Demonstrations of Model-assisted Probability of Detection (MAPOD) Evaluation

John C. Aldrin,
Computational Tools

David S. Forsyth,
TRI/Austin

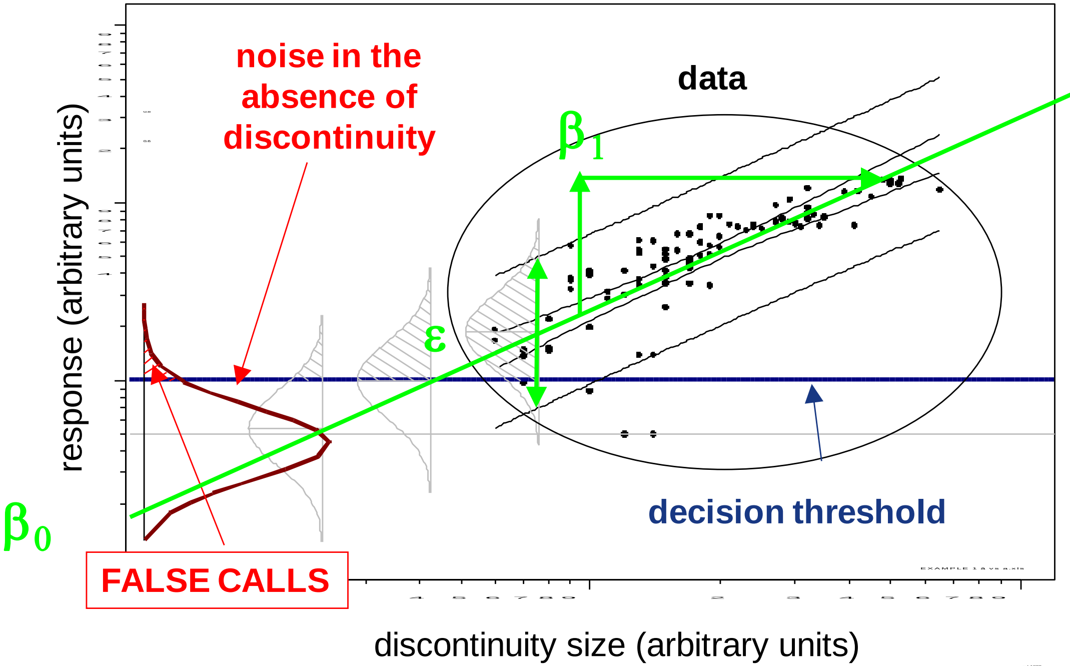
Harold A. Sabbagh,
Victor Technologies, LLC

Eric A. Lindgren, Jeremy S. Knopp, Charles F. Buynak, Enrique A. Medina*
U.S. Air Force Research Laboratory

Case Numbers: 88ABW-2011-4699 , 88ABW-2011-4701, 88ABW-2011-4117

What is Probability of Detection (POD) and Model Assisted POD (MAPOD)?

- **Probability of detection (POD) of a certain discontinuity as a function of some size metric given a defined inspection technique and target population.**



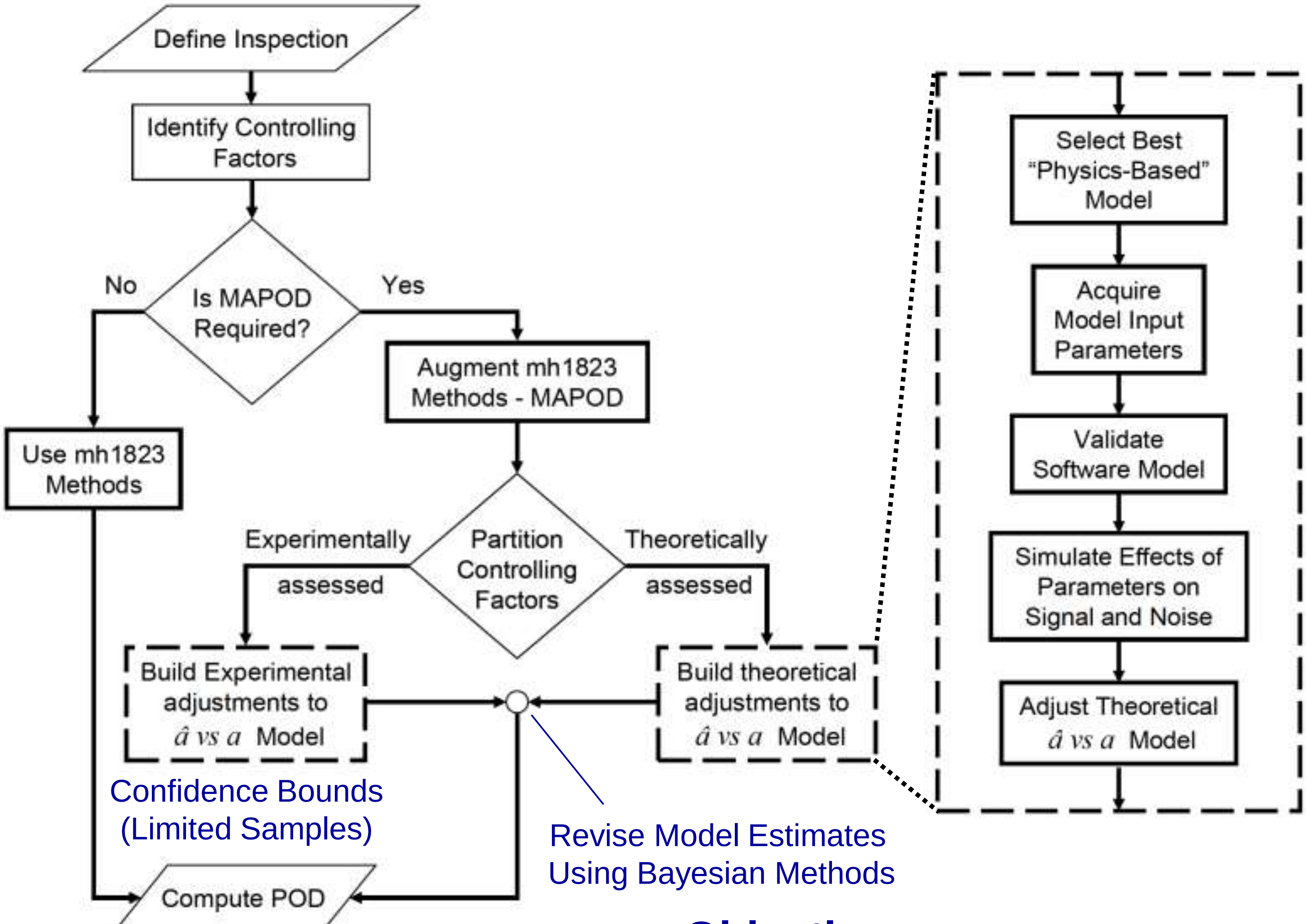
$$\ln \hat{a} = \beta_0 + \beta_1 \ln a + \varepsilon$$

$$POD(a) = 1 - Q\left[\frac{\ln a - \mu}{\sigma}\right]$$

$$\text{where } \mu = \frac{\ln(y_{th}) - \beta_0}{\beta_1} \text{ and } \sigma = \frac{\delta}{\beta_1}$$

- **We define "MAPOD" as the collection of approaches that *use models* of inspections as some portion of the inputs that are processed to yield an *estimate of POD*.**

Model-Assisted POD Model Building Process
[MIL-HNBK 1823A, Appendix H (2009)]



Uncertainty Propagation

Input Parameter Variability (Distributions)

Model Error

Stochastic Models

Model 'Calibration'

Objective:

Develop Complete Approach to Uncertainty Propagation in MAPOD

Mitigating Cost of POD Study

Evaluating Reliability Using Simulated and Empirical Data:

- To **mitigate cost** of validation study, one must better assess the **critical sources of error and variation on reliability performance**
- Hoppe [2009] presented historical case highlighting benefit of **improving the measurement model** through including crack length and depth in fit
  - $\hat{a} = \beta_0 + \beta_1 a_1 + \varepsilon$
  - $\hat{a} = \beta_0 + \beta_1 a_1 + \beta_2 a_2 + \varepsilon$
- **Physics-based models** provide opportunity for *reducing experimental samples* and cost

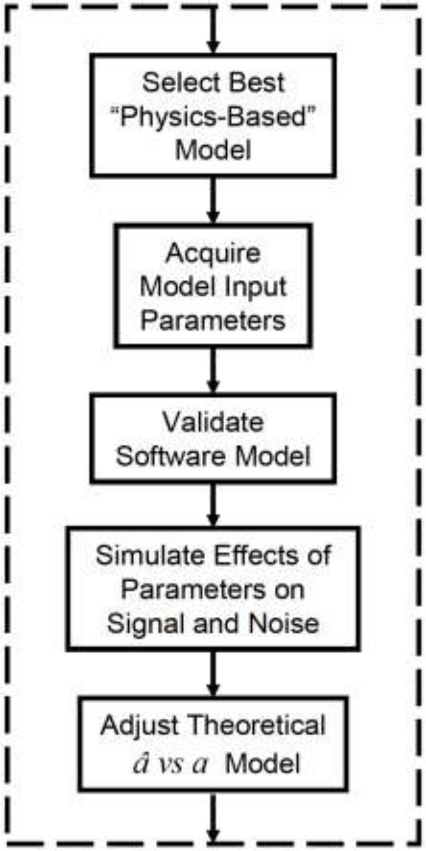
$$\hat{a} = \beta_0 + \beta_1 f\left(a_1, a_2\right) + \varepsilon$$

Increase Model Accuracy
↓
Reduces Residuals in Model Fit
↓
Improves Bounds on Parameter Estimates (POD)
↓
Impacts Experimental Sampling Requirements

Objective: Explore Case Studies to Assess Impact of Measurement Model Quality on POD Estimation and Sample Number

‘Progress’ on Model-assisted POD Evaluation (Highlights of Talk)

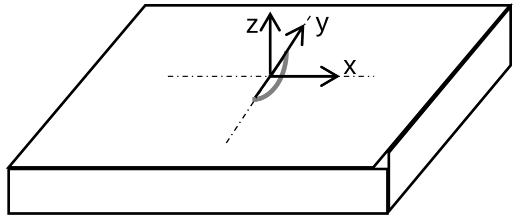
- Leverage ***physics-based models*** in POD evaluation that represent ***key factors*** in an NDE technique:
  - Present status on models to address <u>real cracks in material noise (EC, UT)</u>
  - Assess benefit of <u>more accurate models</u> on POD fit and <u>sample requirements</u>
- Present ***analysis tools*** to address propagation of model error, uncertainty in calibration and Bayesian refinement [TRI/Austin]
- Present demonstration of MAPOD protocol for **SHM (in-situ NDE) validation** [Radiance]
  - Address full spectrum of environmental conditions
  - Consider independence of each inspection site
  - Evaluate POD as function of sensor system durability (time)

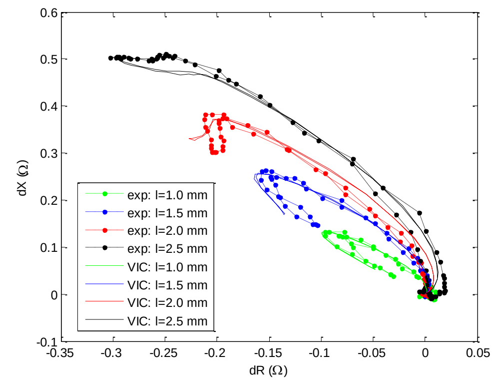


Demonstration: Eddy Current Inspection of Surface-breaking Cracks in Ti-6Al-4V

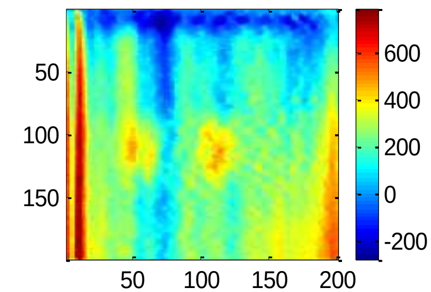
Identify Controlling Factors:

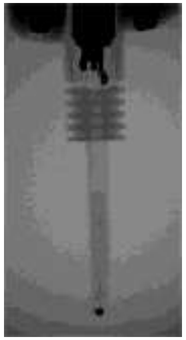
- **Crack Characteristics**
  - **Length and Depth (aspect ratio)**
  - ***Width (cracks, EDM notches)***
  - ***Stress state across crack face (closure)***
  - **Crack morphology**
- **Material Properties**
  - **Conductivity**
  - **Material noise (anisotropy, grain structure)**
  - **Surface condition (roughness, residual stress, coldwork)**
- **Part Geometry (assume locally flat)**
- **Probe (frequency fixed at 2.0 MHz)**
  - **liftoff**
  - **tilt**
  - **dimensions, windings (probe to probe variability)**
- **Scan resolution (fixed)**
- **DAQ hardware (Agilent Impedance Analyzer, Nortec 19eII)**
- **Calibration process** — **- isolate liftoff direction in response** — **- set full screen height for known notch (0.10")**
- **Human data interpretation** — **- use quantitative metrics in evaluation**





1.0 mm crack response in Ti-6Al-4V

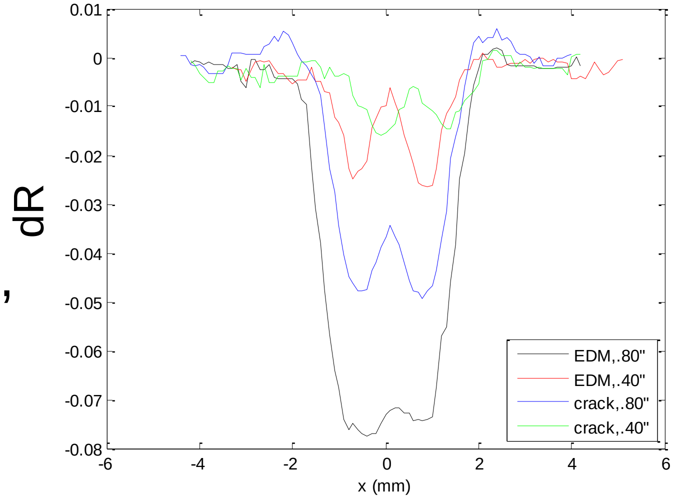


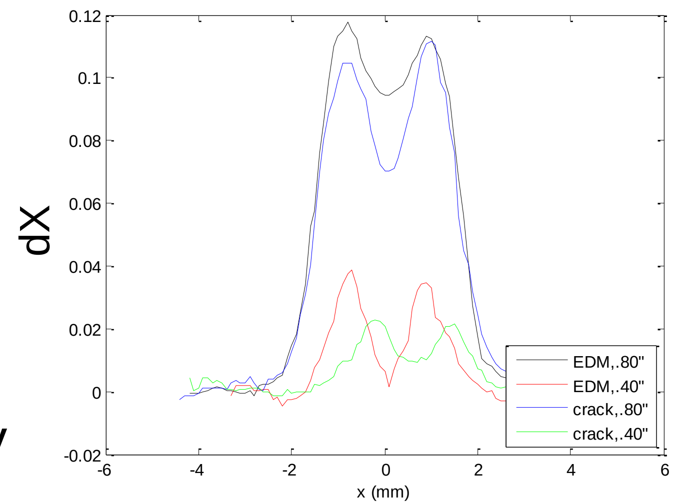


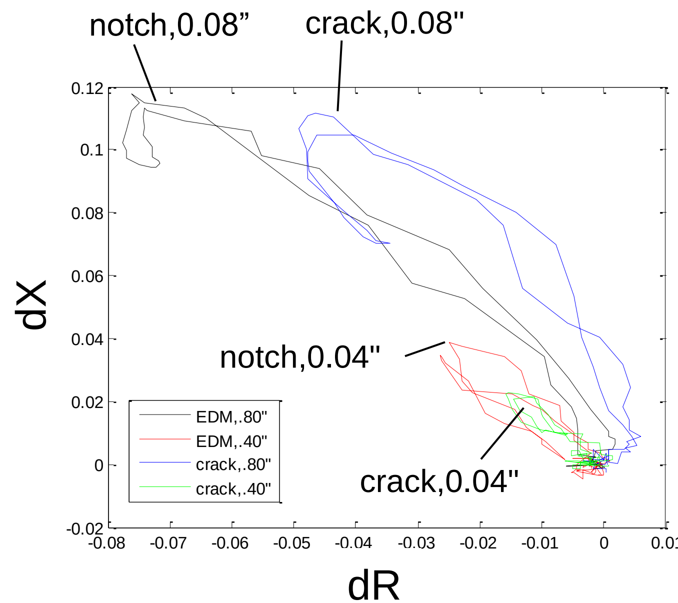
Comparing Cracks and EDM Notch – Experimental and Simulated Data

Compare Cracks and EDM Notch Responses:

- Largest cracks very similar in reactance (dX)
- Lower response in resistance (dR), due to ‘difference’ in width of cracks and notches at surface
- Differences for smallest crack (0.040") may be due to crack closure effect and/or uncertainty in aspect ratio



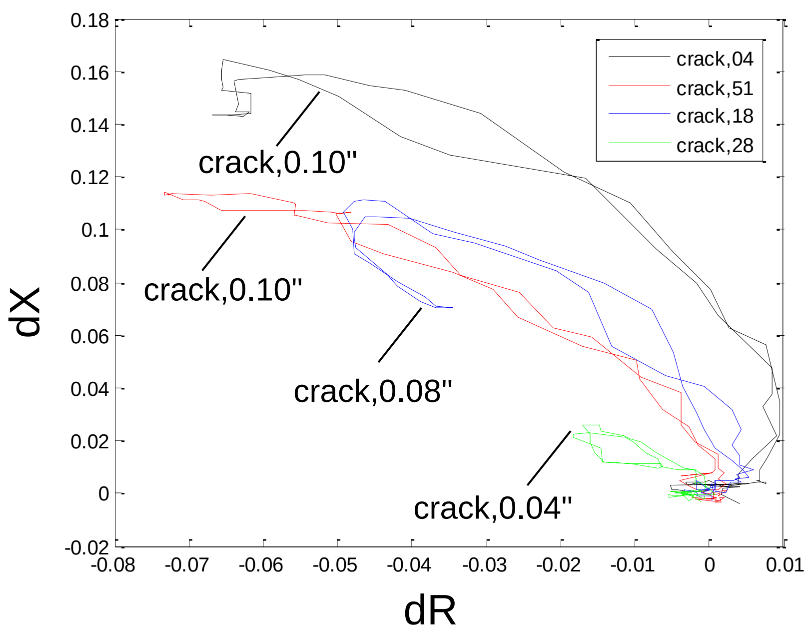




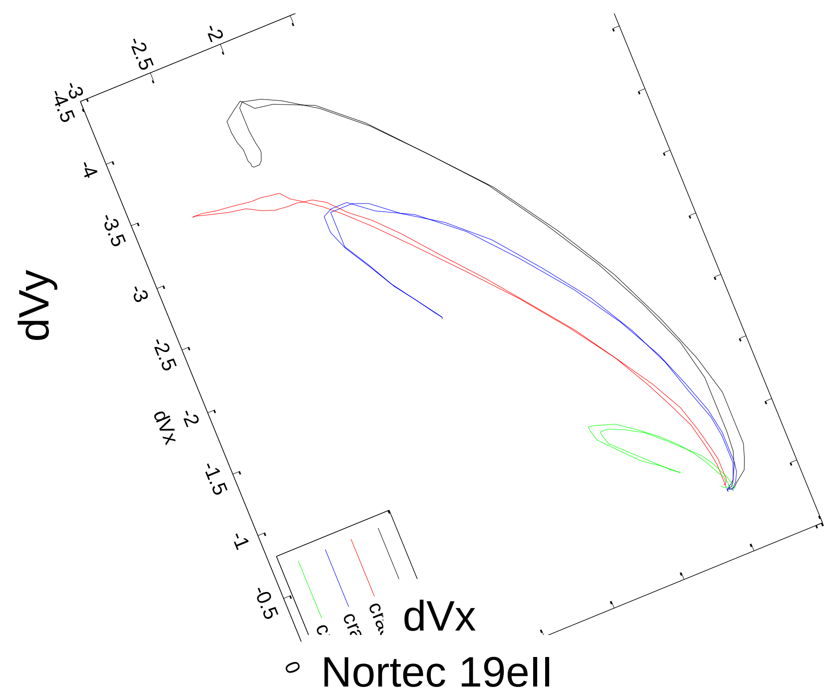
Comparing Cracks and EDM Notch – Experimental and Simulated Data

Compare Agilent and Nortec 19eII Responses:

- Same probe @ 2 MHz was tested over crack specimens [Cherry]
- Signal to noise much improved for Nortec 19eII wrt impedance results
- Increase signal to noise due to signal conditioning
  (zero response over specimen and scaling of signal)
- Background noise seems to be more associated with measurement noise than actual material noise (surface roughness, grain noise)



Agilent (Impedance Analyzer)

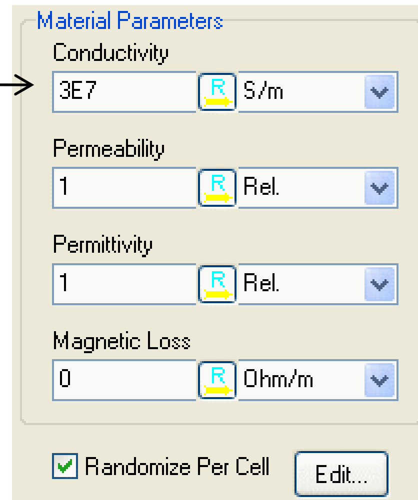


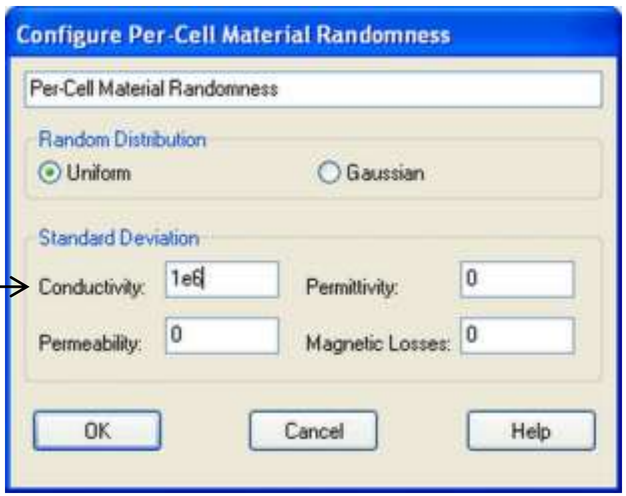
Nortec 19eII

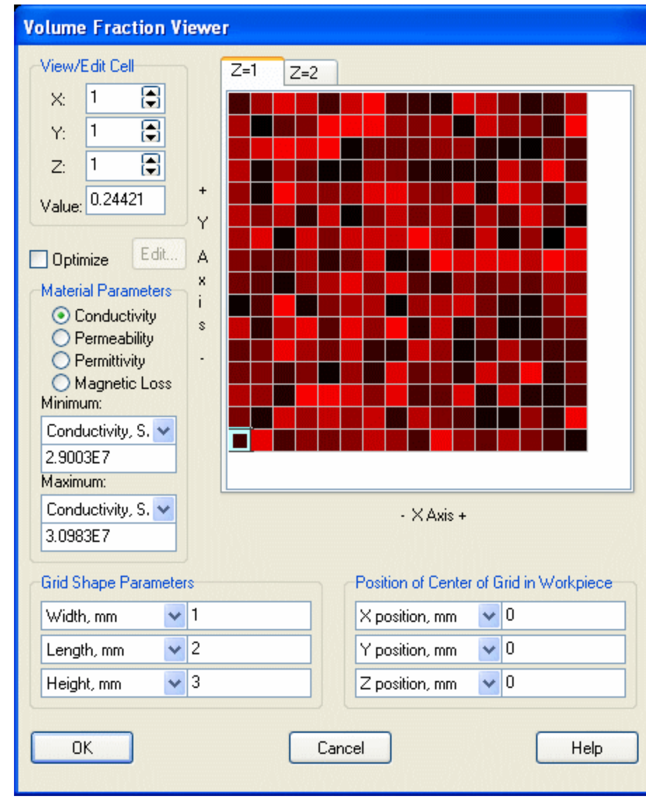
Simulating Cracks in Material Noise in VIC-3D©

Material noise model (anisotropy, grain structure) can simulate random variation of material parameters for a volume grid (flaw region)

- Example: randomize conductivity of material (grains)







Multiscale flaw model enables simulation of cracks (notches) at boundaries (edges, holes) and in the presence of surface roughness, grain structures

[see Murphy et al, "Advances in Developing Multiscale Flaw Models for Eddy-Current NDE", THUR. 1:30]

[see Sabbagh et al, "Characterizing Randomly Anisotropic Surfaces", THUR. 2:00]

Measurement ‘Model’ and POD Evaluation

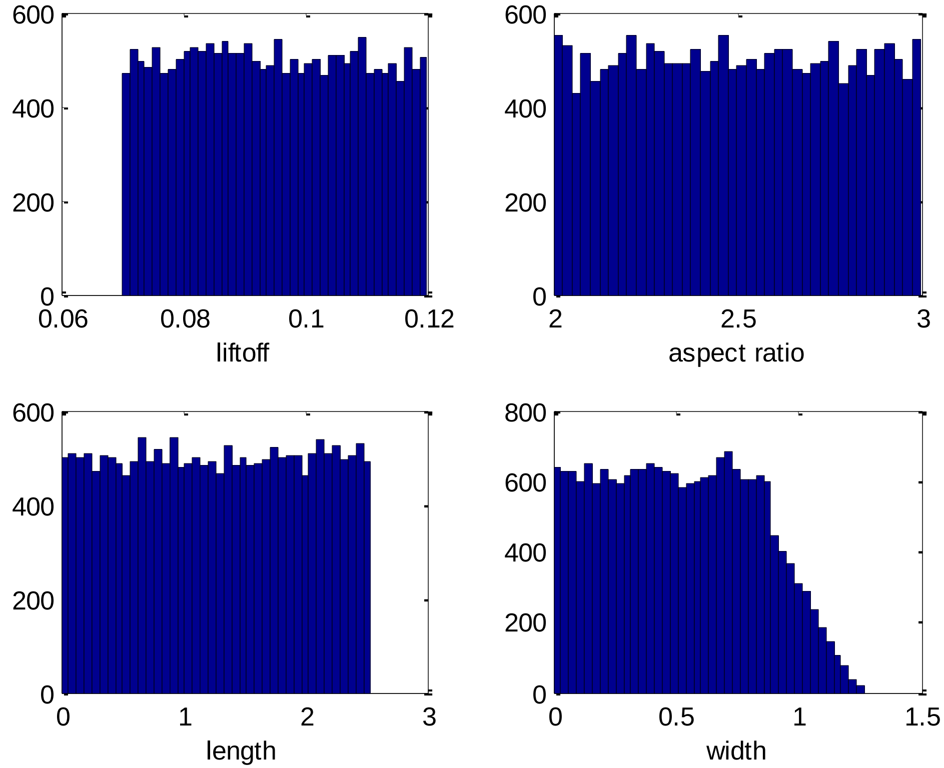
Input Parameters Types:

- 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



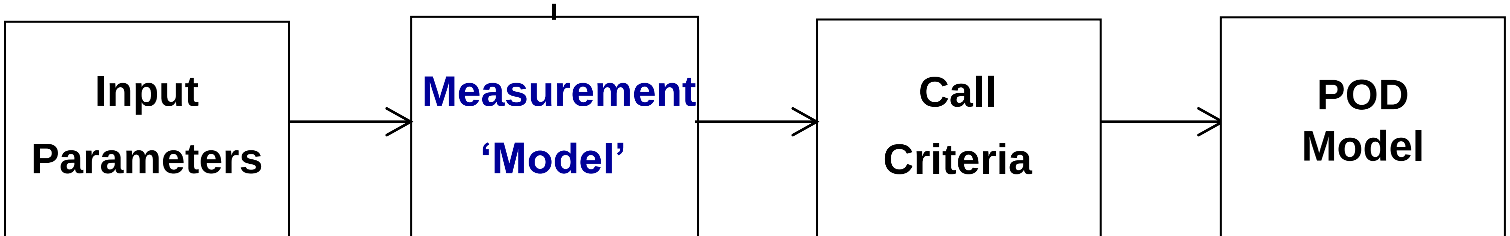
Input Parameters → **Measurement ‘Model’** → **Call Criteria** → **POD Model**

Measurement ‘Model’ and POD Evaluation

Measurement ‘Model’ *Fit* *(mean + error on fit parameters)*

1. **Empirical fit (statistical model)**
$$\hat{a} = \widehat{\beta}_0 + \widehat{\beta}_1 a_1 + \varepsilon$$
2. **Calibrated numerical model**
   - Step 1: Solve numerical model
     - Data table with interpolation
     - PCM model (Data table fit)
   - Step 2: Fit model to experimental data
     - Calibration (Bayes, MLE)
     - Transform model (same as ‘Calibration’)
$$\hat{a} = \widehat{\beta}_0 + \widehat{\beta}_1 f\left(a_1, a_2\right) + \varepsilon$$
3. **Calibrated numerical model with inverse methods** (to estimate uncontrolled parameters)
$$\hat{a} = \hat{\beta}_0 + \hat{\beta}_1 f\left(a_1, a_2; a_3\right) + \varepsilon$$
4. **Transfer function approach**
   - Empirical fit transformation
   - Calibrated numerical model transformation
$$\hat{a} = \hat{\boldsymbol{\beta}}_{nc}\mathbf{a} + \varepsilon$$
$$\widehat{\boldsymbol{\beta}}_{nc} = \widehat{\boldsymbol{\beta}}_{ns} + \widehat{\boldsymbol{\beta}}_{ac} - \widehat{\boldsymbol{\beta}}_{as}$$
$$\widehat{\boldsymbol{\sigma}}^2_{nc} = \widehat{\boldsymbol{\sigma}}^2_{ns} + \widehat{\boldsymbol{\sigma}}^2_{ac} - \widehat{\boldsymbol{\sigma}}^2_{as}$$

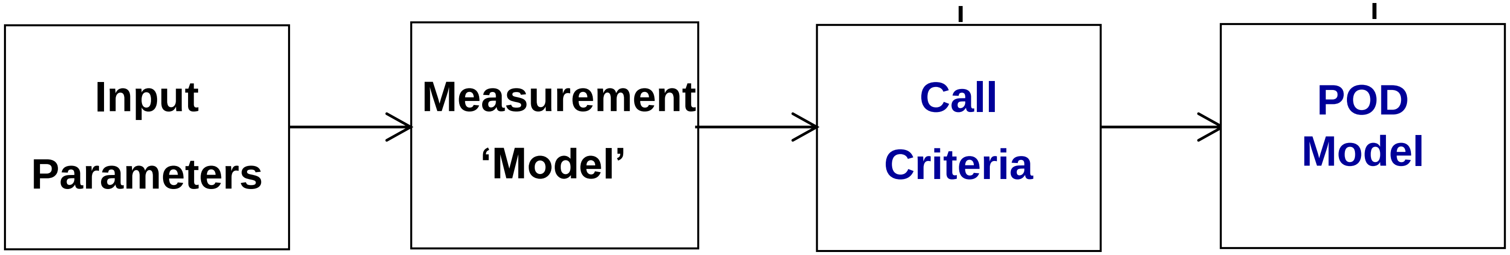
Level 2: Uncertainty in Model Parameter Estimate(s)



Measurement ‘Model’ and POD Evaluation

POD Evaluation Process:

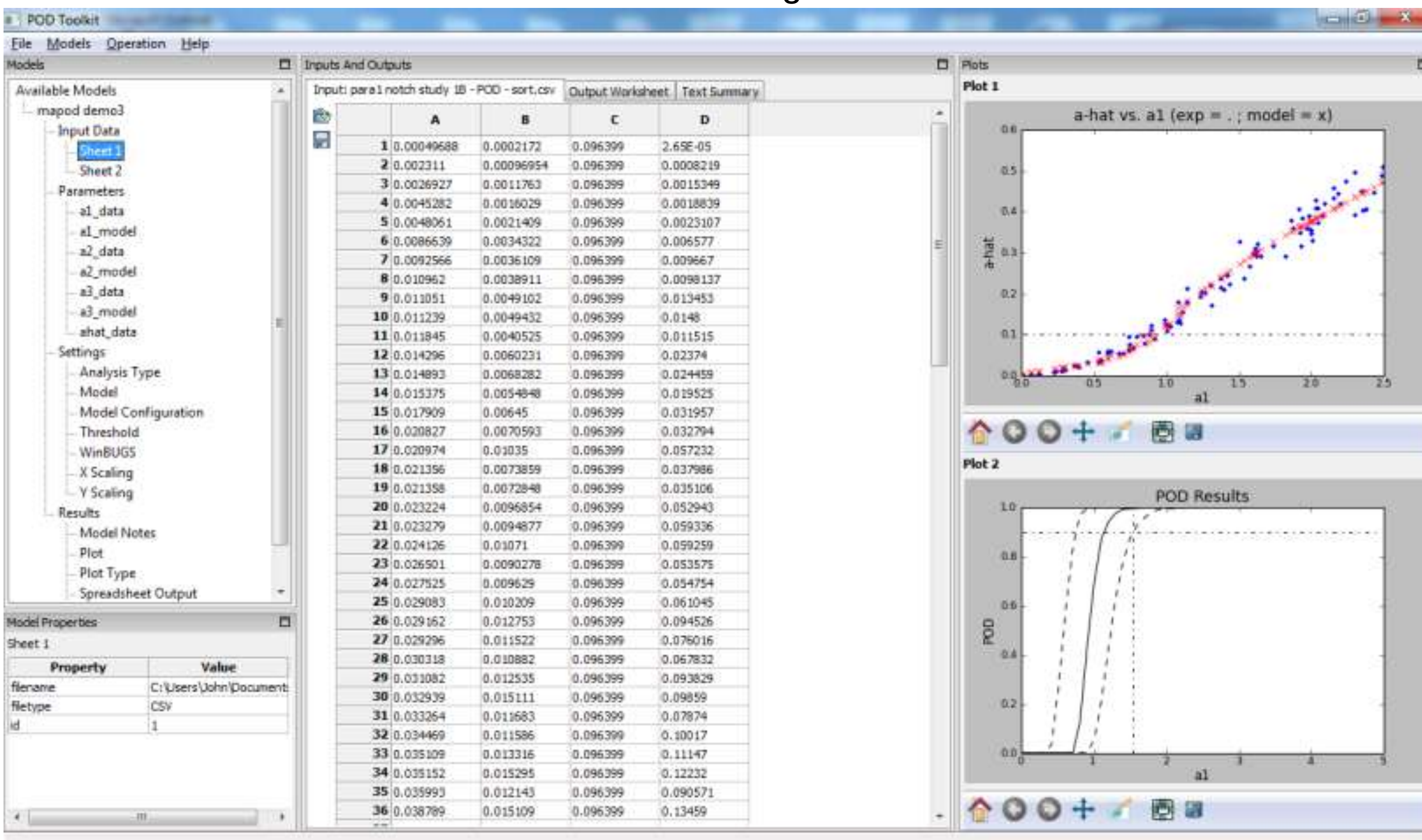
- **Apply threshold for call criteria**
- **Use second order probability analysis**
  - Use **two-level Monte Carlo simulation**
  - Sample from **Input Parameter Distributions (Level 1)**
  - Perform Measurement Model Evaluation and Evaluate Single POD Curve
    - Repeat Evaluation **for Different Samples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



POD/MAPOD Toolkit (TRI/Austin) - Features and Interface Requirements

Perform POD Assessment and Provide Diagnostic Tools:

- Define Model Input Parameters
- Manage Multiple Data Sets
- Select Model Parameter Fitting Approach
- Perform POD Assessment and Provide Diagnostic Tools



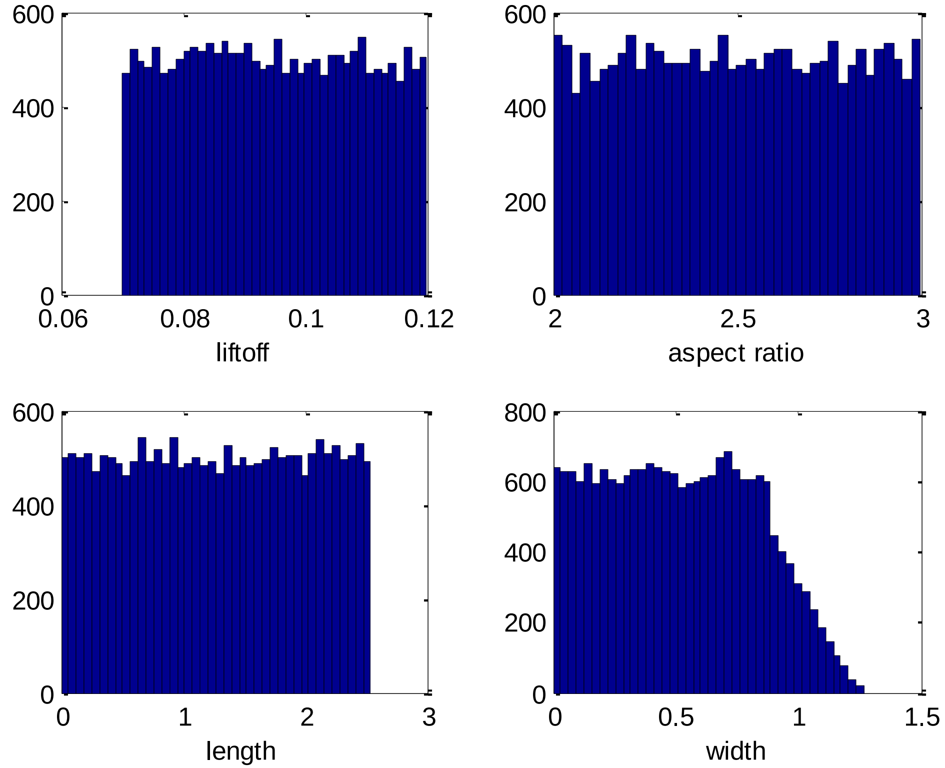
POD/MAPOD Toolkit (TRI/Austin)- Software Architecture

- **POD Toolkit component of NDI Toolbox (open source)**
- **POD Toolkit contains code with example case studies, and directory structure for code, data and temp. files**
  - **ex: hitmiss, ahat_vs_a, ahat_vs_a1a2, bayesmcmc,**
  - **mapod demos**
- ***.cfg files:*** ***Define POD/MAPOD Model Structure (Construct model tree)***
- ***Python code:*** ***Adjust interface for Unique POD / MAPOD Evaluation Features***
- ***R code:*** ***Perform statistical evaluation***
  - ***Optional R link to WinBUGS for Bayesian Analysis***

Simulated POD Studies: EC Inspection of Cracks in Ti-6Al-4V

Input Parameters in Study:

- **a_1 = Crack length**
  - primary variable for POD
- **a_2 = Crack depth (width)**
  - dependent variable on a1 crack length
  - relationship define by function a2(a1) = a4 * a1
  - a4 is the aspect ratio and defined as an random variable
- **a_3 = Liftoff**
  - uncontrolled parameter during study
  - estimation of liftoff could improve POD performance (to verify)

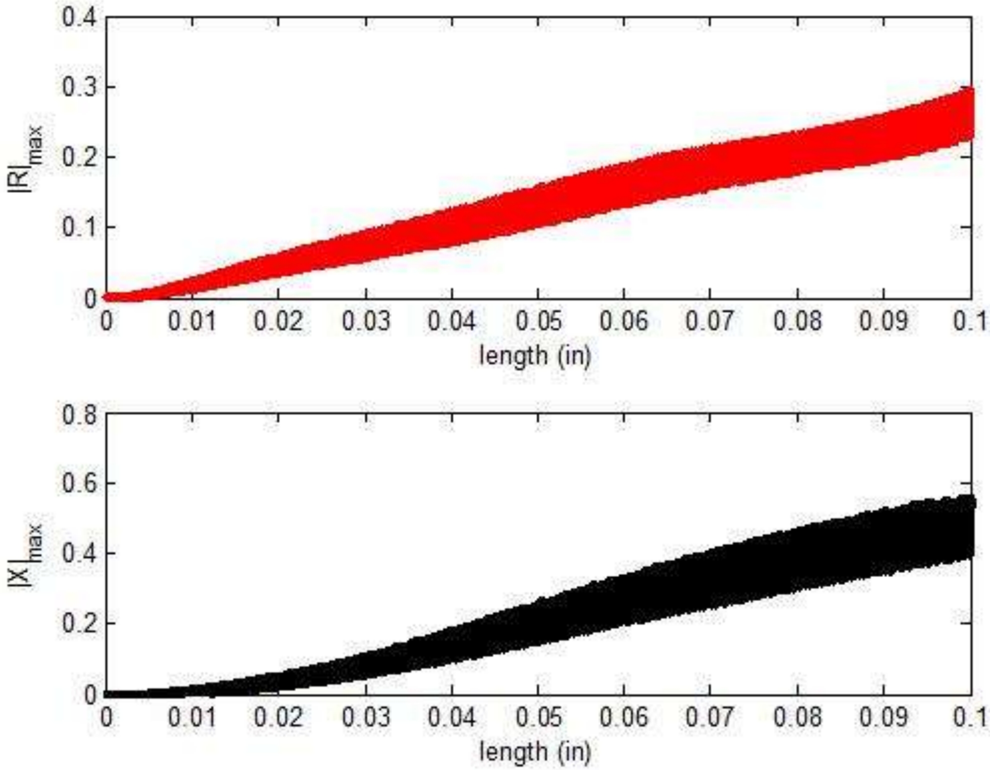


Input Parameters Distributions

Simulated POD Studies: Input Parameter and Model Response

Input Parameters in Study:

- **a_1 = Crack length**
  - primary variable for POD
- **a_2 = Crack depth (width)**
  - dependent variable on a1 crack length
  - relationship define by function a2(a1) = a4 * a1
  - a4 is the aspect ratio and defined as an random variable
- **a_3 = Liftoff**
  - uncontrolled parameter during study
  - estimation of liftoff could improve POD performance (to verify)



EC Response wrt Crack Length
(variation for a2 and a3 included)

Simulated POD Studies: One vs. Two Parameter Models

Perform POD Assessment and Provide Diagnostic Tools:

Ex: ahat versus a_1 and a_2 model fit: $\hat{a} = \beta_0 + \beta_1 a_1 + \beta_2 a_2 + \varepsilon$

- **Explore: Case study 3: dep_fixed - POD(a_1, a_2) generated for varying a_1 and for a dependent variable $a_2(a_1)$ using a deterministic model**
  - **POD plot over a uniform distribution of a_1**
  - **$a_2 = m\, a_1$ where: m is a constant value = 0.33**
- **Compare different model fit and confidence bounds approaches**
  - **Analysis 0: Neglect a_2**
  - **Analysis 1: Regression fit, Delta method for confidence bds (ahat versus a_1 and a_2)**
  - **Analysis 2: Regression fit, Monte Carlo for confidence bds (ahat versus a_1 and a_2)**
  - **Analysis 2: Bayesian (MCMC) for model fit and confidence bds (ahat versus a_1 and a_2)**

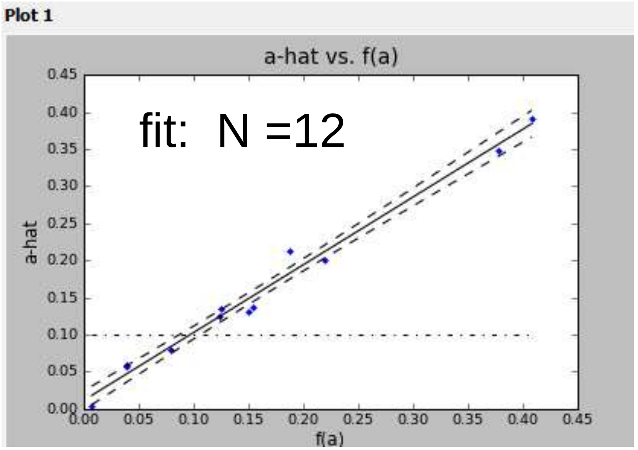
	Analysis 0 survreg() neglect a2	Analysis 1 survreg() use a1, a2	Analysis 2 glm()/MC use a1, a2	Analysis 3 BayesMCMC use a1, a2
B0	-0.05780	-0.05986	-0.05986	-0.05983
B1	5.39532	2.77503	2.77503	2.77668
B2	0.00000	6.65178	6.65178	6.64630
Delta	0.02538	0.02001	0.02001	0.02061
Threshold	0.10000	0.10000	0.10000	0.10000
var11	0.00003	0.00002	0.00002	0.00002
var22	0.00912	0.11971	0.12346	0.12687
var33	0.00000	0.73494	0.75790	0.78247
a50	0.02925	0.03204	0.03204	0.03203
a90	0.03529	0.03719	0.03721	0.03732
a90/95	0.03616	0.03720	0.03837	0.03733

- ***Inclusion of a_2 reduces residual variance (Delta)***
- ***Very little difference observed between the three methods (1-3) for this case***

Simulated POD Studies: Use Physics-based Model, Vary Sample Number

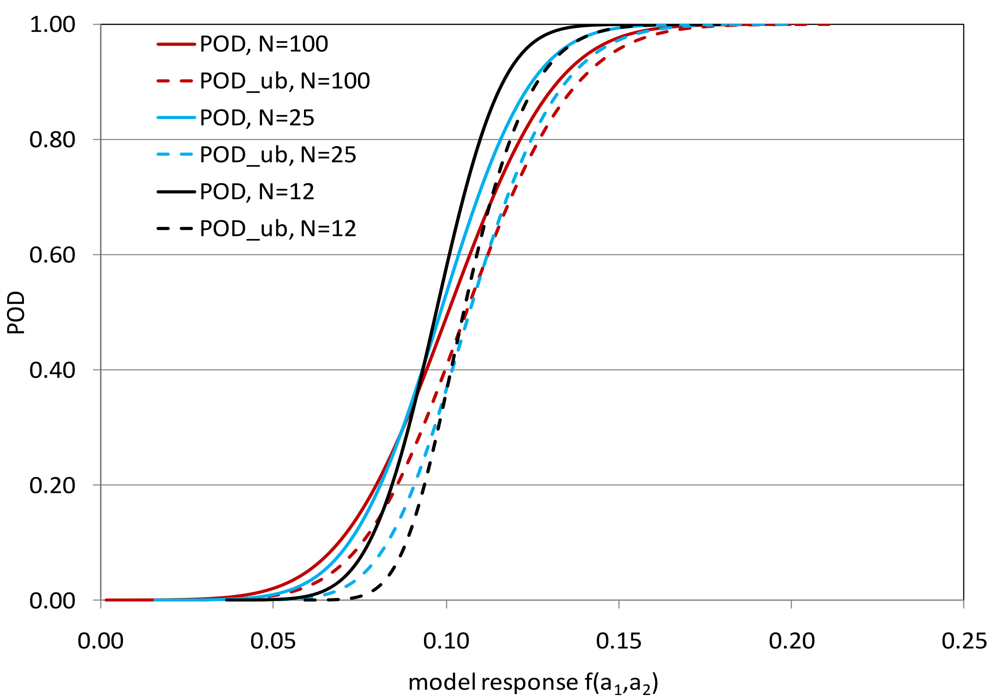
Perform POD Assessment of VIC-3D© Model Fit:

- Calibrated Physics-based Model: $\hat{a} = \beta_0 + \beta_1 f(a_1, a_2) + \varepsilon$
- Use mean liftoff from distribution for model
- Vary Number of Samples (N= 100, 50, 25, and 12)



Results: 'ahat-vs.-a' analysis much less sensitive to sample number used (compared to 'hit miss')

- significant opportunities for sample reduction



samplesz	100	50	25	12
max flaw size	0.100"	0.100"	0.100"	0.100"
liftoff	unknown	unknown	unknown	unknown
B0	0.004	0.000	0.006	0.011
B1	0.952	0.985	0.956	0.915
Tau (scale)	0.024	0.019	0.020	0.014
Mu	0.101	0.101	0.098	0.097
Sigma	0.025	0.019	0.021	0.015
Threshold	0.100	0.100	0.100	0.100
a50	0.101	0.101	0.098	0.097
a90	0.132	0.126	0.125	0.117
a90/95	0.138	0.133	0.135	0.127
a90/95 - a90	**0.006**	**0.006**	**0.010**	**0.010**
var11	*9.66E-06*	***1.05E-05***	***2.56E-05***	***2.41E-05***
var12	*-7.08E-07*	*-5.87E-07*	*-1.88E-06*	*-1.22E-06*
var22	*3.21E-06*	***3.88E-06***	***8.97E-06***	***9.86E-06***
SDa90	0.00362	0.00392	0.00596	0.00610

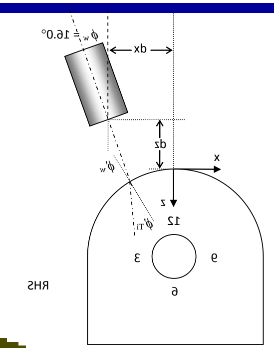
Demonstration: Ultrasonic Inspection of Cracks in Ti-6Al-4V

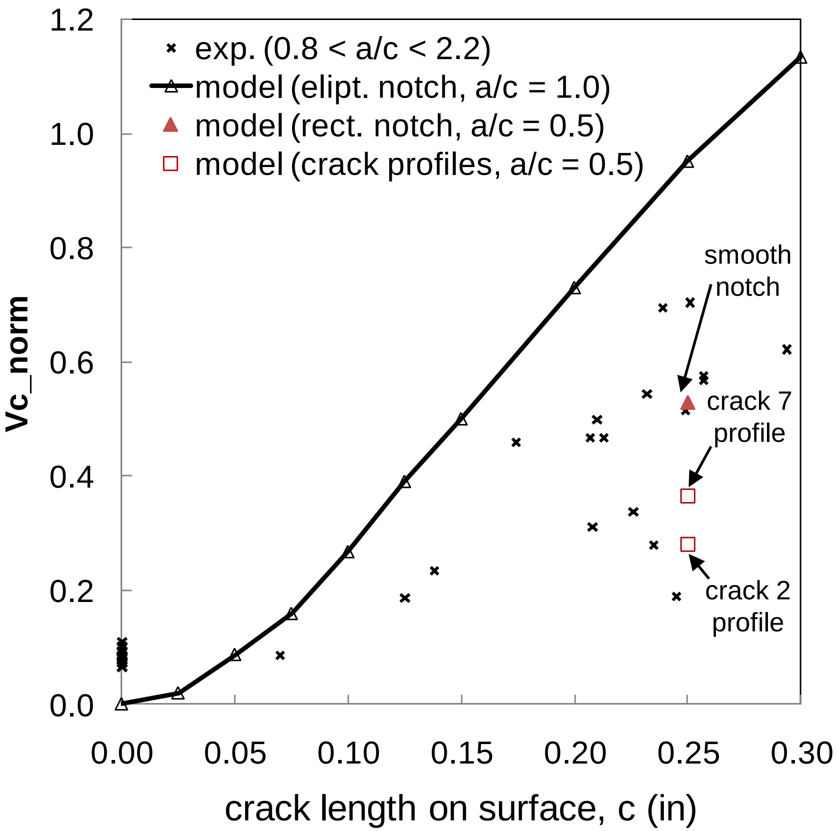
Compare: Simulated (CIVA) and Experimental UT of Ti Lugs

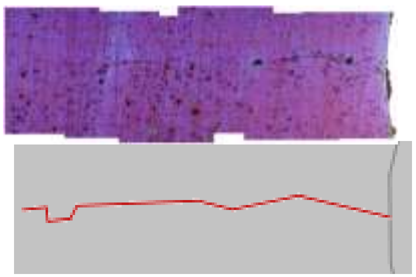
- Vary crack length, aspect ratio, angle, crack morphology

Results:

- Sensitivity to Crack Size, Aspect Ratio, Angle and *Morphology* Demonstrated in Exp. and Simulation

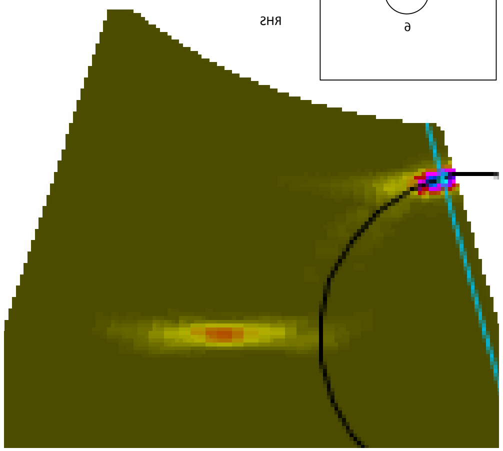


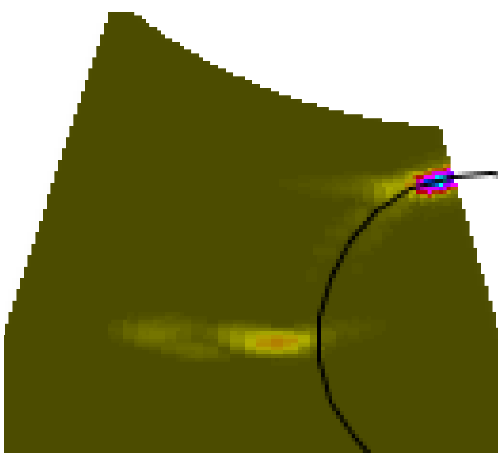




crack 7 profile

crack 2 profile
(more jagged)





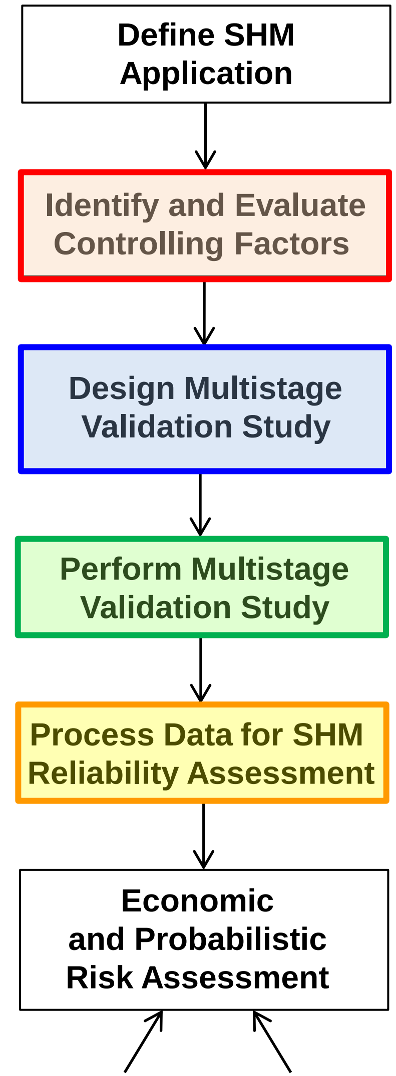
Need to Address Morphology for Crack Sizing

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***)

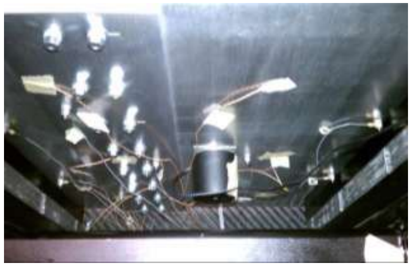
Primary Protocol



[see papers by Lindgren et al, Aldrin et al, and Medina et al, IWSHM conf. 2011]

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)***

Demonstration Study – Identify and Evaluate Controlling Factors

Primary Protocol

Define SHM Application

Identify and Evaluate Controlling Factors

Design Multistage Validation Study

Perform Multistage Validation Study

Process Data for SHM Reliability Assessment

Economic and Probabilistic Risk Assessment

Sub-tasks

Evaluate **Potential Contributing Factors** (Part, Environment, Loading, SHM system)

Is **Variability** (Range) and **Uncertainty** (Confidence Bounds) of Factor Known?

Can **Influence** of the Factor be Evaluated Using Simulated and/or Experimentation?

Approaches

- Prior work
- Elicit expert opinion
- Baseline experiments
- Designed experiments
- Simulated studies
- Inverse methods

Assess SHM System Sensitivity to Following Factors:

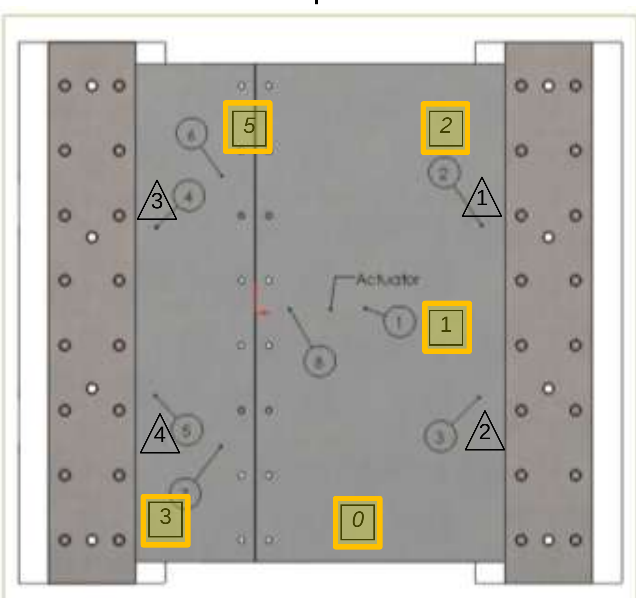
A. Loading and Unloading
B. Fastener Torque
C. End Condition Variation (Stress)
D. Temperature Variation and Temperature Gradients
E. Bond Quality and Sensor Performance
F. Ambient Noise (from Test Chamber on / off)
G. Sensitivity to Flaw Growth

Evaluate Controlling Factors – Temperature Variation and Gradients

Temperature Study: Test article placed in Thermotron temperature chamber

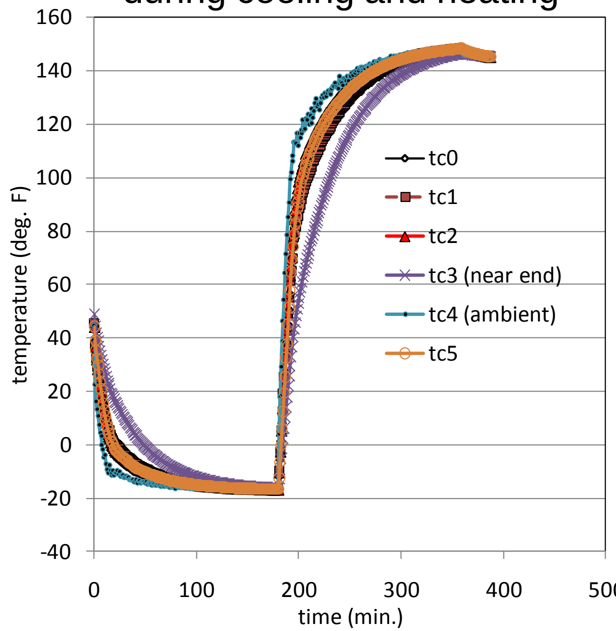
- Temperature testing performed from -20°F to 150°F
- Temperature compensation algorithms are necessary for damage metric
- Significant temperature gradients also observed during study
  - Some gradients considered extreme (>45°F) due to end ‘ thermal sinks’
  - Need to make estimate of expected gradients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

Thermocouple locations

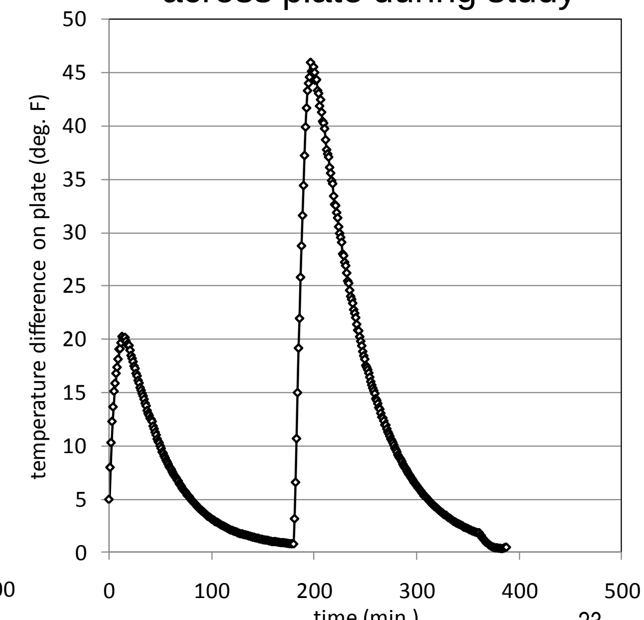


4 (in air on top side)

Temperature response on plate during cooling and heating



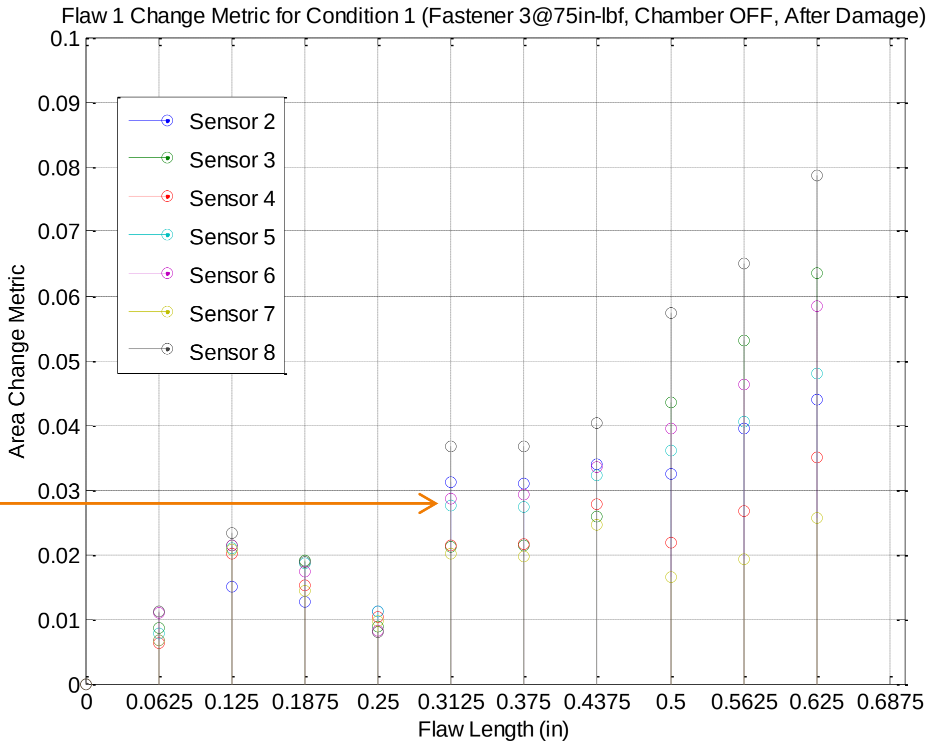
Peak temperature difference across plate during study



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



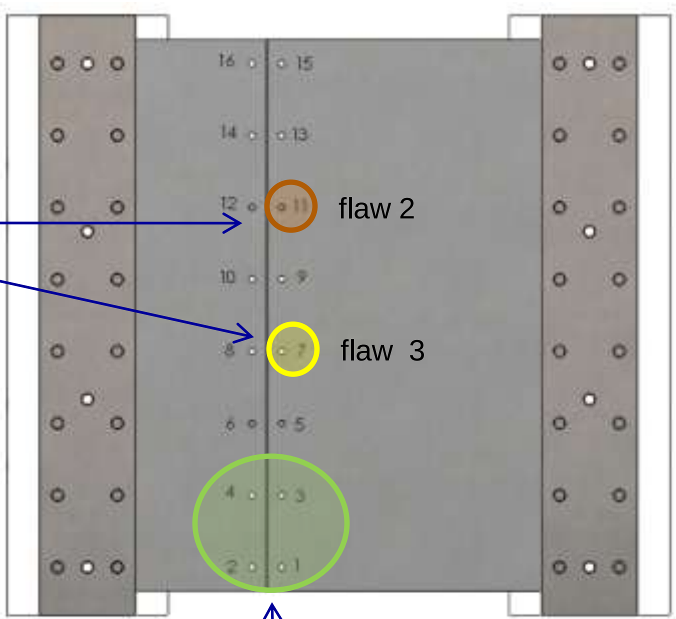
Design of Validation Study

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

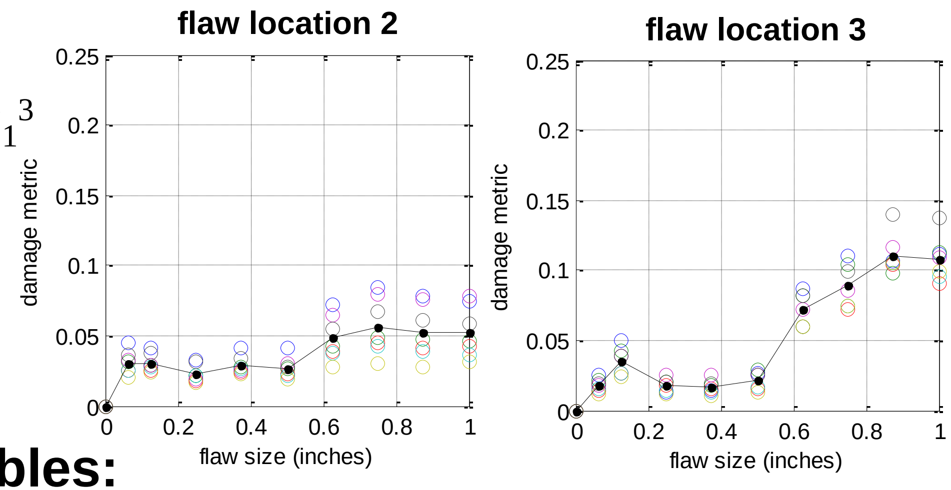


- Environmental conditions: (ambient 72°F)
  - Temperature variation (32°F to 112°F)
  - Temperature gradients (<10°F)
  - Ambient noise (chamber on / off)
- Boundary conditions:
  - Loading / unloading mass on structure (10 lb)
  - Fastener removal and reinstall (75 in-lbs +/- 10 in-lbs) – 'simulate 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

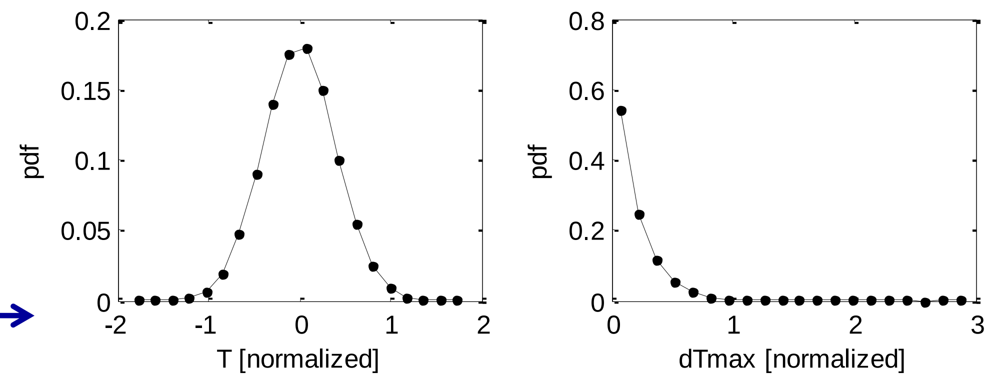
Perform separate statistical tests for significance

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)

Input Parameters → **Measurement 'Model'** → **Call Criteria** → **POD Model**

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)

<table>
<tr><td>Code:</td><td>data.tmp <- read.csv('analy_ref1_flaw3.csv',header=FALSE)
x1 <- data.tmp$V1
x2 <- data.tmp$V2
x3 <- data.tmp$V3
x4 <- data.tmp$V4
x5 <- data.tmp$V5
x6 <- data.tmp$V6
x11 <- x1*x1
x111 <- x1*x11
y1 <- data.tmp$V14
frame1 <- data.frame(y=y1, x1=x1, x2=x2, x3=x3, x4=x4, x5=x5, x6=x6, x7 = x11, x8 = x111)
y.vs.x<- lm(formula = y ~ x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8, data=frame1)
summary(y.vs.x)</td></tr>
<tr><td>Call:</td><td>lm(formula = y ~ x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8, data = frame1)</td></tr>
<tr><td>Residuals:</td><td>Min 1Q Median 3Q Max
-0.035835 -0.007133 0.001119 0.006437 0.026368</td></tr>
<tr><td>Coefficients:</td><td>Estimate Std. Error t value Pr(>|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</td></tr>
<tr><td>Diagnostics:</td><td>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: < 2.2e-16</td></tr>
<tr><td>Significant Factors:</td><td>• x1 <- data.tmp$V1: Flaw size ($a_1$) (Part of flaw size model)
• x3 <- data.tmp$V3: Normalized mean temperature (a_3)
• x5 <- data.tmp$V5: Normalized temperature gradients (a_4),
• x7 <- x11 <- x1*x1 Flaw size model term: $(a_1)^2$
• x8 <- x111 <- x1*x11 Flaw size model term: $(a_1)^3$</td></tr>
</table>

Input Parameters → **Measurement ‘Model’** → **Call Criteria** → **POD Model**

Measurement / POD Model

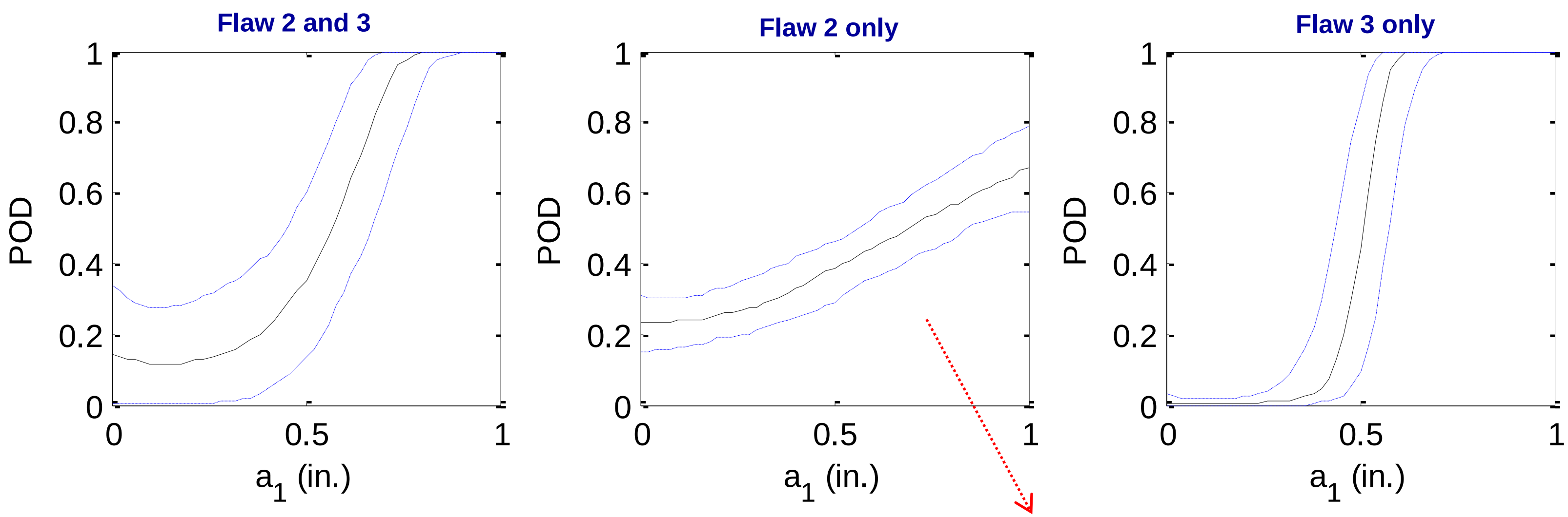
POD Evaluation Process:

- 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.

Input Parameters → **Measurement 'Model'** → **Call Criteria** → **POD Model**

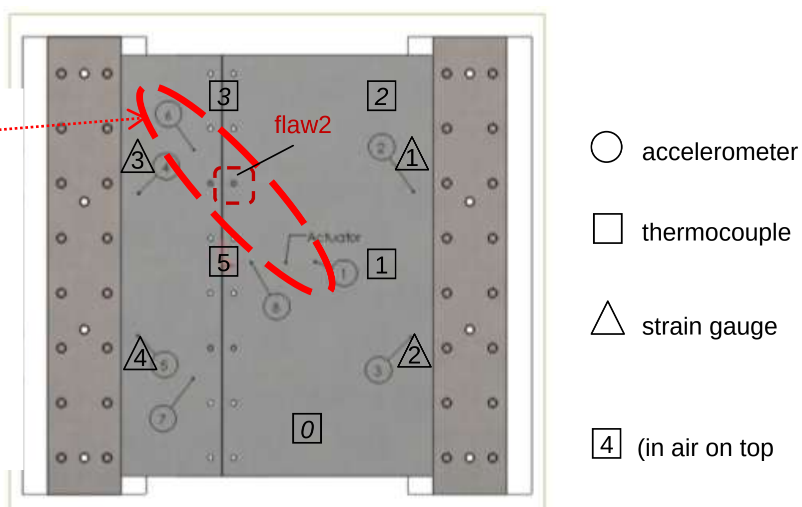
POD Results – Sensitivity to Flaw Location

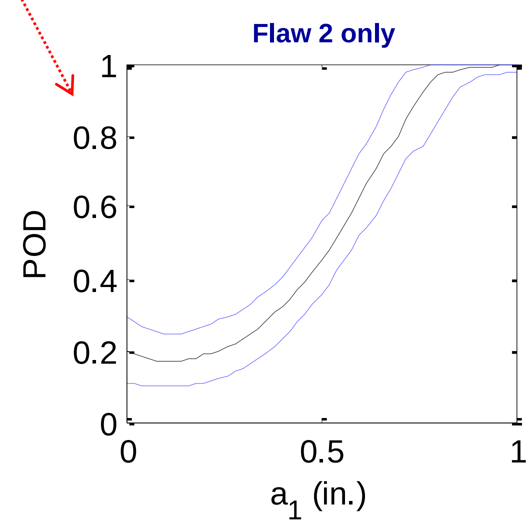
POD Results: Dependency on Flaw Location



Can Improve POD by Choosing *Optimal Sensor Configuration*:

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

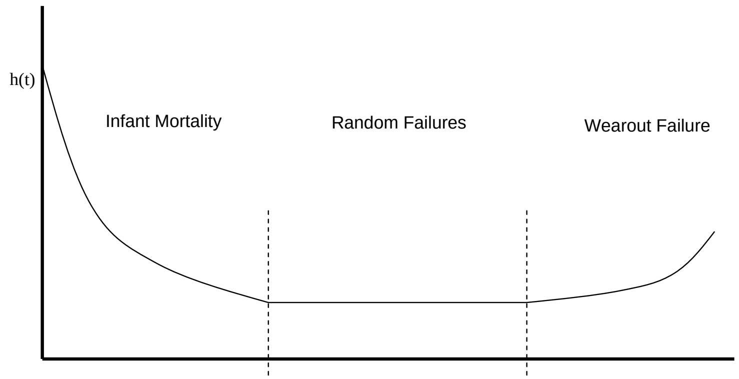


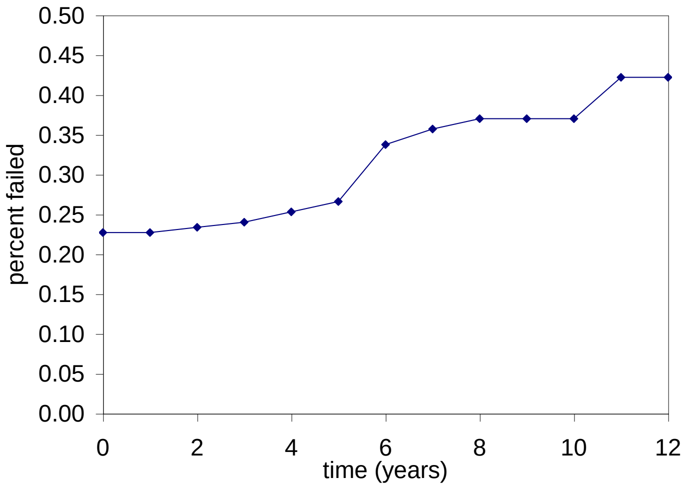


POD Results –
Impact of Sensor Durability

POD Evaluation Must Address Known Sensor Durability Issues:

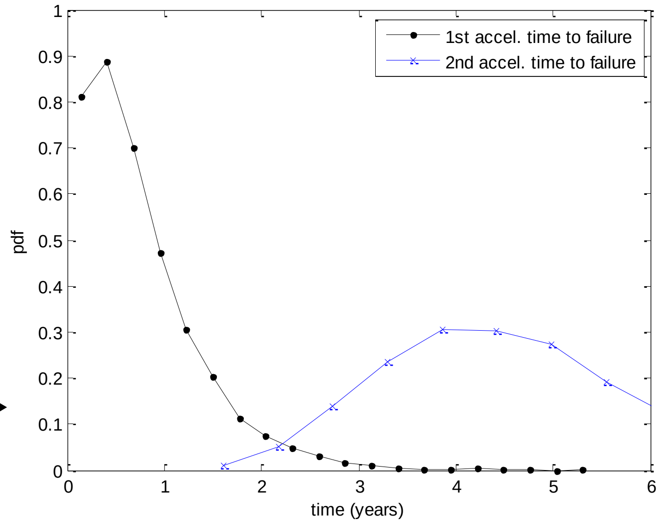
- **Issue demonstrated by percent of C–17 in-service strain gauge failures as a function of time** [Ware et al]
- **Bathtub Curve Model** [Meeker and Escobar]





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**

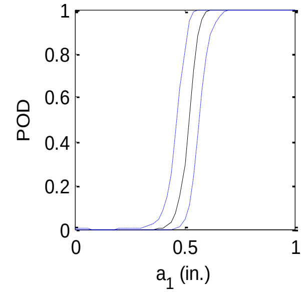


POD Results – Impact of Sensor Durability

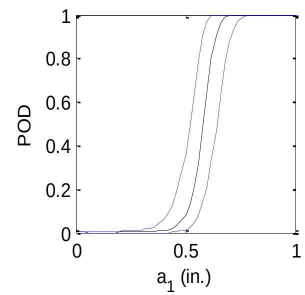
- **Sensor Scenarios with Corresponding Changes in POD and False Call Rate:**

Scenarios Addressing Sensor Failure

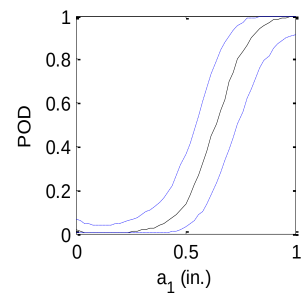
Approach 1: (Best Sensitivity)
- Use accel. #1 as reference
- Use accel. #6 as source



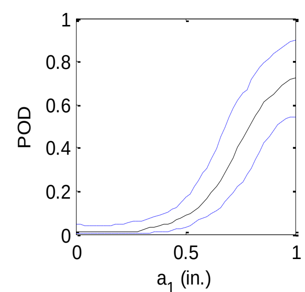
Approach 2: (Accel.#6 Failure)
- Use accel. #1 as reference
- Use median of active sensors



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

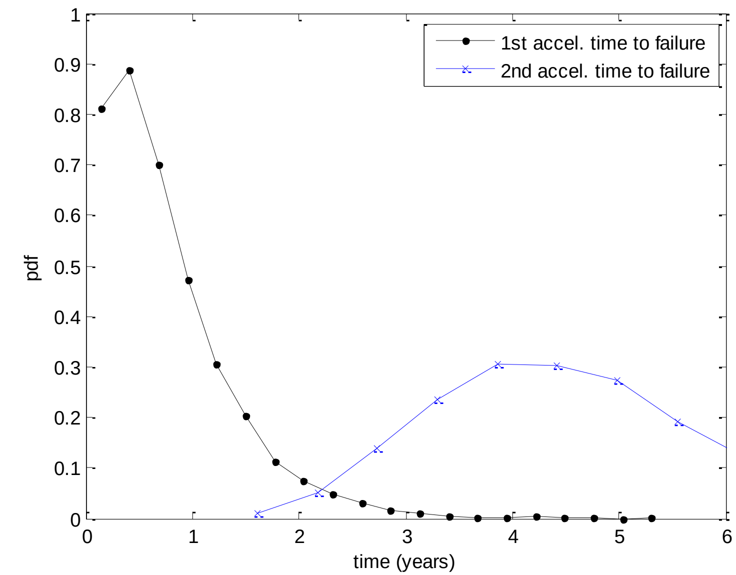


POD Results – Impact of Sensor Durability

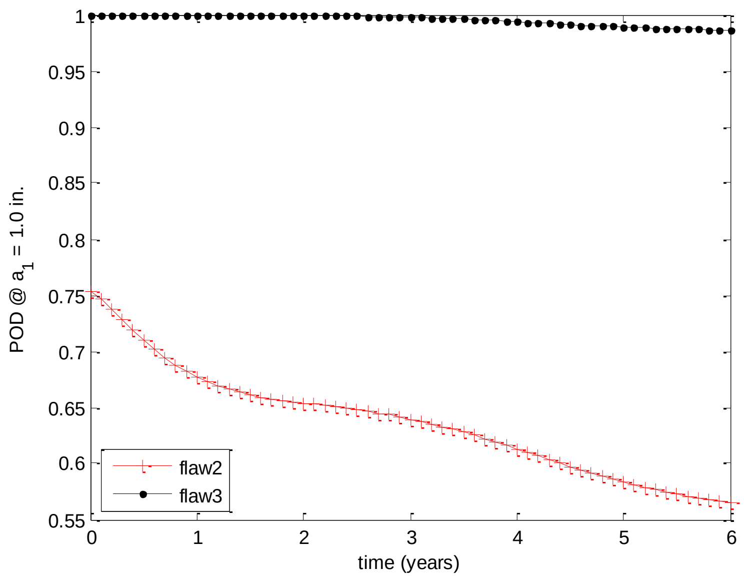
Evaluation of Impact of Sensor Failure:

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

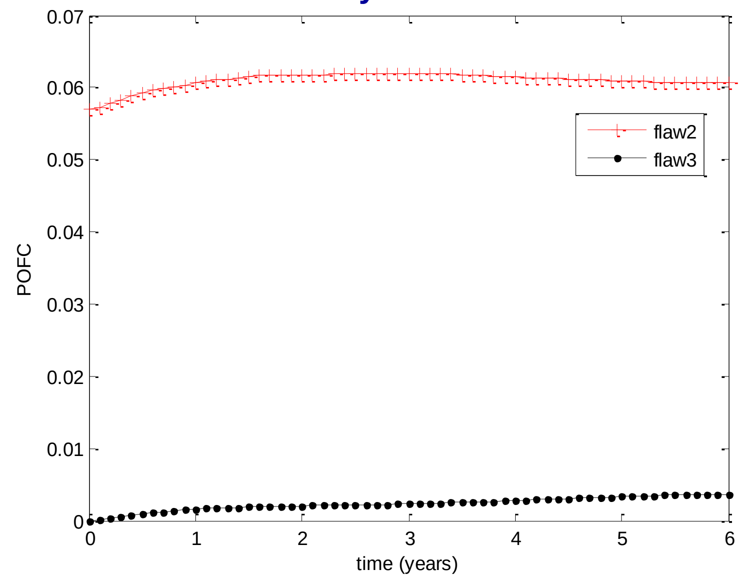
Results:* *Mean* expected POD and POFC at a flaw size of 1.0 in *as a function of time



Probability of Detection



Probability of False Call



Summary and Conclusions

- **Progress on MAPOD for NDE and SHM:**
  - **Protocol:** NDE → MH1823A; SHM → Aldrin et al 2011
  - **Tools:** Validated Models, MAPOD Toolkit [TRI/Austin]
- **Key Insight from EC / UT MAPOD Demonstrations**
  - Models in evaluation has potential to impact sample requirements
  - Crack morphology is a significant factor in NDE measurements
  - Challenges exist to quantify complete source of noise, error
    - Identify limits on purely models assisted approaches
- **Key Insight from SHM MAPOD Demonstration**
  - Must ensure changes in SHM metric are truly damage growth
  - Certain flaw locations may require separate POD models
  - Feasible to evaluate impact of sensor failures on performance
  - Need MAPOD approach to cover all damage scenarios, over time
- **Need better understanding of *variabilities* through empirical data collection, forward and inverse modeling**

Acknowledgements

- Air Force Research Laboratory – NDE Branch (RXLP) Jason Heebl, Josh Shearer, John Brausch, Rick Reibel, Mark Blodgett
- University of Dayton Research Institute (UDRI): Matt Cherry, Ryan Mooers
- Victor Technologies – Elias Sabbagh, R. Kim Murphy
- Radiance Technologies
- Jose Santiago – Univ. of Florida
- TRI/Austin: Chris Coughlin
- CNDE - Iowa State University
- Irving Gray - NDE Technologies
- Floyd Spencer – SfHire
- Charles Annis - Statistical Engineering
- The R software environment for statistical computing and graphics was used for all statistical computation and statistical plots. R is open-source (free) software and is available for download here: www.r-project.org

Future Directions in MAPOD (1)

I. **Modeling and Simulation:**

- **Model Benchmarking and Validation**
  - **Error analysis for uncertainty propagation**
  - **Provide insight to modeling gaps and needs**
- **Forward Model Development Efforts (UT, EC, IR)**
  - **Address gaps through development programs**
  - **Improve simulation time (leverage parallel processing/GPUs)**
- **Stochastic Modeling**
  - **Probabilistic Collocation Method**
  - **Many Unknowns (2D/3D Problems)**

Future Directions in MAPOD (2)

II. Analysis:

- Address Variability and Uncertainty in Input Parameters
  - Statistical Uncertainty Evaluation and Propagation
  - Use of Inverse Methods to Quantify Variability and Reduce Uncertainty
- Develop Comprehensive Approach to A-hat vs A Analysis Using Different Model Types
  - Empirical fit (statistical model)
  - Calibrated numerical model
  - Calibrated numerical model with inverse methods (to estimate uncontrolled parameters)
  - Transfer function approach
- Second Order Probability Analysis
- Merging Empirical and Simulated Results (Bayesian Methods, Diagnostics)

Future Directions in MAPOD (3)

III. Extensions and Validation of Process

- **Model-assisted Measurement System Characterization**
  - **Validation of Localization and Sizing Estimates**
  - **Phase I SBIR 2011-12 Efforts**
- **Comprehensive Validation Studies of MAPOD Process**