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Convergence of Multiple Statistical Methods for Calculating the Probability of Detection from SHM Sensor Networks

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ABSTRACT

The use of in-situ sensors for real-time health monitoring of a wide array of civil structures can be a viable option to overcome inspection impediments stemming from accessibility limitations, complex geometries, and the location and depth of hidden damage. The maturity of Structural Health Monitoring (SHM) sensors has evolved to the point where many networks have demonstrated sensitivities that meet or exceed current damage detection requirements. As a result, there is a growing need for well-defined methods to statistically quantify the performance of sensors and sensor networks. Statistical methods can be applied to laboratory and flight test data to derive Probability of Detection (POD) values for SHM sensors in a fashion that agrees with current nondestructive inspection (NDI) validation requirements. However, while there are many agreed-upon procedures for quantifying the performance of NDI techniques, there are no guidelines for assessing SHM systems. While the intended function of the SHM and NDI systems may be very similar, there are distinct differences in the parameters that affect their performance and differences in their implementation that require special consideration. Factors that affect SHM sensitivity include flaw size, shape, orientation and location relative to the sensors, operational and environmental variables and issues related to the presence of multiple flaws within a sensor network. The FAA Airworthiness Assurance NDI Validation Center (AANC) at Sandia Labs, in conjunction with the FAA WJH Technical Center, has conducted a series of SHM validation and certification programs aimed at establishing the overall viability of SHM systems and producing appropriate precedents and guidelines for the safe adoption of SHM solutions for aircraft maintenance. This paper will present the use of several different statistical methods, some of them adapted from NDI performance assessments and some proposed to address the unique nature of damage detection via SHM systems, and discuss how they can converge to produce a confident quantification of SHM performance. Comparisons of hit-miss, a versus â, and One Sided Tolerance Intervals will provide valuable insights into how the characteristics of the collected SHM data affect the formulation of that system's POD curve. Similarities between NDI and SHM assessments will be highlighted in order to provide a foundation in traditional flaw detection performance measures. In addition, considerations of the controlling factors to be considered when collecting SHM response data will be discussed.

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INTRODUCTION

Multi-site fatigue damage and hidden cracks in hard-to-reach locations are among the major flaws encountered in today's extensive array of aging structures and mechanical assemblies. The costs associated with the increasing maintenance and surveillance needs of aging structures are rising. The application of Structural Health Monitoring (SHM) systems using distributed sensor networks can reduce these costs by facilitating rapid and global assessments of structural integrity. These systems also allow for condition-based maintenance practices to be substituted for the current time- or cycle-based maintenance approach thus optimizing maintenance labor. Other advantages of on-board distributed sensor systems are that they can eliminate costly and potentially damaging disassembly, improve sensitivity by producing optimum placement of sensors, and decrease maintenance costs by eliminating more time-consuming manual inspections. Through the use of in-situ sensors, it is possible to quickly, routinely, and remotely monitor the integrity of a structure in service [1]. This requires the use of reliable structural health monitoring systems that can automatically process data, assess structural condition, and signal the need for specific maintenance actions.

Current aircraft maintenance operations require personnel entry into normally-inaccessible or hazardous areas to perform mandated, nondestructive inspections. To gain access for these inspections, structure must be removed, sealant must be removed and restored, fuel cells must be vented to a safe condition, or other disassembly processes must be completed. These processes are not only time consuming but they provide the opportunity to induce damage to the structure. The use of in-situ sensors for monitoring the condition of aircraft structure, coupled with remote interrogation, can be employed to overcome a myriad of inspection impediments stemming from accessibility limitations, complex geometries, and the location and depth of hidden damage. Furthermore, prevention of unexpected flaw growth and structural failure could be improved if on-board health monitoring systems are used to more regularly assess structural integrity [2, 3]. The ease of monitoring an entire network of distributed sensors means that structural health assessments can occur more often, allowing operators to be even more vigilant with respect to flaw onset.

Comparative Vacuum Monitoring (CVM) is a simple pneumatic sensor technology developed to detect the onset of cracks. CVM sensors are permanently installed to monitor critical regions of a structure. The CVM sensor is based on the principle that a steady state vacuum, maintained within a small volume, is sensitive to any leakage [4]. A crack in the material beneath the sensor will allow leakage resulting in detection via a rise in the monitored pressure. Figure 1 shows top-view and side-view schematics of the self-adhesive, elastomeric sensors with fine channels etched on the adhesive face along with a sensor being tested in a lap joint panel. When the sensors are adhered to the structure under test, the fine channels and the structure itself form a manifold of galleries alternately at low vacuum and atmospheric pressure. Vacuum monitoring is applied to small galleries that are placed adjacent to the set of galleries maintained at atmospheric pressure. If a flaw is not present, the low vacuum remains stable at the base value. If a flaw develops, air will flow from the atmospheric galleries through the flaw to the vacuum galleries. When a crack develops, it forms a leakage path between the atmospheric and vacuum galleries, producing a measurable change in the vacuum level. This change is detected by the CVM monitoring system shown in Figure 2. It is important to note that the sensor detects surface breaking cracks once they interact with the vacuum galleries.

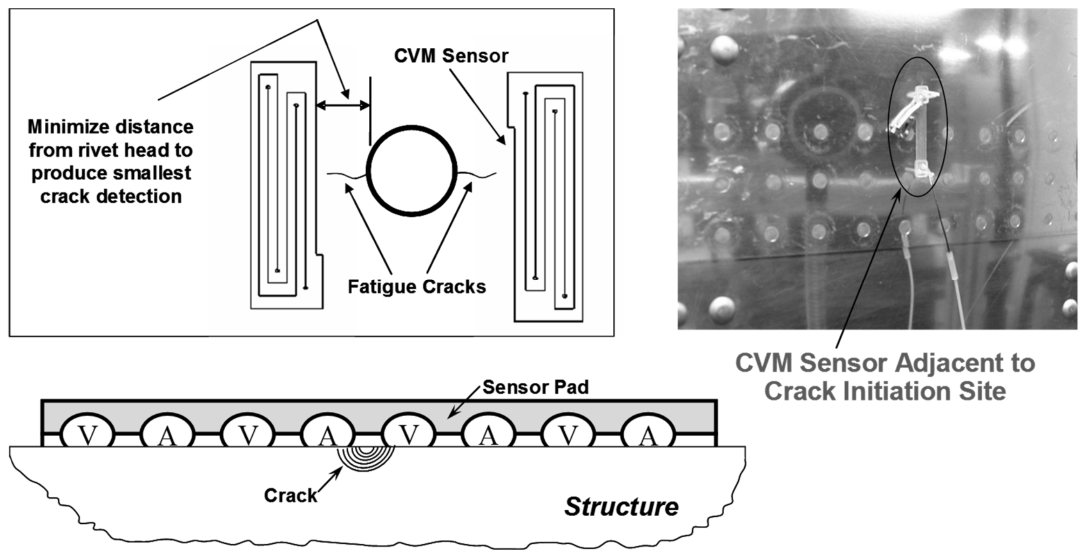

Figure 1: Schematics Depicting Operation of CVM Sensor and Polymer Sensor Mounted on the Outer Surface of a Riveted Lap Joint

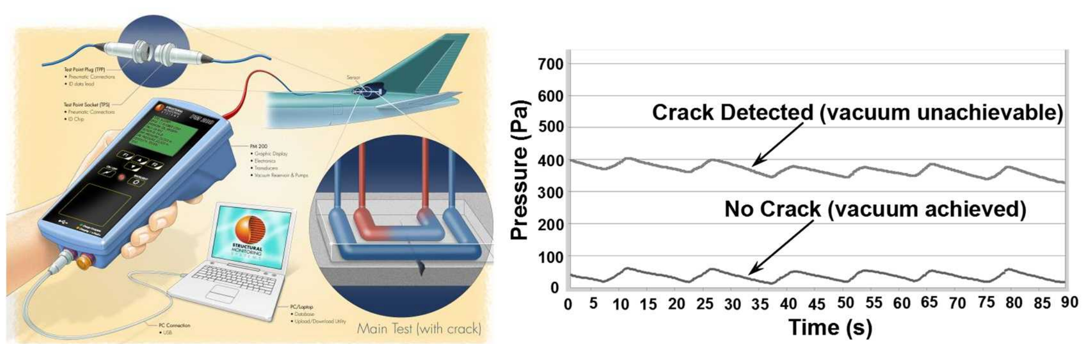

Figure 2: Crack Detection Monitoring with CVM System and Pressure Response Used to Indicate the Presence of a Crack

PERFORMANCE TESTING OF CVM SENSORS

This program was conducted in concert with Sikorsky Aircraft with the overall goal of maturing the integration of Structural Health Monitoring (SHM) solutions for rotorcraft structures with an emphasis on their use in Health and Usage Monitoring Systems (HUMS). Towards that end, probability of flaw detection and durability assessments were conducted to study the performance, deployment, and long-term operation of CVM sensors on rotorcraft. Statistical methods using one-sided tolerance intervals were employed to derive Probability of Detection (POD) levels for SHM sensors. The result is a series of flaw detection curves that can be used to propose CVM sensors for on-board crack detection. The expected outcome for this program is: 1) demonstration of a viable SHM system utilizing proven sensors to detect representative rotorcraft structural damage, 2) a model for the inclusion of structural health data into HUMS-based decision making processes, 3) integration of the results into rotorcraft Advisory Circular 29-2C, MG15 to ensure safe adoption of SHM solutions, and 4) documented efforts to move the proposed system through the certification process possibly including Alternate Means of Compliance (AMOC), modifications to Service Bulletins and Supplemental Type Certificates and the potential accrual of maintenance credits.

The selected application was the S-92 helicopter frame gusset shown in Figure 3. This structural member has a failure history where cracking begins at nutplate holes on the inner cap and grow outward to the edge of the frame. This application also provided a good extrapolation to other high-interest locations for rotorcraft SHM as the material type and thickness of this gusset are common to many frame and beam elements in rotorcraft. Figure 3 also shows the details of the CVM sensor custom-designed to detect any cracks emanating from the nearby fasteners and nutplate holes. Fatigue tests were completed on the frame gusset test specimens using flight load spectrums (see Fig. 4) while the vacuum pressures within the various sensor galleries were simultaneously recorded. A fatigue crack was propagated until it engaged one of the vacuum galleries such that crack detection was achieved and the sensor indicated the presence of a crack by its inability to maintain a vacuum.

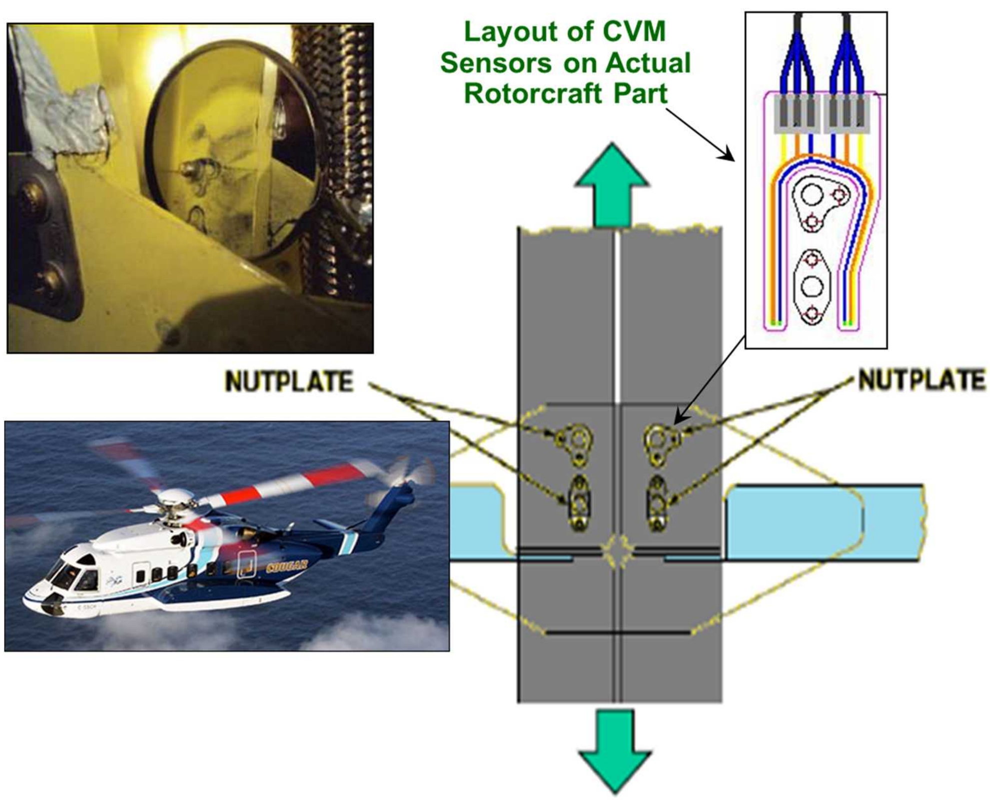

Figure 3: S-92 Gusset Frame Application and Installation of CVM Sensor Design

Figure 4 shows the fatigue test set-up used to grow cracks and a close-up photo of a fatigue crack as it engages the vacuum galleries of a CVM sensor. Crack detection lengths within the sensor ranged from 0.125" to 0.320" in length for the gusset frame application. The crack detection lengths correspond to permanent alarm levels for cracks engaging CVM sensors and the structure in an unloaded condition.

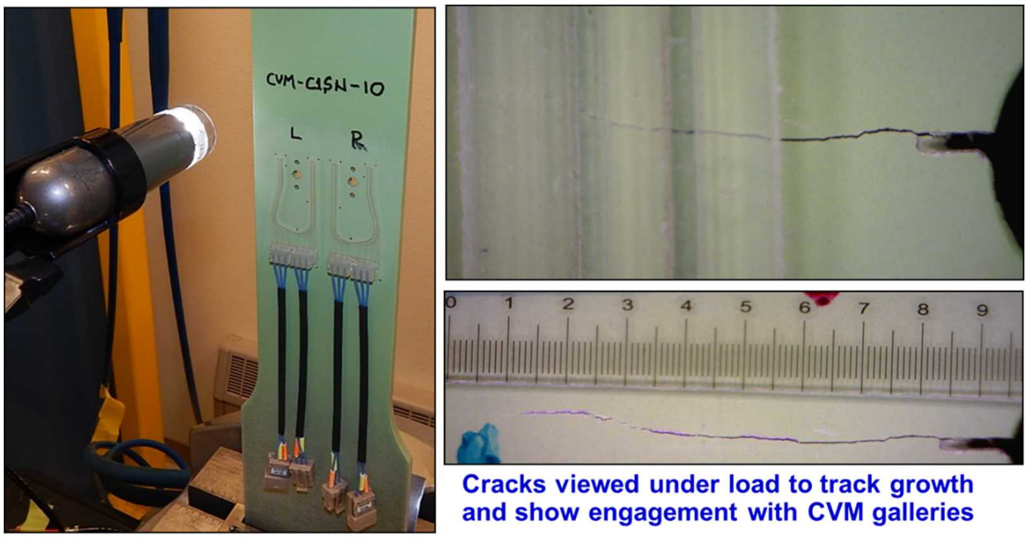

Figure 4: S-92 Gusset Frame Fatigue Test Specimen with CVM Sensor Installed and Close-Up Showing Fatigue Crack Crossing into CVM Sensor Galleries

DATA ANALYSIS USING PROBABILITY OF DETECTION MODELS

One Sided Tolerance Intervals - Some portions of the methodology needed to quantify NDI performance can be adapted to the validation of SHM systems. However, it is important to recognize the unique validation and verification tasks that arise from distinct differences between SHM and NDI deployment and flaw detection. SHM reliability calculations will depend greatly on the complexity of the structure and geometry of the flaw profile. For example, corrosion damage has a widely-varying flaw shape, both in the surface dimensions and in the changing depth. Contrast this with a fatigue crack that grows in a known propagation path such that the damage scenario can be described in a single parameter: crack length. In this latter case, the simplicity of such a one-dimensional entity allows for a more direct calculation of the reliability of the SHM system detecting such damage. The Probability of Detection for a fixed sensor detecting a crack which is propagating in a known direction in the vicinity of the sensor can be determined using the One-Sided Tolerance Interval (OSTI) approach. The OSTI estimates the upper bound which should contain a certain percentage of all measurements in the population with a specified confidence. Since it is based on a sample of the entire population (n data points), the confidence is less than 100%. Thus, the OSTI is greatly affected by two proportions: 1) the percent coverage which is the percent of the population that falls within the specified range (normally chosen as 90%), and 2) the degree of confidence desired (normally chosen as 95%).

Because of physical, time or cost constraints, it is often impractical to inspect an entire population. Instead, a small sample of the total population is tested and the data is used to gauge how well the entire population conforms to specifications. In traditional statistical process control, a significant number of data points are required in order to get a reasonably accurate estimate of process capability. This is because capability is usually calculated to cover a fixed multiple standard deviations. But this percentage only holds true for larger sample sizes; that is, greater than 50. As the sample size decreases, there is greater uncertainty in knowing the true location of the mean and the true magnitude of the population variance. Therefore, the estimate of the range of values encompassing a given percentage of the population must necessarily increase to compensate. In order to maintain a reasonably accurate estimate of the capability of a process for smaller sample sizes, it is necessary to adjust the number of multiple sample standard deviations used to define the region covering the desired proportion of the population distribution with a given confidence. An OSTI can be used for this purpose.

The data captured is that of the flaw length at the time for which the CVM provided sustainable detection. With these assumptions there exists a distribution on the flaw lengths at which detection is first made. In this context, the probability of detection for a given flaw length is just the proportion of the flaws that have a detectable length less than that given length. That is, the reliability analysis becomes one of characterizing the distribution of flaw lengths and the cumulative distribution function is analogous to a Probability of Detection (POD) curve. Assuming that the distribution of flaws is such that the logarithm of the lengths has a Gaussian distribution, it is possible to calculate a one sided tolerance bound for various percentile flaw sizes. To calculate a one sided tolerance bound, it is necessary to find factors $K_{n,\gamma,\alpha}$ to determine the confidence γ such that at least a proportion (α) of the distribution will be less than $X + (K_{n,\gamma,\alpha})S$ where X and S are estimators of the mean and the standard deviation computed from a random sample of size n. There may also be situations where the process capability is measured relative to a single-sided limit. These situations arise when a product characteristic need only meet a minimum specification limit or remain below a maximum specification limit. In this case, the desired POD value is the maximum crack length associated with the 90% POD level so the one-sided tolerance interval is used. The K factor for an OSTI can be obtained from standard statistical tables.

From this reliability analysis a cumulative distribution function is produced to provide the maximum likelihood estimation (POD). This stems from the one-sided tolerance bound for the flaw of interest using the equation:

$$T_{POD(90,\,95)} = X + (K_{n,\gamma,\alpha})(S) \qquad (1)$$

Where,

T = Tolerance interval for crack length corresponding to 90% POD with a 95% confidence
X = Mean of detection lengths
K = Probability factor (~ sample size and confidence level desired)
S = Standard deviation of detection lengths

n = Sample size
α = Detection level
ɣ = Confidence level

The formula in equation (1) is set-up to produce the upper bound for the tolerance interval which represents the actual POD value. With the same parameters described above, the maximum likelihood estimate describing the upper bound or optimal performance on the Probability of Detection for the OSTI approach can be calculated as:

$$\mathbf{POD}(\text{Max Likelihood Est}) = \frac{1}{xS\sqrt{2\pi}} EXP\left(\frac{-(\ln(x)-X)^2}{2S^2}\right) \qquad (2)$$

<u>Log-Regression POD Model</u> - If the SHM system can produce output (detection) that can be reduced to a binary response, such as the CVM data, a Log-Regression (***hit/miss)*** analysis can be used [6]. The Log Regression *Hit/Miss* POD model is used to analyze binary (detect/no detect) data using the following underlying mathematical relationship between POD and crack size:

$$ln[POD(a)/(1 - POD(a))] = \alpha + \beta[ln(a)] \qquad (3)$$

where "a" is the flaw size and α and β are estimated by maximum likelihood estimates.

<u>a vs. â</u>* <u>POD Model</u>** – If the SHM system can produce output for damage detection that can be reduced to a quantitative signal, such as the dCVM parameter produced by the CVM sensor, then use of a critical SHM system response can contain more information, and the amplitude, ***â, of the output makes it possible to extract other POD(a) estimates that could have narrower confidence bounds. The critical data for the SHM system response before, during and after crack detection becomes: *â* the system output and *a* the size of the corresponding damage. The POD(a) depends on a reasonable *â vs a* model where the data plot of *â vs log(a)* should reveal a linear relationship.

<u>POD Performance Comparisons</u> - Data acquired from the CVM fatigue tests described above were used to calculate the 90% POD level for CVM crack detection on the S-92 gusset application. The critical dCVM responses generated by the CVM PM-200 readout device were input into each of the three POD models presented here. Initial checks on the data revealed that the necessary relationships between dCVM values and crack size such that the data a Gaussian distribution existed and all three models could be applied to the data.

For the OSTI POD method, there are limited number of data points in lieu of the 51 or greater that are required in conventional POD calculations. Thus, the reliability calculations induce a penalty by increasing the magnitude of the K (probability) factor. As a result, while most of the crack detection levels were less than 0.25", the overall POD value (95% confidence level) for CVM crack detection was calculated from equation (1) as 0.310". The K values correspond to the desired ɣ (confidence level) of 95%. Figure 5 shows some sample CVM system response data (dCVM measurements) as plotted against the actual crack length measured at each data acquisition interval. The asterisk marks indicate data that was interpolated in order to enhance the statistics and produce a better conversion to the most accurate POD assessment.

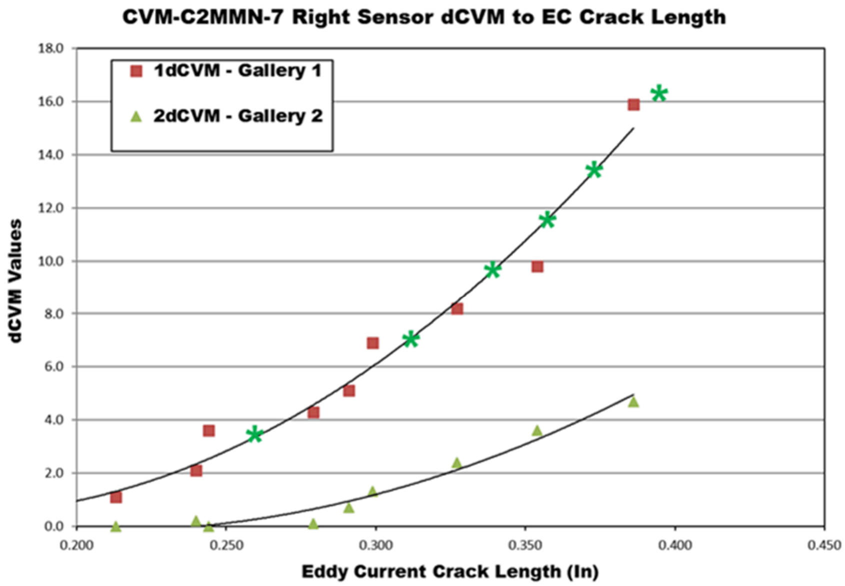

Figure 5: Sample CVM System Response Data dCVM *(â)* vs. Crack Length *(a)*

Sample POD curves, showing the maximum likelihood estimate along with a 95% confidence level, is plotted in Figure 6. This figure also compares the final $POD_{[90/95]}$ levels for each of the three analysis methods: One-Sided Tolerance Interval, Log Regression, and *a vs. â* POD model. It can be seen that all of the POD analysis methods converge to a similar result. In addition, the OSTI method, which requires the least amount of testing and data, produces the most conservative, upper bound on the POD which is a desirable approach. It should be noted that a complete understanding of the parameters involved in the SHM systems response and effect of those parameters on the resulting POD is necessary to properly apply these POD models. In this S-92 gusset application, it was desired to achieve crack detection before the crack reached 0.75" in length so this goal was achieved. Furthermore, in over 200 fatigue tests conducted using CVM sensors there were no false calls produced by the sensors in any of the tests.

CONCLUSIONS

The effect of structural aging and the dangerous combination of fatigue and corrosion has produced a greater emphasis on the application of sophisticated health monitoring systems. In addition, the costs associated with the increasing maintenance and surveillance needs of aging structures are rising. Corrective repairs initiated by early detection of structural damage are more cost effective since they reduce the need for subsequent major repairs and may avert a structural failure. Global SHM, achieved through the use of sensor networks, can be used to assess overall performance (or deviations from optimum performance) of large structures such as aircraft, bridges, pipelines, large vehicles, and buildings. The ease of monitoring an entire network of distributed sensors means that structural health assessments can occur more often, allowing operators to be even more vigilant with respect to flaw onset.

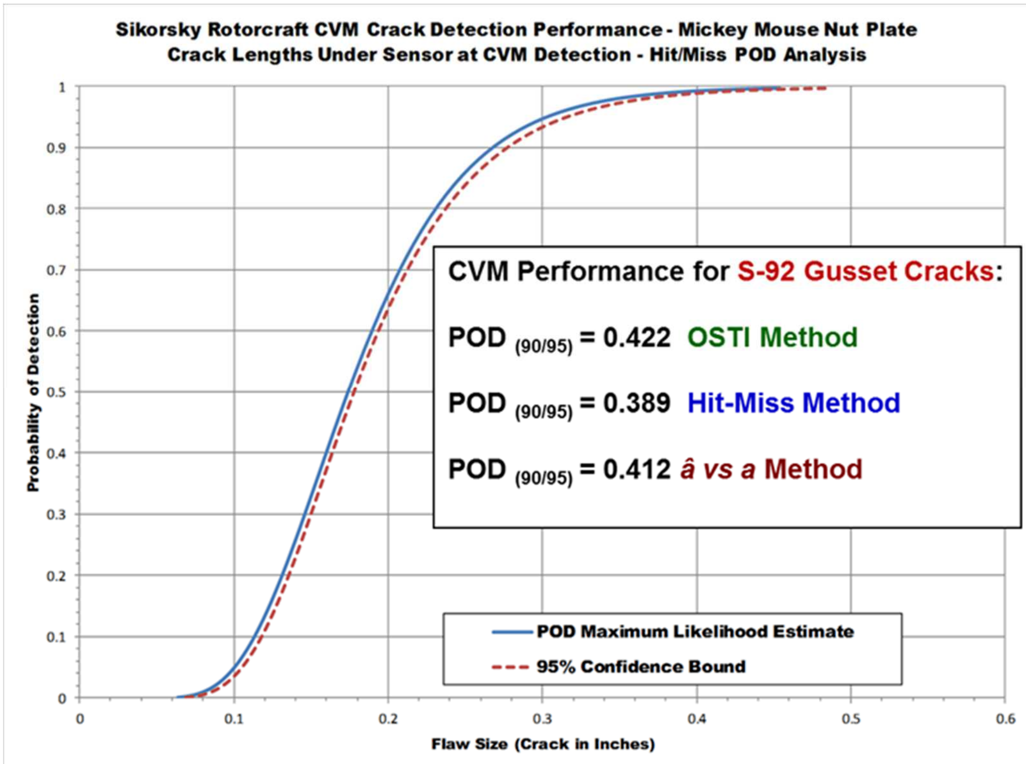

Figure 6: Probability of Crack Detection Curves Showing Detectable Flaw Lengths for CVM Sensor - Data Analysis Using One-Sided Tolerance Intervals

Through the use of in-situ CVM sensors, it is possible to quickly, routinely, and remotely monitor the integrity of a structure in service and detect incipient damage before catastrophic failures occur. These sensors can be attached to a structure in areas where crack growth is known to occur. On a pre-established engineering interval, a reading will be taken from an easily accessible point on the structure. Each time a reading is taken, the system performs a self-test. This inherent fail-safe property ensures the sensor is attached to the structure and working properly prior to any data acquisition.

This study showed the viability of using the One-Sided Tolerance Interval (OSTI) approach to determine the Probability of Detection for a fixed sensor detecting a crack which is propagating in a known direction in the vicinity of the sensor. The OSTI approach yields a reasonable, yet properly conservative, estimate for the CVM crack detection capability even with small data sets. Comparisons with alternative POD calculation methods demonstrated the similarity of OSTI results with recognized Log Regression and *a vs. â* POD models that have been traditionally used to determine similar POD performance levels for nondestructive inspection methods.

In several structural categories studied, the CVM sensors provided crack detection well before the crack propagated to the critical length determined by damage tolerance analyses. In addition, there were no false calls experienced in the fatigue crack detection tests. The sensitivity, reliability, and cost effectiveness of the CVM sensor system was demonstrated in both laboratory and field test environments.

The activities conducted in this program facilitate the evolution of an SHM certification process including the development of regulatory guidelines and advisory materials for the implementation of SHM systems via reliable certification programs. Formal SHM validation will allow the aviation industry to confidently make informed decisions about the proper utilization of SHM.

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