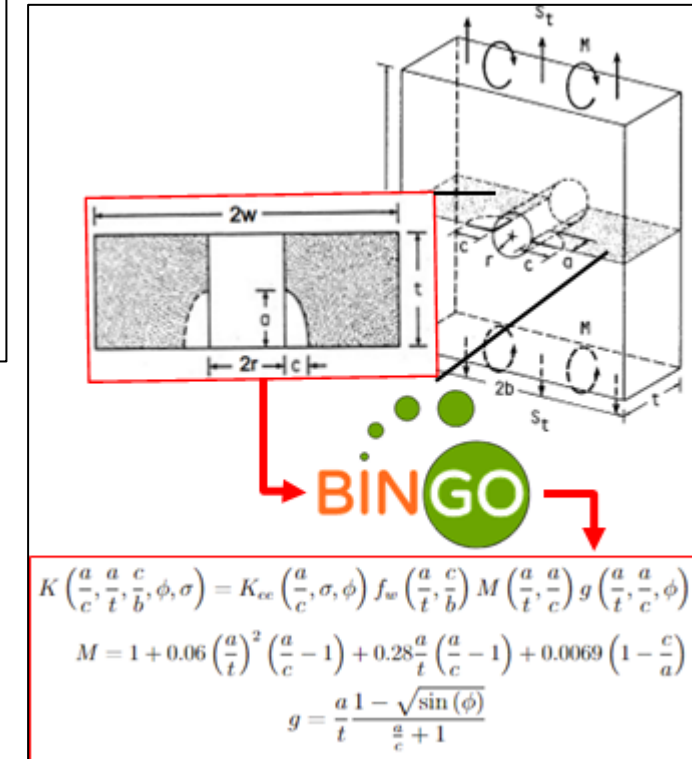
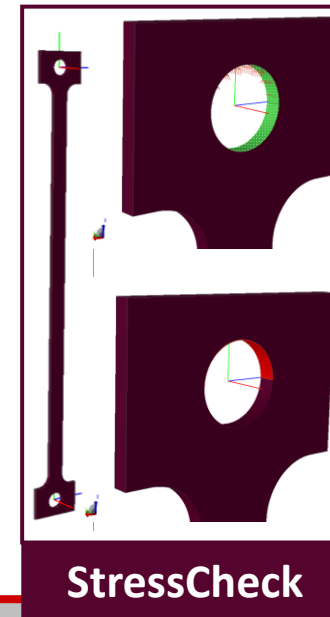
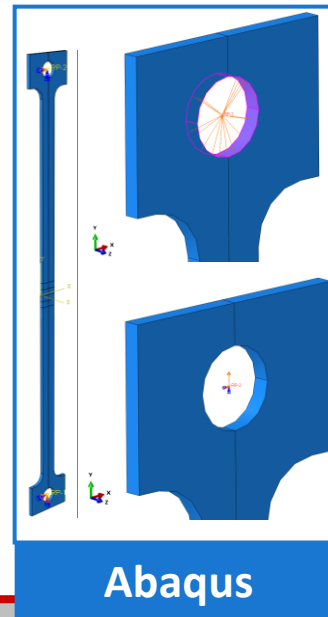
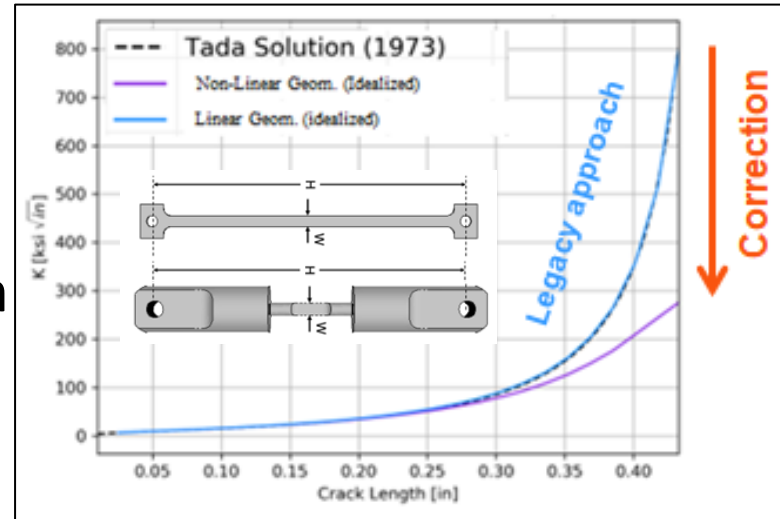


Leveraging machine learning to support modern-day fracture mechanics analyses of aerospace structures

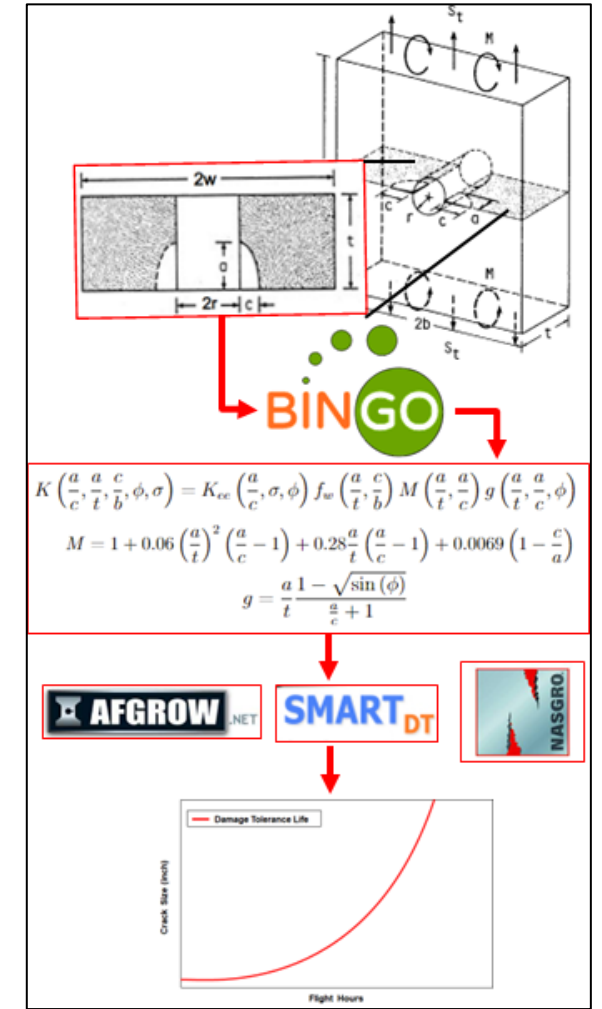
Presenters: Dallen Andrew (*Hill Engineering*), Jacob Hochhalter (*University of Utah*)

Contributors: Eric Lindgren, (*AFRL*), Zach Harris (*Pitt*),
Joseph Cochran, Tushar Gautum, and Mike Kirby (*University of Utah*)

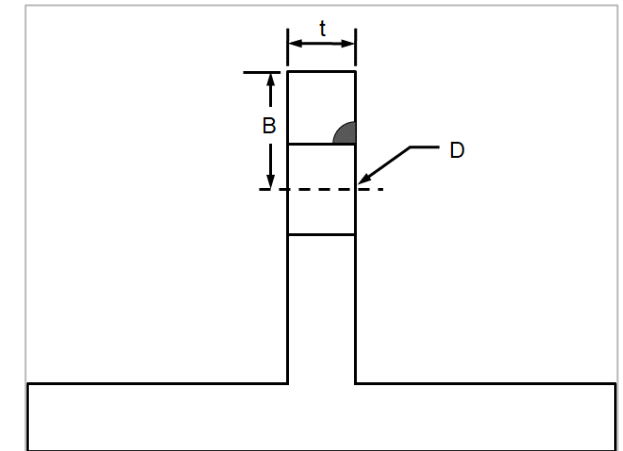
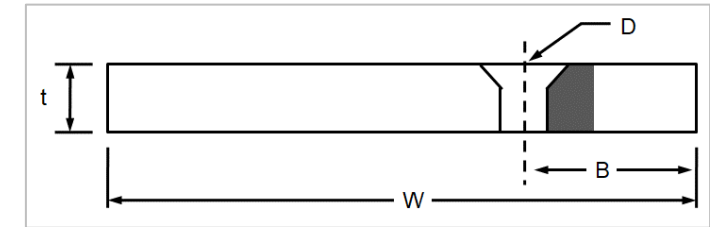
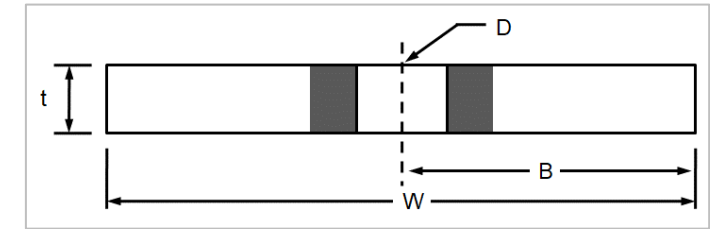
- In January 2024, Hill Engineering and the University of Utah were awarded STTR Phase I
- Machine Learning (ML) used to develop model for SEN(T) specimen
- Served as a proof-of-concept for using ML to develop K-solutions
 - Selected because of results demonstrating errors in Tada K-solution
- ML model significantly less complex in terms of mathematical operations required
- Phase I proof-of-concept demonstrated using ML to develop more accurate K-solutions
 - 50-300% error reduction compared to legacy solutions



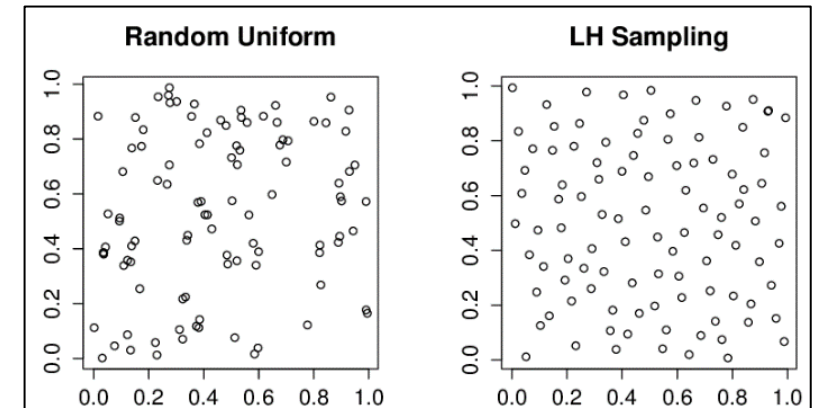
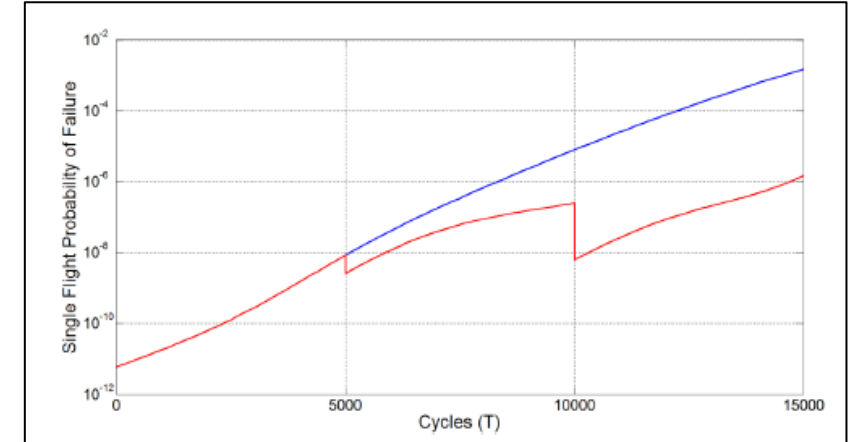
- In May 2024, Hill Engineering and the University of Utah were invited to submit a STTR Phase II proposal
 - Was not selected for award, but the team members were PRETTY good
- Proposal focus
 - Developing ML methodology
 - Defining aircraft-related cases for utilization
 - Performing associated model verification
- Would allow for improved accuracy of the most commonly used handbook solutions
 - Leveraging existing USAFA dataset to train Bingo models for already well-studied use cases
 - Bingo-produced K-equations will be compared to existing handbook solutions



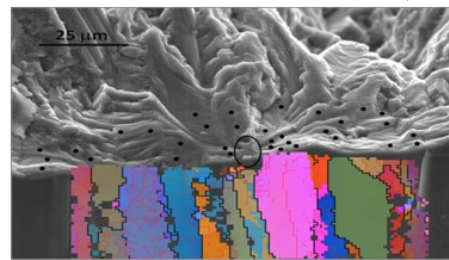
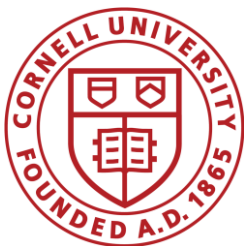
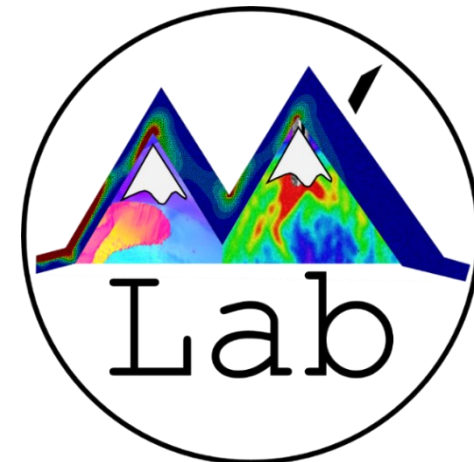
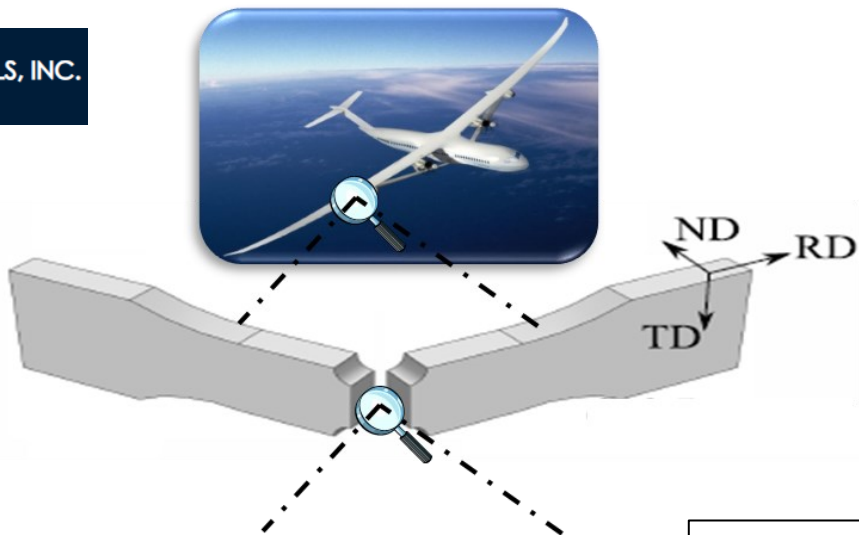
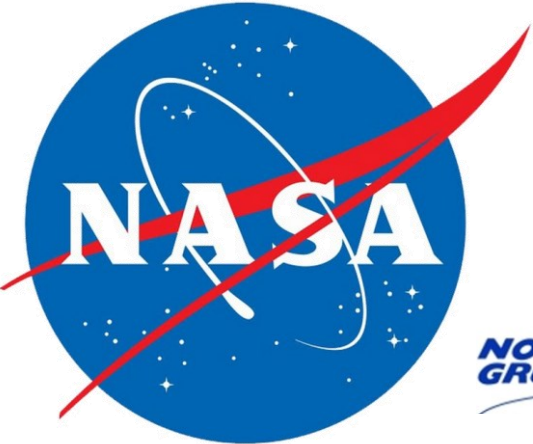
- Extend K-solution methods to more complex conditions
 - Accomplished by generating new training data using ABAQUS and StressCheck
 - Bingo used to develop interpretable K-solutions to be compared between the two software to ensure training data quality
 - At least 3 cases will be identified, increasing in level of complexity
 - Case 1: A representative basic handbook-type condition (e.g. double through crack at a centered hole in a plate)
 - Case 2: Minor variation from basic handbook-type condition (e.g. through crack at a countersunk offset hole in a plate)
 - Case 3: Increased geometric complex condition (e.g. corner crack in a T-shape cross-section with an offset hole in the vertical flange)
 - Additional cases will be considered for application (e.g. bearing load cases that have been difficult to fit K-solution curves to in the past)



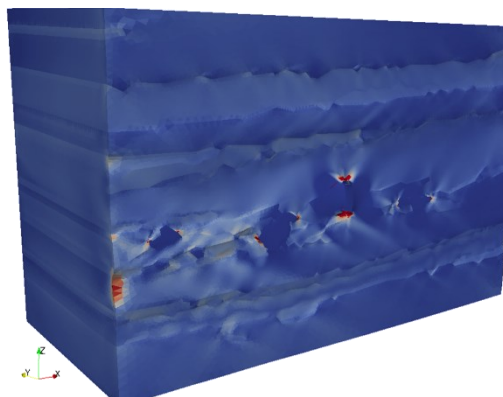
- Conduct a comparison between new and legacy solutions using ultrafast crack growth code and a risk-based criterion across the entire design space
- Utilize a robust verification scheme to establish credibility
 - Evaluate cases using ML model and ABAQUS at specific locations using Latin Hypercube sampling



Introducing Dr. Jake Hochhalter



Microstructure



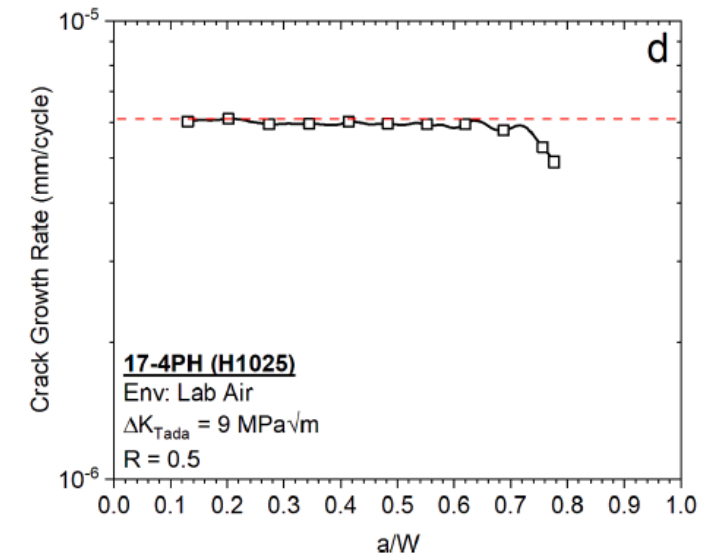
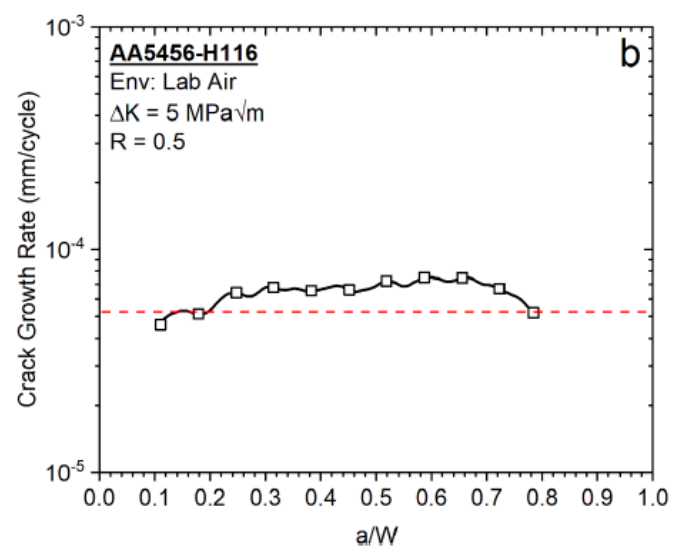
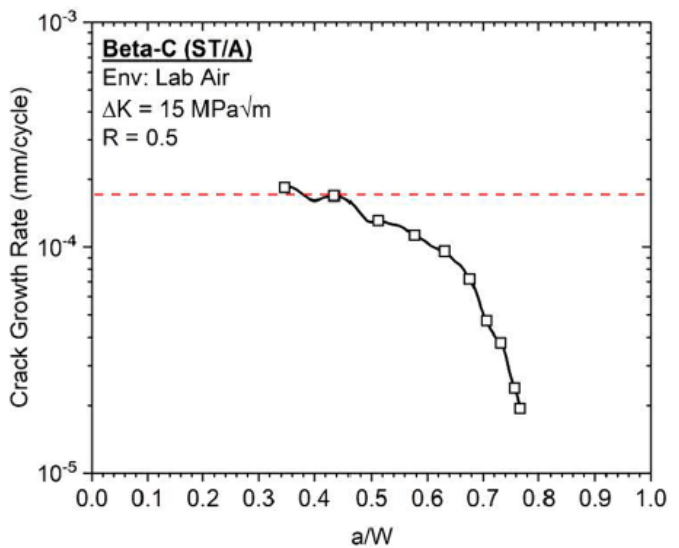
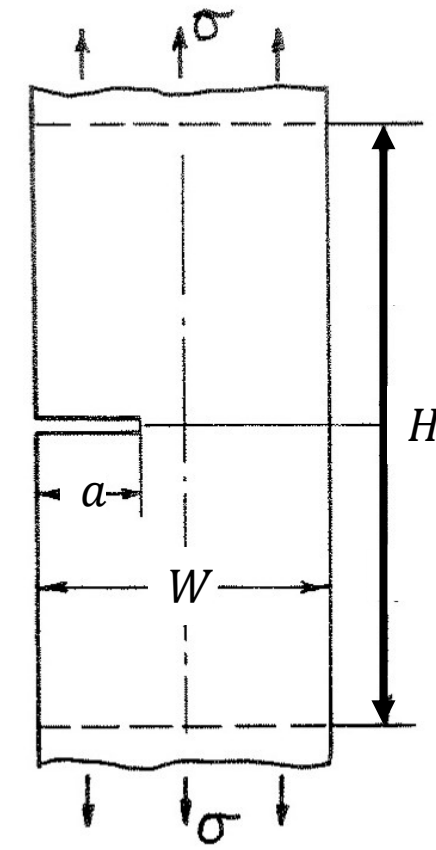
SEN(T) Constant- ΔK Tests

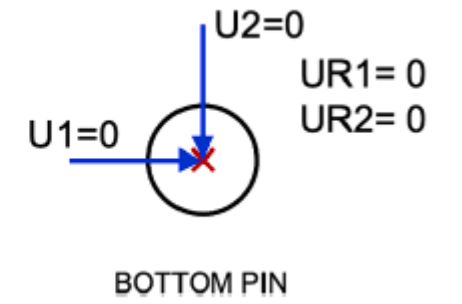
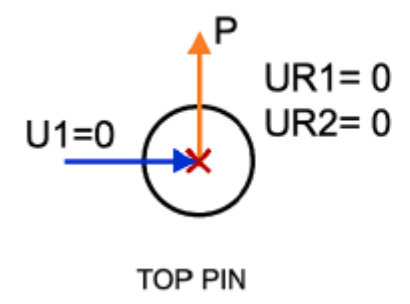
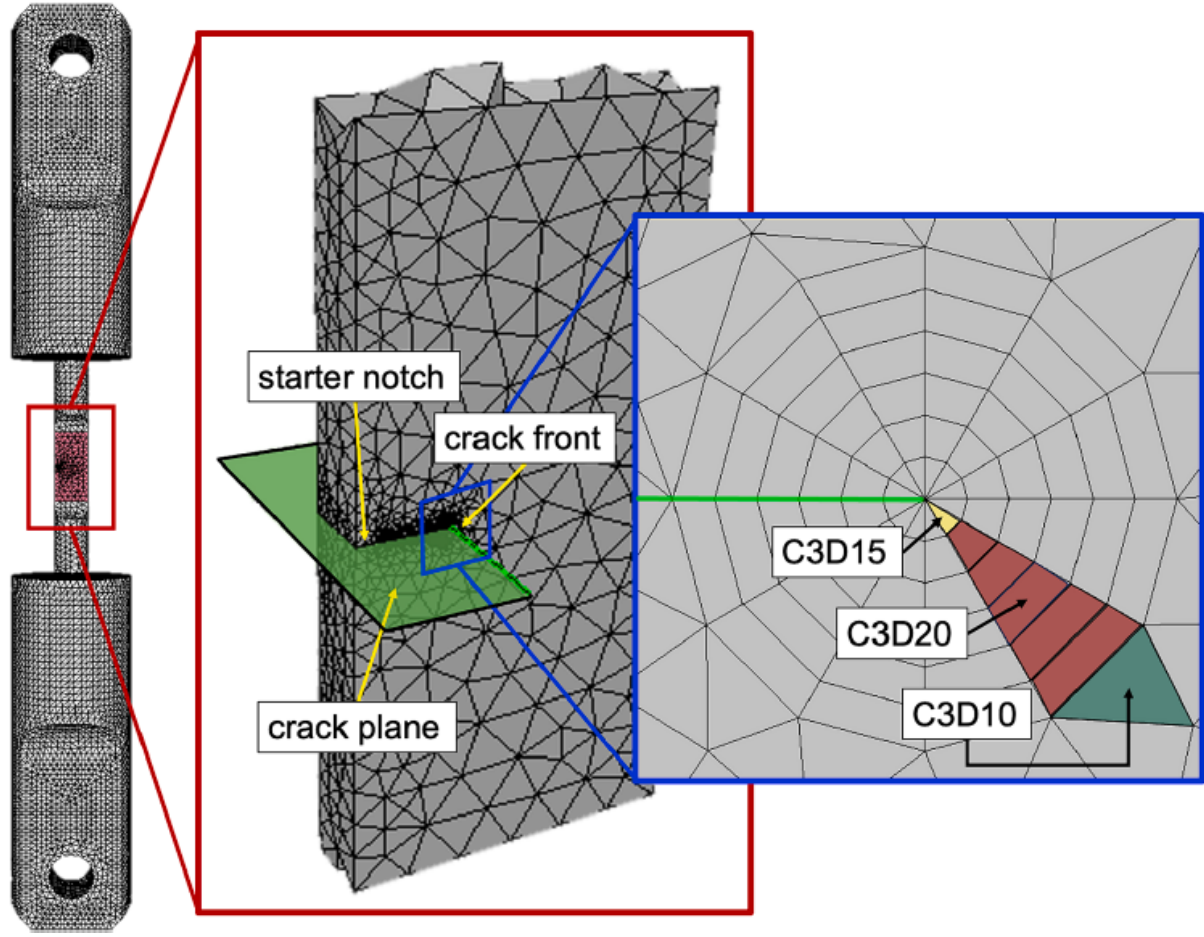
$$K = \sigma\sqrt{\pi a} \left\{ \sqrt{\frac{2W}{\pi a} \tan\left(\frac{\pi a}{2W}\right)} \left[\frac{0.752 + 2.02\left(\frac{a}{W}\right) + 0.37\left(1 - \sin\left(\frac{\pi a}{2W}\right)\right)^3}{\cos\left(\frac{\pi a}{2W}\right)} \right] \right\}$$

where far field stress: $\sigma = \left(\frac{P}{BW}\right)$

Accuracy: better than 0.5% for any a/W

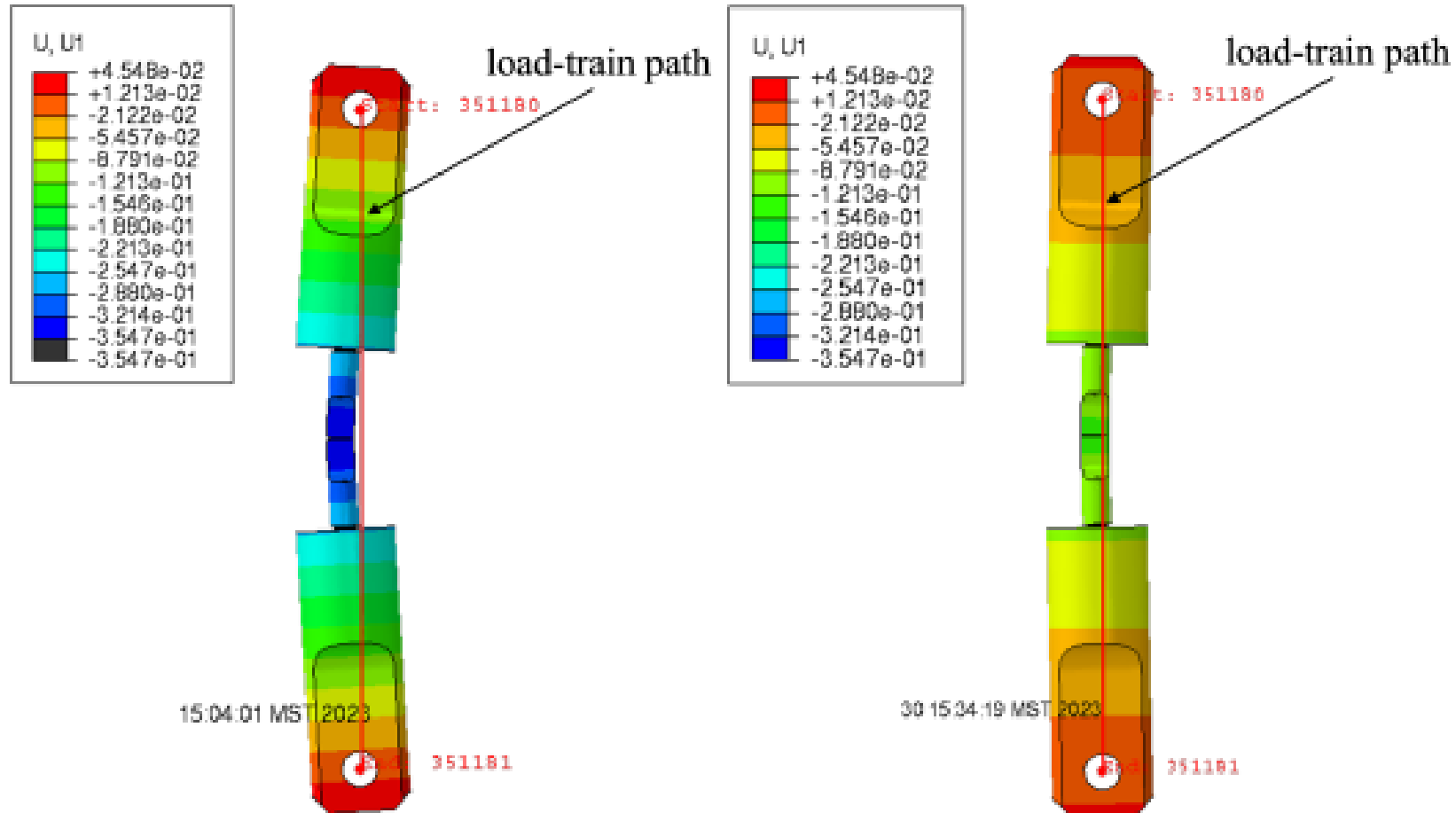
H. Tada et al., Stress Analysis of Cracks Handbook, 1973





Material	Modulus of Elasticity [GPa]
Al-7075T	75
Beta-Ti	100
Inconel 718/Steel	200

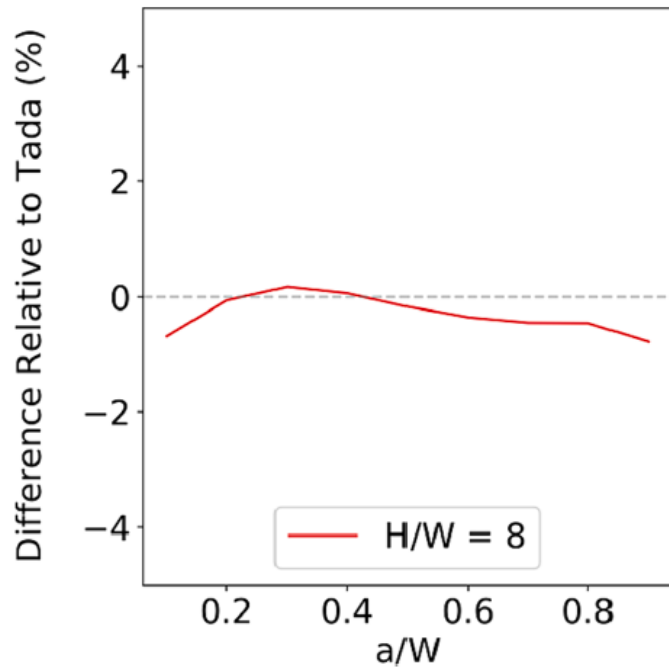
h/W can reach 29 for environmental fatigue crack growth testing



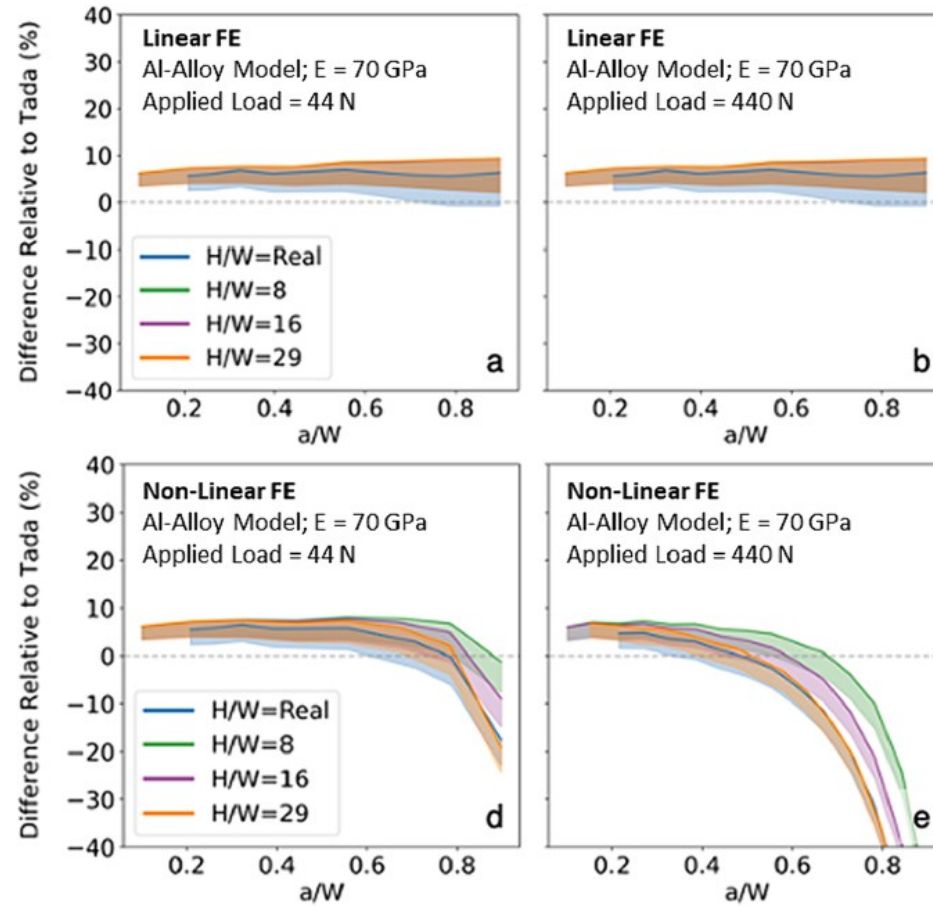
Linear-Geometry

Non Linear-Geometry

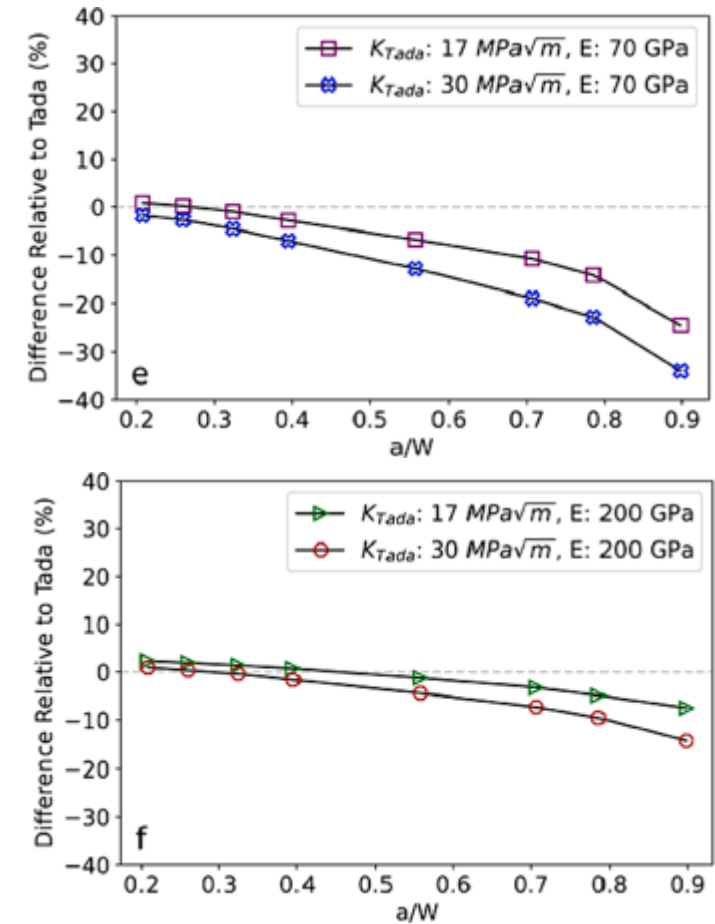
- Linear geometry
- 2D plane strain

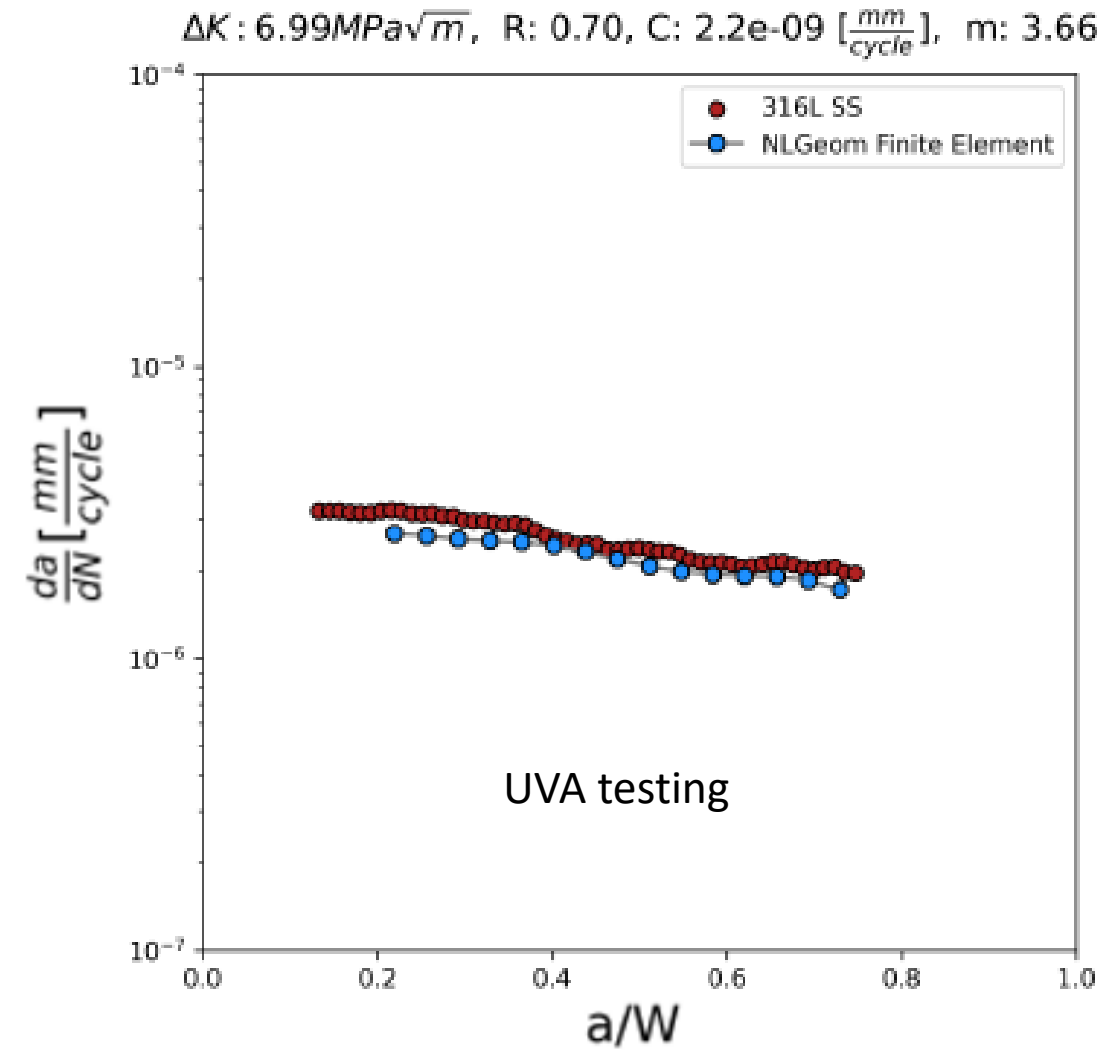
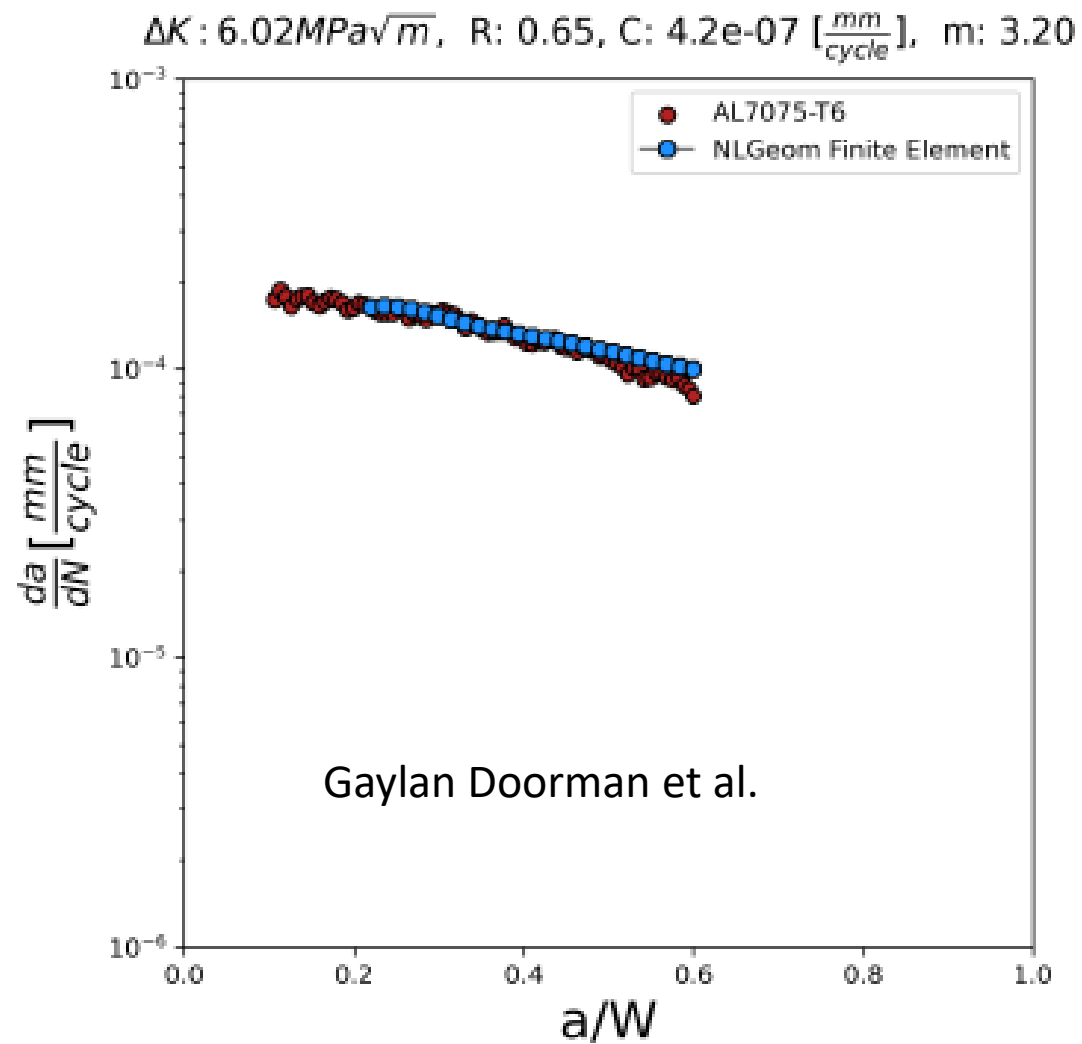


- Linear geometry
- 3D

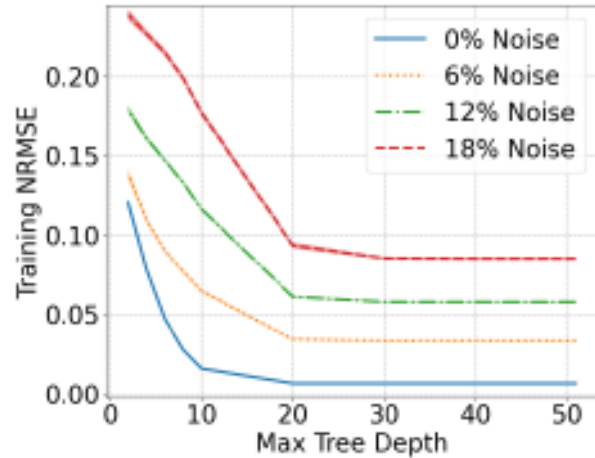


- Nonlinear geometry

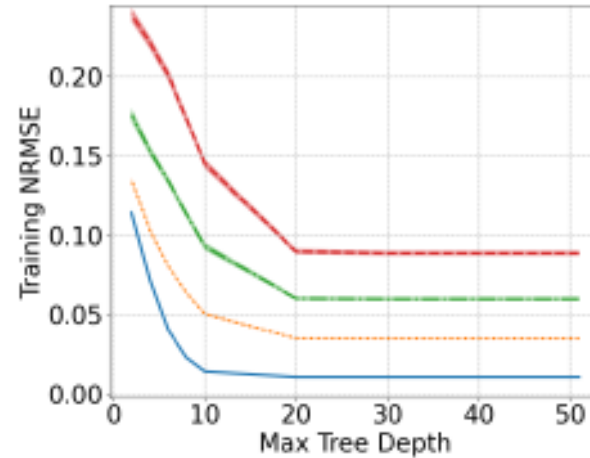




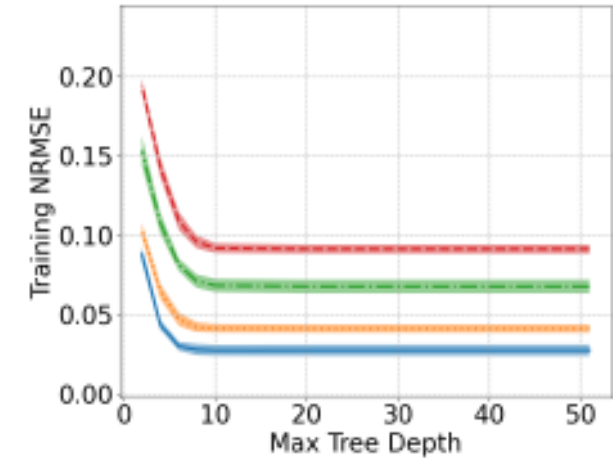
- Parameterize finite element model, e.g., a/W , h/W , etc.
- Compute SIFs using Abaqus + Franc3D
- Extract SIFs along p or homogenize as single representative value
- Test common machine learning (ML) methods
 - Random Forest Regression
 - Support Vector Machines
 - Neural Networks
- All ML methods have hyperparameters that govern model training
- Develop guidelines for method selection as function of data quality, quantity, and method stability



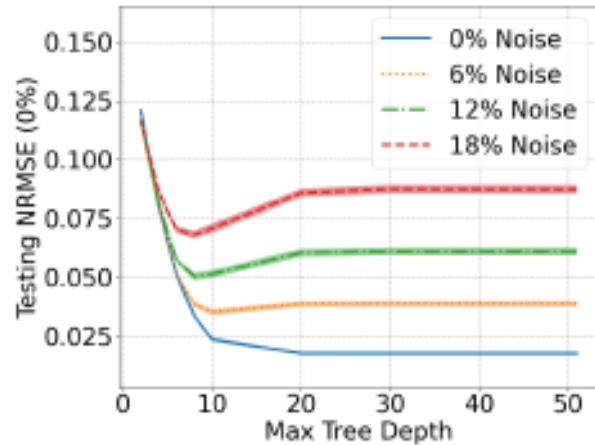
(a) 8000 training points



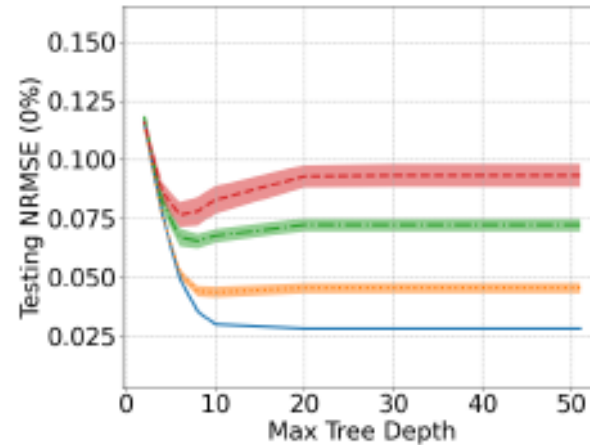
(b) 2000 training points



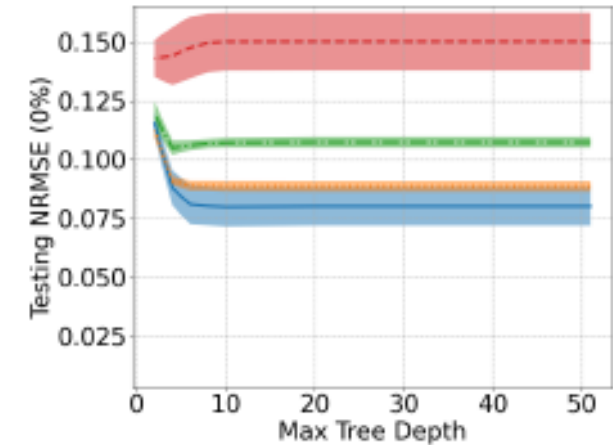
(c) 100 training points



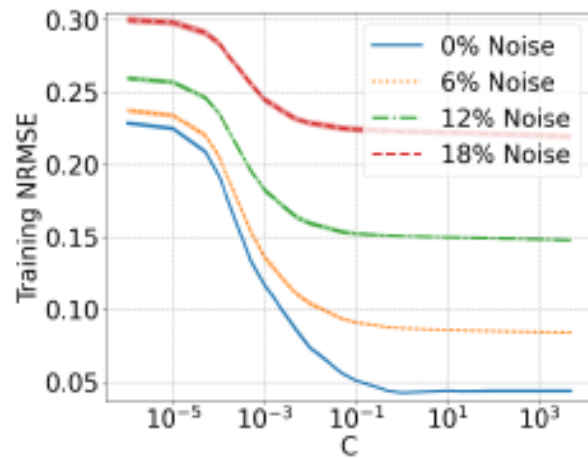
(d) 8000 training points



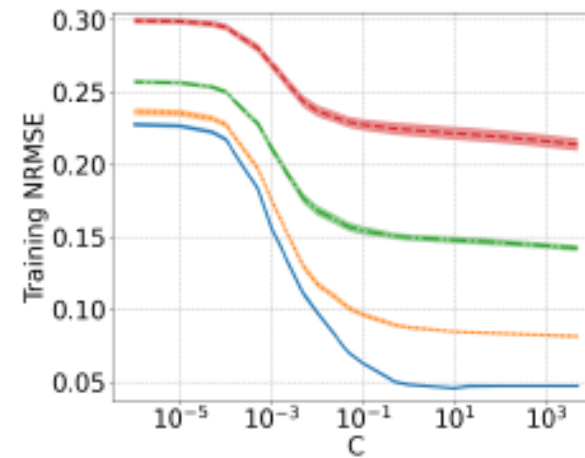
(e) 2000 training points



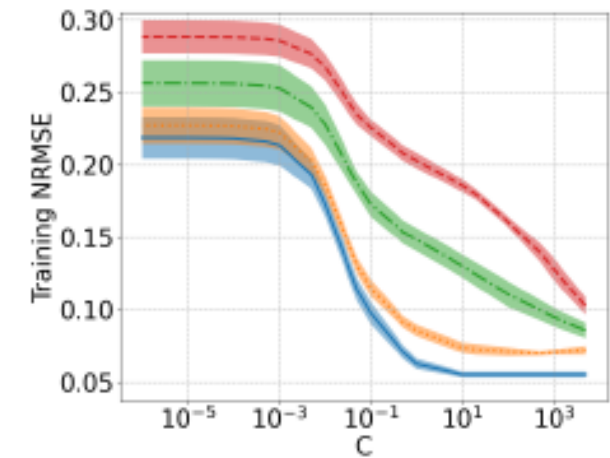
(f) 100 training points



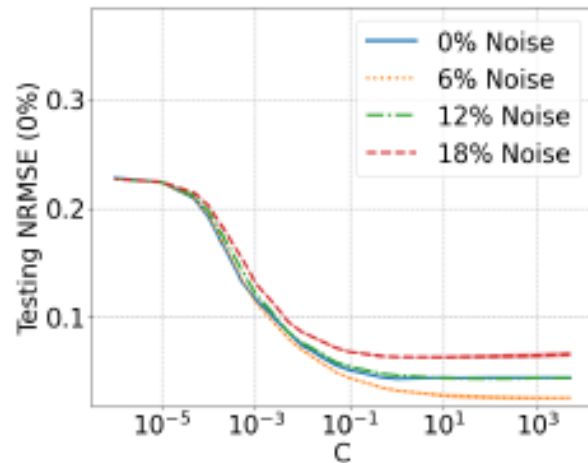
(a) 8000 training points



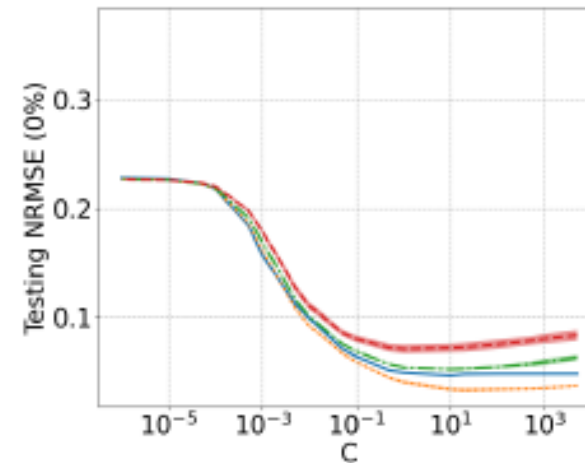
(b) 2000 training points



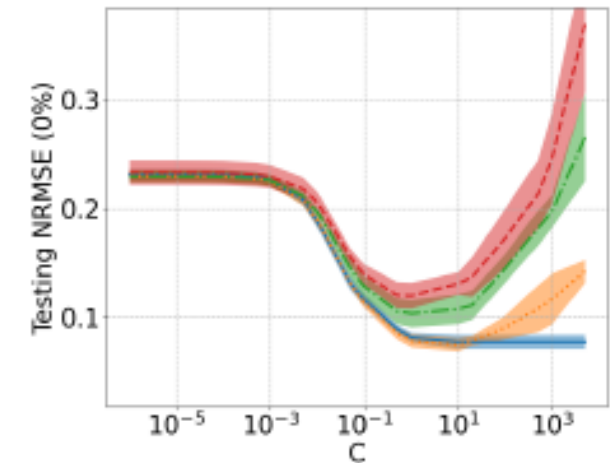
(c) 100 training points



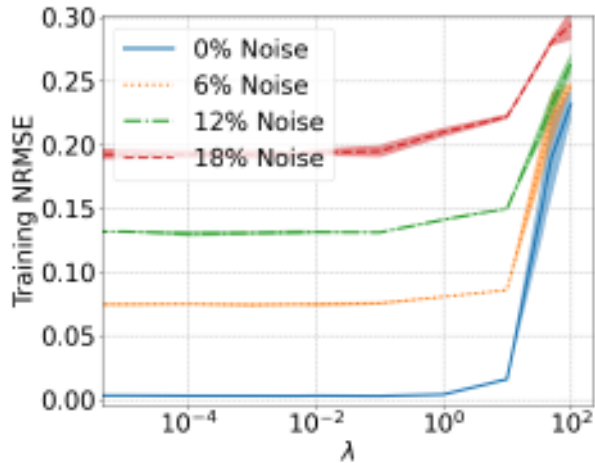
(d) 8000 training points



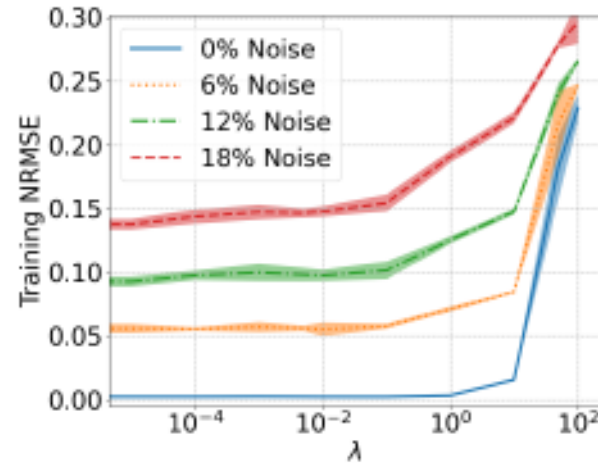
(e) 2000 training points



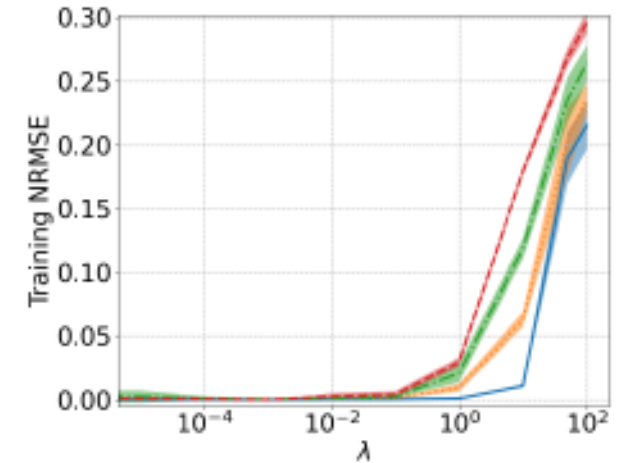
(f) 100 training points



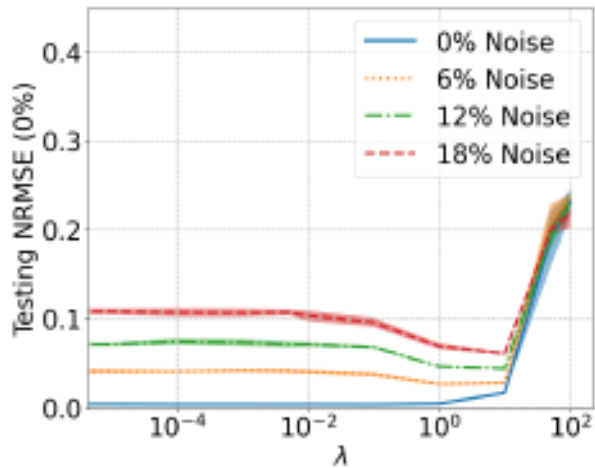
(a) 8000 training points



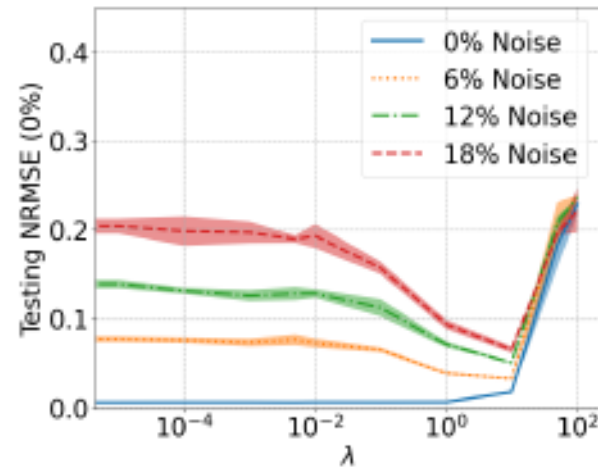
(b) 2000 training points



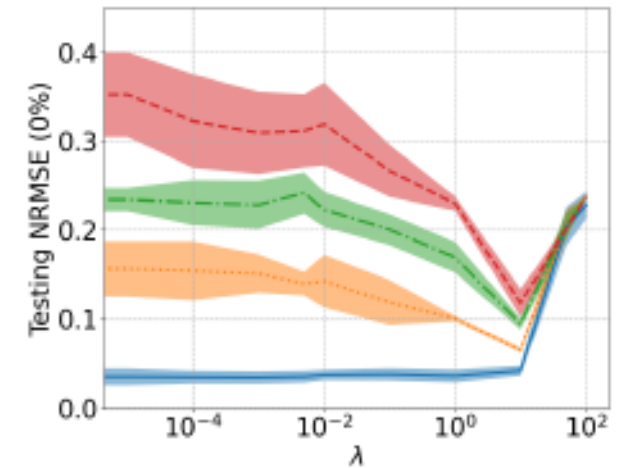
(c) 100 training points



(d) 8000 training points



(e) 2000 training points



(f) 100 training points