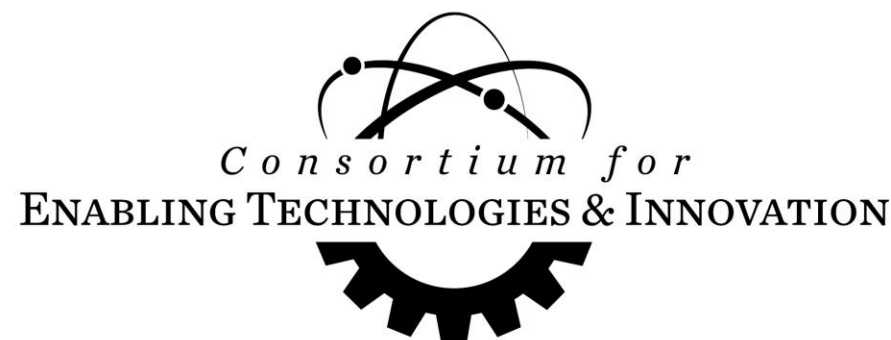


Prediction of optical signatures and their influence on part performance: a model system using 316L stainless steel

William Kunkel, Dan J. Thoma
University of Wisconsin-Madison

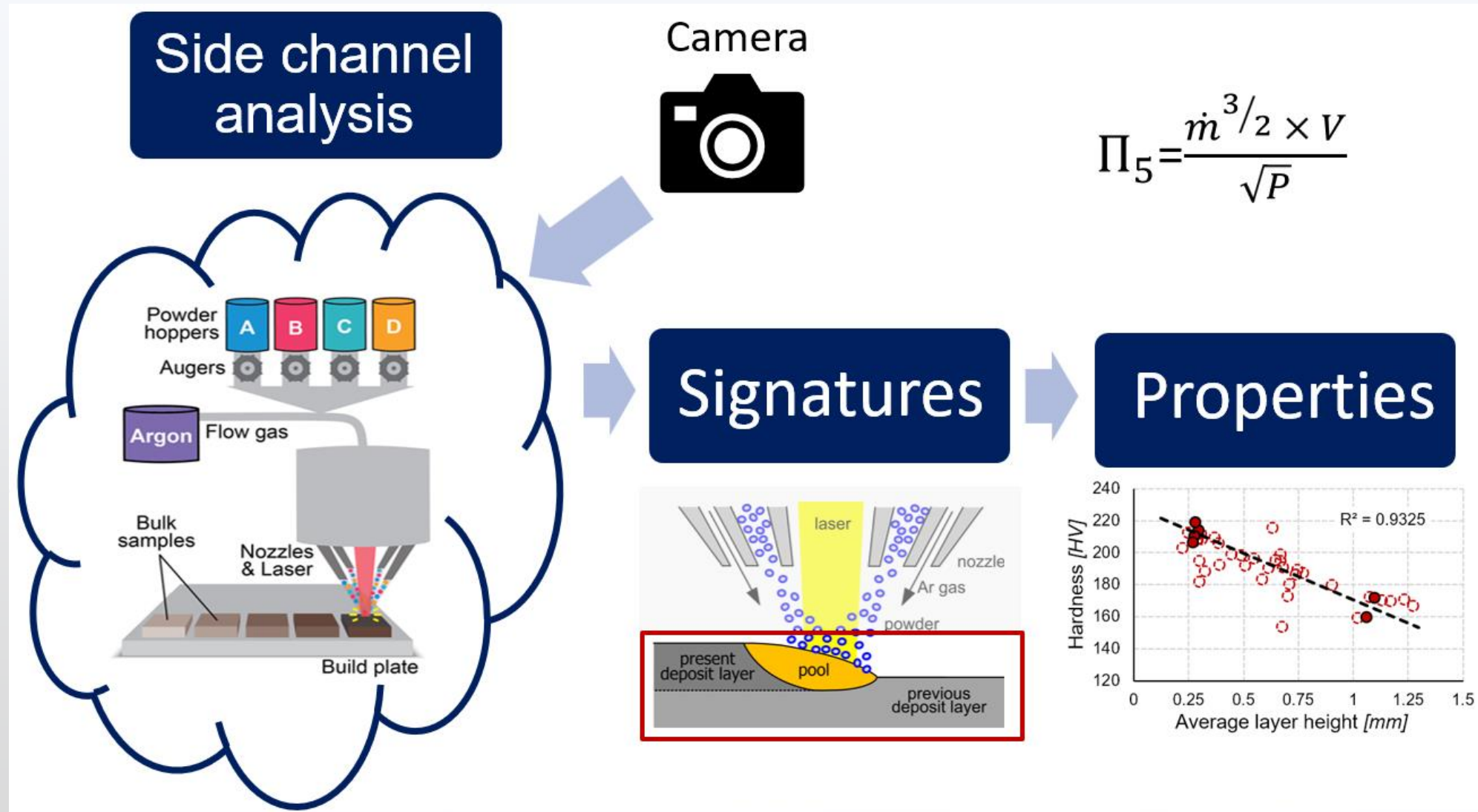
ETI Annual Workshop

February 20 – 21, 2024, Golden, CO



1. Need for safeguards and verification in AM
2. Introduction to directed energy deposition (DED)
3. Existing predictive models for DED
4. Analytical and ML methods to predict signatures
5. Linking signatures to part performance
6. Summary





Develop reduced order model to predict signatures

1. Need for safeguards and verification in AM

- Process any material

2. Introduction to directed energy deposition (DED)

3. Existing predictive models for DED

4. Analytical and ML methods to predict signatures

5. Linking signatures to part performance

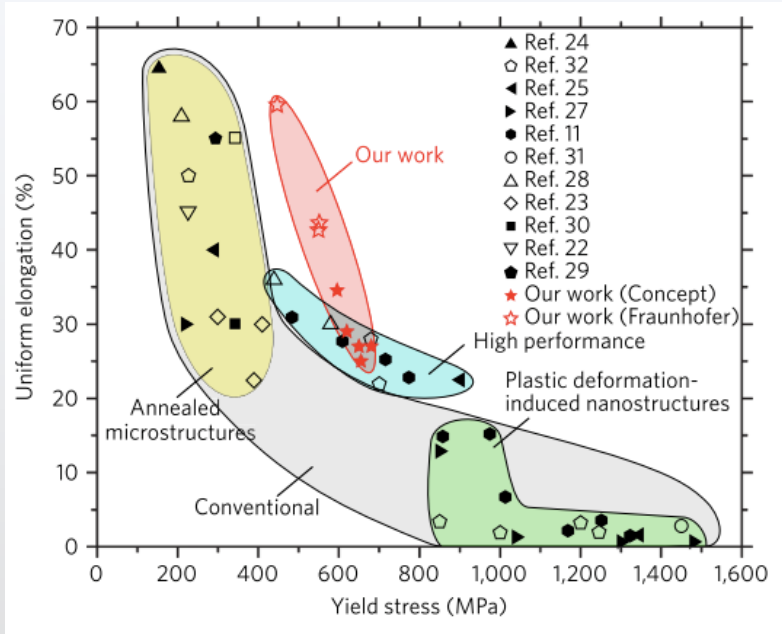
6. Summary



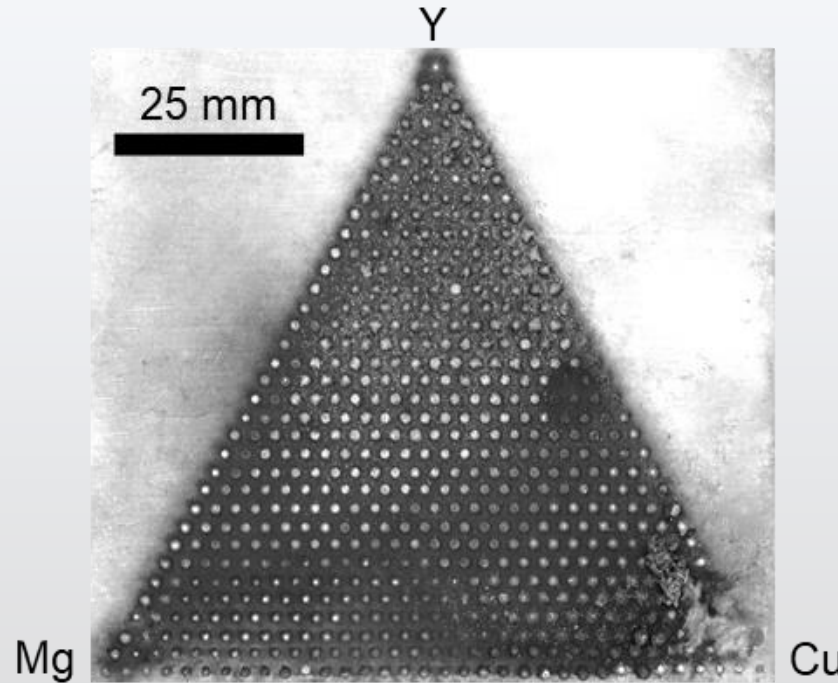
Process any material in complex geometries

Enhanced materials properties

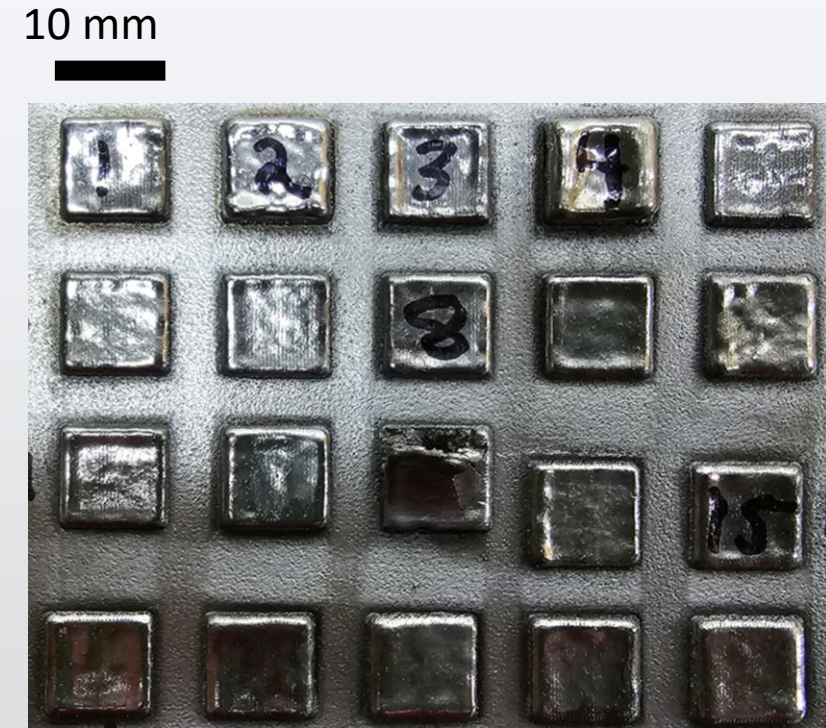
Dense materials



Enhanced strength/ductility ratio [2]



Mg-Cu-Y Metallic Glass [1]



Niobium based HEA

Other examples of superior properties include corrosion [3], irradiated-assisted stress corrosion cracking [4]

[1] Thoma, Dan J., et al. *Metals* 13.7 (2023): 1317

[2] Y.M. Wang et al., Additively manufactured hierarchical stainless steels with high strength and ductility, *Nat. Mater.* 17 (2018) 63–70.

[3] Q. Chao et al., On the enhanced corrosion resistance of a selective laser melted austenitic stainless steel, *Scr. Mater.* 141 (2017) 94–98.

[4] M. Song et al., Radiation damage and irradiation-assisted stress corrosion cracking of additively manufactured 316L stainless steels, *J. Nucl. Mater.* 513 (2019) 33–44.

1. Need for safeguards and verification in AM

2. Introduction to directed energy deposition (DED)

- **Processing-Structure-Property Relationships (*Conventional*)**
- **Signature-Property Relationships (*New*)**

3. Existing predictive models for DED

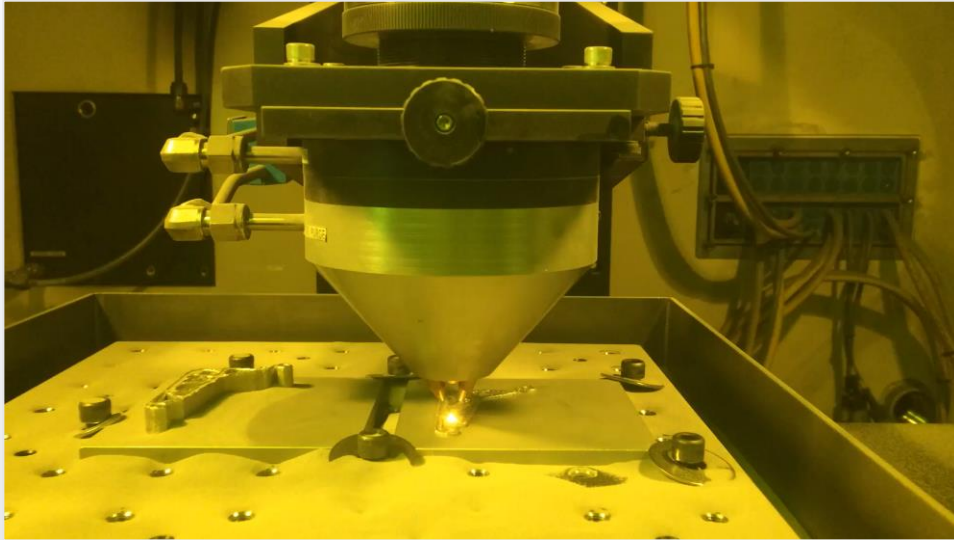
4. Analytical and ML methods to predict signatures

5. Linking signatures to part performance

6. Summary



Directed Energy Deposition (DED) process

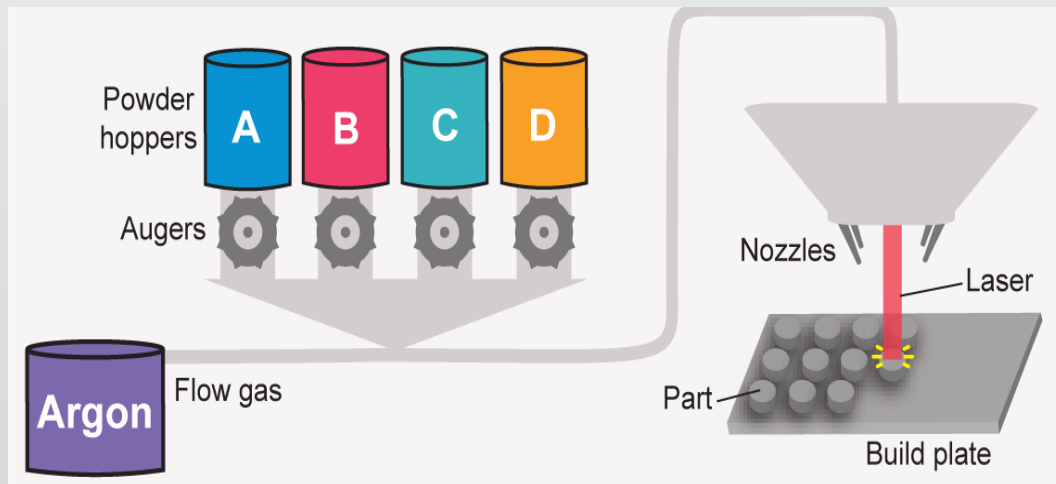


Common uses

- Functionally graded materials
- Repair and cladding

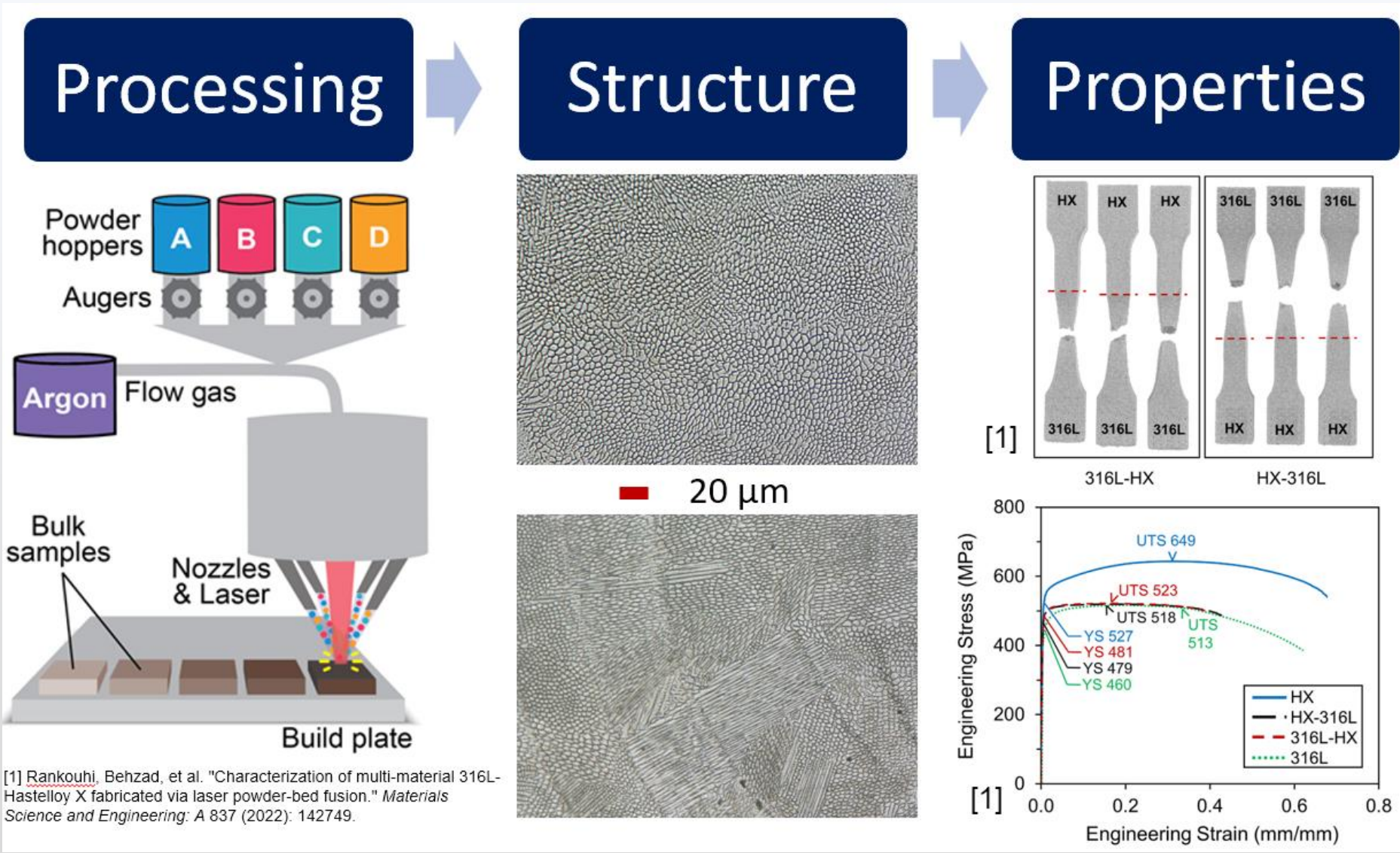
Challenges to nonproliferation

- 100 + variables



Need reduced order model

Conventional understanding of AM parts



Direct access to:

- Parts
- MFG information

Need link from processing to properties

[1] Rankouhi, Behzad, et al. "Characterization of multi-material 316L-Hastelloy X fabricated via laser powder-bed fusion." *Materials Science and Engineering: A* 837 (2022): 142749.

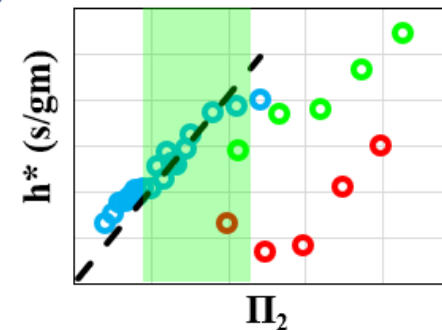
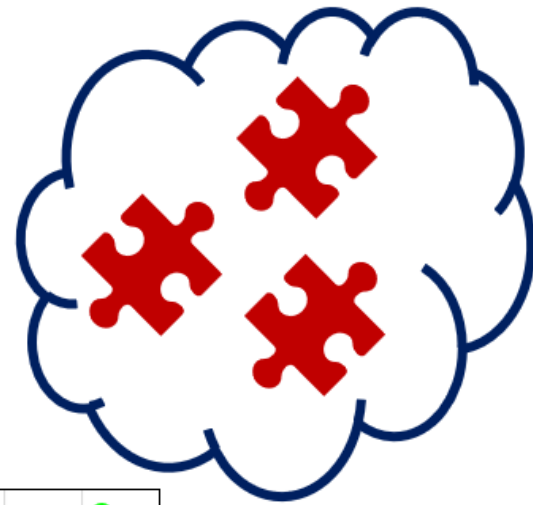
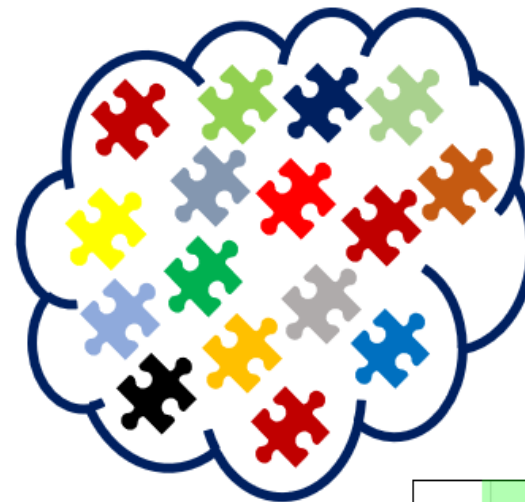
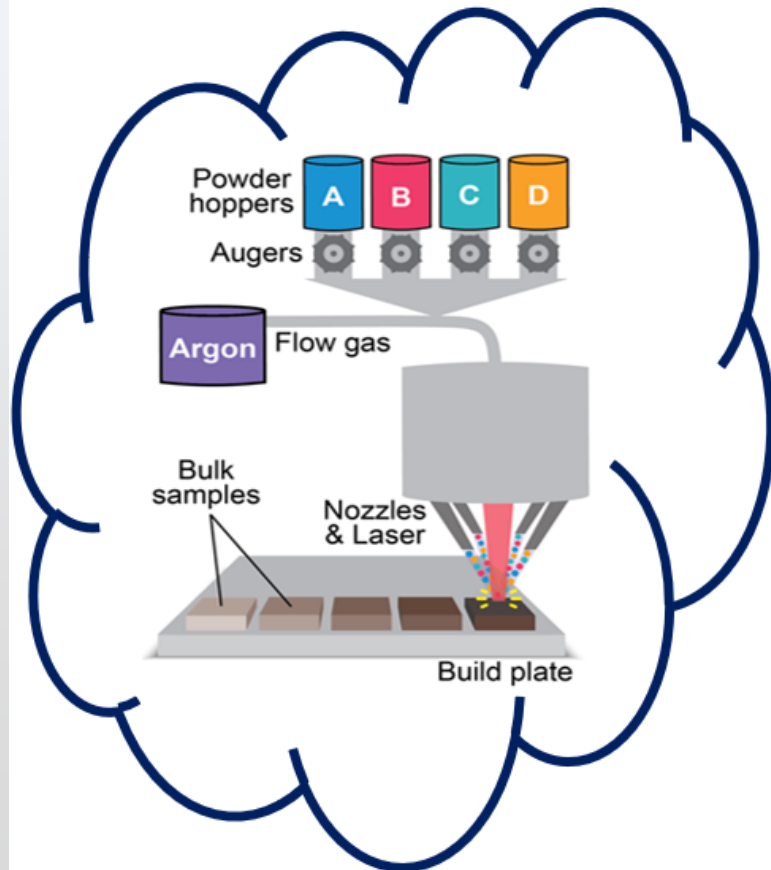


Dimensional analysis provides a pathway to identify the important information to extract

Side channel analysis

Extraneous signatures

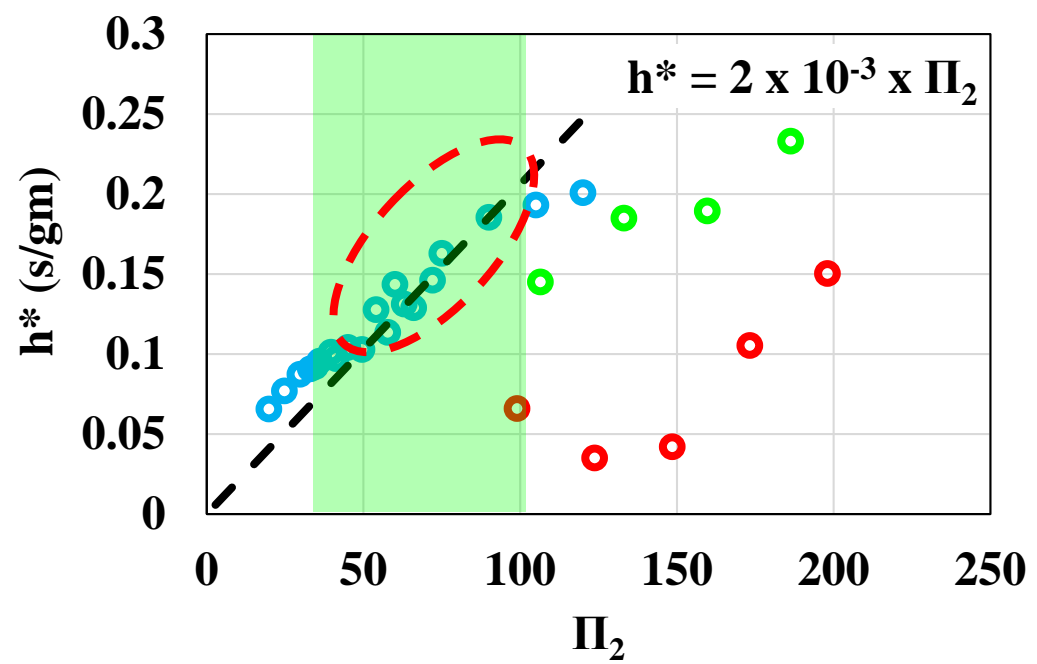
High impact signatures



1. Need for safeguards and verification in AM
2. Introduction to directed energy deposition (DED)
- 3. Existing predictive models for DED**
 - **Predict process parameters for any material**
 - **Model optical signatures**
 - **Developed using dimensional analysis**
4. Analytical and ML methods to predict signatures
5. Linking signatures to part performance
6. Summary



Background: Dimensional analysis to identify process parameters



- Uses electronic signatures, laser spot size and material properties
- **Works across material systems**
- 316L ss, Cr-Fe-Mn-Ni MPEA, Mo-4Si-6B

Quality builds follow $h^* = 2 \times 10^{-3} \times \pi_2$

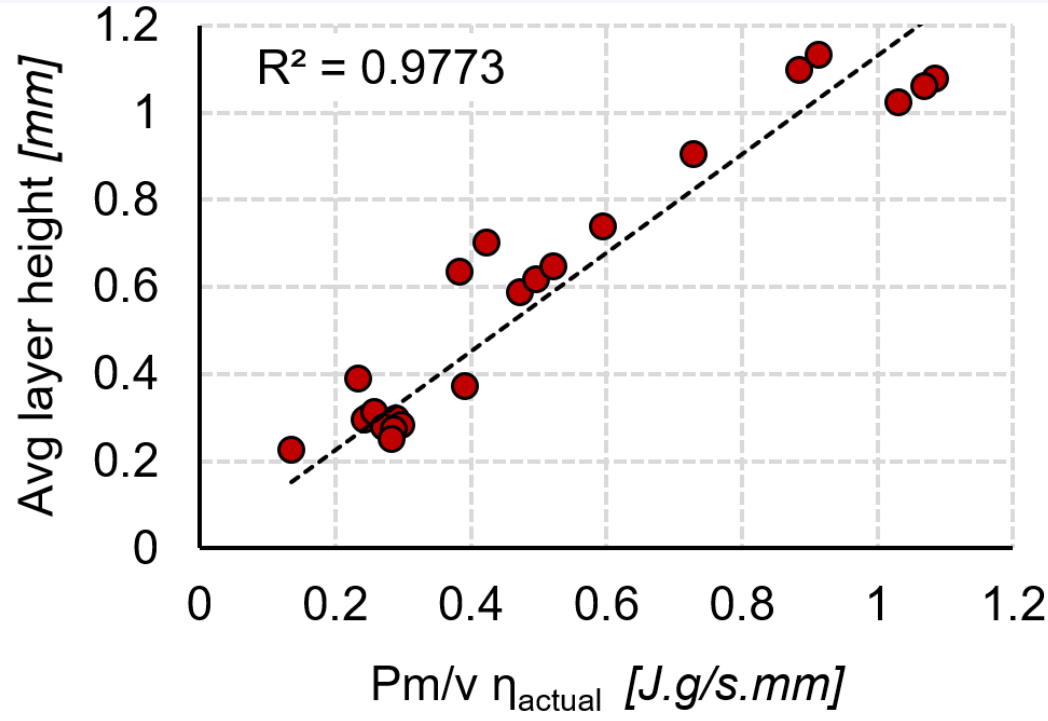
$$h^* = \frac{h_{actual}}{(n \times Z) \times \dot{m}}$$

$$\Pi_2 = \frac{E_g \times \alpha}{\dot{m} \times H} \times \frac{Z}{h} = \frac{P \times \alpha}{v \times D_l \times \dot{m} \times H} \times \frac{Z}{h}$$

[2] Z. Islam et al., Applied Physics Letters 119.23 (2021): 231901.
 [3] Z. Islam et al., "Reactive Synthesis in Additive Manufacturing of an Ultrahigh Temperature MoSiB Alloy" (*Accepted*)



Model: Average layer height (Optical signature)



- Build geometry and capture efficiency are coupled [4],[5]
- Average layer height can be predicted from process information and capture efficiency
- **η_{actual} is a measured value**

[4] S. Donadello et al, *Opt. Lasers Eng.*, vol. 149, p. 106817, Feb. 2022, doi: 10.1016/j.optlaseng.2021.106817.

[5] R. Koike et al, *S.Procedia CIRP*, vol. 78, pp. 133–137, Jan. 2018, doi: 10.1016/j.procir.2018.09.061.

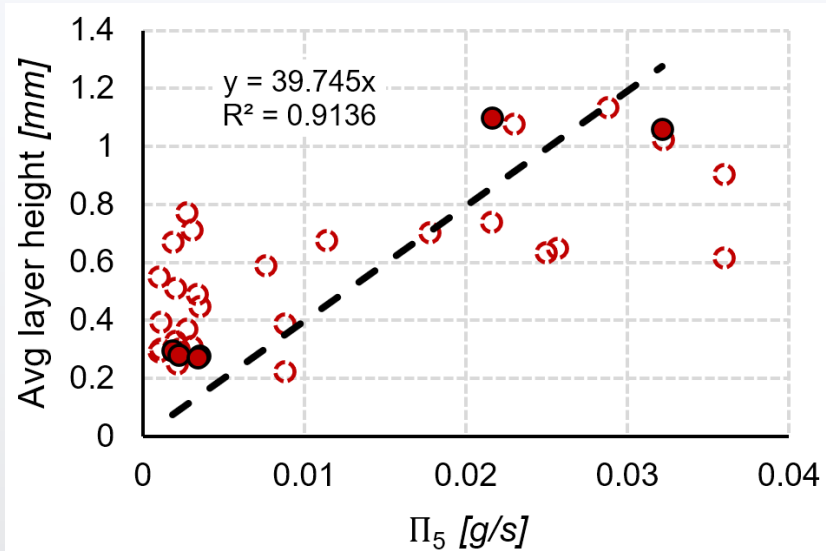
$$\frac{\text{Power} \times \text{Mass flow rate}}{\text{Scanning speed}} \times \eta_{actual}$$



1. Need for safeguards and verification in AM
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3. Existing predictive models for DED
- 4. Analytical and ML methods to predict signatures**
 - **Using reduced order modeling, ML and analytical agree**
5. Linking signatures to part performance
6. Summary



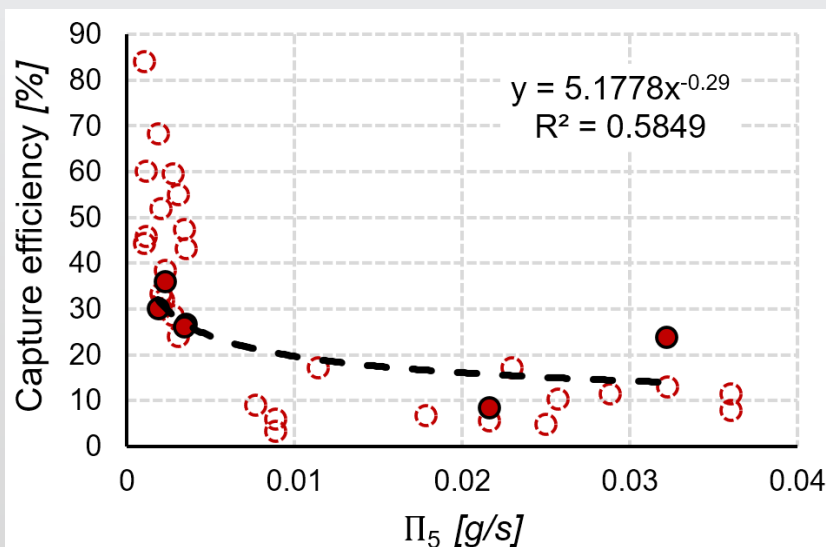
Model for capture efficiency and average layer height



- Defects
- No defects

$$\Pi_5 = \frac{\dot{m}^{3/2} \times V}{\sqrt{P}}$$

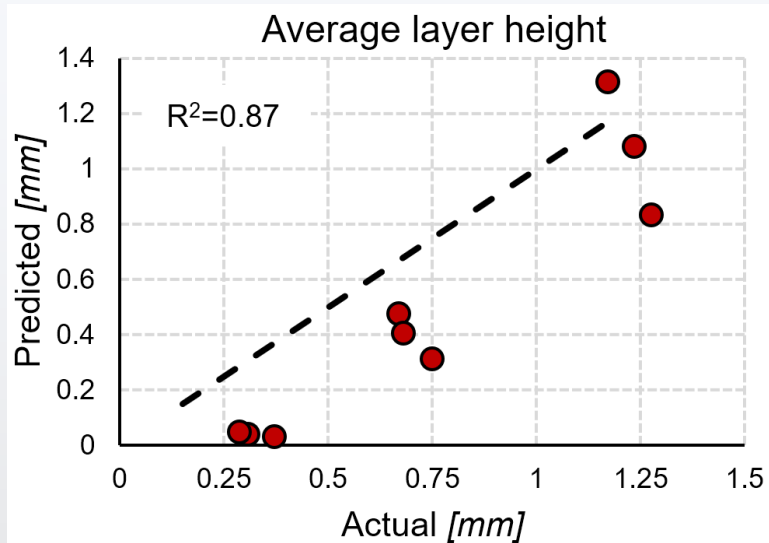
- Buckingham Pi Theory for dimensional analysis
 - Scaled by \dot{m}



- **Capture efficiency is high at high powers (low pi)**
- Capture efficiency is lower at high flow rates
- Layer height increases with mass flow rate
- **Layer height decreases with high powers (spreading)**

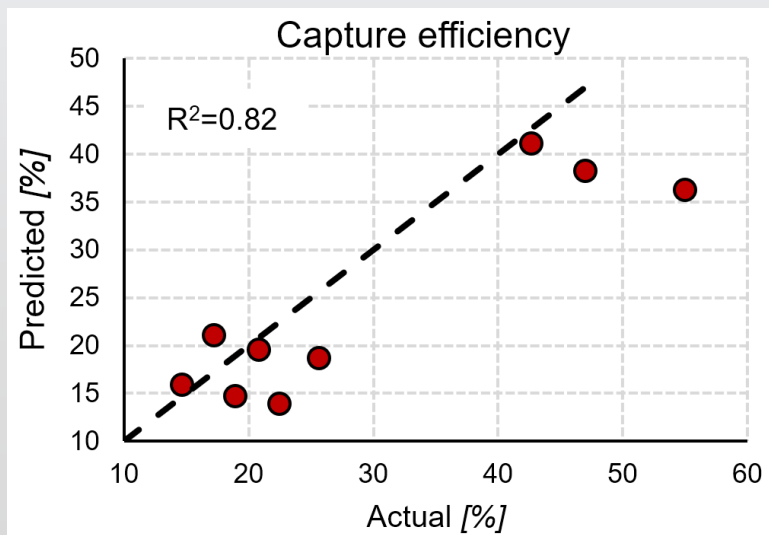
Signatures give information about processing !!!!

Predicting signatures using analytical models

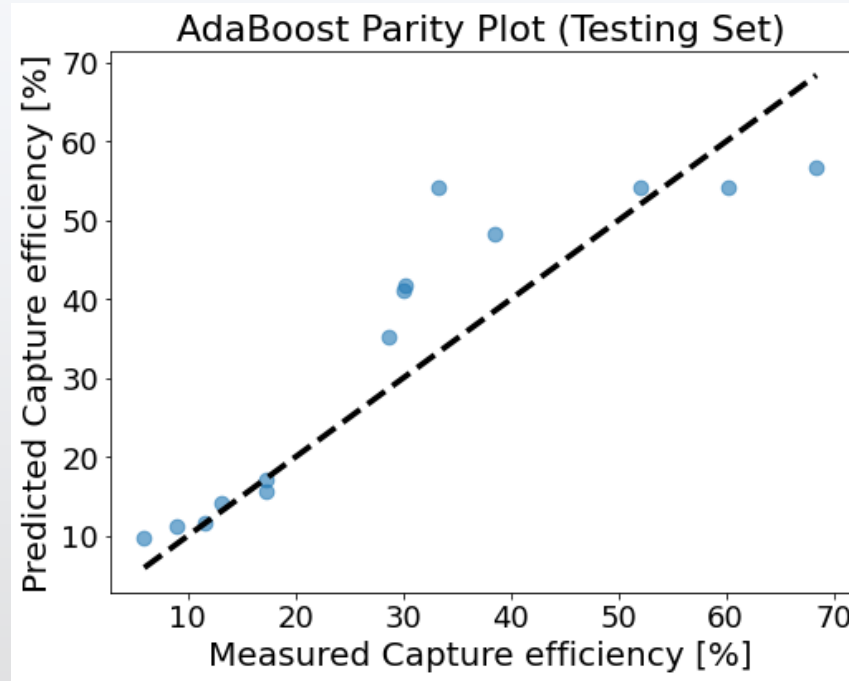
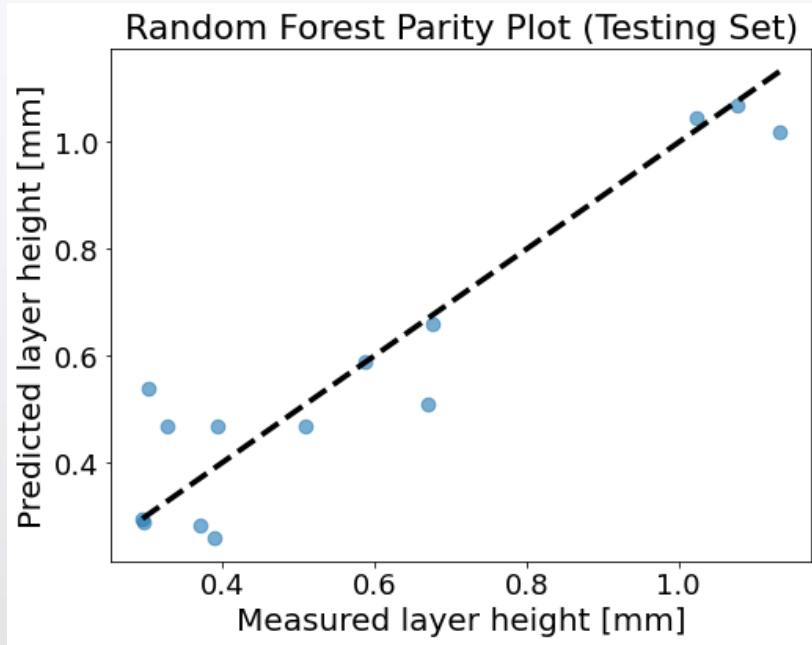


$$\Pi_5 = \frac{\dot{m}^{3/2} \times V}{\sqrt{P}}$$

- Optical signatures were predicted
 - *Predictions were underestimated*
- Simple model → complex phenomena
- **Pathway from optical signatures to processing conditions**



Predicting signatures using ML methods



ML Methods

Agrees with analytical

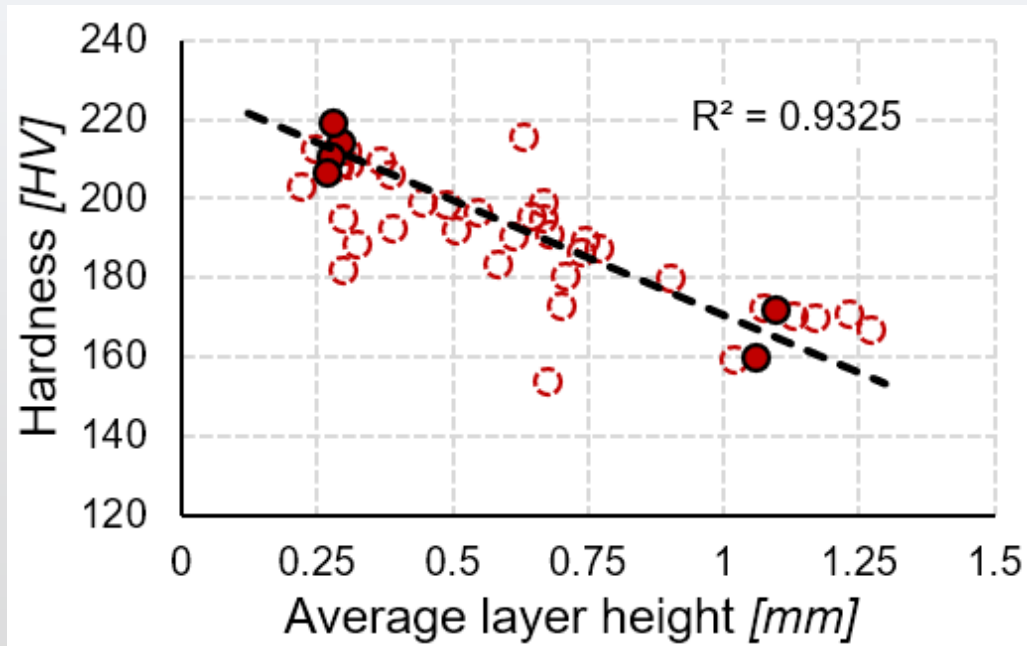
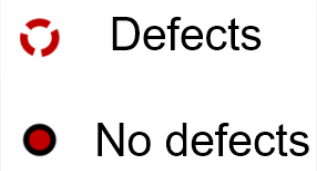
Used:
 \dot{m} , P, V, Z

Model	(Layer height) MSE	(Layer height) R ²	(Efficiency) MSE	(Efficiency) R ²
Random forest	0.1	0.88	11.71	0.61
Gradient boosting	0.14	0.78	15.88	0.29
Adaptive boosting	0.21	0.49	8.59	0.79



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 - **Optical signatures are predictive of material properties**
6. Summary





Optical signatures \leftrightarrow Performance

Δ Height 279%

Δ Hardness 27%

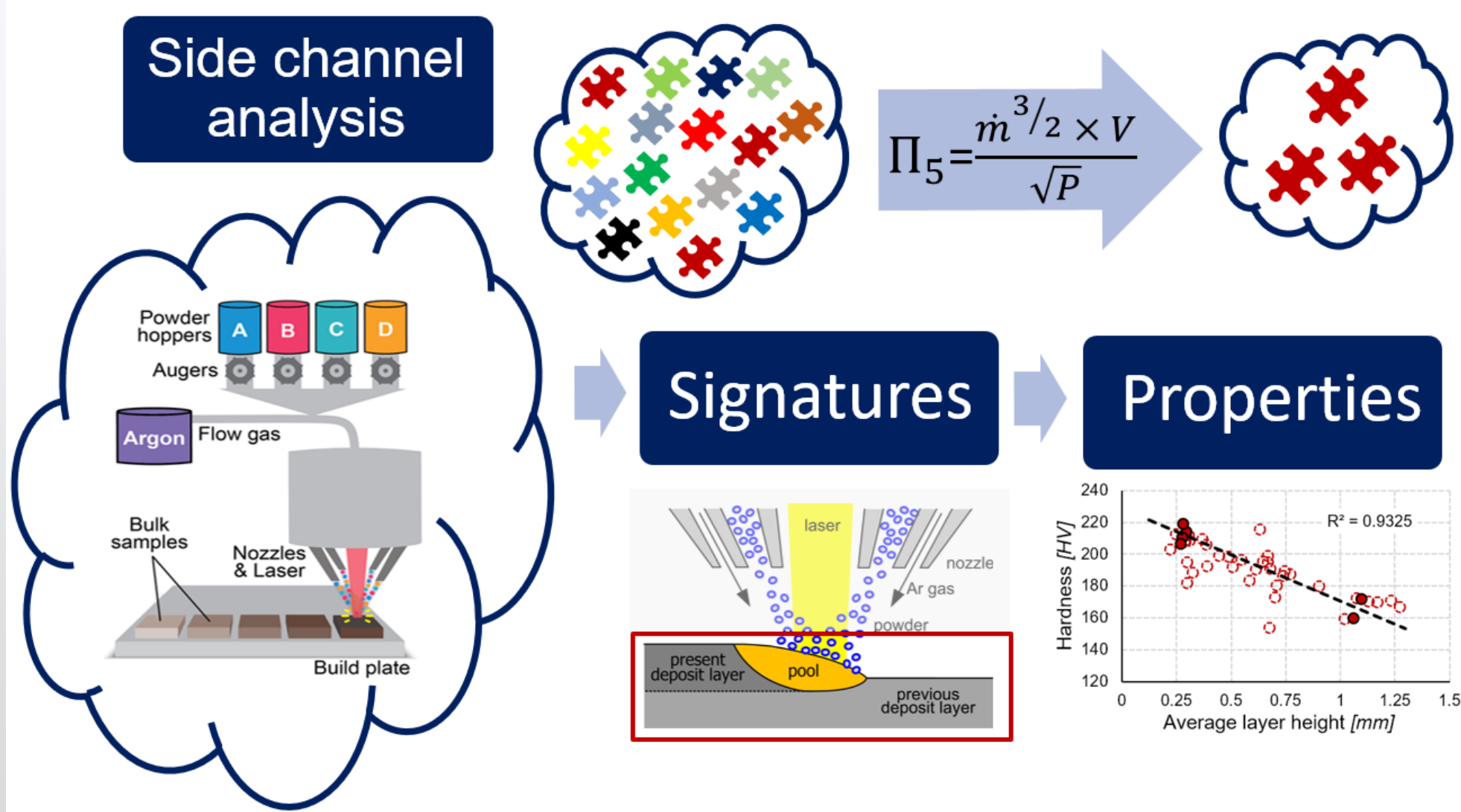
- **Optical signatures scale with performance**
- Hall-Petch relationship links DAS and Hardness
- DAS (cooling rate) \rightarrow governing mechanism
 - Likely other features

1. Need for safeguards and verification in AM
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Summary → Optical signatures predict performance



Reduced order model and ML predict performance



ACKNOWLEDGEMENTS

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