## <u>Hackathon Problem 1</u>: Machine Damage Accumulation Prediction using Heterogeneous Temporal Sensor Data

Subject Matter Expert:

- Christopher McComb, Assistant Professor, School of Engineering Design, Technology and Professional Programs, PennState
- Zhenghui Sha, Assistant Professor, Department of Mechanical Engineering, University of Arkansas
- Faez Ahmed, Postdoctoral Fellow, Department of Mechanical Engineering, Northwestern University

## **Problem Statement**

The Bernard M. Gordon Learning Factory is a hands-on facility for engineering students, which provides modern design, prototyping, and manufacturing facilities. Many of the machines in the Learning Factory are instrumented using a sensor suite that provides monitoring capabilities. The readings from a heterogenous set of sensors is used to report health data metrics continuously for many different machines. One of these metrics is called "Damage Accumulation".

The objective of this problem is to use machine learning for predictive maintenance, by reading sensor data for 12 different machines and doing a time forecast of future machine "Damage Accumulation" for each of them.

## Challenges

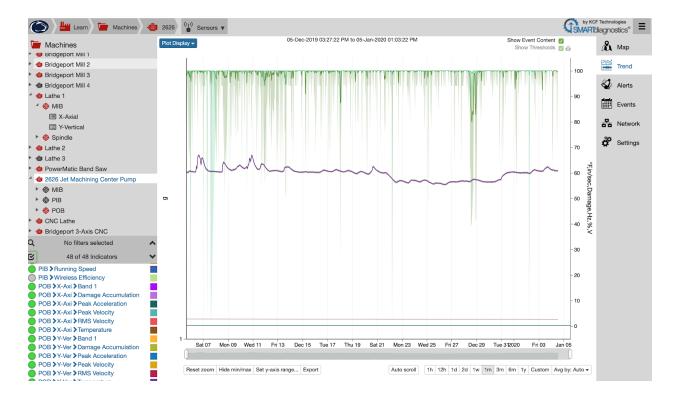
The objective is to extrapolate the values measured by these sensors into the future to provide damage accumulation forecast for up to:

- 30 seconds (beginner)
- 10 minutes (intermediate)
- 1 hour (advanced)

#### Datasets

Data is provided in twelve separate CSV files, one for each machine instrumented in the Learning Factory. Each machine has several sensors, each of which collects peak velocity, RMS velocity, peak acceleration, and temperature. An integrated value, Damage Accumulation, is also reported based on the sensor readings. The specific objective is to project future values of Damage Accumulation.

As noted above, data is collected from a sensor set. A screenshot of the raw interface is provided below.



### Judgement Criteria:

We will use average of Root Mean Squared Deviation (RMSD) for 12 machines to judge a team's forecast model. RMSD will be calculated for each machine individually for the given time period (say 10 minutes).

# <u>Hackathon Problem 2</u>: Smart Manufacturing – In-Process Data Mining for Powder-Bed Fusion Additive Manufacturing

Subject Matter Expert:

- Yan Lu, Senior Research Scientist, Professor, System Integration Division, NIST
- Dehao Liu, School of Mechanical Engineering, Graduate Research Assistant, George Institute of Technology
- Anh Tran, Research Staff, Sandia National Laboratories

### **Problem Statement**

Additive manufacturing (AM) processes build parts layer-by-layer directly from 3D models. AM enables the fabrication of complex heterogeneous parts, which makes it an attractive alternative for high-value, low-volume production. However, the turnkey deployment of the technology hits consistent barriers including low part repeatability and lack of effective qualification tools. Fundamental issues exist with the understanding and control of the dynamic and stochastic nature of AM processes. In-situ monitoring for additive manufacturing is considered as the main enablers to understand AM processes, set optimal material and machine specific process parameters, and close the control loops in real-time to limit the stochastic variability introduced by the dynamic nature of the processes. For manufacturers to build quality AM parts, in-situ data has the potential to be used for quality assurance and certification, which will dramatically reduce the need of lengthy and high-cost post inspections.

The goal of this hackathon subtopic is to promote the use of data science in powder-bed fusion additive manufacturing to accelerate the understanding of powder-bed fusion AM process, to improve PBF process monitoring and control as well as to explore in-process data-based product qualification. This will be achieved by developing sets of data analytics tools, predictive models, and process control and optimization algorithms for PBF processes. This tool will be an early step in allowing industry to move away from 100% testing and towards born-qualified parts.

### Challenges:

- AM in-process data registration how to align the multi-modal in-process monitoring data in time and space to allow for fusion and correlation
- What kind of features to be extracted from the multi-level, multi scale AM in-process monitoring data, e.g., build command, chamber monitoring trended data, co-axial images and layerwise images etc.
- What kind of relationship between build commands and the in-process measurements such as coaxial/layerwise images.
- How to fusion the data fusion from the multi-modal in-process measurements
- How to develop real-time control or layerwise control strategy from the data for the PBF AM processes?

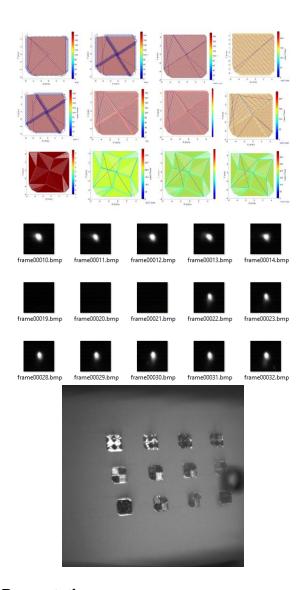
### Datasets:

An experimental L-PBF build was conducted on the Additive Manufacturing Metrology Testbed (AMMT) at 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 high0resolution 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 current laser melting spot. Emitted light from the melt pool, through a 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. The substrate has a dimension of 102 mm x 102 mm x 13 mm. Twelve rectangular parts (with chamfered corners) of dimensions 10 mm x 10 mm x 5 mm were laid on the substrate, with a minimum spacing of 10 mm between parts. Each part was built with a different scan strategy.

Data sets used for the study include:

- 1) STL model
- 2) Part layout
- 3) Process settings; camera settings; and camera calibration models
- 4) Data sets for build command at 100KHz for every part every layer
- 5) Melt-pool images for every part, every layer at 2KHz
- 6) Layerwise images, 2 per layer, before and after exposure settings



## **Hackathon Team and Presentation**

- All participants must be registered via here. Register the event and attend the
  Hackathon physically. Each participant brings his/her own laptop with all the necessary
  computing tools. Everyone will be placed in a team up to three members. You may form
  your own team onsite. All implementation must be based on the original work.
- Each Hackathon team will continue their own meetings and hacking exercises during the two days between 4pm 08/15/20 and 4pm 08/16/20.
- Each team needs to present their teamwork including the technical approach and the results.