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Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

AMMTO & IEDO JOINT PEER REVIEW

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Washington, D.C.

Accelerating Additive Manufacturing Process Design for Energy Conversion Materials using In-situ Sensing and Machine Learning| AMMTO

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DE-EE0009097 | 8/15/2020 – 05/15/2023

Project Overview

- Develop an approach utilizing in-situ sensing to accelerate the additive manufacturing processing development for thermoelectric materials in laser powder bed fusion
  - This project will ***advance additive manufacturing technology*** for energy conversion materials
  - Traditional process development takes a significant amount of time, and the processing-properties relationship for energy conversion materials in additive manufacturing is unknown
  - This work will impact ***accelerated domestic adoption of additive manufacturing*** for thermoelectric devices

Energy, Emissions, & Environment: Improve energy conversion efficiency	**Cost & Competitiveness:** Reduce material waste and processing time
Technical & Scientific: Understand processing-properties relationship for improved properties	**Other Impacts:** Establish criteria for accelerated manufacturing quality assurance

- Collaborative project between university and industry (small business)

Project Outline

Innovation: Develop an approach utilizing in-situ sensing to accelerate the additive manufacturing processing development for thermoelectric materials in laser powder bed fusion.

Project Lead: Wright State University

Project Partners: Colorado School of Mines, George Washington University, Open Additive- an ARCTOS Company

Timeline: 8/15/2020 – 05/15/2023 , 98%

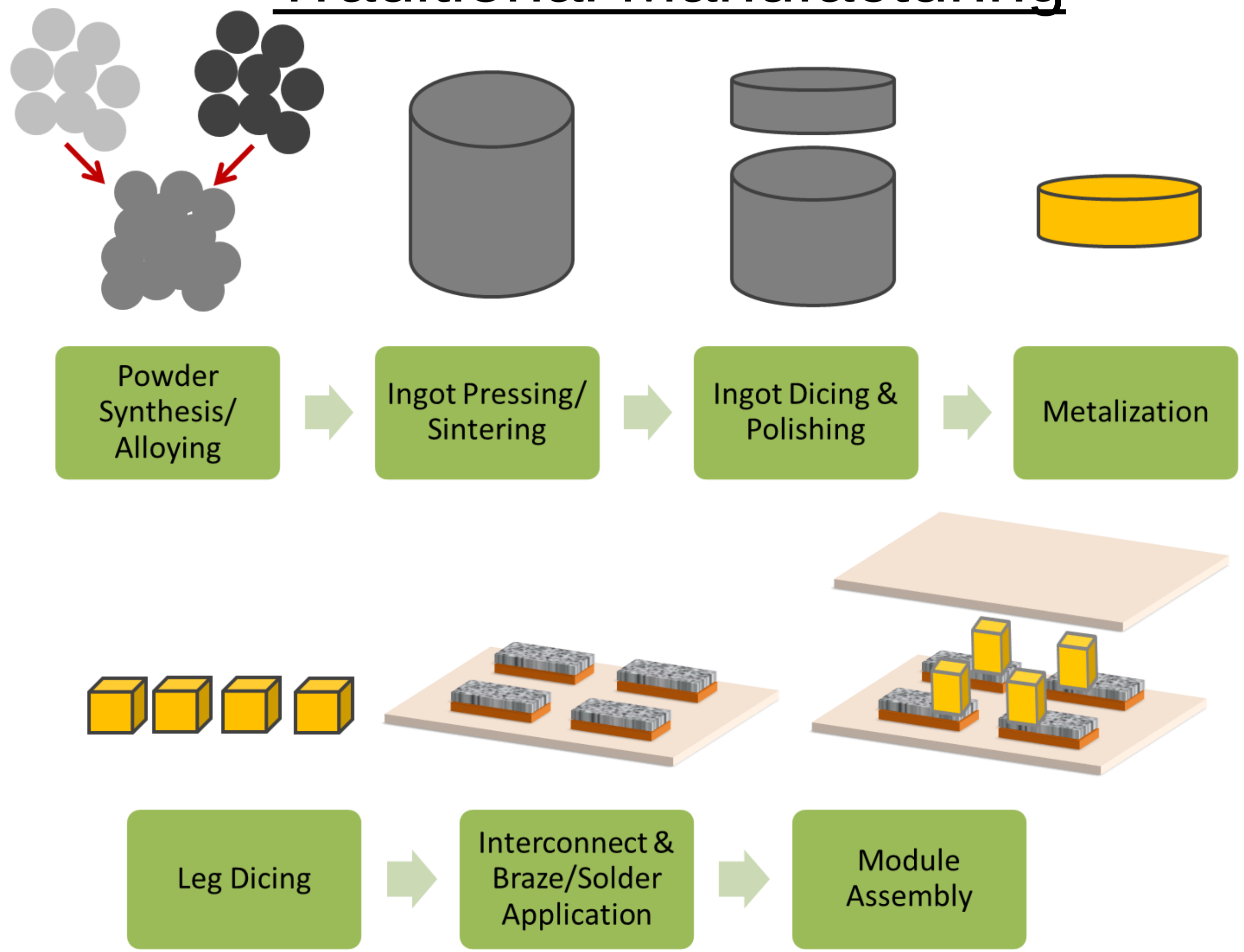
Budget: DOE- $500,000, Cost Share- $140,567, Total- $640,567

	FY21 Costs	FY22 Costs	FY23 Costs	Total Planned Funding
DOE Funded	$134,749	$211,489	$153,762	$500,000
Project Cost Share	$32,795	$78,605	$29,167	$140,567

End Project Goal: When fabricating Bismuth Telluride with laser powder bed fusion additive manufacturing, achieve **>95% relative density** and achieve **a Seebeck coefficient and electrical resistivity comparable to traditional manufacturing**

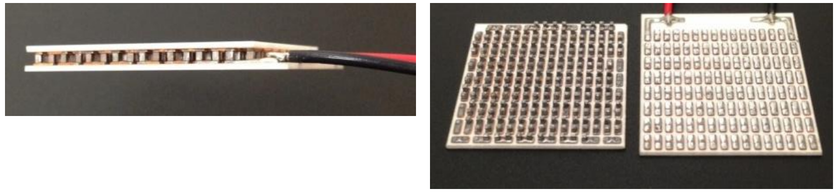
Thermoelectric Devices

Traditional Manufacturing



S. LeBlanc, *Sustainable Materials & Technologies* (2014)

Thermoelectric Module



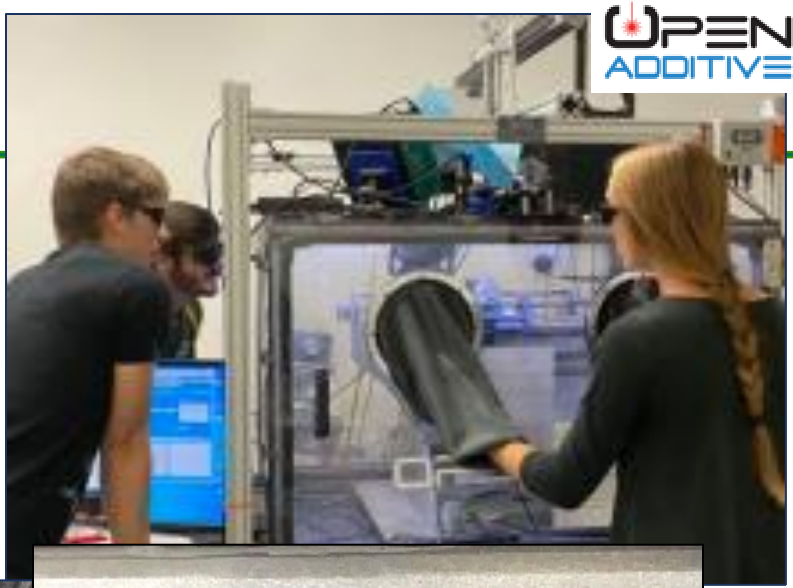
Disadvantages:

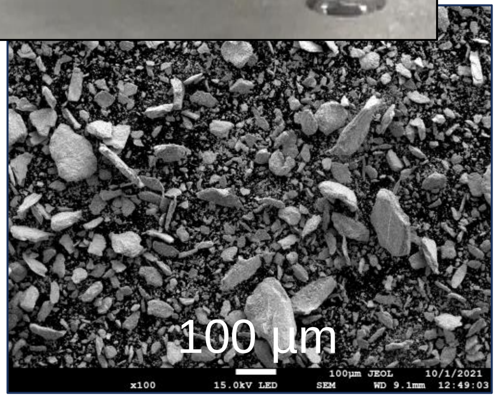
- Limited geometries
- Significant material loss
- Interface & integration challenges
- Lengthy processing time
- Rudimentary assembly

Additive manufacturing could solve many of these challenges!

PBF-LB Process Development

- PBF-LB of Bi_2Te_3 pioneered by Dr. LeBlanc at GWU
- **<u>Challenges:</u>**
  - Bi_2Te_3 powder is difficult to spread and laser process
  - AM is controlled by many processing parameters
- Parameters:
  - Laser power (10-30 W)
  - Laser speed (300-700 mm/sec)
  - Hatch spacing (10-37.5 µm)
  - Layer thickness (100-150 µm)
  - Laser focus (~30-100 µm)
  - Single or Double Scan
- **In-situ sensing and machine learning can help accelerate process development**



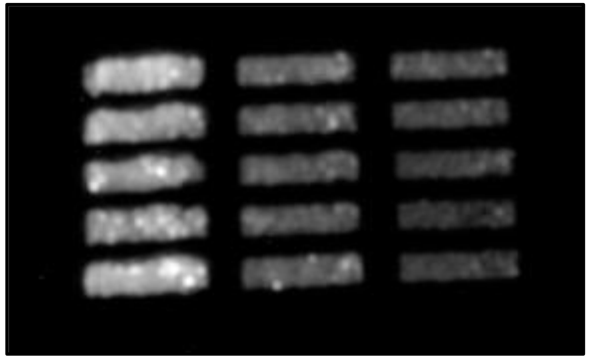


In-Situ Sensors

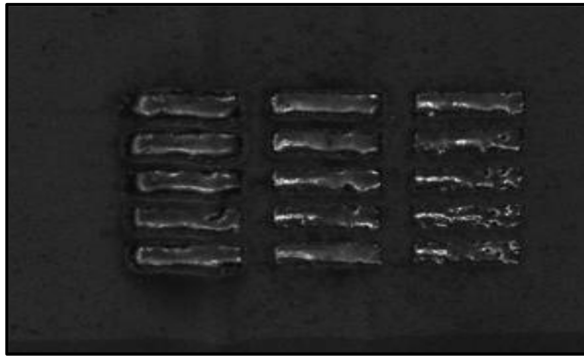
- ***Thermal tomography***
  - 12 MP long exposure CMOS NIR camera produces composite integrated thermal response
- ***Polarimetry***
  - Polarized images post spread and post melt
- ***Spatter***
  - 2 MP high frame rate camera (150 fps) that detects ejected particles
    - » Melt pool- red
    - » Confirmed spatter- green
- ***Long wavelength IR***
  - Observes thermal signatures, not reflected light
  - Temperature measurement during cooling
  - Low spatial resolution

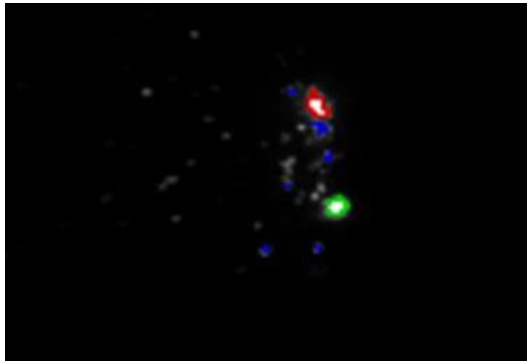
– Relatively low-cost sensors viewing entire build platform

Tomography

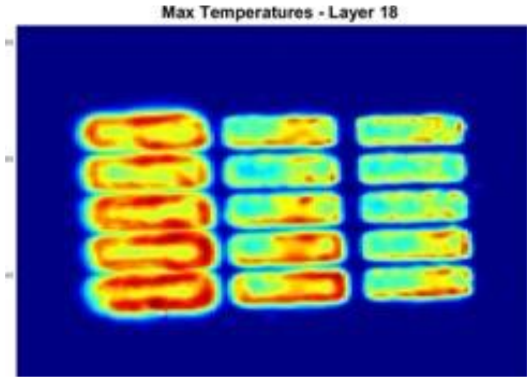


Polarimetry





Spatter



LWIR

OPEN ADDITIVE

ARCTOS | All In.

Our Process Development Approach

- Fabricate samples and collect **in-situ sensor data** across a range of **processing parameters** and measure **thermoelectric properties**
  - A significant amount of data is needed for machine learning
  - Measured thermoelectric properties for 100+ samples
- Treat each layer of build as a data point
  - Processing parameters- Same for all layers
  - Sensor data- Different for each layer
  - Thermoelectric properties- Same for all layers
- Build machine learning models to predict processing-properties relationships
  - Select most relevant features
  - Optimize processing for thermoelectric performance

Machine Learning Model Development

Feature Importance

S. No.	Feature	Mean score and standard deviation
1.	Laser Focus (mm)	0.142 +/- 0.007
2.	Power (W)	0.070 +/- 0.005
3.	Speed (mm/s)	0.052 +/- 0.008
4.	Polarimetry post spread AoP roughness	0.033 +/- 0.005
5.	Layer (mm)	0.030 +/- 0.004
6.	Polarimetry post melt AoP roughness	0.029 +/- 0.006
7.	Hatch (mm)	0.026 +/- 0.002
8.	Polarimetry post spread AoP std	0.017 +/- 0.005
9.	Tomography roughness	0.014 +/- 0.003
10.	Polarimetry post melt DoLP std	0.013 +/- 0.004
11.	Polarimetry post melt AoP std	0.012 +/- 0.005
12.	Polarimetry post spread DoLP max	0.012 +/- 0.004
13.	Tomography median	0.011 +/- 0.004
14.	Tomography avg	0.010 +/- 0.003
15.	Polarimetry post melt AoP median	0.010 +/- 0.004

Note: AoP: Angle of polarization, DoLP: Degree of linear polarization, std: standard deviation, max: maximum, avg: average

Model Performance

Classification Model	P	R	F1	AUC	Acc.
Naive Bayes	0.72	0.72	0.72	0.77	0.72
Logistic Regression	0.68	0.68	0.68	0.76	0.68
Linear SVM	0.68	0.68	0.68	0.75	0.68
Polynomial kernel SVM	0.68	0.67	0.67	0.75	0.67
RBF kernel SVM	0.68	0.68	0.68	0.75	0.68
Decision Tree	0.88	0.88	0.88	0.97	0.88
Random Forest	0.89	0.89	0.89	0.97	0.89
AdaBoost Classifier	0.88	0.88	0.88	0.88	0.88
Bagging Classifier	**0.90**	**0.90**	**0.90**	**0.98**	**0.90**
Multilayer perceptron	0.74	0.73	0.73	0.79	0.73

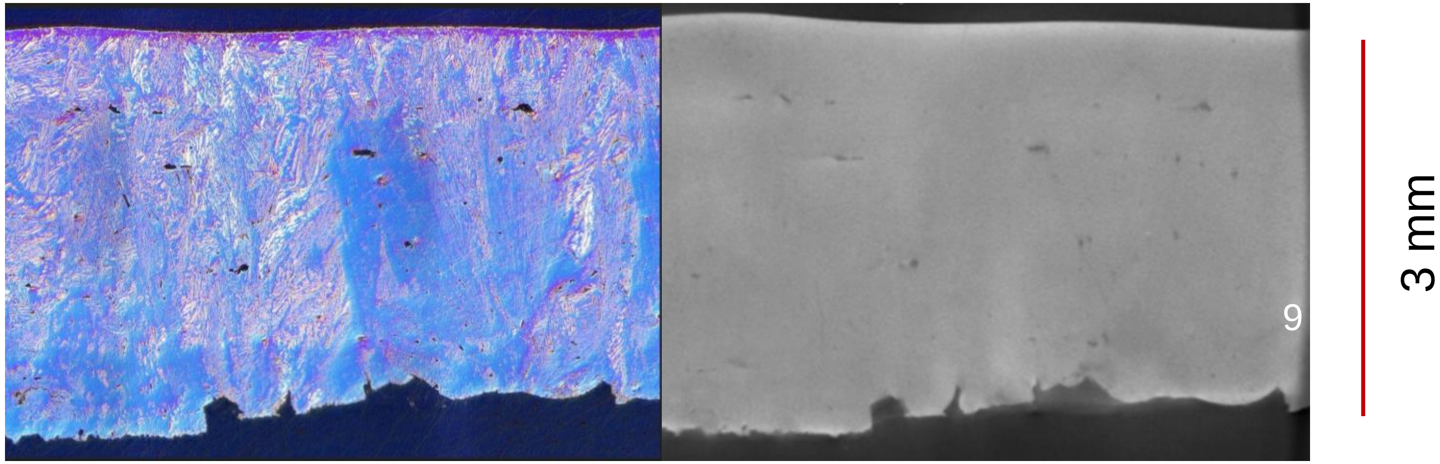
Note: P: Precision, R: Recall, F1: F1 score, AUC: area under the Receiver Operating Characteristic Curve, Acc.: Accuracy

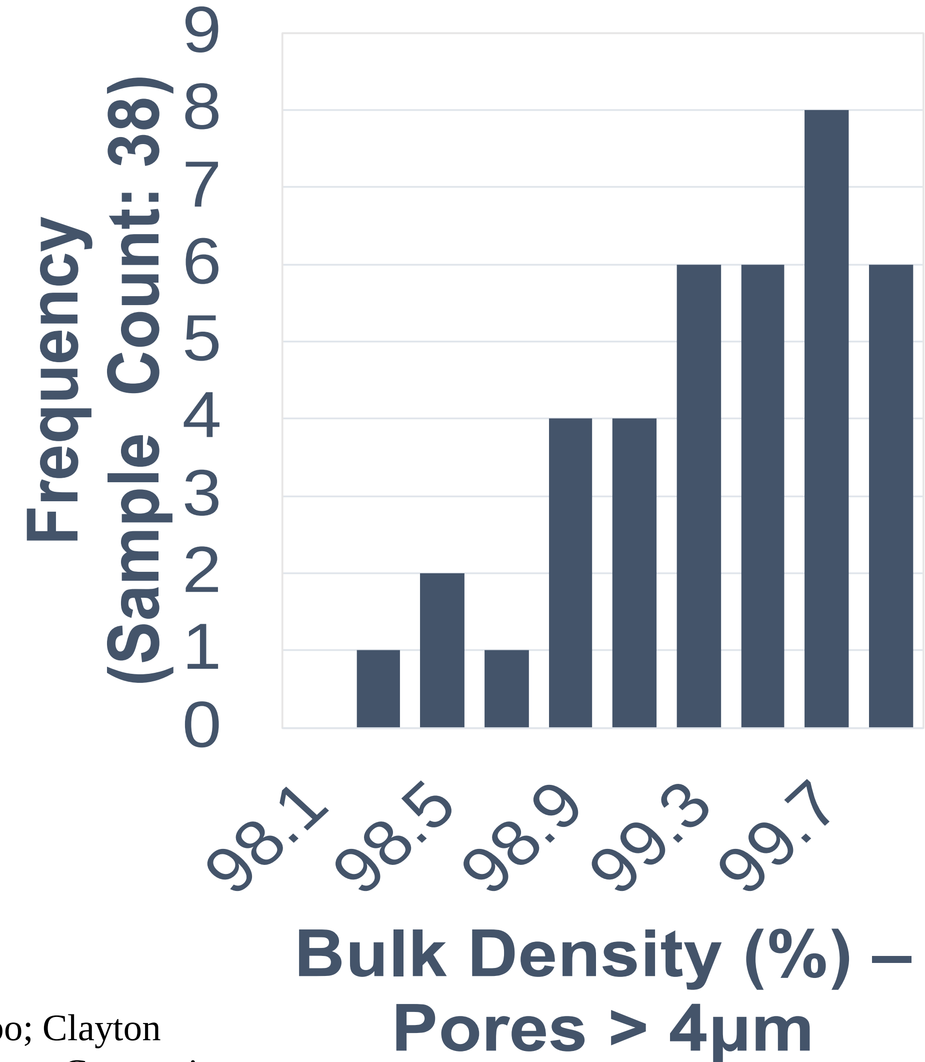
- Machine learning models are developed to connect processing features to thermoelectric properties
- Many top features are processing parameters
  - Inclusion of some monitoring features means not all processing influences are captured
- Use of advanced models improved prediction performance
  - **Final parameter optimization is currently in progress**

Agarwal, A., Banerjee, T., Gockel, J., LeBlanc, S., Walker, J. and Middendorf, J., 2023. Predicting Thermoelectric Power Factor of Bismuth Telluride During Laser Powder Bed Fusion Additive Manufacturing. *arXiv preprint arXiv:2303.15663*.

Porosity

- Mostly dense samples have been achieved
  - Optical and limited computed tomography (CT)
- Porosity analysis paused to not unnecessarily destroy samples



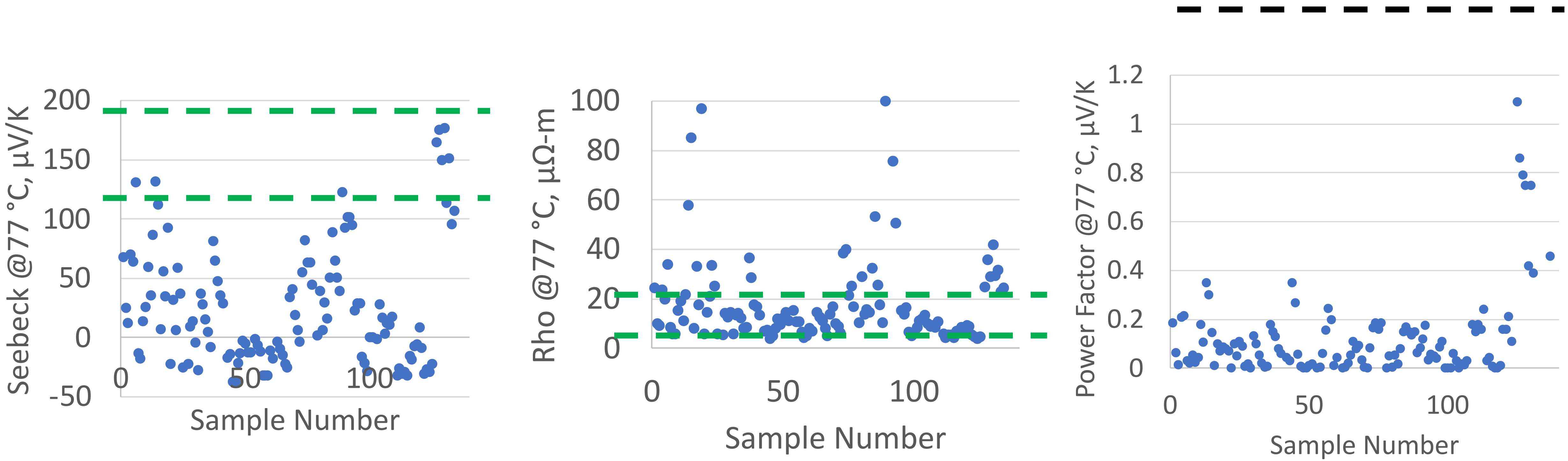


Joy Gockel; Tanvi Banerjee; Saniya LeBlanc; Joe Walker; Vijayabarathi Ponnambalam; Amanuel Alambo; Clayton Perbix; Ankita Agarwal; John Middendorf, Accelerating Additive Manufacturing Process Design for Energy Conversion Materials using In-situ Sensing and Machine Learning, TMS Annual Conference, San Diego, CA, 03/2023

Thermoelectric Properties

– A large range of properties were achieved at different parameters

- Want a High **Power Factor** (High Seebeck and Low Rho)
- Desired Seebeck and Rho achieved, but not power factor **(S^2/ρ)**



Saniya Leblanc; Yahya Oztan; Ryan Welch; Bengisu Sisik; Vijayabarathi Ponnambalam, Process-Structure-Property Relationships for Laser Powder Bed Fusion of Thermoelectric Materials for Low and High Temperature Applications, TMS Annual, 03/2023

Saniya Leblanc, Leveraging Additive Manufacturing to Tailor Thermoelectric Device Configuration, Leg Shape, and Transport Properties, TMS Annual, 03/2023

Future Work, Technology Transfer, & Impact

Future Work:

- Final print with optimized parameters currently being completed
  - Future studies of microstructure influence on properties, geometry effects and mechanistic sensor response planned

Technology Transfer:

- Further processing development (contours, downkins, upskins) is required for fabrication of complex shapes
- Commercialization possibility for unique PBF-LB processing equipment for difficult to spread powder and new sensing techniques by Open Additive
  - **Funded DURIP for George Washington University to purchase Open Additive developed system for processing Bismuth Telluride**

Impact:

- Incorporating in-situ sensors during process development will accelerate process-properties understanding and establish baselines for quality assurance for manufacturing of novel thermoelectric geometries

Questions?

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