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

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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.

\[ \ln a = \beta_0 + \beta_1 \ln a + \varepsilon \]

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

where \( \mu = \frac{\ln(y_{th}) - \beta_0}{\beta_1} \) 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.
Objective:
Develop Complete Approach to Uncertainty Propagation in MAPOD

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

Uncertainty Propagation

Input Parameter Variability (Distributions)
Model Error
Stochastic Models
Model ‘Calibration’
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.

\[
\hat{a} = \beta_0 + \beta_1 a_1 + \epsilon
\]

\[
\downarrow
\]

\[
\hat{a} = \beta_0 + \beta_1 a_1 + \beta_2 a_2 + \epsilon
\]

- **Physics-based models** provide opportunity for **reducing experimental samples** and cost.

\[
\hat{a} = \beta_0 + \beta_1 f(a_1, a_2) + \epsilon
\]

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

**Increase Model Accuracy**

- Reduces Residuals in Model Fit
- Improves Bounds on Parameter Estimates (POD)
- Impacts Experimental Sampling Requirements
Leverage *physics-based models* in POD evaluation that represent *key factors* in an NDE technique:

- Present status on models to address real cracks in material noise (EC, UT)
- Assess benefit of more accurate models on POD fit and sample requirements

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
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)
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

- liftoff
- aspect ratio
- length
- width
Measurement ‘Model’ Fit (mean + error on fit parameters)
1. Empirical fit (statistical model)
2. Calibrated numerical model
   o Step 1: Solve numerical model
     ▪ Data table with interpolation
     ▪ PCM model (Data table fit)
   o Step 2: Fit model to experimental data
     ▪ Calibration (Bayes, MLE)
     ▪ Transform model (same as ‘Calibration’)
3. Calibrated numerical model with inverse methods
   (to estimate uncontrolled parameters)
4. Transfer function approach
   o Empirical fit transformation
   o Calibrated numerical model transformation

Level 2: Uncertainty in Model Parameter Estimate(s)

\[ \hat{a} = \hat{\beta}_0 + \hat{\beta}_1 a_1 + \varepsilon \]
\[ \hat{a} = \hat{\beta}_0 + \hat{\beta}_1 f(a_1, a_2) + \varepsilon \]
\[ \hat{a} = \hat{\beta}_{nc} a + \varepsilon \]
\[ \hat{\beta}_{nc} = \hat{\beta}_{ns} + \hat{\beta}_{ac} - \hat{\beta}_{as} \]
\[ \sigma_{nc}^2 = \sigma_{ns}^2 + \sigma_{ac}^2 - \sigma_{as}^2 \]
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 \( a_1 = 0 \).

Input Parameters → Measurement ‘Model’ → Call Criteria → POD Model
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
Input Parameters in Study:

- $a_1$ = Crack length
  - primary variable for POD
- $a_2$ = Crack depth (width)
  - dependent variable on $a_1$ crack length
  - relationship defined by function $a_2(a_1) = a_4 \times a_1$
  - $a_4$ is the aspect ratio and defined as a random variable

- $a_3$ = Liftoff
  - uncontrolled parameter during study
  - estimation of liftoff could improve POD performance (to verify)
Input Parameters in Study:

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  - $a_4$ is the aspect ratio and defined as a 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 $a_2$ and $a_3$ included)
Simulated POD Studies: One vs. Two Parameter Models

Perform POD Assessment and Provide Diagnostic Tools:

**Ex:** $\hat{a} \text{ versus } a_1 \text{ and } a_2$ model fit: $\hat{a} = \beta_0 + \beta_1 a_1 + \beta_2 a_2 + \epsilon$

- **Explore:** Case study 3: $\text{dep\_fixed}$ - 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 $a_1$
  - $a_2 = m \cdot a_1$ where: $m$ is a constant value = 0.33

- **Compare different model fit and confidence bounds approaches**
  - **Analysis 0:** Neglect $a_2$
    - $B_0 = -0.05780$
    - $B_1 = 5.39532$
    - $B_2 = 0.00000$
    - Delta method for confidence bds
      - (ahat versus $a_1$ and $a_2$)
    - Threshold $0.10000$
      - var11 $0.00003$
      - var22 $0.00912$
      - var33 $0.00000$
      - a50 $0.02925$
      - a90 $0.03529$
      - a90/95 $0.03616$
  - **Analysis 1:** Regression fit, Delta method for confidence bds
    - (ahat versus $a_1$ and $a_2$)
    - Use $a_1, a_2$
    - $-0.05986$
    - $2.77503$
    - $6.65178$
    - $0.02001$
    - $0.10000$
    - $0.00002$
    - $0.73494$
    - $0.03204$
    - $0.03529$
    - $0.03616$
  - **Analysis 2:** Regression fit, Monte Carlo for confidence bds
    - (ahat versus $a_1$ and $a_2$)
    - Use $a_1, a_2$
    - $2.77503$
    - $6.65178$
    - $0.02001$
    - $0.10000$
    - $0.00002$
    - $0.75790$
    - $0.03204$
    - $0.03719$
    - $0.03720$
  - **Analysis 2:** Bayesian (MCMC) for model fit and confidence bds
    - (ahat versus $a_1$ and $a_2$)
    - Use $a_1, a_2$
    - $2.77668$
    - $6.64630$
    - $0.02061$
    - $0.10000$
    - $0.00002$
    - $0.78247$
    - $0.03732$
    - $0.03733$

- Inclusion of $a_2$ reduces residual variance (Delta)
- Very little difference observed between the three methods (1-3) for this case
Perform POD Assessment of VIC-3D© Model Fit:
- Calibrated Physics-based Model: \( \hat{a} = \beta_0 + \beta_1 f(a_1, a_2) + \epsilon \)
- 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

<table>
<thead>
<tr>
<th>samplesz</th>
<th>100</th>
<th>50</th>
<th>25</th>
<th>12</th>
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<td>max flaw size</td>
<td>0.100&quot;</td>
<td>0.100&quot;</td>
<td>0.100&quot;</td>
<td>0.100&quot;</td>
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<td>0.004</td>
<td>0.000</td>
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<td>Mu</td>
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<td>0.098</td>
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<td>Sigma</td>
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<td>0.021</td>
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</tr>
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<td>0.100</td>
<td>0.100</td>
</tr>
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<td>0.098</td>
<td>0.097</td>
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<td>0.125</td>
<td>0.117</td>
</tr>
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<td>0.133</td>
<td>0.135</td>
<td>0.127</td>
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<td>0.006</td>
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<td>0.010</td>
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<td>-1.88E-06</td>
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<tr>
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<td>0.00596</td>
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</tr>
</tbody>
</table>
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

![Graph showing comparison of experimental and modeled data for crack length on surface, c (in). The graph includes markers for different models: exp. (0.8 < a/c < 2.2), model (elliptical notch, a/c = 1.0), model (rectangular notch, a/c = 0.5), and model (crack profiles, a/c = 0.5). The graph highlights the need to address morphology for crack sizing.]

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)

[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**

1. Define SHM Application
2. Identify and Evaluate Controlling Factors
3. Design Multistage Validation Study
4. Perform Multistage Validation Study
5. Process Data for SHM Reliability Assessment
6. Economic and Probabilistic Risk Assessment

**Sub-tasks**

1. 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

20 July 2011
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

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
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)
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 \((a_6)\),

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
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** \( (a_1) \): \[ dm = \beta_0 + \beta_1 \cdot a_1 + \beta_2 \cdot a_1^2 + \beta_3 \cdot a_1^3 \]

• **Flaw location** \( (a_2) \)
  • Evaluate both ‘combined’ and ‘separate’ flaw location scenarios

• **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:
```

```
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)
```
POD Evaluation Process:

- Apply threshold for call criteria ($d_m > 0.06$)
- 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

![Graphs showing POD results for different flaw locations.]

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:

<table>
<thead>
<tr>
<th>Approach 1: (Best Sensitivity)</th>
<th>Approach 2: (Accel.#6 Failure)</th>
<th>Approach 3: (Accel.#1 Failure)</th>
<th>Approach 4: (Accel.#8 Failure)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Use accel. #1 as reference</td>
<td>Use accel. #1 as reference</td>
<td>Use accel. #8 as reference</td>
<td>Use accel. #3 as reference</td>
</tr>
<tr>
<td>Use accel. #6 as source</td>
<td>Use median of active sensors</td>
<td>Use median of active sensors</td>
<td>Use median of active sensors</td>
</tr>
</tbody>
</table>

Scenarios Addressing Sensor Failure
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

<table>
<thead>
<tr>
<th>POD @ a_1 = 1.0 in.</th>
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<tbody>
<tr>
<td>0</td>
</tr>
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<td>0.06</td>
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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**
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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)
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)
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