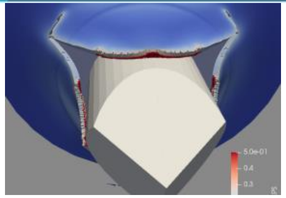
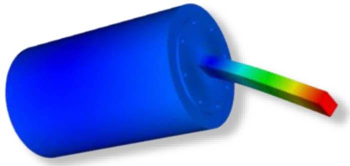
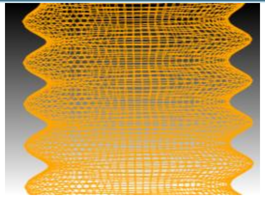
Ductile Failure Prediction in Additively Manufactured Metals via 3D Characterization







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Mentors: Andrew Polonsky (lead), Ashley Spear, John Emery, Chad Hovey, Dan Moser, Paul Chao

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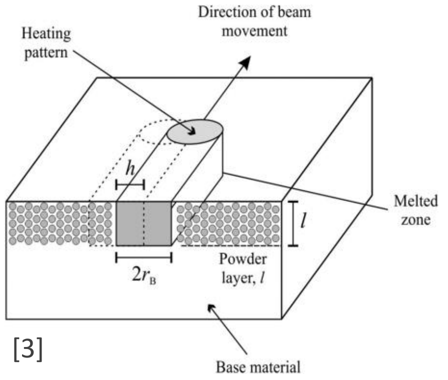
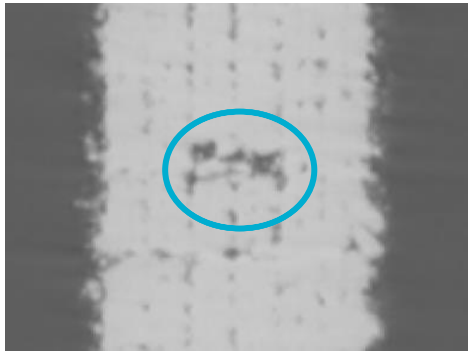
Motivation

- Increasing need for reliability and safety (Ex: Automotive, Healthcare, Aerospace)
- **Additive Manufacturing (AM):**
  - Produces complex geometries with unprecedented design freedom and customization
  - Generates non-uniform material properties, extreme anisotropy, and ***inherent porosity*** [1, 2].

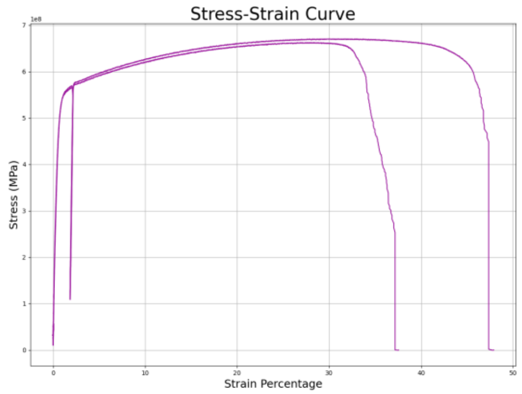
Specimen Build Settings



Anisotropic Pores



Premature Fracture



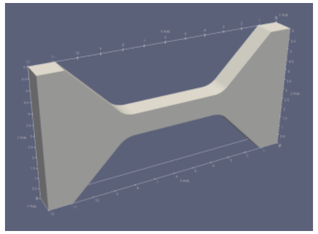
Goal: Validate different failure prediction approaches given the set of experimental data.

- **Prediction models**:
  - Direct Numerical Simulation (DNS): Gold standard of failure prediction [3, 4].
  - Void Descriptor Function (VDF): Lightweight prediction model [5-6].

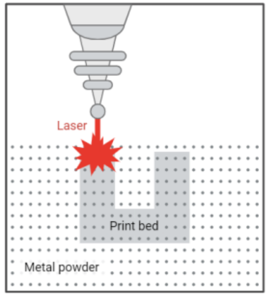
Experimental Data Overview

Additive Manufacturing of Samples

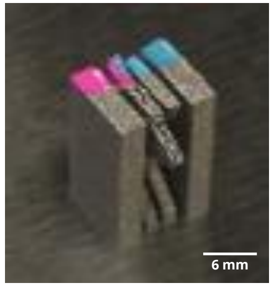
CAD file



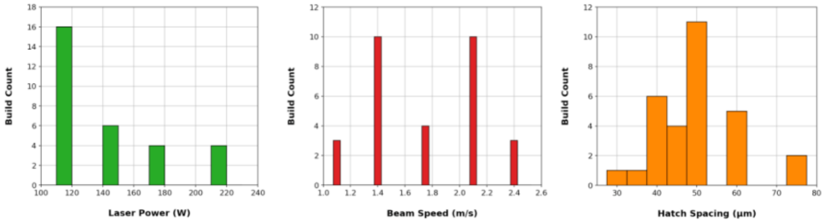
Laser Powder Bed Fusion



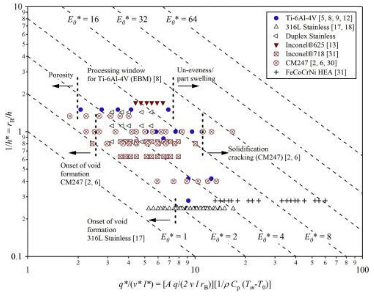
316L SS specimens (26)



Fabrication Parameters



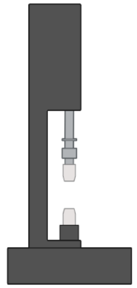
Normalized Energy Calculations [7]



3D Characterization Techniques

Micro-CT before Fracture

Tensile Testing

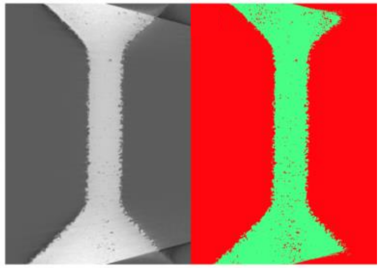


Micro-CT after Fracture

Data Acquisition

As-Built Samples

Grayscale Segmented

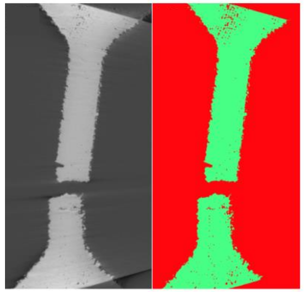


Stress-Strain Data

Stress (MPa)	Strain (%)
26.8918	-0.00402
27.11515	0.001831
27.47726	0.00209
27.78574	0.001993
28.35874	0.001997

Fractured Samples

Grayscale Segmented

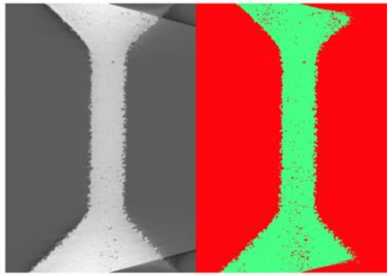


Workflow Outline

Raw and Segmented Data

As-Built Samples

Grayscale Segmented



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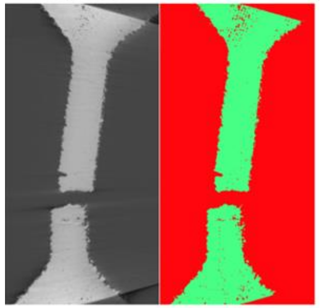


Image and data Pre-processing

Stress-Strain normalization

Crop Data

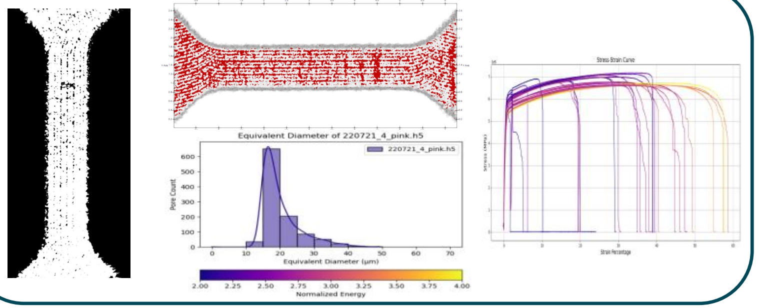
recon3d
GitLab Repository
Binary to Semantic

Instance Analysis
Pore Processing

Downscale

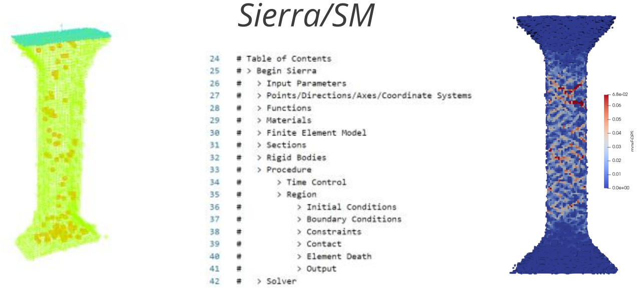
npy to Mesh

Experimental Data Analysis



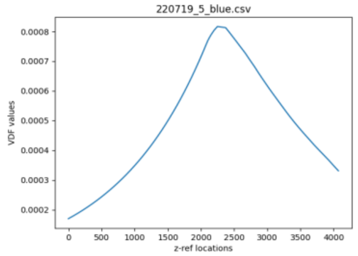
Direct Numerical Simulations (DNS)

Sierra/SM

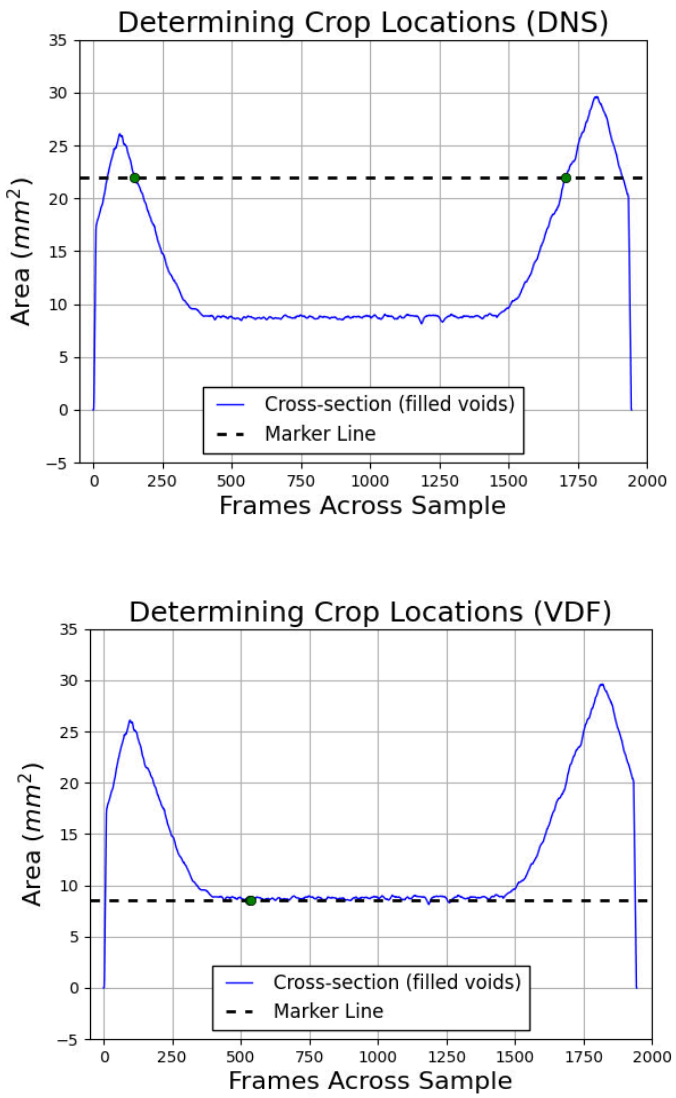


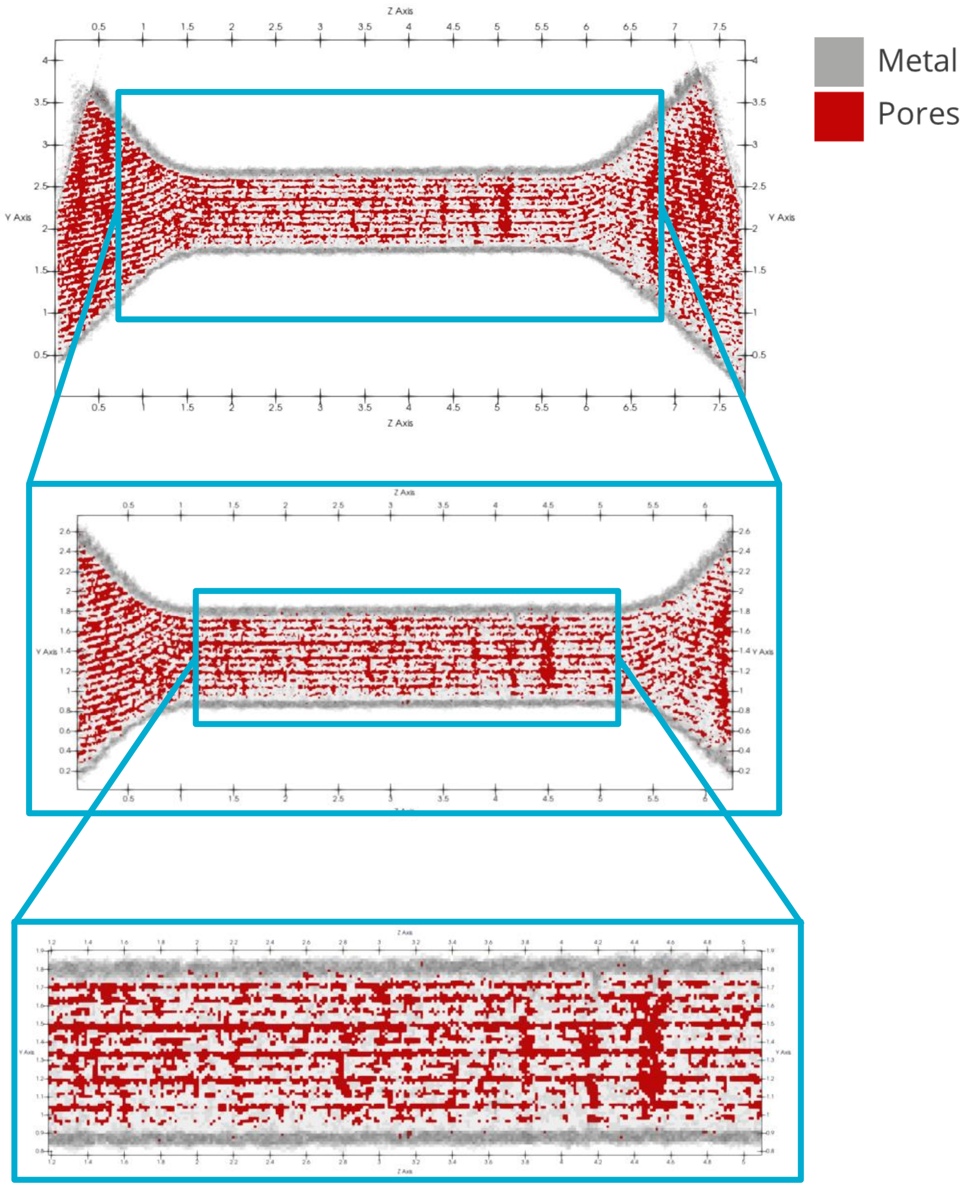
Void Descriptor Function (VDF)

- pores
  - axis_vectors
  - centroids
  - ellipsoid_surface_areas
  - ellipsoid_volumes
  - equivalent_sphere_diameters
  - nearest_neighbor_IDs
  - nearest_neighbor_distances
  - num_voxels
  - semi-axis_lengths



Methods: Pre-processing (Crop Data)





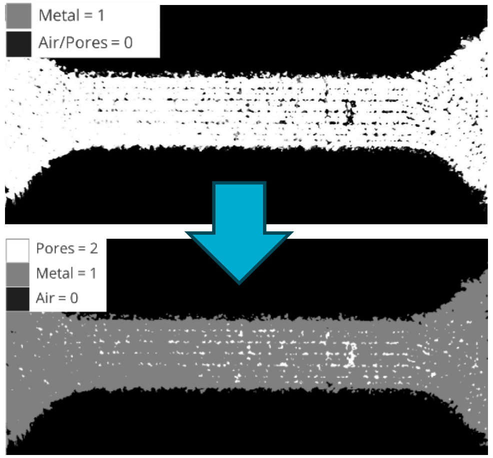
Methods: Pre-processing (Image Analysis)

recon3d
GitLab Repository

binary_to_semantic → instance_analysis → downscale → npy_to_mesh

binary_to_semantic

- Identifies air, pores, and metal independently.
- Converts segmented data (air = 0 & metal = 1) into semantic data, creating three classes:
  - air = 0
  - metal = 1
  - pores = 2
- **Output:** semantic segmentation tiff images.



instance_analysis

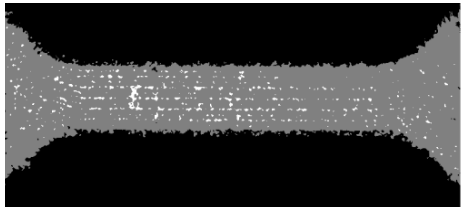
- Identifies each pore individually
- Provides different pore metrics using semantic data as input.
- **Output:** h5 file with all the information collected from each pore

- pores
  - axis_vectors
  - centroids
  - ellipsoid_surface_areas
  - ellipsoid_volumes
  - equivalent_sphere_diameters
  - nearest_neighbor_IDs
  - nearest_neighbor_distances
  - num_voxels
  - semi-axis_lengths

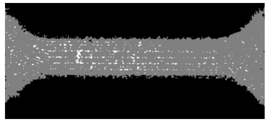
downscale

- Pads an image stack at a given resolution until it is evenly divisible by a target resolution before downscaling to the target resolution.
- **Output:** downscaled tiff images, a .vtr file, and an .npy file.

Resolution = 4 μm

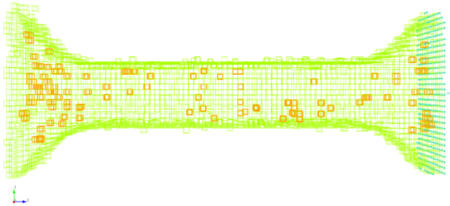


Resolution = 20 μm

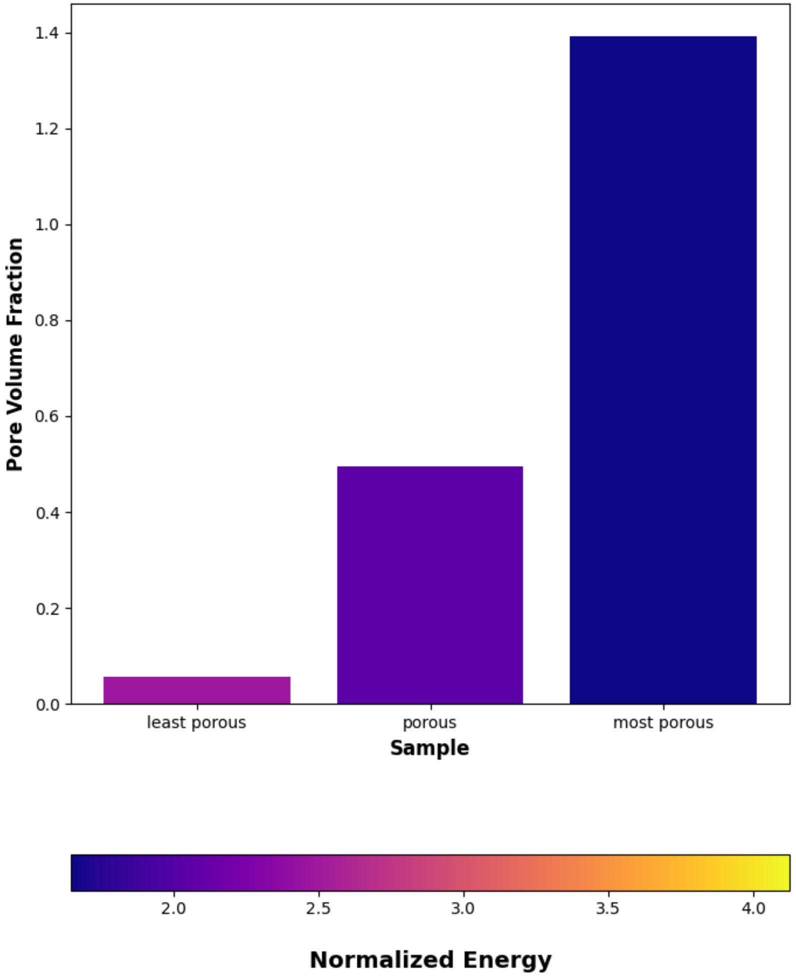


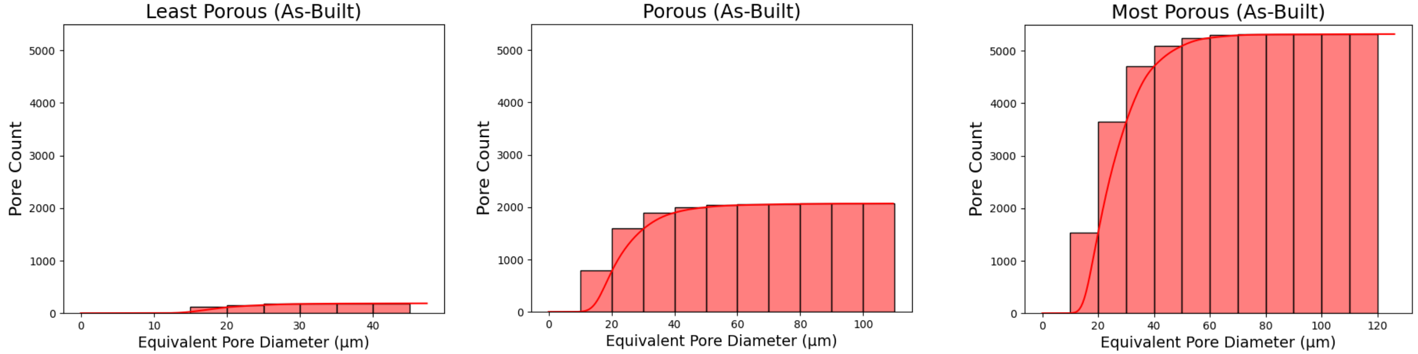
npy_to_mesh

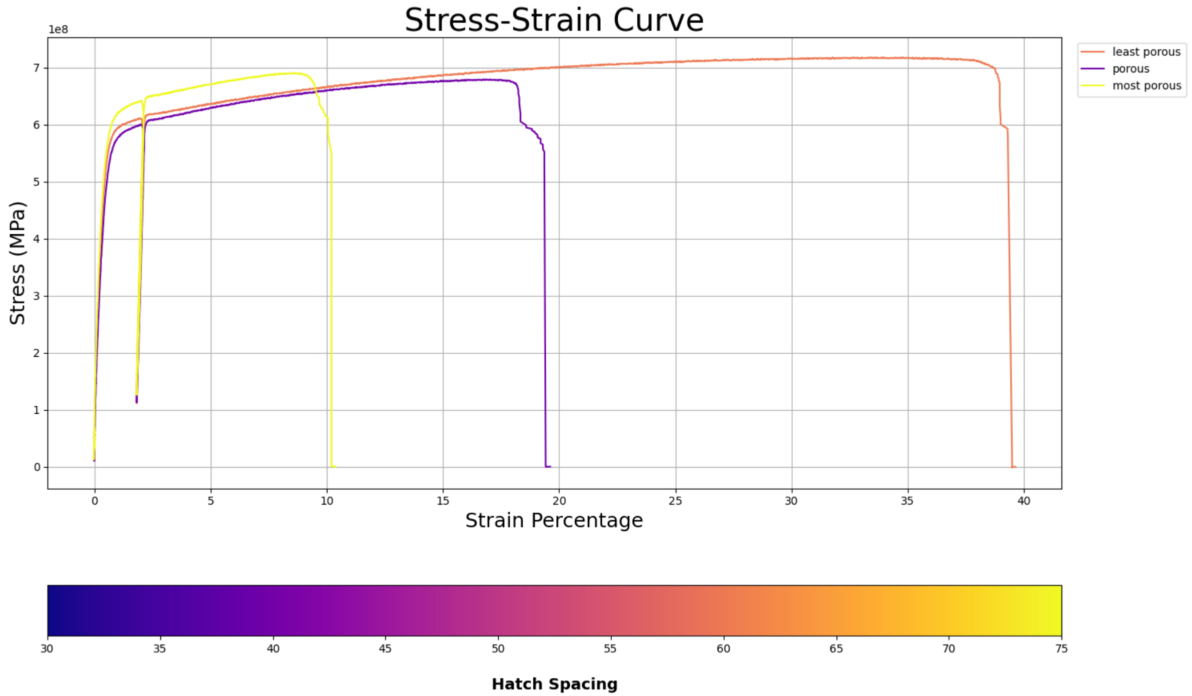
- **Input:** .npy file
- **Intermediate outputs:** Creates a Sculpt (.i) input file
- **Output:** Runs Sculpt to create an Exodus (.e) mesh file



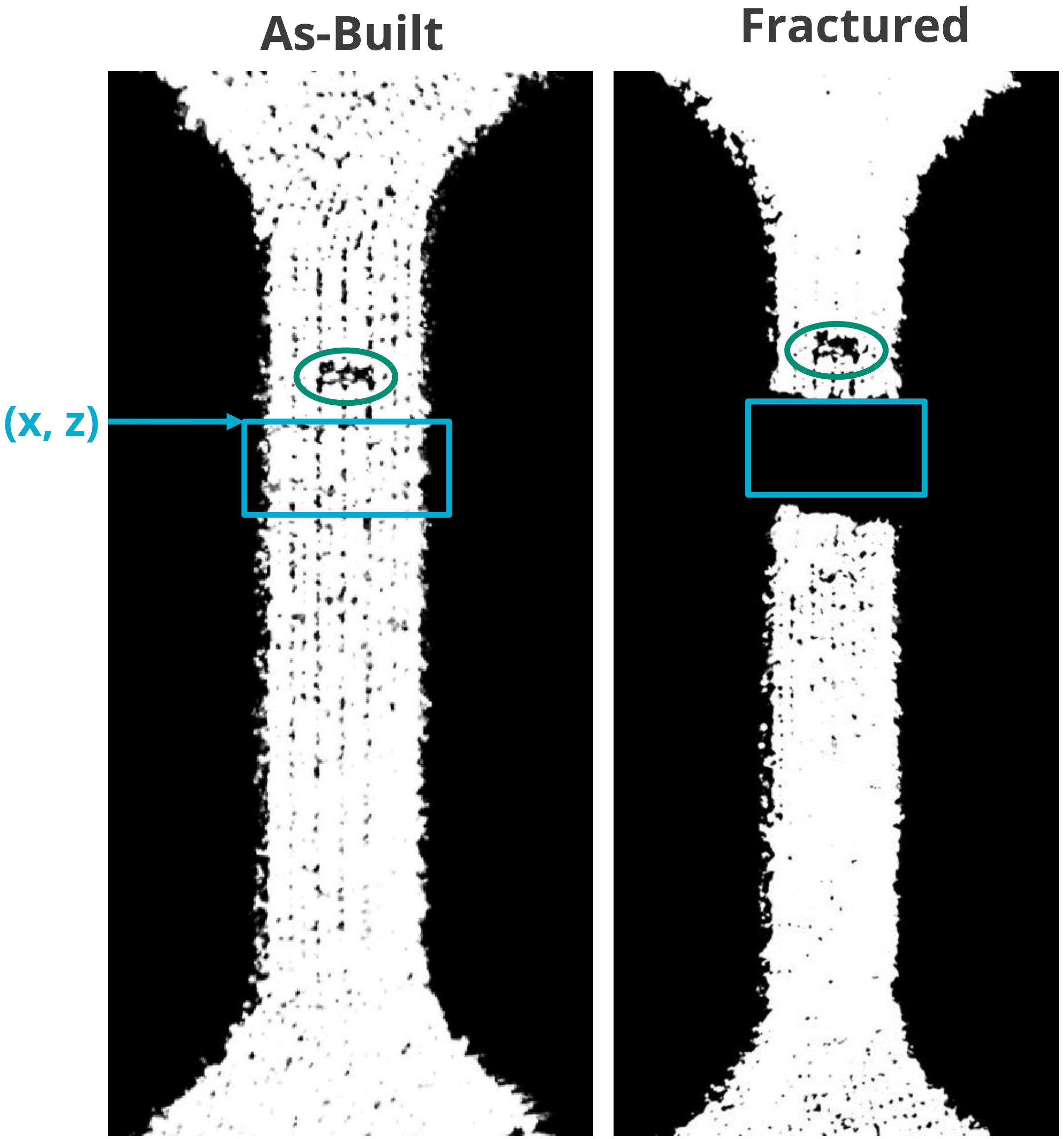
Methods: Pre-Processing (Pore Statistics)







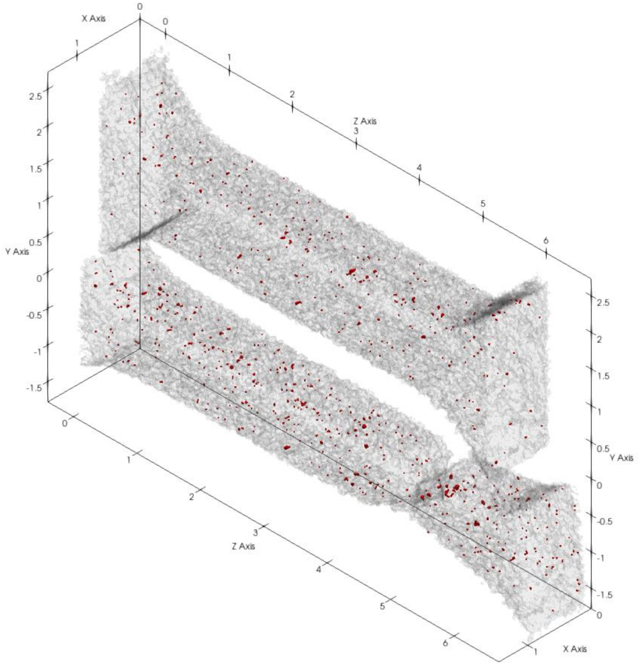
Methods: Experimental Data Analysis

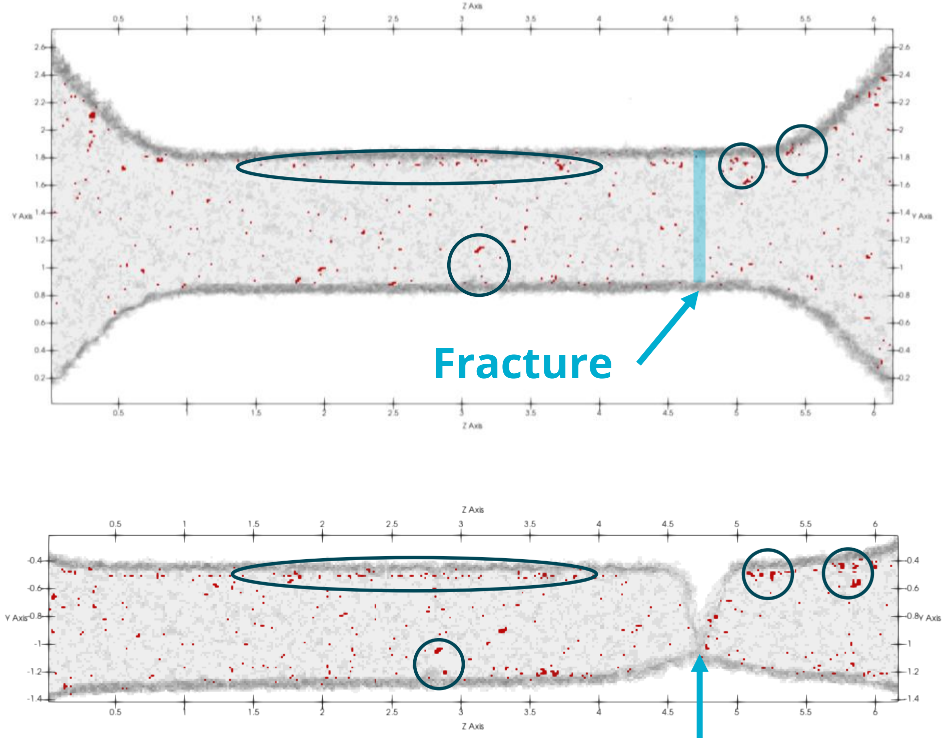


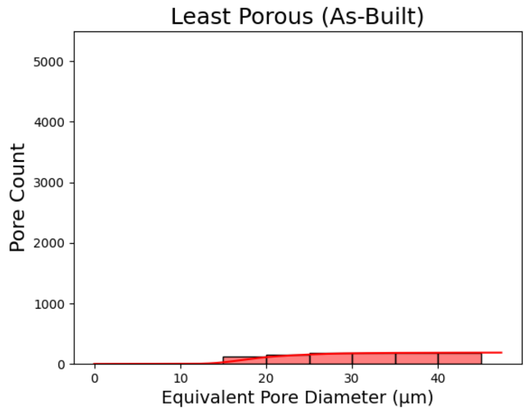
- Image J was used to manually locate fracture site.
- Pixel (2D) data was given which was converted to real space data in µm.
- ParaView was utilized to visualize both the as-built and fractured samples to identify the fracture location.
- This method was applied for all 26 samples.

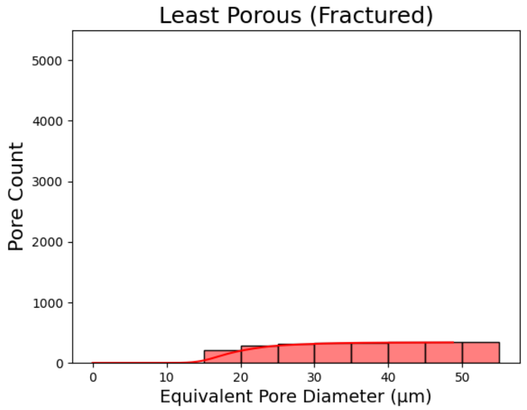
Results: Experimental Data Analysis

Least Porous









Metal

Pores

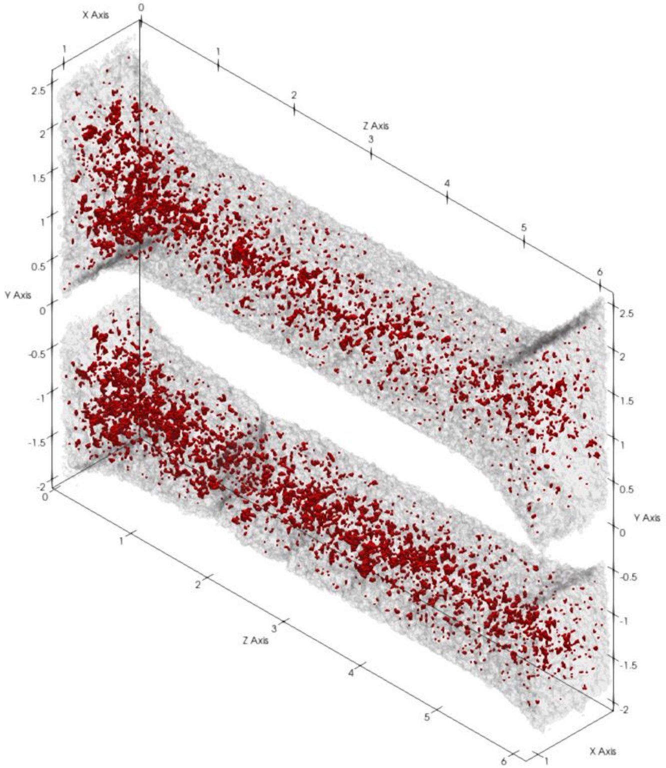
Scale is in mm

Fracture Location ≈ 4.692 mm

Equivalent diameter 0.22% increase

Results: Experimental Data Analysis

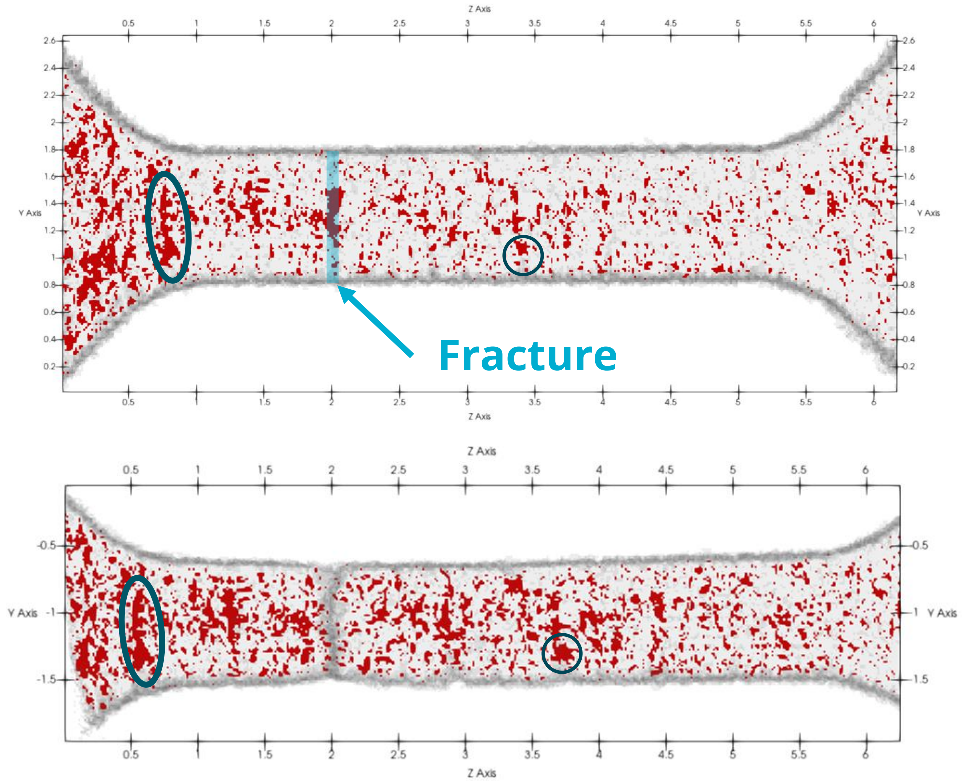
Porous



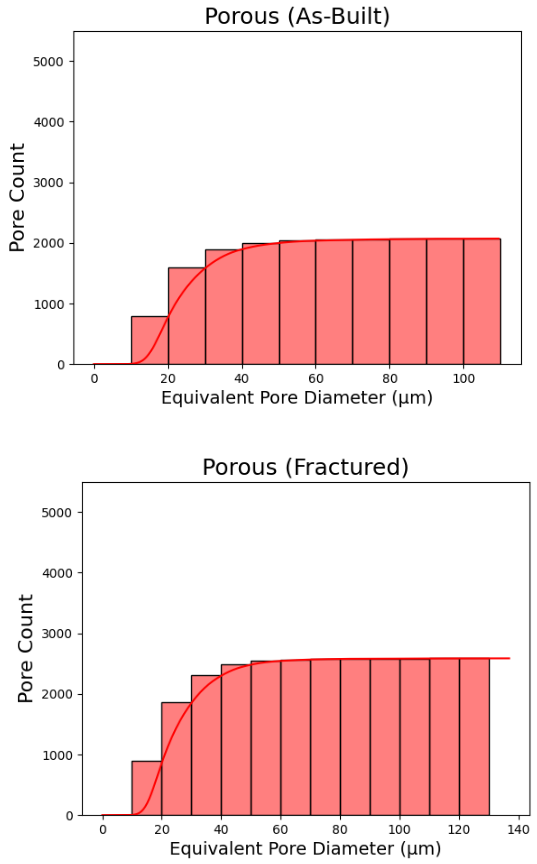
Metal

Pores

Scale is in mm



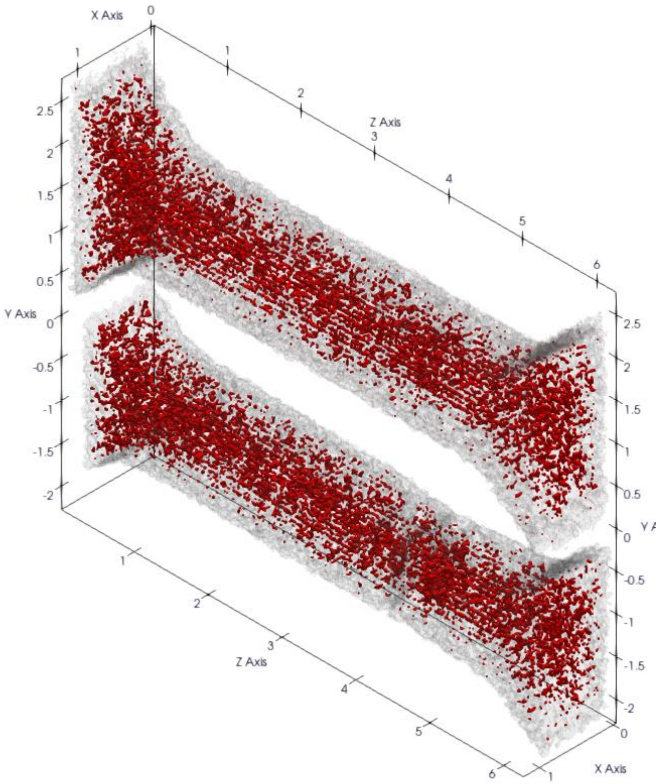
Fracture Location ≈ 2.048 mm



Equivalent diameter 4.36% increase

Results: Experimental Data Analysis

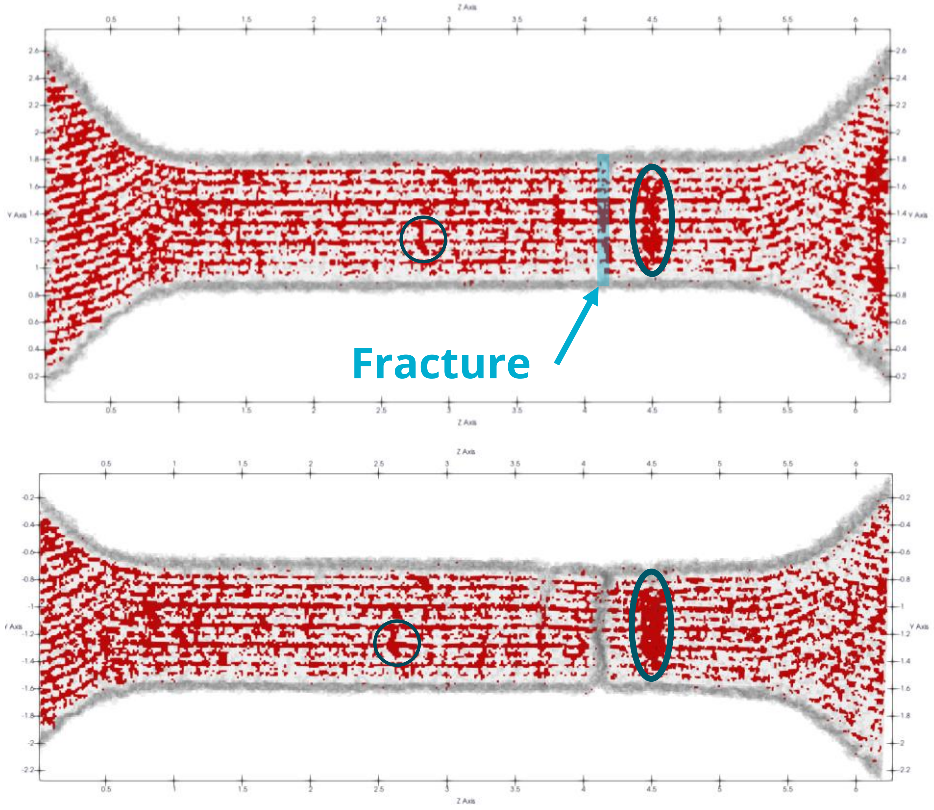
Most Porous



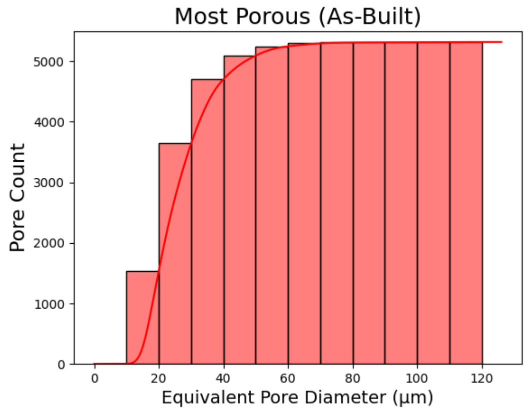
Metal

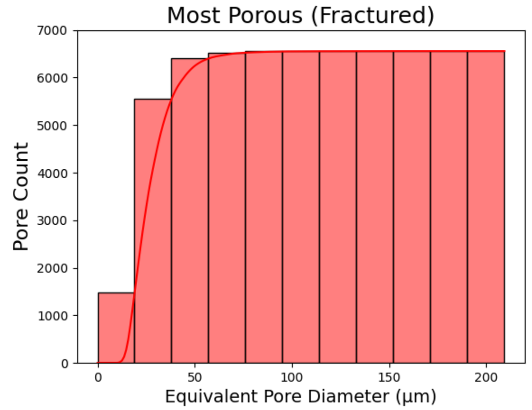
Pores

Scale is in mm



Fracture Location ≈ 4.184 mm

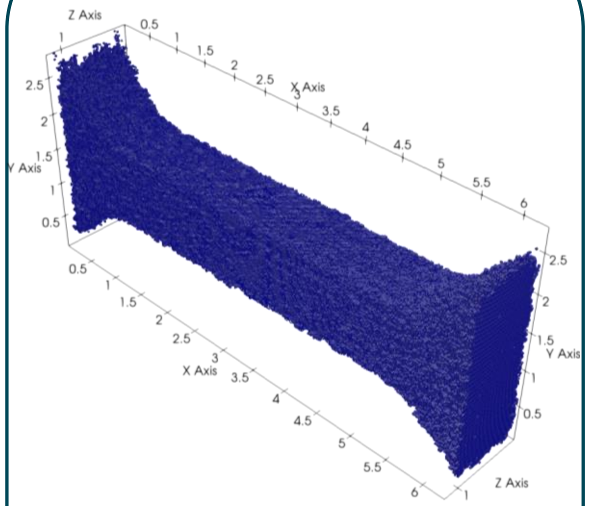




Equivalent diameter 2.29% increase

Methods: DNS Workflow

Mesh creation – voxel size → **Sierra/SM simulation workflow** → **Different sample simulations**



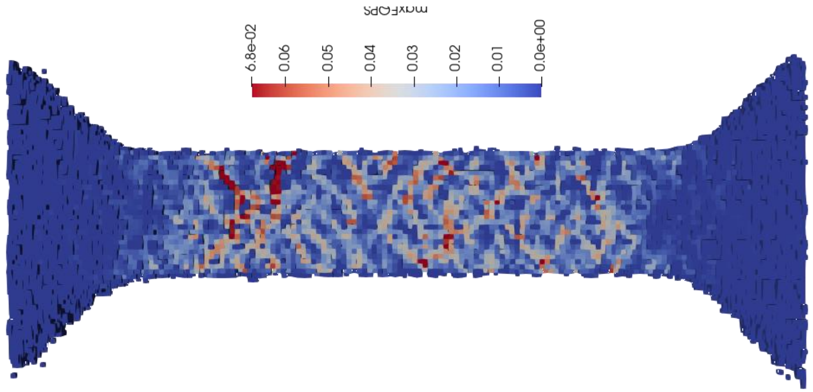
- Select material model
- Material properties
- Build input deck
- Debug input deck

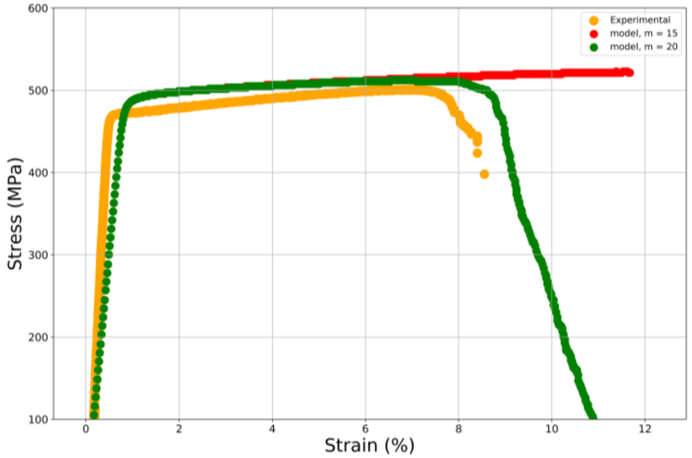
↓

- Run simulations
- Calibrate parameters porous mesh

↓

- Predict failure in porous samples
- Varying resolution simulations



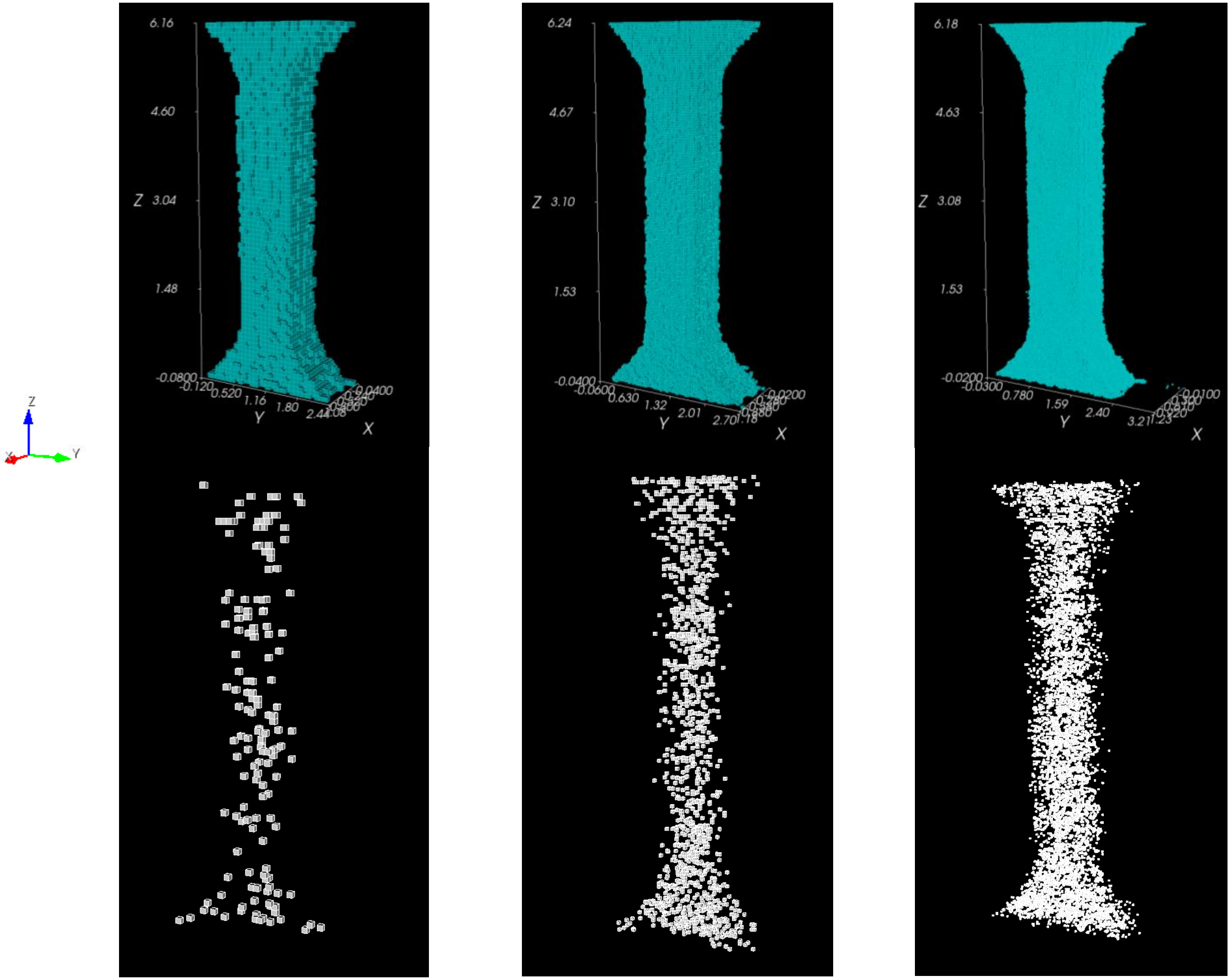


Methods: DNS – Mesh

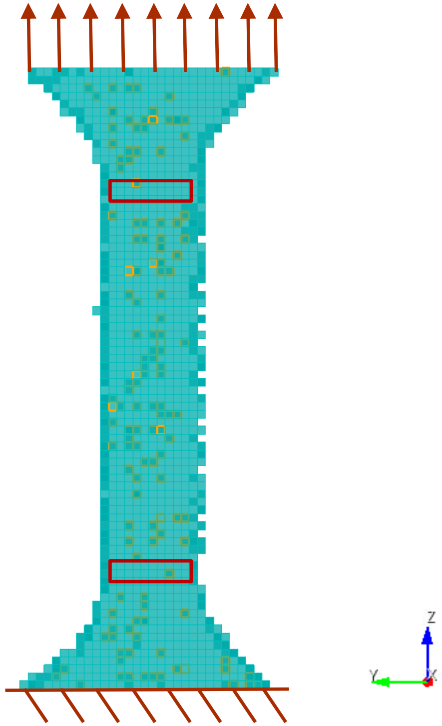
80 μm voxel

40 μm voxel

20 μm voxel



- CUBIT was utilized to add node sets to be used for boundary conditions.
- Pore elements deleted.



Methods: AM 316L SS property specification

- Hill plasticity model:
  - Anisotropic/rate dependent yield
  - Plasticity captured via Voce hardening
  - Scalar damage model

Material Property	Variable	Value	Units
Young's Modulus	E	200e9	Pa
Poisson's Ratio	ν	0.27	-
Density	ρ	7920	Kg/m^3
Material Parameter	**Variable**	**Value**	**Units**
Rate independent yield constant	Y_0	453.3e6	Pa
Hill transverse yield ratio	$R_{11} = R_{33}$	1.124	-
Remaining Hill yield ratios	$R_{22} = R_{12} = R_{13} = R_{23}$	1.0	-
Voce hardening coef	A	883.6e6	Pa
Voce hardening exponential coef	b	1.39	-
Yield rate coef	f	21012	$1/s$
Yield rate exponent	n	10.06	-

Hill plasticity

$$\theta^2(\hat{\sigma}_{ij}) = F(\hat{\sigma}_{22} - \hat{\sigma}_{33})^2 + G(\hat{\sigma}_{33} - \hat{\sigma}_{11})^2 + H(\hat{\sigma}_{11} - \hat{\sigma}_{22})^2 + 2L\hat{\sigma}_{23}^2 + 2M\hat{\sigma}_{31}^2 + 2N\hat{\sigma}_{12}^2$$

Damaged Cauchy stress

$$\hat{\sigma}_{ij} = \sigma_{ij}/(1-\phi)$$

Void volume fraction

Voce Hardening

$$\sigma_f = Y_0\left\{1 + \sinh^{-1}\left[\left(\frac{\dot{\varepsilon}_p}{f}\right)^{1/n}\right]\right\} + A\left((1 - \exp(b\varepsilon_p)\right)$$

Yield

Fitting constant

Fitting exp

[4, 8-9]

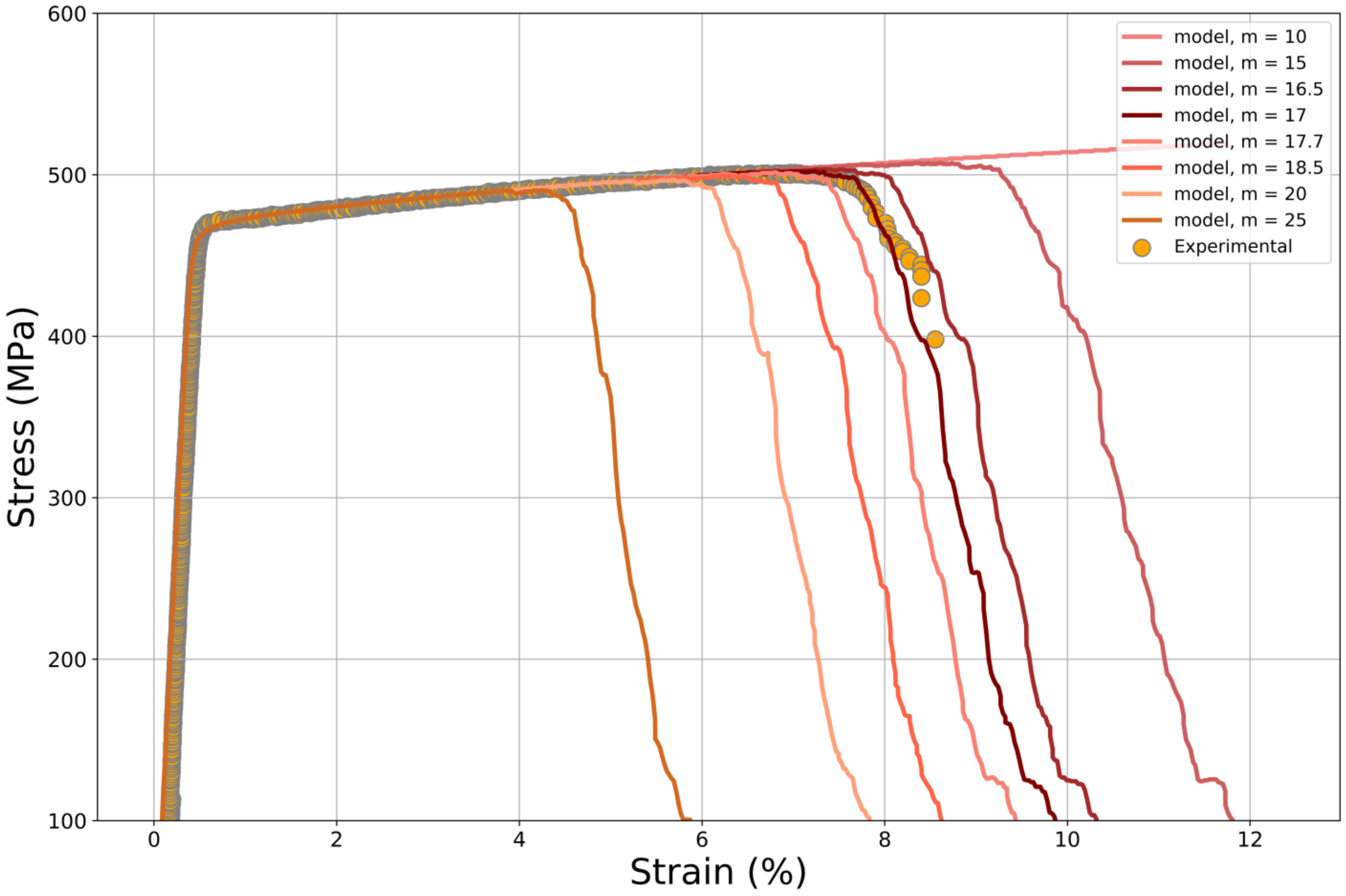
Results: Stress-strain response – different damage exponent (m)

m ∝ damage

$$\dot{v}_v = \sqrt{\frac{2}{3}}\dot{\varepsilon}_p \frac{1}{\eta}(1+\eta v_v)\left[(1+\eta v_v)^{m+1} - 1\right]$$

$$\cdot \sinh\left[\frac{2(2m-1)}{2m+1}\frac{\langle p \rangle}{\sigma_f}\right] - (v_v - v_0)\frac{\dot{\eta}}{\eta}$$

40 µm voxel size

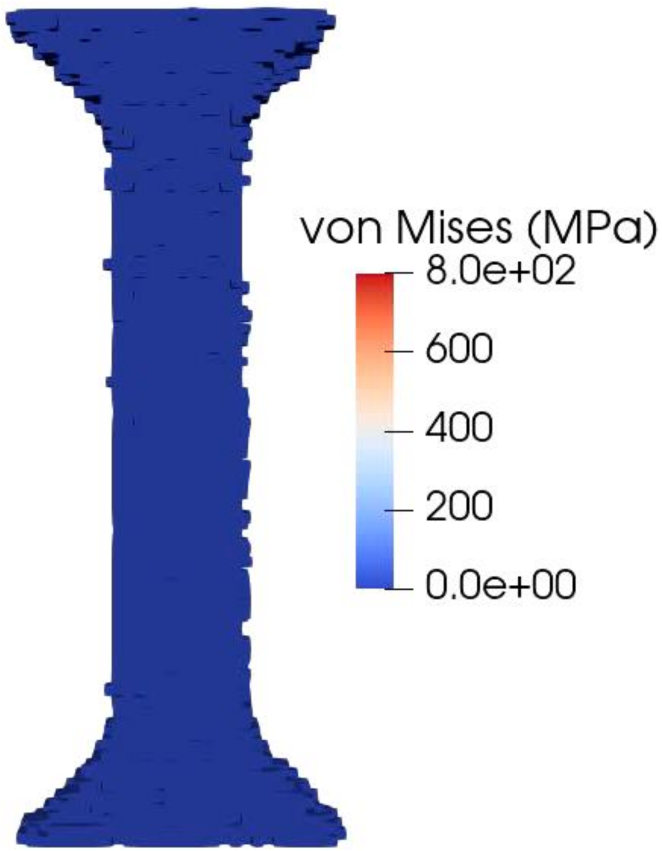


[4]

Results: Mesh size effect

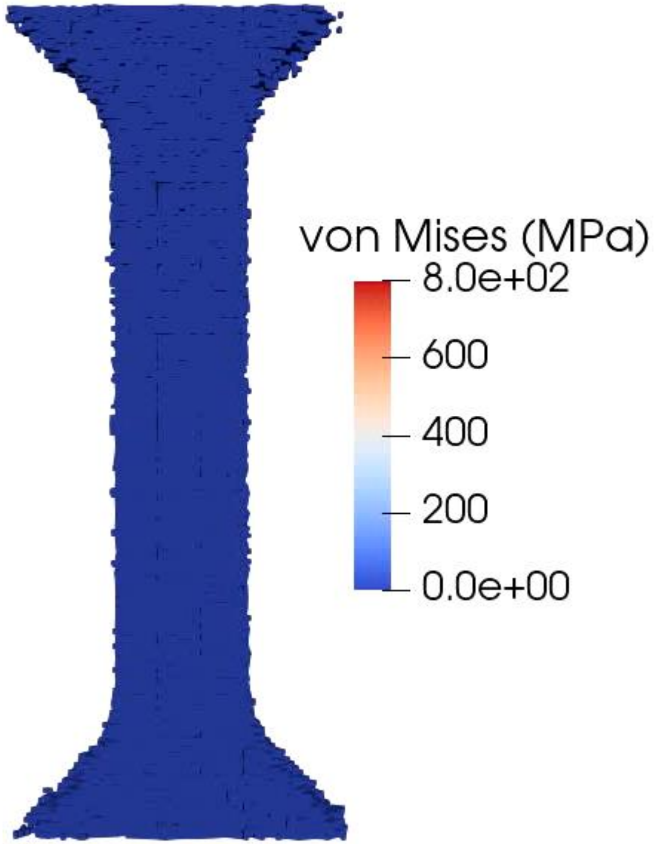
Porous

80 µm voxel



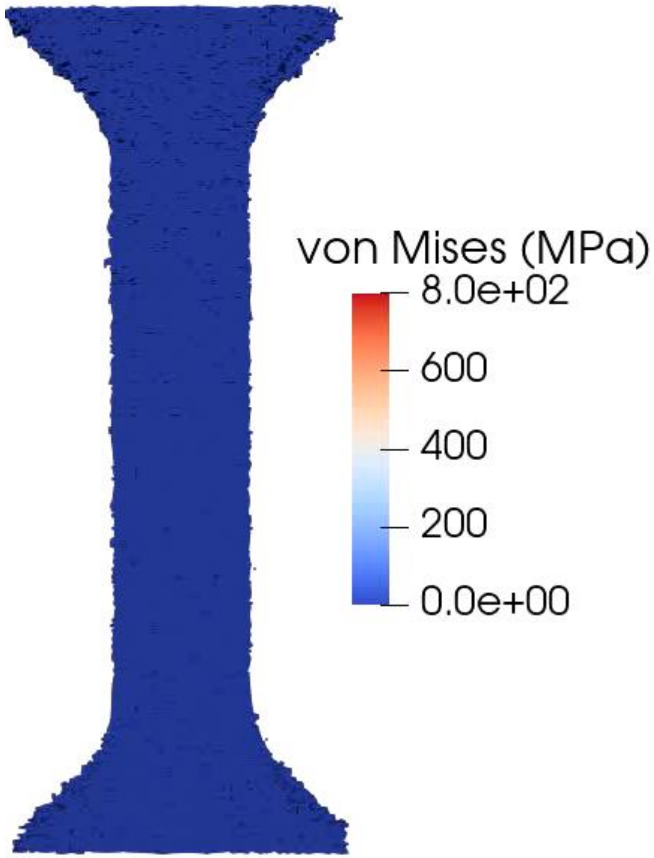
~13k elements
20 processors
0.25 hr wall time

40 µm voxel



~100k elements
40 processors
1.4 hr wall time

20 µm voxel

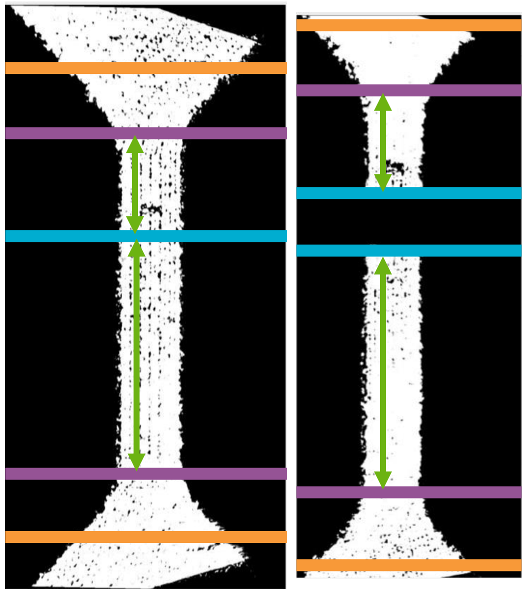


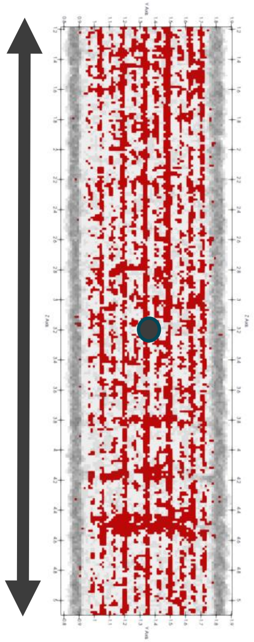
~800k elements
330 processors
2.46 hr wall time

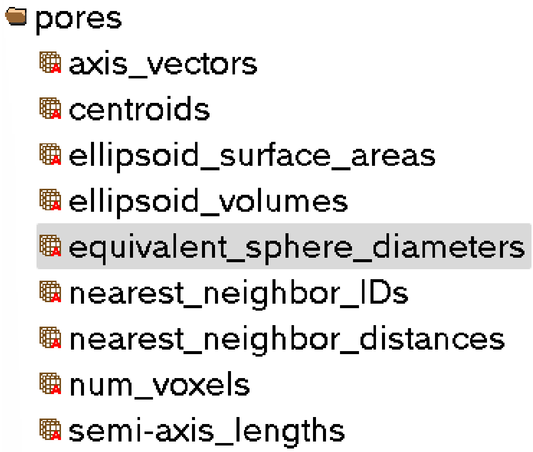
Methods: Void Descriptor Function (VDF)

- Identifies positions along gauge section highly populated by critical pore structures [4]
  - Signals where fracture is likely to occur
- Quantifies the inter-relationships of pores to quickly predict failure [4]
  - Factors: pore location, size, and distance to free surface

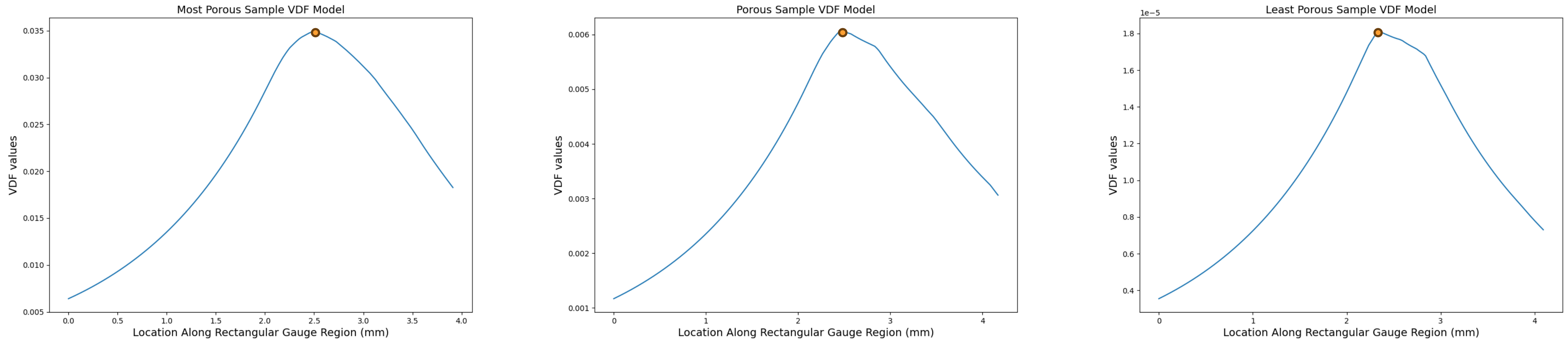
Crop Data → Obtain Geometries → Calculate Pore Metrics







Results: Void Descriptor Function



	Most Porous	Porous	Least Porous
Max VDF value	0.03496	0.00606	0.000175
Location (mm)	3.641	3.462	3.371

Results: Comparison – Fracture Locations

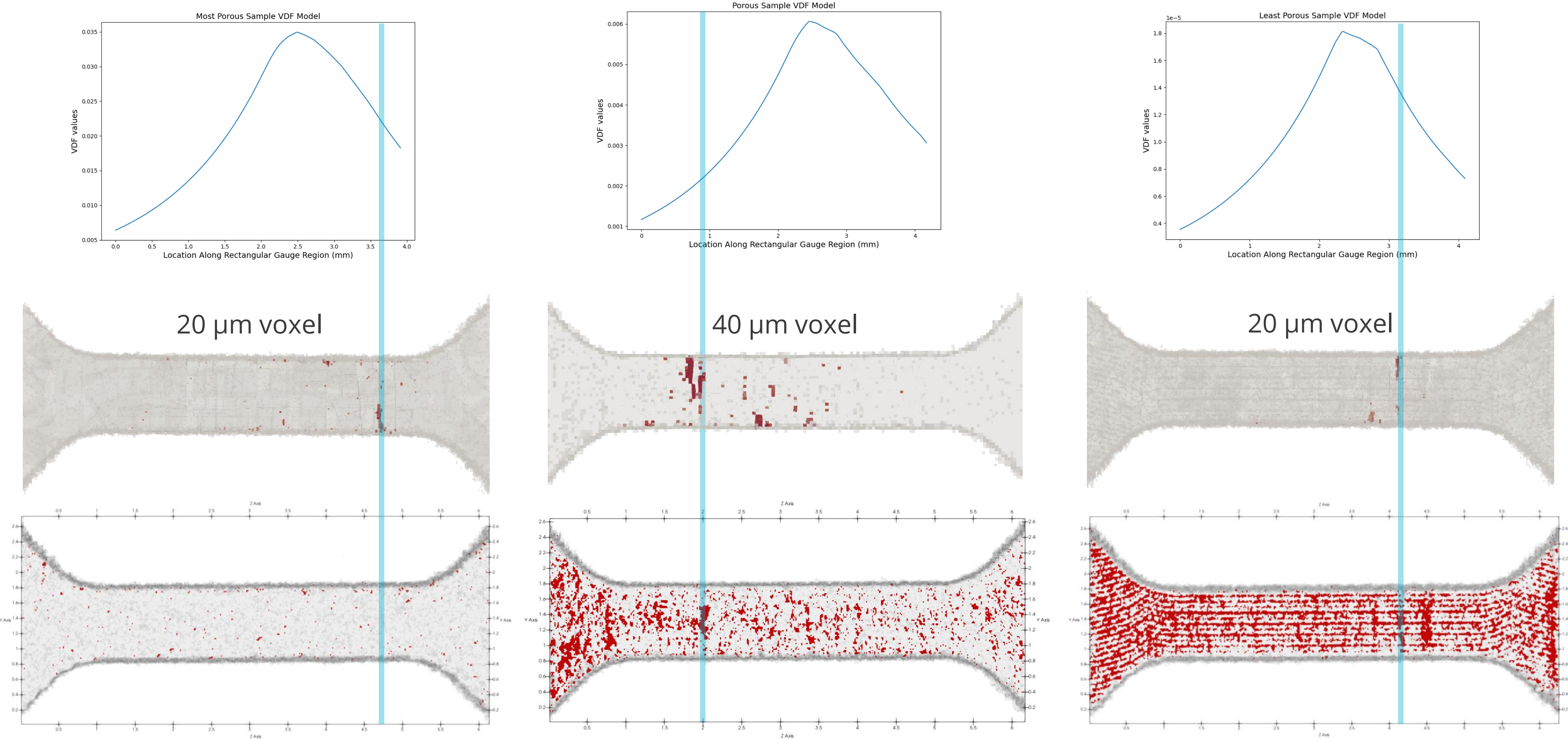
Least Porous | Porous | Most Porous

Scale is in mm

VDF

DNS

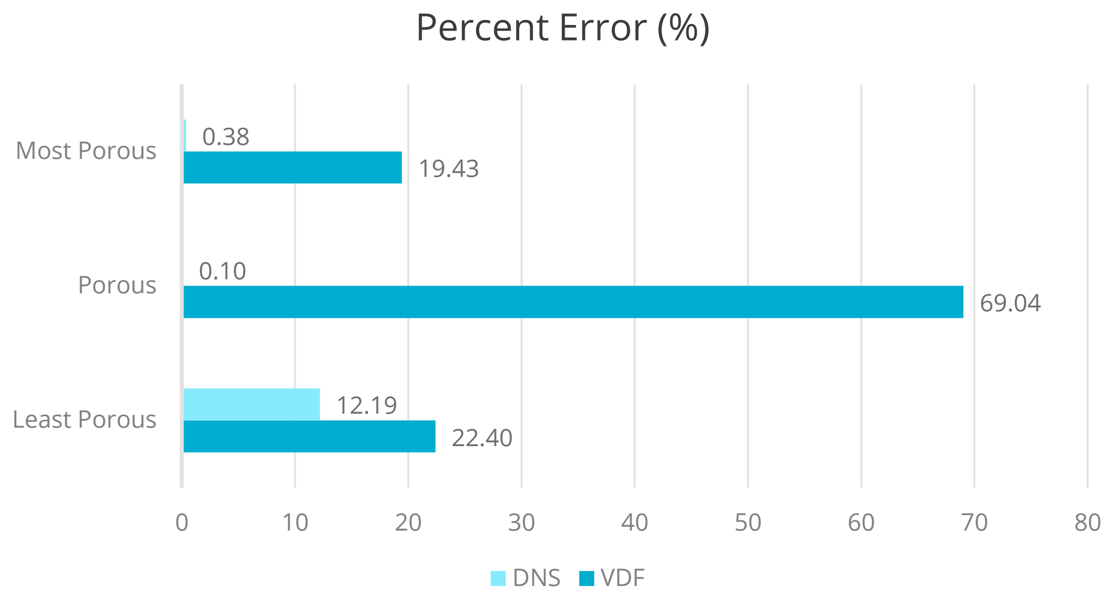
EXP



Conclusion

- VDF takes significantly less time than DNS (~0.269 seconds compared to ~25+ minutes)
- DNS showed a lower percentage error indicating a more accurate model
- Mesh resolution affects failure location accuracy.
- This project serves a stepping stone in advancing the broader scope of the research effort.

	Fracture Location (mm)		
	Least Porous	Porous	Most Porous
EXP	4.692	2.048	4.184
DNS	4.12	2.05	4.20
VDF	3.371	3.462	3.641



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Future Work

Experimental Data Analysis

- Automated fracture location
- Better inform data-driven predictive models
- Further analysis on Normalization energy values

Direct Numerical Simulation

- Full sample set simulations
- Smaller voxel size mesh simulations
- Fracture initiation (void)

Void Descriptor Function

- Optimization in progress
- Account for surface roughness