Digital Twin Research and Development for a Metal Additive Manufacturing Process

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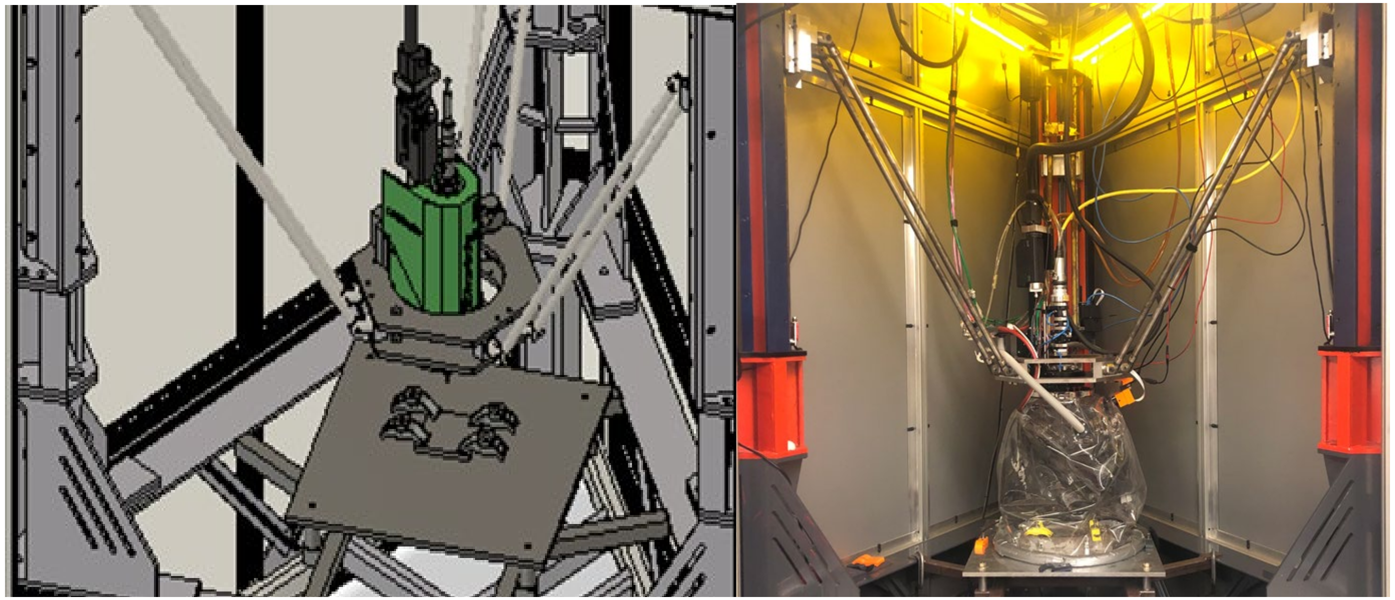
Outline

- Background in Metal Additive Manufacturing (AM)
- Digital Twins (DTs)
- Case Study on Residual Stress Prediction
- DT Graph and Connectivity
- Machine Learning in DT
- Challenges and Future Work



Robotic Wire Feed AM

(Source: Missouri University of Science and Technology [S&T] Laser-Aided Manufacturing Process [LAMP} Laboratory)

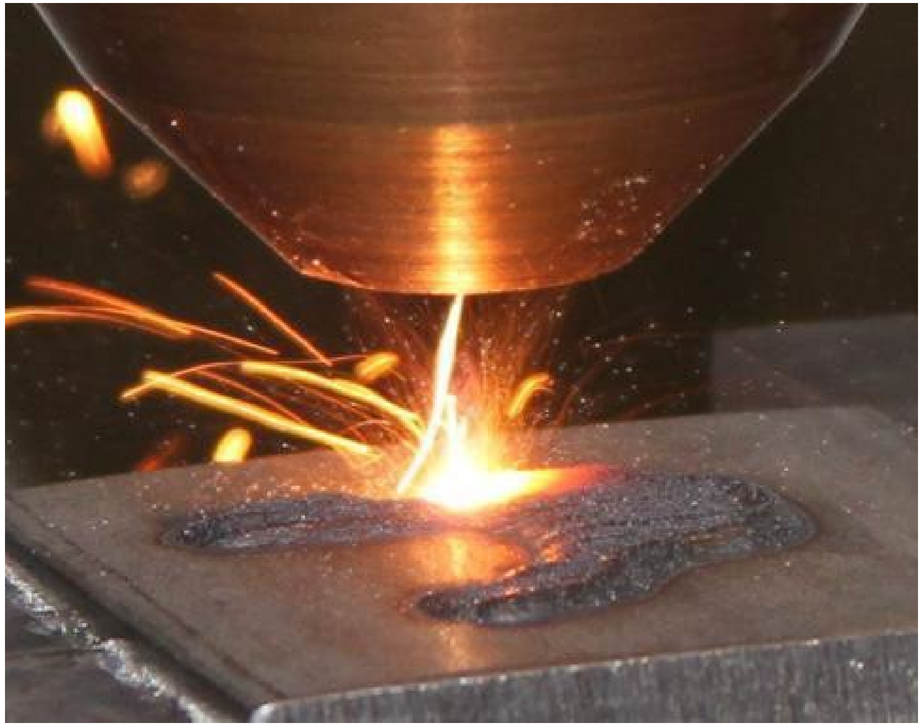
LAMP Laboratory

- Metal AM Research Since 1997
- Custom AM System and Component Design and Integration
- AM Repairing
- AM Monitoring and Control
- AM Part Characterization
- Hybrid System Integration and Process Planning
- DTs for AM Processes
- Digital Factories

Advanced Materials and Manufacturing (AM²) Process
(Source: Missouri S&T LAMP Laboratory)

Directed-Energy Deposition (DED) Powder Feed Process

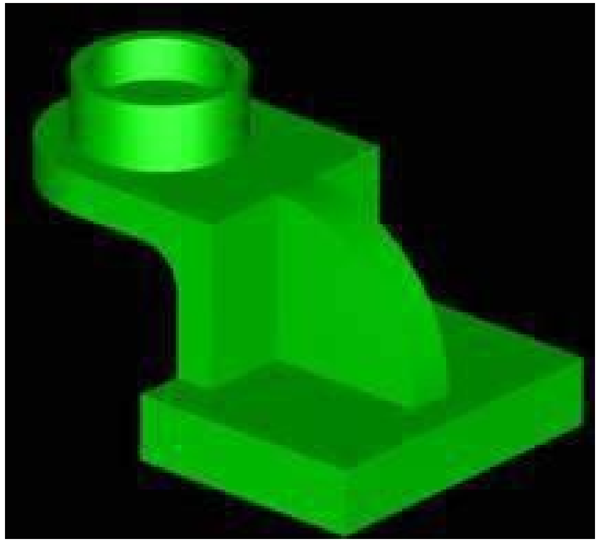
- Lower Heat Input: Less base metal distortion compared to welding
- Metallurgical Bond Between Deposit and Substrate Materials
- Compatible With Many Advanced Materials
- Repair/Remanufacturing

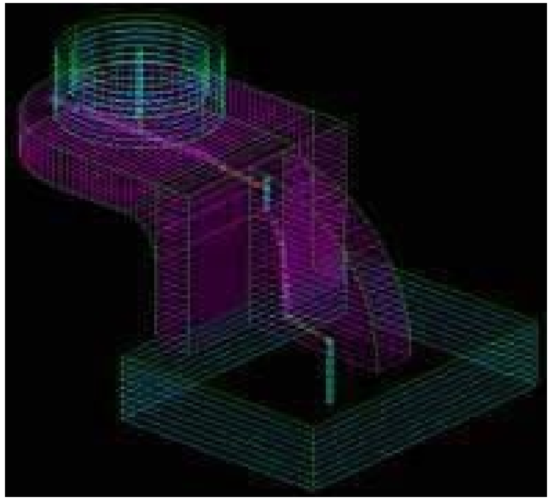


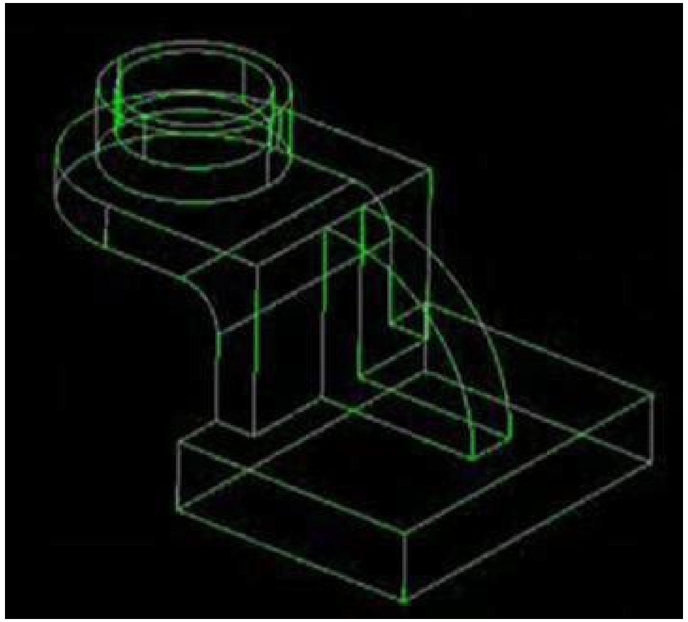
Powder DED Process

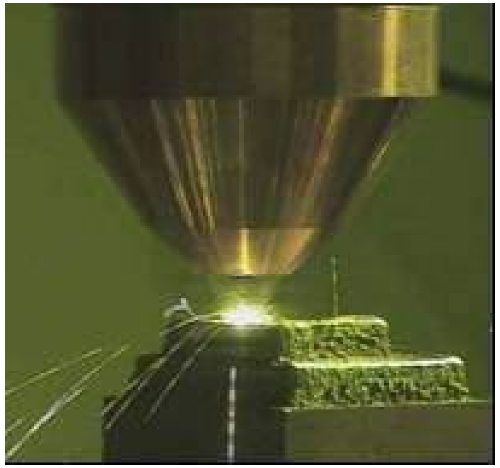
(Source: Missouri S&T LAMP Laboratory)

Hybrid Manufacturing







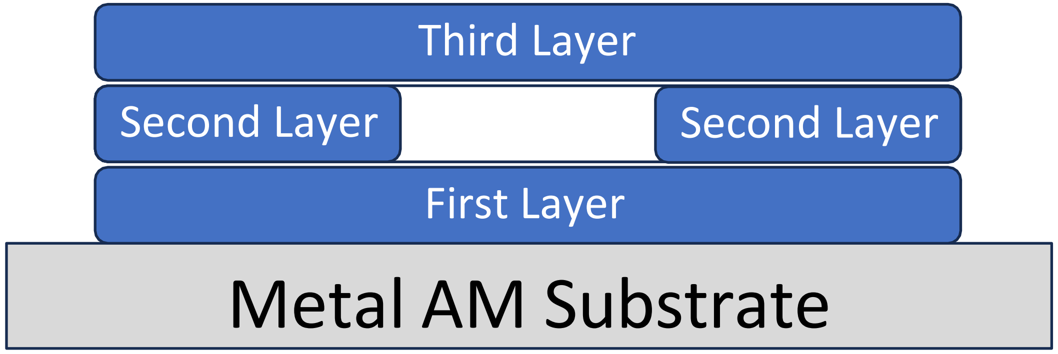


Process Planning of Hybrid DED Process

(Source: Missouri S&T LAMP Laboratory)

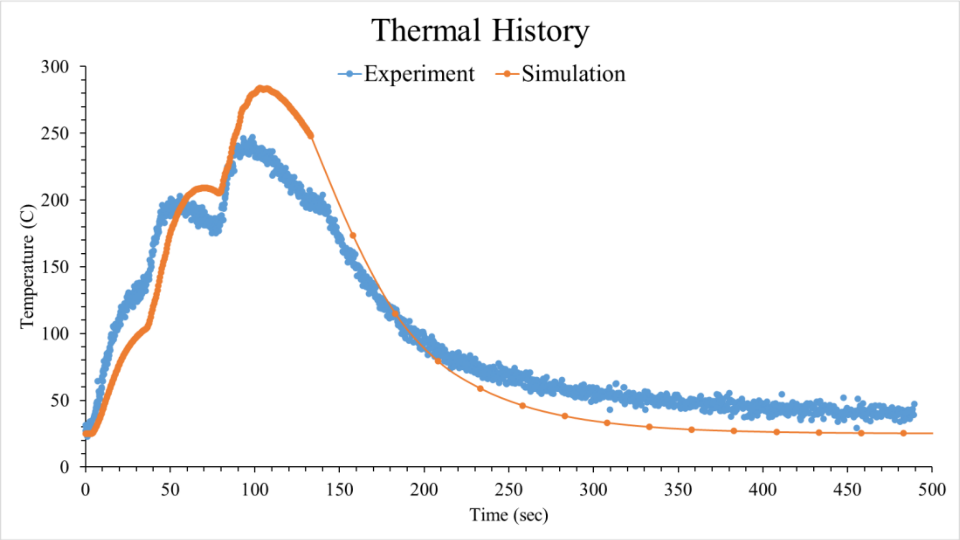
Metal AM: State of the Art

- Metal AM has emerged as a disruptive digital-manufacturing technology.
- However, its broad adoption in industry is still hindered by several issues:
    - Geometries
    - Materials
    - Processing Defects
    - Residual Stresses
    - Multimaterials
    - And More



Possible Technology Helps

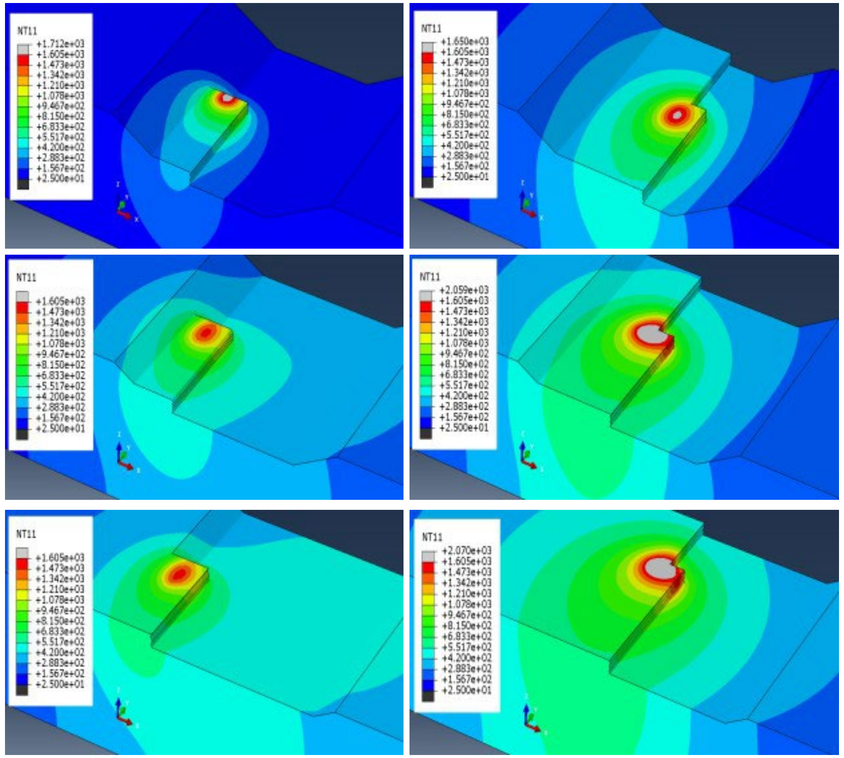
- Model
- Experiments
- Sensors
- And More



First Layer

Second Layer

Third Layer

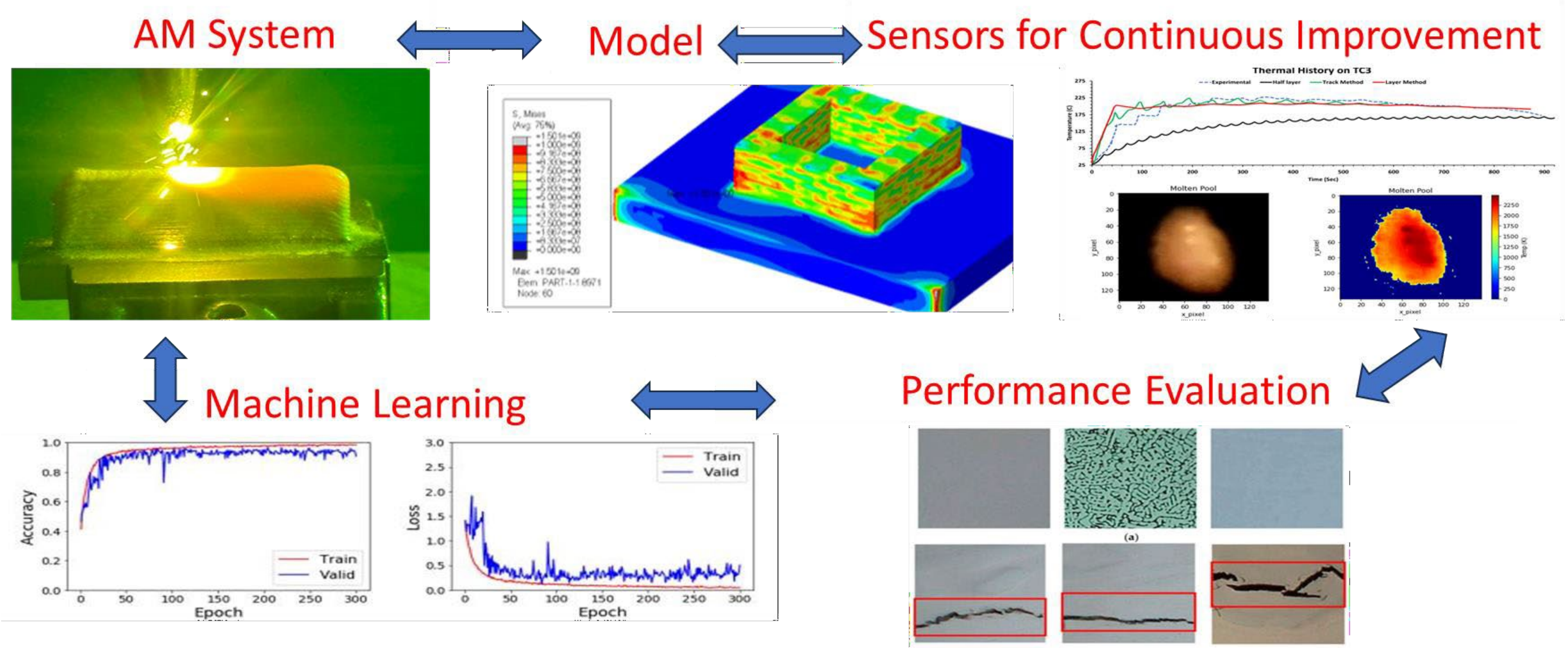


Modeling of Powder DED Process

(Source: Tariq, Missouri S&T LAMP Laboratory)

DT

A virtual representation of a process that spans its lifecycle; is updated from real-time data; and uses process modeling, machine learning, and reasoning to help decision-making.



DT of DED Process

(Source: Missouri S&T LAMP Laboratory)

Why DT?

- Gives insights into many critical aspects of a manufacturing process.
- Has continuous improvement through:
  - Sensor Data From Physical Tests
  - Data From the Virtual Model(s)
- Can be a critical tool for most decision-making.
- Has improved operational efficiency, automation of manual tasks, training, and validation (e.g., to achieve the first-time build success).

Digital

Physical

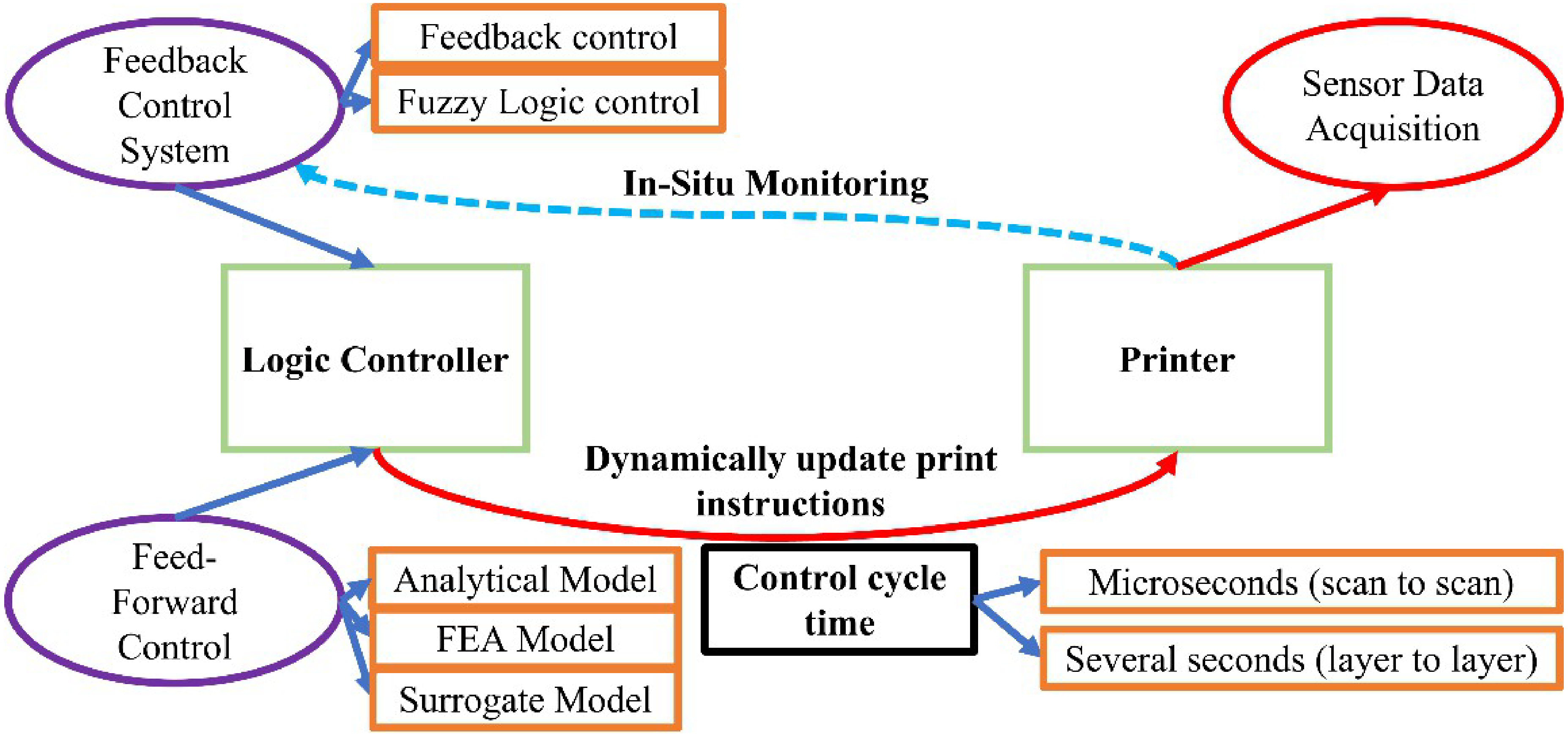
DT of a Robot

(Source: Missouri S&T LAMP Laboratory)

Foundational Research Gaps and Future Directions for DTs (2024)

- National Academies
- Federal Agencies:
    - Recommendation 1: Launch new cross-cutting programs to advance mathematical, statistical, and computational foundations for DTs.
    - Recommendation 2: Ensure that verification, validation, and uncertainty quantification are an integral part of new DT programs.
- And more

Process Control in DT



Note: FEA = finite-element analysis.

Building a DT

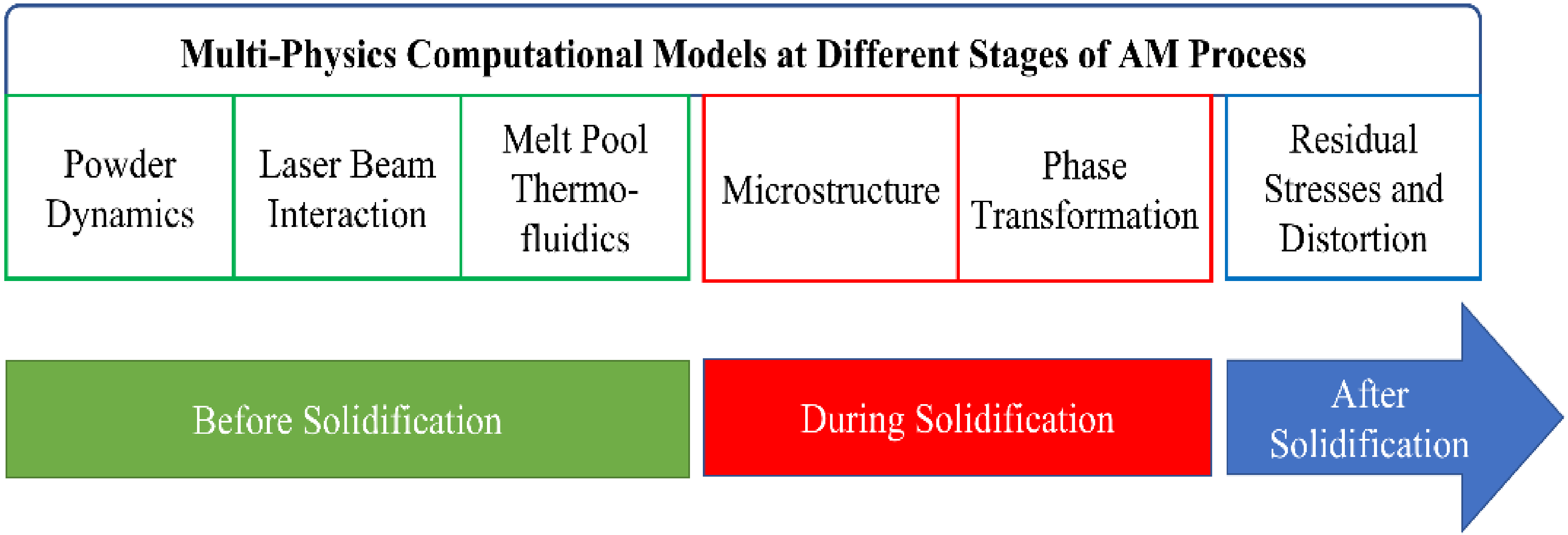
(Source: Missouri S&T LAMP Laboratory)

Case Study on Residual Stress Prediction

- Tensile stress conditions can adversely affect material performance or component life.
- Compressive stress conditions can improve material fatigue strength.
- For integrated aviation structures, deformation caused by residual stress has become one of the most prominent AM problems.

Residual Stress Experiment
(Source: Missouri S&T LAMP Laboratory)

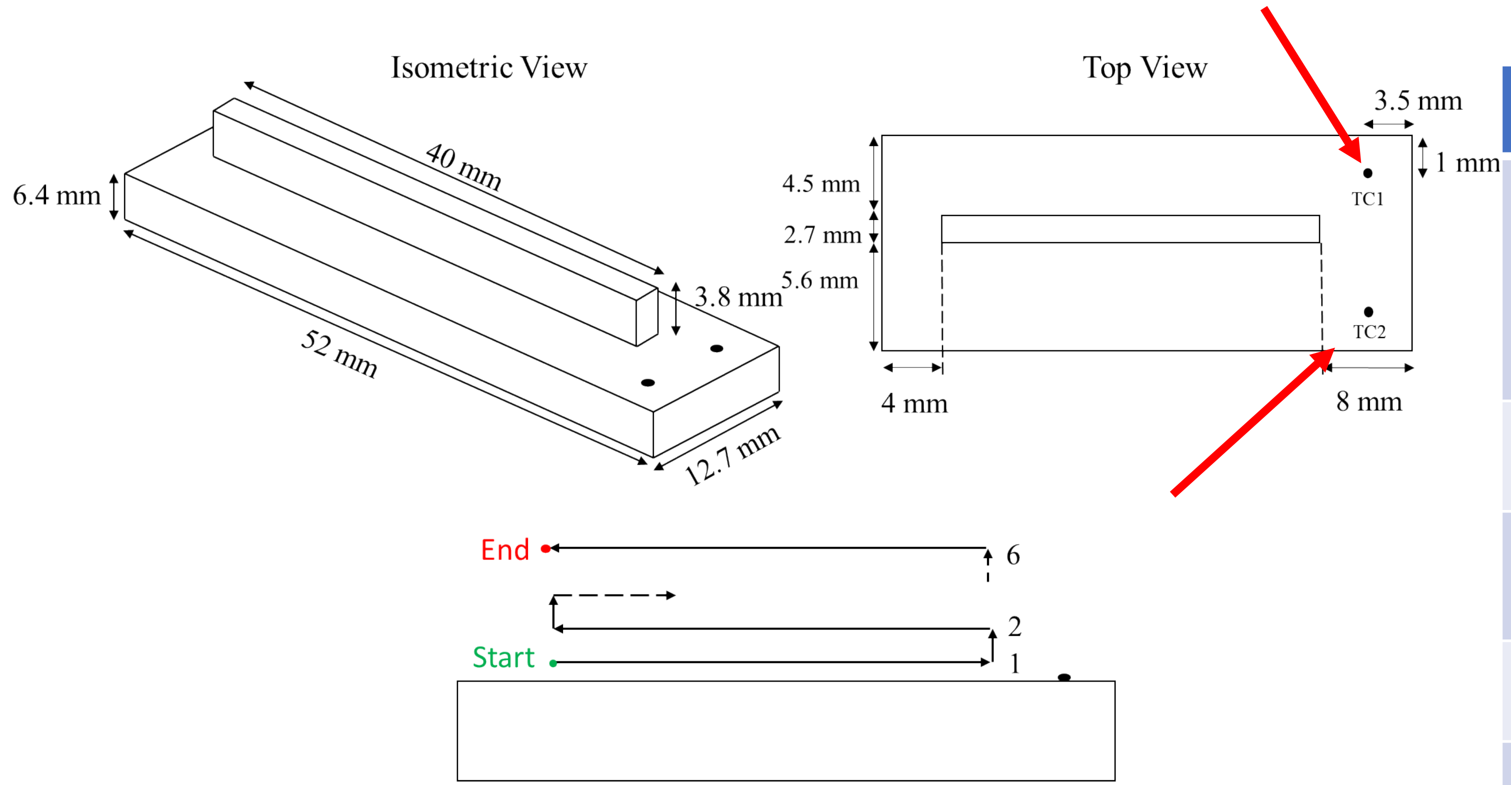
Multiphysics Models for AM at Various Stages



Multiphysics Models

(Source: Missouri S&T LAMP Laboratory)

Specimen and Material



Note: TC1 – Thermocouple 1, TC2 = Thermocouple 2.

DED Specimen and Scan Strategy

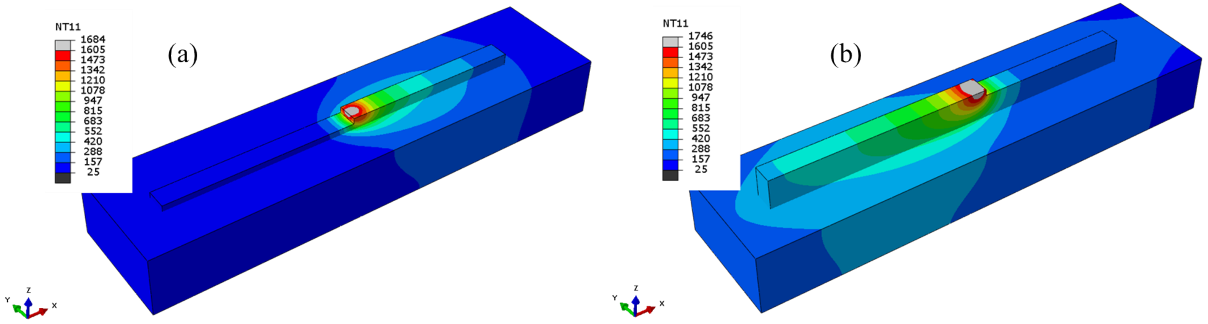
Residual Stress Model

(Source: Missouri S&T LAMP Laboratory)

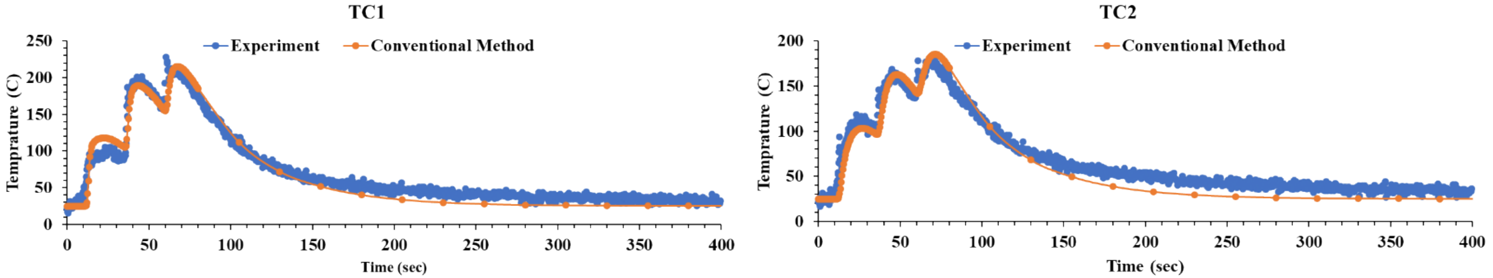
Scan Parameters	
Material	Ti-6Al-4V (Temperature-Dependent Properties)
Powder Feed Rate	2.0 g/min
Shielding Gas Pressure	40 psi
Beam Spot Size	2.2 mm
Power	350 W
Scan Speed	200 mm/min
Dwell Time	0.15 s

Note: Ti-6AL-4V = an alpha-beta titanium alloy.

Conventional Method (Thermal, ~17 hr)



Temperature Profile (°C) Using Conventional Method During DED Deposition (a) Second Layer and (b) Fifth Layer



Thermal Validation (°C) of Conventional Method Using TC1 and TC2

Process Thermal Model

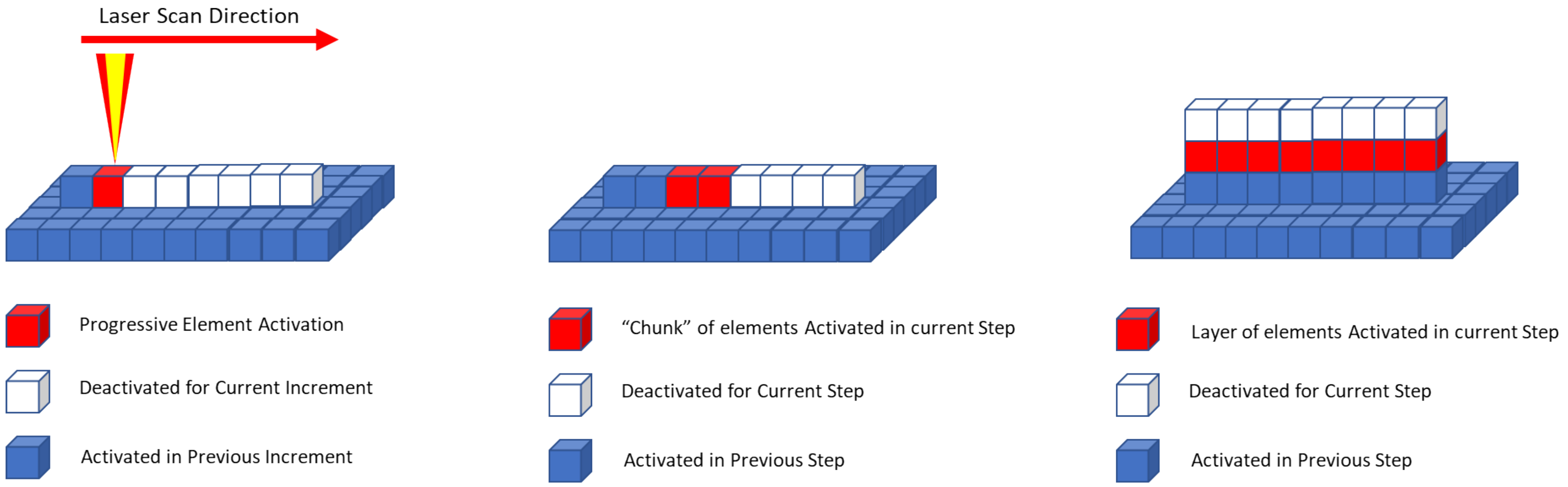
(Source: Missouri S&T LAMP Laboratory)

Methodology

Energy Distribution Due to Laser Heat Source

Uniform Body Heat Flux Using the Chunk Method

Uniform Body Heat Flux Using the Layer Method

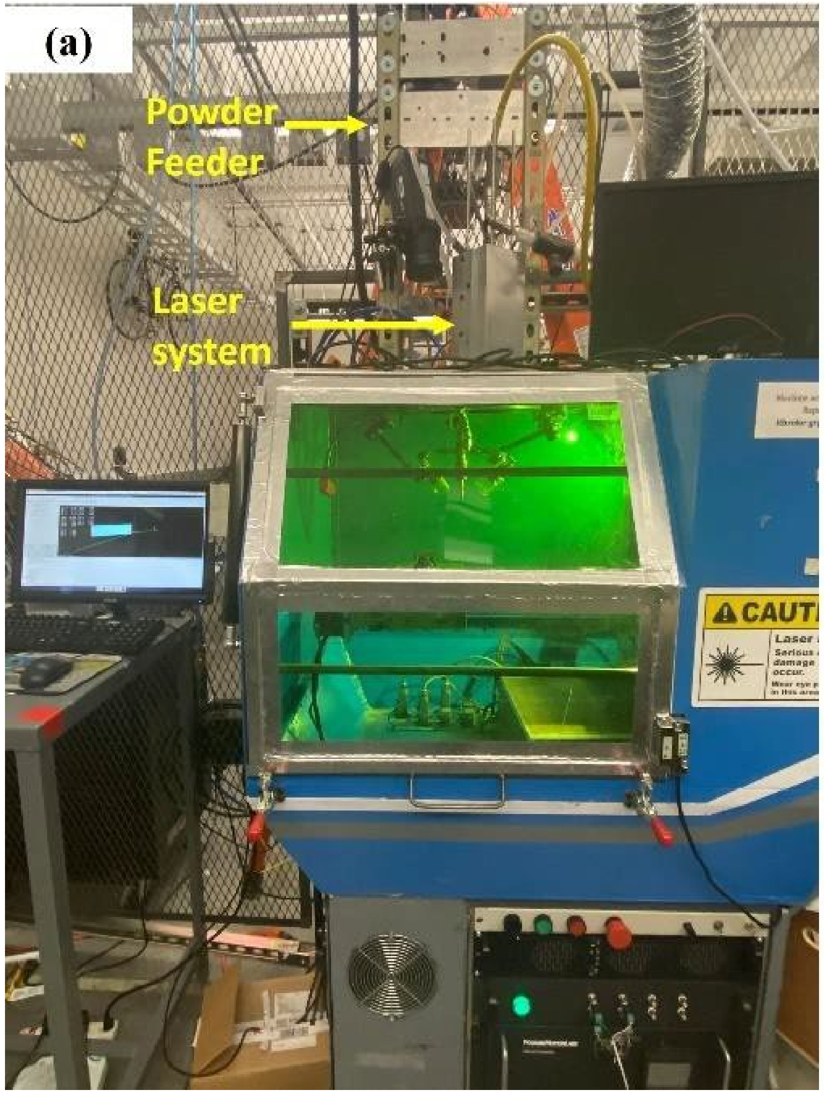


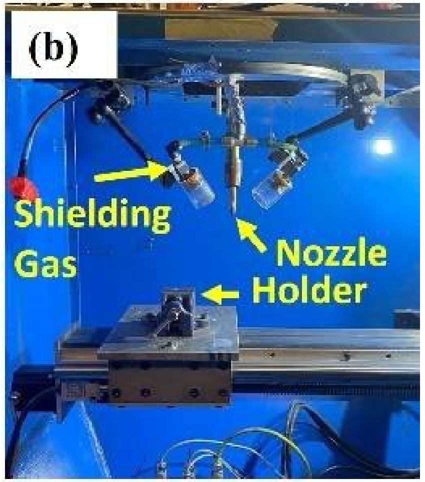
(a) (b) (c)

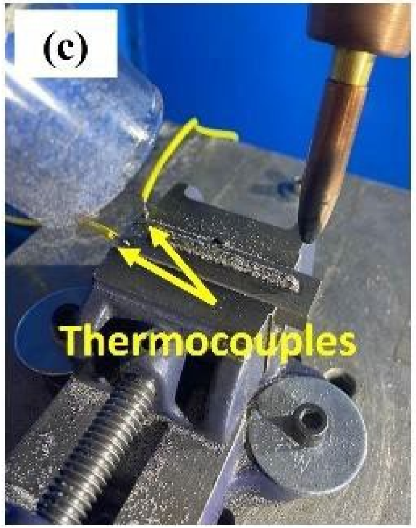
Residual Stress Model Methodology

(Source: Missouri S&T LAMP Laboratory)

Experimental Setup







(Source: Missouri S&T LAMP Laboratory)

(a) In-House-Developed DED System at Missouri S&T
(b) Powder and Shielding Gas System
(c) Built Part Along With Thermocouples

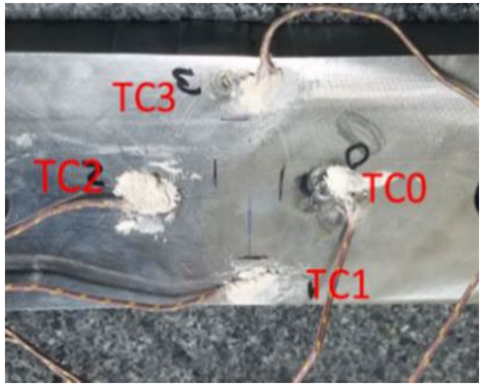
Machine Parameters	
Laser Type	Nd:YAG
Maximum Laser Power	1 kW
Shielding Gas	Argon
Thermocouple	K-type
Data Acquisition Rate	0.01 s

Note: Nd:YAG = neodymium-doped yttrium, aluminum, garnet.

Measuring and Approximation

Sensing/Monitoring in DED: Thermal History

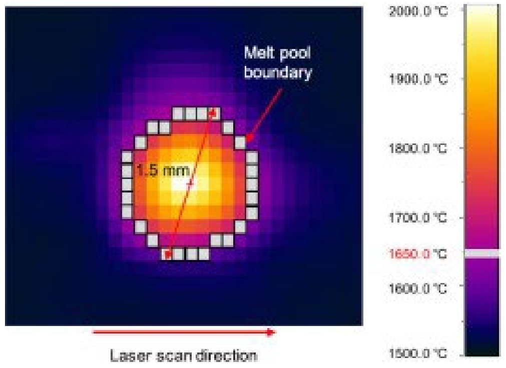
Thermocouple



- Pros: Cost Effective, Useful for Calibration
- Cons: Difficult to Directly Measure Each Layer and All Points Data

Optical Method

- Pros: Distributed Data and Layer-by-Layer Monitoring
- Cons: Expensive and More Complex Experimental Setup and Accessories



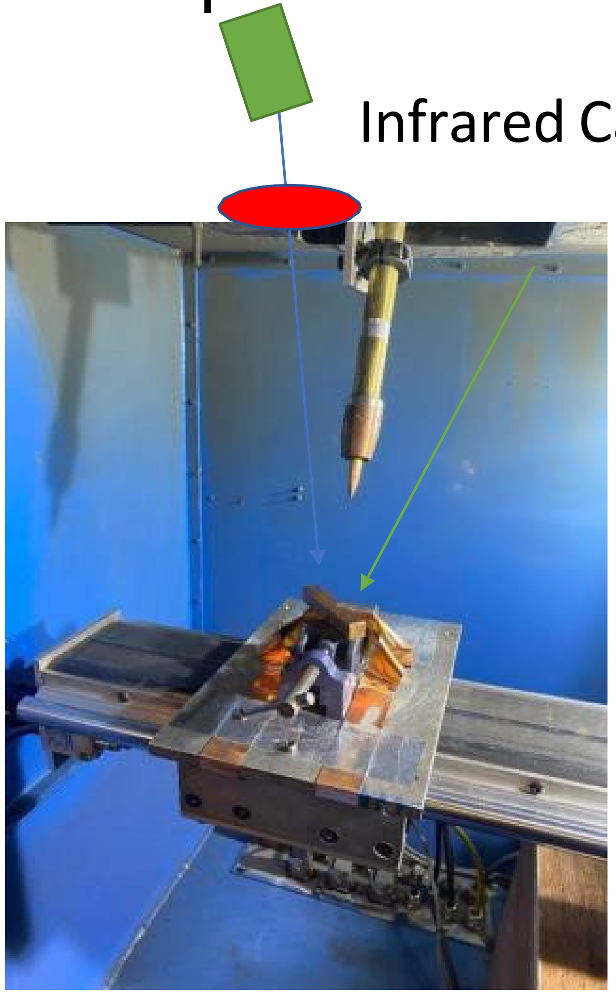
Residual Stress Experimental Setups

(Source: Missouri S&T LAMP Laboratory)

Design of Experiments

Experimental Setup: Thermal History

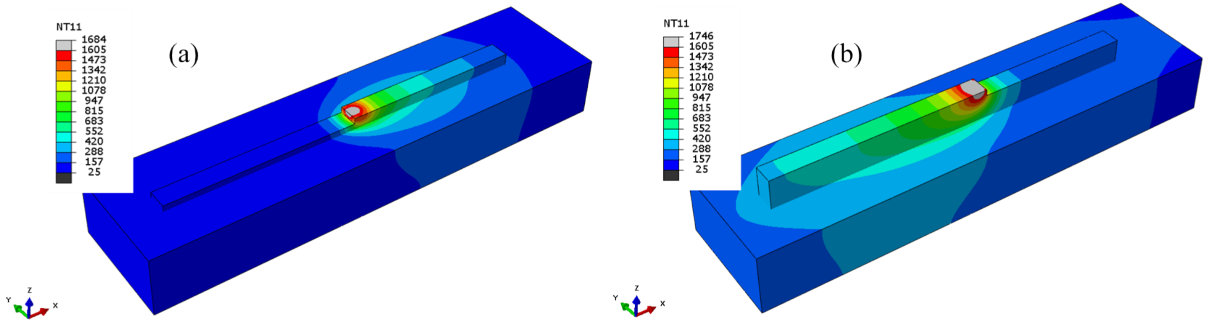
Infrared Camera



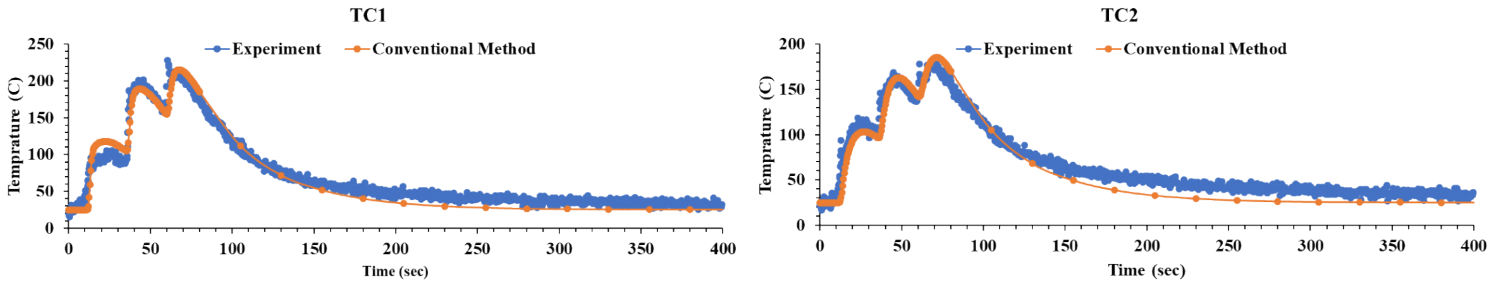
Residual Stress Experimental Setups

(Source: Missouri S&T LAMP Laboratory)

Conventional Method (Thermal, ~17 hr)



Temperature Profile (°C) Using Conventional Method During DED Deposition (a) Second Layer and (b) Fifth Layer



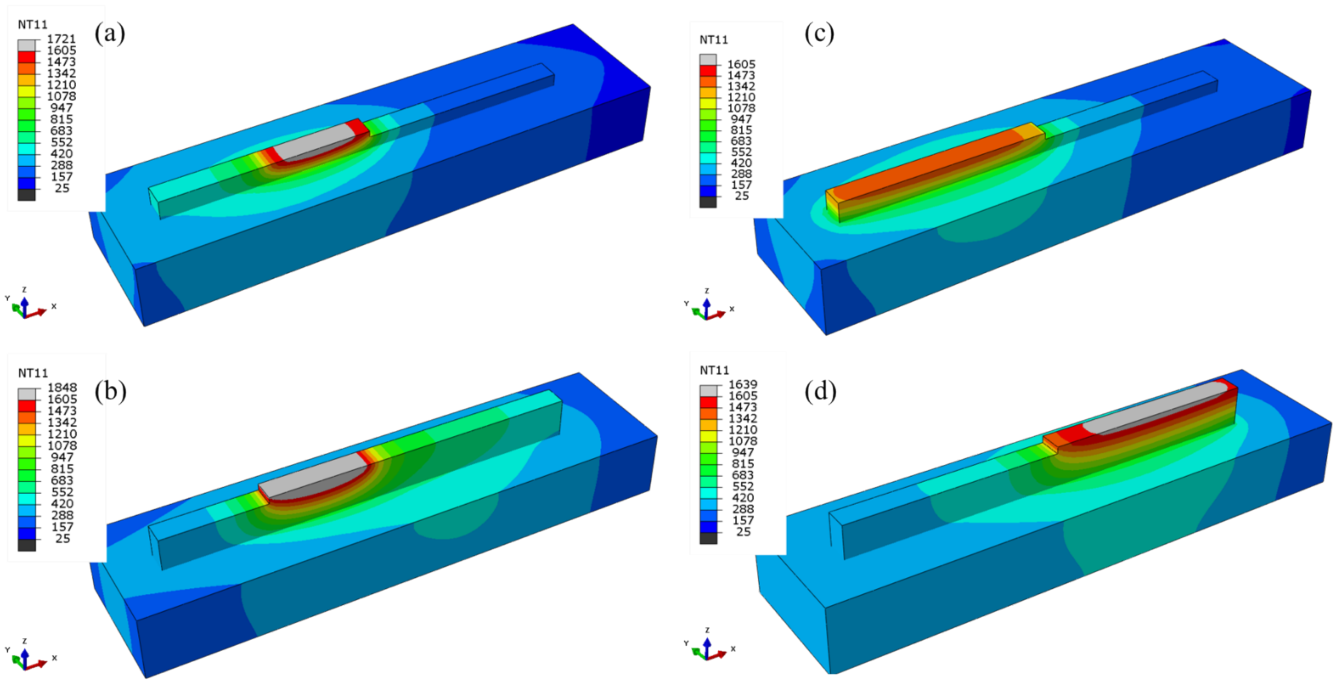
Thermal Validation (°C) of Conventional Method Using TC1 and TC2

Residual Stress Modeling Result

(Source: Missouri S&T LAMP Laboratory)

Chunk Method (Thermal)

¼-Track Length ½-Track Length

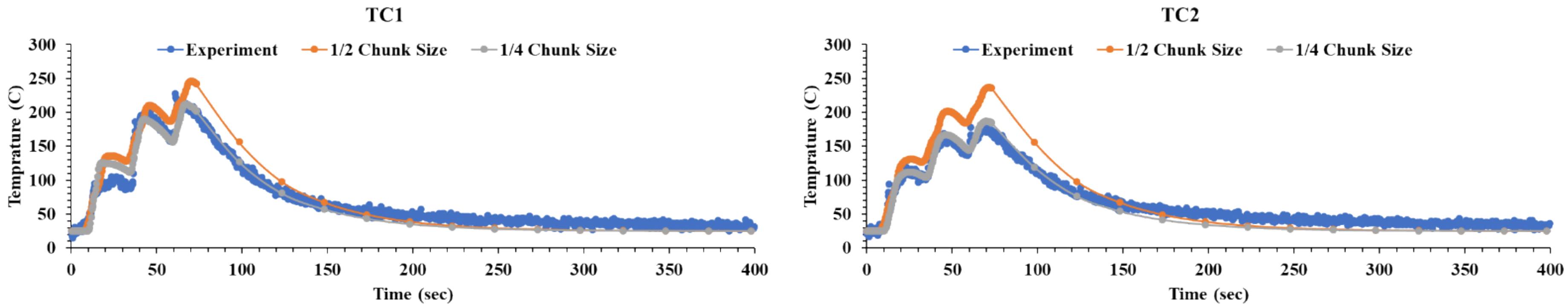


Thermal Loading (°C) Using Chunk Method ¼-Track Length at (a) Third Layer and (b) Sixth Layer and ½-Track Length at (c) Third Layer and (d) Sixth Layer

Residual Stress Modeling Result

(Source: Missouri S&T LAMP Laboratory)

Chunk Method (Thermal) (continued)



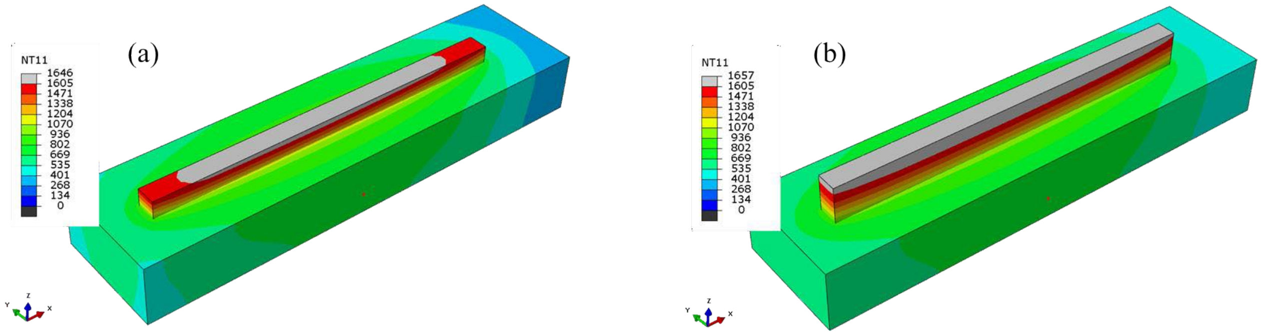
Thermal Validation (°C) of Chunk Method With TC1 and TC2

Residual Stress Modeling Result

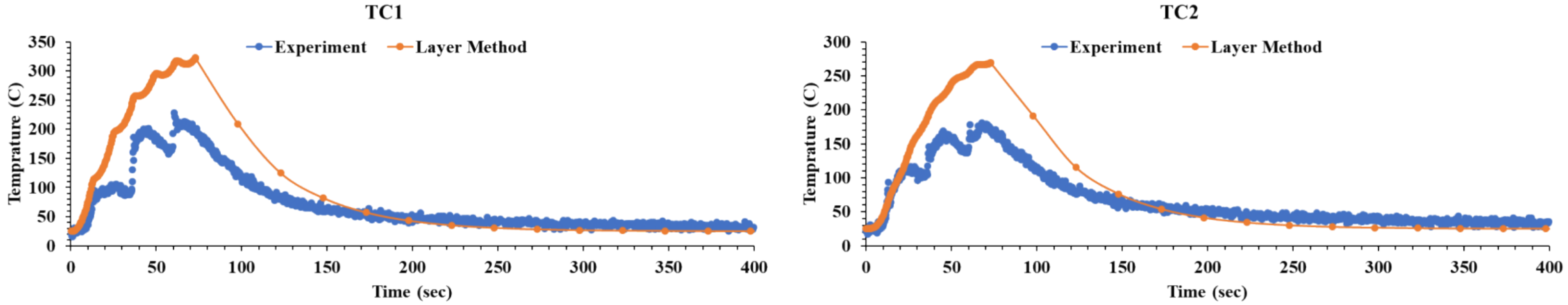
(Source: Missouri S&T LAMP Laboratory)

Results and Discussion

Layer Method (Thermal)



Thermal Loading (°C) Using Layer Method at (a) Third Layer and (b) Sixth Layer

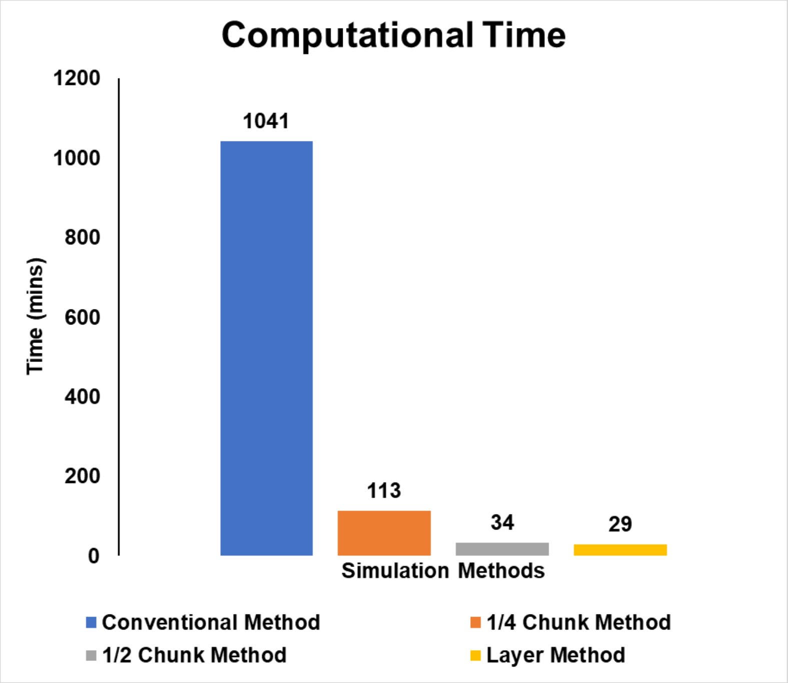


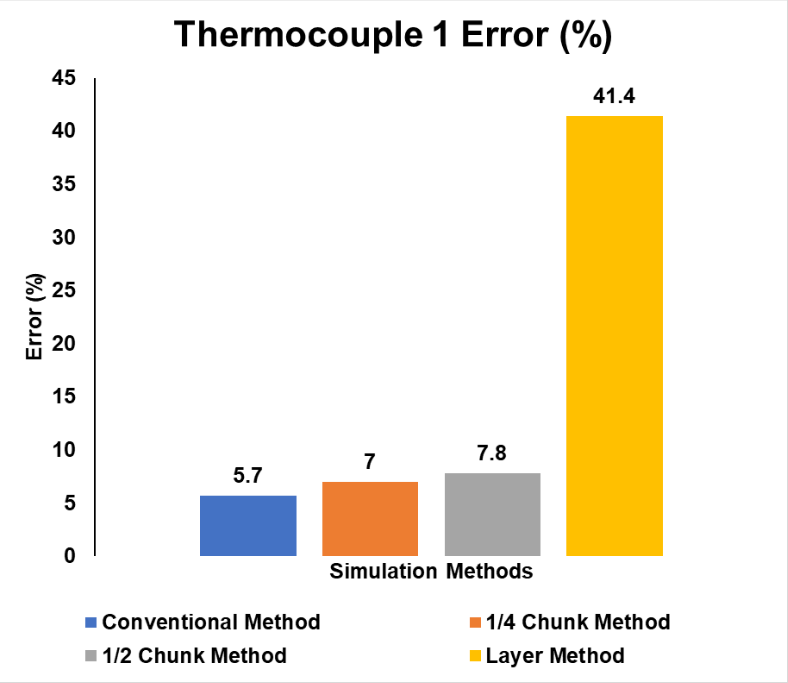
Thermal History (°C) Using Layer Method

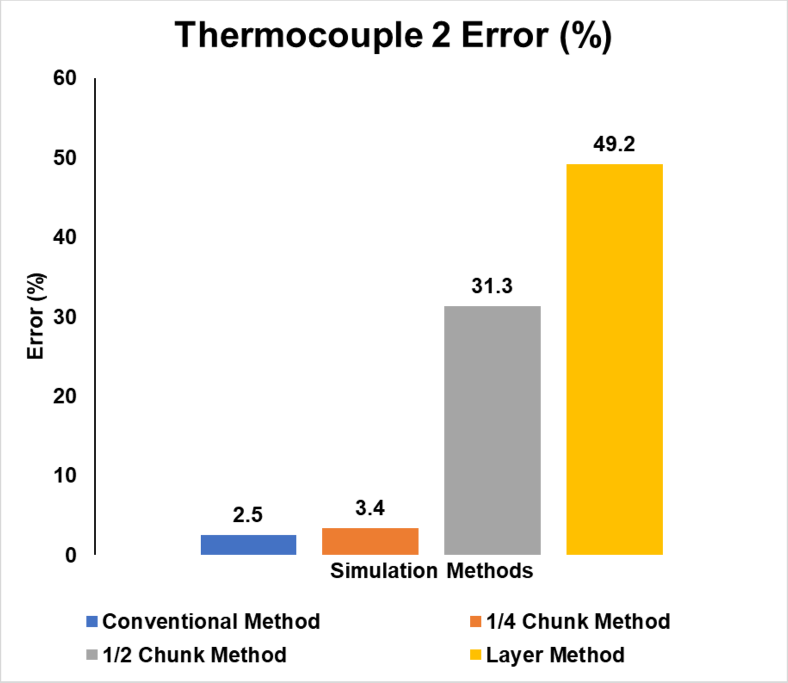
Residual Stress Modeling Result

(Source: Missouri S&T LAMP Laboratory)

Results







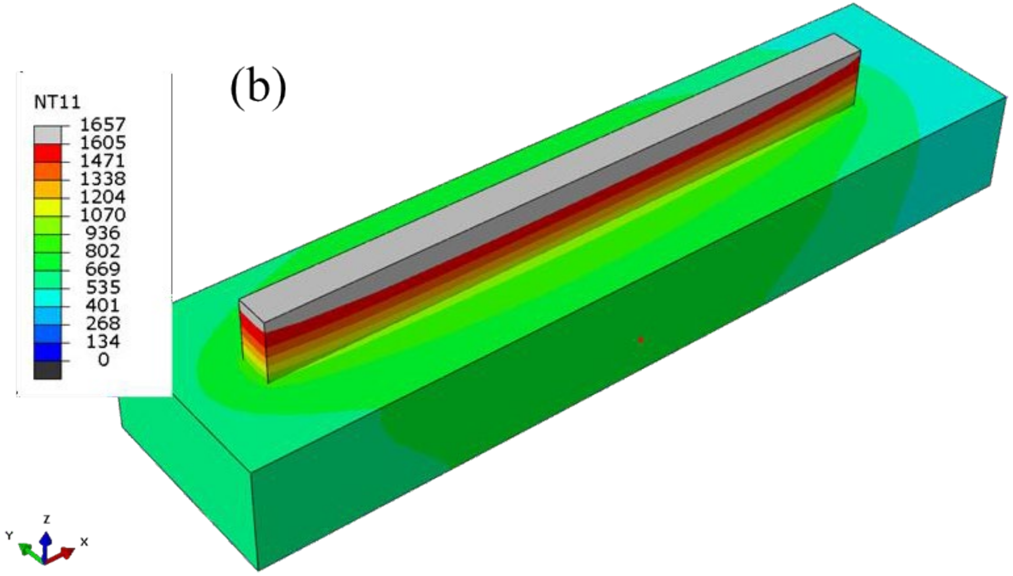
Note: All the simulations were performed in a computer having Intel(R) Xeon(R) W-2295 central processing unit at 3.00 GHz equipped with 18 cores and 128 GB random access memory at 2934 GHz.

Residual Stress Modeling Result

(Source: Missouri S&T LAMP Laboratory)

What's Next?

- It was just a very simple example.
- Stresses can be tool path dependent.
- It is parameter dependent.
- It is geometry dependent.
- It is material dependent.
- It has expensive trial-and-error experiments.
- And more.



Residual Stress Model

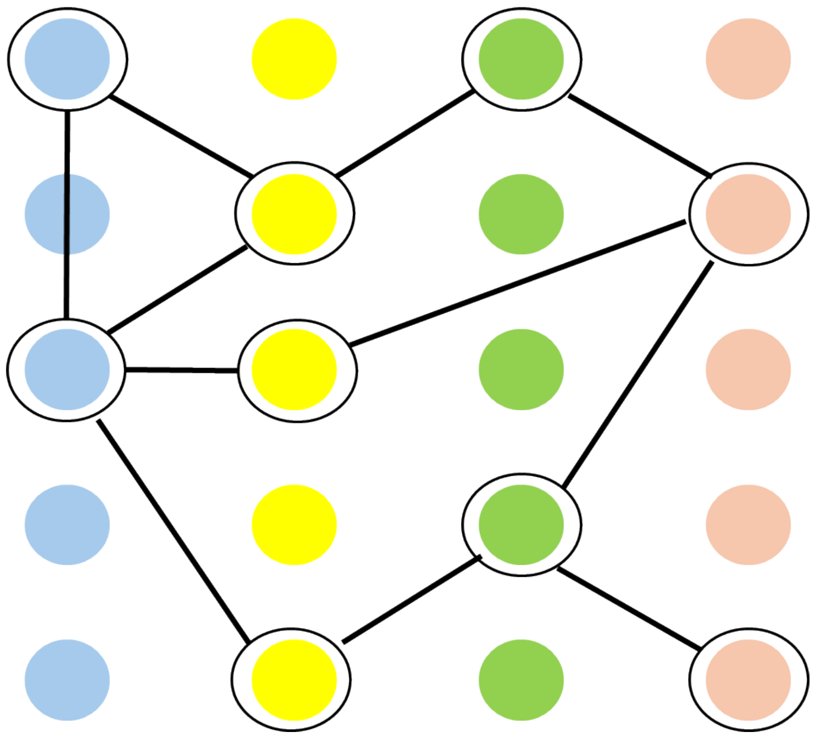
(Source: Missouri S&T LAMP Laboratory)

DT Applications in Metal AM

- Desired Microstructure
- Robust Mechanical Properties
- Strengths:
    - Tensile
    - Fatigue
- Hardness
- Ductility
- Repair/Remanufacturing
- Digital Materials
- And More

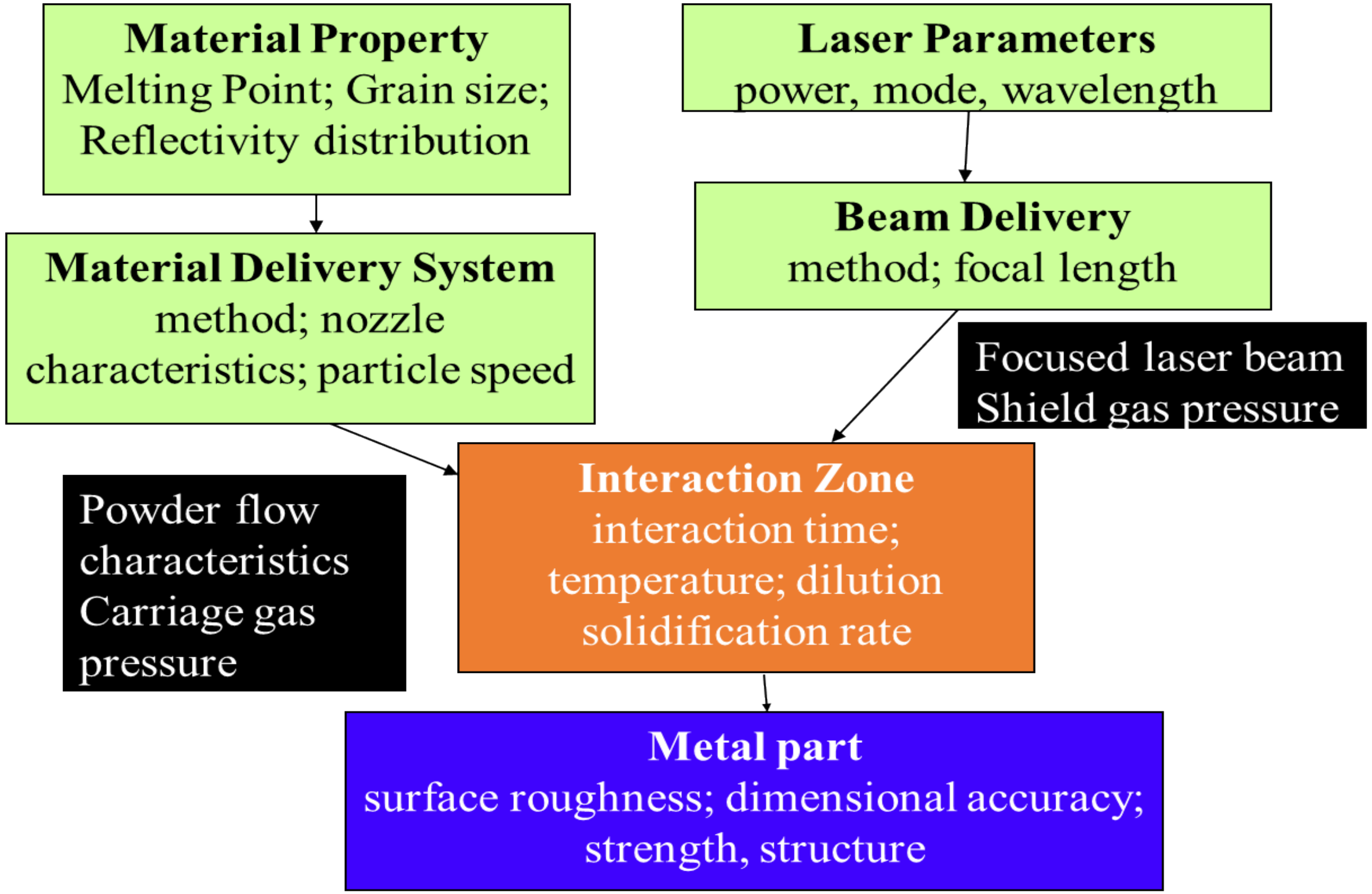
DT Graph and Connectivity

- A representation of an entire system, made up of DTs (model, sensors, performance, etc.) connected by relationships.
- Key model parameters, key sensor signatures, key material parameters, key process parameters, key performance indices, etc.



Overall Parameter Connectivity in DED Process

- Over 50 different process parameters in metal AM processes have influences on the final product quality.
- Computational efficiency remains a significant challenge.
- To address this issue, researchers have attempted to reduce the computation time by employing statistical methods and machine learning.



DED Process Parameters

(Source: Missouri S&T LAMP Laboratory)

Different Defect Sources in Laser AM

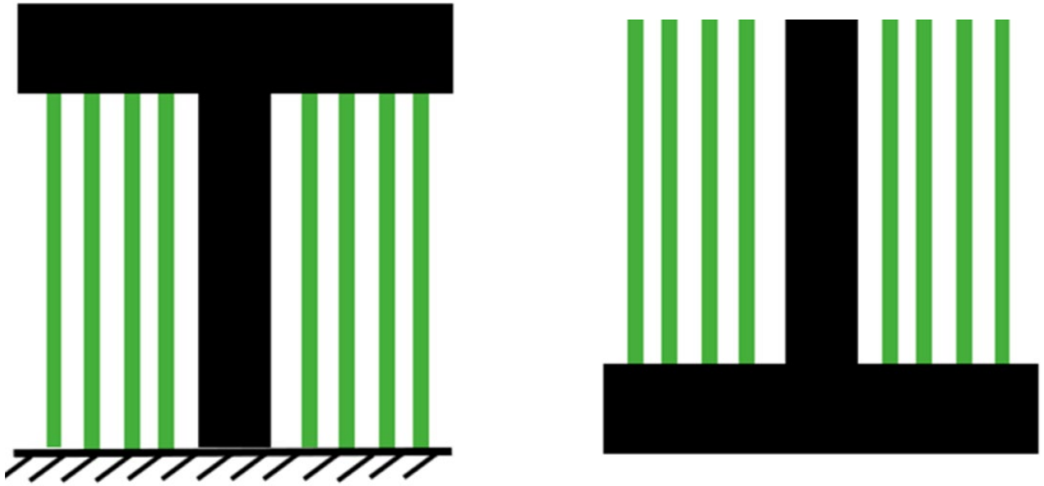
- AM Machine: Faulty or improperly calibrated equipment leads to defects in AM.
- Possible Causes:
  - Issues With the Laser Source
  - Printing Chamber Conditions
  - Faulty Powder Coating/Delivery System
  - Improper Baseplate Dimensions

Different Defect Sources in Laser AM (continued)

- In Situ Defects: There are improper printing conditions when the laser interacts with the material.
- Possible Causes
    - Nonoptimal Conditions
    - Material Composition Not up to the Requirements
    - Material Ejection When Laser Inter Interacts With the Material

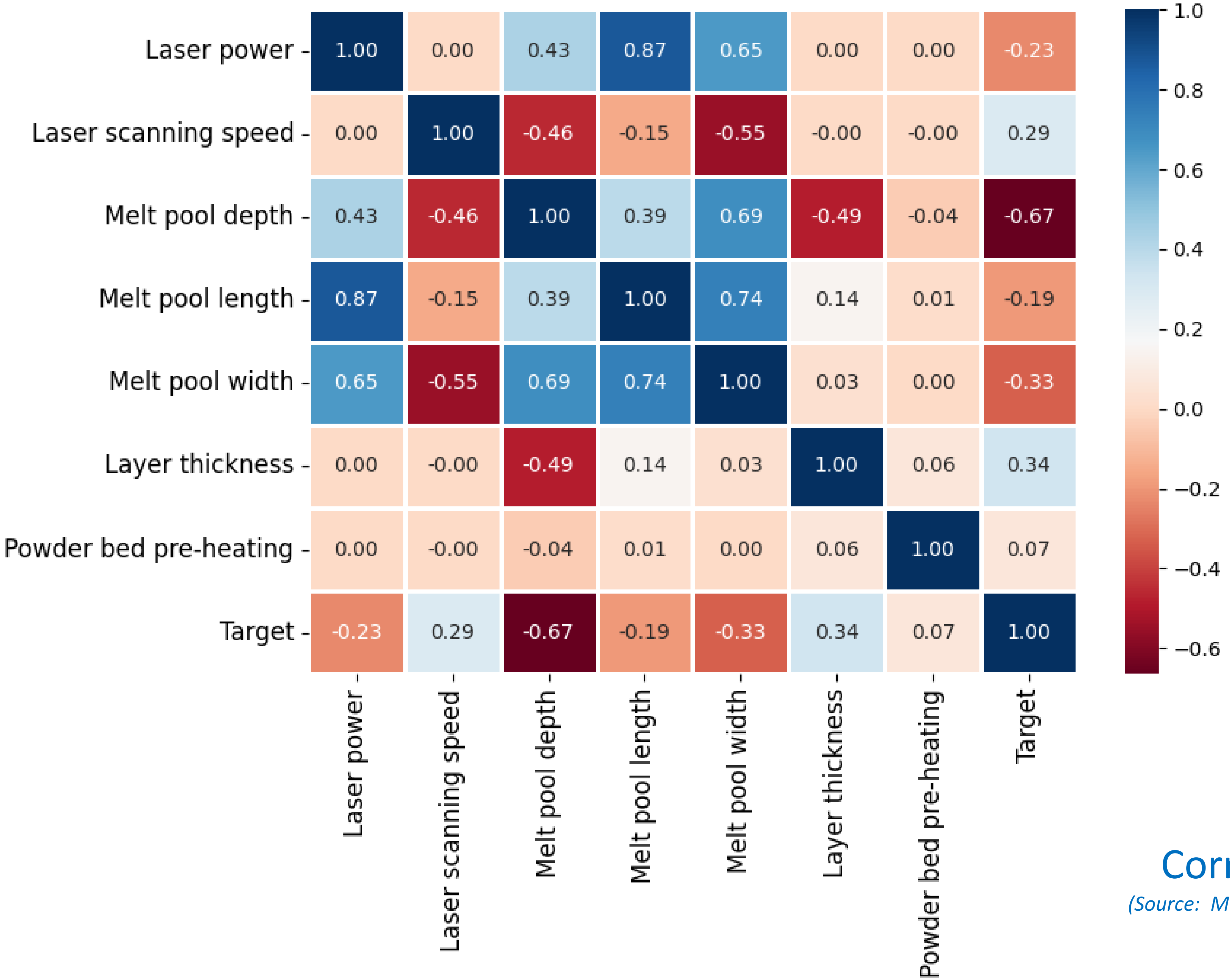
Different Defect Sources in Laser AM (continued)

- Printing Techniques: The printing techniques are applied during part development.
- Possible Causes
  - Nonoptimal Selection of Printing Supports
  - Improper Part of Printing Strategy



Different Defect Sources in Laser AM (continued)

- Raw Material/Feedstock: Material quality used during printing may differ.
- Possible Causes:
  - The Process Applied to Produce Feedstock
  - Recycled Feedstock Utilization
  - External Gases Entrapment During Feedstock Preparation
  - Nondesirable Elements in Powder Feedstock
  - Characteristics of Feedstock

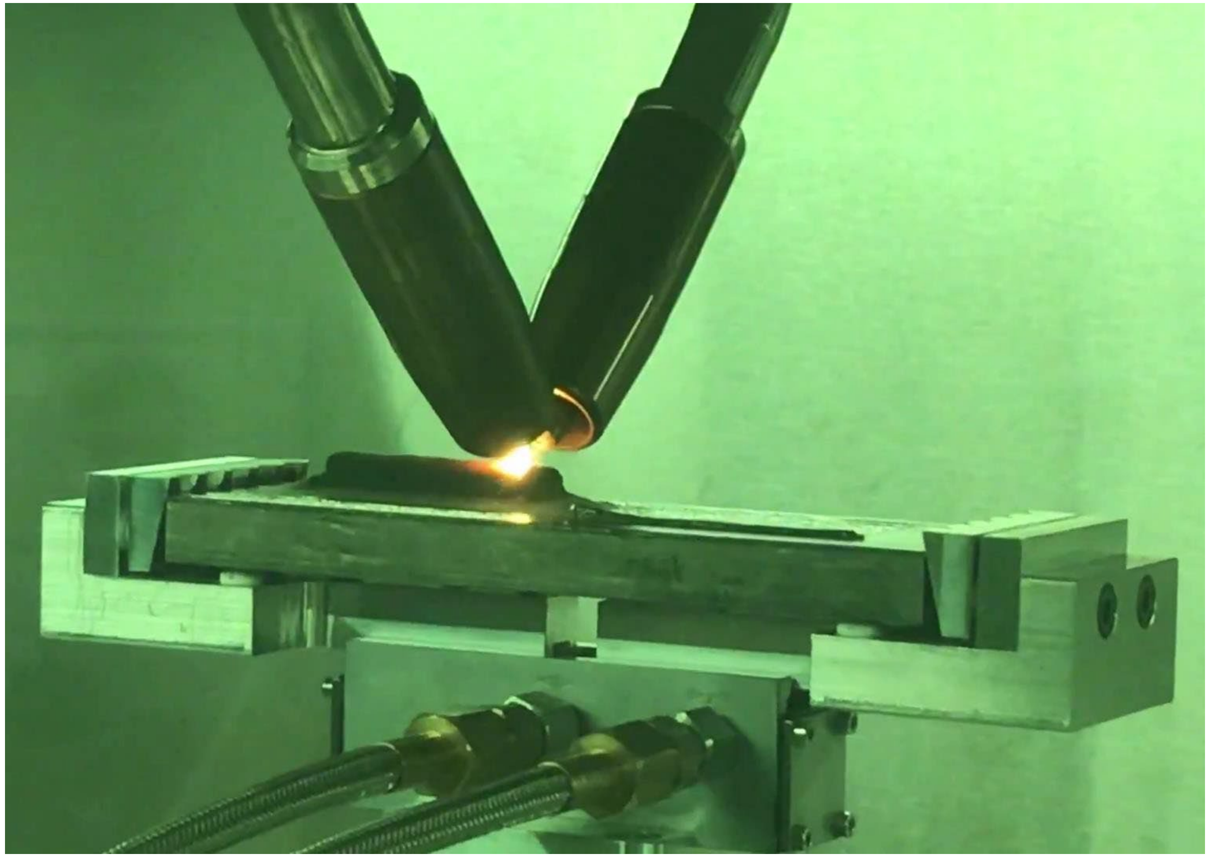


Correlation Map

(Source: Missouri S&T LAMP Laboratory)

Classification of Signatures

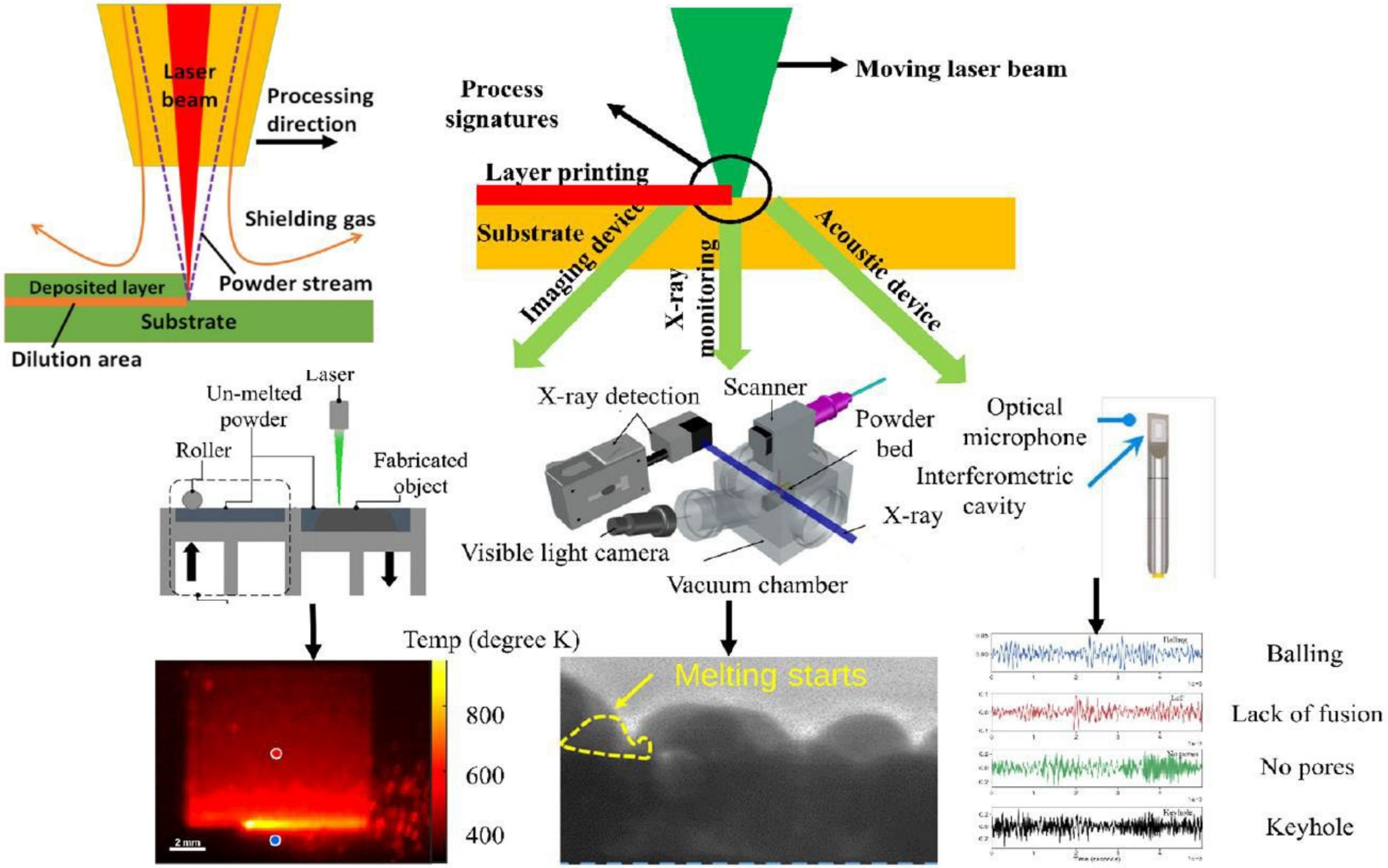
- Molten Pool: Perimeter, shape, temperature field
- Layer Printing: Shape, temperature field, distortion, morphological surface
- Powder Stream (DED): Shape, flow rate, interaction between feedstock and baseplate



AM^2 Processing

(Source: Missouri S&T LAMP Laboratory)

Process Signatures in Laser AM



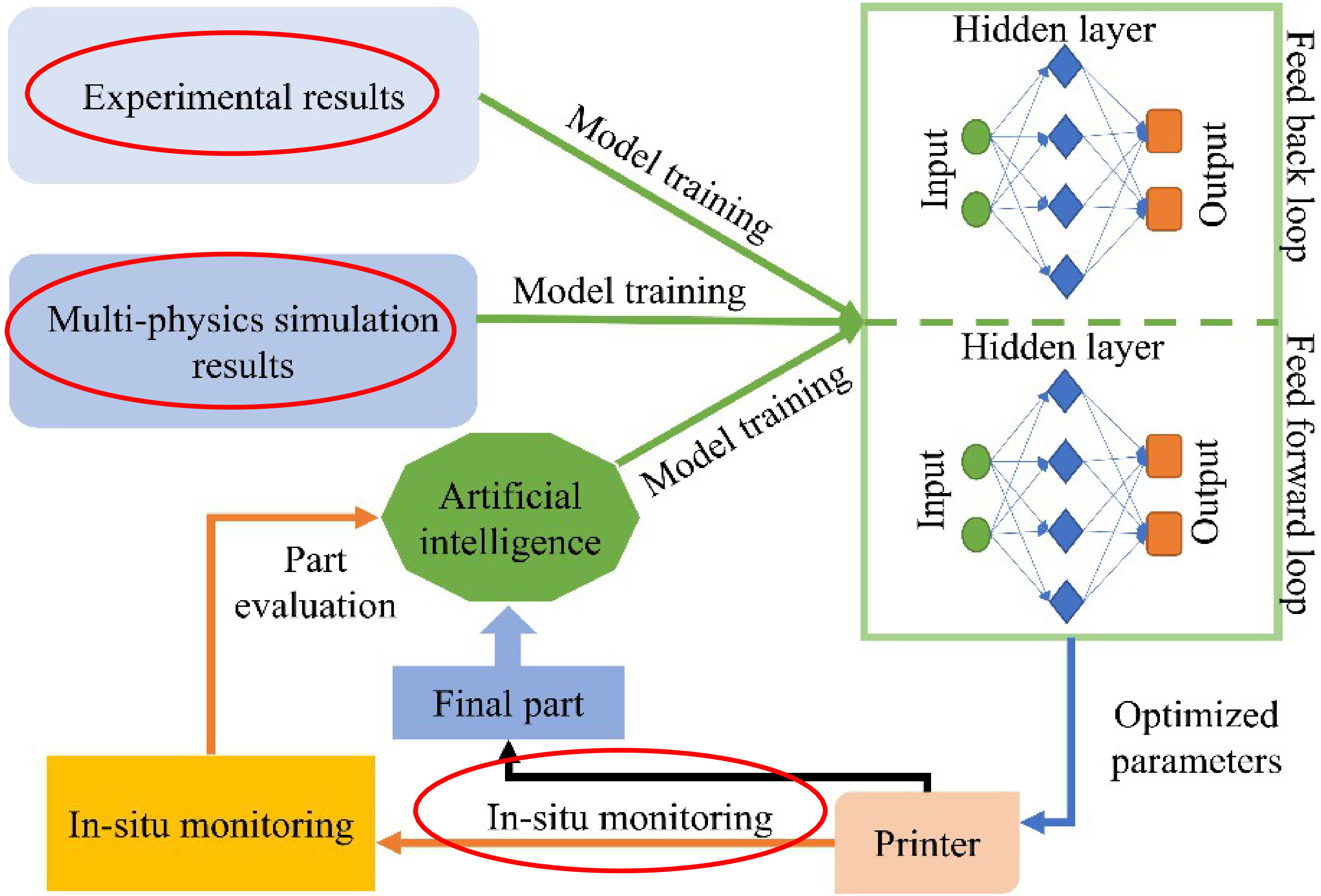
Process Signatures

(Source: Missouri S&T LAMP Laboratory)

Machine Learning in DT AM

- AM processes are very complex.
- Models are generally too slow.
- It needs machine learning, such as surrogate models, to help improve model interpretability and speed up the analysis and decision-making.
- Surrogate models are black-box models that approximate a system's behavior by fitting input-output data to simple functions.

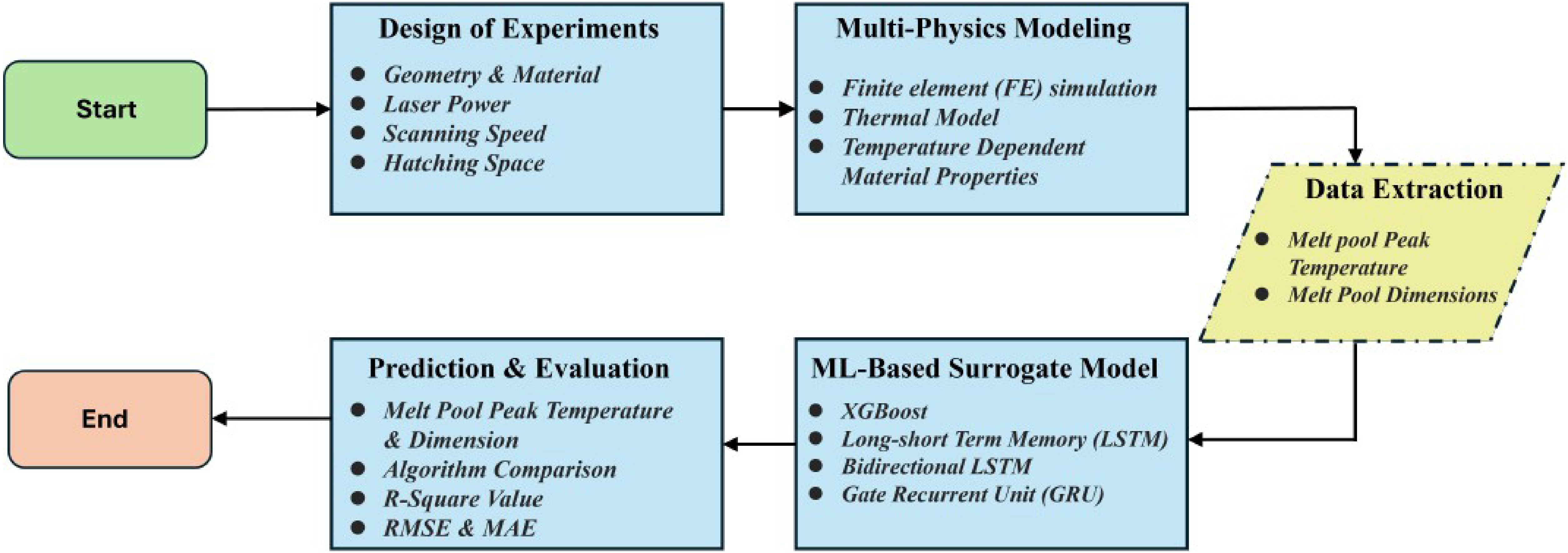
DT of AM



DT AM

(Source: Missouri S&T LAMP Laboratory)

Machine Learning to Build Surrogate Models



Note: RMSE = root mean square error, MAE = mean absolute error, XGBoost = Extreme Gradient Boosting, LSTM = long short-term memory, GRU = gated recurrent unit.

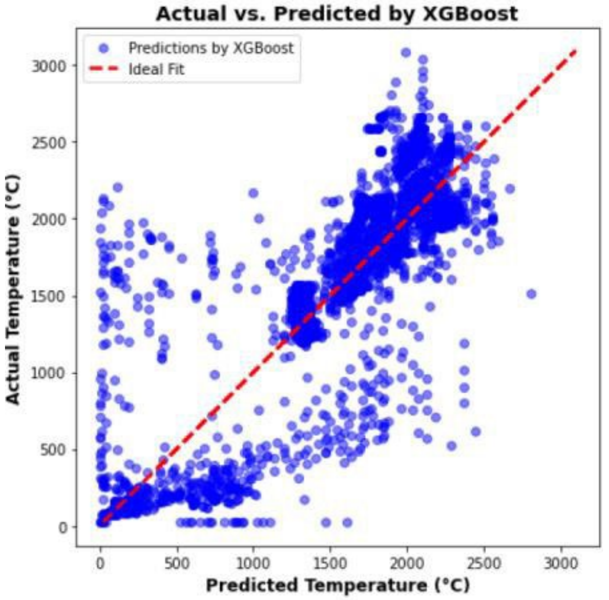
DT AM

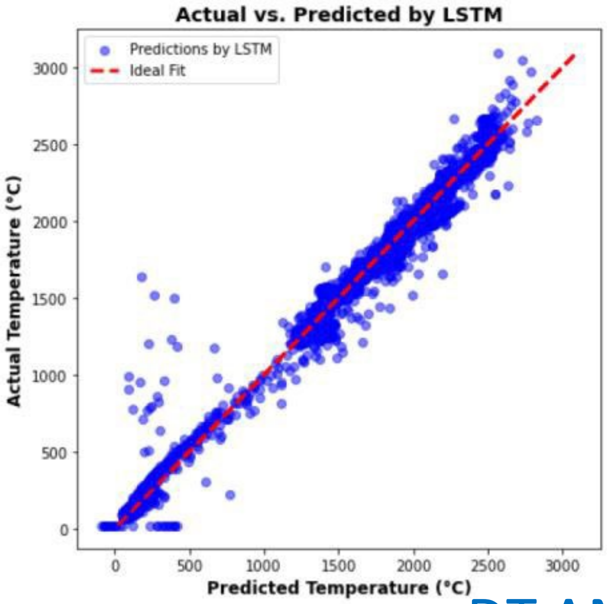
(Source: Missouri S&T LAMP Laboratory)

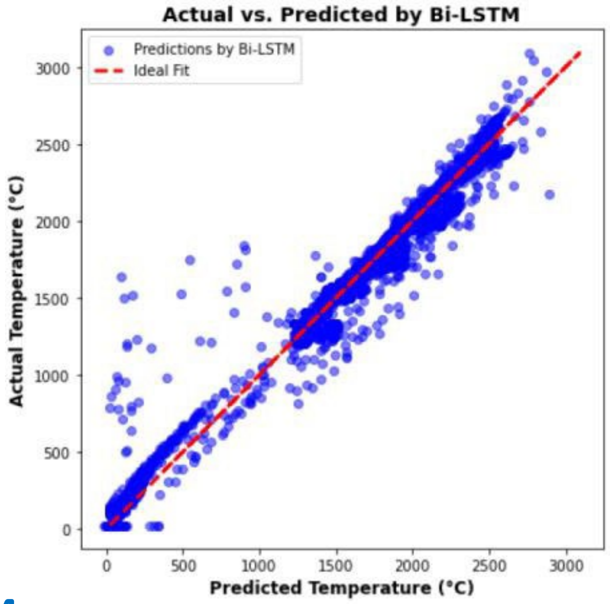
Surrogate Models for Melt Pool Temperature

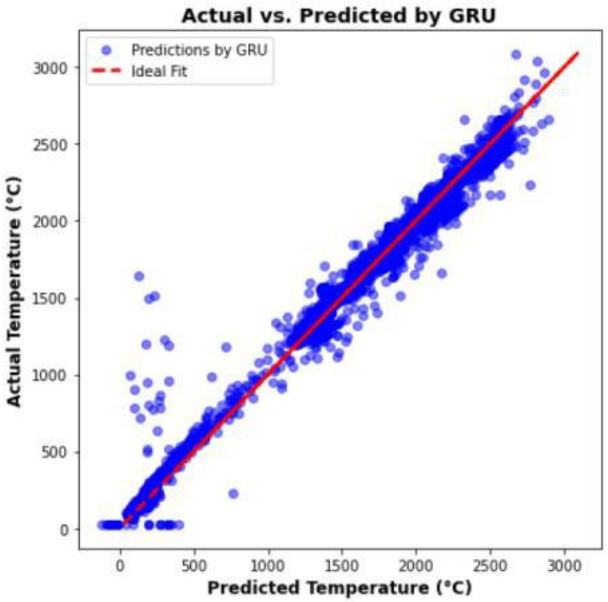
Algorithms	R-Square	RMSE	MAE	Computation Time (s)	Memory Usage (GB)
XGBoost	0.698	0.1031	0.0629	16.22	0.269
LSTM	0.888	0.0539	0.0412	76.23	1.37
Bi-LSTM	0.902	0.0501	0.0369	120.55	2.65
GRU	0.903	0.0503	0.0381	67.75	1.30

Note: Bi-LSTM = bidirectional long short-term memory.





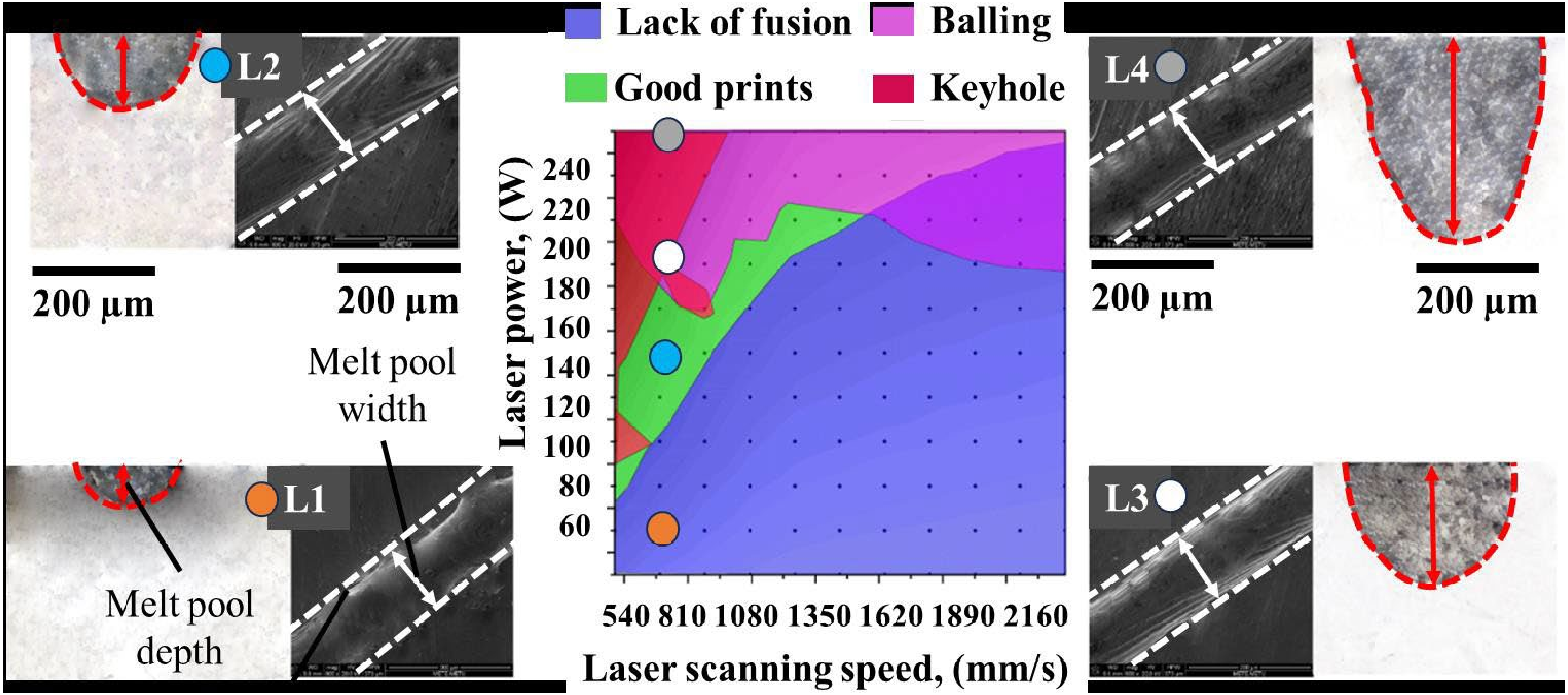




DT AM

(Source: Missouri S&T LAMP Laboratory)

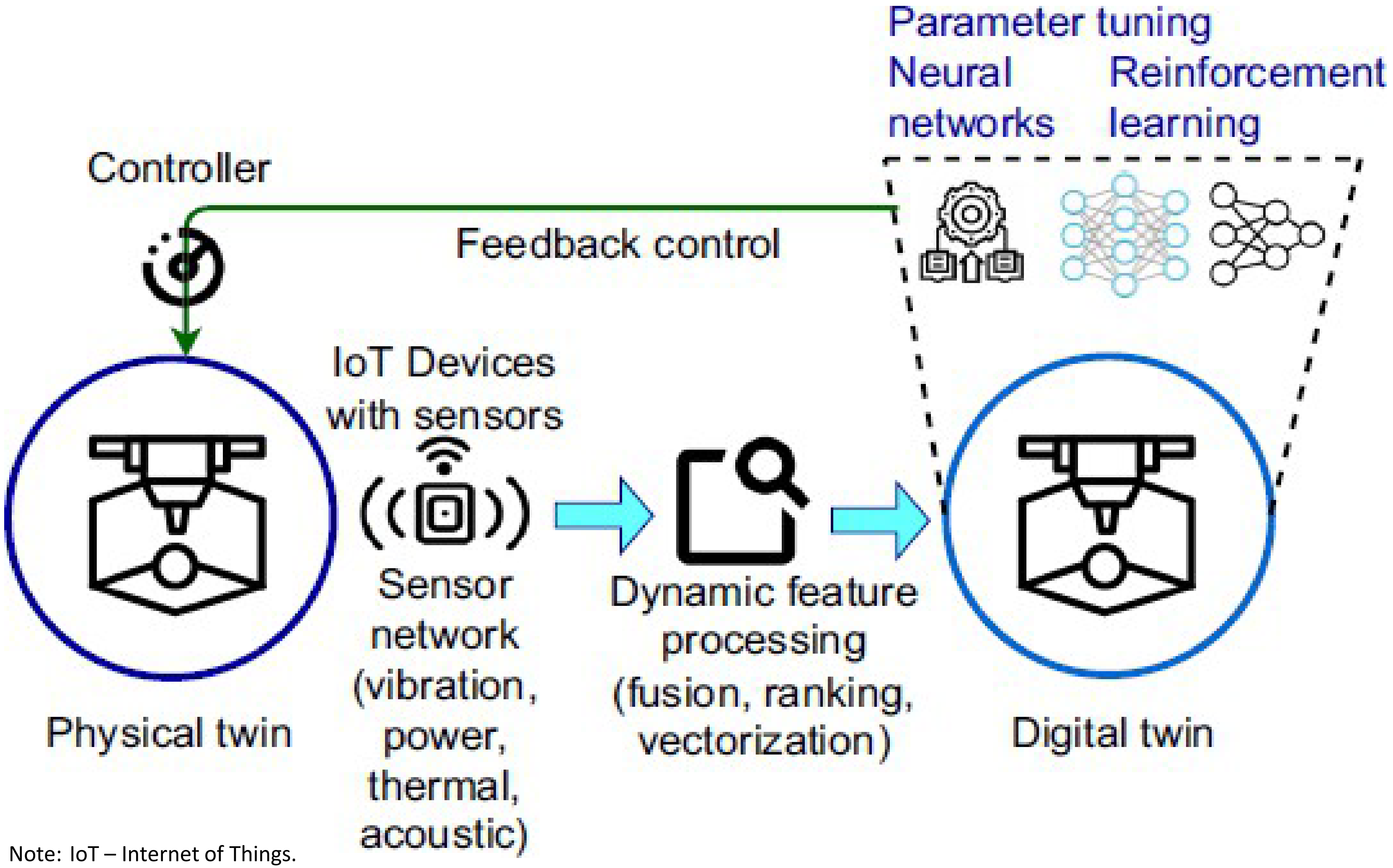
Machine Learning Example



DT AM

(Source: Missouri S&T LAMP Laboratory)

DT for AM Parameter Control

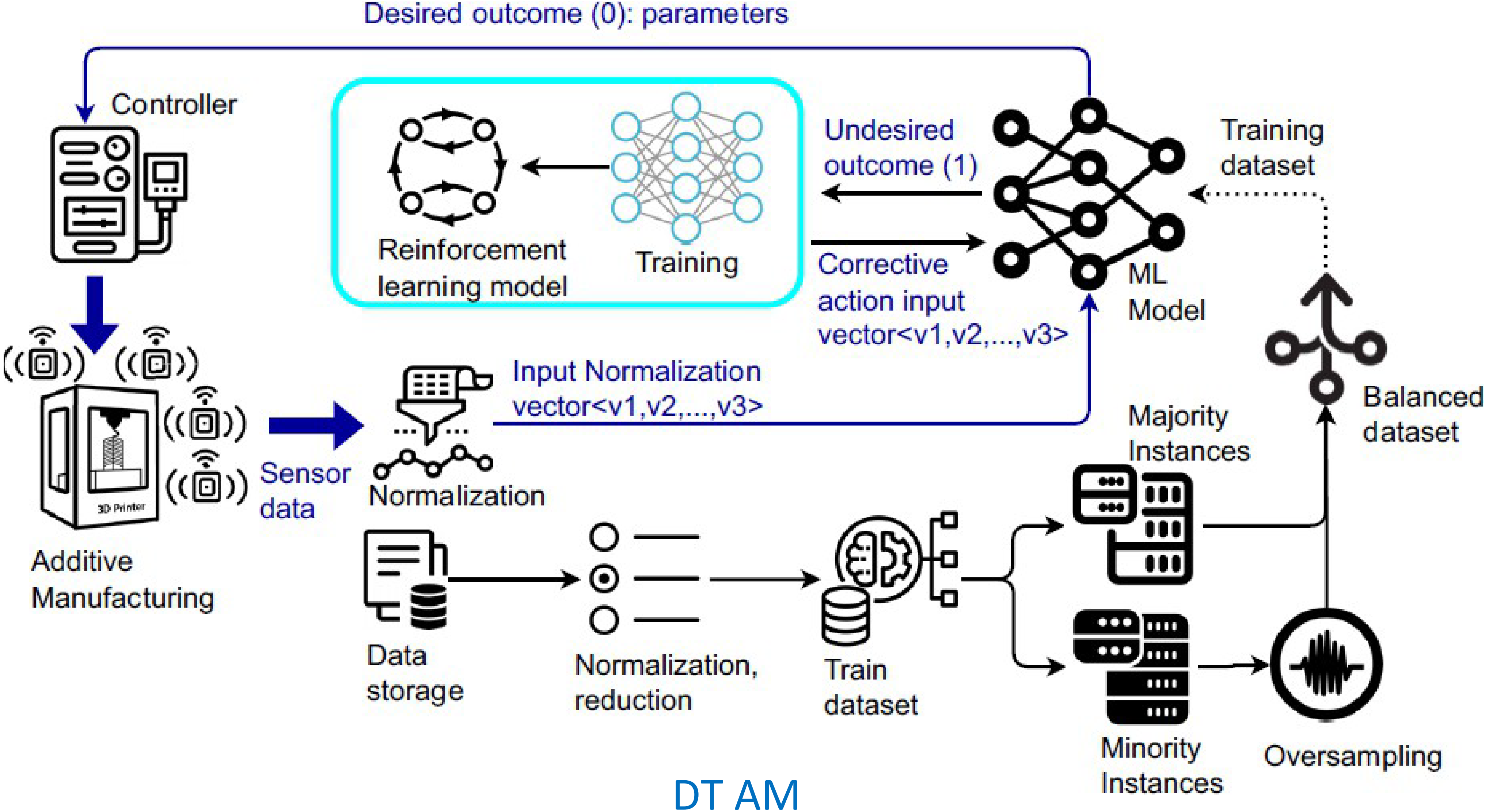


Note: IoT – Internet of Things.

DT AM

(Source: Missouri S&T Intelligent Systems Center)

DT Internal Architecture for AM Process



DT AM

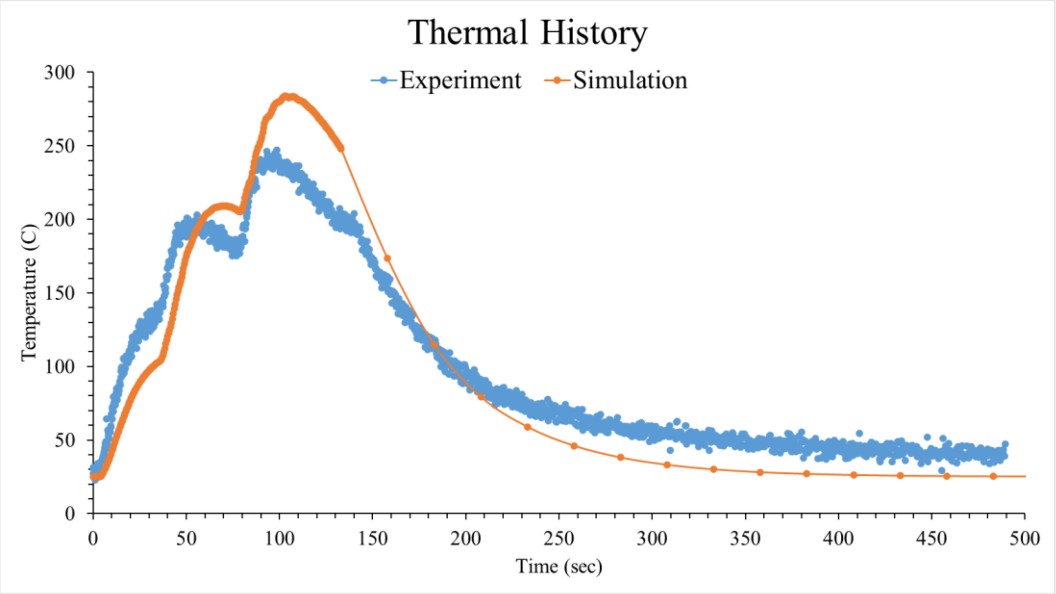
(Source: Missouri S&T Intelligent Systems Center

Transfer Learning (TL)

TL Method	Key Idea	Example in AM	Best for
Instance-Based TL	Adjusts weights of source data	Adapting a melt pool depth model from Machine A to Machine B	Same features, different distributions
Feature-Based TL	Transforms features into a common space	Using a model trained on one material to predict behavior in another	Different features or distributions
Model-Based TL	Transfers a pretrained model	Using a model trained on laser powder bed fusion to predict DED behavior	Similar tasks, different domains
Multitask Learning	Trains multiple tasks together	Predicting mechanical properties and surface roughness simultaneously	Related tasks with limited data

Challenges and Future Work: DT Calibration (Physical to Virtual)

- There is a question on how to use multiphysical feedback to estimate multimodel parameters for virtual representation, especially for large-scale, complex systems.
- Solution may not exist, may not be unique, or may not continuously depend on the data.
- May be a multiple-to-one relationship but can only measure one in situ.

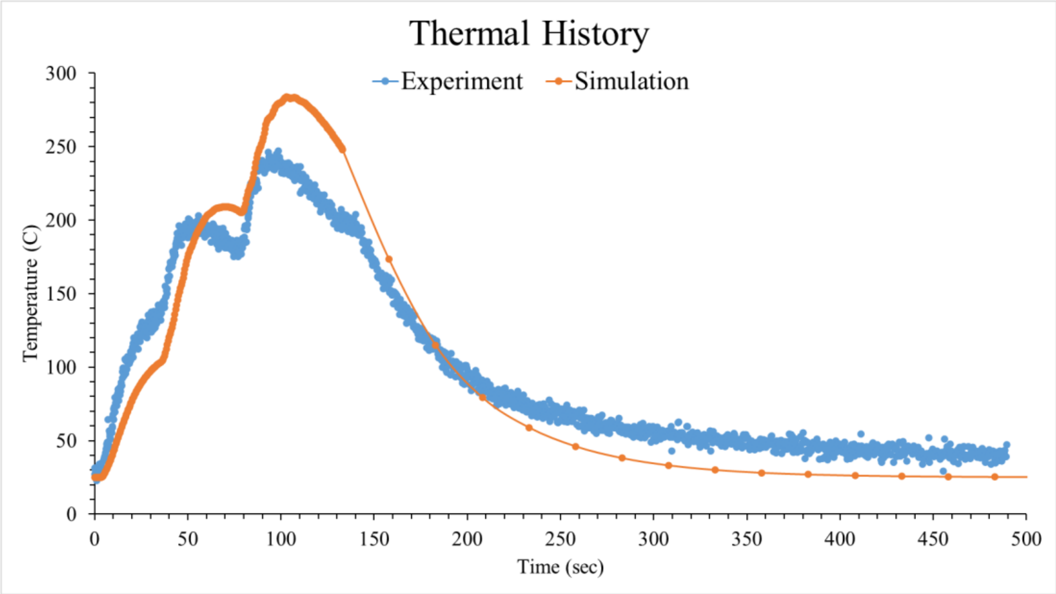


Thermal History

(Source: Missouri S&T LAMP Laboratory)

Challenges and Future Work: Data Assimilation (Physical to Virtual)

- Dynamic nature of DTs and uncertainties and validity of a model's fidelity may evolve over time.
- There is a question on how to integrate data from various cases (different materials, geometry, applications, etc.).
- There are DT demands for actionable time scales.



Thermal History

(Source: Missouri S&T LAMP Laboratory)

Challenges and Future Work: Prediction, Control, Steering, and Decision Under Uncertainty (Virtual to Physical)

- Not only predict how a system will respond to a new action or control but also assess the uncertainty associated with that prediction.
- Make critical decisions for rare events and risk assessment (e.g., failure in an engineering system, material composition, tool path, etc.).

Conclusions

- AM is a disruptive digital manufacturing technology.
- Concepts for developing DTs for metal AM are summarized.
- DT can often learn from the past and resolve processing issues quickly.
- DT can be a key to AM process certification for a new part.
- There are still challenges to overcome.