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Machine Learning based Continuous Knowledge Engineering for Additive Manufacturing

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Abstract— **Additive manufacturing (AM) assisted by a digital twin is expected to revolutionize the realization of high-value and high-complexity functional parts on a global scale. Machine learning (ML) introduced in digitized AM provides potential to transform AM data into knowledge continuously and automatically; hence AM products will be designed and manufactured with improved quality. Conventional product development systems, however, fail to fully adopt ML algorithms on the increasingly available AM data for knowledge acquisition. To address the limitation, this paper proposes an algorithmic framework for constructing AM knowledge automatically and continuously from data. The proposed algorithm develops predictive models to correlate process parameters with part structure and properties using ML algorithms on design, process control, in-situ monitoring, and ex-situ measurement AM data. Based on the predictive models, the algorithm constructs prescriptive rules necessary for decision-making in AM product developments. The constructed rule knowledge is stored in a knowledge base by the algorithm for further AM knowledge query and constructions. Then, the algorithm provides feedback to a knowledge-query formulation phase, which forms the algorithm into a closed loop. Through the algorithm, AM knowledge can self-evolve continuously, while reflecting dynamically generated AM data in an automated and autonomous manner. A case study is presented to illustrate the proposed algorithm and a software prototype is developed to demonstrate the algorithm capability.**

I. Introduction

Additive manufacturing (AM) processes build parts layer-by-layer directly from 3D models. AM technology enables the fabrication of parts with complex shapes and heterogeneous materials that cannot be obtained with traditional manufacturing methods. These advantages make AM an attractive alternative for high-value and low-volume production. However, as a disruptive manufacturing process, there are persistent barriers to AM as a production technology, including low repeatability, lack of effective design, engineering and qualification tools, and limited material choices. The fundamental issue lies in the lack of understanding about the nature of AM processes.

In a digital world, knowledge can be in the form of either quantitative predictive models or qualitative rules. AM predictive models capture all kinds of relationships between process parameters, material structure, and part properties. The models can be built based on physical principles and solved with numerical computational software, such as Finite Element Method (FEM) programs. A predictive model can also be a black box type input-output quantifiable relationship, either as an approximation of high-fidelity physics-based models or derived directly from experimental data.

In contrast, rule-based knowledge often specifies relations, directives, or strategies qualitatively [1]. Traditionally, rules are expressed by using IF-THEN format that can be easily understood by engineers. When combined with reasoning engines, this type of knowledge has led to various expert systems that are widely used by engineers to make decisions during the product development lifecycle, e.g., in selecting appropriate designs, determining process technologies, setting processes parameters, identifying evaluation techniques, and qualifying parts [2]. There are also ongoing efforts on developing formal AM design rules to support engineering decision-making that has the potential of enabling computer processable standards [3-5]. However, building a rule-based knowledge base via knowledge engineering is a labor-intensive process. Domain experts have to work with knowledge engineers to disseminate their accumulated knowledge and experience into structured rules [6]. When knowledge evolves, the process has to be repeated.

Meanwhile, data have become more important in all aspects of the product development lifecycle and value chains. It indeed becomes one of the most critical elements in deriving predictive models for both product design and manufacturing control and operations [7]. During AM processes, increasing amounts of data are generated from product design, material characterization, in-situ monitoring and post nondestructive evaluation tests. Data from heterogeneous AM domains vary in format, volume, and velocity. The types can be design model, process control, in-situ monitoring, and ex-situ measurements. Examples are Computer-aided Design (CAD) files, build files, in-situ monitoring of optical and thermal images or acoustic emission signals [8, 9], and X-Ray Computed Tomography (XCT) images from ex-situ measurements [10, 11]. Advanced data analytics on AM data offers opportunities for better understanding of AM processes. Machine Learning (ML) for AM predictive modeling has been reported to derive the relationship between process parameters and melt-pool geometry [12, 13] and to predict part quality

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from in-situ optical images [14]. There are also a number of methodologies proposed to extract knowledge from data in an automated or semi-automated manner.

To enable data-driven AM, an analytical framework for AM was proposed by combining physical AM systems with digitized AM models and software tools supporting engineering decision-making. Then, a collaborative data management system was built based on the framework [15, 16]. Synchronized with the real world in dual-directions, the framework shows an opportunity to turn into a digital replica of AM systems named AM Digital Twin. As shown in Figure 1, the AM Digital Twin can be updated to better mimic the real world through continuously ingesting and mining the data generated from the AM ecosystem, and consequently it will provide advanced engineering decision support to various AM activities for improved product quality.

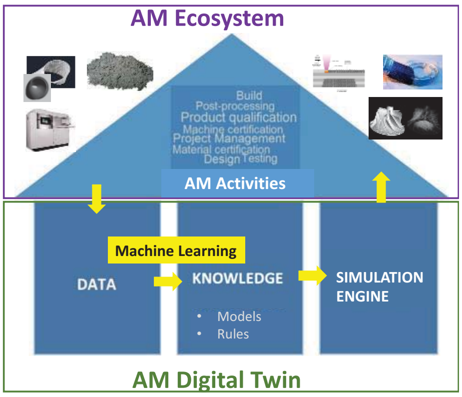


Figure 1. Concept of AM Digital Twin

The circular loop connecting the AM ecosystem and its digital twin is expected to lead to a self-improving knowledge management framework where an adaptive predictive modeling process is demonstrated [17]. This paper continues the effort to investigate a method to accelerate and automate rule-based knowledge acquisition for the AM digital twin. The research efforts focus on taking experimental or simulation AM data as inputs, and then deriving AM design, process planning, operation, or quality assessment rules from the ML results. The rules are necessary for automated rule-based decision-making through AM product development lifecycle and value chains.

Relevant studies have shown individual efforts in introducing AM Process-Structure-Property (PSP) relationship analysis [18] and AM rule representations [3, 4]. However, these efforts fall short of demonstrating automated data and rule transformations. More specifically, previous AM knowledge studies could not extract PSP relationships from AM data in considering AM rule constructions. Consequently, they could not systematically link AM data-PSP relationships-rules, and vice versa, which is necessary for data-driven decision-making automation in AM. Also, collaborations with data- and knowledge-based systems are required. This is because AM data and extracted AM knowledge (AMK) need to be stored in an AM system for further knowledge discoveries with newfound data or for further AI rule-based AM applications. To realize such automation in a new AM data-intensive phenomenon, it is required to create an algorithmic method that will ultimately result in the development of a machine-based and self-adaptive AM system.

To bridge the gap, this paper proposes an algorithmic framework that consists of two phases: i) a top-down goal-oriented decision-making phase and ii) a bottom-up data-driven AMK construction phase. First, the top-down goal-oriented decision-making phase queries rules or AM data to support certain engineering decision-making in AM applications. A goal is formulated into queries to request rules or AM data that are needed for decision-making. Second, the bottom-up data-driven AMK construction extracts predictive models on PSP relationships from AM data, once new AM data are obtained. Based on the predictive models extracted, the algorithm derives new prescriptive AM rules by knowledge reasoning. Then, the extracted AMK (predictive models and prescriptive rules) is represented with semantic definitions and ontological relationships to be systematically stored in a knowledge base. The algorithm forms a closed loop for a continuous AMK evolvement.

The remainder of the paper is organized as follows. Section II introduces a framework of the proposed algorithmic method. Section III presents a case study to demonstrate the proposed algorithm, while Section IV shows a software architecture developed based on the algorithm. Following this, the research is concluded, and future work is discussed in Section V.

II. Proposed Algorithmic Framework

A framework of the proposed algorithm is shown in Figure 2. The algorithm starts with the top-down goal-oriented decision-making phase. This top-down decision-making phase is designed to guide an optimal AMK selection or an AM data obtainment when there are goal-oriented needs on new data. The bottom-up data-driven AMK construction phase starts with a new AM dataset that triggers knowledge extraction, representation, and reasoning. In this section, symbols used in the description of the algorithm are corresponding to the symbols in the algorithm given in Figure 2.

A. *Top-down goal-oriented decision-making*

Top-down decision-making starts with formulating a goal of AM product development decision-making into an AM rule knowledge query. This goal-oriented phase of the algorithm is described in steps as follows.

Step 1: Query for AM rule knowledge needed in decision-making. Let g represent a goal of the decision-making. g is formulated into a knowledge query q^K. The knowledge query is formulated as a subset of the attributes of the knowledge elements (a^K) in the knowledge base (K).

Step 2: Check if the requested rules exist in the knowledge base (K). Such task can be done by checking if the knowledge base has knowledge elements with attributes (a^k) that meet the formulated knowledge query requirements. If a rule is existing in the knowledge base (Case 1 in Figure 2), return the AM rule knowledge for the decision-making. If not, define the AM data necessary to derive the rules.

Step 3: Query for an AM dataset for knowledge engineering. g is formulated into a data query q^d. The data query is formulated as a subset of the attributes of the AM data (a^D) in the database (D).

Step 4: Check if there exist new AM data for knowledge engineering. Such task can be done by checking if the database has new AM data with attributes (a^d) that meet the formulated data query requirements. If there are such AM data (Case 2 in Figure 2), return the AM data (D') for ML. If not (Case 3 in Figure 2), return requirements for a new AM data obtainment to incorporate the requirements into further data obtaining plans such as design of experiments (DOE) for field tests or simulations.

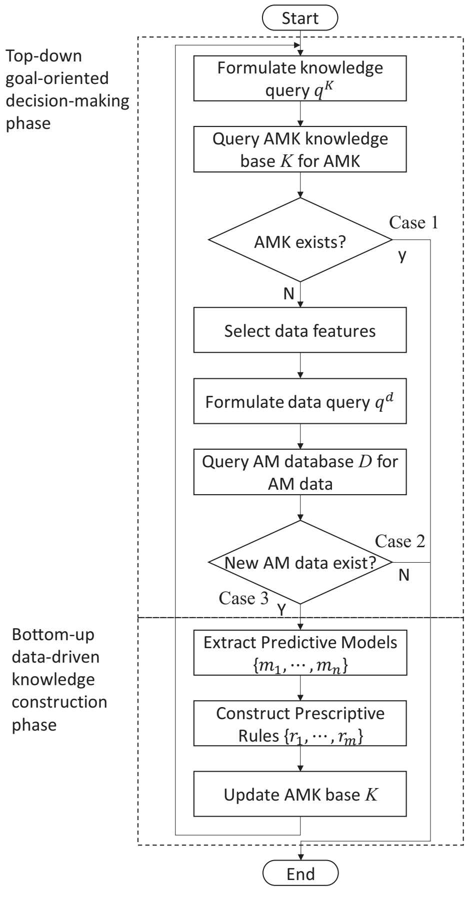


Figure 2. Algorithmic framework

B. Bottom-up data-driven knowledge construction

The bottom-up data-driven AMK construction starts when a new AM dataset is obtained. This data-driven phase of the algorithm is described in steps as follows.

Step 1: The queried AM data is curated for ML algorithms. This step considers i) natures of the AM data constrained by data sources (physical or simulated AM processes) and data obtainment techniques (such as sensor, in-situ monitoring, and ex-situ measurement techniques) and ii) natures of ML algorithms. Considering them, suitable ML algorithms are selected, and then the AM data are curated to be inputs for the ML algorithms, while not losing their original meanings. ML algorithm types depend on the types of their data mining tasks: classification, clustering, association, and feature selections [19]. Among them, this study uses classification ML algorithms that can predict target classes for each test case of datasets. Examples of classification algorithms can be Decision Tree, C4.5, C5, Iterative Dichotomiser 3 (ID3), K-nearest Neighbors (KNN), Neural Networks, Support Vector Machine (SVM), etc. [19]. Then, the data can be split into multiple chunks for training, validating, and testing.

Step 2: ML is conducted to generate models of AM capability, additive manufacturability, based on PSP relationship analysis. Predictive additive manufacturability models are necessary in generating prescriptive AM rules. This is because prescriptive AM rules are developed based upon the predictive models. The prescriptive rules guide what decisions AM practitioners or automated systems have to make for a predictive condition where an AM process provides certain additive manufacturability.

Step 3: Once predictive additive manufacturability models ($\{m_1, \cdots, m_n\}$) are obtained, knowledge reasoning is conducted to fuse the obtained models with a priori AMK (K). The applications of the predictive models and a priori AMK result in new AM rule knowledge. Such process adds explicit design and AM contexts to the predictive models as constraints and guidelines that are required in semantic AM rules ($\{r_1, \cdots, r_m\}$) [4]. While doing so, this step organizes the fused knowledge in structured IF-THEN statements to form it into rule statements.

Step 4: The extracted predictive additive manufacturability models and rules are stored in the knowledge base. They become a priori AMK in the knowledge base, once their qualities are validated.

As shown in Figure 2, the top-down and the bottom-up phases of the algorithm are connected with each other. Specifically, at the end of the bottom-up phase, the algorithm provides feedback on the newly constructed AMK to the knowledge query formulation phase: the starting point of the top-down phase. The feedback includes information on the newfound AMK from the knowledge extraction and reasoning phases. The feedback provides updated knowledge information to a knowledge-query formulator, so the formulator can refer it in the knowledge query formulation of the next iteration.

III. CASE STUDY

This section presents a case study of constructing additive manufacturability rules based on the relation between part location, surface orientation, and surface height. The knowledge data feature types was queried from an AM knowledge base using on an AM ontology. The AM ontology is the main body of this study's AM knowledge base developed with formal Web Ontology Language (OWL)/Resource Description Framework (RDF) representations. The ontology was developed to capture a priori knowledge of experimental reports or benchmark studies on AM [20, 21].

This study uses AM data obtained from a Laser Power Bed Fusion (LPBF) build with 9 identical parts, each of which has 72 surfaces oriented differently in either XY direction or Z direction, as shown in Figure 3 [11].

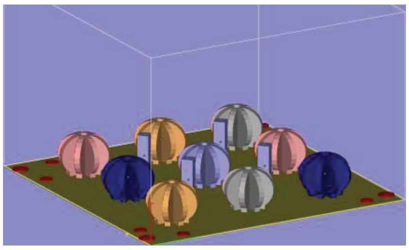


Figure 3. Build for surface roughness study [11]

The 9 parts were built on 3 by 3 grids at the same z level 50mm from each other in both x and y directions. Each part has 8 ribs at increments of 45 degrees in XY plane. Each rib includes 9 surfaces oriented from 45 degrees to 165 degrees against Z axis at 15 degrees of increments. Measurements were conducted to evaluate the surface roughness for all the 648 full factorial designed surfaces. The surface height is measured based on ISO 4287 standards. TABLE I summarizes the datasets used for this study [11].

TABLE I. SUMMARY OF AM DATA FROM SURFACE ROUGHNESS STUDY

Feature Type	Feature Name	Unit	Value
Input variable	Part Location X	mm	{-50, 0, 50}
	Part Location Y	mm	{-50, 0, 50}
	X-Y Orientation	∠ (°)	{0, 45, 90, 135, 190, 225, 270, 315}
	Z Orientation	∠ (°)	{45, 60, 75, ⋯, 135, 150, 165}
Response variable	Surface Height	μm	{7.3, ⋯, 64}

Our study employed the Classification And Regression Tree (CART) algorithm, which is a type of Decision Tree (DT) algorithm. The CART algorithm is suitable for extracting predictive rule models. The algorithm creates conditional tree structures of which inherent patterns that can be directly interpreted as rules in the IF-THEN statement forms [22], which is required in AM rule representations. The response variable considered in the AM data set is the surface height. The input variables are the position of the parts and the orientation of the surfaces.

In Figure 4, we extracted 17 condition criteria (*C1~C17*) and 18 rules (*R1~R18*) directly from the resulted CART. Orientation_Z is the root node followed by the predictive variables of Location_X and Location_Y. The values at each variable in the CART signify the states of the variable at each split that are the conditions for the CART's direct rule interpretation. For example, if the value of Orientation_Z is larger than 68, take the left branch from the root, else consider the right branch. Interpretations are followed in the same way for the other nodes until the final leaf nodes. In this way, the CART model can be interpreted as 18 IF-THEN rules. For example, *R18* in Figure 4 is an IF-THEN statement in TABLE II. The value ranges for the CART's conditions are captured by inequality sets $\{p_i\}$. For example, p_1, p_2, and p_3 represent the value ranges for conditions ¬*C1*, ¬*C3*, and ¬*C7*. ¬ means negation.

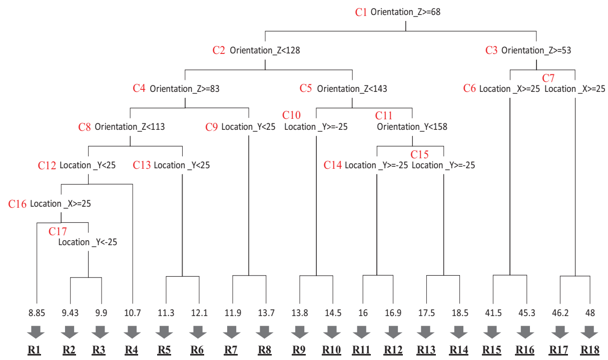


Figure 4. CART extracted from the LPBF part surface measurement datasets

The CART results provide rules on predictive additive manufacturability based on PSP analysis. Then, the CART results are systematically matched to associated classes and properties in the AM ontology and elements in Semantic Web Rule Language (SWRL). Figure 5 shows a representation of *R18* in SWRL. The SWRL is constructed only when the relationships between involved individuals and data are explicitly defined. The CART's IF-THEN statements in TABLE II enable formulating the SWRL statement by appending matched classes, individuals, and properties into the SWRL. The SWRL's knowledge elements are represented as individuals under associated class types in the ontology. Their relationships are captured in object and data properties of the ontology. The relationships reflect the PSP relations generated from the CART models.

TABLE II. REPRESENTATIONS OF *R18*

Type of repr.	Representation
Interpretation in text-based repr.	If a surface's z orientation is less than 53° (¬C1&¬C3) and the surface's X location is less than 25° (¬C7), surface height is 48μm.
IF-THEN statement	IF $p_1 \wedge p_2$ THEN p_3
Param. value range	p_1=(0° ≤α≤360°, 45° ≤β<53°) p_2=(-50° ≤X<25°, -50° ≤Y≤50°, Z=0°) p_3=48μm where, α, β: part surface's x-y and z orientations, respectively X, Y, Z: part's location in X, Y, and Z directions, respectively, on LPBF machine build platform

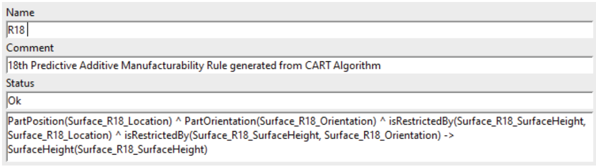


Figure 5. Representation of *R18* in SWRL

Qualified AMK in the knowledge base is used for i) automated rule-based decision-making in AM lifecycle or ii) new knowledge constructions. For knowledge constructions, the rules in IF-THEN statements can be applied to knowledge reasoning to match facts to their antecedents of consequences relations. The knowledge reasoning can extract new AM rules based on the matching whenever new AM datasets are obtained in the database and new predictive models are extracted from ML accordingly. In this way, AMK can self-evolve continuously while reflecting dynamically generated AM data in an automated and autonomous manner.

IV. A Knowledge-intensive AM Information System

The adaptive knowledge engineering is implemented as an extension of an existing collaborative AM data management system: NIST AM material database (AMMD) [16]. Figure 6 shows a high-level software architecture of the enhanced AM information system.

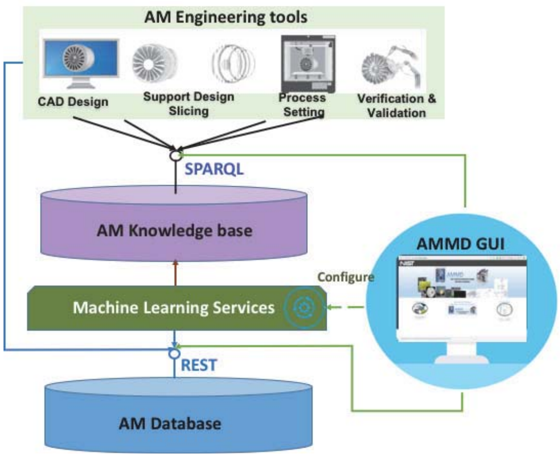


Figure 6. Knowledge-intensive AM information system

As shown in Figure 6, a knowledge base is added to AMMD and accessible through a Simple Protocol and RDF Query Language (SPARQL) interface. Also, a ML-based knowledge extraction module (MLKE) is implemented as a service to connect the knowledge base to the existing database. The MLKE software module runs as an independent service, which continuously monitors the change of the target data sets in the database through a RESTFul Application Programming Interface (API) [23]. Any addition or change of the target type of data sets will trigger the MLKE service to launch a ML training session and sequentially drive new knowledge or update existing knowledge.

The AMMD Graphical User Interface (GUI) in Figure 6 provides a browser for the raw data sets as well as a knowledge query interface to support engineering decision making. Figure 7 shows the surface test data curated in the database and displayed in the navigation pane of AMMD.

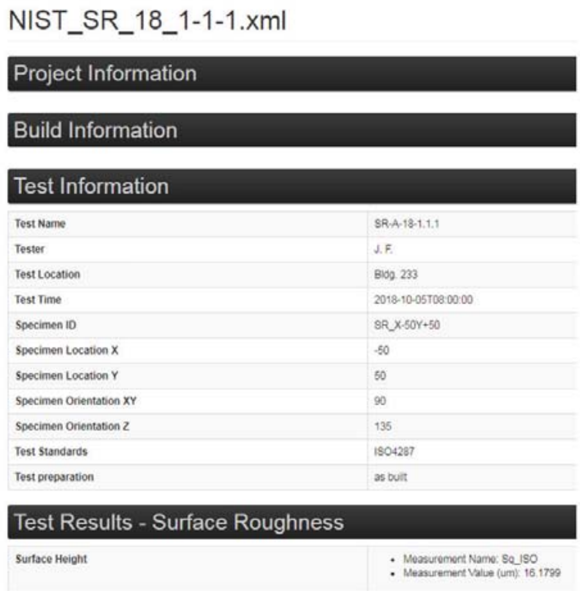
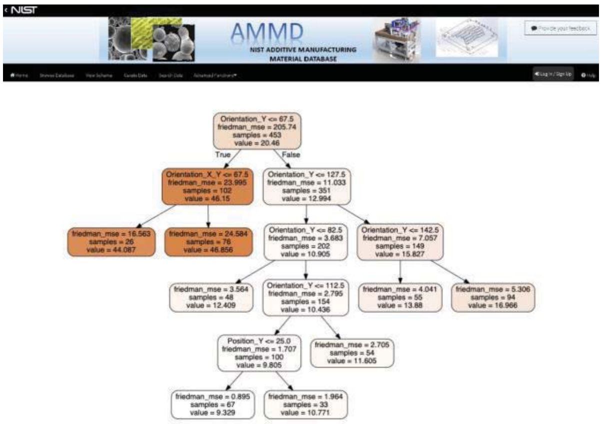


Figure 7. Surface measurement data in AMMD

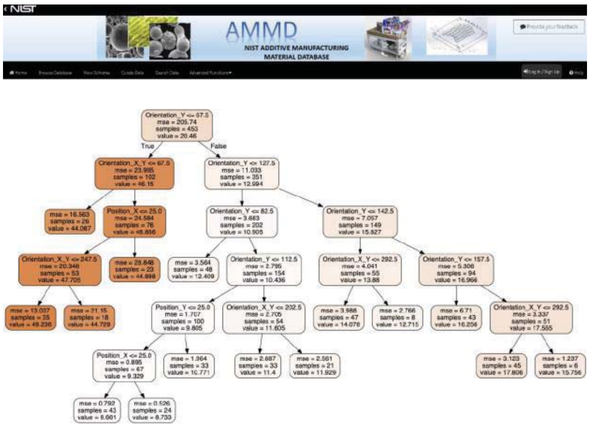
Since the test type "SURFACEROUGHNESS" is registered in the MLKE service module, curation of this new data set triggers the ML service to run a CART analysis. The knowledge on how the part location and the surface orientation affect the surface height is updated. Figure 8 shows the knowledge query results before and after the update.

As seen in Figure 8 (a), the user queries the knowledge tool to get a predicted value of the surface height based on the given input variables: the part's X and Y location and surface orientation. The surface height will be derived based on the prior rules captured in the database. After a new set of surface roughness measurement data is ingested into the AM database, the MLKE service creates a new regression tree in which an updated rule set can be extracted. When the same coordinates are given to query the knowledge base, the regression tree predicts different values of the surface height as shown in Figure 8 (b).

From the results, it can be observed that the knowledge tool creates and automates the generation of additive manufacturability rules directly from the input data. Similar algorithms can be incorporated in the service to derive rules for part property predictions. The toolset is useful to AM engineers to make informed design, planning, and control decisions to improve part quality.



(a) Knowledge query in AMMD before data update



(b) Knowledge query in AMMD after data update

Figure 8. Knowledge update (a) before and (b) after the new data set

V. Concluding Remarks and Future Work

AM is increasingly becoming data-intensive more and more due to in-situ monitoring and ex-situ non-destructive evaluation techniques used in the AM product development lifecycle. Advanced data analytics automation with ML on AM data offers opportunities for better understanding of AM designs and processes and, consequently, constructing new AM knowledge. Automated AM knowledge constructions require an algorithmic method that adopts ML algorithms and continuously collaborates with data- and knowledge-based systems. In this study, we proposed an ML-enabled algorithmic framework for a data-driven continuous construction of AM knowledge. We demonstrated that the use of ex-situ measurement AM datasets, CART ML algorithm, and a data- and knowledge-based system provides self-improving predictive models and prescriptive rules on additive manufacturability.

Future work will look to further refine the proposed algorithm, which includes reviewing the available types of ML and AI algorithms as well as various AM datasets. We will continue investigating the use of the proposed algorithm on unique design, in-situ monitoring, and ex-situ measurement AM datasets such as melting pool monitoring images and XCT images. More advanced methods of knowledge representation and reasoning will be investigated, which is expected to provide formal methods toward an automated AM knowledge construction. We will continue to pursue data- and knowledge-driven design and AM automation.

VI. Acknowledgement

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VII. Disclaimer

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