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Estimating Changes in SHM Performance Using Probability of Detection Degradation Functions

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Abstract: Structural Health Monitoring (SHM) has been proposed by many researchers as a way to reduce maintenance cost and increase availability of aircraft fleets. But long term exposure to the aircraft environment can have a degrading effect on the performance of a given SHM system. Predictable performance of SHM systems after extended exposure to aircraft environmental factors is key to the effective implementation of SHM on aircraft fleets. This study shows how existing NDE reliability techniques can be extended to model changes in SHM system performance due to extended exposure to the aircraft environment. Degradation coefficients are added to the traditional probability of detection, POD(a), formulations described in MIL-HDBK-1823. A POD(a,n) surface is then derived to account for the effects of an environmental factor on SHM system performance. Example degradation coefficient values are derived using experimental results.

Keywords: Structural Health Monitoring, Probability of Detection, Sensor Durability

1 Introduction and Background

Durability of a Structural Health Monitoring system is critical to its viability as a tool to reduce the cost and burden of recurring aircraft structural inspections. Many studies have addressed the installation of SHM systems as a means to improve or replace the current inspection paradigm on legacy and future aircraft [Boller (2000); Boller (2001); Goggin, et al. (2003); Ikegami and Haugse (2001); Malkin, et al. (2007)]. But while SHM technologies continue to advance, SHM systems have yet to gain a foothold on the flightline of an aging aircraft fleet. The good safety record of the current inspection paradigm, combined with uncertainties in SHM affordability, capability and maintainability, contribute to the lack of widespread SHM implementation [Achenbach (2007); Derriso, et al. (2007)].

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Several lines of research [Kuhn, et al. (2009); Kessler (2005); Blackshire, et al. (2007)] have shown that various aircraft environmental factors can have a significant impact on the performance of certain SHM sensors. These impacts must be quantified, modeled and taken into account if subsequent SHM signals analysis is to be accurate for the remaining life of a given aircraft. The object of this research is show to how existing methods of determining nondestructive evaluation (NDE) reliability can be modified and combined with experimental results to estimate the impact of aircraft environmental factors on SHM system performance.

2 NDE Reliability Using MIL-HDBK-1823

The NDE reliability method described in MIL-HDBK-1823 [Department of Defense (1999)] defines experimental and analytical requirements to build probability of detection, POD(a), curves for a range of crack sizes. One type of experimental data used to build POD(a) curves is described as "a vs a_{hat}" data, where a_{hat} represents the measured response of the NDE system for a given crack size a. A controlled experiment using known crack sizes is performed to determine a_{hat} values, and the "a vs a_{hat}" data is transformed so that a linear regression of the experimental data has normally distributed residuals ε with constant variance [Berens (1989); Spencer (2007)]. It has been shown that taking the natural logs of the a vs a_{hat} data often provides the required residual distribution [Department of Defense (1999); Berens (1989)]. This regression line is then used with a threshold detection value (a_{th}, the value below which the NDE signal is indistinguishable from noise) and the system response distribution for a given crack size, g($a_{hat}|a$), to build the POD(a) curve. The probability of detection of a given crack size is the portion of the g($a_{hat}|$ a) distribution that lies above the threshold detection value.

Figure 1 shows the components used to build a POD(a) curve experimentally. Notes 1 and 2 show the transformed a vs a_{hat} data plotted with the regression line; note 3 shows the g($a_{hat} \mid a$) distribution; and note 4 shows the probability of detecting the crack size a.

The equation of the regression line shown in Figure 1 has the form:

$$\ln(a_{hat}) = \beta_0 + \beta_1 * \ln(a) + \varepsilon \tag{1}$$

with β_0 and β_1 being the intercept and slope parameters fit to the experimental data, and ε being the normally distributed residuals described earlier. Since ε is distributed normally, solving for ε and dividing by the variance of the residuals (represented as δ in [Department of Defense (1999)]), results in a standard normal distribution representing the NDE system response distribution for a given crack

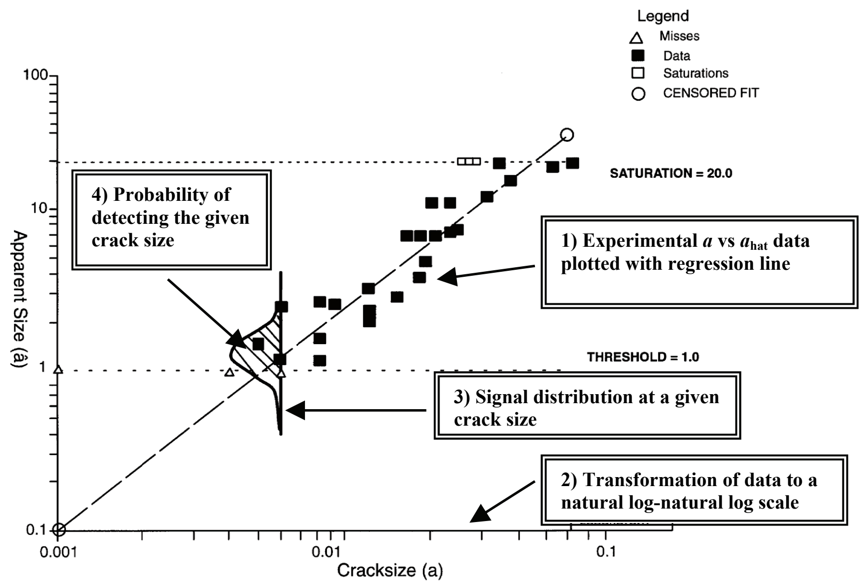

Figure 1: Components used to build a POD(a) curve from experimental data (chart from [Department of Defense (1999)], comments from authors

size:

$$g(a_{hat}|a) = \frac{\ln(a_{hat}) - \beta_0 - \beta_1 \ln(a)}{\delta} \sim \text{ n } (0,1) \tag{2}$$

The probability of detecting crack size a then becomes the probability of the NDE system response at the given crack size being greater than the threshold value:

$$\text{POD}(a) = \text{P}(\ln(a_{hat}) > \ln(a_{th})) = \Phi\left(\frac{\beta_0 - \ln(a_{th}) + \beta_1 \ln(a)}{\delta}\right) \tag{3}$$

POD(a) curves are then built applying equation (3) to a range of crack sizes and plotting crack size against POD. $\Phi(z)$ is a standard normal distribution.

3 Incorporating SHM Degradation Information Into POD(a)

While MIL-HDBK-1823 provides a starting point to describe SHM probability of detection, serious issues surround the direct application of NDE POD(a) techniques to SHM systems. Particularly, the changes a SHM system itself will undergo after installation is a significant concern. The traditional formulation of NDE reliability given above assumes proper NDE system set-up, calibration and testing prior to the NDE inspection. These steps may not be directly applicable to an installed SHM system. Probability of detection of an installed SHM system can and will change depending on how the system withstands its operating environment. Methods to account for these changes must be determined for SHM to be viable over the long term.

Assuming that an installed SHM system can be modeled in the same manner as a traditional NDE technique at the time of installation, as seen by Cobb [Cobb, et al. (2009)], the POD(a) formula given in equation (3) holds for a "new" SHM system. At some point after installation the POD will have changed, and a notional second test to redefine of the a vs a_{hat} relationship would change the POD(a) curve accordingly. If these changes in the a vs a_{hat} relationship can be identified and predicted, a direct link to changes in POD(a) can be made. For example, assume at some point after installation, SHM sensor degradation results in a uniform 20% signal reduction for each crack size (due, for example, to transmit or receive signal loss). In effect, if a second a vs a_{hat} test were performed, the reduced signal would result in data points "translating" down against the given crack sizes. Figure 2 shows the original data, "degraded" data and regression line for a vs a_{hat} data provided in MIL-HDBK-1823. Figure 3 shows the resulting shift in the POD(a) curve, decreasing the probability of detecting cracks less than approximately 0.01 inches.

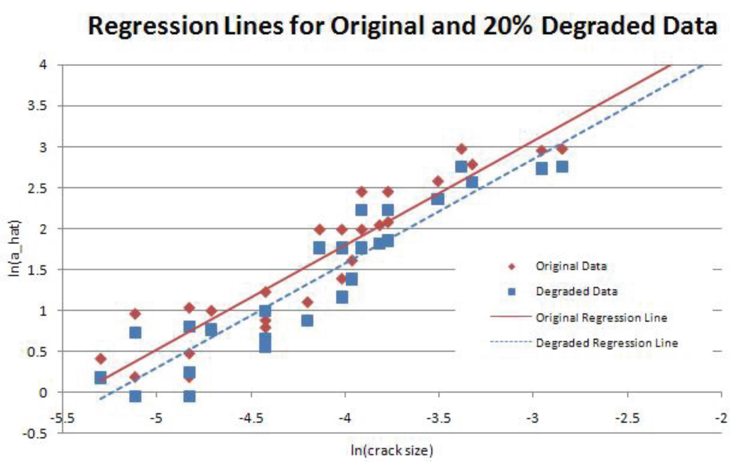

Figure 2: Reducing the received signal by 20% translates the data points at each crack size

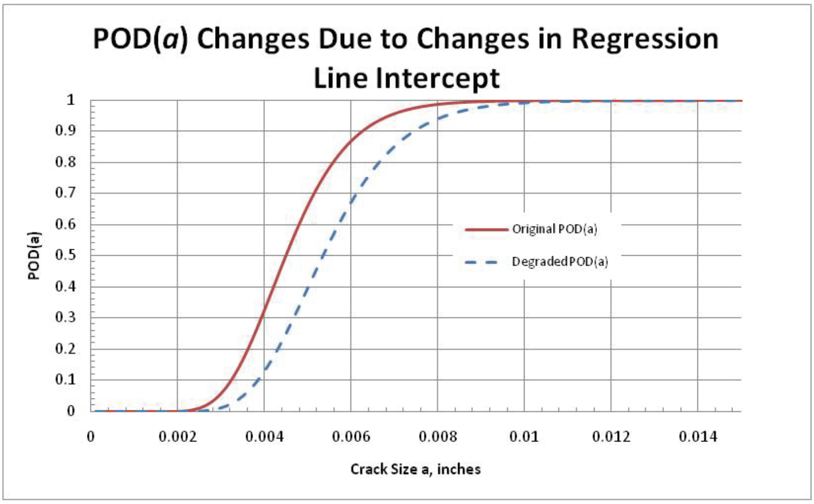

Figure 3: The 20% sensor signal degradation shifts the POD(a) curve

The translation of the data points observed in Figure 2 and the POD(a) curve shown in Figure 3 can be attributed to a change in the intercept of the regression equation (β_0 in equation (3)). This change can be modeled by using a multiplier (call it α_d) with the original regression intercept β_0. Changes to α_d have the same effect on the POD(a) curve as a translation of the entire data set due to sensor degradation.

But changes in sensor performance may affect the a vs a_{hat} relation in ways other than simple translation. A second possibility is that sensor degradation will increase the "noise" in the SHM signal, effectively raising the threshold detection value. In this case, the regression line shown in Figure 1 will not change, but the threshold detection line will rise to a higher value, decreasing POD(a). Figure 4 shows the POD(a) shift due to a 20% increase in threshold detection value.

In addition to changes in the regression line intercept and threshold detection value, changes to the regression slope and residual standard deviation may all result from changes in SHM sensor performance. It is proposed to use changes in these POD(a) parameters to model changes in SHM system performance after installation.

4 Introducing the POD(a) Degradation Model

The proposed POD(a) degradation model uses multipliers called "Degradation Coefficients" to modify the original POD(a) model given in equation (3), based on the

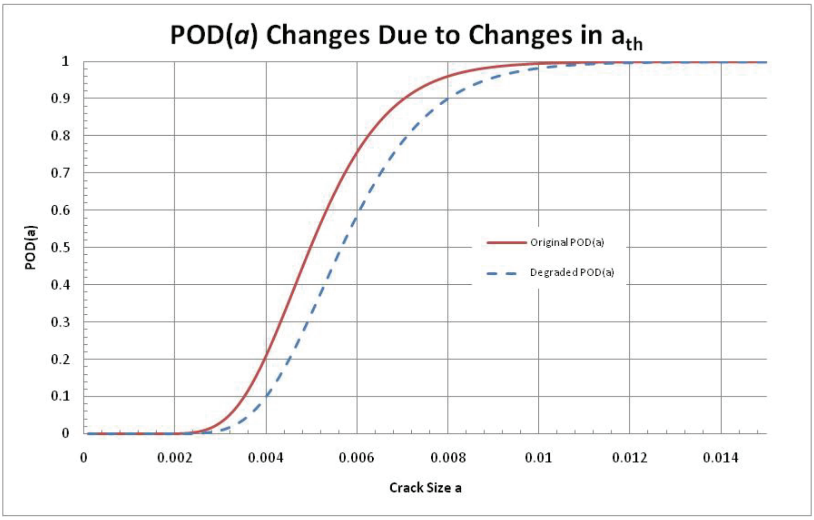

Figure 4: The 20% increase in threshold detection value shifts the POD(a) curve

effects of sensor degradation. The model has the following form:

$$\mathrm{POD}(a)_{\mathrm{Degraded}} = \Phi\left(\frac{(\beta_0 * \alpha_d) + (\beta_1 * \gamma_d) * \ln(a) - \ln(a_{th} * \rho_d)}{\delta * \psi_d}\right) \tag{4}$$

with degradation coefficients α_d, γ_d, ρ_d, and ψ_d ranging from zero to one, and modifying regression intercept, regression slope, threshold detection value and standard deviation of the regression residuals, respectively. Changing each degradation coefficient has a different effect on the POD(a) curve due to the nature of its corresponding POD(a) parameter.

5 Incorporating SHM Sensor Degradation Into the POD(a) Degradation Model

To apply the POD(a) degradation model, the form of the sensor degradation must be defined. Previous experiments by the author [Kuhn, et al. (2009)] showed a type of SHM sensor attached to simulated aircraft structure can be susceptible to signal degradation due to cyclic strain. Figure 5 shows the average SHM sensor response from undamaged structure from zero to 510 000 strain cycles at 1700 micro-strain. The best fit power equation for sensor response is also given.

For illustrative purposes, since no original POD(a) data exists for the type of SHM sensor tested, the data shown in Figure 5 can be combined with the example data

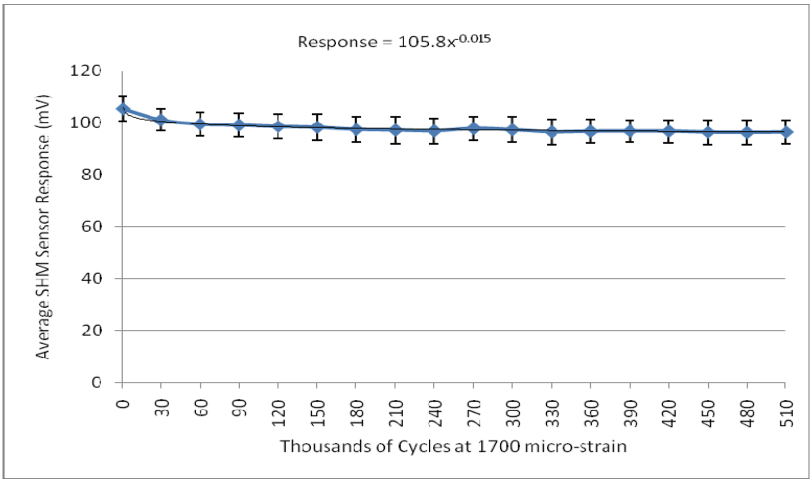

Figure 5: SHM sensor response degradation due to cyclic strain [Kuhn, et al. (2009)]

provided in MIL-HDBK-1823 to show how an existing POD(a) curve can be modified to account for known sensor degradation.

Assuming the signal degradation shown in Figure 5 results in a corresponding signal loss for each crack size, the original regression line shown in Figure 2 will "translate" down based on the response fit equation given in Figure 5:

$$\text{SHM Sensor Response} = 105.8 * (\text{\# strain cycles in thousands})^{-0.015} \tag{5}$$

This fit equation can then be used to specify a value of α_d in thePOD(a) degradation model. Normalizing equation 5 gives the values of α_d based on the number of cycles at 1700 micro-strain:

$$\alpha_d = (\text{\# strain cycles in thousands})^{-0.015} \tag{6}$$

Table 1 shows the values of α_d for various numbers of cycles, and Figure 6 shows the corresponding shift in the POD(a) curve.

Taken to the next level in this context, the probability of detection curve for the notional SHM sensor now depends not only on crack size, but also on the number of cycles (n) at 1700 micro-strain. In effect, the POD(a) degradation model allows the combination of an original POD(a) curve with a known sensor degradation model. The combination in this example gives probability of detection based on crack size and number of cycles: POD(a,n). Figure 7 shows the resulting POD surface.

Table 1: α_d values based on sensor degradation

Thousands of Cycles at 1700 micro-strain	**Degradation Coefficient α_d**
0	1
50	0.9430
100	0.9333
200	0.9236
500	0.9110

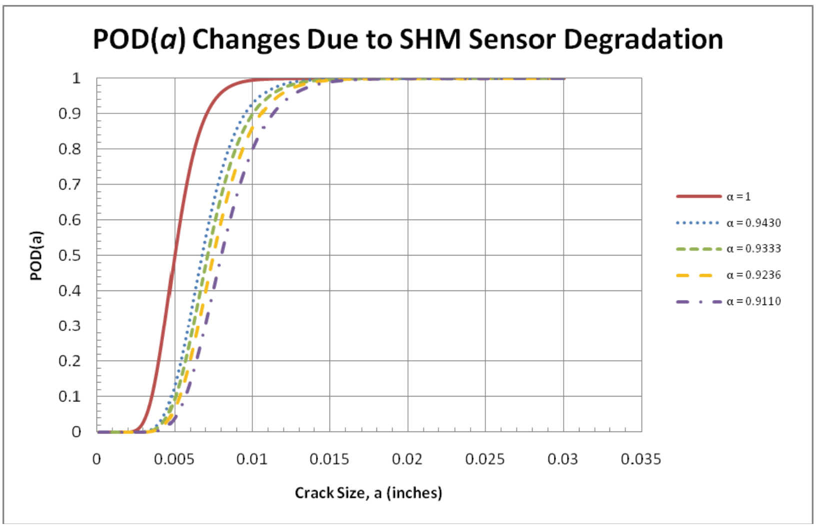

Figure 6: The POD(a) degradation model shows POD(a) curve shifts due to sensor degradation

6 Conclusion

Predictable performance of SHM sensors after extended exposure to the aircraft environment is key to viable SHM systems. This study shows that existing NDE reliability techniques can be extended to model the changes in SHM system performance caused by the degradation of SHM sensors in the aircraft environment. The probability of detection degradation model derived in this study adds degradation coefficients to the standard probability of detection model described in MIL-HDBK-1823. These coefficients, when based on experimental data, can account for changes in SHM sensor performance, and allow the extension of the traditional POD(a) curve into to a POD(a,n) surface, reflecting the environmental factor's im-

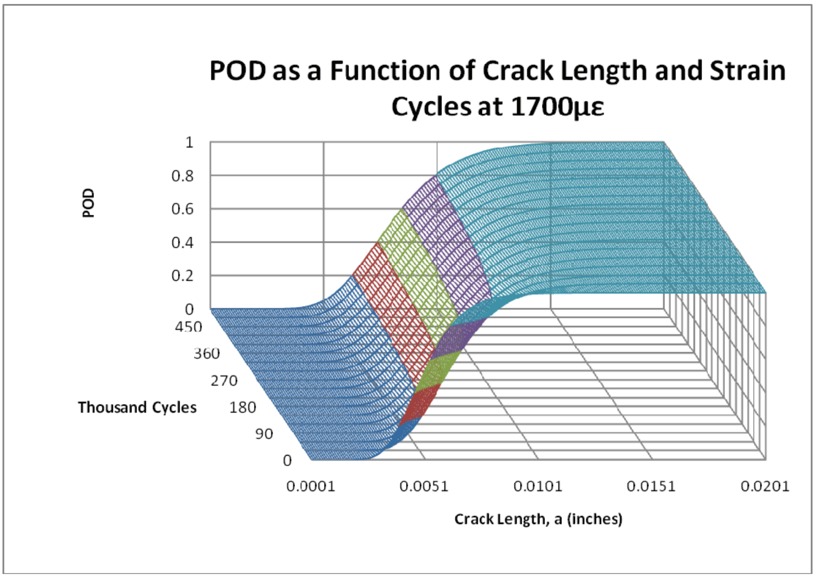

Figure 7: A POD "surface" is formed when SHM sensor degradation is taken into account

pact on SHM POD.

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