Optimal Sensor Placement Design Under Uncertainty for SHM Systems

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Outline

1. Overview & Motivation
2. Methodology
3. Example Application
4. Challenges & Future Investigations
5. Summary & Conclusion

Overview & Motivation

Sponsor: AFRL, WPAFB, Dayton, OH (Project Monitor: Mark Derriso)

Project: Optimization of Structural Health Monitoring System for Hot Aerospace Structures (Space Operations Vehicle - SOV)

Objective: Develop methods for optimization of complex systems under uncertainty

[Courtesy of AFRL]

Motivation:

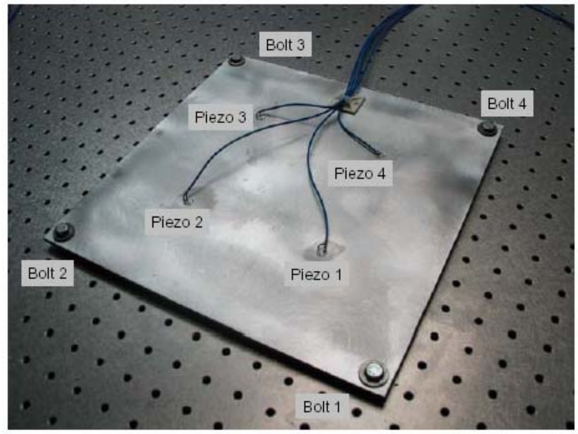
1. Next generation flight vehicles subjected to extreme and uncertain environments
2. Ultimate purpose of SHM system is to provide real-time system-level risk assessments
3. SHM systems must provide dependable and reliable information
4. SHM systems must be designed optimally.

Methodology

1. **Structural Simulation:** development and analysis of finite element models of hot aerospace structures subjected to mechanical and thermal loads
2. **Model Validation:** use experimental data to validate finite element models
3. **Probabilistic Analysis:** integrate uncertainty and spatial/temporal variability into FEM analysis
4. **Damage Detection Algorithms:** post-processing of probabilistic analysis results for state classification
5. **Sensor Placement Optimization:** identify optimal sensor layout for reliable SHM systems of hot aerospace structures

Test Article

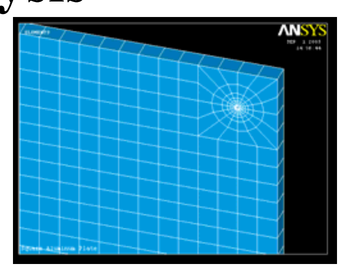
- Perform SHM on simple test article (square aluminum plate attached to optical table via stand-offs and bolts)
- Excite structure via piezoelectric actuator at location 1 (sinusoidal swept-frequency deformation, 0-1500 Hz in 2.0 seconds)
- Collect response at locations 2, 3, and 4
- Extract/select optimal feature set
- Classification based on Bayesian Decision Theory
- Declared structural state:
  - Healthy vs. Damaged
  - Healthy vs. Damage at Location j

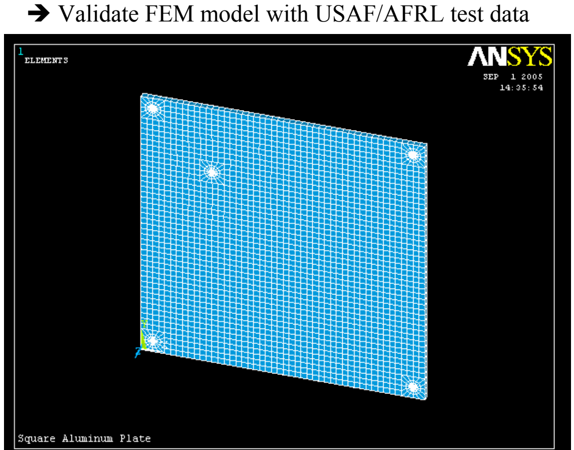


[Courtesy of AFRL]

FEM Analysis

➔ Modeling Square Aluminum Plate via ANSYS
➔ Approx. 3,000 Nodes/2,900 Elements
➔ 4-Noded Shell Elements (Shell63) and 2-Noded Spring Elements (Combin14)
➔ Validate FEM model with USAF/AFRL test data





Model Parameters:
- $F(x_i)$ = Mechanical Loads
- H(xi) = Thermal Loads
- $G(x_i)$ = Geometric Properties
- $E(x_i)$ = Material Properties
- $K(x_i)$ = Boundary Conditions & Damping Constants

Probabilistic FEM Analysis

Include Variability in:
- $F(x_i)$ = Mechanical Loads
- H(xi) = Thermal Loads
- $G(x_i)$ = Geometric Properties
- $E(x_i)$ = Material Properties
- $K(x_i)$ = Boundary Conditions

All parameters vary in space or with time and are best modeled as **Random Fields/Processes**

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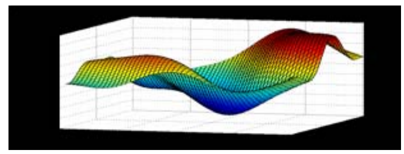
Discretize into sets of Random Variables:
- Spectral Representation
- Karhunen-Loeve Expansion
- Polynomial Chaos Decomposition



Probabilistic FEM Analysis:
1. Response Surface Approach (Output vs. Input)
   - Conventional Regression
   - Polynomial Chaos Based
2. Sensitivity Based Approach
3. Monte Carlo Simulation (including efficient sampling methods)

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Damage Detection: Data Processing & Signal Analysis

- Feature Extraction
- Feature Selection
- State Classification

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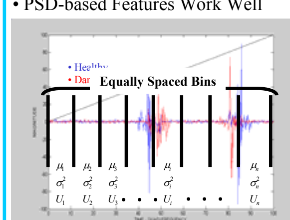
- Many Feature Types to choose from.
- Very Problem/Application Dependent.
- PSD-based Features Work Well



Assign a signal to a state such that features for signals in that state are similar and features for signals in other states different.

- Utilize Discriminant Functions
- Bayesian Decision Theory
- Mahalanobis Distance

$$d_j(x) = (x - \mu_j)' \Sigma_j^{-1} (x - \mu_j)$$

Provides a subset of n features from m-dimensional feature pool most effective for state classification AND such that $n << m$.

- Brand & Bound Search
- Sequential Forward Selection
- Sequential Backward Selection
- Plus-l-Minus-r Search

<u>Data Processing Limitations:</u>
- Finite Sampling Rate
- Finite Sampling Duration

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Performance Measures

Structural Classification:
For 5-Class Problem

Damage 1 vs. Damage 2 vs. Damage 3 vs. Damage 4 vs. Healthy

Confusion Matrix		Classified States				
		Damaged 1	Damaged 2	Damaged 3	Damaged 4	Healthy
True States	Damaged 1	78	21	0	0	1
	Damaged 2	0	98	0	2	0
	Damaged 3	0	1	91	7	1
	Damaged 4	0	10	0	89	1
	Healthy	0	11	0	1	88

Accuracy Measures

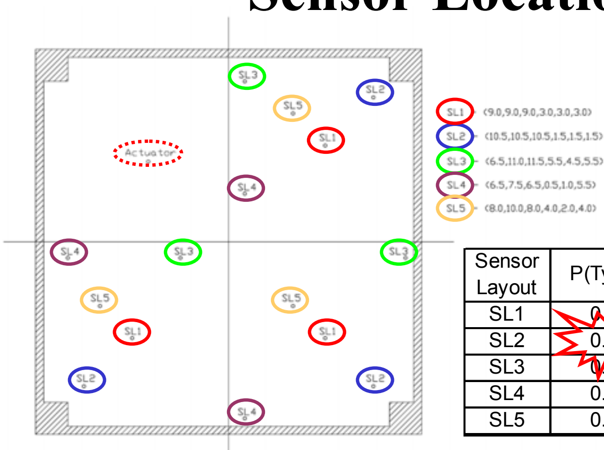
$$P(\text{Correct Detection}) = \frac{\text{Sum of Diagonal Elements of CM}}{\text{Sum of All Elements of CM}}$$

Error Measures

$$P(\text{False Alarm}) = \frac{\text{Sum of First 4 Elements in Row 5 of CM}}{\text{Sum of All Elements in Row 5 of CM}} = P(\text{Type I Error})$$

$$P(\text{Missed Detection}) = \frac{\text{Sum of First 4 Elements Column 5 of CM}}{\text{Sum of All Elements in Column 5 of CM}} = P(\text{Type II Error})$$

Sensor Locations



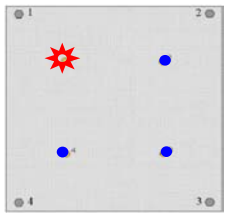
Sensor Layout	P(Type I)	P(Type II)	P(CDD)
SL1	0.12	0.0075	0.916
SL2	0.08	0.0050	0.860
SL3	0.12	0.0	0.866
SL4	0.11	0.0025	0.894
SL5	0.10	0.0075	0.872

- Sensor Placement Optimization is needed
- Multi-Objective Optimization:

$$f(y) = \alpha \cdot P(CD) - \beta \cdot P(Type\ I) - \gamma \cdot P(Type\ II)$$

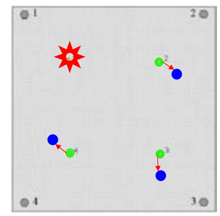
Sensor Placement Optimization

From Probabilistic FEM Analysis &
Damage Detection/Signal Processing



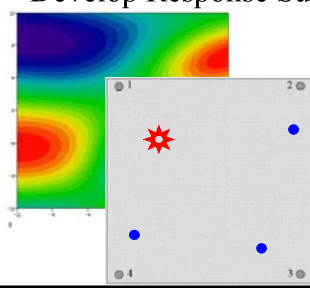
$P(CDD)$
$P(Type\ I)$
$P(Type\ II)$

Perturbation of Sensors



$P^{new}(CDD)$
$P^{new}(Type\ I)$
$P^{new}(Type\ II)$

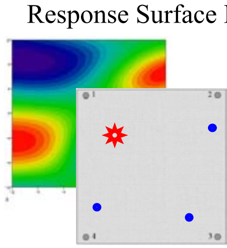
Develop Response Surface



$P^{optimal}(CDD)$
$P^{optimal}(Type\ I)$
$P^{optimal}(Type\ II)$

Sensor Placement Optimization

Response Surface Methods



$P^{optimal}(CDD)$
$P^{optimal}(Type\ I)$
$P^{optimal}(Type\ II)$

SNOBFIT

Stable Noisy Optimization by Branch and Fit

Developed and programmed by
W. Huyer and A. Neumaier,
Universität Wien

Works for problems with:

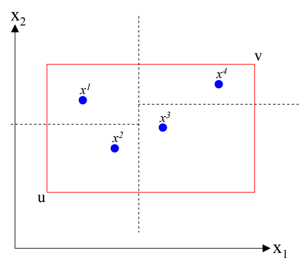
1. Expensive function evaluations
2. Noisy function evaluations
3. Lack of gradient information
4. Bound constrained optimization

$$\min f(y)$$
$$s.t.\ \ y \in [u,v]$$

where y is continuous and $[u,v]$ is a bounded box in $\Re^n$

SNOBFIT

Branch: subdivide search domain such that each sub-space contains exactly one point

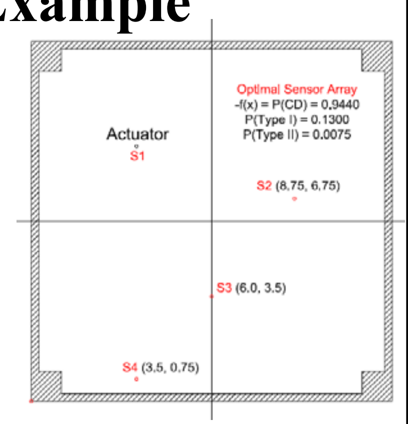


Fit: constructs local quadratic models around x^{best} and all other points by minimizing model errors

Recommended Points: returns evaluation points belonging to five different categories:

1. Minimum of quadratic model around x^{best} inside trust region of radius d
2. Minimum of quadratic model around x^{best} inside trust region of radius ρd
3. Minimums of the quadratic models around all other points
4. Points in unexplored regions
5. Random points to fill up set of requested recommended points

Numerical Example



1. FEM Analysis: Aluminum Test Article
   - excitation from 0 to 1500Hz over 2.0 seconds
   - approximately 3,000 nodes and 2,900 elements
2. Probabilistic FEM Analysis:
   - included variability of plate thickness, modulus of elasticity, density, Poison's ratio, excitation amplitude, and ambient temperature
3. Damage Detection & Signal Processing: perform SHM classification on 5-state problem (bolts @ 100% torque vs. bolts 1,2,3,4 @ 25% torque)
4. Sensor Placement Optimization: utilize SNOBFIT for maximization of $P(\text{Correct Detection})$ with respect to the coordinates of sensors

Numerical Example

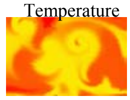
Challenges

1. Transient Analysis:
   - 1500Hz excitation function => time step approaches zero
   - 2,900 element model => ~3Gb result file
2. Optimal Feature Extraction:
   - computationally extensive
   - accessing simulation result files takes time
3. SPO:
   - finite fidelity of FEM model => discrete independent variables
   - noisy and flat objective function
   - multi-objective optimization

Future Investigations

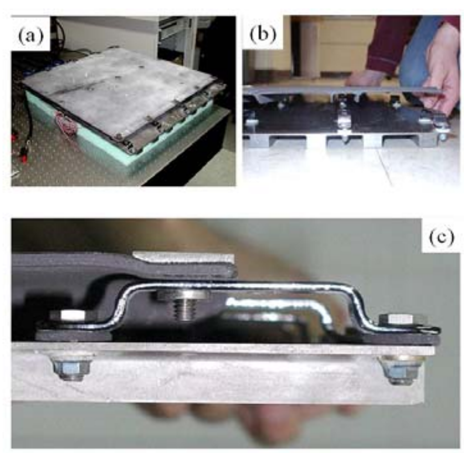
- Consider more complex/realistic component of TPS
- Validate methodology experimentally
- Incorporate into methodology:
  - Sensor sensitivity

Temperature



Moisture

  - Sensor reliability
  - Sensor redundancy



[Courtesy of AFRL]

Summary & Conclusion

Methodology for Optimization of SHM Systems Under Uncertainty:

- **FEM Analysis**
- **Model Validation**
- **Probabilistic FEM Analysis**
- **Damage Detection/Signal Processing**
- **Sensor Placement Optimization**

Challenges:

- **Computational Effort**
  - Transient Analysis
  - Sensor Configuration Optimization (discrete variables)
  - Optimal Feature Extraction

Future Investigations:

- **Sensor Sensitivity and Reliability**
- **Consider Realistic TPS Component**

Questions & Comments