Reducing "Time to First Good AM Part" Through In-situ Sensor Driven NDE

America Makes Project # 5001.006

America Makes & ANSI Virtual Event: *Inspection/Monitoring to Meet Regulatory Requirements: Additive Manufacturing (AM) Standardization*

December 08, 2021

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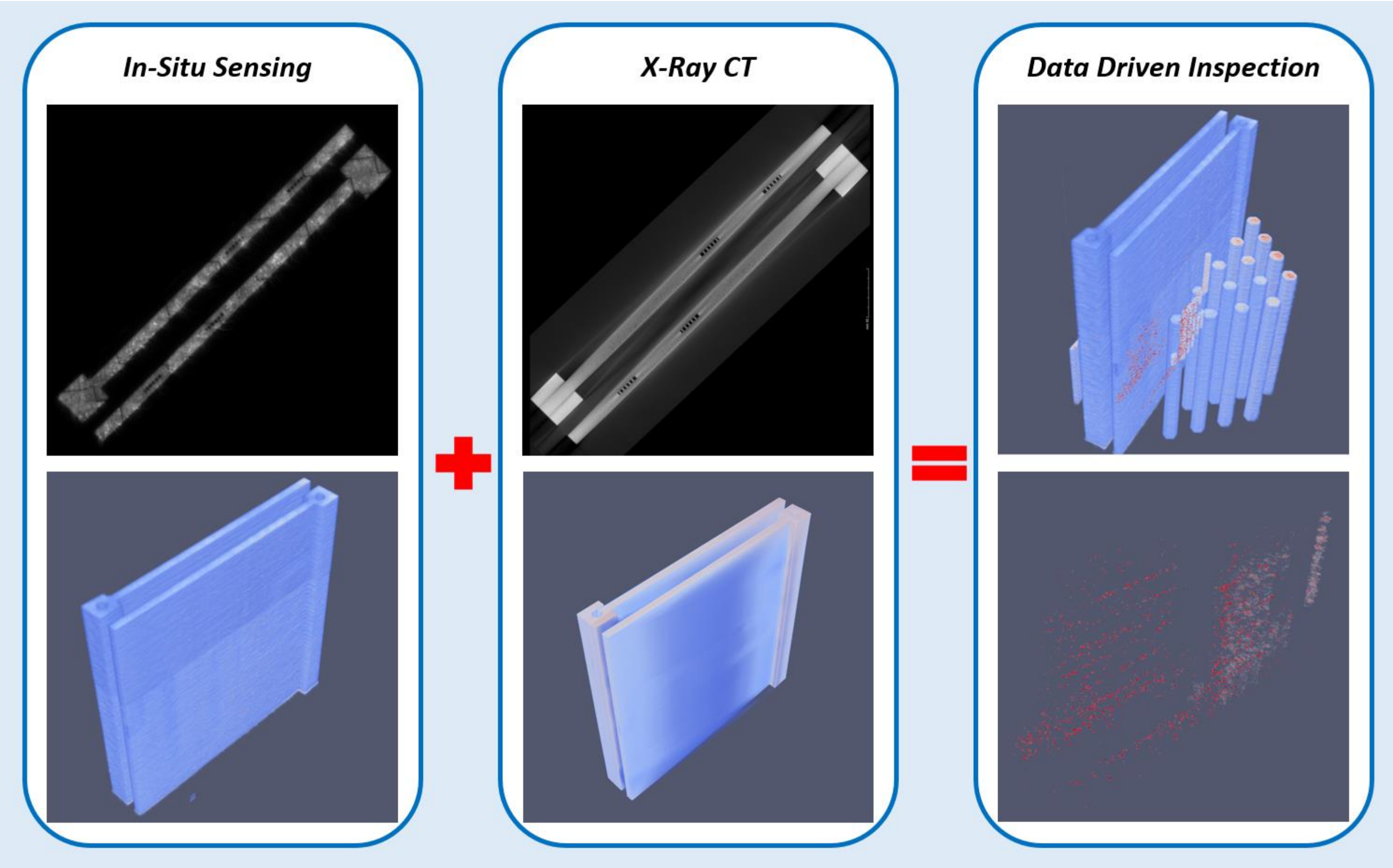
Overview

- Project Call/Source of Funding: America Makes Open Project Call
- Contract ID: FA8650-20-2-5700
- Technology Roadmap Swimlane alignment: Value Chain
- Period of Performance: 6 months
- Start date, End date: November 20, 2020, May 28, 2021
- Total funding, Total Government Funding, Total Cost Share: $254,992, $169,992, $85,000

University of Dayton Research Institute
NORTHROP GRUMMAN
ZEISS
OPEN ADDITIVE
Macy Consulting Inc. Manufacturing Solutions

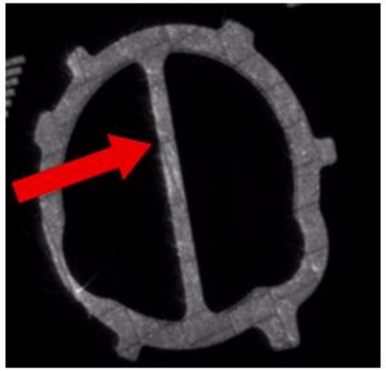
Technical Approach- Problem

- Currently, metal AM is an iterative trial-and-error printing process
  - Time consuming post-inspection steps
  - Long lead times
  - High cost
- High resolution NDE often needed to find non-conformances
  - High resolution often not feasible for entire part
  - Selecting regions to inspect is often based on educated guesses
- In-Situ sensing can inform smarter “point of concern” inspections
  - Data driven decision making
  - Lower Cost
  - Reduced Lead Time



University of Dayton Research Institute	Northrop Grumman	Zeiss	Open Additive	Macy Consulting Inc. Manufacturing Solutions
Project Lead Printing In-situ Sensing for LPBF In-situ analysis/correlation	Part Identification Past print history Non-conformance criteria	NDE (X-Ray CT) In-situ to NDE correlation	Provides and supports AMSENSE In-situ Sensor Suite	Supports supply chain adoption and DoD integration

Part Non-Conformance TDP



Detect Anomaly In-Situ

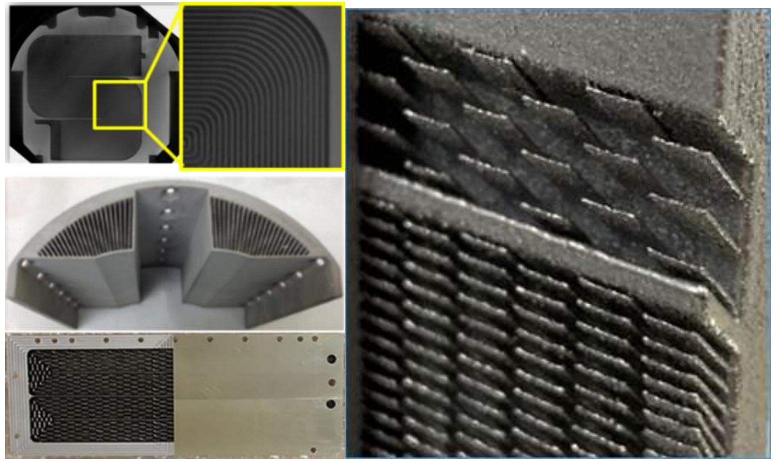
Point of Concern Inspection

Task 1: Part Identification and TDP Extraction

Lead	Tasks	Sub-Tasks	Dec-20	Jan-21	Feb-21	Mar-21	Apr-21	May-21
NGC	Task 1 - Part Identification and TDP Extraction	Identify Part of Interest						
		Indentify Past Print History of Part						
		Identify Non-Conformance Criteria of Part						
		Extract TDP for Correlation to In-situ and NDE Data						

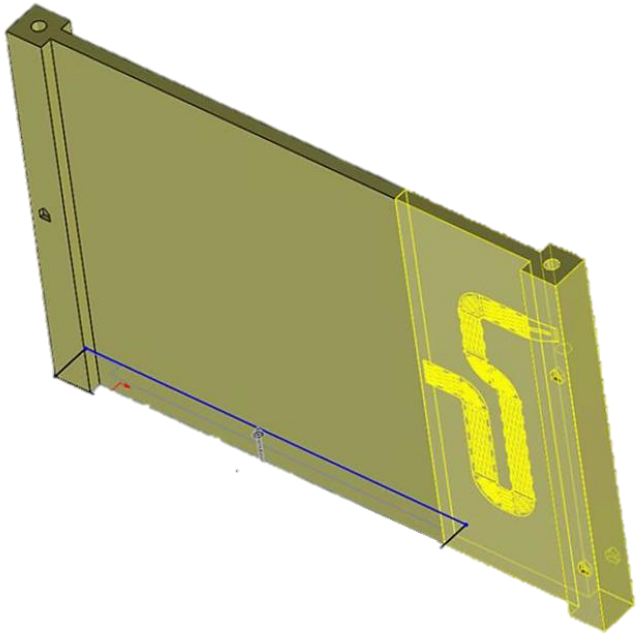
Lead: Northrop Grumman

- Identify Part of Interest
- Identify Past Print History of Part
- Identify Non-Conformance Criteria of Part
- Extract TDP for Correlation to In-situ and NDE Data



Northrop Grumman Part History

- Prior to program, six aluminum heat exchangers were fabricated at NGC
- All six heat exchangers passed visual inspection and pressure drop testing before proceeding to machining and non-destructive evaluation (NDE)
- Unfortunately, it was not until review of the NDE data that significant process induced defects were identified in three of the of the six heat exchangers



Model of the heat exchanger selected for this project with internal cooling channels highlighted

Fabrication Timeline

7/21

AM Fabrication → Bulk Powder Removal → Heat Treatment → Remove from Build Plate → Additional Powder Removal Step → Pressure Drop Testing → Machining → NDE (CT and Digital X-Ray) → **NDE Review Identifies Non-conformances**

Loss of 5 Months and <$20000

11/11

Task 2: Part Printing and In-Situ Data Collection

Lead	Tasks	Sub-Tasks	Dec-20	Jan-21	Feb-21	Mar-21	Apr-21	May-21
UDRI	Task 2 - Part Printing and In-Situ Data Collection	Multiple Prints of Identifed Part w/ Post Process						
		Detect In-situ Data Anomalies						
		Define Region of Interest for High Resolution CT						

Lead: UDRI

- Multiple Prints of Identified Part w/ Post Process
- Detect In-situ Data Anomalies
- Define Region of Interest for High Resolution CT

3 x Correlation Prints

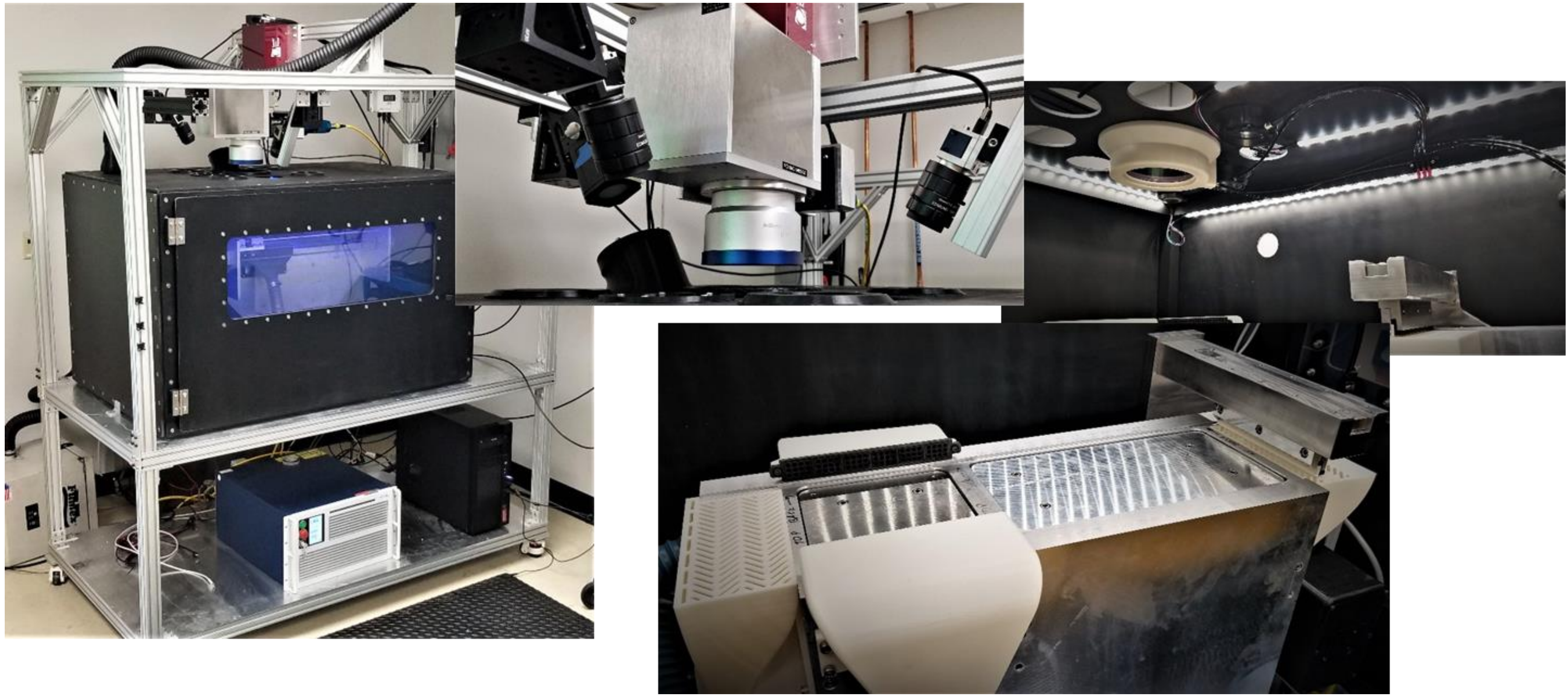
Goal: Establish linkage between In-situ data, NDE, and non-conformance criteria

MVP Print

Goal: Demonstrate in-situ informed inspection decisions

DART Open Architecture LPBF System

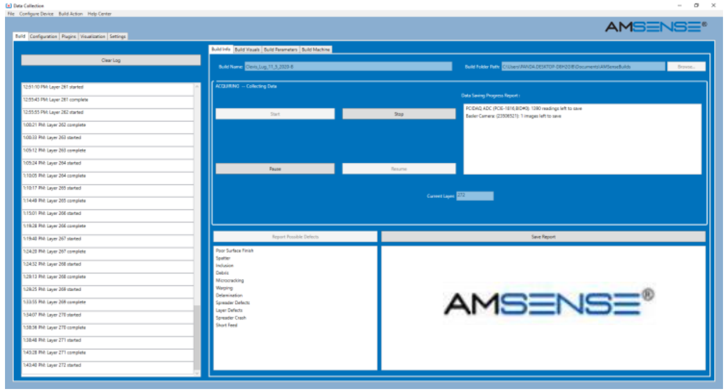
- Up to 500W CW Laser
- Galvanometer Scanhead
- 6”x6”x 12” Custom Powder Bed
- Integrated Computer with Custom Controls
- Variable Cross-Bed Flow
- Atmospheric Glovebox with Filtration



AMSENSE ® : An Open System Approach

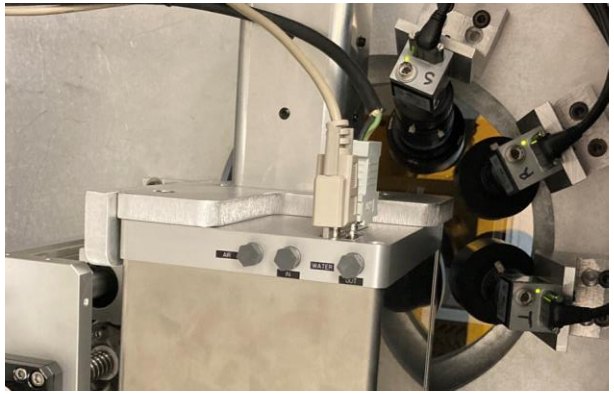
- AMSENSE ® is offered as an integrated option for Open Additive™ systems, or can be used as an add-on monitoring tool for other industrial platforms
- Modular design allows for customization and expansion through software plug-ins
- Users have fully open access to all raw and/or processed data
- Setup can be tailored to the AM process, machine model, and process anomalies of concern
- Recoat, TOMOTHERM™, SPAT-TRAK™ available options

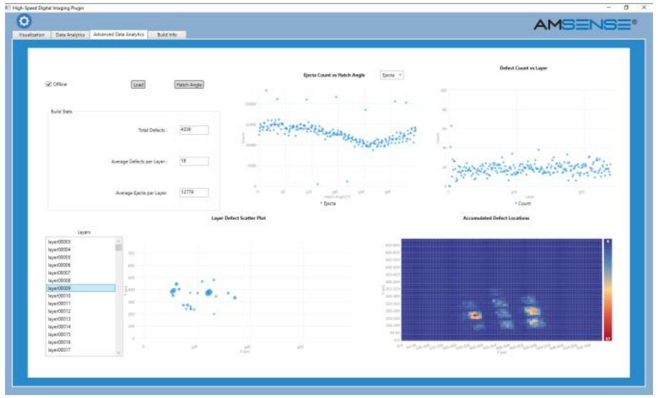
OPEN ADDITIVE™



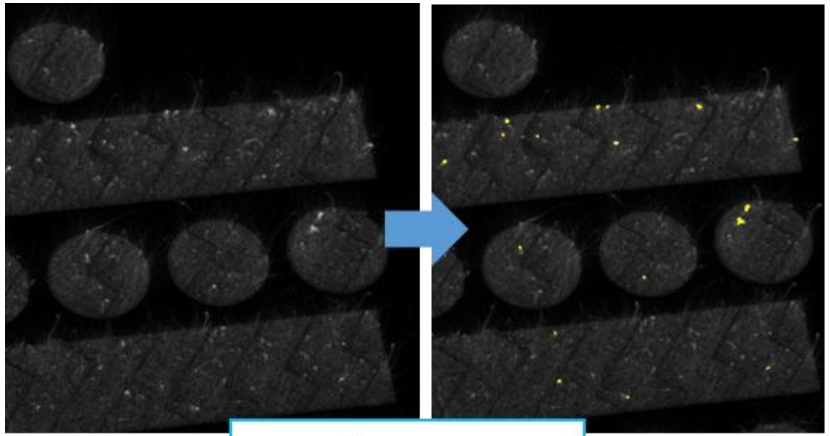
Open-Architecture HW/SW Suite

Sensors			Analytics		
Standard Options	Custom Sensors	User /3rd-Party Sensors	Standard Options	Custom Algorithms	User / 3rd-Party Algorithms

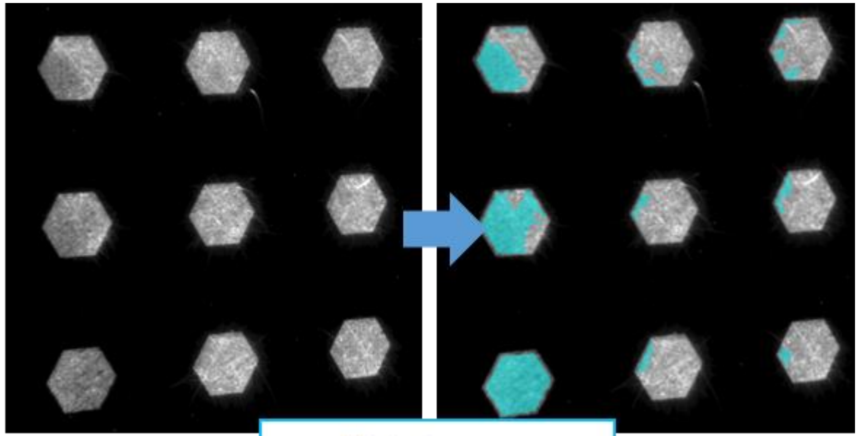




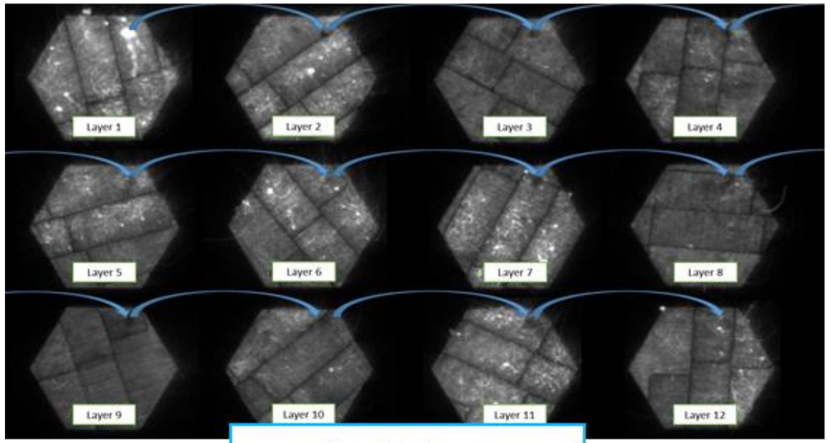
Near IR Tomography Camera- Detectable Anomalies



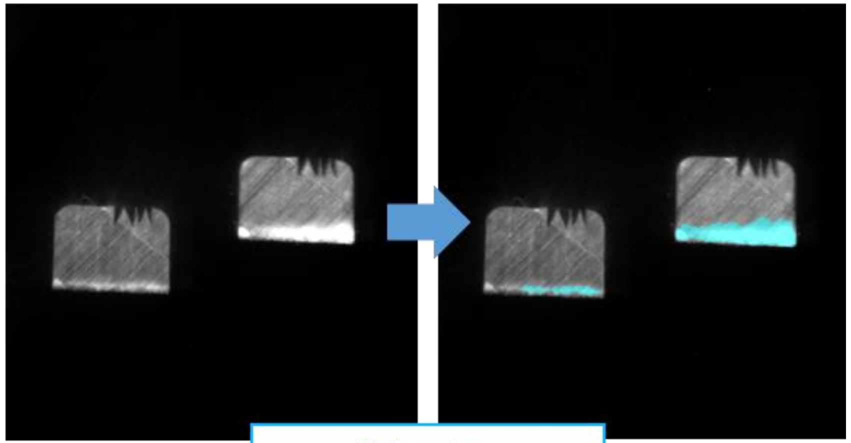
Spatter



Thin Layers

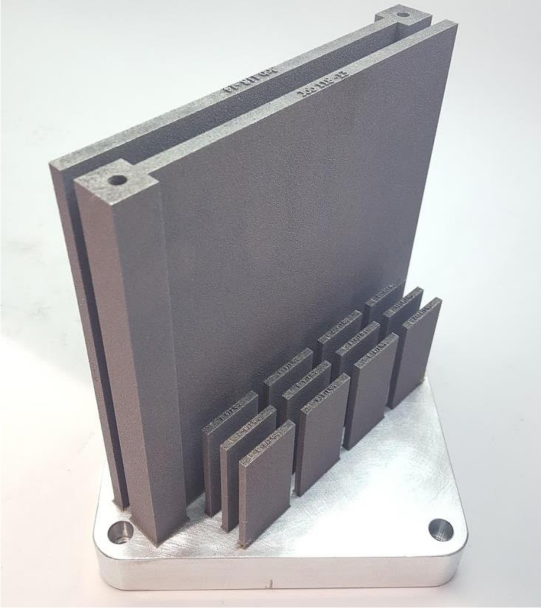


Inclusions



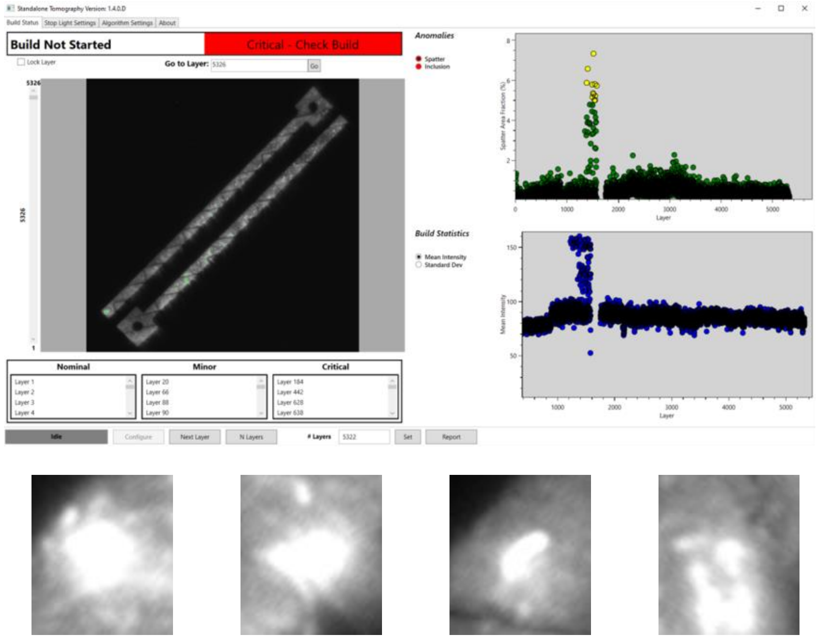
Warping

Print Results and Data Collection

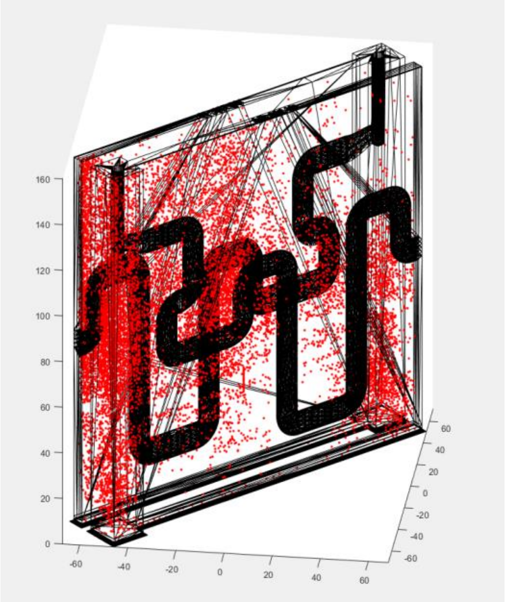


Heat Exchanger Print #1
Job118

Heat Exchanger Print #2
Job119



Example Detected Spatter Events by Tomography Plugin



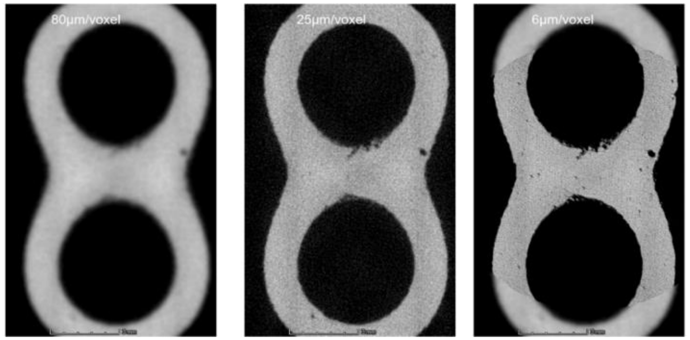
Job 118- All Detected
Spatter Events > 0.040 in^2

Task 3: Ground Truth NDE and Non-Conformance Identification

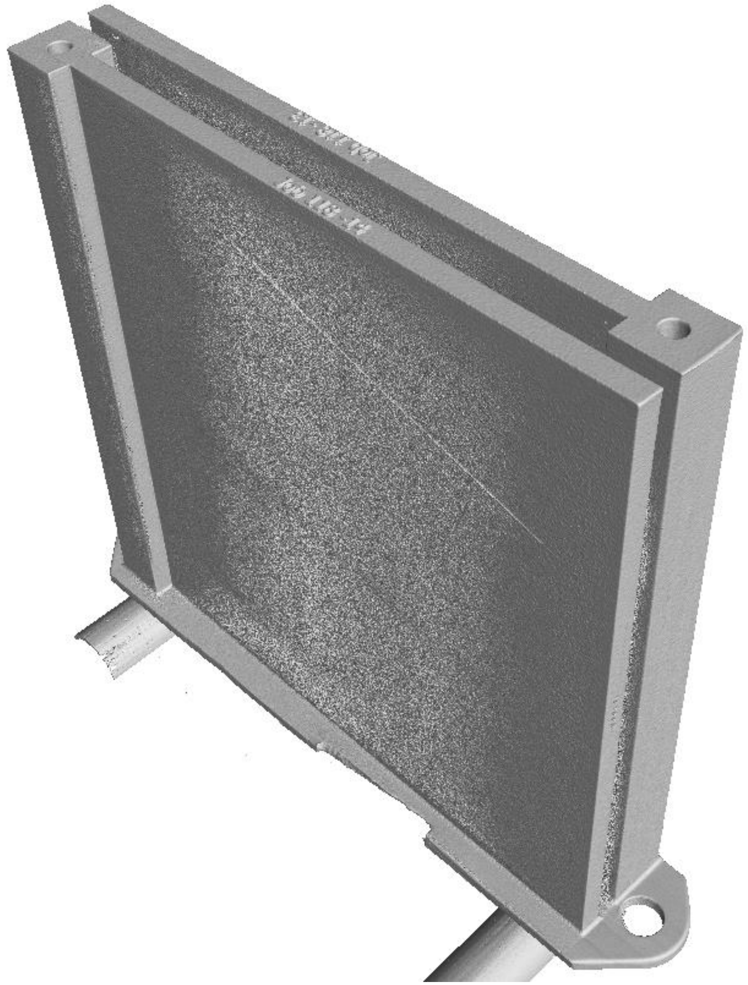
Lead	Tasks	Sub-Tasks	Dec-20	Jan-21	Feb-21	Mar-21	Apr-21	May-21
ZEISS	Task 3 - Ground Truth NDE and Non-Conformance Identification	Low-Resolution CT of Printed Parts						
		High Resolution CT of Defined Region of Interest						
		Detection of Part Non-Conformances as per Part TDP						

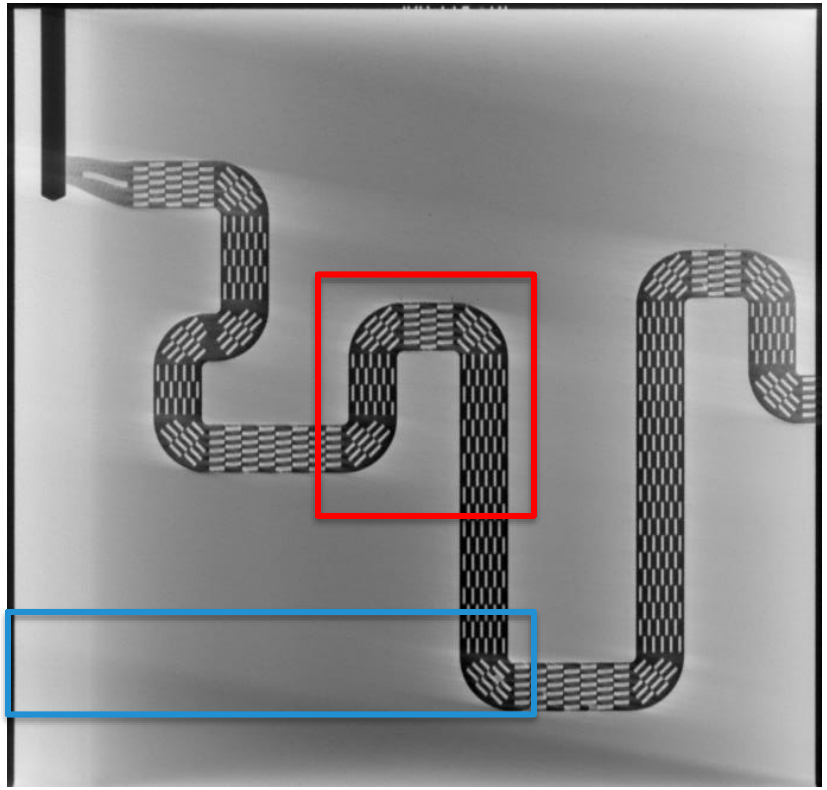
Lead: Zeiss

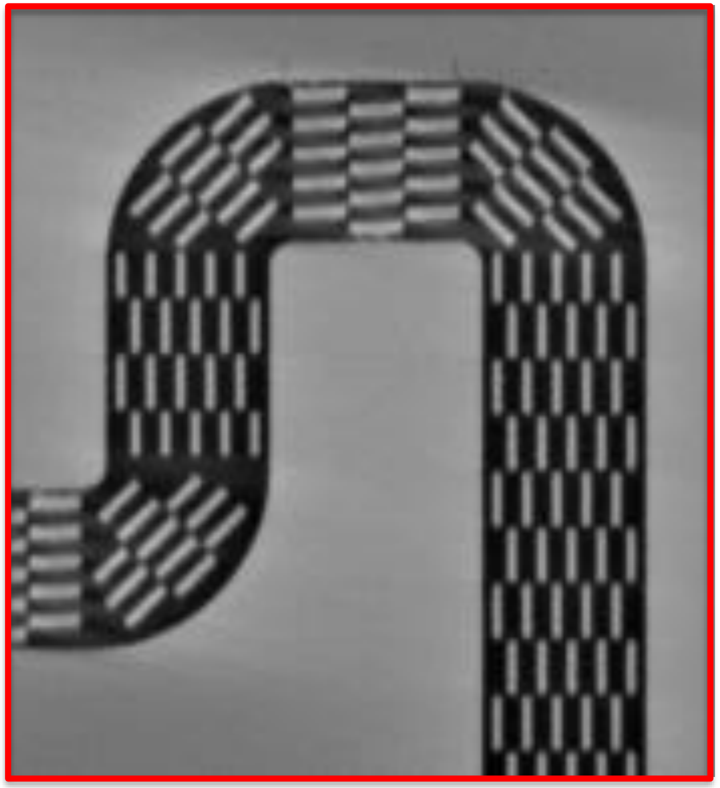
- Low-Resolution CT of Printed Parts (METROTOM 225 kV)
- High Resolution CT of Defined Region of Interest (Versa 620)
- Detection of Part Non-Conformances as per Part TDP

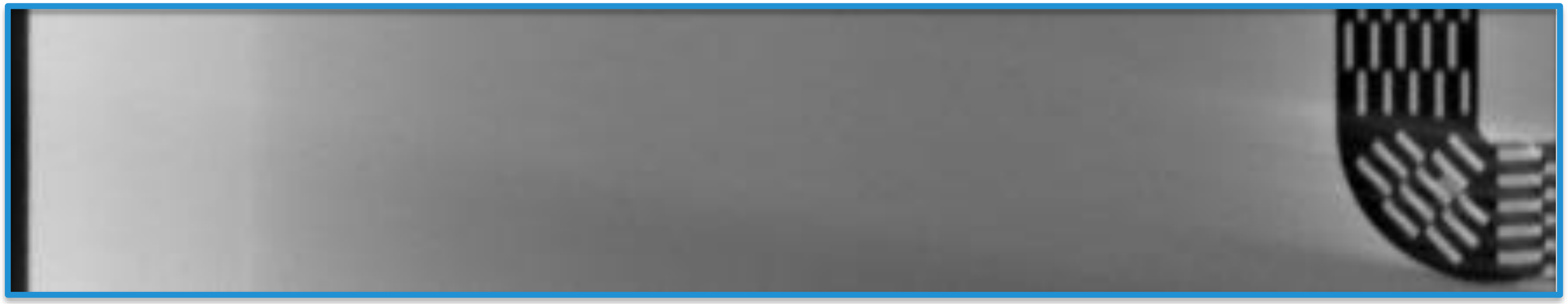


Job 118 CT Results

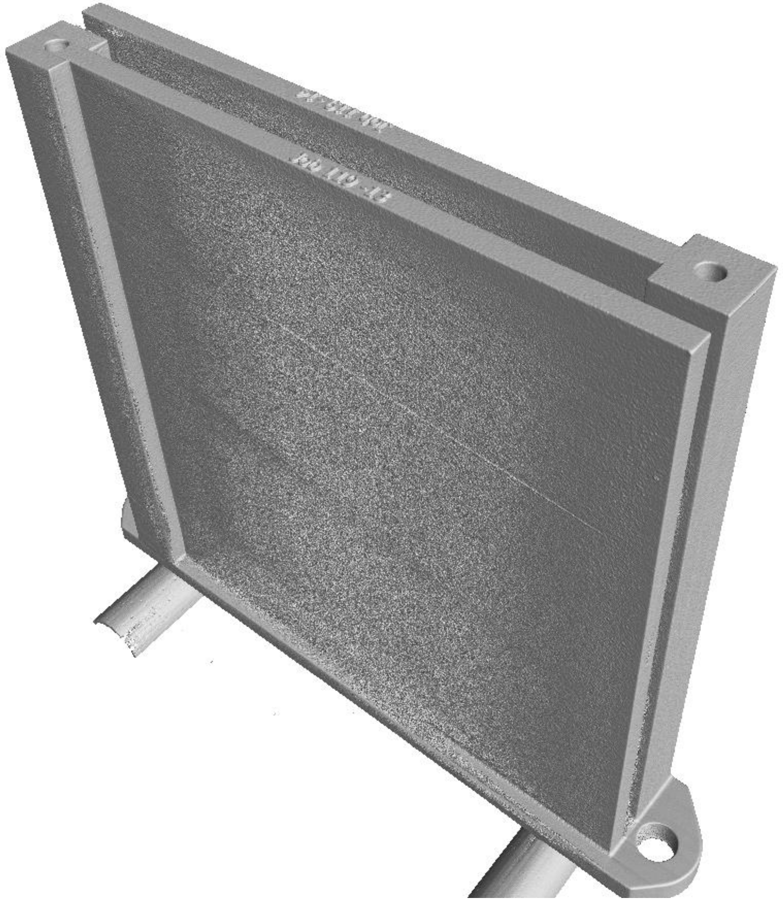


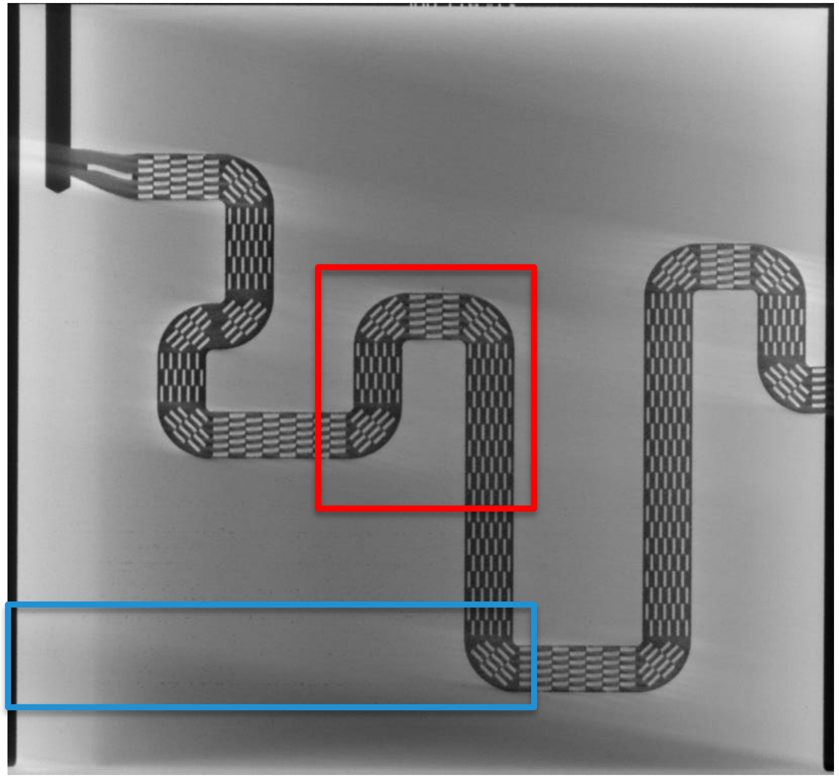


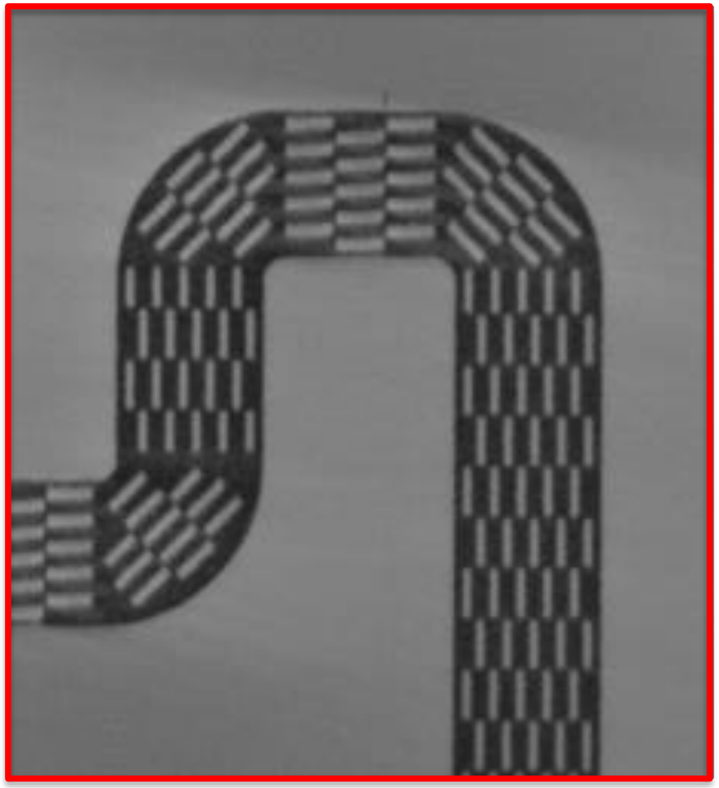


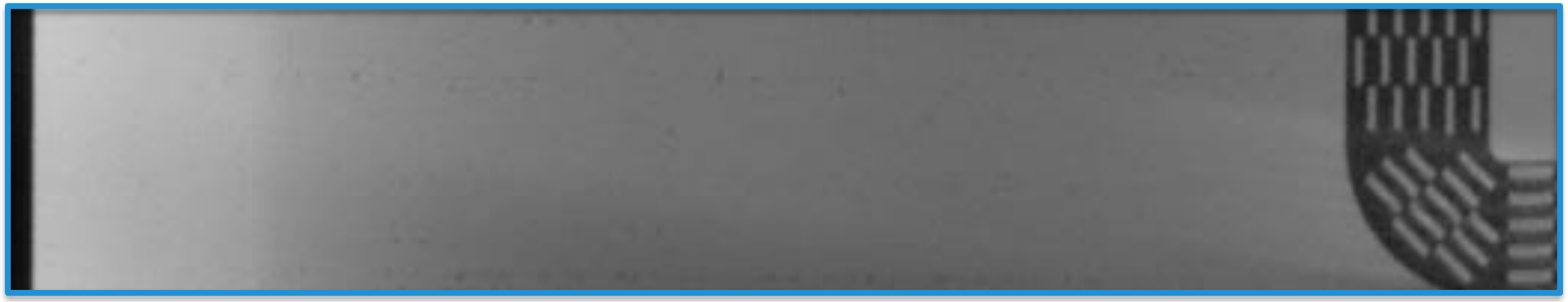


Job 119 CT Results







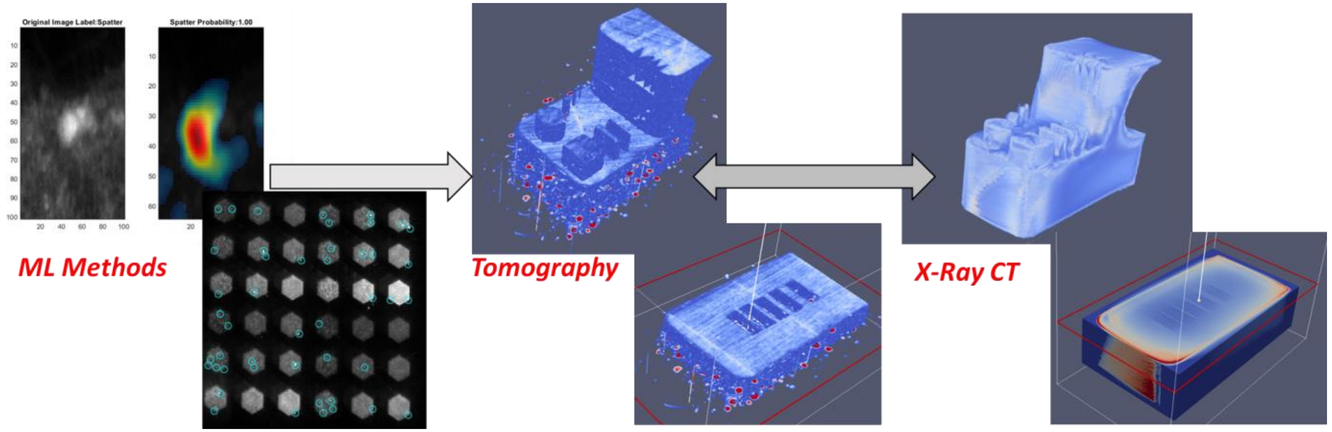


Task 4: In-Situ and NDE Algorithmic Correlation

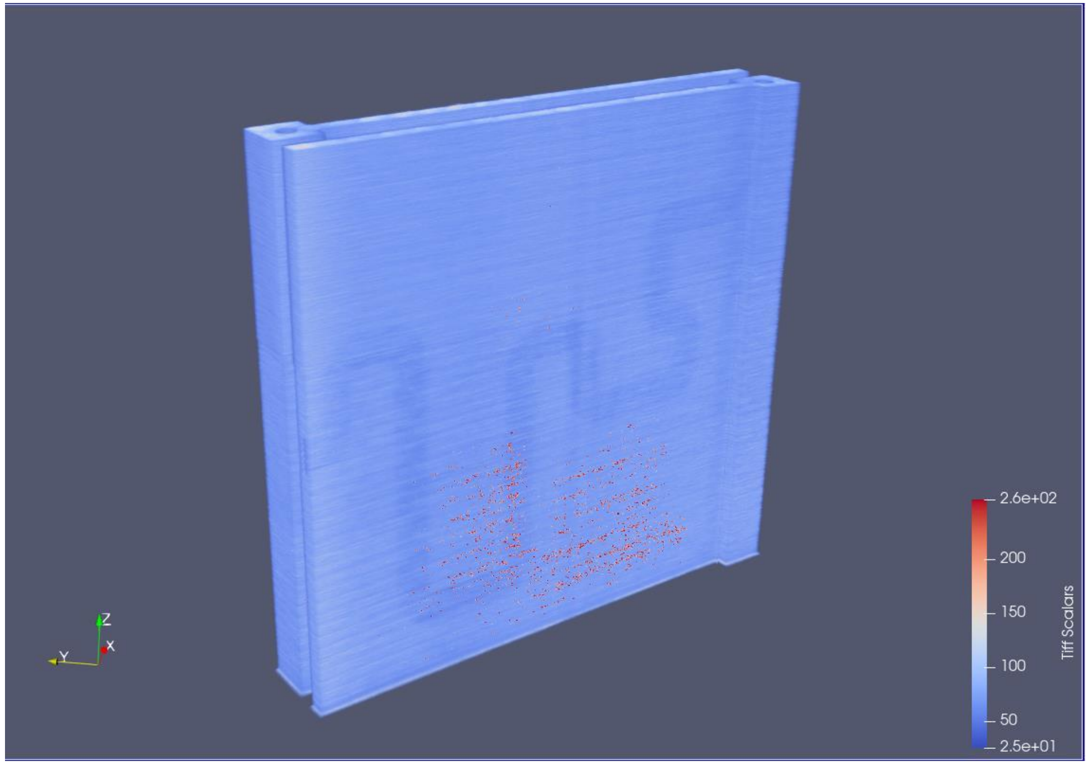
Lead	Tasks	Sub-Tasks	Dec-20	Jan-21	Feb-21	Mar-21	Apr-21	May-21
UDRI	Task 4 - In-Situ and NDE Algorithmic Correlation	Collection of Training Data to Relate In-situ to NDE Data						
		Algorithmic Determination of Region of Interest						

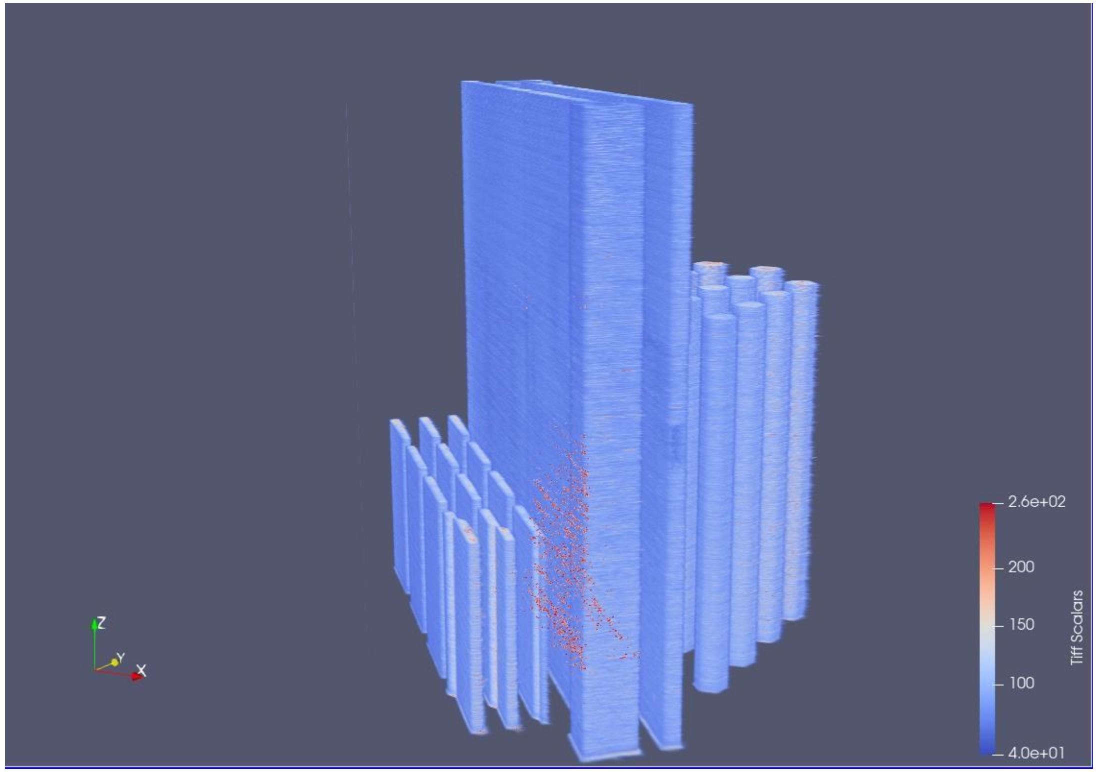
Lead: UDRI

- Collection of Training Data to Relate In-situ to NDE Data
- Algorithmic Determination of Region of Interest



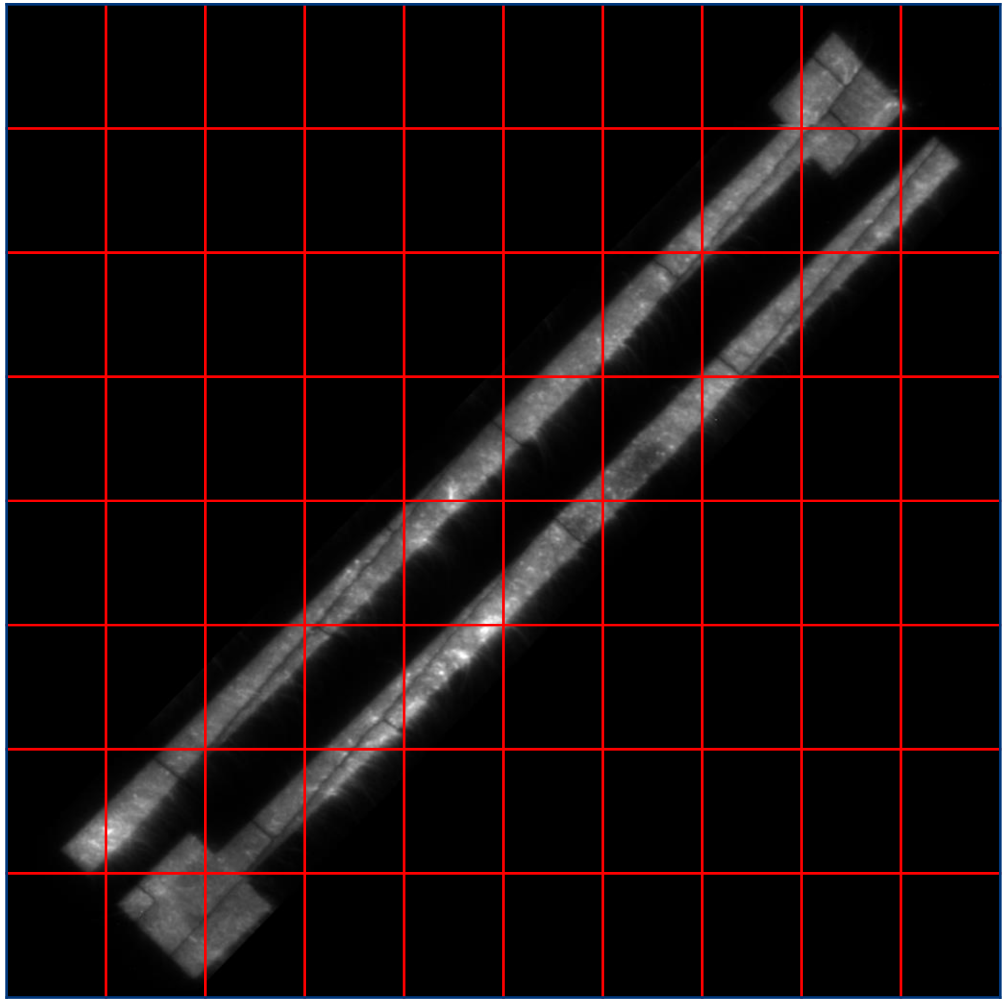
Task 4: Correlating CT Pores with In-Situ Tomography





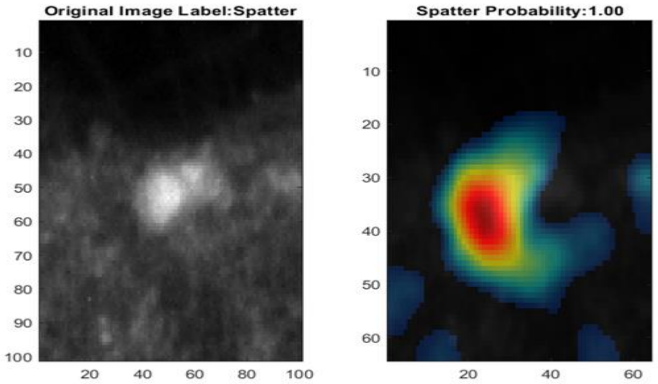
Job 119- CT Pores (Red Spots) Overlaid on In-Situ Tomogaphy
Heat Exchangers Only (left) and Full Build (right)

Task 4: Machine Learning Based Determination of Region of Interest

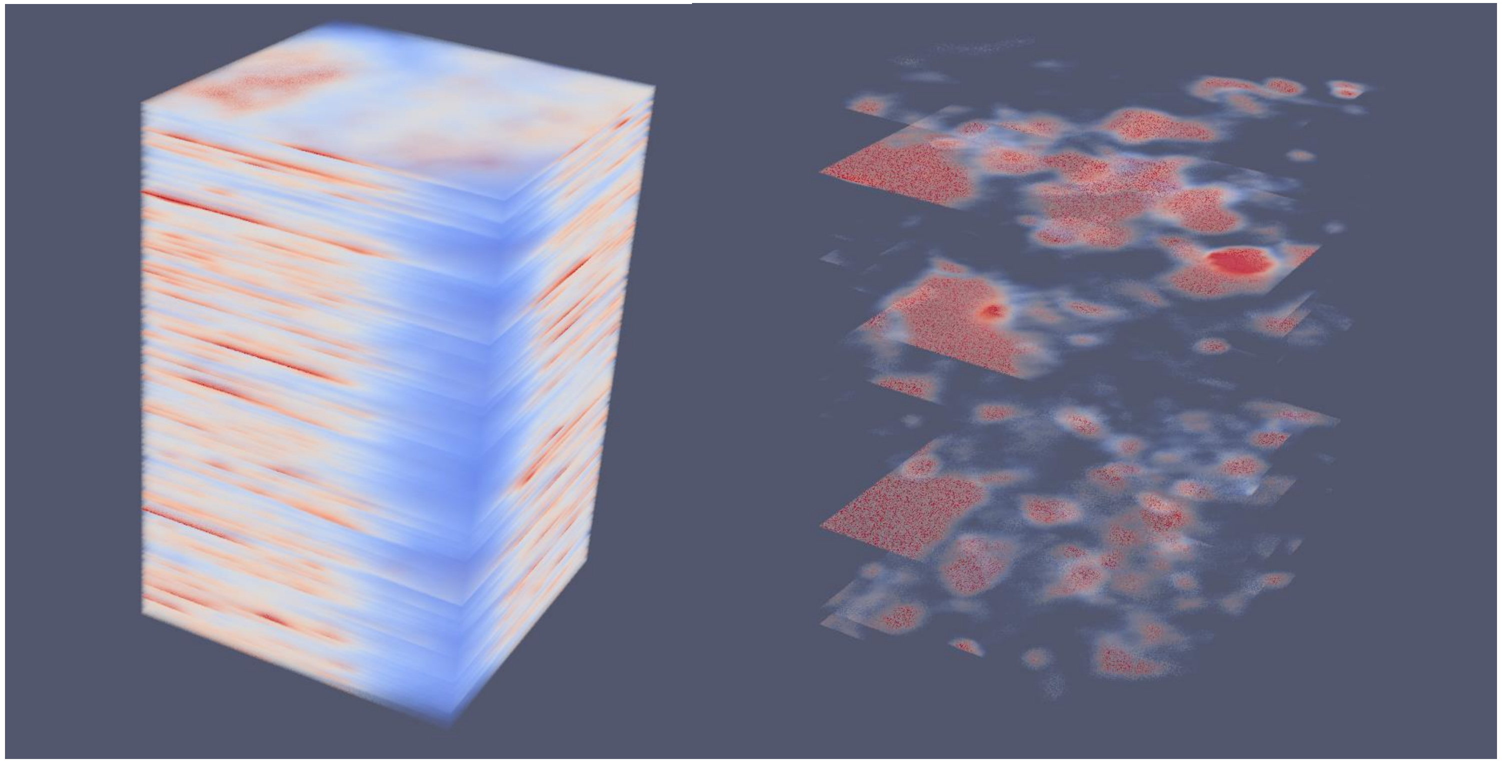


Process

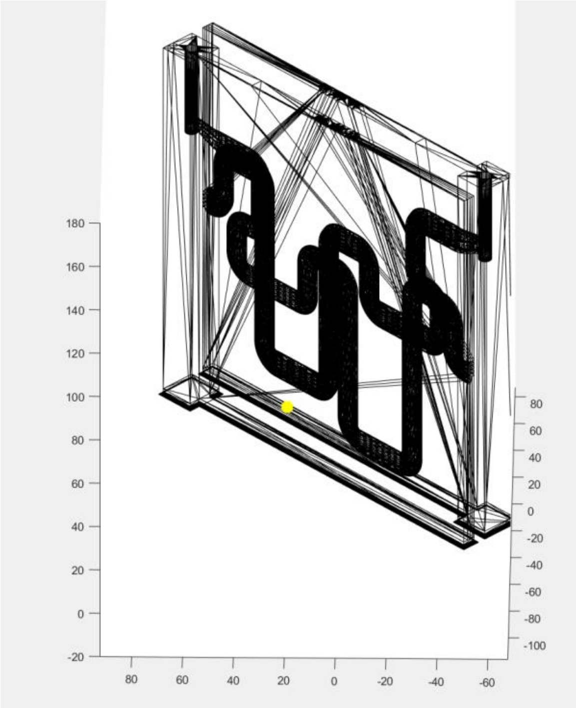
1. Apply a sliding window across image
2. Does this window contain spatter as defined by ML network?
    1. Calculated probability that this window contains spatter
3. Repeat for all images in a defined "voxel" height
4. Calculate the average probability of spatter across image stack / voxel



Task 4: Machine Learning Based Determination of Region of Interest

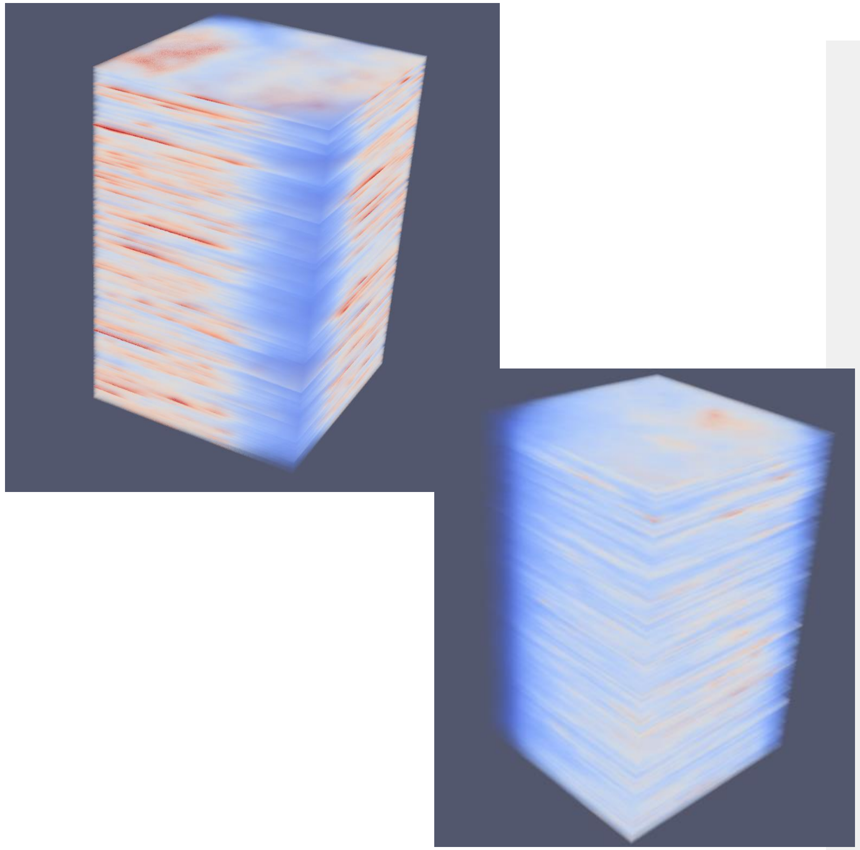


Job 119- Highest Spatter Probability Voxel as Determined by
Machine Learning Network
Full Representation (left) and Pixels over 200 (right)

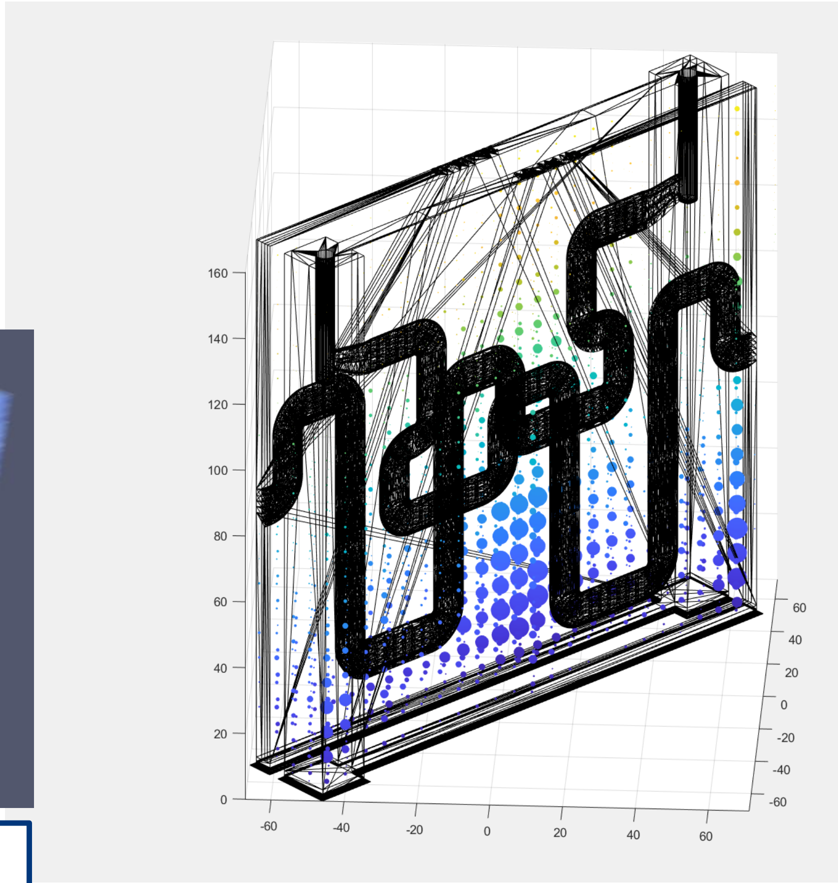


Voxel Location in Part

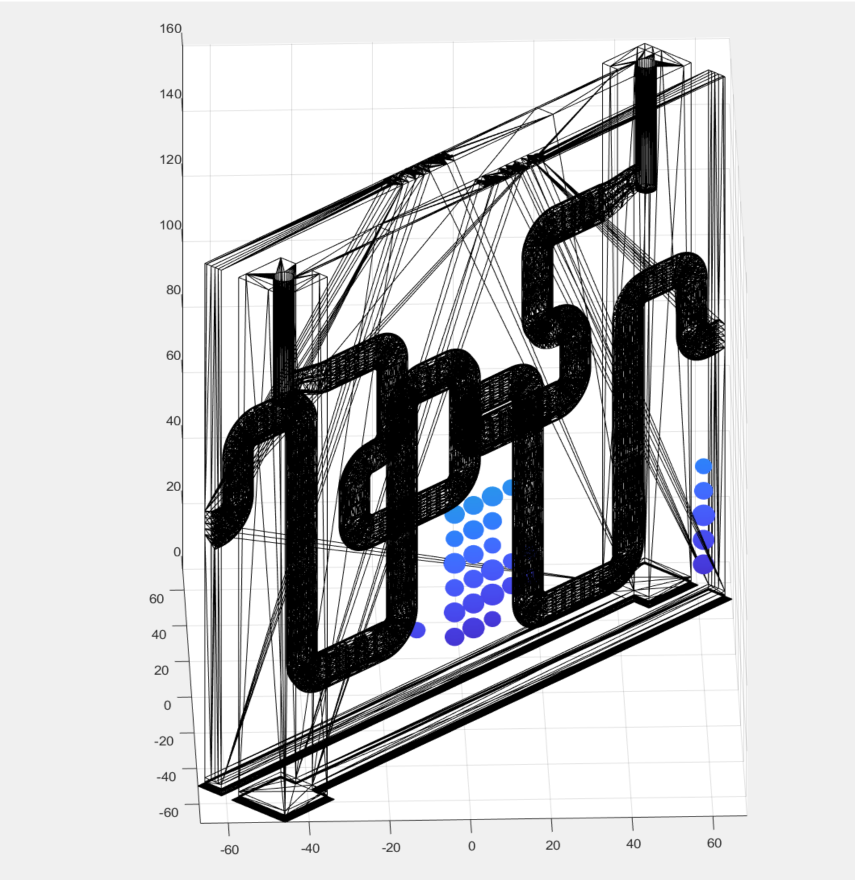
Task 4: Machine Learning Based Determination of Region of Interest



Each "voxel" is represented as a sphere whose size is based on Spatter Probability

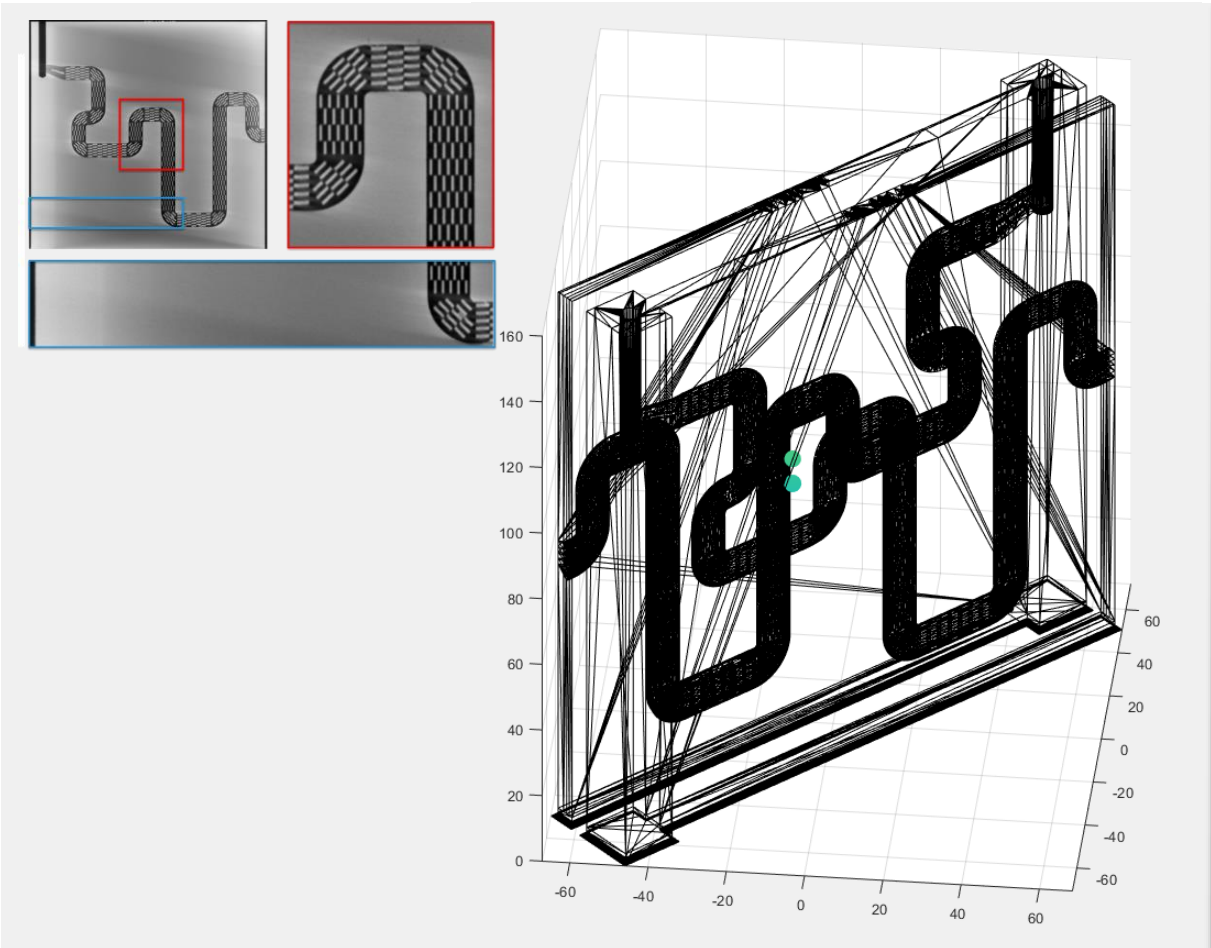


Job 119- Machine Learning Based Spatter Probability

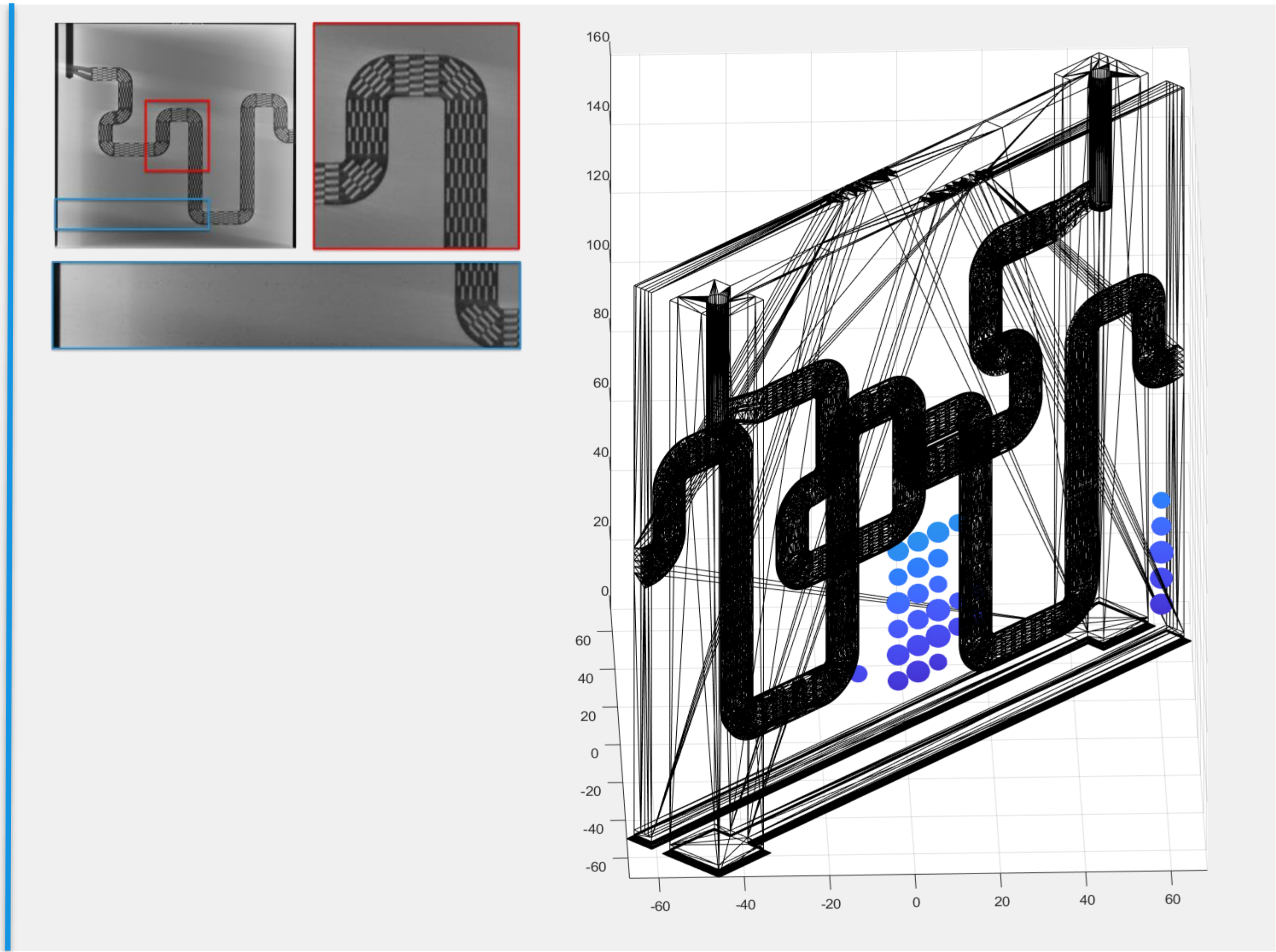


Job 119- Machine Learning Based Spatter Probability (Highest Probability Cases)

Machine Learning Based Determination of Region of Interest



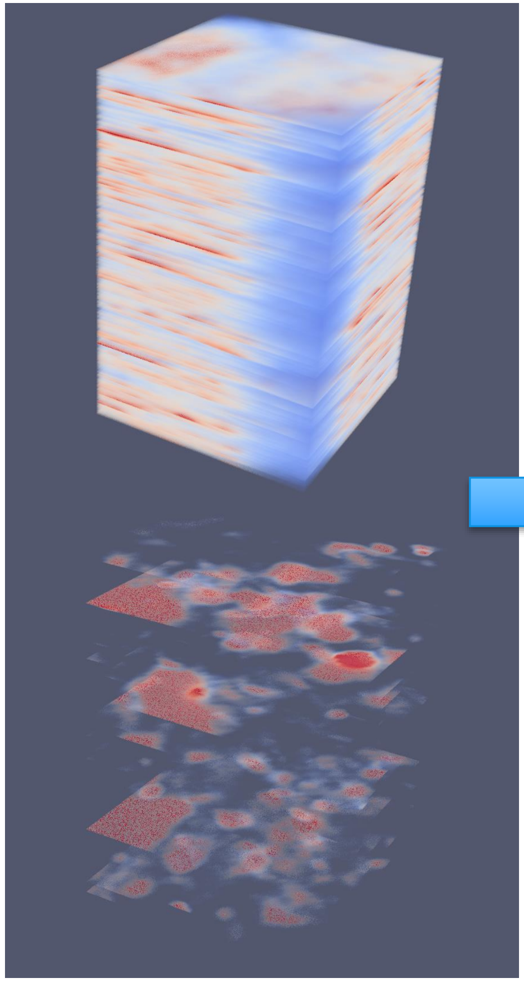
Job 118- Machine Learning Determined ROI

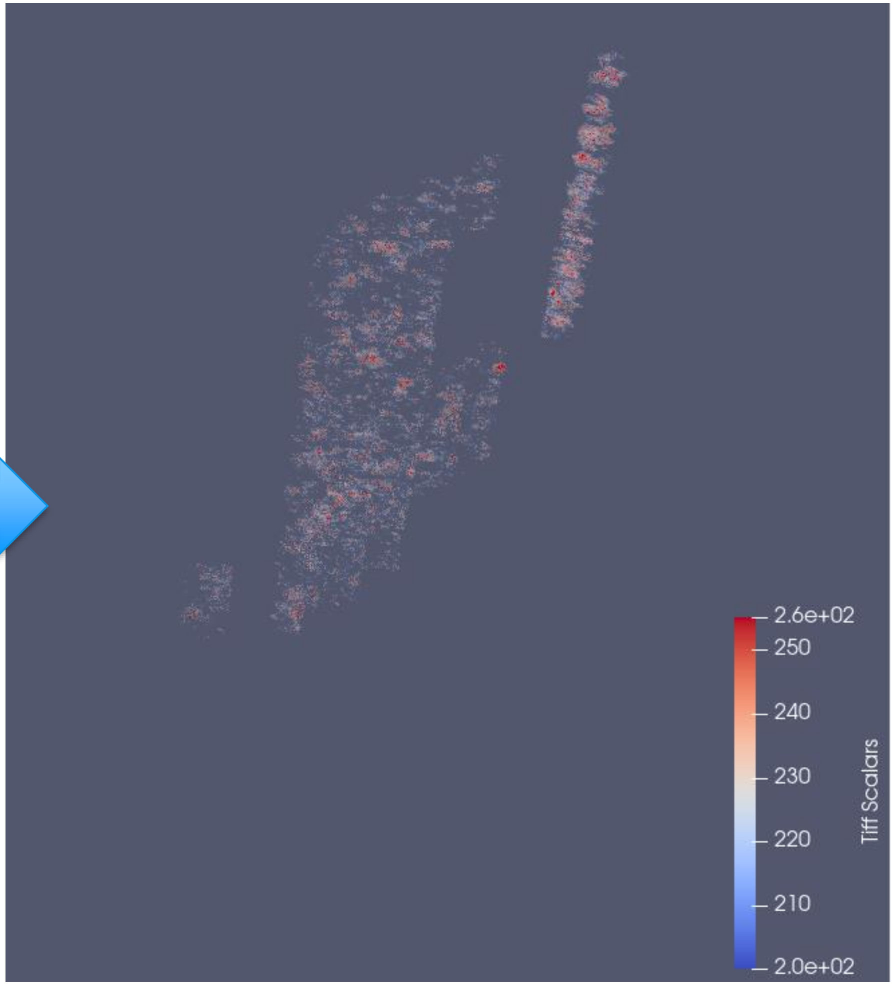


Job 119- Machine Learning Determined ROI

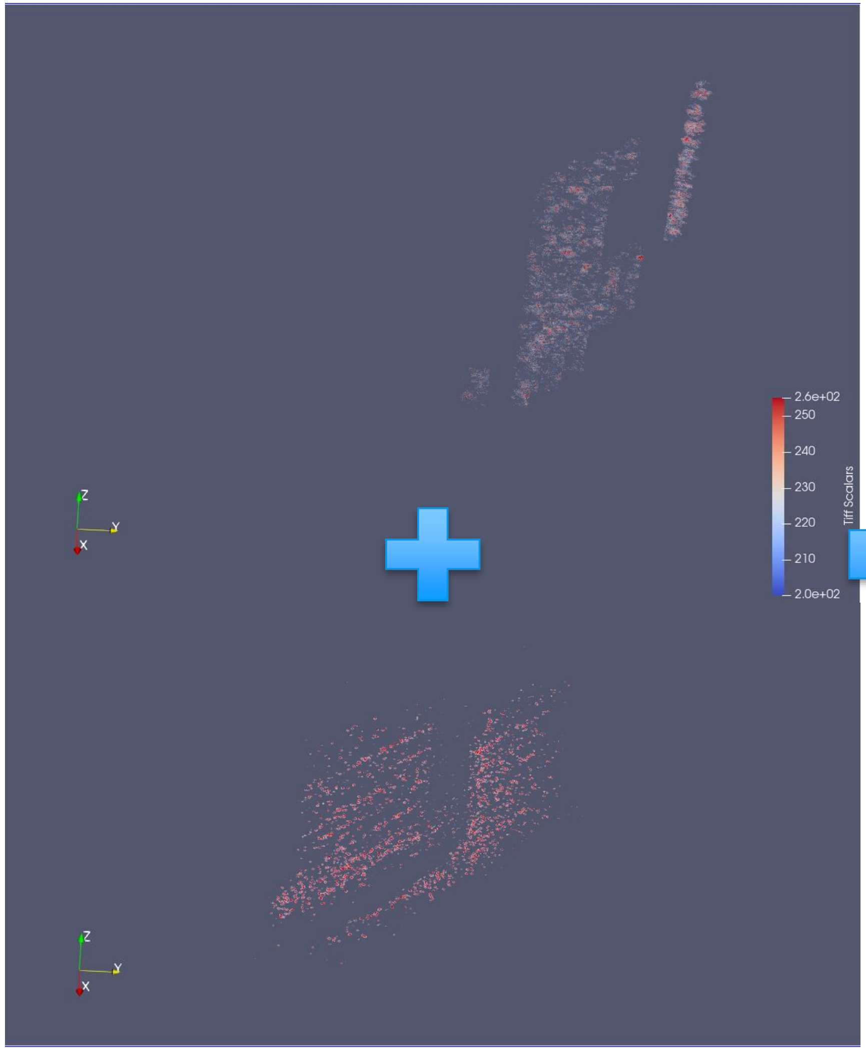
Task 4: ML High Probability Spatter Voxels

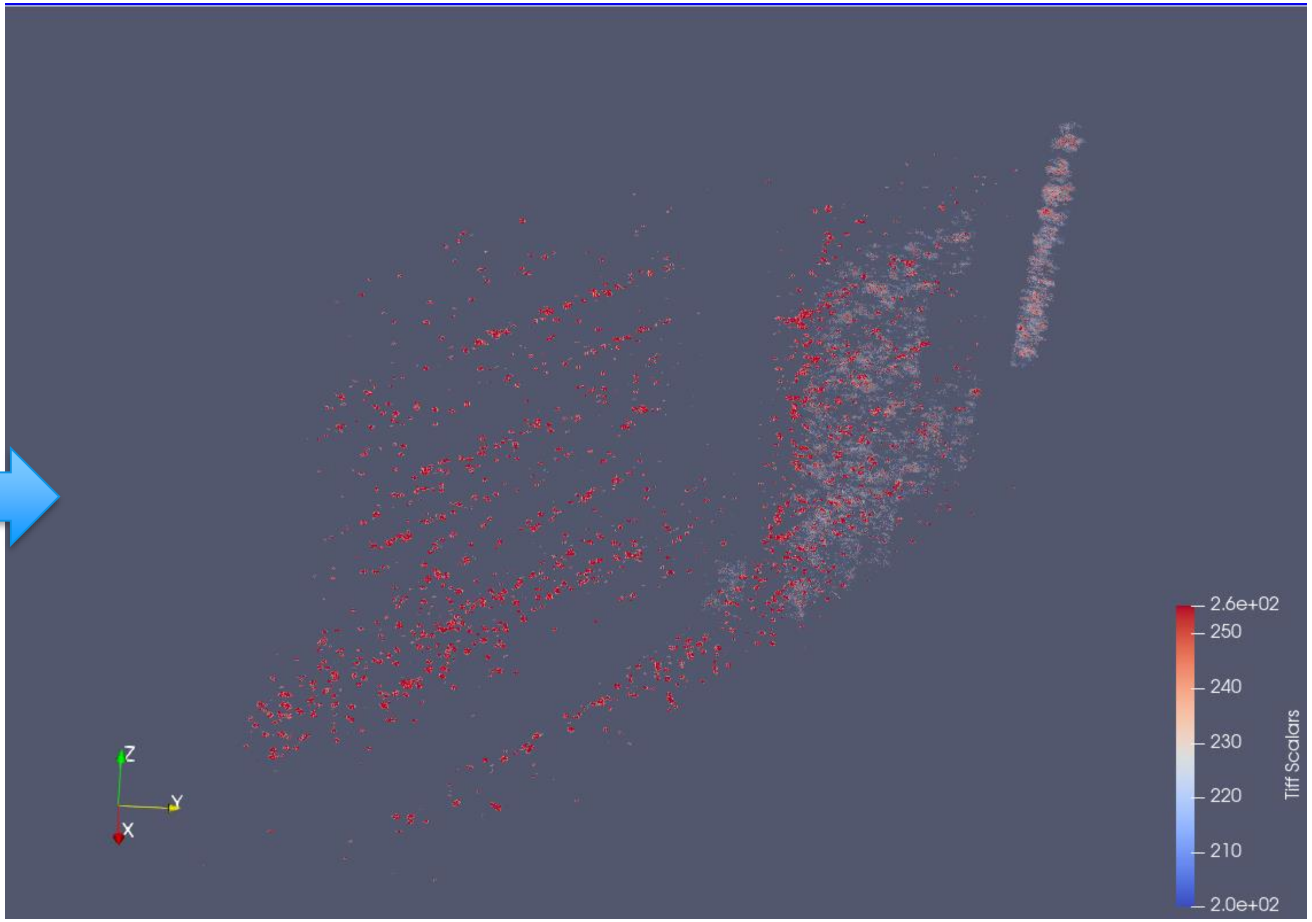
Job 119- Machine Learning Based High Probability Spatter Voxels
(>0.2 for 250 Image Stack)



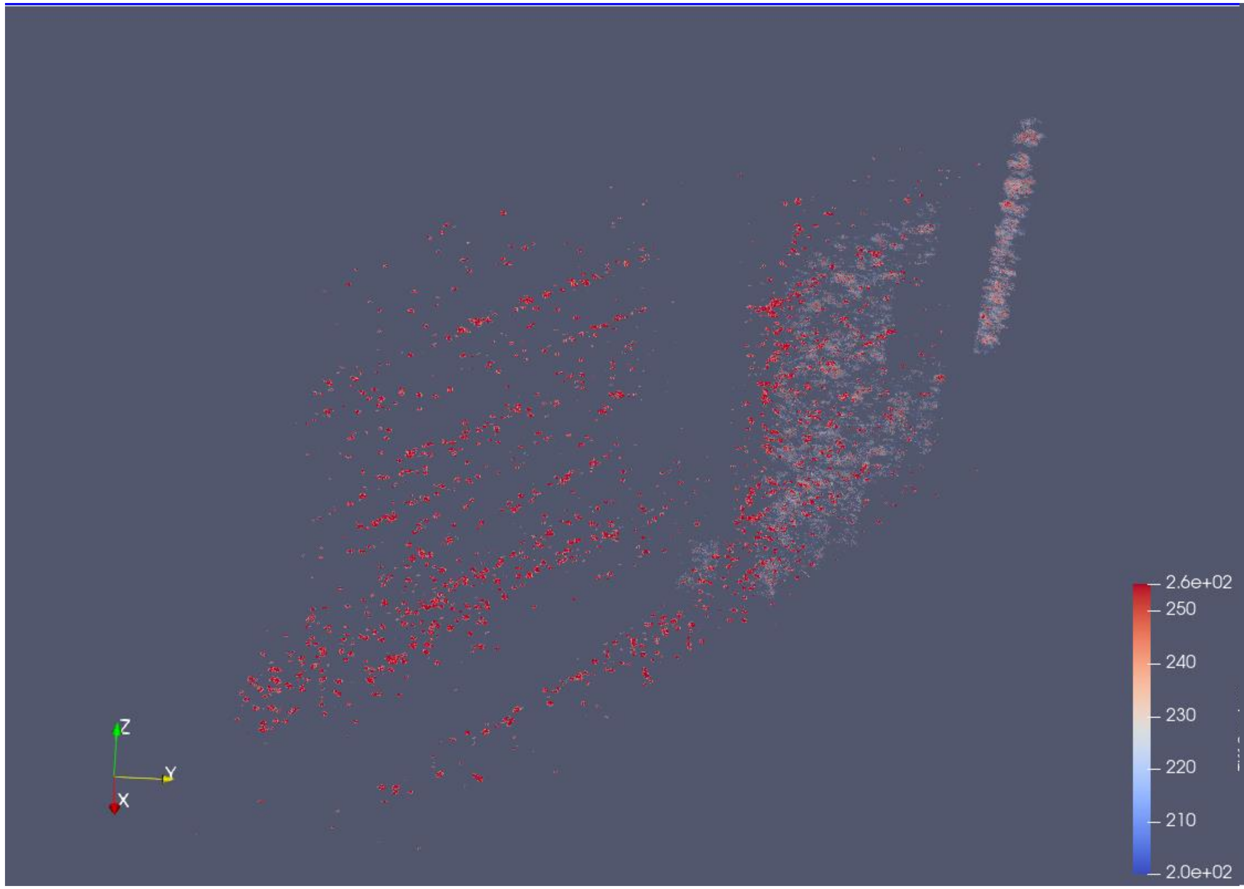


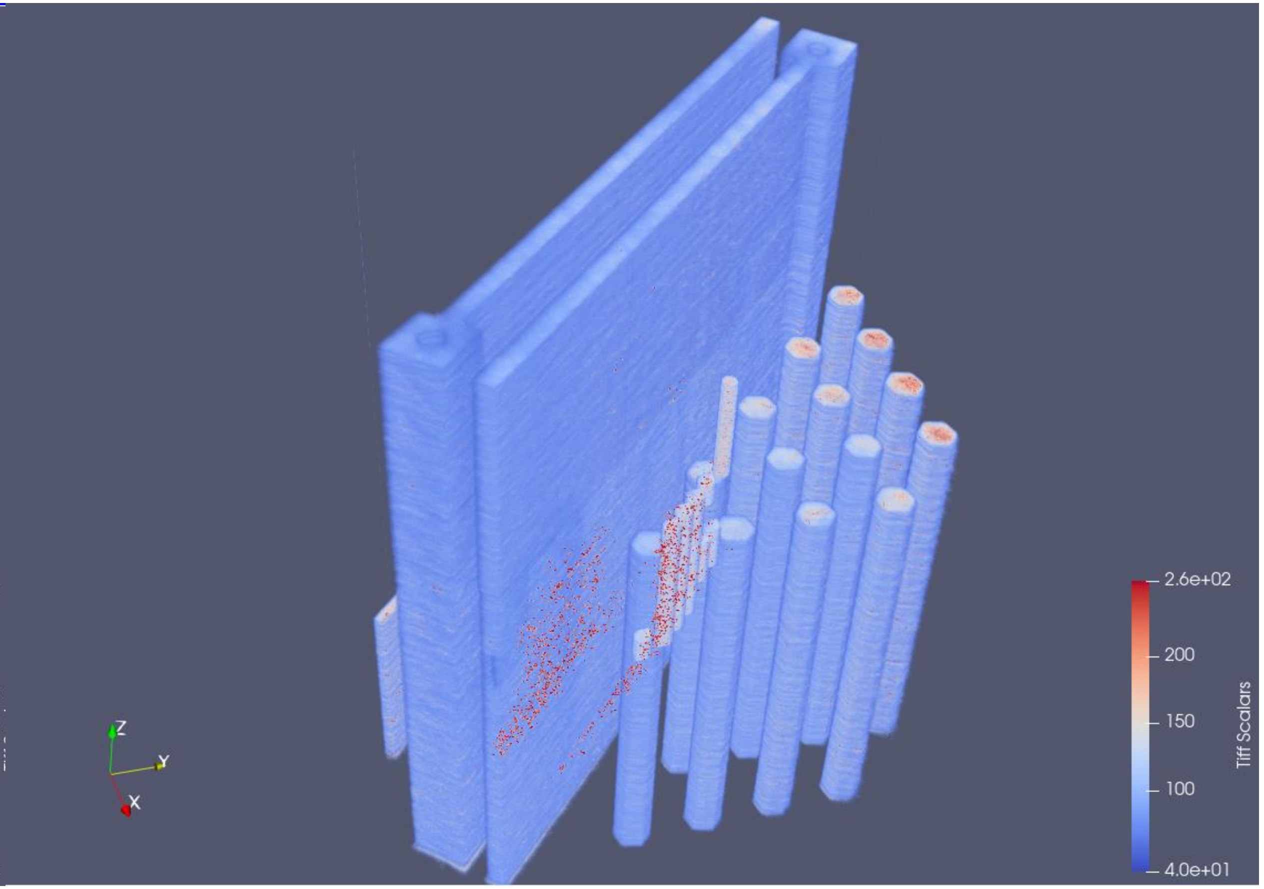
Task 4: ML High Probability Spatter Voxels Overlaid On CT Porosity





Task 4: ML High Probability Spatter Voxels Overlaid On CT Porosity and Full Build Tomography





Task 5: Minimum Viable Product Demonstration

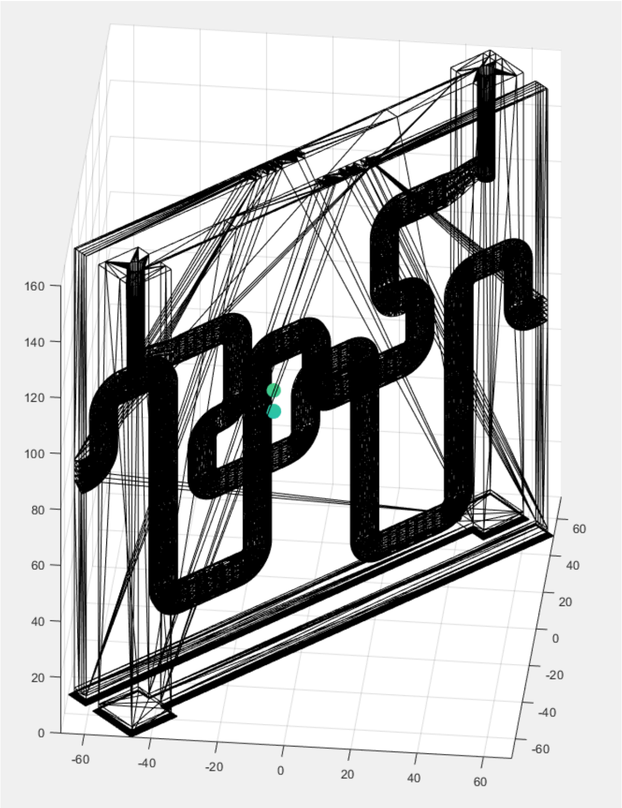
Lead	Tasks	Sub-Tasks	Dec-20	Jan-21	Feb-21	Mar-21	Apr-21	May-21
UDRI	Task 5 - Minimum Viable Product Demonstration	Identificaiton of Regions of Interest via Correlation Algorithm						
		Ground Truth NDE						
		Evaluation of Process in Terms of Accuracy, Cost / Time Savings						

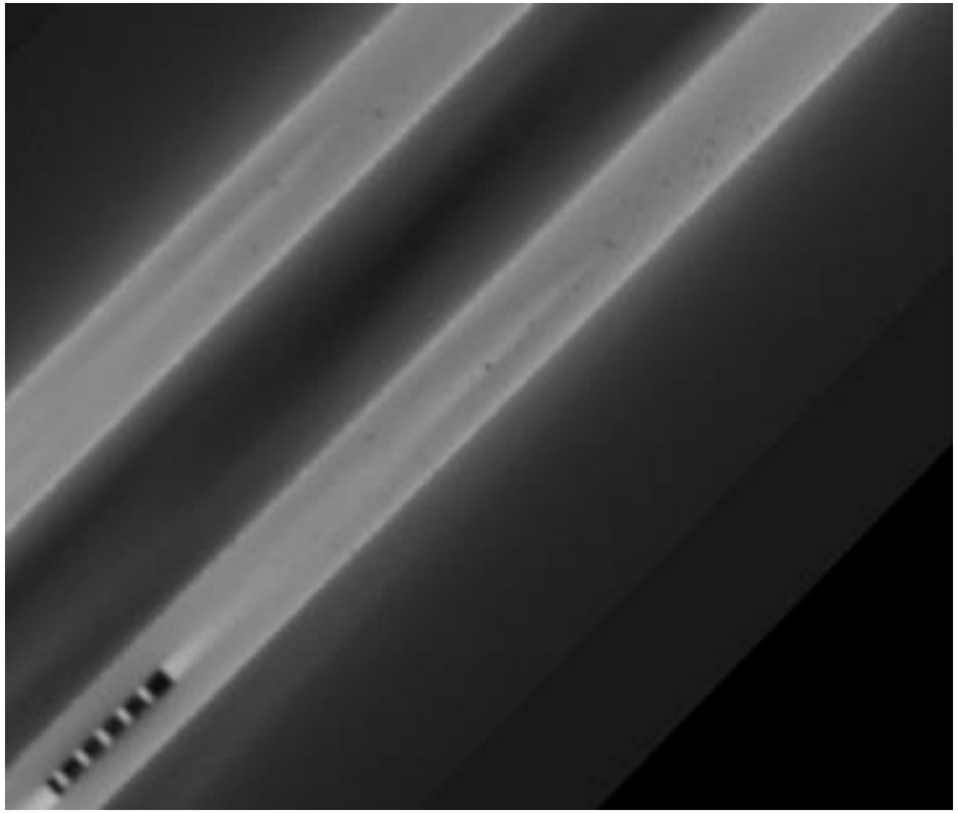
Lead: UDRI

- Identification of Regions of Interest via Correlation Algorithm
- Ground Truth NDE
- Evaluation of Process in Terms of Accuracy, Cost / Time Savings

Task 5: Minimum Viable Product Demonstration

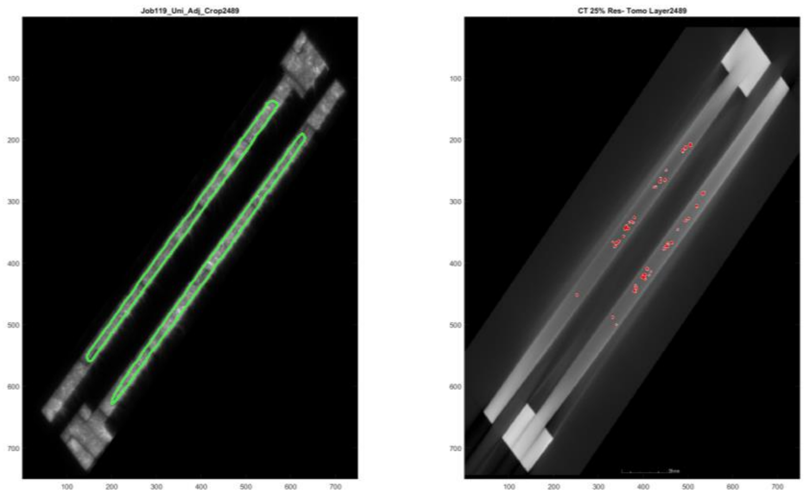
- Job 118 exhibits significantly less porosity in CT
- ML Spatter Density in Job118 also significantly lower
- Only porosity in Job118 is approximately at Layer 3275





Task 5: Machine Learning Prediction of Porosity

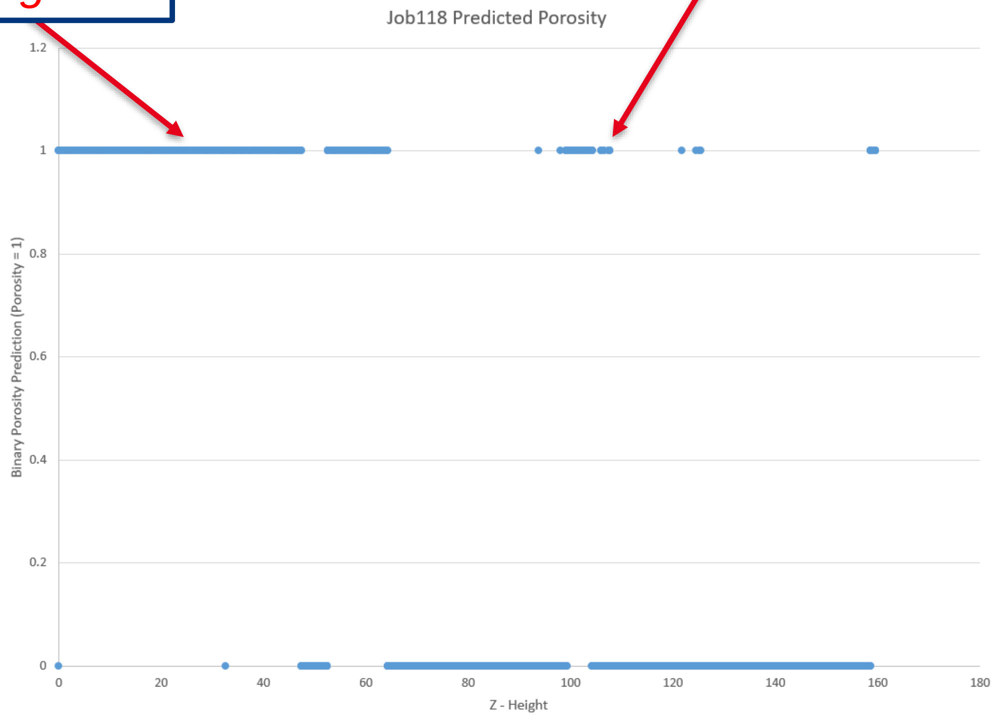
- Using Job119 In-Situ to CT Porosity correlations, can we predict Job118 Porosity with in-situ data?
- Layer-wise correlations used to train network
- Due to limited porosity in Job118, it is difficult to assess accuracy
  - More data is needed
  - Network can be improved by limiting geometric bias



Job 119- Correlation Training Set

Geometric Bias in Training

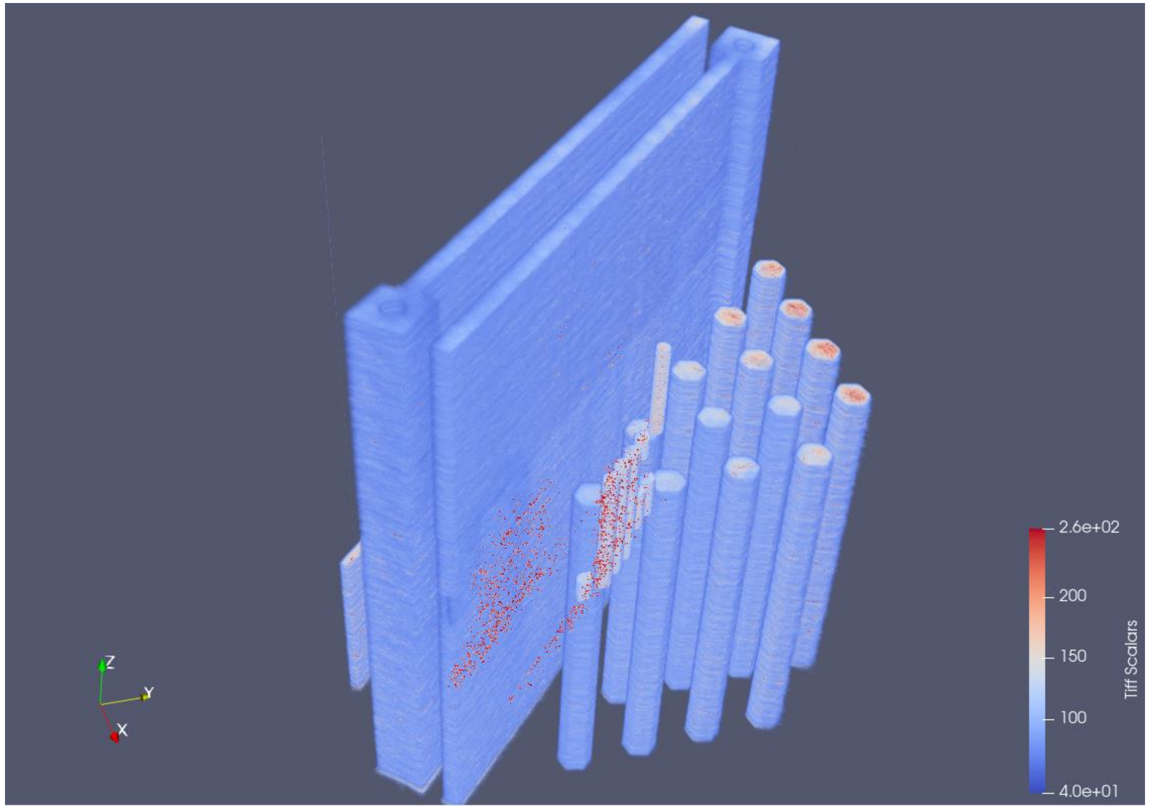
Possible Correct Prediction



Job118- Porosity Prediction

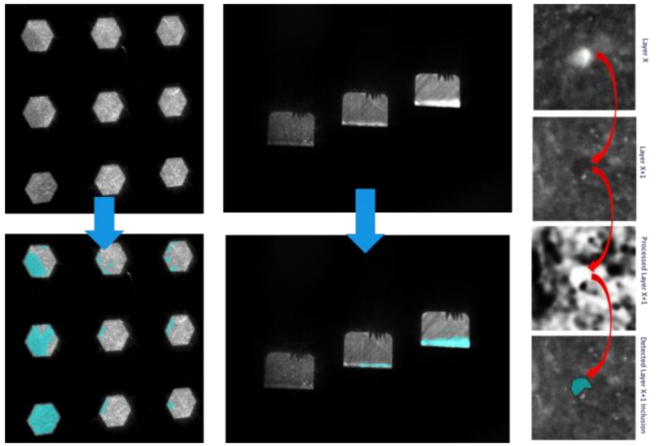
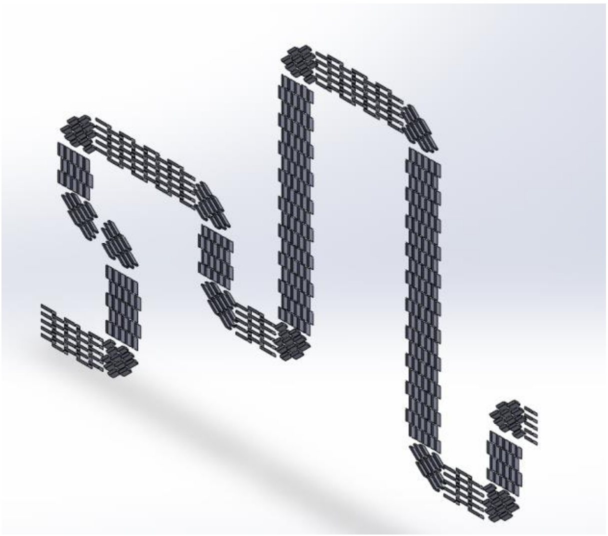
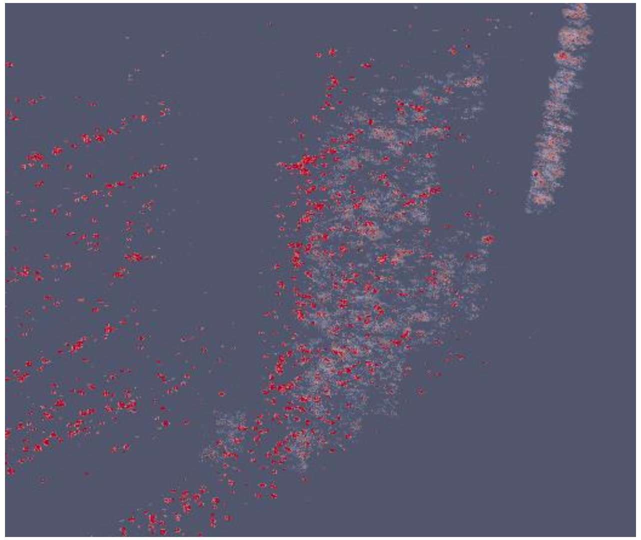
Conclusions/Summary

- High density spatter region determined by Machine Learning shows strong correlation with region of porosity in CT
- Lower density spatter in-situ associated with lower porosity in CT
- Using in-situ data to predict porosity in CT is feasible, but more data is needed
- Currently, in-situ data can enhance CT data, but is not mature enough to be used as a replacement for CT



Next Steps

- **Correlation Database Maturation**
  - More prints, materials, geometries, machines, etc.
  - As the correlation data-base *matures*, the ability to predict non-conformances in process *improves*
- **Analysis of other anomaly types**
  - Project has focused on correlating spatter anomalies to CT non-conformances, but many other anomalies can be investigated
- **Feature level analysis of data**
  - Focus analysis on specific part features to more directly relate to non-conformance criteria
- **Registration Improvements**
  - Improve registration for direct correlation of specific anomalies to end part defects / non-conformances

Questions & Discussion

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