COST BENEFIT ANALYSIS TOOL INCORPORATING PROBABILISTIC RISK ASSESSMENT FOR STRUCTURAL HEALTH MONITORING

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Abstract. Prior work presented the development of a software platform for integrating NDI design and product life management tools to perform design tradeoffs in terms of cost and reliability. This work explores the development of probabilistic model components representing structural health monitoring systems, addressing the use of secondary NDE inspections and SHM system degradation. A discussion is presented concerning opportunities and pitfalls of SHM applications through both a qualitative survey and quantitative studies.

Keywords: cost benefit assessment, models, nondestructive evaluation, probabilistic risk assessment, structural health monitoring
PACS: 02.50.-r, 81.70.-q

INTRODUCTION

The application of in-situ sensors for structural health monitoring has been proposed with significant research and development programs ongoing [1-5]. The primary benefit of structural health monitoring (SHM) concerns integration with prognostics, where the management of high value assets such as military aircraft is improved through the quantitative prediction of future operating capability and accurate determination of remaining life. Potential cost benefits for SHM include (1) reductions in labor cost and time for unnecessary nondestructive evaluation (NDE) inspections, (2) management of locations of limited accessibility to minimize costly teardowns, and (3) availability of robust indications of impending failure of the structure to trigger safe retirement. Improvements in availability of aircraft can also be addressed using SHM by limiting time in maintenance to only when absolutely necessary. In addition, SHM, when considered during the aircraft design phase, has the potential to provide engineers with the means to reduce structure weight by avoiding conservative designs, reduce the need for costly assessments of fatigue critical locations [1], and improve aircraft dynamic performance. Additional benefits may also be realized through the use of in-situ sensor data to indirectly measure wing conditions of interest such as excessive loading or icing conditions, and to support accident investigation, potentially leading to a safer fleet over the long-term.

Limited studies have been presented to date concerning the cost justification for SHM applications [2-5]. The costs associated with structural health monitoring systems can be categorized as development costs, implementation costs, and in-service costs. Development costs include any initial research and system development work for a particular application. Implementation costs are associated with the fixed initial cost for purchasing and installing the on-board SHM system and for performing validation studies to satisfy reliability requirements. Both development and implementation costs are expected to be much higher for SHM system with respect to those of NDE techniques, given the increasingly difficult system requirements concerning inspection and reliability. Lastly, in-service costs can include the additional cost of fuel due to added SHM system weight, data interpretation labor costs, SHM maintenance costs, and the cost of secondary inspection and unnecessary repair due to false calls or unnecessary calls when flaws are very small. While in-service costs of SHM systems are expected to be low in relation to those of NDE procedures, design-time consideration must be given to the possibility for such costs to be significant in order to minimize their impact on total life cycle cost.

Many challenges exist for the practical application of in-situ sensors for SHM. First, there is the significant challenge to quantify the damage state of a structure, distinguishing mission critical defects such as fatigue cracks, excessive corrosion, or delaminations from coherent noise features present in distributed sensor signals. For example, regular depot maintenance actions such as grindout of corrosion, replacement of select panels, and application of patches, will alter the dynamic characteristics of a structure, and the corresponding changes in sensor signals must be differentiated from the detection and characterization of critical defects. Likewise, time-driven variations in the structural contact conditions at joints and fastener sites or changes in the sealant properties will also impact the global dynamics of a structure. Many in-situ SHM approaches are also sensitive to changes in the dynamic, thermal, and mass loading of the structures, which can be considerable during flight or at different bases around the world. In addition, observability and sensor placement are critical considerations when attempting to evaluate the damage state on both global and local levels. Another significant issue is the degradation of the in-situ health monitoring system, where a variety of sub-systems such as the sensors, the bonds between sensors and structures, the wiring harnesses, the measurement hardware, and the power (battery) system have the potential to decay over time. Lastly, to transition SHM systems from research to application, a key step is ensuring the reliability of the system through validation studies. To address the high cost of validating NDE procedures, model-assisted probability of detection (MAPOD) approaches have been proposed and demonstrated [6]. Such methods will become even more valuable to in-situ SHM approaches where it is highly expensive and time consuming to conduct experimental studies that address all significant variables under in-service conditions.

To properly address these issues, a methodology incorporating cost benefit analysis with probabilistic risk assessment is proposed for evaluating the overall value of SHM systems. These design tradeoffs must be examined from an economic service life management perspective where reliability, availability, and total cost of aircraft sustainment processes are quantified. This effort builds upon prior work concerning the development of a strategy and software framework for integrating NDI design and product life management tools [7]. This model is based on prior work by Berens et al., who developed a software tool, PROF, for probabilistic risk assessment of fatigue crack growth and fracture incorporating NDE [8]. This work presents the development of probabilistic model components that represent a wide range of SHM system configurations and address the use of secondary inspections and SHM system degradation. Lastly, case studies are utilized to provide key insight into the potential benefits and pitfalls of SHM applications.

TWO CLASSES OF STRUCTURAL HEALTH MONITORING SYSTEMS

Two classes of structural health monitoring systems are considered for representation in the software framework for integrated NDE design and product life management. The first approach is based on the acquisition of data for life prediction models. During in-service periods, distributed in-situ sensors can be used to measure the loading and environmental conditions experienced by the structure. Subsequently, these data can be used to improve fracture mechanics models to better predict the flaw state. This approach can be considered ‘indirect’, since the damage state in the future is estimated using a model prediction based on measurement input data. The most significant benefit of ‘indirect’ SHM schemes is a reduction in the uncertainty of the fracture mechanics models due to direct measurement of the loading and environmental conditions during in-service periods. As a preliminary approach to represent ‘indirect’ SHM systems within the analysis software, the capability to perform Monte Carlo simulations was provided to explore the sensitivity of performance measures such as cost and reliability with respect to SHM system parameter variability and uncertainty in the economic service life model.

The second approach is based on the acquisition of nondestructive evaluation data using in-situ sensors to quantify the damage state of a structure. This approach is classified as a ‘direct’ method, requiring that the damage state be observable in distributed sensor data. In the next section, the theory and software implementation of a probabilistic model for ‘direct’ SHM systems will be presented

PROBABILISTIC MODEL FOR STRUCTURAL HEALTH MONITORING

A strategy is presented for incorporating SHM systems into a design platform for integrating various nondestructive inspection (NDI) design and product life management tools and for enabling analysis and optimization of design tradeoffs in terms of reliability, cost, fleet availability, and mission capability. A key objective for this work is to develop the capability to evaluate SHM design parameters and cost benefits addressing a wide range of potential SHM implementations. The approach adapts object-oriented building blocks, originally developed to represent maintenance programs incorporating NDI, for the case of SHM systems [7].

Figure 1 represents a diagram of a generic SHM process. First, there are two time intervals to consider: one associated with each opportunity for decision on maintenance (*i*) to be performed in the field, and an in-service SHM data acquisition time interval (*j*) at which an assessment of the damage state can be performed. It is important to distinguish between these two time intervals, since data may be acquired and a damage state estimate may be performed at a rate different than the rate corresponding to the opportunity for decisions on performing in-field maintenance (in the form of secondary inspections and/or repairs.) For each data acquisition time interval (*j*), data can be acquired from each sensor

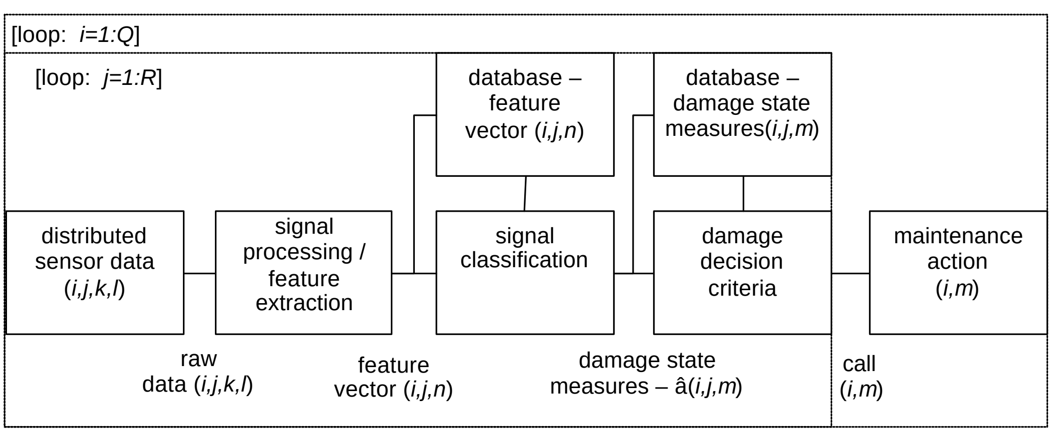

FIGURE 1. Flow diagram representing model of structural health monitoring system identifying the analysis steps from the sensor data to the decision on a mainenance action such as a secondary inspection or repair.

(k) in the array for a given number of samples (l). The number of samples (l) may be large for the case of acoustic emission measurements for impact damage or quite small for humidity sensors for corrosion monitoring. Starting with the raw data, signal processing and feature extraction algorithms are applied to filter and extract features as a set of scalar values (n). Signal classification can subsequently be applied to a database of feature vectors collected over time to estimate the damage state ($\hat{a}$) for each critical location (m). For each opportunity to assess the damage state and perform a maintenance action, a damage decision criterion is applied based on a maximum acceptable critical flaw size (a_{cr}). A database of damage state estimates ($\hat{a}$) for prior decision intervals and data acquisition periods (i,j) may be used in the decision process. The final step is the decision of whether or not to perform a maintenance action such as a secondary inspection or repair.

From the perspective of quantifying the reliability of a SHM system, there is an underlying relationship that must be evaluated between accuracy in the damage state estimate ($\hat{a}$) with respect to the actual damage state (a), with special interest placed on the critical flaw size (a_{cr}) that prompts a maintenance action. This probability of detection assessment is no different from the "$\hat{a}$ versus a" analysis procedure previously devised for NDE systems [9]. Although a model-based approach including each analysis step for the SHM process shown in Figure 1 would be ideal, it is proposed, as a first approximation, to represent the relationship between the flaw size and the probability of detection and false call rate directly using a four parameter probability of detection model:

$$POD(a) = \boldsymbol{a} + (\boldsymbol{b} - \boldsymbol{a})\left\{1 + \exp\left[\frac{p}{\sqrt{3}}\left(\frac{\ln a - m}{s}\right)\right]\right\}. \tag{1}$$

where $\boldsymbol{a}$ corresponds to the false call rate and $\boldsymbol{b}$ is defined as 1 minus a random miss rate. Use of a four parameter POD model has been explored to address the observation that both hits and misses are often made for reasons that are independent of crack length [10].

Figure 2 presents a flow diagram for a basic SHM system integrated with an in-service period, with the opportunity for in-field maintenance incorporating a secondary inspection and repair process (with j = 1). A probabilistic analysis methodology is utilized for evaluating the model component blocks 'Inspect 1 - SHM', 'Inspect 2 - NDE' and 'Repair' found in Figure 2. In this formulation, $F_p^{(1)}$ and $f_p^{(1)}$ are defined as the cumulative density function (cdf) and probability density function (pdf) respectively, representing the flaw size distribution for feature type 1 (given by the superscript) at stage p (given by the subscript) in the inspect-repair sub-process. The subscripts A, B, and C are associated with flaw size distributions for the start of the SHM process, the portion associated with no call made (flaws not found), and the portion associated with a call made (flaws detected). $P_{SHM}^{(1)}$ is defined as the percentage of the pdf called (flaws detected) by the SHM process, and is given by

$$P_{SHM}^{(1)} = \int_0^\infty POD_{SHM}(a) f_A^{(1)}(a)\,da\,, \tag{2}$$

where a is associated with flaw size and $POD_{SHM}(a)$ is the probability of detection function for the SHM process. The corresponding 'no call' and 'called' distributions resulting from SHM are respectively given by

$$f_B^{(1)}(a) = (1 - POD_{SHM}(a)) * f_A^{(1)}(a)\,, \tag{3}$$

$$f_C^{(1)}(a) = POD_{SHM}(a) * f_A^{(1)}(a)\,. \tag{4}$$

A secondary inspection given in block 'Inspect 2 - NDE' can also be evaluated in a similar fashion, where $P_{NDE}{}^{(1)}$ is defined as the percentage of the pdf called (flaws detected) by the NDE procedure, and is given by

$$P_{NDE}{}^{(1)} = \int_0^\infty POD_{NDE}(a) f_C^{(1)}(a)da = \int_0^\infty POD_{NDE}(a) POD_{SHM}(a) * f_A^{(1)}(a)da\,. \tag{5}$$

The corresponding 'no call' and 'called' distributions resulting from the secondary NDE procedure are respectively given by

$$f_D^{(1)}(a) = (1 - POD_{NDE}(a)) * f_C^{(1)}(a) = (1 - POD_{NDE}(a)) POD_{SHM}(a) * f_A^{(1)}(a)\,, \tag{6}$$

$$f_E^{(1)}(a) = POD_{NDE}(a) * f_C^{(1)}(a) = POD_{NDE}(a) POD_{SHM}(a) * f_A^{(1)}(a)\,. \tag{7}$$

For this example, the resulting repair distribution represents a return to the original state of the part for those flaws called both by the SHM process and the NDE technique, and can be expressed as

$$f_R^{(1)}(a) = P_{NDE}{}^{(1)} \cdot f_{R\_EIFS}^{(1)}(a)\,, \tag{8}$$

where $f_{R\_EIFS}(a)$ represents the equivalent initial flaw size pdf for the original part. This process is repeated for N iterations corresponding to each SHM manager decision and maintenance opportunity (i). Following this process, depot maintenance or end of life may be reached depending on the design life of the aircraft.

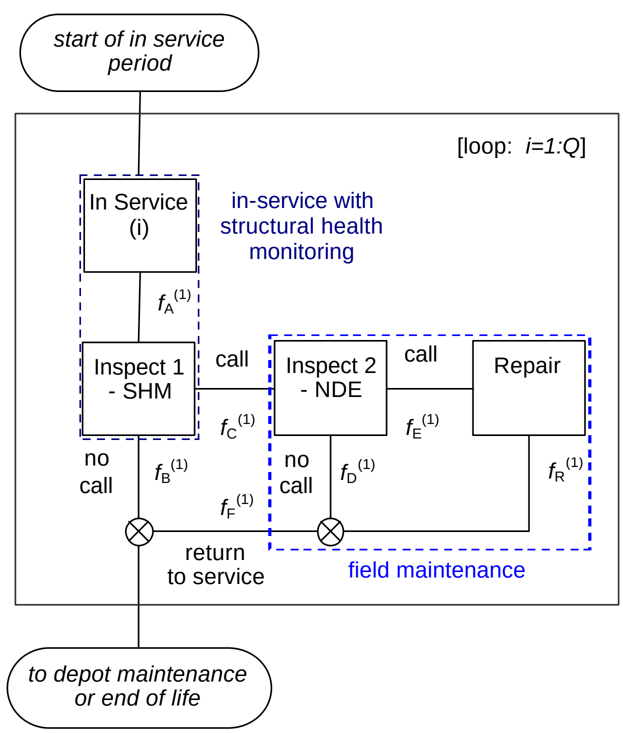

FIGURE 2. Flow diagram representing model of in-service period with structural health monitoring and optional in-field maintenance.

Another important issue concerns the degradation of the SHM system over time. This can be modeled by defining the probability of detection function in terms of parameters that vary with time, as

$$POD(a,t) = a(t) + \left(b(t) - a(t)\right)\left\{1 + \exp\left[\frac{p}{\sqrt{3}}\left(\frac{\ln a - m(t)}{s(t)}\right)\right]\right\}. \tag{9}$$

Figure 3 presents a plot of a POD function that varies with time, representing potential degradation of the SHM process through changes in the 50% detectable flaw size and the random missed flaw rate.

CASE STUDIES

Several case studies are presented to both demonstrate the capability of the software platform and gain a better understanding of the dynamics of the SHM system model. The first study explores the effect of varying the frequency of SHM calls for a fixed total service life. This hypothetical study only includes variable costs associated with structural health monitoring calls and repairs. Figure 4 shows the simulated results for probability of failure and cumulative maintenance cost as a function of time and number of SHM cycles. For this study, a higher frequency of SHM calls will result in higher life-cycle cost. The source of this higher cost is twofold. First, the total cost associated with labor hours for data interpretation is increased with the frequency of SHM calls. In theory, this cost could be quite small if robust automated algorithms for data interpretation are used. In practice, given the high cost for repairs and potential for false calls due to unknown conditions not considered in the original design, secondary assessments of the SHM data by an expert inspector are often necessary. The second source for higher costs occurs over the later part of the in-service period, where non-critical flaws are called by the SHM system. Ideally, minimizing the frequency of calls while maintaining an acceptable level of reliability in terms of probability of failure is a fundamental design principle for minimizing life-cycle costs. Alternatively, higher frequency rates of SHM calls can significantly improve reliability. This strategy is particularly valuable when the SHM system is designed to only detect very large flaws, the crack growth model is nonlinear, or uncertainty is present in the crack growth model parameters.

A second case study explores variations in the detectable flaw size for both an SHM system (Inspection 1 – SHM) and a secondary NDE inspection technique (Inspect 2 – NDE). Specifically, the 50% detectable flaw size parameters for the SHM and NDE inspection models were both varied from 0.02" to 0.10" as a full-factorial study. Figure 5 presents the design solution space resulting from the study in terms of maximum probability of failure and total cost. This design solution space plot provides the means to

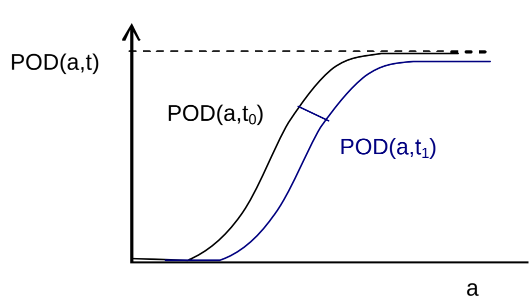

FIGURE 3. Probability of detection (POD) function with variability in model parameters over time.

select the Pareto solutions providing the optimal tradeoff between the two objectives. Furthermore, it is possible to select from this reduced solution set a design that minimizes cost while maintaining an acceptable probabilty of failure, typically set at 10^{-6}. Using these criteria, the optimal SHM system 50% detectable flaw size was found to be 0.06", with the secondary NDE system 50% detectable flaw size set to any value greater than 0.05".

A third case study explores the sensitivity of cost and reliability measures to SHM system false call rate. Due to space limitations, only a discussion of the trends in the results is presented. As previously mentioned, the issue of false calls can hinder the application of SHM systems. Given the challenging problem of reliably detecting cracks using distributed sensors, false calls rates are expected to be comparable or higher with respect to NDE cases, typically on the order of 1%. However, although a 1% false call rate may be acceptable for less frequent NDE inspections, when SHM calls are made at a more frequent rate, a greater number of locations will be falsely called over the life of the aircraft and thus prompt some form of secondary maintenance action. This is especially problematic given that the model predicts that most calls that are initially made are most likely false calls, thus having a negative impact on the product life management program and its sponsors. Secondary inspections were found to be quite beneficial in mitigating cost by limiting unnecessary repairs due to false calls. However, if the cost of secondary inspections is not small, the total cost may be excessive and thus hinder practical use.

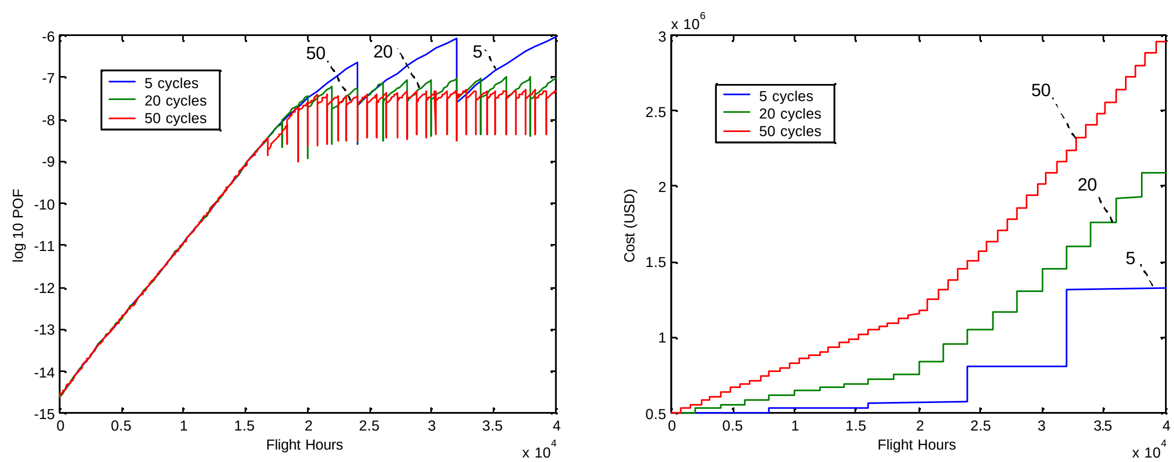

FIGURE 4. Plots of (a) probability of failure and (b) cumulative maintenance cost as a function of time and SHM cycle number.

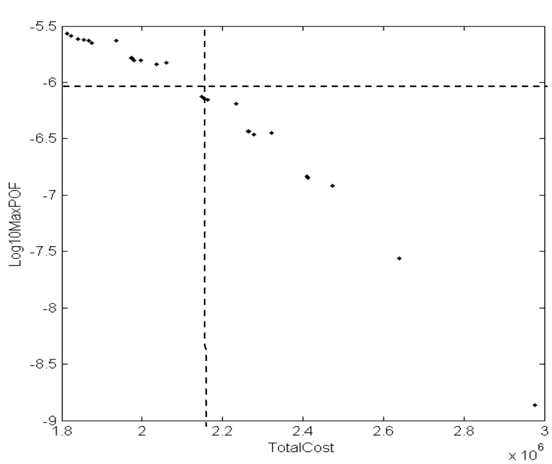

FIGURE 5. Design solution space for varying SHM and secondary NDE sensitivity in terms of maximum probability of failure and total cost.

CONCLUSIONS AND RECOMMENDATIONS

An overview of the potential benefits, costs, and challenges of structural health monitoring was presented. To achieve a quantitative evaluation of SHM applications, probabilistic models were developed and integrated into a software platform including virtual NDE design and product life management assessment. Through simulated studies, insight was presented concerning possible opportunities and pitfalls of SHM applications. To best address the management of the vast array of critical structural locations over the service life of an aircraft fleet, a 'hybrid approach' to fleet management is proposed considering a case-by-case evaluation of the most appropriate maintenance approach: 1) fail-safe design (no inspection), 2) scheduled nondestructive inspection, 3) loading condition monitoring, 4) damage state monitoring, 5) load condition monitoring with condition-based maintenance, 6) damage state monitoring with secondary nondestructive inspection. Future work will explore the sensitivity of model trends to cost parameter levels, the impact of degradation of the SHM system over time, and the effect of variation of the SHM and NDE design parameters such as false call rate and random missed call rate. Lastly, analysis including real cost numbers for promising applications is of high interest.

ACKNOWLEDGEMENTS

This work is supported by the U.S. Air Force Research Laboratory, Nondestructive Evaluation Branch, through a small business innovation research program (F33615-03-C-5226).

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