



Instrumentation and Sensors: Acoustics

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Motivation

Development of acoustic monitoring techniques that can be coupled with embedded fiber-optic sensors for in-situ structural monitoring of inaccessible microreactor components

FY24 Goals

Integrate acoustic processing methods, analytical techniques, and new experimental data for defect location information and other metrics

- Evaluate methods of machine learning, FEA modeling, and analysis using prior demonstration data for defect location information and other metrics
- Integrate with ORNL optical sensing development to incorporate technology capabilities & limitations into our modeling and experimental designs

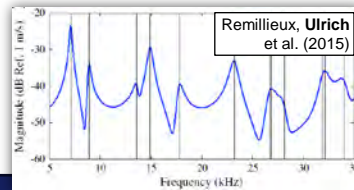
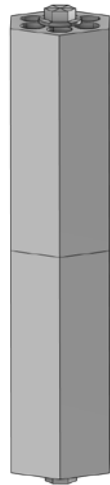
Can we leverage resonance from ambient vibrations to monitor for structural changes?

Experiment

Methods

Outcomes

Acoustic testing of stressed core-block proxy intact and damaged



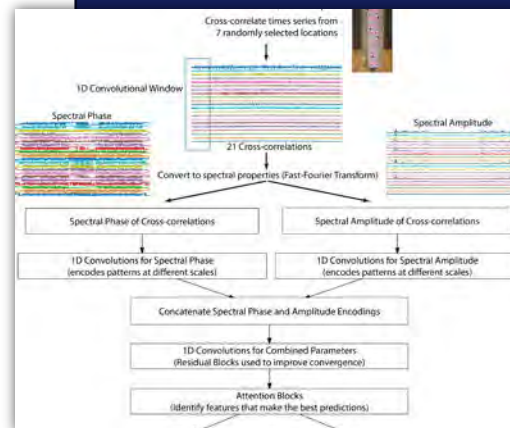
**Resonant Ultrasound Spectroscopy
linear & nonlinear**

**Machine Learning
neural networks (NN)**

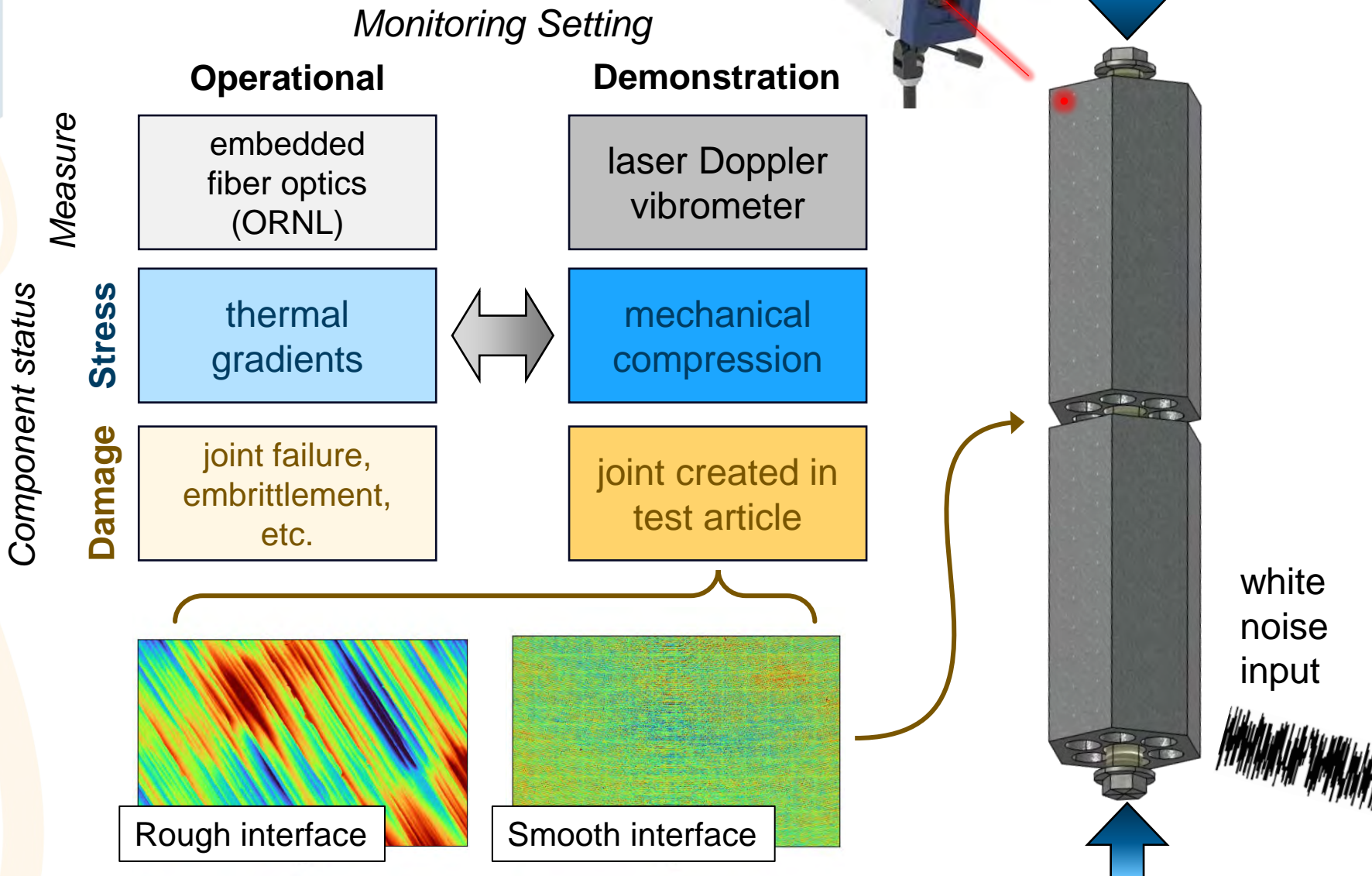
Elastic material properties

Identify variations in stress & damage states

Inform future embedded sensing designs



Demonstration test matrix and operational relevance

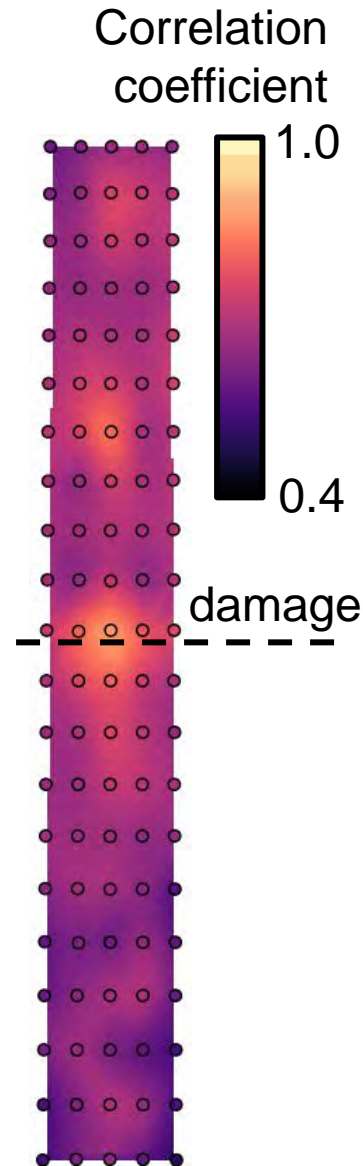


Damage identification and localization

Basic damage identification demonstrated in FY23

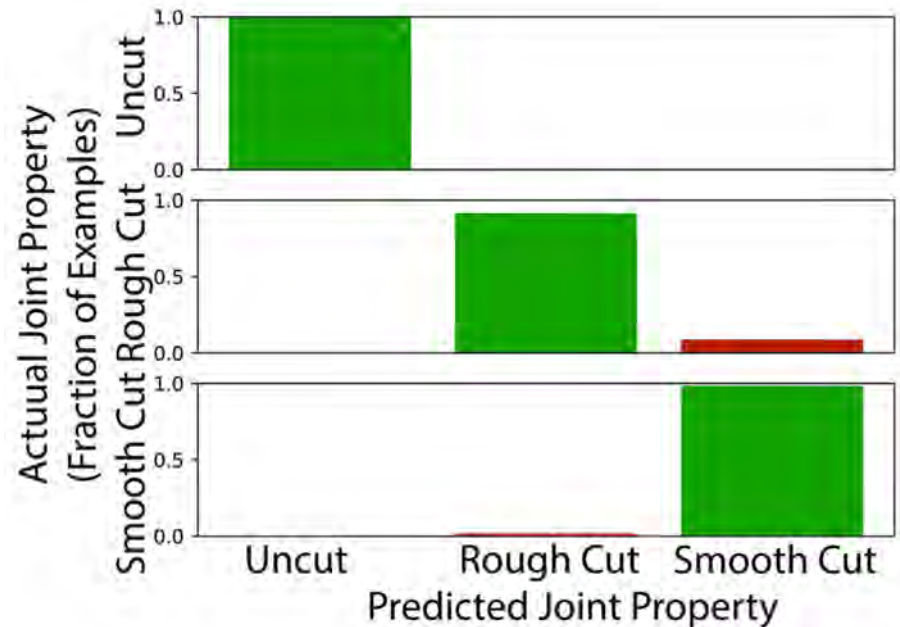
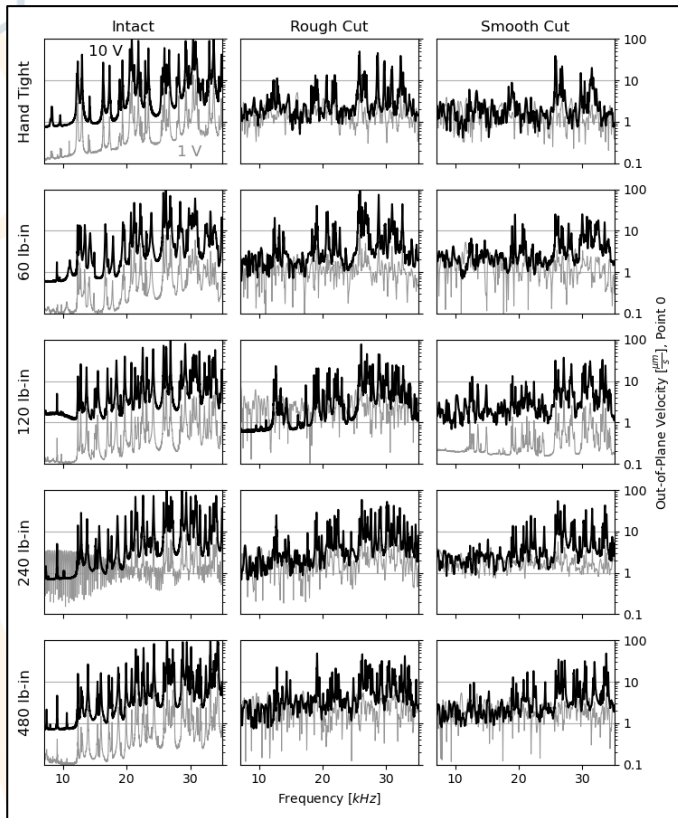
Graph neural network (GNN) currently being tested against convolutional neural network

- Target outputs: Component state of health and damage location from existing vibrational dataset
- Current priority: develop optimization scheme to identify a reduced set of stations without sacrificing prediction power
 - To mimic current & expected limitations of ORNL embedded sensing technology



Convolutional NN predictions of **damage state**:

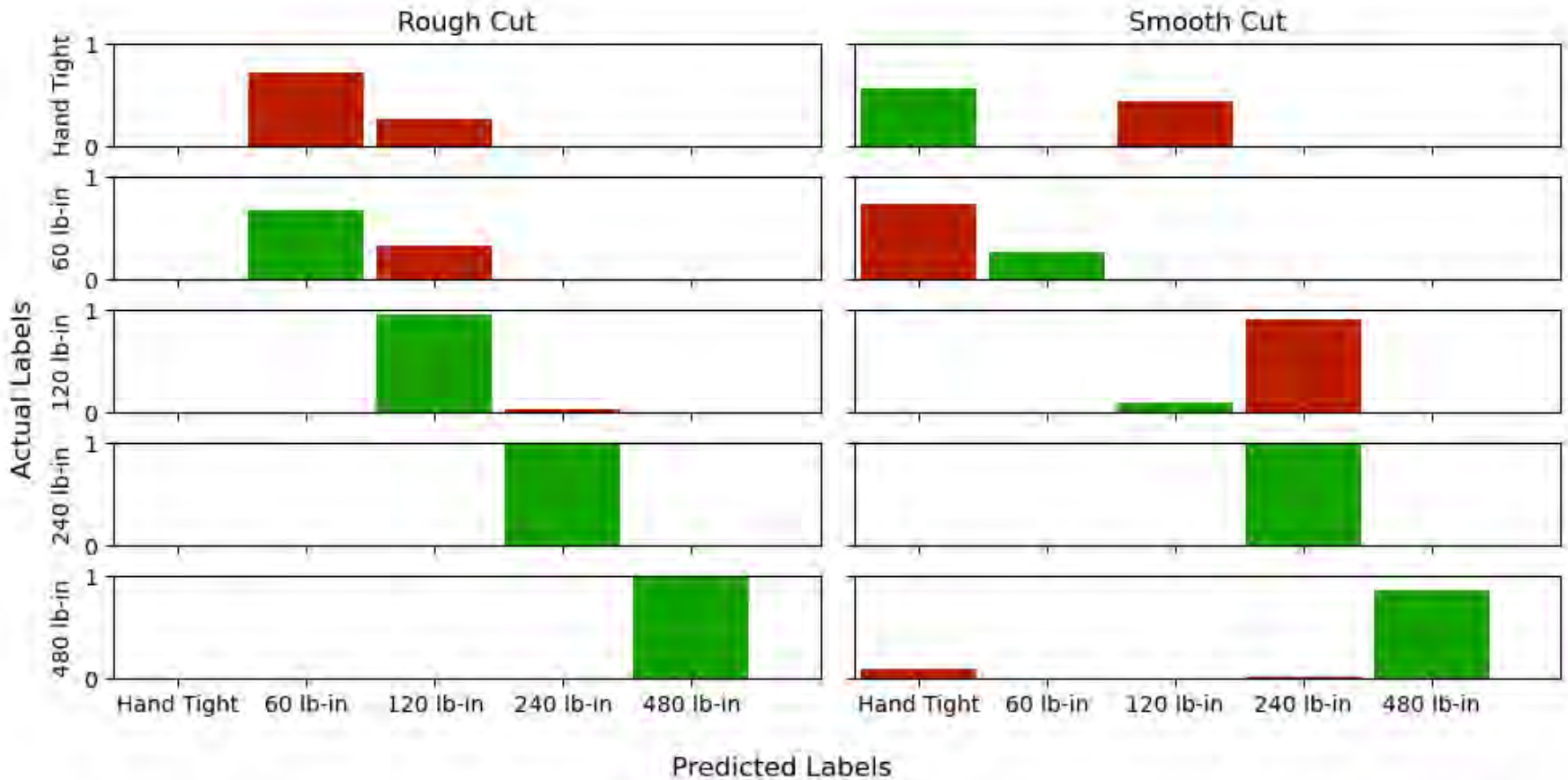
100% correct identification of presence of joint
 94% correct prediction of joint roughness



Predictions of combined stress & damage states:

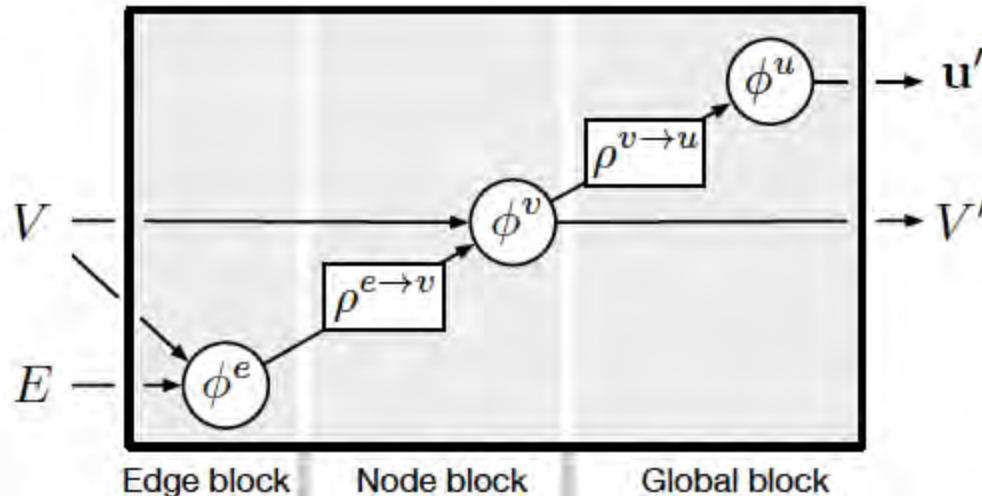
75% accurate for rough cut, 60% for smooth cut

Improved accuracy at higher stress levels



Graph neural networks

- Nodes & edges connect features of importance, similar to physical experiment design
- Expected behavior: the most important edges & subgraphs will correlate with damage location

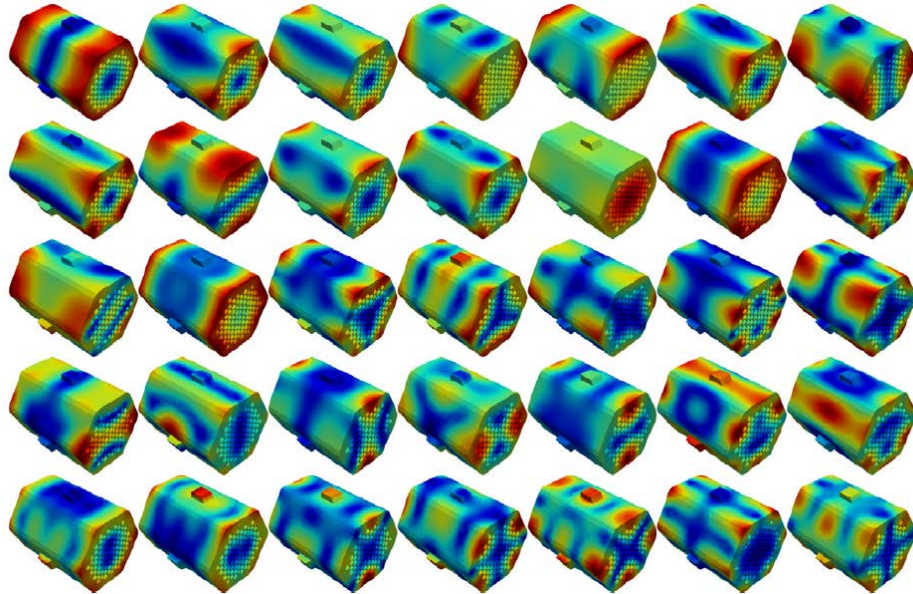


V = Station Information (time series recorded at each station)

E = Interstation Relationships (cross-correlations)

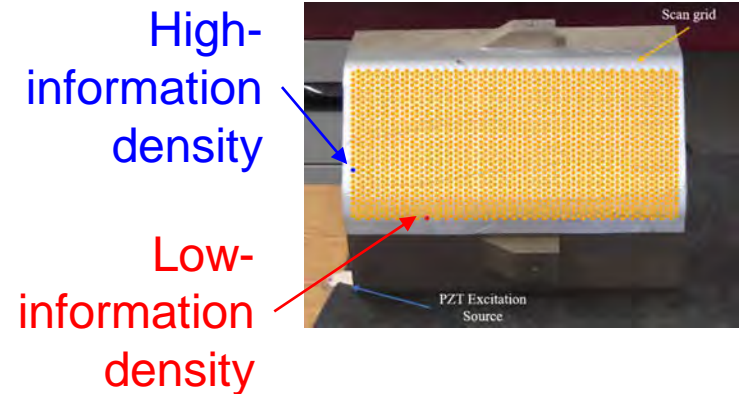
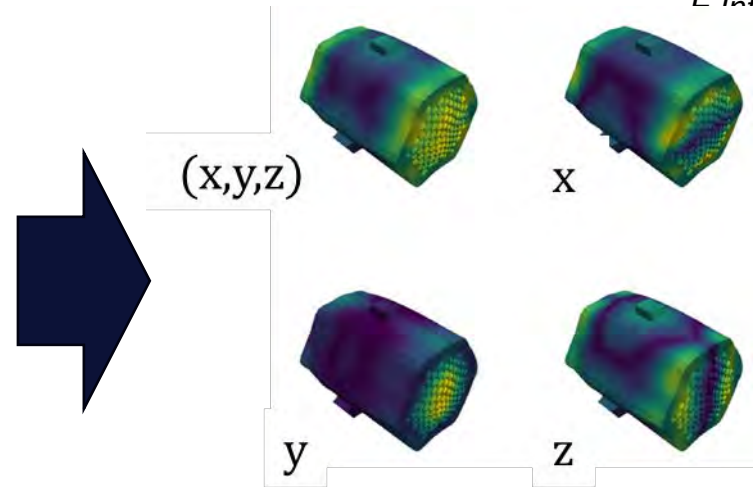
u = Universal Properties (strain, damage state, etc.)

Predicting optimal sensor placement



- Prior to measurement: predict optimal sensor placement using principal component analysis (PCA) on mode shapes
- Regenerate analysis for any combination of physical components

Beardslee, Shokouhi, Ulrich (2024). *NDT & E Int.*



Takeaways of capstone project



- Mentorship provided for Masters-level data science capstone project at Texas A&M
- Neural network trained and tested on a subset of 2TB vibrational dataset from FY23 (1 input amplitude chosen out of 10)
- Prediction performance:
 - 81.2% accuracy for component of motion (**2.4x** better than random guess)
 - 51.2% accuracy for stress state (**2.6x** better than random guess)
- PCA provided best dimensionality reduction
- Suggested next steps: increase diversity of damage & stress states in training dataset
- Project has prompted interest from other data science students at A&M, plans for A&M to host data in open access repository

Model architecture
[# of units/neurons]

Flatten time series [50000]

Dense – ReLU activation [128]

Dropout – prevent overfitting (rate=0.5)

Dense [64]

Dropout

Output [3]

Next steps: experimental

- Collect new dataset on intact/damaged sample with an emphasis on activation of nonlinear elastic behavior for damage detection
 - Unify data acquisition settings to improve ML processing
 - Utilize infrared vibrometry for improved sensitivity to mode shapes during excitation
- Refine data acquisition processes for implementation in reactor test bed

Questions for potential implementation at MARVEL

- What are the expected vibration sources?
 - Frequency bandwidth, amplitude, propagation distance
- Are there opportunities to make exploratory measurements with a laser vibrometer or will any measurements require embedded transducers or fiber optic?
 - Which high-concern components/systems/materials can be monitored in-situ?
 - Core block, heat pipe, interfaces, other non-rad components?

FY24 milestone status

Completed: Develop plan for integration with ORNL embedded sensing advancements (M4 carryover from FY23)

In-progress and on track:

1. Evaluate methods of machine learning, FE modeling, and analysis using prior demonstration data for defect localization and other metrics (M4, due Mar 2024)
2. Integrate selected processing methods, analytical techniques, and new acoustic data for defect localization and other metrics (M3, due Sep 2024)

Recent MRP-supported papers & presentations

[Beardslee, L., Shokouhi, P., and Ulrich, T.J. \(2023\). Optimal measurement point selection for resonant ultrasound spectroscopy of complex-shaped specimens using principal component analysis. *Nondestructive Testing & Evaluation International*.](#)

Conference Presentations

[Geimer, P.R., Ulrich, T.J., Moore, J.R. \(2023, June 5–9 \). *Modeling quantification of nonlinear resonant ultrasound spectroscopy* \[Conference presentation\]. 25th International Conference on Nonlinear Elasticity in Materials, Ghent, Belgium.](#)

(invited) [Geimer, P.R., Beardslee, L., Ulrich, T.J. \(2023, December 4-8\). *Nonlinear resonant ultrasound spectroscopy using white-noise excitation*.](#)

[Conference presentation]. Acoustics 2023, Sydney, Australia.