High Throughput, Rapid and Automated NDE for Optimizing Additive Manufacturing in Nuclear Applications

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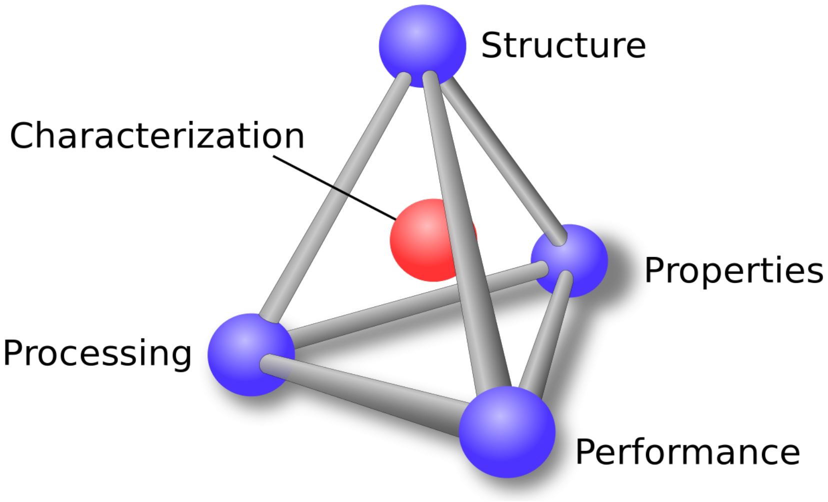
Oct 25, 2023

Characterization is critical for understanding processing, microstructure, properties, and performance



Challenges in Additive Manufacturing (AM):

- ❑ Characterizing complex, spatially varying, multi-scale microstructures
- ❑ Characterize defect distribution
- ❑ Correlate to performance
- ❑ Learn to drive AM processes towards predictable, repeatable results

With current qualification approaches, it can take a decade to qualify a material for **nuclear applications.**

Rapid Qualification requires fast high-throughput characterization

AMMT Rapid Qualification Thrust Pathway

- ❑ Develop and leverage **automated fast characterization** to aid in understanding of **process-structure-property-performance** relationships, and in turn **finding optimum printing process window for fully dense 316 printing**.

Multi-Dimensional Data Correlation (MDDC)

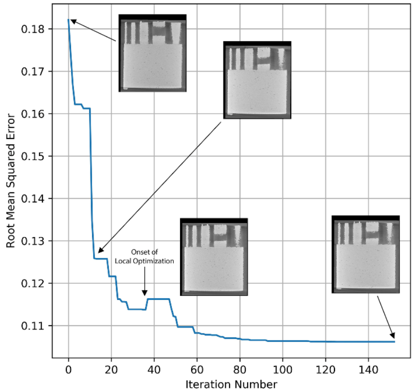
.stl file

XCT

X-ray CT Registration

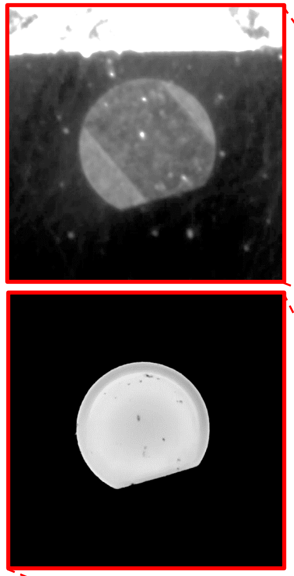
registered XCT

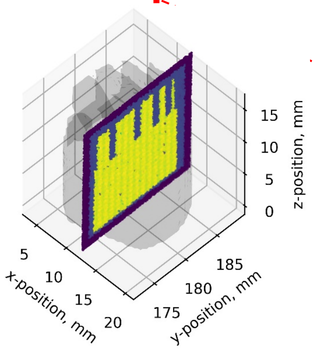
raw micrograph



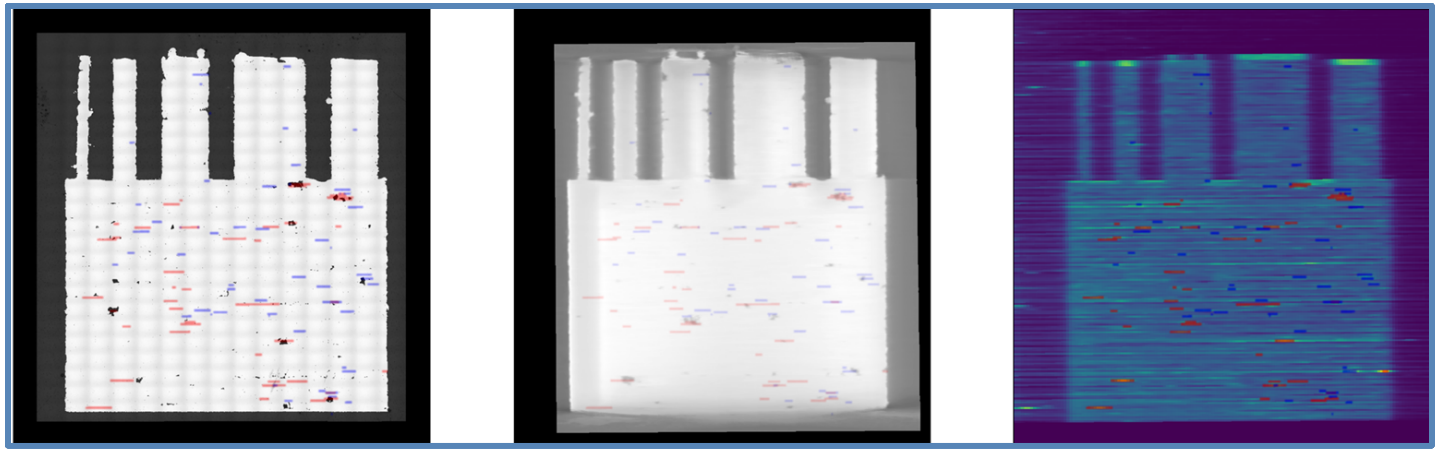
Microscopy Registration

registered micrograph





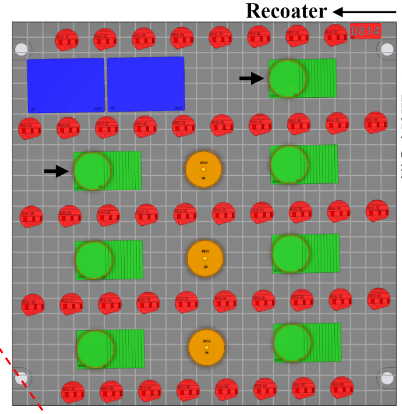
registered digital twin



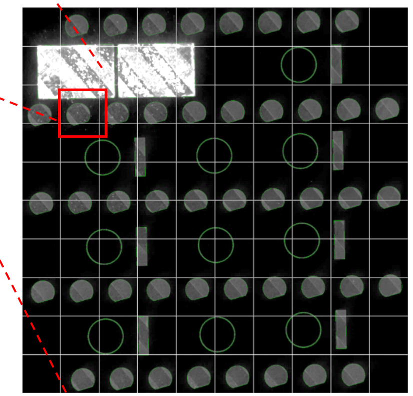
Registered Micrograph

X-ray CT Cross-section

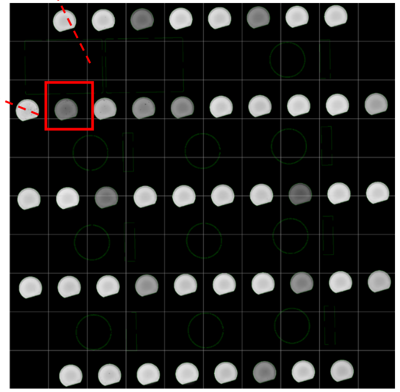
Registered Sensor Data



Build Design



In Situ Sensing



Characterization

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High Level Connection between Thrusts

Understanding Process-Structure-Property-Performance Relationships

Process understanding for qualifying LPBF 316 SS (*Thrust-CM*)
ORNL, ANL, LANL
(Massey, Xuan, Montoya, et al.)

Improve and Optimize LPBF 316 SS to Improve Heterogeneity in AM Material (*Thrust-PN*)
ORNL (Nandwana, et al.)

This Thrust
Automated, High-Throughput Materials Characterization Techniques

Multi-Dimensional Data Correlation (MDDC) Platform
ORNL (Paquit, Scime, et al.)

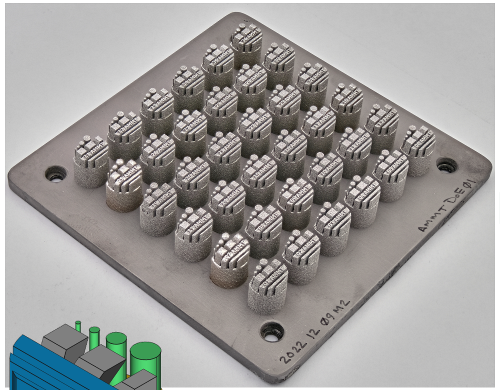
Process Modeling and Variability in AM SS316
ORNL (Plotkowski, et al.)

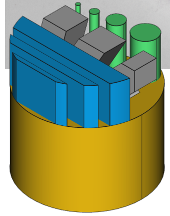
Improving and Optimization of Existing Reactor Materials for Advanced Manufacturing
ORNL, PNNL, ANL, INL (Dryepondt, et al.)

- ❑ This diagram is solely based on current collaborations.

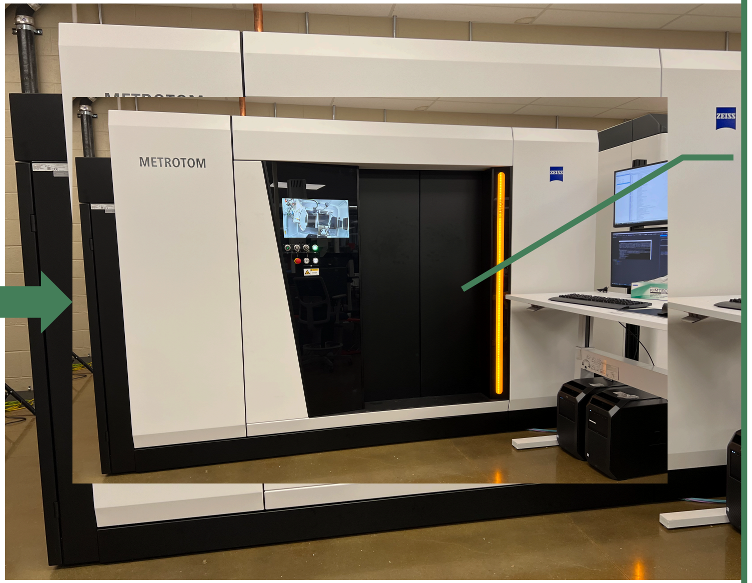
Rapid Characterization Process

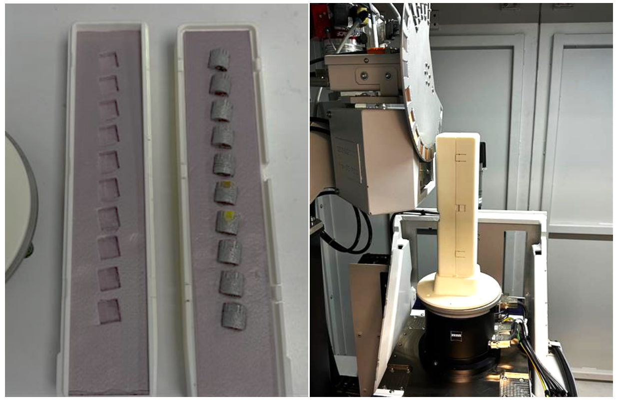
Design of Experiment



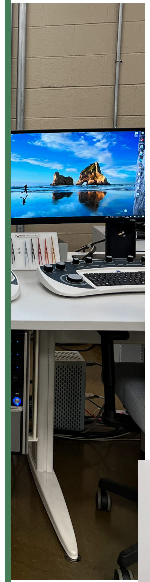


Thrust-CM, Thrust-PN





1. Loads 10 coupons at a time
2. Quickly scan a coupon
3. Output the data



1. Receive the data (after each scan)
2. **Perform fast DL-based reconstruction, segmentation, and image analysis**
3. Generate and save output

1. Register the data to the in-situ and Peregrine data
2. Produce report
3. Store the data

Characterization summaries and data

MDDC

Non-Destructive Characterization (NDC) Process Using XCT

Sample

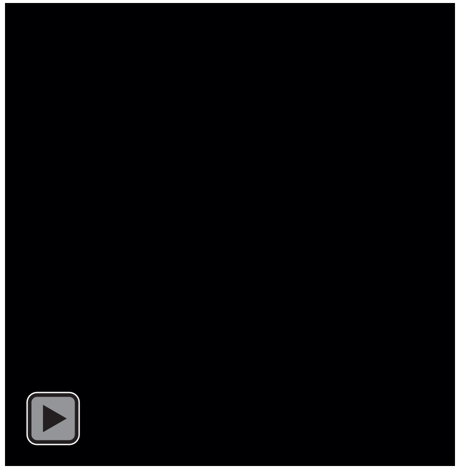
Reconstruction

Analytics

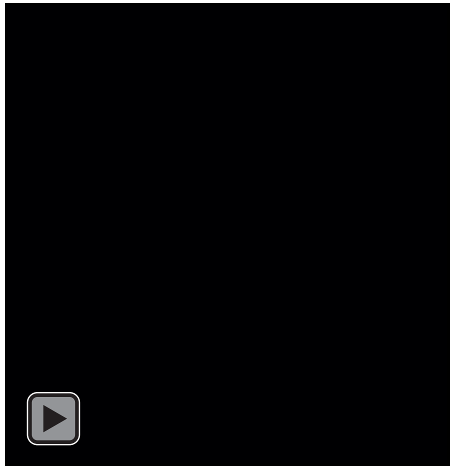
Information
1. Flaws
2. Anomalies
3. Defects
4. Dimensions
5. Surface

Sample

Raw Measurement

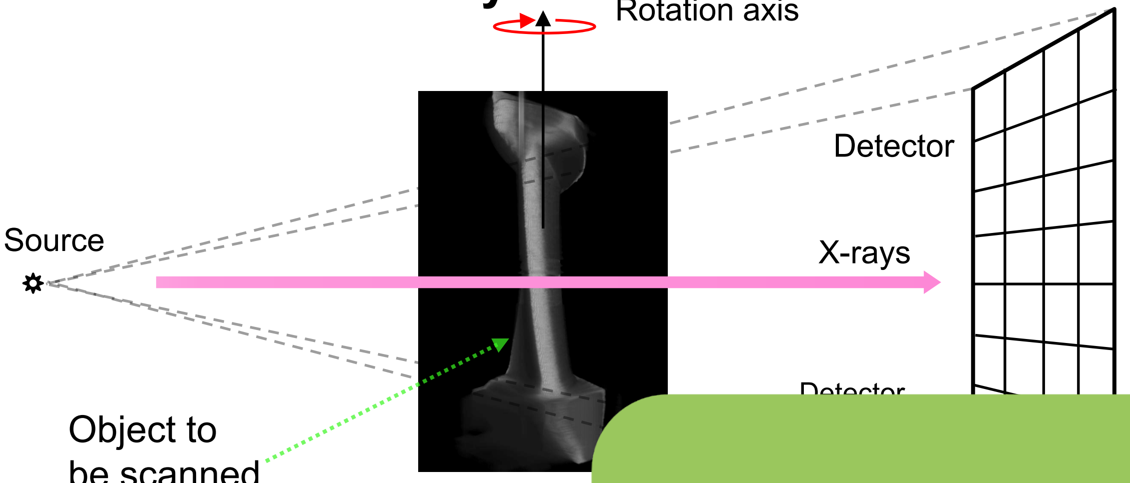


Reconstruction

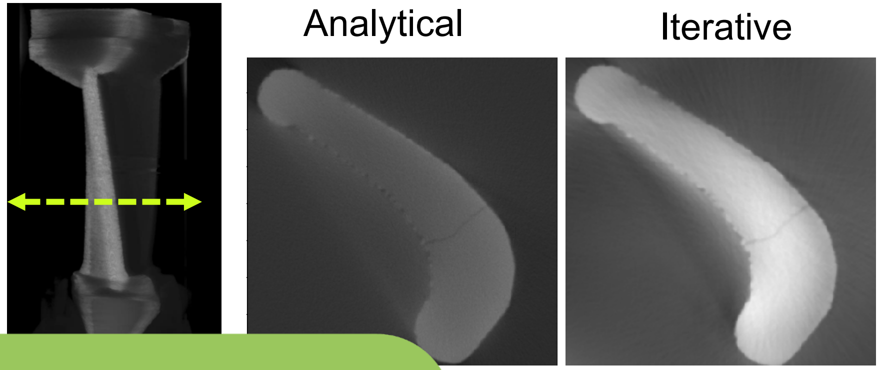


Segmentation

Cone-Beam Geometry



A Turbine B



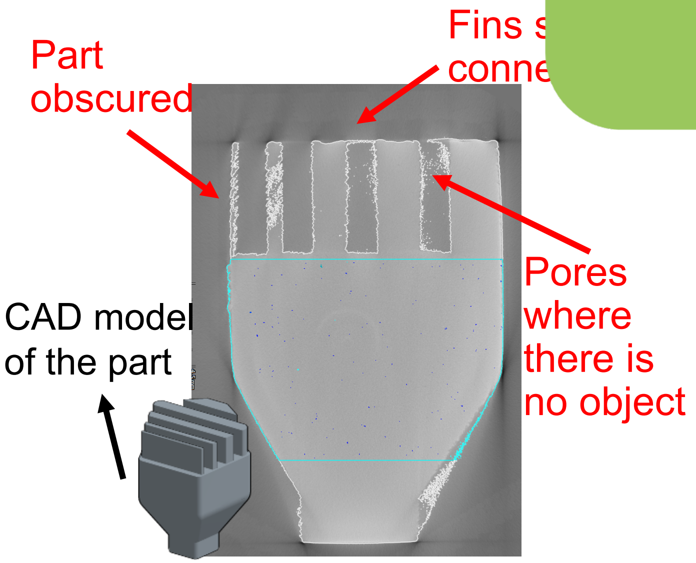
ds) but less quality

but computationally expensive (hours)

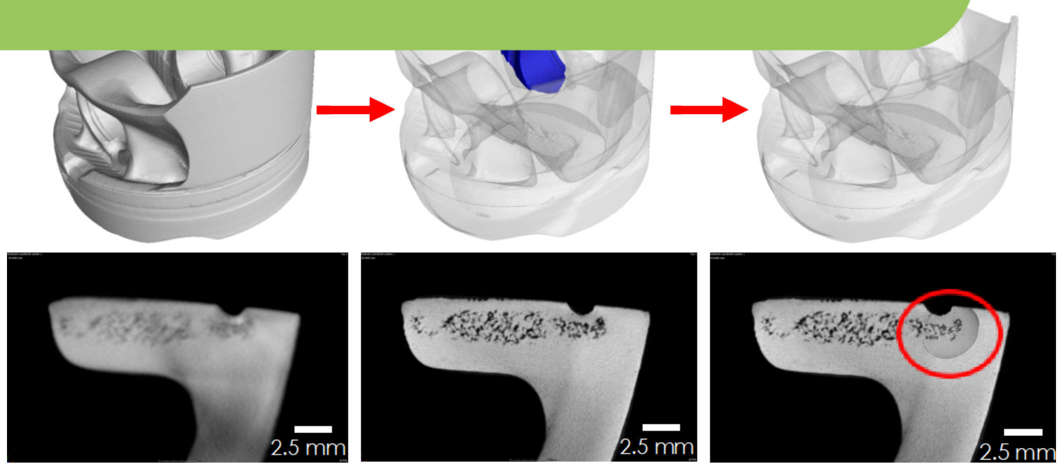
AI-Based Algorithm for Fast and High-Quality 3D Image Reconstruction

- ❑ Noise and artifacts limits d
- ❑ Trade-off between resolutio

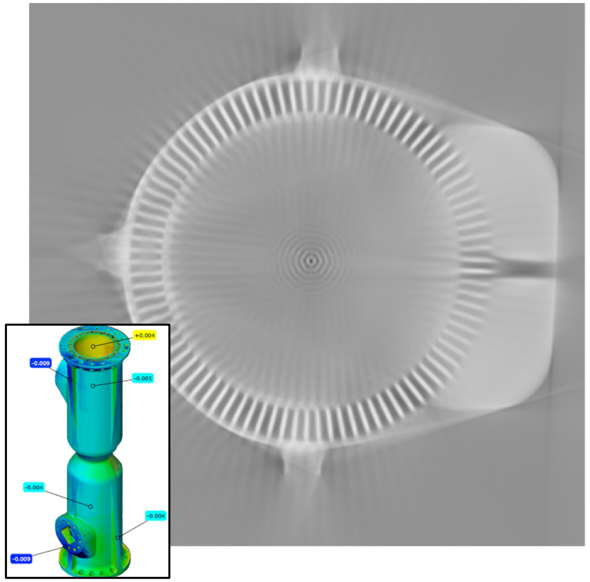
- ❑ Artifacts due to complex geometries of Metal AM



Cross section of a real measurement



Locate Bulk Defects **Confirm Bulk Defects** **Understand Defects**



IMPROVED THE RECONSTRUCTION QUALITY w/o TIME COMPROMISE

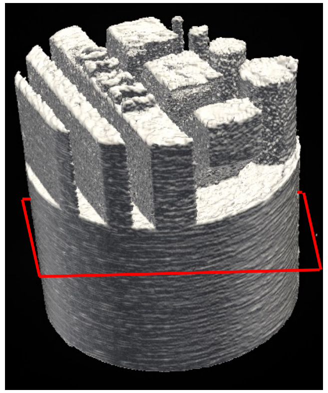
REDUCED THE SCAN TIME AND COST

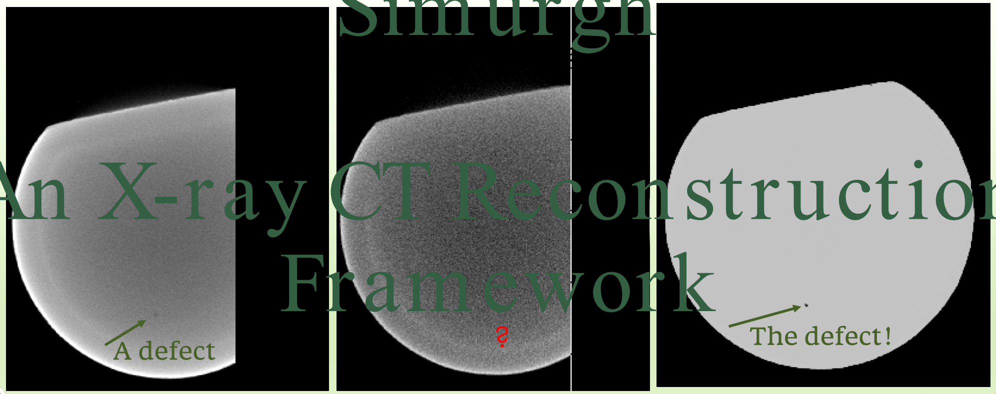
LOWER THE COST OF IMPLEMENTATION

X-ray CT Reconstruction Framework

Simurgh

An X-ray CT Reconstruction Framework





- ❖ DOE TCF award
- ❖ Licensed by ZEISS
- ❖ Patent and paper

REDUCE MAINTENCANCE NEEDs AND COST

ENABLE HIGH-THROUGHPUT and SCALABLE CHARACTERIZATION

ENABLES FAST POSTPROCESS DATA ANSLYSIS w/ ENHANCED DEFECT DETECTION CAPABILITY

CAD-, Physics- and Deep Learning-Based Image Reconstructions

2.5D CAD-DLMBIR

1. Generate Reference Data

- ❑ CAD Models
- ❑ Physics-based Beam Hardening parameters

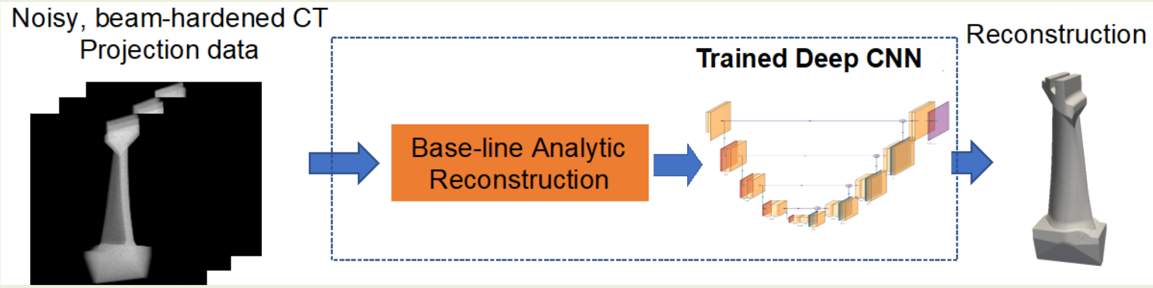
→ MBIR → Reference High-quality Reconstruction

2. Tr… NN)

A… Lo… …nce …ality

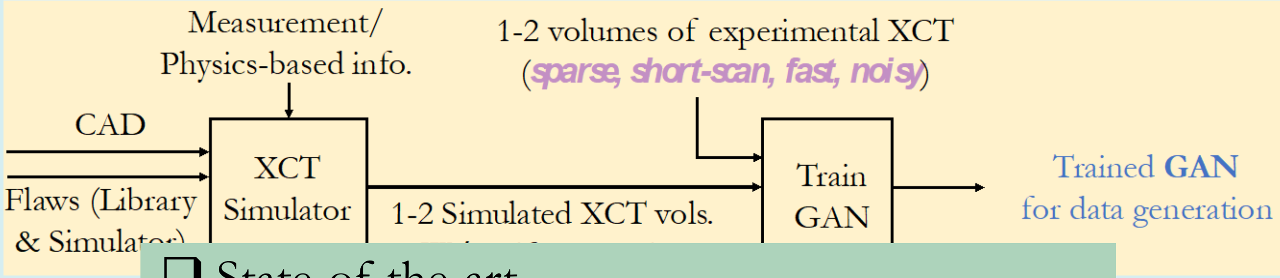
- ❑ Fast, high-quality reconstructions, reducing scan-time, reducing cost and labor.
- ❑ Higher TRL research product.
- ❑ Has been integrated into the characterization framework

3. Test Deep CNN on new data!



Simurgh

1. Train GAN using CAD (Data Generator!)

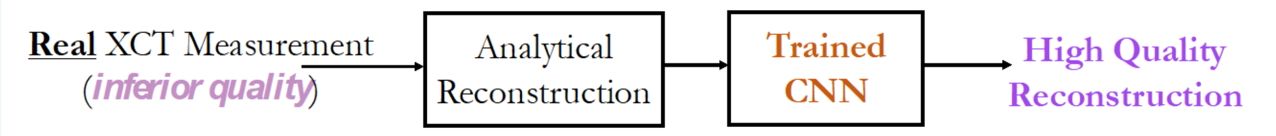


2. Syn… N!

CAD
Flaws (Lib…
& Simulat…
Trained CNN

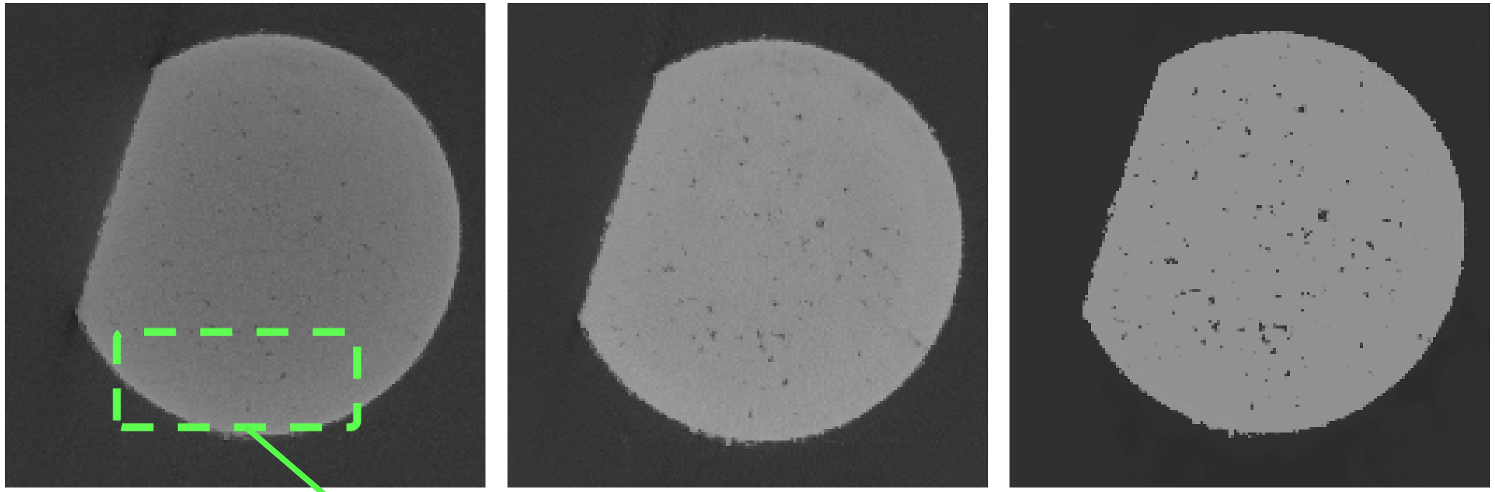
- ❑ State-of-the-art
- ❑ Addresses challenges with CAD-DLMBIR and can produce even more high-quality reconstructions
- ❑ To be integrated into the characterization framework

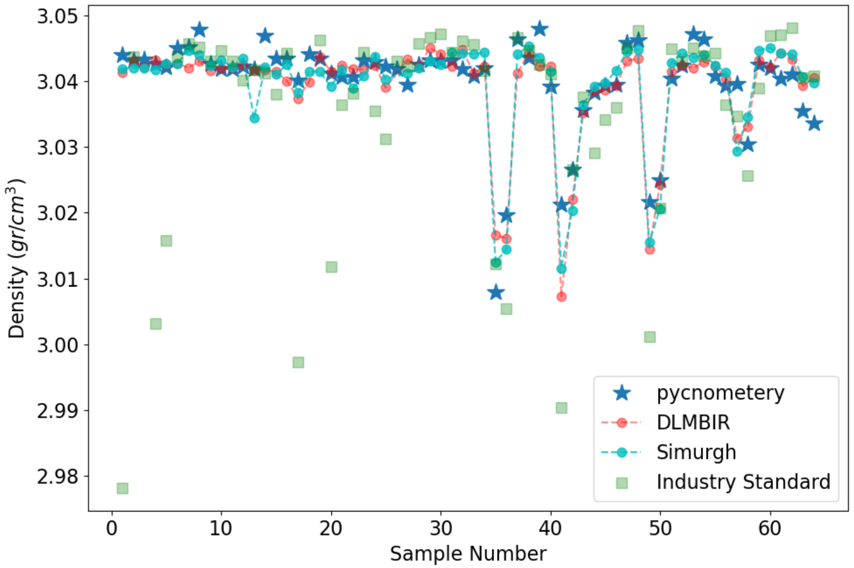
3. Test Deep CNN on new data!

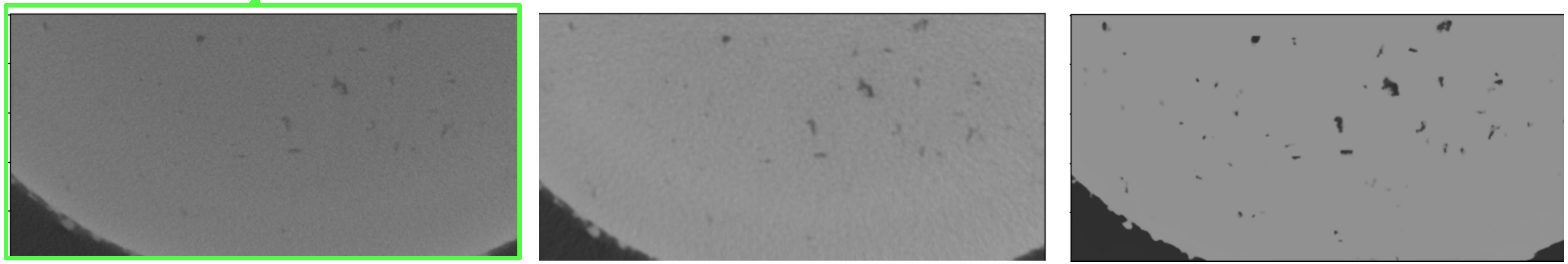


Results for a Lower Density Alloy

Standard | **2.5D CAD-DLMBIR** | **Simurgh**



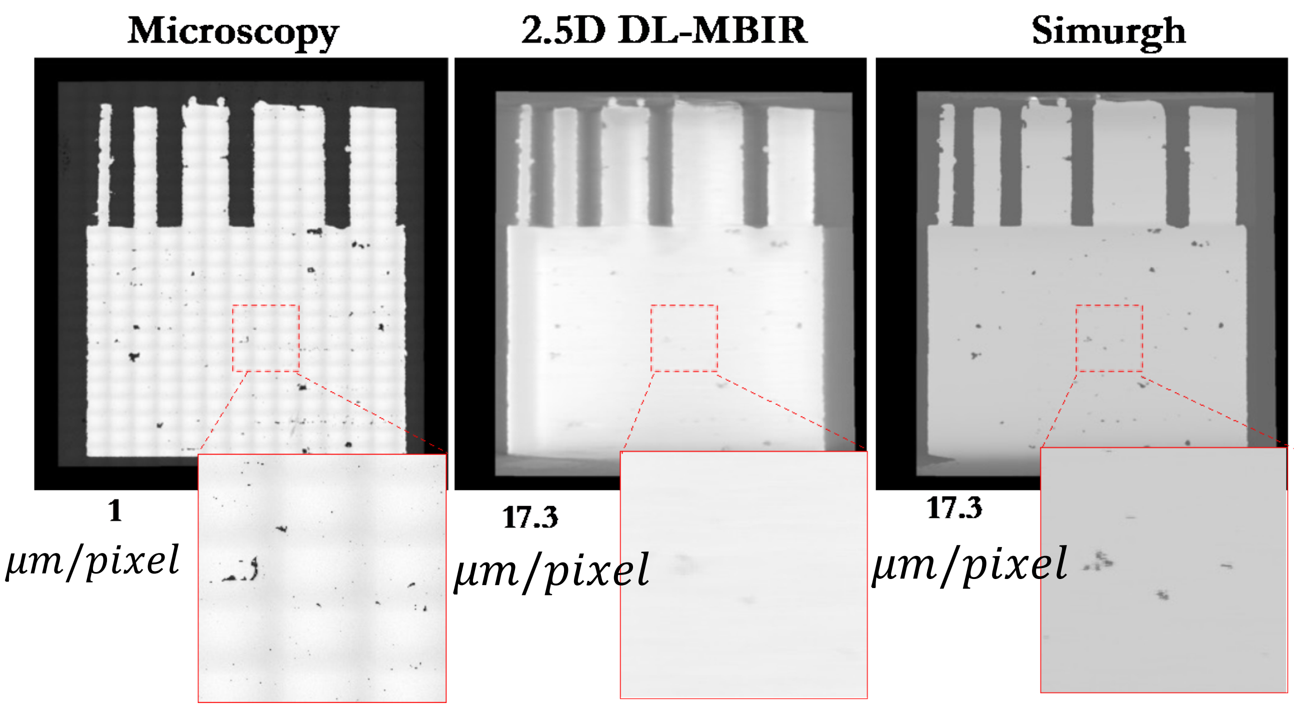




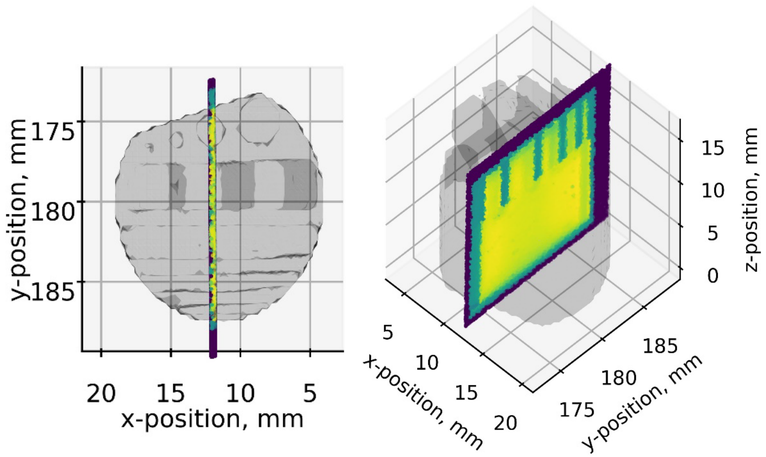
- ❑ 64 test data volumes
- ❑ Simurgh is only trained on synthetic data
- ❑ Further reduce the scan time and dealing with denser materials

Ziabari, et al. IEEE ICIP, 2022.

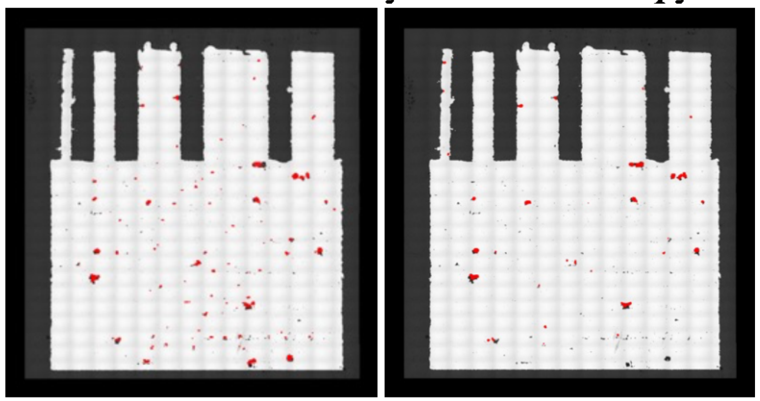
Inconel 718 Results (Highly Density Alloy)



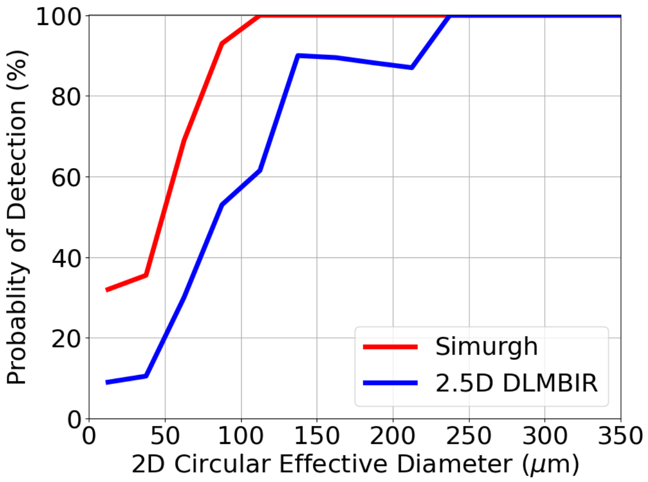
- ❑ 1μm resolution optical microscopy as ground truth.
- ❑ 3.5X better detection capability at sub-voxel resolution.
- ❑ Allows for detection of 100% of defects >100μm effective diameter!
- ❑ 2.5D DLMBIR already outperforms standard approaches by ~4X!



Detections Overlayed on Microscopy

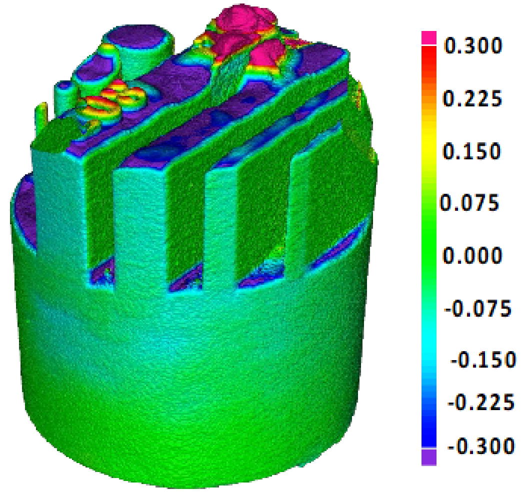


Detection based on Simurgh XCT   Detection based on 2.5D-DLMBIR

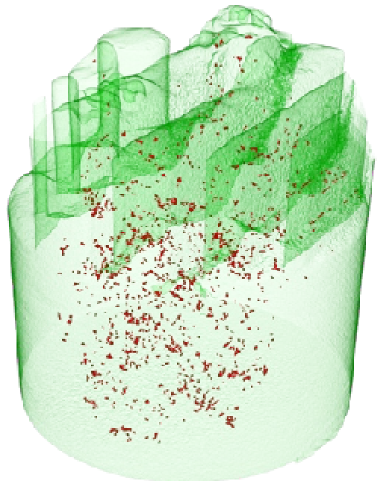


Fast Automated Characterization for Process Parameter Selection

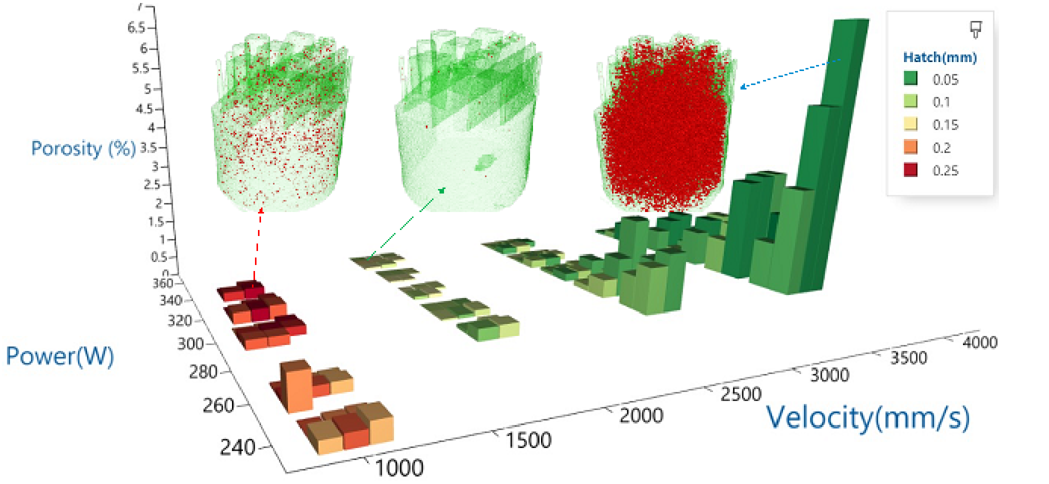
1. Design of Experiment (DoE) Parameters (**A Novel Material**)
2. Print the build plate. Remove parts from plate: (~100 parts per plate)
3. X-ray CT **at fraction** of optimal scan time based on material
4. **Fast, consistent and accurate AI-Based X-ray CT Reconstruction**
5. Analysis (segmentation, flaw detection, porosity & morphology,Metrology)



Deviation Map



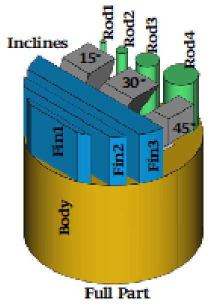
Segmented Flaws

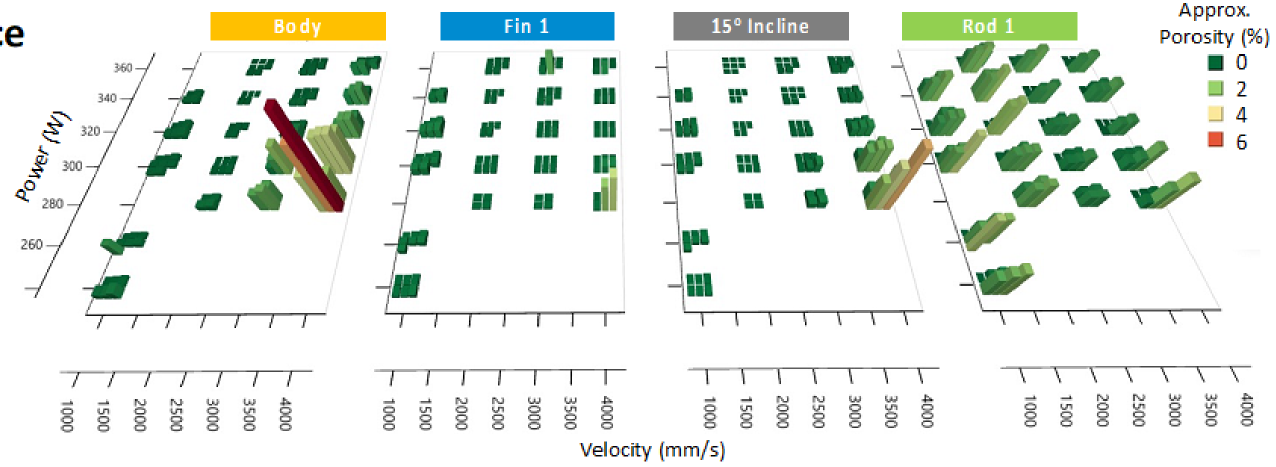


Window of desired process parameters for the new alloy

Build Plate: Each coupon a Process Parameter

Geometry dependence of optimum process parameters





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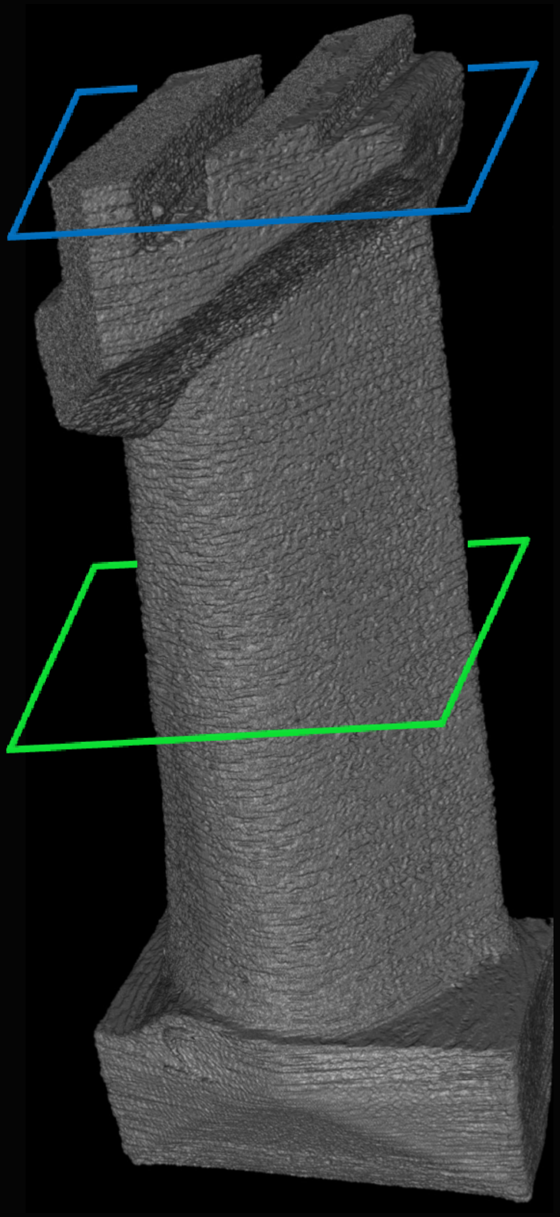
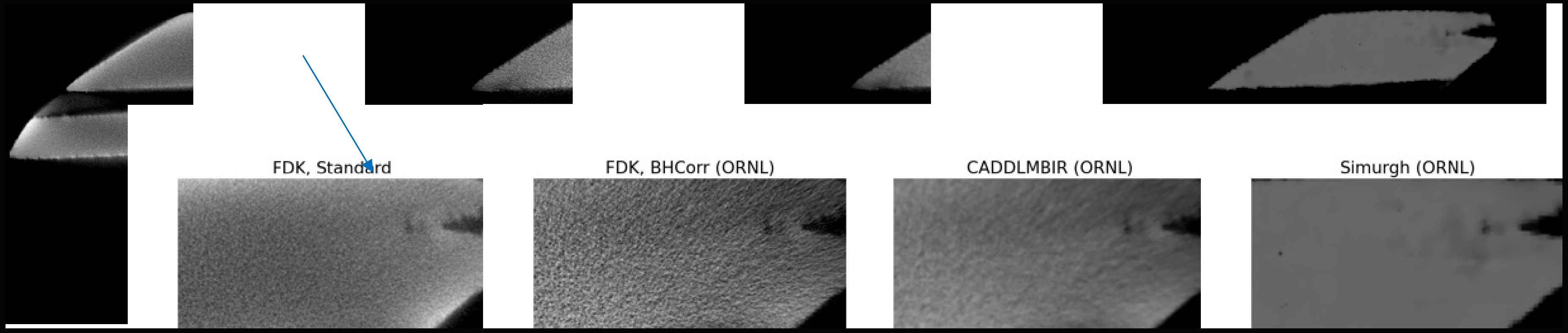
Ziabari, et al. Nature Computational Materials, 2023.

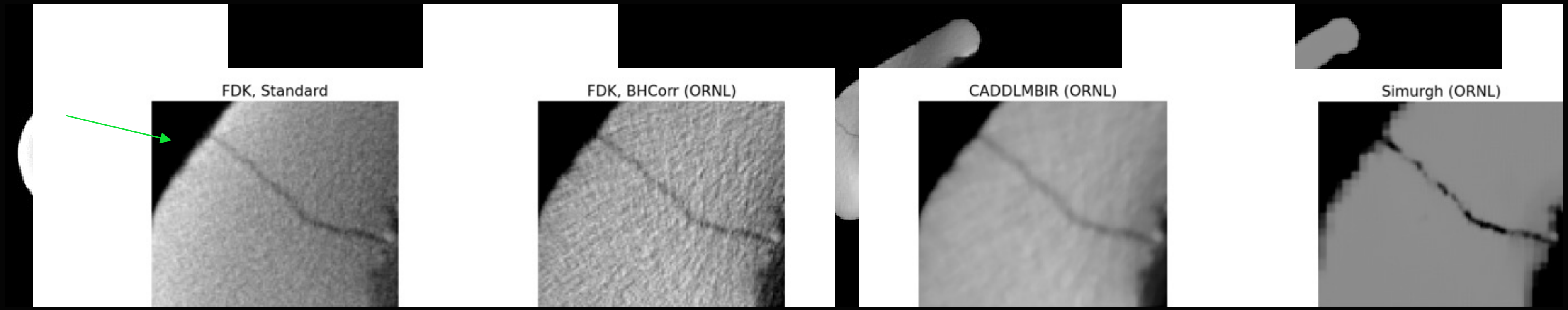
Large Complex Geometries



ORNL Technologies

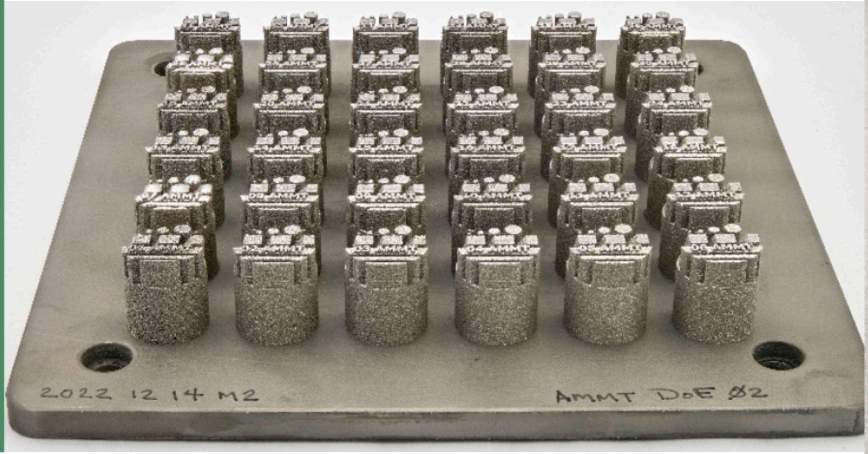
Standard FDK | FDK w/ BH corr. | CAD-DLMBIR | Simurgh



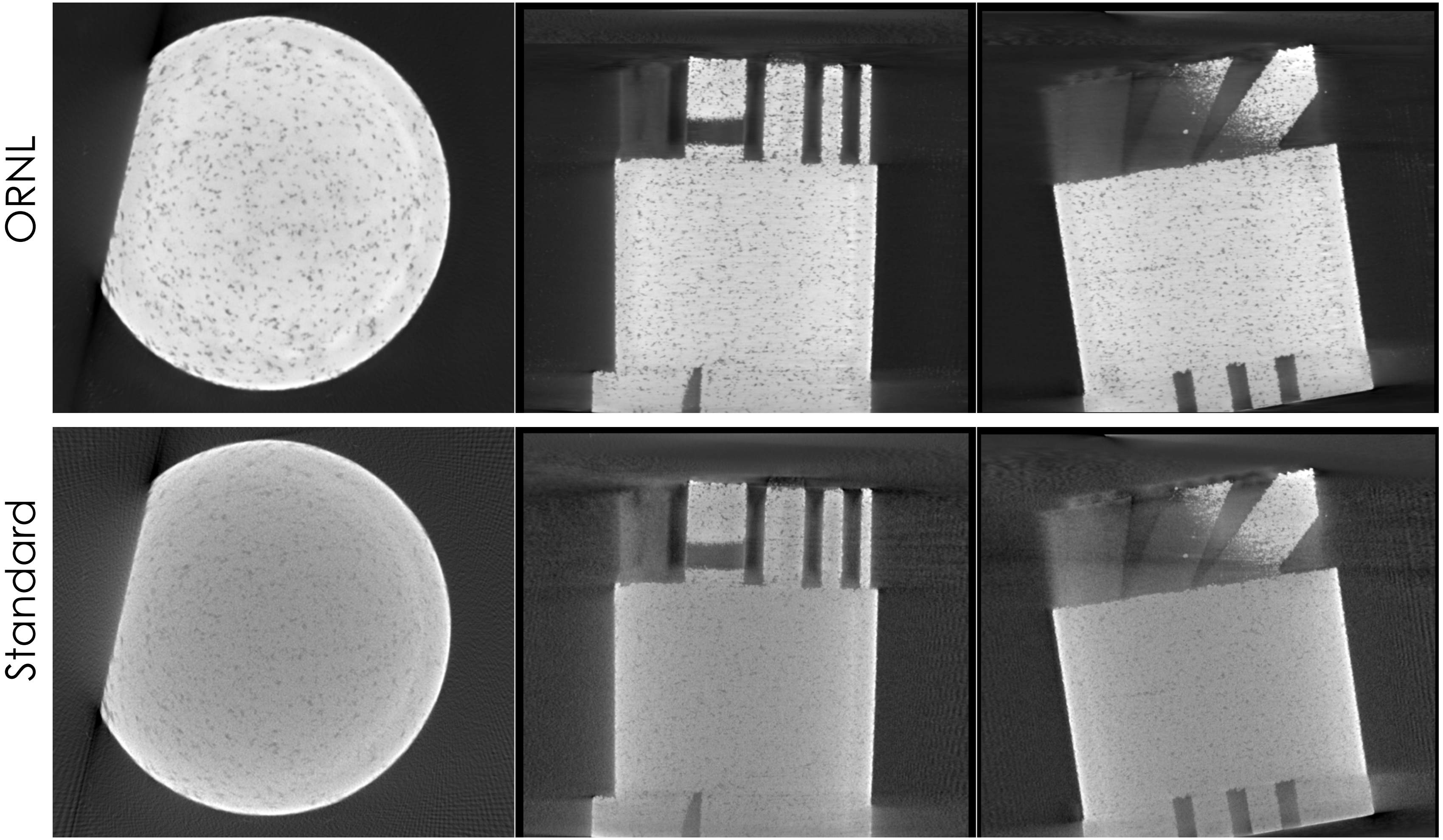


ORNL and AMMT

- ❑ 15 builds, >540 coupons
- ❑ Two systems
- ❑ Builds with various process parameters per coupon
- ❑ 316L and 316H



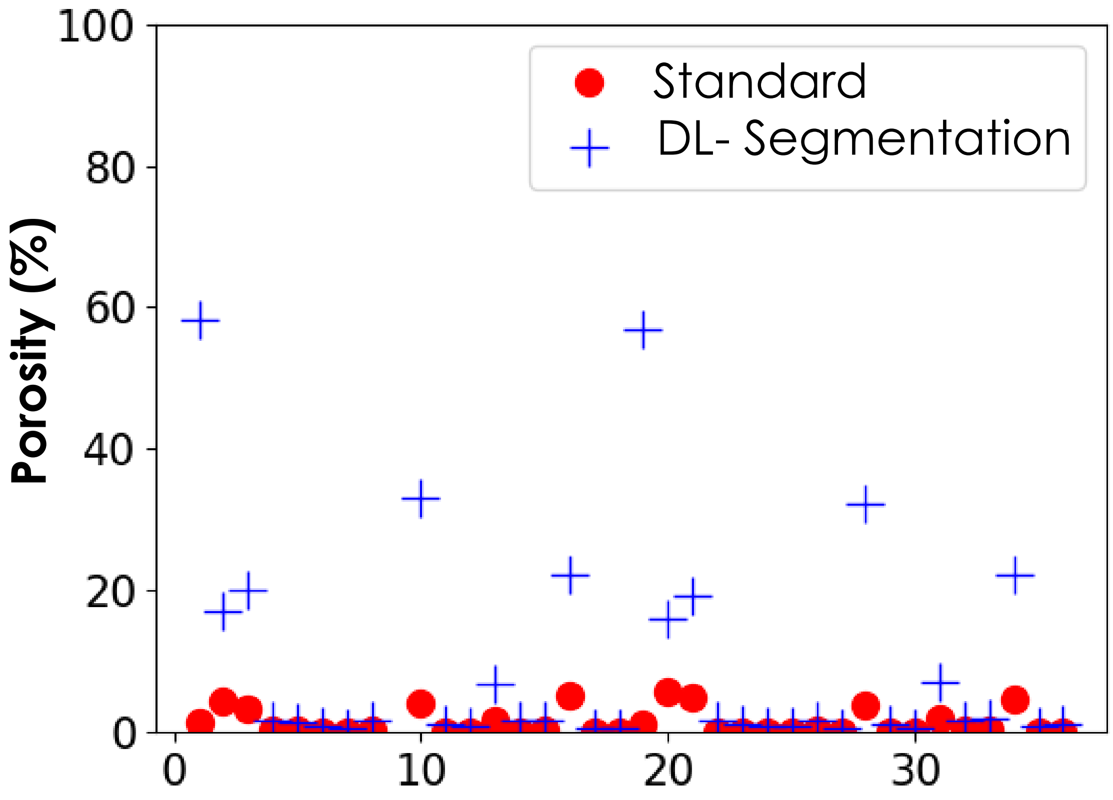
Deep Learning (DL) Based X-ray CT Reconstruction

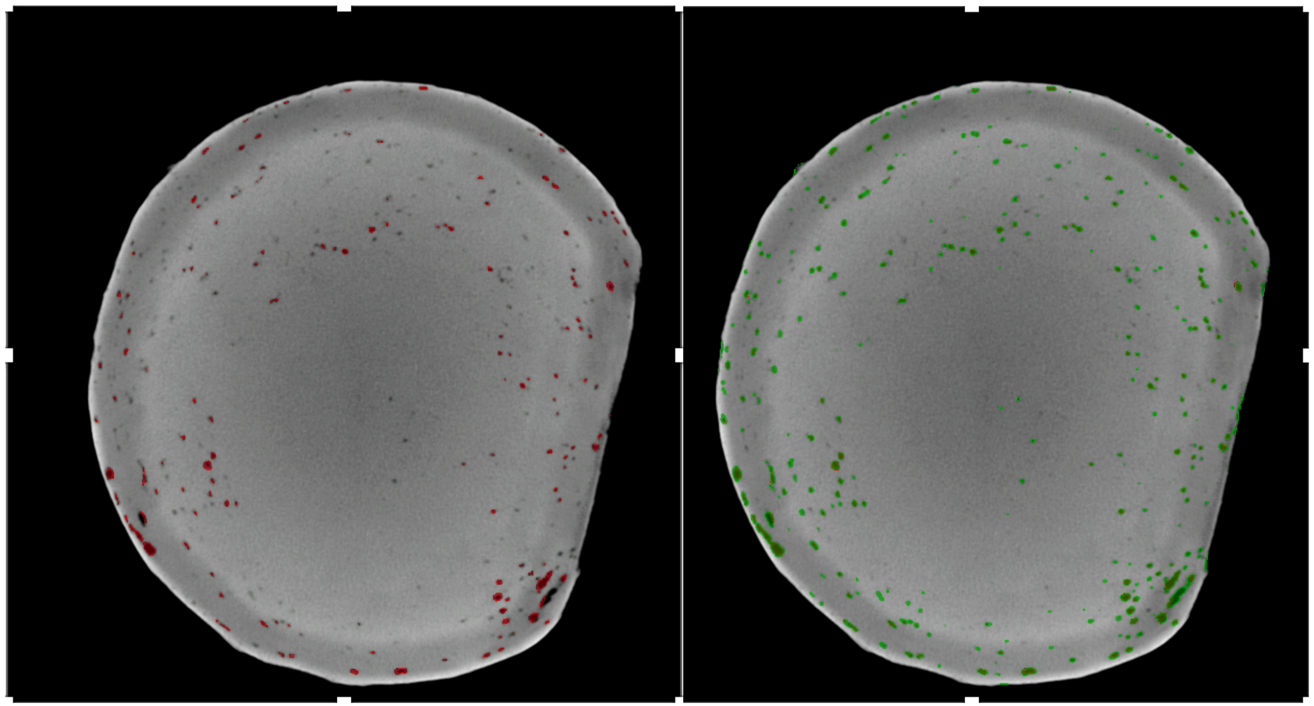


DL-reconstruction allows for resolving the flaws using 6X faster scans in thick dense 316L/H

Deep Learning (DL) Based X-Ray CT Segmentation

- *Noticed that Standard segmentation has limited accuracy (through comparison to high resolution microscopy data).*
- *Developed DL-based segmentation approach in this thrust*

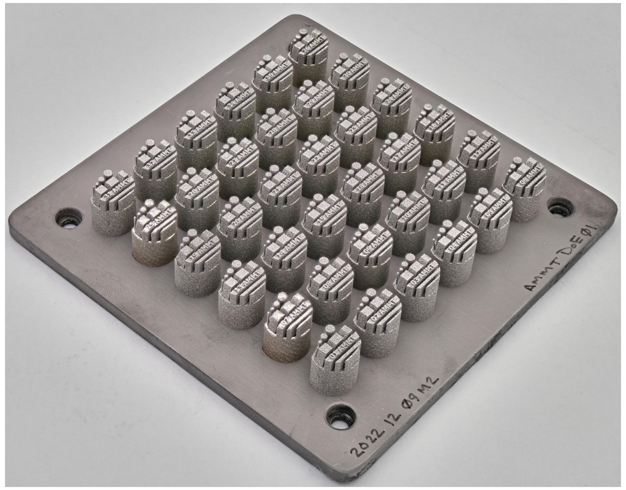




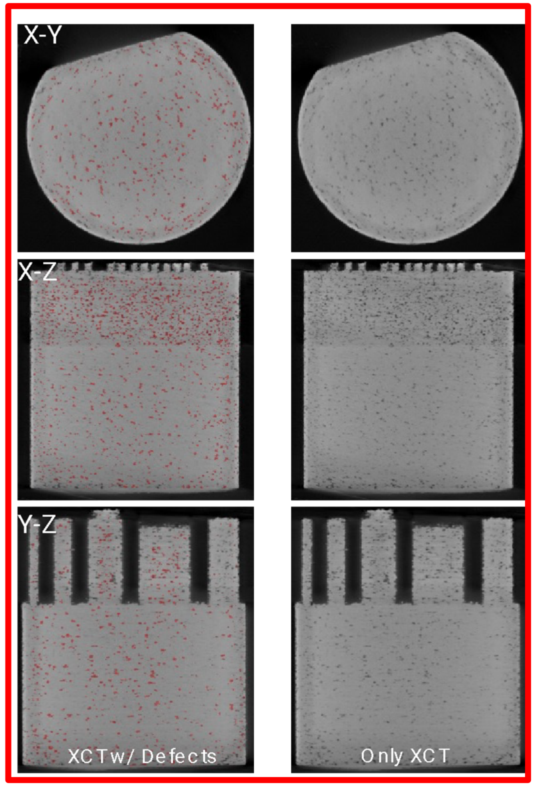
Red: Standard; **Green**: ORNL DL- Segmentation

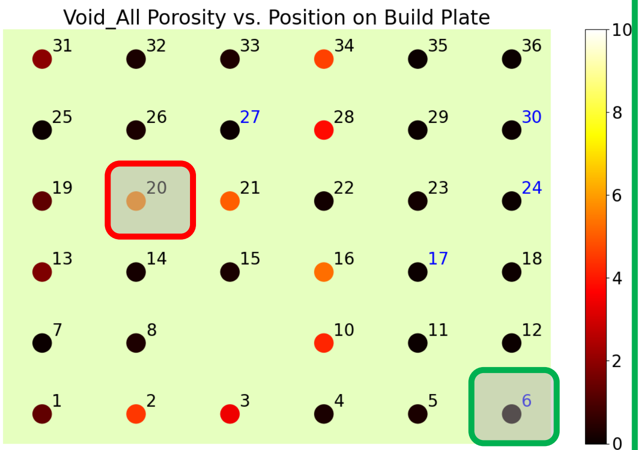
DL-Segmentation, verified through high-res microscopy, demonstrates that true porosity can be underestimated by 60X with standard algorithms

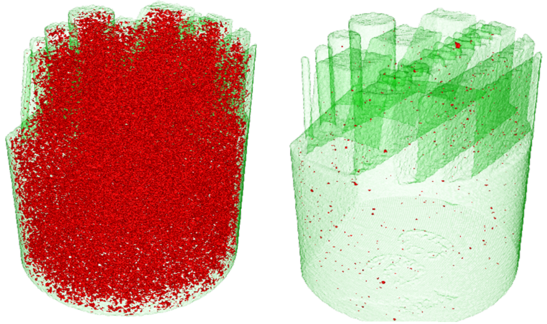
Build Consistency Analysis (B1 vs. B2)

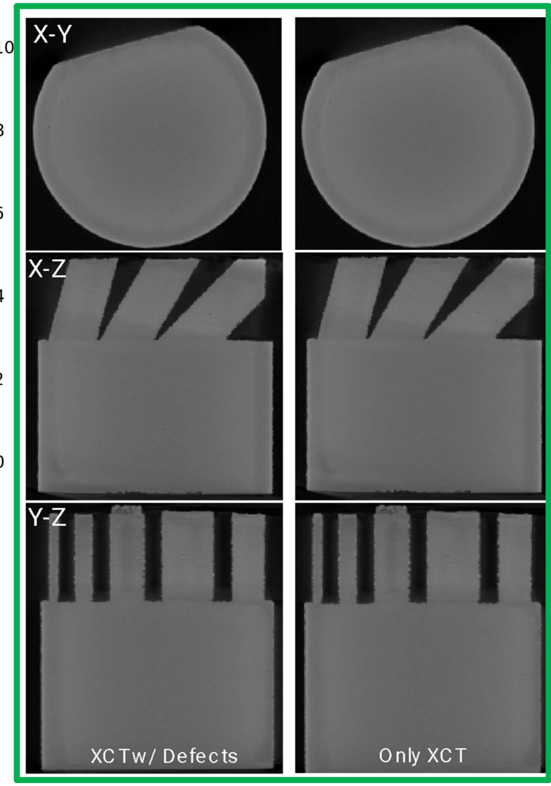


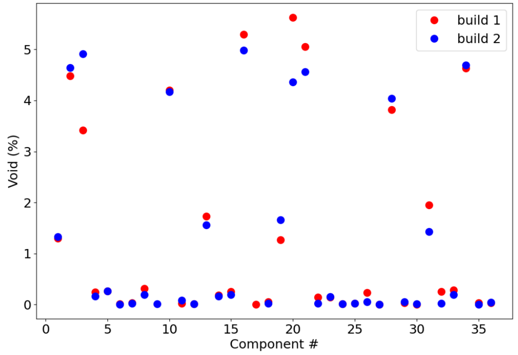
- ❑ Parameters repeated on Parts 01-18 & 19-36
- ❑ Randomized order to avoid systematic errors
- ❑ XCT, 20min per coupon
- ❑ Two builds showed consistent behavior



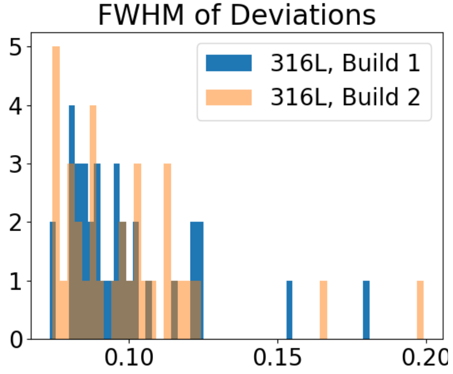


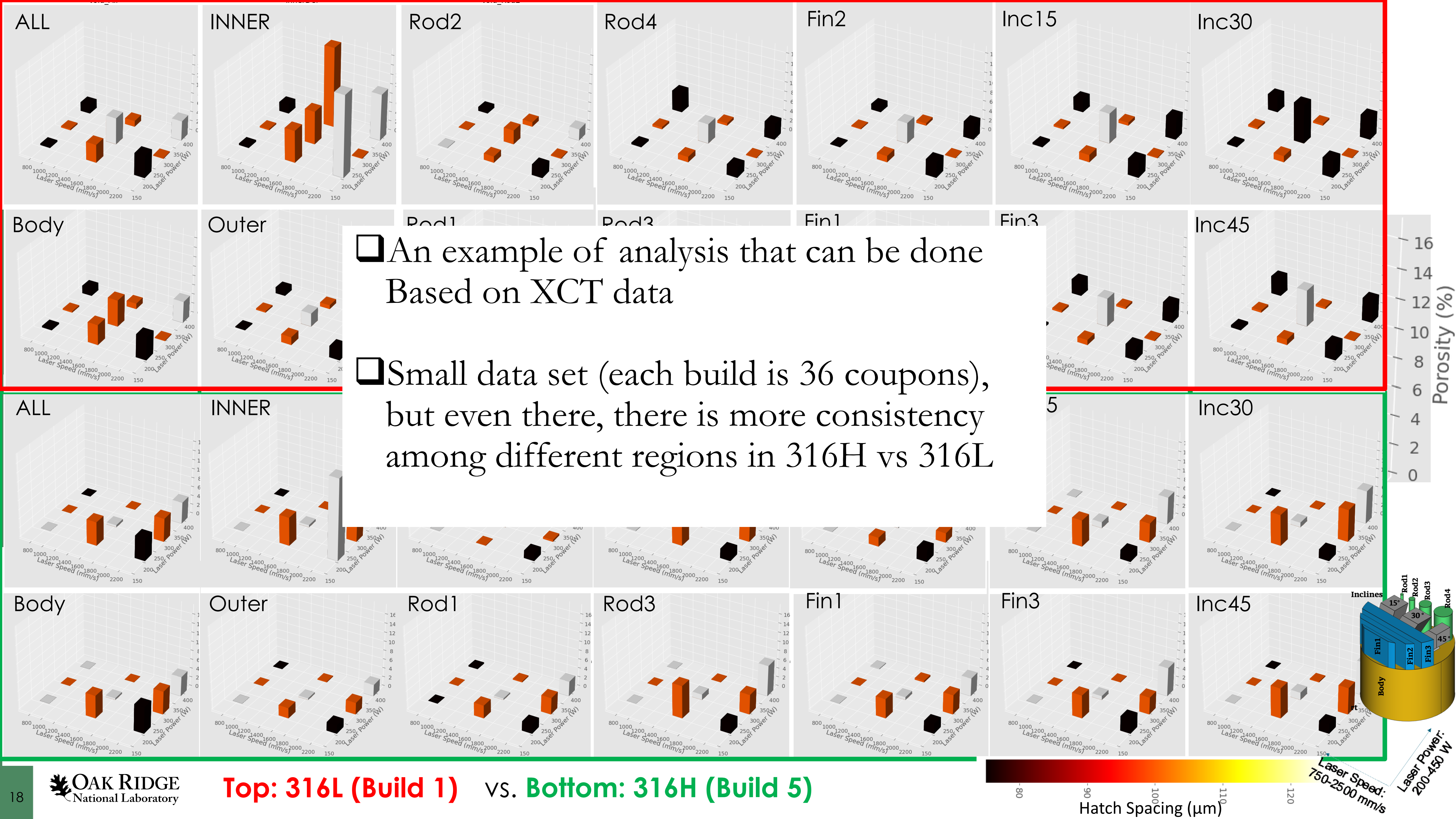






Correlation = 0.98

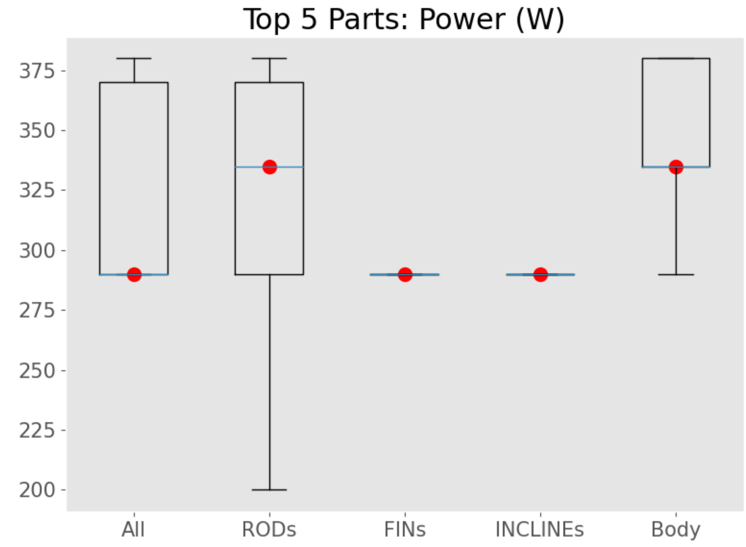


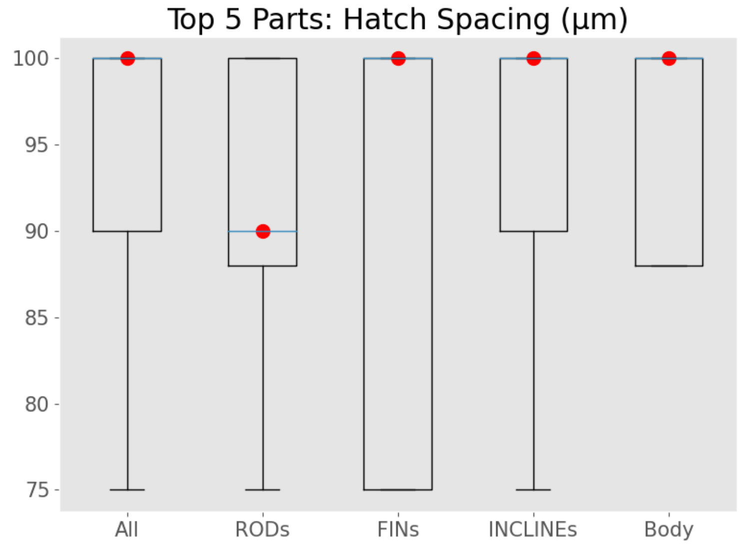


- An example of analysis that can be done Based on XCT data
- Small data set (each build is 36 coupons), but even there, there is more consistency among different regions in 316H vs 316L

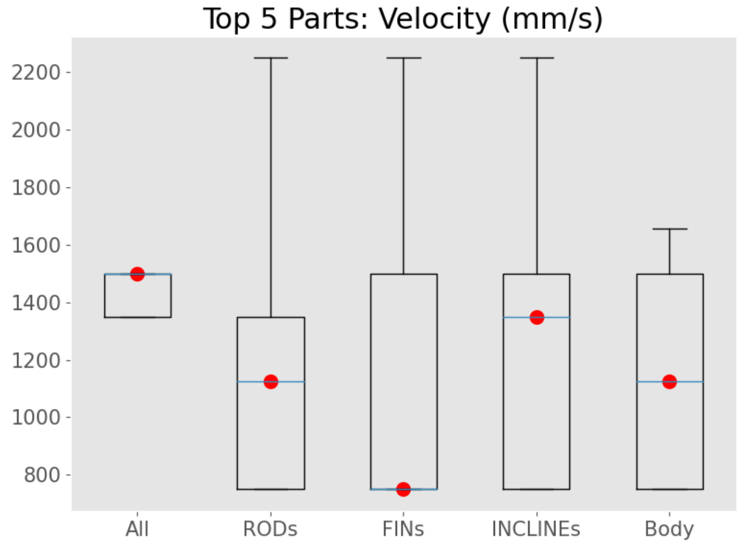
Top: 316L (Build 1) vs. **Bottom: 316H (Build 5)**

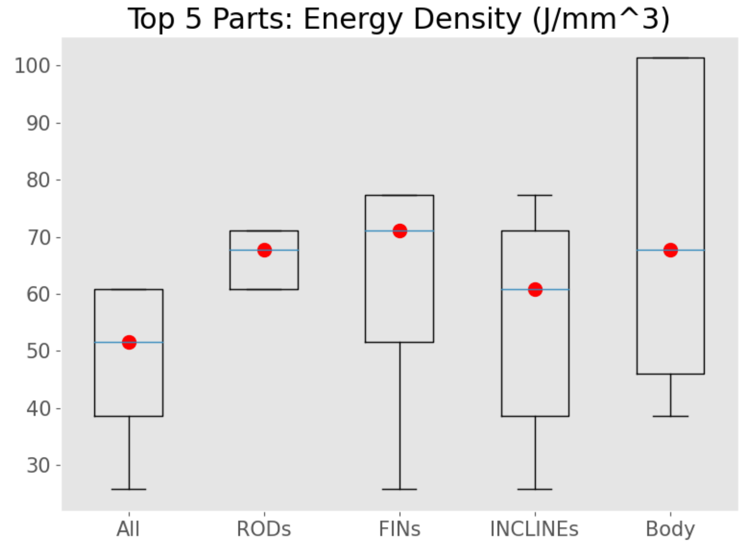
ROI Dependence of Process Parameters of Top 5 Coupons

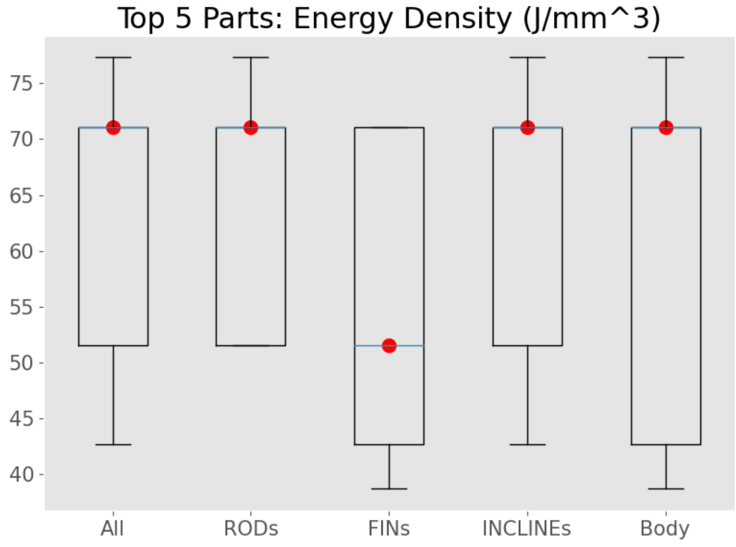




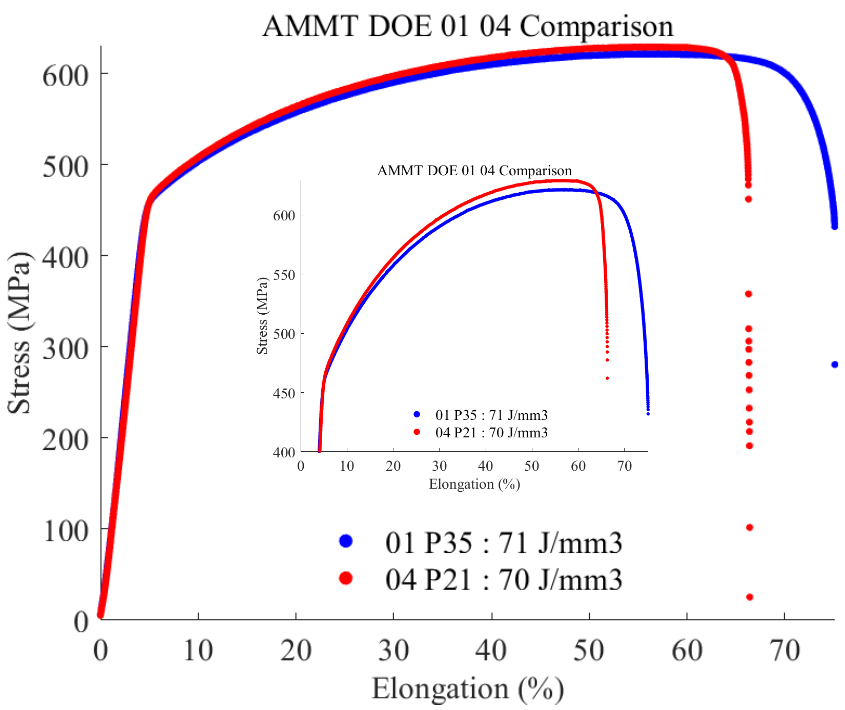
- 316L, 4 builds, 141 coupons
- 316H, 1 build, 36 coupons
- Single track characterization (LANL), EOS:
  316L: 54 J/mm^3
  316H: 95 J/mm^3
- Here with M2, is about 70J/MM^3 for both





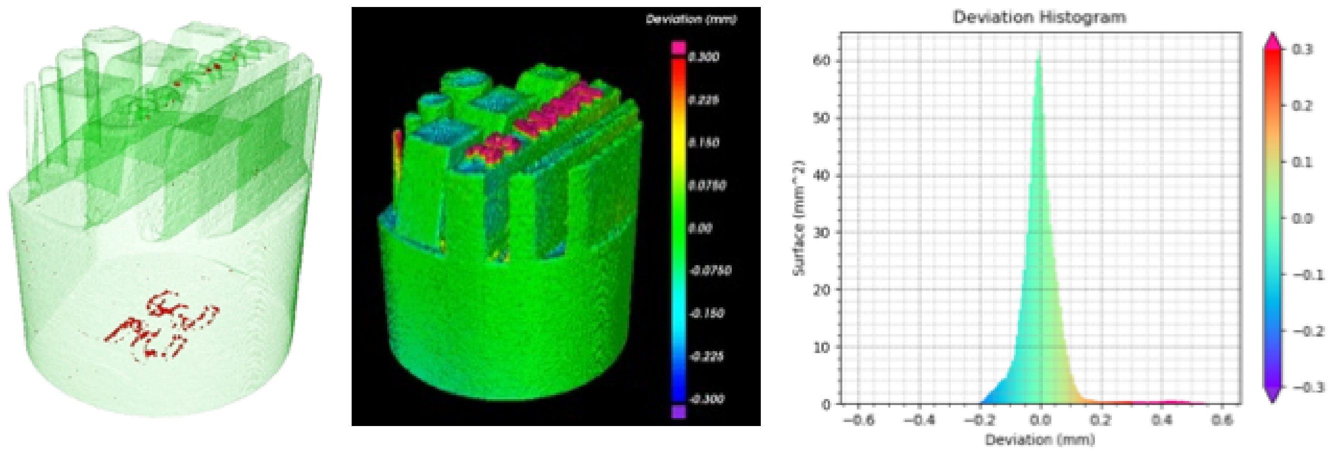


Parts With Same Energy Density ($71 J/mm^3$) And Different Process Variables



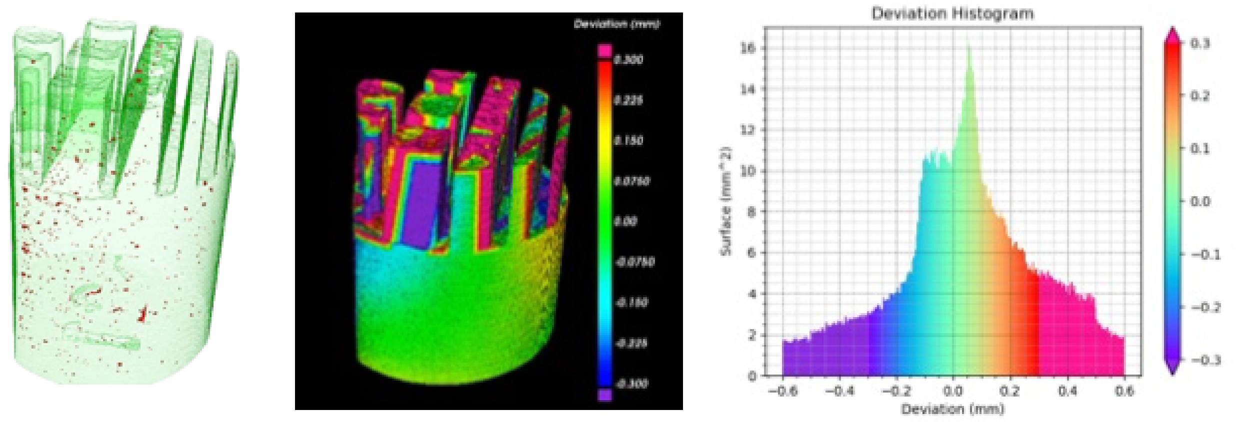
Similar energy density, despite the change in individual parameters results in **same yield strength** and insignificant differences in UTS, **BUT:**

B1-P35



- Geometric features closer to desired tolerances
- Low power (200W), low speed (750mm/s), higher hatch (75mm)

B4-P21



- Pores distributed across the whole sample
- **Larger geometric deviations**
- High power (380W), higher speed (1800mm/s), smaller hatch (60mm)

Variations in LPBF 316H SS Microstructure Within Minimized Porosity Process Space

Scientific Achievement

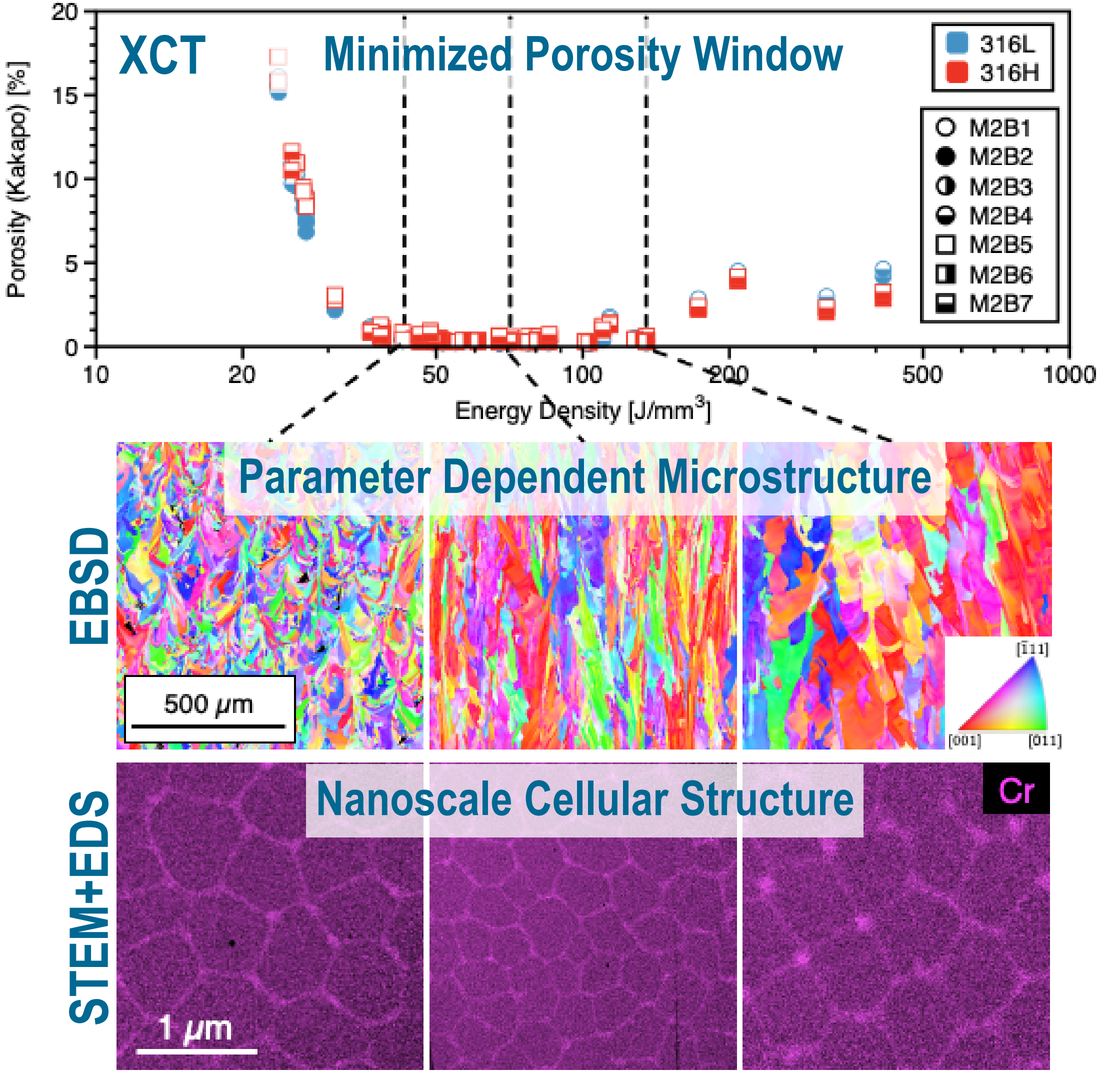
- A total of 252 SS Zeiss specimens (144 in 316L & 108 in 316H) printed as part of the concept laser experiments.
- Two characteristic microstructures identified for future campaign testing (refined chevron structure and columnar structure).

Impact & Potential Application Space

- For complex components, both of these characteristic microstructures may be present, invalidating assumptions in historical qualification frameworks.

Details

- High-throughput X-ray computed tomography (XCT) used to identify a minimum porosity process window for 316L and 316H SS, followed by targeted electron microscopy.



Multiscale characterization using XCT, EBSD and STEM-EDS reveals variations in porosity, grain structure, and nanoscale segregation as a function of varying processing parameters.

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High-Throughput XCT Identified Alternative Renishaw Processing Window for 316H

Scientific Achievement

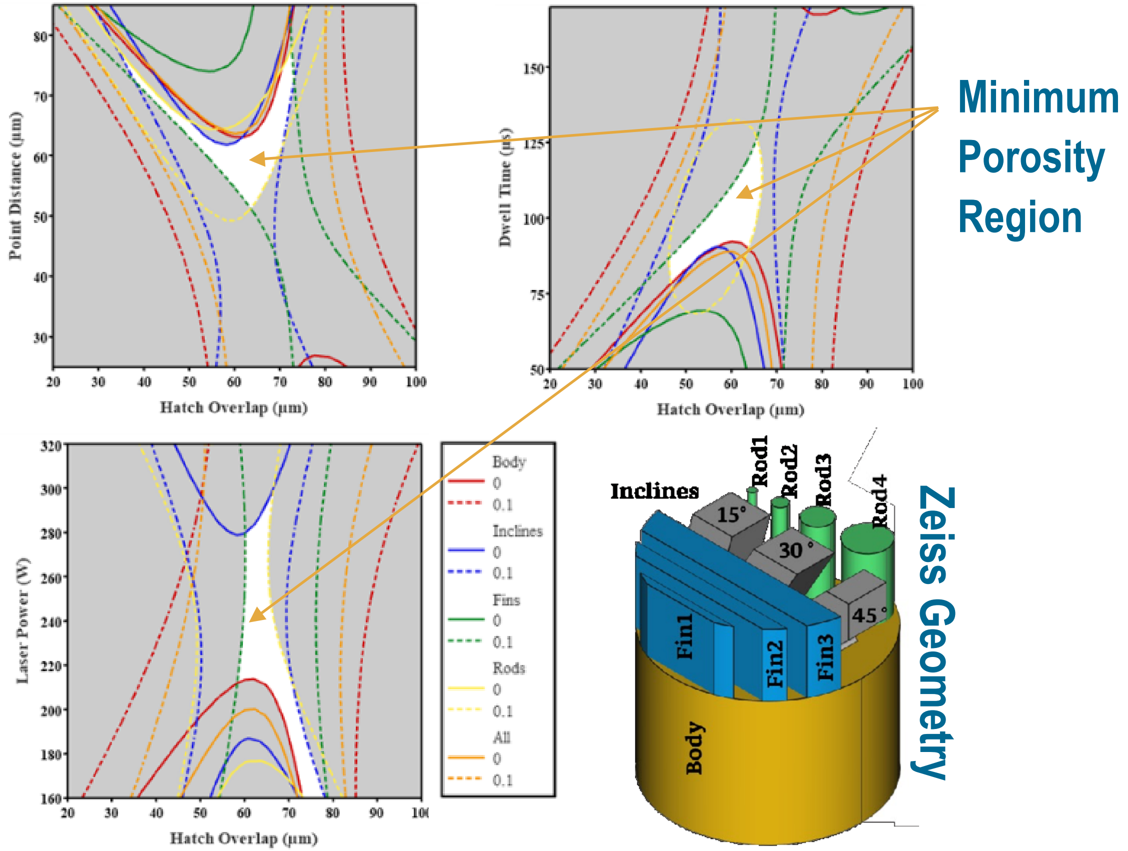
- A total of 390 SS Zeiss specimens (210 in 316L and 180 in 316H) printed as part of the Renishaw LPBF optimization efforts.
- High-throughput X-ray computed tomography (XCT) successfully used to probe geometry-specific porosity trends in AM parts.

Impact & Potential Application Space

- For samples printed using 316H SS, there is only a small processing window that successfully minimizes porosity within all geometric features in the experimental Zeiss coupon, requiring additional modeling and experimentation.

Details

- High-throughput XCT used to map porosity in different regions (inclines, rods, fins, etc.) in a miniature Zeiss specimen used for LPBF print optimization at ORNL.



XCT porosity trends for one 316H build PB performed on the Renishaw varying three processing parameters. In each plot, the area between solid and dashed lines indicates porosity below 0.1%. White regions indicate processing space where porosity is minimized for all overlaid curves.

- Deep Learning (DL) models developed, tested, modified for our reconstruction framework for 316L and H.
- A new DL-Based Segmentation is developed to address some challenges with characterization
- >540 coupons characterized (15 build plates on two printing systems)
- Multimodal data from X-ray CT, microscopy, EBSD, as well as in-situ and mechanical testing were combined to identify optimum process parameter window for two printer systems.
- Work ongoing on expanding the process parameter set, and for complex geometries

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