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Integrating Process Data in Motion for Additive Manufacturing Industrialization

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Abstract

Metal Additive Manufacturing (AM) is poised to revolutionize industrial production but faces challenges in scaling to large-scale operations due to the complexity of managing part quality for top-tier component production. Advanced in-process monitoring techniques not only track AM process stability for quality control, but also provide datasets crucial for enhancing material, process, and product development and optimizing supply chains. Yet, real-time integration and processing of this multivariate data for feedback control and process optimization remains challenging. To address these issues, the NIST AM Data Integration Testbench was developed, utilizing an ISA-95-based framework, to facilitate secured data integration and sharing, manufacturing intelligence, and decision-making. This platform includes in-situ monitoring emulators, high-speed data streaming, automated metadata curation, and cloud-based data archiving, alongside an open edge-computing system for real-time data analysis and a Manufacturing Execution System (MES) to support AM industrialization and improve efficiency and part quality.

1. Introduction

Metal Additive Manufacturing (AM) is promising for transforming industrial production processes. Despite advances over the past decade, it has yet to reach widespread production using AM technology. To qualify the production of top-tier components, advanced in-process monitoring techniques are applied to meticulously track the stability of AM processes. These techniques not only enable timely control measures to ensure the part quality, but also provide valuable datasets to advance AM technology and optimize supply chain efficiency. However, integrating and managing high-speed, high-volume AM in-process data during production is challenging and predominantly done manually after the build processes are complete. Processing multivariate, multi-modality, and high-dimensional in-process observations in real-time is even more difficult for feedback control. In addition, there is a growing demand to integrate processes and systems with manufacturing operations, enterprise applications, and supply chain management for scaling up the AM technology. To address these challenges, both industrial practitioners and researchers from academic or government institutes are working on AM integration standards, advanced in-process data analytics, and data management methods. However, the applications are rarely reported, and standard practices have not been established and shared due to a lack of a test platform to measure and validate the effectiveness of the information models, monitoring and control algorithms, and integration methods [1].

The NIST team has leveraged the ISA 95 model and developed a 3-level reference integration architecture that identifies the key components and major information flows for AM industrialization [2]. Provisions of common functions, standardized integration methods, and information models minimize engineering costs, shortens time-to-market, and increases flexibility [3]. A lot of AM systems are equipped with connectivity for integration and support industrial automation. While most of the integrations are proprietary, few vendors adopt standard protocols such as OPC-UA, RESTful and MQTT, etc. Data-driven solutions are also emerging to monitor the process stability and part quality in real-time. The AM software industry offers real-time advanced data analytics for detailed process insights and enhanced factory monitoring. In parallel, academia has been committed to developing sophisticated machine learning algorithms for AM process anomaly detection and part quality estimation. Unfortunately, most of the results are validated offline and lack implement ability for on-the-fly applications. For example, the computation requirements of deep learning-based melt-pool anomaly detection make it challenging for implementation due to the high speed. The NIST AM Data Integration Testbench is proposed and developed for AM researchers and practitioners to explore and validate various data integration strategies and the computational feasibility for real-time data analytics algorithms.

In addition to manufacturing operations, the integration of AM data and the means for data availability through the development lifecycle play a crucial role in advancing AM technology, including material development, process planning, and part design. Consistent data management and global standards are important to make data findable, accessible, interoperable, and reusable (FAIR). The testbench is also designed to test comprehensive data management capabilities, focusing on automated metadata curation for in-process data integration. The rich metadata associated with AM data, along with the ability to track the source and history of the data, allows researchers to confidently reuse the data for various purposes, such as process optimization, quality control, and predictive modeling [4].

Another important feature is AM-MES integration. MES software is the key to AM industrialization. Traditional MES software is highly limited in its ability to manage the unique requirements of AM. This has led to the rise of AM specialized MES systems that enables manufacturers to successfully manage their AM workflows and scale up their operations, ultimately harnessing the full potential of the technology. Hence, integrating AM systems with AM-MES software requires a radically new approach as well as enhanced information models compared to that defined in ISA 95 and ISA 88. Because most of the AM-MES are deployed in the cloud, the security concern has to be addressed.

This paper presents the design and implementation of the NIST AM Data Integration Testbench, along with a successful test case scenario. In section 2, we outline the testbench design based on requirements, detailing the implementation of the architecture and components. In section 3, we present a test case which monitors the performance of integrating data streaming and archiving data with metadata within the testbench. Section 4 discusses the potential utilization of the AM-MES for enhancing production management. After that, we summarize the progress and future work in section 5.

2. Testbench Design

In this section, we describe how we leverage the AM Integration Framework (AMIF) to design the testbench architecture and list the required features that we want to test. We demonstrate what specific hardware, software, and functions we are using for the current testbench implementation [2].

2.1 NIST AM Data Integration Testbench Requirements

To design the testbench, several key elements are required to ensure a completely integrated AM ecosystem, which also aligns with the goal to make AM data FAIR and facilitate the AM industrialization. By addressing these key requirements, the NIST AM Data Integration Testbench can be a versatile platform to drive the advancement and adoption of AM technologies.

2.1.1 Constructing an AM Emulator

We need this testbench to be non-disruptive to the current system so that when testing the data integration, we do not need to interfere with a real AM machine. To satisfy this requirement, we need an AM Emulator, which can provide the information just like an AM machine to the edge system, such as publishing the machine status by standard communication protocols, sending out the sensor data, receiving the decision-making command, etc.

2.1.2 In-Process Data Integration

Another critical requirement is capturing and integrating data in real-time during the building process. The testbench needs to handle the high-speed, high-volume data enabling effective monitoring, anomaly detection, and feedback control. Common sensors for process environment monitoring include temperature, pressure, and humidity. Common sensors for building behavior monitoring include laser beam position, actual laser power, melt-pool temperature, melt-pool images, and building overview images, which are all in different data formats, transfer rates, dimensions, and protocols making data integration a challenge [5].

2.1.3 Metadata Management

Capturing the complex relationships and dependencies within the data can make AM data FAIR to accelerate the sharing and collaboration within the AM community. The testbench should be designed with the capability to test the various information models for integration with metadata management tools.

2.1.4 AM-MES Integration

To automate the production order, scheduling, and planning for resource management, the MES is needed for mass production. Build preparation, process optimization, and quality control can be provided by AM-MES. The AM-MES integration requires bi-directional data exchange with communication protocols to function properly, which would be tested using the testbench and the commercial AM-MES.

2.1.5 Security Concerns

AM production machines for high value products are sophisticated Operational Technology (OT) systems and are typically expensive. As such, their components are expected to have a longer lifespan than lower-cost commodity hardware and software found in IT systems providing cloud services. This means that the AM machine is more likely to have legacy components lacking protection against recently discovered vulnerabilities. Therefore, integrating an AM machine with cloud-based MES and ERP systems introduces threats to intellectual property confidentiality, integrity of printed parts, and availability of the materials and hardware needed to ensure continuity and consistency of the manufacturing process. Judicious selection and implementation of security controls such as encryption, access control, and intrusion detection can lower these risks. Protecting the AM machine and process from attacks originating from the cloud is of particular concern. NIST's Guide to OT Security (Special Publication 800-82) [6] recommends that organizations develop and deploy a security architecture providing network segmentation and isolation to protect OT systems from such attacks. One implementation approach is to use unidirectional gateways—data diodes, for example—combined with automated verification of all information from the cloud to the OT. Only traffic permitted by the verification rules is allowed through. This approach was utilized in a recent pilot implementation of the NAMUR Open Architecture, a reference security architecture for decoupling IT and OT component life cycles [7].

2.1.6 Evaluate Computational Performance

Some AM in-process analytical functions are time-sensitive and require high-speed computation. For example, if we want to implement anomaly detection for in-situ monitoring or real-time feedback control to reduce process variability or generate datasets using generative models at high frequency, can data processing algorithms catch up with the AM processing speed without causing process delays? If the computational performance is inadequate, how far or what gaps remain, and what advancements are needed? A testbench can help evaluate the performance of these functions to determine if they are ideal for practical use in AM.

2.2 AM Data Integration Testbench Architecture

To meet the requirements, a three-tier testbench architecture is designed based on the NIST AM Data Integration Framework [2], as shown in Figure 2. The **AM Emulator PC** hosts an AM Process Event Generator to simulate the operation status of an AM machine and multiple In-Situ Sensor Data Generators to mimic the real data collecting sensors. The **Edge PC** uses Communication Protocols and In-situ Sensor Data Acquisition to receive machine status and sensor data respectively. At the Edge level, we can implement various functions to achieve Real-Time Analysis and Process Control. These include the Data Streaming Gateway for streaming data, Analytics Configuration for setting up the tools or parameters necessary for conducting analytics, and the MES Adapter, which acts as an interactive intermediary between the Edge PC and MES. The **Cloud** level contains three services. A Big Data Repository serves as a data lake to store high-volume data. AI Model Generation is used to develop and train AI models in the cloud before deploying them to the edge. MES and ERP indicate the software for production management, quality assurance, and enterprise applications like supply chain management.

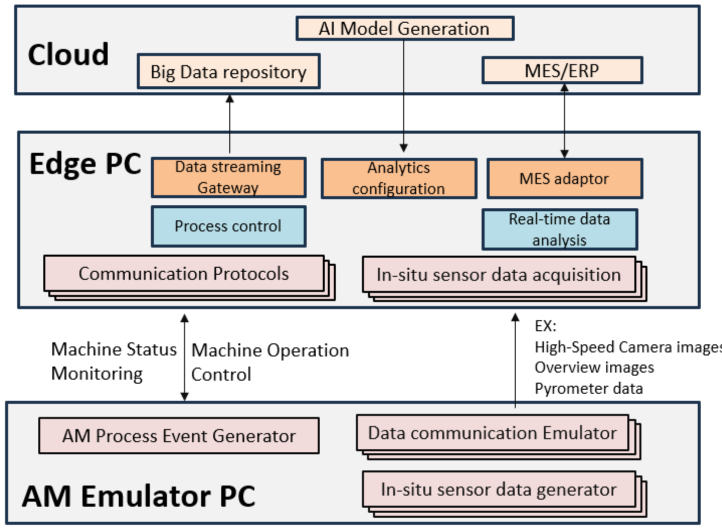

Figure 2. Testbench Design

2.3 Current NIST AM Data Integration Testbench Implementation

We decided to make incremental implementations based on the three-tier architecture. The current implementation is shown in Figure 3 and the modules currently implemented are indicated by the colored blocks.

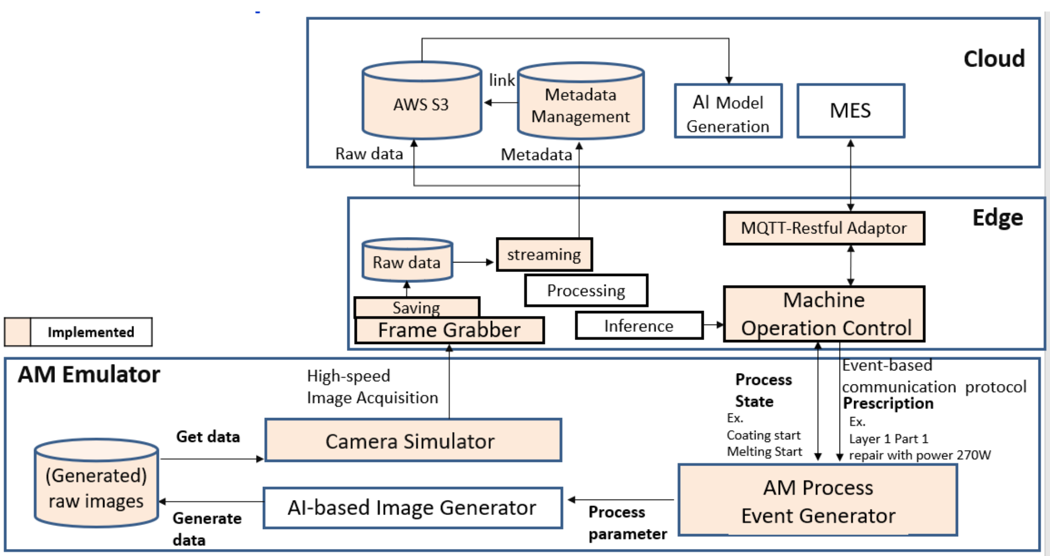

Figure 3. Current Implementation

2.3.1 AM Emulator PC

We are using a commercial **Camera Simulator,** which has the CoaXPress high-speed camera interface to transmit images from its on-board memory [8]. Those images could be archived images from a real AM in-situ monitoring system. An alternative method to generating raw images is an **AI-based Image Generator**. The CoaXPress is a common protocol adopted by high-speed camera manufacturers enabling the testbench to evaluate the performance of vision and imaging systems used for in-situ monitoring and control. To synchronize the camera data with the AM process events, as shown in the lowest stack in Figure 4, the **AM Process Event Generator** incorporates a **Socket** for triggering the Camera Simulator. This mechanism triggers a camera based on the occurrence of specific events, which are published by the MQTT Server [9].

The **MQTT Server** plays a crucial role in the event-driven architecture of the testbench, serving as the communication hub for the AM Emulator PC, Edge PC, and Cloud PC components. By publishing AM process events through the MQTT server, the testbench ensures that the Edge and Cloud functions can receive and respond to these events in real-time. This event-driven approach is essential for enabling timely monitoring and decision-making for real time control during the AM process.

2.3.2 Edge PC

The **Frame Grabber** shown in Figure 3 is also based on the CoaXPress [10]. This component can receive and process the high-speed camera data streams generated from the AM Emulator PC. The Frame Grabber contains an on-board FPGA, which has the potential to perform real-time image processing and feature extraction. This capability enables advanced in-situ monitoring and control functionalities, allowing for the detection of anomalies or defects during AM process to generate timely feedback for process adjustments.

The Edge PC has the **Streaming Function** leveraging the **Amazon Boto3 API** to automatically upload the camera data and other relevant process information to the cloud-based data lake. By minimizing the data backlog and ensuring timely data availability, the Streaming Function plays a crucial role in supporting the data sharing and process analytics.

The cloud-based MES system we are using has the RESTful API as its communication interface. To enable seamless integration with the Edge PC, we implemented an **MQTT-RESTful Adapter** allowing our Edge PC to interact with this MES.

2.3.3 Cloud

We use **Amazon S3** as a scalable data lake for archiving the raw data generated during the AM process. In addition, the Cloud also integrates a graph-based metadata management system, **DeepLynx** [11], to capture the complex relationships and dependencies within AM data. The automated metadata curation process is needed for future analysis and research. **AI Model Generation** can use the data with metadata stored in the Amazon S3 bucket to develop and train the AI models. Commercial **MES** would be used to test various data models and functions that can benefit and facilitate the AM industrialization.

3. Testbench Test Case – Melt Pool Image Streaming and Archiving with Metadata

To achieve the objective of automatic process flow, the testbench underwent stress testing methods. We implemented automatic high-speed data streaming from AM machines to cloud storage services to increase the data flow efficiency. By simulating AM in-situ process monitoring and measuring the duration of each function, we gained insight into the current capabilities and limitations of rapid data transfer. The present implementation of streaming and storing data allows quicker data availability, which can enable improved research and more opportunities to accomplish crucial AM data analytics.

3.1 Testing Configuration

The conducted test case was modeled from our previous accomplishments [2] and used an existing melt-pool image (MPI) dataset alongside estimated pre-testing parameters, which simulate AM processing events and internet configurations. The overhang part X4 from NIST Additive Manufacturing Metrology Testbed (AMMT) [12] is the selected dataset to supply melt-pool image data for swift data upload from local to S3 cloud storage. This build consists of 4 identical parts each constructed up to 250 layers total.

The overhang part X4 dataset size per layer is estimated around 200 - 370 MB and for 150 layers the average data size per layer is 259.705 MB. For this test case, the testbench utilizes an RJ45 ethernet cable for internet connectivity and each of the 4 parts are consolidated into 1 dataset file per layer. A total AM process event time to complete one layer of an AM build is estimated to be 12 seconds. The **process time per layer** portrays an estimated duration of AM data generation and serves to set a minimum required time to finish the dataset cloud upload. An upload that takes longer than the approximate 12 seconds would indicate that AM data transfer from local to cloud would be too slow to keep up with AM process events.

3.2 Function Time Sequence

The AM emulator, edge, and cloud functions work in parallel; however, the functions of all three modules perform asynchronously and do not follow a linear pathway from the beginning of melt-pool image generation to the end of the dataset and metadata storage. This optimizes the data streaming process but increases the potential for in-process streaming errors, for example, a significantly slower upload process and faster data generation process. Due to strict timing constraints, establishing a punctual workflow schedule will lower the possible failure risks. In Figure 4, the process and function flow graph demonstrate the multiple AM processes performed in real-time. The purpose of the figure is to obtain an idea about the timing measurement of AM data transfer speed based on our current configuration, and also represents an ideal flow scenario when every function executes tasks on schedule.

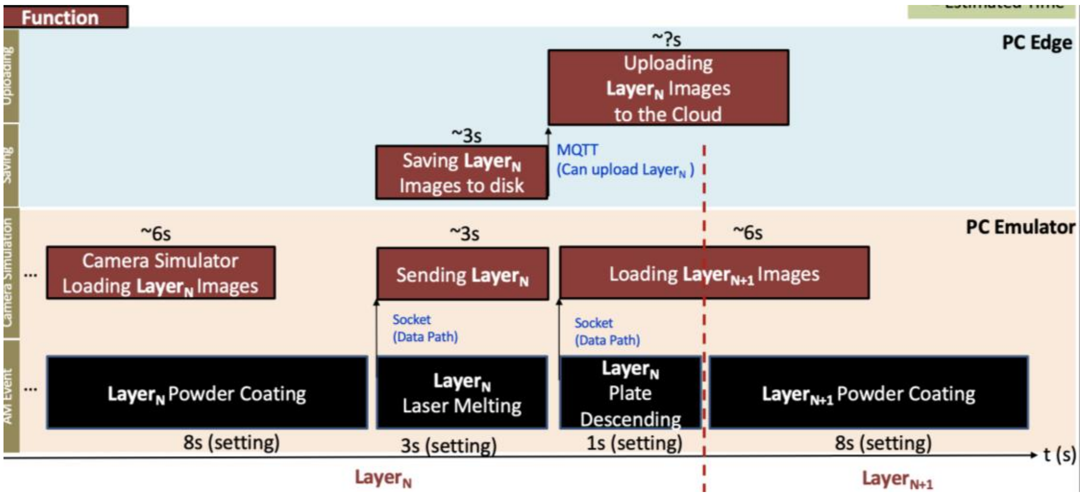

Figure 4. Function Time Sequence

3.3 Test Result

To achieve ideal process and function flow of AM data, Table 1 displays the result of the test case which must be higher than the estimated minimum required upload speed. AM data upload speed is calculated by **Avg Data Size per Layer / Avg Upload Time per Layer**.

Table 1. Test Case Upload Speed Minimum Requirement vs. Test Result

	Minimum Requirement	Test Result
Avg Data Size per Layer	259.705 MB	259.705 MB
Avg Upload Time per Layer	12 sec	3.584 sec
Avg Data Upload Speed	21.727 MB/sec	72.584 MB/sec

Results of the test case display approximately triple the upload speed compared to the minimum required upload speed. Streaming MPI data from local to cloud is able to keep up with local MPI data generation for this test case configuration; however, changes to the testing set up may yield different results. Many factors contribute to the end result of the upload speed which include data size, file quantity, internet connectivity, and the volume of testbench processes. Our current test case contains MPI data for 4 parts, but in future tests, the size of the dataset may increase. For example, we must determine if generating 16 parts with each part containing the same size of data per part as overhang part X4 can maintain a higher average data upload speed than the minimum requirement. Additionally, a dual ethernet connection may improve network bandwidth and can result with a higher average data upload speed; however, dual connections have not been proven effective due to the current limitations of the test case and laboratory configuration.

4. Data Interoperability for AM-MES Integration

Among all the challenges, data interoperability is the primary concern when integrating AM with manufacturing operations or enterprise applications. In this context, "Interoperability" refers to MES software's ability to work alongside and communicate with AM systems from different Original Equipment Manufacturer (OEMs). Interoperability can be specified at different levels. At a lower level, data can be transferred using communication protocols, for example, MQTT, AMQP or Apache Kafka. However, sending and receiving data are not the only requirements for interoperability. The semantic level interoperability allows data to be reused correctly, which is essential for decision making.

Various existing standards are utilized in the AM industry for AM system and MES integration, including OPC-UA, RESTful API, and MQTT, etc. However, there lacks semantic interoperability standards that provide a common information model to represent the data exchanged between AM systems and AM-MES software. Some ongoing efforts generated preliminary results, including the extension of MTConnect and Umati data models from the machining industry to AM systems. In MTConnect, several new data items and information models were added for AM, including a high-frequency data display and new data types and subtypes, such as humidity which is a critical environmental control process variable [13]. Umati, representing universal machine technology interface, is an open standard based on OPC-UA for machine tool integration. OPC 40540 for AM, is intended to facilitate the exchange of information between an AM machine and software systems such as MES, SCADA, ERP, or data analysis systems. Based on the plan, AM-specific job and component characteristics, material and consumable properties, and the material cycle are likely to be available in these standards [14].

While at NIST, our AM-MES interaction data modeling approach is to leverage on ISA 95, ISA 88, PACKML, as well as MTConnect data models. Our first test of AM-MES integration is based on the object types defined by the AM-MES software we acquired. In Table 2, we listed the data model from the AM-MES to the testbench. **Part Information -** This includes the CAD/3D model files that define the geometry and design of the part being manufactured in the AM process. **Material Information** - This includes details about the material being used, such as the material type and the batch number. This information is crucial for ensuring consistency and traceability in the manufacturing process. **Process Parameters** - This includes the key parameters that define the AM process, such as the layer thickness, laser power, scan speed, and build plate preheat temperature. These parameters directly impact the quality and performance of the final part. **Quality Control Tolerance** - This includes the acceptable tolerances for various quality metrics, such as density, coating homogeneity, and surface roughness. These tolerances are used to ensure that the final part meets the required specifications. Quality indicators should be adjusted according to requirement.

Table 2. Data Model from AM-MES to Testbench

Item	Information
Part Information	CAD/3D Model Files
Material Information	Material Type Batch Number
Process Parameters	Layer Thickness Laser Power Scan Speed Build Plate Preheat Temperature
Quality Control Tolerance	Density Coating Homogeneity

	Surface Roughness

In Table 3, we listed the data model from the testbench to the AM-MES. **Production Progress** - This includes the layer number which provides the AM-MES with the current layer number being processed in the AM machine. Knowing the layer progress is crucial for monitoring the overall production status and ensuring the build is proceeding as expected. **Operation Status** - This includes the powder coating, laser melting, and build plate descending, which are the critical steps in the LPBF AM process. Monitoring this status helps the MES understand the current state of the machine and identify any potential issues that could affect the quality of the final part. **Scheduling Information -** By receiving release time information from the AM machine, MES can effectively schedule other manufacturing timelines so that resources are allocated efficiently, and production processes are synchronized to meet production targets. **Quality Estimation Result -** This includes density, coating homogeneity, and surface roughness. MES can use this information to ensure that the part meets the design and requirement specifications.

Table 3. Data Model from Testbench to AM-MES

Item	Information
Production Progress	Layer Number
Operation Status	Powder Coating Laser Melting Build Plate Descending
Scheduling Information	Machine Release Time
Quality Estimation Result	Density Coating Homogeneity Surface Roughness

In this section, we list critical information essential for status monitoring, scheduling, and quality assurance. Interoperability within AM and MES is crucial for achieving mass production. However, without standardized models, each system may interpret data differently, causing compatibility issues. Therefore, our team plans to develop a standardized data model based on the key requirements for integrating AM with MES. This will ensure seamless integration for enhanced efficiency and scalability for manufacturing operations.

5. Conclusion

We implemented the NIST data integration testbench, which is a platform to help researchers and collaborators assess various AM data integration scenarios and showcased the currently implemented components from our underlying integration framework. In the case study, we demonstrated the integration capability of the testbench to stream high-speed data, archive large volumes of raw data with metadata automatically, and assist researchers in evaluating its performance. We also listed the data essential for bidirectional message transfer between the AM-MES and the AM machine. The testbench can be used to simulate and study the interaction between the data for automated production operation management.

In the future, we can include commercial emulators to work with this testbench for testing data interoperability. OPC-UA and MTConnect can also be included for testing purposes.

Additionally, investigating the computational performance or memory requirements for deep learning-based algorithms, whether at embedded or PC levels, is essential. Exploring various mechanisms that can protect the testbench from cyber threats will also be included. Researchers interested in data integration or system automation at any level are welcome to collaborate with us to foster the growth of AM ecology and facilitate industrialization.

Disclaimer and Acknowledgement

Certain commercial equipment, instruments, or materials identified in this paper are not intended to imply recommendation or endorsement by the National Institute of Standards and Technology, nor is it intended to imply that the materials or equipment identified are necessarily the best available for the purpose.

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