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Capturing Deformation Mechanisms in Additively Manufactured Parts through High-fidelity Modeling and Computed Tomography

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TMS Annual Meeting

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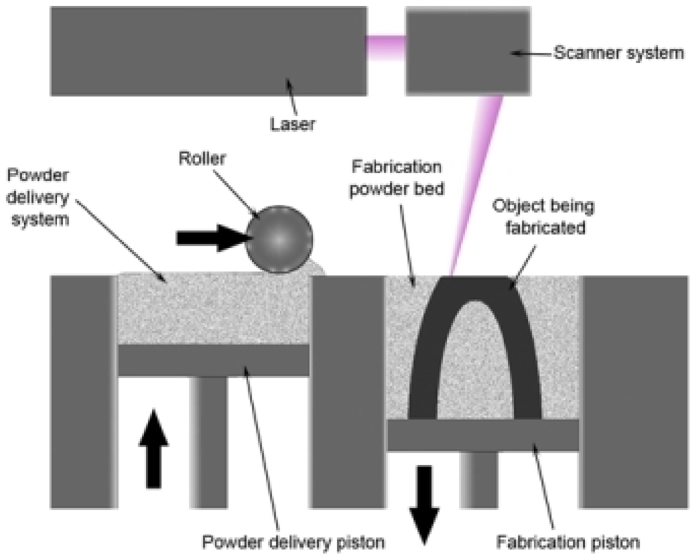
Outline

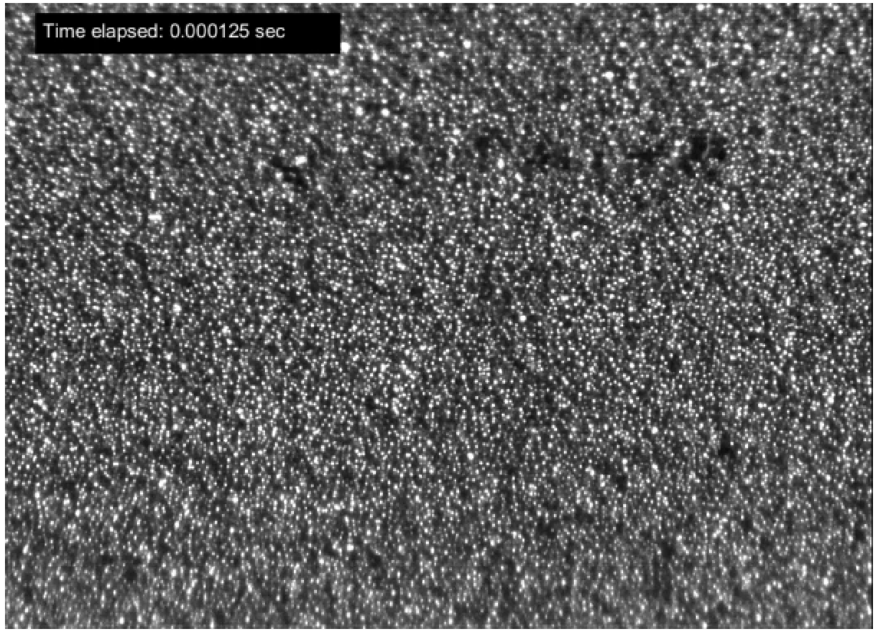
- Background on Additive Manufacturing Characterization
- Motivation – Machine Learning
- Mechanical Testing and CT Characterization
- Model Calibration
- Fracture Predictions

Laser Powder Bed Fusion (LPBF)



LPBF Process[1]

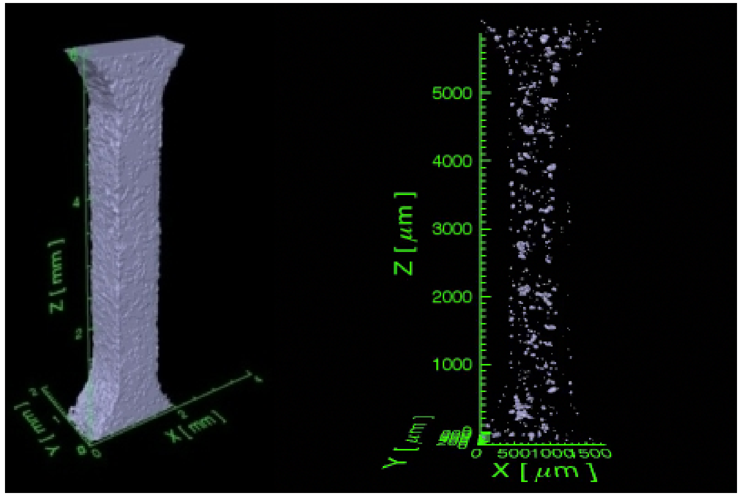
Different LPBF Scan Paths
Bradley Jared (UTK)



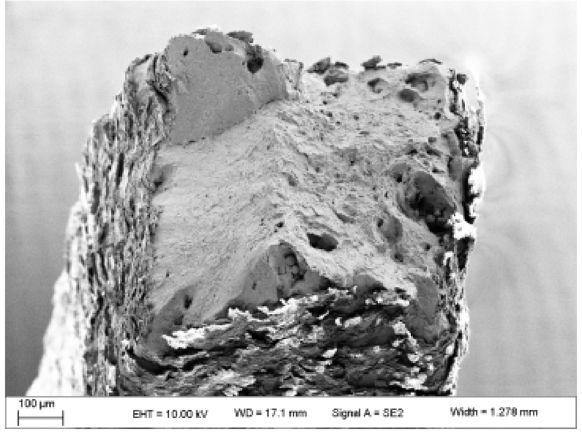
Bidare, P. et al. *Acta Mat 2018*

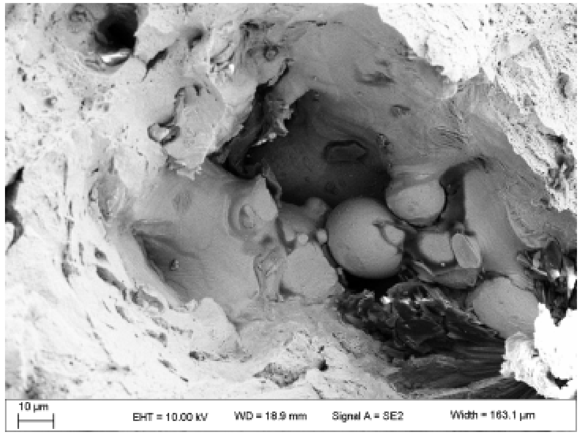
[1]www.wikipedia/selective_laser_sintering

LPBF can produce significant mechanical variability

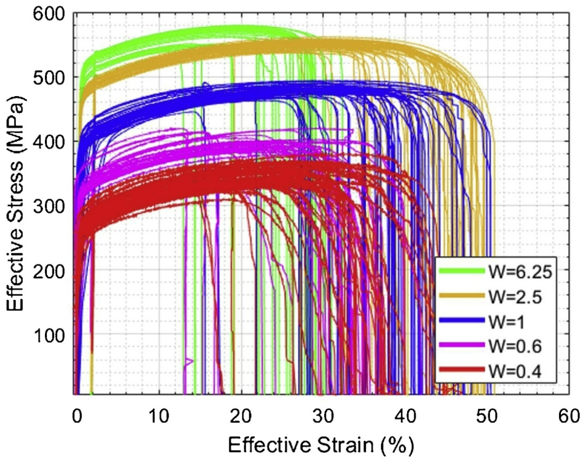


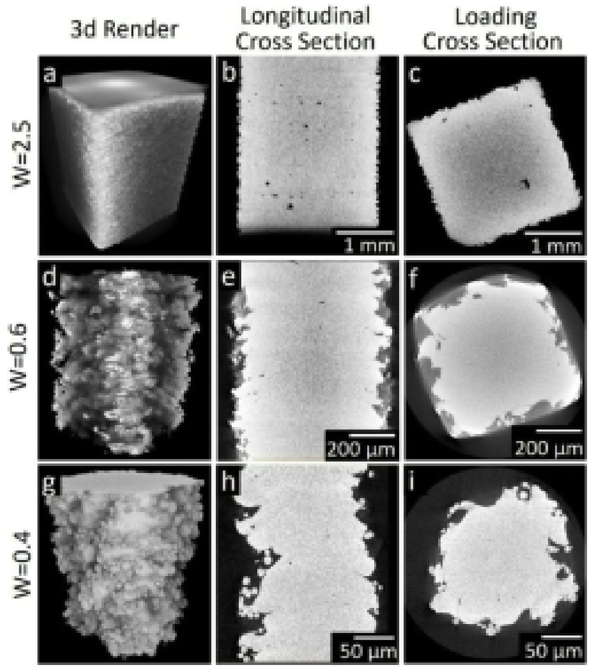
(J. Madison, T. Ivanoff, O. Underwood, SNL)





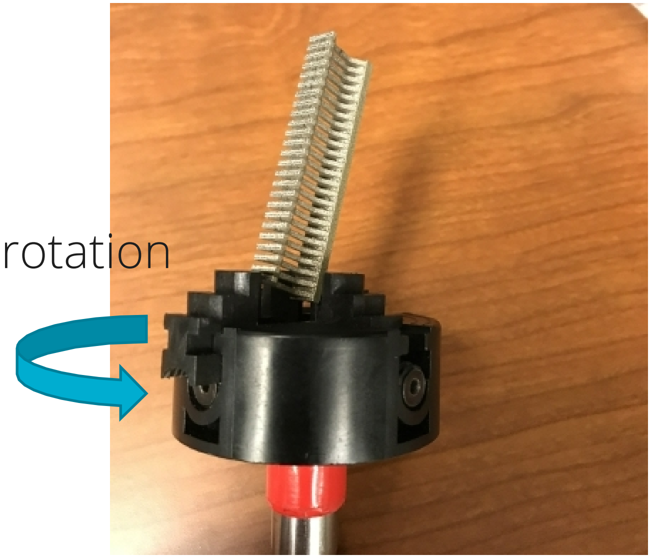
Kramer et al., *IJF* 2019

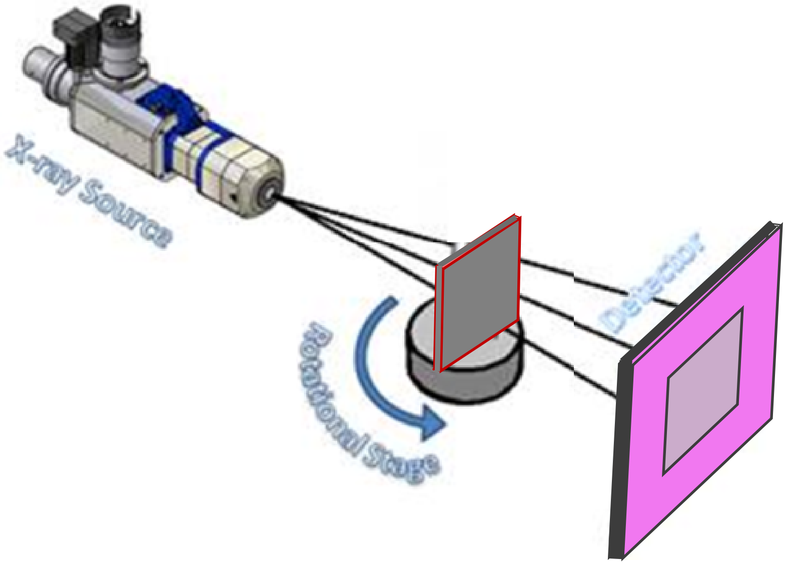


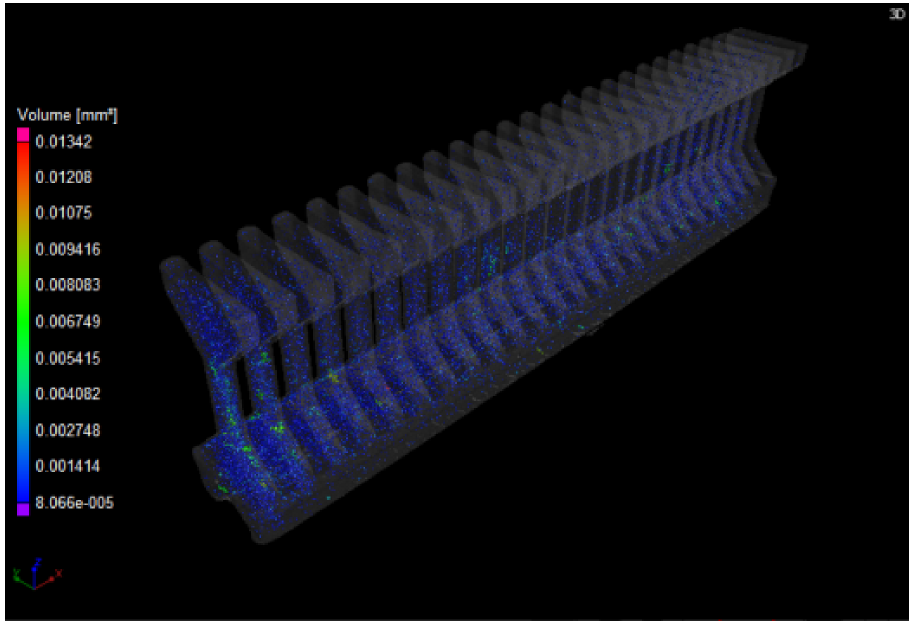


Roach, A.M. et al. *Additive Manufacturing* 2020

Computed Tomography (CT) offers a way to quantify defect structure



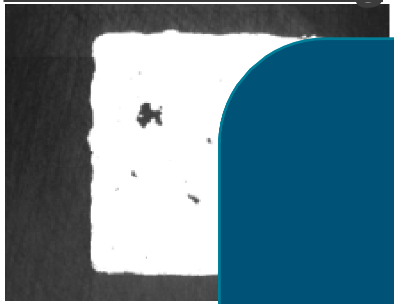




Challenges remain in use of CT data

Serial sectioning

Low threshold (80) | Middle threshold (155) | High threshold (230)

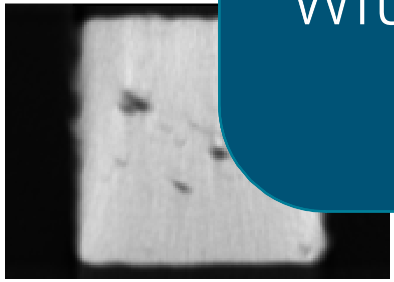


t edges
possible

Motivation: Can we make meaningful performance predictions with knowledge of defect structure?

CT

eshold (210)



Retain object edges
Lose all void detail

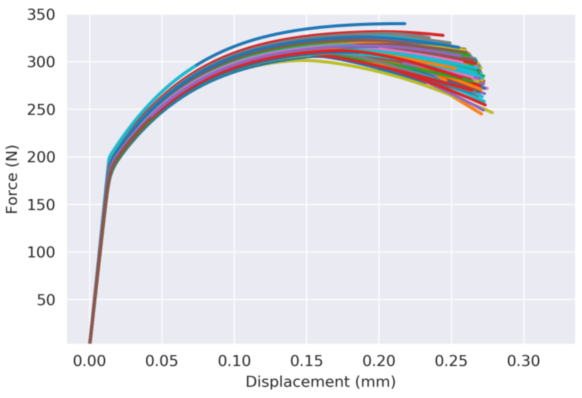
Retain object edges
Capture some detail

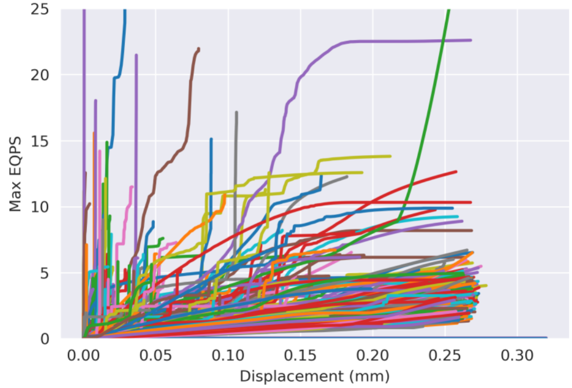
Lose object edges
Capture voids (slightly enlarged)

Predicting behavior of additively manufactured parts using Deep Learning

3D Convolutional Neural Networks were used to predict behavior, such as peak load, based on pore distributions orders of magnitude faster than traditional FEA.

Pore distributions significantly impacted force-displacement behavior and evolution of equivalent plastic strain (EQPS)





- Convolutional neural networks was used to classify part performance based on chosen failure metrics (peak load, EQPS, etc.) by learning effects of complex pore networks
- Synthetic data did not account for pore metrics other than volume.

Experimental CT pore distributions were used to generate synthetic pore realizations in tension specimens, which cause variations in mechanical performance

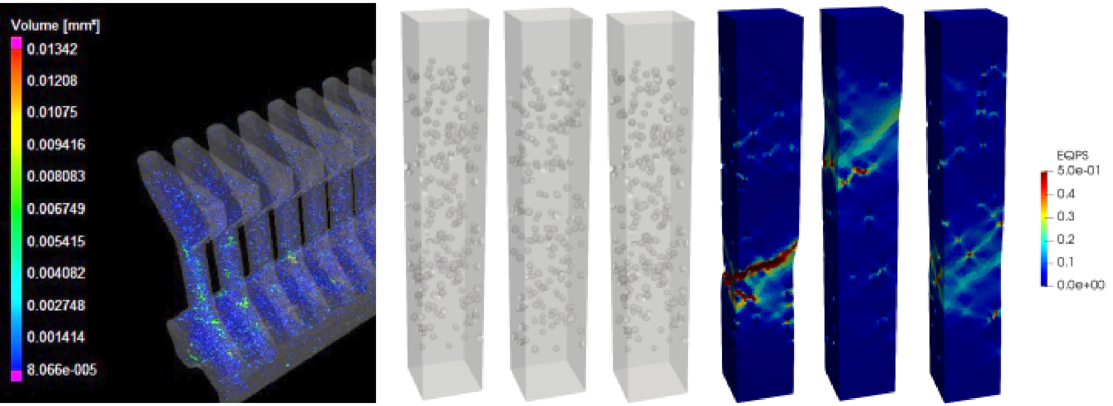
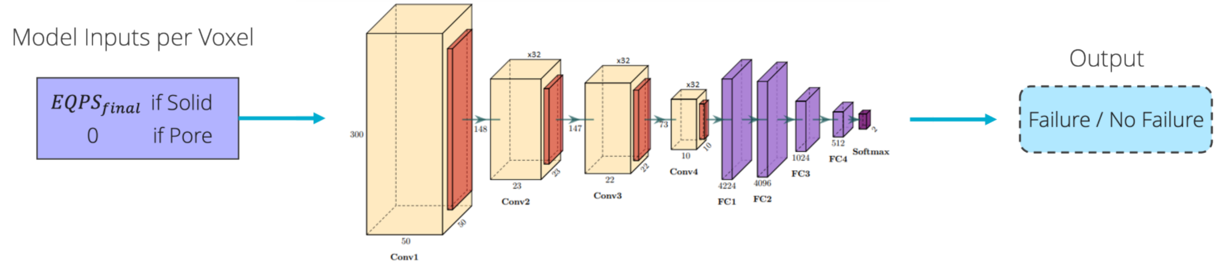


Image: Jay Carroll

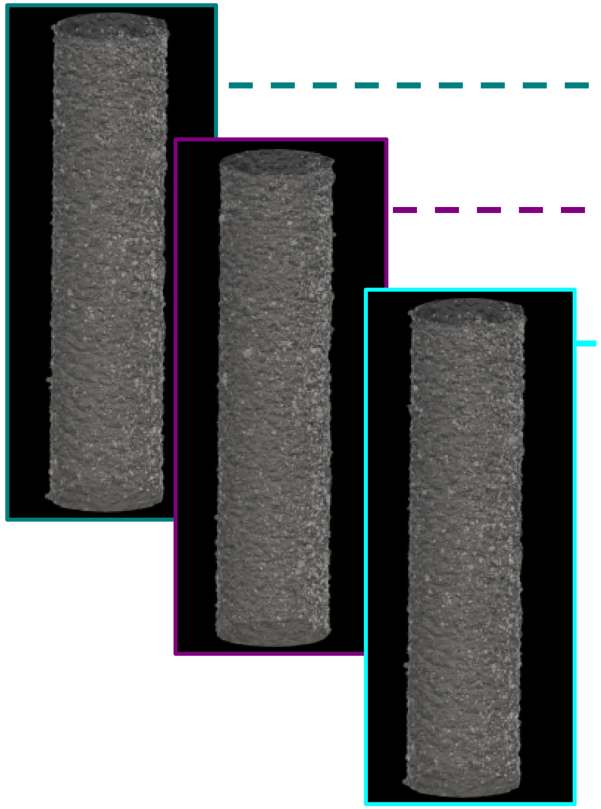
3D CNN Formulation



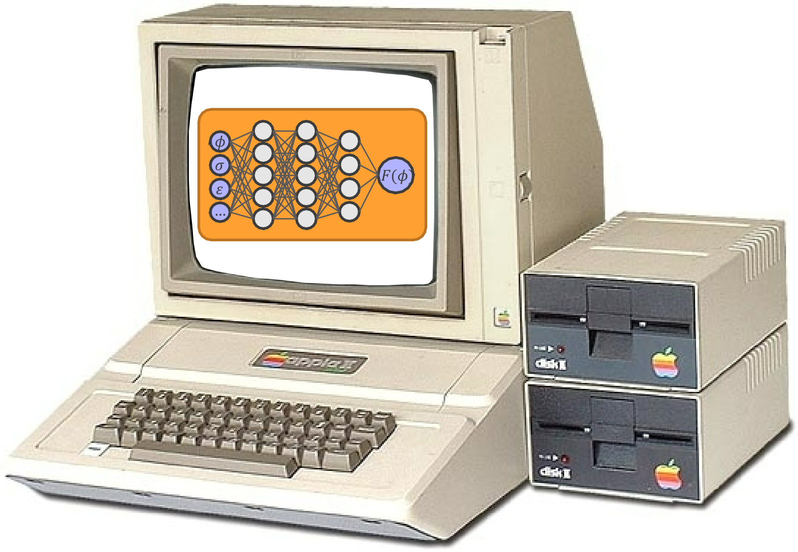
Johnson, K.L. et al. *Computational Materials Science* 2022

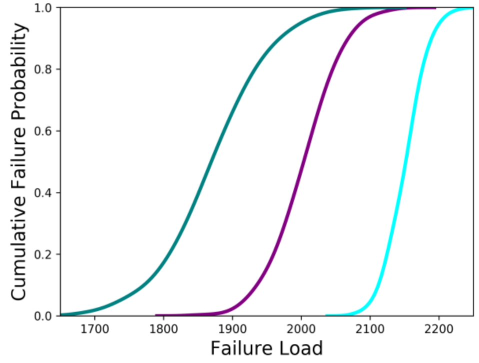
Vision: Rapid failure prediction based on microstructure enabled by Machine Learning

Microstructure



Simulation Code



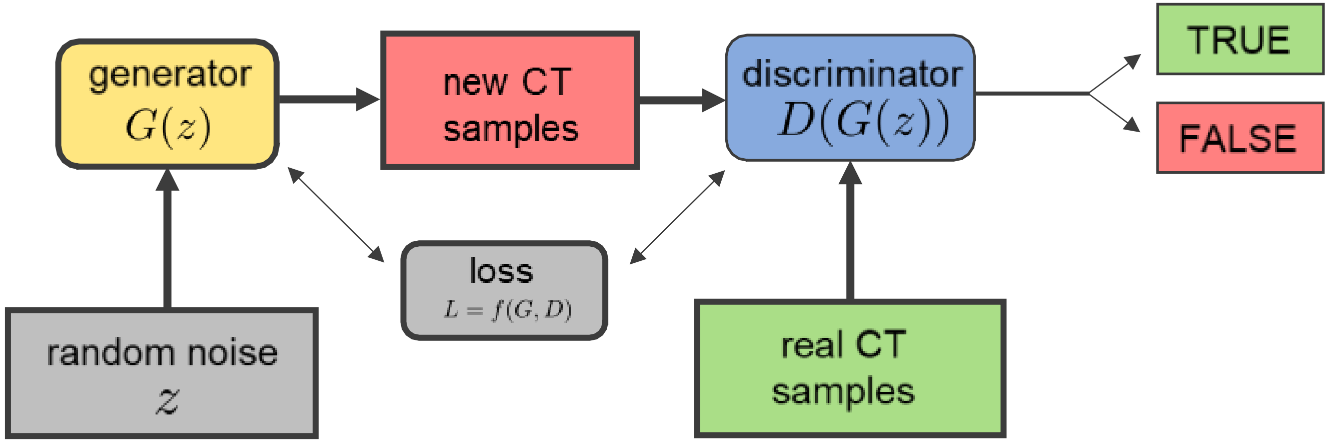


Requirements: Training data with accurate microstructure and mechanical behavior

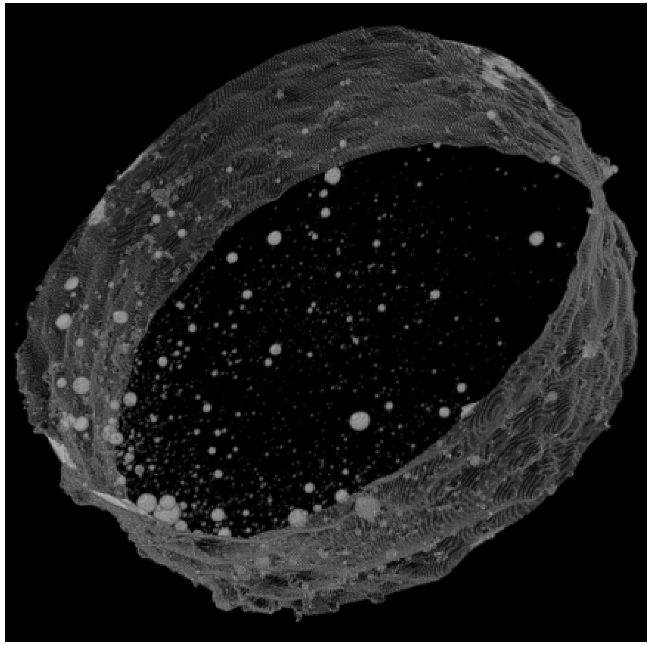
Image: oldcomputers.net

Ongoing work: Using GANs to augment CT images of AM material to preserve underlying pore statistics

- Generative Adversarial Networks (GANs) produce new samples from a training set while preserving the underlying statistics.
- GANs are trained to minimize the distance between the distribution of the training data and the generated samples.
- Collaboration with Prof. Amir Farimani and Francis Ogoke (CMU)



GAN network schematic



Metric	Notes
Volume Distribution	
Nearest Neighbor Distances	
Location Distribution	
Ellipticity	$\sqrt{\frac{a^2-c^2}{a^2}}$
Moment of Inertia	
Surface Area	
Mallat Scattering Transform	$\|\|x * \psi_{\lambda_p}\| * \psi_{\lambda_{p'}}\| * \phi_J$

Ogoke, O.F. et al. "Deep-Learned Generators of Porosity Distributions Produced During Metal Additive Manufacturing" (in preparation)

Can we accurately predict failure in AM parts?

Questions to be answered:

1. What level of scan resolution do we need?
2. Are surfaces or pores more important?
3. How do plasticity and damage models affect results?

Study carried out on Al-Si10-Mg specimens with pre-test CT scans and post-test blue light scans

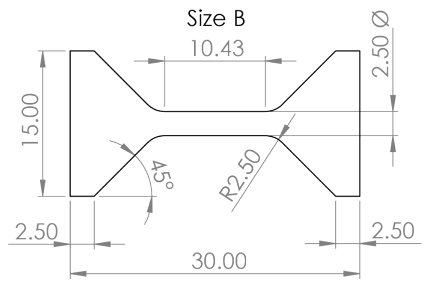
Resolutions studied

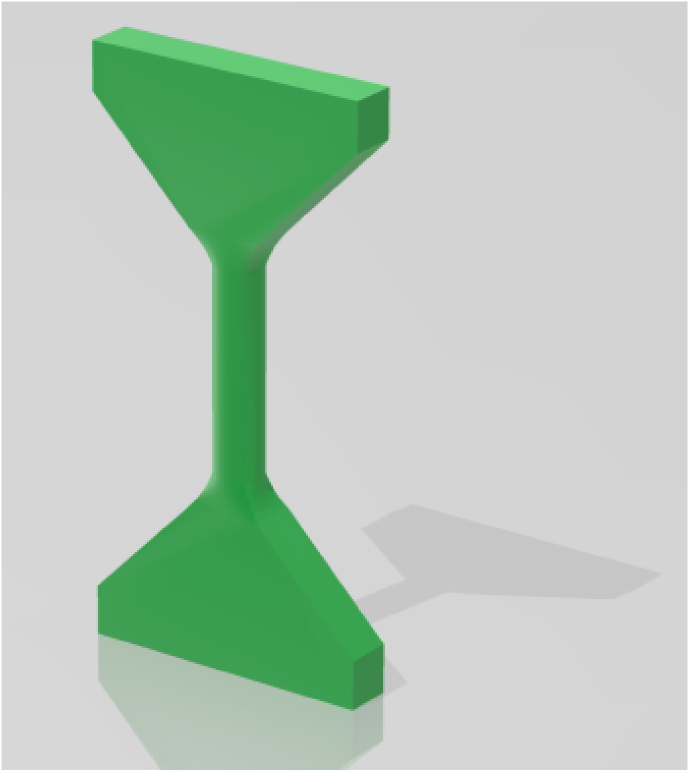
- 64x64: ~43 μm voxels
- 128x128: ~21 μm voxels
- 256x256: ~10 μm voxels
- Actual Scan: 4.56 μm voxels

LPBF process and µCT scanning parameters

- Material: AlSi10Mg
- Heat Treatment: “Stress Relief Anneal” 290°C for 2 hrs
- Sample Orientation: Tensile direction normal to build
- Cylindrical gauge high-throughput tensile samples
  - Equipment: SLM Solutions 280HL
  - Laser Power: 350 W
  - Speed: 1100 mm/s
  - Hatch Spacing: 150 µm
  - Layer Thickness: 30 µm
- CT resolution: HF26 - 4.56 µm

Jay Carroll talk – “Dominant microstructural features impacting failure in Additively Manufactured AlSi10Mg” Feb. 3, 10:15AM-10:45AM

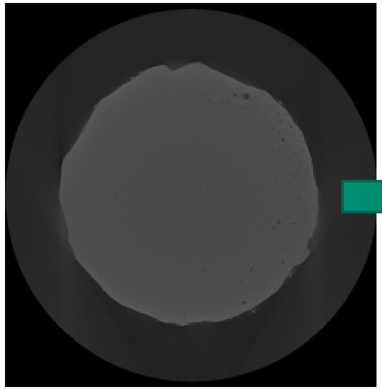




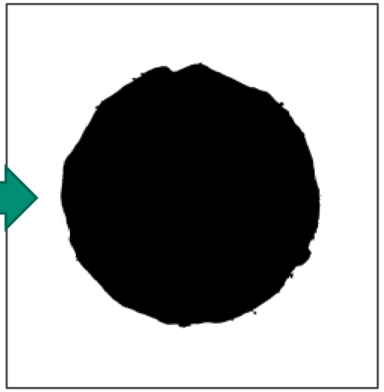
Modeling Workflow

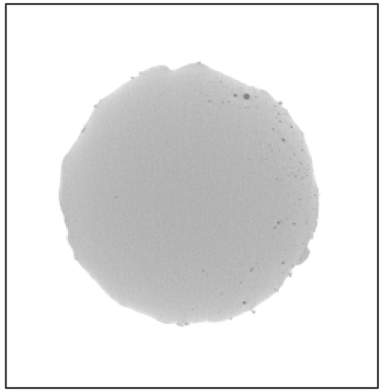
CT Processing

Import Image



Threshold

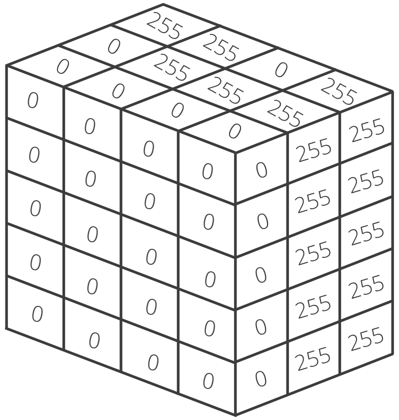




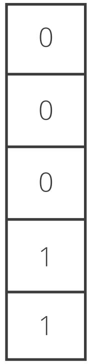
"High Res" Tiff Stack

Meshing

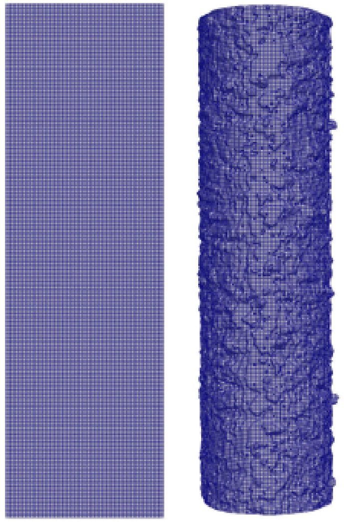
Numpy Array



SPN File



Cubit/Sculpt Mesh



Simulation

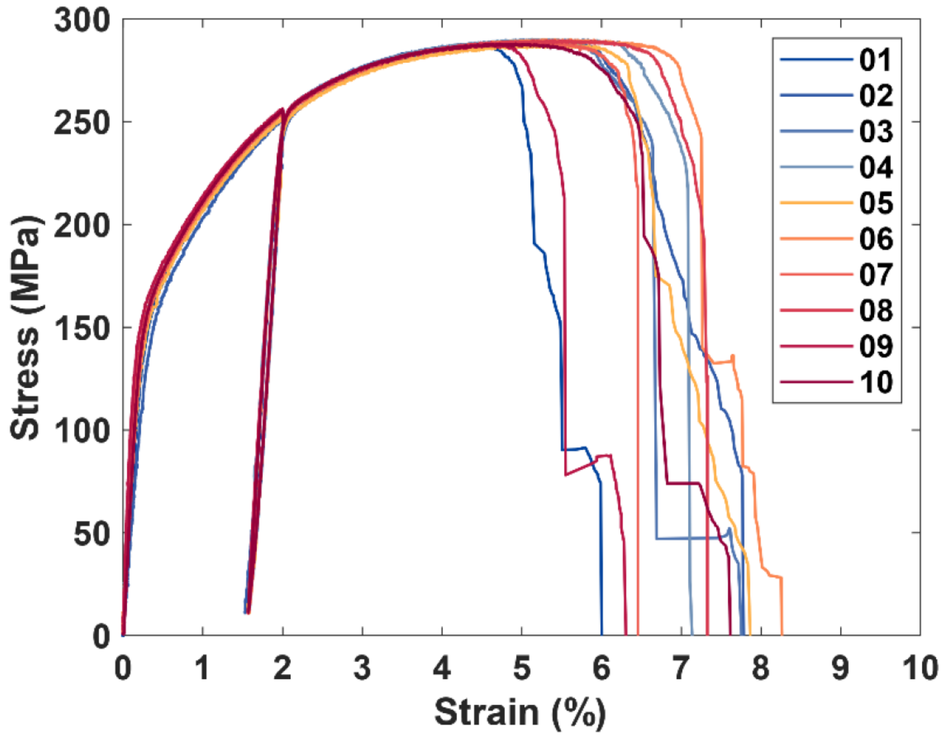
Calibrate plasticity parameters with coarse, pore-free mesh of one sample

With plasticity parameters fixed, calibrate damage parameters with coarse, porous mesh of one sample

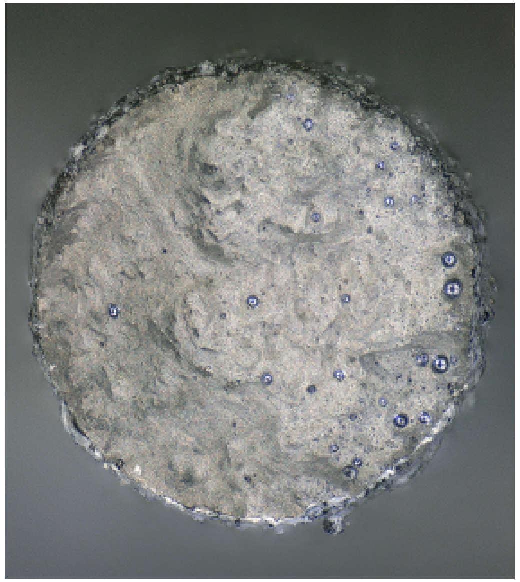
Predict failure in all 10 porous samples using varying resolution

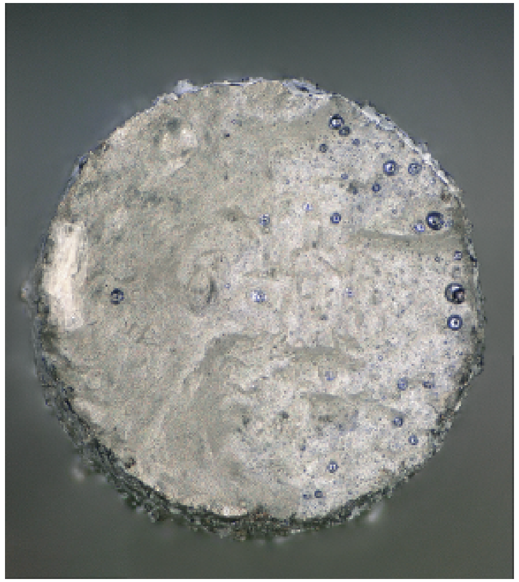
Mechanical Testing

	UTS (MPa)	UNFelg (%)	Ductility (%)	Unloading Modulus (GPa)	Yield Stress (MPa)	Yield Strain (%)
H-BR05-4	288.3	4.927	5.738	60.4	196.1	0.526
H-BR05-5	284.2	4.997	6.350	58.6	175.9	0.500
H-BR05-6	287.6	5.412	6.941	58.3	177.7	0.505



Top

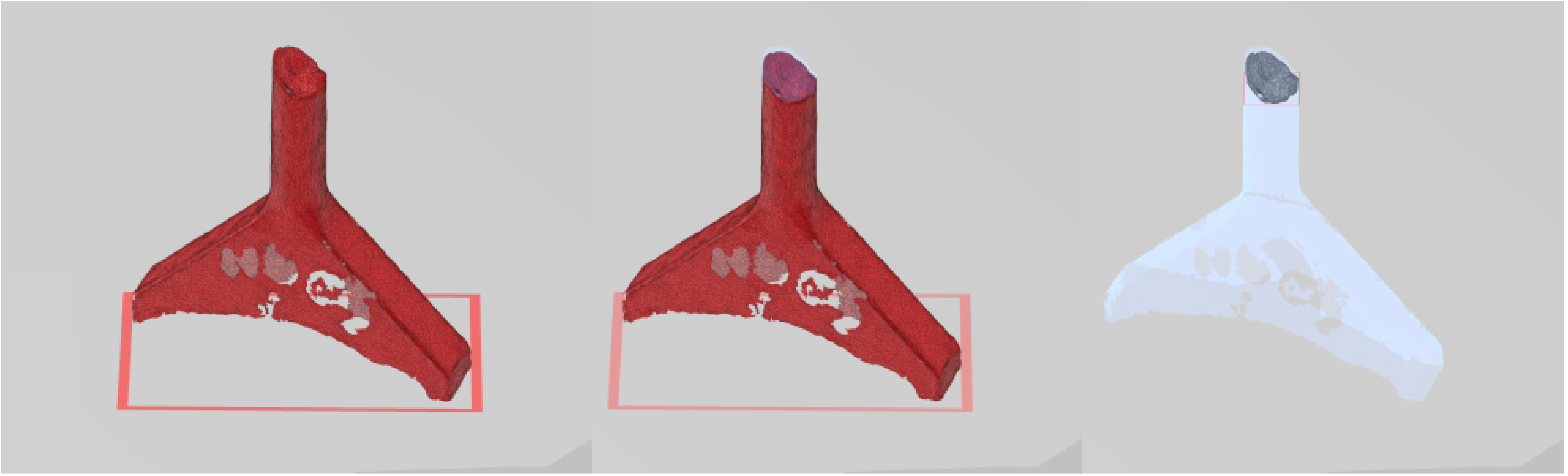




Bottom

Post Mortem Fracture Surface Processing

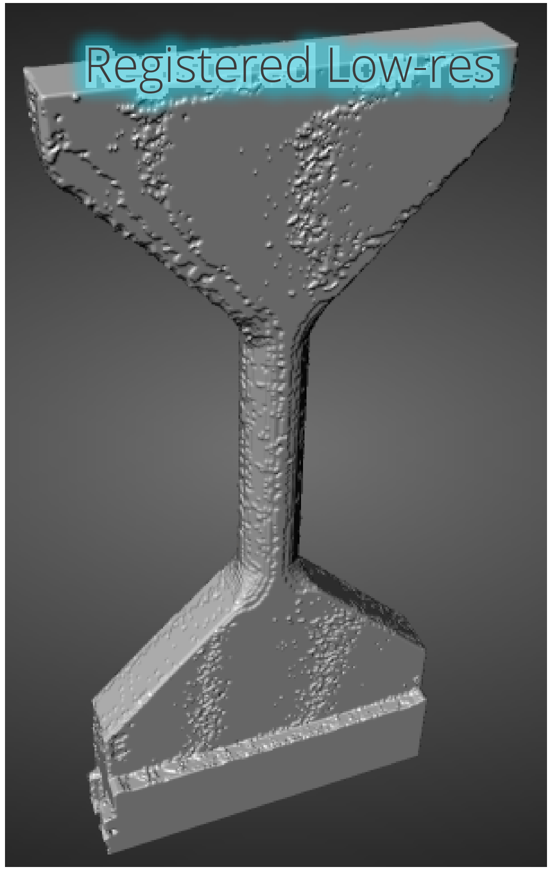
- Acquire data using the ATOS 3D structured light scanner (GOM)
- Import STL file into custom MATLAB script to adjust for plastic strain in the tensile axis ($\varepsilon_{unf} - \varepsilon_y$)
- Manually select the nodes of the fracture surface

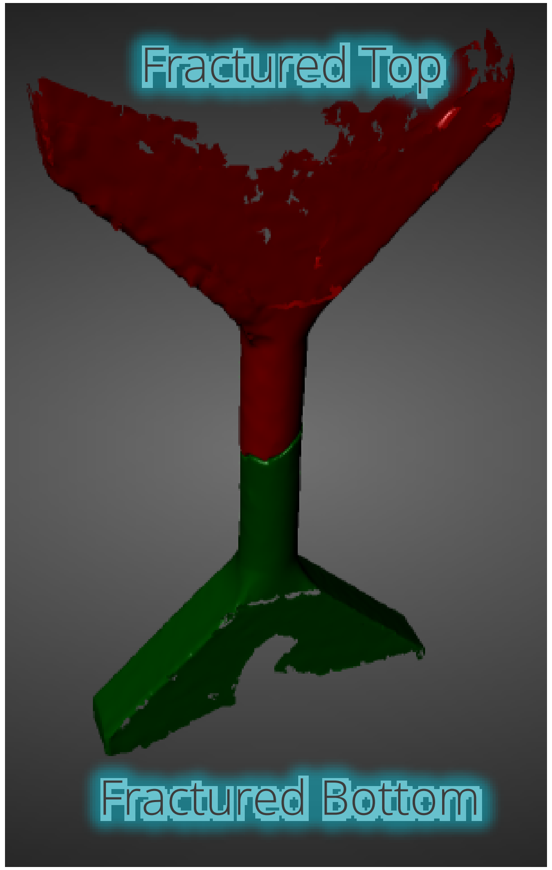


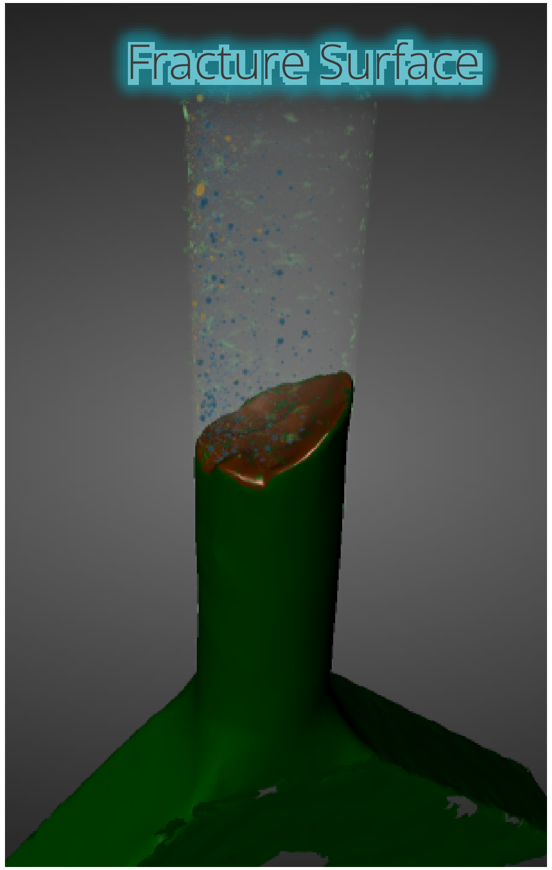
Scanned Component Strain Adjusted Component Fracture Surface

Coupling the Data

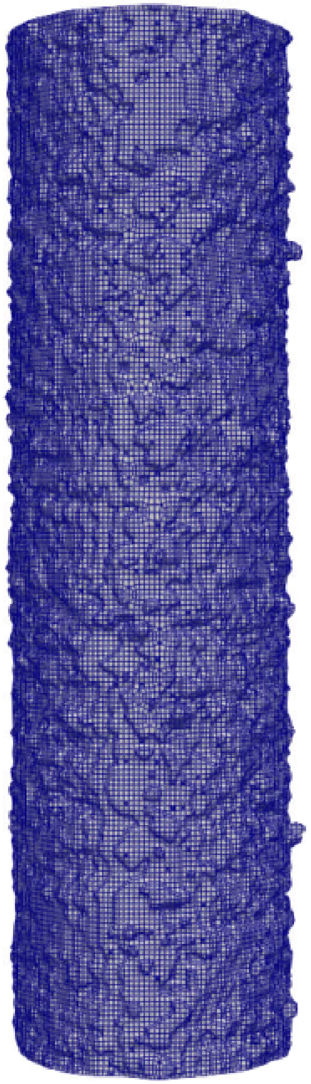
- Use the high-resolution scan as the datum for all processing
- Register low-resolution μCT scan to high-resolution μCT scan
- Import and register fracture components to the low-resolution scan
- Import and register the fracture surface to the fractured tensile sample
- Additional data registered to the high-resolution scan: Sample Surface, Regression Surface, Surface Voids



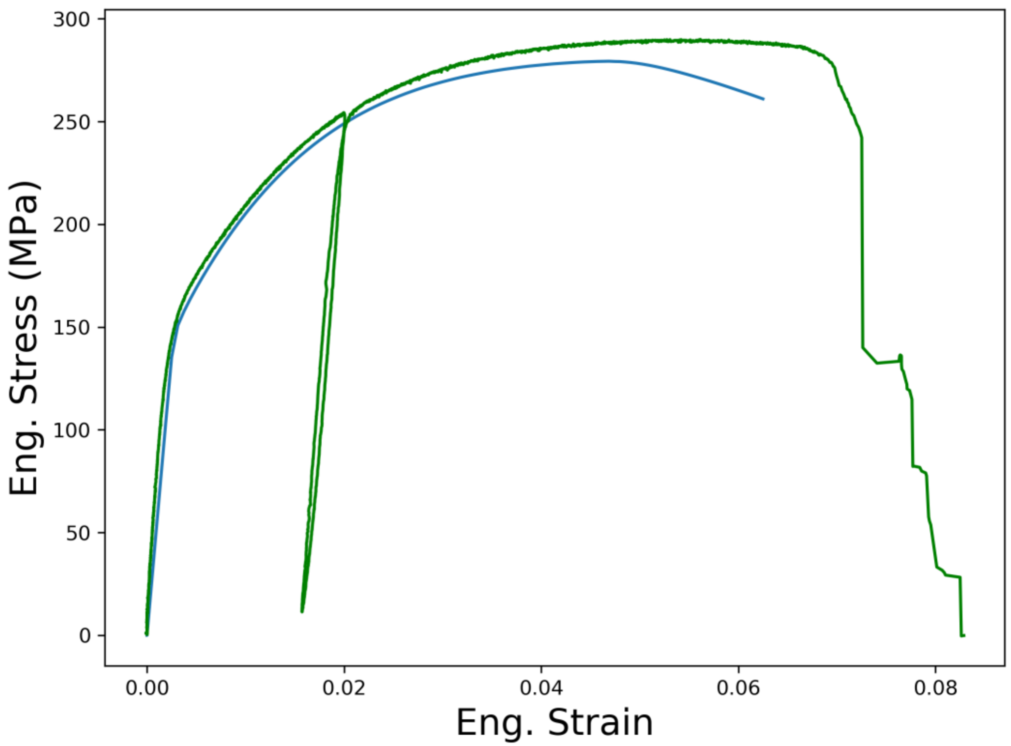


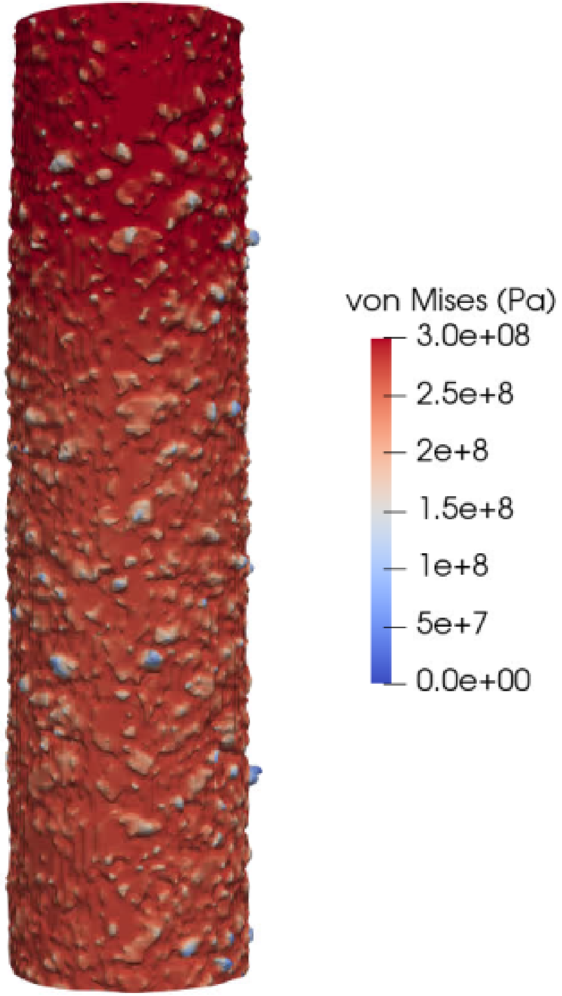


Calibration step 1: Capture plasticity response



No Pores



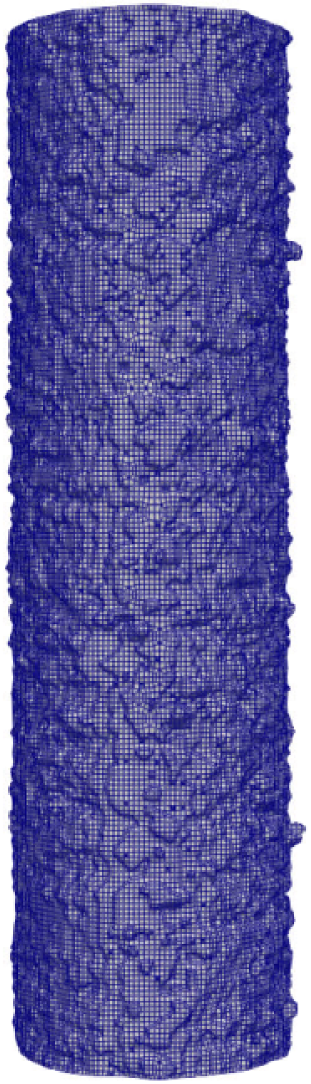


- Initial calibration using coarse scan resolution with no pores
- Plasticity is captured with Voce[1] hardening model

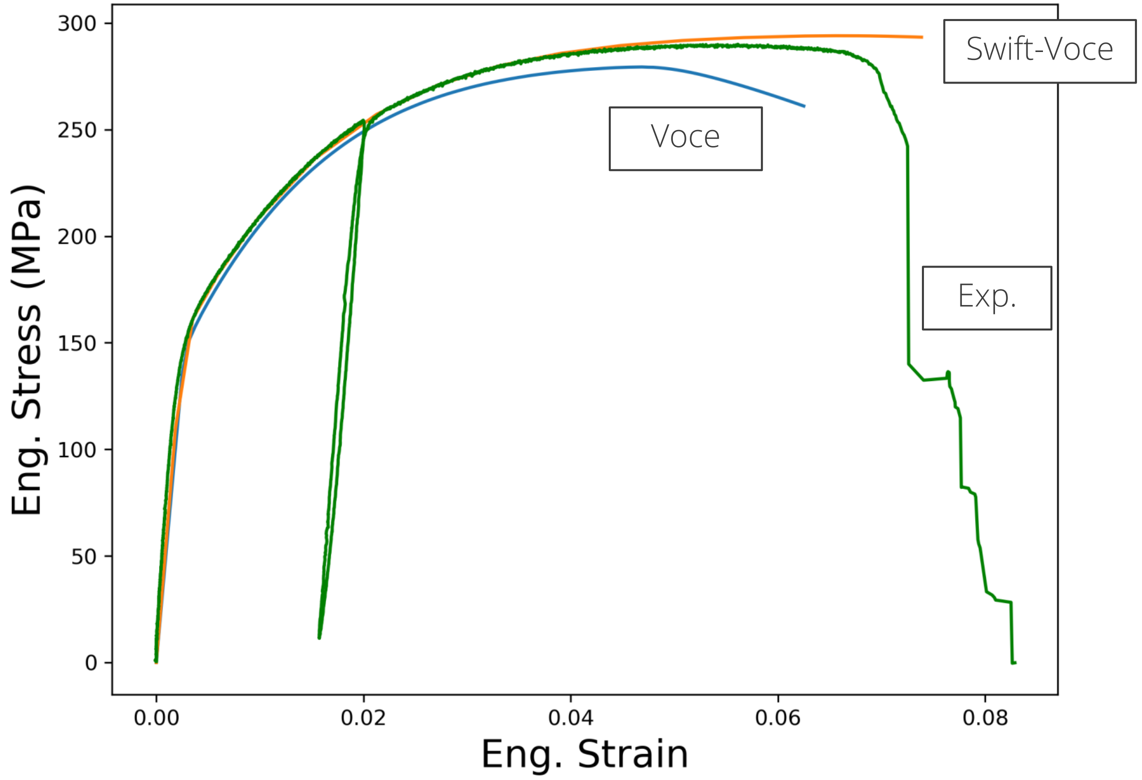
$$\bar{\sigma} = \sigma_y + A(1 - \exp(-n\bar{\varepsilon}^p))$$

[1]Voce, E., J. Inst. Metals 1948

Accurate plasticity response requires right model form

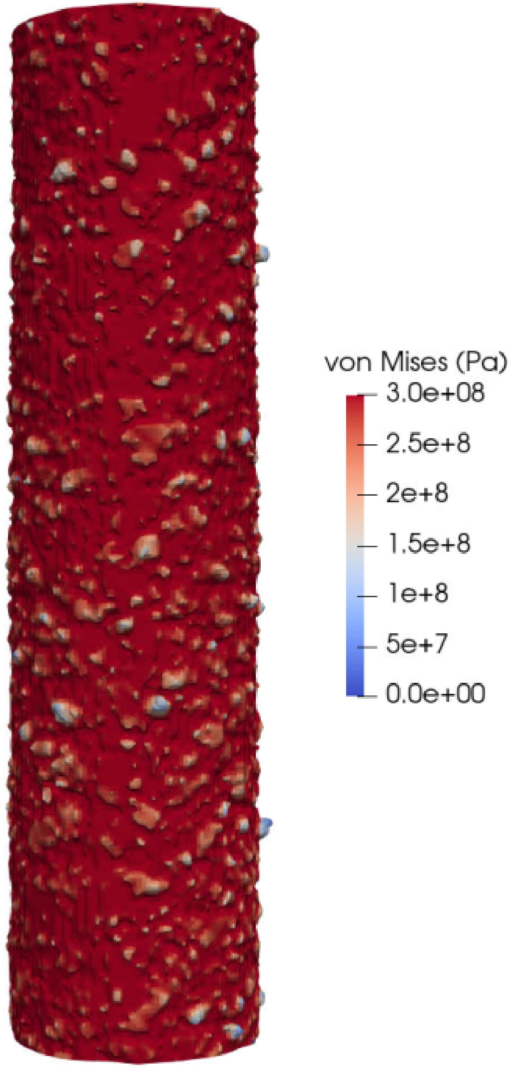


No Pores



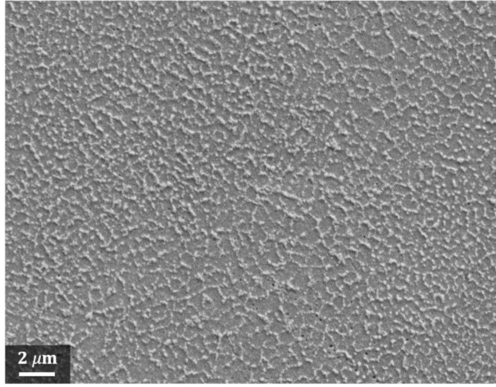
- Addition of extra Swift[1] hardening term improves response

$$\bar{\sigma} = \sigma_y + h\bar{\varepsilon}^p + A(1 - \exp(-n\bar{\varepsilon}^p))$$

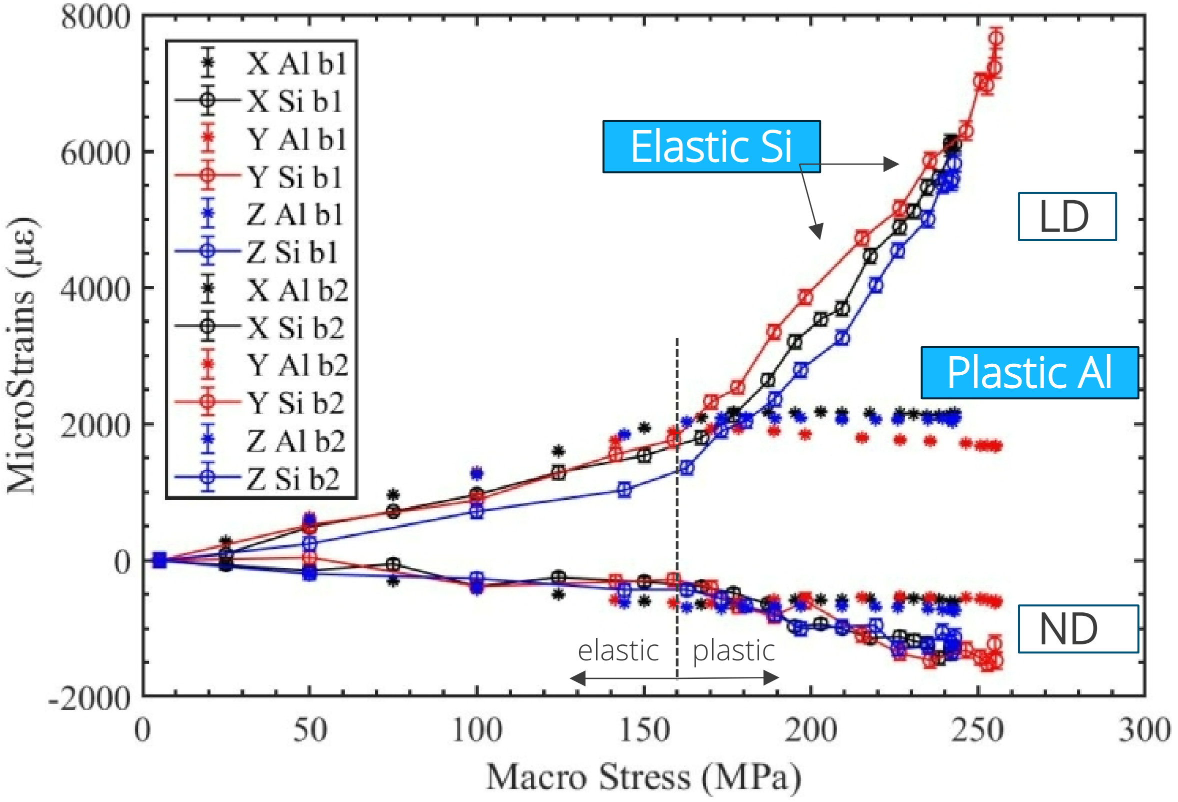


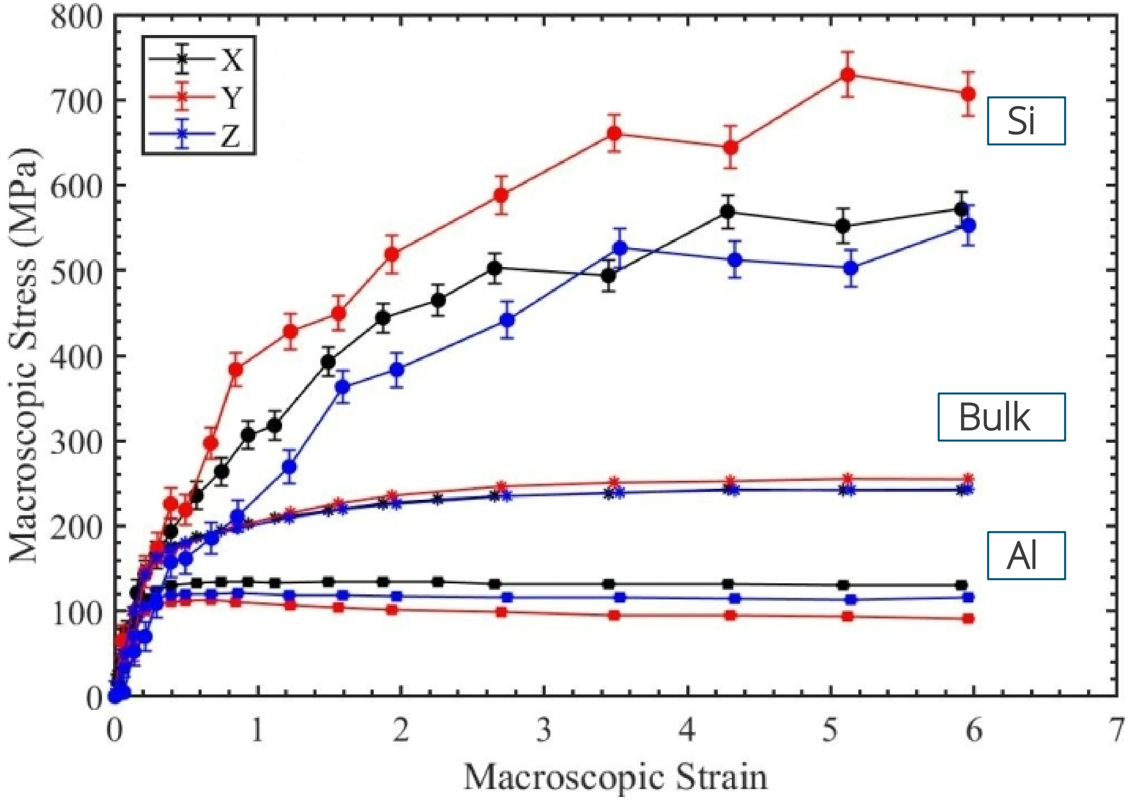
[1]Swift, H.W., JMPS 1952,

A mechanism for late stage hardening in bulk response



LD = Longitudinal Direction (Tensile Axis)
ND = Normal Direction





- Stress partitioning study at Los Alamos Neutron Science Center revealed Si particles (~10%) remain elastic until failure

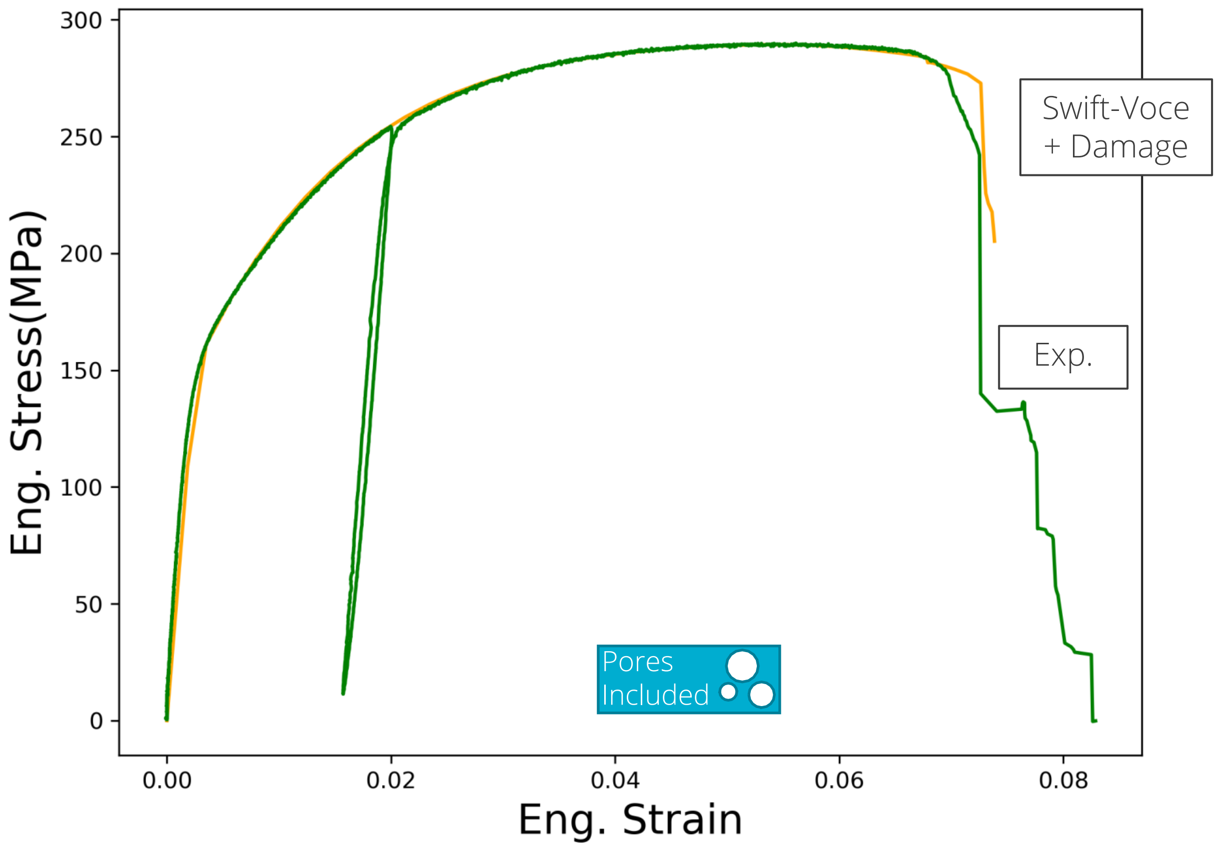
Bjørn Clausen, Don Brown, and Milan Agnani

Calibration step 2: Capture failure with damage model

- Add coarse scan mesh with pores
- Voids below scan resolution assumed to be captured by initial void volume fraction and Cocks-Ashby[1] void growth:

$$\dot{\phi} = \sqrt{\frac{2}{3}}\dot{\epsilon}_p \frac{1-(1-\phi)^{m+1}}{(1-\phi)^m} \sinh\left[\frac{2\,(2m-1)}{2m+1}\frac{\langle p \rangle}{\sigma_e}\right]$$

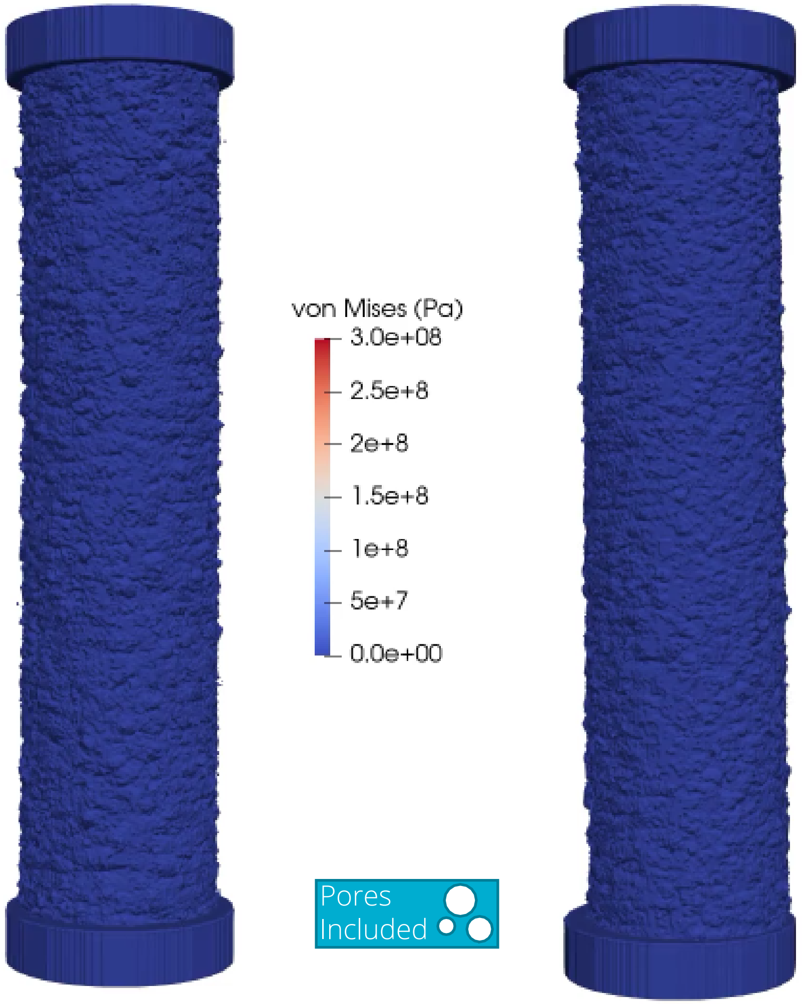
- Modular damage model is not coupled to stress response (no softening)
- Elements are removed when critical damage (ϕ) threshold of 0.15 is reached



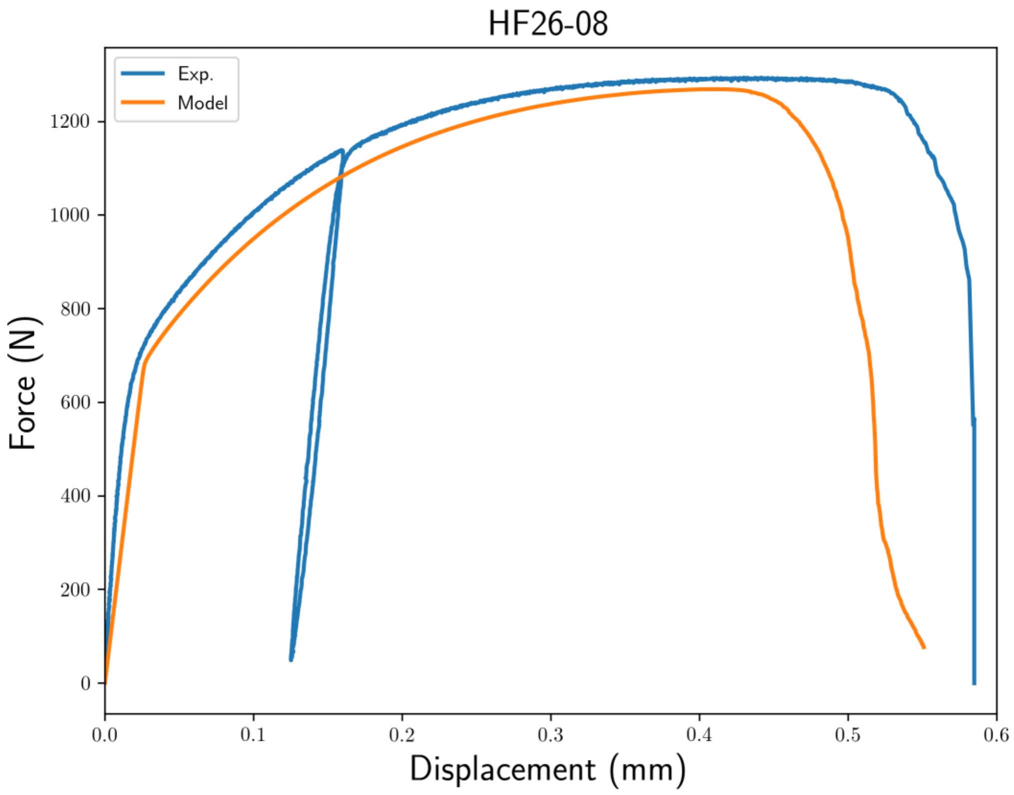
[1]Cocks, A.C.F. and Ashby, M.F., Metal Science 1980

Crack path can accurately be captured (for certain samples)

Sample 08



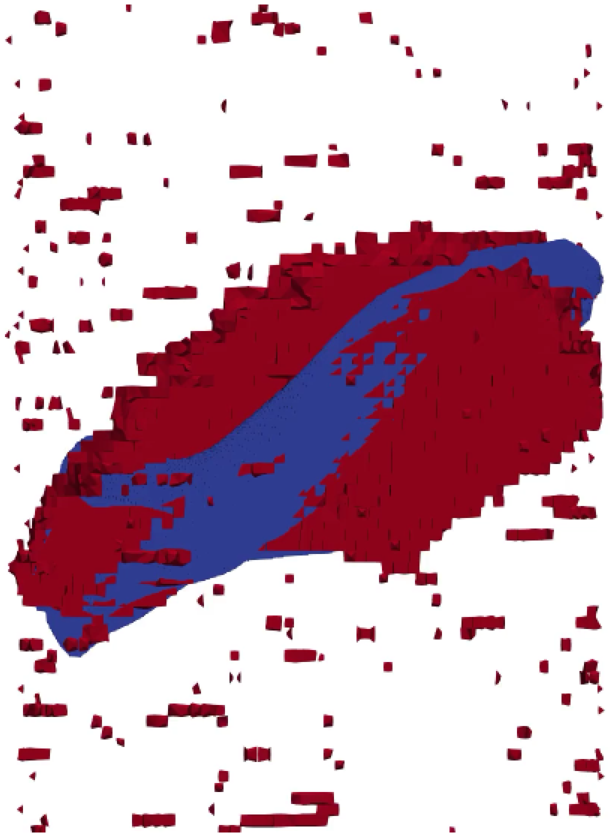
~21 μm voxels, different views



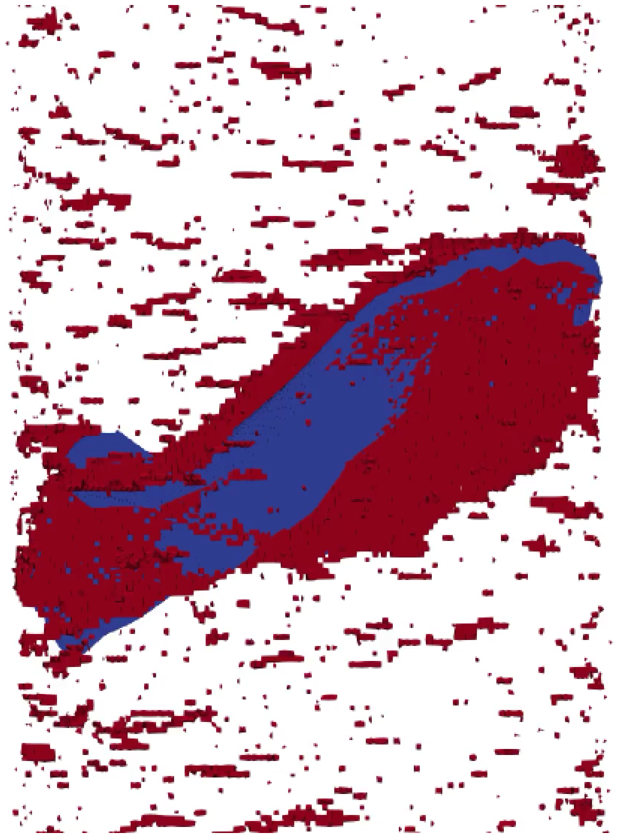
- Higher resolution reduces force response
- Smaller elements decrease failure strain with local damage model

Higher resolution scans improve crack path predictions

Sample 08



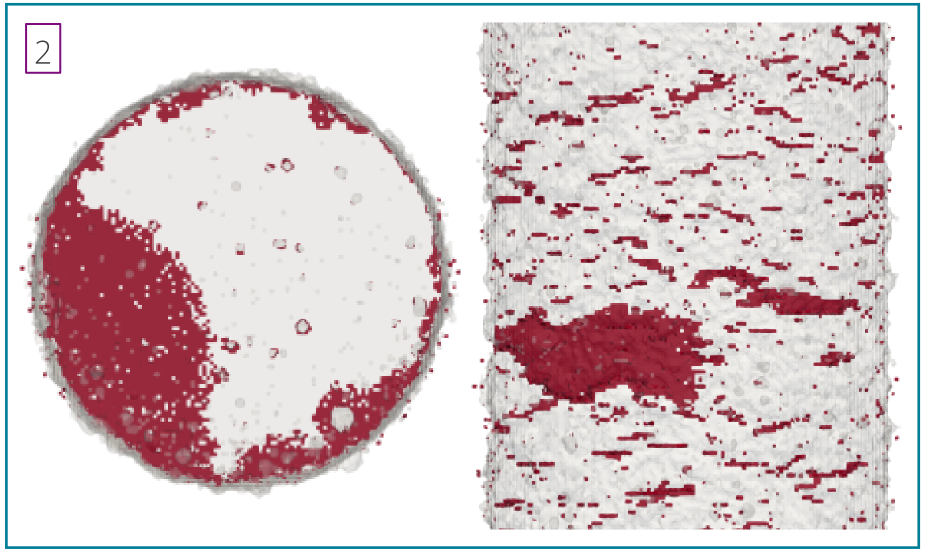
Experiment – Blue
Model - Red

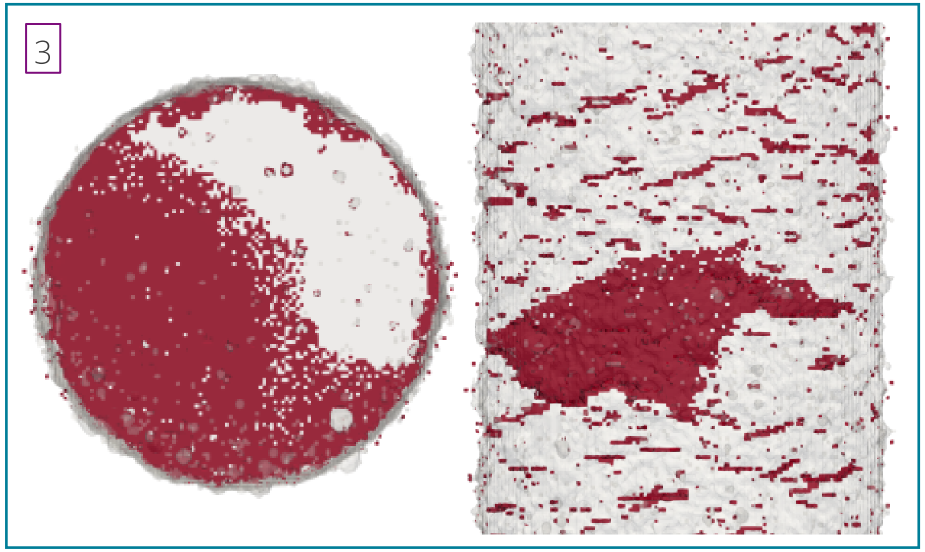


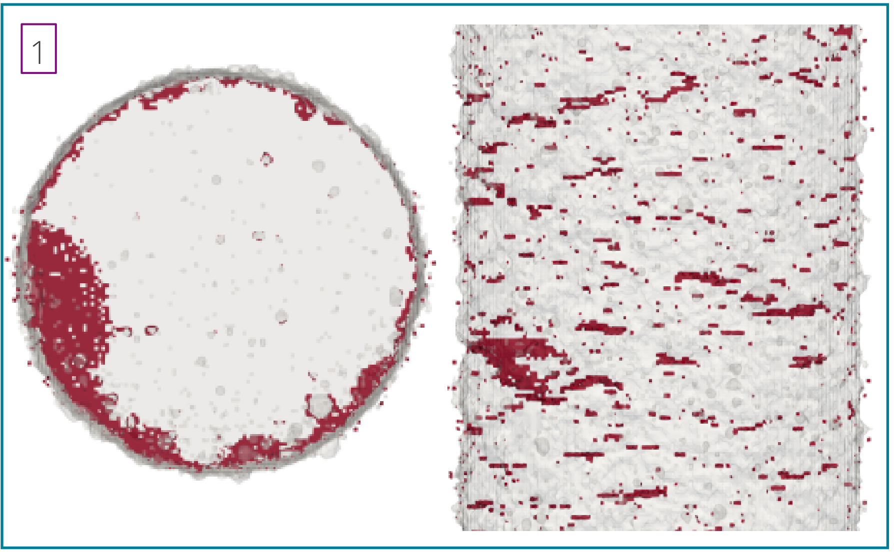
~43 μm voxels
688k elements
144 cpus
16 hour run time

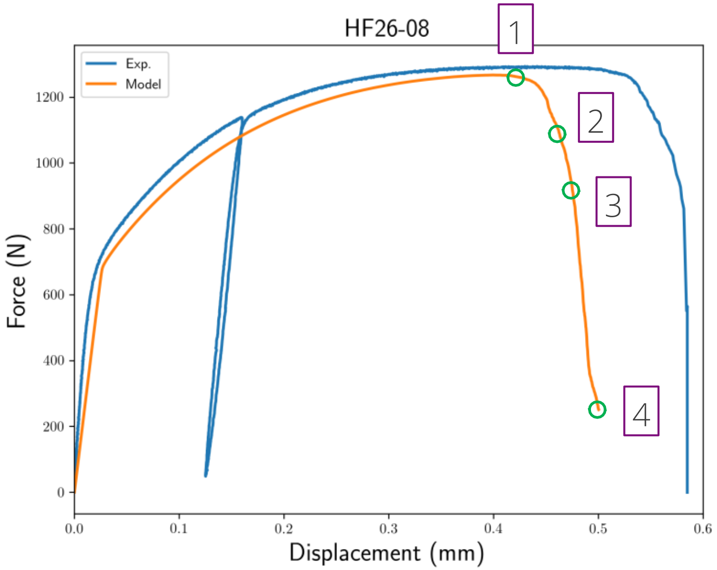
~21 μm voxels
5.2M elements
1056 cpus
24 hour run time

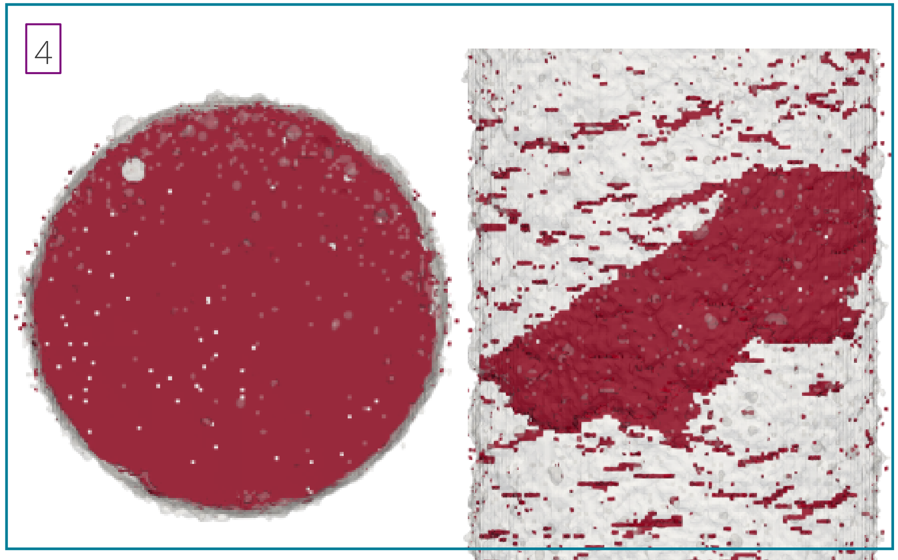
Crack initiates at large surface defect





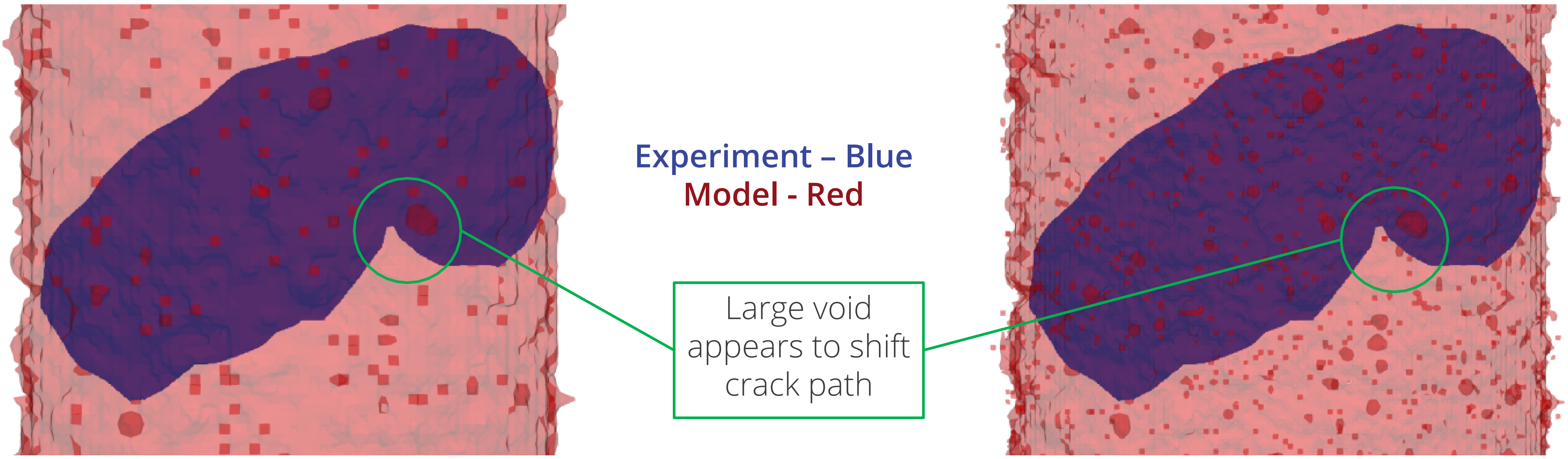






Crack path is affected by large defects

Sample 08

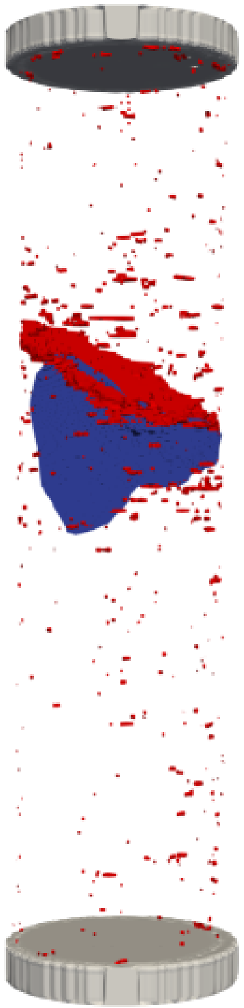


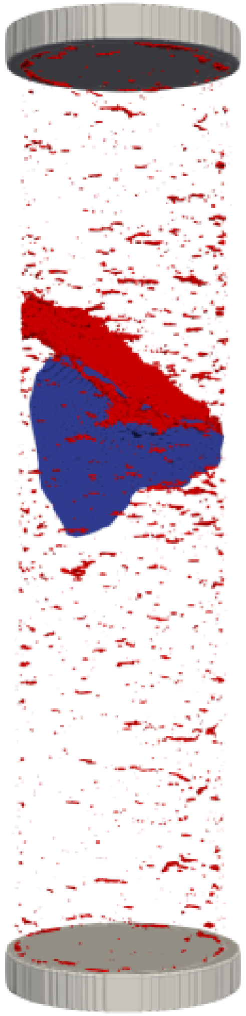
~43 µm voxels

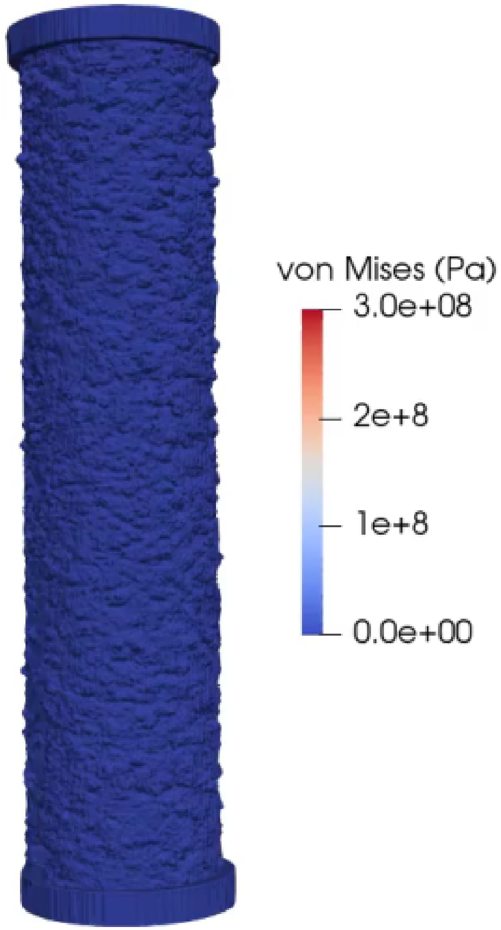
~21 µm voxels

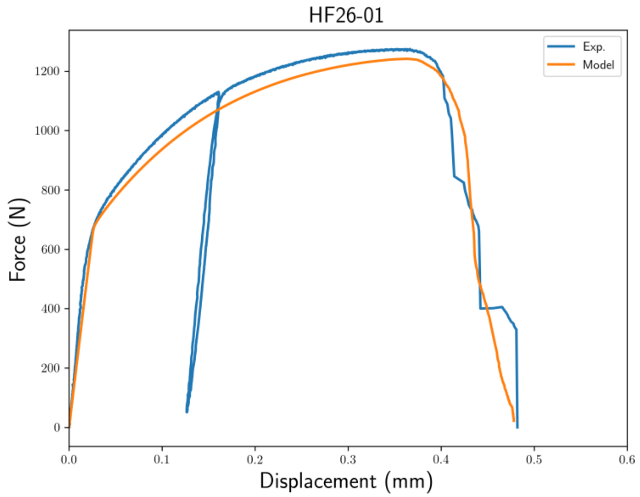
In a different sample, surface roughness appears to drive initiation, while pore structure affects propagation

Sample 01

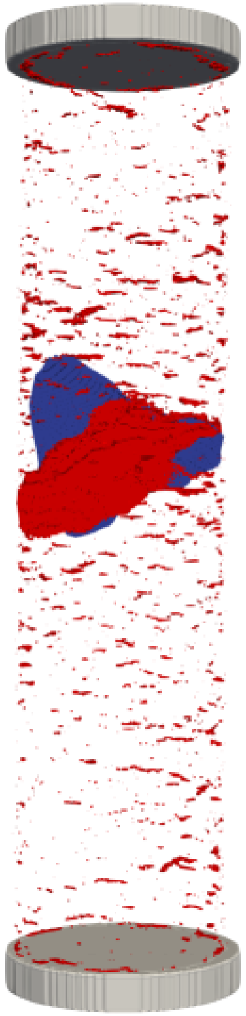








No Pores



~43 µm voxels
with pores

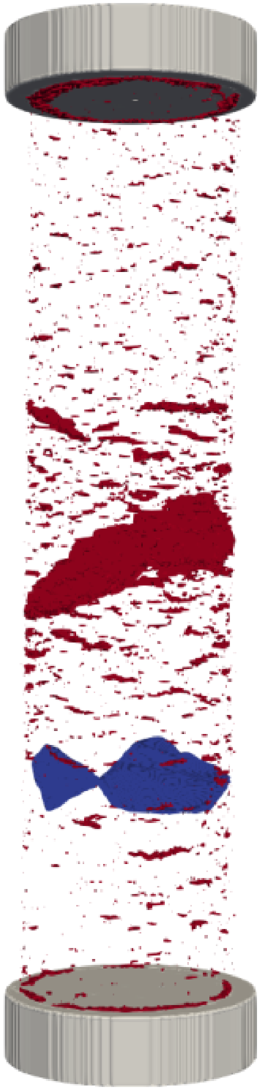
Pores Included

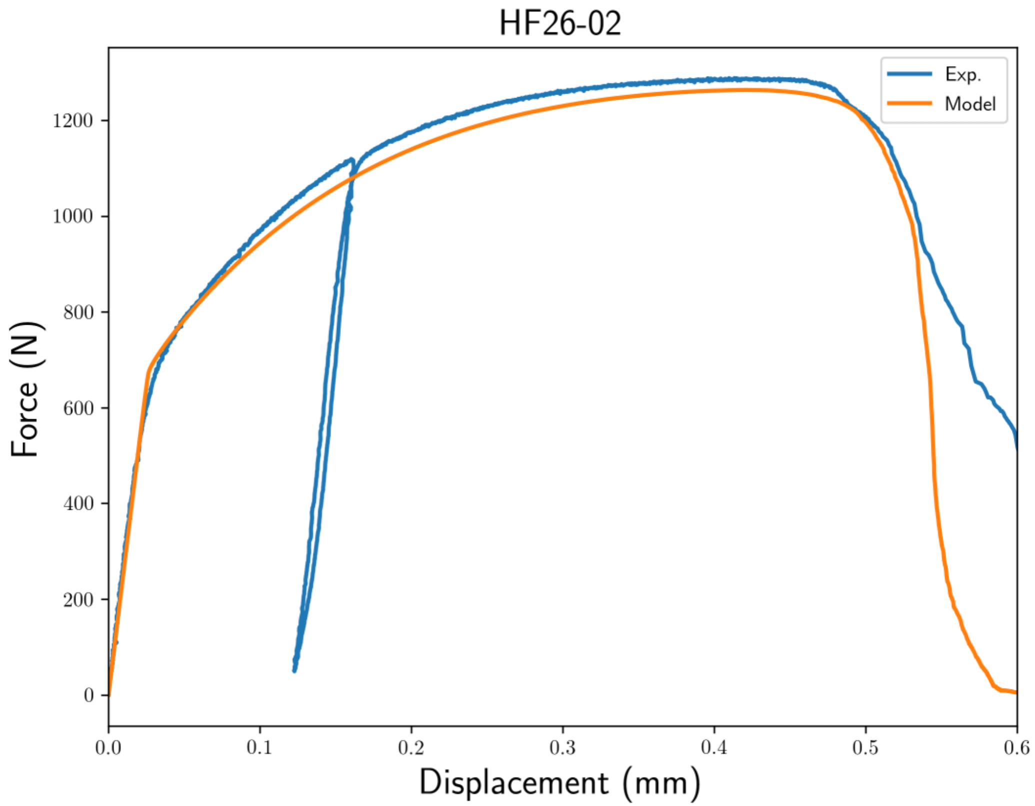
~21 µm voxels
with pores

~21 µm voxels
no pores

Additional work is needed to determine why crack paths in some samples are incorrectly predicted

Sample 02





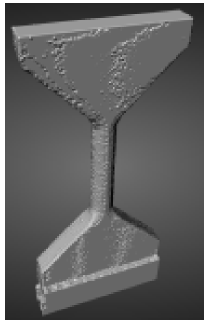
Summary

- Computed Tomography can be a powerful tool for assessing defects and model validation/improvement
- Plasticity model form has large impact on accurately capturing response
- Surface roughness appears to drive initiation in *these samples*
- Coarse resolution was able to capture initiation location correctly
- Pores have minimal effect prior to peak load
- Pores have an effect on crack propagation
- Crack path is still incorrect at 21um voxel size for some samples
  - 10 um voxel size running now

Challenges

- Simulations are very expensive, 10 um size ~46M elements
- Meshing can take hours in parallel
- Registration – easy to flip array axes
- Small decisions on boundary conditions have major effects
- Visualization

Future Work



- Incorporate low resolution scan of grips into model for better boundary condition representation
- Iteratively smoothing surfaces up to smooth cylinder – isolate pore effect
- Update damage parameters for smaller mesh size in higher resolution models
- Mesh size study for same voxel resolution

Questions?

Interested in a postdoc position in this area?

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