

2021 ASME-CIE Hackathon

Exploring the Power of Data and Cybersecurity for Mechanical Engineering

Virtual Event, August 14-15, 2021

In conjunction with the ASME IDETC-CIE 2021 Conferences

Sponsored by

ASME Computers & Information in Engineering Division (CIE)

Hackathon Problem Proposers

- Prof. Nikhil Gupta, New York University
- Mr. Anant Kumar Mishra, Siemens Corporation
- Dr. Yan Lu, National Institute of Standards and Technology

For more details and sample datasets, please visit the [Hackathon GitHub](#)

Registration: \$25 for the hackathon (can be a conference add-on or stand-alone)

[Click to Register for the Hackathon](#)

Access to the Sample Datasets [HERE](#)

Meeting Location: Zoom Links TBA

Important Dates:

- **Sign-up Deadline: August 6, 11:59 pm EDT**
- **August 14, 2021: Hackathon Kick-off**
- **August 15, afternoon: Due for Hackathon deliverables**
- **August 15, evening: Awarding ceremony**

Awards: \$7,500 that the winners from three topic areas will share

Hackathon Problem 1: Digital Manufacturing – Obfuscating the design with security features

Problem Statement

A digital manufacturing (DM) process chain requires the use of computers, network connectivity, and cloud systems. Industry 4.0 continues to evolve towards the digital transformation of manufacturing, leading to concerns of hacking for sabotage and intellectual property protection. The unique threats faced by DM are side channel attacks, direct sabotage, reverse engineering, and counterfeit production.

The objective of this hackathon problem is to assess the robustness of security strategies to hide design information in DM and stimulate the critical thinking process. An STL file of a dice will be provided, and participants are expected to determine the correct number for each face on the 6-sided dice. Teams would be required to present their solution approaches for completing each benchmark to a panel of judges.

Challenges

- How can security strategies be developed and incorporated into a DM cyber-physical system? [1]
- What is the optimal approach to test the effectiveness of developing security strategies and to account for every classification of attacks in the DM supply chain? [2]
- How can the cybersecurity threats be minimized in digital manufacturing?
- Is current 3D printing technology safe from threats?

Datasets

The STL file shows a 3D model of a 6-sided dice, and each side of the dice will contain 9 spherical indentations on the surface. Each side of the dice should represent a numbered face of the dice from 1 to 6 and no number is repeated on any of the sides. Clues will be hidden in the file for participants to reveal and determine which number corresponds to which exact face of the dice. The hints will reveal which of the 9 spherical dots are extraneous and the true numbered side of the dice can be determined. Teams will receive points based on how many puzzles they can decode correctly.

Participants will be required to submit their solution based on the labeled dice shown in Figure 1. **For reference, the face of the dice numbered “6” is on the side labeled “C”.** In your submission, provide a table with your answers for the corresponding letters for each side, based upon the layout in the figure.

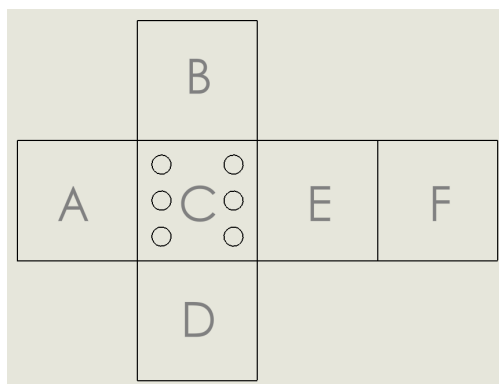


Figure 1: Flattened view to show the relationship between the faces of the 6-sided die.

Results submission table:

Die face letter	Die face value/number	Clue
A	?	
B	?	“Mountaintops inspire leaders, but valleys mature them”
C	6	“The best practice is to follow the advice posted on every railroad crossing. Stop to look at both sides.”
D	?	
E	?	
F	?	

Submission

1. The presentation slides describing the overall approach to obtain the solution for each benchmark and outlining the difficulties faced.
2. Each team will submit a zip file containing:
 - a. A detailed word document which includes:
 - i. The completed submission table from above for each die face value
 - ii. A description of the brainstorming process
 - iii. A summary of any other approach attempted that may not have been successful to provide insight into your effort level and thought process.
 - b. Complete the “Submission Template.csv” by adding the value corresponding to each die face letter.
 - c. Any supplementary file to support your report (CAD/STL files, programming scripts, images)

Judgement Criteria

Category	Criteria	Scoring
Results (70%): Output solution	<ul style="list-style-type: none"> • The objective is achieved by showing the correct numbered face of dice • Clear and concise explanation of obtaining solution of each side 	Correctly determining: 10 points for each side, 10 bonus points for solving the entire puzzle.
Creativity (10%): A new direction in the field to approach the problem	<ul style="list-style-type: none"> • Derived solution through critical thinking • The approach is a major departure from other submissions • Team demonstrates creativity in solving each puzzle • Use of appropriate software to aide in problem solving 	Excellent (9-10 pts) Very good (7-8 pts) Good (5-6 pts) Limited (3-4 pts) Poor (1-2 pts)
Overall presentation (20%): Organization,	<ul style="list-style-type: none"> • Title, headings, labels: Appropriate size, location, spelling, and content • The demonstration of teamwork • Structure and Clarity 	Excellent (9-10 pts) Very good (7-8 pts) Good (5-6 pts) Limited (3-4 pts) Poor (1-2 pts)

structure, and message conveying		
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References

1. Mahesh, P., et al., *A Survey of Cybersecurity of Digital Manufacturing*. Proceedings of the IEEE, 2021. **109**(4): p. 495-516.
2. Linares, M., et al. *HACK3D: Crowdsourcing the Assessment of Cybersecurity in Digital Manufacturing*. 2020. arXiv:2005.04368.
3. Practice problems and previous challenges are available at: <https://www.csaw.io/hack3d>

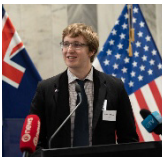
Subject Matter Experts and Mentors:



Nikil Gupta, Professor, Department of Mechanical and Aerospace Engineering, New York University



Gary Mac, Ph.D. Candidate in Mechanical Engineering, Department of Mechanical and Aerospace Engineering, New York University



Hammond Pearce Postdoctoral Associate, Department of Mechanical and Aerospace Engineering, New York University



Zhenghui Sha, Assistant Professor, J. Mike Walker Department of Mechanical Engineering, The University of Texas at Austin

Problem Statement 2: Automated Testing in Production Planning in Test based Engineering

In the age of digitalization, it is critical to test, validate, and optimize real-world designs within the limitations of shorter testing cycles, conflicting performance requirements, growing product complexity, and reduced costs. The employment of data-based production resource management is geared toward reducing the total time required for flexible sequence of testing processes. Automated testing of engineering parts based on resource availability is a crucial part of production planning process. To ensure efficient testing solutions optimizing the speed of their testing cycles for so many possible feature combinations is complex and time-consuming without a powerful algorithmic approach.

The Objective of this hackathon is to build a robust algorithm to predict and reduce the amount of time required by the engineering parts for testing on the test machines. Candidates will work with a dataset which represents different combinations of part features to predict and optimize the time it takes to pass testing. The second part of the challenge is to build a scheduling tool based on the predicted test time for automated testing and resource planning.



Figure 1. (H)EV Powertrain Testing on Siemens Factory floor

Task 1 Dataset

This dataset contains a series of undisclosed variables, each representing a component in a (H)EV Powertrain machinery. Each single row represents a component like battery, Motor, torque, coupler, drive, wheel, Aerodynamic drag coeff, Rolling resistance coeff, etc. Variables can be categorical, continuous, or binary. For example, a categorical variable could be speed, torque range and control strategies on sound quality, (torsional) vibrations, or energy efficiency. Continuous variable could be cell temperature, humidity %, fuel consumption, simulation error or number of resources used. Binary variables could be availability of pneumatic nozzles, sensor application, safety appliance status, phase # etc.

The ground truth is labeled 'y' and represents the time (in seconds) that the rotating machinery took to pass testing for each variable.

File descriptions

Variables with letters are categorical. Variables with 0/1 are binary values. And others are continuous variables.

- train.csv - the training set
- test.csv - the test set, you must predict the 'y' variable for the 'ID's in this file

Task 2 Dataset

This dataset is a (H)EV Powertrain component assembly dataset. This dataset consists of 1 file: matrix.csv

File descriptions

Matrix.csv consists of test IDs (these test IDs can be found in test.csv from task 1), available material quantity and machine numbers on which test is performed. Each test ID is divided into categories (A1 – A6) which resemble a component in rotating machinery. For successful testing of the rotating machinery, test IDs from these categories should be tested in a specific sequence of component categories.

The general sequence of Test IDs to start a test - A1 → A2 → A3 → A4 → A6 **OR** A1 → A2 → A3 → A5 → A6.

Example test - 1004 → 6450 → 185 → 1466 → 2080, total time taken by the test is the addition of predicted 'y' (from test.csv in task 1) for respective test IDs.

Machine selection - Machines numbers ranging from 1 to 12 form a matrix with test IDs. Y/N under machines signify whether machine is allocated for performing the test.

If matrix(test ID , machine #) = "Y" then that specific test can be performed on the corresponding machine number. You must select suitable Machine which can be used to test the sequential test IDs.

For the example test - 1004 → 6450 → 185 → 1466 → 2080 suitable machines for testing are 1, 5. Based on the machine availability user can select a machine for testing.

Each test id uses use a single resource for testing. After each test resources are exhausted by 1.

Submission File

Task 1: Prediction of time required for testing: For each 'ID' in the test set, you must predict the 'y' variable. The file should contain a header and have the following format:

```
ID,y
1,150
2,150.23
3,155.78
```

...

Task 2: Building a Scheduling tool: Design and build a scheduling tool for automating the test schedule and planning resources for (H)EV Powertrain planner.

Tool input: test sequence

- 1) 1004 → 6450 → 185 → 1466 → 2080
- 2) ...
- 3) ...

Output: test sequence order, Machine #, resources used, wait time, If resources are exhausted or no machine available, print a message accordingly.

Judgment Rubric

It is important to note that only 30% of your score will rely on the results from your algorithm, while the rest will be based on your approach, creativity, and presentation.

Category	Criteria	Scoring
<p>Technical approach (25%) Methods and algorithms of the proposed data analysis and prediction</p> <p>BONUS: for solving Scheduling task (10%)</p>	<ul style="list-style-type: none"> • Requirement analysis and problem formulation • Literature review and exploration of ideas • Data exploration and preparation • Model comparison, selection, optimization, and evaluation • The readiness of the idea and the approach • The results are appropriately interpreted and can be supported by existing theories, physics, or principles. • Discovered additional (hidden) features that would be influential to time prediction beyond the provided features. • Correct logic accurate results for test automation, planning 	<p>Excellent (25-30 pts) Very good (20-25 pts) Good (15-19 pts) Limited (9-15 pts) Poor (1-8 pts)</p> <p>BONUS: 10 pts</p>
<p>Creativity and innovation (20%) A new direction in the field to approach the problem</p>	<ul style="list-style-type: none"> • The technology breaks new ground • The project makes a profound break from established design • The project adds a major departure from established design • The code adds a new twist on established design • The chosen technology and design is already deeply established 	<p>Excellent (17-20 pts) Very good (13-16 pts) Good (11-12 pts) Limited (5-8 pts) Poor (1-4 pts)</p>
<p>Results (35%)</p>	<ul style="list-style-type: none"> • The objective is successfully achieved, which is measured by the Mean Absolute Error and the R-squared metric. 	<p>Team with the best performance (Both tasks completed and correct) (35 pts) Team with the second-best performance (24 pts) Team with the third-best performance (18 pts)</p>

		Teams at fourth and fifth ranks (10 pts) Rest (3 pts)
Overall presentation (10%) Organization, structure, and message conveying	<ul style="list-style-type: none"> Title, headings, labels: Appropriate size, location, spelling, and content The demonstration of teamwork Structure and Clarity Boarder impact of the idea to ME subfields 	Excellent (9-10 pts) Very good (7-8 pts) Good (5-6 pts) Limited (3-4 pts) Poor (1-2 pts)

Subject Matter Experts and Mentors



Anant Kumar Mishra, Research and Technology Manager, Future of Automation at Corporate Technology, Siemens Corporation



Mayuri Deshpande, Research Scientist, Siemens Corporation



Christopher McComb, Associate Professor, Department of Mechanical Engineering, Carnegie Melon University

Hackathon Problem 3: Melt Pool Monitoring Data Registration for Powder Bed Fusion Additive Manufacturing

Problem Statement

The powder bed fusion (PBF) process builds part layer-by-layer. The new layer is on either raw powder or previously solidified material. PBF-built part quality highly depends on process parameters such as laser power, scan speed, scan pattern, and other machine settings. There are also uncontrollable environmental factors or geometrical effects that may affect process stability. A common solution to this issue is to implement in-situ monitoring and real-time control.

Coaxial camera-based melt pool monitoring (MPM) systems can generate high-resolution images at a high sampling rate, which provides an attractive solution to monitor the PBF process. In order to use MPM information for process monitoring and part quality control, relationships between metal PBF process parameters, melt pool characteristics, and material structure and properties need to be discovered. Proper data registration is a prerequisite for correlating melt pool characteristics to local structure and mechanical properties. The objective of this hackathon subtopic is to reconstruct the scan path from coaxial MPM images. Furthermore, each image frame should be registered with an estimation of the laser beam position associated with this frame. Participants need to use the given information such as scan profile, part geometry, and other process parameters to predict where each MPM frame was taken.

Challenges

- How to correlate the MPM characteristics with scan path and process parameters? Hint, what specific characteristics in the scan commands can cause changes in the melt pool?
- How to extract useful features from MPM data to make the correlation?
- What is the best approach to efficiently register the MPM frames?
- How to remove the initial defects such as signal delay or missing data in the raw in-situ data?
- What are the uncertainty sources of your registration method? How to quantify them?

Datasets

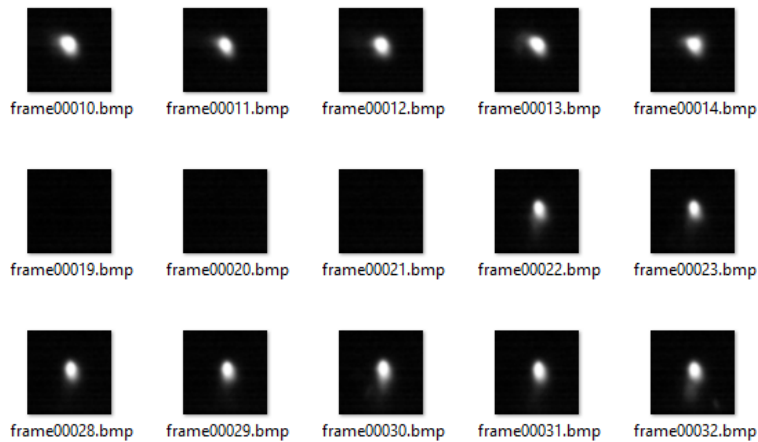
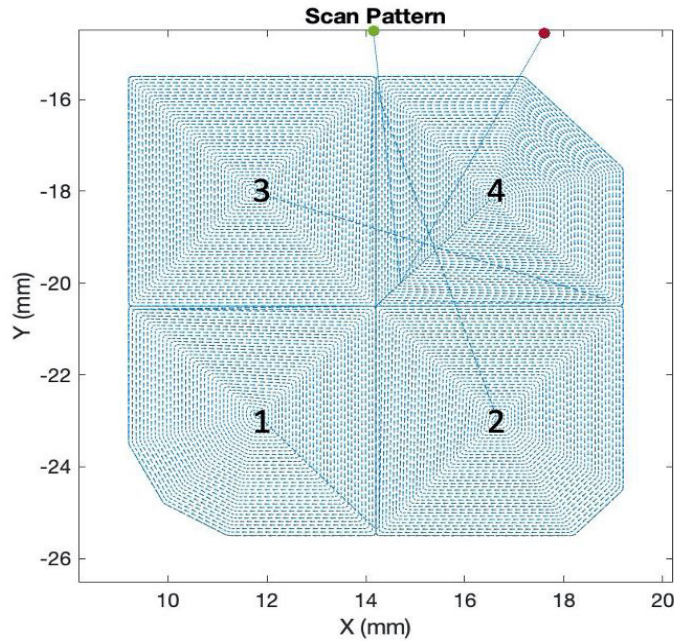
An experimental L-PBF build was conducted on the Additive Manufacturing Metrology Testbed (AMMT) at the National Institute of Standards and Technology (NIST). The AMMT is a fully customized metrology instrument that enables flexible control and measurement of the L-PBF process. Two cameras were installed for process monitoring, including a high-resolution camera that captures the layerwise images of the entire part and a high-speed camera used to capture melt pool images. The Galvo mirror system and the beam splitter allow the high-speed camera to focus on the current laser melting spot. Emitted light from the melt pool, through an 850 nm bandpass filter (40 nm bandwidth), is imaged on the camera sensor. On AMMT, both Galvo and laser command are updated on field-programmable gate array (FPGA) at 100 kHz. The digital commands are developed to specify the motion of the Galvo scanner of the L-PBF system. It is transformed into a time series of scanner positions and laser power as control commands.

Inconel 625 powder and build plate were used. A rectangular part (with chamfered corners) of dimensions 10 mm x 10 mm x 5 mm was laid on the substrate.

Datasets and data formats used for this subtopic include

- 1) Part design model (STL file)
- 2) Process settings; camera settings; and camera calibration models (PNG, jpg, XML)
- 3) Scan path description (.docx)

4) Melt-pool images for one part one layer at 10KHz (BMP/JPG/AVI/PNG)



What to submit

- A .csv file for the predicted position of each MPM frame.
- The slides of your final presentation

Judgement Criteria:

The final score will be determined by three judges based on the technical approach, results, data visualization, and presentation. Each team should submit a single column .csv file that lists predicted melt-pool size following the triggering index.

Category	Criteria	Scoring
Technical Approach (30%) Methods and algorithms	<ul style="list-style-type: none"> • Requirement analysis and problem formulation • Literature review and exploration of ideas • The development and design of the idea 	Excellent (9-10 pts) Very good (7-8 pts) Good (5-6 pts)

	<ul style="list-style-type: none"> • Scientific soundness of the approach • Creativity of the approach • Soundness of the algorithm (data pre-processing expected) • Readiness of the idea and the approach • Automated workflow: data/meta data acquisition through open interface 	Limited (3-4 pts) Poor (1-2 pts)
Results (40%) Output performance	<ul style="list-style-type: none"> • The objective is successfully achieved, with a distance between the estimated position and the ground truth evaluated by the Root Mean Squared Error (RMSE) • Uncertainty analysis 	Excellent (9-10 pts) Very good (7-8 pts) Good (5-6 pts) Limited (3-4 pts) Poor (1-2 pts)
Data Visualization (10%) Clarity, information	<ul style="list-style-type: none"> • Overall clarity of data presented • Visualization of data registration • Model development • Trend or correlation analysis 	Excellent (9-10 pts) Very good (7-8 pts) Good (5-6 pts) Limited (3-4 pts) Poor (1-2 pts)
Overall Presentation (20%) Organization, structure and message conveying	<ul style="list-style-type: none"> • Title, headings, labels: Appropriate size, location, spelling, and content • The demonstration of teamwork • Structure and Clarity • Boarder impact of the idea to ME subfields 	Excellent (9-10 pts) Very good (7-8 pts) Good (5-6 pts) Limited (3-4 pts) Poor (1-2 pts)

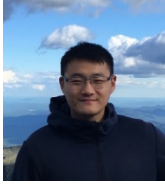
Reference

- [1] Lane B, Mekhontsev S, Grantham S, Vlasea M, Whiting J, Yeung H, Fox J, Zarobila C, Neira J, McGlaufflin M, Hanssen L. Design, developments, and results from the NIST additive manufacturing metrology testbed (AMMT). In Solid freeform fabrication symposium, Austin, TX 2016 August 10 (pp. 1145-1160).
- [2] Lane, Brandon, and Ho Yeung. "Process Monitoring Dataset from the Additive Manufacturing Metrology Testbed (AMMT):" Three-Dimensional Scan Strategies". *Journal of Research of the National Institute of Standards and Technology* 124 (2019): 1-14.
- [3] Fox, Jason C., Brandon M. Lane, and Ho Yeung. "Measurement of process dynamics through coaxially aligned high speed near-infrared imaging in laser powder bed fusion additive manufacturing." In *Thermosense: Thermal Infrared Applications XXXIX*, vol. 10214, p. 1021407. International Society for Optics and Photonics, 2017.
- [4] Yeung, Ho, and B. Lane. "A residual heat compensation based scan strategy for powder bed fusion additive manufacturing." *Manufacturing Letters* 25 (2020): 56-59.

Subject Matter Experts and Mentors



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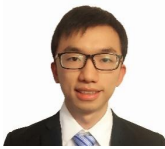


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Hackathon Tutorial Team Members:



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Dehao Liu, Incoming Postdoctoral Researcher, School of Materials Science & Engineering, Institute of Data Science, Texas A&M University



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