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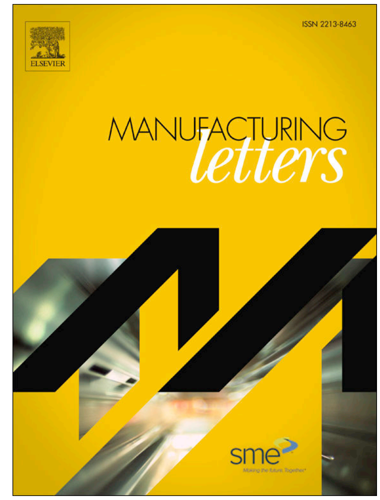

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A scalable digital platform for the use of digital twins in additive manufacturing

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Abstract

While Additive Manufacturing promises to reshape the manufacturing landscape, challenges related to part, and process qualification hinder its widespread adoption. The Instance-Qualified approach seeks to qualify individual parts, even for processes with high variability, by leveraging the concept of a *digital twin*. This work proposes a scalable cyberphysical infrastructure to enable the construction and use of such *digital twins*. This work also introduces the concept of an Augmented Intelligence Relay, which allows Artificial Intelligence algorithms to predict component performance for a given application even when it is impractical to perform a large number of physical tests.

Keywords

Additive manufacturing; Digital twin; Artificial intelligence; Instance-qualified; Cyberphysical infrastructure

1 Introduction

Additively Manufactured (AM) components are constructed directly from feedstock, typically in a layer-wise fashion. Nominally, AM is ideal for fabricating complex geometries for high-value industries [1]. However, significant variability in AM processes leads to inconsistent properties (particularly with respect to microstructure and defects) [2–4], hindering broader adoption [1]. Low production volumes further complicate the application of traditional manufacturing quality assurance methodologies. In lieu of alternatives, industries currently leveraging AM rely on non-destructive testing for part qualification; which is often not cost-effective.

For these reasons, many researchers have suggested that a new qualification paradigm is needed. Referred to as "Instance-Qualified," this approach seeks to qualify components using a *digital twin* [5] based on instance-specific, as opposed to aggregate, data. First proposed by Grieves and Vickers [6], a *digital twin* is a computer model of a real object, assembly, or system which is updated based on data collected from its *physical twin*. This approach is particularly promising as the layer-wise nature of AM allows data to be collected during production. While several papers have explicitly addressed the application of *digital twins* to AM, they have primarily focused narrowly on thermo-mechanical modeling [7,8].

Here we propose a cyberphysical infrastructure designed to enable the production of Instance-Qualified AM components, as it is being developed at ORNL's Manufacturing Demonstration Facility (MDF). The proposed methodology pays special attention to scalability and the application of Artificial Intelligence (AI). Processing knowledge collected over the last century of subtractive manufacturing now enables high-quality production. The proposed methodology strives to achieve similar results for AM in a fraction of the time.

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2 Methodology

2.1 Scalability

We refer to the cyberphysical infrastructure required to implement a *digital twin* as the *digital platform*. The *digital platform* is a network of manufacturing equipment, data storage systems, and computation capabilities. In our implementation, only metadata are stored within a relational database while the data are stored within indexed file systems. By enforcing a minimally-viable data structure, we can integrate new manufacturing processes more quickly into the *digital platform*. Data can be queried and accessed using a web portal or an application programming interface embedded in custom software. While the web portal supports some data visualization, most visualization and analytics are performed using software deployed on networked computers.

To construct a *digital twin* for an AM component, the entire manufacturing process, including design, simulation, printing, post-processing, and characterization, must be captured. Therefore, we define the *digital workflow* as the interaction between the physical manufacturing process, the technicians and engineers, and the *digital platform*. To maintain scalability, each manufacturing process is decomposed into a sequence of *operations*. These *operations* may create a part, modify a part, characterize a part, act on a feedstock, or modify a printer. During each *operation*, data are collected and transmitted to the *digital platform* either manually or automatically via *operation*-specific software tools. Fig. 1 shows an example *digital workflow* for the manufacture of silicon carbide fuel elements for a nuclear reactor, starting with binder jet printing and ending with component characterization [9,10].

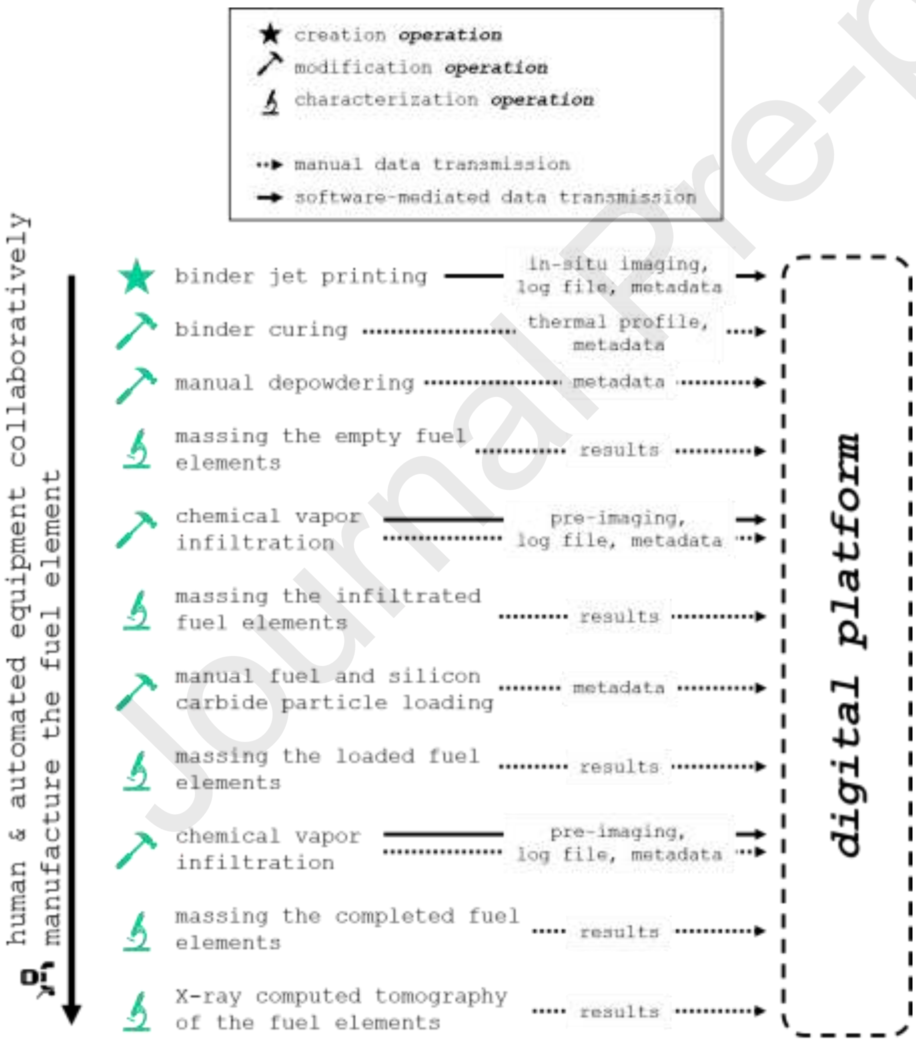

Fig. 1. The *digital workflow* for producing a silicon carbide fuel element for a nuclear reactor via binder jet AM.

The totality of the design intent and data collected during the fabrication of a given component is considered a *digital thread* and it instantiates the corresponding *digital twin*. A corollary of this approach is that each part must be uniquely identifiable to facilitate the linkage between the *digital* and *physical twins*. Strictly, each *digital thread* stored in the *digital platform's* database is the sequential list of *operations* which were performed during manufacturing, while the collected data remain associated with the corresponding *operation*. While this less-structured approach is not ideal for data analytics, it is necessary because (1) a given *operation* may act on multiple parts which may not be separable in the data, (2) any part may be broken into child parts or integrated into an assembly and the duplication of data should be minimized, and (3) the relevant datasets can be diverse requiring flexibility in their transmission, storage, and analysis. The *digital thread* for each part must also include historical information about the feedstock and machines used in its creation. Fig.2 shows a *digital thread* within the *digital platform*.

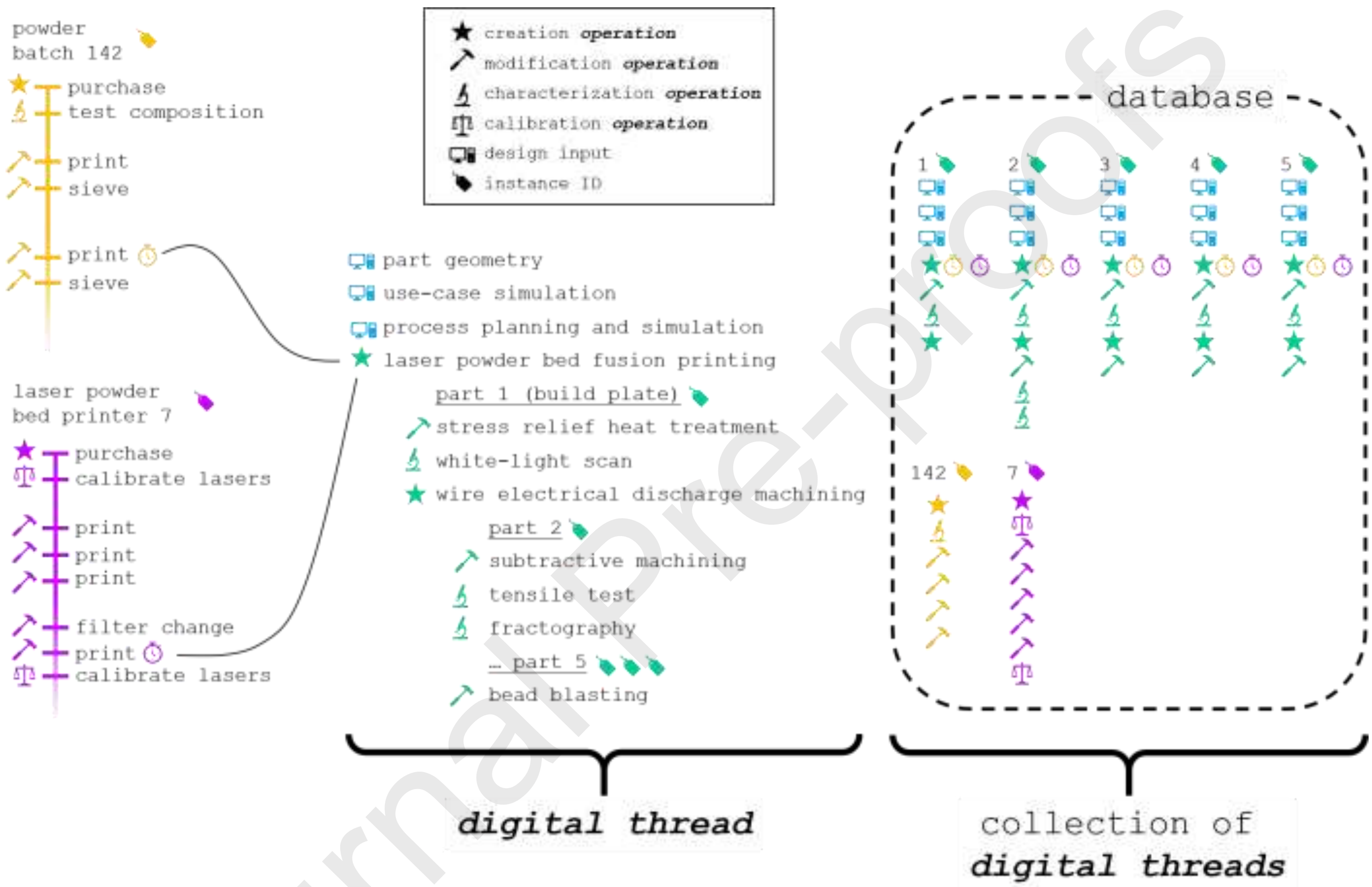

Fig. 2. *Digital threads* for parts produced via laser powder bed fusion AM. Parts 2 – 5 are considered children of part 1 and inherit its *digital thread*. Each part's *digital thread* links to the feedstock and manufacturing equipment at a specific point in time.

2.2 Artificial intelligence

Creating an Instance-Qualified component requires modeling the *physical twin's* performance. While such models may be physics-based, the large quantity and high dimensionality of data collected during AM suggests that targeted use of AI is appropriate. While the use of machine and deep learning [11] for AM part qualification is actively researched, most work has focused primarily on defect detection [12–17]. Less progress has been made toward scalable property predication, particularly as it relates to geometry agnosticism and applicability across materials and printers.

Ideally, an AI would ingest *digital threads* and learn to predict part performance based on the collected in-situ processing data and characterization results. Unfortunately, contemporary AI requires vast quantities of labeled training data [11,18]. For example, using deep learning to directly predict part performance based on in-situ imaging might require 10^9 physical tests, which is impractical. This problem is compounded when part geometry, application environment, and post-processing *operations* are considered. Therefore, we propose an Augmented Intelligence Relay (AIR) in which a sequence of AIs solve different aspects of a problem.

In an AIR, human experts observe intermediate results at the interface between each AI and perform feature-engineering to structure the data. While the work remains preliminary, Fig. 3 shows one implementation of an AIR. In this scenario, in-situ images from a laser powder bed fusion printer are used to predict local tensile properties by leveraging data from three different types of builds (1) SS-J3 tensile samples, (2) representative tube geometries, and (3) application-specific geometries. First, data collected from all three sets of builds – representing 10^8 labeled pixels – are used to train the anomaly detection deep learning algorithm implemented by *Peregrine* [12]. At the first interface, a human engineers voxelized feature vectors which summarize the anomaly detections, encode local part geometry information, and incorporate post-processing *operation* data. These feature vectors are input to a machine learning algorithm which predicts voxelized tensile properties and is trained by 10^4 tensile testing *operations*. Finally, validation can be performed by combining the voxelized properties with a physics-based model of the tube geometries and performing 10^2 burst tests. Throughout the AIR, the AIs become less data-intensive as the ground truths become more difficult to acquire.

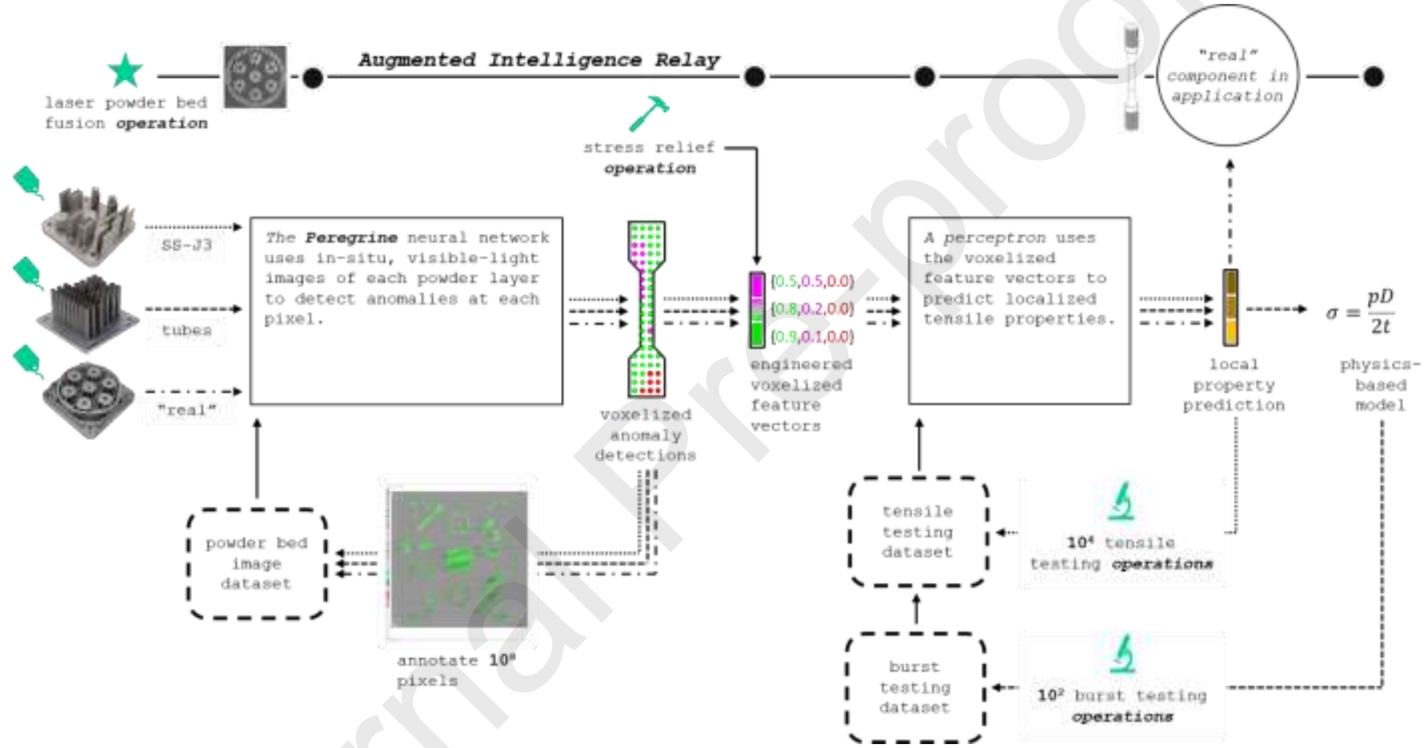

Fig. 3. An example AIR which uses in-situ imaging to predict localized tensile properties for a laser powder bed fusion AM process.

3 Results and Discussion

Development of the MDF *digital platform* initially focused on seven powder bed printers and is currently scaling to another 80+ printers. In CY2020, 6.7 TB of data from 410 builds were uploaded to the *digital platform* and analyzed. During this process, several axioms became clear – flexibility over structure, automation over manual data entry, and scalability necessitates streamlined software tools. Another realization is that the success of a *digital platform* is dependent upon the data discipline of the overall organization. We found that providing immediate "digital" value to the person uploading the data (e.g. allowing builds to be remotely monitored) improved acceptance of new data collection procedures. Finally, addressing process scalability has facilitated rapid transfer of MDF-developed technologies to the broader manufacturing community.

4 Conclusions

While the schemas presented in this work will evolve, the current methodology has allowed data visualization and analytics efforts to rapidly scale across the MDF and add substantial value to ongoing research. In this work, we argue that decomposition of manufacturing processes into discrete *operations* is key to deploying *digital workflows*. Furthermore, we propose the use of an AIR to achieve part property prediction based on in-situ data. Notably, the proposed methodology only extends to instantiation of a *digital twin*, the full value of a *digital twin* will only be realized once data from the entire product lifecycle can be integrated into the digital model. Finally, while this work focused on AM, the proposed *digital platform* is broadly applicable across manufacturing processes.

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