# A Framework for Identifying and Prioritizing Data Analytics Opportunities in Additive Manufacturing


Hyunseop Park
*Department of Industrial and Management Engineering*
*Pohang University of Science and Technology*
Pohang, Republic of Korea
hyunseop.park@postech.ac.kr

Hyunwoong Ko
*School of Mechanical and Aerospace Engineering*
*Nanyang Technological University,*
Singapore
kohy0060@e.ntu.edu.sg

Yung-Tsun T. Lee
*Engineering Laboratory*
*National Institute of Standards and Technogy*
Gaithersburg, MD
United States of America
yung-tsun.lee@nist.gov

Hyunbo Cho
*Department of Industrial and Management Engineering*
*Pohang University of Science and Technology*
Pohang, Republic of Korea
hcho@postech.ac.kr

Paul Witherell
*Engineering Laboratory*
*National Institute of Standards and Technology*
Gaithersburg, MD
United States of America
paul.witherell@nist.gov



***Abstract*— Many industries, including manufacturing, are adopting data analytics (DA) in making decisions to improve quality, cost, and on-time delivery. In recent years, more research and development efforts have applied DA to additive manufacturing (AM) decision-making problems such as part design and process planning. Though there are many AM decision-making problems, not all benefit greatly from DA. This may be due to insufficient AM data, unreliable data quality, or the fact that DA is not cost effective when it is applied to some AM problems. This paper proposes a framework to investigate DA opportunities in a manufacturing operation, specifically AM. The proposed framework identifies and prioritizes AM potential opportunities where DA can make impact. The proposed framework is presented in a five-tier architecture, including value, decision-making, data analytics, data, and data source tiers. A case study is developed to illustrate how the proposed framework identifies DA opportunities in AM.**



***Keywords—Data analytics, opportunity identification and prioritization, architecture, additive manufacturing***


## I. INTRODUCTION

Additive Manufacturing (AM) is a set of manufacturing technologies that join materials to produce three-dimensional (3D) objects from 3D solid models in layer-upon-layer ways opposed to the traditional subtractive manufacturing [1]. The tool-less and layer-upon-layer nature of AM provides unique capabilities of shape complexity, material complexity, hierarchical complexity, and functional complexity [2]. Such AM-enabled capabilities have largely lessened manufacturing constraints and significantly broadened design freedom, which offers new opportunities for developing functionally enhanced customized products [3]. AM is expected to lead the next generation of the manufacturing industry, the 1-batch customization era. To reach this expectation, it is important to improve performance in AM processes that eventually contributes to achieving the objectives of AM on first-part-correct and lead-time reduction.

Data analytics (DA) tools are expected to analyze data and produce actionable intelligence for the decision-makers. In recent years, the technology of DA has rapidly advanced [4]. Many researchers have demonstrated DA can help solve various manufacturing problems [5]. In this context, AM has been generating increasingly available data in the sense of volume, variety, and velocity [6]. The AM big data is providing great opportunities to use DA technologies and leverage DA capabilities to improve AM decision-making. Indeed, DA has been attracting attention in AM for data-driven decision-making [7].

DA studies in AM are still in the early stage. The majority of the existing DA studies in AM focuses on data analysis supporting only a few typical decision-making phases such as melt pool analysis for in-situ process signature monitoring [8]–[10]. This is because it is difficult to systemically map the decision-making and value chains to available DA capabilities and data, especially in AM where well-structured guidelines lack compared to other traditional manufacturing processes. It is necessary to systemically identify and prioritize DA opportunities in a complete view of AM decision-making that improves AM in general.

This paper proposes a novel framework for identifying and prioritizing DA opportunities in AM. The proposed framework has a five-tier architecture that consists of value, decision-making, data analytics, data, and data source tiers. Based on the architecture, the framework enables (1) identifying DA opportunities in AM and (2) prioritizing the identified DA opportunities. At the former phase, DA opportunities are identified with a top-down approach. The latter phase evaluates importance and feasibility (data readiness) of each identified DA opportunity.

The remainder of the paper is organized as follows. The second section describes background of AM data and DA opportunities. The third section introduces a five-tier architecture for AM data analytics that forms the foundation of the proposed framework. The fourth section presents the proposed framework for identifying and prioritizing DA opportunities in AM using the five-tier architecture. A case study in the fifth section implements the proposed framework. The paper is concluded with a brief conclusion and future work.

## II. BACKGROUND

### A. AM Data

Advancements in sensor technologies have led to an unprecedented increase in AM data, encompassing many of


Funding agency: National Institute of Standards and Technology

the aspects of big data. From the volume perspective, AM generates terabyte (TB) size of in-situ monitoring data per build and TBs of computed tomography (CT) scan data [7]. From the variety perspective, AM generates data types including numerical data (e.g., machine logs), 2D images (e.g., thermal, optical), 3D (e.g., CAD models, CT scans), Audio (e.g., acoustic signals), and videos (e.g., thermal, optical) [7]. From the velocity perspective, up to 600 variables may be logged per second during the build [7]. The examples of each AM data are categorized and listed in Section III.

To capture, store, and properly manage for AM data, [11] proposes an additive manufacturing integrated data model (AMIDM) based on a product lifecycle management data modeling methods. Reference [12] presents a collaborative AM data management system, which is set to evolve through sharing of both the AM schema and AM development data among the stakeholders in the AM community. Reference [13] presents a digital thread and data package for AM to address not only data manageability but also traceability and accountability. As noted with the above studies, AM data management is studied actively but there are only few cases of DA using AM data.

### *B. DA Opportunity Identification and Prioritization*

A DA opportunity can be defined as "a set of circumstances that makes DA possible to support and make impact on a decision-making issue". Due to the lack of existing cases to refer, it is difficult to identify and prioritize DA opportunities in AM. Besides, there is no systematic method available to discover a DA opportunity. To address this issue, this paper proposes a two-phase approach: (1) identifying opportunities, and (2) prioritizing the identified opportunities. The methods for each phase used currently are reviewed as follows.

For opportunity identification, DA architectures that help describe each DA opportunity can be leveraged. Two popular architectures are used to describe DA. The Data, Information, Knowledge, Wisdom (DIKW) hierarchy uses four main components such as data, information, knowledge, and wisdom to describe DA [14]. However, the DIKW hierarchy has been criticized for its hard-to-consent definition of each tier [15]. The Analytics Canvas uses four-layer model including analytics use cases, data analysis, data pool, and data sources to describe DA use cases and the necessary data infrastructure [16]. However, the Analytics Canvas does not have a component that describes the value that each DA opportunity pursue. The DA opportunities may differ depending on the values pursued even in the same use case. For example, in the use case of predictive maintenance, the DA opportunity solves different problems depending on whether the value pursued is quality (good parts), performance (as fast as possible), or availability (no stop time).

For opportunity prioritization, multi-criteria decision-making methods, such as Fuzzy analytic hierarchy process (AHP), Fuzzy technique for order of preference by similarity to ideal solution (TOPSIS), and Fuzzy quality function deployment (QFD), can be used. Reference [17] uses Fuzzy AHP and Fuzzy TOPSIS to prioritize newly identified business model alternatives. Reference [18] uses Fuzzy QFD and Data Envelopment Analysis (DEA) to prioritize project portfolio. Reference [19] uses Fuzzy AHP and Fuzzy TOPSIS to prioritize solutions for reverse logistics barriers. Reference [20] uses Fuzzy AHP to select sustainable energy conversion technologies for agricultural residues.

## III. Five-tier Architecture for AM Data Analytics

A five-tier architecture for AM data analytics is presented in Fig. 1. The architecture is composed of the following tiers: (1) 'Value Tier' where values pursued in AM lifecycle are defined, (2) 'Decision-Making Tier' where AM decision-making activities are defined, (3) 'Data-Analytics Tier' where DA problems are defined, (4) 'Data Tier' where AM data and information are defined, and (5) 'Data-Source Tier' where AM data sources are defined. DA opportunity can be represented as a package composed of these five tiers.

There are relationships that drive the interactions between each tier. 'Value Tier' gives motivation to 'Decision-Making

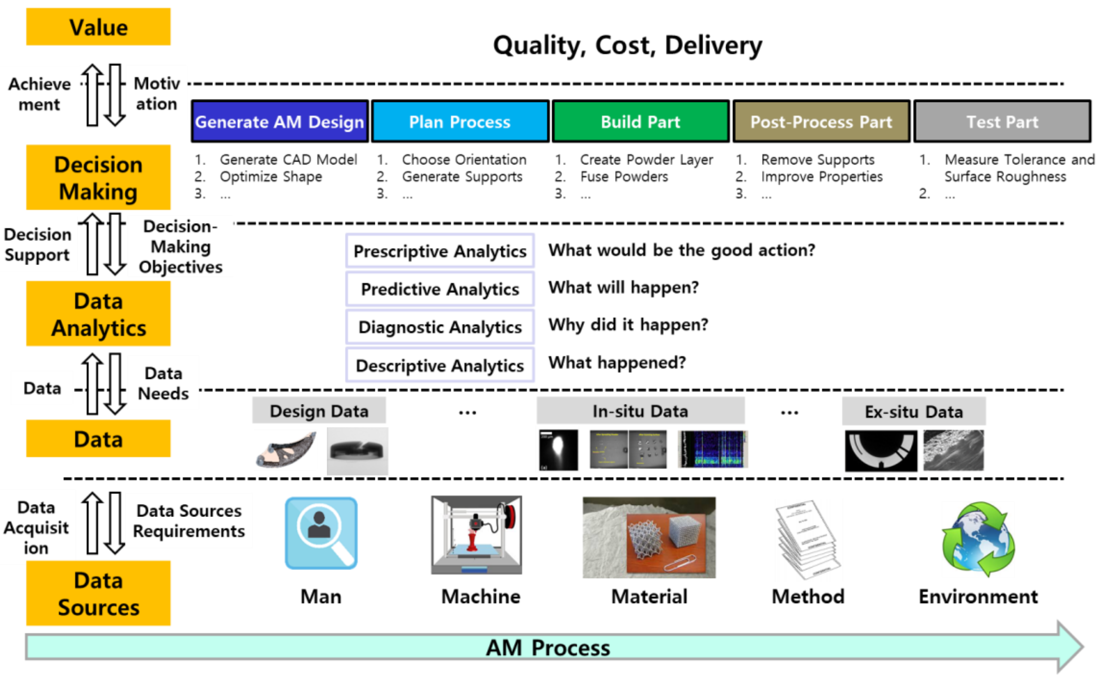


Fig. 1. 5-tier architecture for AM data analytics

Tier', 'Decision-Making Tier' achieves 'Value Tier'. 'Decision-Making Tier' gives decision making objectives to 'Data-Analytics Tier', 'Data-Analytics Tier' supports 'Decision-Making Tier'. 'Data-Analytics Tier' gives data requirements to 'Data Tier', 'Data Tier' provides data to 'Data-Analytics Tier'. Finally, 'Data Tier' gives data source requirements to 'Data-Source Tier' and 'Data-Source Tier' provides data sources to 'Data Tier'. Each tier is explained in more detail as follows.

### *A. Value Tier*

At the Value Tier, values pursued in AM lifecycle are defined in terms of Quality, Cost, and Delivery (QCD) [21]. QCD is about value dimensions used to assess production process. Quality in AM can be performance, conformance, durability, and aesthetics. Cost in AM can be labor costs, material costs, energy costs, and maintenance costs. Delivery in AM can be on-time delivery, right amount delivery, and right location delivery. Examples of related research works in AM are in improving quality [22], reducing cost [23], and realizing on-time delivery [24].

### *B. Decision-Making Tier*

At the Decision-Making Tier, decision-making activities for AM are defined. These activities follow the design-to-product transformation of the part, beginning at early design stages and ending with a finished part. The predefined activity model for Laser Powder Bed Fusion (LPBF) process [13], [25], which is represented using the IDEF0 [26], is used as an example. The top three levels of the decision-making activities listed in that model are shown in Table I. It includes six of Level-1 activities: 'Generate AM Design', 'Plan Process (Machine Independent)', 'Plan Process (Machine Dependent)', 'Build Part', 'Post-process Part', and 'Test Part'. These six activities are decomposed to twenty-two (22) Level-2 and thirty-four (34) Level-3 sub-activities. Decision-making objectives for each decision-making activity are also defined at this tier.

Using IDEF0, the decision-making activities can be defined by functions and related components such as input (I), control (C), output (O), and mechanism (M), or ICOM [26]. A function describes what an activity should accomplish. An input can be data, objects, or materials that are transformed by the activity. A control can be one or more conditions necessary for the activity to create correct outputs. An output is a set of results generated by the activity. A mechanism is the means that support the execution of the activity such as software, equipment, and personnel. An example is shown in Fig.2 [25]. The activity 'A11: Generate CAD Model' itself is a function. The input of the activity is a design, which refers to the conceptual design of a part and related design requirements. The control of the activity is guidelines, which refers to the design guidance that may be provided from feedback opportunities or part of governing design or process or material requirements. It is at the controller where many of the decision-making opportunities can be identified, as the configuration of the controller will impact the output of the activity. Here, the output of the activity is a CAD model, which refers to the computer-generated geometry that was developed using a CAD software. The mechanism of the activity is software, which is used to transform the design into a CAD model.

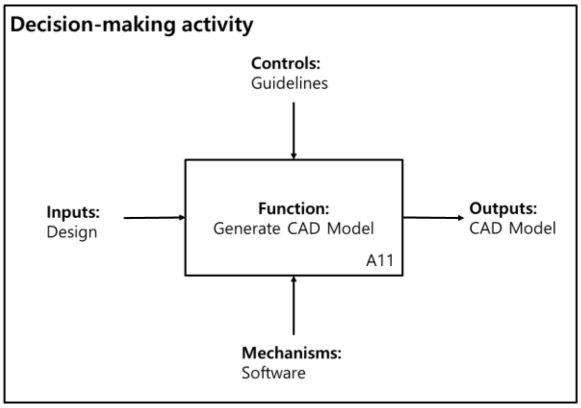


Fig. 2. Representation of a decision-making activity [25]

TABLE I. HIGH LEVEL DECISION-MAKING ACTIVITIES IN AM

| ***Level-1*** | ***Level-2*** | ***Level-3*** |
|---|---|---|
| A1: Generate AM Design | A11: Generate CAD Model | - |
| | A12: Optimize Shape | - |
| | A13: Tessellate Model | - |
| | A14: Repair Tessellated Model | - |
| | A15: Modify Tessellated Model | - |
| A2: Plan Process (Machine Independent) | A21: Choose Orientation | - |
| | A22: Generate Supports | - |
| A3: Plan Process (Machine Dependent) | A31: Setup Tessellated Model | A311: Determine Orientation |
| | | A312: Design Supports |
| | A32: Create Build Model | A321: Place Part |
| | | A322: Generate Slices |
| | | A323: Generate Scan Strategy |
| | A33: Plan Powder Fusion Strategy | A331: Set Quality Parameters |
| | | A332: Set Control Parameters |
| | | A333: Set Powder Fusion Parameters |
| | | A334: Set Recoating Parameters |
| | A34: Plan Monitoring Strategy | - |
| A4: Build Part | A41: Create Powder Layer | - |
| | A42: Fuse Powders | - |
| | A43: Monitor Fusion | - |
| A5: Post-process Part | A51: Remove Supports | - |
| | A52: Improve Properties | - |
| | A53: Finish Part | - |
| A6: Test Part | A61: Measure Tolerances and | A611: Measure External Tolerances |

| ***Level-1*** | ***Level-2*** | ***Level-3*** |
|---|---|---|
| | Surface Roughness | A612: Measure Internal Tolerances |
| | | A613: Measure Surface Roughness |
| | A62: Measure Porosity and Cracks | A621: Measure Part Porosity |
| | | A622: Identifying and Measure Cracks |
| | A63: Measure Part Properties | A631: Measure Mechanical Properties |
| | | A632: Measure Microstructures Properties |
| | | A633: Measure Electrical Properties |
| | | A634: Measure Chemical Properties |
| | | A635: Measure Thermal Properties |
| | A64: Evaluate Test Results | - |

### *C. Data-Analytics Tier*

At the Data-Analytics Tier, each decision-making objective may be translated in DA perspectives with the following four types of analytics: prescriptive analytics, predictive analytics, diagnostic analytics, and descriptive analytics [16]. Each type of analytics is described as follows. Prescriptive analytics is to answer the question of what action should be done. Prescribing optimized powder fusion parameters is an example of prescriptive analytics in AM. Predictive analytics is to answer when and what will happen. Predicting porosity is an example of predictive analytics in AM. Diagnostic analytics is to answer the question of why it happened. Identifying the relationship between design parameters and surface roughness is an example of diagnostic analytics in AM. Descriptive analytics is to answer the question of what happened. Characterizing melt pool behavior is an example of descriptive analytics.

As the type of DA is defined, it is often easier to choose suitable algorithms in a practical use. For prescriptive analytics, reinforcement learning algorithms, such as Deep Q-Learning, and recommender system algorithms, such as associate rule mining, can be used to find best action or optimize problems [27]. For predictive analytics, supervised learning algorithms, such as neural networks and support vector machine, can be used to develop predictive model [27]. For diagnostic analytics, unsupervised learning algorithms, such as K-means clustering, can be used for grouping a set of objects; and supervised learning, such as linear regression, can be used to identify causal relationships [28]–[30]. For descriptive analytics, general statistics, like mean, min, and max; and signal processing algorithms, like Wavelet Transform and Fast Fourier Transform, can be used to obtain meaningful descriptive information from raw data [31].

### *D. Data Tier*

At the Data Tier, AM data types are defined. AM generates a variety of data. Examples are listed as follows [7].

- Material properties: material chemistry, material microstructure, powder size distribution, etc.
- Design parameters: wall thickness, orientation, overhang angle, etc.
- Process parameters: laser power, scan speed, hatch spacing, machine logs, etc.
- Process signatures: thermal data (e.g., melt pool width, temperature), optical images and videos, acoustic signals, etc.
- Part property: tensile toughness, hardness, etc.
- Product performance: fatigue life, corrosion, meets design criteria, etc.

AM data can be stored in database systems. The Additive Manufacturing Materials Database (AMMD) [32] built by National Institute of Standards and Technology (NIST) is an example.

### *E. Data-Sources Tier*

An AM lifecycle is composed of five stages: (1) Design, (2) Process Plan, (3) Build, (4) Post Process, and (5) Test and Validation [11]. Each stage produces data from its data sources. In this tier, the data sources can be categorized into Man, Machine, Material, Method, and Environment (4M1E) [33].

4M1E are the foundation resources managed for QCD in production systems. To achieve QCD, data from 4M1E needs to be analyzed. Among 4M1E, Man means participants in the AM lifecycle such as part designers and process planners. Machine can be every machine used in the AM lifecycle including coordinate measuring machine and AM machine, also known as 3D printer. Material can be any material used in the AM lifecycle such as plastic, metal powder, or ceramic. Method in the AM lifecycle can be AM standards, part measurement methods, test specifications, etc. Finally, Environment in the AM lifecycle can be software, workplace, temperature, energy usage, etc.

## IV. Proposed Framework

The proposed framework uses a five-tier architecture with sequential steps. By applying the proposed framework to set an overall DA -direction in AM, we use a two-phase approach. First, the proposed framework helps to identify DA opportunities through a top-down approach. Second, the proposed framework helps prioritize the identified DA opportunities in terms of importance and feasibility. Here, the feasibility refers to data readiness. The detail processes are described as follows.

### *A. Phase 1 - Identifying DA Opportunities*

DA opportunities are identified with a top-down approach, as shown in Fig. 3. First, AM-lifecycle values are determined using QCD at the Value Tier. The value(s) can be one or more of the following: ‘Quality’, ‘Cost’, and ‘Delivery’, or their extensions, such as “Aesthetics” and “labor costs efficiency”.

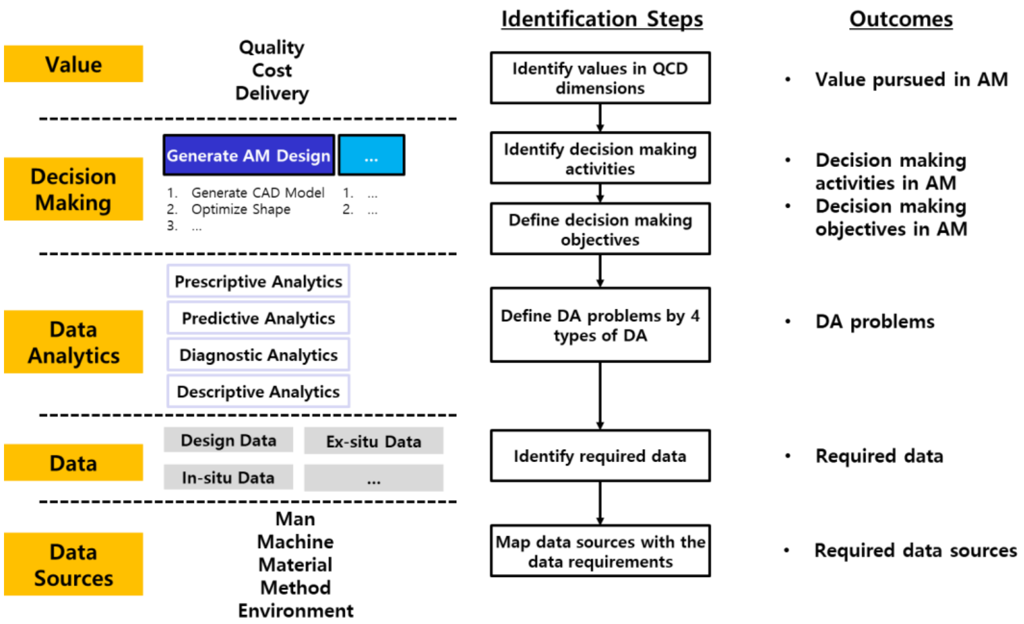


Fig. 3. Identification of DA Opportunities

Decision-making activities and decision-making objectives are identified in the 'Decision-Making Tier'. Decision-making activities are related to a pre-defined value from the Value Tier, here identified from the existing activity models, e.g., Table I. As mentioned in Section III, the decision-making activities can be broken into a set of functions and ICOMs. Once the value and decision-making activities are defined, a decision-making objective can be stated as "**Improving + [value] + when + [decision-making activity]**", where "Improving" and "when" provide syntax. For example, if the target value and decision-making activity are defined as "Material cost efficiency" and "A11: Generate CAD Model", then the corresponding decision-making objective can be stated as "Improving material cost efficiency when Generate CAD Model".

Once a decision-making objective is defined, potential types of DA problems are defined for each decision-making objective at the 'Data-Analytics Tier'. The syntax of each DA problem is summarized as follows. Note that these syntaxes are examples and are for the illustration purpose. A more complete syntax is currently under development.

- Prescriptive analytics: **"Prescribing + [C] + to maximize + [V]"**
- Predictive analytics: **"Predicting + [V] + based on given + [ICOM]"**
- Diagnostic analytics: **"Identifying relationship between + [ICOM] + and + [V] + based on their characteristics"**
- Descriptive analytics: **"Characterizing + [I] + [C] + [O] + [M] + [V]"**

Where V represents a predefined value from the Value Tier, and I is a input, C is a control, O is an output, M is a mechanism defined in the ICOM.

The goal of the prescriptive analytics is to directly support the achievement of the objectives of the corresponding decision-making activity in the IDEF0. Therefore, the prescriptive analytics tier in the framework identifies prescriptive analytics problems that consider DA objectives based on V, which aims to construct data-driven prescriptive guidelines. Based on the structured syntax of prescriptive analytics problems, following prescriptive analytics supports the development of a condition in C that can maximize V. The syntax is intended to lead associated prescriptive analytics to specifically support a transformation of an input I to a desired O with a consideration of M identified from the IDEF0 representation. Based on the syntax, prescriptive analytics can be then designed under possible situations or scenarios, to suggest courses of actions or strategies.

The predictive analytics tier aims to identify analytics problems to predict the target V. V is intended to be maximized in the prescriptive analytics. Therefore, V is used as criteria for suggesting courses of actions or strategies in the prescriptive analytics. To support this, the predictive analytics tier sets problems to predict information about possible situations or scenarios influencing V. Leveraging V and ICOM, the proposed syntax of predictive analytics problems helps to design data analytics that provides predictive criteria for associated prescriptive analytics.

The diagnostic analytics tier sets analytics problems for identifying the corelationships between ICOM and V in the past, or identifying which ICOM relationships influenced V in the past. The proposed syntax of diagnostic analytics problems helps to set data analytics approaches that provide bases the associated predictive analytics selects/extracts predictive parameters based upon. An example of the diagnostic analytics that can be considered is data analysis of ICOM relationships as root causes of the target V. Such analysis can be pursued leveraging the proposed syntax to support the V prediction of which analytics is designed in the upper-level predictive analytics tier.

The descriptive analytics tier identifies analytics problems to characterize ICOM and V to support the identification of relationships in the diagnostic analytics. It generates descriptive parameters representing data requirements that describe the required characteristics or behaviors of ICOM- and V-specific data. The ICOM- and V-specific data are then adaptively requested in the data tier to support the identification of DA opportunities.

The following examples illustrate the four DA problem types by using the same decision-making objective discussed previously, i.e., “Improving material cost efficiency when Generate CAD Model”. Note that the ICOM of A11 are I: Design, C: Design Guidelines, O: CAD Model, and M: CAD Software. To achieve that objective, a prescriptive analytics problem can be defined as “Prescribing Design Guidelines to maximize Material cost efficiency”. A predictive analytics problem can be “Predicting Material cost efficiency based on given Design, Design Guidelines, CAD Model, CAD Software”. A diagnostic analytics problem can be “Identifying relationship between Design, Design Guidelines, CAD Model, CAD Software and Material cost efficiency based on their characteristics”. Finally, a descriptive analytics problem can be “Characterizing each Design, Design Guidelines, CAD Model, CAD Software, and Material cost efficiency”.

Each defined DA problem, presented using the proposed syntax, with some grammar modifications when necessary, is treated as the title of a DA opportunity. Note that descriptive analytics can be sometimes substituted by the outputs of other decision-making activities. For example, when “Characterizing aesthetic”, other quality indicators such as surface roughness of ‘A613: Measure Surface Roughness’ can be used.

To realize the objectives of the DA problems data requirement for each DA problem should be defined at the ‘Data Tier’. For the above example, the descriptive analytics for “Characterizing each Design, Design Guidelines, CAD Model, CAD Software, and Material cost efficiency” requires data related to the Design, Design Guidelines, CAD Model, and Material cost efficiency. The prescriptive analytics for “Prescribing Design Guidelines to maximize Material cost efficiency” requires not only to have data related to the Design, Design Guidelines, and CAD Model, and Material cost efficiency but also the results of other analytics including the predicted Material cost efficiency as well. The data requirements of the DA problem will influence the feasibility of each DA opportunity. This is because the feasibility is mainly measured based on the data readiness level.

Finally, data sources are defined in the ‘Data-Source Tier’. For instance, to satisfy the data requirements for the “Characterizing Design, Design Guidelines, CAD Model, CAD Software, Material cost efficiency,” it requires data from these data sources: part designer, design guideline documents, CAD software, and cost measurement method.

Often, we identify many DA opportunities through the phase 1 process. In reality, it is difficult and also not necessary to research and develop all the identified DA opportunities, due to the constraints of time, cost, and importance. Therefore, prioritizing the DA opportunities is an important task.

### *B. Phase 2 - Prioritizing DA Opportunities*

As shown in Fig. 4., the prioritization phase is broken into two parts: evaluating the importance of each DA opportunity and evaluating the feasibility of each DA opportunity. Decision makers (DMs) are the key persons to participate in the evaluation.

To evaluate the importance of each DA opportunity, the evaluation is performed by the DMs, starting from the ‘Value Tier’ to the ‘Decision-Making Tier’, and then to the ‘Data-Analytics Tier’. First, the importance of each identified value is assessed. Then, the importance of improving each identified value for the corresponding decision-making activity is evaluated and rated. At last, the importance of each DA problem for the decision-making activity is evaluated and rated. Finally, using a hierarchical multi-criteria decision-making method, the importance of each DA opportunity can be calculated.

To evaluate the feasibility of each DA opportunity, the evaluation is performed through ‘Data Source Tier’ to ‘Data Tier’ and ‘Data Tier’ to ‘Data-Analytics Tier’. First, the feasibility of data satisfying the requirements for each DA opportunity is investigated. Then, the importance of each data for each DA problem is evaluated. Finally, the data readiness

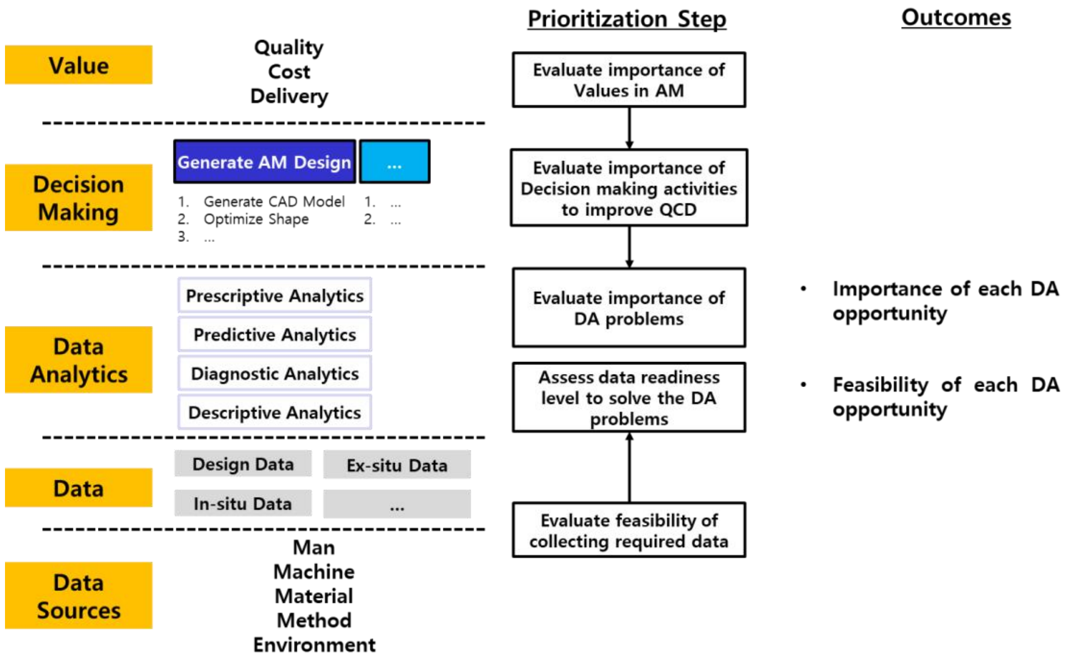


Fig. 4. Prioritization of DA opportunities

level for each DA opportunity is assessed by performing a gap analysis between the feasibility and the importance of the required data.

A sample output of the prioritization, i.e., Phase 2, using the proposed framework is shown in Fig. 4. The identified DA opportunities from Phase 1 are mapped into the prioritization matrix, where x-axis represents feasibility and y-axis represents importance. Based on the prioritization matrix, the identified DA opportunities can be classified into four groups, as shown in Fig. 5.

When mapping DA opportunities, the DA opportunities in the high importance and high feasibility groups are critical to work on. On the other hand, the DA opportunities in the low importance and low feasibility group are considered the lowest priority. The DA opportunities in the high importance and low feasibility group are potentially critical projects, where new solutions may be needed to improve the data readiness level and hence upgrade the prioritization group of the opportunity. The DA opportunities in the low importance and high feasibility group may be easy to develop but most likely the effort is not beneficial, however, sometimes such opportunities might be useful for proof of DA concept in emerging areas.

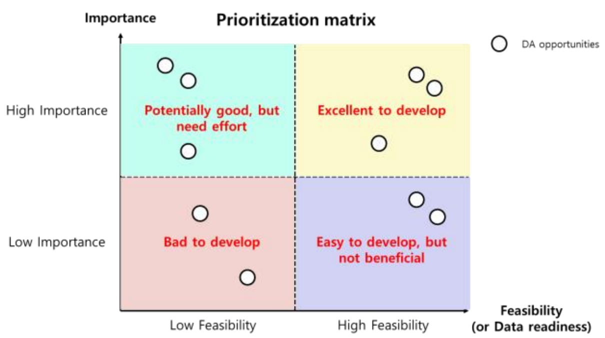


Fig. 5. Prioritization matrix

## V. CASE STUDY

Phase 1 of the proposed framework is illustrated in this case study on LPBF processes. Table II shows the outputs of the proposed framework in the overall cases. Three cases, Case 1, Case 2, and Case 3 are identified by the proposed top-down approach.

The case study begins by taking the input Vs: surface texture quality, part porosity reducibility, and time efficiency. The Vs are mapped to associated decision-making activities of 'Design', 'Build Part', and 'Test Part' in Case 1, Case 2, and Case 3, respectively, in the Decision-making Tier. Then, the target levels of decision-making abstraction are systematically identified through the decomposition of the functional relationships in the IDEF0 that represents the Decision-making Tier. The AM activities identified at the target abstraction levels are "Generate Detailed Design Model for LPBF", "Monitoring In-situ Process Signatures of LPBF Behaviors", and "3D Scan Part". Once the target AM activity is determined, its corresponding ICOMs and decision-making objectives are also identified for the DA.

At the Data Analytics Tier, the target Vs, ICOMs, and decision-making objectives are leveraged to define DA objectives utilizing the proposed DA objective structures. For example, in Case 1, the Prescriptive Analytics has an objective of "Prescribing design rule to maximize surface texture quality". This objective is identified to prescriptively guide what specific design actions the activity A12-n should pursue to maximize surface texture quality for LPBF. The required information for this prescriptive analytics is the predicted surface texture quality (V for Case 1) based on based on given overhang design model, design rule, process plan, material properties, redesigned part. Based on this requirement, the Predictive Analytic formulates "Predicting surface texture quality based on given overhang design model, design rule, process plan, material properties, redesigned part".

The Dignostic Analytics in Case 1 aims to solve an associated problem to support the predictive analytics. Case 1's predictive analytics requires identified relationships between the overhang design model (I for Case 1), design rule for overhang features, process plan, material properties (C for Case 1), and surface texture quality (V for Case 1). Based on this requirement, a diagnostic analytics objective is set as "Identifying relationship between overhang design model, design rule, process plan, material properties, and surface texture quality based on their characteristics". Such objectives help group data features and set necessary hypotheses in predictive analytics. Finally, the Descriptive Analytics has an objective of "Characterizing each overhang design model, design rule, process plan, material properties" to generate descriptive parameters that describe the characteristics and behaviors of Case 1-specific data.

In the proposed top-down approach, the DA objective structures enable selecting or requesting AM data sets suitable for each type of data analytics. At the same time, the DA objective structures become a bridge that links values and decision-making objectives to data requirements. Therefore, the top-down approach adaptively generates data requirements that are goal-oriented as well as DA type-specific. Such advantage provides varying DA opportunities even for the same data sources that bottom-up approaches may not be able to capture. The data of material type are good examples while they are commonly required in the 3 cases for different values, decision-making objectives, and DA types. When required data sets are not available, the top-down approach can generate a request for new AM data to incorporate data requirements into plans for further data obtainments [34]. Examples of the further data obtainment can be fusions of available data, field tests and simulations, and installations of sensor environments guided by the top-down approach.

The case study identified twelve DA opportunities from the three cases in the AM lifecycle. It is meaningful that the DA opportunities are identified without heavily referring to existing opportunities identified from other existing DA studies. This study is expected to serve as a structured guideline for researchers and practitioners who seek new DA opportunities in AM. However, the case study did not prioritize the identified DA opportunities yet. More opportunities remained to be identified so we will prioritize them in the future work.

TABLE II. AN OVERVIEW OF CASE STUDIES: OUTPUT OF EACH TIER

| **Tier** | **Sub-items** | **Case Studies** | | |
|---|---|---|---|---|
| | | ***Case 1*** | ***Case 2*** | ***Case 3*** |
| Value | Quality | Surface texture quality | Part porosity reducibility | - |
| | Cost | - | - | - |
| | Delivery | - | - | Time efficiency |
| Decision Making | Decision Making Activity | A1: Design<br>A12: Optimize shape<br>A12-n: Generate Detailed Design Model for LPBF<br>• I: Overhang design model<br>• C: Design rule for overhang features, Process plan, Material properties<br>• O: Redesigned part<br>• M: CAD Software | A4: Build Part<br>A43: Monitoring fusion<br>A43-n: Monitoring in-situ process signatures of LPBF behaviors<br>• I: In-situ process signatures<br>• C: In-situ defect evaluation rule/guideline, Process plan, material properties<br>• O: Evaluation results<br>• M: In-situ monitoring cameras and software | A6: Test Part<br>A61: Measure Tolerance and Surface Roughness<br>A611: Measure External Tolerances<br>A611-n: 3D Scan part<br>• I: Target part<br>• C: 3D Scan path, material properties<br>• O: Reconstructed 3D model<br>• M: Robotic 3D scanning system |
| | Decision Making Objective | Improving surface texture quality when generating detailed design model for LPBF | Improving part porosity reducibility when monitoring in-situ process signatures of LPBF behaviors | Improving time efficiency when 3D Scan part |
| Data Analytics | Prescriptive Analytics | Prescribing design rule to maximize surface texture quality | Prescribing in-situ defect evaluation rule/guideline to maximize part porosity reducibility | Prescribing 3D scan path to maximize time efficiency |
| | Predictive Analytics | Predicting surface texture quality based on given overhang design model, process plan, material properties | Predicting part porosity reducibility based on given in-situ process signatures, process plan, material properties | Predicting time efficiency based on given target part, 3D scan path, and material properties |
| | Diagnostic Analytics | Identifying relationship between overhang design model, process plan, material properties, and surface texture quality based on their characteristics | Identifying relationship between in-situ process signatures, process plan, material properties, and part porosity reducibility | Identifying relationship between target part, 3D scan path, material properties and time efficiency based on their characteristics |
| | Descriptive Analytics | Characterizing overhang design model, design rule, process plan, material properties | Characterizing in-situ process signatures, process plan, material properties, part porosity reducibility | Characterizing target part, 3D scan path, material properties, time efficiency |
| Data | For Prescriptive Analytics | Data of predictive surface roughness with given overhang geometry, process plan, and material properties changes | Data of predictive porosity density, shape, location with given in-situ process signatures, process plan, and material properties | Data of predictive scan time with given target part, scan path, reconstructed 3D model, material properties, scanning environment |
| | For Predictive Analytics | Historical data on the surface roughness as response variable<br>Selected/extracted features from overhang geometry, process plan, and material properties as input variables | Historical data on the porosity density, shape, location as response variable<br>Selected/extracted features from in-situ process signatures, process plan, and material properties as input variables | Historical data on the scan time as response variable<br>Selected/extracted features from target part, scan path, reconstructed 3D model, material properties, and scanning environment as input variables |
| | For Diagnostic Analytics | Historical data on the surface roughness as response variable<br>Historical data on overhang geometry, process plan, and material properties as input variable | Historical data on the porosity density, shape, location as response variable Historical data on in-situ process signatures, process plan, and material properties as input variable | Historical data on the scan time as response variable<br>Historical data on target part, scan path, reconstructed 3D model, material properties, and scanning environment as input variables |
| | For Descriptive Analytics | Surface roughness data, Overhang geometry data (e.g. overhang type, downskin, surface angle, overhang dimension), Process plan data (e.g. tool path, energy source, power, speed, hatching distance, layer thickness, part position and orientation), and Material properties (e.g. density, powder distribution, material type), Design rule data | Porosity data (e.g. density, shape, location), In-situ process signatures (e.g. melt pool size, shape), Process plan data (e.g. tool path, energy source, power, speed, hatching distance, layer thickness, part position and orientation), and Material properties (e.g. density, powder distribution, material type), Design rule data | Scan time data, Target part data (e.g. CAD data), Scan path data, Reconstructed 3D model (e.g. point cloud), Material properties (e.g. material type), and Scanning environment data (e.g. light condition) |
| Data Source | Man | - | - | - |
| | Machine | LPBF machine, Ex-situ part measurement machine (e.g., XCT scanner) | LPBF machine, in-situ monitoring camera (e.g., optical camera), ex-situ part measurement machine (e.g., XCT scanner) | 3D scanning robot |
| | Material | Process planning model, LPBFed part model | In-situ process signature model, process planning model, LPBFed part model | Target part |
| | Method | CAD development, LPBF machine control method, surface and volume measurement system (e. g., XCT scanner) | LPBF machine control method, in-situ monitoring method, surface and volume measurement system (e. g., XCT scanner) | 3D reconstruction method |
| | Environment | - | - | Scanning environment, CAD software |

## VI. Conclusion

Although AM generates big data that provides opportunities to use DA, the AM community does not have many successful stories of the DA applications. The lack of DA cases makes it difficult for researchers and practitioners in AM to define the AM problems where DA can have an impact. To address this issue, this paper proposes a framework in a five-tier architecture, including value, decision-making, data analytics, data, and data sources, to help (1) identify and (2) prioritize DA opportunities in AM. For the former phase, a top-down approach in the five-tier architecture is formulated with a set of suggested syntaxes for describing potential DA opportunities. For the latter phase, there are two dimensions to be evaluated for prioritization: importance and feasibility. By using the proposed framework, a case study identified twelve DA opportunities in LPBF processes. These DA opportunities were identified from different values, decision-making activities, and DA types, where values are the targets the improvement aims at, decision-making activities are the AM activities that could potentially be improved in terms of quality, cost and delivery, and DA types include prescriptive, predictive, diagnostic, and descriptive analytics. The case study demonstrates the proposed framework could systematically identify potential DA opportunities in a complete view of the AM lifecycle, without heavily relying on the existing DA studies in AM. Since this framework does not stick to a certain domain so it is expected to contribute to not only AM but also other domain where DA is pre-mature.

The future work will focus on formalizations of the proposed framework that will enable the identification and prioritization of DA opportunities in a consistent way. We will continue to develop novel sets of syntax structures where the proposed formulations of DA objectives are expanded. The range of the syntax structure formulation will be expanded for the other tiers in the proposed architecture as well. The future work will then transform the prioritization phase into a formal method. The formal method will be equipped with the prioritization techniques mentioned in Section II. Furthermore, the formalized framework will be implemented in software environments with AM data and knowledge bases to automatically support identifying and prioritizing DA opportunities. The continuation of this study will eventually provide a set of DA opportunities with higher data readiness level and higher impact to the AM community.

## Acknowledgment

The authors acknowledge the support by the Additive Manufacturing Program at the National Institute of Standards and Technology (NIST), US Department of Commerce. Certain commercial systems are identified in this article. Such identification does not imply recommendation or endorsement by NIST; nor does it imply that the products identified are necessarily the best available for the purpose. Further, any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of NIST or any other supporting U.S. government or corporate organizations.

## References

[1] "ASTM F2792-12a, Standard Terminology for Additive Manufacturing Technologies (Withdrawn 2015)." ASTM International, West Conshohocken, PA, 2012.

[2] I. Gibson, D. Rosen, and B. Stucker, "Design for Additive Manufacturing," in *Additive Manufacturing Technologies: 3D Printing, Rapid Prototyping, and Direct Digital Manufacturing*, New York, NY: Springer New York, 2015, pp. 399–435.

[3] H. Ko, S. K. Moon, and J. Hwang, "Design for additive manufacturing in customized products," *Int. J. Precis. Eng. Manuf.*, vol. 16, no. 11, pp. 2369–2375, 2015.

[4] S. J. Qin and L. H. Chiang, "Advances and opportunities in machine learning for process data analytics," *Comput. Chem. Eng.*, vol. 126, pp. 465–473, 2019.

[5] T. Wuest, D. Weimer, C. Irgens, and K. D. Thoben, "Machine learning in manufacturing: Advantages, challenges, and applications," *Prod. Manuf. Res.*, vol. 4, no. 1, pp. 23–45, 2016.

[6] P. Witherell, "Emerging Datasets and Analytics Opportunities in Metals Additive Manufacturing," in *Direct Digital manufacturing Conference*.

[7] S. S. Razvi, S. Feng, A. Narayanan, Y.-T. T. Lee, and P. Witherell, "A review of machine learning applications in additive manufacturing," in *Proceeding of the ASME 2019 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 2019. in press.

[8] L. Scime and J. Beuth, "Using machine learning to identify in-situ melt pool signatures indicative of flaw formation in a laser powder bed fusion additive manufacturing process," *Addit. Manuf.*, vol. 25, no. November 2018, pp. 151–165, 2019.

[9] Z. Yang, L. Yan, H. Yeung, and S. Krishnamurty, "Investigation of Deep Learning for Real-Time Melt Pool Classification in Additive Manufacturing."

[10] Y. Zhang, G. S. Hong, D. Ye, K. Zhu, and J. Y. H. Fuh, "Extraction and evaluation of melt pool, plume and spatter information for powder-bed fusion AM process monitoring," *Mater. Des.*, vol. 156, pp. 458–469, 2018.

[11] Y. Lu, S. Choi, and P. Witherell, "Towards an integrated data schema design for additive manufacturing: Conceptual modeling," *Proc. ASME Des. Eng. Tech. Conf.*, vol. 1A-2015, no. August, 2015.

[12] Y. Lu, P. Witherell, and A. Donmez, "A collaborative data management system for additive manufacturing," *Proc. ASME Des. Eng. Tech. Conf.*, vol. 1, pp. 1–7, 2017.

[13] D. B. Kim, P. Witherell, Y. Lu, and S. Feng, "Toward a Digital Thread and Data Package for Metals-Additive Manufacturing," *Smart Sustain. Manuf. Syst.*, vol. 1, no. 1, p. 20160003, 2017.

[14] J. Gu and L. Zhang, "Data, DIKW, big data and data science," *Procedia Comput. Sci.*, vol. 31, pp. 814–821, 2014.

[15] M. Fricke, "The knowledge Pyramid: A Critique of the DIKW Hierarchy," *J. Inf. Sci.*, vol. 35, no. 2, pp. 1–13, 2007.

[16] A. Kühn, R. Joppen, F. Reinhart, D. Röltgen, S. Von Enzberg, and R. Dumitrescu, "Analytics Canvas - A Framework for the Design and Specification of Data Analytics Projects," *Procedia CIRP*, vol. 70, pp. 162–167, 2018.

[17] K. Im and H. Cho, "A systematic approach for developing a new business model using morphological analysis and integrated fuzzy approach," *Expert Syst. Appl.*, vol. 40, no. 11, pp. 4463–4477, 2013.

[18] H. Jafarzadeh, P. Akbari, and B. Abedin, "A methodology for project portfolio selection under criteria prioritisation, uncertainty and projects interdependency – combination of fuzzy QFD and DEA," *Expert Syst. Appl.*, vol. 110, pp. 237–249, 2018.

[19] P. Sirisawat and T. Kiatcharoenpol, "Fuzzy AHP-TOPSIS approaches to prioritizing solutions for reverse logistics barriers," *Comput. Ind. Eng.*, vol. 117, no. September 2017, pp. 303–318, 2018.

[20] B. Wang, J. Song, J. Ren, K. Li, H. Duan, and X. Wang, "Selecting sustainable energy conversion technologies for agricultural residues: A fuzzy AHP-VIKOR based prioritization from life cycle perspective," *Resour. Conserv. Recycl.*, vol. 142, no. October 2018, pp. 78–87, 2019.

[21] M. Imai, "Gemba Kaizen. A Commonsense, Low-Cost Approach to Management," Jan. 2007.

[22] P. Chesser *et al.*, "Extrusion control for high quality printing on Big Area Additive Manufacturing (BAAM)systems," *Addit. Manuf.*, vol. 28, no. September 2018, pp. 445–455, 2019.

[23] A. Mahadik and D. Masel, "Implementation of Additive Manufacturing Cost Estimation Tool (AMCET) Using Break-down Approach," *Procedia Manuf.*, vol. 17, pp. 70–77, 2018.

[24] D. Zindani and K. Kumar, "An Insight into Additive Manufacturing of Fiber Reinforced Polymer Composite," *Int. J. Light. Mater. Manuf.*, 2019.

[25] R. Lipman, P. Witherell, S. Leong, and Y. Lu, "An Activity Model for Additive Manufacturing Powder Bed Fusion," 2016. unpublished.

[26] N. I. of S. and Technology, "Integration Definition for Function Modeling (IDEF0)," 1993.

[27] K. Lepenioti, A. Bousdekis, D. Apostolou, and G. Mentzas, "Prescriptive analytics: Literature review and research challenges," *Int. J. Inf. Manage.*, vol. 50, no. October 2018, pp. 57–70, 2020.

[28] H. Lorentz, O. P. Hilmola, J. Malmsten, and J. S. Srai, "Cluster analysis application for understanding SME manufacturing strategies," *Expert Syst. Appl.*, vol. 66, pp. 176–188, 2016.

[29] E. Uhlmann, R. P. Pontes, C. Geisert, and E. Hohwieler, "Cluster identification of sensor data for predictive maintenance in a Selective Laser Melting machine tool," *Procedia Manuf.*, vol. 24, pp. 60–65, 2018.

[30] I. Baturynska, "Statistical analysis of dimensional accuracy in additive manufacturing considering STL model properties," *Int. J. Adv. Manuf. Technol.*, vol. 97, no. 5–8, pp. 2835–2849, 2018.

[31] S. A. Shevchik, C. Kenel, C. Leinenbach, and K. Wasmer, "Acoustic emission for in situ quality monitoring in additive manufacturing using spectral convolutional neural networks," *Addit. Manuf.*, vol. 21, pp. 598–604, 2018.

[32] National Institute of Standards and Technology, "NIST ADDITIVE MANUFACTURING MATERIAL DATABASE," 2019. [Online]. Available: Ammd.nist.gov.

[33] M. Yihua and X. Tuo, "Research of 4M1E's effect on engineering quality based on structural equation model," *Syst. Eng. Procedia*, vol. 1, pp. 213–220, 2011.

[34] H. Ko, P. Witherell, Y. Ndiaye, and Y. Lu, "Machine Learning based Continuous Knowledge Engineering for Additive Manufacturing," in *2019 IEEE 15th International Conference on Automation Science and Engineering*, 2019.