Advanced Materials and Manufacturing Technologies (AMMT) Program

Digital Thread for Additive Manufacturing

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Oak Ridge National Laboratory

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AMMT – Digital Platform

Objectives:

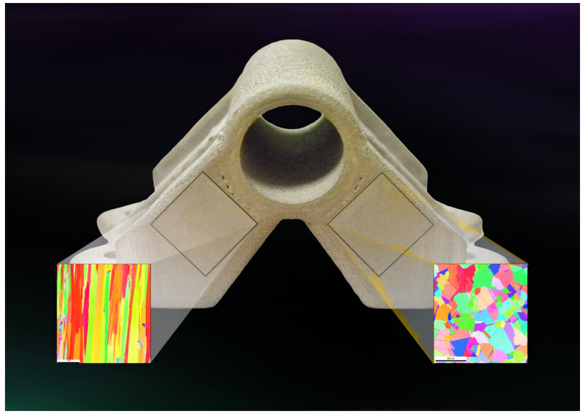
- Develop a digital platform and associated processes to couple data analytics with design and manufacturing data for use in rapid prototyping and quality evaluations of manufactured products.
- Demonstrate part quality predictive capability of the digital platform

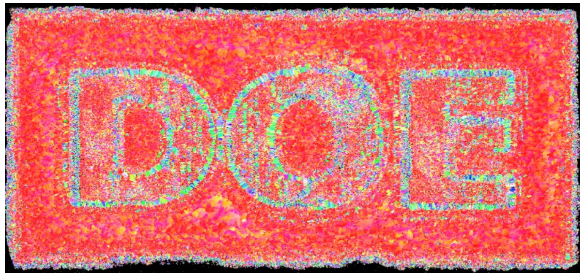
FY 22 Milestone

Lead	Milestone ID	Milestone/Activity Title	DOE Finish
Paquit	M2CT-22OR1305013	Submit Report on Digital Platform Diagnostic and Predictive Capability Development	9/30/2022

Data Analytics Framework for Advanced Manufacturing

Scientific drivers





Develop new certification methodologies

Accelerate production of complex components

Improve manufacturing technologies

Smart Manufacturing Approach

ORNL has developed a technology agnostic data analytics framework for manufacturing.

A four-steps data driven approach toward processes optimization, and qualification, and certification of manufactured parts

Step 1: Understanding the process

Step 2: Optimizing the process

Step 3: Feedback loop for self-optimization/correction

Step 4: Certifying and qualifying components

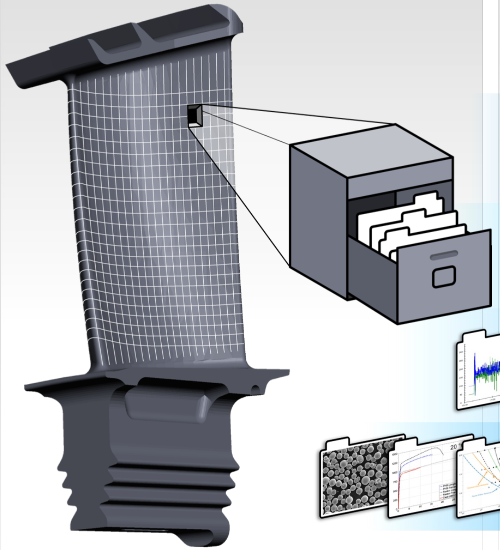
Digital Platform for Manufacturing

Advanced manufacturing technologies produce valuable datasets at every stage of the manufacturing workflow. Collecting, structuring, and analysis such data is paramount to understanding, optimizing and validating the manufacturing process.

Digital Factory

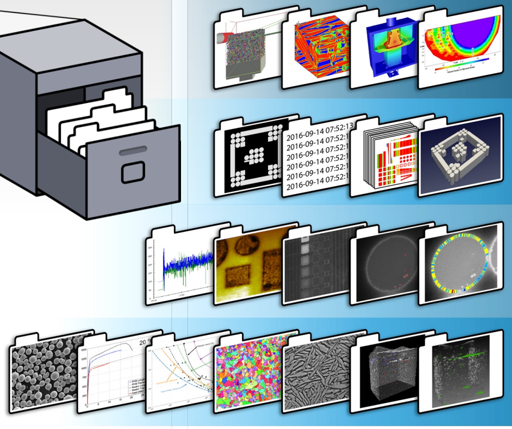
- Wired network
- WiFi network
- IoT
- Storage systems
- HPC systems
- Embedded Systems

Voxelized Parts



Data Producers

Sensor data



- Modeling
- Intent
- In-Situ
- Ex-situ & Properties

Digital Clone

Unified Data Architecture

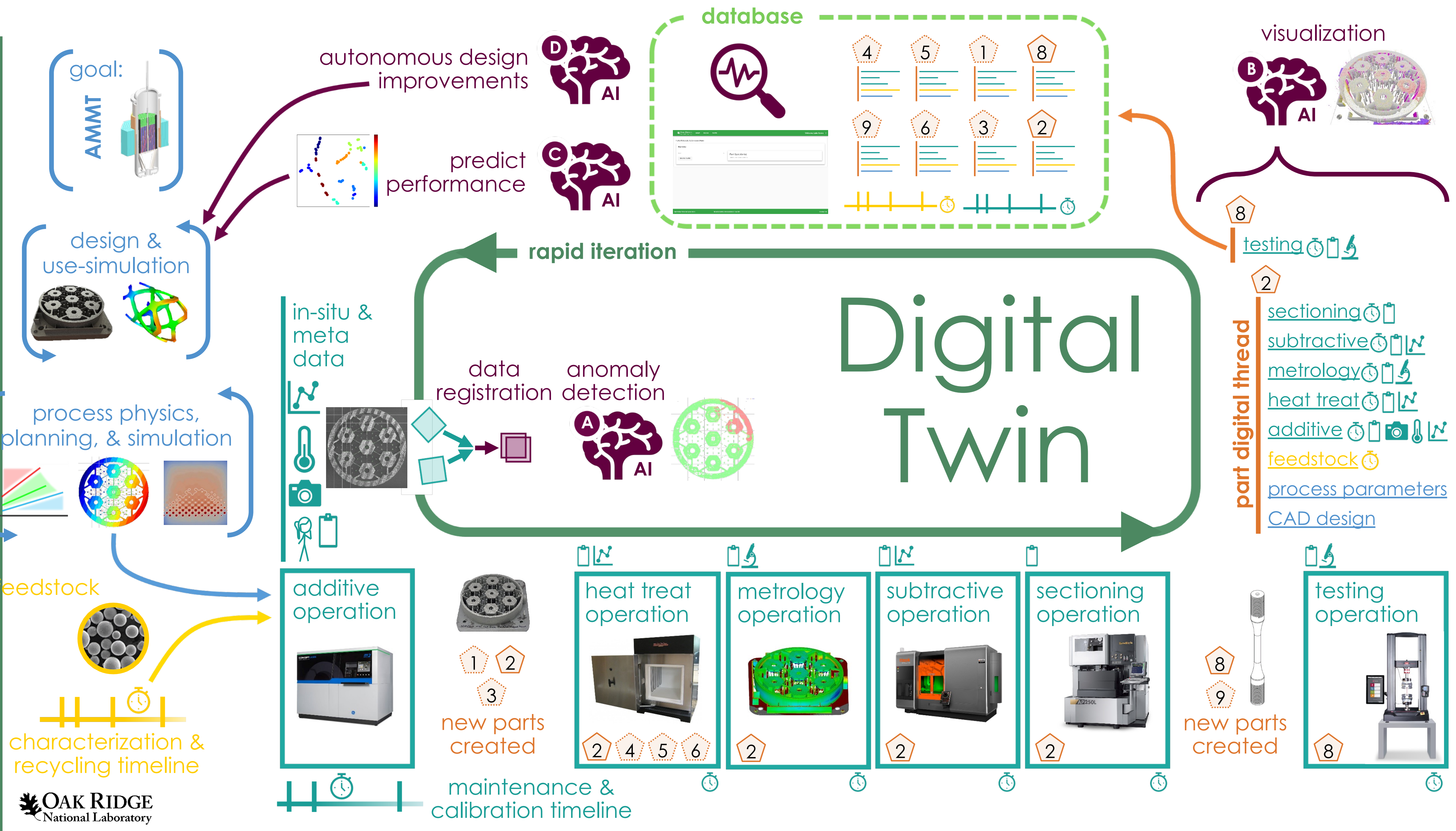
MDFLIB

Data Workflow

- Data Management & Tracking
- Signal Processing
- Computer Vision & Image Processing
- n-D Data Visualization
- Modeling & Simulation
- Data Analytics & Machine Learning
- Process Optimization
- Certification, Verification & Validation

Cybersecurity

Digital Thread



goal:
AMMT
autonomous design improvements
D
AI
predict performance
C
AI
database
4
5
1
8
9
6
3
2
visualization
B
AI
design & use-simulation
process physics, planning, & simulation
rapid iteration
in-situ & meta data
data registration
anomaly detection
A
AI
Digital Twin
8
testing
2
sectioning
subtractive
metrology
heat treat
additive
feedstock
process parameters
CAD design
part digital thread
feedstock
characterization & recycling timeline
additive operation
1
2
3
new parts created
heat treat operation
2
4
5
6
metrology operation
2
subtractive operation
2
sectioning operation
2
8
9
new parts created
testing operation
8
maintenance & calibration timeline
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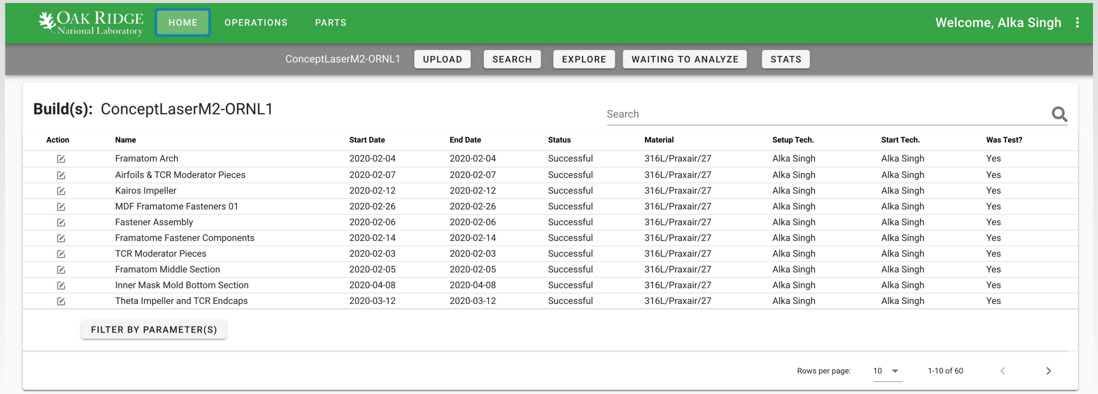
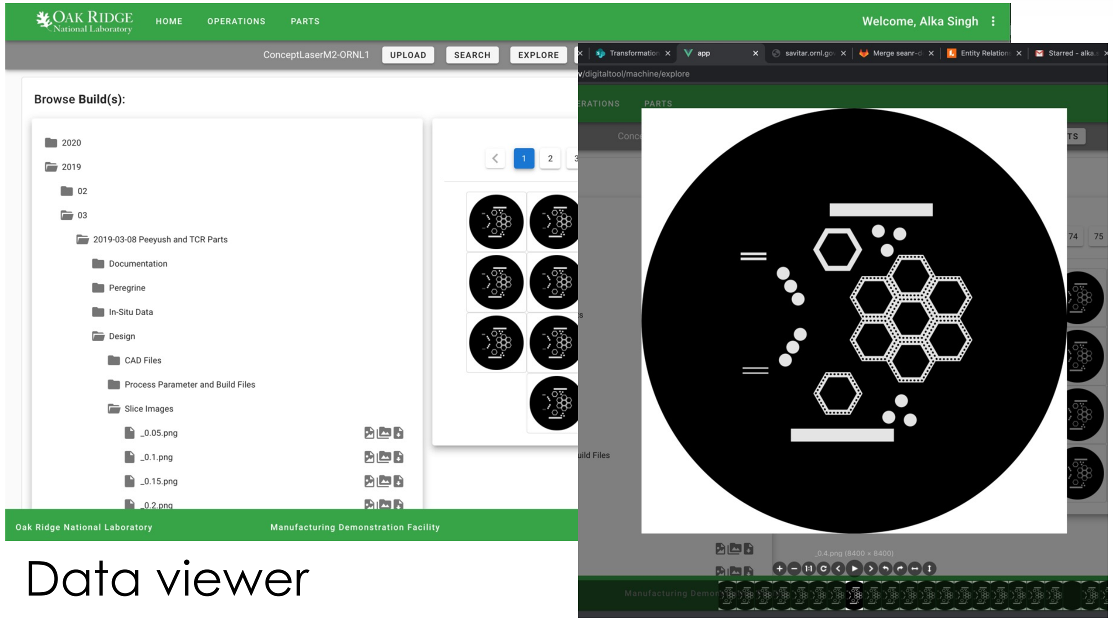
R&D Activities – Data Management

Web-based Digital Tool

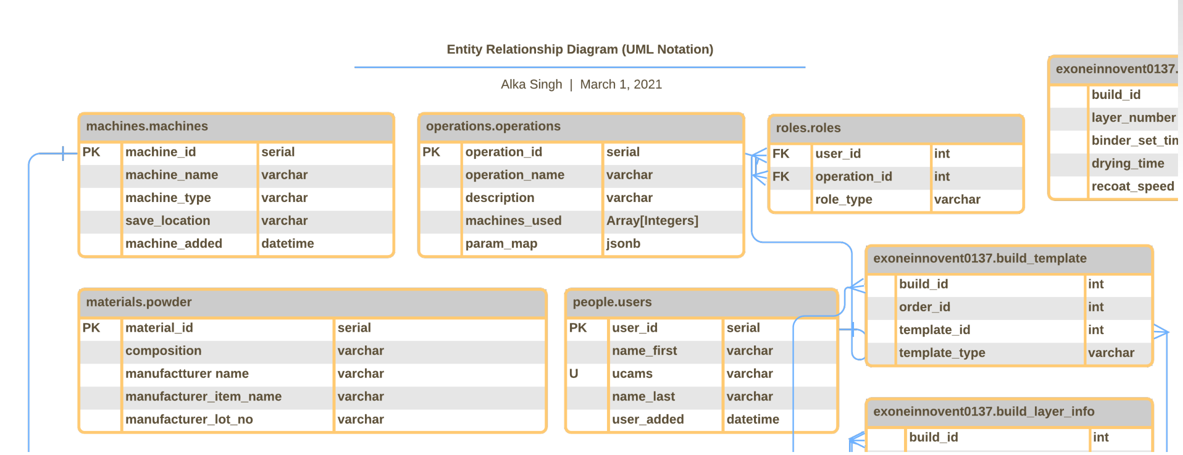


Metadata search

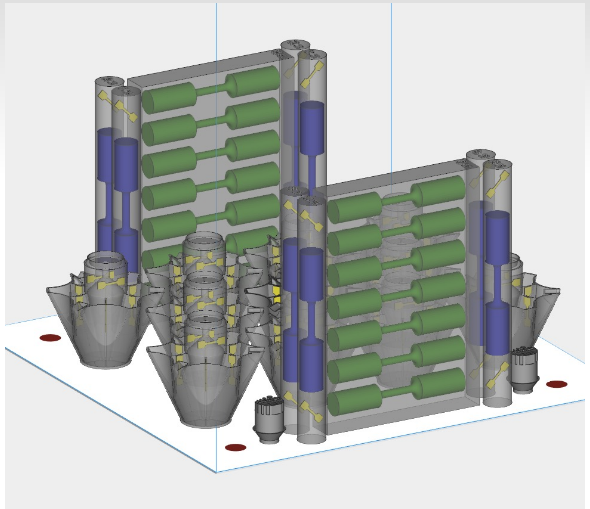


Data viewer

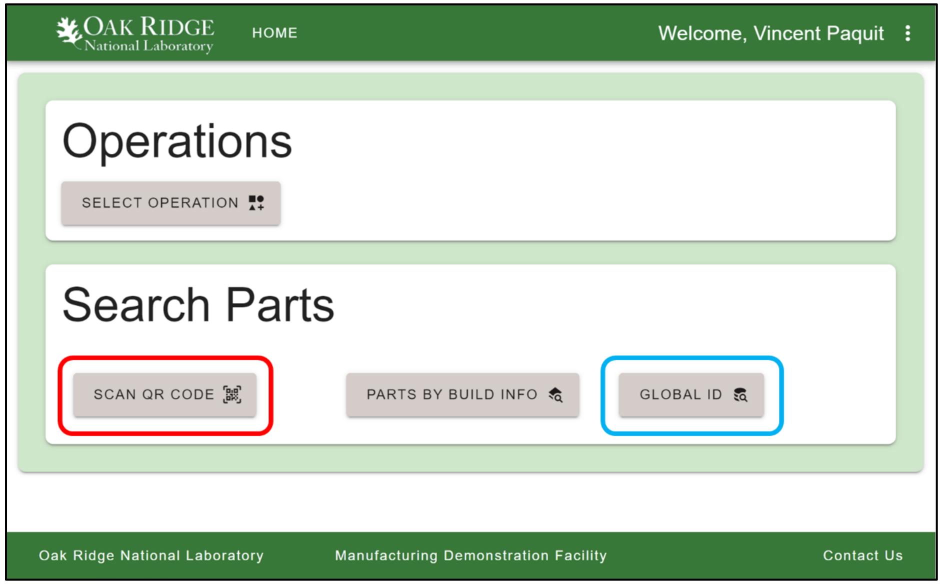
Database & API

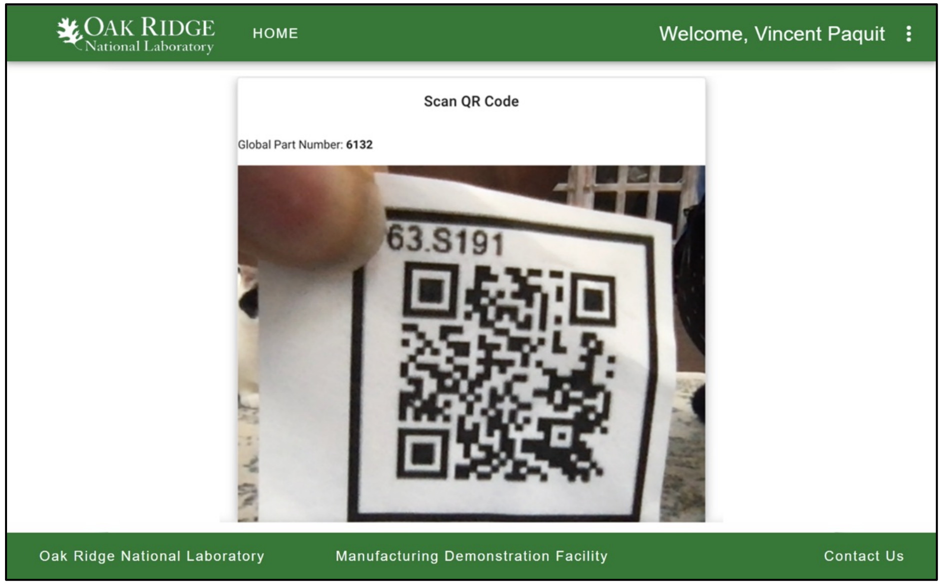


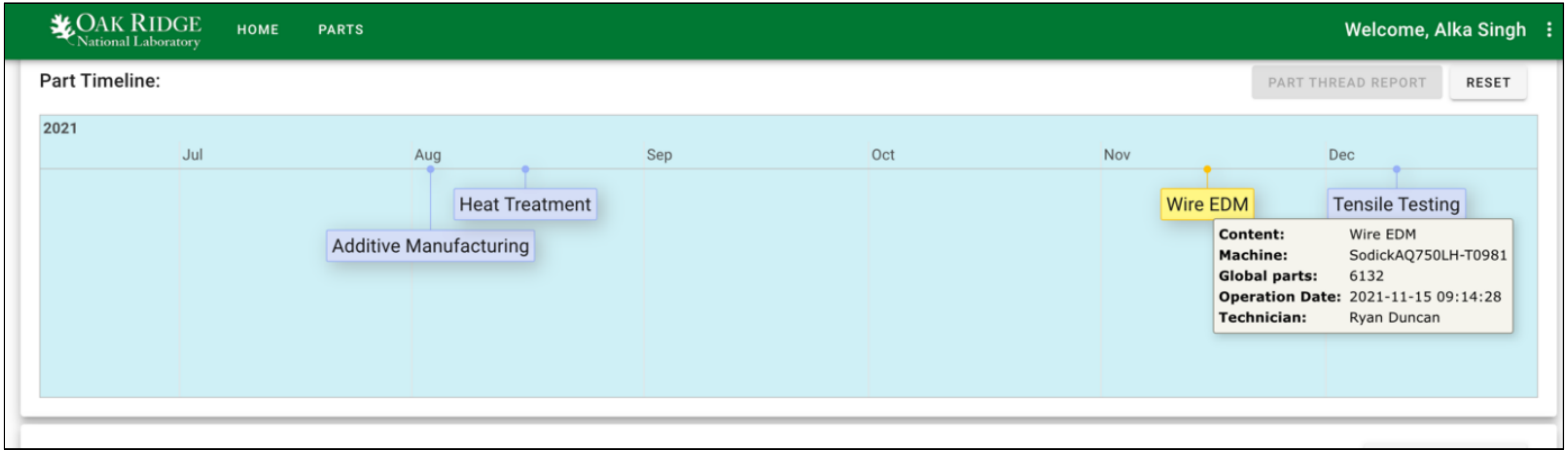
Physical and Digital Traceability



R&D Activities – Data Management







Research platform : Concept Laser M2 – laser powder bed

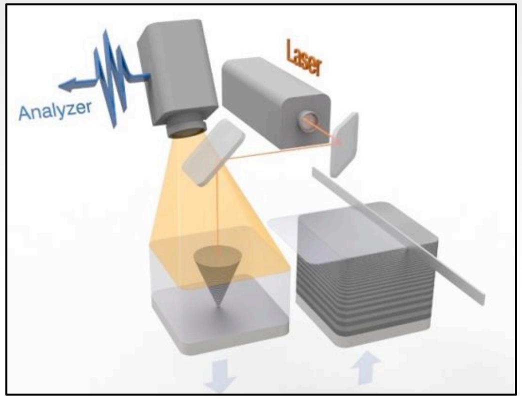
Machine

- Description Technology
  - Thin layer of powder spread over a build plate
  - Laser beam scans the surface at selected locations to fuse the powder

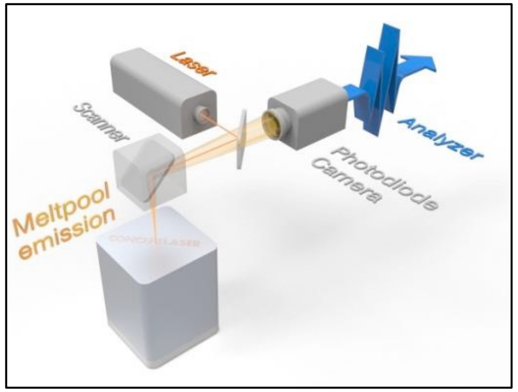
How it works

Sensor suite

- Onboard sensors (log file)
- Pyrometer
- High resolution camera

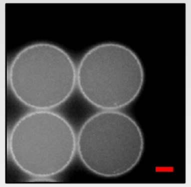


- Melt-pool monitoring

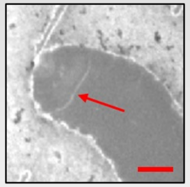


Typical Powder Bed Defects

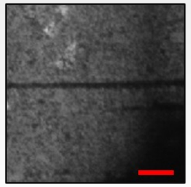
EBM



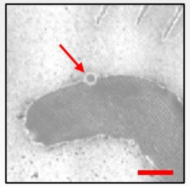
powder & printed
Arcam Q10 (EB-PBF)
NIR (fusion)



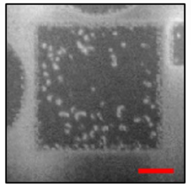
cracking
Arcam Q10 (EB-PBF)
NIR (fusion)



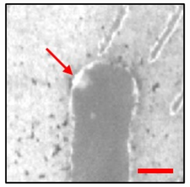
recoater streaking
Arcam Q10 (EB-PBF)
NIR (spreading)



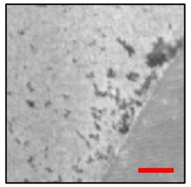
balling
Arcam Q10 (EB-PBF)
NIR (fusion)



porosity
Arcam Q10 (EB-PBF)
NIR (fusion)

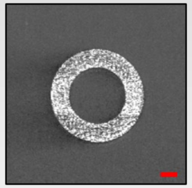


swelling
Arcam Q10 (EB-PBF)
NIR (fusion)

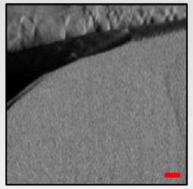


spatter
Arcam Q10 (EB-PBF)
NIR (fusion)

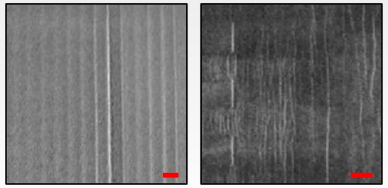
LPBF



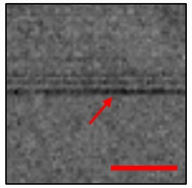
powder & printed
ConceptLaser M2 (L-PBF)
visible-light (fusion)



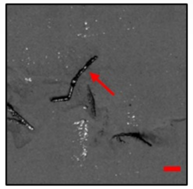
incomplete spreading
EOS M290 (L-PBF)
visible-light (spreading)



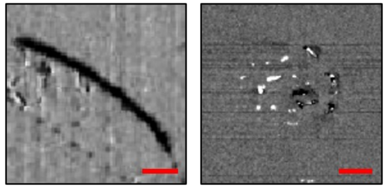
recoater hopping
EOS M290 & AddUp FormUp 350 (L-PBF)
visible-light (spreading)



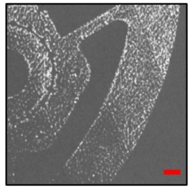
recoater streaking
ConceptLaser M2 (L-PBF)
visible-light (spreading)



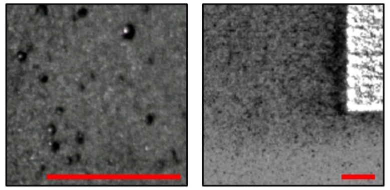
debris
ConceptLaser M2 (L-PBF)
visible-light (spreading)



swelling
EOS M290 & ConceptLaser M2 (L-PBF)
visible-light (spreading)

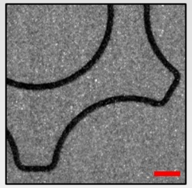


super-elevation
ConceptLaser M2 (L-PBF)
visible-light (spreading)

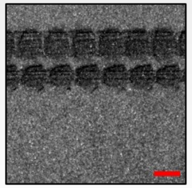


spatter or *soot*
Renishaw AM250 & ConceptLaser M2 (L-PBF)
visible-light (fusion)

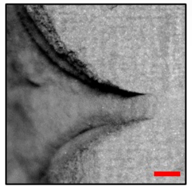
BinderJet



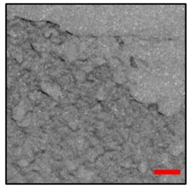
powder & printed
ExOne Innovent (Binder Jet)
visible-light (binder)



recoater streaking
ExOne Innovent (Binder Jet)
visible-light (powder)

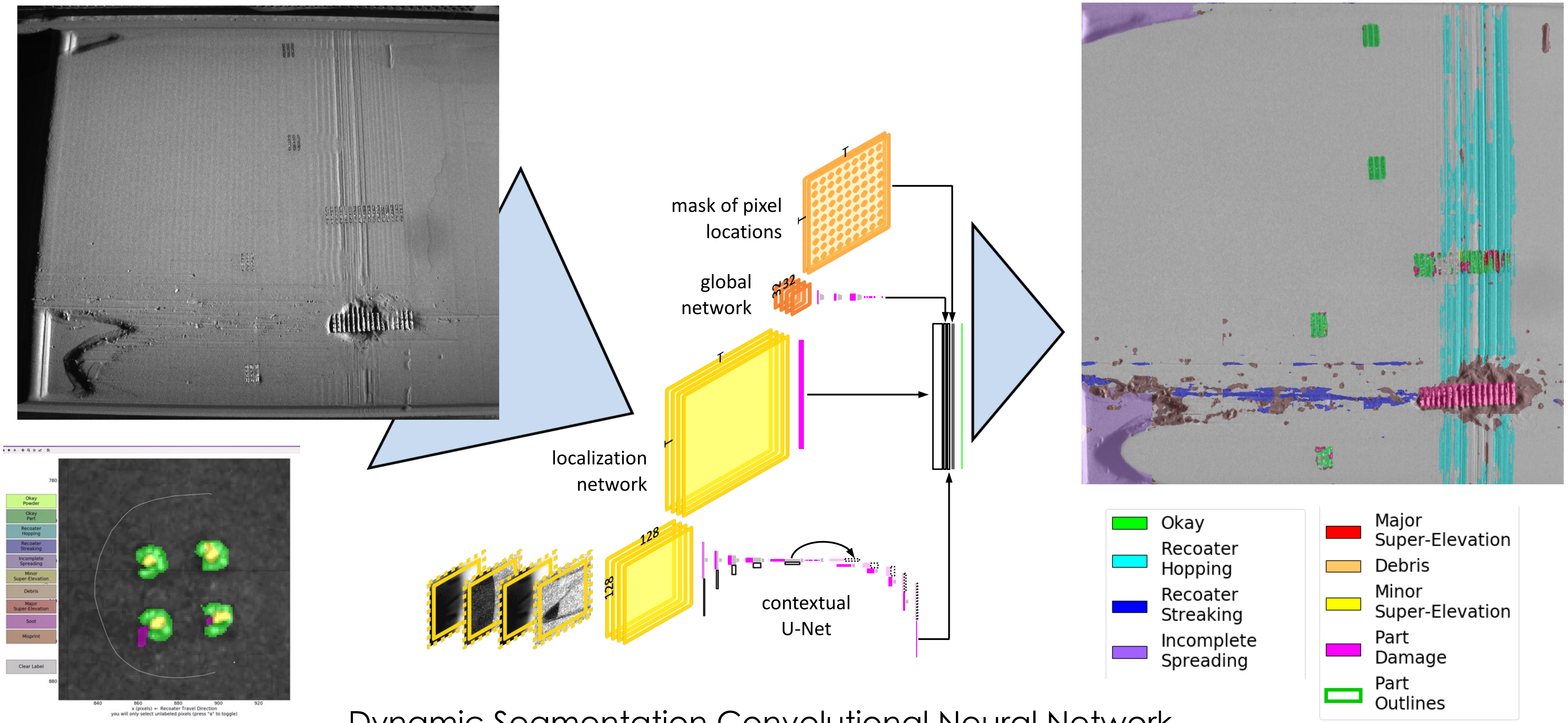


incomplete spreading
ExOne Innovent (Binder Jet)
visible-light (powder)



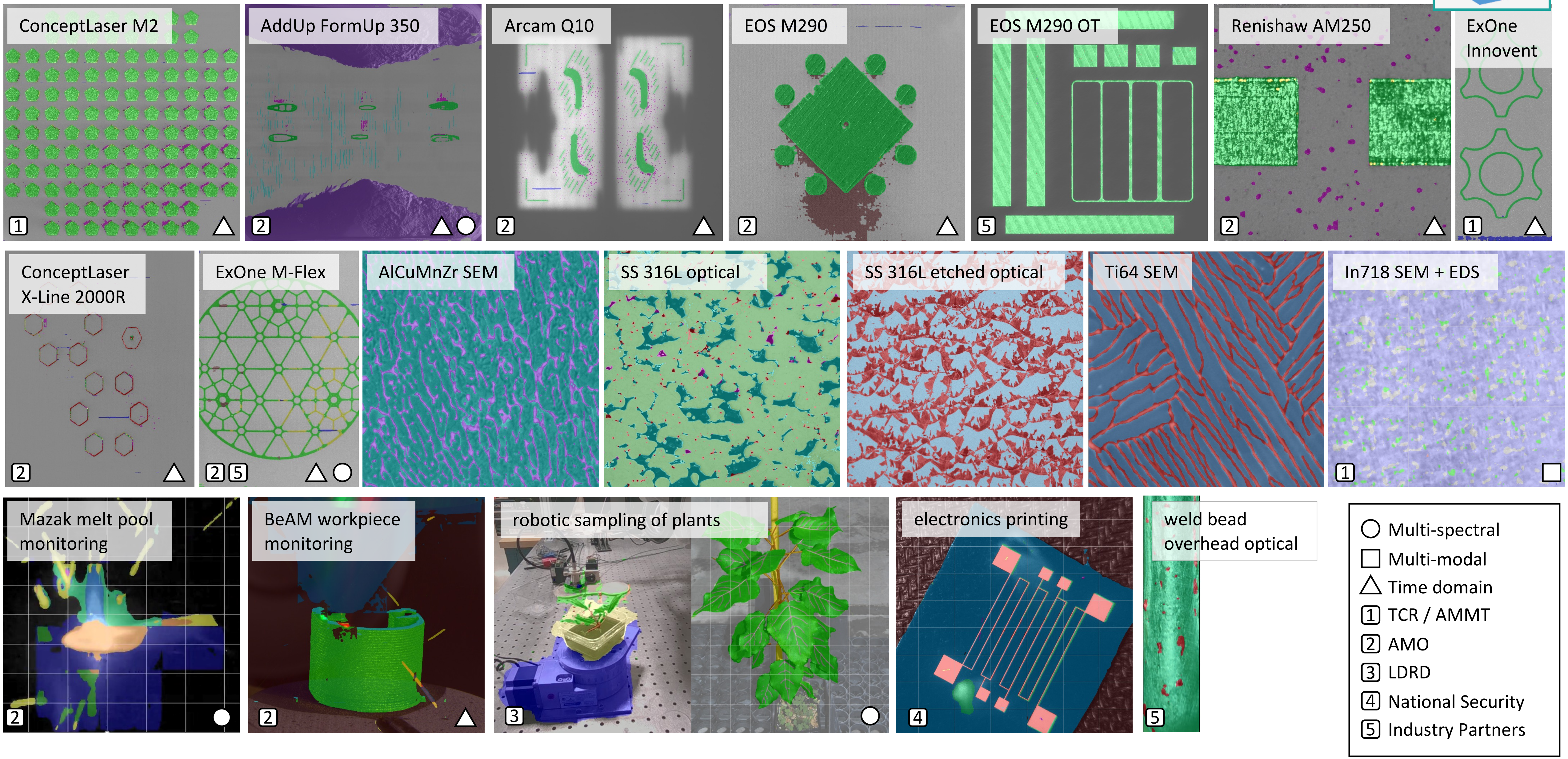
debris
ExOne Innovent (Binder Jet)
visible-light (powder)

Defect detection AI workflow and transfer learning



Dynamic Segmentation Convolutional Neural Network

Summary of DSCNN Applications



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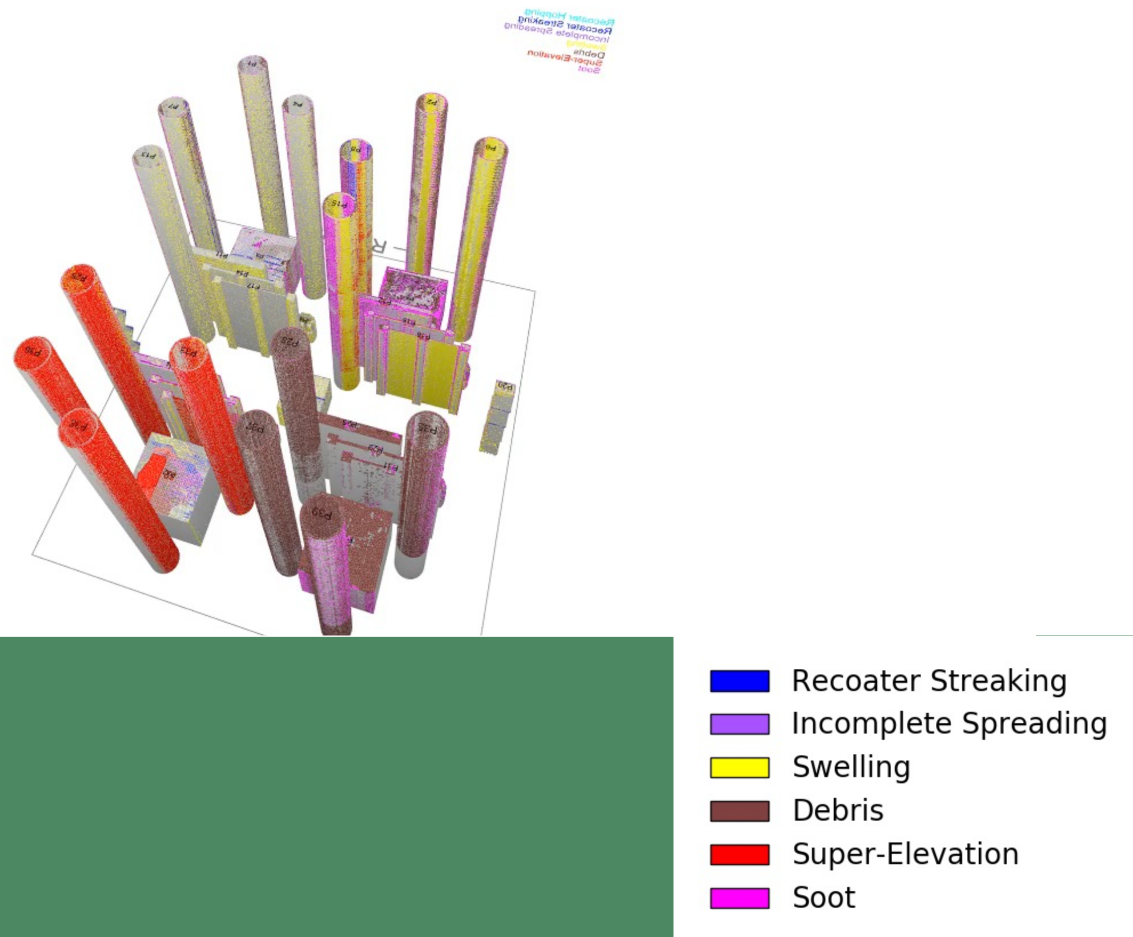
Peregrine

MDF

- AI software for real-time 3D print monitoring
- Main platform for most of the TCR data analytics activities
- Commercial copyright license available
- **Licensed to 10 companies**
- **2022 FLC Excellence in Technology Transfer Award**
- Publication DOI: 10.1016/j.addma.2020.101453



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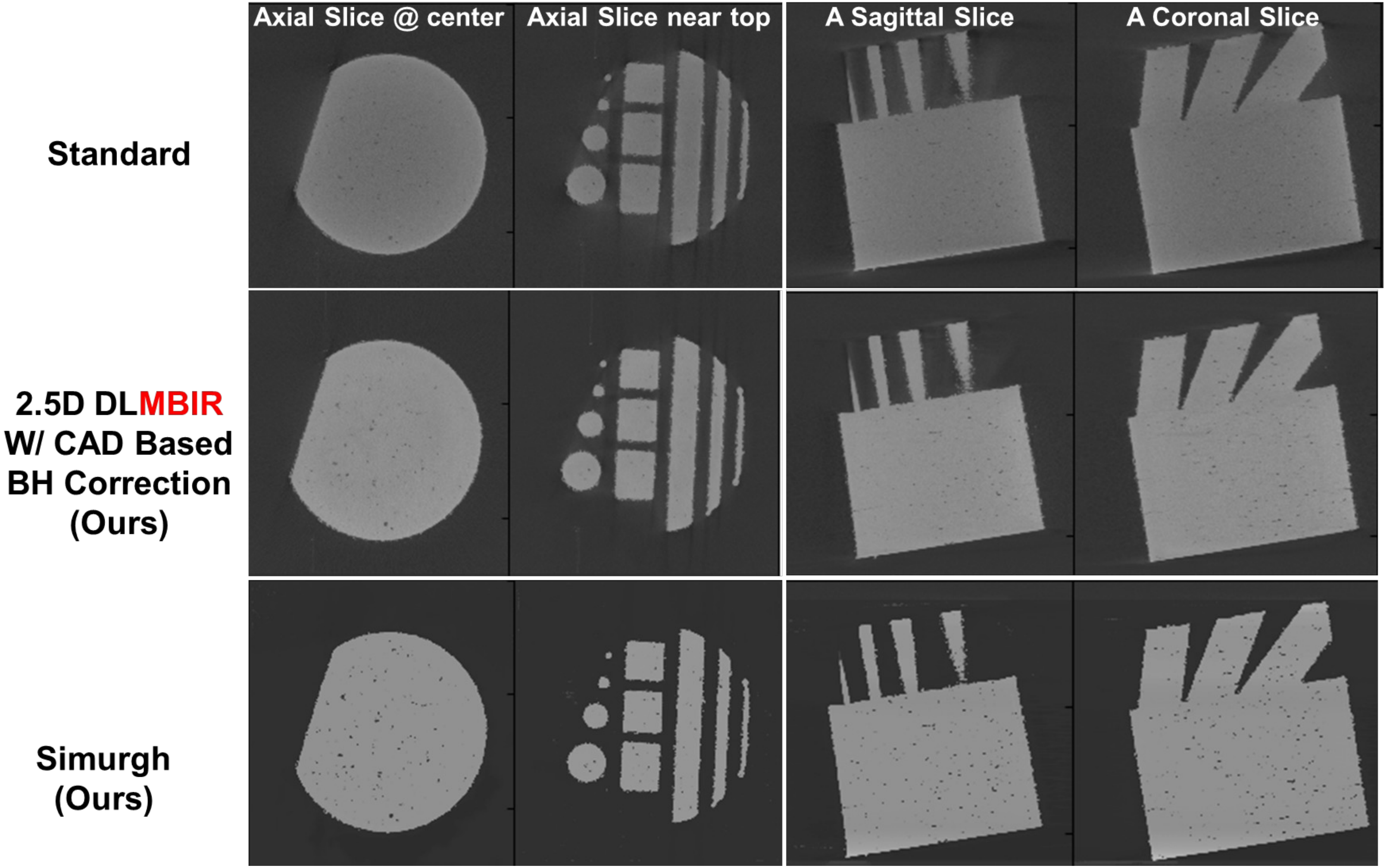
Simurgh AI / CT reconstruction



- Technology provides a x10 improvement in feature resolution
- Commercial copyright license available
- Provisional patent
- **Licensed by Zeiss**
- Publication DOI: 10.1115/IMECE2020-23766

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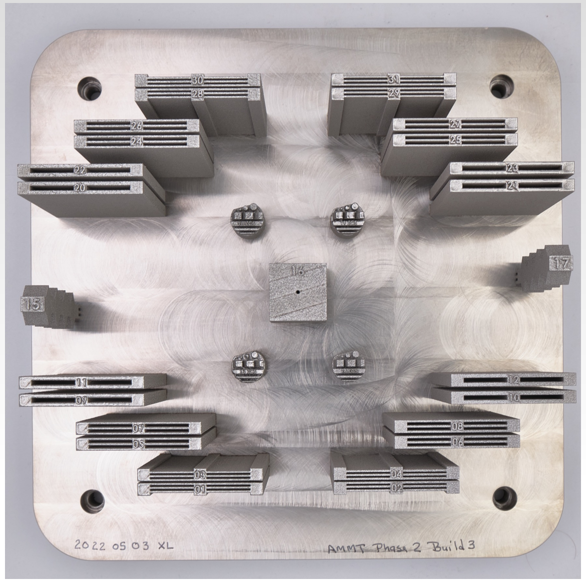
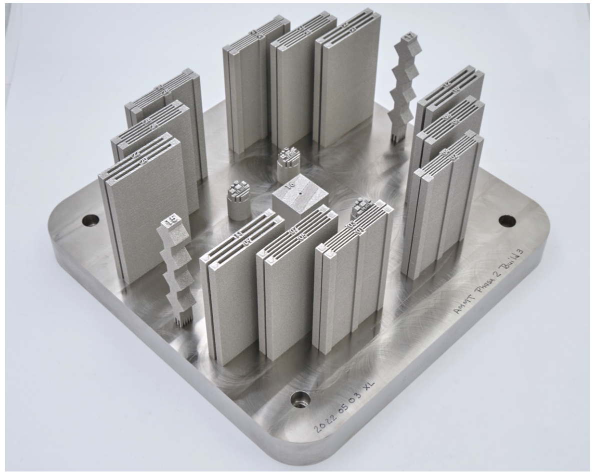
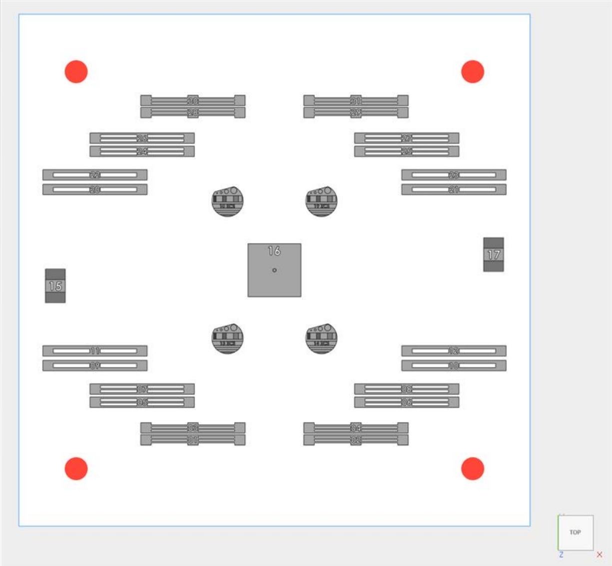
Example Geometry: Phase 2, Build 3

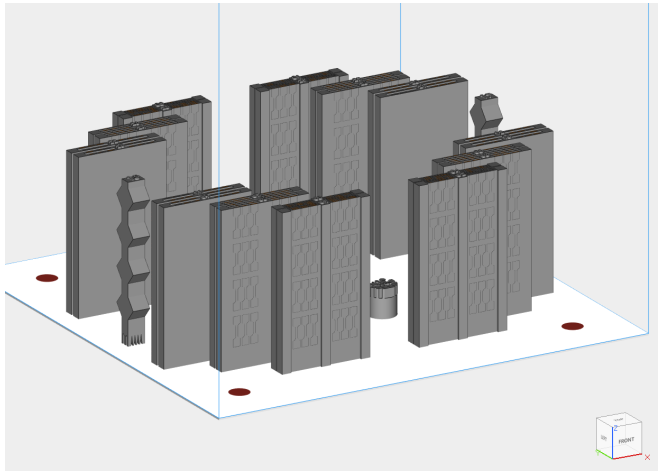
As built component



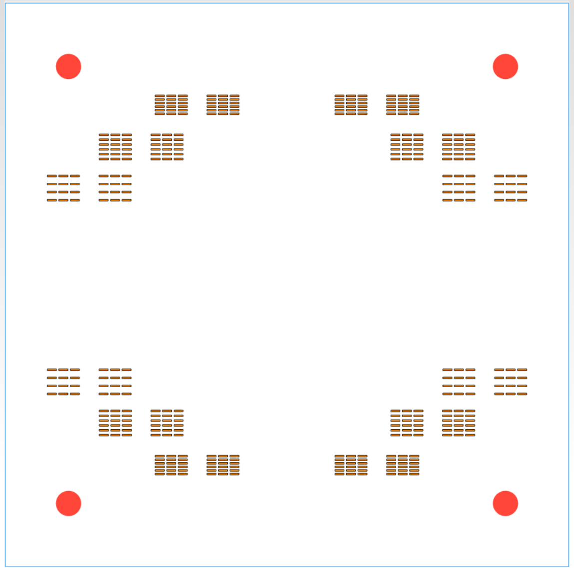


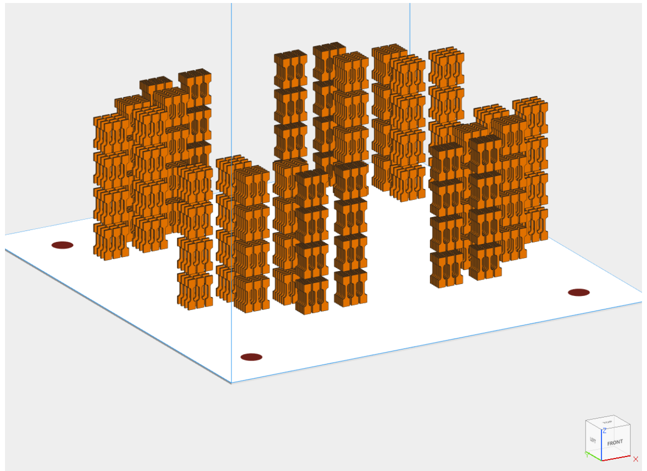
Design layout





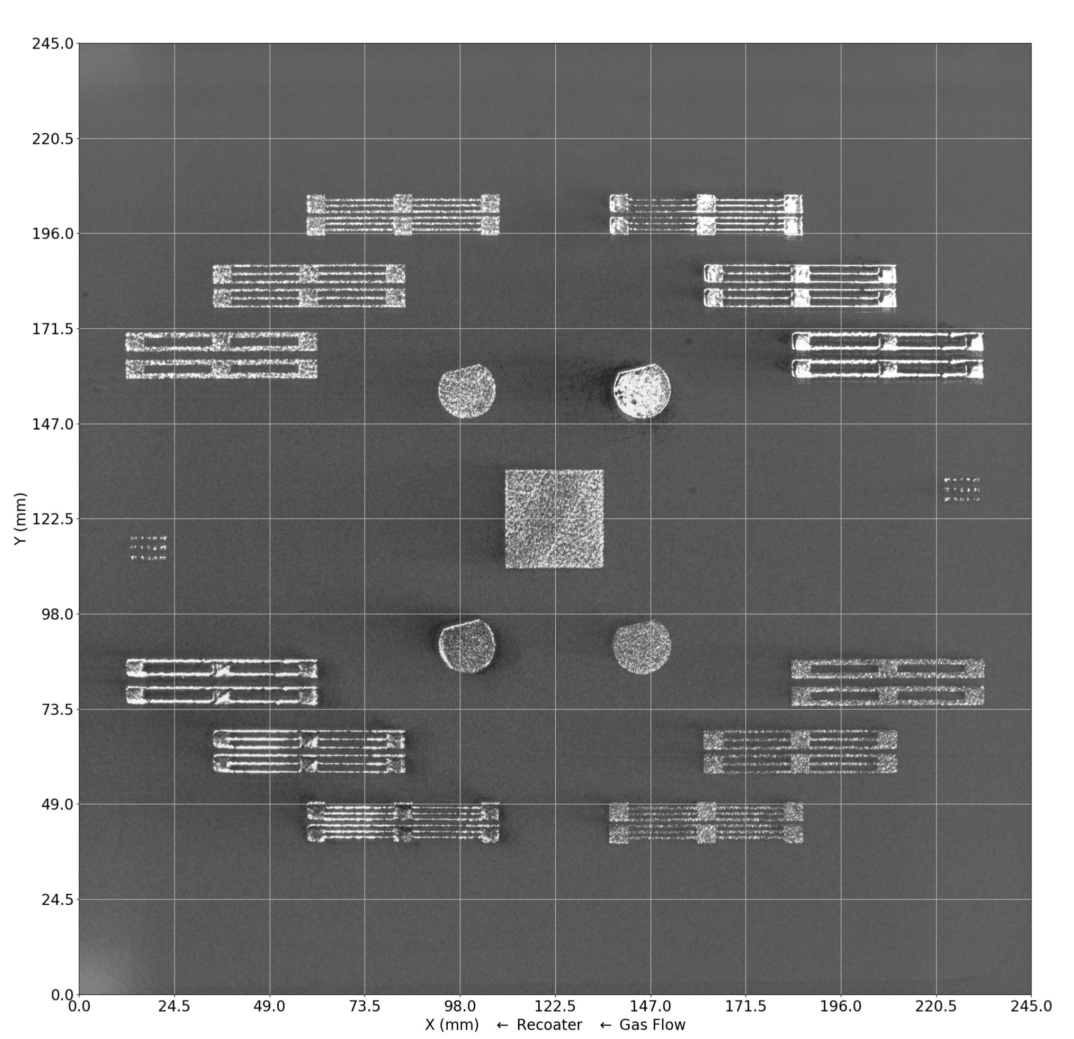
Mech. Test Placement



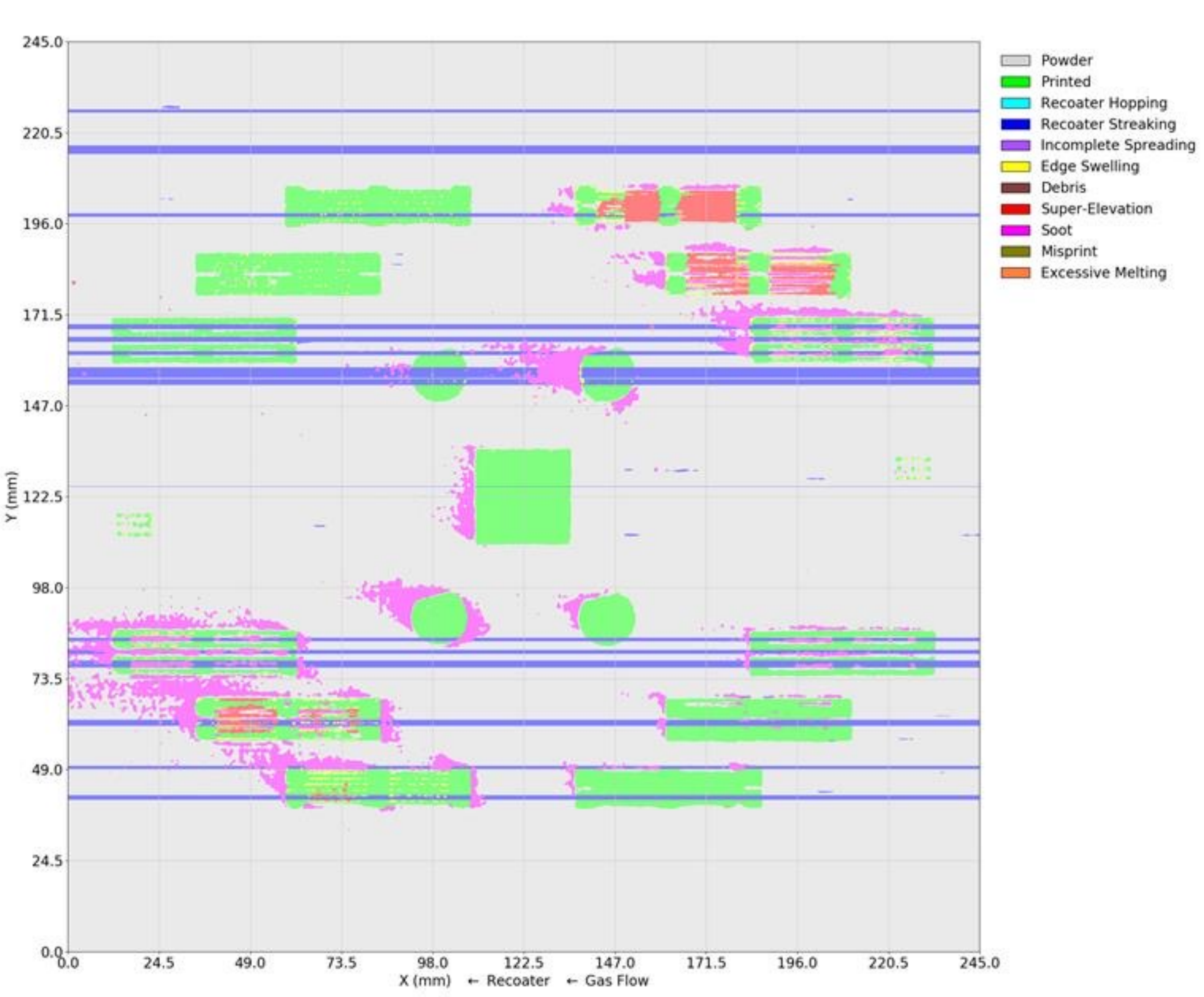


Example Geometry: Phase 2 – Build 3

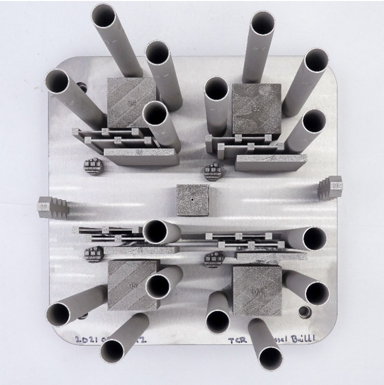
In-situ Image



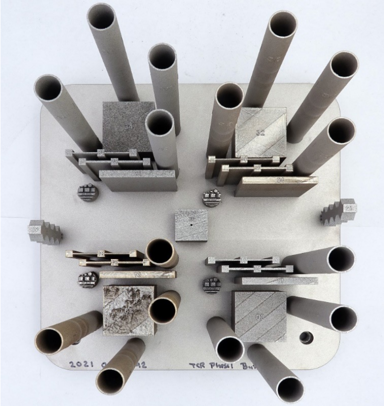
Peregrine Classification Result



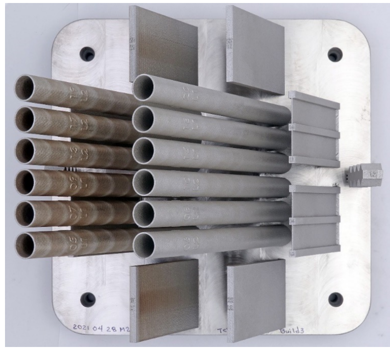
First sample manufacturing campaign

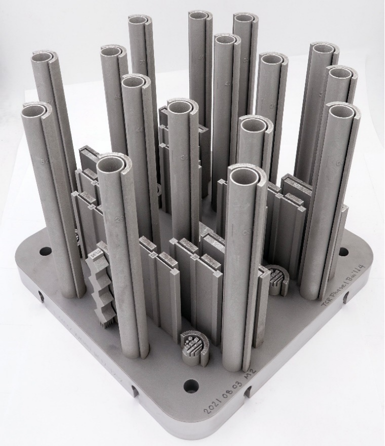
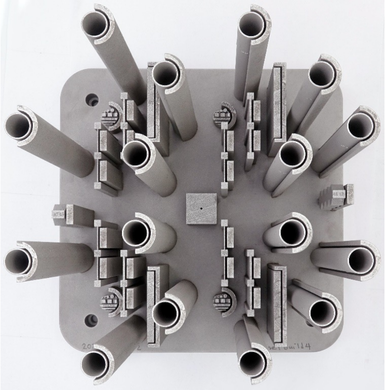
Build 1.1 – designed to capture baseline data i.e., thermal history based on part geometry and laser module used to fuse the material

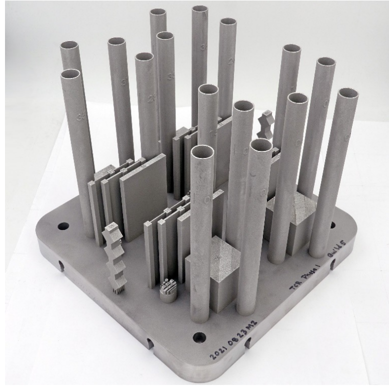
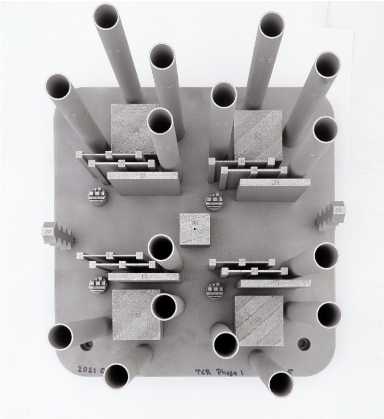
Build 1.2 – designed to induce porosity and microstructure differences from different melting parameters

Build 1.3 – designed to investigate the effects of overhanging geometries on thermal history and on surface roughness

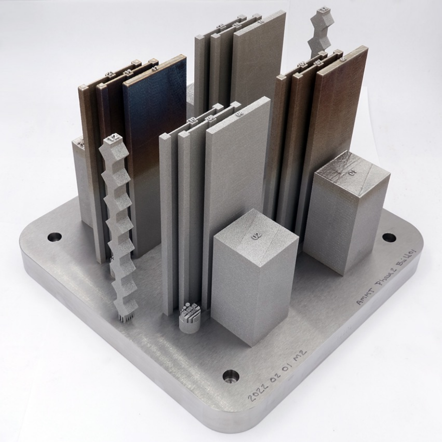



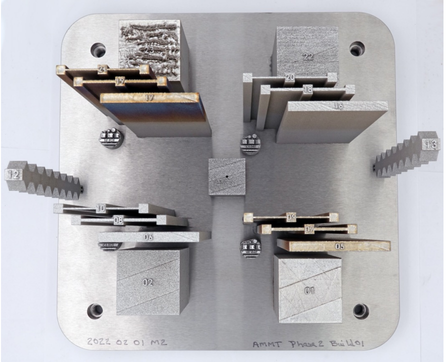
Build 1.4 – designed to investigate porosity population and microstructural differences resulting from increased spatter landing on the samples

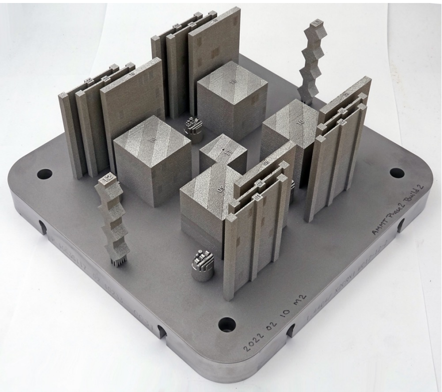
Build 1.5 – designed to investigate the effects of recoater streaking anomalies and atypical inter-layer bonding from incomplete powder spreading

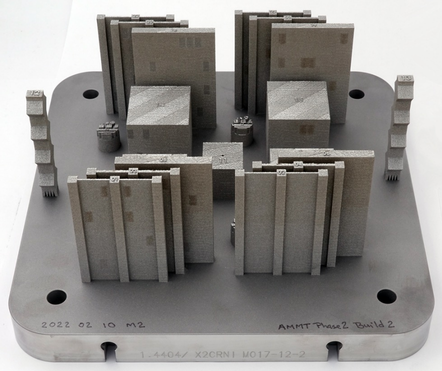
Second sample manufacturing campaign



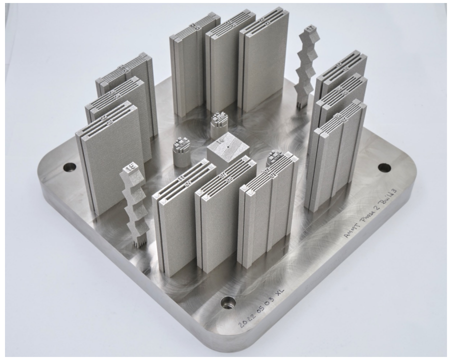


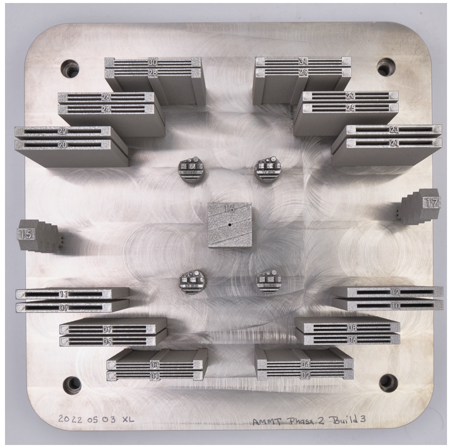
Build 2.1 - designed to capture tensile property trends at **taller build heights and** acquire examples of **intermediate** UTS and YTS values





Build 2.2 - designed to capture the effects of more **localized** process parameter differences





Build 2.3 - designed to capture the effects of **adjacent thin walls**, **build pauses**, and **missed powder spreads**

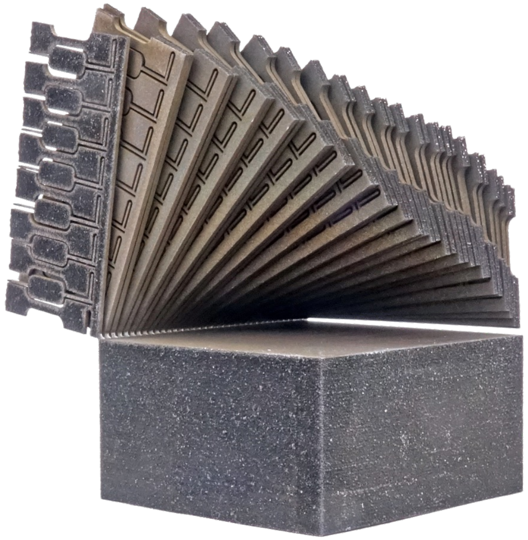
Mechanical testing

Testing Regimen

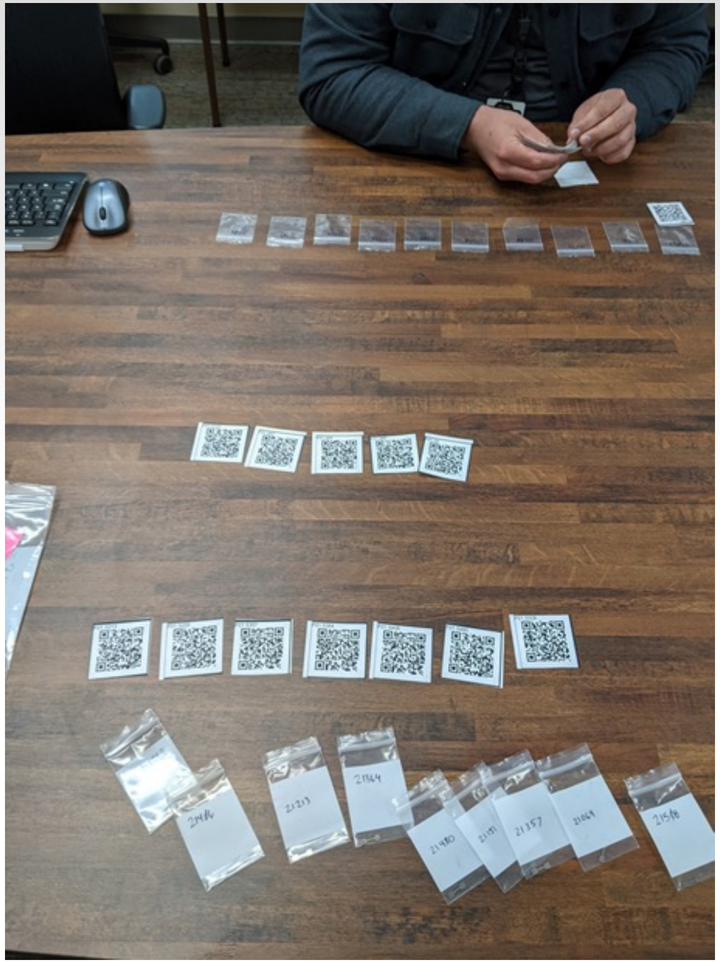
- Tensile
- Z orientation
- SSJ3 Dog Bone Geometry
  - 5 mm nominal gauge length
  - 1.20 mm nominal gauge width
  - 0.75 mm nominal gauge thickness
  - 16 mm nominal total length
- Room temperature only
- 0.5 mm/min displacement rate

Testing campaign to date

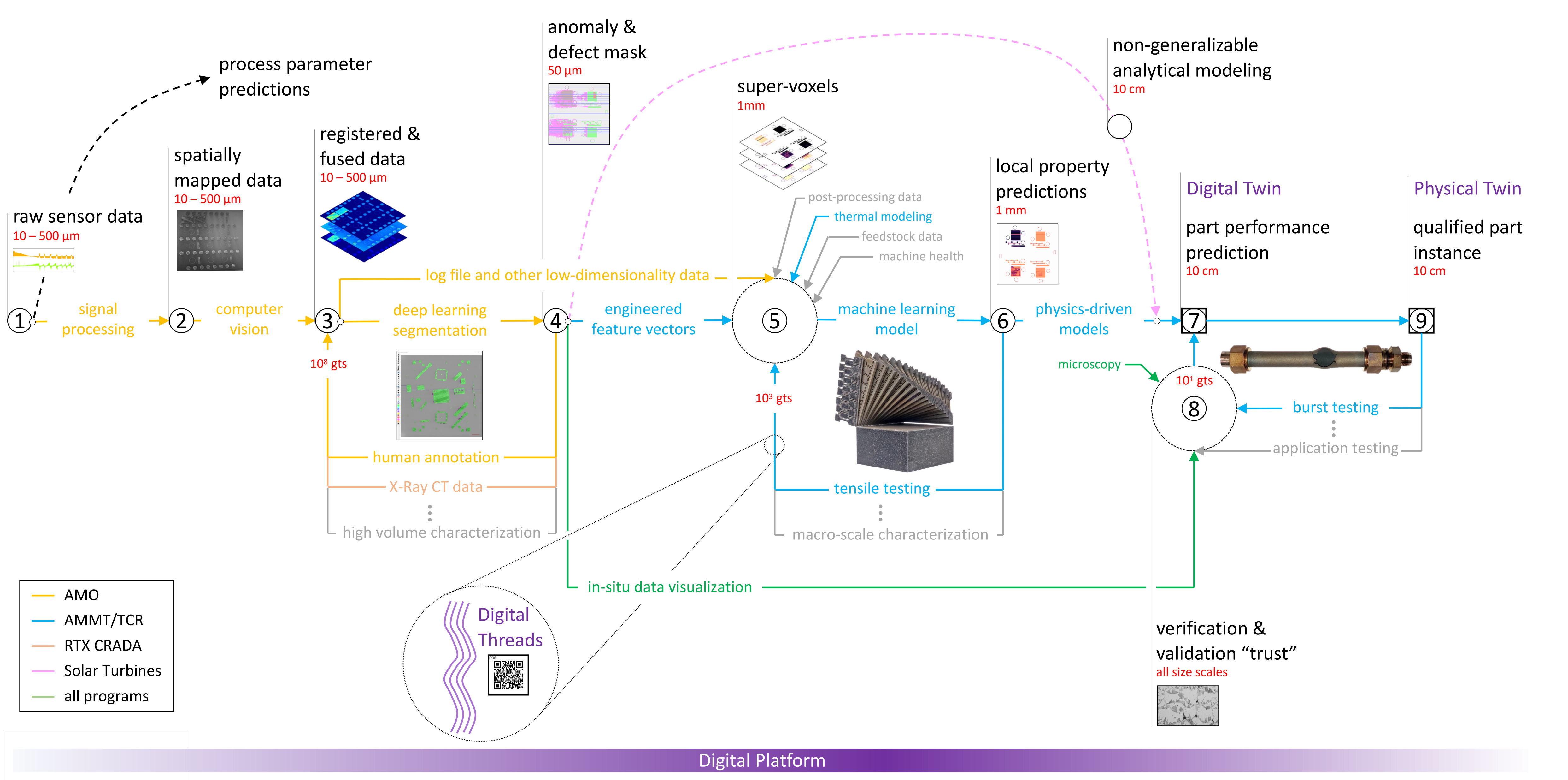
- Phase 1 tensile testing campaign complete
  - Tested 6,331 out of 8,480 samples
- Phase 2 tensile testing campaign in progress
  - Tested 1,121 out of 6,432 samples



Sample tracking

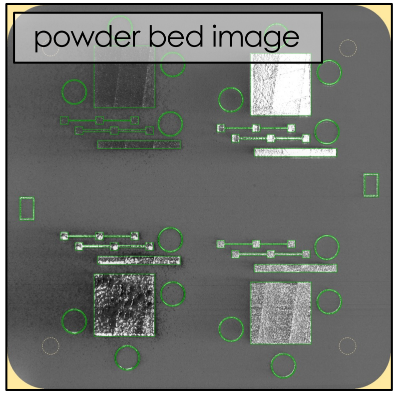


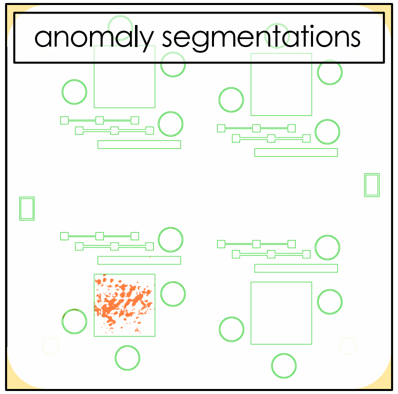
A Generalizable Framework for AM Part Qualification using an Augmented Intelligence Relay

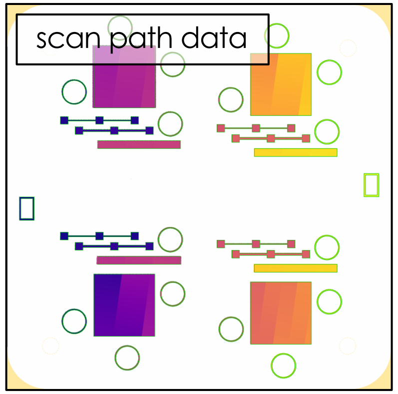


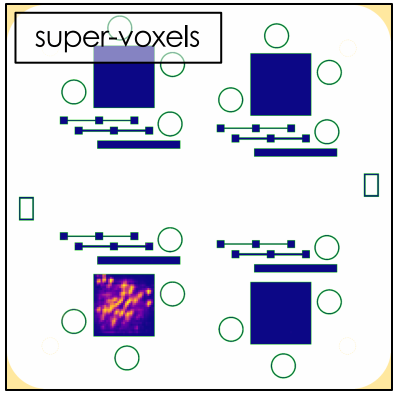
FY22 Digital Platform Improvements

- Reduction of super-voxel edge effects
- Increased control over the construction of the super-voxels
- Integration of the SWAN module into Peregrine to enable inclusion of scan path data in super-voxels
- Increased capabilities to interrogate and visualize super-voxel features and local property predictions

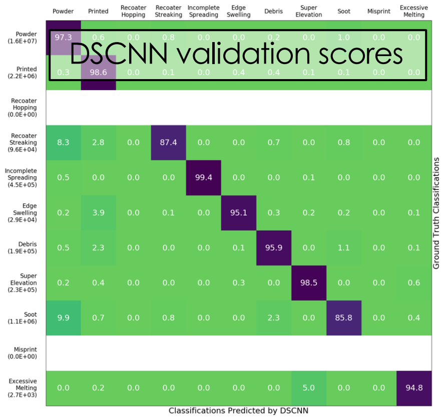




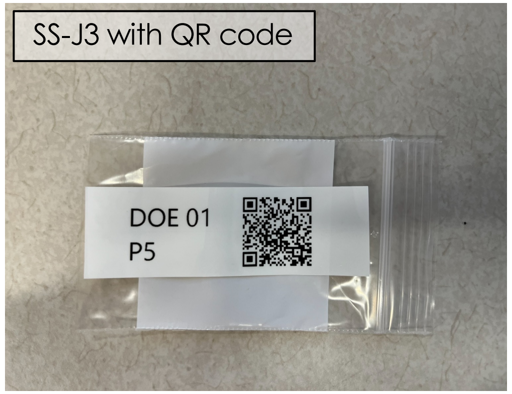


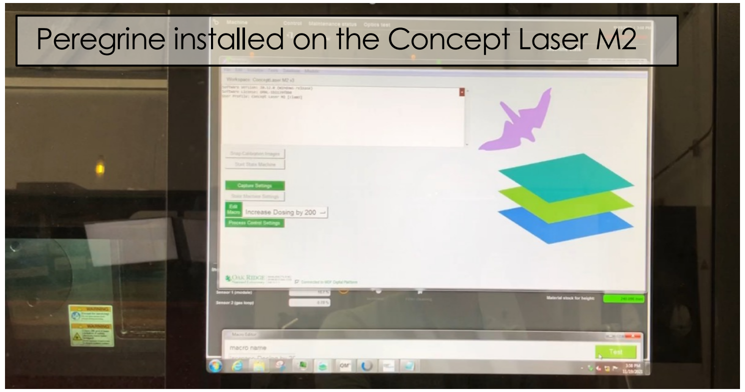


- Reduction in computation time for the end-to-end AIR workflow
- Improved implementation of pixel-wise segmentation heuristics and improved DSCNN accuracy
- Streamlined implementation of QR codes and the Digital Platforms web interface
- Implementation of real-time monitoring and control of the Concept Laser M2 printer

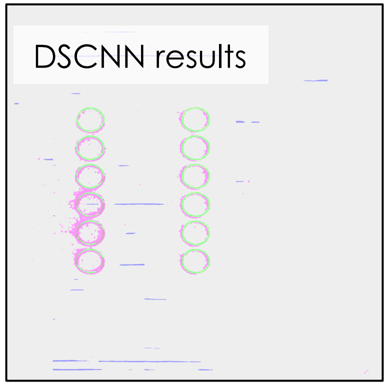


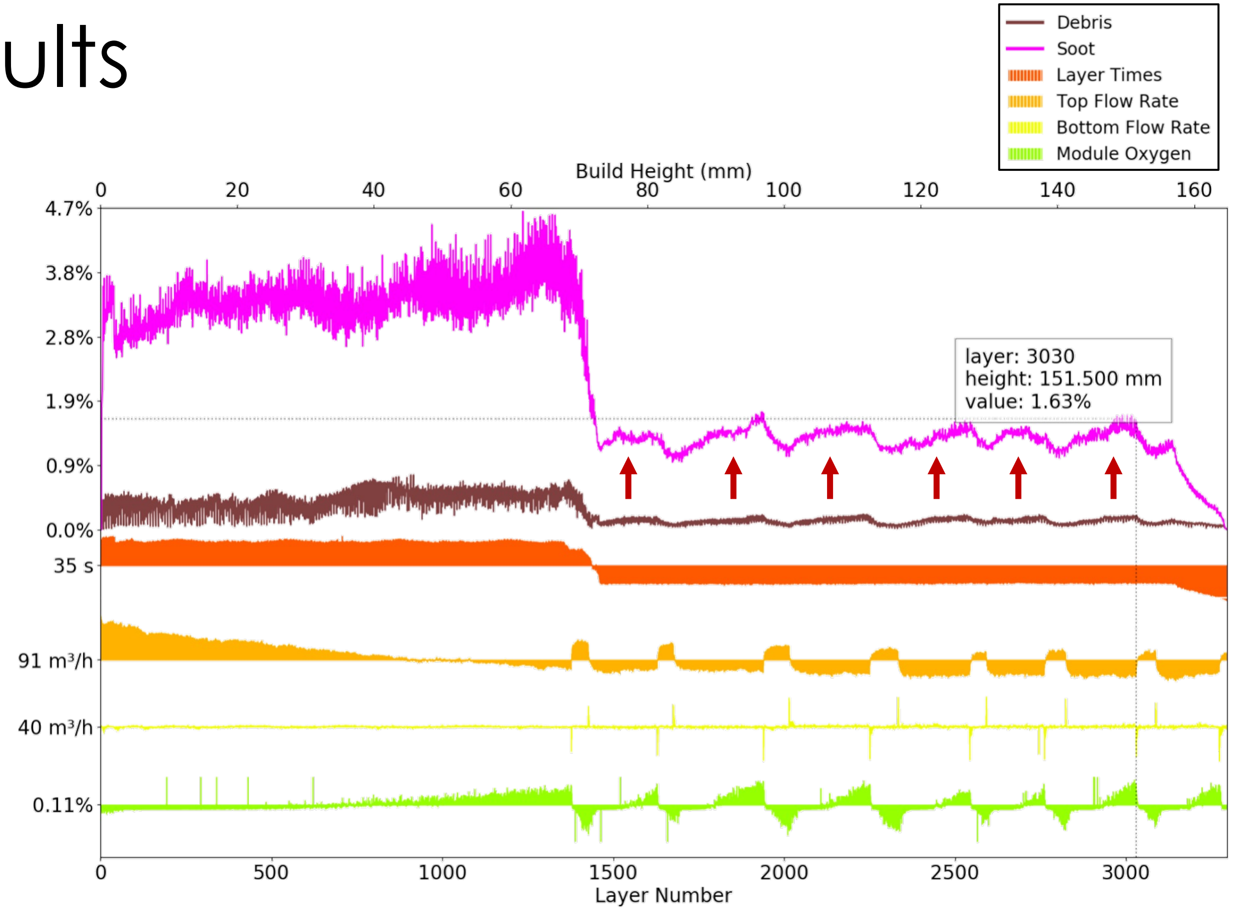
Ground Truth \ Predicted	Powder	Printed	Recoater Hopping	Recoater Streaking	Incomplete Spreading	Edge Swelling	Debris	Super Elevation	Soot	Misprint	Excessive Melting
Powder (1.6E+07)	97.3	0.6	0.0	0.8	0.0	0.0	0.2	0.0	1.0	0.0	0.0
Printed (2.2E+06)	0.3	98.6	0.0	0.1	0.0	0.4	0.4	0.1	0.1	0.0	0.0
Recoater Hopping (0.0E+00)											
Recoater Streaking (9.6E+04)	8.3	2.8	0.0	87.4	0.0	0.0	0.7	0.0	0.8	0.0	0.0
Incomplete Spreading (4.5E+05)	0.5	0.0	0.0	0.0	99.4	0.0	0.0	0.1	0.0	0.0	0.0
Edge Swelling (2.9E+04)	0.2	3.9	0.0	0.1	0.0	95.1	0.3	0.2	0.2	0.0	0.1
Debris (1.9E+05)	0.5	2.3	0.0	0.0	0.0	0.1	95.9	0.0	1.1	0.0	0.1
Super Elevation (2.3E+05)	0.2	0.4	0.0	0.0	0.0	0.3	0.0	98.5	0.0	0.0	0.6
Soot (1.1E+06)	9.9	0.7	0.0	0.8	0.0	0.0	2.3	0.0	85.8	0.0	0.4
Misprint (0.0E+00)											
Excessive Melting (2.7E+03)	0.0	0.2	0.0	0.0	0.0	0.0	0.0	5.0	0.0	0.0	94.8





Example L-PBF *Peregrine* Results





- Unexpected **discoloration** bands appeared in the as-printed parts
- The domain experts leveraged *Peregrine* to investigate

- Each layer of in-situ visible-light imaging data is analyzed by the DSCNN
- The outputs are pixel-wise anomaly detections throughout the height of the build

- The DSCNN results show that **soot** levels increased at **time intervals** corresponding to the **discoloration** bands
- Plotted alongside the temporal data, it is apparent that the **oxygen concentration** in the build chamber increased during these periods
- Which resulted in more oxidized (darker) **soot** particles and **discoloration** of the part until the printer detected a reduction in **argon flow rate** and adjusted its setpoints

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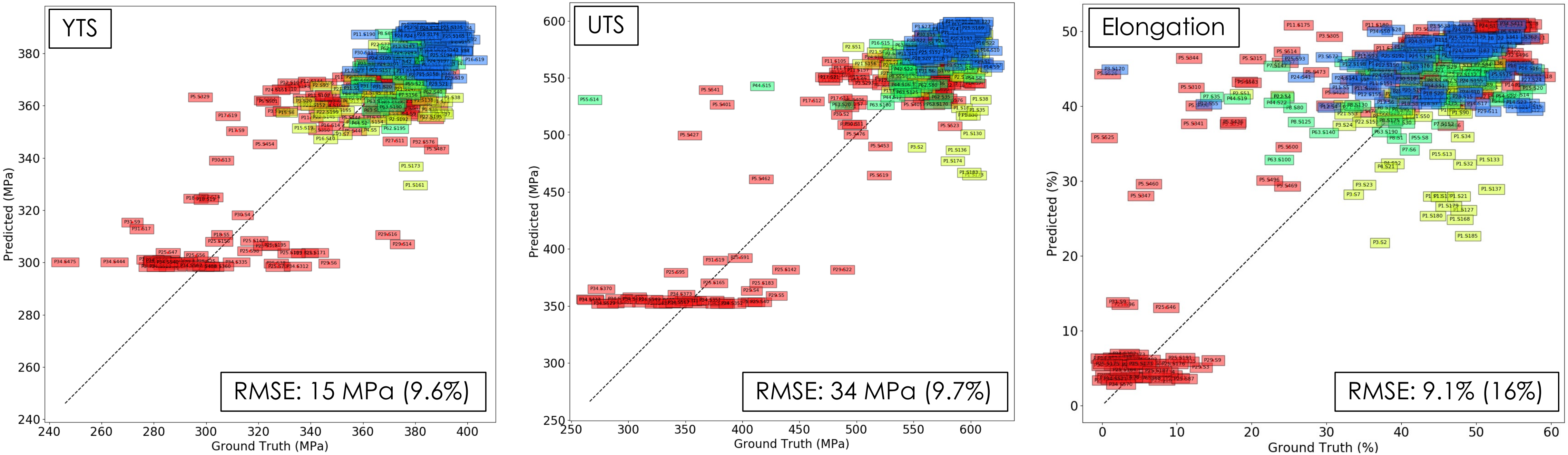
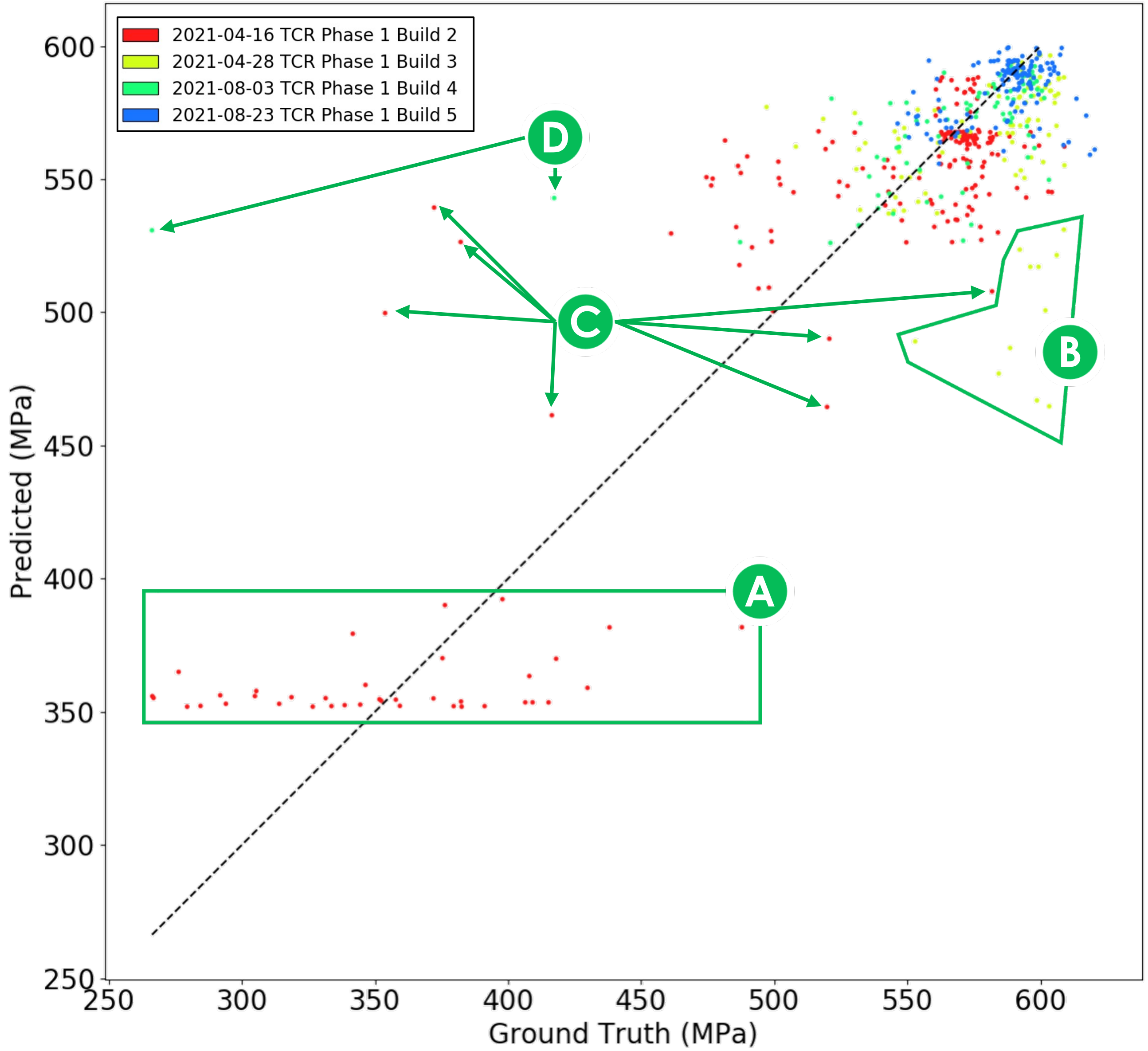
Voxelized Property Prediction Model (VPPM) Performance



- **4,500** and **500** SS-J3 samples have been used for training and validation of the AIR, respectively
- The AIR is currently using a **Multi-Layer Perceptron (MLP)** for the VPPM
- If a VPPM had perfect predictive abilities, all the data points would lie on the dashed line
- RMS errors range from **9.6%** to **16%** of the ground truth property ranges

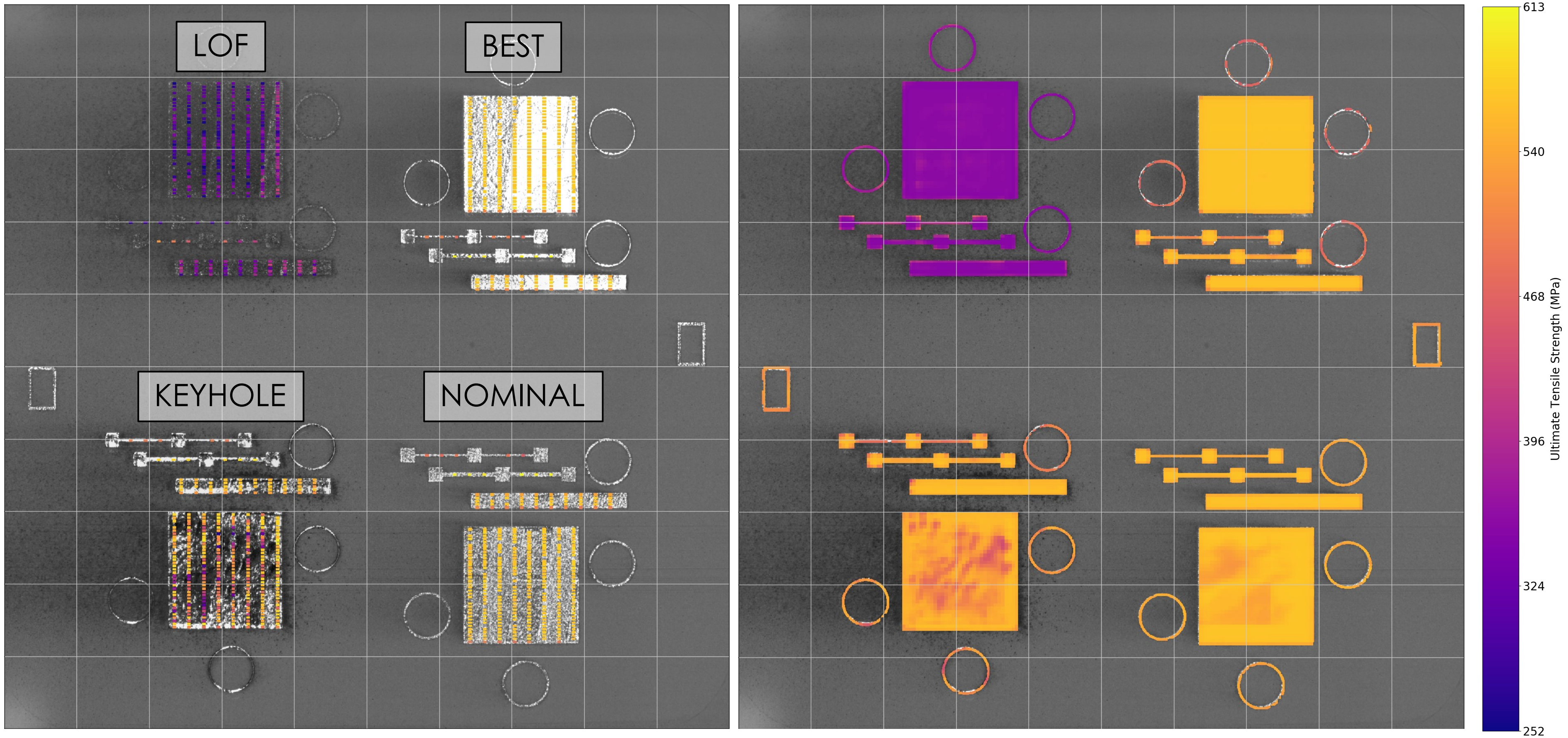
2021-04-16 TCR Phase 1 Build 2
2021-04-28 TCR Phase 1 Build 3
2021-08-03 TCR Phase 1 Build 4
2021-08-23 TCR Phase 1 Build 5

Investigating UTS Prediction Outliers



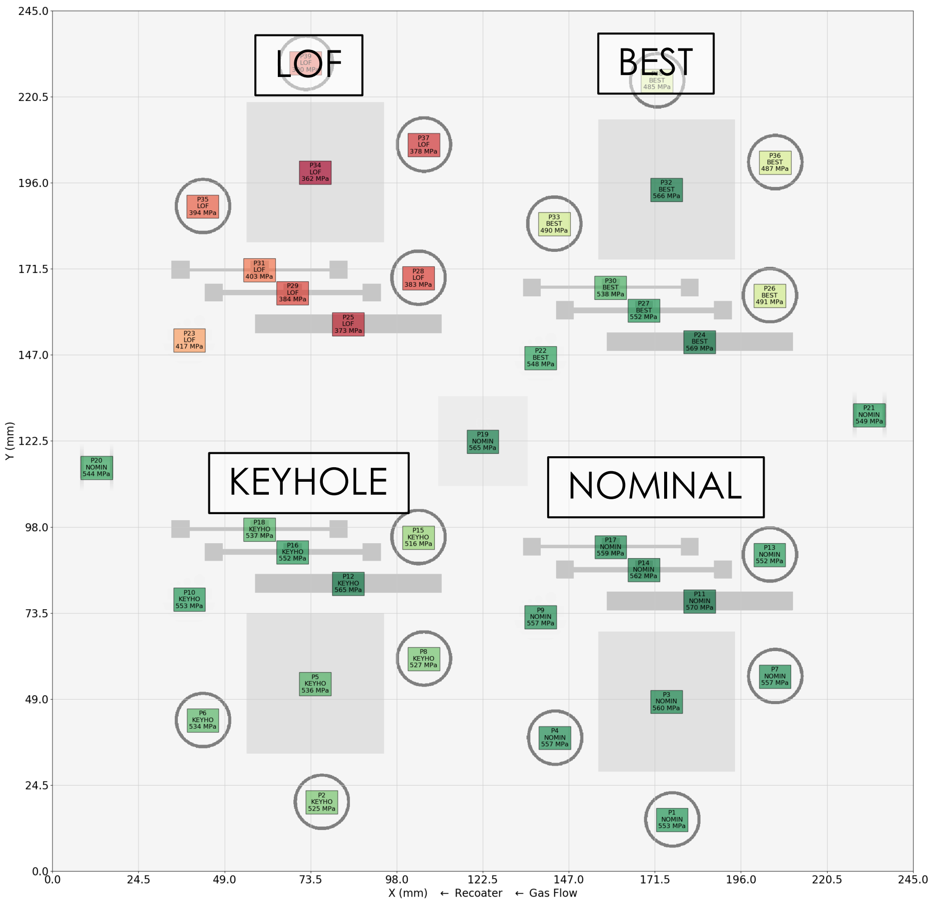
- **A** These samples were printed with Lack-of-Fusion (LOF) parameters, the in-situ data look similar across the samples but the variation in measured UTS is very high (between 250 MPa and 500 MPa)
- **B** These samples came from two parts, both of which contained a lot of soot and debris detections, yet the measured tensile properties are still good; the oxygen concentration is high for this build which might account for the increase in detections
- **C** These samples are all from bulk regions processed with Keyholing (KEYHOLE) parameters
- **D** These samples came from a build with intentionally generated soot, but had relatively low soot detections

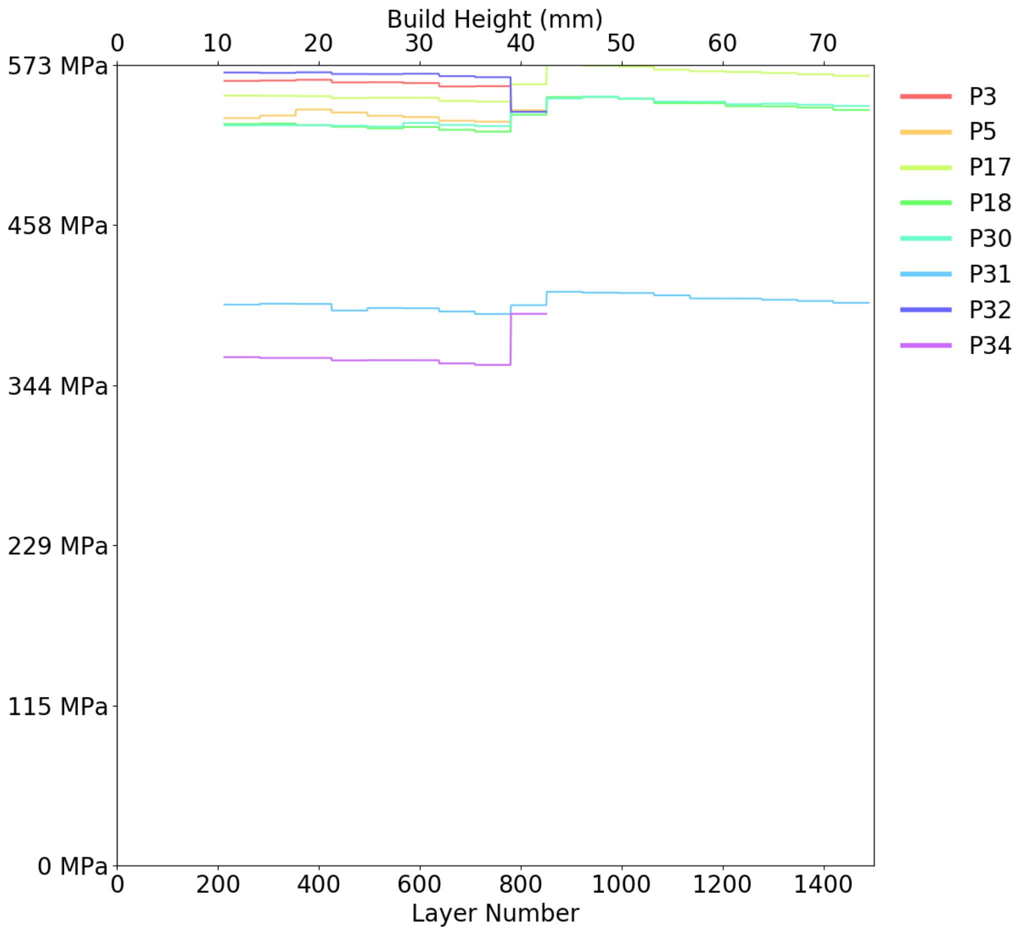
Predicting Local UTS at a Specific Layer within Phase 1 Build 2



- Average differences in UTS due to **process parameter differences** are well predicted by the VPPM
- Increased UTS **variability** for parts melted with KEYHOLE parameters is captured by the VPPM
- Both the ground truth measurements and the VPPM indicate slightly reduce UTS for **thin walls** and **near part edges**

Predicting Local UTS for the Entirety of Phase 1 Build 2





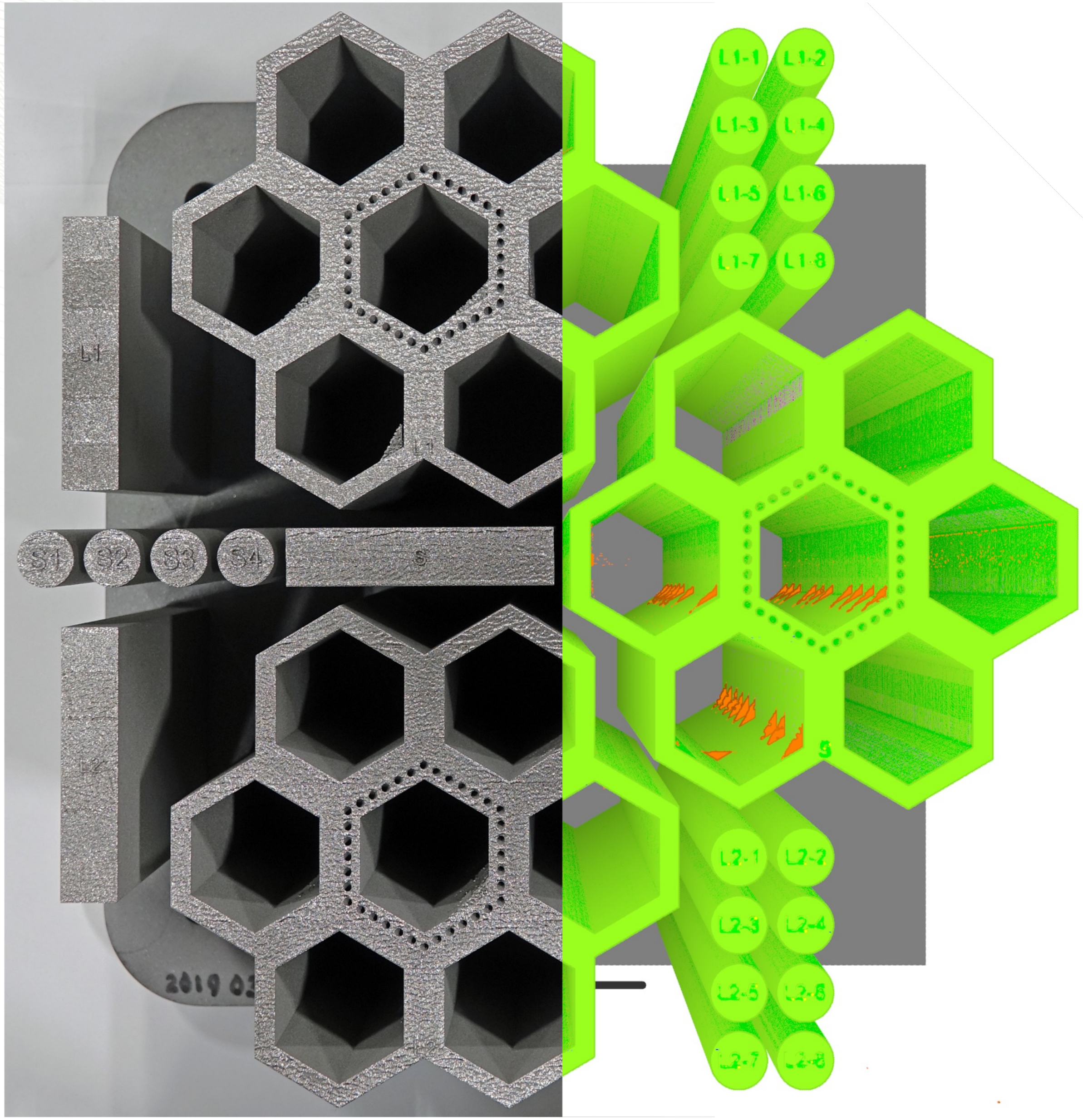
- Largest UTS differences are aligned with **process parameters**
- There is a prediction of slightly decreasing local UTS as **build height increases** across all process parameters
- **Predictions are not possible at the start of the build** because VPPM was not trained on data near the build plate

Conclusions

- Predictive capability demonstrated for mechanical tensile test results for UTS
- Strong correlation between super-voxel digital signature and mechanical test results
- Digital discipline ensures collection of pedigree datasets
- Digital twins of component contains link between intent, manufacturing, and part quality

Future work

- Improve and expend approach to other mechanical testing measurements
- Validate AIR approach with burst tubes and geometry
- Automated mechanical testing to build AM material database for nuclear application
- Transfer digital discipline and tools to participating members of AMMT program
- Use digital twin information to identify target sample to reduce number of tests for fatigue, creep, etc.



Questions?

Contact: paquitvc@ornl.gov

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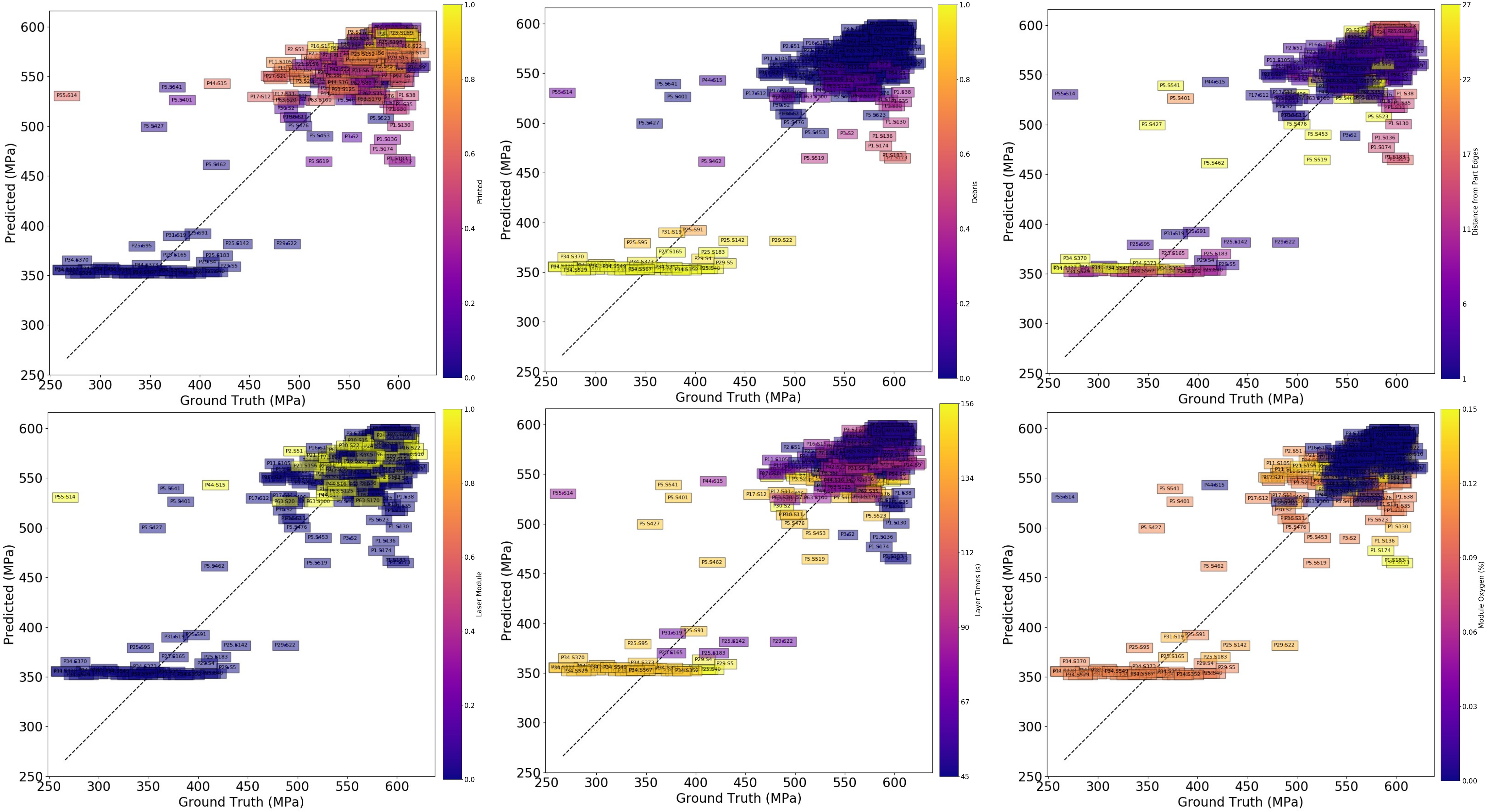
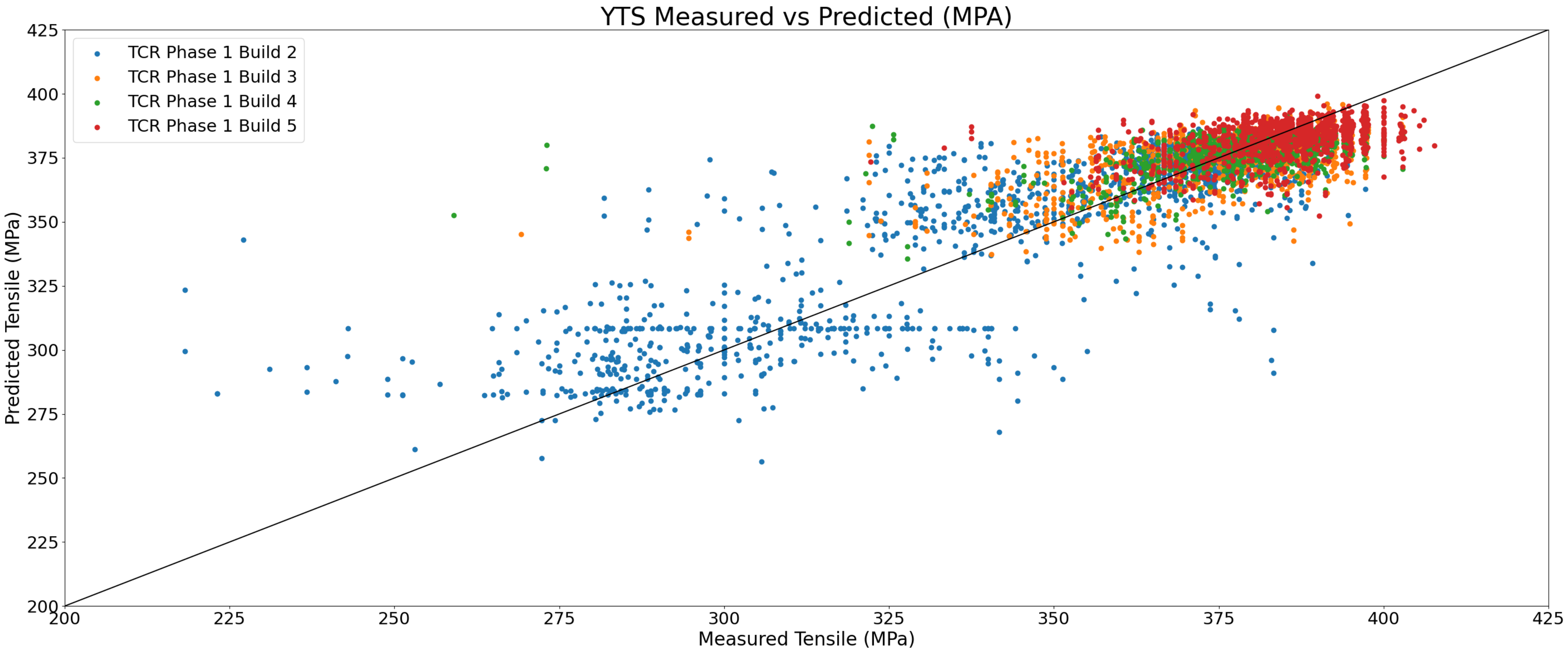
UTS Behavior by Feature



Yield Tensile Strength, RMSE (14.09)



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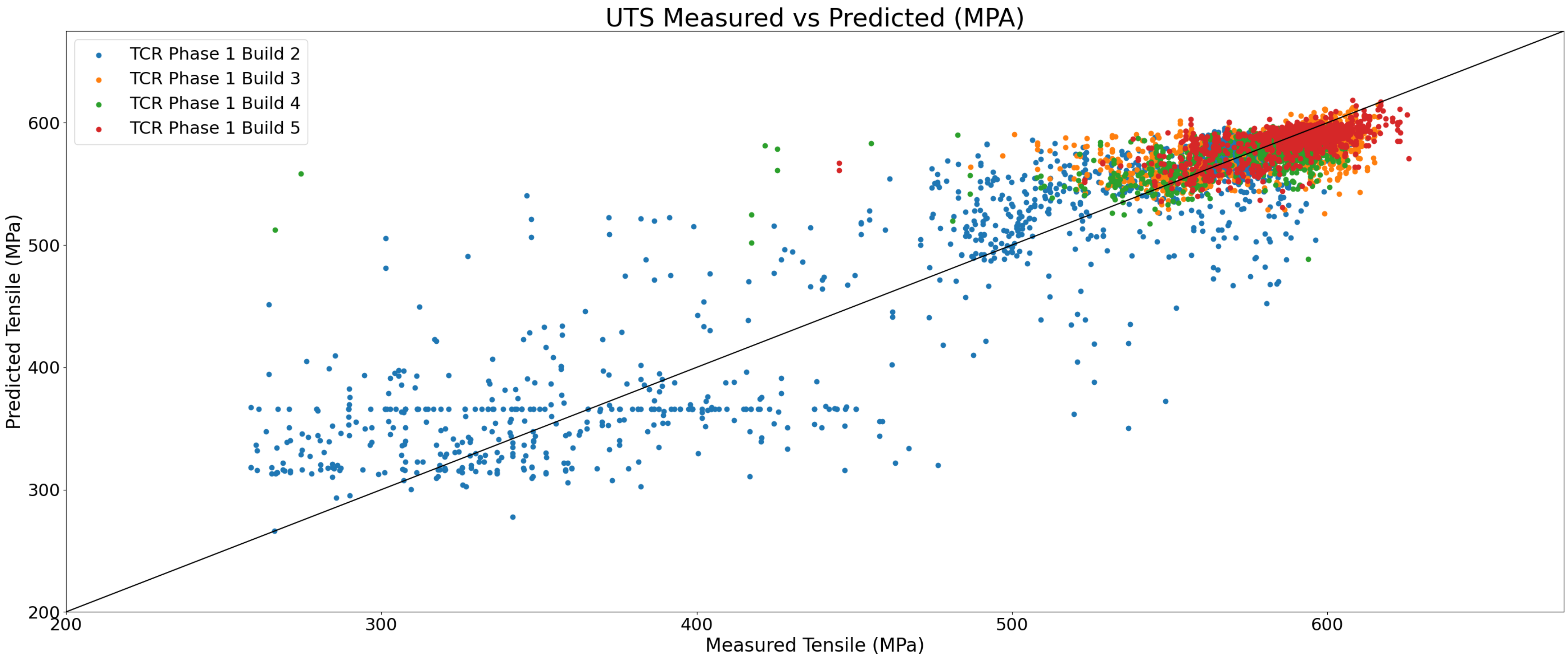
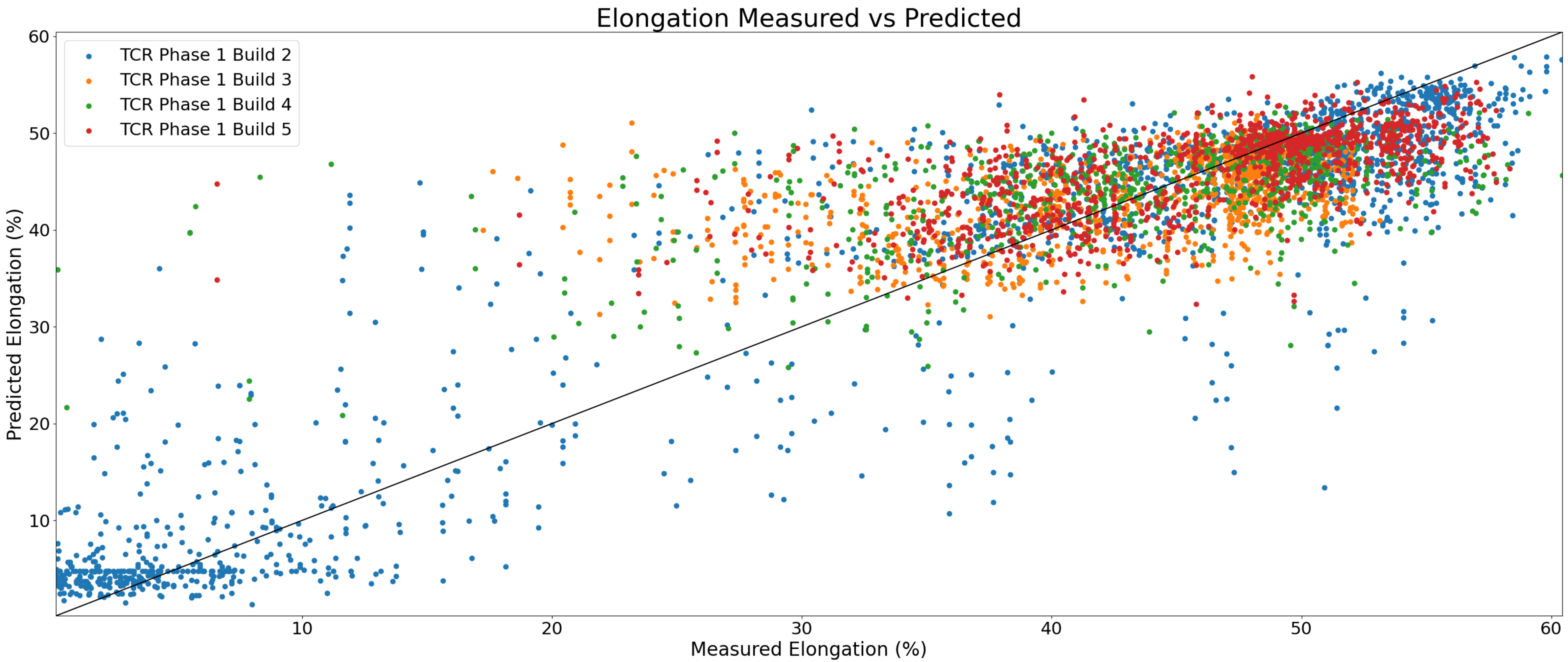
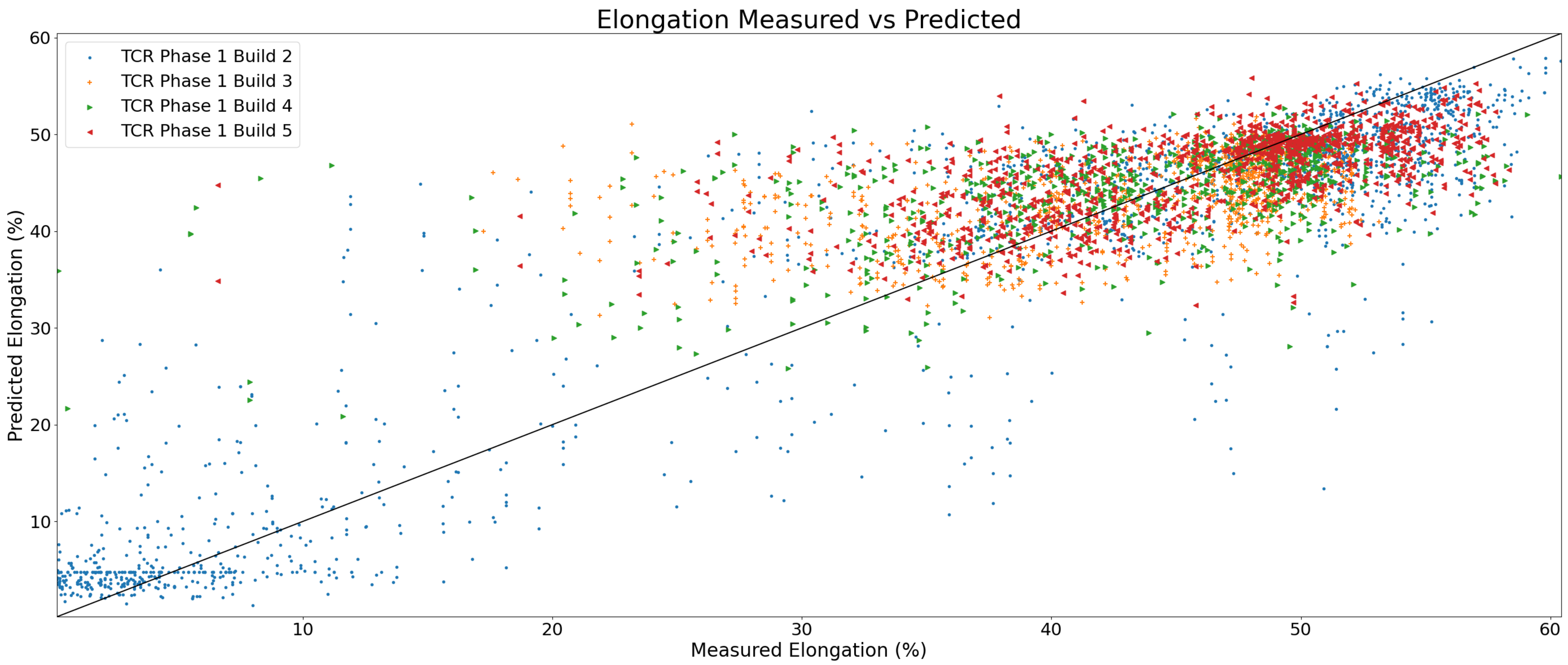
Ultimate Tensile Strength, RMSE (27.14)



Elongation, RMSE (6.68)



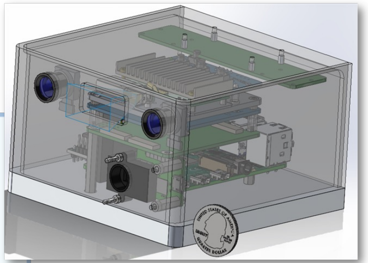
Elongation, RMSE (6.68)



National Testbed for **Digital Manufacturing** Science Research

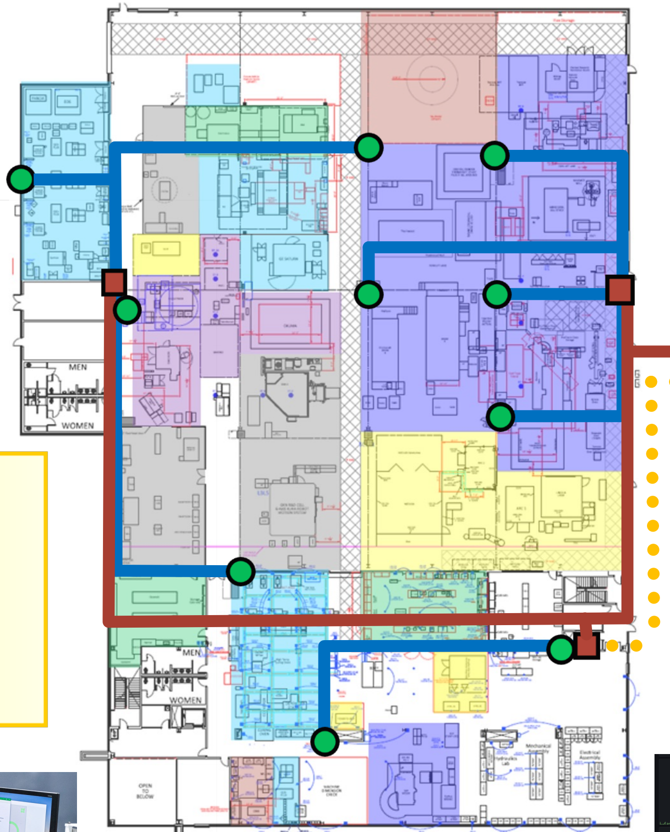
The MDF Digital Factory is a System of Systems delivering scientific solutions for the digital transformation of the US manufacturing industry

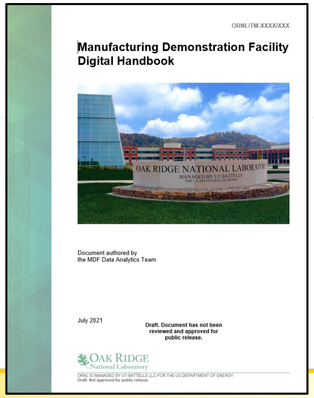
- Digital infrastructure
- Sensing and instrumentation
- Data analytics and artificial intelligence
- Augmented Intelligence
- Data-driven methodologies
- External collaborators access
- Cyber security



Sensing and Instrumentation
- Quality Control
- AI at the Edge
- Feedback Loop Control

ORNL HPC Facilities
- Large Data Sets
- High Fidelity Modeling and Simulation
- AI Models Training




ORNL/TM-XXXX/XXX

Manufacturing Demonstration Facility Digital Handbook

Document authored by the MDF Data Analytics Team

July 2021

Draft. Document has not been reviewed and approved for public release.

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Knowledge and Technology Transfer
- Digital Handbook
- Open Datasets
- Patents & Copyright
- Technical Reports

Local Data Processing and Storage
- Data Management
- Digital Thread

MDFLIB

Data visualization
- Dashboards
- Interactive Apps
- Secure Web Access
- Virtual Reality

Data Analytics
- Algorithm Development
- Machine Learning and AI
- Software Release