Multi-scale feature prediction and signature identification for directed energy deposition

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Introduction

Additive manufacturing (AM) techniques provide novel opportunities for the fabrication of advanced materials and multi-functional properties of complex geometries with reduced processing routes as compared to conventional manufacturing techniques. However, the ability to define and predict these responses within the processing-structure-property (PSP) relationships is not mature. In this study, we present a machine learning (ML) approach that can be used to identify both macro and micro-scale signatures of 316L stainless steel components manufactured using directed energy deposition (DED) to enable predictive processing strategies of AM signatures.

Goal

Understand, predict, and control the PSP relationships between process parameters, dendrite arm spacing (DAS), and build height.

Equations

$$\Pi_2 = \frac{p \times \alpha}{v * D * \dot{m} * H} * \frac{z}{h}$$

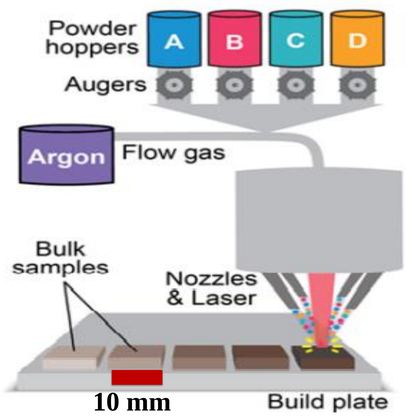
$$VED = \frac{p}{h * z * v}$$

$$COH = \frac{\text{Actual Build Height}}{n * z}$$

Variable	Units
Laser power, (p)	W
Hatch spacing, (h)	mm
Z step, (z)	mm
Scanning speed, (v)	mm/s
Number of layers, (n)	(-)
Laser spot size, (D)	mm
Mass flow rate, ($\dot{m}$)	g/s
Thermal diffusivity, (α)	mm^2/s
Latent heat of fusion, (H)	j/g

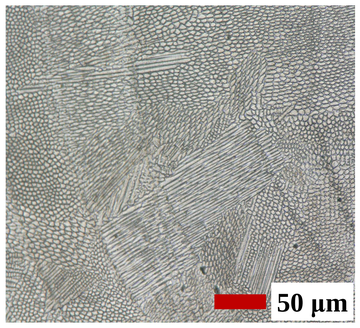
Experiments

High throughput (HT) processing and characterization



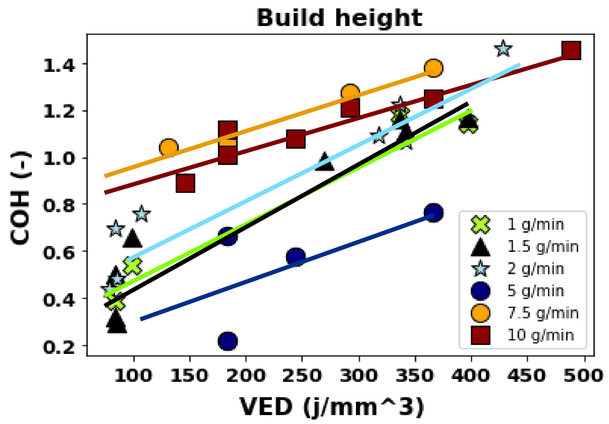
Printed 35 cubes with π_2 values ranging from 10.5-143. Varied, p, h, v, $\dot{m}$, z and n.

Low throughput (LT) characterization



Measured the DAS and hardness of cubes with π_2 values ranging from 10.5-52.6.

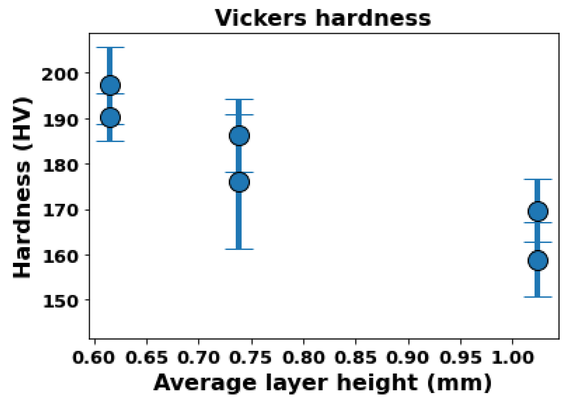
Conclusions from regression analysis



r^2: **1** = .95, **1.5** = .91, **2** = .91, **5** = .41, **7.5** = .97, **10** = .94

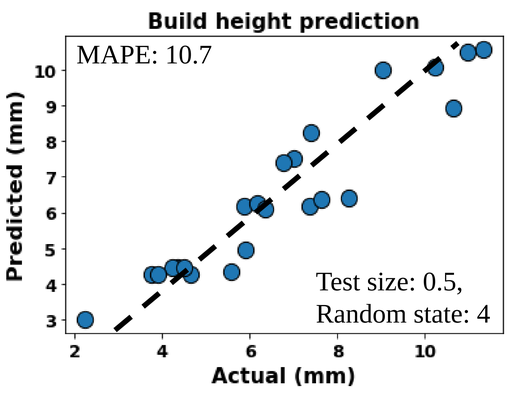
3. Build height can be explained by VED as a function of mass flow rate; mass flow rate is the dominant process variable with respect to COH.

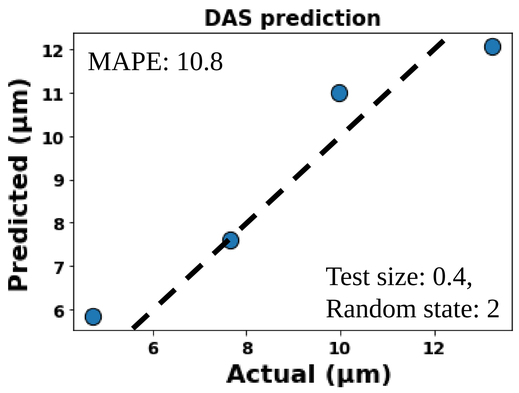
1. Random forest regression can predict multi-scale PSP relationships.
2. Build height, DAS and hardness can all serve as process signatures from which the processing conditions of DED can be determined.

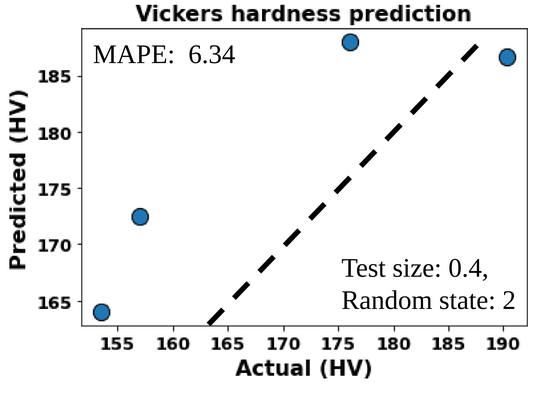


4. Hardness has a strong linear relationship with average layer height; indicating that layer height may serve as an effective mechanism for microstructural control.

Machine learning using random forest regression







Next Steps

Advance the understanding of PSP relationships for DED by:

1. Further characterization of macro and micro-scale signatures utilizing a wider variety of $\pi_2$values.
2. Utilizing in situ layer-height control to predict/tailor microstructural signatures.
3. Evaluating yield strength as a function of processing conditions.

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