Solid Freeform Fabrication Symposium, 2019

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Room no. 412

Time: 2:30 PM

The Digital Twin in Metal Additive Manufacturing – A Paradigm Integrating Modeling, Sensing and Machine Learning for Defect Prediction

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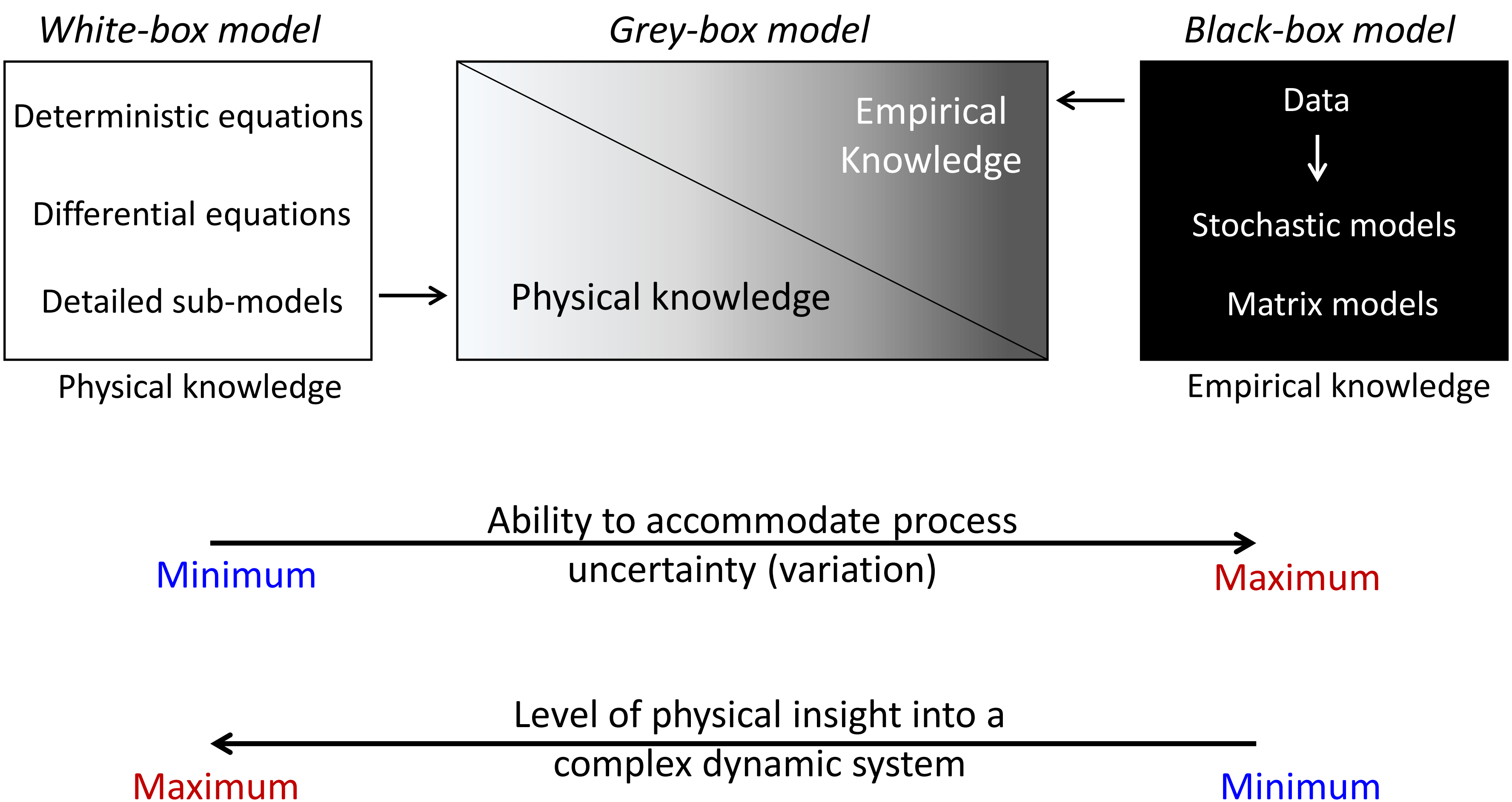
The data for this work was generated at Mississippi State University (MSU) and National Institute of Standards and Technology (NIST).

Defect-free production of AM parts by integrating in-situ sensor data and knowledge of process physics.

Digital Twin – A Gray-Box Model



Outline

- Introduction
- Objective and Hypothesis
- Thermal Modeling using Graph Theory
- Experimental Studies and Results
- Conclusions and Future Work

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  - Background
  - Motivation
  - Previous work in the Digital Twin
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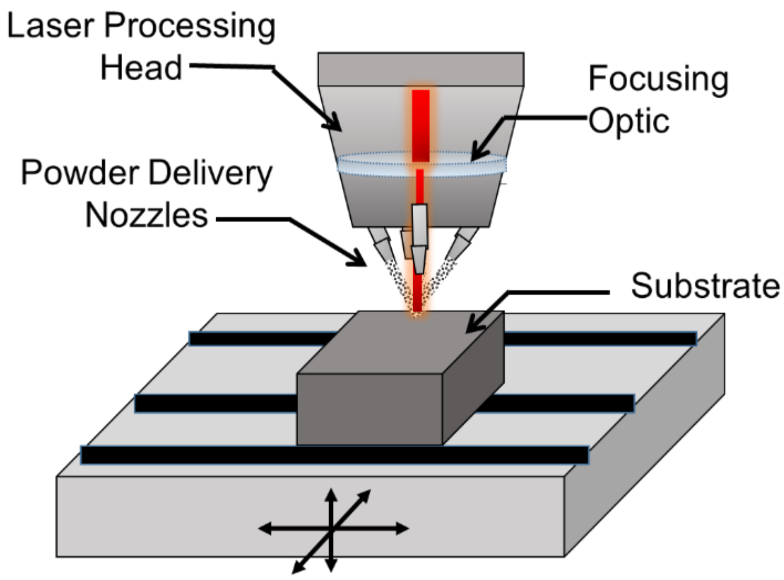
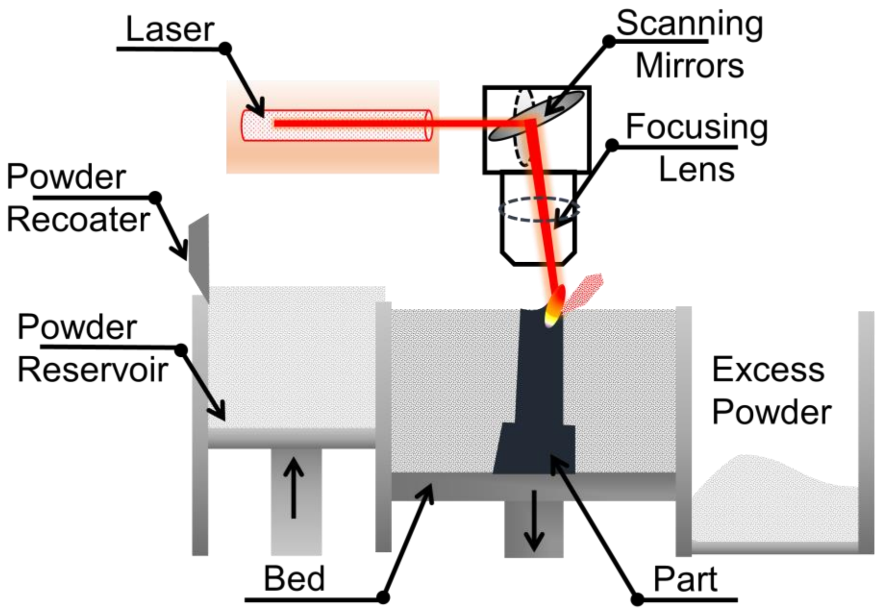
Background

This work focusses on two of the following metal additive manufacturing processes



Directed energy deposition (DED) process

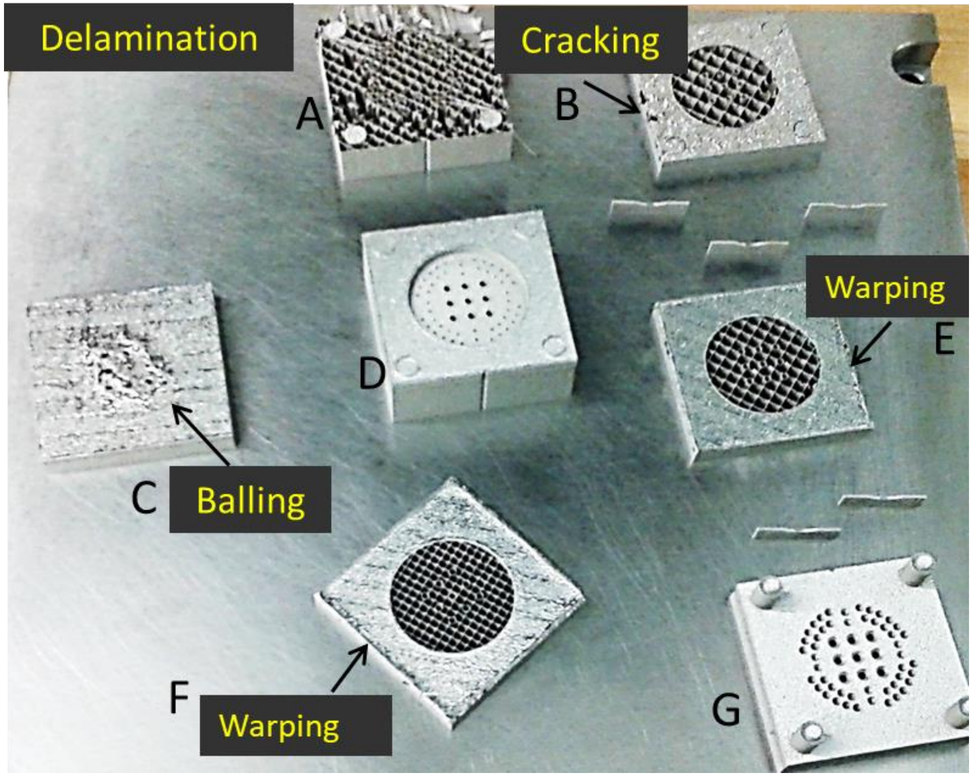


Laser powder bed fusion (LPBF) process

Motivation

Part quality inconsistency is major impediment in AM

Only 2 out of 7 parts were built defect free

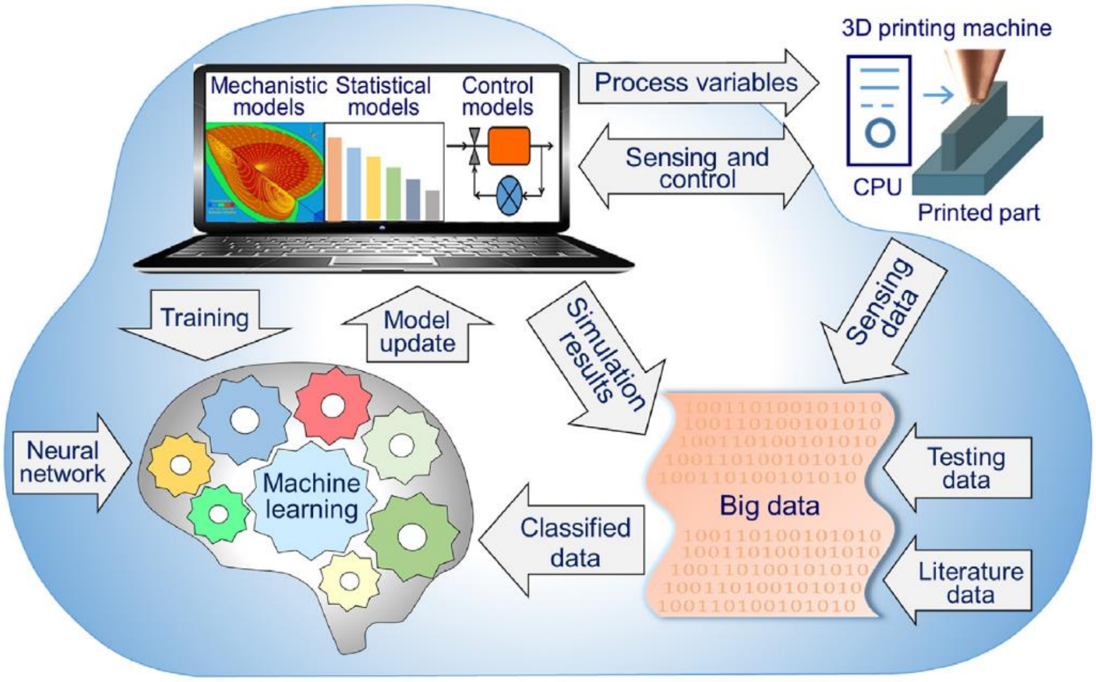


Can we build parts without having to print-and-pray?

Previous work in the Digital Twin

- G.L. Knapp, T. Mukherjee, J.S. Zuback, H.L. Wei, T.A. Palmer, A. De, **T. *DebRoy***Building blocks for a digital twin of additive manufacturing, Acta Materialia, Volume 135, 2017.

- **T. *DebRoy***, W. Zhang, J. Turner, S.S. Babu, Building digital twins of 3D printing machines, Scripta Materialia, Volume 135, 2017.



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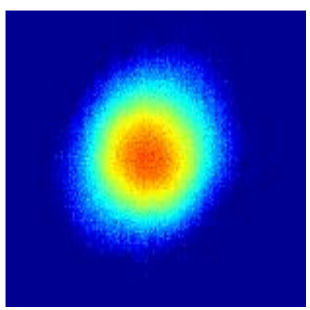
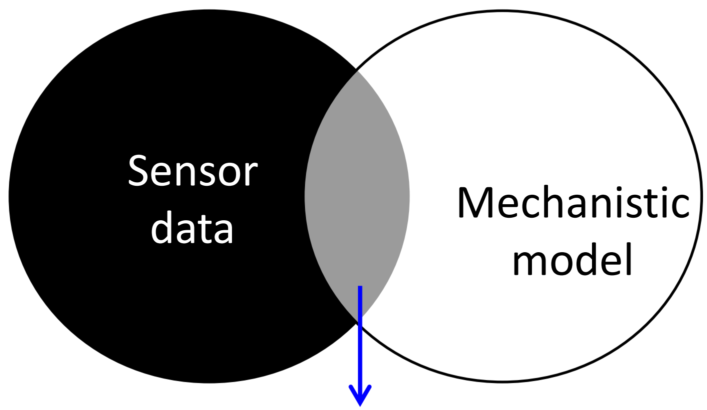
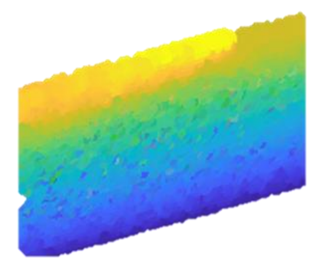
Objective and Hypothesis

Predict the instantaneous spatiotemporal temperature distribution with graph-theory and combine with in-process sensor data to monitor the process condition.

Hypothesis







Improved defect prediction accuracy

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Yavari, M. Reza, Kevin D. Cole, and Prahalada Rao. "Thermal Modeling in Metal Additive Manufacturing Using Graph Theory." *Journal of Manufacturing Science and Engineering,*141, no. 7 (2019): 071007.doi: 10.1115/1.4043648

Thermal Modeling using Graph Theory

The following heat continuum equation is solved

$$\rho c_p \frac{\partial T(x,y,z,t)}{\partial t} - k\left(\frac{\partial^2 T(x,y,z,t)}{\partial^2 x} + \frac{\partial^2 T(x,y,z,t)}{\partial^2 y} + \frac{\partial^2 T(x,y,z,t)}{\partial^2 z}\right) = Q(x,y,z,t)$$

Representing the continuous Laplacian operator as

$$\Delta[T(x,y,z,t)] \stackrel{\text{def}}{=} \left(\frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2} + \frac{\partial^2}{\partial z^2}\right) T(x,y,z,t)$$

$$\alpha = \frac{k}{\rho c_p}$$

Boundary condition: $Q\,(x,y,z,t=0) = T_0$, i.e. melting temperature of the material.

Yavari, M. Reza, Kevin D. Cole, and Prahalada Rao. "Thermal Modeling in Metal Additive Manufacturing Using Graph Theory." *Journal of Manufacturing Science and Engineering*141, no. 7 (2019): 071007.

Thermal Modeling using Graph Theory

Therefore, heat equation reduces to a steady state form

$\frac{\partial T(x,y,z,t)}{\partial t} - \alpha\Delta[T(x,y,z,t)] = 0$; with initial condition $T_{t=0} = T_0$

The continuous Laplacian operator (Δ) is approximated by a discrete Laplacian operator called the graph Laplacian matrix ($\mathbb{L}$)

The solution takes the form

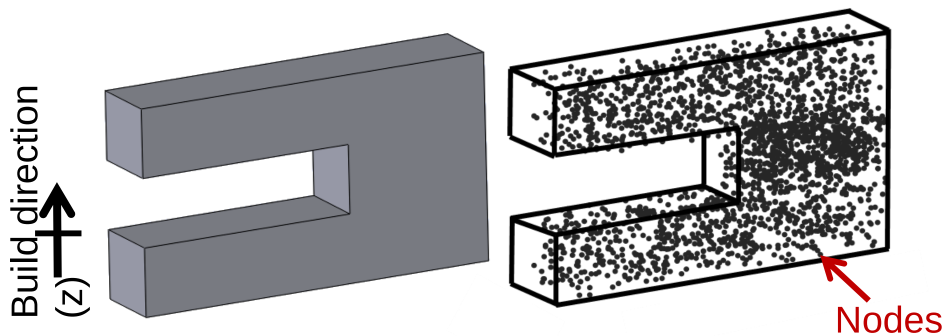
$$T(x,y,z,t) = \Phi e^{-\alpha g \Lambda t} \Phi' T_0$$

Λ and Φ are the Eigen spectrum of the Laplacian matrix.

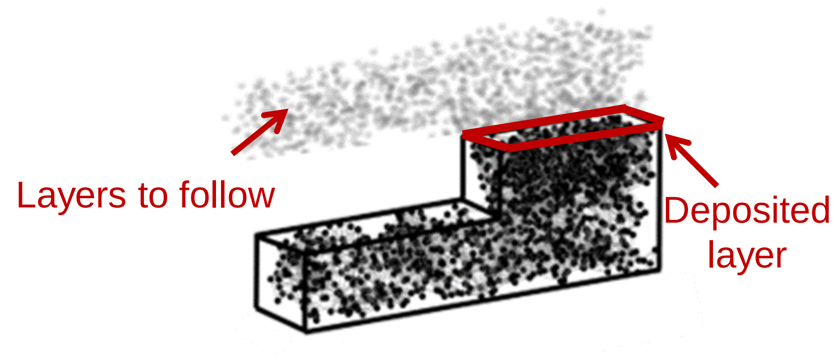
Yavari, M. Reza, Kevin D. Cole, and Prahalada Rao. "Thermal Modeling in Metal Additive Manufacturing Using Graph Theory." *Journal of Manufacturing Science and Engineering*141, no. 7 (2019): 071007.

Thermal Modeling using Graph Theory

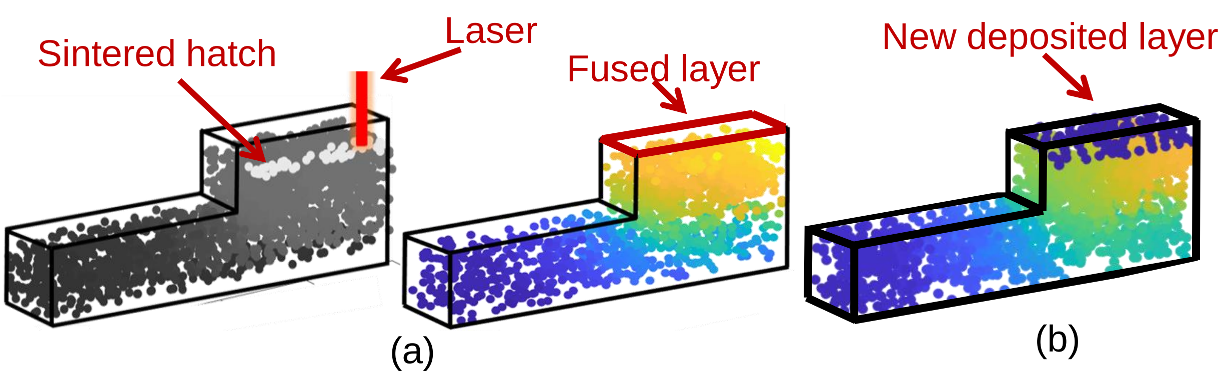
Steps involved in graph theory-based thermal modeling



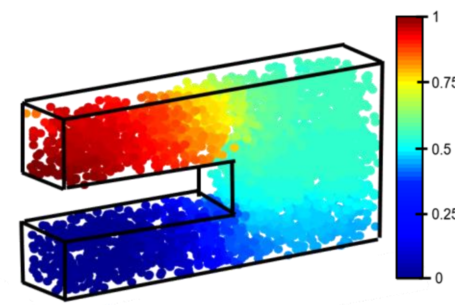
Step 1- Obtain the geometry of a part and convert it to a set of discrete nodes.



Step 2- Construct a network graph from the sampled nodes.



Step 3- (a) Heat a layer hatch-by-hatch to diffuse heat through the part (b) Deposit a new layer.

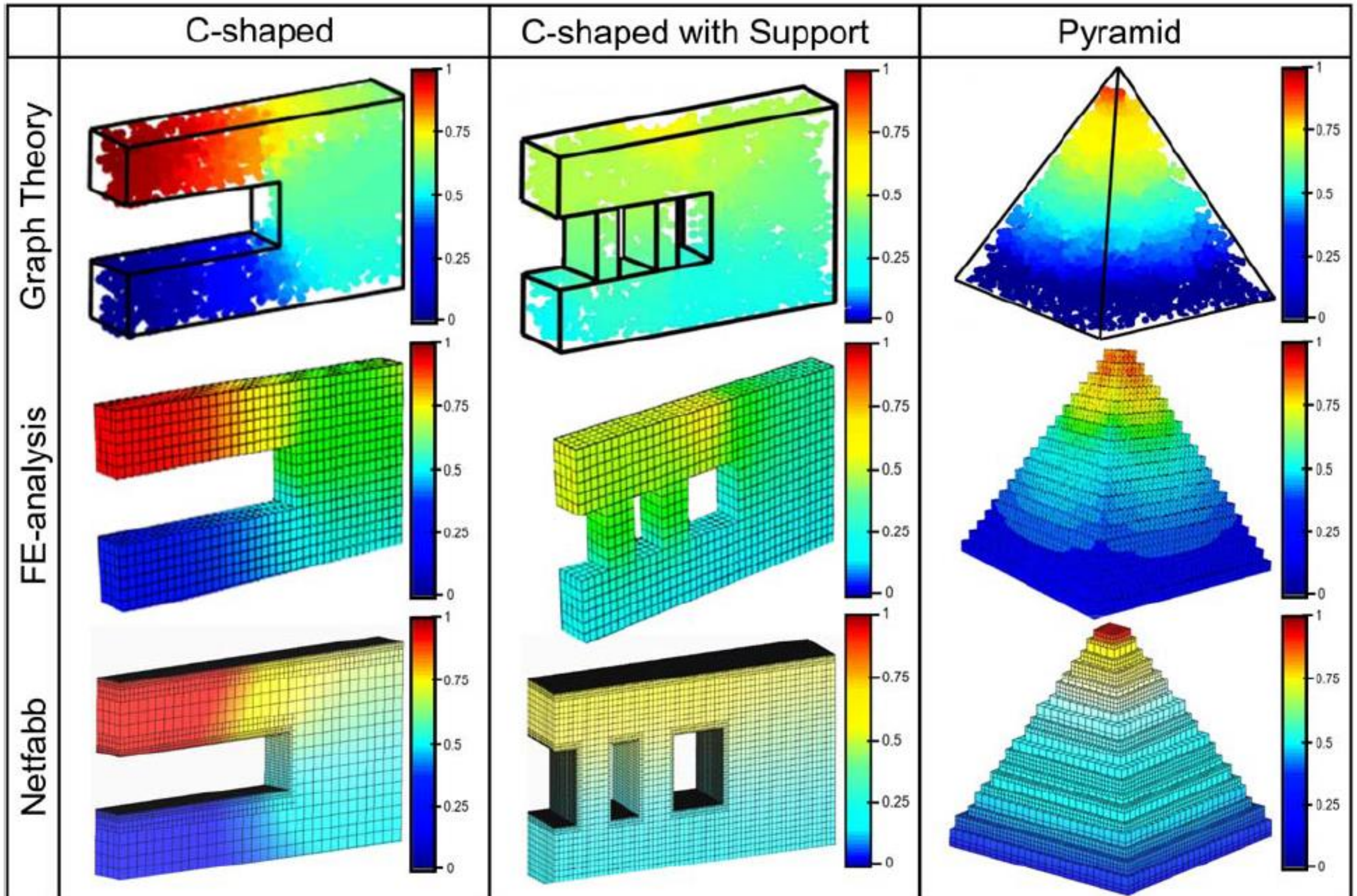


Step 4 – Obtain the result as temperature array (**T**) which shows the temperature history of the part.

Yavari, M. Reza, Kevin D. Cole, and Prahalada Rao. "Thermal Modeling in Metal Additive Manufacturing Using Graph Theory." *Journal of Manufacturing Science and Engineering*141, no. 7 (2019): 071007.

Thermal Modeling using Graph Theory

Reduces the time taken for thermal simulation to 1/10th of FE analysis with error less than 10%.



Yavari, M. Reza, Kevin D. Cole, and Prahalada Rao. "Thermal Modeling in Metal Additive Manufacturing Using Graph Theory." *Journal of Manufacturing Science and Engineering* 141, no. 7 (2019): 071007.

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- Introduction
- Objective and Hypothesis
- Thermal Modeling using Graph Theory
- Experimental Studies and Results
  - Case Study 1

    Flaw Prediction in thin-wall made using DED
  - Case Study 2

    Predicting process state in LPBF
- Conclusion and Future Work

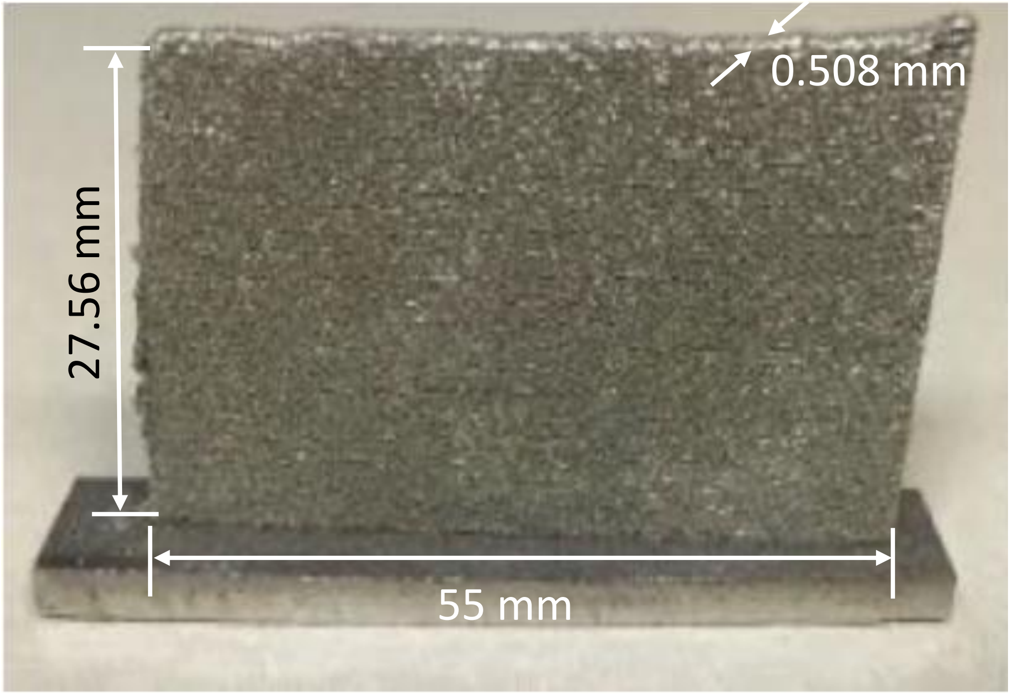
Case Study 1
Experimental data was generated at Mississippi State University by Dr. Linkan Bian

Mojtaba Khanzadeh, Sudipta Chowdhury, Mark A. Tschopp, Haley R. Doude, Mohammad Marufuzzaman & Linkan Bian (2018) *In-situ* monitoring of melt pool images for porosity prediction in directed energy deposition processes, IISE Transactions, DOI: 10.1080/24725854.2017.1417656

Test Artifact

Detecting flaws in thin-walls by combining in-situ pyrometer data and the corresponding graph theory-derived simulated temperature

Single track thin wall part with Ti6Al4VOptomec LENS 750

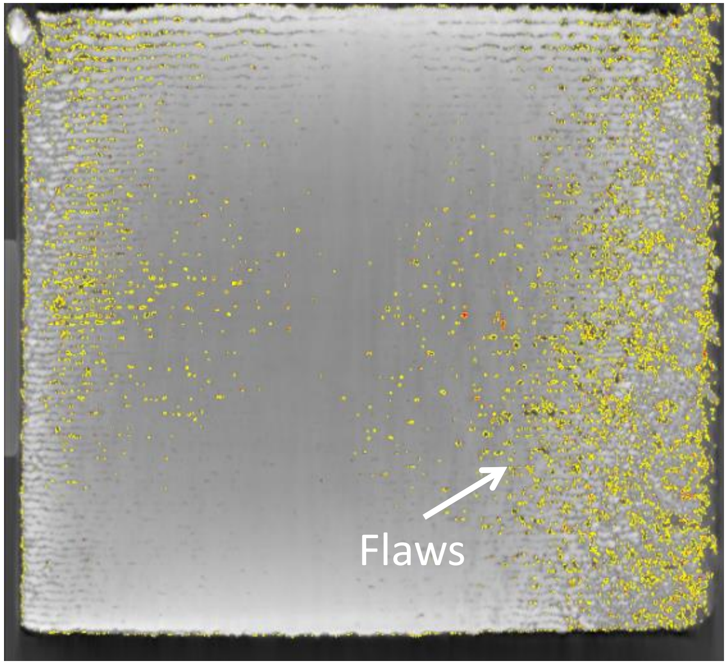


Power: 300 W

Scan Speed: 12.7 mm/s

Layer Thickness: 0.508 mm

Post-process characterization with X-ray computed tomography



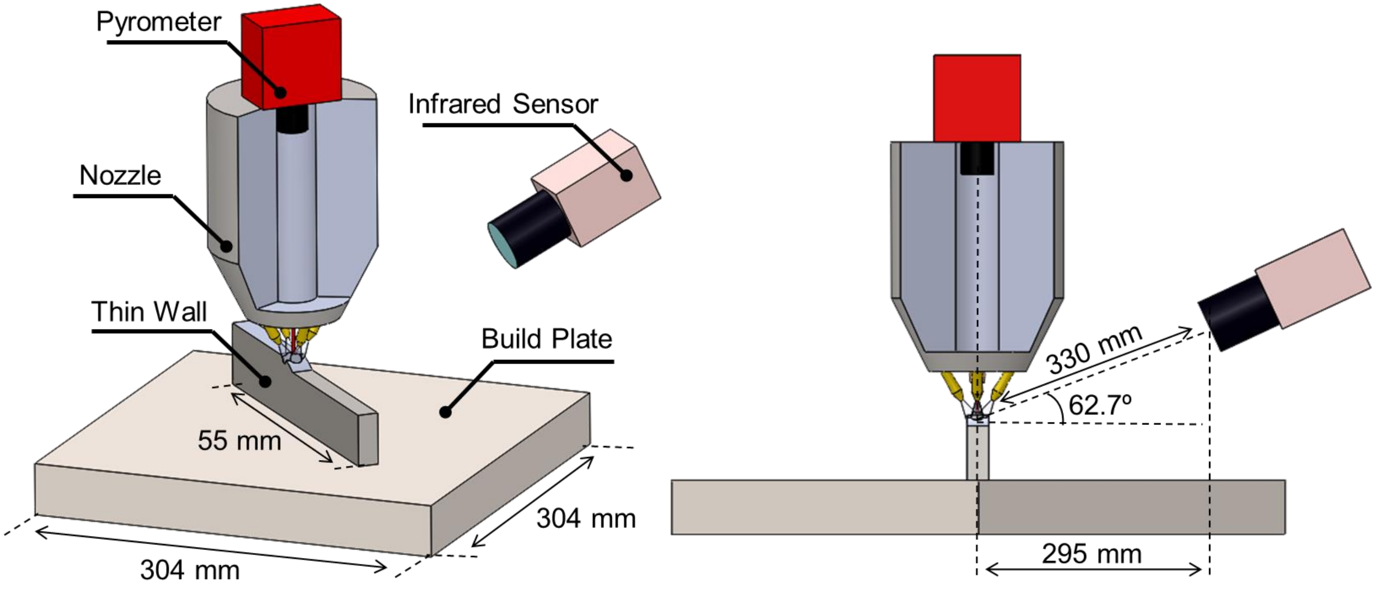
Experimental Setup

Dual-wavelength pyrometer

- CMOS detector with array size of 752 pixel × 480 pixel
- Exposure time (2.0274 ms)
- Coaxial view the laser shaft

Short-wave infrared (SWIR) camera

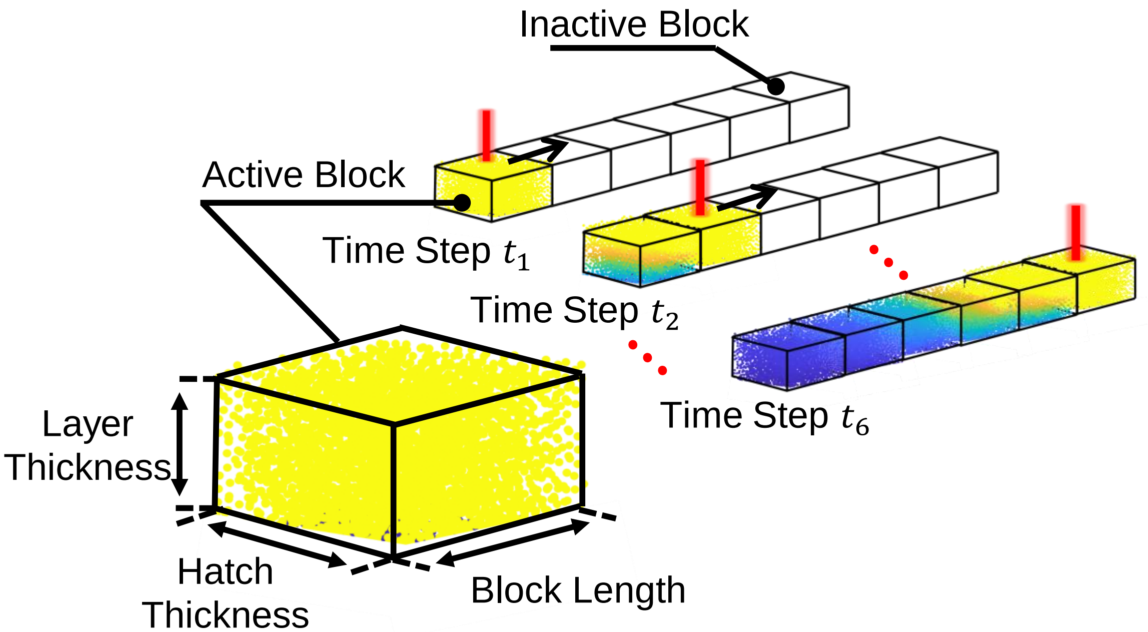
- Oriented at approximately 45^{o} to the table

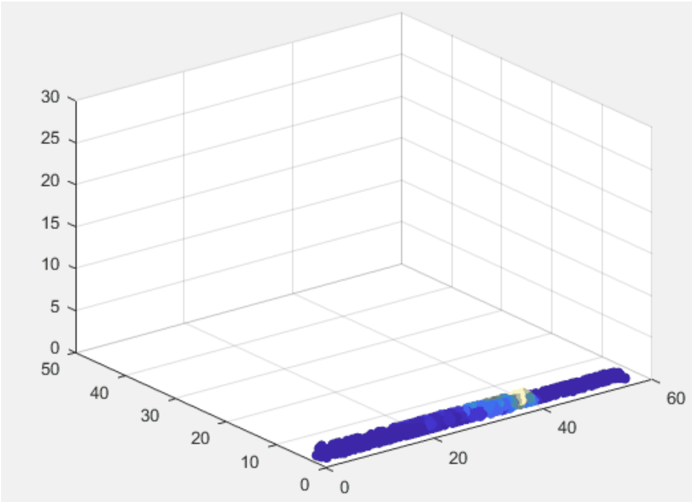


a) Isometric View b) Side View

Simulation of thin-wall

Block-by-block regime is adopted to simulate the thin-wall

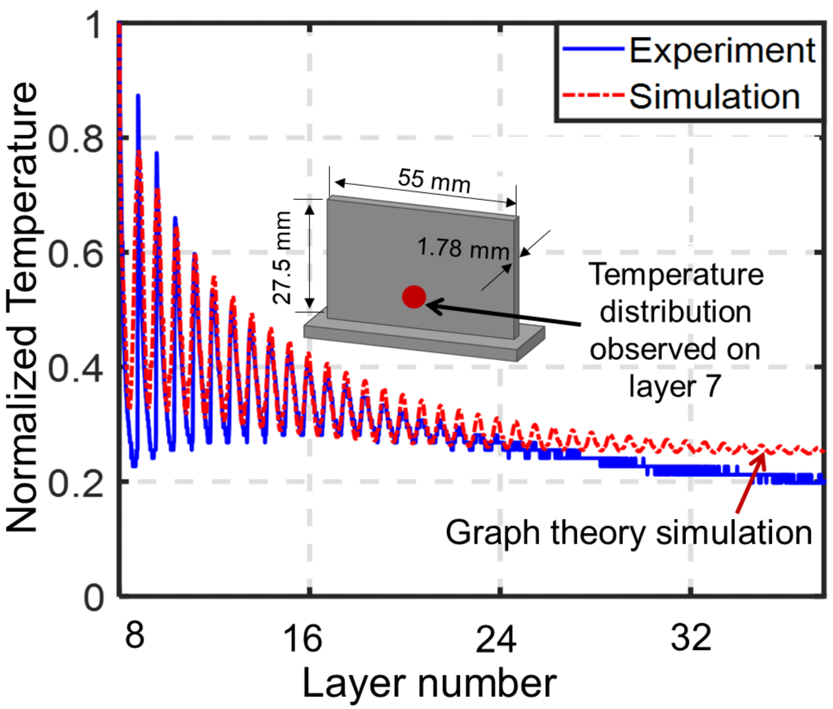


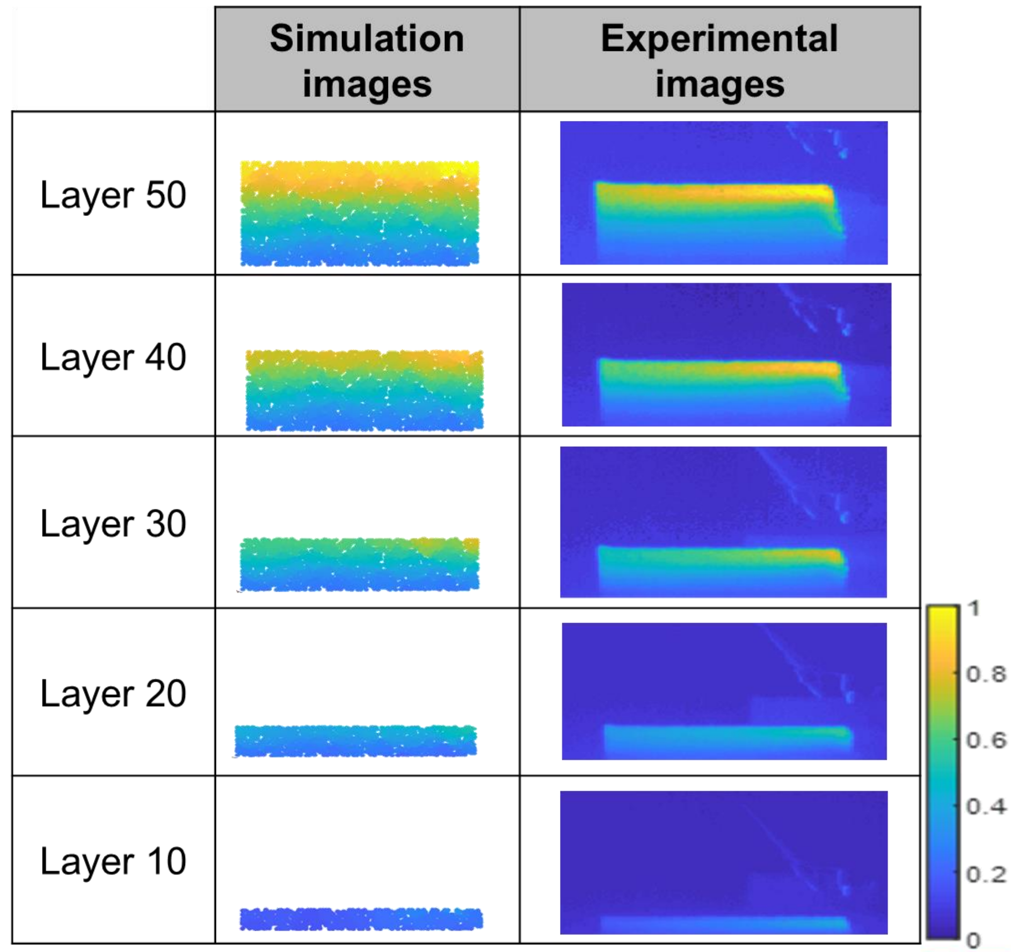


Comparison Between Experimental and Simulation Data

There is a high correlation between simulated part-level temperature and experimental meltpool temperature data.

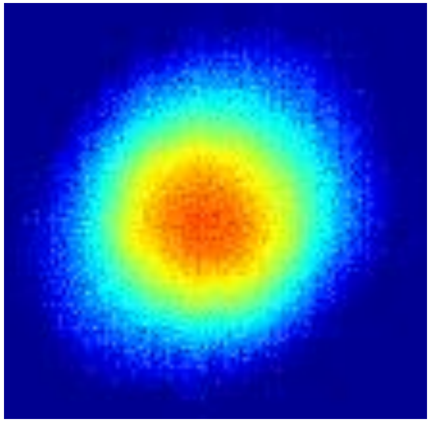
Temperature reading observed on Layer 7



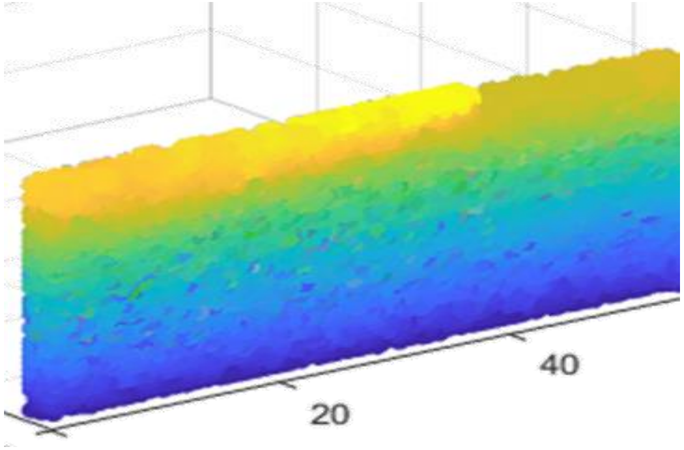


Combining Simulation and Sensor Data

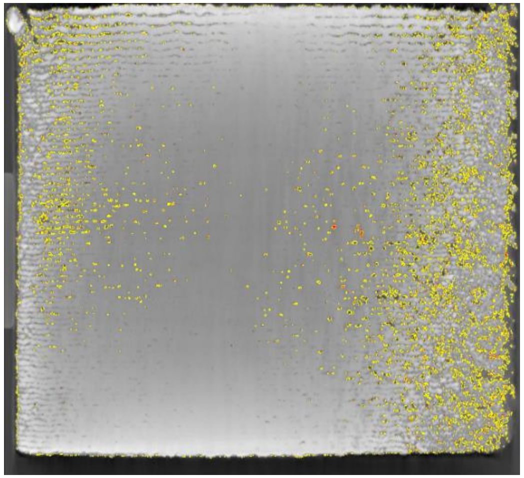
Experimental Data
Meltpool Images



Part-level Simulation



Ground Truth: XCT



- Obtain features (mean, standard deviation) of each melt pool image where pixel values are above 1600 ^{o}C.
- Calculate the statistical features (mean, standard deviation) of the part temperature from simulation.
- Use X-ray CT data to label locations with flaw size larger than 100 µm.

Prediction of Porosity

Data	Input features	F-Score
Pyrometer data	2: mean, standard deviation of meltpool area.	81.6% (3.2%)
Simulation data	2: mean, standard deviation of temperature readings.	82.9% (2.7%)
Digital Twin: Pyrometer + Simulation data	2: mean, standard deviation of pyrometer readings. + 2: mean, standard deviation of temperature readings.	**91.0% (1.2%)**

Confusion Matrix for two-level classification (Digital Twin)		
True Classes ↓	Predicted Classes	
	Non-Porous	Porous
Non-Porous (38 total)	38	0 (False Alarm, Type I error)
Porous (38 total)	6 (Failing to detect , Type II error)	32

The digital twin predicts the occurrence of porosity with higher accuracy in comparison to individual sensor and simulation data

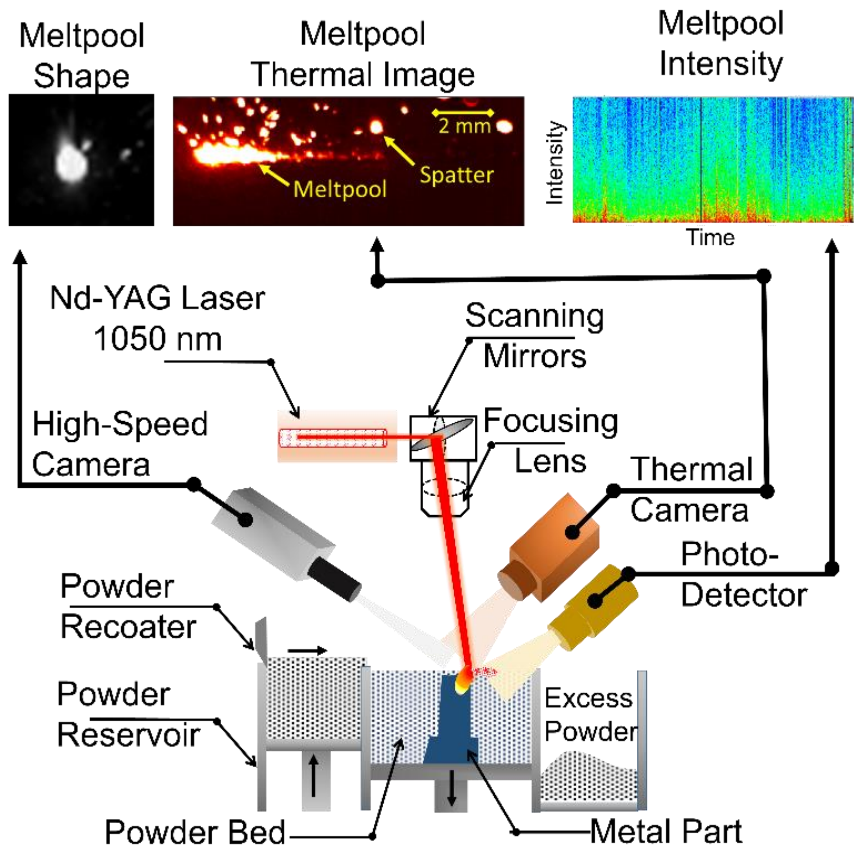
Case Study 2

Experimental data was generated at NIST by Dr. Brandon Lane and Dr. Jarred Heigel

Montazeri M, and Rao P., *Sensor-Based Build Condition Monitoring in Laser Powder Bed Fusion Additive Manufacturing Process Using a Spectral Graph Theoretic Approach*. ASME. *J. Manuf. Sci. Eng.* 2018;140(9):091002-091002-16. doi:10.1115/1.4040264.

Experimental Setup

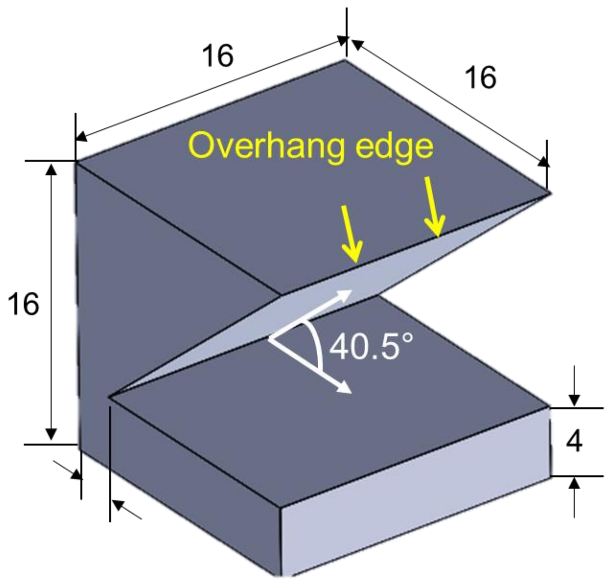
Heterogeneous sensor setup used in this work



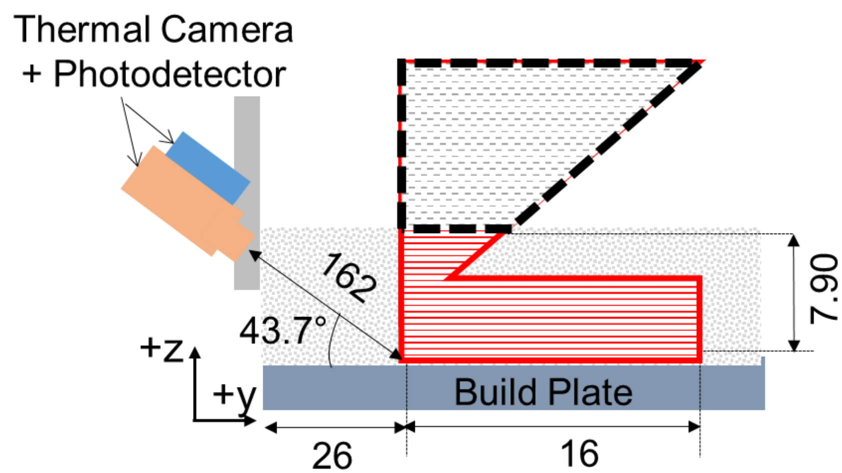
- Thermal camera
  Frame rate 1800 fps
  Wavelength 1350 nm – 1600nm
- High speed camera: Frame rate 4000 fps
- Photodetector: Sampling rate 1MHz

Test Part Geometry

16 mm × 16 mm × 16 mm test part (Inconel 625) with 40.5° overhang



3-D part schematic

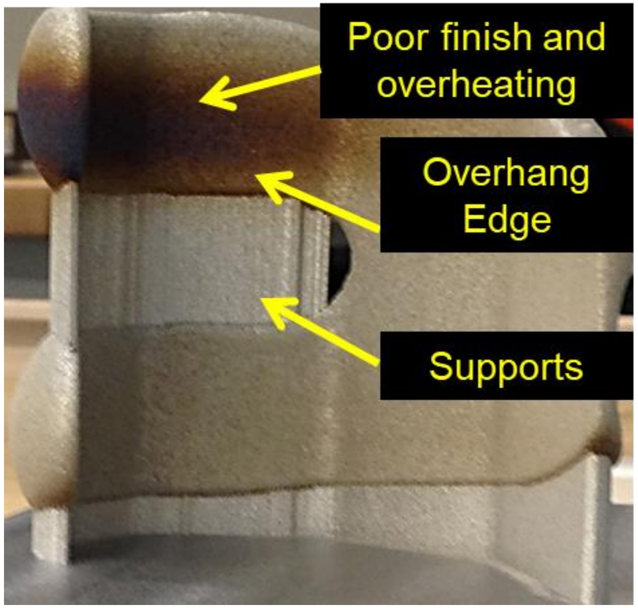


Side view schematic

Classify the difference between the overhang and bulk section by combining photodetector and thermal model data

Rationale

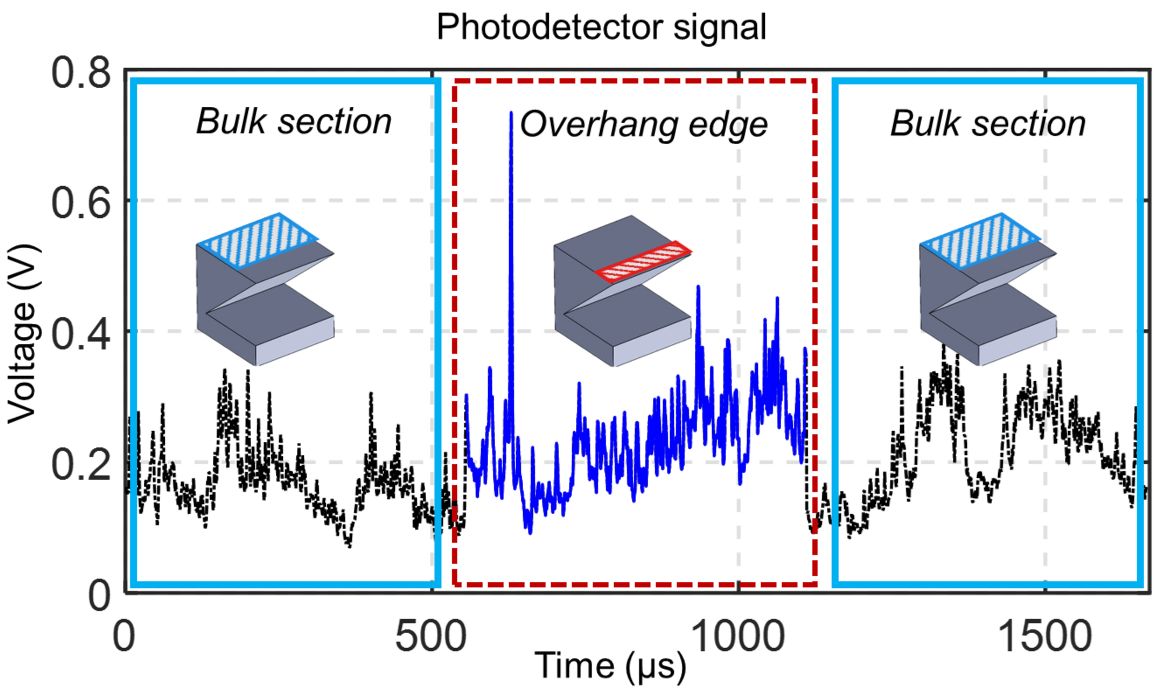
Overhang geometries are challenging to build and prone to failure

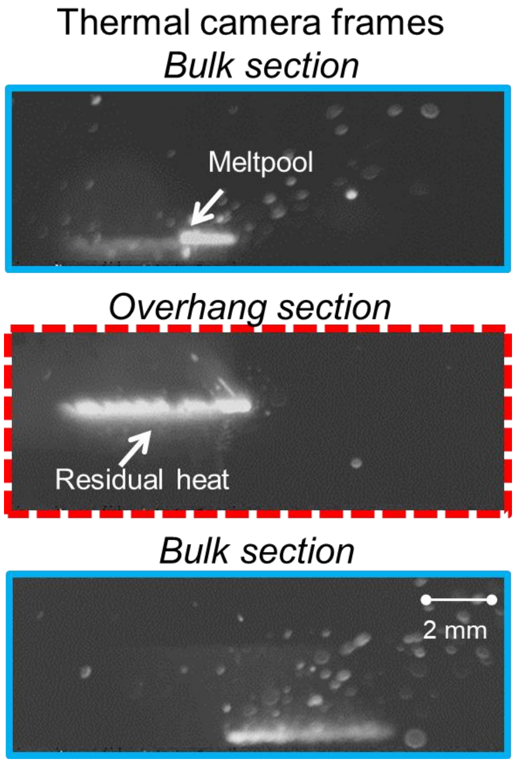


Heat tends to accumulates in the overhang region which leads to flaw formation, e.g., poor surface finish

Sample Sensor Data

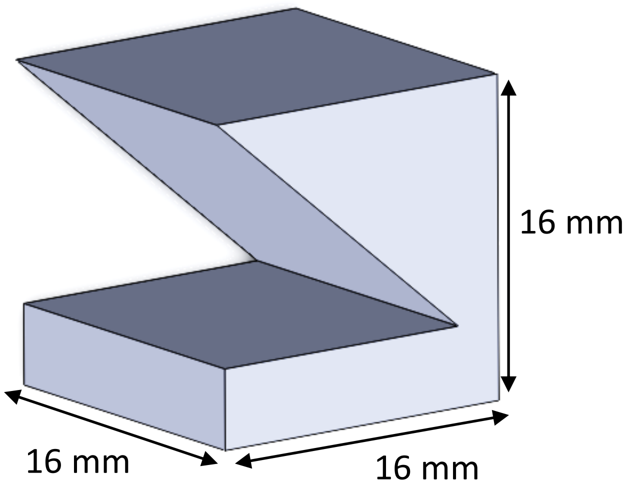
The photodetector and thermal camera capture the change in laser position from bulk section to overhang edge

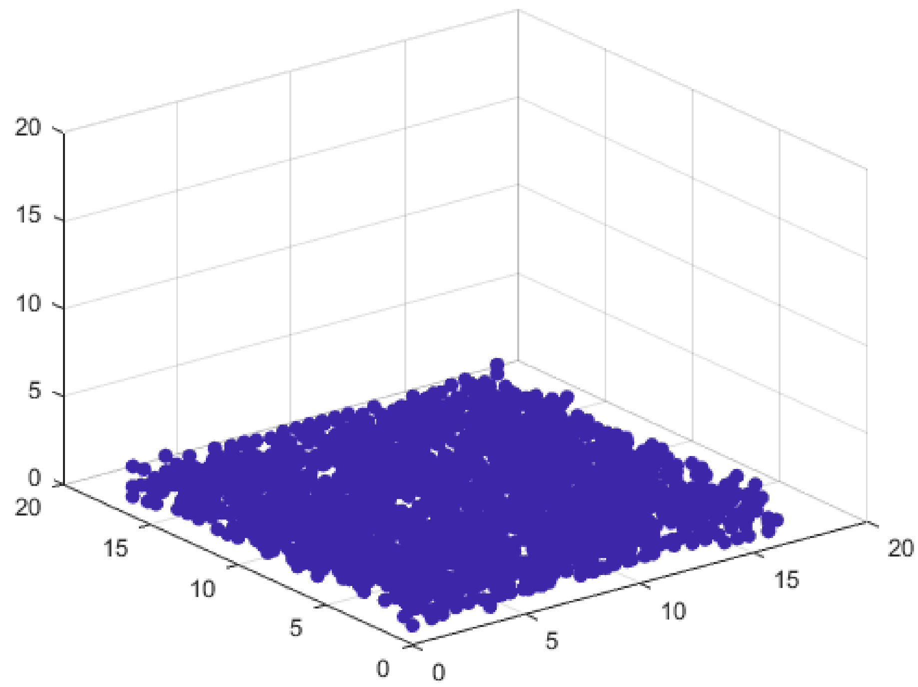




Simulation of Test Artifact

The graph theoretic model predicts the overheating of the overhang structure

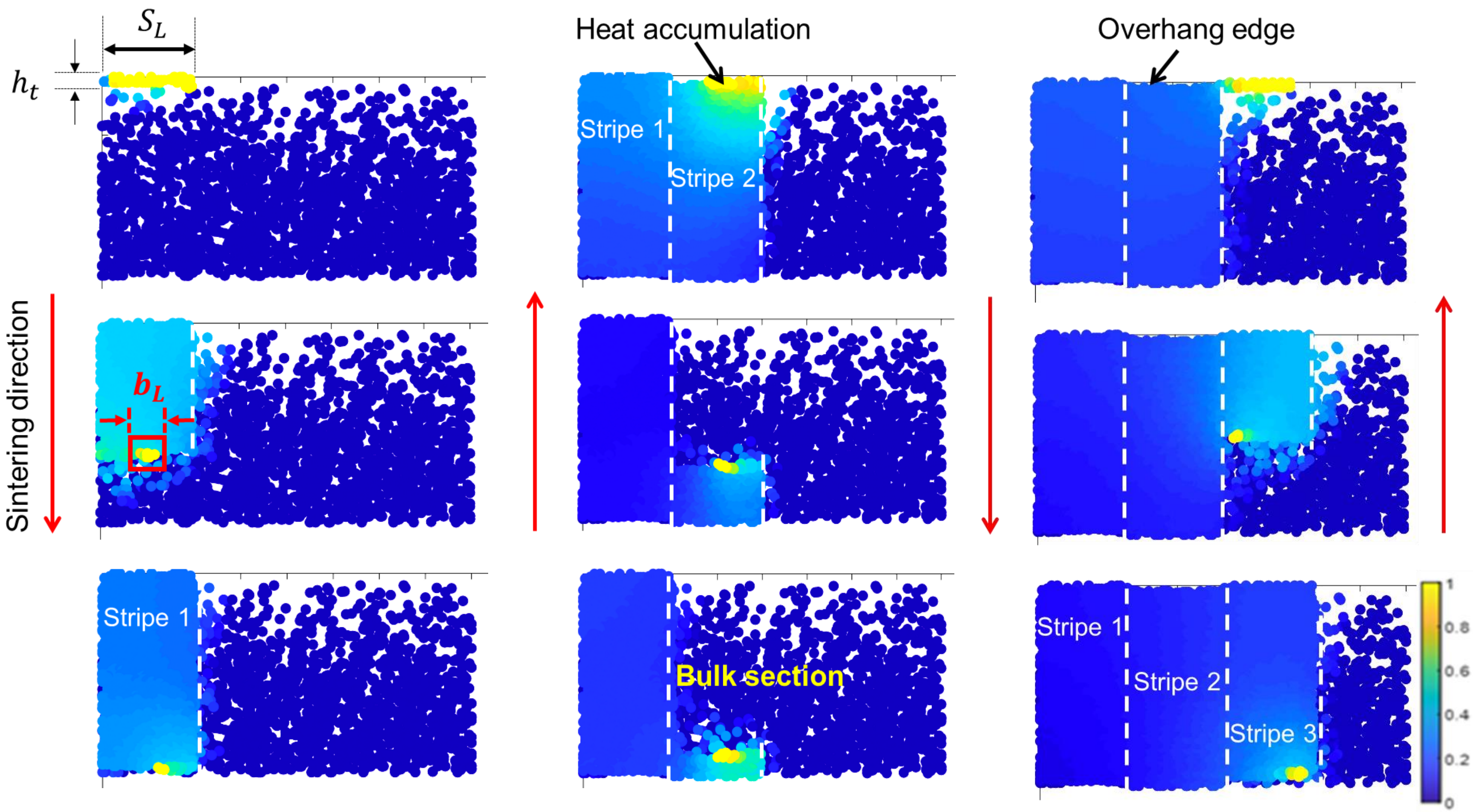




Heat accumulates in the overhang region which leads
to flaw formation, e.g., poor surface finish

Modified Stripe-wise Simulation

The simulation is modified to accurately to correspond with the sensor data



h_t = hatch thickness S_L = Stripe length b_L = Block length

Predicting Signatures Belonging to Different Section

Data	Input features	F-score
Photodetector data	2: mean, standard deviation of intensity readings taken over 60 consecutive hatches in a moving window. Data is available for 320 total hatches.	79.6% (1.5)
Simulation data	2: mean, standard deviation of temperature predictions for 15 consecutive blocks. There are 10 blocks per hatch, for a total of 3200 simulation blocks.	76.3% (1.1)
Digital Twin: Photodetector + Simulation data	2: mean, standard deviation of intensity readings + 2: mean, standard deviation of temperature readings.	**87.5% (1.4)**
Ground truth: Thermal camera data	2: mean, standard deviation of intensity readings.	93.2% (1.9)

Confusion Matrix for two-Level Classification (Digital Twin)

True Classes ↓	Predicted Classes	
	Bulk	Overhang
Bulk	57 (out of 59)	2 (False Alarm)
Overhang	12 (Failing to detect)	47 (out of 59)

The digital twin predicts the occurrence of porosity with higher accuracy in comparison to individual sensor and simulation data

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Conclusion and Future Work

Combining the theoretical simulations with in-process sensor data leads to higher statistical fidelity of detecting process flaws.

- Prediction fidelity increases to over 85% compared to 75% using only sensor data or simulation alone.

Extend for prediction of different types of flaws, such as cracking and deformation, with data acquired from multiple in-process sensors.

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