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PROBABILISTIC RISK ASSESSMENT: IMPACT OF HUMAN FACTORS ON NONDESTRUCTIVE EVALUATION AND SENSOR DEGRADATION ON STRUCTURAL HEALTH MONITORING (PREPRINT)

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14. ABSTRACT

Managing human factors in nondestructive evaluation is critical to maintain inspection reliability. Reliability of structural health monitoring systems is particularly sensitive to sensor degradation over time. To investigate the impact of these issues, probabilistic models for risk assessment and cost-benefits analysis have been developed. Quantitative studies are presented evaluating the effects of variations in probability of detection associated with human factors, plus in-situ sensor degradation on life cycle measures such as cost and probability of failure.

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PROBABILISTIC RISK ASSESSMENT: IMPACT OF HUMAN FACTORS ON NONDESTRUCTIVE EVALUATION AND SENSOR DEGRADATION ON STRUCTURAL HEALTH MONITORING

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Abstract. Managing human factors in nondestructive evaluation is critical to maintain inspection reliability. Reliability of structural health monitoring systems is particularly sensitive to sensor degradation over time. To investigate the impact of these issues, probabilistic models for risk assessment and cost-benefits analysis have been developed. Quantitative studies are presented evaluating the effects of variations in probability of detection associated with human factors, plus in-situ sensor degradation on life cycle measures such as cost and probability of failure.

Keywords: cost benefit assessment, models, nondestructive evaluation, probabilistic risk assessment, structural health monitoring
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INTRODUCTION

The reliability of nondestructive evaluation techniques is critical for aircraft maintenance programs. Issues in nondestructive inspection discovered through probability of detection studies has generated an interest in determining the impact of inspection performance on total service life [1]. For inspection problems that include manual scanning, complex procedures, and low frequencies of finding critical flaws, there is a potential for some critical sites to not be inspected effectively due to the requirements of the inspection process, or there are inconsistent requirements for calling marginal defects [2]. Options to address NDE reliability associated with human factors include improved NDE design of equipment and procedures, consistent evaluation of NDE reliability through POD studies, and improved NDE process controls using quality calibration standards, increased inspector training and evaluation, and improved management oversight. The application of structural health monitoring (SHM) system with in-situ sensors also has the potential to improve inspection reliability by eliminating problematic human factors. To properly assess the best approach to maintain acceptable inspection reliability and minimize total life cost, methods to evaluate NDE and SHM systems using probabilistic risk assessment with cost-benefits analysis are needed.

The application of in-situ sensors for structural health monitoring has become a important research topic [3-5]. 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. However, many challenges exist for the practical application of in-situ sensors for SHM including 1) distinguishing mission critical defects from coherent noise features present in distributed sensor signals, 2) sensitivity to dynamic and environmental conditions, 3) sensor placement for optimal damage state observability, and 4) ensuring the reliability of the on-board SHM system through the life of the structure. In particular, the issue of degradation of the in-situ health monitoring system is of high interest, where a variety of sub-systems such as 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.

To investigate these critical issues concerning human factors in NDE and in-situ sensor degradation in SHM, a methodology incorporating cost benefit analysis with probabilistic risk assessment is proposed. Prior work has addressed development of a strategy and software platform to enable analysis of tradeoffs in NDE and SHM design in terms of product life cycle outcomes [6-7]. 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 to study the impact human factors on NDE reliability and maintenance cost. The effects of variations in probability of detection associated with human factors are explored. Lastly, probabilistic models incorporating time-dependent SHM parameters and case studies are utilized to provide insight into the impact of SHM sensor degradation.

HUMAN FACTORS IN NONDESTRUCTIVE EVALUATION

There are a variety of human factors that impact the reliability of inspection techniques and potentially degrade performance from their intrinsic capability of detecting defects of varying size [9]. Several studies have been performed to understand the influence of human factors on NDE performance [1,10]. Key human factors include the NDE skill level of the operator, and the amount of operator training and recent experience with a procedure and equipment of interest. The psychological state of the operator also plays a critical role in inspection performance through qualities such as integrity, concentration, persistence, tolerance to the environmental conditions, and a pre-existing bias concerning the expected frequency of detected flaws. Also, management oversight and level of accountability also facilitate reliable inspection programs. Contributing factors play a key role as well in determining the sensitivity of a procedure to human factor variations. In particular, the design of NDE equipment, calibration samples, and the NDE procedures in terms of level of complexity, usability, environmental conditions, and potential for interpretation will contribute to the variability in performance for different operators.

Representing Human Factors in Probabilistic Models

The VNDE software platform [6,7] is used to explore the effect of changes to the NDE probability of detection (POD) model related to human performance on probability of failure and total cost estimates. A four parameter POD model is defined as follows:

$$POD(a) = \alpha + (\beta - \alpha)\left\{1 + \exp\left[-\frac{\pi}{\sqrt{3}}\left(\frac{\ln a - \ln a_{50}}{\sigma}\right)\right]\right\}^{-1}. \tag{1}$$

where a corresponds to the flaw size, a_{50} (a50) corresponds to the median (50%) detectable flaw size, σ represents the skewness in the central slope of the POD curve, α corresponds to the false call (FC) rate and β is defined as 1 minus the random miss call (RMC) rate

[11]. Figure 1 presents a diagram of this model highlighting these four parameters. The real challenge in understanding the sensitivity of human factors on inspection reliability and maintenance cost concerns representing their influence on each of the four parameters. False call rates can be generally attributed to a lack of recent experience and training with the procedure, poor concentration during setup and data acquisition, and over-sensitivity to image or signal noise. Random missed calls can be attributed to several factors: poor integrity of the operator, lack of persistence in performing the procedure under all conditions, and a false expectation of the frequency that cracks will be found. In addition, differences in the sensitivity of inspectors to visual features associated with flaws, often associated with varying levels of training and skill, will result in differences in the median (50%) detected crack length parameter. Likewise, some inspectors will be better skilled at discriminating between subtle flaw signals in varying levels of noise, resulting in differences in the slope (skewness, σ) of their associated POD curves. The formulation of quantitative models for human factors for varying procedure and environmental conditions is a long-term need and a significant challenge, but would benefit this evaluation process.

Software for Parametric Design Studies

Prior work has addressed development of a software platform to enable analysis of tradeoffs in NDE and SHM design in terms of product life cycle outcomes [6-7]. Several new features have recently been incorporated in the software platform to facilitate specialized design studies. Any model factor can now be selected and defined as a variable for a parametric study. In particular, the inspection interval can be varied both in length of time for each in-service period and number of total inspection intervals. Also, new visualization and tabular features have been included in the software to explore the design space in terms of key measures, total cost and maximum probability of failure.

Case Study

A full factorial parametric study was performed varying each of parameters in the four parameter POD model between two levels: a baseline and a degraded performance level (Table 1). The hypothetical maintenance case study was designed including three in-service intervals with two inspection periods. The POD model was held constant for the two inspection periods. The probability of failure (POF) model included both probability of fracture and probability of a crack growing to critical. The critical flaw size was 0.75".

The results from the parametric study are displayed as a function of total life-cycle cost and maximum probability of failure in Figure 2. Each of the sixteen results are identified by labels indicated the factor level varying between baseline (0) and degraded (1) conditions for each of the four parameters (a50,σ,FC,RMC). Trends for each parameter are also presented using vectors in the plot. Degraded performance in terms of increased

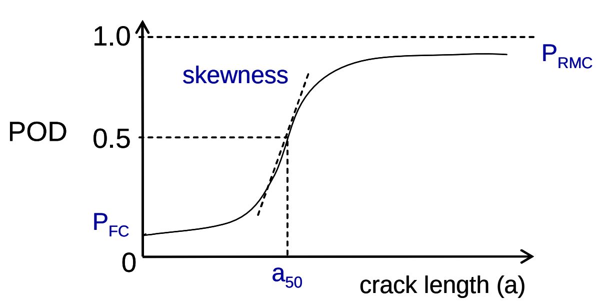

FIGURE 1. Four parameter POD model.

TABLE 1. Baseline and degraded performance levels for parametric study.

Parameter	Baseline Level (0)	Degraded Level (1)	Units
a50	0.060	0.070	(in.)
σ (skewness)	0.02	0.2	()
FC	0.0	1.0	(%)
RMC	0.0	10.0	(%)

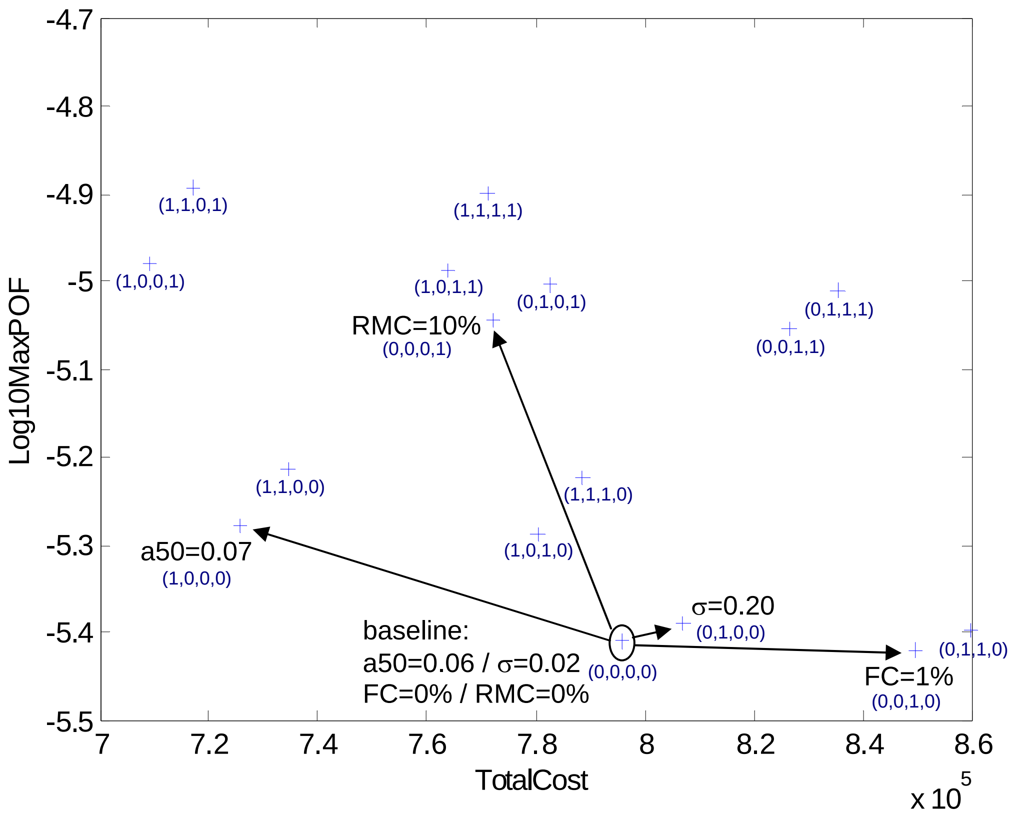

FIGURE 2. Plot of total cost versus probability of failure for varying the four POD model parameters (a50,σ,FC,RMC) between two levels, highlighting the main trends with respect to the baseline case (0,0,0,0).

median detected crack lengths by 0.010" (*associated with level of procedure experience of the operator*) was found to result in a higher POF and lower total cost. A reduction in the skewness or slope of the POD curve (*associated with differences in skill and experience*) resulted in only vary small increases in both POF and total cost. An increase in the false call rate of 1% (*associated with degraded concentration and over-sensitivity to noise*) was found to increase total cost with little impact on POF. Lastly, an increase in the percentage of random missed calls by 10% (*associated with a lack of integrity, poor focus, or a bias concerning the expected frequency of detected cracks*) was found to significantly increase the probability of failure with a slight decrease in total cost.

Although the random missed call rate was found to significantly impact the probability of failure, the degree of sensitivity was found to be less than expected. There are several reasons for the probability of failure results not being more significant for an increase in the random missed flaw rate from 0% to 10%. The first source concerns the nature of the POF calculation. Although consisting of both probability of fracture and probability of a crack growing to critical, the POF function is often dominated by the probability of fracture component. Since probability of fracture is dependent upon the relation between stress intensity factor and crack size, which is quite sensitive to changes in flaw distribution for very small crack lengths but less for cracks in the mid-range, the function is generally less sensitive to changes in the random missed call rate (RMC) and more to the median detectable flaw size (a50). If the probability of failure calculation was solely dependent upon a crack growing to the critical flaw size, changes to the random missed call rate were found to be much more significant on POF with respect to similar changes the median detectable flaw size. Second, multiple inspection opportunities also significantly reduce the probability of a missed flaw. In particular, if inspections are independent and intervals between inspections are short, multiple inspections can be used to mitigate poor inspection performance. Finally, these observed changes should not be considered to be absolute trends, but are dependent on the equivalent initial flaw size distribution, flaw growth model and interval of inspection. Through these simulated studies, unexpected insight was achieved concerning the influence of the POD parameters on cost and reliability.

SENSOR DEGRADATION IN STRUCTURAL HEALTH MONITORING

Understanding the likelihood and impact of degradation on an in-situ sensor network for structural health monitoring is critical for deployment of these systems. Two classes of SHM systems are considered here: global health monitoring systems incorporating distributed sensors such as strain gauges and acoustic emission transducers, and local methods for critical structural locations using ultrasonic and eddy current sensors. Evidence from existing strain gauge sensor data on C-17 aircraft demonstrated this issue, where 22% of the sensors were infant failures and about 40% of the total failed within the first ten years of the aircraft life [12]. This likelihood for a significant percentage of sensors to fail during the service-life of an aircraft mandates sensor redundancy for global SHM methods and sensor self-monitoring and maintenance for local SHM methods. Certification requirements for in-situ sensors are being prescribed for military and commercial SHM applications [13]. In addition to standard certification tests for electrical components, in-situ sensors must also demonstrate their reliability to detect a range of expected flaw conditions over the total expected life of the structure and beyond. However, NDE sensors do not maintain a consistent sensitivity and require frequent recalibration. Also, degradation of the sensor bond through thermal and dynamic loading has been recently demonstrated and must be addressed [14]. Self-calibration methods have been proposed to help address some sensor and bond variation over time [15,16]. However, a better understanding of the cost-benefit of maintaining in-situ sensor networks for an aircraft service life is needed. In this paper, probabilistic models are presented to study the impact of SHM degradation and maintenance on reliability and cost.

Probabilistic Model for SHM Degradation

A methodology has previously been presented for incorporating SHM systems into a design platform for enabling analysis and optimization of tradeoffs in terms of reliability, cost, and availability [7]. A summary of the SHM probabilistic model and new features addressing sensor degradation are presented. 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. As with NDE procedures, the relationship between the flaw size and the probability of detection and false call rate for the SHM system is directly represented using a four parameter probability of detection model. To represent degradation over time, the four parameters of the probability of detection curve can be defined as a function of time, where

$$POD(a,t) = \alpha(t) + \left(\beta(t) - \alpha(t)\right)\left\{1 + \exp\left[-\frac{\pi}{\sqrt{3}}\left(\frac{\ln a - \mu(t)}{\sigma(t)}\right)\right]\right\}^{-1}. \qquad (2)$$

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. Time dependent models should include early (infant) failures occurring over short periods and slow degradation changes in time of the sensor system.

The costs associated with the degradation of structural health monitoring systems can be categorized as development costs, implementation costs, and in-service costs. Additional development costs are necessary to design in-situ sensors with self-diagnostics capability and optimize sensor redundancy in case of sensor failure. Implementation costs will include additional validation costs to ensure the sensor system will maintain acceptable reliability over the life of the aircraft. In-service costs include the additional cost of fuel due to added SHM system weight, data interpretation labor costs, SHM maintenance costs associated with failed and degrading sensors, and the cost of secondary inspection and unnecessary repair due to false calls or unnecessary calls when flaws are very small. The percentage of secondary inspections and repairs can be evaluated through probabilistic models and used as inputs into the cost model. Probability of failure models for sensors, in particular for local sensors requiring immediate replacement upon failure to maintain damage observability, may also be included to supplement the maintenance cost model.

Case Study

A case study explores degradation in SHM system performance over time. The total service life was divided into ten service periods separated by nine maintenance events consisting of SHM data processing and subsequent field inspection and repair. A variable probability of detection function was assigned to the SHM system as follows: maintenance events 1 – 5 were assigned the SHM POD labeled t_0 in Figure 4(a), t_1 was assigned to the SHM system at maintenance event 6, t_2 to maintenance event 7, and t_3 to maintenance events 8 and 9. Only slow sensor degradation is considered in this hypothetical case study.

Figure 4(b) compares the probability of failure history for the time varying SHM POD case just described to that of a case where the POD of the SHM system is fixed to that labeled t_0 in Figure 4(a). Figure 4(b) shows that the variable POD case results in an undesirable increase in probability of failure. If such a condition is experienced in the field, replacement of the sensors to maintain inspection reliability is suggested. Not shown here is the fact that the total cost for the variable POD case is lower than that of the fixed

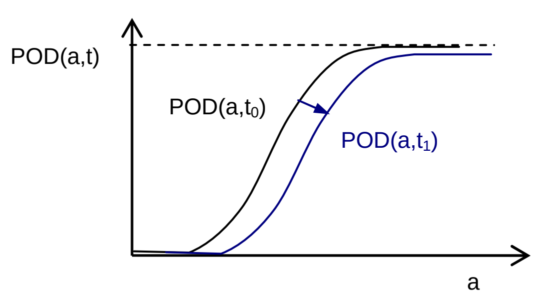

FIGURE 3. Probability of detection (POD) function with variability in model parameters over time.

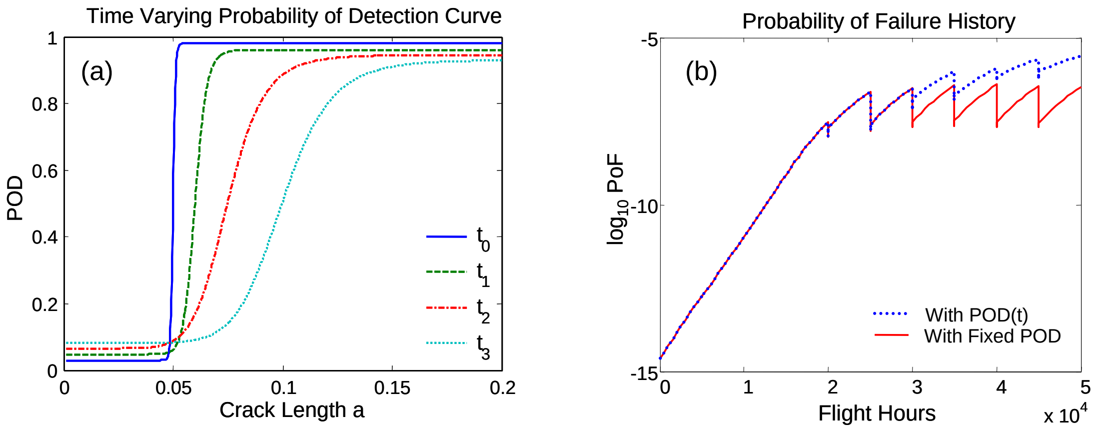

FIGURE 4. Effects of SHM system deterioration: (a) time varying POD, (b) resulting probability of failure.

POD case, because finding and repairing less flaws results in lower costs at the expense of a higher risk of failure. However, if degraded performance leads to increased false calls, the model indicates that much of the earliest calls will be either false or premature calls of very small cracks. Procedures must be in place to manage the occurrence of such false calls early in the implementation of SHM systems through secondary expert review of data and inexpensive follow-up inspections to mitigate unexpected costs and issues concerning trust in the system with the aircraft maintainer.

CONCLUSIONS AND RECOMMENDATIONS

To perform a quantitative evaluation of the influence of human factors on NDE and sensor degradation on SHM applications, probabilistic models were developed. Quantitative probabilistic risk assessments and cost evaluations were presented concerning the effects of variations in probability of detection associated with human factors. In addition, in-situ sensor degradation on life cycle measures was studied in terms of cost and probability of failure. Through simulated studies, insight was presented concerning possible opportunities and pitfalls of SHM applications. Design tools have also been integrated in the software platform to easily explore a variable number of inspection intervals and variable length of each service period.

Future work will explore the sensitivity of model trends to cost parameter levels, and acquire better data on flaw size distributions and real costs (of repairs) for promising applications. Long term efforts plan to explore the development of numerical and empirical models to better represent variations in human factors in NDE models and sensor degradation in SHM models. Probabilistic models will be studied to address the assumption of statistical independence for multiple measurements of the same component or inspection system over time. Lastly, 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 encouraged 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, and 6) damage state monitoring with secondary nondestructive inspection.

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