

AM & AI

Predictive Performance in Additive Manufacturing



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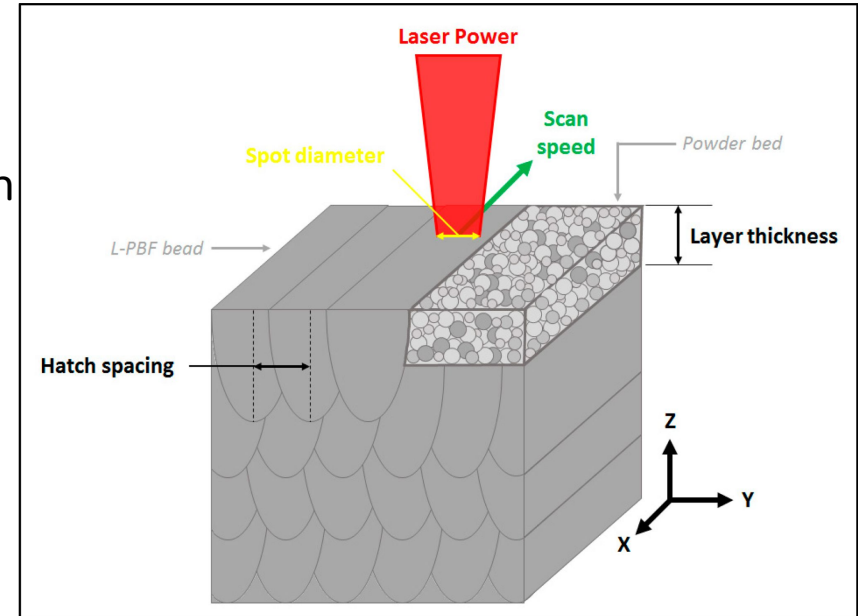
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Problem

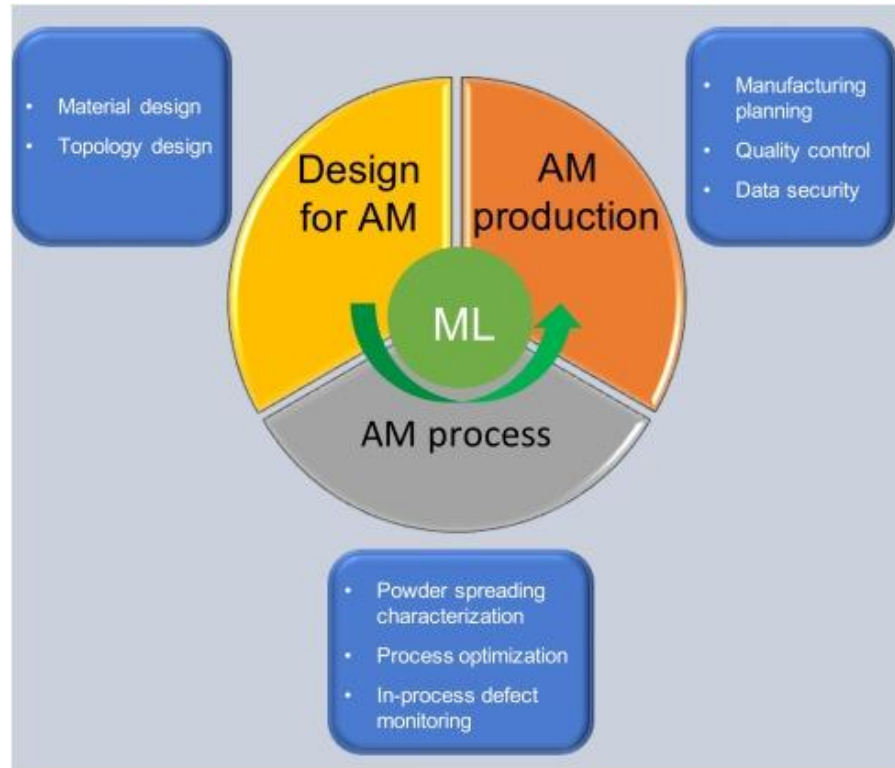
- What problem are we trying to solve?
 - ◆ Limitations in AM part performance
 - ◆ Expensive trial and error procedure
- Why should we care?
 - ◆ Mass customization: design, geometries, material control, unique microstructures & properties, etc.
 - ◆ Shrink the supply chain
 - ◆ Applications in aerospace, defense, biomedical industries, others
- How are we approaching the problem?
 - ◆ ML for AM roadmap

Goal

- Outline a standard that allows consistent, quality printing of metals using laser powder bed fusion with a focus on process parameter optimization
- Scrape the internet for data and build high performing models that guide process parameter selection
- Report findings
- Validate models in the lab with actual builds (time and COVID-19 allowing)



AM & ML Roadmap



¹ C. Wang, X.P. Tan, S.B. Tor, C.S. Lim, "Machine learning in additive manufacturing: State-of-the-art and perspectives", *Additive Manufacturing*, Volume 36, 2020, 101538, ISSN 2214-8604, <https://doi.org/10.1016/j.addma.2020.101538>.

Data

- [NIST build data](#)
 - ◆ Tensile strength tests
 - ◆ ASTM test standards
 - ◆ Data augmentation
- Research papers
- Outreach
- AM organizations
- Finite Element & [Simulation techniques?](#)

Feature Selection

Table 1

NN application to build process–property–performance linkage.

AM technique	Processing parameters	Property/performance	Ref.
FDM	Layer thickness, orientation, raster angle, raster width, air gap	Compressive strength	[39]
FDM	Layer thickness, orientation, raster angle, raster width, air gap	Wear volume	[40]
FDM	Orientation, slice thickness	Volumetric error	[41]
FDM	Layer thickness, orientation, raster angle, raster width, air gap	Dimensional accuracy	[42]
FDM	Layer thickness, orientation, raster angle, raster width, air gap	Dimensional accuracy	[43]
BJ	Layer thickness, printing saturation, heater power ration, drying time	Surface roughness	[44]
BJ	Layer thickness, printing saturation, heater power ration, drying time	Shrinkage rate (Y-axis)	[44]
BJ	Layer thickness, printing saturation, heater power ration, drying time	Shrinkage rate (Z-axis)	[44]
SLS	Laser power, scan speed, scan spacing, layer thickness	Density	[45]
SLS	Laser power, scan speed, scan spacing, layer thickness	Dimension	[46]
SLS	Z height, volume, bounding box	Build time	[47]
SLS	Laser power, scan speed, hatch spacing, layer thickness, scan mode, temperature, interval time	Shrinkage ratio	[48]
SLS	Layer thickness, laser power, scan speed	Open porosity	[49]
SLS	Laser power, scan speed, hatch spacing, layer thickness, powder temperature	Tensile strength	[50]
SLS	Laser power, scan speed, hatch spacing, layer thickness, scan mode, temperature, interval time	Density	[51]
SL	Layer thickness, border overcure, hatch overcure, fill cure depth, fill spacing and hatch spacing	Dimensional accuracy	[52]
LMD	Laser power, scanning speed, powder feeding rate	Geometrical accuracy	[53]
EBM	Spreader translation speed, rotation speed	Volume, roughness	[54]
WAAM	Bead width, height, center distance of adjacent deposition paths	Offset distance	[55]

SL: stereolithography; LMD: laser metal deposition; WAAM: wire and arc additive manufacturing.

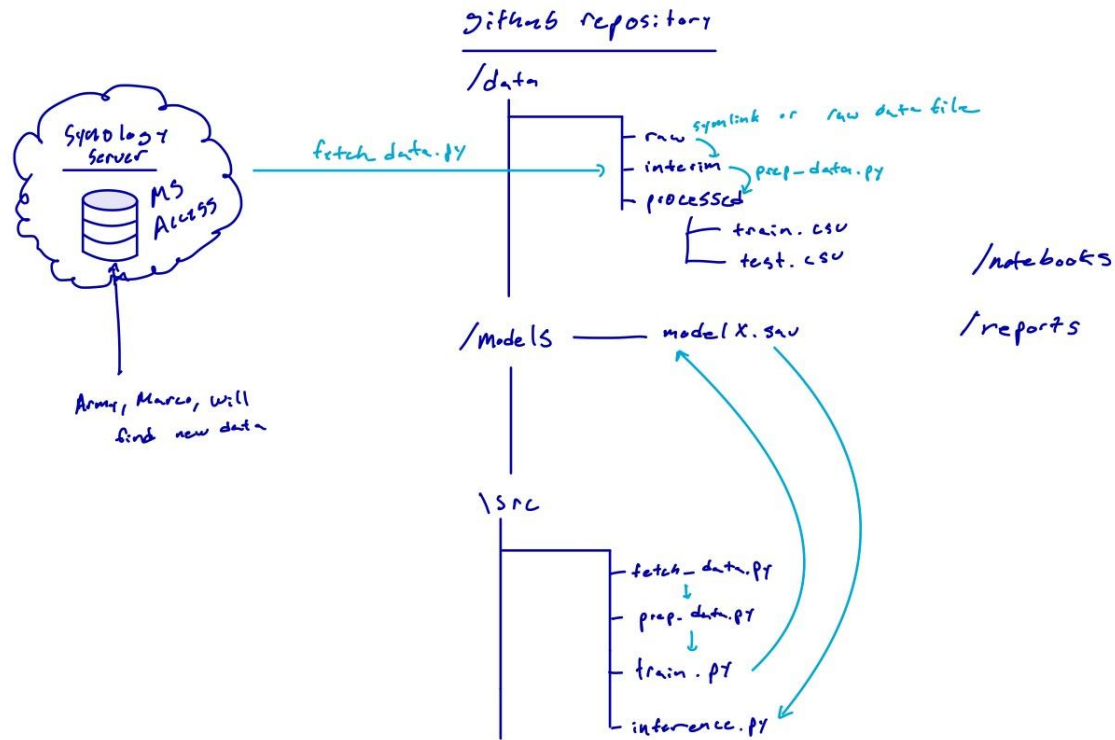
³ Xinbo Qi, Guofeng Chen, Yong Li, Xuan Cheng, Changpeng Li, "Applying Neural-Network-Based Machine Learning to Additive Manufacturing: Current Applications, Challenges, and Future Perspectives," *Engineering*, Volume 5, Issue 4, 2019, Pages 721-729, ISSN 2095-8099, <https://doi.org/10.1016/j.eng.2019.04.012>.

Algorithm Selection

- Performance metric prediction
 - ◆ Regressions
 - ◆ Support vector machines
 - ◆ Recurrent Neural Network
- Parameter Optimization
 - ◆ Genetic algorithm
- Dynamic parameter adjustment
 - ◆ [Reinforcement learning](#)

² Francis Ogoke, Amir Barati Farimani, "Thermal control of laser powder bed fusion using deep reinforcement learning," *Additive Manufacturing*, Volume 46, 2021, 102033, ISSN 2214-8604, <https://doi.org/10.1016/j.addma.2021.102033>.

Codebase



References

1. C. Wang, X.P. Tan, S.B. Tor, C.S. Lim, "Machine learning in additive manufacturing: State-of-the-art and perspectives," *Additive Manufacturing*, Volume 36, 2020, 101538, ISSN 2214-8604, <https://doi.org/10.1016/j.addma.2020.101538>.
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