

# **Best Practices for Evaluating the Capability of Nondestructive Evaluation (NDE) and Structural Health Monitoring (SHM) Techniques for Damage Characterization**

**John C. Aldrin**

Computational Tools

**Charles Annis**

Statistical Engineering

**Eric Lindgren**

Air Force Research Laboratory

**Harold Sabbagh**

Victor Technologies

**Review of Progress in QNDE,  
Minneapolis, MN – July 27, 2015**

# Overview of Talk

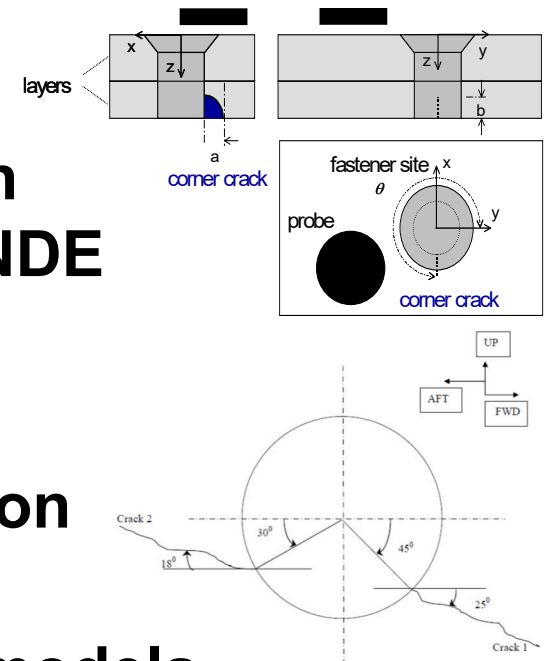
---

- **Process for evaluating NDE ‘sizing’ capability**
- **Emphasize *understanding assumptions* in evaluation**
  
- **Challenges with SHM Capability Evaluation**
- **Best Practices from Demonstration Study**
- **Opportunities for Models in Evaluation (MAPOD)**

# Drivers for Damage Characterization in Aircraft Structures

## Opportunities for Accurate Characterization Techniques:

- Need for *small crack size 'binning'*
  - Better guide *maintenance actions*
- Fatigue crack parametric characterization (sizing, localization) using eddy current NDE
  - Significant opportunity for support of *condition-based maintenance (CBM)*
- Complete crack characterization evaluation (*multiple cracks at single site*)
  - Provide better data for life prediction models
  - Supports *digital twin* concept



**Validation Procedures are Needed to Ensure Accurate Characterization and Localization Techniques**

# Quality Metrics for Damage Localization / Characterization

---

## Review of Evaluation Methods (Metrics) for Characterization:

- 1) Statistics Community:

- A) Measurement System Analysis (MSA), ANOVA Gauge R&R (Repeatability and Reproducibility)

- ASTM E2782 - Standard Guide for Measurement Systems Analysis
- NIST: Guide to the Expression of Uncertainty in Measurement

$y = f(x_1, x_2, \dots, x_n)$  where:  $y$ : measurement

$$\sigma_y \approx \sqrt{\sum_{i=1}^n \left( \frac{\partial f}{\partial x_i} \sigma_{x_i} \right)^2}$$

$f$ : measurement model

$x$ : uncertainty components ( $n$ )

- Brown, J., ASNT Fall Conference, 2011

- **Issues:**

- **Conventional analysis approaches (ANOVA) don't naturally address complex models with multiple parameters**
- **Uncertainty propagation often assume 'independent parameters'; They typically do not address joint probability (covariance)**
- **Need to address aleatory and epistemic uncertainty in evaluation**
- **These approaches are solely dependent upon raw data.**

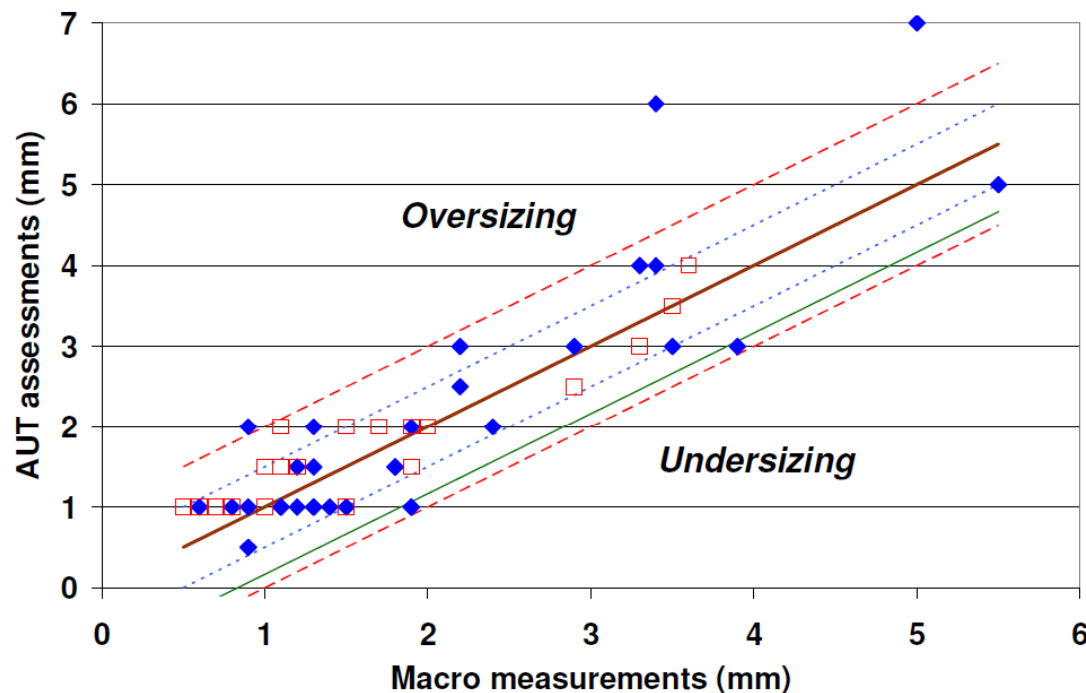
# 1. Capability Evaluation and Metrics for Damage Localization / Characterization

## Review of Evaluation Methods (Metrics) for Characterization:

- 1) 'Statistics' Community:

- 95% Limit Against Undersizing:

$$H_{95} = Average(H_i) - 1.64 * RMS(H_i)$$



Nordtest. 1998. *Guidelines for NDE Reliability and Descriptions*, NT Techn Report 394. 1998.

\* Figure from: Ducharme et al., "Automated ultrasonic phased array inspection of fatigue sensitive riser girth welds with a weld overlay layer of corrosive resistant alloy (CRA)" (2012).

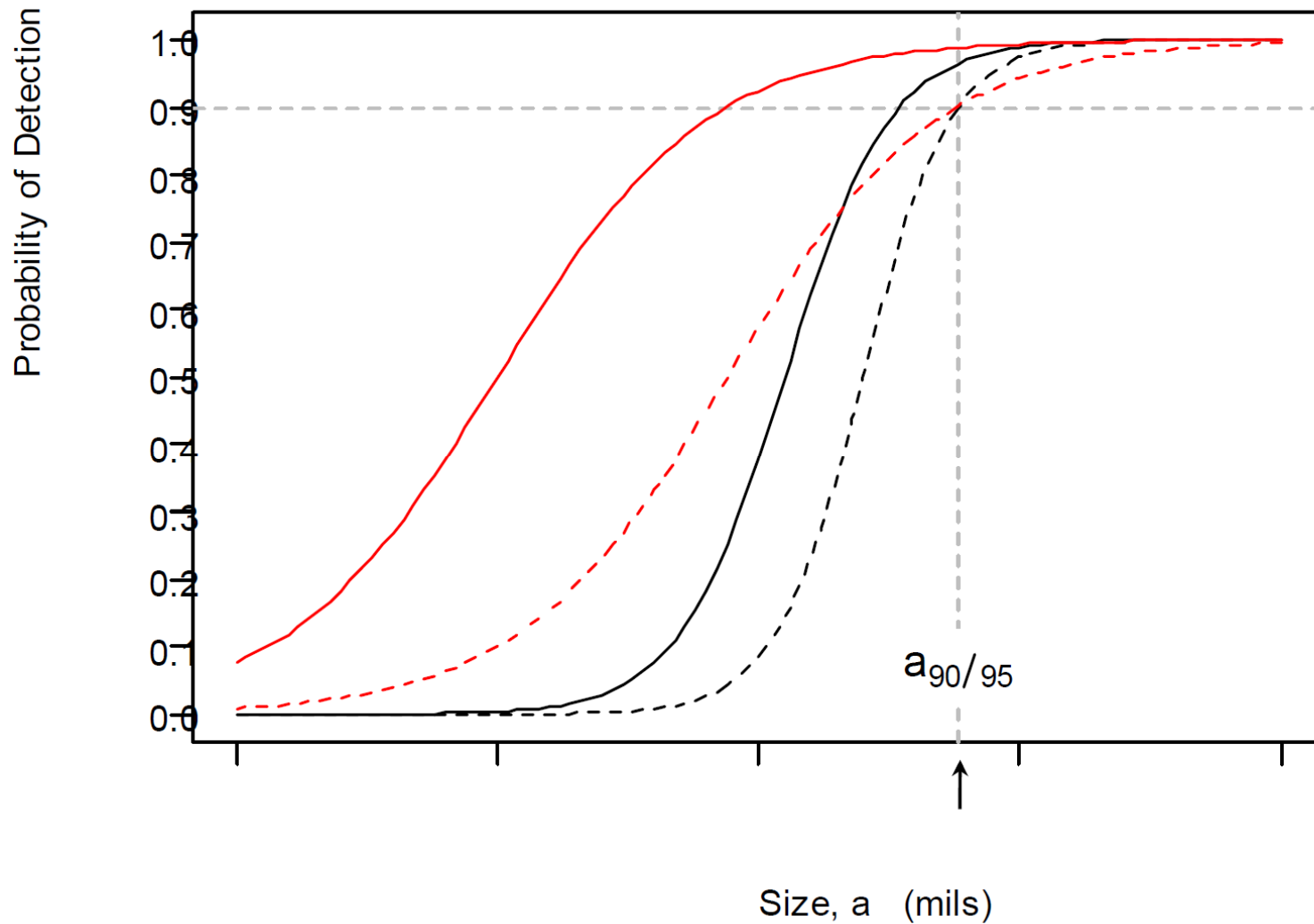
Figure 5: Comparison between AUT assessments and DT measurements

( — Ideal sizing; - - - +/- 0.5 mm; - - - +/- 1 mm; — Safety limit against undersizing; □ Surface flaw scatter; ◆ Embedded flaw scatter)

\* [http://www.ndt.net/article/ndtnet/2012/1\\_Ducharme.pdf](http://www.ndt.net/article/ndtnet/2012/1_Ducharme.pdf)

# Why a single number summary, $a_{90/95}$ , is an incomplete NDE summary [Annis]

---



# Quality Metrics for Damage Localization / Characterization

---

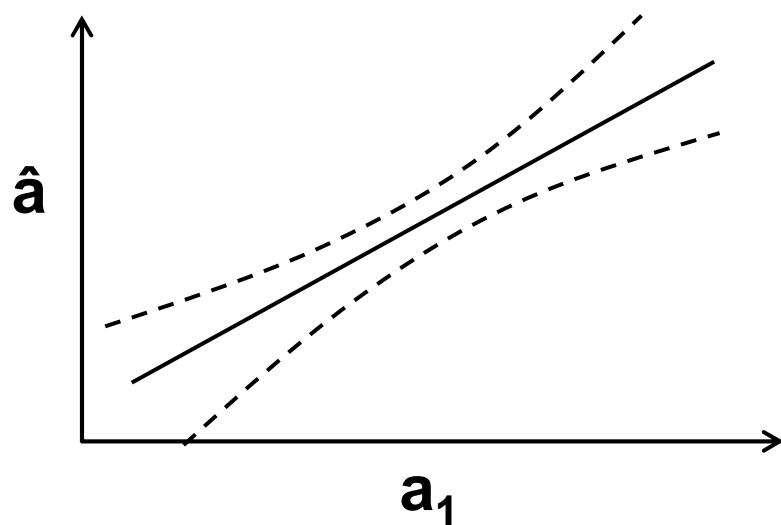
## Review of Evaluation Methods (Metrics) for Characterization:

- 2) Parameter Estimation / Inversion Community:
  - Estimation Metrics (e.g. CRLB)
  - Knopp et al, 2008, “Estimation Theory Metrics in Electromagnetic NDE”
    - **Issue: These metrics are often purely model-based. Do not naturally address parameters/conditions not well-defined by models.**
- 3) Uncertainty Quantification Community (Models, MAPOD)
  - Verification & Validation (Emphasis on Scientific Computing)
  - Stochastic Numerical Methods (e.g. Polynomial Chaos)
  - Bayesian Calibration
  - SIAM – UQ12
  - Error Estimate with Uncertainty Bounds
    - **Challenge: Quality metric is an evaluation of error with *uncertainty bounds* given the full application context (experiment + simulation)**
- 4) Foundations for Quality Metrics for NDE/SHM Characterization:
  - **Sensitivity Analysis in Inverse Methods [Aldrin et al, 2009]**
  - **MAPOD for SHM / Radiance Program [Aldrin et al, 2009-2011]**

# Compare NDE 'Ahat-vs-a' POD and NDE Characterization Error (CE) Evaluations

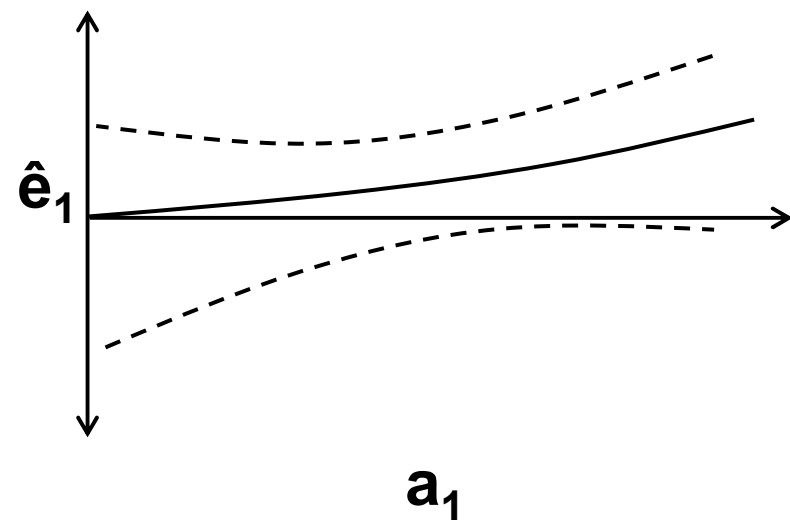
## Ahat-vs-A POD Analysis:

- Follow MIL-HDBK 1823A
- Perform evaluation studies
  - experimental measurements
  - *simulated* measurements
- Evaluate *model of measurement* ( $\hat{a}_j$ ) with respect to flaw size ( $a_k$ )
  - *mean* model
  - *confidence* (uncert.) bounds



## Characterization Error Analysis:

- Build on Protocol for NDE/SHM
- Perform evaluation studies
  - experimental *sizing results*
  - *simulated sizing results*
- Evaluate *characterization error* ( $\hat{e}_j$ ) with respect to flaw size ( $a_k$ )
  - *error* model ( $\hat{e}_j = \hat{a}_j - a_j$ )
  - uncertainty bounds





# Compare NDE 'Ahat-vs-a' POD and NDE Characterization Error (CE) Evaluations

## Ahat-vs-A POD Analysis:

- Follow MIL-HDBK 1823A
- Perform evaluation studies
  - experimental measurements
  - *simulated* measurements
- Evaluate *model of measurement* ( $\hat{a}_j$ ) with respect to flaw size ( $a_k$ )
  - *mean* model
  - *confidence* (uncert.) bounds

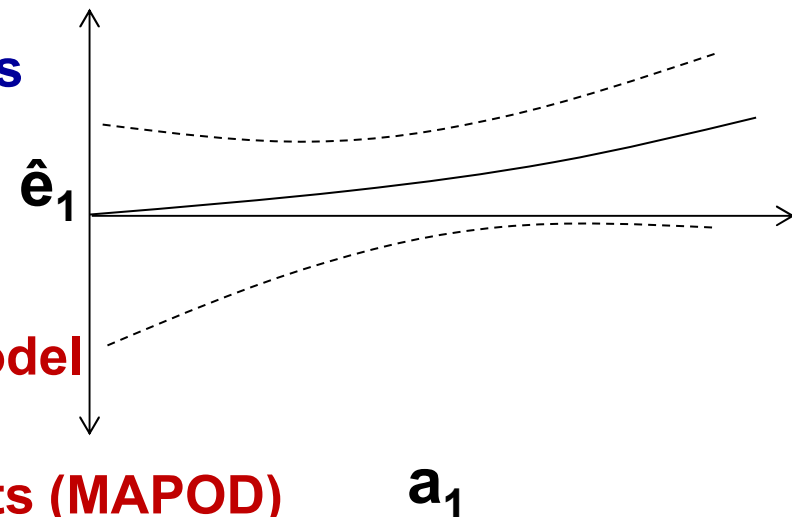
## Characterization Error Analysis:

- Build on Protocol for NDE/SHM
- Perform evaluation studies
  - experimental sizing results
  - *simulated* sizing results
- Evaluate *characterization error* ( $\hat{e}_j$ ) with respect to flaw size ( $a_k$ )
  - *error* model ( $\hat{e}_j = \hat{a}_j - a_j$ )
  - uncertainty bounds

Characterization Error (CE) Evaluation is Similar to Ahat-vs-A POD Assessment

## Differences:

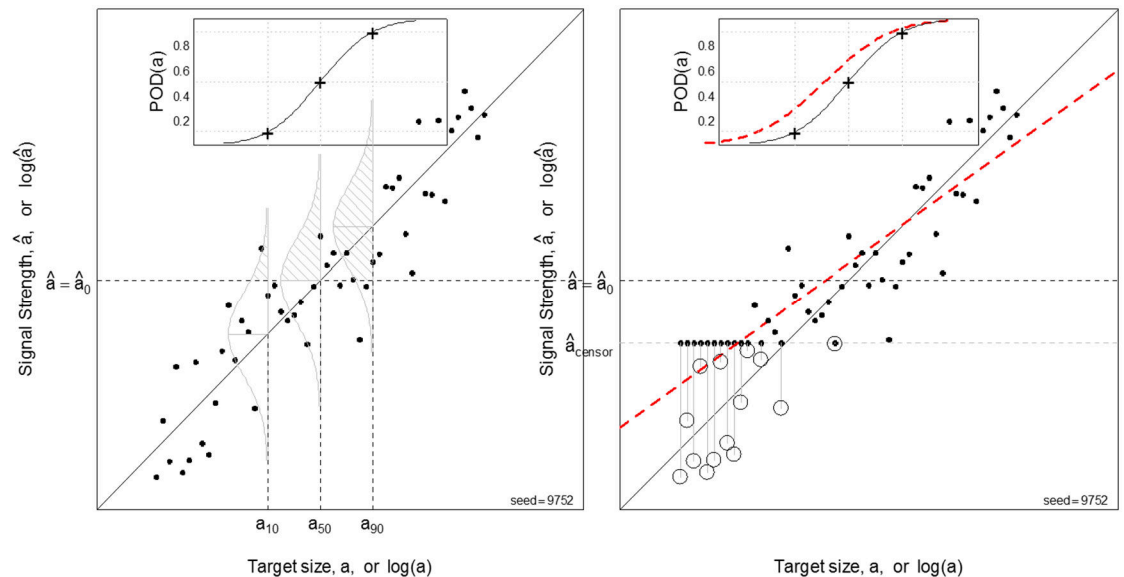
- **Complex multi-dimensional error model**
- ***Simulating 'characterization' more complicated than NDE measurements (MAPOD)***



# What's Missing in NDE Capabiltiy Evaluation? [Annis et al., Mat Eval. 2015]

Understand implicit statistical assumptions in regression analysis:

1. *The model must look like the data!*
2. The response must be continuous and observable.
3. The model must be linear in the parameters.
4. The variance must be homoscedastic (uniform variance)
5. The observations must be uncorrelated:
  - with respect to time
  - with respect to space
6. The errors must be Normal



Replacing censored values with the censoring value  
skews the result anticonservatively.

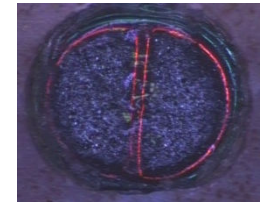
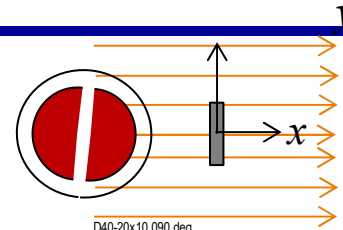
**If assumptions are not met, you need to pick a different 'correct' model!**

*“Simply not understanding the nature of the assumptions being made does not mean that they do not exist.” Frank et al (1993).*

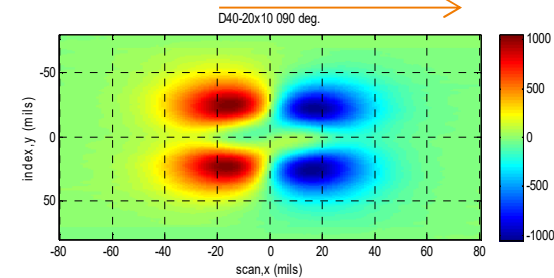
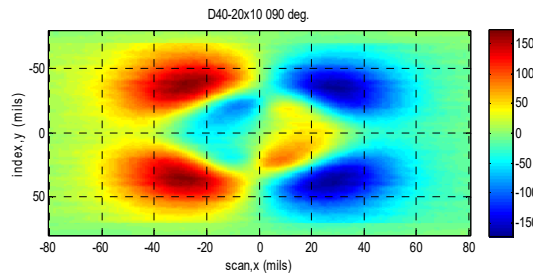
# Case Study - Model-based Inversion of EM Signals for Crack Characterization [Shell et al., QNDE 2014]

Parameters:

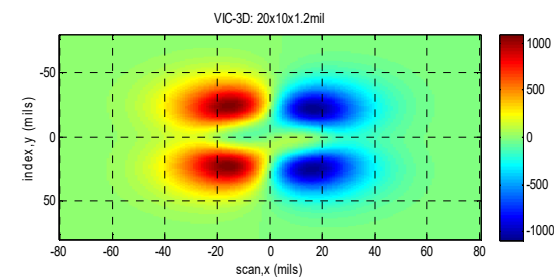
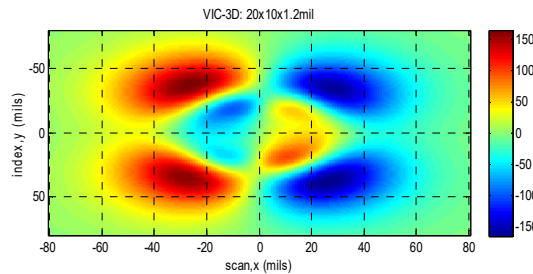
20x10x1.2 mil notch, D40 Probe, Tangential (90°) Orientation: 5°



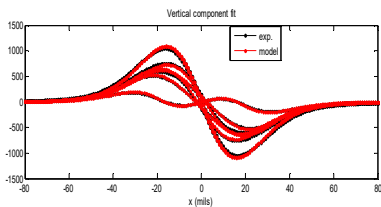
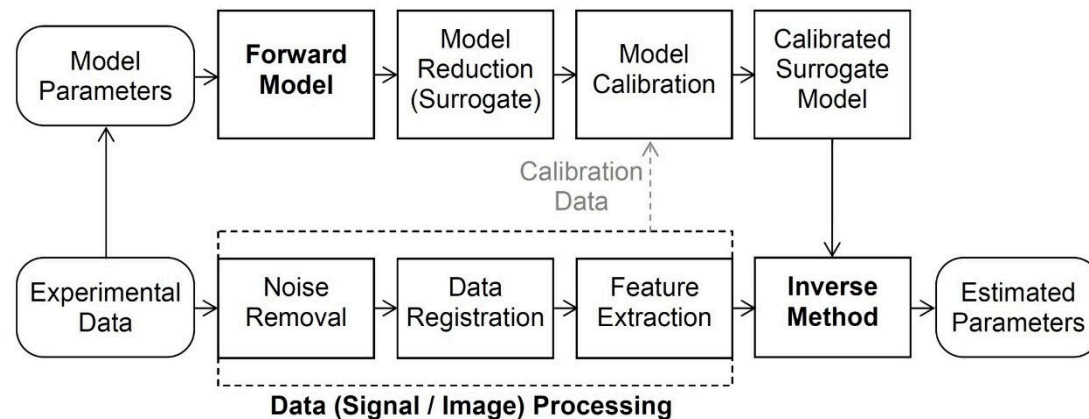
Experimental Data (Wyle):



Model (VIC-3D<sup>©</sup>):



Inversion Process:



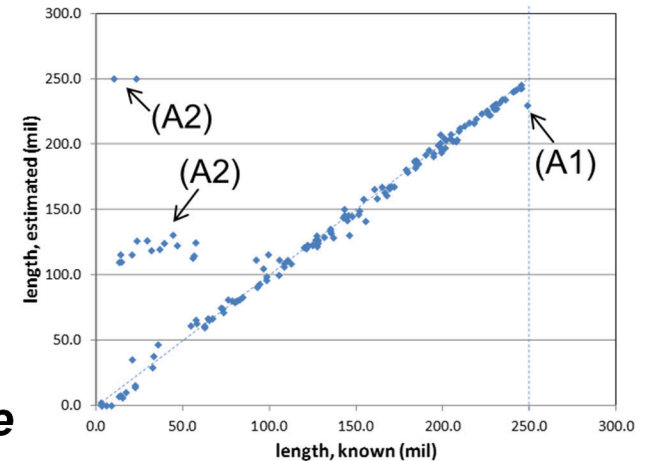
Characterization Case Study:

- (a) crack length,
- (b) crack depth,
- (c) crack width,
- (d) crack angle.

# Developing Characterization Error Models for Inversion Performance [QNDE 2013]

## Group Characterization Error Samples into Unique Data Classes:

1. P(good classification: with some error)
  - associated with linear  $\hat{a}$ -vs- $a$  model
2. P(poor classification: due to weak signals)
  - correlated with *small flaw geometry*
  - associated with left 'censoring' in POD
3. P(poor classification: due to saturated signals)
  - poor classification, *signals smaller than true value*
  - associated with right 'censoring' in POD
4. P(poor classification: conditions exceed inversion parameter constraint(s))
  - observed as '*clusters*' at specific parameter estimate plane bounds
  - analogous with 'censoring' in POD
5. P(poor classification: problem ill-posed / solution stuck in local minima)
  - *secondary 'clusters' in error plane*
  - need for more complex POD models (mixture models, higher order)
6. P(poor classification: due to poor NDE technique )
  - complete failure in sizing procedure
  - result *independent of flaw parameters*
  - associated with 'random missed call rate' in POD



# Developing Characterization Error Models for Inversion Performance [QNDE 2014]

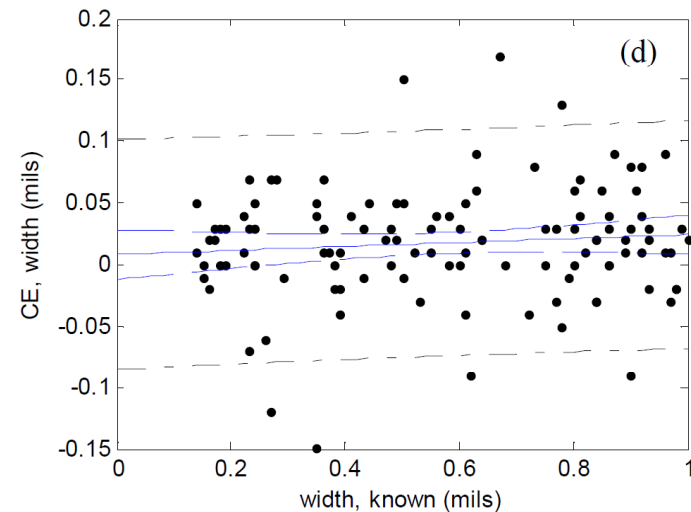
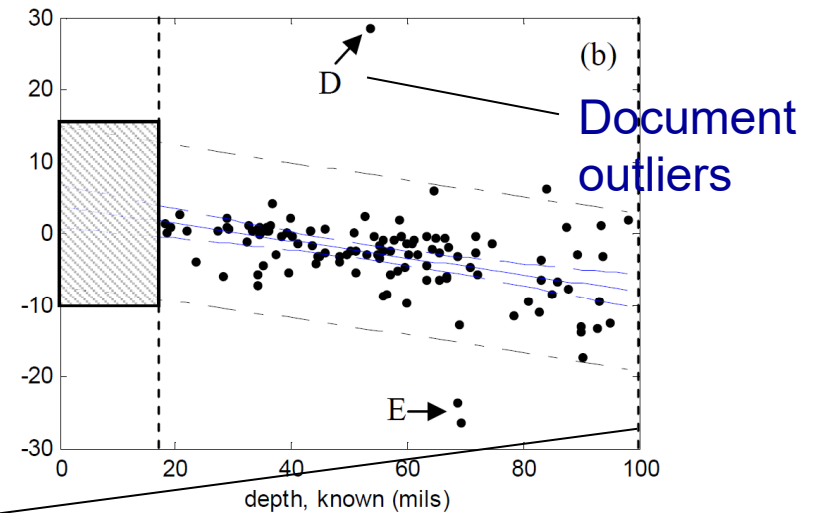
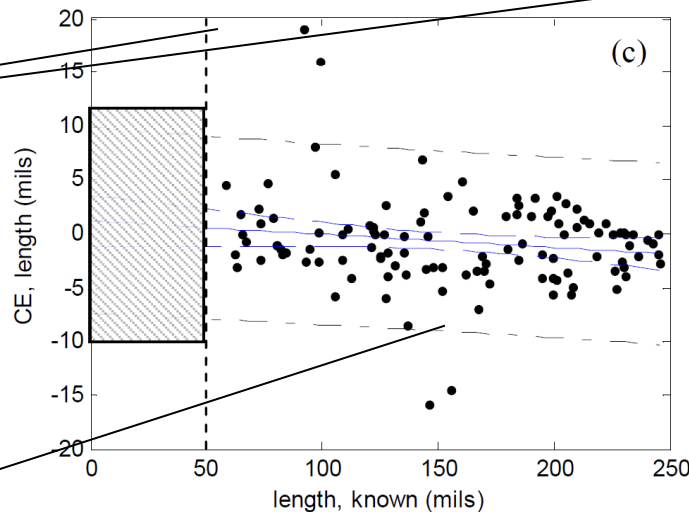
## A. Leverage Insight from POD Evaluation in Characterization Error Model Building:

- Censoring / constraints
- Interactions and mixture models
- Random missed classifications

## B. Critical to Check Assumptions in Characterization (Statistical) Model

Define clear limits of error model fits

Consider confidence and prediction bound in fit



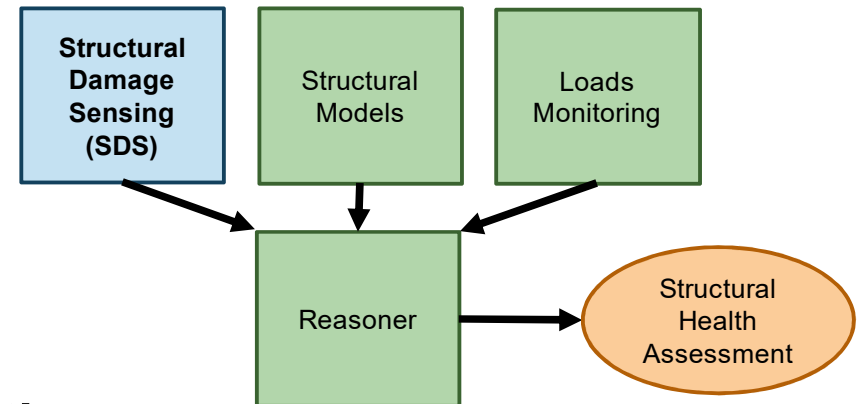
**FIGURE 4.** (a) RMS of characterization error for three crack dimensions with respect to varying estimated cross-sectional area of crack. Characterization error for censored inversion results for (b) crack depth, (c) crack length and (d) crack width. Plots include a linear model fit (solid line) with confidence bounds (dashed line) and corresponding prediction bounds (dash-dot line).



# Verification and Validation of Structural Damage Sensing Systems



- **Structural Damage Sensing is a component of SHM**
- **SDS System Certification requires Qualification Testing that includes Capability (Reliability) Validation**
- **SDS System Verification and Validation:**
  - **Verification:** Demonstrate design requirements under *controlled conditions* (laboratory environment)
  - **Validation:** Demonstrate design requirements with *representative operational environment and user*
- **Required capability depends on expected application**
- **Validating SDS capability is a requirement for use of SHM in USAF structures managed via Aircraft Structural Integrity Programs (ASIP)**





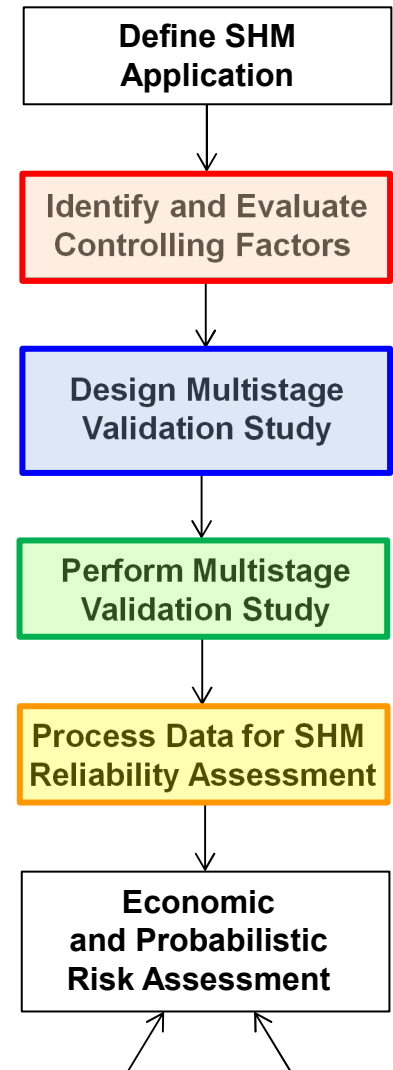
# Probabilistic Reliability Assessment for SDS Systems



## Protocol comprises:

- Procedure for analyzing all pertinent **characteristics** of the SDS system
  - Identify all **critical factors** that affect system performance
- **Multistage** approach for system validation
- Modeling and experimental methodology for efficiently addressing a **wide range** of damage and operational conditions
- Effective methods for evaluating **metrics** of capability and reliability depending on system type and function (***uncertainty propagation***)

## Primary Protocol





# Analyzing Pertinent Characteristics of an SDS System



## SDS System Characteristics

- **Type of Damage Sensing**
  - Direct / active, Passive, Indirect
- **SHM System Output**
  - Damage detection, localization, characterization
- **Coverage and Sensor Location**
  - Local, semi-global (sub-structure), or global
- **Measurement Type**
  - Eddy current, ultrasonic, vibration, pressure
- **Time of Data Acquisition (DAQ)**
  - During flight, select condition, on ground
- **Location of DAQ Hardware**
  - On the ground or onboard the aircraft

## SDS Maintenance and Process Controls

- **System Maturity** (input data for assessment)
- **Secondary Inspections and Maintenance** (combined POD / False call assessment)
- **SHM Process Controls**
  - Maintain calibration, detect sensor failure
  - Redundant sensors systems coverage
- **SHM System Maintenance**
  - Repair scheduled or unanticipated
- **SHM Failure Modes Effects Analysis**

## SDS Data Analysis

- **Data Classification Approach**
  - Human interpretation only (human factors)
  - Automated signal classification (software certification)

**Structure Characteristics**

**Damage Characteristics**

## Impact (on ASIP)

- **Criticality of the Damage State**
- **Credit Associated with SHM Application**
  - e.g. increase in maintenance cycle
- **Effect of Worst Case Occurrence** (should SHM application fail)



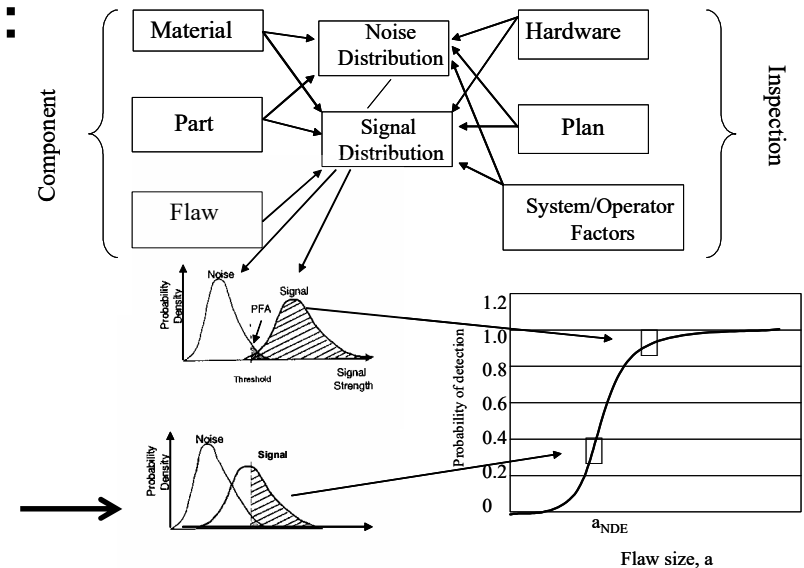


# Model Assisted Probability of Detection (MAPOD)



## Model Assisted POD (MAPOD) method:

- Uses models to *minimize* the need for empirical samples to evaluate POD and False Call (FC) rate
- Consensus protocol developed by international working group [2003-11]
  - Transfer function (XF) and full model-assisted [Thompson, 2001]
  - Protocol added to MIL-HDBK-1823A (2009), Appendix H. See also [www.cnde.iastate.edu/MAPOD/](http://www.cnde.iastate.edu/MAPOD/).
- Feasibility of approach demonstrated for a number of ultrasonic and eddy current inspection demonstrations:
  - MAPOD/WG Demonstrations [Forsyth, 2008]: XF and FMA<sup>1</sup> examples
  - PICASSO EU project: Several successful POD validation cases



1. J.C. Aldrin, J. S. Knopp, E. A. Lindgren, K. V. Jata, "Model-assisted Probability of Detection (MAPOD) Evaluation for Eddy Current Inspection of Fastener Sites", Review of Progress in QNDE, (to be published, 2009).

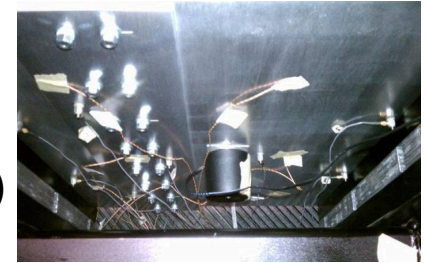


# Demonstration Study – Define SHM System



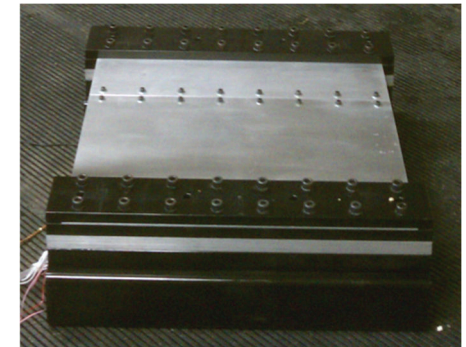
## SDS System Characteristics:

- **Type:** Direct damage detection using active sensing
- **SHM System Output:** Damage detection call
- **Coverage and Sensor Location:** Semi-global (sub-structure)
- **Measurement Type:** **Vibration (low frequency) response**
- **Time of Data Acquisition (DAQ):** While aircraft is on the ground
  - **Vary temperature (gradients), loading/unloading, boundary cond., fastener torques**
- **Location of DAQ Hardware:** Onboard the aircraft



## Structure Characteristics: **Include joints in test article**

- **Center joint with sites for simulating damage growth**
- End conditions with optional shims (to change boundary)



## Damage Characteristics:

- **Damage Types (Failure Conditions) to Detect:** **(Large) fatigue cracks**
  - **Approximate crack growth by cutting notches**
  - **Fastener removal necessary for growing flaw (*must maintain equal torque, verify damage metric change not due to changes in boundary conditions*)**

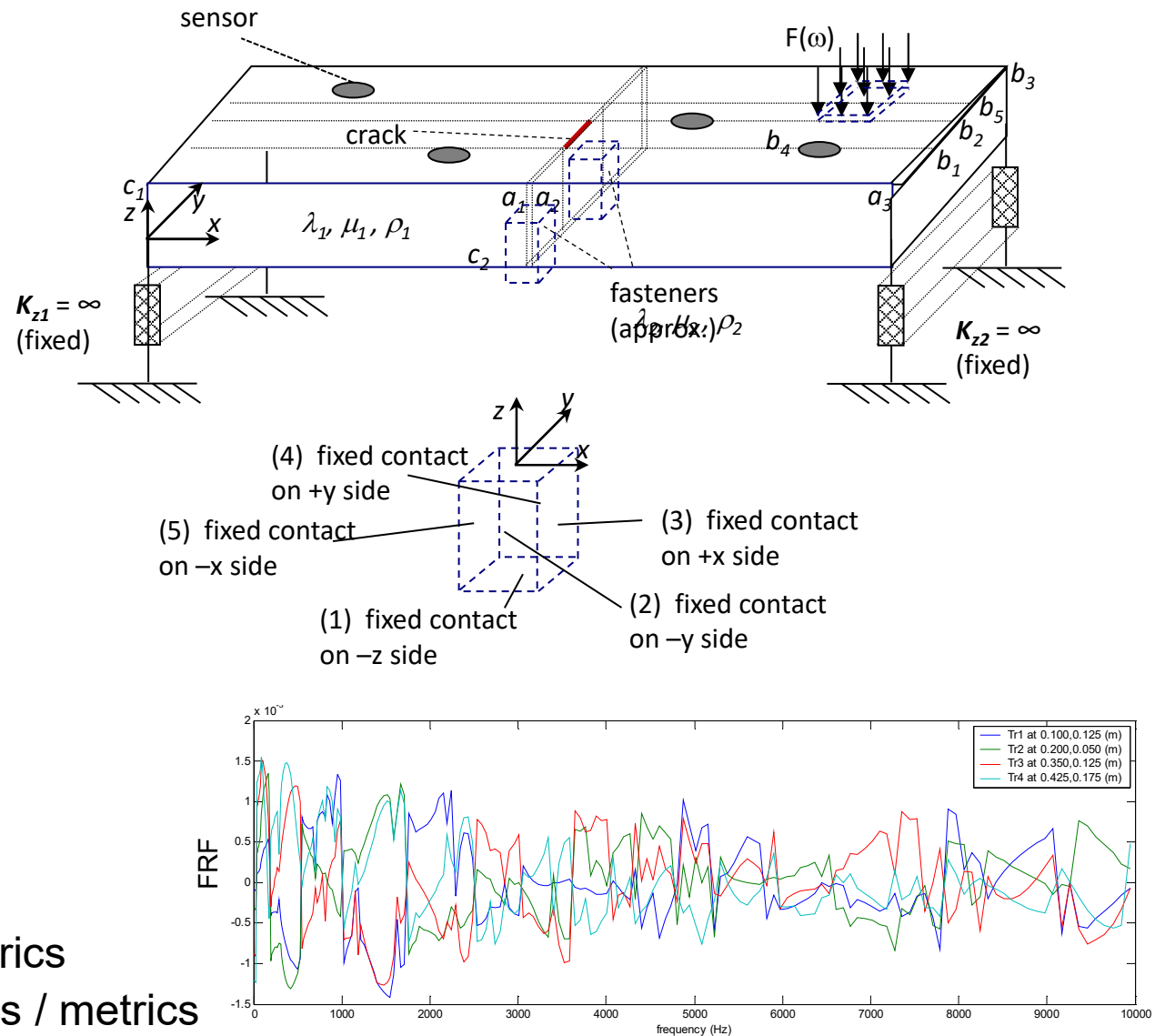


# Simulated Sensitivity Analysis for Representative Low Frequency Global Vibration-based Damage Sensing



## Parametric Study

- Frequency
- Source Excitation
  - location
  - orientation
  - distribution
- Sensor(s)
  - location
  - orientation
  - measurements
- Crack (notch) length
- Temperature (elastic property variation)
- Boundary conditions
  - Fastener stiffness
  - Fastener contact
  - End stiffness
- Detection algorithms / metrics
- Characterization algorithms / metrics





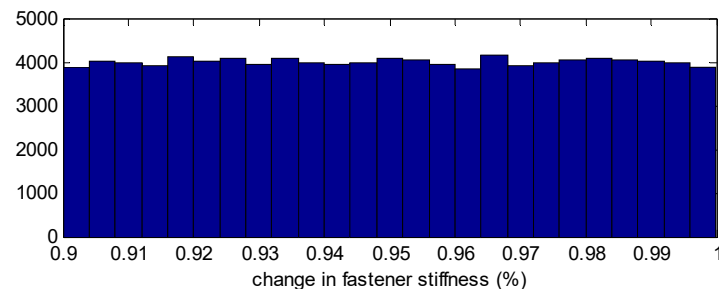
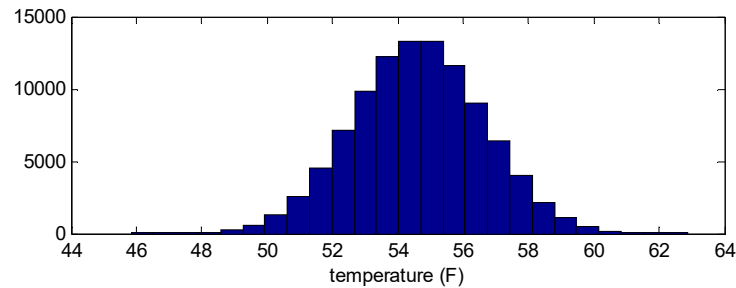
# Simulated Sensitivity Analysis for Representative Low Frequency Global Vibration-based Damage Sensing



**Determine Output Variance on Damage Measures (POD)  
Given Uncontrolled Environmental Variables and Uncertainty**

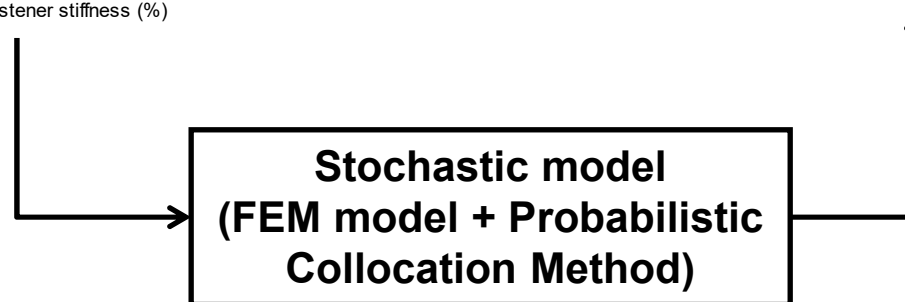
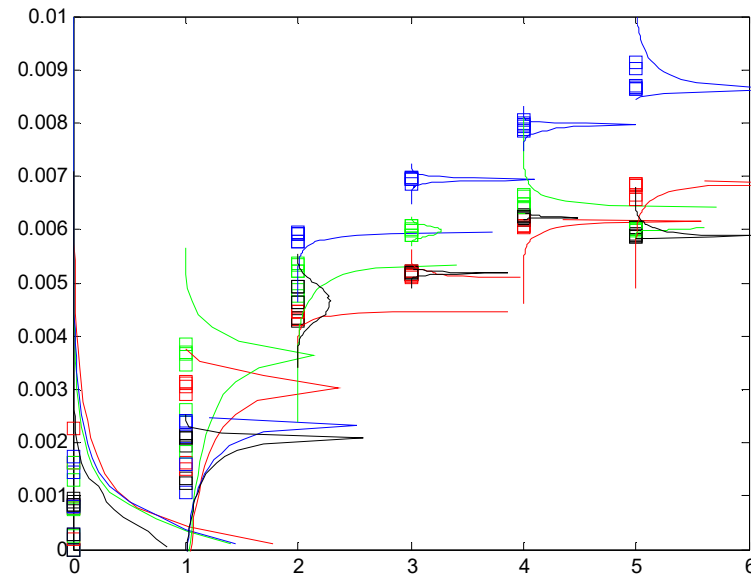
## Input Parameters with Variation

- Temperature : (elastic property variation)
- Boundary condition: Fastener stiffness



## Output Results

- Damage metric 'distributions' as a function of transducer location and crack length





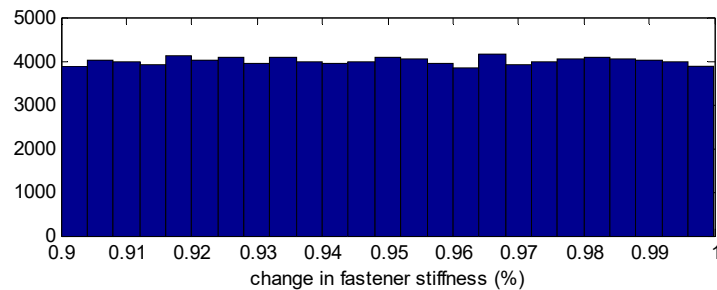
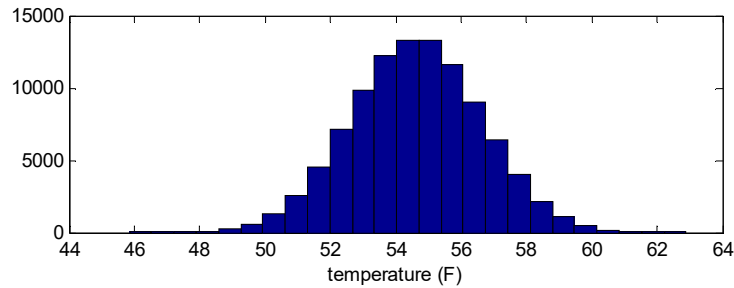
# Simulated Sensitivity Analysis for Representative Low Frequency Global Vibration-based Damage Sensing



Determine Output Variance on Damage Measures (POD)  
Given Uncontrolled Environmental Variables and Uncertainty

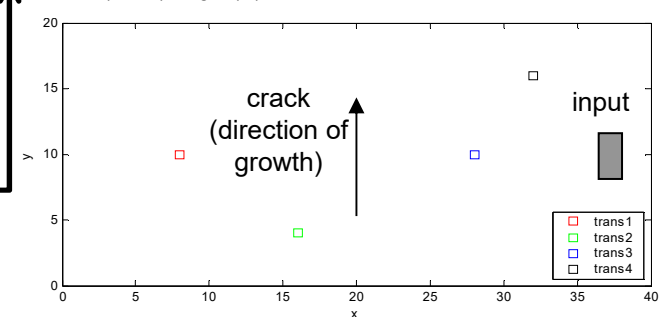
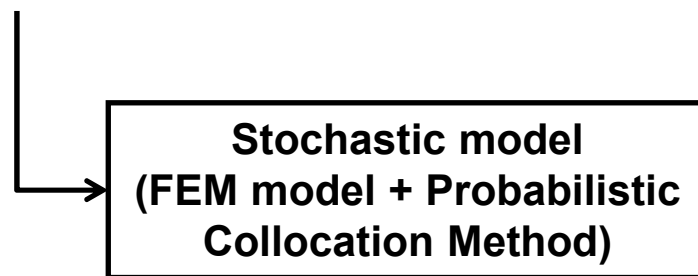
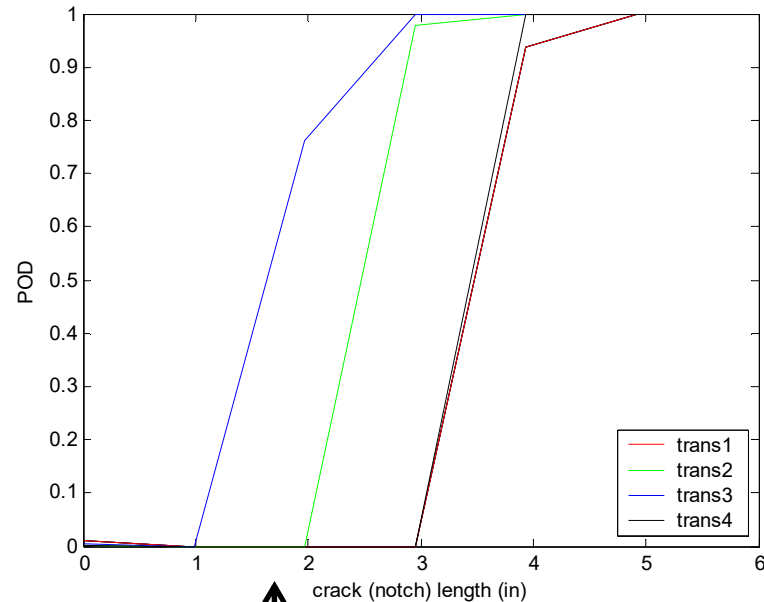
## Input Parameters with Variation

- Temperature : (elastic property variation)
- Boundary condition: Fastener stiffness



## Output Results

- POD for varying transducer location and crack length





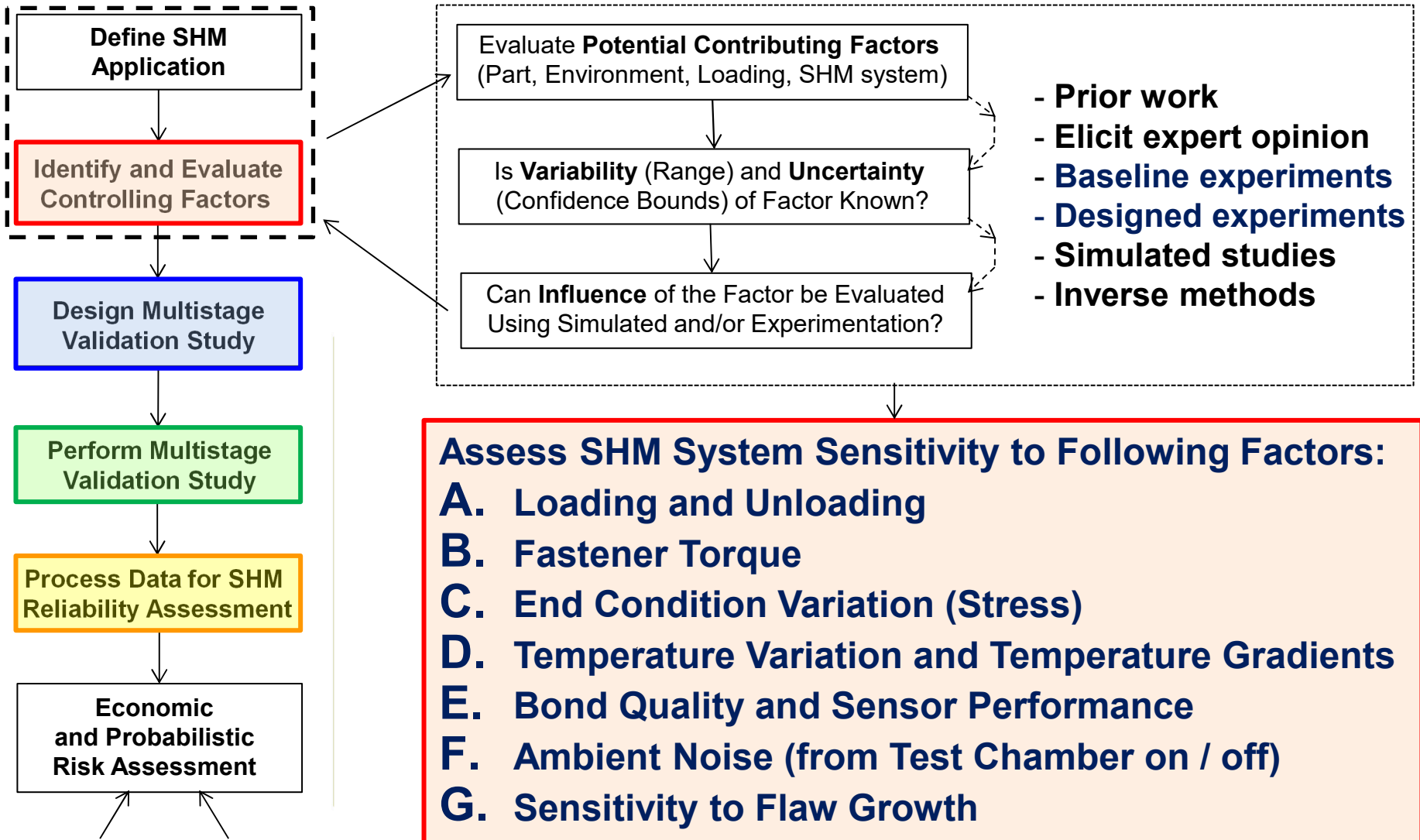
# Demonstration Study – Identify and Evaluate Controlling Factors



## Primary Protocol

## Sub-tasks

## Approaches





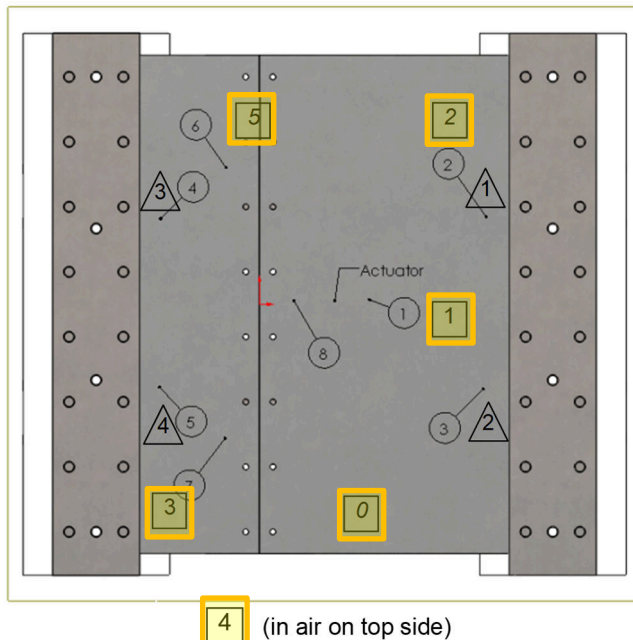
# Evaluate Controlling Factors – Temperature Variation and Gradients



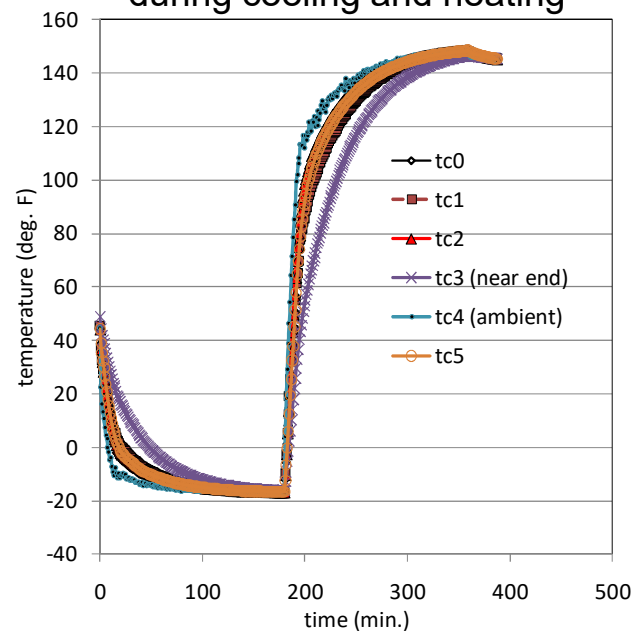
**Temperature Study:** Test article placed in Thermotron temperature chamber

- Temperature testing performed from  $-20^{\circ}\text{F}$  to  $150^{\circ}\text{F}$
- Temperature compensation algorithms are necessary for damage metric
- Significant temperature gradients also observed during study
  - Some gradients considered extreme ( $>45^{\circ}\text{F}$ ) due to end ‘thermal sinks’
  - Need to make estimate of expected gradients ‘in the field’ ( $10\text{-}20^{\circ}\text{F}$  ?)

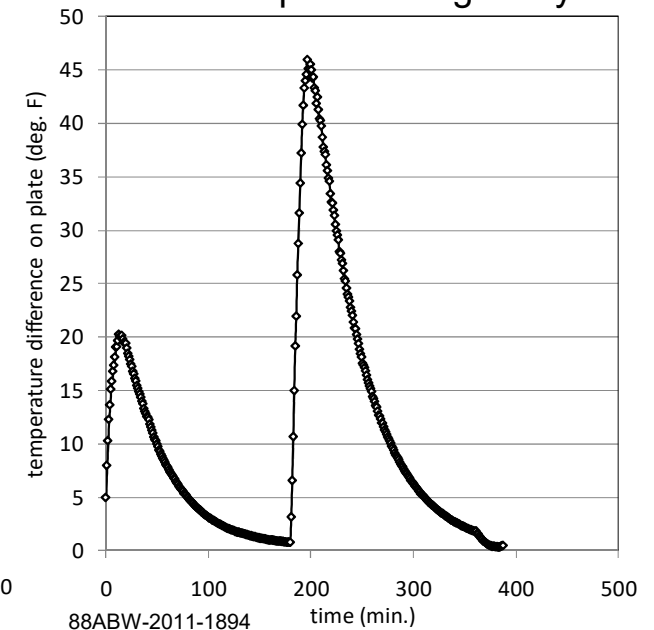
Thermocouple locations



Temperature response on plate during cooling and heating



Peak temperature difference across plate during study



88ABW-2011-1894

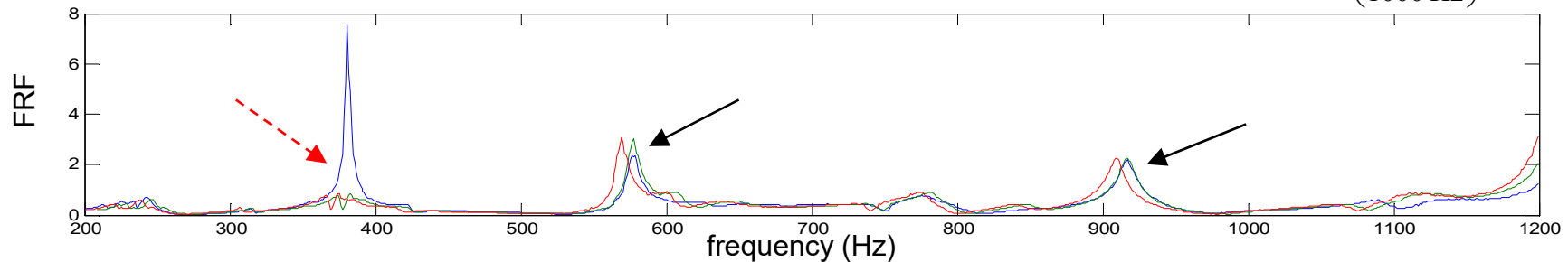


# Temperature Compensation Algorithm



**Issue 1:** Varying shift wrt frequency in FRFs with temperature changes

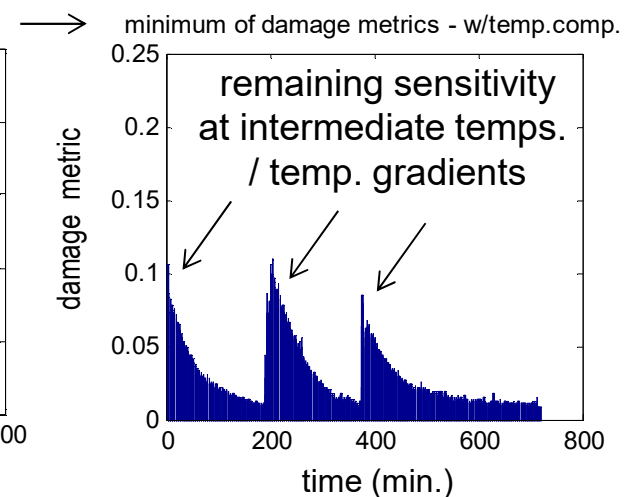
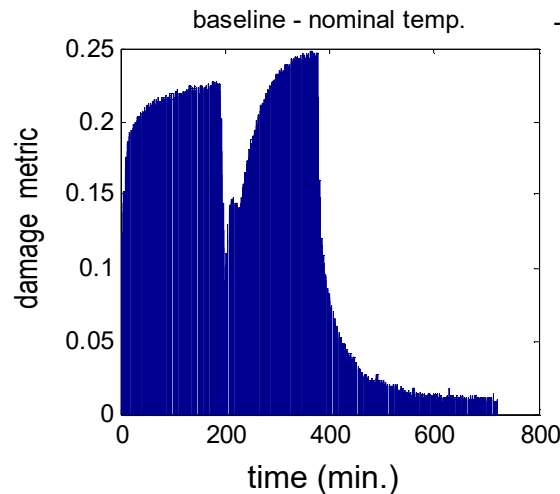
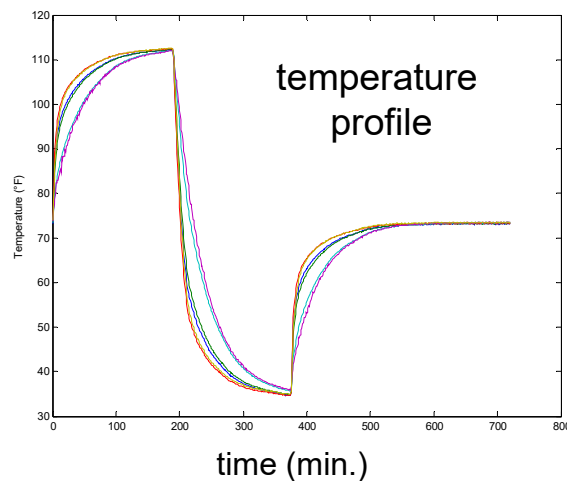
➤ **Fit nonlinear model** with bias and slope corrections:  $f_{new}(f) = f + \left(\frac{\phi_1}{1000 \text{ Hz}}\right)f + \phi_0$



**Issue 2:** Temperature variation also produces shape changes in FRFs

➤ **Use three references** (FRFs) addressing different temperature bands

**Study:** Vary Temperature - Up to 112°F, Down to 32°F, Return to 75°F





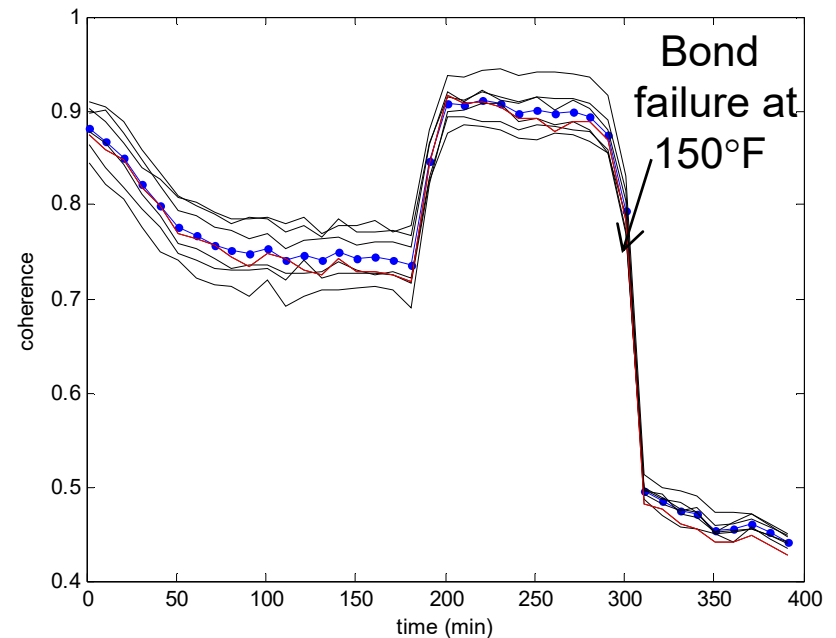


# Evaluate Controlling Factors – Bond Quality and Sensor Performance



## Observations:

- Several accelerometer bonds failed during temperature testing
- Failure was observed at prolonged exposure to 150°F
- Coherence measures can be used to track sensor failure (example below)
  - Differences were observed with sensor ‘in partial contact’ and ‘in air’
- One of the sensor failures was the reference accelerometer (#1)
- *Losing the reference sensor is especially detrimental to performance of vibration-based SDS system (FRF)*
- SHM computer algorithms need to detect failures and schedule repairs
- Validation studies should include bond failure and repair as varying condition



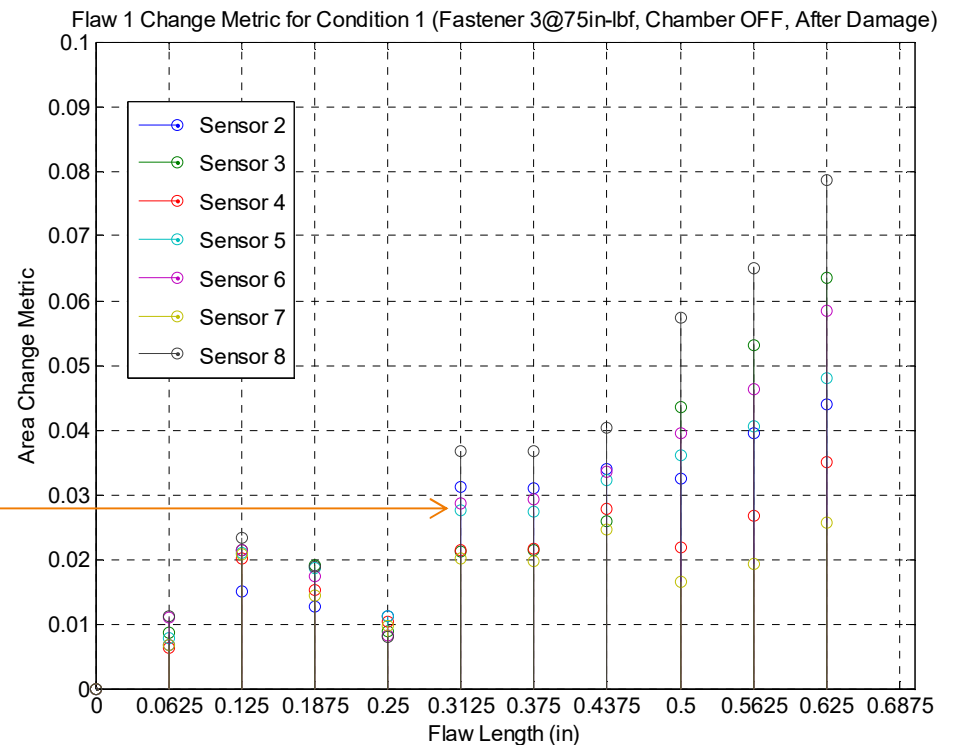


# Evaluate Controlling Factors – Sensitivity to Damage



## Observations:

- Damage grown at 1/16" increments up to 0.688" at only one site to verify sensitivity (thin saw blades provided by NIAR)
- Simulated flaw growth (SFG) attempted to mimic forcing of plate structure without creating damage – *no significant effect on damage metric*
- Sensitivity observed to certain notch increases, but trend not linear
  - sensitive to first notch cut
  - significant drop after fastener installed and removed (FIR)
  - Metric grows with larger notches
- *Jump observed after two week delay in testing – 'still in noise'*
- Larger cuts will be applied for validation studies





# Design of Validation Study

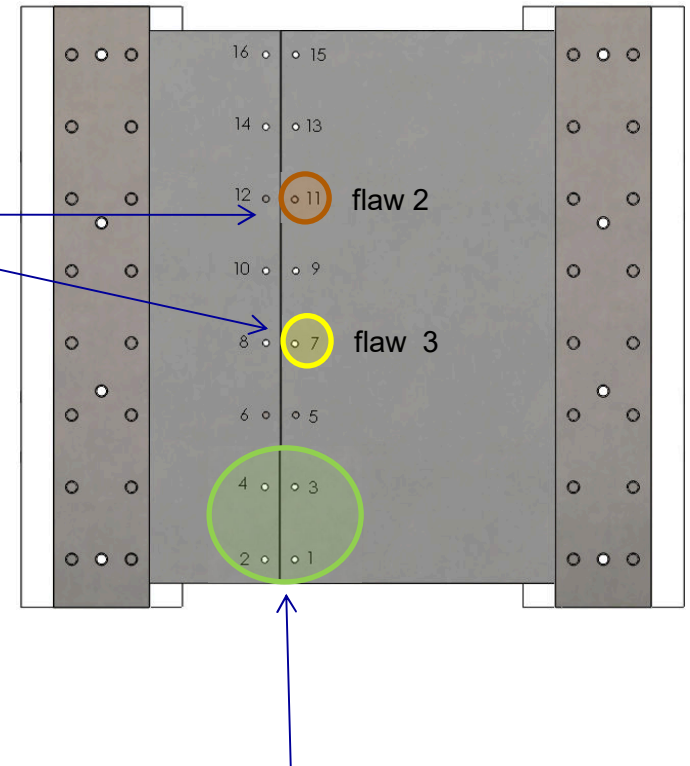


## Demonstration Study: Focused on Single Stage

- Phase II – Laboratory Testing of Relevant Structures / Environment
- Assumption: Key SDS Factors can be Demonstrated in Single Study

## Factors in Study:

- Flaw growth (notch):
  - First cut: 0.063", Second to 0.125", repeat 0.125" cuts to 1.00" (10 levels)
  - At two fastener locations with relief notches
- Environmental conditions: (ambient 72°F)
  - Temperature variation (32°F to 112°F)
  - Temperature gradients (<10°F)
  - Ambient noise (chamber on / off)
- Boundary conditions:
  - Loading / unloading mass on structure (10 lb)
  - Fastener removal and reinstall (75 in-lbs +/- 10 in-lbs) – 'simulate maintenance'
- Sensor conditions: Evaluate accelerometer bond reinstallation (ref., second)



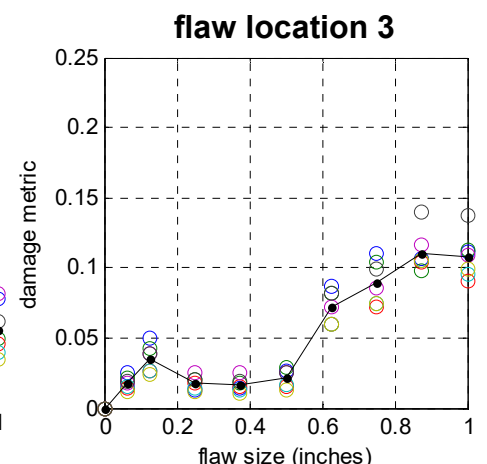
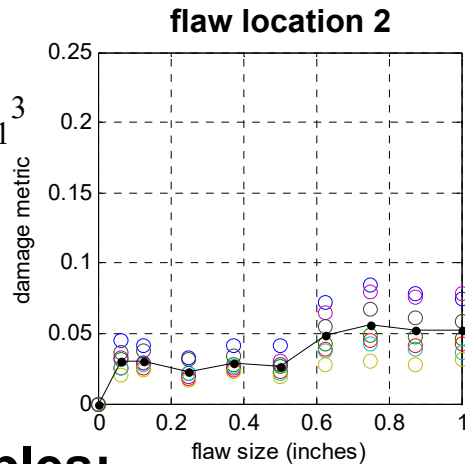


# Measurement / POD Model



## 1) Model Flaw Length and Location:

- **Length:**  $dm = \beta_0 + \beta_1 * a_1 + \beta_2 * a_1^2 + \beta_3 * a_1^3$
- **Sensitivity to location** → **must be addressed in model**  
[Compare *combined and separate* measurement model fits]



## 2) Model for Secondary (Envir.) Variables:

- Normalized mean temperature ( $a_3$ ), and absolute value  $|a_3|$
- Normalized temperature gradients ( $a_4$ ),
- Abs. difference between temp. and nearest reference ( $a_5$ )
- Ambient noise level ( $a_6$ ),

**Include in measurement model / regression fit (ANOVA)**

## 3) Model Impact of *Random* Conditions (Change from Before vs. After):

- *Sensor failure\**
- Sensor bond degradation
- Sensor replacement
- Minor fastener loosening
- Local maintenance action (fasteners uninstall/install)
- Added mass
- Structure load / unloading

**Perform separate statistical tests for significance**



# Measurement / POD Model



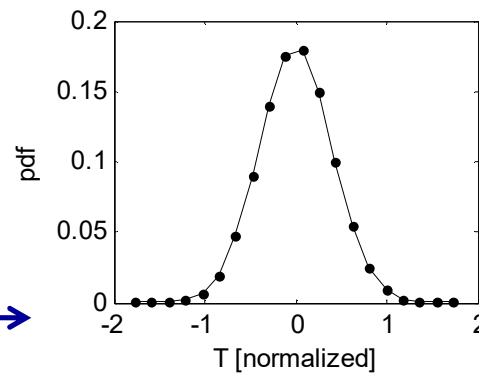
## Input Parameters Types:

- Controlled Parameters,  $a_j (N_j)$ 
  - Flaw size
  - Flaw location
  - Temperature Conditions
  - Ambient noise
- Uncontrolled Parameters,  $a_k (N_k)$ 
  - Boundary conditions
  - Flaw morphology

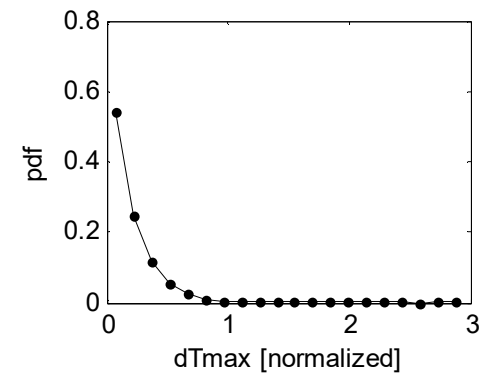
## Input Parameter Characteristics:

- Expected Variation Represented as a *Distributions* (ex. Gaussian, Uniform, Gamma, Beta)
- *Uncertainty in Distribution Parameters (Not Addressed)*

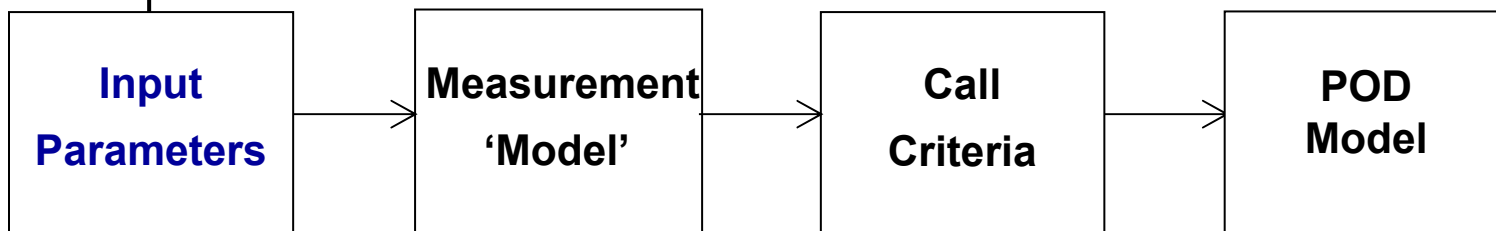
## Level 1. Input Parameter Variability



Temperature (normalized)



Temperature Gradients (normalized, 10°F)





# Measurement / POD Model



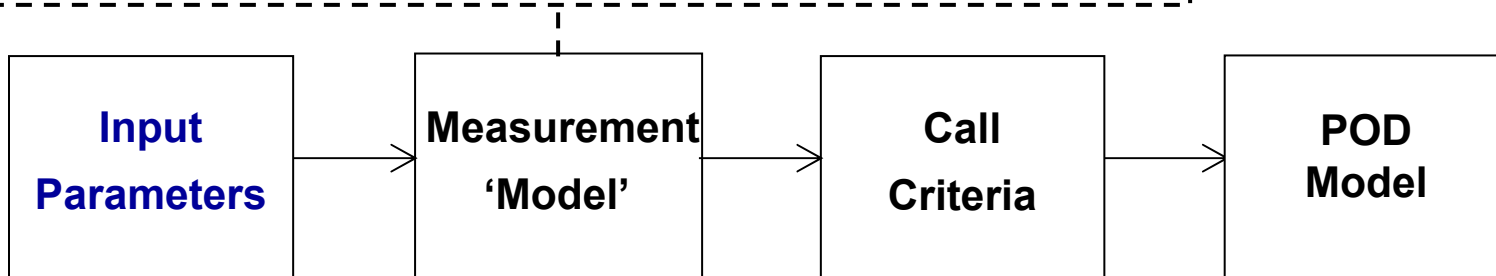
## Fit Measurement 'Model' (Using Empirical Data)

- Flaw length ( $a_1$ ):  $dm = \beta_0 + \beta_1 * a_1 + \beta_2 * a_1^2 + \beta_3 * a_1^3$
- Flaw location ( $a_2$ )
  - Evaluate both 'combined' and 'separate' flaw location scenarios fits
- Normalized mean temperature ( $a_3$ ), and absolute value  $|a_3|$
- Normalized temperature gradients ( $a_4$ ),
- Abs. difference between temp. and nearest reference ( $a_5$ )
- Ambient noise level ( $a_6$ ),
- Sensor status (active, failed)

**Level 2: Uncertainty in Model Parameter Estimate**

## Regression Analysis Example (R)

Code:	<pre>data.tmp &lt;- read.csv('analy_refl_flaw3.csv',header=FALSE) x1 &lt;- data.tmp\$V1 x2 &lt;- data.tmp\$V2 x3 &lt;- data.tmp\$V3 x4 &lt;- data.tmp\$V4 x5 &lt;- data.tmp\$V5 x6 &lt;- data.tmp\$V6 x11 &lt;- x1*x1 x111 &lt;- x1*x11 y1 &lt;- data.tmp\$V14 frame1 &lt;- data.frame(y=y1, x1=x1, x2=x2, x3=x3, x4=x4, x5=x5, x6=x6, x7 = x11, x8 = x111) y.vs.x &lt;- lm(formula = y ~ x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8, data=frame1) summary(y.vs.x)</pre>
Call:	lm(formula = y ~ x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8, data = frame1)
Residuals:	<pre>Min      1Q  Median      3Q      Max -0.035835 -0.007133  0.001119  0.006437  0.026368</pre>
Coefficients:	<pre>Estimate Std. Error t value Pr(&gt; t ) (Intercept) 0.018921  0.003902  4.849 6.8e-06 *** x1          -0.081361  0.041766 -1.948 0.05526 . x2          -0.003323  0.003465 -0.959 0.34072 x3           0.010309  0.003690  2.794 0.00665 ** x4          -0.009321  0.005813 -1.603 0.11315 x5           0.032816  0.010755  3.051 0.00318 ** x6           0.005763  0.013645  0.422 0.67402 x7           0.373822  0.109798  3.405 0.00108 ** x8          -0.205131  0.072407 -2.833 0.00596 ** --- Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</pre>
Diagnostics:	<pre>Residual standard error: 0.01303 on 73 degrees of freedom Multiple R-squared: 0.9133, Adjusted R-squared: 0.9037 F-statistic: 96.07 on 8 and 73 DF, p-value: &lt; 2.2e-16</pre>
Significant Factors:	<ul style="list-style-type: none"> <li>• x1 &lt;- data.tmp\$V1: Flaw size (<math>a_1</math>) (Part of flaw size model)</li> <li>• x3 &lt;- data.tmp\$V3: Normalized mean temperature (<math>a_3</math>)</li> <li>• x5 &lt;- data.tmp\$V5: Normalized temperature gradients (<math>a_4</math>),</li> <li>• x7 &lt;- x11 &lt;- x1*x1: Flaw size model term: (<math>a_1</math>)<sup>2</sup></li> <li>• x8 &lt;- x111 &lt;- x1*x11: Flaw size model term: (<math>a_1</math>)<sup>3</sup></li> </ul>



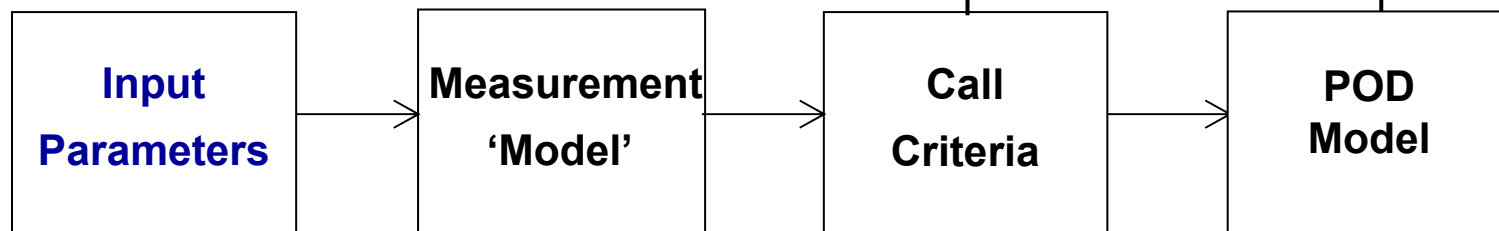


# Measurement / POD Model



## POD Evaluation Process:

- Apply threshold for call criteria ( $dm > 0.06$ )
- Use second order probability analysis
  - Use two-level Monte Carlo simulation
    - Sample from **Input Parameter Distributions (Level 1)**
    - Perform Measurement Model Evaluation and Estimate Single POD Curve
  - Repeat Evaluation **for Different Samples due to Uncertainty in Model Parameters (Level 2)**
- Obtain 'Set' of POD Curves (*Uncertainty / Credibility Bounds on POD Curve*)
- Probability of False Call corresponds with POD curve result at  $a_1 = 0$ .

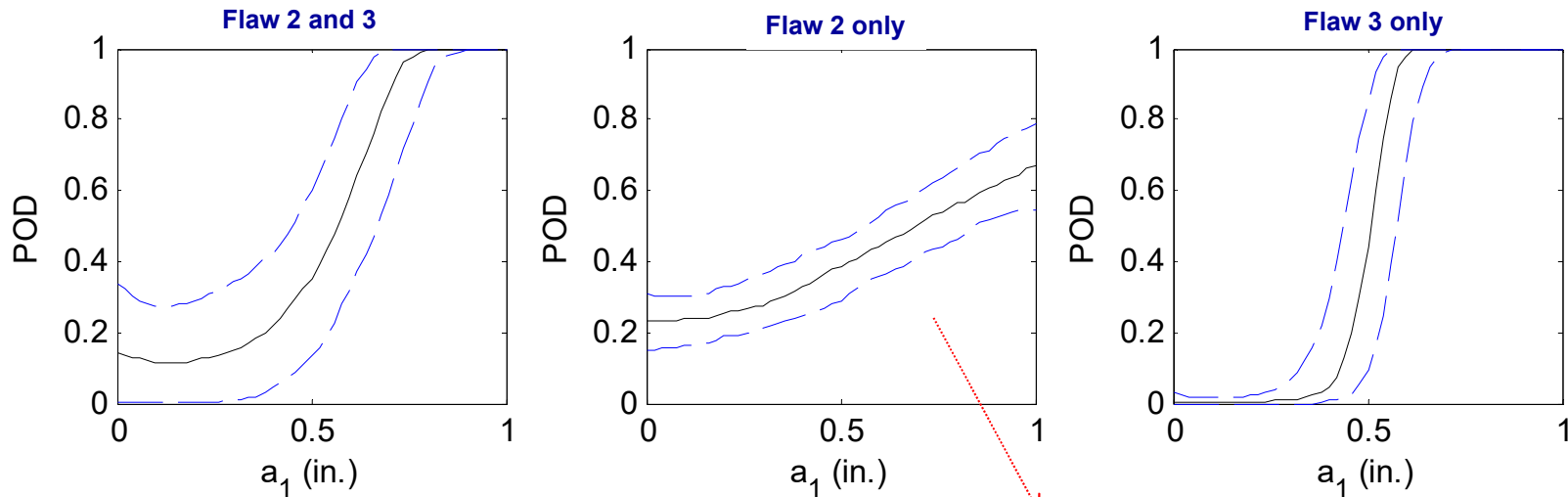




# POD Results – Sensitivity to Flaw Location

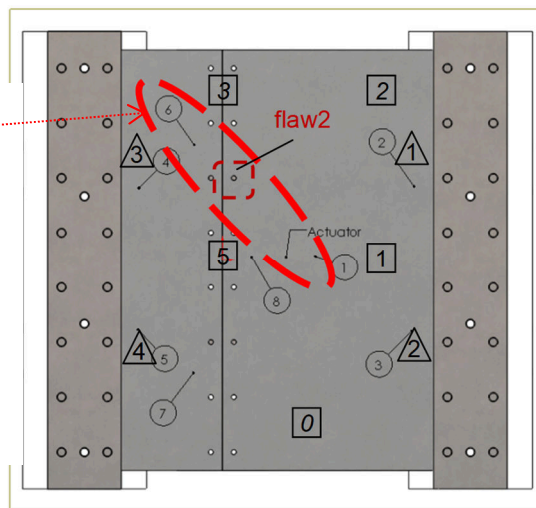


## POD Results: Dependency on Flaw Location

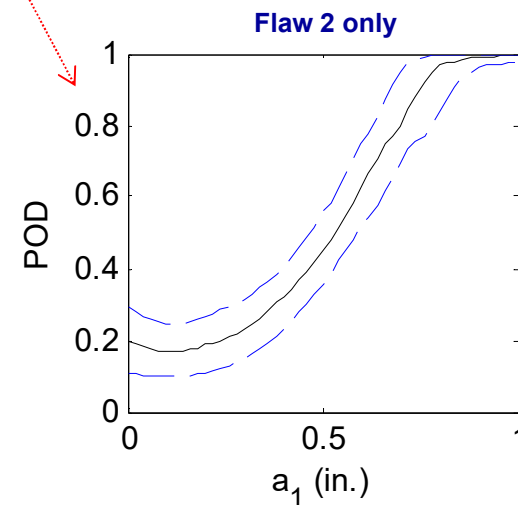


## Can Improve POD by Choosing *Optimal Sensor Configuration*:

**Only use damage metric for accelerometer #6 (with reference #1)**



- accelerometer
- thermocouple
- △ strain gauge
- ④ (in air on top)





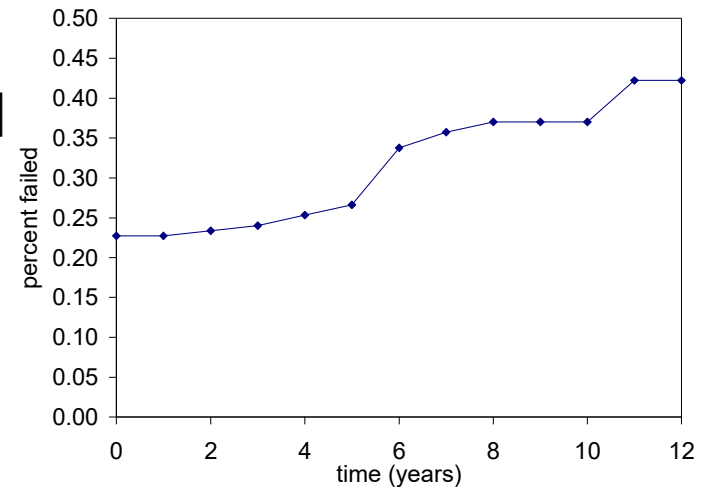
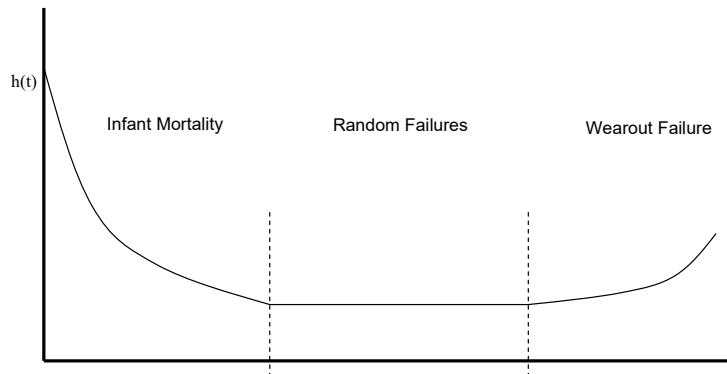


# POD Results – Impact of Sensor Durability



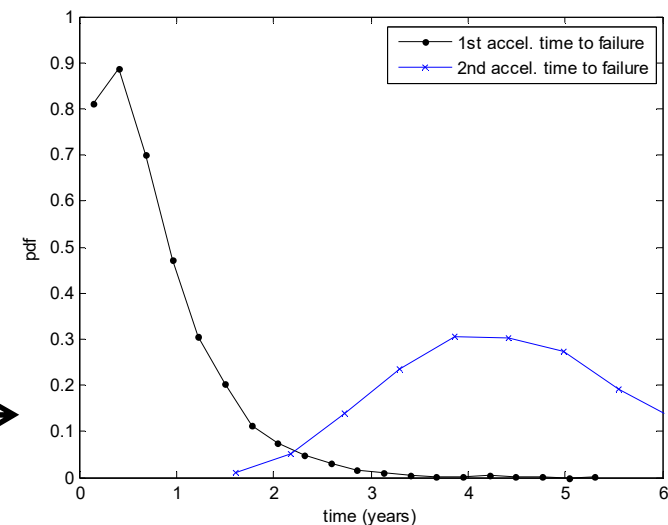
## POD Evaluation Must Address Known Sensor Durability Issues:

- Issue demonstrated by percent of C-17 in-service strain gauge failures as a function of time [Ware et al] →
- **Bathtub Curve Model** [Meeker and Escobar]



## Evaluation of Impact of Sensor Failure:

- Evaluate changes in POD due to random sensor failure over time
- Explore failure of two sensors (25%) over first six years of service life
- Distributions of Time to Failure → Considered in Evaluation



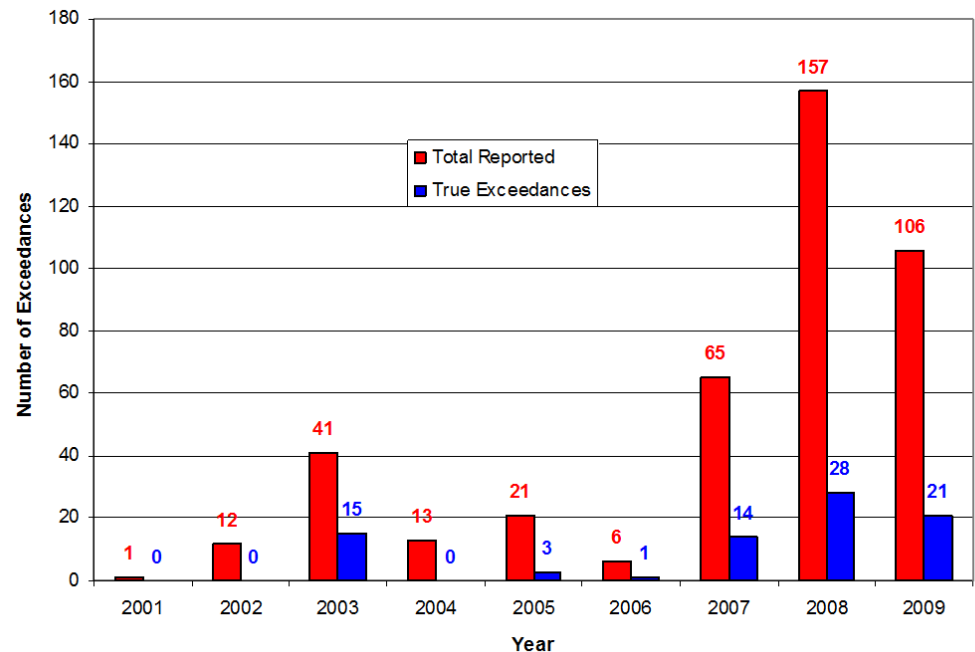
# Consequence of SHM False Calls- KC-130J Exceedances

## Monitoring system:

- **Sensors: Fuel Quality, Accelerometers, Differential Pressure, Discrete, Position**
- **25 Parameters Measured**

## Consequence of Indication

- **All reported KC-130J exceedances require engineering disposition due to**
- **Squadron sends SHM download files**
- ***Aircraft Structural Life Surveillance engineers assess data/provide recommendation to Fleet Support Team (FST) [engineering costs]***
- ***FCs result in unnecessary inspections, affect aircraft availability***



\* Lindgren and Walbusser, "Experience/Lessons Learned using Flight Parameter Sensors on US Department of Navy C-130 Aircraft", Aircraft Airworthiness and Sustainment, (Austin, TX, 2010).



# POD Results – Impact of Sensor Durability



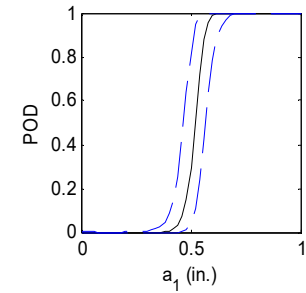
- **Sensor Scenarios with Corresponding Changes in POD and False Call Rate:**

Scenarios  
Addressing  
Sensor Failure



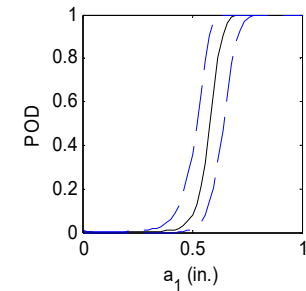
## Approach 1: (Best Sensitivity)

- Use accel. #1 as reference
- Use accel. #6 as source



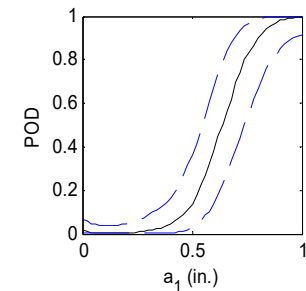
## Approach 2: (Accel.#6 Failure)

- Use accel. #1 as reference
- Use median of active sensors



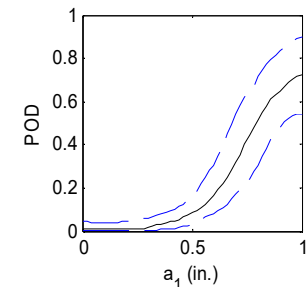
## Approach 3: (Accel.#1 Failure)

- Use accel. #8 as reference
- Use median of active sensors



## Approach 4: (Accel.#8 Failure)

- Use accel. #3 as reference
- Use median of active sensors





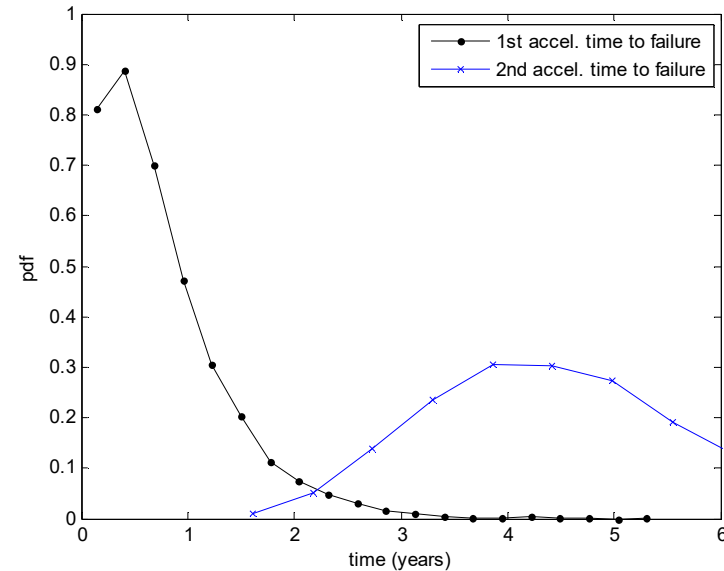
# POD Results – Impact of Sensor Durability



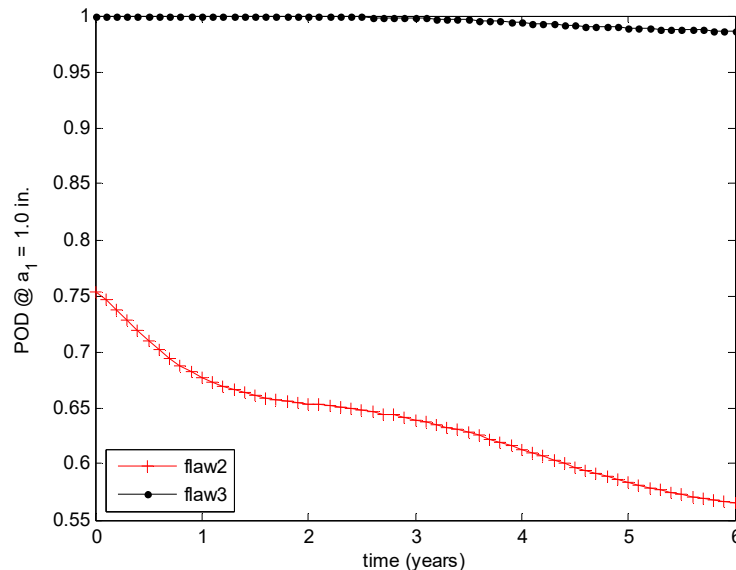
## Evaluation of Impact of Sensor Failure:

- Evaluate changes in POD due to random sensor failures over time
- Distributions of Time to Failure Considered in Evaluation

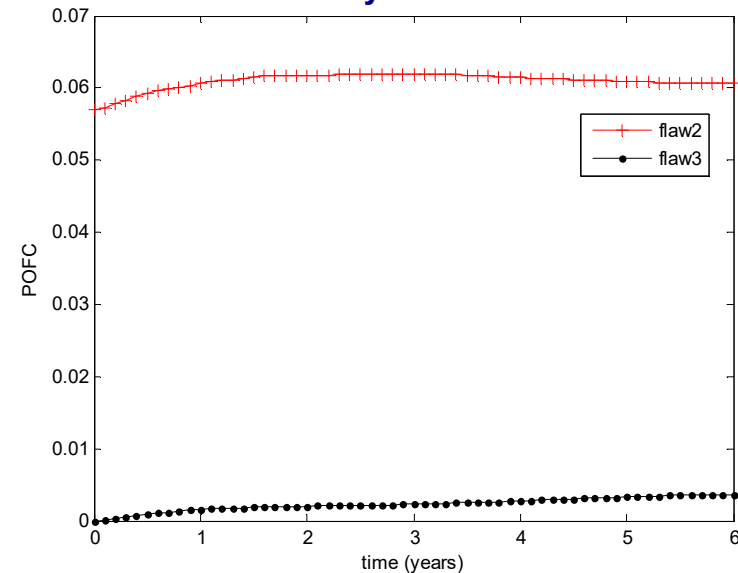
**Results:** Mean expected POD and POFC at a flaw size of 1.0 in as a function of time



Probability of Detection



Probability of False Call





# Summary of 'Best Practices' for NDE / SHM Characterization



- **Characterization error analysis should follow standard practice for POD evaluation [e.g. MIL-HDBK 1823A]**
  - **Must understand implicit statistical assumptions in regression analysis [Annis et al., 2015]**
  - **If assumptions are not met, *pick a different 'correct' model!***
- **Protocol presented for SHM capability evaluation**
  - **Thorough factor evaluation is critical for proper assessment [*environment, varying structure, sensor and damage state*]**
- **Demonstrated 'need' for representative models in SHM capability evaluation [empirical and/or numerical]**
  - ***Certain flaw locations will require separate POD models [global SHM]***
  - ***Feasible to evaluate impact of sensor failures on performance***
  - **Must address varying conditions and *model uncertainty (error)***



# Acknowledgements



- Various parts of this work have supported by the U.S. Air Force Research Laboratory, (AFRL) under the following contracts:
  - SBIR Phase II Contract (Topic AF112-130) to Victor Technologies LLC. Contract Number: FA8650-13-C-5180
  - Contract with Radiance Technologies, Inc., Contract Number: FA8650-09-C-5204
  - Research Initiatives for Materials State Sensing (RIMMS), Numerical and Computational Methods for Nondestructive Evaluation, (Contract: FA8650-10-D-5210, Independent Contractor Agreement 11-S7103-01-C1)