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Research Article

Keywords:

Posted Date: October 27th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10667575/v1>

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Additional Declarations: No competing interests reported.

X-ray investigations of stainless steel 316L produced via directed energy deposition

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Abstract

Directed energy deposition (DED) can produce complex pore populations and residual stress states in stainless steel 316L (SS316L), requiring quantitative evaluation to assess suitability for high-consequence structural applications. This work combines laboratory X-ray computed tomography (XCT) with X-ray diffraction (XRD) to characterize 18 DED-fabricated SS316L specimens produced over a range of laser power, scan speed, and powder feed conditions. XCT, with a voxel size of $\sim 8\mu\text{m}/\text{voxel}$, imaged the specimens and analyzed the porosity while XRD measurements evaluated phase constitution, texture, and near-surface residual stress. A sparse-view machine-learning image processing workflow reduced XCT acquisition from 4801 to 481 projections, corresponding to an 89% reduction in scan-time while maintaining 90% flaw detection. Porosity was observed to range from 0.01 to 6.77 vol%, with 16 of the specimens below 0.5 vol%. The largest porosity occurred in low-energy, low-power conditions near the build plate. XRD confirmed a single-phase face-centered-cubic structure with persistent (111)-type preferred orientation, with integrated intensity ratios of (111)/(200) of ~ 1.6 -2.8. Residual stresses were predominantly compressive and non-equibiaxial. The largest in-plane stress component was between -200

and -450 MPa. The combined XCT-XRD workflow provides quantitative, spatially resolved evidence linking DED processing conditions to defect formation, texture, and residual stress.

1. Introduction

As global energy demand continues to rise with a projected 30% increase by 2050 [1], advanced nuclear reactors are being pursued as a high-power density, low-carbon energy source capable of supporting long-term grid stability [2]. However, the economic viability and deployment timeline of new reactor concepts are strongly influenced by the cost, lead time, and qualification requirements associated with safety-critical structural components. Additive manufacturing (AM) offers a potential pathway to reduce fabrication complexity, enable nontraditional geometries, support repair and replacement strategies, and improve supply chain resilience for nuclear systems. Realizing this potential requires rigorous qualification of AM-fabricated materials, particularly with respect to internal defects, AM-specific defect morphologies, and residual stress states that can influence fracture resistance, part lifetime, stress corrosion cracking susceptibility, and irradiation performance. Qualification efforts of AM materials are complicated by the fact that AM materials exhibit different microstructures and failure mechanisms compared to traditionally fabricated materials and these AM microstructures can vary depending on build parameters used by individual manufacturers.

Among metal AM processes, directed energy deposition (DED), which utilizes a feedstock fed into the energy source and a user-specified path to generate each individual layer [3], has emerged as a promising AM fabrication technique to produce large metal parts, while minimizing waste [3-8]. Austenitic stainless steels such as stainless steel 316 (SS316) can be readily fabricated with DED and are widely used in nuclear systems due to their corrosion resistance and strength. However, steep thermal gradients, cyclic reheating, and complex melt pool dynamics during DED can generate lack-of-fusion defects, keyhole porosity, and significant residual stresses. While DED offers advantages in repairing and cladding components, its drawbacks include poor surface finishes and low print resolution [9, 10]. Surface roughness of DED parts can be larger than several hundred microns [11, 12], while porosity is caused by

either lack of fusion or gas inclusions [13-15]. The layered, non-line of sight fabrication can also introduce subsurface or “hidden” defects.

Previous work has examined various DED fabrication parameters’ effect on part structure [14-17], including the nozzle position [18] and deposition angle [19] effects on the melt pool [17–21]. Laser parameters during fabrication can also affect the melt pool [20, 21], with turbulent flow in the melt pool coupled with rapid cooling causing keyhole porosity [22]. Cooling rate can also influence the microstructure of AM fabricated components [8, 23, 24]. Particle size distribution and defects and internal stresses introduced by humidity have also been examined [7]. These microstructure changes all impact the part’s mechanical properties [16, 18, 25-28].

Consequently, nondestructive X-ray–based characterization methods are essential for establishing process–structure relationships and supporting regulatory acceptance of AM components for nuclear service. Recent studies have begun integrating nondestructive examination (NDE) techniques, such as X-ray computed tomography (XCT) and diffraction-based techniques (laboratory XRD and high-energy synchrotron diffraction), to study DED processing parameters’ influence on porosity and residual stress in AM samples [29-35]. Powder-based DED investigations have combined two-dimensional (2D) XRD with micro-XCT to relate variations in laser power and scan speed to crystallographic features and three-dimensional pore distributions [31]. Other work has explicitly correlated energy density with residual stress, porosity, and mechanical performance using complementary nondestructive neutron-based bulk characterization methods [36]. Collectively, these efforts demonstrate a growing state of the art in coupling volumetric defect quantification with diffraction-based strain measurement to develop process–structure–property relationships for DED-fabricated 316L stainless steel.

Despite these advances, systematic correlative investigations that integrate XCT-based porosity quantification with XRD-derived residual stress measurements in DED-fabricated SS316L, particularly within a nuclear-relevant qualification framework, remain comparatively limited. This work expands upon these previous efforts by employing laboratory-based XCT and XRD to investigate the influence of

processing parameters on defect generation, such as keyhole porosity, lack of fusion defects, and residual strain, in AM DED-fabricated 316L stainless steel. Three-dimensional porosity metrics, including pore size distribution, morphology, and volumetric fraction, are correlated with diffraction-based residual stress measurements to elucidate the relationships between energy input and stress development. XRD has proven useful in the analysis of the phase evolution, microstructure and grain growth of AM fabricated parts [37, 38].

This study improves understanding of how fabrication parameters can be optimized to create components that can meet acceptance criteria while qualifying the defects that are produced from sub-optimal process parameters. By establishing quantitative links between DED process parameters, internal defect populations, and residual stress states, this study contributes to the development of data-driven qualification strategies for AM components intended for high-consequence nuclear reactor applications.

2. Theory

During DED fabrication the primary laser parameters, including laser power, scan speed, beam diameter, and travel path, directly control the instantaneous heat input and interaction time between the laser and the substrate. Laser power determines the magnitude of thermal energy delivered, while scan speed governs the dwell time of the beam on a specific area, and therefore the degree of heating per unit length. Together with beam size and material delivery, these parameters define the peak temperature, melt pool dimensions, penetration depth, cooling rate, and solidification conditions. Variations in these settings influence bead geometry, microstructural evolution, residual stress development, and the likelihood of defects such as lack of fusion or keyholing. Consequently, laser parameters strongly affect both the geometric fidelity and mechanical performance of the final build in the DED process.

However, the melt pool behavior and resulting microstructure are governed not by the absolute laser settings alone, but by the balance between energy input and material delivery. Therefore, fabrication conditions are more appropriately described using specific energy (e.g., linear or volumetric energy

density) and powder density (mass feed rate per unit length or volume), rather than individual parameters such as laser power and scan speed. Specific energy normalizes laser power by the interaction time and deposition geometry, providing a physically meaningful measure of the thermal input delivered to a given amount of material [39]. Likewise, powder density quantifies the rate of material introduction relative to the melt pool, capturing the mass balance that controls melt pool stability, dilution, bead geometry, and defect formation [40]. Different combinations of power and travel speed can yield similar energy per unit length, and identical laser settings can produce different outcomes if the powder feed rate changes. Expressing process parameters in terms of specific energy and powder density therefore normalizes the deposition conditions to the underlying thermodynamic interaction between the laser and the feedstock, improving physical interpretability by directly correlating observed defects such as porosity to laser thermodynamics.

A high specific energy relative to the amount of delivered powder can promote the formation of deep vapor depressions and unstable melt-pool dynamics, increasing the likelihood of keyhole-induced porosity. Conversely, insufficient energy input relative to the delivered powder may result in incomplete melting and reduced melt-pool penetration, thereby limiting interlayer bonding and promoting lack-of-fusion defects. Equation 1 describes specific energy in relation to laser parameters used in this study while Equation 2 illustrates powder density's relationship to laser parameters [40]. In these equations S_E is the specific energy, P_D is the powder density, P is the laser power, V is the laser scanning speed, D_S is the laser spot size, and W is the powder feed rate.

$$S_E = \frac{P}{V \times D_S} \quad (1)$$

$$P_D = \frac{W}{V \times D_S} \quad (2)$$

3. Experimental

3.1 Sample Fabrication

Fabrication was performed using an Optomec® MTS 500 LENS system (Optomec®, Inc., Albuquerque, NM, USA) equipped with a continuous-wave 1070 nm fiber laser. Feedstock powder was supplied through a four-nozzle delivery system directed at a slightly defocused laser beam, producing an effective spot size of approximately 0.6 mm on the substrate. All processing occurred within an argon atmosphere, the chamber was initially evacuated to 4.5 torr and then backfilled with 99.9% purity argon, which also functioned as both the carrier and shielding gas. Powder feedstock was commercially supplied, gas atomized SS 316L material (Höganäs Belgium S.A., Ath Belgium), with a particle size distribution ranging from 45-150 μm and spherical morphology. Rectangular prisms with nominal dimensions of 6 mm x 6 mm x 12.5 mm were fabricated using a variety of process parameters with a single pass contour to discern parameter effect on porosity and residual stress. Hatch angle, hatch spacing, and layer thickness were held constant throughout the study to eliminate geometric and thermal-path variability associated with changes in scan strategy. By fixing these parameters, the impact of the targeted processing variables could be isolated, ensuring that observed differences in porosity and residual stress originated from the parameters under investigation rather than from variations in melt track overlap, energy distribution, or layer-wise heat accumulation. The 67° hatch angle was used to disrupt continuous columnar grain growth and reduce crystallographic texture by altering the solidification path between layers. The hatch spacing produces an approximate 25% melt track overlap under optimal processing conditions, ensuring sufficient remelting and track cohesion while maintaining stable deposition. Layer thickness was set to the standard default value for the system. Depositions were performed at room temperature onto a 152 x 152 x 6.35 mm SS 316L build plate to reduce dilution and thermal distortion. Upon completion of sample fabrication, the samples were ground down using silicon carbide (SiC) paper to remove excessive surface roughness which would impact XRD measurements and preclude accurate residual stress measurements. Images of the completed samples are shown in Figure 1, while Table 1 lists sample fabrication parameters.

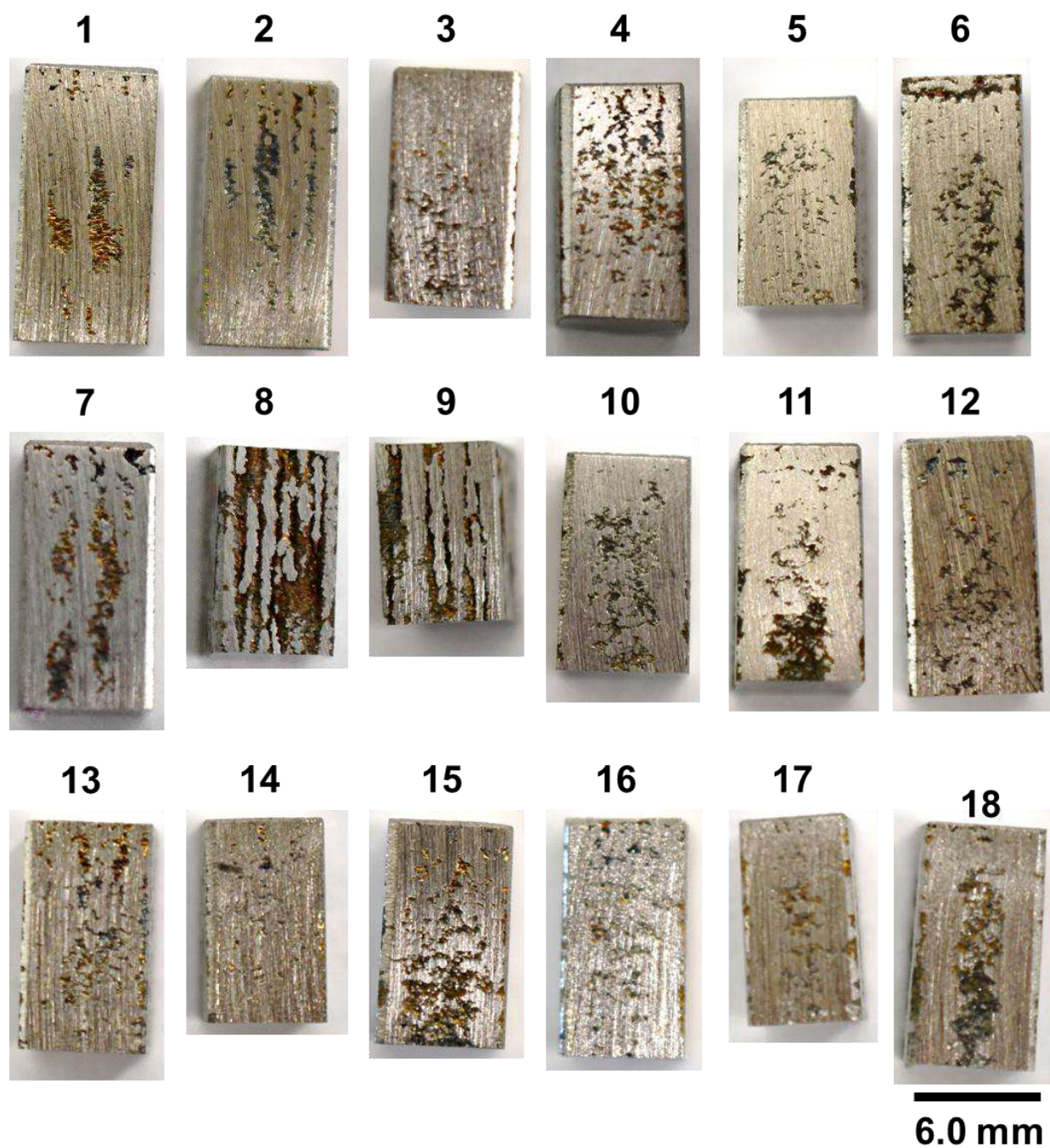


Figure 1. Optical images showing the AM SS316 samples used in this study, fabricated under 18 different processing conditions.

Table 1. Parameters used for fabrication of the AM SS316 samples used in this study.

Sample ID	Laser Power (J/s)	Linear Feed-rate (mm/s)	Linear Feed-rate (ipm)	Powder Feed-rate (g/min)	Powder Feed-rate (rpm)	Powder feed per unit length (g/m)	Hatch Distance (mm)	Hatch angle (°)	Layer Thickness (mm)	Specific Energy (J/mm ²)	Powder Density (g/mm ³)
1	200	6.35	15.00	10.51	6	27.5853	0.3556	67	0.127	45	0.039
2	200	10.58	25.00	10.51	6	16.5512	0.3556	67	0.127	27	0.024
3	250	6.35	15.00	6.79	4	17.8215	0.3556	67	0.127	56	0.025
4	250	10.58	25.00	10.51	6	16.5512	0.3556	67	0.127	34	0.024
5	300	6.35	15.00	10.51	6	27.5853	0.3556	67	0.127	67	0.039
6	300	8.47	20.00	21.70	12	42.7166	0.3556	67	0.127	51	0.061
7	200	7.00	16.50	18.00	10	42.8571	0.3556	67	0.127	41	0.061
8	150	10.00	23.60	10.51	6	17.5167	0.3556	67	0.127	21	0.025
9	150	9.00	21.30	6.79	4	12.5741	0.3556	67	0.127	24	0.018
10	350	6.35	15.00	10.51	6	27.5853	0.3556	67	0.127	79	0.039
11	350	6.35	15.00	21.70	12	56.9554	0.3556	67	0.127	79	0.081
12	250	6.35	15.00	10.51	6	27.5853	0.3556	67	0.127	56	0.039
13	250	10.00	23.60	10.51	6	17.5167	0.3556	67	0.127	36	0.025
14	250	9.00	21.30	6.79	4	12.5741	0.3556	67	0.127	40	0.018
15	300	6.35	15.00	10.51	6	27.5853	0.3556	67	0.127	67	0.039
16	300	9.00	21.30	10.51	6	19.4630	0.3556	67	0.127	48	0.028
17	400	10.50	24.80	6.79	4	10.7778	0.3556	67	0.127	54	0.015
18	400	10.50	24.80	21.70	12	34.4444	0.3556	67	0.127	54	0.049

3.2 Density Measurements

Sample density was measured using both the Archimedes density method as well as with a pycnometer.

Results are summarized in Table 2. Note that Archimedes density method measurements were conducted on the samples before they were polished. However, pycnometry and X-ray computed tomography measurements were conducted on samples after they were polished so a direct comparison with the Archimedes measurement is not possible. This explains why the sample masses reported in the Archimedes measurements are consistently higher than the pycnometry measurements. The difference between Archimedes and pycnometry density therefore reflects changes in surface condition, surface-

connected features, and specimen volume after polishing rather than a true assessment of open and closed porosity.

Table 2. Summary of density measurements determined using Archimedes method and pycnometry.

Archimedes Density					Pycnometry Measurements				
Sample ID	Dry Mass (g)	Submerged Mass (g)	Density (g/cm ³)	Error (%)	Mass (g)	Density (g/cm ³)	Error (%)	Volume (cm ³)	Error (%)
1	4.6734	4.0838	7.9105	1.10	4.1783	7.9570	0.18	0.5251	0.01
2	4.3717	3.8205	7.9154	1.10	4.1373	7.9570	0.23	0.5200	0.01
3	4.6125	4.0325	7.9367	0.80	4.0181	7.9742	0.29	0.5039	0.02
4	4.4501	3.8881	7.9025	1.20	4.0915	7.9679	0.32	0.5135	0.02
5	4.7752	4.1768	7.9640	0.45	4.0762	7.9676	0.32	0.5116	0.02
6	4.7898	4.1710	7.7250	3.60	4.7901	7.9629	0.08	0.6016	0.01
7	4.6843	4.0937	7.9156	1.10	4.1127	7.9574	0.24	0.5168	0.02
8	4.2088	3.6746	7.8629	1.70	3.1133	7.9347	0.31	0.3924	0.02
9	3.8850	3.3904	7.8391	2.10	2.7269	7.9271	0.32	0.3440	0.01
10	5.1242	4.4790	7.9261	0.93	4.1939	7.9632	0.27	0.5267	0.02
11	6.0967	5.3261	7.8958	1.30	4.9734	7.9490	0.48	0.6257	0.04
12	4.8656	4.2557	7.9617	0.48	4.2145	7.9638	0.35	0.5292	0.02
13	4.6468	4.0590	7.8896	1.40	3.9862	7.9562	0.33	0.5010	0.02
14	4.3720	3.8227	7.9433	0.71	3.7594	7.9628	0.41	0.4721	0.02
15	4.8134	4.2093	7.9520	0.60	4.0878	7.9610	0.42	0.5135	0.03
16	5.0399	4.4014	7.8776	1.60	4.3732	7.9553	0.31	0.5497	0.02
17	5.5592	4.8583	7.9157	1.10	4.6663	7.9571	0.47	0.5864	0.03
18	5.9780	5.2238	7.9104	1.10	4.9464	7.9454	0.54	0.6226	0.04

3.2.1 Archimedes Density Measurement

Density was first measured by the Archimedes density method according to ASTM Standard B962-23 to determine the bulk density of samples by submerging them in a fluid and measuring the buoyant force acting upon them [41]. First, the dry mass of the sample in air was measured. Water was then boiled to degas it, preventing any air bubbles from adhering to the sample, and the samples were submerged in water with their immersed mass being recorded. The difference in the samples' mass measured in air was compared with the immersed mass, which corresponds to the buoyant force and equals the mass of the displaced fluid. The sample's volume is then calculated knowing the density of water and the sample's bulk density is determined by dividing the dry mass by the calculated volume.

3.2.2 Pycnometer Density Measurement

Gas pycnometry was employed to determine the skeletal density of the specimens by quantifying their true solid volume via gas displacement. Measurements were taken using an AccuPyc pycnometer (Micromeritics Instrument Corporation, Norcross, GA, USA). Sample mass was measured and dried samples were sealed within the calibrated measurement chamber which was pressurized with helium. Helium gas was used because its small atomic size allows for infiltration into smaller pore volumes and it exhibits minimal adsorption under the given measurement conditions. Upon pressurization, the gas was expanded into a reference chamber of known volume, and equilibrium pressures were recorded. The sample volume was calculated from the measured pressure differential using the ideal gas law. The measured volume corresponds to the skeletal volume of the solid framework of the sample because helium penetrates accessible open pores but does not enter closed pores. Skeletal density was then obtained by dividing the measured mass by the calculated volume.

3.3 X-ray Computed Tomography

XCT measurements of the DED samples were conducted at Idaho National Laboratory's Irradiated Materials Characterization Laboratory (IMCL) using a ZEISS Xradia 620 Versa X-ray microscope (Carl Zeiss X-ray Microscopy Inc., Dublin, CA) [42]. This machine uses a tungsten target to produce an X-ray

spectrum with a maximum peak voltage that can vary from 160 kVp to 30 kVp, with a maximum power of up to 25 W. Depending on the desired field-of-view and spatial resolution, images could be captured either with a flat panel detector or an X-ray microscope coupled to a CCD camera.

For this study, the Versa's flat panel detector was used with no binning factor, producing radiographs with dimensions of 3064-pixels wide by 1936-pixels tall. The source was run at 160 kVp and 25 W, and radiographs had a spatial resolution of $\sim 8.0 \mu\text{m}/\text{pixel}$, resulting in the ability to quantify features of $\sim 80 \mu\text{m}$. A BR4 filter, provided by ZEISS, was utilized to improve the signal to noise ratio and pre-harden the X-ray beam to mitigate the beam-hardening effect, which appears as cupping and streaking artifacts in the reconstructed image cross-sections. A total of 4801 radiographs were initially collected. Data was reconstructed into a 3D volume using the ZEISS Scout-and-Scan Control System Reconstructor software.

3.3.1 Machine-Learning for Expedited XCT Acquisitions

The acquisition process described above resulted in a full data acquisition taking ~ 8 hours, which was not feasible for all 18 samples due to instrument time constraints. Sample throughput was increased by leveraging the Simurgh framework, an AI-powered framework that reduces the scan time without compromising the reconstruction quality or detection capability [43, 44]. Simurgh was trained on previous datasets of samples of the same composition and similar dimensions to those examined in this work and then deployed to expedite data acquisition. Using Simurgh, only 481 projections were necessary to produce comparable quality tomograms- resulting in a reduction of 7 hours, 55 minutes per scan down to 52 minutes, an 89% reduction in scan time.

The Simurgh model was trained on 3 similar samples. The model learns to remove artifacts from a standard sparse-view reconstruction volume thus obviating the need to perform slow dense-view scans (4801 projections). The model was trained on low- and high-quality image pairs. Low-quality image volumes (input) are reconstructed from FDK [45], the industry standard reconstruction technique which is fast but does not model the noise in the measurement. The high-quality image volumes (target) are

reconstructed from MBIR (model-based iterative reconstruction) [46, 47], a technique that models the measurement noise and assumes a prior model on the underlying image and solves the estimation problem iteratively (significantly slower than FDK), producing a higher-quality reconstruction volume than FDK does. The sparse-view FDK volume serves as the low-quality input and the dense-view MBIR volume serves as the high-quality target. Note that slow MBIR reconstruction is only needed for training the model, and during deployment only the fast FDK technique is employed. To make the model robust to different view sparsity conditions, several levels of sparsity were employed to get the input image volumes. This was done because it is unknown beforehand how many sparse views will be needed for a new sample, therefore the model is trained to work with a range of view-sparsity factors (making it robust to change in view-sparsity), thus letting the user choose what suits best depending on the trade-off between speed and flaw detection accuracy. Figure 2 shows an axial slice of the ground truth of one of the samples and three levels of view-sparsity that were used for the input.

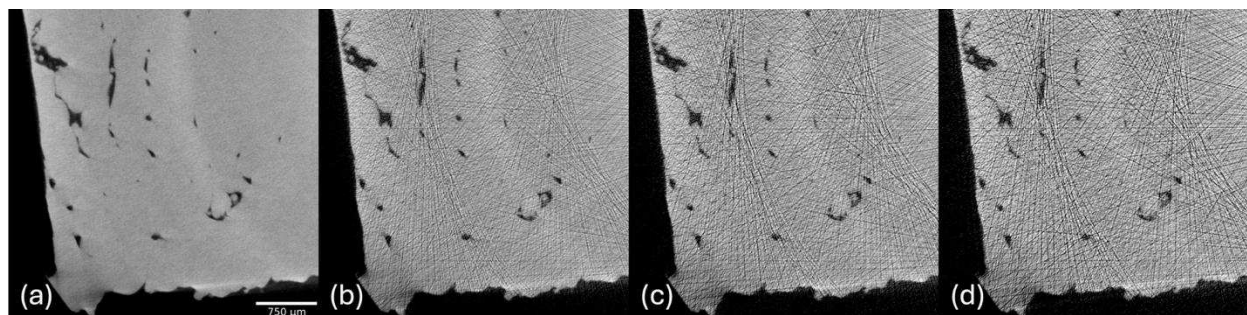


Figure 2. 3 levels of view sparsity for the input image. (a) Ground truth (from 4501 views), sparse-view volumes with (b) 901 views, (c) 451 views, and (d) 301 views, all show varying level of streaking artifacts. Simurgh learns to map these inputs to the high-quality ground truth. The model was trained on 600,000 patches of size 256x256 (depth of 5 for input and 1 for target) for 195 epochs, taking about 4 days. A DGX-box with 6 NVIDIA H100 GPUs (80 GB/GPU) were used.

Once the model is trained, during inferencing the user can choose the desired level of view-sparsity. To determine the number of views for a new sample, it was scanned with 4801 views (dense-view scan).

Reconstruction using all views served as the reference for this sample. Then, FDK reconstructions were generated with 2401, 961, 481 and 241 views (empirically chosen) and fed to the trained Simurgh network. As an example, Figure 3 shows an axial slice of FDK (481 views) input, Simurgh output (481 views) and the reference/ground truth (4801 views). Simurgh removes streaks and noise and preserves the flaws.

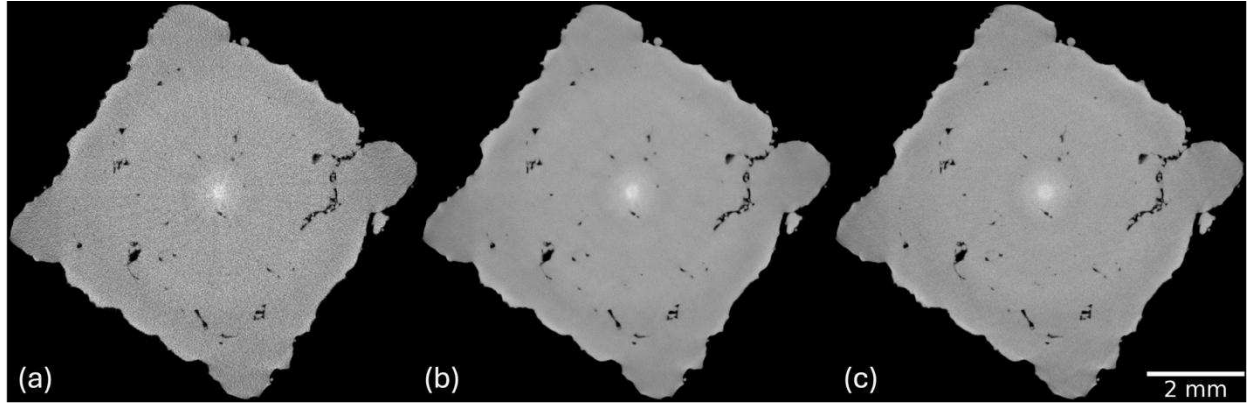


Figure 3. An axial slice from (a) FDK (481 views), (b) Simurgh (481 views) and (c) Reference. Simurgh output suppresses the noise. Simurgh’s overall quality is close to the reference.

The reference and the Simurgh outputs were segmented [48] into background, alloy, and flaw regions.

Figure 4 shows an axial slice of the volumes, a region of interest, and the corresponding segmentation map. As the number of views decrease, a few tiny flaws lose contrast and are unable to be detected.

Visually Simurgh (481 views) misses some flaws but fares significantly better than Simurgh (241 views).

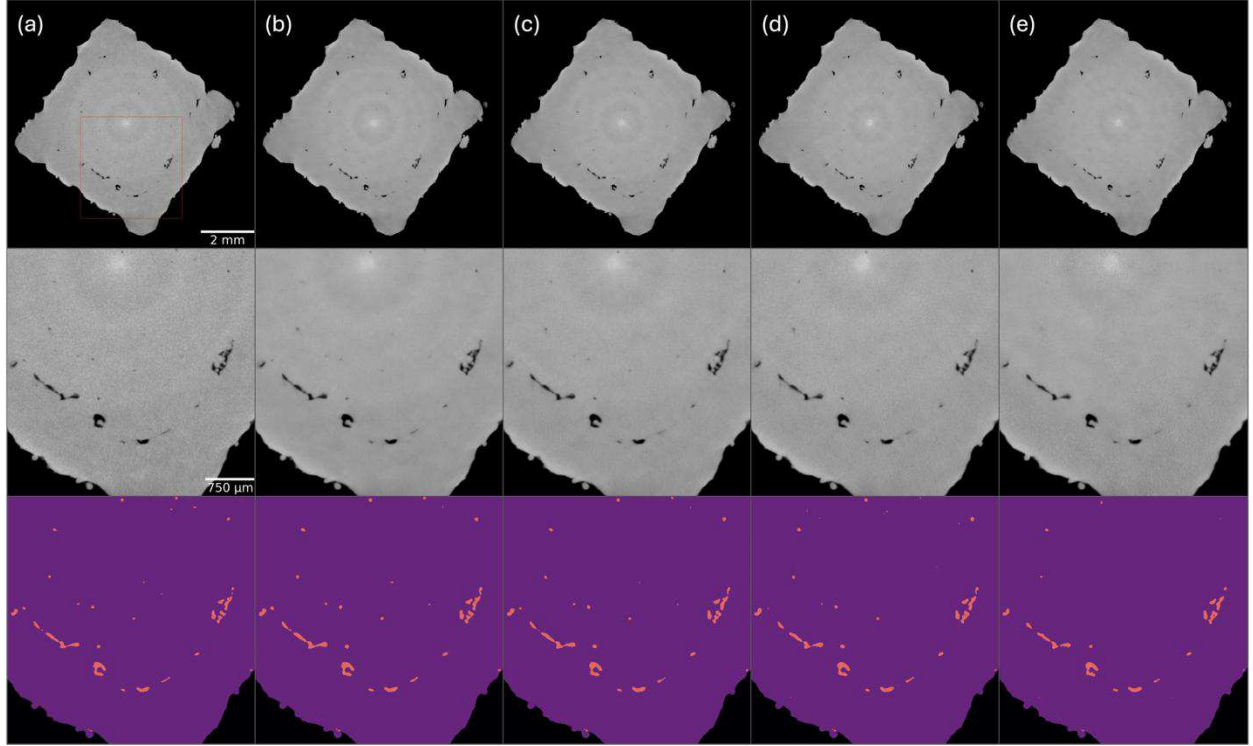


Figure 4. (Top row) An axial slice from different reconstruction volumes, (Middle row) Zoomed-in region of interest (Bottom row) Zoomed-in segmentation map (flaw: orange, alloy: purple, background: black). (a) Reference (4801 views), (b) Simurgh (2401 views), (c) Simurgh (961 views), (d) Simurgh (481 views), (e) Simurgh (241 views). Fewer projections show some loss of flaw contrast.

For quantitative comparison, an F1 score (harmonic mean of recall and precision) for flaw detection was computed for all volumes with the ground truth as reference. The F1 score curve is presented in Figure 5 as a surrogate for detection capability evaluation while ensuring the effect of both false positives and negatives are considered. Here d_{90} is defined as the minimum flaw size that can be detected with 90% F1-score (>0.9). For 2401, 961, 481 and 241 views, the d_{90} is $\sim 33 \mu\text{m}$, $40 \mu\text{m}$, $42 \mu\text{m}$ and $56 \mu\text{m}$, respectively. The large gap between d_{90} (481 views) and d_{90} (241 views), makes Simurgh (481 views) a practical choice for fast scanning with acceptable flaw detection. Even with this reduction in scan time, flaws ~ 5 times the voxel size can be detected with 90% F1-score.

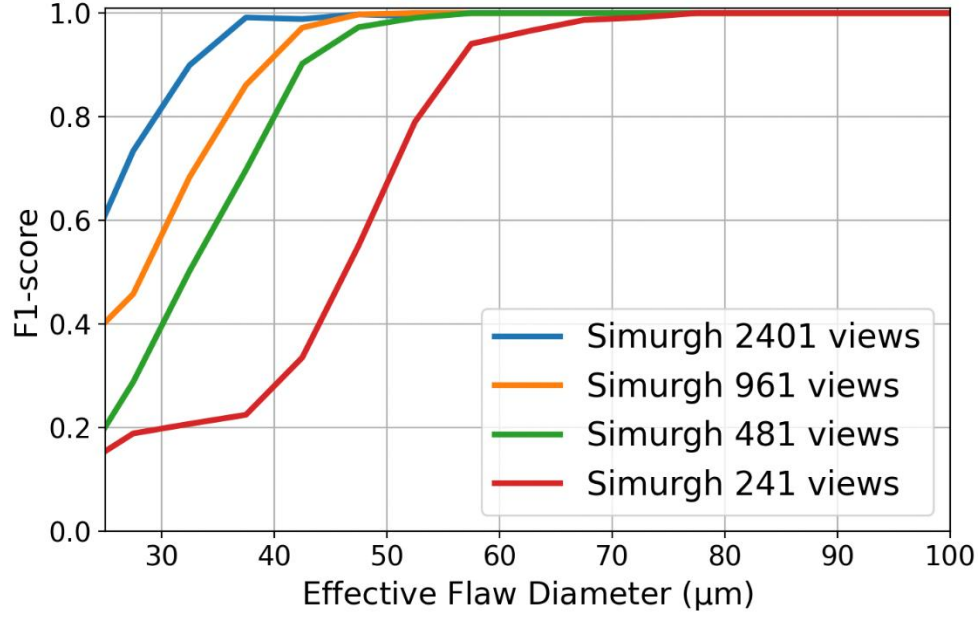


Figure 5. F1 score curve for flaw detection for different view-sparsity Simurgh volumes. Scanning with 481 views is an ideal choice for practical high-throughput characterization and process optimization with a small drop in performance while gaining significant scanning speed-up.

3.3.2 XCT Data Segmentation

The 3D tomograms were segmented to isolate porosity using MATLAB (version 2024a, Mathworks, Natick, MA, USA). First, data was cropped to encapsulate the whole sample while removing most of the background. Manual grayscale thresholding was applied to get a coarse segmentation of the sample and then adaptive thresholding was applied to refine the segmentation. The data was then binarized and morphologically closed with a disk-shaped structuring element to create a solid volume. The initial segmentation was inverted, and a mask of the solid volume was applied to isolate the porosity. An example showing the segmentation steps is displayed in Figure 6.

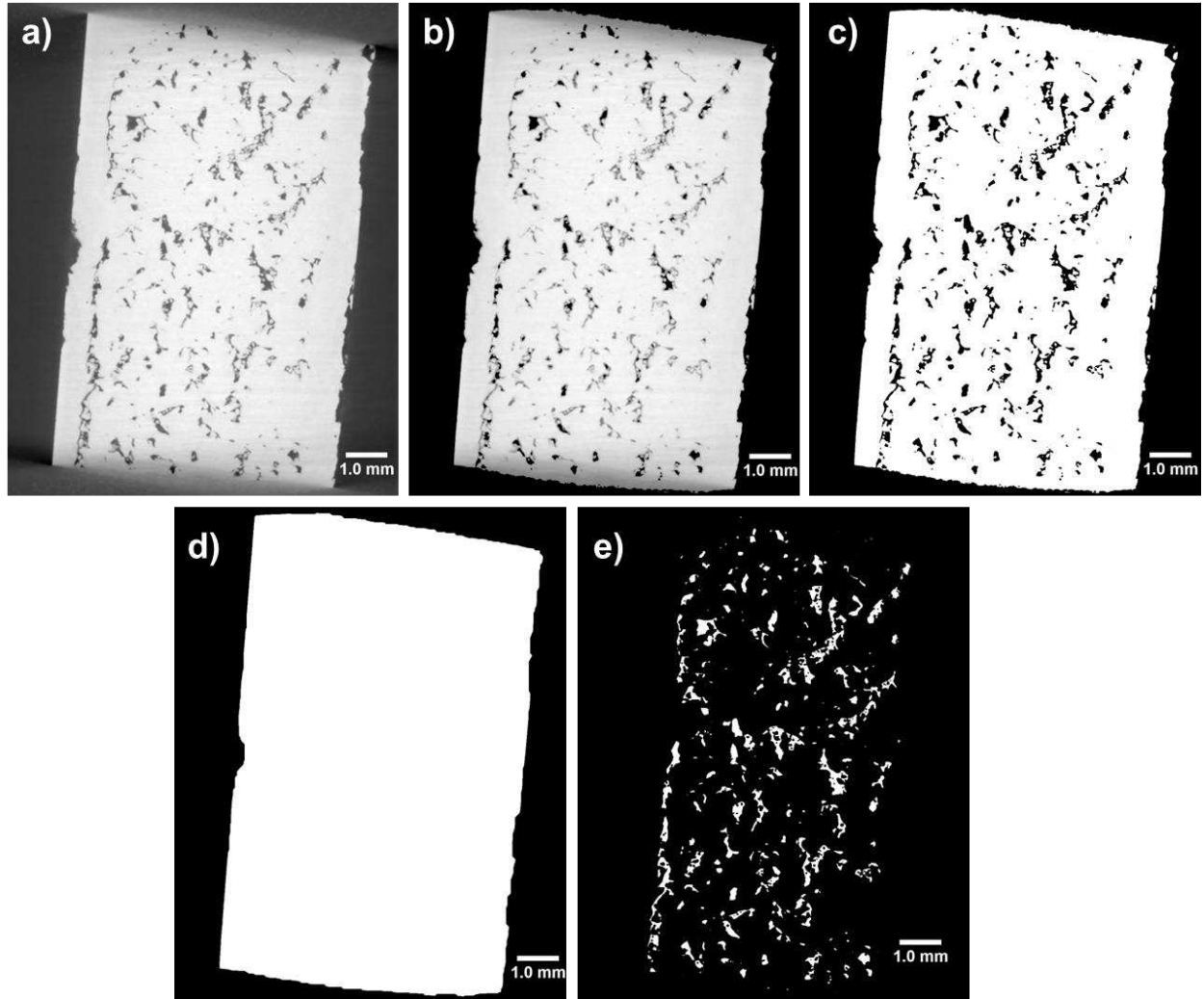


Figure 6. Two-dimensional cross-sections of the three-dimensional data showing the segmentation process of the XCT data. (a) The original data is cropped down and undergoes (b) manual grayscale thresholding followed by (c) adaptive grayscale thresholding. (d) Morphological closing is used to fill in the entire volume of the sample, which is then (e) used as a mask on the inverted image in (c) to generate segmented porosity.

3.3.3 XCT Data Analysis

Once the porosity in the datasets was segmented, the porosity in each sample could be directly quantified. This was done by counting the number of voxels in the segmented porosity (Figure 6e) and then dividing it by the volume of the entire filled segmented volume (Figure 6d). Since each sample has a slightly

different volume due to print aberrations, porosity is reported in the percentage of the total sample volume, as shown in Equation 3, as well in the total volume of the pores to provide a measurement of pore volume uninfluenced by total sample volume.

$$Porosity(\%) = \frac{Number\ of\ Pore\ Voxels}{Number\ of\ Filled\ Sample\ Voxels} * 100 \quad (3)$$

3.4 X-ray Diffraction

X-ray diffraction (XRD) is a nondestructive technique that is based on constructive interference of monochromatic X-rays with a crystalline sample. The interaction of the incident rays with crystalline planes of a sample produces constructive interference, leading to diffraction, when the conditions of Bragg's Law are satisfied according to the equation:

$$n\lambda = 2d \sin \theta \quad (4)$$

where λ is the wavelength of the incident X-rays, d is the interplanar spacing, and θ is the diffraction angle. The diffracted X-rays are then detected, processed and counted. Conversion of the diffraction peaks to d -spacings allows identification of the material by comparison of d -spacings with standard reference patterns.

XRD data of the DED AM samples were acquired at INL's IMCL using a Bruker D8 Discover with a DaVinci diffractometer utilizing a Bragg-Brentano geometry (Co-K $_{\alpha}$ radiation, $\lambda = 1.78897$ Å). The primary goniometer radius was 450 mm, and the secondary goniometer radius was 242 mm. X-ray source voltage and current values of 35 kV and 40 mA, respectively, were used with an Eiger 2R 500K (2D mode) detector with a region of interest (ROI) of $2\theta = 8.112^{\circ}$ and $\gamma = 17.309^{\circ}$. The X-ray beam was collimated to a 1.0 mm spot size. XRD patterns were collected from 20 to $130^{\circ} 2\theta$ with a 0.02° step-size and 0.5 s acquisition time per step. Measurements were performed on three spots on all 18 samples. Additionally, XRD (2θ) scans and strain measurements were performed on the same three spots on all 18 samples. The measurement locations are represented in Figure 7. Calculations and refinements to the data

were performed using DIFFRAC.EVA (v8.0, Bruker AXS, Inc.), DIFFRAC.LEPTOS (v7.14, Bruker AXS, Inc.), TOPAS (v7.0.1.4, Bruker AXS, Inc.), and the International Centre for Diffraction Database (ICDD) PDF-5+.

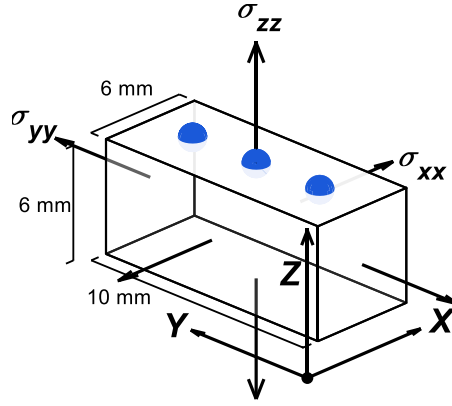


Figure 7. AM sample dimensions and coordinate system. The sample dimensions shown are representative of the AM samples analyzed but the sample dimension shown along the y-axis varies across the sample set. The blue dots indicate where XRD data were collected.

XRD residual-stress analysis is based on macroscopic elastic stress changes to the interplanar spacing d , shifting the Bragg angle. The experimentally observed strain for a given sampling direction is given by the equation:

$$\varepsilon_n = \frac{d - d_0}{d_0} \quad (5)$$

where d_0 is the stress-free lattice spacing for the chosen (hkl) reflection. The ASM International standard [49] describes the method as the determination of residual strains by XRD followed by conversion to stresses under the assumption of linear elastic distortion. A convenient common description for the XRD² method is the diffraction-vector representation. Let the unit diffraction vector, $\mathbf{n}$, be expressed as

$$\mathbf{n} = \begin{bmatrix} n_1 \\ n_2 \\ n_3 \end{bmatrix} = \begin{bmatrix} \sin \psi \cos \phi \\ \sin \psi \sin \phi \\ \cos \psi \end{bmatrix} \quad (6)$$

Then the strain measured along $\mathbf{n}$ is

$$\varepsilon_n = n_1^2 \varepsilon_{11} + n_2^2 \varepsilon_{22} + n_3^2 \varepsilon_{33} + 2n_1 n_2 \varepsilon_{12} + 2n_1 n_3 \varepsilon_{13} + 2n_2 n_3 \varepsilon_{23} \quad (7)$$

Miyazaki and Sasaki [50] show that, in diffraction-vector form, the fundamental equations of the classical $\sin \psi^2$ method, the $\cos \alpha$ method, and the XRD² method are identical; the practical difference between methods lies primarily in the set of diffraction vectors sampled and how the data are gathered. Haase et al. [51] likewise describe generalized $\sin \psi^2$ as a matrix method based on Dölle–Hauk’s equation that can accommodate arbitrary distributions of measurement directions.

For k measured strains ε_{n_i} obtained from k diffraction vectors $\mathbf{n}_i = (n_{i1}, n_{i2}, n_{i3})$, define:

$$\boldsymbol{\varepsilon}_n = \begin{bmatrix} \varepsilon_{n_1} \\ \varepsilon_{n_2} \\ \vdots \\ \varepsilon_{n_k} \end{bmatrix}, \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_{11} \\ \varepsilon_{22} \\ \varepsilon_{33} \\ \varepsilon_{12} \\ \varepsilon_{13} \\ \varepsilon_{23} \end{bmatrix} \quad (8)$$

The design matrix, $\mathbf{F}$, is then given by:

$$\mathbf{F} = \begin{bmatrix} n_{11}^2 & n_{12}^2 & n_{13}^2 & 2n_{11}n_{12} & 2n_{11}n_{13} & 2n_{12}n_{13} \\ n_{21}^2 & n_{22}^2 & n_{23}^2 & 2n_{21}n_{22} & 2n_{21}n_{23} & 2n_{22}n_{23} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ n_{k1}^2 & n_{k2}^2 & n_{k3}^2 & 2n_{k1}n_{k2} & 2n_{k1}n_{k3} & 2n_{k2}n_{k3} \end{bmatrix} \quad (9)$$

so that $\boldsymbol{\varepsilon}_n = \mathbf{F}\boldsymbol{\varepsilon}$. For isotropic X-ray elastic response, strain and stress are related by:

$$\boldsymbol{\varepsilon} = \mathbf{S}\boldsymbol{\sigma}, \boldsymbol{\sigma} = \begin{bmatrix} \sigma_{11} \\ \sigma_{22} \\ \sigma_{33} \\ \sigma_{12} \\ \sigma_{13} \\ \sigma_{23} \end{bmatrix} \quad (10)$$

with

$$\mathbf{S} = \frac{1}{E_X} \begin{bmatrix} 1 & -\nu_X & -\nu_X & 0 & 0 & 0 \\ -\nu_X & 1 & -\nu_X & 0 & 0 & 0 \\ -\nu_X & -\nu_X & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (11)$$

Here E_X and ν_X are the diffraction elastic constants for the selected reflection; equivalently, one may use X-ray elastic constants S_1 and $1/2 S_2$. Tensorial shear strain notation was used in the compliance matrix formulation. Combining the above gives

$$\varepsilon_n = \mathbf{M}\sigma, \mathbf{M} = \mathbf{F}\mathbf{S} \quad (12)$$

The generalized least-squares solution is

$$\hat{\sigma} = \mathbf{M}^\dagger \varepsilon_n \quad (13)$$

where $\mathbf{M}^\dagger$ is the Moore–Penrose pseudoinverse. This is the exact matrix form written explicitly in Miyazaki and Sasaki [50] for the unified treatment of $\sin \psi^2$, XRD², and ring-based methods.

Based on the above, residual stresses were evaluated in Bruker DIFFRAC.LEPTOS from diffraction-peak shifts measured with 2D detector frames. For each measurement direction, the lattice strain was computed from the relative change in interplanar spacing. Stress determination was formulated using the diffraction-vector fundamental equation and the elastic compliance relation between strain and stress. The resulting overdetermined linear system was solved by least squares for the stress tensor components. Stress uncertainties were obtained by propagating strain-fit uncertainties through the least-squares estimator. This formulation is consistent with generalized XRD² analysis as described in the XRD stress-analysis literature and with Bruker’s published description of LEPTOS residual-stress functionality.

For the determination of residual stress from the measured strain, the selection of diffraction elastic constants directly influences the calculated residual stresses, although it does not alter the overall trends when comparing different regions of a component. Consequently, understanding the uncertainty associated with these constants is important, as it helps define the bounds on the reported stress values. In

this work, values of $E_{311} = 183.97$ GPa and $\nu_{311} = 0.294$ were adopted from the ISODEC X-ray elastic constant software package [52, 53]. For comparison, Chen reported an experimentally measured E_{311} of 179.6 GPa for AM 316L stainless steel [54]. Meanwhile, studies of wrought 316L stainless steel have yielded E_{311} values of 183.2 GPa (Clausen [55]) and 183.7 GPa (Zhang [56]) based on theoretical calculations. Texture may also influence the effective diffraction elastic constant, but overall, the variation among these values is only a few percent which is well within the range of other measurement uncertainties. A comparable level of uncertainty is expected for G_{311} as well. The FCC lattice parameter obtained from the Rietveld refinement of the feedstock powder was $a \approx 3.60$ Å, corresponding to a stress-free d_{311} spacing of ≈ 1.085 Å and is consistent with the literature [57]. This approach introduces a potential source of systematic uncertainty if the actual composition or temperature of the measured material differs from the reference; however, given the nominal 316L stainless steel composition of the AM samples and the use of diffraction elastic constants appropriate for this alloy, this uncertainty is expected to be small relative to the observed stress magnitudes.

3.4.1 XRD Data Analysis

XRD was used to characterize the crystallographic structure, texture, and residual stress state of the AM samples. Measurements were performed at three distinct locations on each of 18 samples, providing spatially resolved data across the full specimen set. To quantify crystallographic texture, the ratio of peak intensities $R_{(111)/(200)} = I_{(111)}/I_{(200)}$ was evaluated at all 54 measurement locations. This ratio provides a systematic means of assessing the degree and type of preferred crystallographic orientation across the dataset.

Residual stresses were evaluated using the (311) crystallographic reflection, which is commonly selected for stress analysis in face-centered cubic (FCC) alloys due to its reduced sensitivity to intergranular (type II) strain effects, thereby providing a more reliable measure of the macroscopic (type I) residual stress state [58-60]. The principal stress components σ_{xx} , σ_{yy} , and σ_{zz} were determined from the (311) peak at

each measurement location. For free-surface XRD measurements, the stress component normal to the surface (σ_{zz}) is expected to relax due to the absence of external constraint, such that the stress state can be approximated as plane-stress, with σ_{xx} and σ_{yy} representing the dominant in-plane components [59, 60]. The spatial resolution of the measurements was considered necessary given the known heterogeneity of residual stress fields in additively manufactured metallic systems.

4. Results

4.1 X-ray Computed Tomography Analysis

Porosity of all 18 samples was measured with XCT, as shown in Table 3. Renderings of the segmented porosity encapsulated in the SS316 matrix in the most porous sample (Sample #8) and the least porous sample (Sample #13) are displayed in Figure 8. Porosity was generally below 0.5% for most samples, indicating relatively high density prints since density of 99.5% is a traditional metric for AM process optimization [61]. However, two prints showed significantly higher porosity values, emphasizing the impact of different fabrication parameters on component density.

Table 3. Porosity measurements of each sample.

Sample ID	Specific Energy (J/mm ²)	Powder Density (g/mm ²)	Porosity (%)	Pore volume (mm ³)
1	45	0.04	0.35	1.83
2	27	0.02	0.45	2.35
3	56	0.03	0.05	0.25
4	34	0.02	0.05	0.26
5	67	0.04	0.04	0.19
6	51	0.06	0.15	0.88
7	41	0.06	0.43	2.27
8	21	0.03	6.77	27.23
9	24	0.02	3.00	10.89

10	79	0.04	0.02	0.09
11	79	0.08	0.03	0.17
12	56	0.04	0.05	0.24
13	36	0.03	0.04	0.20
14	40	0.02	0.01	0.06
15	67	0.04	0.05	0.29
16	48	0.03	0.04	0.25
17	54	0.02	0.05	0.27
18	54	0.05	0.04	0.26

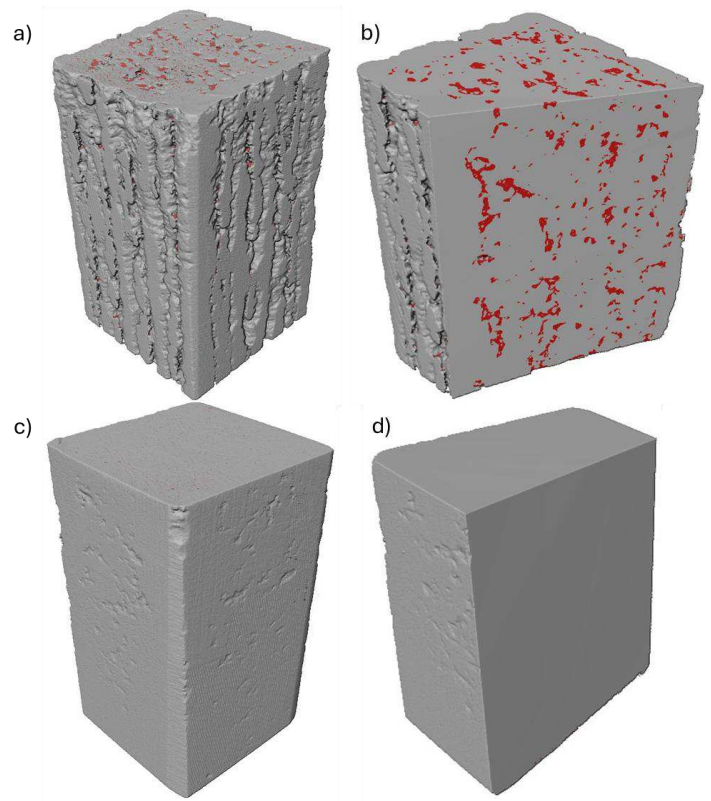


Figure 8. Three-dimensional renderings showing porosity (red) of the sample with the most porosity (Sample #8, in a) and b)) and the sample with the least porosity (Sample #14, c) and d)). Full volumes are shown (a) and c) as well as quartered volumes showing internal porosities (c) and d).

Volumetric percent porosity as a function of various sample fabrication parameters (specific energy, powder density, laser power, linear feed rate, and powder feed rate) is shown in Figure 9. Lower specific energy was observed to create larger volumes of porosity, most likely due to insufficient energy deposition to fully melt and consolidate the powder. Powder density does not seem to provide a clear correlation to porosity. Increased laser power strongly reduces porosity as more energy is provided to fully melt and consolidate the powder. The general trend for both linear feed rate and powder feed rate suggests increasing the feed rate increases the porosity, although outliers exist. This is most likely because as powder is more quickly incorporated into the print, it does not have sufficient time to receive enough energy to fully melt and consolidate into the print.

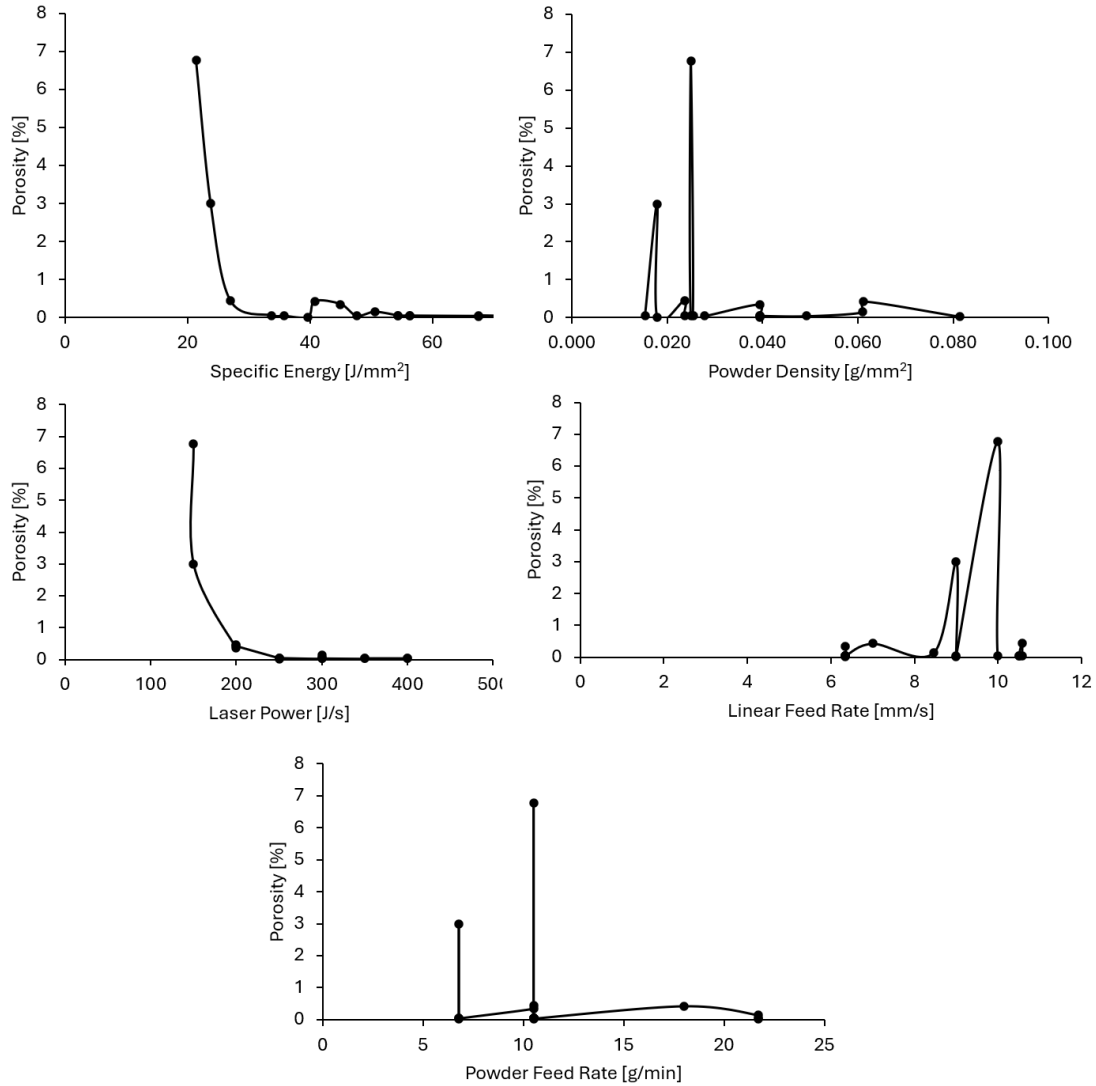


Figure 9. Porosity as a function of various fabrication parameters including (a) specific energy, (b) powder density, (c) laser power, (d) linear feed rate, and (e) powder feed rate.

4.2 XRD Phase and Texture Characterization

The XRD pattern is consistent with a single-phase FCC structure, as evidenced by the presence of all major reflections (Figure 10). No additional peaks corresponding to secondary phases or significant oxide formation are observed, indicating that the sample is a single-phase within the detection limits of XRD [58]. The relative intensities of the higher-order reflections, including (220), (311), and (222), are

consistent with an FCC structure. The (311) reflection remains well defined and sufficiently intense across all samples, confirming its suitability for residual stress determination. Stacked XRD patterns collected from all 18 samples at three locations per sample confirm consistent peak positions and a single-phase FCC structure throughout the dataset (Figure 11).

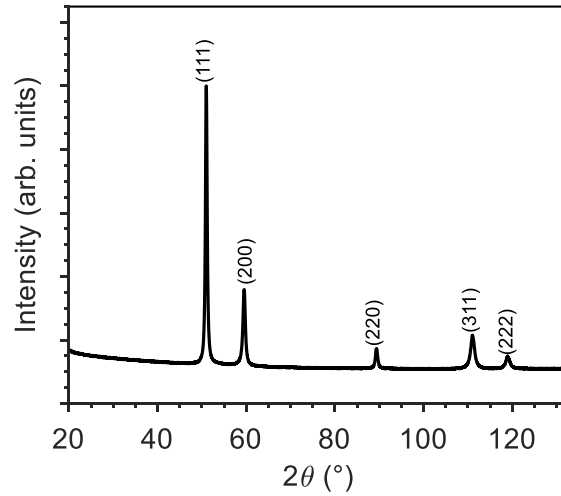


Figure 10. XRD pattern of the AM sample #1 (spot #1, 2θ range from 20° to 130°) showing characteristic reflections corresponding to an FCC structure. The (111) peak exhibits the highest intensity, indicating a preferred crystallographic orientation (texture), while the presence of all major FCC reflections confirms phase purity with no detectable secondary phases within the resolution limits of the measurement.

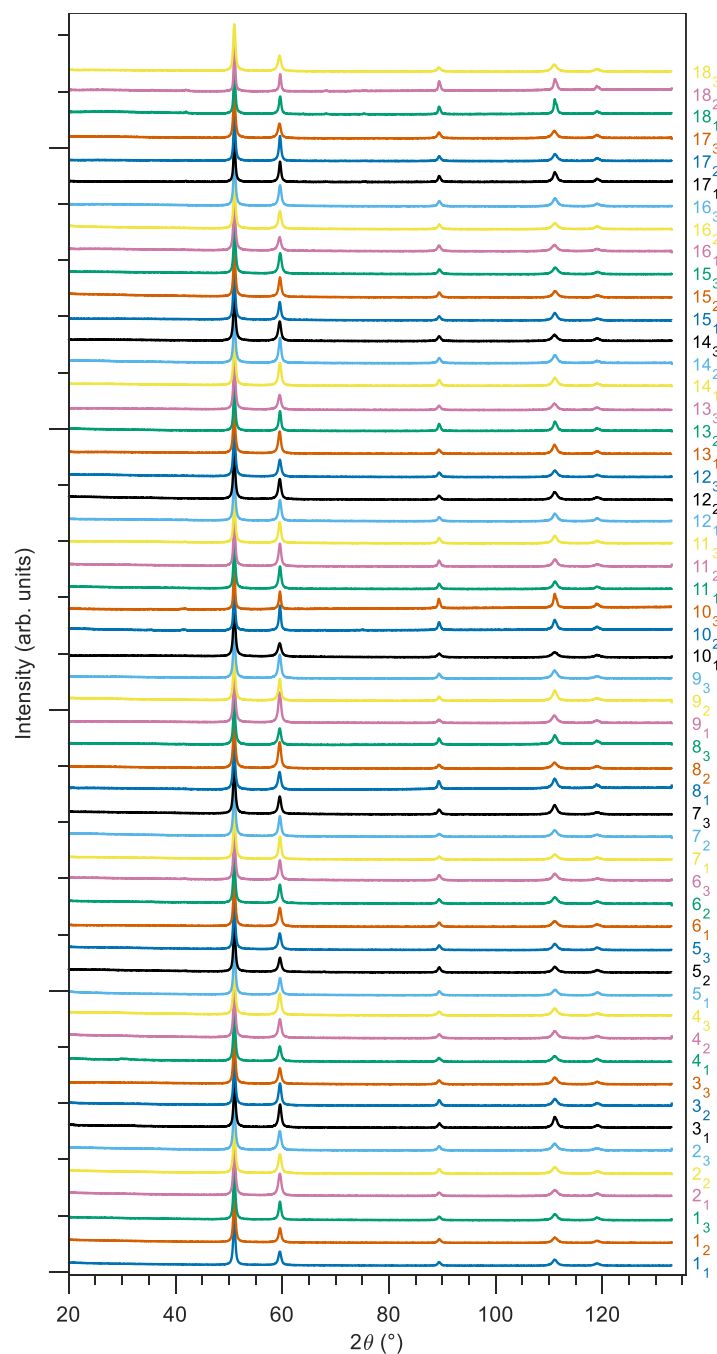


Figure 11. Stacked XRD patterns collected from the 18 samples at three distinct locations per sample, 2θ range from 20° to 130° . All patterns exhibit characteristic reflections corresponding to a single-phase FCC structure. The diffraction profiles are vertically offset for clarity. Consistent peak positions across all measurements indicate phase stability and negligible variation in lattice parameter, while variations in relative peak intensities suggest spatial heterogeneity in crystallographic texture.

Table 4. Mean and standard deviation of the XRD texture ratio $R_{(111)/(200)}$ for each of the 18 DED-fabricated SS316L samples. Values were calculated from integrated peak intensities measured at three distinct locations per sample. The consistently elevated texture ratio $R_{(111)/(200)}$ indicates a dominant (111)-type preferred crystallographic orientation throughout the sample set, while variations in the mean ratio and standard deviation reflect spatial heterogeneity in texture strength associated with local differences in thermal history, melt pool geometry, and scan strategy during the DED process.

Sample ID	Specific Energy (J/mm ²)	Powder Density (g/cm ³)	Number of measurements (n)	$R_{(111)/(200)}$	$R_{(111)/(200)}$
1	45	0.039	3	2.798559	0.279932
2	27	0.024	3	1.919643	0.150864
3	56	0.025	3	1.981605	0.442995
4	34	0.024	3	2.180374	0.446883
5	67	0.039	3	2.557177	0.160632
6	51	0.061	3	2.048657	0.011228
7	41	0.061	3	2.209035	0.245888
8	21	0.025	3	1.982081	0.358401
9	24	0.018	3	1.644477	0.270046
10	79	0.039	3	2.225019	0.594266
11	79	0.081	3	1.737855	0.037229
12	56	0.039	3	2.078874	0.22844
13	36	0.025	3	2.192046	0.462468
14	40	0.018	3	1.841023	0.22236
15	67	0.039	3	2.101175	0.279372
16	48	0.028	3	2.311475	0.555136
17	54	0.015	3	2.076686	0.465973
18	54	0.049	3	2.278473	0.154108

Evaluation of the texture ratio $R_{(111)/(200)}$ across all 54 measurement locations yields a mean value of approximately 2.2, with values ranging from approximately 1.6 to 2.8 (Figure 12 and Figure 13). The dominant intensity of the (111) reflection relative to the (200), as reflected in the consistently high texture ratio $R_{(111)/(200)}$ values, indicates a preferred crystallographic orientation favoring the (111) planes across all samples and locations, consistent with a (111)-type texture.

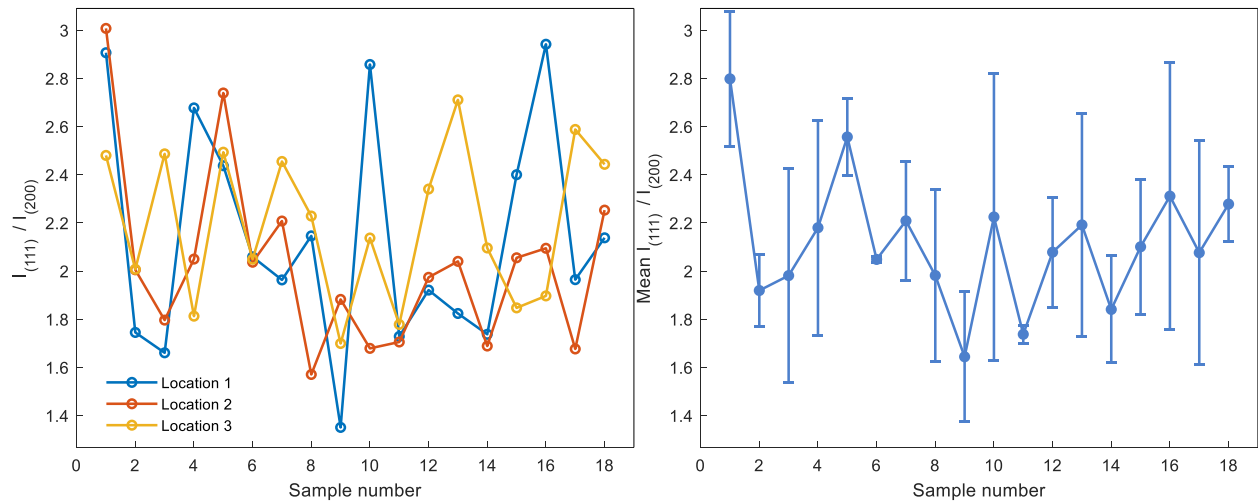


Figure 12. Quantitative analysis of the XRD texture ratio across all 18 AM samples and three measurement locations per sample. (Left) Variation in the integrated intensity ratio $I_{(111)}/I_{(200)}$ of the texture ratio $R_{(111)/(200)}$ for each measurement location, illustrating spatial heterogeneity in crystallographic texture both within individual samples and across the dataset. The consistently elevated $I_{(111)}/I_{(200)}$ values indicate a dominant (111)-type preferred orientation throughout the sample set. (Right) Sample-averaged values of $I_{(111)}/I_{(200)}$ with error bars representing one standard deviation of the three measurements acquired on each sample. Variability in the averaged texture ratio reflects local differences in melt pool geometry, thermal history, and scan strategy associated with the DED fabrication process.

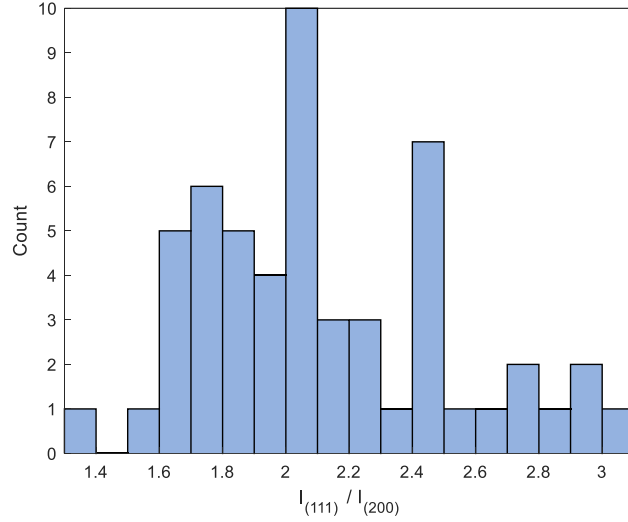


Figure 13. Distribution of the XRD texture ratio $R_{(111)/(200)}$ obtained from all 54 measurement locations across the 18 AM samples. The distribution demonstrates that the texture ratio remains consistently greater than unity throughout the dataset, confirming a persistent (111)-type preferred crystallographic orientation. The spread in values indicates moderate spatial heterogeneity in texture strength, consistent with localized variations in thermal gradients, solidification conditions, and epitaxial grain growth during additive manufacturing. No evidence of distinct multimodal populations is observed, suggesting that texture evolution remains broadly consistent across the investigated processing conditions.

4.3 Residual Stress Characterization

The residual stresses derived from the (311) reflection indicate a predominantly compressive in-plane stress state across all samples and measurement locations (Figure 13). The σ_{yy} component exhibits the largest compressive magnitudes, generally ranging from -200 MPa to -450 MPa. The σ_{xx} component is also compressive, though typically lower in magnitude and with greater variability across measurement locations and samples. The calculated σ_{zz} component remained near zero for all measurements, consistent with the plane-stress condition expected for the free-surface XRD measurements (Figure 14). Lamé stress ellipsoid plots further illustrate the three-dimensional stress state at each measurement location (Figure 15).

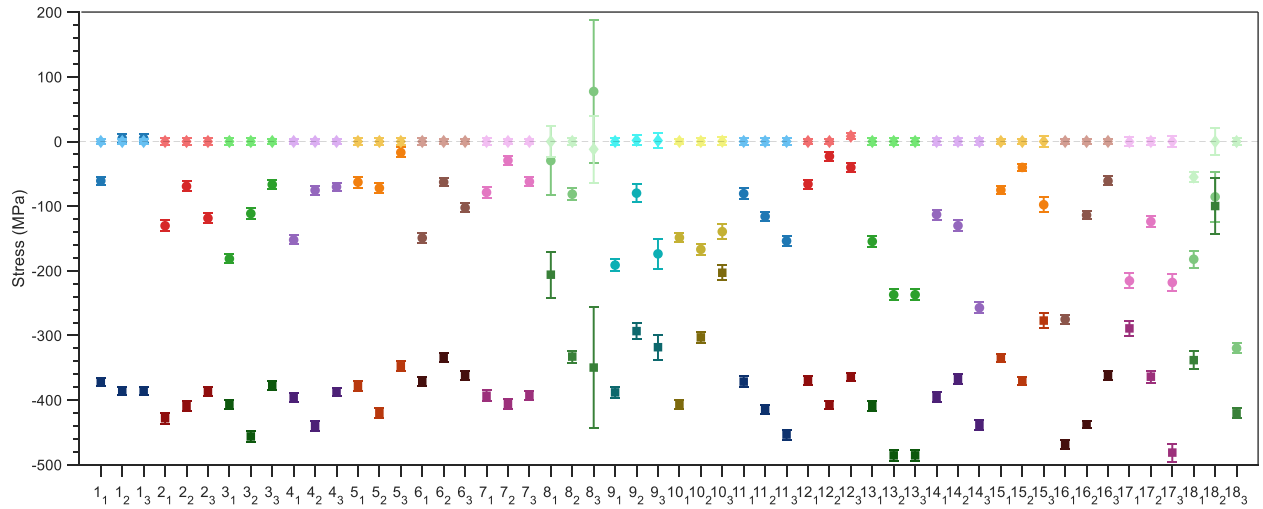
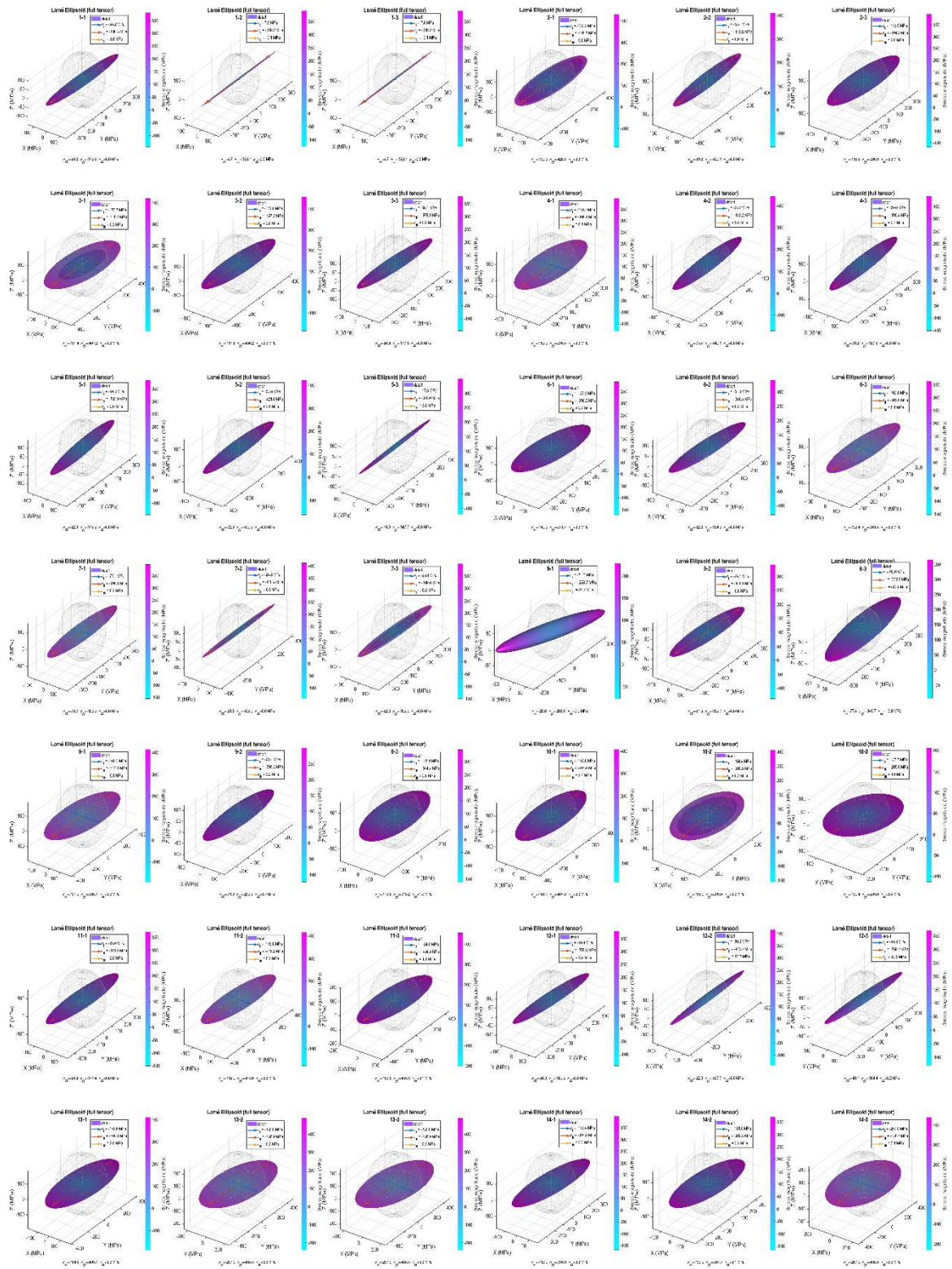


Figure 14. Residual stress components determined from XRD² analysis of the (311) reflection for all 18 AM samples at three measurement locations per sample. The measured stress components include the in-plane stresses σ_{xx} and σ_{yy} , as well as the out-of-plane component σ_{zz} . The σ_{yy} component exhibits the largest compressive magnitudes, generally ranging from approximately -200 MPa to -450 MPa, while σ_{xx} remains compressive but with greater variability across the dataset. The σ_{zz} component remains near zero for all measurements, consistent with the plane-stress condition expected for free-surface XRD measurements. Error bars represent uncertainties propagated through the least-squares fitting procedure used in the generalized XRD² stress analysis. The observed spatial heterogeneity in the stress components reflects localized process-induced variations associated with melt pool geometry, scan strategy, and thermal history during DED fabrication.



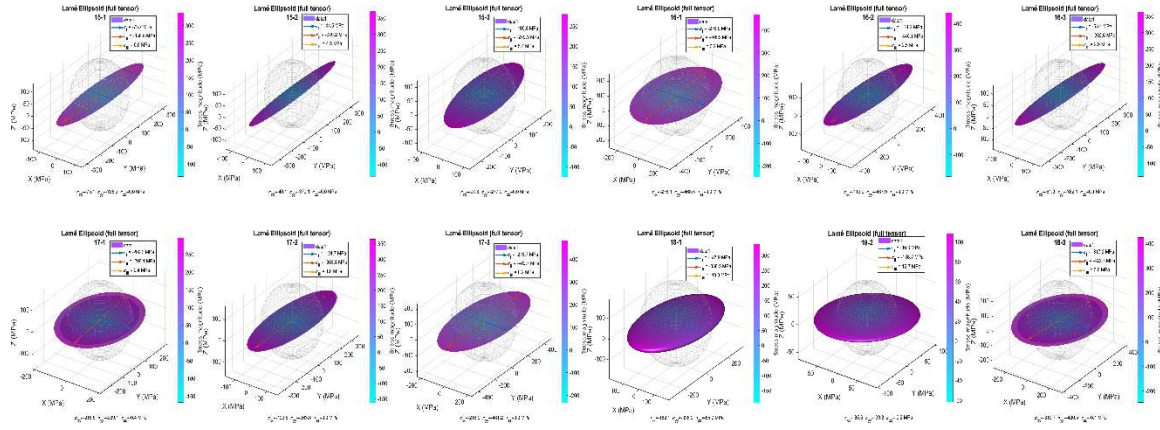


Figure 15. Lamé stress ellipsoid representations of the measured residual stress state for all 18 samples at three measurement locations per sample, derived from the (311) XRD² stress analysis. Each ellipsoid encodes the magnitude and directionality of the principal stress components σ_{xx} , σ_{yy} , and σ_{zz} , where the size of the ellipsoid along each axis reflects the magnitude of the corresponding stress component. The consistent elongation along the σ_{yy} axis across samples reflects the dominant compressive stress in that direction, while variability in the σ_{xx} dimension illustrates the spatial heterogeneity.

Significant spatial heterogeneity in residual stress is observed both within individual samples and across the set of 18 specimens. Measurements obtained at different locations on the same sample frequently exhibit substantial variation, particularly in the σ_{xx} component, while σ_{yy} consistently maintains higher compressive values. No clear monotonic trend in stress with position is observed across the dataset.

Measurement uncertainties are generally moderate; however, increased scatter and larger error bars are observed in certain data points, particularly for σ_{xx} , most likely due to some remaining surface roughness and imperfections on specific samples.

5. Discussion

5.1 Porosity

Since both the pycnometry and XCT measurements were taken on polished samples, the pycnometry measurements were used to calculate porosity-equivalent density deficits and equivalent pore volumes

which were then compared with the segmented XCT data to serve as an independent assessment on the segmentation of the XCT data. Agreement between the two methods within propagated pycnometry uncertainty supports the reliability of the XCT segmentation, whereas large discrepancies may indicate differences in pore measurements of the two techniques. Small pores within the sample below the spatial resolution of the XCT data lead to pycnometry measuring a higher pore volume while surface-connected pores may be measured with XCT but not registered as closed-pore density deficits by pycnometry, causing the XCT data to measure more porosity.

Pycnometry equivalent porosity (P_{pyc}) is the pycnometry-derived porosity-equivalent density calculated using the assumed fully dense SS316L reference density ($\rho_0 = 8.000 \text{ g/cm}^3$) and the pycnometry measured density (ρ_{pyc}) in conjunction with Equation 14. Uncertainty ($u_{P_{pyc}}$) is propagated from the pycnometry density uncertainty (u_p) as shown in Equation 15. The absolute porosity difference (ΔP) is the difference between the pycnometry equivalent porosity and the XCT porosity (P_{XCT}), displayed in Equation 16. Absolute porosity difference is normalized by the pycnometry porosity uncertainty (Equation 17) to indicate whether disagreement between the pycnometry and XCT porosity measurements is large relative to pycnometry measurement uncertainty.

$$P_{pyc} = 100 * (1 - \frac{\rho_{pyc}}{\rho_0}) \quad (14)$$

$$u_{P_{pyc}} = \frac{100}{\rho_0} u_p \quad (15)$$

$$\Delta P = P_{pyc} - P_{XCT} \quad (16)$$

$$\Delta P_{Normalized} = \frac{\Delta P}{u_{P_{pyc}}} \quad (17)$$

Similar calculations are also conducted for the pore volume measurements. Pycnometry equivalent pore volume ($V_{pore,pyc}$) converts the pycnometry-equivalent porosity into an equivalent pore volume using Equation 18. Uncertainty in this calculation is propagated following Equation 19, where $u_{V_{pyc}}$ represents

the uncertainty in the pycnometry volume measurement. The absolute volume difference and normalized volume difference are calculated in the same manner as for the porosity using the corresponding volume values. Results of the comparisons between the two measurement techniques are summarized in Table 5.

$$V_{pore\ pyc} = V_{pyc} \left(\frac{P_{pyc}}{100} \right) \quad (18)$$

$$u_{pore\ pyc} = \sqrt{\left(\frac{V_{pyc}}{100} u_{P_{pyc}} \right)^2 + \left(\frac{P_{pyc}}{100} u_{V_{pyc}} \right)^2} \quad (19)$$

Table 5. Comparison of pycnometry and XCT measurements.

Sample	Pycnometry Density (g/cm ³)	Pycnometry Volume (mm ³)	Pycnometry Equivalent Porosity (%)	XCT Porosity (%)	$\Delta P = P_{yc} - P_{XCT}$ (%)	$\Delta P / uP$	Pycnometry Equivalent Pore Volume (mm ³)	XCT Pore Volume (mm ³)	$\Delta V = P_{yc} - P_{XCT}$ (mm ³)	$\Delta V / uV$
1	7.9570 ± 0.0143	525.1 ± 0.053	0.538 ± 0.179	0.35	+0.188	+1.05	2.82 ± 0.94	1.83	+0.99	+1.05
2	7.9570 ± 0.0183	520.0 ± 0.052	0.538 ± 0.229	0.45	+0.088	+0.38	2.80 ± 1.19	2.35	+0.45	+0.38
3	7.9742 ± 0.0231	503.9 ± 0.101	0.323 ± 0.289	0.05	+0.273	+0.94	1.63 ± 1.46	0.25	+1.38	+0.95
4	7.9679 ± 0.0255	513.5 ± 0.103	0.401 ± 0.319	0.05	+0.351	+1.10	2.06 ± 1.64	0.26	+1.80	+1.10
5	7.9676 ± 0.0255	511.6 ± 0.102	0.405 ± 0.319	0.04	+0.365	+1.14	2.07 ± 1.63	0.19	+1.88	+1.15
6	7.9629 ± 0.0064	601.6 ± 0.060	0.464 ± 0.080	0.15	+0.314	+3.93	2.79 ± 0.48	0.88	+1.91	+3.98
7	7.9574 ± 0.0191	516.8 ± 0.103	0.533 ± 0.239	0.43	+0.103	+0.43	2.75 ± 1.23	2.27	+0.48	+0.39
8	7.9347 ± 0.0246	392.4 ± 0.078	0.816 ± 0.307	6.77	-5.954	-19.39	3.20 ± 1.21	27.23	-24.03	-19.86
9	7.9271 ± 0.0254	344.0 ± 0.034	0.911 ± 0.317	3.00	-2.089	-6.59	3.13 ± 1.09	10.89	-7.76	-7.12
10	7.9632 ± 0.0215	526.7 ± 0.105	0.460 ± 0.269	0.02	+0.440	+1.64	2.42 ± 1.42	0.09	+2.33	+1.64
11	7.9490 ± 0.0382	625.7 ± 0.250	0.638 ± 0.477	0.03	+0.608	+1.27	3.99 ± 2.98	0.17	+3.82	+1.28
12	7.9638 ± 0.0279	529.2 ± 0.106	0.453 ± 0.348	0.05	+0.403	+1.16	2.39 ± 1.84	0.24	+2.15	+1.17
13	7.9562 ± 0.0263	501.0 ± 0.100	0.548 ± 0.328	0.04	+0.508	+1.55	2.74 ± 1.64	0.20	+2.54	+1.55
14	7.9628 ± 0.0327	472.1 ± 0.094	0.465 ± 0.408	0.01	+0.455	+1.12	2.20 ± 1.93	0.06	+2.14	+1.11
15	7.9610 ± 0.0334	513.5 ± 0.154	0.488 ± 0.418	0.05	+0.438	+1.05	2.50 ± 2.15	0.29	+2.21	+1.03
16	7.9553 ± 0.0247	549.7 ± 0.110	0.559 ± 0.308	0.04	+0.519	+1.68	3.07 ± 1.69	0.25	+2.82	+1.67
17	7.9571 ± 0.0374	586.4 ± 0.176	0.536 ± 0.467	0.05	+0.486	+1.04	3.14 ± 2.74	0.27	+2.87	+1.05
18	7.9454 ± 0.0429	622.6 ± 0.249	0.682 ± 0.536	0.04	+0.642	+1.20	4.25 ± 3.34	0.26	+3.99	+1.19

The low-porosity samples (particularly Samples 1, 2, and 7) show reasonably well agreement between the pycnometry-equivalent porosity and pore volume and the XCT values within the pycnometry uncertainty, providing evidence the XCT segmentation is capturing the resolvable pores in these samples. Many other low-porosity samples show pycnometry yielding slightly higher values than XCT, likely indicating the combined effects of pycnometry uncertainty and smaller porosity not resolved within the XCT spatial resolution. The highest porosity samples (Samples 8 and 9) have much higher pore values for XCT than pycnometry, which is physically consistent with large surface-connected or helium-accessible lack-of-fusion defects that are counted as voids by the XCT measurements but not the pycnometry measurements. Overall, these results emphasize the quality of the segmentation for the lower-porosity samples while the samples with larger disagreements demonstrate the sensitivity of pycnometry and XCT to different pore-connectivity conditions.

X-ray computed tomography measurements indicate porosity can be minimized by increasing energy input relative to the power delivery and travel speed. Higher feed rates should be avoided unless they are paired with higher laser power sufficient to completely melt the powder. In this study, the two samples produced with a laser power of 150 W exhibited the highest porosity while all samples fabricated with a laser power of 200 W or greater had a porosity below 0.5 vol%. Combined with the statistically significant relationship between increased laser power/specific energy and decreased porosity, laser power should be above a determined minimum threshold when producing samples.

While a couple of samples exhibited widespread porosity, the majority of the porosity, as observed in the segmented XCT datasets, was at the base of the sample near the build plate. This is consistent with other observations in the literature which note an increase in porosity in the initial print layers near the build plate, which may be due to melt pool gradient caused in part by the colder substrate or unstable powder flow during the initial fabrication steps [62]. Increased porosity was also observed at higher powder flow rates which is consistent with other work describing how reduced flow rate can allow the powder to be caught by the melt pool and create denser parts [39].

5.2 Texture

The consistently high texture ratio $R_{(111)/(200)}$ values confirm a (111)-type preferred crystallographic orientation, which is commonly observed in AM FCC materials and is associated with directional solidification and epitaxial grain growth under strong thermal gradients [38, 63, 64]. The observed (111)-type texture indicates preferred crystallographic orientation produced by directional solidification and repeated thermal cycling during DED. Because AM textures are strongly dependent on thermal gradients, scan strategy, melt pool geometry, and measurement geometry, additional EBSD pole figures would be needed to unambiguously relate the diffraction texture to a specific crystallographic growth direction [38, 63, 64]. The observed spread in the texture ratio $R_{(111)/(200)}$ values, ranging from 1.6 to 2.8, indicates spatial heterogeneity in texture strength, reflecting local variations in processing conditions such as melt pool geometry, scan strategy, and thermal history [38, 63]. The deviations in relative peak intensities from standard powder diffraction intensities further support the presence of preferred orientation throughout the sample set. Additionally, crystallographic texture can influence both mechanical properties and residual stress development, as well as the material's response to irradiation and corrosion [38, 54, 57, 65-78]. The observed spatial variation in texture strength may also contribute to the anisotropic residual stress distribution through orientation-dependent elastic and plastic accommodation during thermal contraction.

5.3 Residual Stress

The predominance of compressive in-plane residual stresses is consistent with the rapid thermal cycling and constrained solidification inherent to AM processes, which typically result in surface and near-surface compressive states following cooling [38, 63, 64]. The near-zero σ_{zz} values across all measurements confirm that the plane-stress approximation is appropriate for this dataset and are consistent with expectations for free-surface XRD measurements [59, 60].

The observed difference between σ_{xx} and σ_{yy} indicates a non-equibiaxial in-plane stress state, reflecting directional dependencies associated with the AM process. The significant spatial heterogeneity in

measured stresses, particularly in σ_{xx} , suggests that process-induced anisotropy arising from scan strategy, melt pool geometry, build orientation, and repeated thermal cycling plays a dominant role in governing the residual stress distribution [58-60]. This behavior is consistent with prior observations in additively manufactured metallic systems and highlights the importance of spatially resolved measurements for accurate stress assessment.

The increased scatter and larger error bars observed in certain σ_{xx} measurements likely arise from local microstructural variability, including crystallographic texture and steep stress gradients within the small X-ray sampling volume [59, 60]. Importantly, the absence of a clear monotonic trend in stress with position suggests that the residual stress state is governed by localized process-induced phenomena rather than a simple macroscopic gradient. Given the reduced sensitivity of the (311) reflection to intergranular strain, the observed scatter is interpreted as representative of true spatial variations in the bulk residual stress field rather than artifacts of grain-to-grain elastic anisotropy [58-60].

5.4 Statistical Evaluation

Pearson [79] and Spearman [80] statistical analysis were applied to evaluate the relationship of laser power, specific energy, powder density, linear feed rate and powder feed rate on porosity. Porosity data was log transformed to reduce the large dynamic range of porosity values, which spanned several orders of magnitude. The Pearson r value quantifies the strength and direction of the linear relationship between each DED fabrication parameter and the logarithmically transformed porosity values measured with XCT. The Pearson p value indicates the statistical significance of the linear relationship. Meanwhile the Spearman ρ value assesses the strength and direction of the rank-order/monotonic relationship between the same variables while Spearman p tests whether the monotonic association is significant. The results of these analyses are summarized in Table 6. Higher laser power and specific energy were found to have a statistically significant and consistent trend with reduced XCT-measured porosity while the other parameters did not display a statistically significant trend.

Table 6. Results of correlation testing between fabrication parameter and porosity.

Parameter	Pearson (<i>r</i>)	Pearson (<i>p</i>)	Spearman (<i>ρ</i>)	Spearman (<i>p</i>)	Significance	Direction	Interpretation
Laser Power	-0.739857	0.000448	-0.697493	0.001292	Significant and Robust	Negative	Higher laser power correlates with lower log porosity
Specific Energy	-0.682333	0.001810	-0.585139	0.010743	Significant and Robust	Negative	Higher specific energy correlates with lower log porosity
Powder Density	-0.141943	0.574226	-0.153110	0.544149	Not Significant	Negative	No statistically significant univariate relationship
Linear Feed Rate	0.216393	0.388438	0.220089	0.380184	Not Significant	Positive	Positive trend is weak and not statistically significant
Powder Feed Rate	-0.067194	0.791077	-0.051667	0.838664	Not Significant	Negative	Not statistically significant

6. Conclusion

X-ray computed tomography results confirm the majority of fabrication parameters employed in this study produce parts with acceptable levels of porosity (<0.5 vol%). Porosity is primarily observed in the initial few layers near the base plate, most likely due to incomplete powder deposition and thermal gradients caused by the cold base plate. Laser power was the strongest correlation to porosity as lower power levels caused insufficient energy deposition to fully melt and consolidate the powder. Powder flow rate that was too quick to uniformly deposit the powder also resulted in high porosity levels. Individual parameters should not be optimized but rather the combination of parameters must be such to maintain a stable melt pool by providing sufficient energy per unit length and energy per powder mass to avoid lack-of-fusion porosity while also avoiding too much energy which will result in keyhole porosity caused by evaporation.

The XRD characterization confirms a single-phase FCC structure with a consistent (111)-type crystallographic texture across all 18 AM samples, with moderate spatial variation in texture strength

attributable to local differences in processing conditions. Residual stress analysis reveals a predominantly compressive, non-equibiaxial in-plane stress state, with σ_{yy} exhibiting the largest compressive magnitudes (–200 to –450 MPa) and significant spatial heterogeneity observed throughout the dataset.

The predominance of compressive in-plane residual stresses, particularly in σ_{yy} , may be beneficial in mitigating crack initiation and propagation under corrosive or irradiation-assisted degradation conditions. However, the non-equibiaxial stress state and spatial variability could promote localized stress concentrations, which may act as preferential sites for damage accumulation under service conditions such as neutron or ion irradiation and corrosive environments [69-78, 81]. These findings underscore the need for spatially resolved stress characterization in AM components intended for high-consequence nuclear applications, including those subject to neutron or ion irradiation and corrosive service environments, and highlight the critical role of process parameter control in governing texture development and residual stress evolution in DED-fabricated SS316L.

Overall, this work addresses a gap between additive manufacturing process development and qualification-relevant evidence for nuclear service by correlating DED processing conditions with internal defect populations and residual stress states in SS316L. These results illuminate which fabrication parameters most strongly influence porosity, how porosity defects are distributed within the part, and how the resulting material state is reflected in crystallographic texture and spatially heterogeneous residual stresses. Additionally, the use of XCT and XRD in this work helps demonstrate that nondestructive examination techniques can provide the necessary quantitative, spatially resolved information needed to identify potential performance-limiting defect and stress conditions, and support data-driven qualification of advanced manufactured components. For nuclear applications, future work should include using nondestructive examination techniques in conjunction with destructive examinations for validation to qualify nondestructive techniques to examine neutron irradiation-induced defects and stress states in advanced manufactured material. The findings in this study help lay a foundation for integrating

nondestructive characterization into qualification pathways for additively manufactured materials intended for high-consequence nuclear applications.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRedit authorship contribution statement

W. Chuirazzi: Conceptualization, Resources, Methodology, Supervision, Project administration, Formal analysis, Investigation, Writing –original draft, Writing –review & editing, Visualization. **B. Newell:** Methodology, Formal analysis, Writing –original draft, Writing –review & editing. **M. McMurtrey:** Funding acquisition, Methodology, Formal analysis, Supervision, Investigation, Writing –review & editing. **A. Monson:** Resources, Writing –review & editing. **A. Ziabari:** Resources, Methodology, Investigation, Writing –original draft. **O. Rahman:** Resources, Methodology, Investigation, Writing –original draft. **D. Lovato-Admire:** Investigation, Writing –review & editing. **C. Tsai:** Resources, Methodology, Writing –review & editing. **R.R. Kancharla:** Resources, Methodology, Writing –review & editing.

Acknowledgements

The authors thank Craig Marshall and Narayan Poudel for pycnometry measurements.

Funding: This work was supported by the Department of Energy, Office of Nuclear Energy Advanced Materials and Manufacturing Technologies (AMMT) program. Damian Lovato-Admire's work was supported under a RENEW internship, Office of Science Isotopes Program Field Work Proposal No: D000-22-2765.

Data Availability: Data sets generated during the current study are available from the corresponding author on reasonable request.

Declarations

Competing Interest: The authors declare no competing interests.

Ethics declaration: not applicable.

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