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Machine-Learned Surrogate Models for Threaded Fastener Geometries Subjected to Multiaxial Loadings

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U.S. DEPARTMENT OF ENERGY

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Motivation

An essential part of Sandia's mission is predicting through analysis the performance of complex systems and structures subjected to various normal and abnormal environments.

Fasteners are an integral connector in many of these system and structures, but there are limitations to conventional fastener modeling approaches.

Challenges (Solid Mechanics):

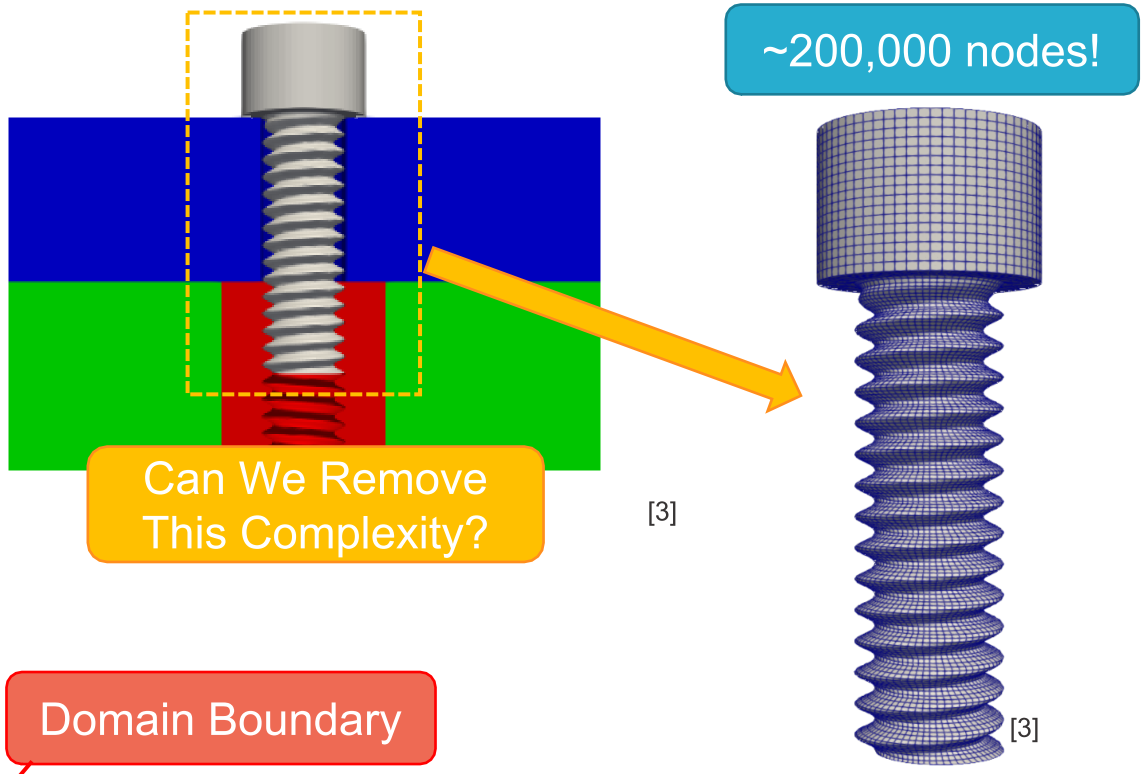
- It is infeasible to test all fasteners in all environments to obtain expected behavior.
  - Different fastener materials, sizes, loadings, etc.
- Modeling fidelity requirements of system-level models are restrictive and create challenges for capturing relevant behavior while maintaining feasibility of the larger simulation.

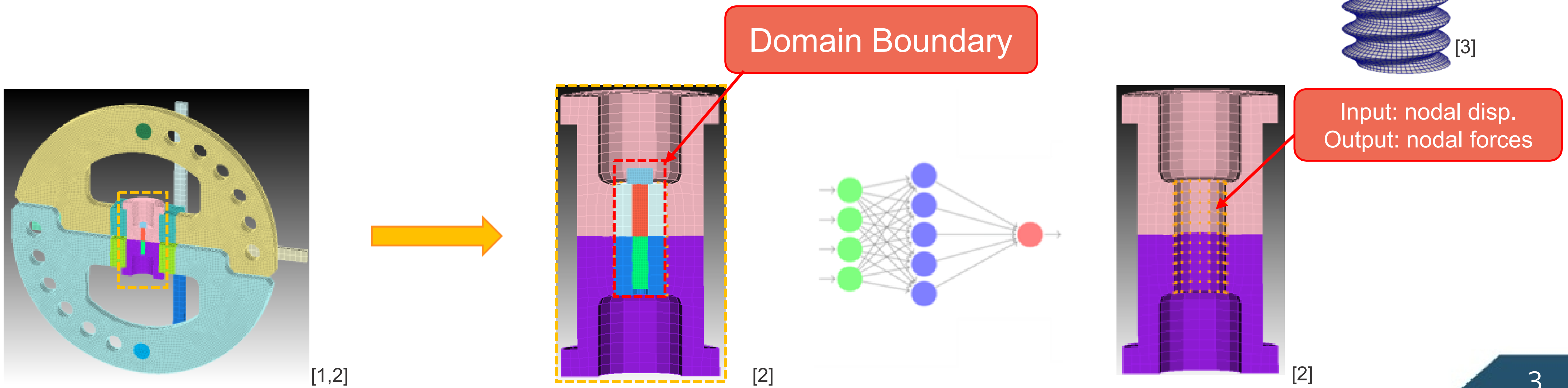
Question:

Can we replace our fastener models with a low-cost, machine-learned surrogate that can transfer loads and accurately predict relevant QoIs while quickly and robustly running in large-scale FEA?

A Machine Learned Surrogate Modeling Approach for Fasteners

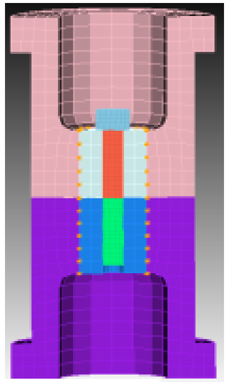
- What are we even trying to replace?
  - High complexity fastener model/behavior.
- How do we replace it?
  - Subdivide model into complicated inner domain and simple outer domain.
- How will the surrogate communicate with the rest of the model?
  - Model needs to receive nodal displacements and return nodal forces.





Machine learning approach

- Our approach uses principal component analysis (PCA) and regression models to learn a mapping from the interface displacement field to the interface force field



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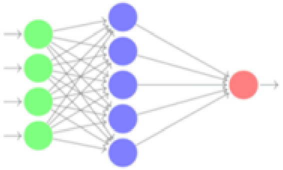
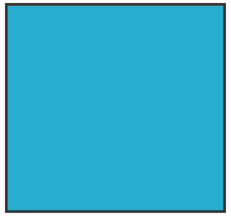
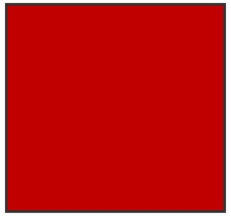
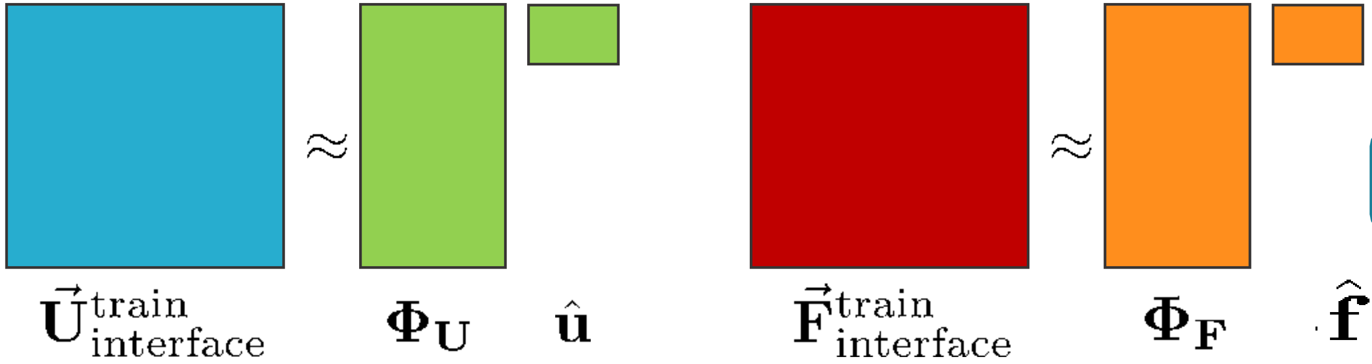


1. Generate training data

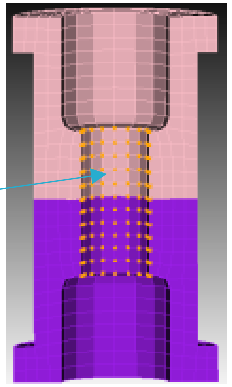
$\vec{\mathbf{U}}^{\text{train}}_{\text{interface}} =$  $\in \mathbb{R}^{3N_{\text{interface}} \times N_{\text{samples}}}$

$\vec{\mathbf{F}}^{\text{train}}_{\text{interface}} =$  $\in \mathbb{R}^{3N_{\text{interface}} \times N_{\text{samples}}}$

2. Perform PCA on the training data to obtain low-dimensional representations of the displacement and force fields



Can be a large mesh!



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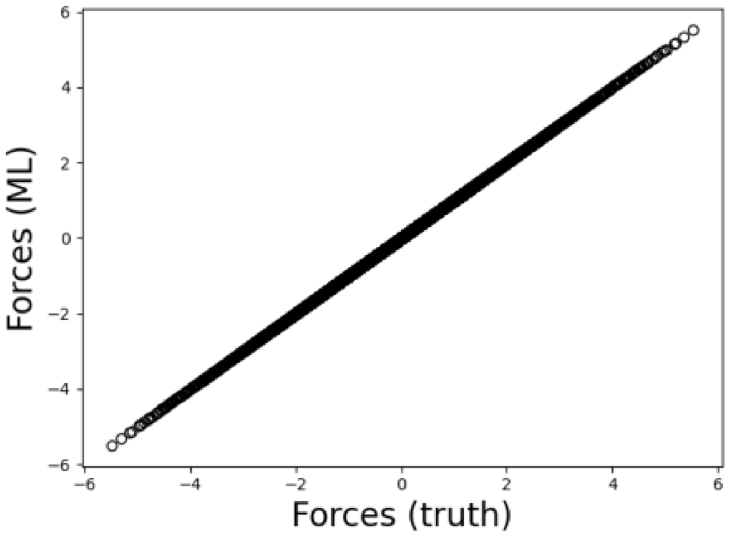
3. Learn a mapping from the reduced coordinates of the displacement field to the reduced coordinates of the force field

Dense Neural Networks
Random Forest
Polynomial Regressor

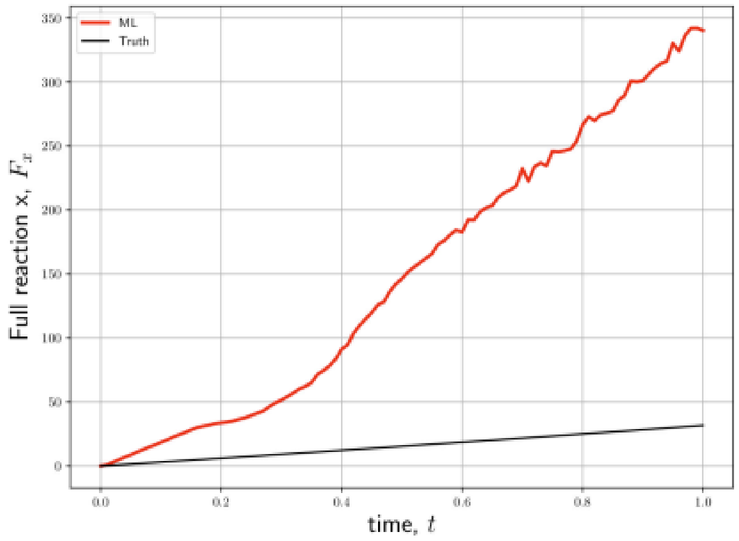
Results

Training results



Great! **Models are very accurate in training**

Coupled ML-FEM results



Bad! **Very inaccurate when coupled to solver (often failed to converge)**

What's happening?

- **Our hypothesis:** ML models don't preserve important physical and mathematical structure
  - Results in negative interplay between model and solver
- **Our solution:** Embed structure into our model

A physics-constrained machine learning approach

- Follow a similar approach to before, but instead learn a stiffness matrix

$$\vec{\mathbf{F}} = \boxed{\mathbf{K}(\vec{\mathbf{U}})}\vec{\mathbf{U}}$$

↑
Machine-learned stiffness matrix

Decomposing K, Actually learning *L*

- **Why?** We can enforce symmetric positive definiteness (SPD) into our model by learning

$$\mathbf{K}\left(\vec{\mathbf{U}}\right) = \mathbf{L}(\vec{\mathbf{U}})\left[\boxed{\mathbf{L}}(\vec{\mathbf{U}})\right]^T$$

  - SPD is **a key mathematical structure** of stiffness matrices in FEM
  - Can be used to **provide energetic stability** statements
  - Model form **is appropriate for conjugate gradient** solvers

- **Result:** a new model that **preserves important physical structure**

❖ Note: we still leverage principal component analysis to reduce the input and output dimension, so the full model looks like:

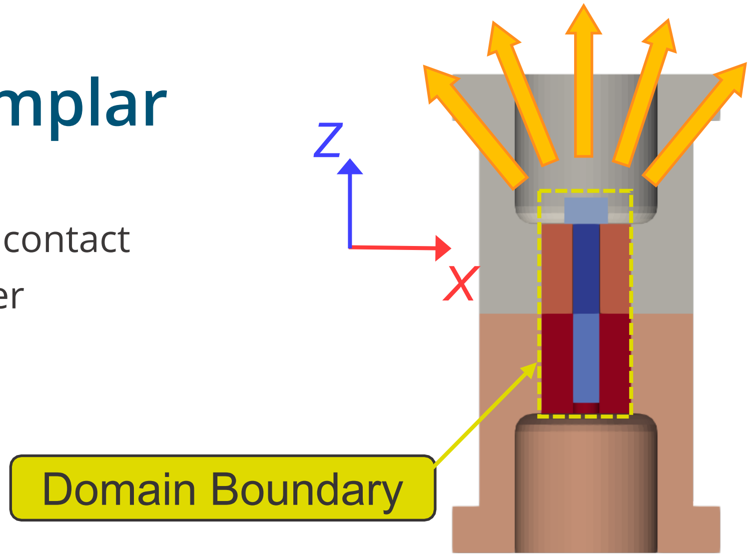
$$\mathrm{K}\left(\vec{\mathrm{U}}\right) = \Phi\hat{\mathrm{L}}(\Phi^T\vec{\mathrm{U}})\left[\mathrm{L}(\Phi^T\vec{\mathrm{U}})\right]^T\Phi^T$$

We require the same basis for both the force and displacement for symmetry

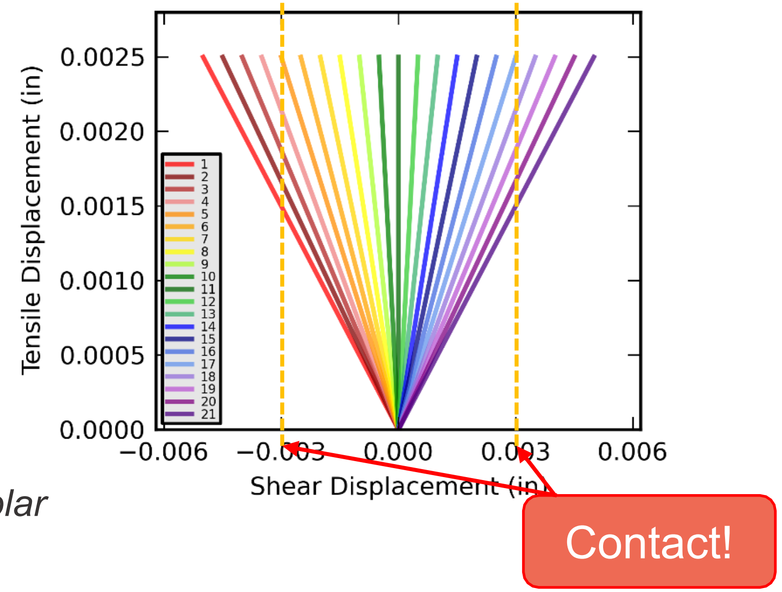
Results: fastener exemplar

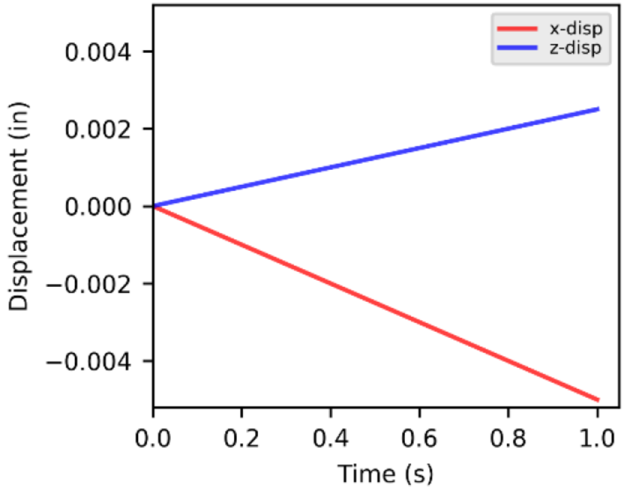
- Problem setup
  - Fastener undergoing deformation with contact
  - Remove middle domain around fastener
  - Mechanics
    - Elastic material model
    - Contact
- Training dataset:
  - 21 quasi-static trajectories w/ 100 points per trajectory
  - Radial loadings from ~-65 to 65 degrees
- ML models
  - **LLS-POD:** Linear least-squares model (not structure preserving)
  - **NN-POD:** Neural network model (not structure preserving)
  - **SPD-LLS-POD:** Linear model for the stiffness matrix that preserves SPD property
  - **SPD-NN-POD:** Neural network model for the stiffness matrix that preserves SPD property

All models perform well in training

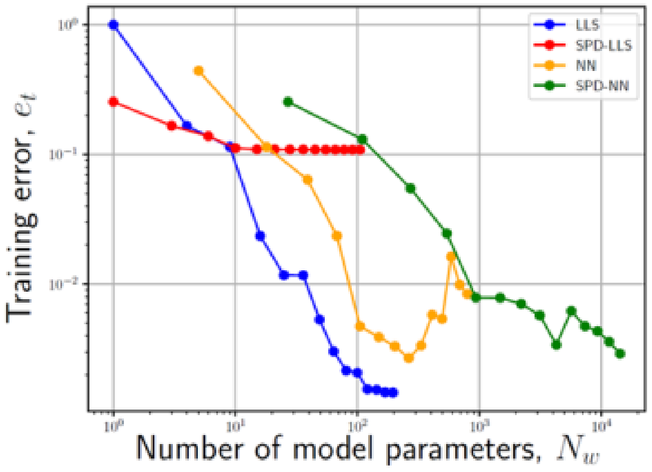


Schematic of fastener exemplar





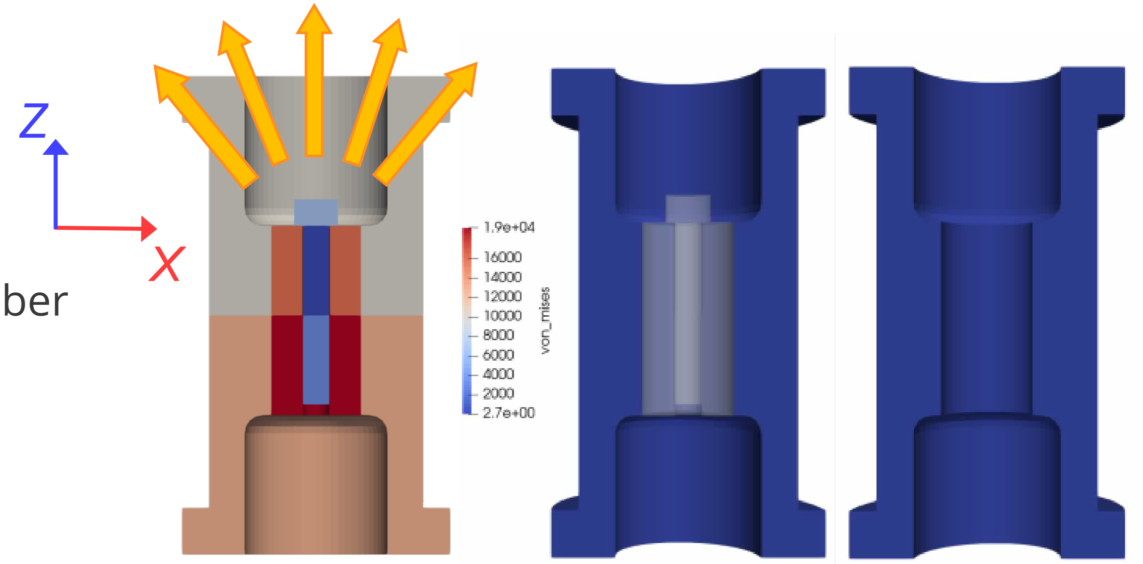
Example of Loading



Training results

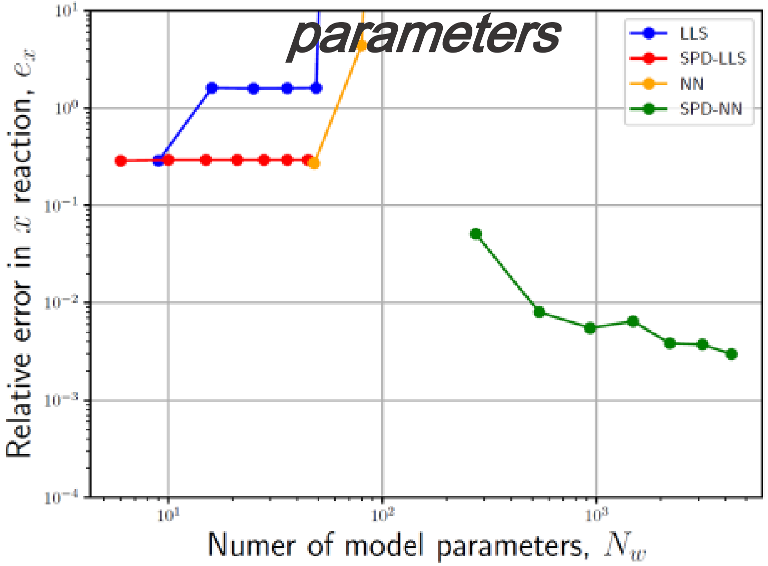
Results: fastener exemplar

- Now deploy models on new testing configurations
  - ML model is now coupled to solver
- **Non structure preserving models go unstable** as the number of model parameters grow
- **Only the SPD model is robust**
- Linear models bisect contact behavior
- SPD neural network model is robust *AND* accurate!



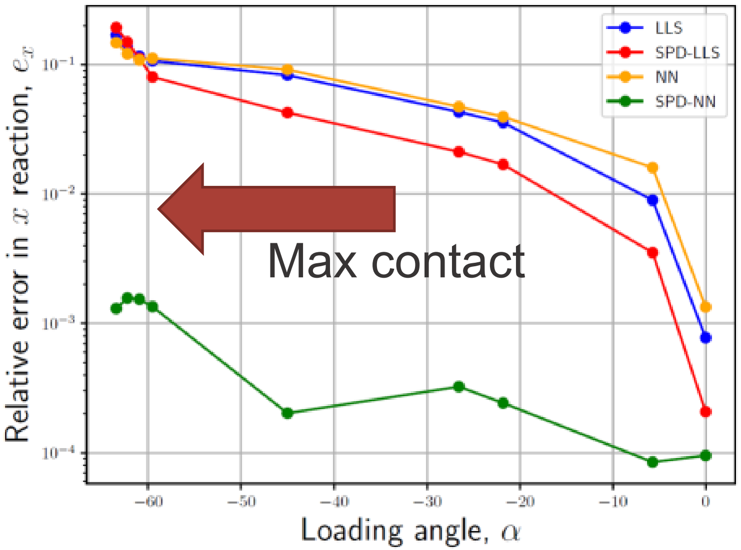
fastener exemplar geometry

FEA Errors vs. # model parameters



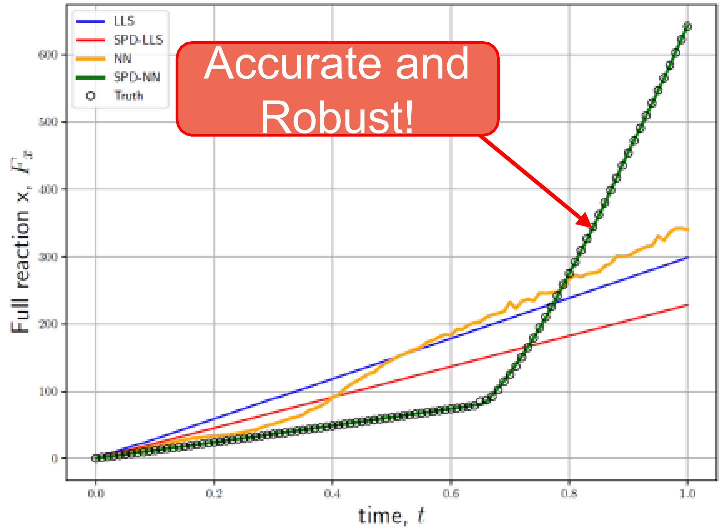
Average relative error on testing cases as a function of model parameters

Errors vs. loading angles



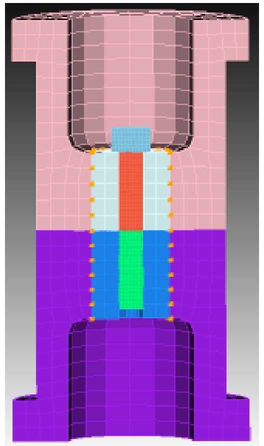
Relative error on testing cases for the best performing models as a function of loading angle

Predicted QoIs



Integrated force quantity-of-interest for max contact condition as a function of time for the best models

Conclusions /Future Work



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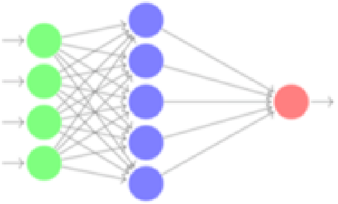

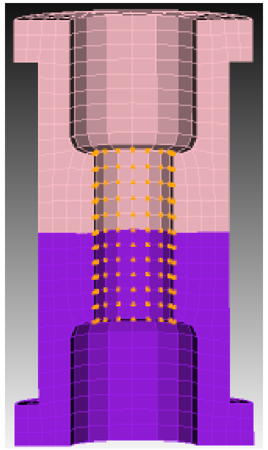

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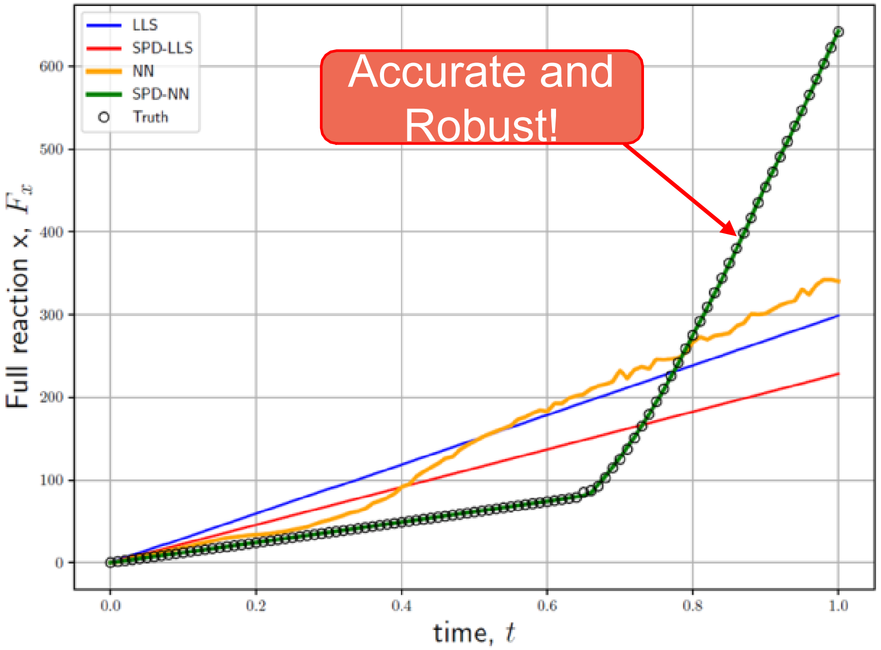
Conclusions

- Retaining physical structure is very important!
- This approach continues to show promise.
  - Simple (so far), but successful.
  - Maybe other applications can benefit.

Future Work

- Introduce additional complexity to the analysis.
  - Plasticity
  - Preload
  - Etc.
- Assess and optimize run times
  - Are we maintaining feasibility of larger simulation?
- Make model corotational



[1] Moreno, K, Murugesan, A, Sheng, M, Alqawasmi, L, Khraishi, TA, & Hubbard, NB. "Correlation of Reduced-Order Models of a Threaded Fastener in Multi-Axial Loading." *Proceedings of the ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. Volume 9: 17th International Conference on Multibody Systems, Nonlinear Dynamics, and Control (MSNDC).* Virtual, Online. August 17–19, 2021. V009T09A004. ASME.

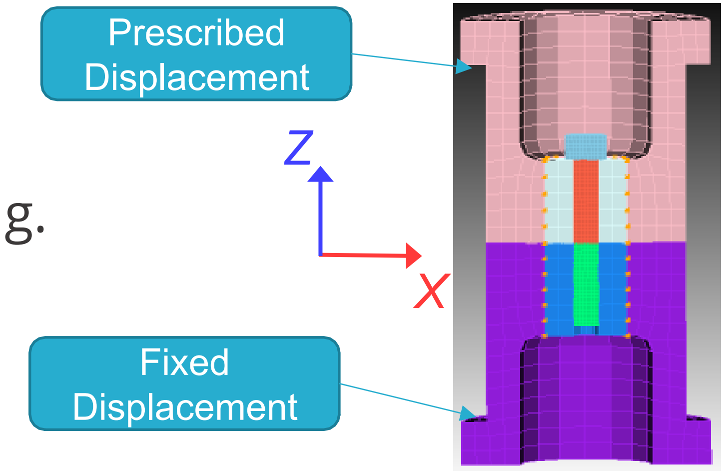
[2] Mersch, J.P., Hoang, C., Parish, E., "Machine learned surrogate models for threaded fastener geometries in finite element analysis", *Mechanistic Machine Learning and Digital Twins for Computational Science, Engineering & Technology,* San Diego, CA, 2021, SAND2021-11637C.

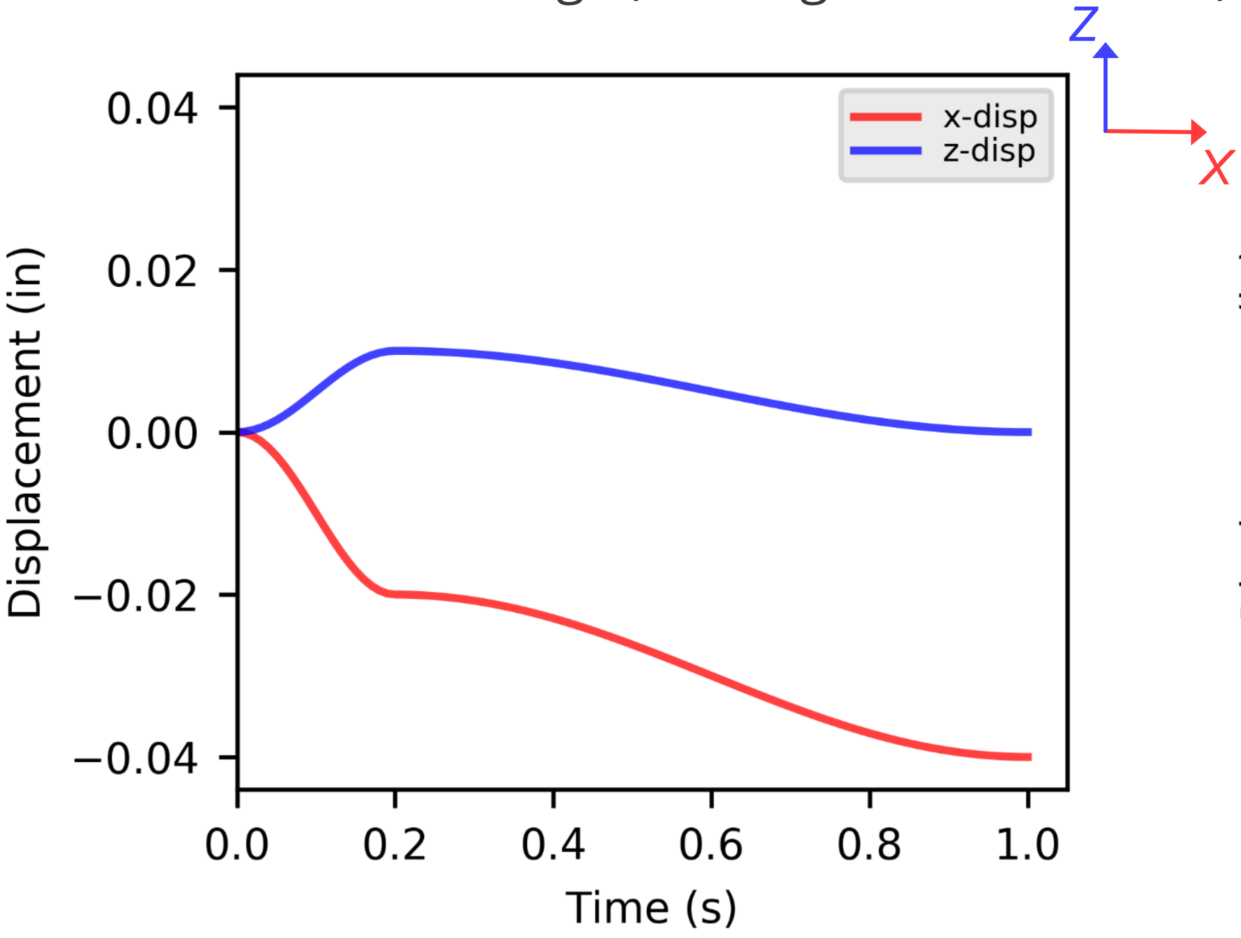
[3] Grimmer, P.W., Mersch, J. P., Smith, J. A., Veytskin, Y.B., Susan, D.F., "Modeling Empirical Size Relationships on Load-Displacement Behavior and Failure in Threaded Fasteners" *2019 AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference,* AIAA SciTech Forum, AIAA2019-2268, San Diego, CA, 2019.

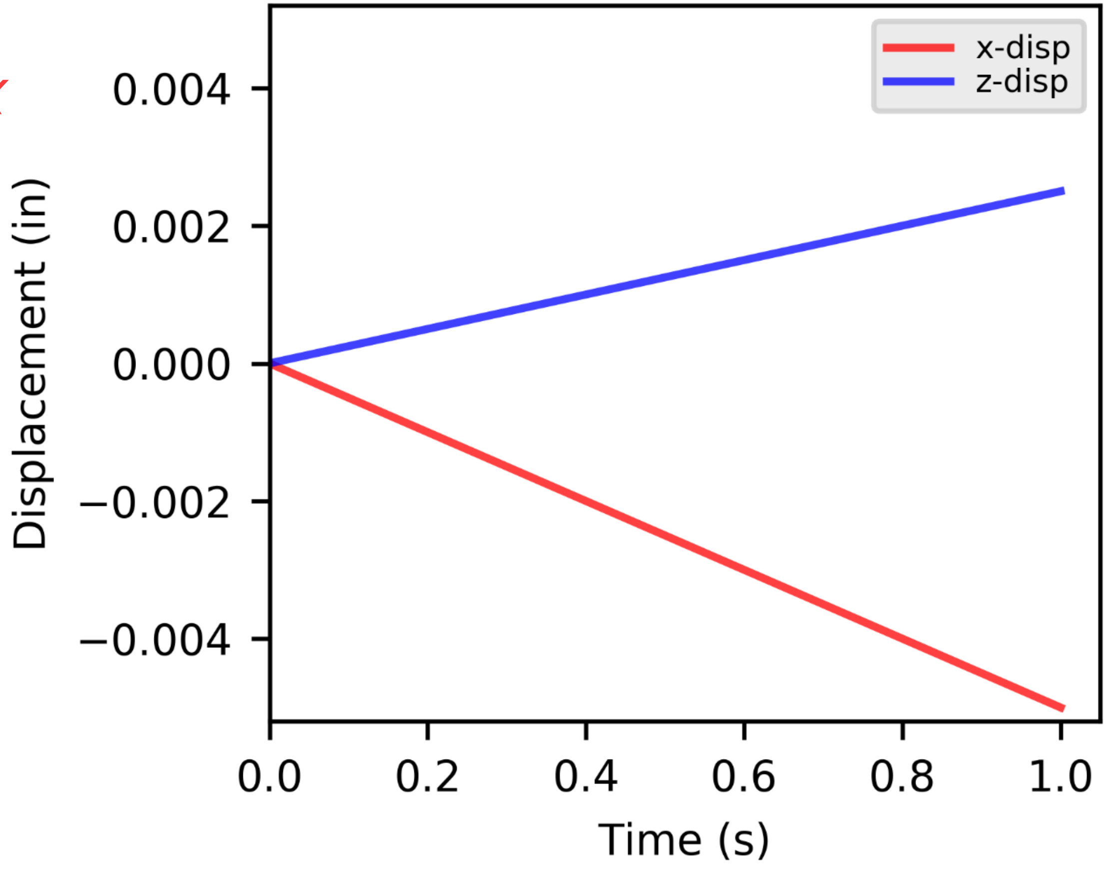
Extra Slides

Environment/Loading

- First Try: quasistatic, multiaxial loading with possible unloading.
- Maybe we should try something a little easier!
- Radial Loadings (although still multiaxial).







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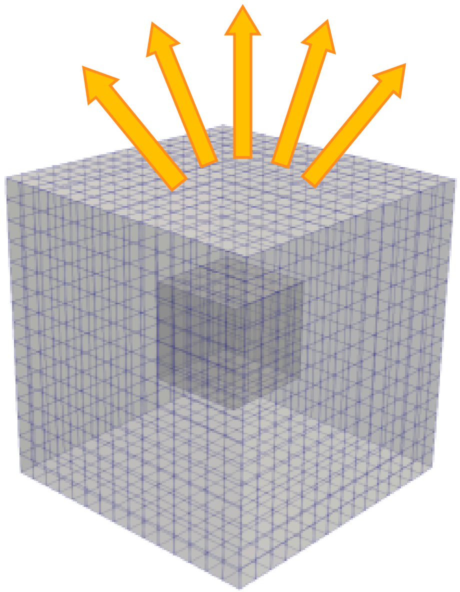
Results: cube exemplar

- Problem setup
  - 15x15x15 cube undergoing deformation
  - Remove middle 5x5x5 elements
  - Mechanics:
    - Elastic material model
    - Deformations of 10-15% leads to small nonlinearities

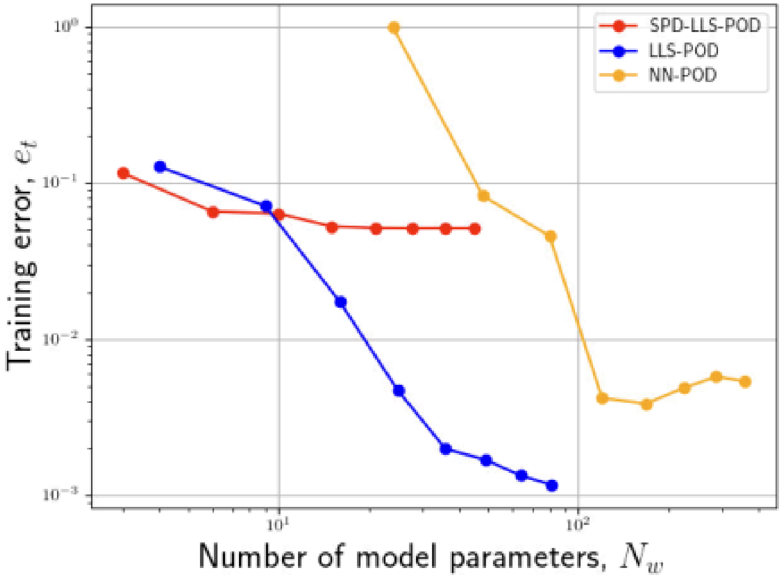
- Training dataset:
  - 16 quasi-static trajectories w/ cosine loading
  - 100 points per trajectory

- Train three ML models
  - **LLS-POD:** Linear least-squares model
  - **NN-POD:** Neural network model
  - **SPD-LLS-POD:** Linear model for the stiffness matrix that preserves SPD property

- Training results
  - All models perform well
  - Linear model performs the best



Schematic of cube exemplar



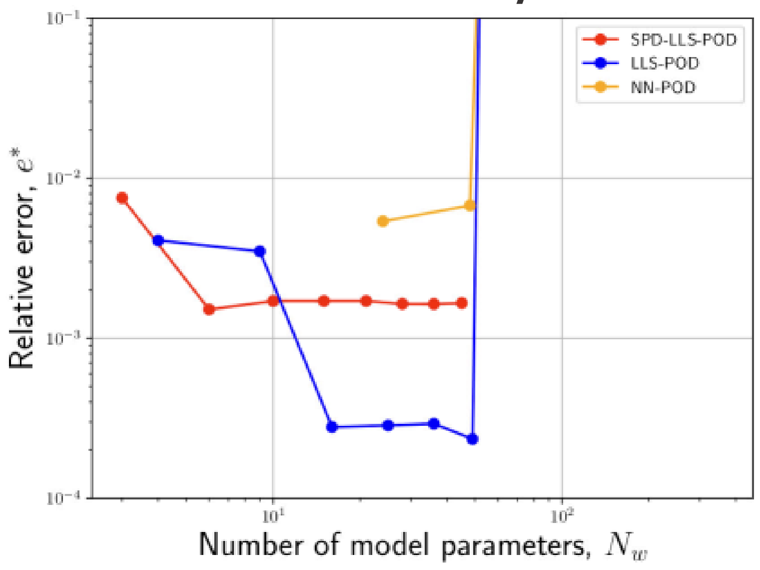
Training results

All models perform well in training

Results: cube exemplar continued

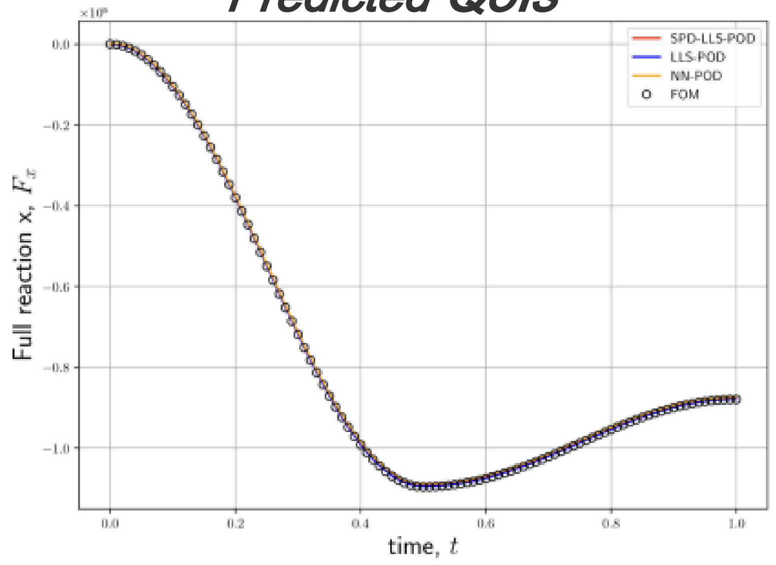
- Now deploy models on new testing configurations
  - ML model is now coupled to solver

Errors vs. # model parameters



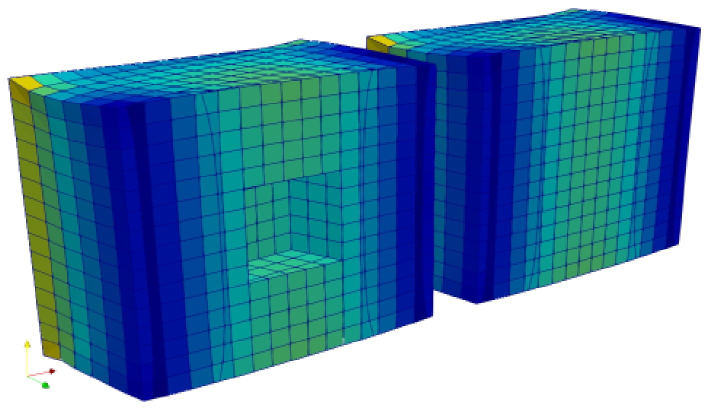
Average relative error on testing cases as a function of model parameters

Predicted QoIs



Integrated force quantity-of-interest as a function of time for various models

Field solution



Max von-mises stress as predicted by the ML-FEM simulation (left) and FEM simulation (right)

- All models *can* be accurate, but
  - **Non structure preserving models go unstable** as the number of model parameters grow
  - **Only the SPD model is robust**
    - **Robustness is required on more complex exemplars**