a number of cost benefits studies for integrated system or vehicle health monitoring ISHM/IVHM. A fewer number of studies focus on the structural health monitoring system SHM LCC benefits. It is found by this literature review that a business case that relates LC events and aircraft availability to crack propagation, crack detection and sensor degradation has not been investigated. The sensors used for crack detection degrade over time due to flight stress. This is also accompanied by crack propagation due to the same flight stress. The use of current crack propagation modeling techniques accompanied with current structural health monitoring sensor degradation models should yield more realistic LC benefit analysis for the decision maker. In this effort, the overall LC model should also account for the effect on safety and availability due to sensor replacement triggered by SHM scheduled and unscheduled maintenance.

The following is Chapter III and it contains a journal article accepted by the Tech Science Press Structural Durability and Health Monitoring (SDHM) journal on July 2014. The title of the article is (Structure Health Monitoring (SHM) System Trade Space). Previously (Kuhn and Soni, 2009) described performance of SHM sensors and an approach to modeling them vs. accumulated flight hours on an aircraft. This paper builds on the work of Kuhn and others to explore the trade space associated with detection, false alarms, unscheduled maintenance actions and mishaps associated with an installed SHM system with realistic crack growth assumptions. In this paper, an approach to modeling the SHM detection performance as well as the changes occurring with the aircraft structure is demonstrated. This model is used to evaluate candidate levels for a sensor threshold with predictable performance regarding detection, missed detections and false alarms. It provides an analytic basis for establishing a business case for SHM implementation.

III. Structure Health Monitoring (SHM) System Trade Space Analysis

Salman A. Albinali and David R. Jacques

Abstract

An analytic approach to exploring the tradespace associated with Structural Health Monitoring (SHM) systems is presented. Modeling and simulation of the life cycle of a legacy aircraft and the expected operational and maintenance events that could occur is shown. A focus on the SHM system detection of a significant crack length and the possibility of False Alarm (FA), miss detection and mishap events is investigated. The modeling approach allows researchers to explore the tradespace associated with safe and critical crack lengths, sensor thresholds, scheduled maintenance intervals, falsely triggered maintenance actions, and mishaps due to missed detections. As one might expect, it was observed that setting the SHM system very conservatively (closer to safe crack levels) increases detection but causes a high number of FA events. On the other hand setting the SHM system threshold higher to tolerate a greater crack length reduces FA events but increases the number of Miss Detection events. Furthermore as cracks propagate to a greater length it was observed that Miss Detection events can lead to catastrophic failures causing (mishap) events. The analytic approach described herein allows one to determine an acceptable balance between safety of flight and acceptable FA rates. The novelty of this approach is providing a life cycle analysis for a legacy aircraft equipped with SHM system with expected events (FA, Miss Detections) that could impact the life cycle and cost-benefit analysis. This was accomplished by combining the

method used in MIL-HDBK-1823 and Paris's model and integrating it into a life cycle

model reflecting changing crack size and detection in every flight sortie until the end of

the life of the aircraft. This enables users to estimate the frequency of event occurrences

and the costs associated with these events, thus contributing to a more accurate life cycle

cost (LCC) analysis for an aircraft equipped with an SHM system. While the current

model is applicable to crack propagation in metallic structures, analytic expressions for

sensor signal variation associated with other damage/structure types would allow the

current model to be extended for those applications.

Keywords: Structural Health Monitoring, Fatigue Crack Growth, Probability of

Detection, False Alarms, Missed Detections

Nomenclature

a crack length

a_{cr} critical crack length at which failure occurs

$\hat{a}$ system response signal to a crack length

a_{th} a crack size detected 50% of the time by the SHM system

$\hat{a}_{th}$ signal threshold for a crack size detected 50% of the time by the SHM

        system

a_{safe} minimum significant crack length

a_0 initial flaw size (crack length)

β_1 regression line slope

β_0 regression line intercept

C material constant

$\Delta\delta$ pressure differential due to the stress load

ΔK difference between the stress intensity factors

K_{IC} fracture toughness

K_{max} maximum stress intensity factor

K_{min} minimum stress intensity factor

m material constant

N number of load cycles

σ standard deviation associated with probability of $\hat{a}$ given a

Introduction

Operation and Maintenance (O&M) of aircraft often accounts for 70-80% or more of the total Life Cycle Costs (LCC) of military and civilian aircraft (Gilmore and Valaika, 1992). For this reason, aircraft operators and maintainers are always looking for ways to reduce the O&M burden for both new and legacy aircraft. Maintenance schedules are selected conservatively based on flight safety, but a higher frequency of scheduled maintenance increases O&M cost and may make it more likely that the maintenance actions themselves introduce system faults. Performing maintenance tasks in a timely manner, with reduced cost and improved safety, is critically important for successful operation of any system, especially as resources are becoming scarce. If we examine the military aerospace field we note that many legacy systems will be operating beyond their original design life due to funding delays or schedule slips associated with new replacement aircraft. Life extension programs have often been implemented on these

legacy systems so that they can operate safely and effectively until a replacement system is available. Even with a life extension program, however, operating a legacy system can incur significant operations and support costs.

One of the major concerns for aging aircraft is the structural health of the system. As the structure accumulates flight hours, cracks develop and propagate in that structure. In response, Non-Destructive Inspections (NDI) are used by the maintenance crews to find these cracks and perform maintenance if they grow beyond what is considered a safe length. These NDI are preformed periodically, usually based on flight hours. These inspections have some negative aspects associated with them. NDI causes aircraft down time affecting mission readiness, and increasing labor hours and maintenance costs. Further, between NDI intervals the length of the existing cracks in the structure are not known, which raises safety concerns. Condition-Based Maintenance (CBM) has been investigated in recent years to overcome these shortcomings by performing maintenance when needed as opposed to relying on more conservative maintenance intervals (Cutter and Thompson, 2005; Ellis, 2008).

One of the necessary tools to achieve CBM is to continuously monitor the system. Structure Health Monitoring (SHM) is an approach that employs methods and tools to monitor the health of the structure continuously through on-board sensors, promising higher safety level and reduction in cost through extended inspection intervals and continuous monitoring. Many of the necessary SHM technologies are available, yet we see a slow implementation of these systems on operational platforms. Further, challenges involved in the development and transition of SHM technology including issues concerned with design, installations and validation methods for damage detection are still

present (Beard and Banerjee, 2011). It has been suggested that the lack of a solid business case clearly analyzing the cost benefit of a SHM system is one of the main causes of the slow implementation of such a system (Derrisoet al., 2007; Perez et al., 2010). False Alarms (FA) from a SHM system will cause unnecessary maintenance actions, thus raising cost and aircraft availability concerns. Missed detections that might also occur when using a SHM system also create safety concerns. It is clear that these factors have a major impact on the business case. Trade space analysis that considers fatigue crack growth rates, SHM sensor performance, scheduled inspection intervals, and event costs is needed. This paper presents a trade space analysis for a legacy fighter equipped with an SHM system throughout its life cycle. Modeling and simulation using Monte Carlo analysis in the MATLAB® programming environment will be used as the trade space analysis tool. While the current model is applicable to crack propagation in metallic structures, analytic expressions for sensor signal variation associated with other damage/structure types would allow the current model to be extended for those applications.

Fatigue crack growth

Fatigue crack growth predictions are used to estimate the design life of aircraft structural components. They are used in design where a structural component is expected to operate safely with an existing crack until the crack reaches a length that is detectable by NDI, but less than a critical length (Roylance, 2001). Paris's Law is one of the most widely used fatigue crack growth models and was used in this research effort (Paris and Erdogan, 1963).

Paris's Law

Under a fatigue stress regime Paris's Law relates sub-critical crack growth to stress intensity factor. The basic formula has the following form:

$$\frac{da}{dN} = C\Delta K^m \tag{2}$$

The term on the left side is known as the crack growth rate, where a is the crack length and N is the number of load cycles. The crack growth rate indicates the crack length growth per accumulated number of load cycles. C and m are material constants and ΔK is the difference between the stress intensity factor at maximum loading and minimum loading:

$$\Delta K = K_{max} - K_{min} = \Delta\delta\sqrt{\pi a} \tag{3}$$

where K_{max} is the maximum stress intensity factor, K_{min} is the minimum stress intensity factor and $\Delta\delta$ is the pressure differential due to the stress load.

Probability of detection (POD)

The primary focus of a SHM system is to reliably detect a significant crack length a just like the NDI does, but to perform this task continuously during operation of the system. The performance of a SHM system can be demonstrated using $POD(a)$ curves. (Kuhn and Soni, 2009; Kuhn, 2009) showed that $POD(a)$ can be evaluated using the following formula:

$$POD(a) = P(\hat{a} > \hat{a}_{th}) = \Phi \left(\frac{\beta_0 + \beta_1 * \ln(a) - \ln(\hat{a}_{th})}{\sigma} \right) \qquad (4)$$

$POD(a)$ is modeled by performing linear regression on an a vs. $\hat{a}$ functional

relation that has normally distributed residuals with constant variance, where $\hat{a}$ is the

measured system response of a NDI system to a crack of length a. Units depend on the

particular inspection system. MIL-HDBK-1823 (Department of Defense, 1999),

describes NDI experimental data showing a linear regression line relationship relating

$\ln(a)$ to $\ln(\hat{a})$, where β_0 is the regression line intercept, β_1 is the slope, $\hat{a}_{th}$ is the signal

threshold for a NDI system (the value of $\hat{a}$ below which the signal is determined to have

been caused by a crack of insignificant length) and σ is the standard deviation of the

residuals of a linear regression fit of a vs. $\hat{a}$ data as represented in Figure 1 (Department

of Defense, 1999). A more intuitive explanation of the generation of the POD equation

showing practitioners how properties of SHM data affect the rotation and translation of

the POD curve was pressed by (Pado et al., 2013).
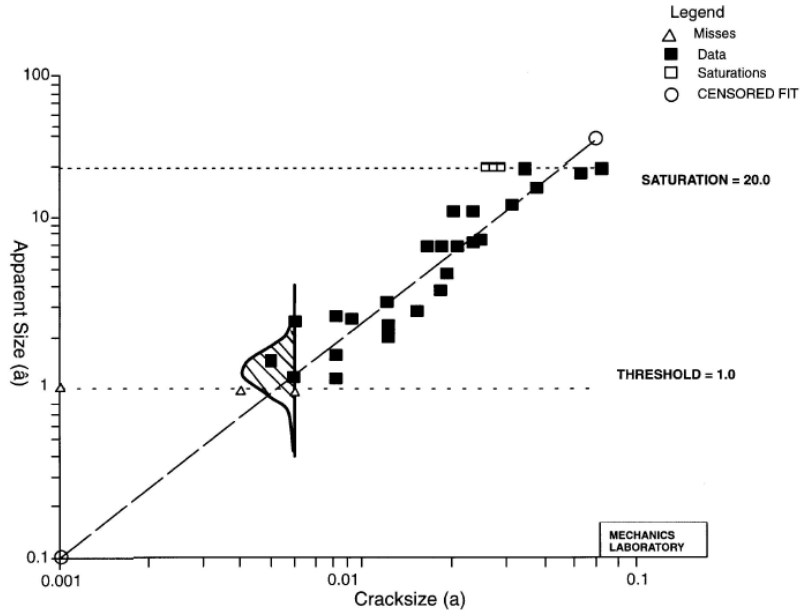
Figure

Figure 1: Linear regression fit of $\ln(a)$ vs. $\ln(\hat{a})$ data (Department of Defense, 1999)

Confusion Matrix

In a scenario where a NDI or SHM system is attempting binary detection (crack/no-crack) of a crack of length a there are four possible outcomes:

1) The system detects a crack and a crack of significant length actually exists; this is declared a True Detection event;

2) The system detects a crack and either the crack does not exist or the length of the crack is not considered significant; this is declared a FA event;

3) The system does not detect a crack and a crack of significant length does not exist; this is a True Negative event;

4) The system does not detect a crack but a crack of significant length exists; this is a Missed Detection event.

These four probabilities can be represented in a "Confusion Matrix" shown in Figure 2 (Fawcett, 2006). The confusion matrix is used for predictive analysis. Typically, the probabilities appearing in the matrix are determined through test or historical data collection.

Figure 2: Confusion Matrix

In operating an aircraft, FA rates or false calls raise concerns due to the fact that these will drive unnecessary maintenance actions that will affect mission readiness and cost. Even beyond concerns for unnecessary maintenance actions, false alarms could result in premature mission terminations. Missed Detections raise concerns due to the fact that they might cause an aircraft mishap due to unforeseen/undetected structural problems. A graphical representation of the confusion matrix probabilities distributions plus the threshold level of an NDI or SHM system is represented in Figure 3 (Kuhn, 2009).
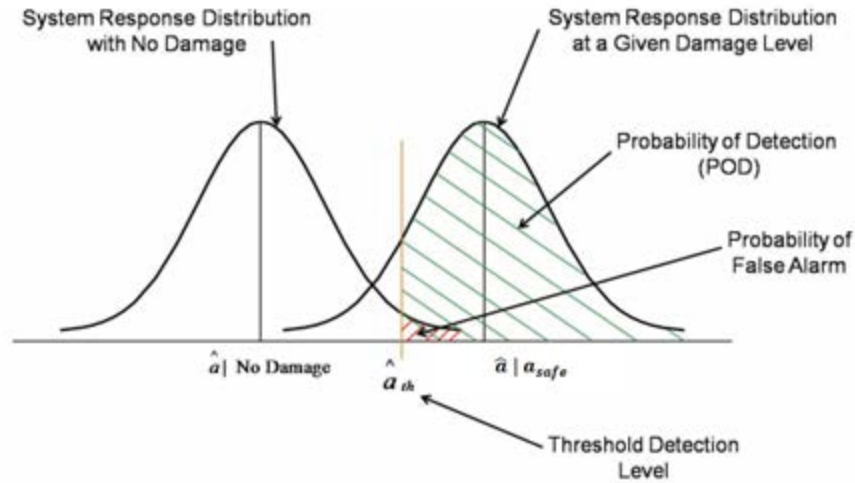
Figure 3: Graphical representation of the probabilities and the Threshold Detection Level

(Kuhn, 2009)

It is important to note that adding the FA and True Negative probabilities equals 1. Likewise adding the True Detection and Miss Detection probabilities equals 1. It can be observed from Fig. 3 that varying the threshold $\hat{a}_{th}$ will affect sensor performance. Moving $\hat{a}_{th}$ to the right will result in less FA and less Detections. Moving $\hat{a}_{th}$ to the left will result in more Detections and more FA. The variance (standard deviation) of the response signal $\hat{a}$ can also affect sensor performance as it will determine the amount of overlap for pdfs associated with a given crack length and that associated with a "safe" structure. In this research the effect of a crack growth on a legacy fighter will be simulated for each sortie up to the time when a mishap (catastrophic failure) occurs or the end of the design life of the aircraft is reached, whichever occurs first. For every sortie,

corresponding to a set number of load cycles, SHM system detection will be simulated

based on the current crack size and sensor performance, POD(a).

For this analysis, the SHM system will be assumed to follow an NDI-like

detection trend whereby a larger crack will generate a larger mean signal response; the

analysis approach easily supports a piezo-like sensor whereby the trend is reversed

(larger cracks generate smaller mean signal response). An event corresponding to one of

the quadrants of the confusion matrix will occur at each sortie. First, a true detection

event will trigger an inspection and a repair action will occur. Second, a FA event

triggering an inspection can occur. For an FA event, subsequent NDI will identify the

true crack size. In this research, NDI performed post-flight is assumed to be perfect; in

future work this assumption will be relaxed. Third, a missed detection event triggering

the possibility of a mishap can occur. A missed detection of a crack that is still less than

some defined critical length will not cause a mishap; however, missed detection of a

crack that grows to a length equal to or exceeding a critical length will result in a mishap.

Finally, a true negative event triggers no action, and the aircraft is assumed ready for the

next sortie.

Varying the sensor detection threshold, $\hat{a}_{th}$, minimum crack length detected

requiring a repair action, a_{safe}, and the standard deviation of the distribution will be

investigated to study the effects of these SHM system sensor performance parameters on

the number of maintenance events and mishaps that occur. For this research, a single

critical crack location is modeled, but the methods described herein are extensible to

multiple crack locations, and future work will extend the model to accommodate them.

Further, this method is applicable for damage detection in composite panels where the

extent of the damage is an area (compared to crack length) and the extent of the damage

includes severity. As long as experimental data can show and reflect a relationship

existing between damage characteristics/severity and signal response by SHM system

that could be later modeled this method is applicable.

Methodology

Modeling and simulation using MATLAB® was the method used in this research.

Figure 4 shows an event flow diagram depicting SHM related events for a legacy aircraft

equipped with SHM system.
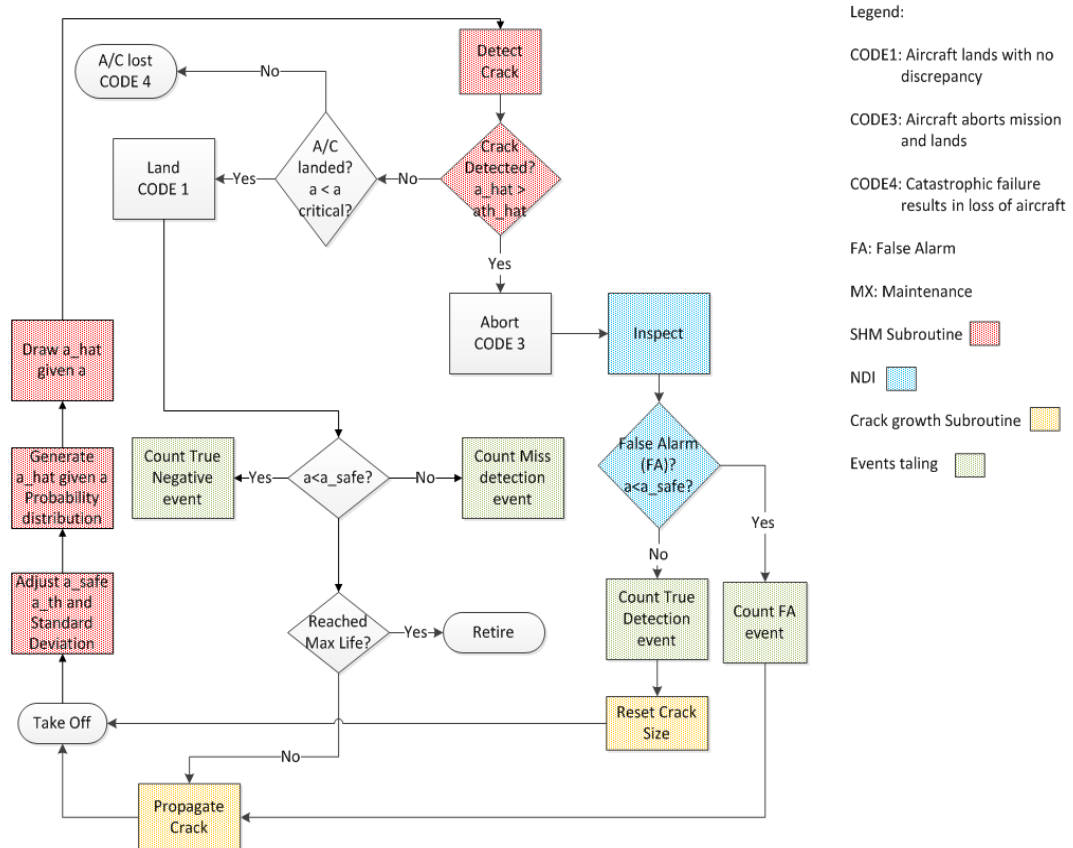
Figure 4: Flow diagram for SHM equipped aircraft

The simulation model starts at takeoff, depicted on the bottom left side of Figure 4. To initialize the model, a threshold, $\hat{a}_{th}$, safe crack length, a_{safe}, and a standard deviation σ are set and kept for the life time of the aircraft. An initial flaw size is used to initialize the crack growth model based on the Paris model discussed previously (Paris and Erdogan, 1963). After takeoff, the model generates a probability distribution for the crack length in that specific sortie based on the growth model and the number of accumulated flight hours in service or since previous crack repair. A Monte Carol draw is initiated simulating SHM system detection. If the system response signal $\hat{a}$ is less than $\hat{a}_{th}$ no SHM detection occurred. The model will check if the crack length a is greater than the critical crack length, a_{cr}. If that is true the model will declare a catastrophic structure failure leading to an aircraft mishap. Otherwise the aircraft will land. Then the model will check if a is greater than a_{safe}, and if that is true a missed detection event will be recorded. Note that while missed detections are recorded in the simulation for later analysis, the SHM system has no knowledge that a missed detection has occurred. If no detection occurs and $a < a_{safe}$, a true negative event will be recorded. If the aircraft reached its maximum life the simulation run for this aircraft will end and a new simulation run will start; otherwise, the model will propagate the crack length by the amount simulated for one sortie and takeoff again. For any sortie, if $\hat{a}$ is greater than $\hat{a}_{th}$, SHM detection occurs and the sortie will be aborted. An inspection will occur and if a is greater than a_{safe}, a true detection event will be recorded. The crack length will be reset simulating a repair or a replacement of a structural component and the aircraft will take off again. If a is less than a_{safe}, a FA event will be recorded, the crack a will be

propagated, and the aircraft will takeoff again. This will continue until the end of design

life or catastrophic failure of the aircraft. For a given set of a_{safe}, $\hat{a}_{th}$ and σ, 100

simulation runs will be performed, each one having a randomly selected initial flaw size

and growth rate parameter. After that a different set of a_{safe}, $\hat{a}_{th}$ and σ will be used so

trade space analysis on the affect of SHM sensor performance and crack length on events

can be performed.

Fatigue crack growth subroutine

A fatigue crack growth subroutine model was developed to simulate the crack

length propagation in every sortie. By integrating the Paris model Equation 2 and solving

for a_i which is the crack length after N_i cycles (flights) we get (An et al., 2012):

$$a_i = \left[N_i C \left(1 - \frac{m}{2} \right) \left(\Delta\delta\sqrt{\pi} \right)^m + a_0^{1-\frac{m}{2}} \right]^{\frac{2}{2-m}} \tag{5}$$

where a_0 is assumed to be the initial flaw size (crack length) existing in a new or repaired

structural component (Heida and Grooteman, 1998). Uncertainty is applied to the value

of a_0 to reflect that this value is different every time a repair or replacement is done to the

structure. The pressure differential, Δδ, due to the stress load can be evaluated by using

the expression (An et al., Chol, 2012):

$$\Delta\delta = \frac{K_{IC}}{\sqrt{a_{cr}\pi}} \tag{6}$$

where K_{IC} is the fracture toughness, a material property provided by the manufacturer of the structural component. $\Delta\delta$ is modeled with uncertainty to simulate the variation in loads an aircraft structure is exposed to for any given sortie. Figure 5 is a presentation of the fatigue crack growth simulation with 10 runs reflecting 10 repairs or replacements to the structural component.
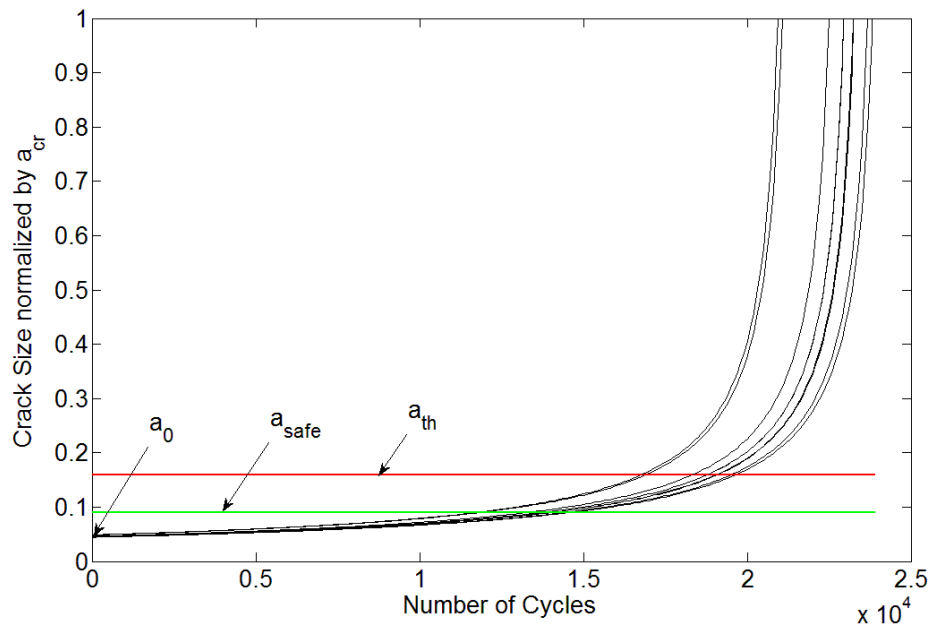
Figure 5: Fatigue crack growth simulation results for 10 runs

It is shown in Figure 5 that every run has a different a_0 and the growth rate with different loads $\Delta\delta$ causing the crack to propagate differently after each replacement or repair. Also a representation of a_{safe}, a minimum crack considered to be significant for SHM monitoring is shown on the figure. Detected cracks of length smaller than a_{safe} will not be repaired. The figure also shows a_{th}, a crack size having an associated SHM

response designated as the threshold for detection, $\hat{a}_{th}$. Both a_{safe} and $\hat{a}_{th}$ will be varied to simulate the performance of the SHM system.

Probability of detection subroutine

A probability of detection (POD) simulation subroutine was developed to simulate the SHM system response to a crack length occurring for every sortie. A probability of detection of the threshold crack a_{th}, detected 50% of the time, will be evaluated using Equation 4 in the following form:

$$POD(a) = 0.5 = \Phi\left(\frac{\beta_0 + \beta_1 * \ln(a_{th}) - \ln(\hat{a}_{th})}{\sigma}\right) \tag{7}$$

The signal threshold $\hat{a}_{th}$ will be solved for and used in the following equation:

$$POD(a) = P(\hat{a} > \hat{a}_{th}) = \Phi\left(\frac{\beta_0 + \beta_1 * \ln(a) - \ln(\hat{a}_{th})}{\sigma}\right) \tag{8}$$

where the crack length a from the fatigue crack growth simulation will be used and a Monte Carlo draw will be preformed every sortie. The constants β_0 and β_1 are evaluated by performing linear regression on experimental data provided by MIL-HDBK-1823 (Department of Defense, 1999). Since varying a_{th} will directly vary $\hat{a}_{th}$ as shown from the previous equations, only a_{th} will be used in the rest of the discussion. The variables a_{th} and a_{safe} are held constant for a given run, but varied for different simulation runs as a percentage of a_{cr}. Also, the standard deviation σ associated with the $\hat{a}$ vs. a pdf will be set for a given simulation run and varied for different runs.

Parameter Values and Recorded Events

The main simulation routine tallies several different events for the tradespace analysis. The number of FA events and Miss Detection events will be recorded for

different sets of a_{safe}, a_{th} and σ. The parameter a_{safe} will have five values, and for every value of a_{safe}, a_{th} will have a corresponding eight values and σ will have four values. For each combination of a_{safe}, a_{th}, and σ, 100 simulation runs will conducted and the average FA and Miss Detection events will be calculated. The results will be displayed and discussed in the following section.

Results and Discussion

FA events

Figure 6 (a) displays the effect of fixing the standard deviation σ at 0.1 and varying a_{safe} with the values 5, 6, 7, 8 and 9% of a_{cr}. For every a_{safe} value, the a_{th} value was incremented eight times starting at a_{safe} using increments of 1% of a_{cr}. For example, if a_{safe}= 5% a_{cr} then a_{th} will be incremented as 5, 6, 7, 8, 9, 10, 11 and 12% of a_{cr}. This is repeated for Figure 6 (b), (c) and (d) with standard deviation σ = 0.2, 0.3, and 0.4. It is observed from Figure 6 (a) that as a_{th} is moved about 2% from a_{safe} a significant drop in the number of FA events is noticed. The greater the a_{safe} percentage the greater the number of false alarm events recorded. From Fig. 6(b), as the standard deviation is increased from σ = 0.1 to σ = 0.2, it is observed that we have the same trend shown in Figure 6 (a) but with an increase in FA events. Also it is observed that an increase of a_{th} by about 3% over a_{safe} essentially eliminates FA events. From Figure 6 (c), as the standard deviation is increased from σ = 0.2 to σ = 0.3, it is observed that we have the same trend shown in Figure 6 (b) with very close FA events, but it now requires an increase of a_{th} by about 5% over a_{safe} to essentially eliminate FA events. Similarly in Figure 6 (d), as the standard deviation is increased from σ = 0.3 to σ = 0.4, it is

observed that it now requires an increase of a_{th} by about 8% over a_{safe} to essentially

eliminate FA events. 95% confidence intervals bars are shown on all figures based on

100 simulation runs.

Figure 6: % a_{th} of a_{cr} for a crack detected 50% of the time vs. Average number of FA

events for different standard deviation levels σ

Miss Detection events

From Figure 7 (a) we observe that if a_{th} is moved about 3% above a_{safe} a

significant increase in number of Miss Detection events is noticed. Note that a single

missed detection is not fatal as long as detection on a subsequent sortie occurs prior to the

crack reaching a critical length. From Figure 7 (b) it is observed that, as the standard

deviation is increased for $\sigma = 0.1$ to $\sigma = 0.2$, the same trend as Figure 7 (a) is shown, but

a_{th} needs to be at least 4% more than a_{safe} to reach the same number of Miss Detection events shown in Figure 7 (a). A similar trend is shown in Figure 7 (c) where it is observed that, as the standard deviation is increased from σ = 0.2 to σ = 0.3, a_{th} needs to be at least 5% more than a_{safe} to reach the same number of Miss Detection events as shown in Fig. 7(b). For σ = 0.4, shown in Figure 7 (d), a_{th} needs to be at least 6% more than a_{safe} to reach the same number of Miss Detection events as shown in Figure 7 (c). In general, a decrease in the standard deviation and an increase in the difference between a_{th} and a_{safe} results in an increase in the average number of Miss Detection events. Referring back to Figure 3, an increase in the standard deviation of the distributions results in greater overlap, improving the Miss Detection performance at the expense of higher FA rates.
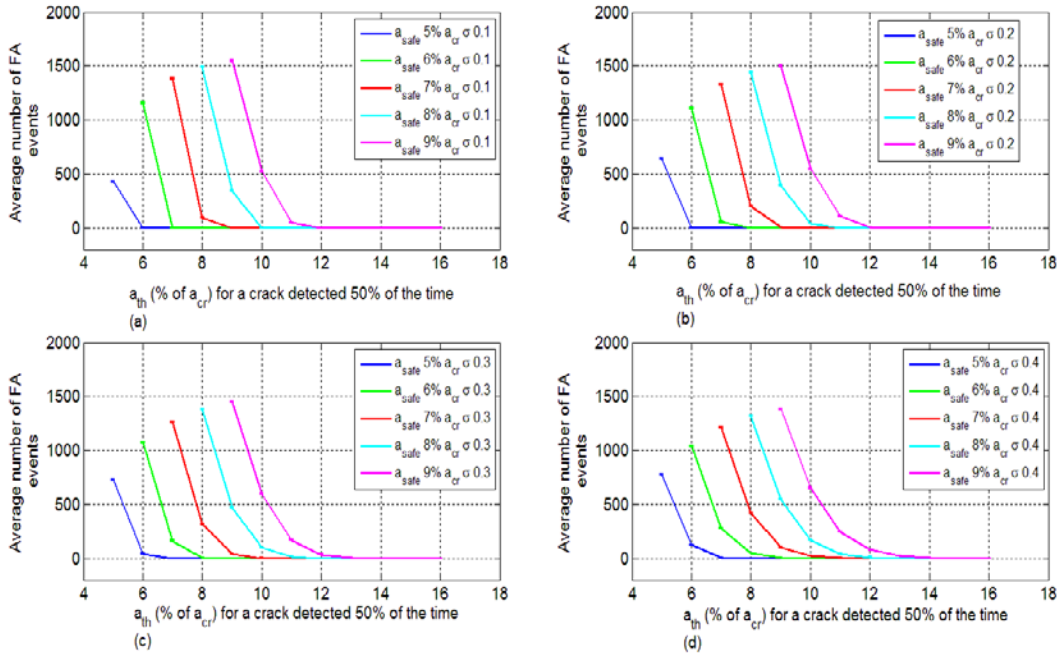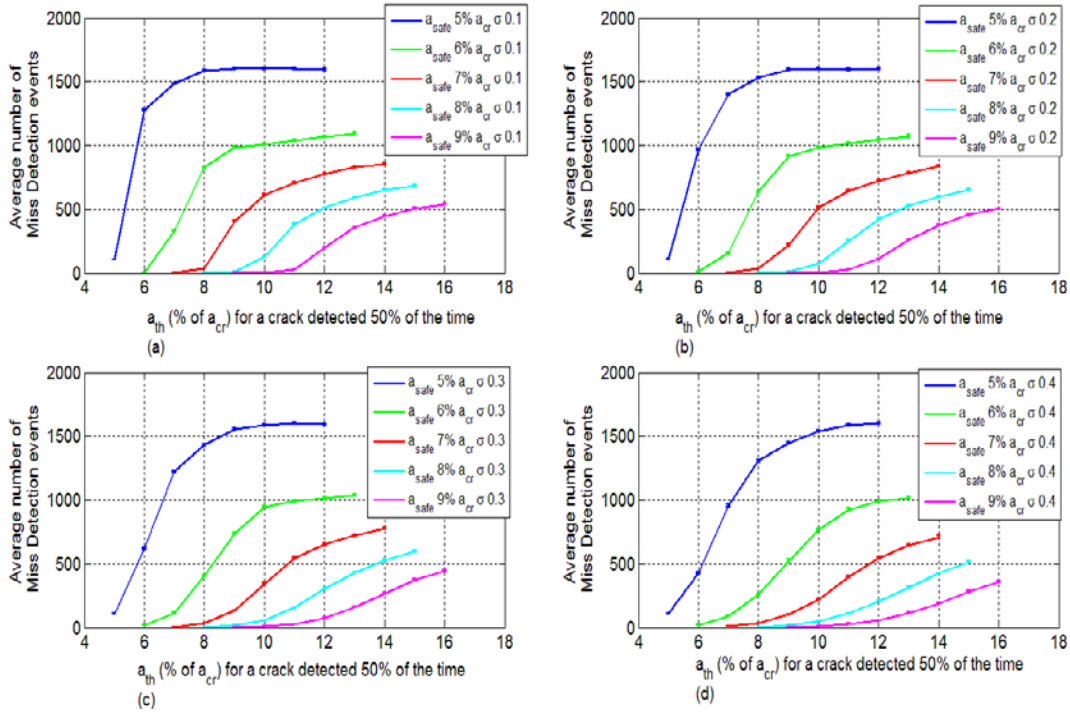
Figure 7: % a_{th} of a_{cr} for a crack detected 50% of the time vs. Average number of Miss Detection events for different standard deviation levels σ

Average crack length detected after a Miss Detection event

It is of interest to know the average crack length once detected after a Miss Detection event as percentage of a_{cr} as it reflects a safety concern. As noted previously, an initial missed detection can be detected during a later sortie as long as it does not reach the critical length causing a mishap. Before discussing these results, it is important to note that each detection attempt is treated independently, and the treatment herein assumes no degradation of the sensor (although research accounting for sensor degradation over time is ongoing). The following plots represent the simulation output for the crack length once detected as a percentage of a_{cr}.
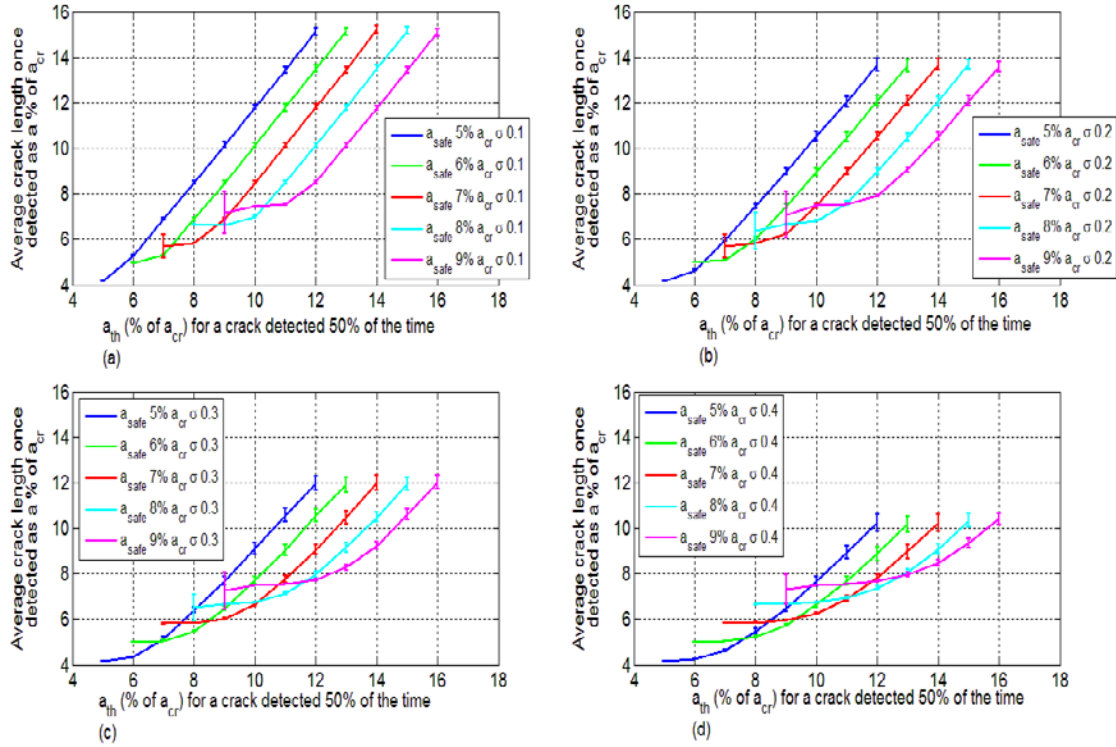
Figure 8: % a_{th} of a_{cr} for a crack detected 50% of the time vs. Average length of a crack detected after a miss detection event as a percentage of a_{cr} for different standard deviation levels σ

From Figure 8(a) it can be observed that, as a_{th} is increased further away from a_{safe}, the crack length once detected after initial miss detection increases. Also, as expected, a greater value of a_{safe} results in greater crack lengths once detected, which can become problematic as they approach a critical length. The obvious contribution to this increase is the fact that, as a_{safe} is increased, the size of the smallest crack that you intend to detect increases. However, it is important to note that the crack growth rate monotonically increases (see Figure 5); higher values for a_{safe} result in higher growth

rates for $a > a_{safe}$. Sweeping across Figure 8(a), (b), (c) and (d) to observe the effect of change in standard deviation, it is noted that the length of the crack once detected is the greatest for the smallest $\sigma = 0.1$ and the greatest a_{th}. This can be expected as the combination of these parameter trends increases the separation and decreases the overlap between the "safe" and "detectable" crack distributions. As the standard deviation increases there is a smaller change in the length of the crack detected after a Miss Detection event is observed due to greater overlap between the distributions.

Miss detection leading to a catastrophic failure

The previous section leads one to the question as to what values for a_{th} and a_{safe} result in a significant chance that a Miss Detection leads to a catastrophic failure ($a \geq a_{cr}$) of the structure component. Based on the crack growth model, growth is very slow for low numbers of load cycles (or sorties), but increases significantly as the load cycles accumulate. The simulation is coded to flag every time the crack length a is equal or greater than the critical length a_{cr} and declare a catastrophic failure, and these results will be shown for increasing values of a_{safe} and a_{th}.

Figure 9 displays the effect on the percentage of mishaps based on varying the threshold a_{th} from 50% to 90% of a_{cr}. For this analysis, a_{safe} was set at 50% of a_{cr} and the standard deviation σ was set at 0.4. It is observed that varying a_{th} from 50% to about 55% of a_{cr} did not result in any aircraft mishap events from the simulation runs. Once the threshold is increased beyond 55% of a_{cr} mishap events are noticed. Setting the threshold set at 65% a_{cr} resulted in approximately 10% mishap events (based on 100 simulation runs). As expected, the trend of increasing mishap rates for increasing

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detection thresholds continued. This preliminary analysis clearly shows how tradespace

analysis can be conducted to show safe operating regimes resulting in minimal

probabilities of catastrophic failure and acceptable false alarm rates.

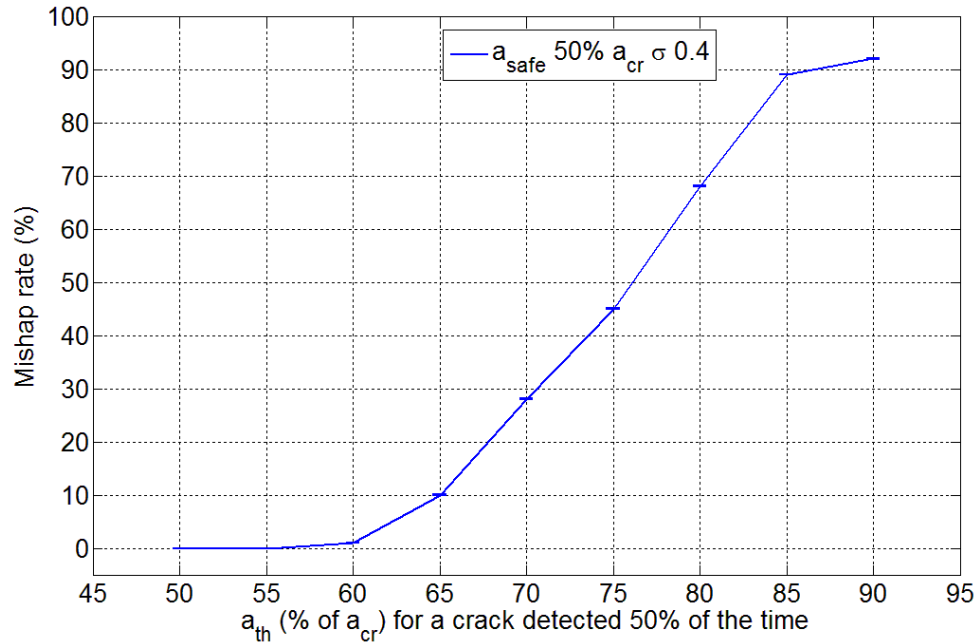Figure 9: % a_{th} of a_{cr} for a crack detected 50% of the time vs. Average mishap

percentage of number of simulation runs

Conclusion

Summary and findings

The tradespace analysis approach described herein shows how SHM sensor

performance design parameters a_{safe}, a_{th} and σ can affect the number of FA, Missed

Detections and mishap events that could occur over the expected life of an aircraft. If

design parameters are set conservatively with regards to safety, a high number of false

alarms will result, with a subsequent increase in maintenance events and cost.

Conversely, higher value for a_{th} with respect to a_{cr} result in a reduction in FA events,

but an increase of Miss Detection. Further increase in a_{th} with respect to a_{cr} can result in

Miss Detection events leading to mishaps. With safety of flight as a primary

consideration, the SHM system sensor parameters can be adjusted to reduce the

probability of mishap events to an acceptably low level while also keeping FA rates, and

related maintenance costs, at an acceptable level.

Future work

Although installing an SHM system with a certain expected performance might

produce expected cost savings, better operational readiness and improved safety, the

degradation of the SHM system will be a concern in its own right. Any system installed

on an aircraft is likely to degrade with operation. Systems installed on aircraft typically

require maintenance and inspection schedules to ensure continued acceptable operation.

The same is true for the SHM system. Kuhn's research (Kuhn and Soni, 2009; Kuhn,

2009) concluded that degradation to the SHM system sensors due to flight loads affect

the performance of such a system. Ongoing work is investigating the effect of

degradation on SHM performance parameters such as $\hat{a}_{th}$ and σ, amongst others, on the

FA, Miss Detection and mishap events an aircraft might experience. Also maintenance of

the SHM system itself will be considered. SHM system unscheduled maintenance will be

based on the maximum FA events encountered between SHM system scheduled

maintenance intervals which will be based on flight hours. Extensions to this work for

composite structures and other damage types are also being investigated.

The following is Chapter IV and it contains a journal article that will be submitted to the Journal of Structure Health Monitoring. The title of the article is (Utility and Effect of Employing a Variable Threshold for Countering the Effect of Degrading SHM Sensors). Kuhn and Soni (2009) previously described performance and degradation of SHM sensors and an approach to modeling them vs. accumulated flight hours on an aircraft. This paper builds on the work of Kuhn and others to explore the effect of sensor degradation on detection, false alarms, unscheduled maintenance actions and mishaps associated with an installed SHM system with realistic crack growth assumptions. In this paper, an approach to modeling the SHM detection performance/ sensor degradation as well as the changes occurring with the aircraft structure is demonstrated. Also the utility and effect of employing a variable threshold is discussed. This model is used to evaluate sensor performance under degradation with predictable performance regarding detection, missed detections and false alarms. It provides an analytic basis for establishing a business case for the SHM system implementation.

IV. Utility and Effect of Employing a Variable Threshold for Countering the Effect of Degrading SHM Sensors

Salman A. Albinali , David R. Jacques, Christine M. Schubert Kabban and Alan Johnson

Abstract

The degradation associated with a Structural Health Monitoring (SHM) system's sensors is considered using an analytic approach. Expected operational and maintenance events that could occur due to degradation is explored though modeling and simulation of the life cycle of a legacy aircraft. The SHM system's ability to detect a crack of significant length degrades over time, and it affects both the possibility of False Alarm (FA) and Miss Detection events. Degradation in the SHM system increases the number of FA events which raises a maintenance cost concern. Degradation also causes a concurrent reduction in the number of Miss Detection events. The analysis demonstrates that employing a variable detection threshold to counter the effect of degradation can significantly lower the number of FA events while maintaining Miss Detection events at an acceptable and safe level. Uncertainties in the assumed degradation factors are accounted for in the model, resulting in degraded performance, but a variable threshold is still capable of maintaining FA events lower than they would be for the constant threshold case. Determining acceptable FA and Miss Detection rates by employing a variable threshold to counter the effect of degradation can be achieved using the analytic approach described herein. This paper provides a life cycle analysis for a legacy aircraft equipped with a SHM system with degrading sensors leading to events (FA, Miss Detections) that could impact the life cycle and cost-benefit analysis. The frequency of event occurrences and the costs associated with these events can be estimates by users, thus contributing to a more accurate Life Cycle Cost (LCC) analysis for an aircraft equipped with a degrading SHM system.

Keywords

Structural Health Monitoring, Fatigue Crack Growth, Probability of Detection, Degradation, Threshold, False Alarms, Missed Detections

Nomenclature

a	crack length
a_{cr}	critical crack length at which failure occurs
$\hat{a}$	system response signal to a crack length
a_{th}	a crack size detected 50% of the time by the SHM system
$\hat{a}_{th}$	signal threshold for a crack size detected 50% of the time by the SHM system
a_{safe}	minimum significant crack length
a_0	initial flaw size (crack length)
α	degradation in the intercept factor
β_1	regression line slope factor
β_0	regression line intercept factor
C	material constant
$\Delta\delta$	pressure differential due to the stress load
γ	degradation in the slope factor
ΔK	difference between the stress intensity factors
K_{IC}	fracture toughness
K_{max}	maximum stress intensity factor
K_{min}	minimum stress intensity factor

ψ degradation in the standard deviation factor

m material constant

N number of load cycles

σ standard deviation associated with probability of $\hat{a}$ given a

Introduction

It has been reported that 70-80% or more of the total Life Cycle Costs (LCC) of military and civilian aircraft is due to the Operation and Maintenance (O&M) cost (Gilmore and Valaika, 1992). Therefore, aircraft operators and maintainers are always looking for ways to reduce the O&M burden for both new and legacy aircraft. Maintenance schedules are selected conservatively based on flight safety, but a higher frequency of scheduled maintenance increases O&M cost and may make it more likely that the maintenance actions themselves introduce system faults. Performing maintenance tasks in a timely manner, with reduced cost and improved safety, is critically important for successful operation of any system, especially as resources are becoming scarce. Examining the military aerospace field, one notes that many legacy systems are or will be operating beyond their original design life due to funding delays or schedule slips associated with new replacement aircraft. Life extension programs have often been implemented on these legacy systems so that they can operate safely and effectively until a replacement system is available.

Even with a life extension program, however, operating a legacy system can incur significant operations and support costs. One of the major concerns for aging aircraft is the structural health of the system. As the structure accumulates flight hours, cracks develop and propagate in that structure. In response, Non-Destructive Inspections (NDI) are used by the maintenance crews to find these cracks and perform maintenance if they grow beyond what is considered a safe length. These NDI are preformed periodically, usually based on flight hours. These inspections have some negative aspects associated

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with them. NDI cause aircraft down time affecting mission readiness, and increasing labor hours and maintenance costs. Further, between NDI intervals the length of the existing cracks in the structure are not known, which raises safety concerns. Condition-Based Maintenance (CBM) has been investigated in recent years to overcome these shortcomings by performing maintenance when needed as opposed to relying on more conservative maintenance intervals (Cutter and Thompson, 2005; Ellis, 2008).

One of the necessary tools to achieve CBM is to continuously monitor the system. Structure Health Monitoring (SHM) is an approach that employs methods and tools to monitor the health of the structure continuously through on-board sensors, promising higher safety level and reduction in cost through extended inspection intervals and continuous monitoring. Many of the necessary SHM technologies are available, yet we see a slow implementation of these systems on operational platforms. It has been suggested that the lack of a solid business case clearly analyzing the cost benefit of a SHM system is one of the main causes of the slow implementation of such a system (Derriso et al., 2007; Perez et al., 2010). Further, challenges involved in the development and transition of SHM technology including issues concerned with design, installations and validation methods for damage detection are still present (Beard and Banerjee, 2011). False Alarms (FA) from a SHM system will cause unnecessary maintenance actions, thus raising cost and aircraft availability concerns. Further, Missed detections from a SHM system can cause safety concerns.

Degradation of the SHM system over the life time of an aircraft can have a great impact on the SHM system performance, adversely effecting FA and Miss Detection events. Many studies show degradation of SHM sensors over time due to static loads,

cyclic loads, temperature and corrosion. Research by Achenbach (2007) indicated that some of the technical challenges for sensors are that they need to be small, autonomous, cheap, robust, repairable, accurate, densely distributed, measure local and system level responses and designed to measure relevant damage parameters. There are typically competing objectives that must be balanced by the system designer. Beard et al. (2005) found that environmental conditions such as temperature can affect the signal obtained from sensors. His research used calibration to compensate for temperature variation based on the structure and application. A sensor diagnostics and validation process was presented by Park et al. (2006). It performs in situ monitoring of the operational status of a piezoelectric (PZT) active-sensor in SHM applications. Both degradation of the mechanical/electrical properties of a PZT transducer and the bonding defects between a PZT patch and a host structure could be identified by the proposed process. The proposed process can provide a metric that can be used to determine the sensor functionality over a long period of service time or after an extreme loading event. An investigation on the effect of cyclic loads on sensor performance was conducted by Kuhn (2009). Degradation was identified in sensor performance having a direct relationship with cyclic strain which was estimated by using a power equation model in his research. A probability of detection (POD) degradation model was also developed to show the overall performance of a SHM system over time.

It is clear that these factors have a major impact on the business case. A benefit study that considers fatigue crack growth rates, realistic probability of detection, SHM sensor degradation, scheduled inspection intervals, SHM maintenance actions, and Life cycle analysis and operation events is needed. This research is a follow on work of

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Albinali and Jacques (2014). The novelty of this research described herein is the benefit study and analysis for a legacy fighter equipped with a SHM system that degrades throughout the life cycle. SHM sensor degradation and its effect on operation and maintenance events is considered. Realistic fatigue crack growth rates and probability of detection is employed. Modeling and simulation using Monte Carlo analysis in the MATLAB® programming environment is used to model the operational life of an aircraft equipped with a degrading SHM system, and the potential impact of that system on life cycle maintenance events.

Crack propagation model

Fatigue crack growth predictions are used to estimate the design life of aircraft structural components. They are used in design where a structural component is expected to operate safely with an existing crack until the crack reaches a length that is detectable by NDI, but less than a critical length (Roylance, 2001). Paris's Law is one of the most widely used fatigue crack growth models and was used in this research effort (Paris and Erdogan, 1963).

Paris's Law

Under a fatigue stress regime Paris's Law relates sub-critical crack growth to stress intensity factor. The basic formula has the following form:

$$\frac{da}{dN} = C\Delta K^m \tag{9}$$

The term on the left side is known as the crack growth rate, where a is the crack length and N is the number of load cycles. The crack growth rate indicates the crack

length growth per accumulated number of load cycles. C and m are material constants and ΔK is the difference between the stress intensity factor at maximum loading and minimum loading:

$$\Delta K = K_{max} - K_{min} = \Delta\delta\sqrt{\pi a} \tag{10}$$

where K_{max} is the maximum stress intensity factor, K_{min} is the minimum stress intensity factor and $\Delta\delta$ is the pressure differential due to the stress load.

Fatigue crack growth subroutine

A fatigue crack growth subroutine model was developed to simulate the crack length propagation in every sortie. By integrating the Paris model Equation 9 and solving for a_i which is the crack length after N_i cycles (flights) we get (An et al., 2012):

$$a_i = \left[N_i C \left(1 - \frac{m}{2} \right) \left(\Delta\delta\sqrt{\pi} \right)^m + a_0^{1-\frac{m}{2}} \right]^{\frac{2}{2-m}} \tag{11}$$

where a_0 is assumed to be the initial flaw size (crack length) existing in a new or repaired structural component (Heida and Grooteman, 1998). Uncertainty is applied to the value of a_0 to reflect that this value is different every time a repair or replacement is done to the structure. The pressure differential, $\Delta\delta$, due to the stress load can be evaluated by using the expression (An et al., 2012):

$$\Delta\delta = \frac{K_{IC}}{\sqrt{a_{cr}\pi}} \tag{12}$$

where K_{IC} is the fracture toughness, a material property provided by the manufacturer of the structural component. $\Delta\delta$ is modeled with uncertainty to simulate the variation in loads an aircraft structure is exposed to after a repair or replacement of structural component.

Crack detection model

Probability of detection (POD)

The primary focus of a SHM system is to reliably detect a significant crack length a just like the NDI, but to perform this task continuously during operation of the system. The performance of a SHM system can be demonstrated using $POD(a)$ curves. Kuhn and Soni (2009) and Kuhn (2009) showed that $POD(a)$ can be evaluated using the following formula:

$$POD(a) = P(\hat{a} > \hat{a}_{th}) = \Phi\left(\frac{\beta_0 + \beta_1 * \ln(a) - \ln(\hat{a}_{th})}{\sigma}\right) \tag{13}$$

$POD(a)$ is modeled by performing linear regression on an a vs. $\hat{a}$ functional relation that has normally distributed residuals with constant variance, where $\hat{a}$ is the measured system response of a NDI system to a crack of length a. Units depend on the

particular inspection system. MIL-HDBK-1823 (Department of Defense, 1999),

describes NDI experimental data showing a linear regression line relationship relating

$\ln(a)$ to $\ln(\hat{a})$, where β_0 is the regression line intercept, β_1 is the slope, $\hat{a}_{th}$ is the signal

threshold for a NDI system (the value of $\hat{a}$ below which the signal is determined to

have been caused by a crack of insignificant length) and σ is the standard deviation of

the residuals of a linear regression fit of a vs. $\hat{a}$ data. A more intuitive explanation of

the generation of the POD equation showing practitioners how properties of SHM data

affect the rotation and translation of the POD curve was pressed by Pado et al. (2013).

In an SHM system using piezoelectric sensors (PZT) using pitch-catch signals we get a

smaller signal response $\hat{a}$ for a greater crack length a. This is opposite to NDI where a

greater signal response $\hat{a}$ for a greater crack length a. The PZT *POD* relationship is

represented in Equation 14 and Figure 10 (Kuhn, 2009).

$$POD(a) = P(\hat{a}_{th} > \hat{a}) = \Phi\left(\frac{\ln(\hat{a}_{th}) - \beta_0 - \beta_1 * \ln(a)}{\sigma}\right) \tag{14}$$
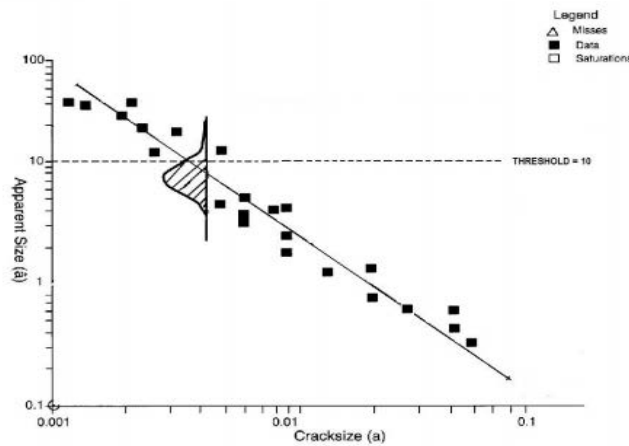

Figure 10: Linear regression fit of $\ln(a)$ vs. $\ln(\hat{a})$ data for SHM using PZT sensors (Kuhn, 2009)

Confusion Matrix

In a scenario where an NDI or SHM system is attempting binary detection

(crack/no-crack) of a crack of length a there are four possible outcomes:

1) The system detects a crack and a crack of significant length actually

exists, thus declared a True Detection event;

2) The system detects a crack and either the crack does not exist or the length of

the crack is not considered significant, thus declared a FA event;

3) The system does not detect a crack and a crack of significant length does not

exist, thus declared a True Negative event;

4) The system does not detect a crack but a crack of significant length exists; this

is a Missed Detection event.

These four probabilities can be represented in a "Confusion Matrix" shown in

Figure 11 (Fawcett, 2006). The confusion matrix is used for predictive analysis.

Typically, the probabilities appearing in the matrix are determined through test or

historical data collection.

Figure 11: Confusion Matrix

A graphical representation of the confusion matrix probability distributions with the threshold level of an SHM system is represented in Figure 12. In operating an aircraft, FA rates or false calls (shaded part of the no damage distribution plot to the left of $\hat{a}_{th}$) raise concerns due to the fact that these will drive unnecessary maintenance actions that will affect mission readiness and cost. Even beyond concerns for unnecessary maintenance actions, false alarms could result in premature mission terminations. Missed Detections (un-shaded part of the damage distribution plot to the right of $\hat{a}_{th}$) raise concerns due to the fact that they might cause an aircraft mishap due to unforeseen/undetected structural problems.
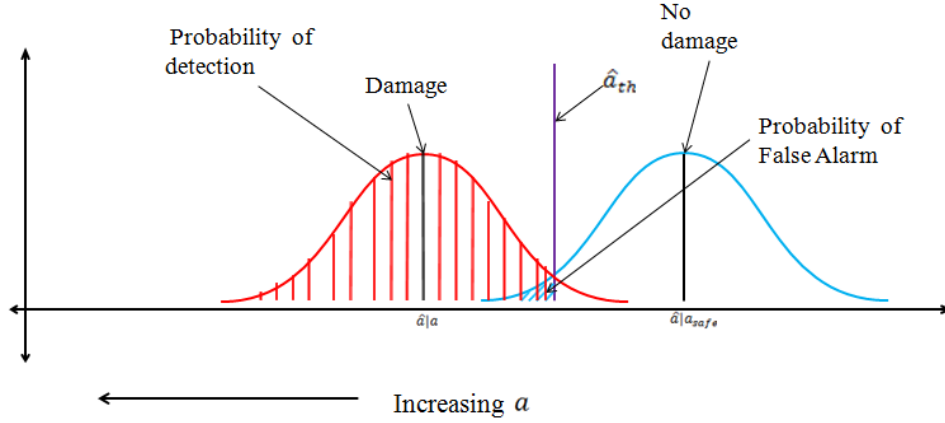
Figure 12: Graphical representation of the probabilities and Threshold detection Level

Probability of detection with degradation

A probability of detection (POD) simulation subroutine was developed to simulate the SHM system response to a crack length occurring for every sortie following a normal distribution. A probability of detection of the threshold crack a_{th}, detected 50% of the time, will be evaluated using Equation 13 in the following form:

$$POD(a) = 0.5 = \Phi \left(\frac{\ln(\hat{a}_{th}) - \beta_0 - \beta_1 * \ln(a_{th})}{\sigma} \right) \tag{15}$$

The signal threshold $\hat{a}_{th}$ will be solved for and used in the following equation by (Kuhn, 2009):

$$POD(a)_{Degraded} = \Phi \left(\frac{\ln(\hat{a}_{th}) - (\beta_0 * \alpha) - (\beta_1 * \gamma) * \ln(a)}{\sigma * \psi} \right) \tag{16}$$

where the crack length a from the fatigue crack growth simulation will be used and a Monte Carlo draw will be performed every sortie. The constants β_0, β_1 and σ are evaluated by performing linear regression on experimental data provided by MIL-

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HDBK-1823 (Department of Defense, 1999). The variables a_{th} (set equal to 10% of a_{cr}) and a_{safe} (set equal to 5% of a_{cr}) are held constant for all runs, but α, γ and ψ are varied for different simulation runs as a percentage of β_0, β_1 and σ , respectively. While a_{th} and a_{safe} were kept constant relative to a_{cr} for this research, previous research has investigated the effect of varying them relative to a_{cr} (Albinali and Jacques, 2014).

The previous discussion pertains to the constant $\hat{a}_{th}$ case. For the variable threshold case the threshold was adjusted to maintain a 50% detection as follows:

$$0.5 = \Phi \left(\frac{\ln(\hat{a}_{th}) - (\beta_0 * \alpha) - (\beta_1 * \gamma) * \ln(a)}{\sigma * \psi} \right) \qquad (17)$$

Using Equation 17, $\hat{a}_{th}$ was calculated with different degradation factors to always maintain a 50% detection threshold. Then the calculated $\hat{a}_{th}$ was used in Equation 16. This caused $\hat{a}_{th}$ to be reduced, i.e. move to the left, as was described in Figure 12. For the varying threshold case with uncertain degradation level 20% uncertainty was applied to degradation factors α, γ and ψ in Equation 16 and the simulation was repeated to see the effect of varying the threshold with uncertainty.

It is important to note that FA and True Detection are competing objectives, and for a given detection system both cannot be simultaneously improved. It can be observed from Figure 4 that false alarms are calculated from the (no damage) distribution, and if sensor degradation occurs the distribution shifts to the left (no damage-degradation) due to a change in the mean, or a spreading of the distribution

occurs due to a change in standard deviation (assuming a constant threshold), resulting in more false alarms. It also can be observed from Figure 13 the missed detection portion of the (damage) probability distribution is the unshaded portion to the right of $\hat{a}_{th}$. If sensor degradation occurs the distribution shifts to the left (damaged-degradation) due to change in the mean of the distribution (again assuming a constant threshold detection threshold), resulting in less missed detections. For a static crack with $a > a_{th}$, a spreading of the distributions in Figure 13 without a change in the mean could potentially result in an increase in both FA events and Missed Detections (given a static threshold) due to greater overlap between the damage and no damage distributions. However, when considered with cracks that transition from $a < a_{safe}$ to a larger value, the POD($a_{safe} < a < a_{th}$) distributions lie to the right of the $\hat{a}_{th}$ line, and it will be shown that this results in a drop in the number of Missed Detections. If a moving threshold is considered, the threshold will need to move to the left with the mean of the POD(a_{th}) distribution in order to counter the effect of increased FAs. While FA probability in the (no damage-degradation) distribution will be reduced (the intended result), the Miss Detection probability in the (damaged-degradation) distribution will increase over the corresponding amount that would be seen with a constant threshold.
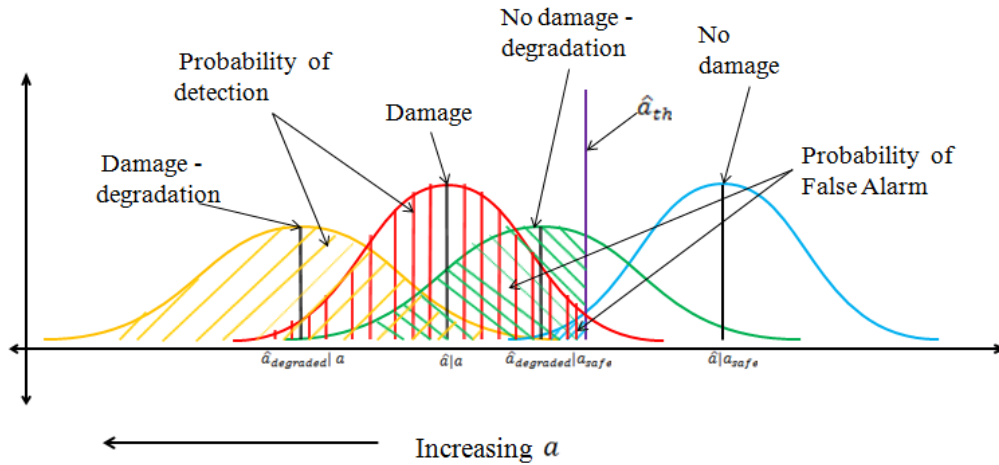
Figure 13: Graphical representation of the probabilities and Threshold detection Level with Degradation

In this research, the effect of a crack growth on a legacy fighter will be simulated for each sortie up to the time when a mishap (catastrophic failure) occurs or the end of the design life of the aircraft is reached, whichever occurs first. For every sortie, corresponding to a set number of load cycles, SHM system detection will be simulated based on the current crack size and sensor performance (POD(a)) / degradation (POD(a)$_{Degraded}$). For this analysis, the SHM system will be assumed to follow an SHM-like detection trend using PZT sensors, whereby a larger crack will generate a smaller mean signal response. An event corresponding to one of the quadrants of the confusion matrix will occur at each sortie.

- A true detection event will trigger an inspection and a repair action will occur;

- An FA event triggering an inspection can occur. For an FA event, subsequent NDI will identify the true crack size. In this research, NDI performed post-flight is assumed to be perfect;

- A Missed Detection event triggering the possibility of a mishap can occur. A missed detection of a crack that is still less than some defined critical length will not cause a mishap; however, missed detection of a crack that grows to a length equal to or exceeding a critical length will result in a mishap;

- Finally, a true negative event triggers no action, and the aircraft is assumed ready for the next sortie.

Varying the sensor detection POD(a)$_{\text{Degraded}}$ due to degradation by varying the degradation factors where α is the degradation factor applied to the regression line intercept β$_0$, γ is the degradation factor applied to the regression line slope β$_1$, ψ is the degradation factor applied to the regression line standard deviation σ. For this research, a single critical crack location is modeled, but the methods described herein are extensible to multiple crack locations.

Structural health monitoring model

Modeling and simulation using MATLAB® was the method used in this research. Figure 23 shows an event flow diagram depicting SHM related events for a legacy aircraft equipped with SHM system.

The simulation model starts at takeoff, depicted on the bottom left side of Figure 14. To initialize the model, a threshold, $\hat{a}_{th}$, and safe crack length, a_{safe}, are set and

kept for the lifetime of the aircraft. An uncertain initial flaw size is used to initialize the

crack growth model based on the Paris model discussed previously (Paris and Erdogan,

1963). After takeoff, the model generates a probability distribution for the crack length

in that specific sortie based on the growth model and the number of accumulated flight

hours in service or since previous crack repair.
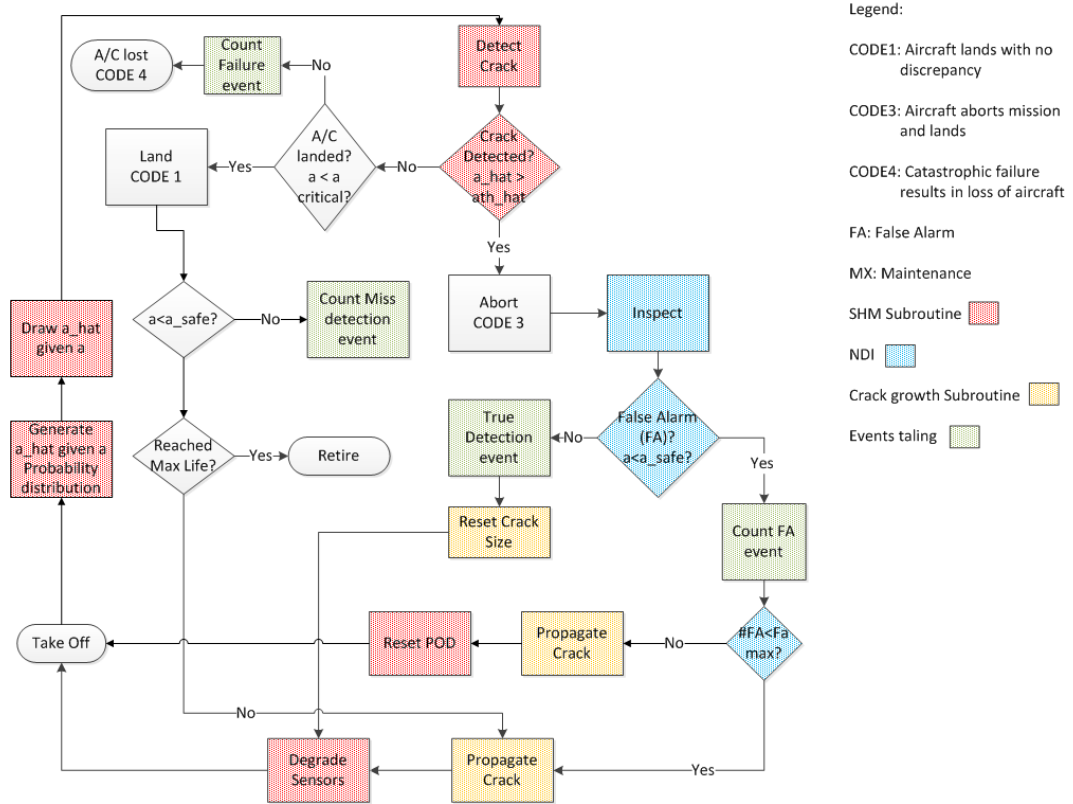
Figure 14: Flow diagram for SHM equipped aircraft

It is shown in Figure 15 that every run has a different a_0 and growth rate (corresponding to variation in loads, $\Delta\delta$) causing the crack to propagate differently after each replacement or repair. Also a representation of a_{safe}, the minimum crack considered to be significant for SHM monitoring, is shown on the figure. Detected cracks of length smaller than a_{safe} are not repaired. The figure also shows a_{th}, a crack size having an associated SHM response designated as the threshold for detection, $\hat{a}_{th}$. The parameters a_{safe} and a_{th} were set at 5% and 10% of a_{cr} respectively for this research, but earlier research explored variations of a_{safe} and a_{th} with respect to a_{cr} (Albinali and Jacques, 2014).
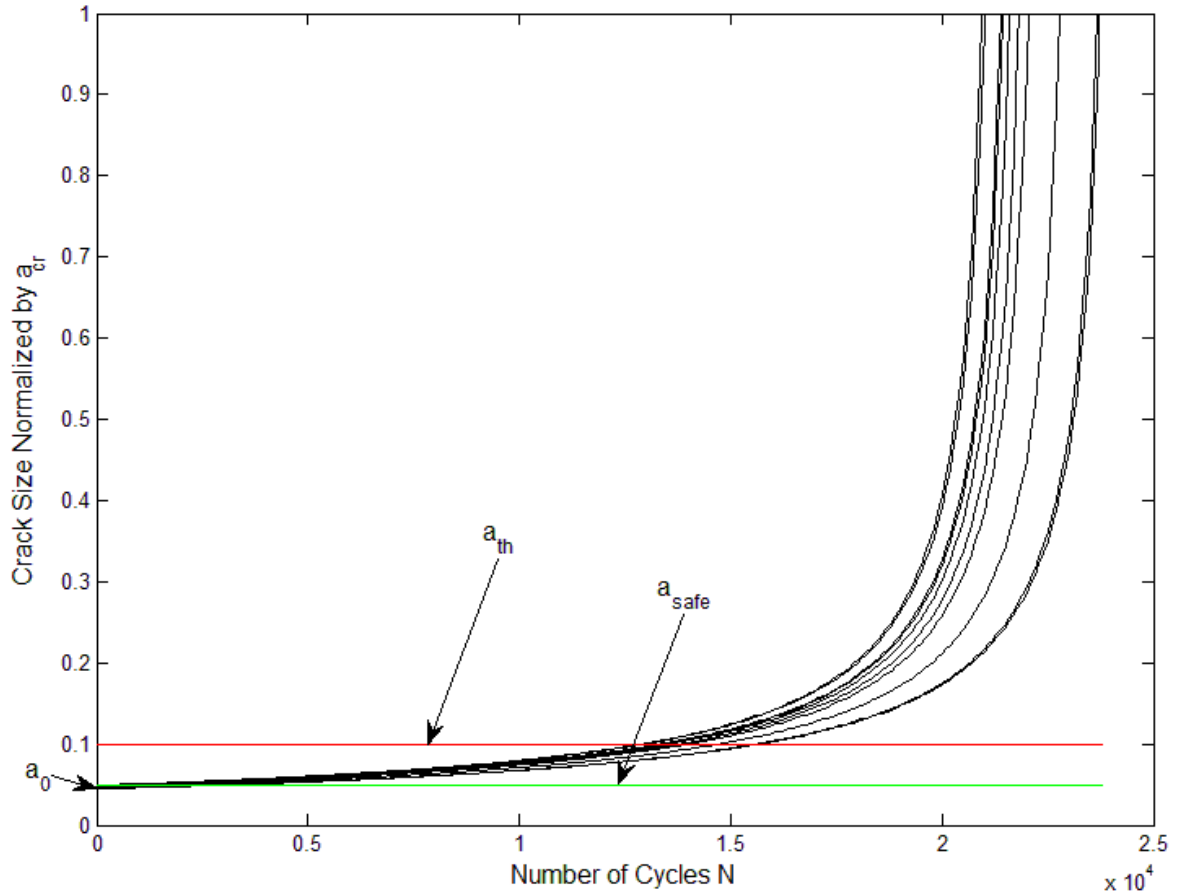
Figure 15: Fatigue crack growth simulation results for 10 runs

At each sortie, a Monte Carlo draw is initiated simulating SHM system detection. If the system response signal $\hat{a}$ is greater than $\hat{a}_{th}$ no SHM detection occurred. The model will check if the crack length a is greater than the critical crack length, a_{cr}. If that is true the model will declare a catastrophic structure failure leading to an aircraft mishap. Otherwise the aircraft will land. If no catastrophic failure occurs, the model will check if a is greater than a_{safe}, and if that is true a missed detection event will be recorded. Note that while missed detections are recorded in the simulation for later analysis, the SHM

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system has no knowledge that a missed detection has occurred. If the aircraft reached its

maximum life the simulation run for this aircraft will end and a new simulation run will

start; otherwise, the model will propagate the crack length and degrade the SHM sensors

by the amount simulated for one sortie and takeoff again. For any sortie, if $\hat{a}$ is less than

$\hat{a}_{th}$, SHM detection occurs and the sortie will be aborted. An inspection will occur and if

a is greater than a_{safe}, a true detection event will be recorded. The crack length will be

reset simulating a repair or a replacement of a structural component and the aircraft will

take off again. If a is less than a_{safe}, a FA event will be recorded, the crack a will be

propagated, SHM sensors will be degraded, and the aircraft will take off again. If the

number of FA events reach a maximum number identified FA_{max} between SHM

scheduled maintenance intervals, the crack a will be propagated, SHM sensors will be

replaced resetting the POD(a)$_{Degraded}$, and the aircraft will take off again. This will

continue until the end of design life or catastrophic failure of the aircraft. For a given set

of α, γ and ψ, 100 simulation runs will be performed, each one having a randomly

selected initial flaw size and growth rate parameter. After that a different set of α, γ and ψ

will be used so trade space analysis on the affect of SHM sensor degradation and crack

length on events can be performed.

Parameter Values and Recorded Events

The main simulation routine tallies several different events for the tradespace

analysis. The number of FA events and Miss Detection events are recorded for different

sets of α, γ and ψ. For each combination of α, γ and ψ, 100 simulation runs will

conducted and the average FA and Miss Detection events will be calculated. The results will be displayed and discussed in the following section.

Results and Discussion

Fixed detection threshold

Figure 16 displays the effect of degradation in the intercept, slope and standard deviation on the average number of Miss Detection events. Every point on the graph represents one life of an aircraft simulated by 100 iterations. It is observed from Figure 16 that as the degradation factors α, γ and ψ are increased a significant drop in the number of Miss Detection events is noticed. The greater the degradation of α, γ and ψ, the lower the number of Miss Detection events recorded. While fewer missed detections is a desirable outcome, this is at the expense of a significant increase in the number of FA events. Figure 17 displays the effect of degradation in the intercept, slope and standard deviation on the average number of FA events. Again, every point on the graph represents one life of an aircraft simulated by 100 iterations. It is observed from Figure 17 that as the degradation factors α, γ and ψ are increased a significant increase in the number of Miss Detection events is noticed. The greater α, γ and ψ percentage the greater the number of FA events recorded. We notice the degradation in standard deviation does not show a significant increase in FA events for the ranges shown; however, Kuhn's (2009) experimental data showed that degradation could cause up to 400% degradation in the standard deviation. This was implemented in the simulation and showed an average of 50 FA events at 400% degradation in the standard deviation. Confidence intervals of 95% are shown on all figures.
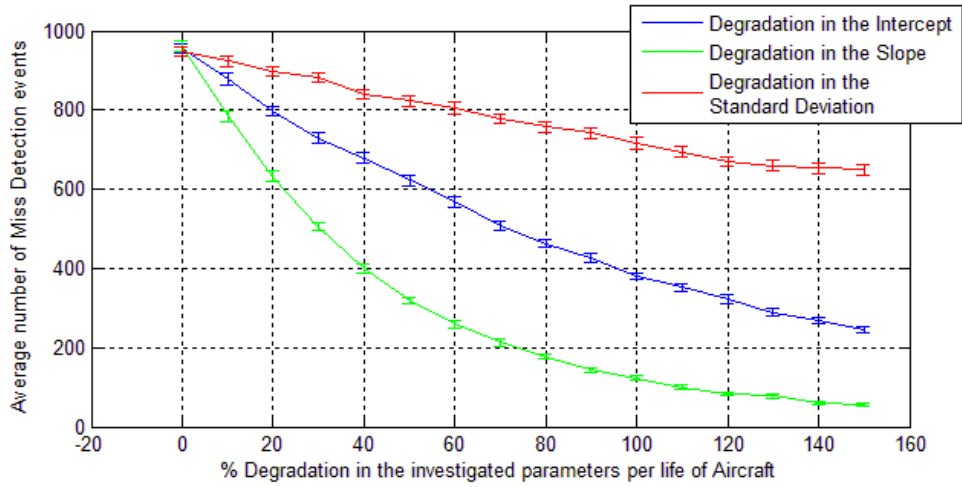
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Figure 16: Degradation in the Intercept, Slope and Standard Deviation vs. Average
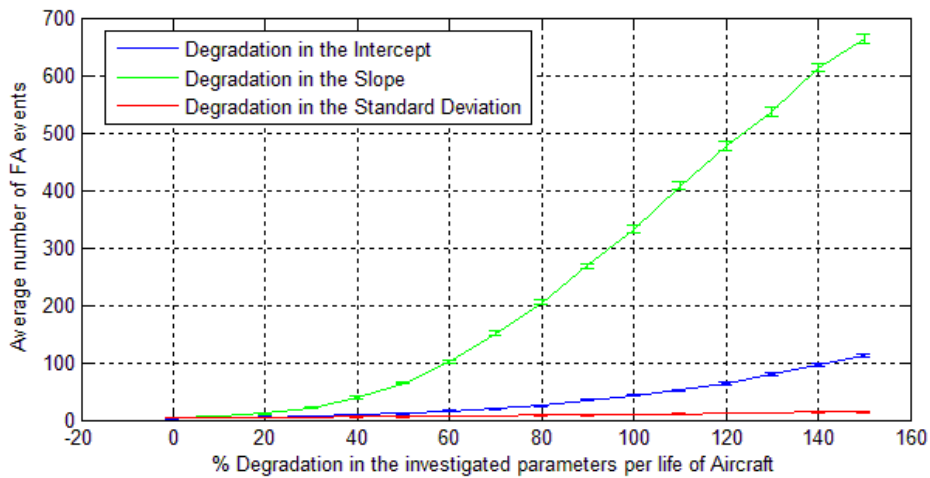
number of Miss Detection Events

Figure 17: Degradation in the Intercept, Slope and Standard Deviation vs. Average

number of FA Events

Figure 18 displays the effect of degradation in the intercept and standard deviation while keeping the slope constant (non-degraded) to see the effect of combined factors on the average number of Miss Detection events. From Figure 18 we observe that as the degradation factors α and ψ are increased a significant drop in the number of Miss Detection events is noticed, and combining both factors causes an even greater decrease in the Miss Detection events. Figure 19 displays the effect of degradation in the intercept and standard deviation while keeping the slope constant to see the effect of combined factors on the average number of FA events. From Figure 19 we observe that as the degradation factors α and ψ are increased a significant increase in the number of FA events is noticed where combining both factor will cause even greater increase in the FA events. Considering that FA events trigger unnecessary and costly maintenance events, this increase in the FA rate would be unacceptable for fielded system.
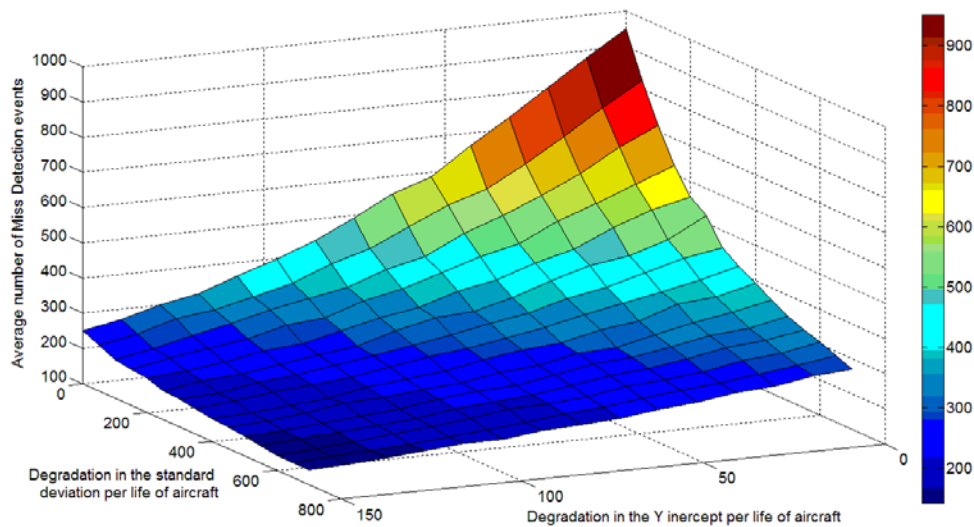

Figure 18: Degradation in Intercept and Standard Deviation vs. Average number of Miss Detection events

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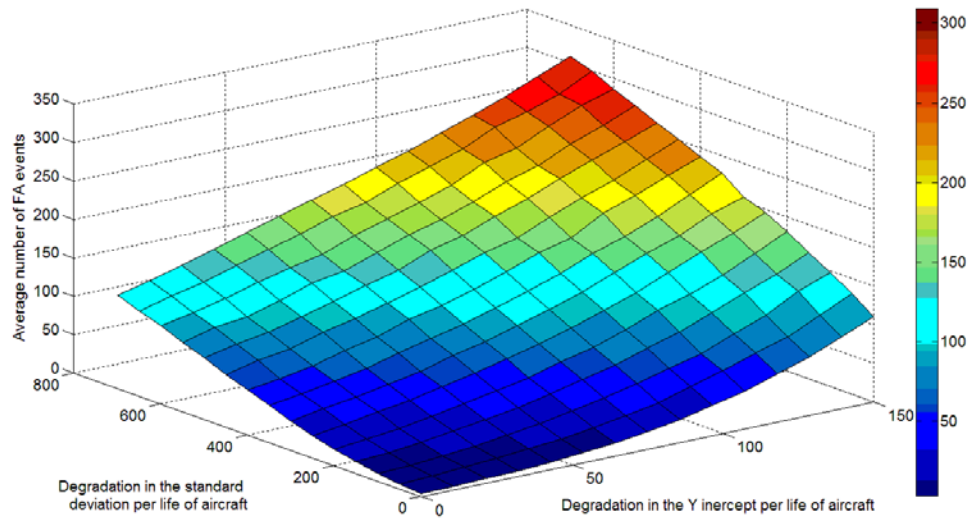
Figure 19: Degradation in Intercept and Standard Deviation vs. Average number of FA events

Figure 20 displays the effect of degradation in the intercept and standard deviation while keeping the slope at a constant 30% degradation to see the effect of combined all factors on the average number of Miss Detection events. From Figure 20 we observe that the same trend demonstrated in Figure 20 is evident, but combined degradation of all factors results in an even greater decrease in the Miss Detection events. The greater α and ψ percentage, the lower the number of Miss Detection events recorded. Figure 21 displays the effect of degradation in the intercept and standard deviation while keeping the slope also at constant 30% degradation to see the effect of combined factors on the average number of FA events. The trend from Figure 10 is repeated in Figure 21 but with a greater increase in FA events resulting from the combined degradation factors.
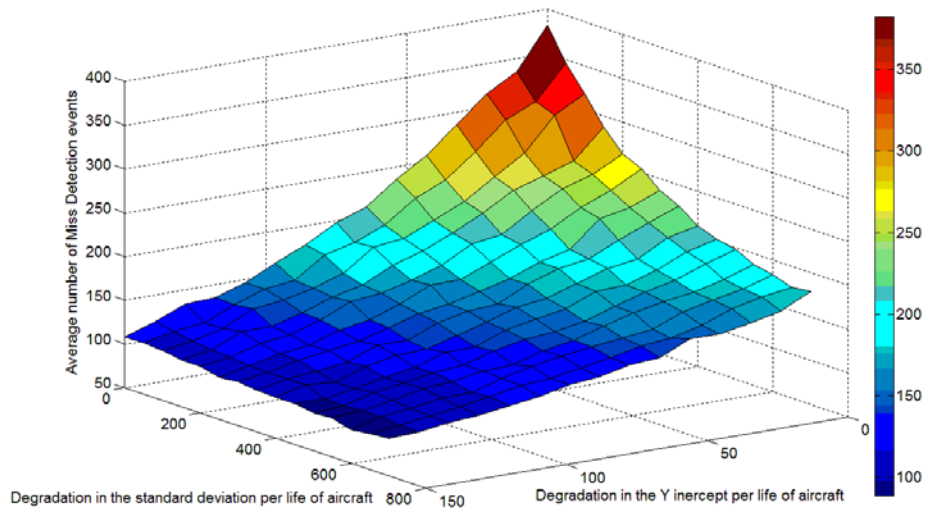
Figure 20: Degradation in Intercept, Standard Deviation and Slope at 30% Degradation

vs. Average number of Miss Detection events
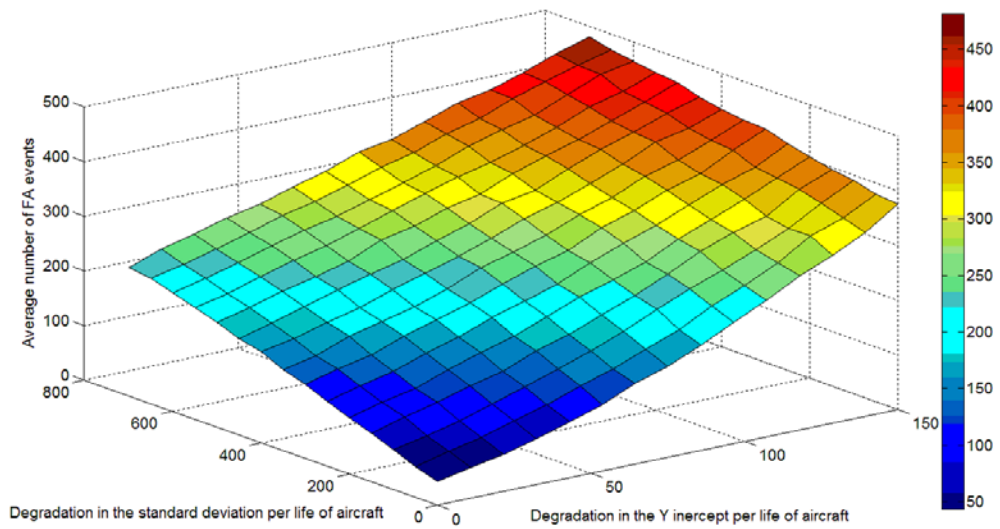
Figure 21: Degradation in Intercept, Standard Deviation and Slope at 30% Degradation

vs. Average number of FA events

Setting a_{safe} to 5% of a_{cr} and a_{th} to 10% a_{cr} did not result in any simulated

catastrophic failure leading to loss of aircraft in this study. This is true for all simulated

events with varying threshold and varying degradation factors effect. Recall that a

Missed Detection event does not typically result in a catastrophic failure because the

SHM system continues to have opportunities for detection for each sortie. As long as

the crack growth rate is sufficiently slow it will typically get detected during a later

sortie. Figure 22 represents degradation in the slope effect versus average crack length

detected after a Miss Detection event. The crack detected after miss detection is

acceptably small relative to the critical crack length. Effect of setting different a_{safe} and

a_{th} values was demonstrated in a previous study (Albinali and Jacques, 2014).
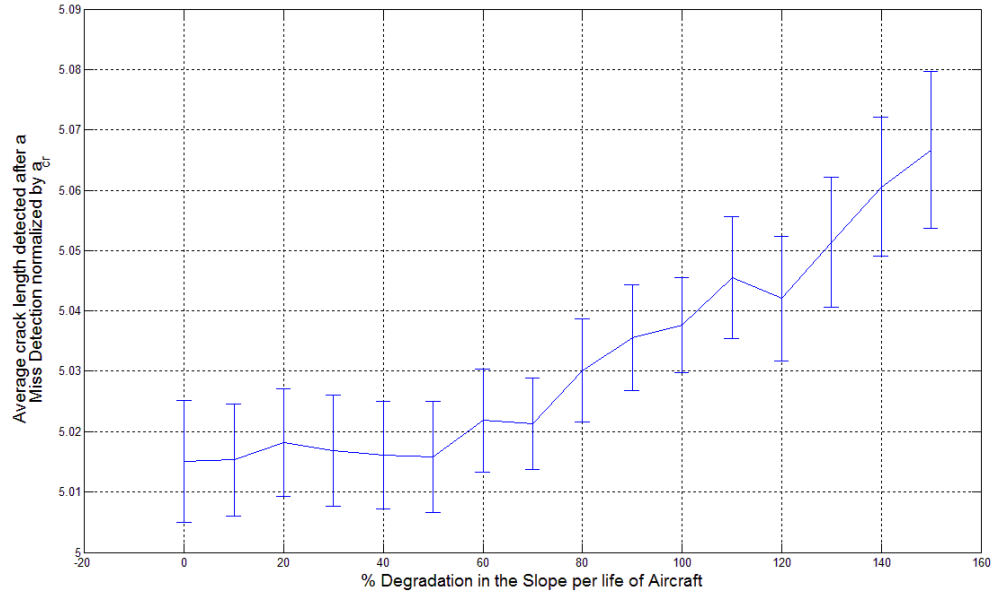
Figure 22: Degradation in the Slope vs. Average crack length after a Miss

Detection event

Varying detection threshold

Figures 23 and 24 display the effect of degradation in the intercept to observe the

effect of a variable threshold on the SHM system performance. From Figure 23 we

observe that as the degradation factor α is increased, a significant increase in the number

of FA events occurs for the constant threshold case as shown before. Varying the

threshold according to assumed degradation models serves to stem the growth of FA

events, thus avoiding the unnecessary and costly maintenance events. Even for the case

of a variable threshold, random error associated with the assumed intercept degradation

factor while the number of FA events is higher than the ideal case in which the intercept

degradation factor is known, that FA event growth is still halted at a far lower value than

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that experienced by the system with a constant threshold which continues to grow for higher values of the intercept degradation factor.

Figure 23: Degradation in the Intercept vs. Average FA events for threshold being constant, varying and varying with random degrading Slop factor

From Figure 24 we observe that as the intercept degradation factor α is increased a significant drop in the number of Miss Detection events occurs for the constant threshold case as shown previously. If the threshold is varied a relatively constant number of Miss Detection events are recoded. This is a result of the constant drop in mean of the regression line in Figure 13 and moving the threshold to maintain a 50% detection level based on assumed degradation levels. If the threshold is varied but the assumed intercept degradation factor has random error associated with it, a lower number of Miss Detection events are recorded, but with a cost of more FA events as discussed previously.

Figure 24: Degradation in the Intercept vs. Average Miss Detection events for threshold being constant, varying and varying with random degrading Slope factor

Figures 25 and 26 show the benefit of a variable detection threshold in the presence of degradation in the slope of the POD curve. From Figure 25 we observe that as the degradation factor γ is increased, a significant increase in the number of FA events occurs for the constant threshold case, again as shown previously. As in the case for the degrading intercept factor, a variable threshold serves to restrain the growth in FA events to a manageable case, even when there is random error associated with the assumed degradation factor.

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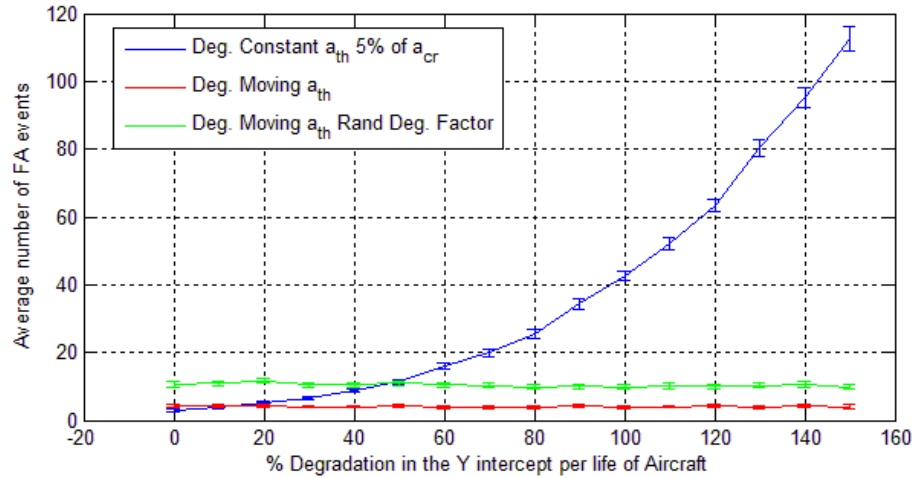Figure 25: Degradation in the Slope vs. Average FA events for threshold being constant, varying and varying with random degrading Slope factor

From Figure 26 we observe that as the degradation factor α is increased a significant drop in the number of Miss Detection occurs for the constant threshold case, as shown previously. With a variable threshold there is a proportional drop in the number of Miss Detection events as the slope is degraded. This is a result of the proportional drop in mean of the regression line in Figure 13 and moving the threshold to maintain a 50% detection level. If the threshold is varying with random error associated with the assumed slope degradation factor it is observed that lower proportional Miss Detection events are recorded.
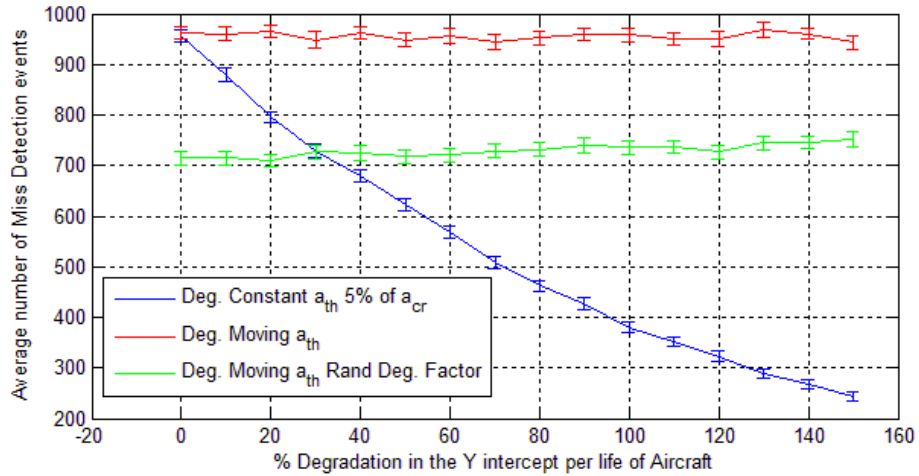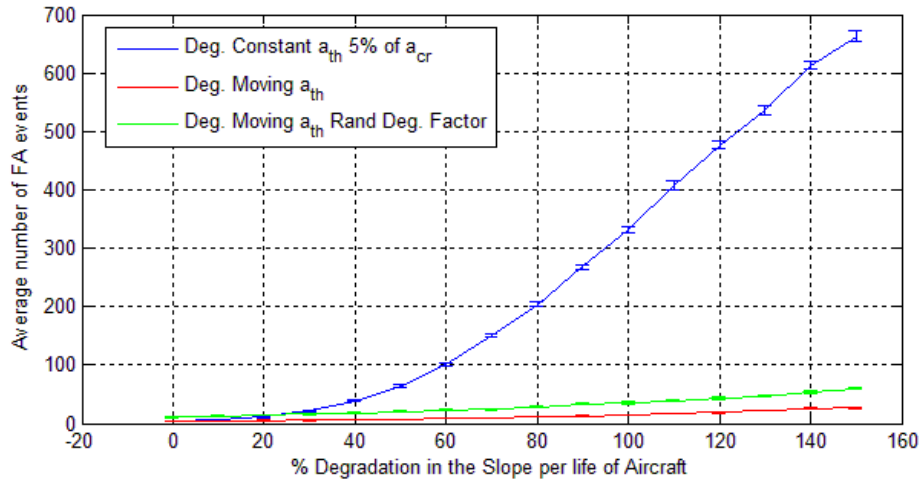
76
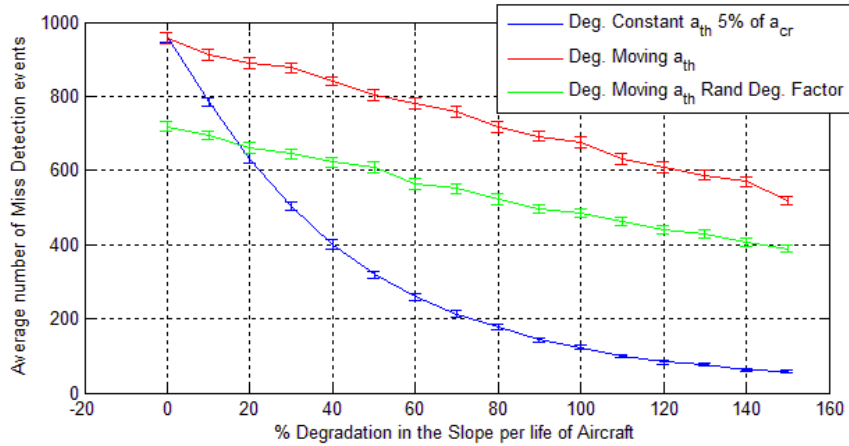
Figure 26: Degradation in the Slope vs. Average Miss Detection events for threshold

being constant, varying and varying with random degrading Slope factor

Figures 27 and 28 show the impact on SHM performance for the cases of known

and uncertain degradation in the standard deviation of the POD curve. In this case, no

movement in the threshold occurs because the mean of the associated distribution is

stationary. From Figure 27 we observe that the known degradation factor ψ results in a

significant increase in the number of FA events as shown before. If the standard

deviation is increased with a random degradation factor it is observed that a higher

number of FA events are recorded. The increasing spread of the POD distribution for

cracks smaller than the a_{safe} will cause a greater proportion of that distribution to fall

below $\hat{a}_{th}$, resulting in more FA events. From Figure 28 we observe that as the

degradation factor ψ increases, a significant drop in the number of Miss Detection

events is recorded. To understand this trend, one needs to consider the distribution for

POD($a_{safe}<a<a_{th}$). For a piezo-like sensor this distribution is centered on an $\hat{a} > \hat{a}_{th}$,

but the spreading of this distribution will cause a greater proportion to fall below $\hat{a}_{th}$.
This represents correctly detected cracks; an increase in the proportion of correctly detected cracks (for a given crack size) can only occur if there is a complementary reduction in Missed Detections. If the standard deviation is increased with a random degradation factor it is observed that lower Miss Detection events are recorded. This is due to the uncertainty in the standard deviation degradation factor. As in the prior degradation cases, one notes that uncertainty in the standard deviation degradation parameter adversely affects the FA rate, but has a positive effect on Missed Detections (lower numbers).
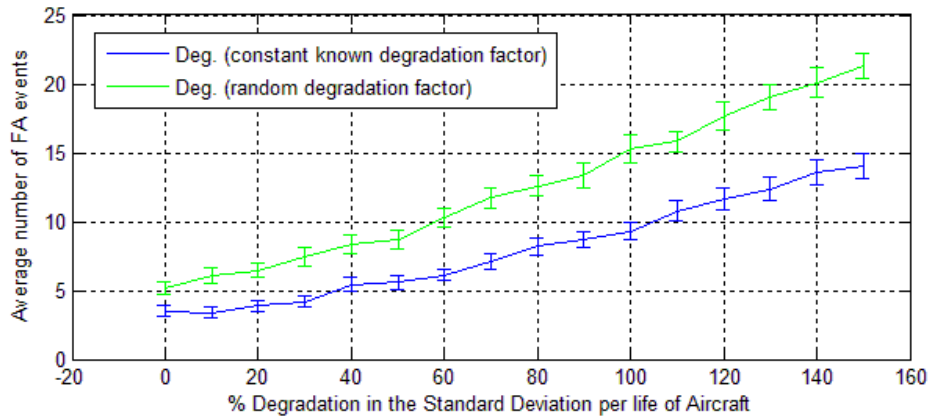
Figure 27: Degradation in the Standard Deviation vs. Average FA events for threshold being constant and varying
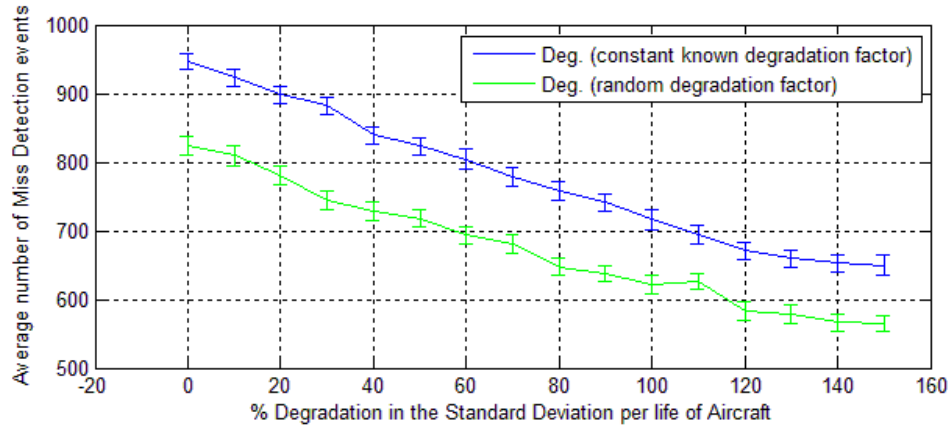
Figure 28: Degradation in the Standard Deviation vs. Average Miss Detection events for threshold being constant and varying

Conclusions and recommendations

Although installing an SHM system with a certain expected performance might produce expected cost savings, better operational readiness and improved safety, the SHM system degradation will be a concern. Any system installed on an aircraft is likely to degrade with operation. Systems installed on aircraft typically require maintenance and inspection schedules to ensure continued acceptable operation. The same is true for the SHM system. This work studied the affect of degradation on SHM performance parameters on the FA and Miss Detection events an aircraft might experience The tradespace analysis approach described herein shows how SHM sensor degradation factors α and γ can affect the number of FA and Missed Detections events that could occur over the expected life of an aircraft. With increased degradation while keeping a constant threshold a high number of false alarms will result, with a subsequent increase

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in maintenance events and cost. On the other hand if the threshold is varied to overcome the degradation effect, lower FA events will occur with an increase in Miss Detection events. Further, varying the threshold with a random degradation factor lowers false alarms but less effective that the previous case. Also, the standard deviation degradation factor ψ can affect the number of FA and Missed Detections events that could occur over the expected life of an aircraft. With increased degradation while keeping a constant threshold a high number of false alarms will result, with a subsequent increase in maintenance events and cost. Further, varying the threshold with a random degradation factor increases false alarms but reduces Miss Detection events. With safety of flight as a primary consideration, the SHM system sensor parameters a_{safe}, $\hat{a}_{th}$ and degradation parameters α, γ and ψ can be adjusted to reduce the probability of mishap events to an acceptably low level while also keeping FA rates, and related maintenance costs, at an acceptable level while mitigating the degradation effects.

V. Conclusions and Recommendations

Conclusions of Research

There are a number of important conclusions that arose as a result of this research topic. The key conclusions can be summarized as follows:

- Setting the SHM system design parameters very conservatively (closer to safe crack levels) increases detection but causes a high number of FA events;

- Setting the SHM system threshold higher to tolerate a greater crack length reduces FA events but increases the number of Miss Detection events;

- As cracks propagate to a greater length it was observed that Miss Detection events can lead to catastrophic failures;

- Degradation in SHM PZT-Like sensors (POD mean) while keeping a constant threshold will result in a high number of false alarms, with a subsequent increase in maintenance events and cost;

- If the threshold is varied to overcome degradation effects, lower numbers of FA events will occur with a concurrent increase in Miss Detection events;

- Varying the threshold in the presence of random degradation factor lowers false alarms as compared to the constant threshold case, but less effectively than would be achieved with perfect knowledge of the degradation factors;

- The standard deviation degradation factor can affect the number of FA and Missed Detections events that could occur over the expected life of an aircraft. With increased degradation a high number of false alarms will result, with a subsequent increase in maintenance events and cost;

- Varying the threshold in the presence of a random degradation factor associated with the standard deviation causes a greater increase in false alarms but a reduction in Miss Detection events is observed.

Significance of research

This research provided a life cycle analysis for a legacy aircraft equipped with SHM system with expected events (FA, Miss Detections) that could impact the life cycle and cost-benefit analysis. This was accomplished by combining the method used in MIL-HDBK-1823 and Paris's model and integrating it into a life cycle model reflecting changing crack size, with detection and sensor degradation in every flight sortie until the end of the life of the aircraft. This enables users to estimate the frequency of event occurrences and the costs associated with these events, thus contributing to a more accurate life cycle cost (LCC) basis for an aircraft equipped with an SHM system.

This research developed a decision support model to explore the tradespace associated with implementation of an SHM system on aging aircraft. This model was able to capture representative crack propagation with respect to accumulated flight hours, and it captured representative performance of SHM sensors as influenced by SHM detection thresholds and acceptable crack lengths. The model provided the capability for system sensor parameters to be adjusted to reduce the probability of mishap events to an

acceptably low level while also keeping FA rates, and related maintenance costs, at an acceptable level. This is significant for system design requirement. The model provided the capability to capture representative changes in detection of SHM sensors due to degradation as a result of accumulated flight hours. Representative maintenance events (both scheduled and unscheduled) and aircraft unavailability encountered due to structural or sensor maintenance (or replacement of the SHM system) can also be captured from the model. This will provide a better basis for a LCC estimate as sensor degradation and SHM system unscheduled maintenance is taken into consideration.

The model also investigated the utility and effect of employing a variable threshold for countering the effect of degrading SHM sensors. This resulted in better SHM performance when compared to the static threshold case (significantly lower numbers of FA events), while maintaining levels of Miss Detection within acceptable limits.

Recommendations for Future Research

With respect for future tasks, there are a number of tasks that could be investigated. For this research, a single critical crack location is modeled, but the methods described herein are extensible to multiple crack locations, and future work is recommended to extend the model to accommodate them. Further, this method investigated damage in metallic structures, and has not been adapted for damage detection in composite panels where the extent of the damage is an area (compared to crack length). In order to adapt the model for modeling damage detection in composite structures, an analytic model for sensors capable of detecting composite damage will be

required. As long as experimental data can show and reflect a relationship between existing damage characteristics/severity and signal response the SHM system model could be extended to include this type of damage detection. It is recommended that future work extend the model to investigate damage in composite structures.

While cost drivers such as maintenance and/or repair events were captured in the current model, a true LCC analysis was not performed. Representative cost/event data could be used with the post processed data from the existing model to perform a cost-benefit analysis associated with monitoring aircraft structural hot spots.

Finally, a longer term goal should be to consider structural health monitoring within the larger scope of integrated system health monitoring and condition based maintenance. This will significantly increase the scope of the model, but many of the lower level sub-models associated with specific monitoring types/locations and/or the maintenance and supply chain are maturing and may be available for integration into the larger model.

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Vita

Maj. Salman Albinali served as the Engine Flight Commander for the Royal Bahraini Air Force (RBAF) Fighter Wing form April 1998 to September 2003. He specialized in J85 and F110 fighter engine maintenance. From March 2005 up to being selected for the PhD Program at AFIT MAJ Albinali was the Acting Back Shops Squadron Commander for the RBAF fighter wing, responsible for the F-5 and F-16 fighter jet maintenance.

Appendix

Model Inputs and Outputs

      Table 1 Lists model inputs and Table 2 List Model outputs. Some outputs like the average unscheduled maintenance events can be used in the future once a cost and time required by these events is available. This will allow the model to have a better LCC estimates.

Table 1. SHM Model Inputs

Description	Value
a_{cr} = critical crack length at which failure occurs	4.744 mm
a_0 = initial flaw size (crack length)	0.1778 mm
β_1 = regression line slope	1.4195
β_0 = regression line intercept	7.5271
C = material constant	1.5e-10
K_{IC} = fracture toughness	53 $Pa\sqrt{m}$
m = material constant	4.6
N = number of load cycles	200,000
σ = standard deviation associated with probability of $\hat{a}$ given a	0.38221
Aircraft scheduled Maintenance	1000 Hrs
Aircraft total life	8000 Hrs

SHM system scheduled Maintenance	2000Hrs
Total Flight sorties	2000
Single sortie	4 Hrs

Table 2. SHM Model Outputs

Description
a = crack length at each sortie
Average number of catastrophic failures leading to loss of aircraft
Average number of True Detection events
Average number of False Alarm events
Average number of Miss detection events
Average number of True Negative events
Average crack length detected after a Miss Detection event
Average number of aircraft unscheduled repairs
Average number of aircraft unscheduled inspections
Average number of SHM system unscheduled repairs/sensor replacement

The following is a conference paper titled (Integrated Health Monitoring for

Aircraft-A Literature Review and Gap Analysis) presented to the Conference on Systems

Engineering Research (CSER) 2011. It covers a detailed literature search of the

Integrated Health Monitoring research area.

Integrated Health Monitoring For Aircraft – A Literature Review and Gap Analysis

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Abstract

This paper is a literature review and gap analysis for Integrated Health Monitoring (IHM) systems focused on aircraft application. Some of the main challenges slowing the implementation of an IHM system are technology performance, implementation issues and a solid business case. False alarms that could be produced from this system can cause more maintenance than needed, and the large amount of data produced from monitoring needs improved statistical tools to clearly identify defects without false alarms. Durability and robustness are additional technology performance issues for an IHM system. Design of an IHM system should be part of a systems engineering framework that integrates health monitoring and maintenance with all other requirements for the system. In the near future an IHM system could be implemented on aging aircraft to monitor known failure modes. Longer term, the use of an IHM system on new aircraft could result in monitoring the full system in real time. Application of IHM to new military jets has started to appear, but implementation in aging aircraft is lagging far behind. The presentation of a solid business case for the IHM system is a great challenge and arguably is the main factor contributing to the slow implementation of this technology.

Introduction

IHM for aircraft is a research area that could lead to a major change in the way we manage the health of our fleet in the future. Relatively few IHM systems are in operation on aircraft today. A review and a gap analysis of some of the relevant IHM literature lead us to identify the current challenges facing the implementation of an IHM system. Some of the main IHM system's challenges are the technology performance, implementation

issues and a solid business case. The presentation of a solid business case for such a system is considered very important as this challenge has a great impact on the decision to implement an IHM on an operational aircraft.

A perspective of the structural mechanics program of the Air Force Office of Scientific Research on structural health monitoring (SHM) and non-destructive evaluation (NDE) was presented by (Giurgiutiu, 2008). NDE and SHM have an essential role in the operational readiness and safety of the Air Force fleet. Considerable challenges face the operators and the maintainers due to aging aircrafts. NDE techniques have proven to be reliable in detecting damage during phase inspections due to their maturity. SHM has great potential due to its on board sensors and systems that provide structural health assessment on demand. In particular, the study indicated a desire to use SHM to provide remaining life prognosis and quantifying structural variability. This study concludes that considerable applied and fundamental research is needed to develop, integrate and implement SHM technology.

Technology Performance

Much research in the field of IHM for aircraft has been motivated by the promise of increased performance, reduction of life cycle cost and increased availability. Yet we still have gaps that slow the implementation of IHM systems. Many believe that the current maturity level for IHM technology falls short of what is required for fielded implementation. In a research on SHM by (Derriso et al., 2007) technical feasibility is described as facing three fundamental challenges: small-scale damage must be detected

in relatively large-scale structures, SHM systems must work in an unsupervised learning

mode, and the SHM system must be robust and reliable.

Reliability

      False alarms from an IHM system can cause more maintenance action than

needed. A simulation model of a prognostics and health management (PHM) system used

as an Autonomic Logistics System (ALS) for the Joint Strike Fighter (JSF) was

developed and used by (Miller et al., 2007). Their simulation utilized a large number of

commonly used flight line measures of performance for aircraft availability and mission

effectiveness. Multivariate statistical analysis of these measures provided ways to analyze

the positive impact of a PHM on aircraft sortie generation. On the other hand their

analysis showed a great sensitivity to false alarms. This sensitivity implies that more

research effort should be devoted to investigating and trying to minimize false alarms

without significantly degrading detection performance.

      An experiment was conducted on a fast military jet by (Read et al., 2008) to try to

test SHM in a near real-world application. A BAE Hawk jet carrying an experimental test

pod with specimens containing crack initiators was used to test flight the effect of

maneuvers on the SHM system detection capability and the possibility of detecting crack

growth during flight. The conclusion was that this system was effective in detecting a

crack and the growth of the crack during flight. They noted a very large number of

spurious noise events/signals, but were able to avoid an associated large amount of false

positive indications through the use of guard sensors surrounding the area of interest.

Test points were obtained that spanned the entire flight envelope, to include 6g turns,

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acoustic noise levels in excess of 135 decibels, and considerable electromagnetic interference. While providing significant flight test results, a shortcoming is the fact that the test specimen was not part of the actual aircraft structure.

Given the large amount of data produced from IHM, improved statistical tools to clearly identify defects are necessary. A synopsis review conducted by (Sohn and Los Alamos National Laboratory, 2004) identified a shortage of well developed tools and algorithms for statistical pattern recognition in IHM. Many damage detection methods try to identify damage by solving an inverse problem (predicting a condition based on a measured response), which requires the construction of analytical models. These models have uncertainty and need to be validated by experimental results, making this approach less attractive for some applications. Neural network approaches can be used to map the inverse relationship between the parameter of interest and the measured response. The main drawback for this approach is that a large amount of data is needed for the damaged and undamaged component and this is not always available. Statistical process control and hypothesis testing methods can be employed without the same level of effort developing analytical models, but these approaches tend to be limited to damage onset detection without knowledge of the failure condition triggering the onset.

Durability and Robustness

Many studies show degradation of IHM sensors over time due to static loads, cyclic loads, temperature and corrosion. Durability and robustness of a candidate IHM system must be characterized prior to any implementation decision. An investigation into the effect of cyclic loads on sensor performance was conducted by (Kuhn, 2009). In this

research sensor degradation associated with cyclic strain was identified. Experimental data was used to construct an analytic model of the sensor degradation. A probability of detection (POD) degradation model was also developed to show the effect of the degradation on the overall performance of an SHM system. In their experiment (Beard et al., 2005) found that environmental conditions such as temperature can affect the signal obtained from sensors. This research used calibration to compensate for temperature variation based on the structure and application. More research is needed to characterize fully the degradation due to environmental factors such as vibration, temperature and corrosion.

Implementation Issues

Design of an IHM system should be part of a system engineering framework that integrates health monitoring and maintenance with all other requirements for the aircraft. For a new aircraft design, this would begin with the conceptual design of the system and would affect decisions regarding operating conditions, levels of maintenance and inspection intervals, among others. Less extensive implementations are being proposed for aging aircraft. A framework for SHM system design was presented by (Malkin et al., 2007) which could be applied to aging aircraft through hot spot monitoring. The initial step in their framework, understanding the structure, involves characterization of the materials, loads, stresses and strains, environment and interfaces. The data needed to support an implementation decision for an SHM system can be obtained by focusing on the following points: benefits and drawbacks of the SHM system, requirements for the SHM system, available SHM technologies, detail design of the SHM systems, identifying

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the SHM design that meet the requirements and the cost of the SHM system that meet the requirements. Although this framework was developed for hot spot monitoring it could be modified for other applications as mentioned by the study.

A research by (Millar, 2007) identifies barriers that have slowed acceptance and use of prognostics health management tools in military propulsion systems over the past two decades. In particular, they note incomplete total life cycle systems engineering management (TLCSM) as a barrier to implementation. The US Department of Defence Acuisition Guidebook states in Section 4.1.3 TLCSM in Systems Engineering: "It is fundamental to systems engineering to take a total life cycle, total systems approach to system planning, development, and implementation." It is also important to implement TLCSM not only on new systems but also on legacy systems currently operating to control the high maintenance cost as the systems continue to operate beyond their design life. This research describes up and down periods of development associated with engine condition monitoring. The up periods are triggered by the cost benefits that could be gained by successful monitoring, and the down periods occur when technology is not available for the monitoring system. This study concludes that the use of TLCSM through the systems engineering process is the right tool to close the gaps that are holding up large scale applications and implementation of IHM.

Advanced Integrated Vehicle Health Monitoring systems (IVHM) are expected to formulate a response based on the extent of the damage. This is contrasted with pure monitoring systems that only report damage (Price et al., 2003). This study sub-divided the problem as follows:

- Detection of damage. Requires knowledge of the environment and anticipated damage modes;

- Development of sensors will depend on the time required for the system to respond;

- Characterization of damage. This may be accomplished during detection of damage or may require additional and/or different sensors;

- Prioritization of the seriousness of damage. Damage that can compromise the mission of the vehicle will obviously be given greater urgency;

- Identification of the cause of the damage. This may require an intelligent system populated by large numbers of sensors providing information on the vehicle as a whole;

- Formulation of a response. This could be an individual or sequence of actions, to include panic responses where appropriate;

- Execution of a response. This could involve reconfiguration of the vehicle or restriction of operating conditions.

The integration process associated with both aging and new aircraft is considered a major weakness in the implementation of IHM. In the near future an IHM system could be integrated on aging aircraft to monitor known failure modes. Aging aircraft face a challenge on how to integrate an IHM system with conditional based maintenance (CBM) because design choices will be limited by the existing system architecture. A number of integration issues were researched by (Buderath, 2004) and concluded the following. There should be a clear process for integration to ensure the right selection of an IHM

system, data analysis, and sensor location. Integration should be addressed to reach acceptance on all system levels. An integrated process is needed during the development phase of an IHM system to be able to fully integrate with CBM to meet safety concerns and reduce the costs associated with maintenance and repair actions.

Business Case

The presentation of a solid business case for the IHM system is a great challenge and arguably is the main factor contributing to the slow implementation of this technology. Factors that could help create a business case are the understanding of the customer needs and requirements and performing a credible cost and risk analysis (Perez et al., 2010).

Quantifying cost reduction in the total life cycle of a system through use of IHM needs to be presented. Few research attempts to quantify the cost benefit of IHM are found in literature, and wide discrepancies can be noted in the cost savings estimates. In one study it is estimated that implementation of SHM on a commercial transport aircraft could result in a 30% to 40% reduction in maintenance requirements. This would result in a recovery of the initial implementation costs in only two to three years (Kent et al., 2000). Another research study (Schmidt et al., 2004) showed only a one percent reduction of the maintenance costs by using SHM systems on an AIRBUS aircraft; however, the authors noted the omission of consideration for increased availability due to reduced inspection times. Another finding of this study was a reduced fuselage panel weight by up to 15 percent using SHM. This impacts cost in many ways such as lower fuel consumption and longer operation range. Research on aging military aircraft showed

cost benefits of using an SHM on some hot spots of the structure of a tornado fighter, but suggests the implementation should be limited to hot spots where real payoff can be identified (Boller, 2001).

A unique cost-benefit analysis for the allocation and cost justification of an Integrated System Health Management (ISHM) at the conceptual design level was presented by (Hoyle et al., Mehr, 2007). An optimization framework was used to determine the optimal allocation of ISHM to maximize profit. This was calculated using a profit function formulated using single attribute objectives as the product of system availability and revenue per unit availability minus the summation of costs associated with detection and risk. This framework also addressed the optimal detection/false alarm threshold and inspection interval, assuming the availability of parameters characterizing the sensor in terms of detection, false alarm rate and failure rate. When this framework was applied to an aerospace system it was shown that applying ISHM increased profit by 11%, reduced cost by a factor of 2.4 and increased the inspection intervals by a factor of 1.5. A useful extension of this work would involve modification and application for systems not driven by revenue generation, such as military aircraft, which can still benefit by reduction in the total life cycle cost (LCC).

The number of sensors needs to be optimized to provide desired effectiveness within cost and weight constraints. A balance between detection sensitivity, false alarms and the number of sensors needs to be achieved. Many models are developed in the general area of structural monitoring. For example a Reliability-Based System Assessment was used by (Hosser et al., 2004) for monitoring buildings structures with sensors. This computer code consists of a data base module, a computational module and

a statistical module for the optimization of the assessment cycle. Another promising area for optimization is the use of genetic algorithms, which can be used for discrete value and/or non-convex solution spaces to determine the optimal number and location of sensors for damage locations (Boller, 2000).

Another approach to quantify cost benefit was used by (Kapoor et al., 2008) using optimization and simulation of a maintenance phase with SHM technology applied to commercial aircraft. The effect of using SHM technologies to reduce maintenance downtime was presented. The concept of this approach was to identify the critical paths along the maintenance process. After a critical maintenance path was identified it was modified with an SHM alternative approach. After optimization and simulation a reduction factor of 6 for a critical path task was achieved, resulting in an increase of 100 hrs of aircraft availability over the life cycle. This study indicates that cost benefit analysis for SHM should involve consideration of defined maintenance phases scheduling.

Standardization of IHM systems across different platforms should help in reducing the ownership cost as well. In the automobile industry IHM has seen wider application than in the aircraft industry, as evidenced by systems like General Motor's On-Star (You et al., 2005). These authors investigated remote diagnostics and maintenance systems and identified the cost reduction associated with standardization across different automobile models.

Conclusion

IHM systems face many obstacles and gaps that have resulted in the slow implementation in real-world applications. These obstacles include technology performance, implementation issues and a solid business case that justifies the investment in an IHM system.

A major technology performance issue is the reliability of an IHM system. False alarms that could be produced from this system can cause more maintenance than needed. More research should be devoted to investigating and trying to minimize false alarms without significantly degrading detection performance. The large amount of data produced from monitoring needs improved statistical tools to clearly identify defects. Current tools such as Numerical Modeling, Neural Networks and Analysis Hypotheses are available but have their disadvantages. Durability and robustness are additional technology performance issues for an IHM system. Many studies show degradation of IHM sensors over time due to static loads, cyclic loads, temperature and corrosion.

Design of an IHM system should utilize a Systems Engineering framework that integrates health monitoring and maintenance with all other requirements for the system. For a new aircraft design, this would begin with the conceptual design of the system and would affect decisions regarding levels of maintenance and inspection intervals, among others. Less extensive implementations are likely appropriate for aging aircraft. In the near future an IHM system could be implemented on aging aircraft to monitor known failure modes. Aging aircraft face a challenge on how to implement an IHM system for conditional based maintenance (CBM) because design choices will be limited by the existing system architecture. More research must be done before full integration of an

IHM system into CBM can be achieved. Longer term, the use of an IHM system on new aircraft could result in monitoring the full system in real time.

The presentation of a solid business case for the IHM system is a great challenge and arguably is the main factor contributing to the slow implementation of this technology. Approaches and models to quantify the reduction in life cycle cost by using these systems is an important field of study. The number of sensors needs to be optimized to provide desired effectiveness within cost and weight constraints. Further, the health monitoring throughout the aircraft must be extensive enough to result in a lengthening of scheduled inspection intervals if it is to provide maintenance cost savings. Standardization of IHM systems across different platforms should help in reducing the ownership cost as well. The literature indicates that adoption of IHM in the commercial world is further along than in the military due to more aggressive cost saving measures. Application of IHM to new military jets has started to appear, but implementation in aging aircraft is lagging far behind. A solid business case for the aging military aircraft remains as an open area of investigation.

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14. ABSTRACT

The presentation of a solid business case for the SHM system is a great challenge and arguably is the main factor contributing to the slow implementation of this technology. The research intent is to focus on the business case by providing a tool to aid decision makers. An analytical model was developed to address the business case and the integration of SHM system into Conditional Based Maintenance (CBM). The model captures the events and effect on aircraft availability due to different SHM detection threshold settings and replacement of degraded sensors. The model captures false alarm rates, crack growth, probability of detection, and sensor degradation amongst other parameters. The model is a useful tool that provides the decision makers the confidence to either implement SHM system on an aging military aircraft or not. Three major subcomponents of the SHM model will be the sensor detection model, the crack growth model and the sensor degradation model. Linking these three models where the main parameters of interest are not static and accounting for senor replacement will provide useful data of LC cost estimation that have not been accomplished before.

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