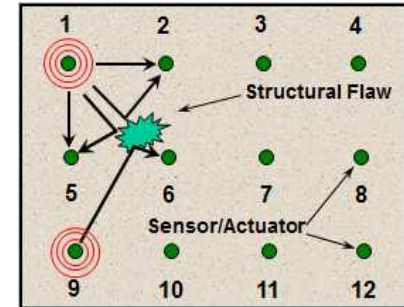
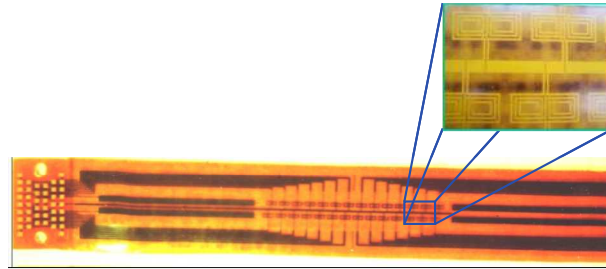


Automated Health Monitoring of Rail Cars and Railroad Bridges Using Embedded Sensors

SAND2016-9385C



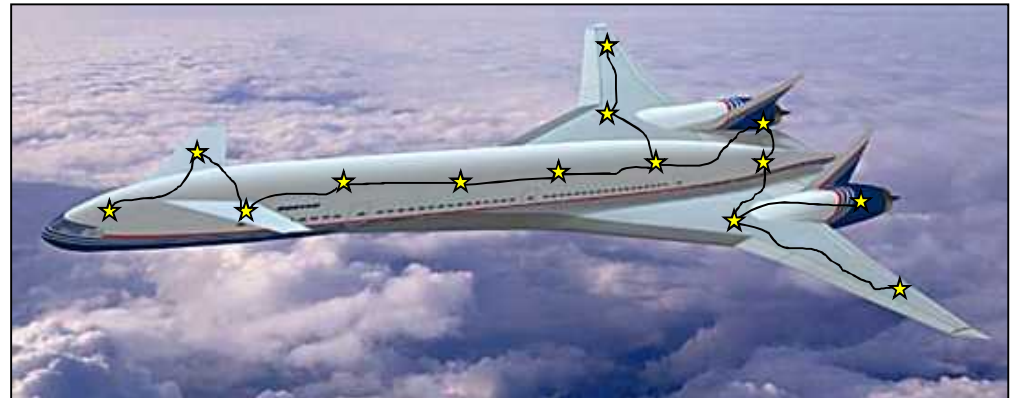
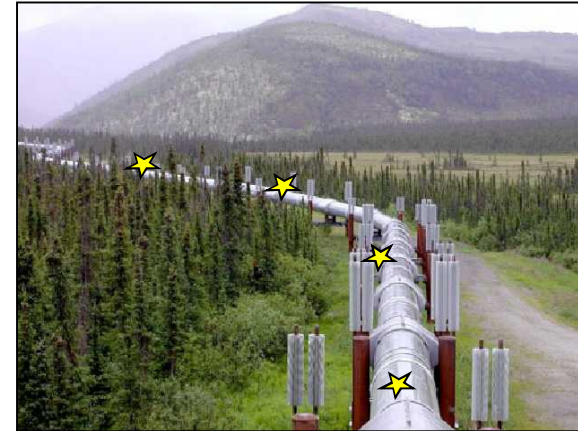
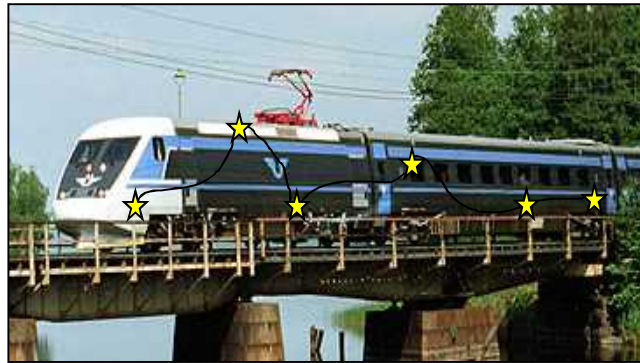
Dennis Roach
Sandia National Labs
FAA Airworthiness Assurance Center



Distributed Sensor Networks for Structural Health Monitoring

Smart Structures: include in-situ distributed sensors for real-time health monitoring; ensure integrity with minimal need for human intervention

- Remotely monitored sensors allow for condition-based maintenance
- Automatically process data, assess structural condition & signal need for maintenance actions



Structural Health Monitoring

**Structural
Damage Sensing
(in-situ NDI)**

**Structural Models
and
Analyses**

**Loads
and
Environmental
Monitoring**

Reasoner

Structural Health

Prognostic Health Management

SHM for:

- **Flaw detection**
- **Flaw location**
- **Flaw characterization**
- **Condition Based Maintenance**





NDI vs. SHM – Definition

Nondestructive Inspection (NDI) – examination of a material to determine geometry, damage, or composition by using technology that does not affect its future usefulness

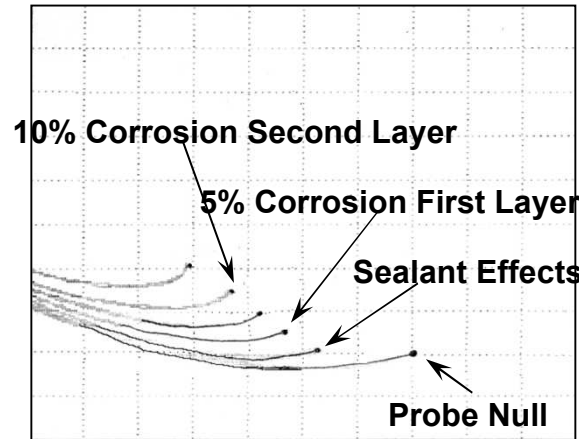
- High degree of human interaction
- Local, focused inspections
- Requires access to area of interest (applied at select intervals)

Structural Health Monitoring (SHM) – “Smart Structures;” use of NDI principles coupled with in-situ sensing to allow for rapid, remote, and real-time condition assessments (flaw detection); goal is to reduce operational costs and increase lifetime of structures & mechanisms

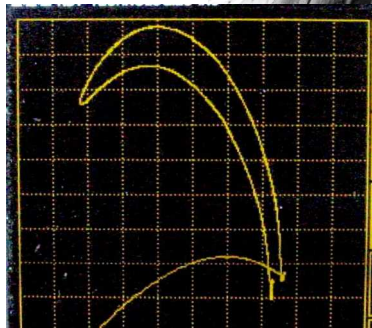
- Greater vigilance in key areas – address DTA needs
- Overcome accessibility limitations, complex geometries, depth of hidden damage
- Eliminate costly & potentially damaging disassembly
- Minimize human factors with automated data analysis



Typical A-Scan Signals Used for Flaw Detection with Hand-Held Devices

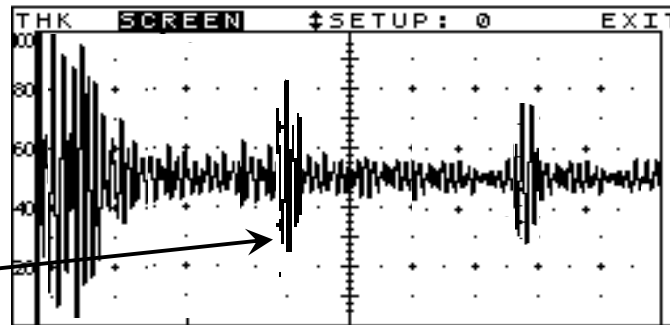


**Corrosion Detection
with Dual Frequency
Eddy Current**



**Eddy Current
Signal at
Crack Site**

Intermediate Echo
Caused by
Delamination



**Ultrasonic Pitch-Catch UT Signals Comparing
Flawed and Unflawed Signatures**





Potential Benefits of SHM

Near-Term

- Elimination of costly & potentially damaging structural disassembly
- Reduced operating and maintenance costs
- Detection of blunt impact events occurring during operation
- Reduction of inspection time
- Overcome accessibility & depth of flaw impediments
- Early flaw detection to enhance safety and allow for less drastic and less costly repairs
- Minimized human factors concerns due to automated, uniform deployment of SHM sensors (improved sensitivity)
- Increased vigilance with respect to flaw onset – life extension

Long Term

- Optimized structural efficiency (weight savings)
- New design philosophies (SHM designed into the structure)
- Substitution of condition-based maintenance for current time-based maintenance practices



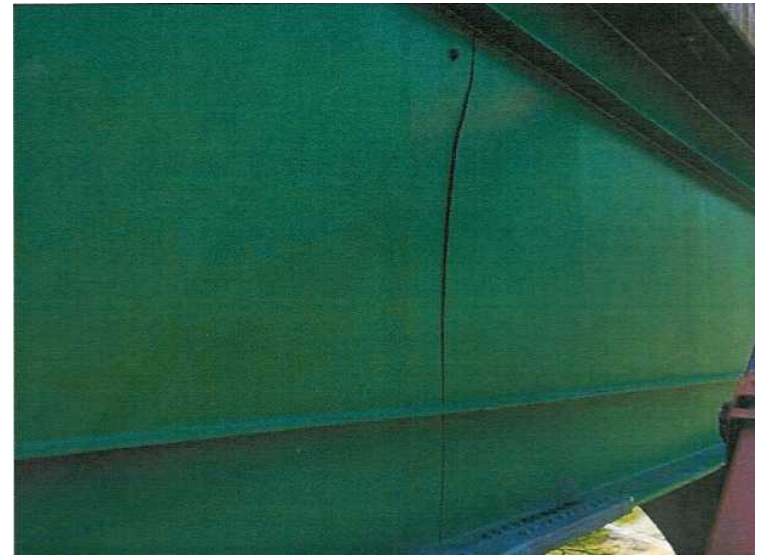
Wide Range of Uses for SHM Systems



Sample Bridge Damage



Brandywine River Bridge
Interstate Highway 95
Delaware

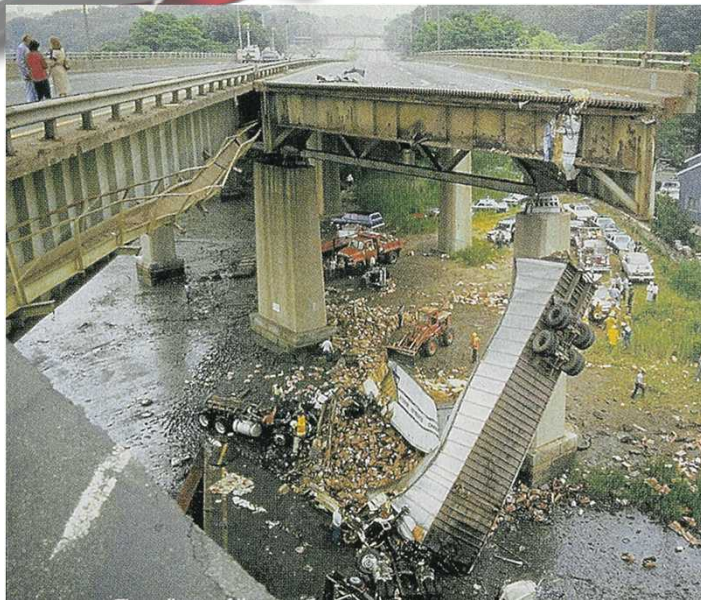


*30% of 600,000 bridges
in U.S. are listed as
“structurally deficient”
(Fed. Highway Admin.
Nat. Bridge Inventory)*

*Majority of RR bridges
in U.S. are operating
beyond their initial
design life*



Sample Bridge Health Monitoring Needs



ASCE 2006 Report on U.S. Infrastructure (ranges from roads to hazardous-waste systems):

- Gives the country a grade of “D”
- Warns that “rotting” infrastructure poses risks to safety & economic growth
- Urges wholesale changes including increased R&D

“Even modest gains in the efficiency of construction and repair could yield huge overall savings.”

**-Tom Warne, Chairman
Transportation Research Board**



**FAA William J. Hughes
Technical Center**



Sample Bridge & Rail Car Health Monitoring Needs

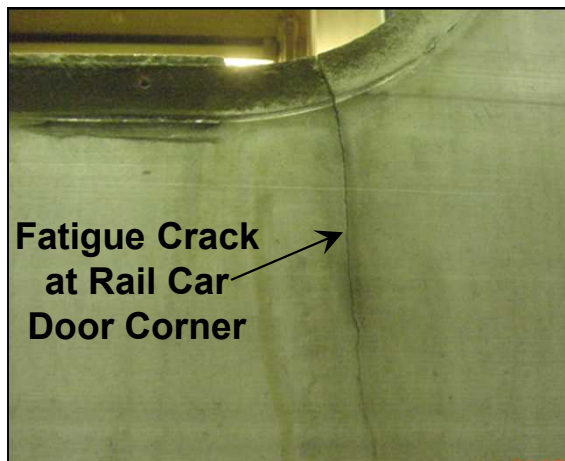
Many bridges are surpassing their initial design lifetime while budget restrictions limit or eliminate inspections.



**Monitor Bridges –
Interstate 35 Failure in USA**



**Collapse of Waegwan
Railroad Bridge in S. Korea**

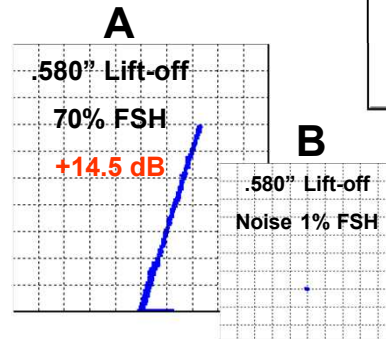
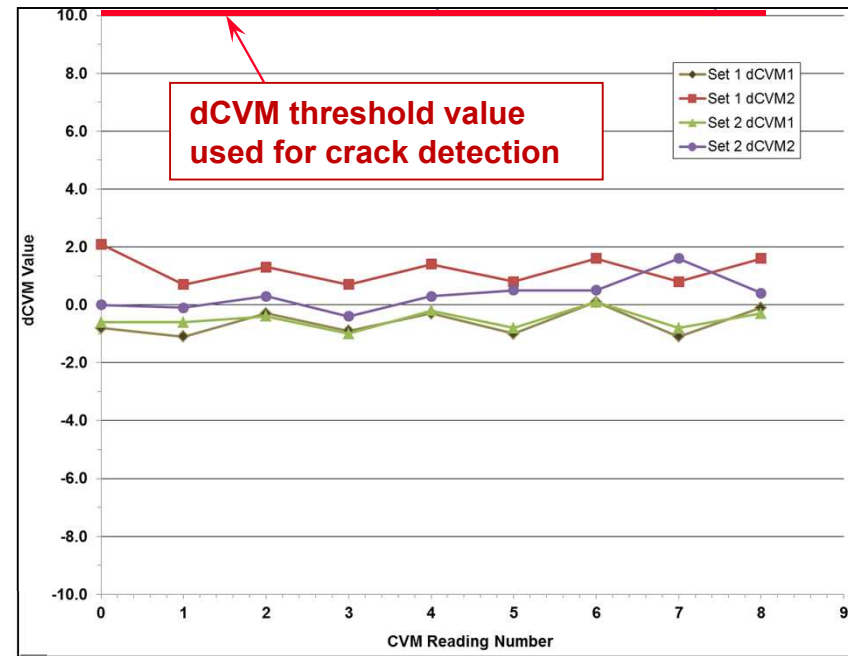
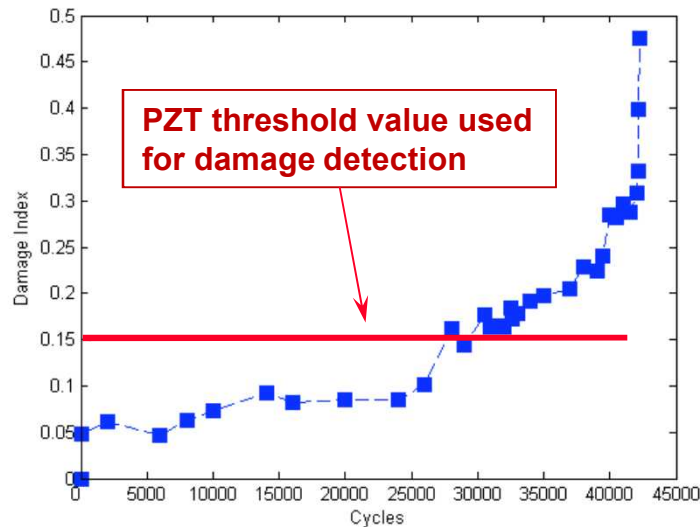


**Rail Car from
Washington DC
Transit Authority**



SHM Information – Minimize Interpretation or Data Analysis

- Automated data analysis is the objective – produce a “Green Light – Red Light” approach to damage detection
- Final assessment and interpretation by trained NDI personnel



A = Sensor Response to Crack (flaw signal)
B = Sensor Response at Uncracked Region (signal noise)

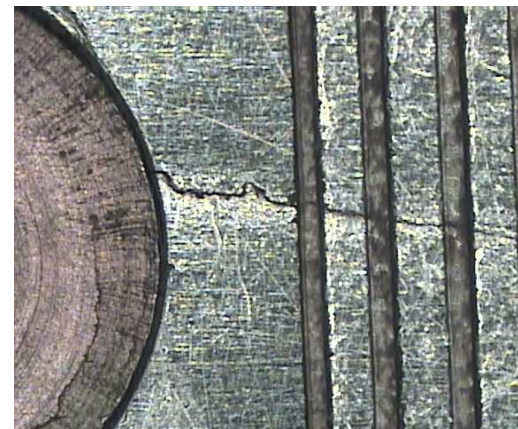
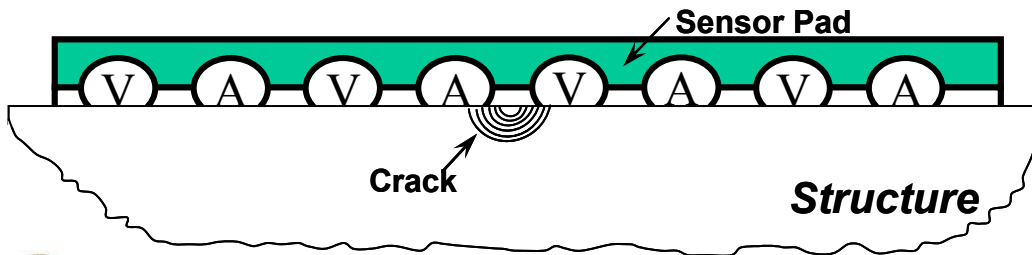
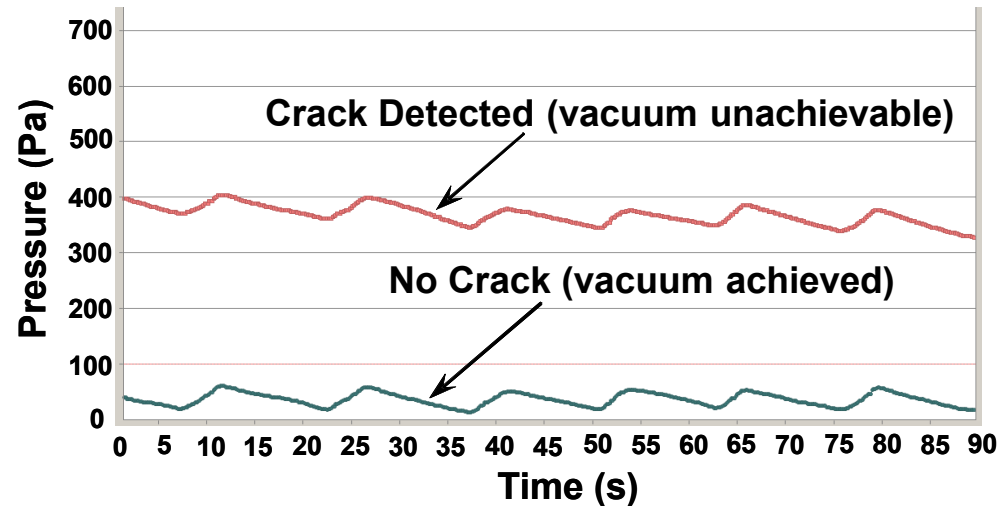


Comparative Vacuum Monitoring System

- Sensors contain fine channels - vacuum is applied to embedded galleries
- Leakage path produces a measurable change in the vacuum level
- Doesn't require electrical excitation or couplant/contact

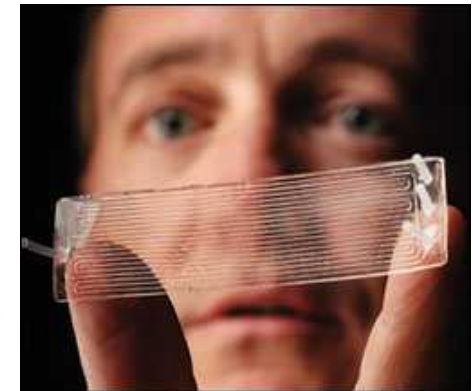


CVM Sensor Adjacent to Crack Initiation Site



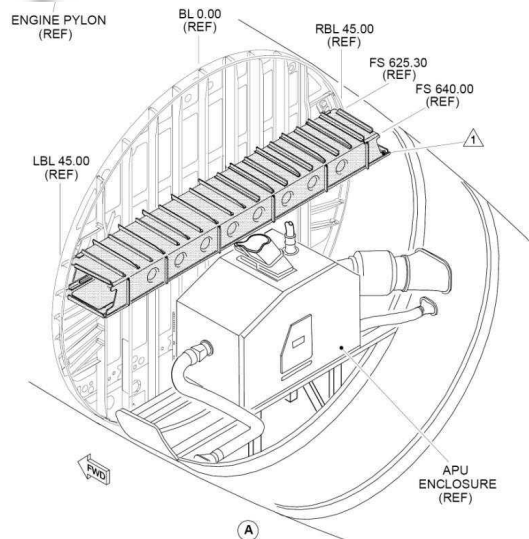
Drivers for Application of CVM Technology

- Overcome accessibility problems; sensors ducted to convenient access point
- Improve crack detection (easier & more often)
- Real-time information or more frequent, remote interrogation
- Initial focus – monitor known fatigue prone areas
- Long term possibilities – distributed systems; remotely monitored sensors allow for condition-based maintenance

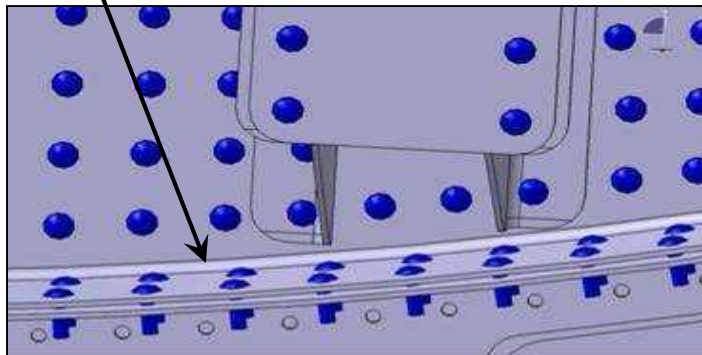


CVM Success on CRJ Aircraft

Pilot program with Bombardier and Air Canada



Inspect in
the radius

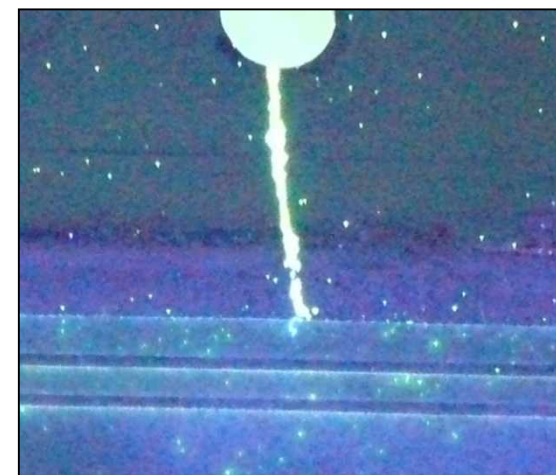


Sensor Issues:

- Design
- Surface preparation
- Access
- Connection
- Quality control



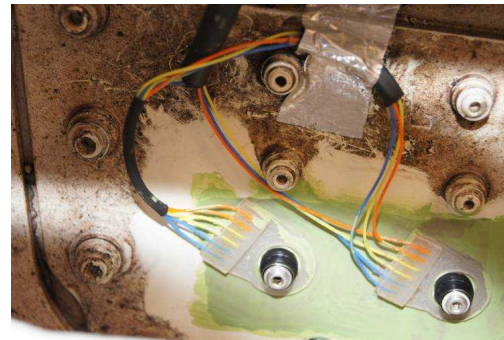
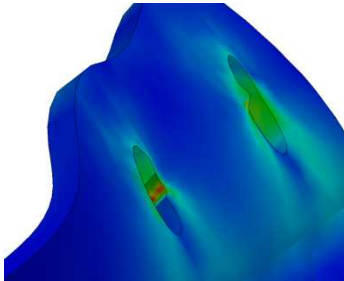
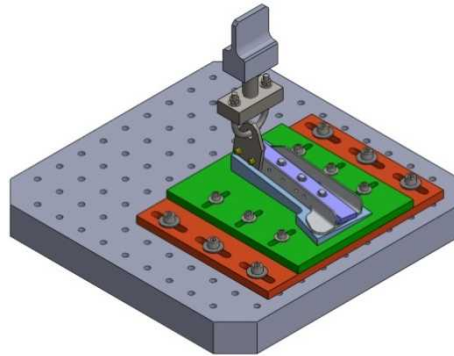
Aft Equipment Bay



Validation of SHM Capability – Certification for Use

Laboratory Tests

- Quantify performance
- Env/durability
- POD – statistically relevant evaluation
- Reliability/repeatability



Flight Tests

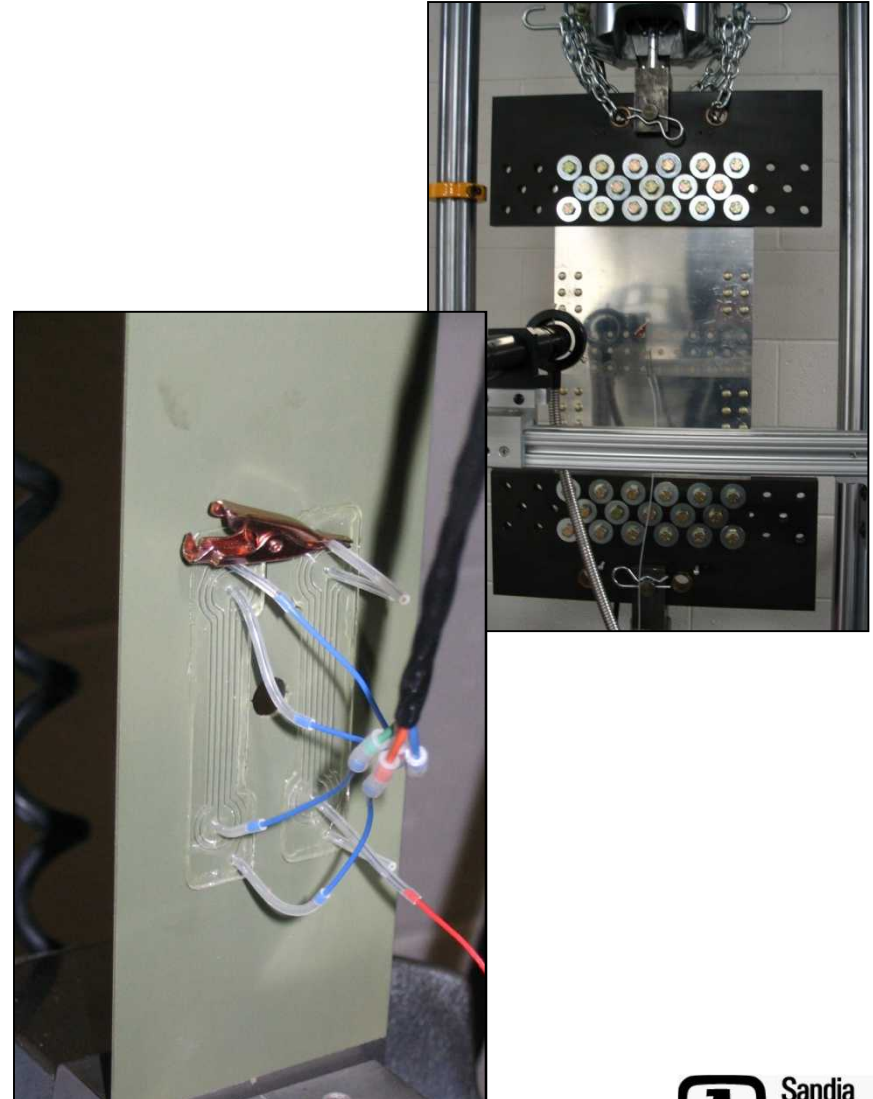
- Incomplete response statistics – lack of damage
- Deployed with airlines
- Need suite of monitoring data points (how many?, access to aircraft)
- Establish ability of current tech base to properly deploy SHM
- Establish ability of maintenance program to adopt SHM – admin obstacles



Test Matrix to Quantify Probability of Crack Detection

Test Scenarios:

| <u>Material</u> | <u>Thickness</u> | <u>Coating</u> |
|-----------------|------------------|----------------|
| 2024-T3 | 0.040" | bare |
| 2024-T3 | 0.040" | primer |
| 2024-T3 | 0.071" | primer |
| 2024-T3 | 0.100" | bare |
| 2024-T3 | 0.100" | primer |
| 7075-T6 | 0.040" | primer |
| 7075-T6 | 0.071" | primer |
| 7075-T6 | 0.100" | primer |





POD Assessment Using One-Sided Tolerance Interval

- Interval to cover a specified proportion of a population distributed with a given confidence – related to measures of process capability
- One-sided Tolerance Interval – 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), confidence is less than 100%. Thus, it includes two proportions:
 - Percent coverage (90%)
 - Degree of confidence (95%)
- 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:

$$TI = X \pm (K_{n, \gamma, \alpha})(S) \quad [\log \text{ scale calculation}]$$

- Interested in a 1-tailed interval (utilize “+” in equation); upper limit of TI.
Uncertainty in knowing the true mean and population variance requires that the estimate of the range of values encompassing a given percentage of the population must increase to compensate.



CVM Validation – Data Analysis Using One-Sided Tolerance Intervals

- Crack detection based on PM-200 “Green Light” – “Red Light” results
- Data captured is the crack length at the time when CVM provided permanent (unloaded) detection
- Reliability analysis – cumulative distribution function provides maximum likelihood estimation (POD)
- One-sided tolerance bound for various flaw sizes:

$$\text{POD}_{95\% \text{ Confidence}} = \bar{X} + (K_{n, 0.95, \alpha}) (S)$$

X = Mean of detection lengths

K = Probability factor (~ sample size, confidence level)

S = Standard deviation of detection lengths

n = Sample size

α = Detection level

γ = Confidence level



POD Calculations - One-Sided Tolerance Interval

POD Determined from CVM Response Data

Statistic Estimates on Log Scale

| Statistic | Over Bare metal | Over Primer |
|---------------|-----------------|-------------|
| Mean | -2.1566 | -2.1679 |
| Std deviation | 0.40889 | 0.22809 |

CVM Crack Detection Data (0.040" th)

| Bare Metal | | Over Primer | |
|------------------|-----------------|------------------|-----------------|
| Flaw size (inch) | Log (flaw size) | Flaw size (inch) | Log (flaw size) |
| 0.003 | -2.52 | 0.002 | -2.70 |
| 0.007 | -2.15 | 0.007 | -2.15 |
| 0.002 | -2.70 | 0.010 | -2.00 |
| 0.030 | -1.52 | 0.009 | -2.05 |
| 0.009 | -2.05 | 0.004 | -2.40 |
| 0.005 | -2.30 | 0.006 | -2.22 |
| 0.004 | -2.40 | 0.010 | -2.00 |
| 0.002 | -2.70 | 0.009 | -2.05 |
| 0.014 | -1.85 | 0.011 | -1.96 |
| 0.005 | -2.30 | 0.007 | -2.15 |
| 0.013 | -1.89 | | |
| 0.032 | -1.49 | | |

POD Detection Levels

($\gamma = 95\%$, $n = 12$ for bare, $n=10$ for primer)

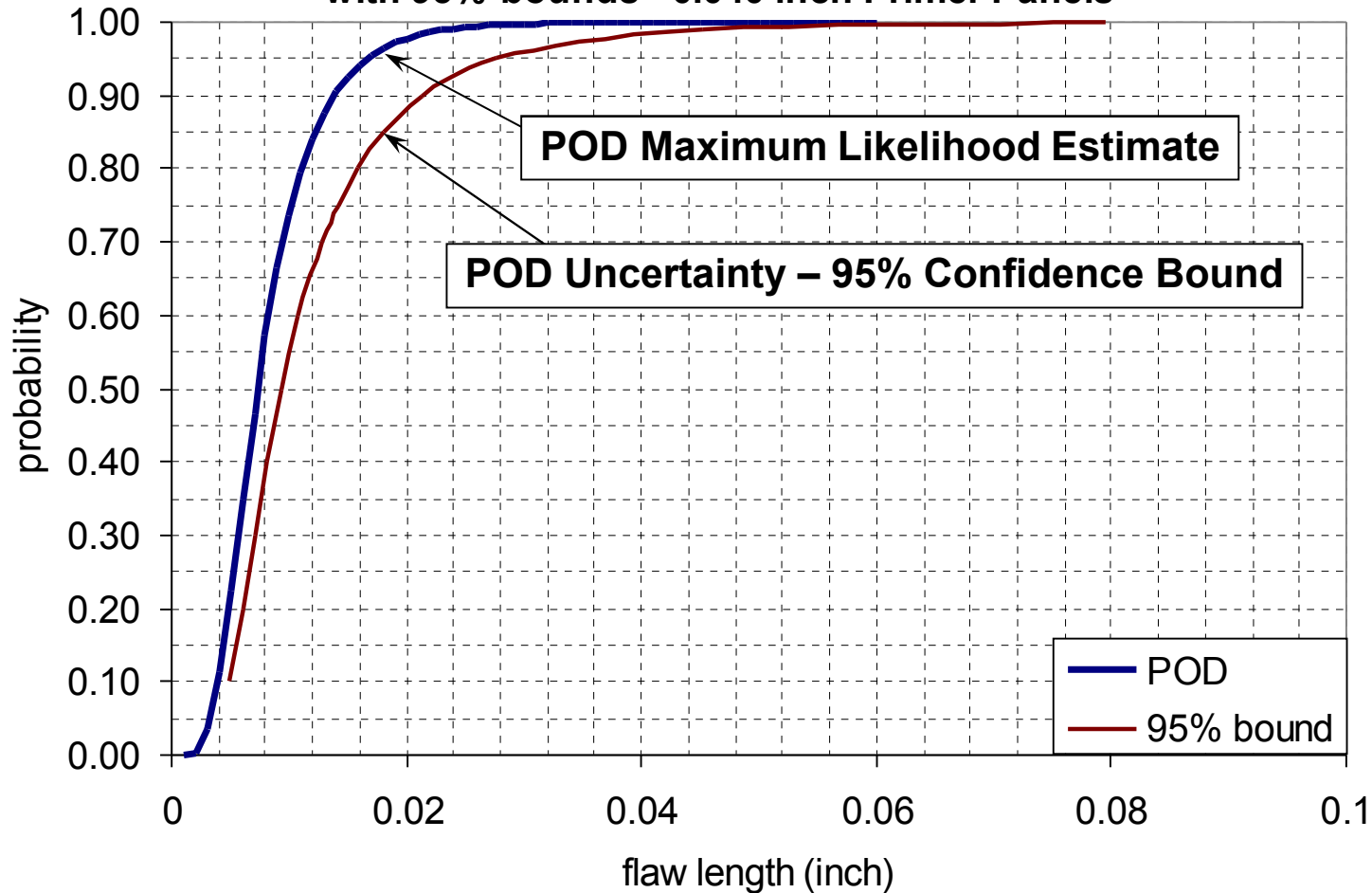
| Detection level ($1 - \alpha$) | $K_{n,0.95,\alpha}$ | | $\bar{X} + K_{n,0.95,\alpha} \cdot S$ (log scale) | | Flaw size in inches | |
|-------------------------------------|---------------------|--------|--|--------|---------------------|--------|
| | bare | primer | bare | primer | bare | primer |
| 0.75 | 1.366 | 1.465 | -1.598 | -1.834 | 0.025 | 0.015 |
| 0.90 | 2.210 | 2.355 | -1.253 | -1.631 | 0.056 | 0.023 |
| 0.95 | 2.736 | 2.911 | -1.038 | -1.504 | 0.092 | 0.031 |
| 0.99 | 3.747 | 3.981 | -0.624 | -1.260 | 0.237 | 0.055 |
| 0.999 | 4.900 | 5.203 | -0.153 | -0.981 | 0.703 | 0.104 |

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

It is possible to calculate a one sided tolerance bound for various percentile flaw sizes - 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

Sample Probability of Detection Curves for CVM

Cumulative Distribution Function Detectable Flaw Lengths -
with 95% bounds - 0.040 inch Primer Panels



CVM Sensor Network Applied to 737 Wing Box Fittings

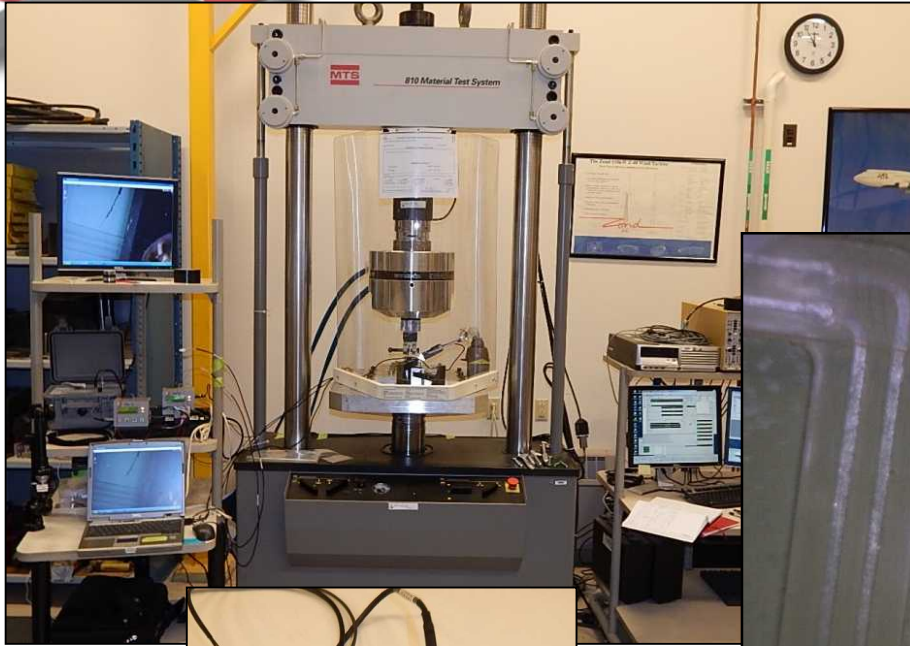
Alternate Means of
Compliance with Current
Visual Inspection Practice



FAA William J. Hughes
Technical Center

 Sandia
National
Laboratories

737NG Center Wing Box – CVM Performance Tests



FAA William J. Hughes
Technical Center



POD Calculations - One-Sided Tolerance Interval

POD Determined from CVM Response Data on Wing Box Fitting

CVM Crack Detection Data

| Eddy Current Crack Length at CVM (In) | Log of Crack Length at CVM Detection a (In) |
|---------------------------------------|---|
| 0.215 | -0.66756154 |
| 0.193 | -0.714442691 |
| 0.193 | -0.714442691 |
| 0.205 | -0.688246139 |
| 0.200 | -0.698970004 |
| 0.243 | -0.614393726 |
| 0.180 | -0.744727495 |
| 0.205 | -0.688246139 |
| 0.238 | -0.623423043 |
| 0.240 | -0.619788758 |
| 0.258 | -0.588380294 |
| 0.218 | -0.661543506 |
| 0.178 | -0.749579998 |
| 0.175 | -0.756961951 |
| 0.220 | -0.657577319 |
| 0.198 | -0.70333481 |
| 0.208 | -0.681936665 |
| 0.193 | -0.714442691 |
| 0.235 | -0.628932138 |
| 0.183 | -0.73754891 |

Statistic Estimates on Log Scale

| Statistic | Value in Log Scale | Value in Linear Scale |
|-------------------|--------------------|-----------------------|
| Mean (X) | -0.682724025 | 0.209 |
| Std Deviation (S) | 0.049124663 | 0.023962471 |

POD Detection Levels ($\gamma = 95\%$, $n = 20$)

Flaw Size: POD = X + K(S) 0.258160667



737NG Center Wing Box – Accumulating Successful Flight History



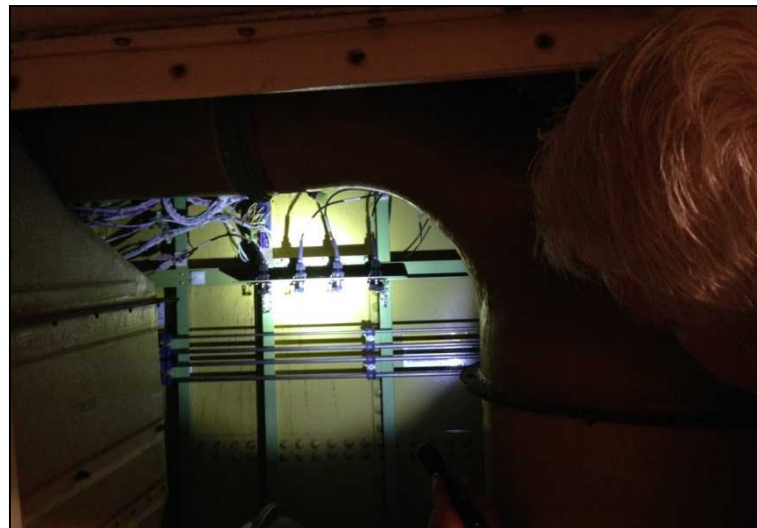
Aircraft Parked at Gate After Final Flight of the Day



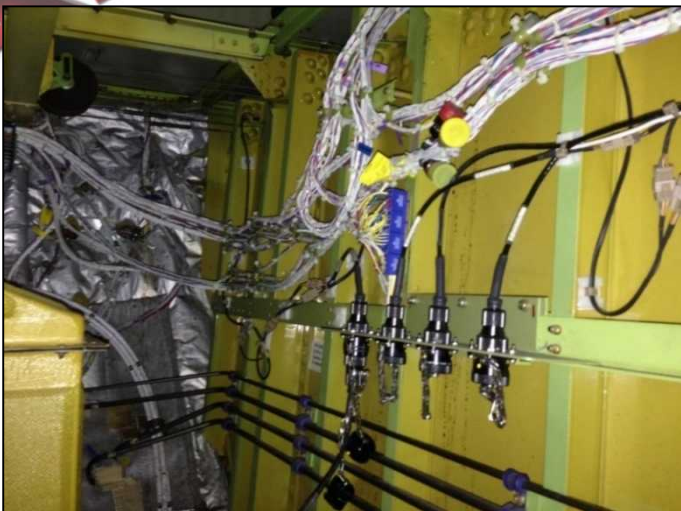
Access to SLS Connectors Through Forward Baggage Compartment



Removal of Baggage Liner to Access 4 SLS Connectors Mounted to Bulkhead



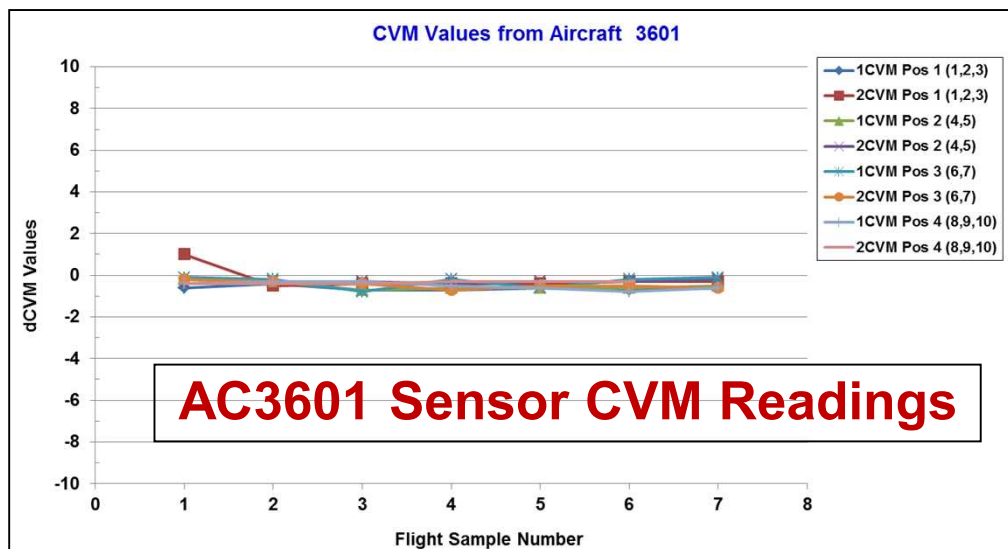
737NG Center Wing Box – CVM Sensor Monitoring



Connecting SLS Leads and Running PM-200 to Monitoring Device to Check Sensor Network



Logging Inspection Completion at Aircraft Gate

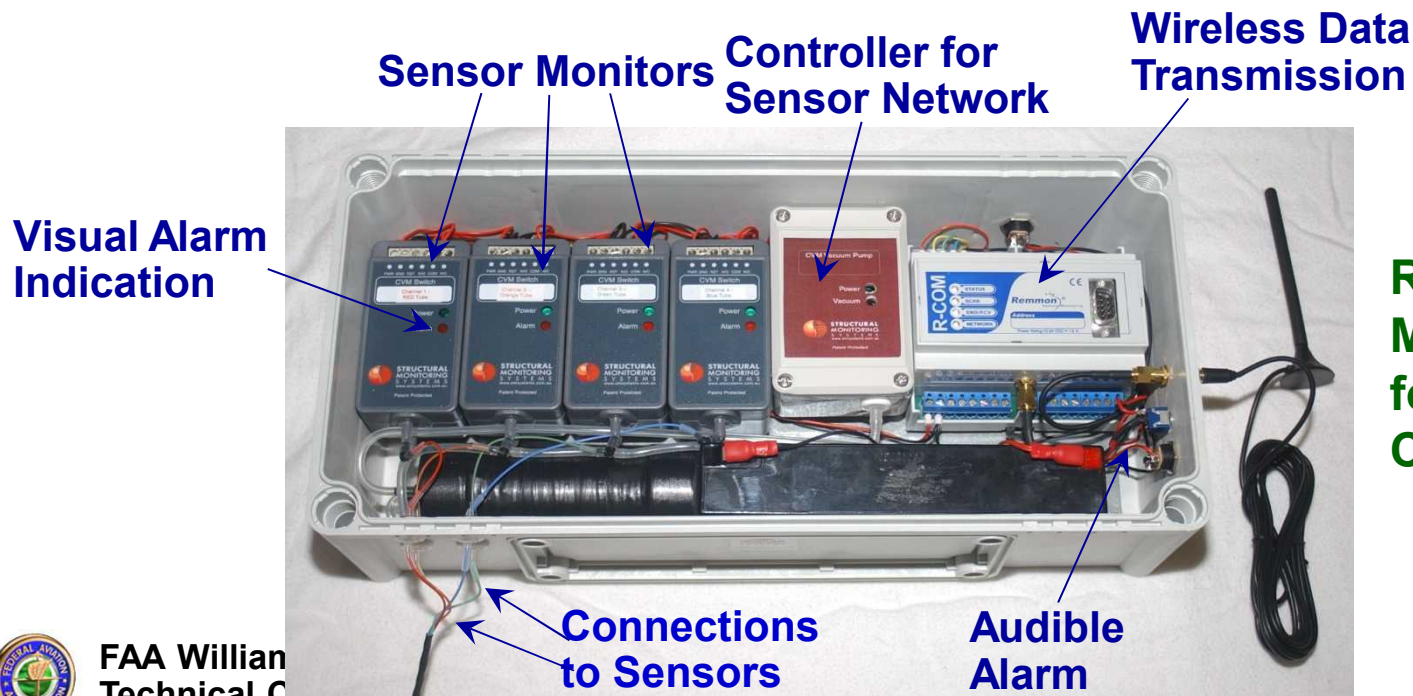
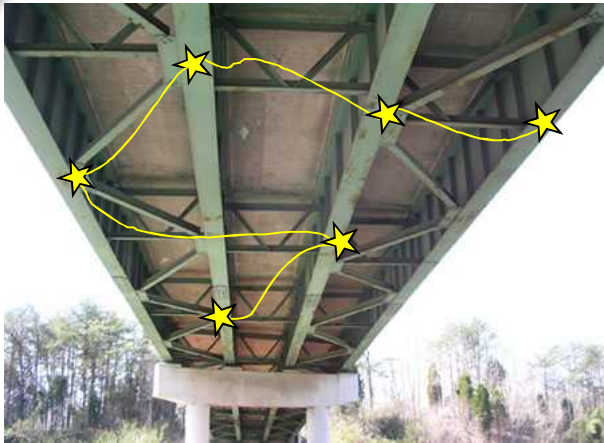


Syncrude Equipment Repair Applications

- Oil sand mining operation followed by mechanical and chemical processing to produce crude oil (260,000 barrels/day)
- Extreme fatigue, temperature, erosive, corrosive environments induce equipment damage
- Shutdowns to repair equipment can cost \$1M per day
- **CVM POD on thick steel structures = 0.5"**



Real-Time Structural Health Monitoring Using Distributed CVM Sensor Networks



Real-Time, Remote
Monitoring System
for a Network of
CVM Sensors



FAA William
Technical Center





Validation of CVM Sensors for SHM Crack Detection

- **Structural aging, combined with difficulties in monitoring widely-spaced infrastructure, produces a significant safety concern**
- **Real-time SHM systems can address these concerns by automating rapid, frequent structural assessments**
- **Early damage detection = less costly repairs**
- **CVM sensor detects cracks in the component it is adhered to – automated, remote diagnosis of a structure to avoid failure**
- **CVM sensors have been proven - multi-year lab performance assessment (sensitivity/POD and durability) & flight test programs have been completed**
- **Multiple successful aircraft applications - SHM Chapter in Boeing NDT Manual, Boeing Service Bulletin**
- **Proof-of-concept was successful on a thick, steel-member bridge and mining equipment**
- **Sensor networks can produce global SHM to assess performance of large structures**



Automated Health Monitoring of Rail Cars and Railroad Bridges Using Embedded Sensors

