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Structure Health Monitoring (SHM) System Trade Space Analysis

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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 larger 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. 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 an 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.

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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 factor
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

1 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 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 levels 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 [Derriso, Olson, Desimio and Pratt (2007); Perez, DiUlio, Maley, and Phan (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 cause 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 remaining life cycle. Modeling and simulation using Monte Carlo analysis in the MATLAB® programming environment will be used as the tradespace 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.

2 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)].

2.1 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:

$$\frac{da}{dN} = C\Delta K^{m} \tag{1}$$

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:

$$\Delta K = K_{\max} - K_{\min} = \Delta\delta\sqrt{\pi a} \tag{2}$$

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.

2.2 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:

$$POD\,(a) = P\,(\hat{a} > \hat{a}_{th}) = \Phi\left(\frac{\beta_0 + \beta_1 * \ln(a) - \ln(\hat{a}_{th})}{\sigma}\right) \tag{3}$$

$POD\,(a)$ 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 Fig. 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 published by [Pado, Ihn, and Dunne (2013)].

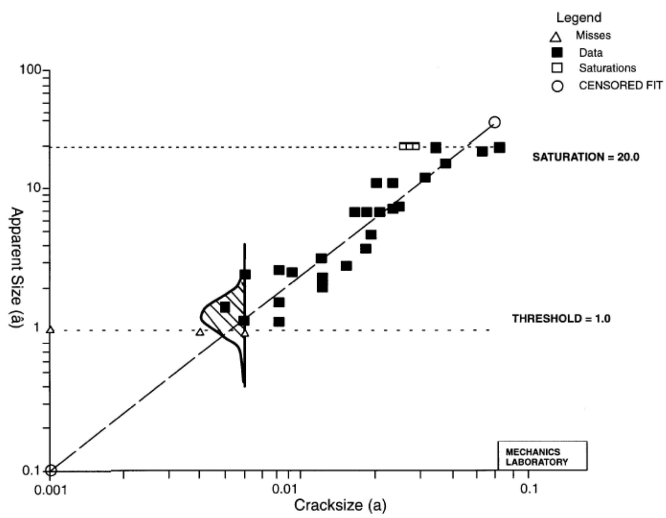

Figure 1: Linear regression fit of ln(a) vs. ln($\hat{a}$) data [Department of Defense (1999)]

2.3 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 Fig. 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.

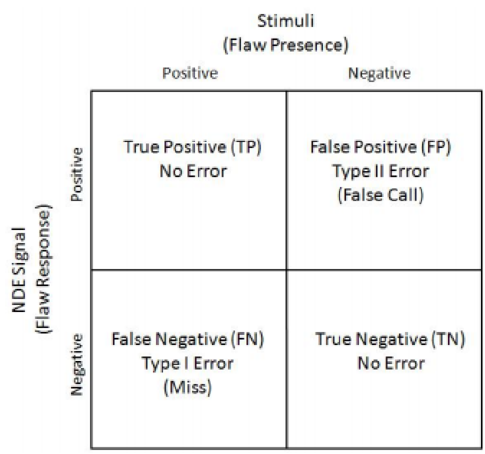

Figure 2: Confusion Matrix.

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 Fig. 3 [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) can also affect sensor performance as it will determine the amount of overlap for pdf's 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 fail-

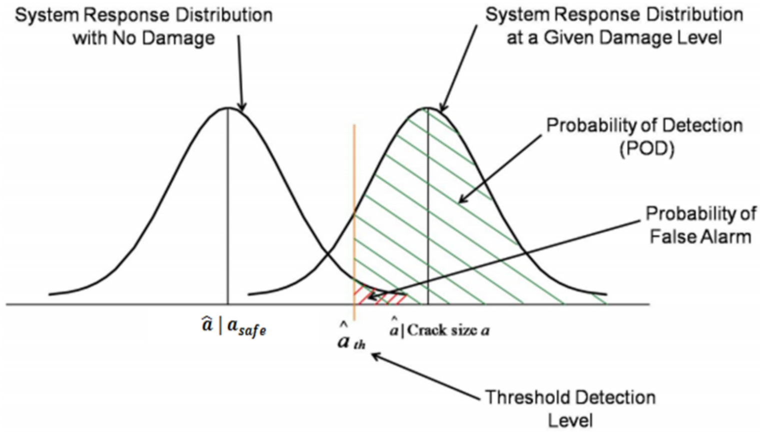

Figure 3: Graphical representation of the probabilities and the Threshold Detection Level [Kuhn (2009)].

ure) 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. 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. 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 undetected 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.

3 Methodology

Modeling and simulation using MATLAB® was the method used in this research. Fig. 4 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 Fig. 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. A stochastic 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 probability of detection in that specific sortie based on the actual crack length from the growth model and the number of accumulated flight hours in service or since previous crack repair. A Monte Carlo 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.

3.1 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 (1) and solving for a_i which is the crack length after N_i cycles (flights) we get [An, Chol, and Kim (2012)]:

$$a_i = \left[N_i c\left(1-\frac{m}{2}\right)\left(\Delta\delta\sqrt{\pi}\right)^m + a_0^{1-\frac{m}{2}}\right]^{\frac{2}{2-m}} \tag{4}$$

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, Chol, and Kim (2012)]:

$$\Delta\delta = \frac{K_{IC}}{\sqrt{a_{cr}\pi}} \tag{5}$$

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 every time a repair or replacement is done to the structure. Fig. 5 is a presentation of the fatigue crack growth simulation with 10 runs reflecting 10 repairs or replacements to the structural component.

It is shown in Fig. 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. 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.

3.2 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 (3) in the following form:

$$POD(a) = 0.5 = \Phi\left(\frac{\beta_0 + \beta_1 * \ln(a_{th}) - \ln(\hat{a}_{th})}{\sigma}\right) \tag{6}$$

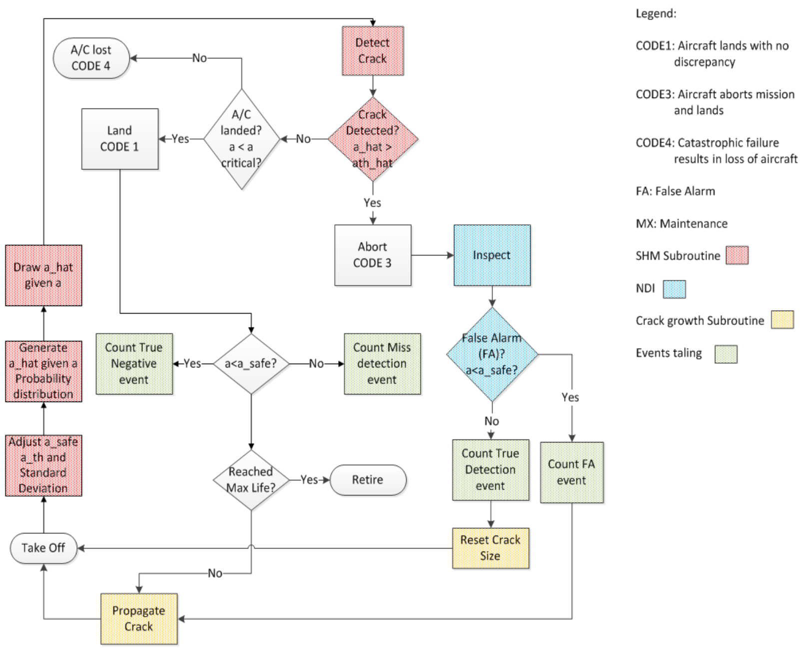

Figure 4: Flow diagram for SHM equipped aircraft.

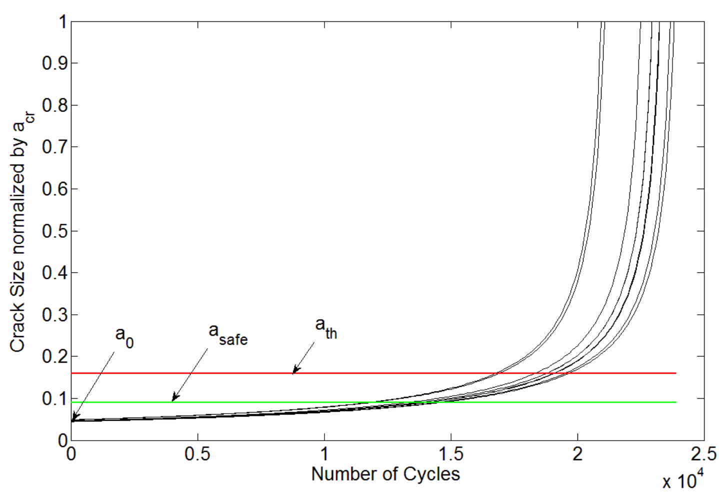

Figure 5: Fatigue crack growth simulation results for 10 runs.

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

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

where the crack length a from the fatigue crack growth simulation is used and a Monte Carlo draw is performed 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 is set for a given simulation run and varied for different runs.

3.3 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 is recorded for different sets ofa_{safe}, a_{th} and σ . Five values for the parameter a_{safe} are considered, and for every value ofa_{safe}, a_{th} takes on eight corresponding values and σ takes on four values. For each combination of a_{safe}, a_{th}, and σ , 100 simulation runs are conducted and the average FA and Miss Detection events are calculated. The results are displayed and discussed in the following section.

4 Results and Discussion

4.1 FA events

Fig. 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 is incremented 8 times starting at a_{safe} using increments of 1% of a_{cr}. For example, if a_{safe}= 5% a_{cr} then a_{th} is incremented as 5, 6, 7, 8, 9, 10, 11 and 12% of a_{cr}. This is repeated for Fig. 6(b), (c) and (d) with standard deviation σ = 0.2, 0.3, and 0.4. It is observed from Fig. 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 Fig. 6(a) but with a slight 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 Fig. 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 Fig. 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 Fig. 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

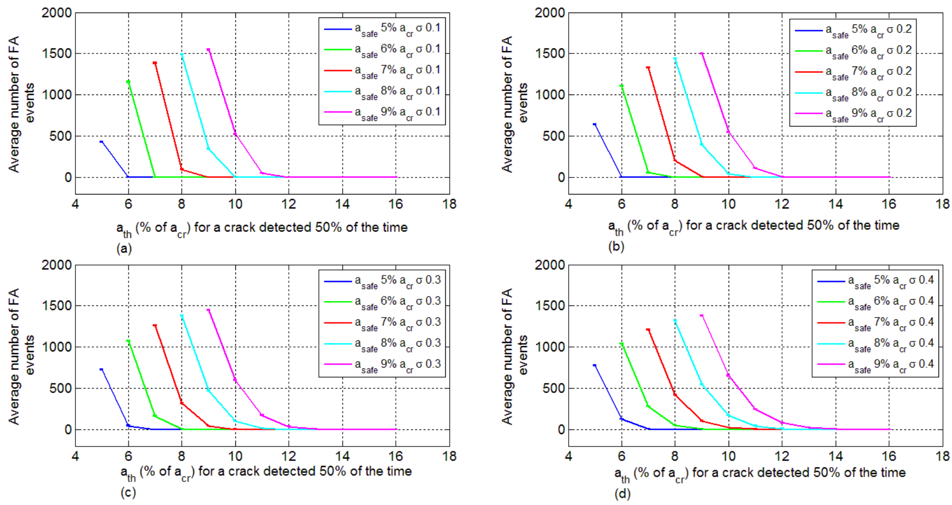

Figure 6: a_{th} (% of a_{cr})) for a crack detected 50% of the time vs. average number of FA events for different standard deviation levels σ.

4.2 Miss Detection events

It is observed from Fig. 7(a) 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 a detection on a subsequent sortie occurs prior to the crack reaching a critical length. From Fig. 7(b) it is observed that, as the standard deviation is increased for σ = 0.1 to σ = 0.2, the same trend as Fig. 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 Fig. 7(a). A similar trend is shown in Fig. 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 Fig. 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 Fig. 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 Fig. 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.

4.3 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 runs output for the crack length once detected as a percentage of a_{cr}.

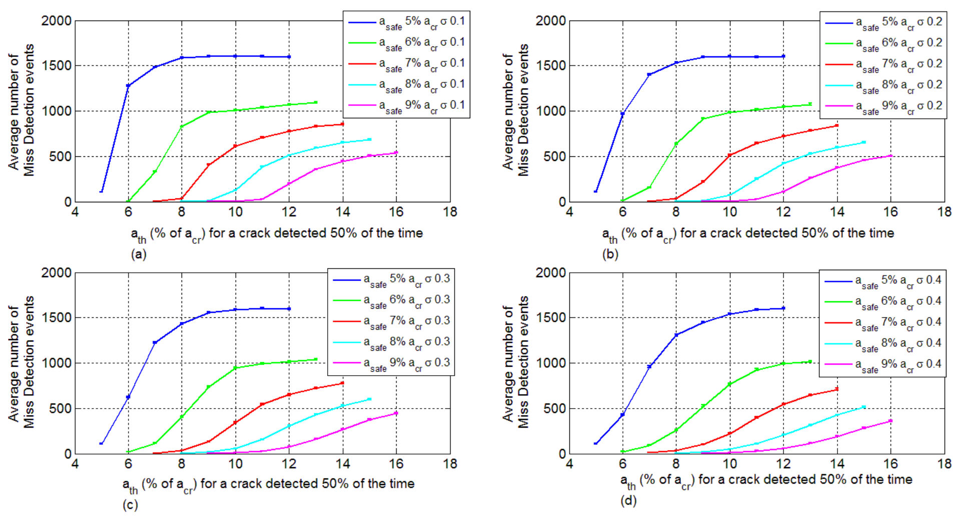

Figure 7: a_{th} (% of a_{cr})) for a crack detected 50% of the time vs. average number of Miss Detection events for different standard deviation levels σ.

From Fig. 8(a) it can be observed that, as a_{th} is increased further away from a_{safe} , the crack length once detected after an 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 monitonically increases (see Fig. 5); higher values for a_{safe} result in higher growth rates for $a > a_{safe}$. Sweeping across Fig. 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.

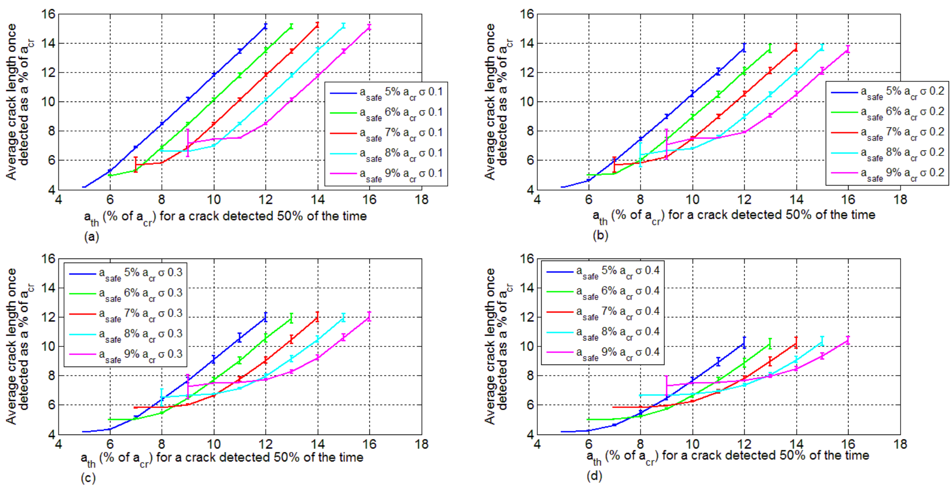

Figure 8: a_{th} (% of a_{cr})) vs. average length of a crack detected after a miss detection event.

4.4 *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($a > a_{cr}$) 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 are shown for increasing values of a_{safe} and a_{th}.

Fig. 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.

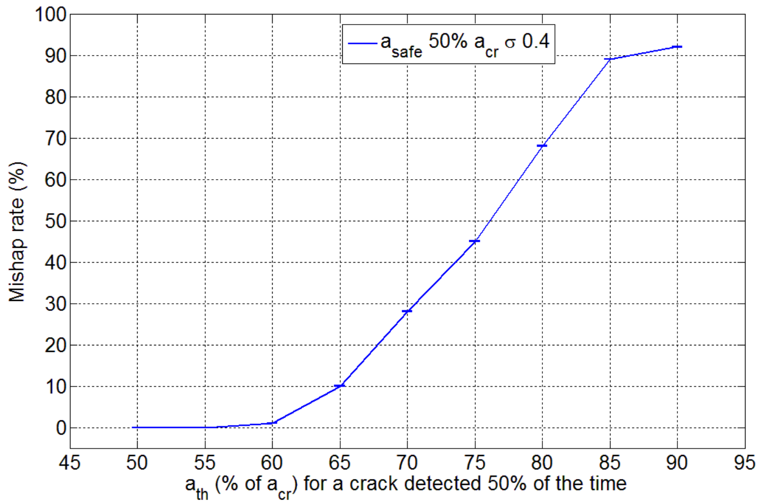

Figure 9: a_{th} (% of a_{cr})) for a crack detected 50% of the time vs. mishap rate

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 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.

5 Conclusion

5.1 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 too 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.

5.2 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/ allowed 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.

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