

Towards the Development of a Multi-Modal Community-Based AM Database

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Metal additive manufacturing (AM) is increasingly being sought after in critical military, aerospace, and biomedical manufacturing applications for its capability to create near-net shaped parts while minimizing time and material cost. In order to fabricate critical parts with orientation dependent properties required by industries, a complete understanding of microstructural heterogeneities (MH) and the ability to control these MH using AM process parameters is needed. These knowledge gaps are a serious impediment to AM part qualification and industry adoption [1]. Additionally, the non-equilibrium process conditions during AM of parts have led to the development of new alloys suitable for AM processes [2]. Therefore, strategies to accelerate AM part qualification is a major challenge that faces the AM community. The reasons for these barriers to qualification of AM parts are 1) the lack of spatial understanding in the hierarchy of defects and MH found in AM parts, 2) the lack of data-driven approaches for discovering new materials/alloys suitable for AM and 3) the lack of standardized high-volume process-structure-property (PSP) datasets for AM builds.

Overcoming these barriers necessitates the aggregation of multi-format, multi-dimensional datasets (often spanning multiple terabytes) required to develop such standards. These datasets must contain experimental, computational, and empirically derived data about processing pedigree, microstructural features, and performance parameters of parts spanning multiple builds. Moreover, the data must be able to be accessed in such a way that the community can readily derive relationships in the PSP space. In recent years, these challenges have been addressed in several ways. The creation of the propnet Python module has been created to empirically derive secondary properties from datasets and is a way to increase the dimensionality and informational footprint of the data collected [3]. Another is the advent of quality standards for the management and stewardship of scientific data known as the FAIR guiding principles [4]. FAIR data stands for Findable, Accessible, Interoperable, and Reusable/Reproducible data. These principles dictate how metadata is to be represented within a federated system. HyperThought™ is designed with features to allow users to upload data to a secure location on the cloud and ensure that their data meets FAIR standards [5]. HyperThought™ is capable of accepting data from users via REST API, attaching relevant metadata tags to files uploaded, run community-created algorithms on files for processing, and most importantly, represent the overall structure of an industrial process or scientific study through its process-modeling sub-application, Workflow. HyperThought™ enables users to develop a persistent machine-representation of knowledge gained from their data collection efforts.

This study will present a systematic workflow to collect multi-modal datasets, with secondary properties of the material system derived using propnet. The entire dataset with explained pedigree will then be uploaded onto HyperThought™. The data will be available for public access. This dataset will consist of spatially collected microstructural data obtained from an AM block using a high-throughput characterization methodology established in our previous work [6]. The extent of spatial variations in microstructure due to process conditions across the sample will then be related to the changes in local performance parameters within the sample. We envision that this could further stimulate a community-wide effort to create a collection of datasets that can be used as a starting point for AM

inferential/predictive model building and benchmarking, as well as initial exploration of AM PSP relationships.

References

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