Intelligence Augmentation for Aviation-based NDE Data

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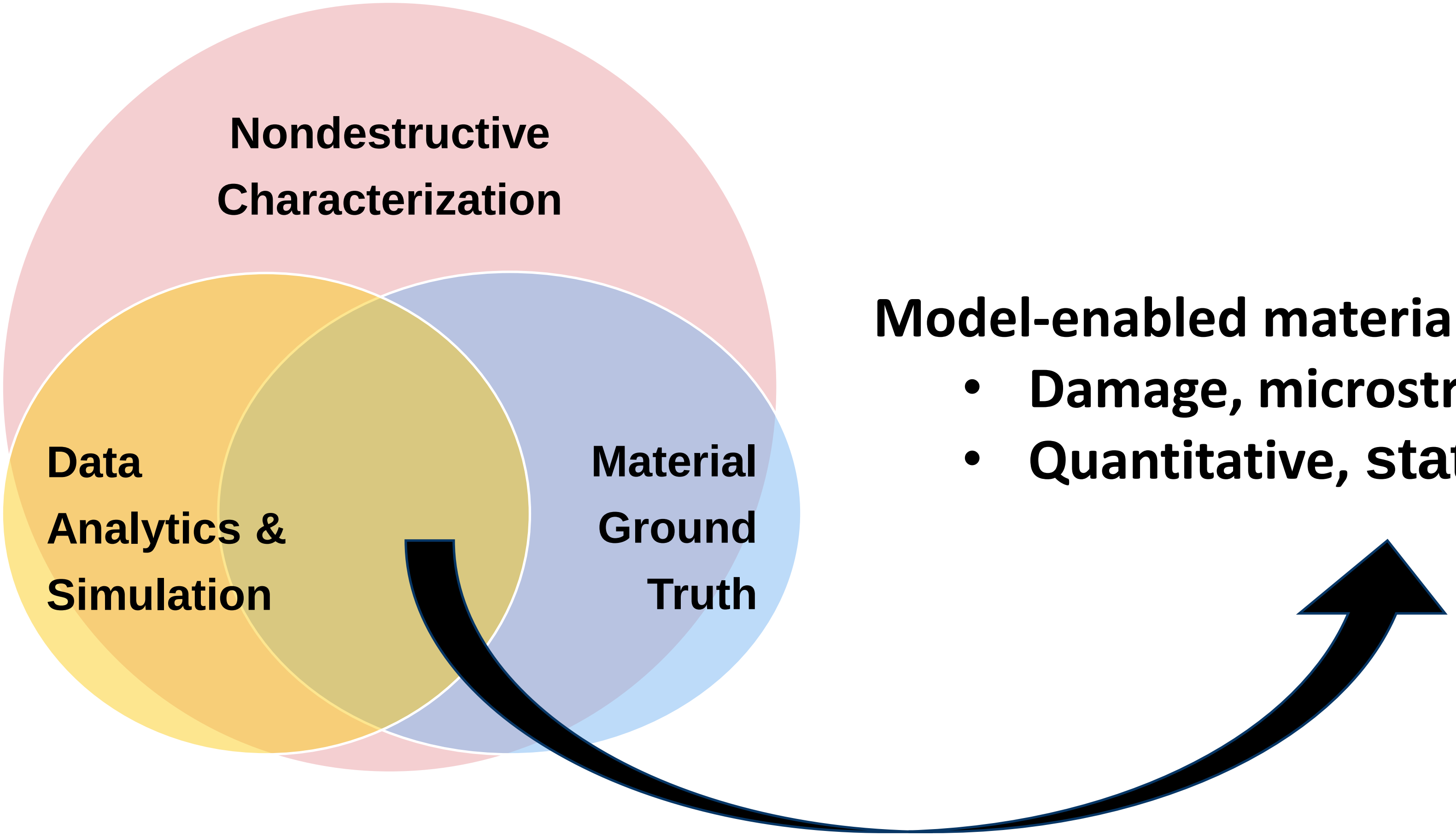
30AUG2022

Outline

- Introduction to Material State Awareness
- Background – Defining Intelligence Augmentation (IA)
- Nature of Aviation-based Data
- Alternatives to Artificial Intelligence / Machine Learning
- Successful Implementation of IA
- Current Exploration
- Thoughts for the Future
- Discussion

Materials State Awareness

Reliable, Quantitative, Digitally-Enabled Materials & Damage Nondestructive Characterization; regardless of scale



Model-enabled material representation

- **Damage, microstructure, properties**
- **Quantitative, statistical metrics**

Defining Intelligence Augmentation

Integrates three general classes of algorithms:

- Expert / heuristic-based algorithms
    - “Rules of the road” to help make decisions
- Model-based algorithms
    - Mental “what-if” scenarios
- Machine Learning, i.e. Artificial Intelligence
    - Data-driven experience, aka “lessons learned”

All three in use today as part of daily life:

- Optimal decision making can include two or more
    - Depends on circumstances

Required outcomes depend on function / location

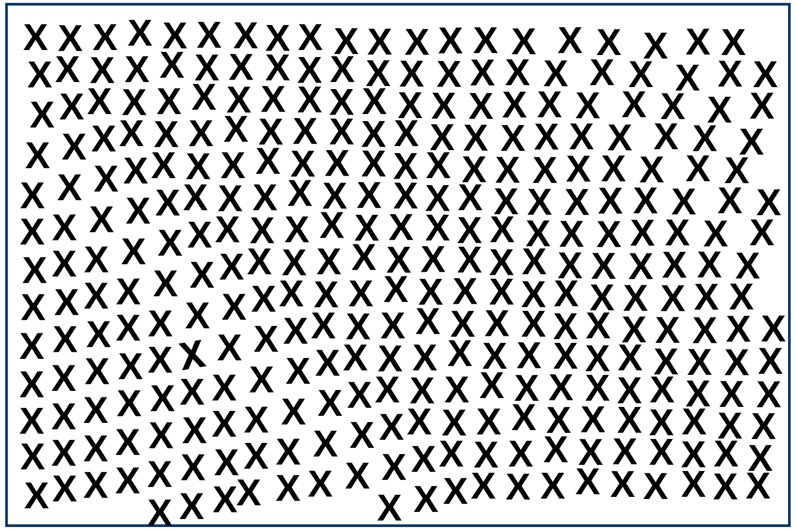
AFRL Testing

Representative Manufacturing

Representative Depot Maintenance

- Research, manufacturing, and sustainment: differing requirements on accuracy / precision
- NDT capabilities must meet requirements of each location

Defining Artificial Intelligence / Machine Learning (AI/ML)

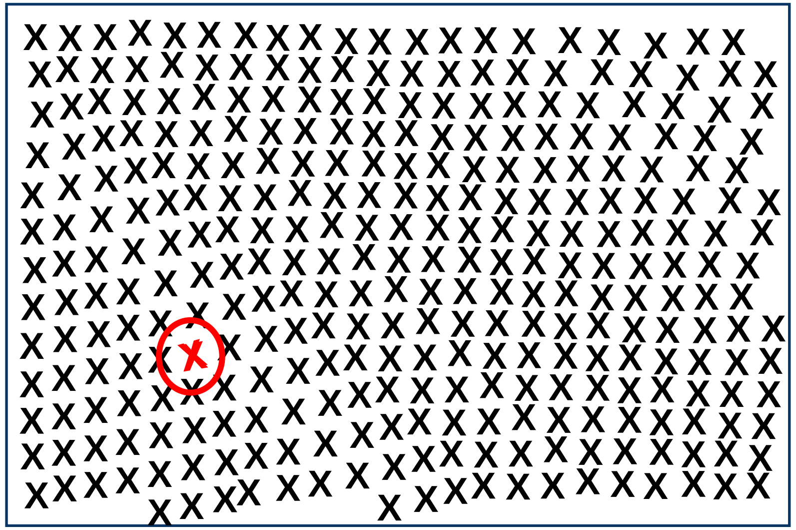


Challenge: which one is different?

- Statistical classification
- Statistical regression
- Can be unsupervised or supervised
  - Guard rails on data

- Challenge is nuances or outliers
- Hard to identify a nuanced change
- Tends to ignore outliers
- These are the challenges of NDE Data

Defining Artificial Intelligence / Machine Learning (AI/ML)



Challenge: which one is different?

- Statistical classification
- Statistical regression
- Can be unsupervised or supervised
  - Guard rails on data

- Challenge answer in red
- Criteria: slight rotation
- Not too different from detecting indications in large C-scan data sets

Pros and Cons of AI/ML

Pros:

- Handle Laborious and Repetitive Tasks
- Error Reduction (Complex Tasks)
- Faster Decisions/Actions
- Reduction in Overall Risk
- Act as ‘Digital Assistant’
- Repository for Human ‘Expertise’

Cons:

- Cannot make decisions well for scenarios not trained
  - **e.g. Air France flight 447 crash**
- Lack of Inherent Flexibility / Poor at Judgement Calls
- Degradation of Human Skills
- High Cost: Development, Validation
- Lack Moral Values
- Change in Employment

Potential for Automated or Assisted Defect Analysis (ADA)

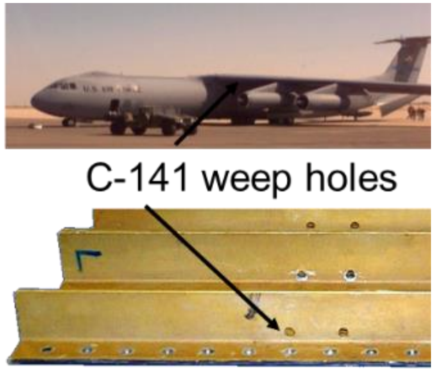
- Faster, cheaper, better!
- Initial thoughts to minimize reliance on inspector skills, but….
- Experience has shown that replacing a human is very challenging!

Example:

- A continuous issue for AI/ML methods is a question of how much data is required to enable training and how high of fidelity is required for such training. Recent examples of potential limits of AI/ML techniques when applied to large sets, such as decision to not use facial recognition for the Internal Revenue Service [1], have provided illustrative examples of this challenge.

    From: “IRS announces transition away from use of third-party verification involving facial recognition,” IRS News Release available at: https://www.irs.gov/newsroom/irs-announces-transition-away-from-use-of-third-party-verification-involving-facial-recognition

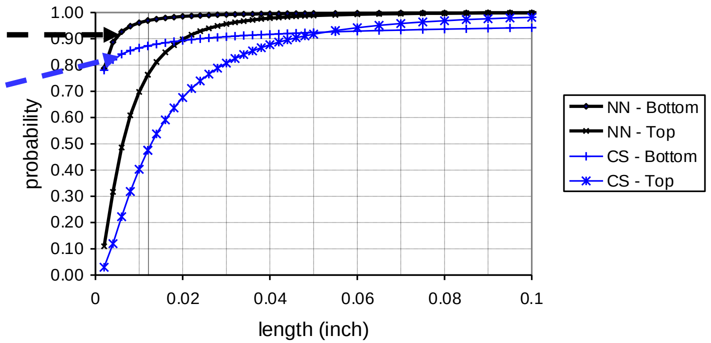
Previous Successes and Implementation

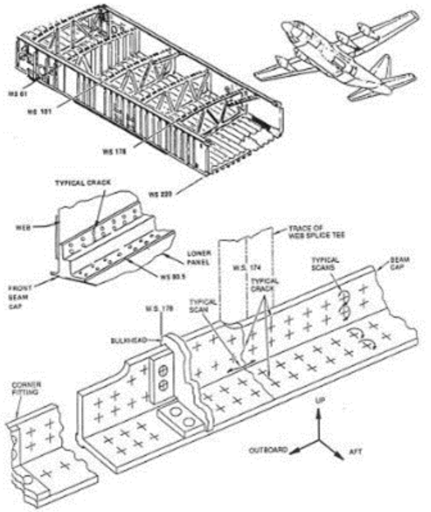


NN = automated

CS = visual

False Call Rate	
NN - Bottom	1.1%
NN - Top	0.1%
CS - Bottom	1.6%
CS - Top	1.4%





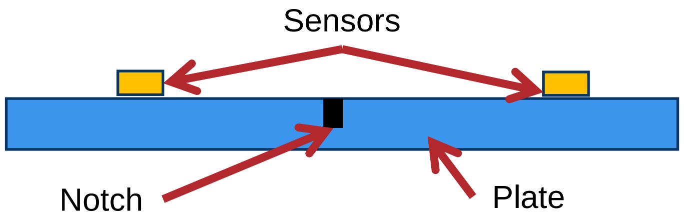
- C-141 Weep Hole Crack Detection*
- Leveraged leaky Rayleigh wave (Nagy 1997)
- BEM model of wave propagation
- Automated analysis of data
- Validated by full POD study

*Materials Evaluation – 2001 Authors: John Aldrin, Jan Achenbach, Glenn Andrew, Charlie P'an, Bob Grills, Tommy Mullis, Floyd Spencer, Matt Golis

- C-130 Lower Forward Spar Cap**
  - Leveraged C-141 successes
- Leaky Rayleigh waves for holes with fasteners installed
- Automated analysis of data
- Verified by human review
- Validated by full POD study

**Lindgren, E., Judd, D., Concordia, M., Mandeville, J., Aldrin, J. C., Spencer, F., Fritz, D., Pratt, E., Waldbusser, R., Mullis, R. T., "Validation and Deployment of Automated Ultrasonic Inspections for the C-130 Center Wing," ASIP Conference, Savannah, Georgia, (December 2 - 4 2004).

Challenges: Damage / Materials Detection / Characterization



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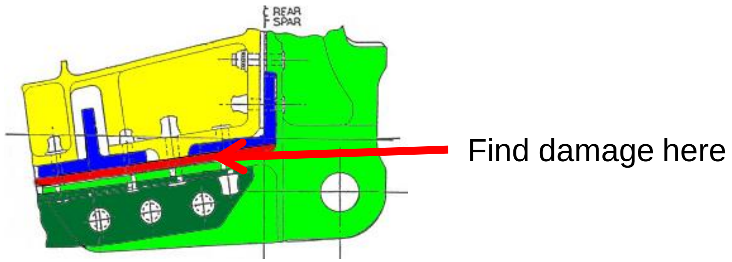
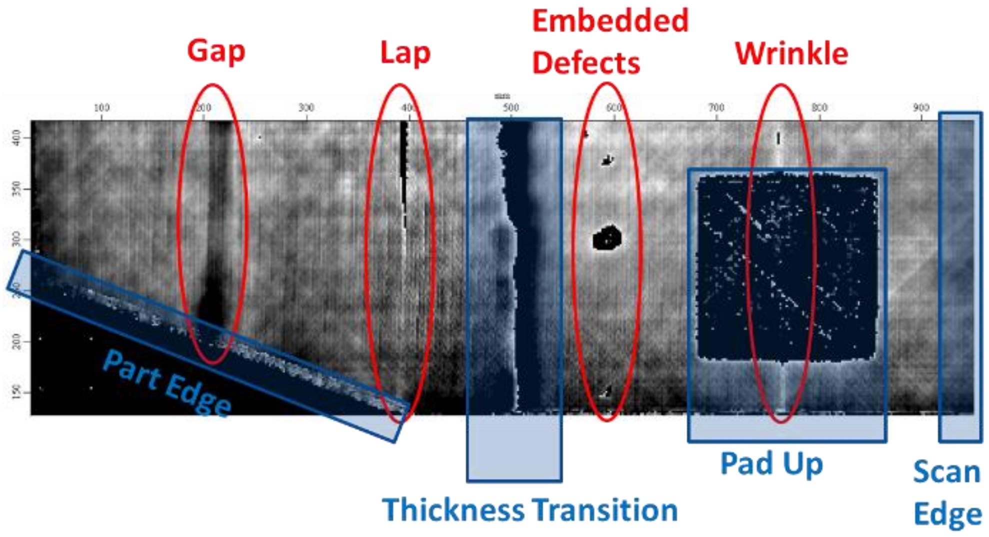


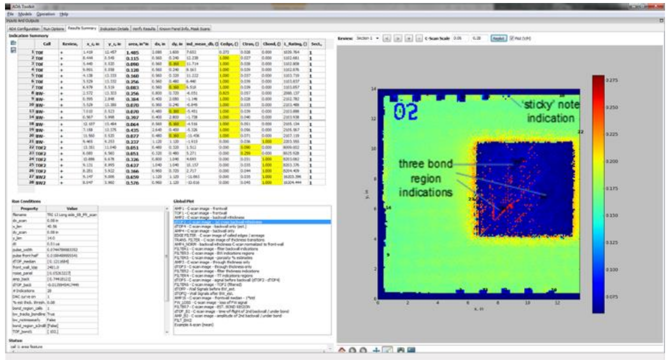
- Equipment Variability
- Structural Complexity / Variability
  - From design, manufacturing, repair, modification, maintenance, and usage
- Defect / Material Complexity / Variability
  - Stochastic variability (e.g. cracks)
  - Boundary Conditions

- Validation of Capability
  - Required for ASIP / PSIP driven applications
  - POD or equivalent
- Qualification
- Time variance in performance
  - Includes durability
- Environment
  - Temperature, loads, etc.

Directly affects ability to reproducibly detect damage

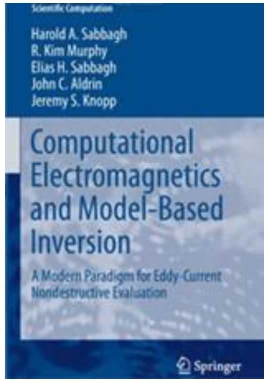
Heuristic Methods Algorithms

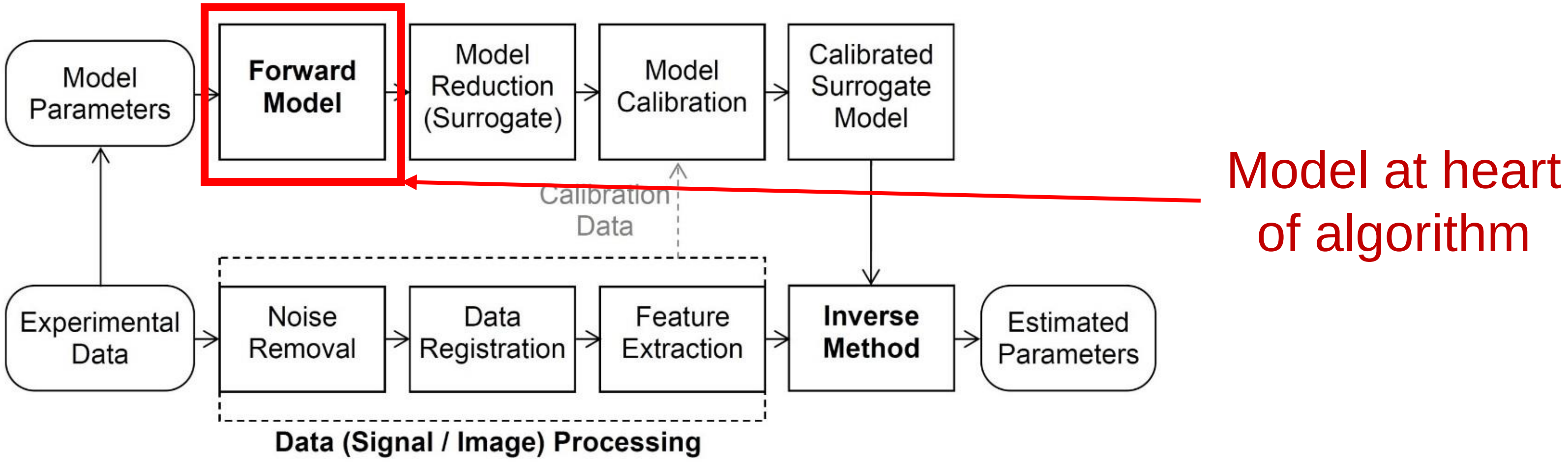




- Implement Human Data Review Procedures in Algorithms
- Example: Assisted Data Analysis (ADA) for UT of Composite Panels
    - 100% Ultrasonic inspection for manufacturing QA
    - Not required for fielded systems: localized inspections only

Model-based Algorithms





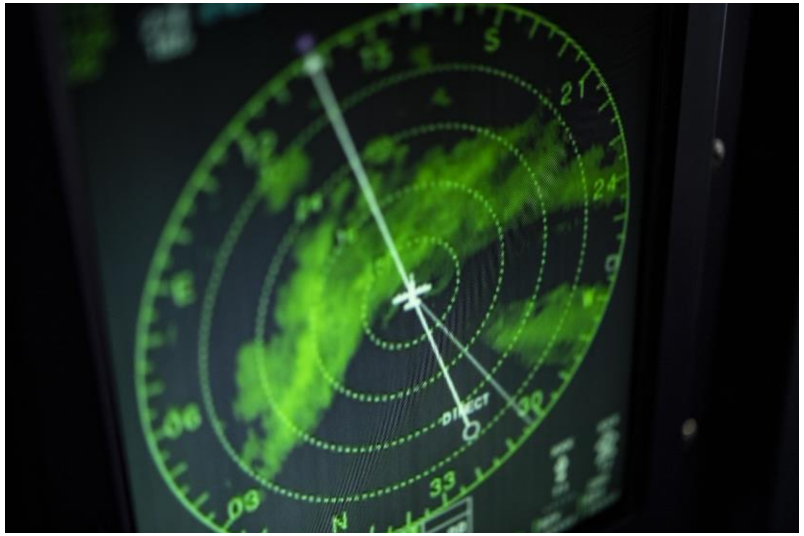
- First principles (physics) ‘model’ with optimization (iterative) scheme to solve classification problems
- Current R&D application: crack sizing in turbine engine components
  - Structural variability minimized

AI/ML – based Algorithms

Statistical Classifiers / Machine Learning

- Statistical classifiers: Use statistical representation of data classes
  - Frequentist (e.g. Fisher's linear discriminant)
  - Bayesian (e.g. MCMC computations)
- Artificial Intelligence, Neural Networks, and Deep Learning
  - Layered algorithms mimics a 'network of neurons'
  - Requires large well characterized data set
  - 'Deep learning' strategies overcoming past issues with learning complex patterns and robustness to input variability

AI/ML Data Challenge: how much, how good?

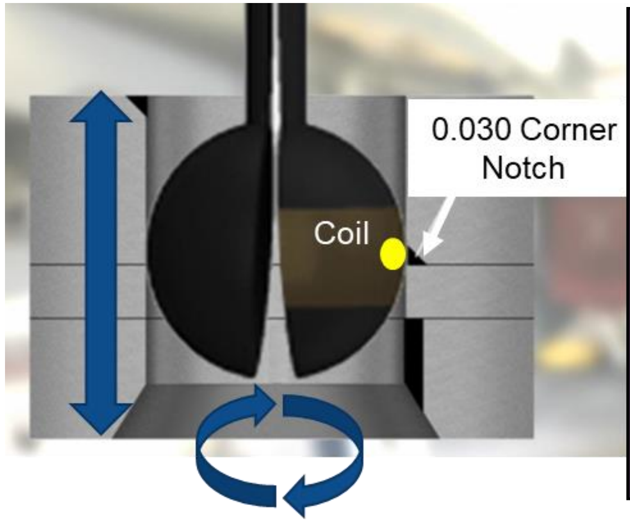


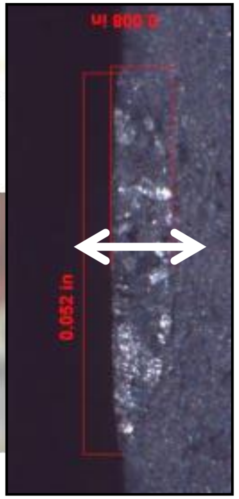
USAF Hurricane Hunter Data

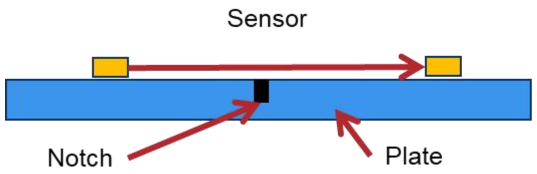
Checking Switch Matrix Equipment

- Independent data required!
- Cannot use same data to train and verify algorithms
- Model-based data must be representative – includes all anticipated variability
    - Otherwise must collect real data, e.g. Hurricane Hunters
- Automated algorithms extremely hard, algorithms to assist much more practical

Representative Success – Combine all three







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Out-of-round / Skew / Oblong / Repaired / Over-sized / Flaw type (maintenance-induced)

- Algorithms to size bolt-hole cracks (length and depth)
    - Mainly heuristic and model-based, plus leveraging data
- **Accuracy achieved to within 8.5% of actual depth**
    - Mitigated all equipment / sensor variability
    - Within bounds of first oversize
    - Enables one-step disposition
    - Enhances risk management, including unexpected cracks
- Next step: address structural variability

Way Forward to Realize Pervasive ADA

To be successful combine any and/or all to realize objectives!

- No two situations are identical
- Heuristic: capture and replicate human interpretation
  - C-scans to A-scans, Strip charts to impedance planes…
  - Integrate artisan expertise!
- Model-based: validated models that include variability
  - Time and effort to take model from demonstrate to validate
  - Do not expect CAD to be representative – as built and as maintained!
- AL/ML-based: needs lots and lots of data
  - Must be fully representative
  - Challenge when detecting/characterizing nuances and outliers in data
- Cannot discount value of human review
  - Work to minimize workload and augment effectiveness
- Must consider availability/volume of data:
  - Manufacturing vs. in-service
  - Features of interest

Bonus: Methods can Streamline Inspection Development

TRI
AUSTIN

Model Driven Development and Validation of Nondestructive Inspection

David Forsyth, John Aldrin, Mark Warchol, Lyudmila Warchol, Jennifer Flores-Lamb, Ajay Shah,
John Nagel, Sarah Williams, Kaleb Liburd

2021 Aircraft Structural Integrity Program (ASIP) Conference,
November 21 – December 2, 2021
Austin, TX

Summary

- NDE plays critical role in managing risk
- NDE "applications" continue to grow
  - New materials / process acceptance
  - Risk / life management of aging assets
- Desired Attributes: Capability / Reliability / Efficiency
- Developing solutions with simulation, automation, and assisted analysis
- Success depends on application of all three primary analysis methods:
  - Heuristic, rules-based
  - Model-based
  - Data-based, i.e. AI/ML
- Recall value of human analysis, but seek to minimize workload
- Lots of opportunities

Discussion

- **Distribution Statement A: Unlimited release, AFRL Case Number 2022-2579**

Photograph