Computed Tomography-Based Modeling of Process-Structure Relationships for Additively Manufactured Microscale Features

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Abstract

Laser powder bed fusion (LPBF) additive manufacturing (AM) enables the creation of geometries, such as lattice structures, which are impossible to manufacture using traditional methods. Lattice structures are favored for their high strength-to-weight ratios [1], tunable and gradable properties [2], and energy absorption capacity [3]. However, due to their small features, tortuous surfaces, and internal defects, which are inextricably linked to manufacturing parameters, lattice performance is detrimentally impacted [4,5]. Manufacturing strategies for mitigation, and effects on performance are either underdeveloped or not yet fully understood. To address this knowledge gap, this study focuses on understanding the influence of manufacturing parameters on structural outcomes by modeling the process-structure (PS) relationships in microscale LPBF features. Herein, it is demonstrated that high-throughput CT-based inspection can enable the creation of statical and machine learning models which can predict geometric characteristics of lattices with up to 98% accuracy.

Background

- Lattice structures exemplify the design freedom offered by laser powder bed fusion (LPBF) additive manufacturing (AM) [6]
- Lattices offer unique capabilities [7], but are hampered by many manufacturing, inspection, and post-processing challenges.

Research Gap: The complex relationships between the LPBF process parameters and resulting strut characteristics are not well-understood.

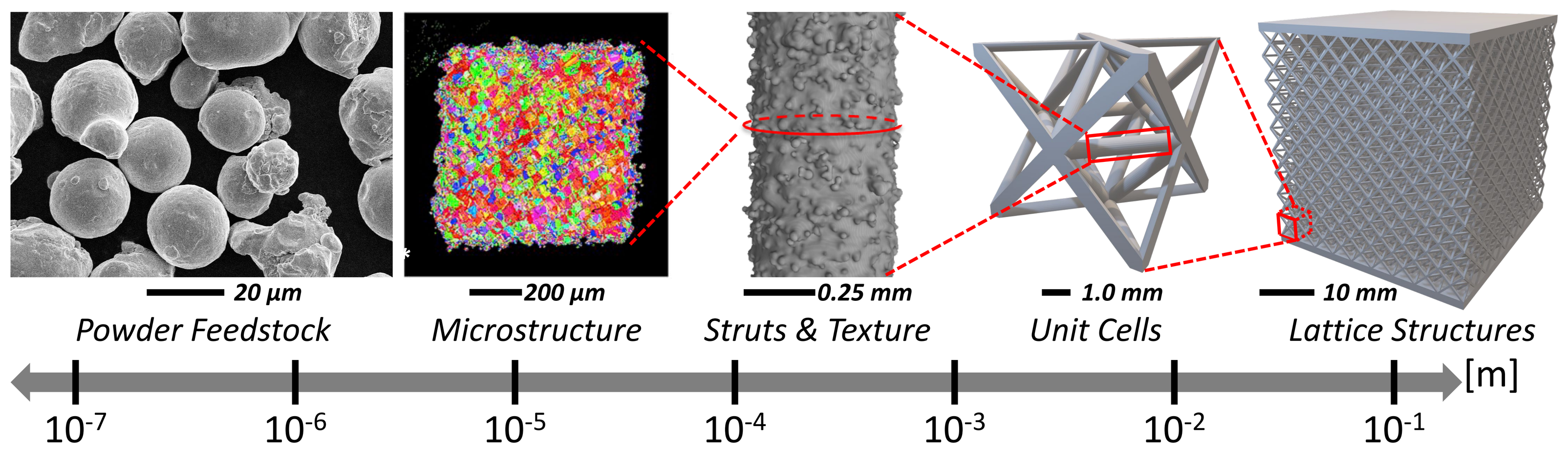

Figure 1. Scales of complexity within AM lattice structures

Methodology

Manufacture: Design and manufacture high-throughput CT inspection sample(s) for high-throughput characterization of lattice strut geometry.

Geometry: Characterize 450 strut parameter combinations using rapid, high-fidelity, automated CT inspection methodology.

Modeling: Develop statistical and machine learning models to predict strut geometry using manufacturing process parameter inputs.

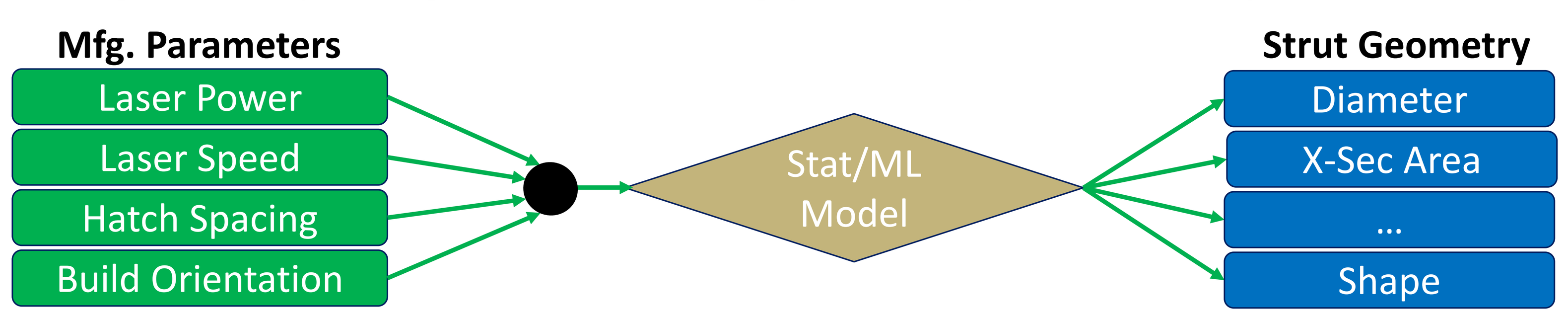

Figure 2. Structure of model predicting strut geometry from manufacturing parameter inputs

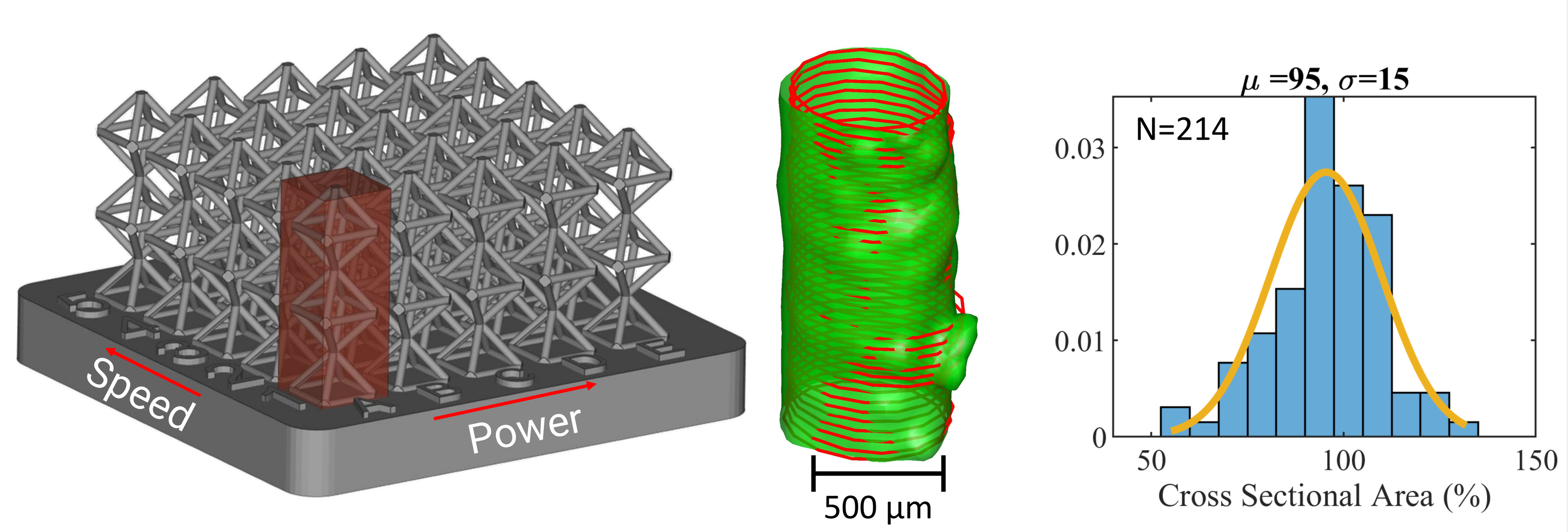

Figure 3. Geometry inspection process. a) CT scan part, isolate parameter stack, b) Analyze strut geometry through best ellipses, c) Create statistical information about struts for models.

Results

Manufacturing Results Summary

- Struts built for full-factorial (450 combinations) evaluation of:
  - Laser power (5 levels)
  - Laser speed (5 levels)
  - Hatch spacing (3 levels)
  - Strut orientation (6 levels)
- Strut geometry visually varied as a function of processing parameter (see figure at right)
- Ellipse geometry was modeled using a cross-sectional analysis and best fit ellipse approach:
  - BF ellipse major & minor axis length
  - BF ellipse axis ratio & eccentricity
  - Cross sectional area
  - Area moment of inertia

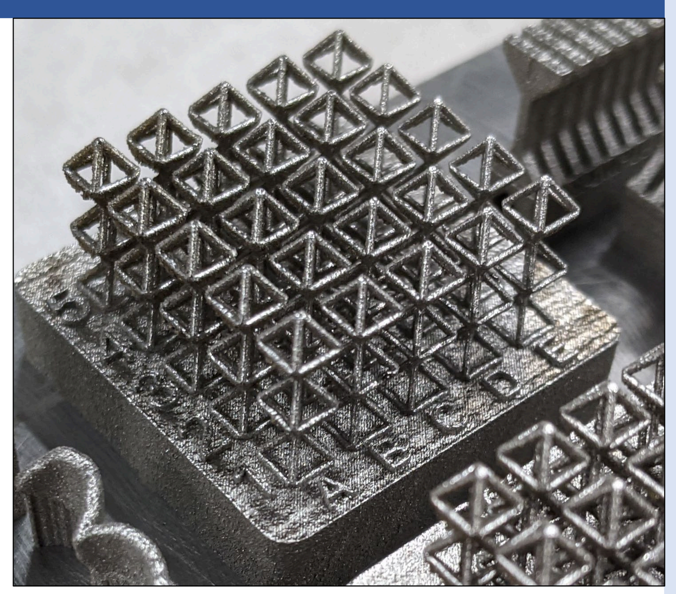

Figure 4. Printed CT artifact

Geometry Inspection Summary

- Strut geometry was found to change significantly as a function of processing parameter.
- Struts were highly non-cylindrical
- No process combination produced a consistently cylindrical strut

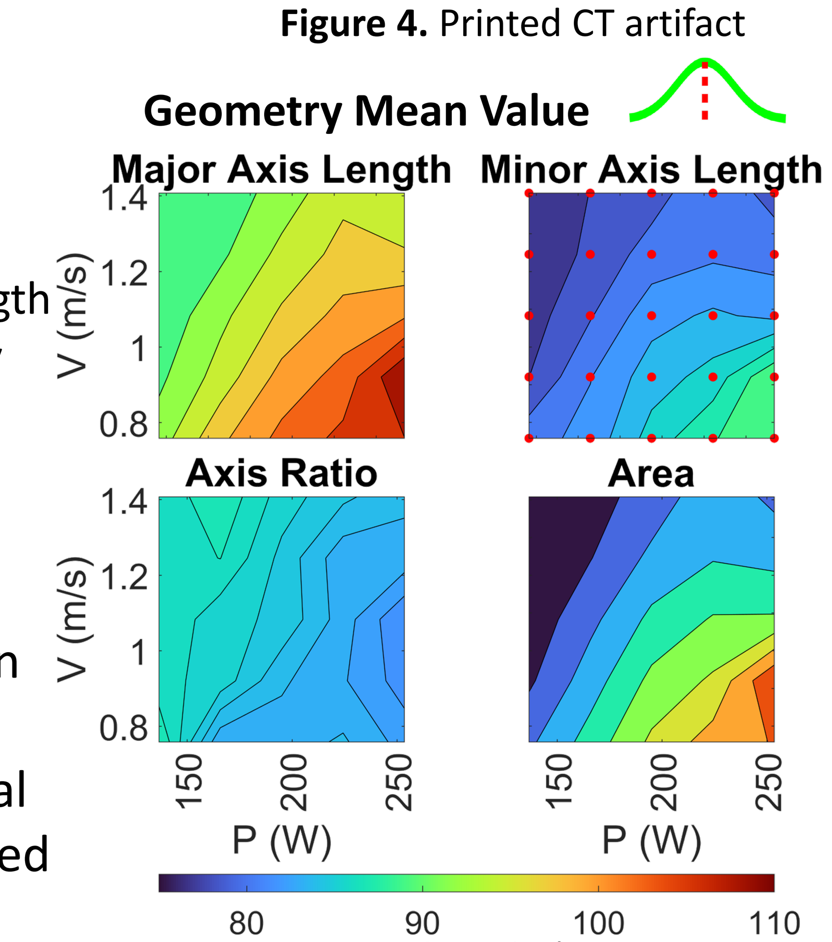

Figure 5. Strut geometry maps

Statistical & Machine Learning Summary

- Process-structure models predicted process with high accuracy across a range of processing parameters
- Accuracies of models exceeded >98% in certain cases
- ML performed better than statistical modeling in nearly all cases

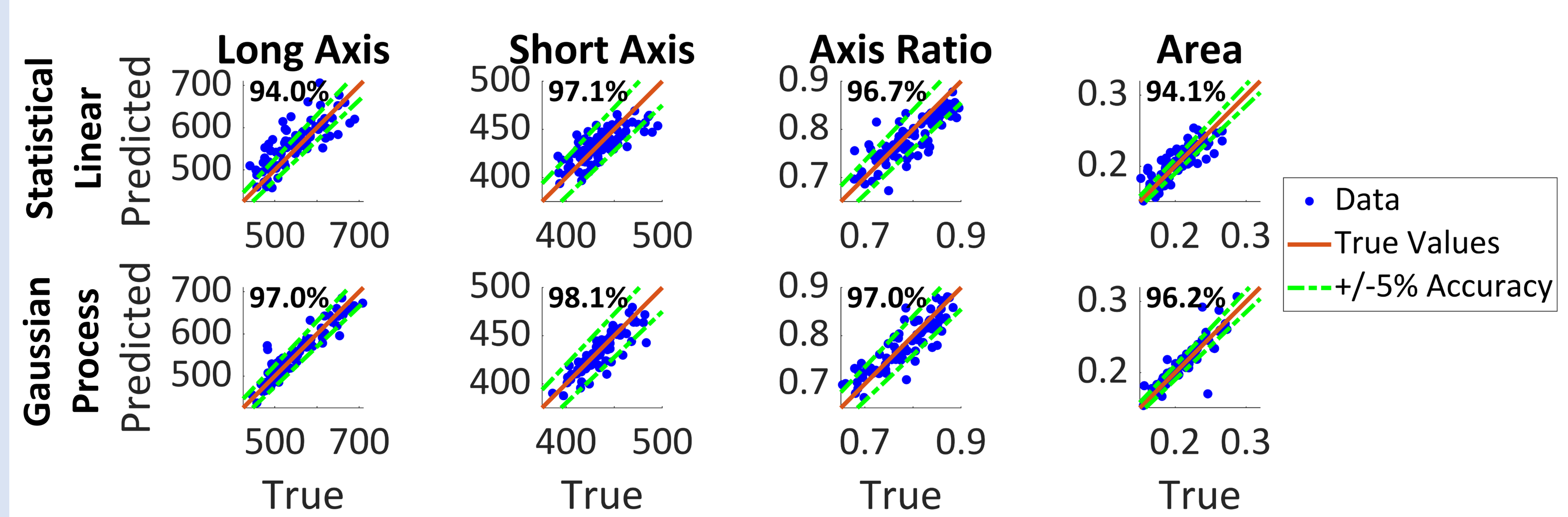

Figure 6. Results overview of statistical linear and gaussian process regression models

Discussion

- Strut geometry varied significantly, with mean major axis values in excess of 50% above nominal, but followed a clear trend
- Multiple ML models were developed to test relative performance, with varying accuracy
- Full-factorial design of experiment approach provided for increased confidence in observed trends due to its exhaustive nature
- The developed models can be used for optimization of lattice manufacture and are transferable to strut-based lattices of all types.
- Model prediction error assessed using Normalized Root Mean Squared Error (NRMSE) to compare across model types.

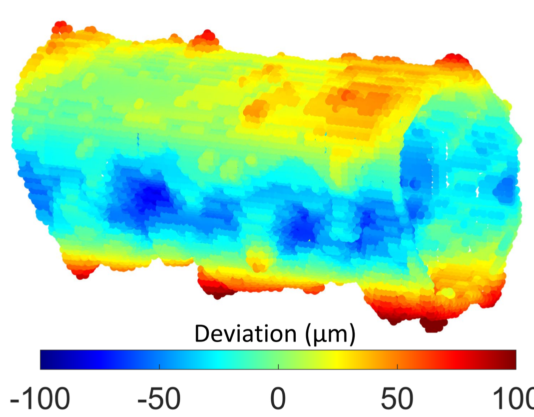

Figure 7. Strut geometry deviation from nominal

$$NRMSE = \sqrt{\frac{1}{n}\frac{\sum(y_{pred}-y_{true})^2}{y_{true}}}$$

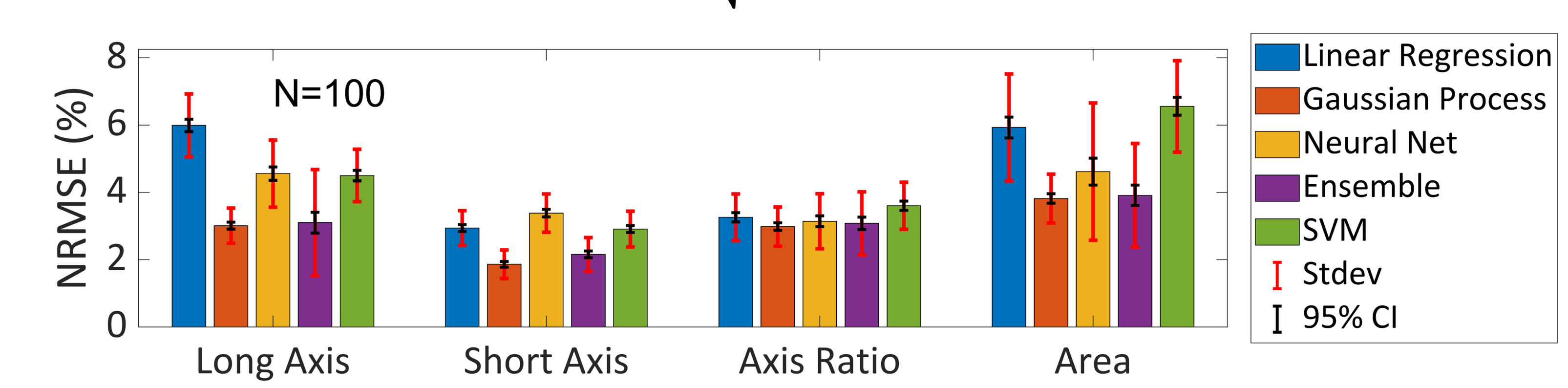

Figure 7. Performance comparison of developed models.

Conclusions

1. Lattice strut structure and geometry varies widely (+/- 30% nominal in worst cases) due to process parameter variation.
2. Statistical regression models performed well in predicting strut geometry. NRMSE <3% in the best cases.
3. Machine learning models equaled or outperformed statistical regression models in nearly all cases, with NRMSE of <2%.
4. Statistical models provide for further intuition into physical drivers of observed trends compared to machine learning.

Next Steps/Future Work:

- Incorporate more lattice characteristics into modeling framework
  - Microstructural aspects of lattices
  - Hardness properties of lattices
- Include mechanical performance of lattices in modeling framework

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