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SELF-IMPROVING ADDITIVE MANUFACTURING KNOWLEDGE MANAGEMENT

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ABSTRACT

The current additive manufacturing (AM) product development environment is far from being mature. Both software applications and workflow management tools are very limited due to the lack of knowledge supporting engineering decision making. AM knowledge includes design rules, operation guidance, and predictive models, etc., which play a critical role in the development of AM products, from the selection of a process and material, lattice and support structure design, process parameter optimization to in-situ process control, part qualification and even material development. At the same time, massive AM simulation and experimental data sets are being accumulated, stored, and processed by the AM community. This paper proposes a four-tier framework for self-improving additive manufacturing knowledge management, which defines two processes: bottom-up data-driven knowledge engineering and top-down goal-oriented active data generation. The processes are running in parallel and connected by users, therefore forming a closed loop, through which AM knowledge can evolve continuously and in an automated way.

Keywords: additive manufacturing, knowledge management, manufacturing system integration

1. INTRODUCTION

Many hurdles continue to hinder the widespread adoption of additive manufacturing (AM) technologies for production, including low repeatability and quality inconsistency, high cost and time in qualification, and constrained material choices [1]. A key step in overcoming each of these hurdles is to obtain the knowledge needed to support engineering decision making through the AM product development lifecycle and across its value chain. In recent years, through the acquisition of "know how" startups, major CAD/CAM vendors have quickly expanded their offerings to include reverse engineering, geometry repairing, topology optimization, build preparation and process simulation in support of "Design for AM" engineering activities [2]. There are also services like 3D Hubs where engineers can get instant feedback on part manufacturability and the best processes for the design [3].

However, existing AM software know-how is still far from being mature enough to allow engineers to fully grasp the requirements and limitations to bring optimized AM parts to production [4]. Albright [5] lists some missing capabilities from the existing AM software, including design rules to validate issues of the minimum wall thickness, printability of the part overhang angle, shrinkage/warping prediction, support design, orientation selection, lattice structure analysis and post-process planning, etc. These desired but lacking software functions demand a new set of knowledge about AM capabilities, limitations and design rationales, which not only depends on the choice of material and technology but is also determined by the product definition and process parameters. Both today's design and manufacturing engineers and university graduates are encouraged to seek out the knowledge associated with the 'physics' of how AM processes work and how within each process category each type of material may respond differently when trying to build a specific geometry in a specific orientation [4].

While some researchers are working on physics-based modeling and simulation techniques to understand AM processes, others are diligently conducting field studies and disseminating information to derive process-structure-property (PSP) relationships directly from data. Data-driven modeling and information fusion are foundational to AM knowledge development [6]. Such approaches take experimental or simulation data, using advanced data analytics techniques, such as metamodeling and machine learning, to identify AM material PSP relationships and derive AM design, process planning, and operation rules. Illustrated as a bottom-up process in Figure 1, new data sets emerge first, whether from research experiments in the lab or real production on the manufacturing shop floor, leading to new information fused and analyzed, so that new AM knowledge is acquired, and AM software functions are enhanced.

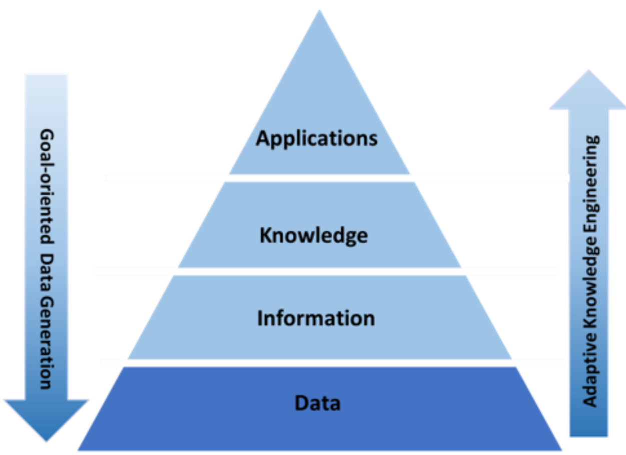

Figure 1: A modified Data-Information-Knowledge-Wisdom (DIKW) model

Many individual techniques have been studied and reported to support data-driven AM knowledge engineering. Kim et al. gave a comprehensive description of the types of heterogeneous data sets generated and consumed during an AM development lifecycle [7]. Lu et al. have reported a common information model and a collaborative database to structure and fuse the heterogeneous data sets contributed by different stakeholders in the AM community [8, 9]. Towards advanced data analytics, intensive research has been done by Yang et al in employing metamodeling techniques in design and optimization [10, 11]. AM builds are well suited for the reported collaborative data and information management in [9], especially for metal parts, where costs for conducting large scale sampling over many variables can be prohibitive. Generative learning and transfer learning are two methods reported in other domains, which might be used for AM metamodeling based on heterogeneous data sets.

At the same time, a few research activities were reported related to the techniques required for an application-driven data generation process, shown in Figure 1 as a top-down process. An Information Fusion Enterprise Model proposed by Kessler and White provides an approach about how to derive information needs from user's queries [12]. Adaptive sampling or sequential sampling has been used widely for metamodel improvement through new data acquisition.

The top-down and bottom-up processes are running in parallel and isolated without the AM community being aware of the opportunity and benefit to integrate and streamline them. The existing research works surveyed above only address the individual functions and links of the processes without a vision of creating an integrated workflow. Current disconnected AM knowledge management makes it harder for AM engineers to fully grasp the benefits and limitations of AM technology and bring optimized AM designs to production. In this paper, we proposed a self-improving additive manufacturing knowledge management approach which consists of a bottom-up data-driven knowledge engineering process and a top-down goal-oriented active data generation process and forms a closed-loop for continuous knowledge improvement. The proposed approach is based on a four-tier data-information-knowledge-wisdom (DIKW) model variant as shown Figure 1. The original DIKW model [13] is modified to have the top layer renamed as "Applications" to make it more understandable for AM engineers. Besides, a bottom-up and a top-down process are added to the pyramid to capture the need of workflow integration and automation for the proposed self-improving knowledge management. The bottom-up process is named as "Adaptive Knowledge Engineering" while the top-down one is called "Goal-oriented Data Generation".

The paper is organized as follows. Section 2 introduces the layer model for the four-tiers knowledge engineering framework. Section 3 describes the top-down and bottom-up processes and how they are connected into a closed loop. Section 4 provides an example to show how a self-improving AM knowledge management system works. Section 5 summarizes the paper and discusses our future work.

2. A FRAMEWORK FOR SELF-IMPROVING ADDITIVE MANUFACTURING KNOWLEDGE MANAGEMENT

An elaborated four-tier knowledge management framework for AM is shown in Figure 2. The Data layer sits at the bottom, captures diverse data sets generated and used in AM lifecycle and value chains. The Information tier fuses the heterogeneous data sets and manages them in a collaborative way. The Knowledge layer sits on top of the information layer, capturing process, machine and material capabilities, design rules, operating guidance, process models and asset health models

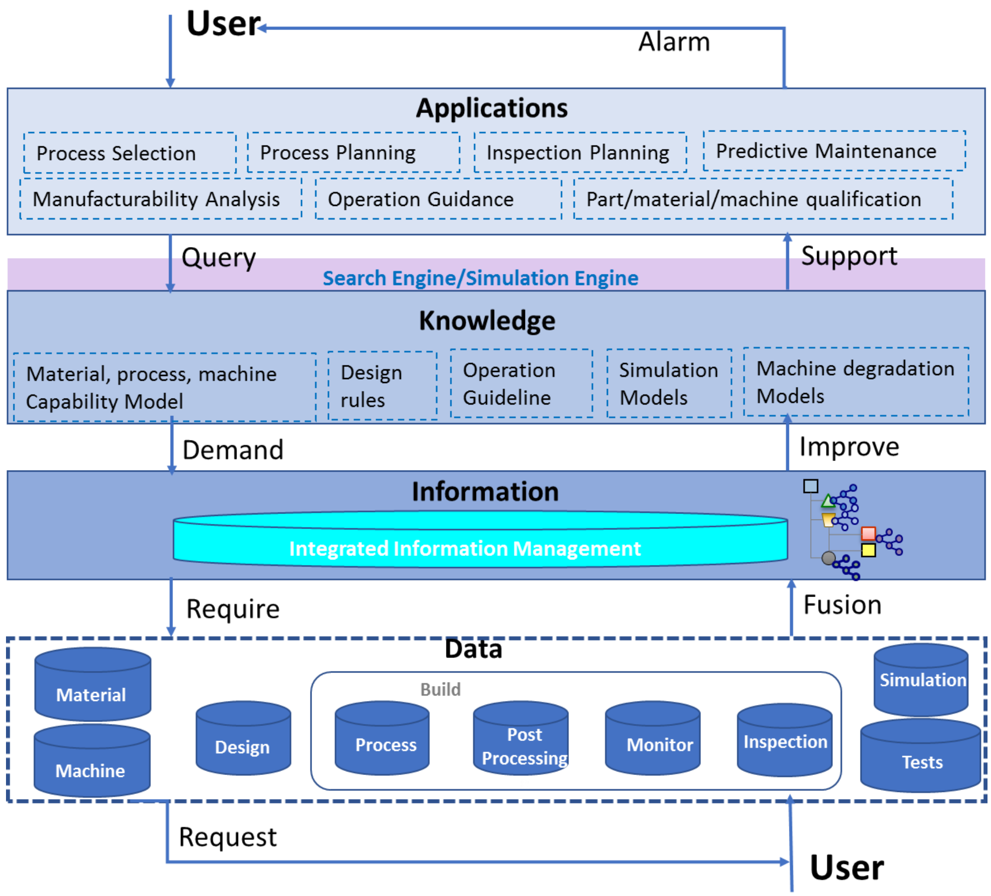

Figure 2: A 4-tier analytical framework for self-improving AM knowledge management

which can be queried and simulated using various search engines and simulation engines. The top tier is the Applications layer, which consists of software applications in support of AM lifecycle and value chain activities. Knowledge is the key for AM engineers to conduct their activities and make correct design or operation decisions. A summary of the components at each layer is provided below.

Data Layer:

The data components are heterogeneous, covering vendor provided machine and material data, asset and feedstock data from their owners, design data from designers, process data from manufacturers, test data from inspectors and all kinds of experimental data from AM researchers. They are summarized in Table 1.

Information Layer:

A common conceptual information model captures the data sets generated from AM lifecycle and value chain, as shown in Figure 3 [7]. Based on the common data model, heterogeneous data sets are fused into a collaborative information system based on NoSQL technology for both easy query and efficient storage [8].

Table 1: AM data types summary

Data Category	Data Description
Material	Material type and grades; Vendor provided material properties (feedstock and as-built); Material stock information and actual material properties
Machine	Process type; Vendor provided machine specifications; Machine information as an asset; asset maintenance information
Design	CAD models; Design meta data; Design intents and PMIs; design features
Build	Build meta information; Feedstock material information; Equipment information; Structure and support as designed; Process parameters; Preprocess pedigree; In-situ monitoring data; Post processing information; Inspection data
Tests	Test meta information; Sample information; Test type/standards; Operator information; Test results.
Simulation	Simulation models; simulation configurations; simulation results

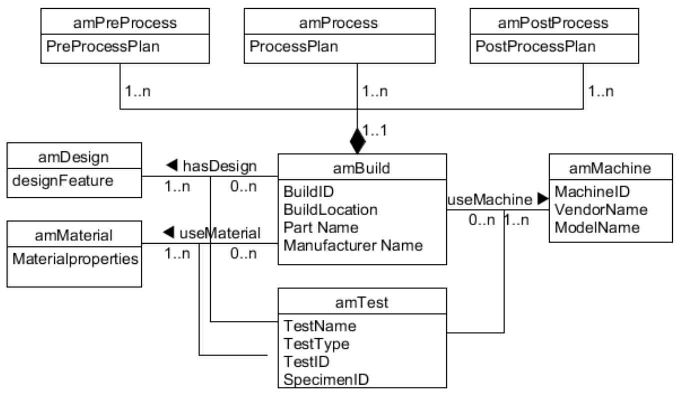

Figure 3: An AM common information Model [8]

Knowledge Layer:

AM knowledge can be classified into two categories: descriptive and prescriptive. The descriptive knowledge could be either physics-based models or metamodels, both of which can be used to simulate AM processes and allow engineers to perform *'what if'* scenarios for potential parametric optimization. MathML [14] and PMML [15] are two markup languages frequently used to represent and communicate the models.

The prescriptive knowledge includes design rules, operation guidance and diagnosis rules, which can be applied directly to AM applications. Dedicated AM design rules that relate to process capabilities are necessary for both CAD tools and AM process planning tools. Design rules can be represented and executed using an ontology. Figure 4 shows an ontology that can be used to select the best manufacturing process, considering AM as an option to compare, for a given part [16],17].

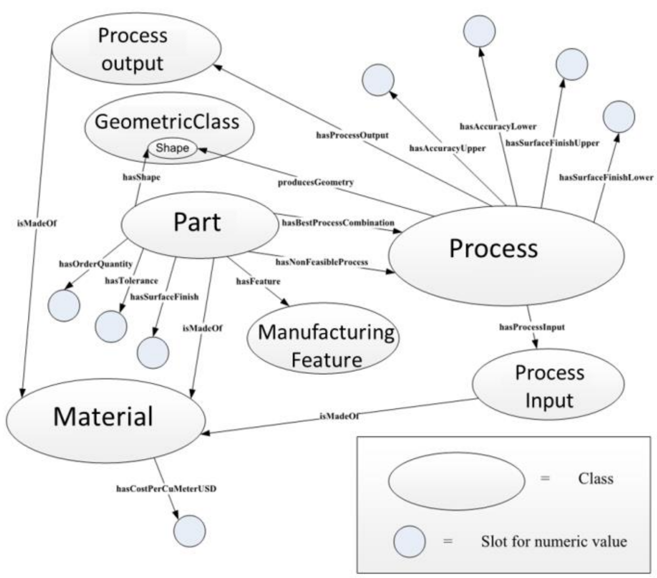

Figure 4: An Ontology for manufacturing process selection [16],17]

Applications Layer:

This layer captures software applications that support end-to-end digital processing during the AM product lifecycle and across its value chain. The software can be hosted on clouds and provided as services to AM stakeholders. Aided by effective workflow management, compositions of software functions can greatly streamline how AM products are designed, manufactured and tested. Figure 5 shows a list of AM applications hosted on a collaborative development platform supported by a shared knowledge base.

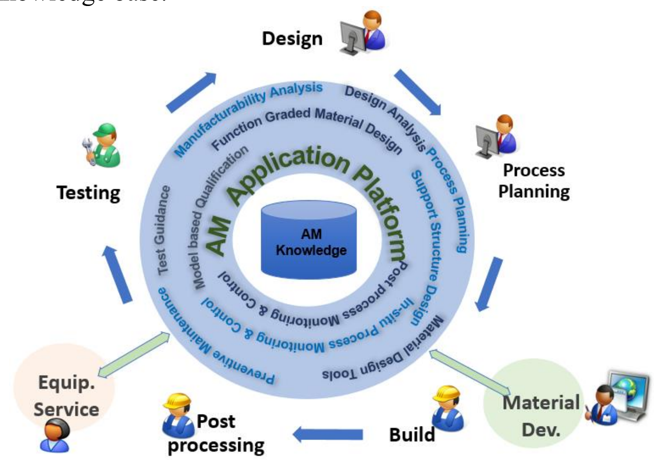

Figure 5: A collaborative development platform for AM

3. PARALLEL PROCESSES FOR SELF-EVOLVING AM KNOWLEDGE MANAGEMENT

Our previous work has been focused on how to identify, model and represent the data, information, and knowledge for each layer of the framework [6]. This section introduces our latest work on streamlining the process of engineering AM knowledge from data. In addition, a complementary top-down process is introduced to prescribe data sets to accelerate AM knowledge accumulation and enable the self-evolving AM knowledge management. Requirements on individual technologies are identified corresponding to those links between the layers of the tiered framework as well as the connections between the two-way processes.

3.1 Bottom-up Process

The bottom-up process, Adaptive Knowledge Engineering, consists of multiple sub-processes including heterogonous data generation and curation, data integration and information fusion, knowledge extraction and fusion, and knowledge query and access. Substantial research has been conducted on the sub-processes individually. The focus of our framework is to provide a method to automate the data-driven knowledge engineering process and allow for a continuously improved knowledge management system.

Figure 6 illustrates a typical adaptive knowledge engineering workflow. It starts with a new data set being available for knowledge engineering, which kicks off a sequential workflow consisting of sub-processes to extract knowledge out of the data sets and fuse it with the existing knowledge.

Step 1: Check the data trustworthiness and quality; after the data source is verified and the data quality is validated, curate the data set.

Step 2: Check if the new data set brings in any new information, for example, a new type of material, a new model of AM machine or a new build, etc. If the answer is affirmative, fuse the new information into the existing information system. Information fusion could involve feature recognition to characterize a part design when a new set of build data is ingested. In addition, the links between the build and the material/machine products used for such a build, if already captured, should be established.

Step 3: Check if the new information leads to any knowledge update. If yes, extract knowledge from the new information and update the knowledge base. For example, minimum thin wall thickness is a measure characterizing the capability of an AM machine. This capability can be assessed based on a statistical analysis of all the builds made on the machine. Therefore, a new build will likely update that knowledge of the machine capability. Similarly, existing predictive models or design rules for a material-process combination can be updated with new information.

Step 4: Check if any ongoing design decisions are still valid after the knowledge base update. If not, re-initiate the affected design processes. If yes, actions will be taken into the corresponding AM activities, and new data sets are expected.

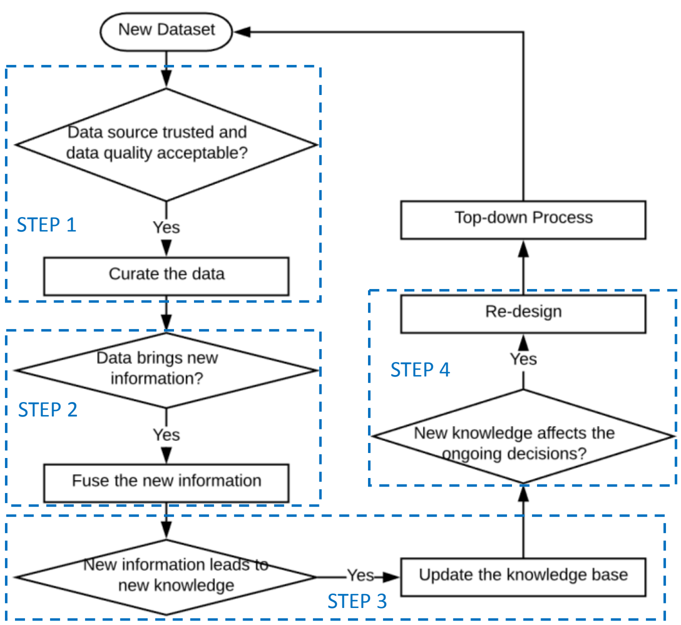

Figure 6: A typical bottom-up process

Various data integration approaches have been proposed to enable the automation of Step 1 and Step 2 of the bottom-up process. At NIST, we proposed to use a common information model to ingest diverse data sets, which is more suitable for greenfield data integration. If legacy databases exist, an ontology based data integration will be more appropriate [18].

Automation of Step 3 is still a very open problem. The challenges lie in today's immature model/knowledge characterization and representations methods [19,20]. Both rules and models in the knowledge base should be characterized for their validity and applicability in order to evaluate if a certain piece of information will enrich the knowledge or not. However, strong dependencies of AM process outputs on part geometry make the standardization and representation of AM design rules very challenging to automate. The next section takes a case study to illustrate how metamodels can be improved with new data sets. The final step can be easily realized through a publish/subscribe software implementation, where AM applications are programmed to receive knowledge updates and check the consistency between the ongoing decisions and the newly updated knowledge.

3.2 Top-down Process

Individual experimental studies often contain only a few measurements and focus on specific sub-processes. Costs for conducting large scale sampling over many process variables can be prohibitive for AM data generation. However, the small sets of data captured do not adequately represent the inherently large sets of process variables and material microstructure variances that must be analyzed for establishing AM PSP relationships. Therefore, it is critical for the AM community to work jointly in a coordinated and systematic fashion to generate data sets which can maximize AM knowledge discovery. The top-down process is designed to solve an optimal data generation problem based on a goal-oriented method.

As shown in Figure 7, the top-down process starts when a query is made in an AM application for knowledge to support engineering decision making. Five steps are involved in completing an optimal data set generation process.

Step 1: Query for design rules for design decisions or a request for simulations to conduct "what-if" analysis.

Step 2: Check if the requested design rules or simulation models exist in the knowledge. If not, define the information necessary to derive such rules or models and issue a query for the information.

Step 3: Check if the information already exists in the information system. If not, identify the various data sets needed for the information formation.

Step 4: Check if all the data sets already exist in distributed data sources. If not, call for the design of experiments (DOE) and data contribution.

Step 5: DOE is conducted, and the list of experiments is distributed to the AM community. Individual data contributors conduct the experiments and make new data set submissions, which kicks off a new round of the bottom-up process.

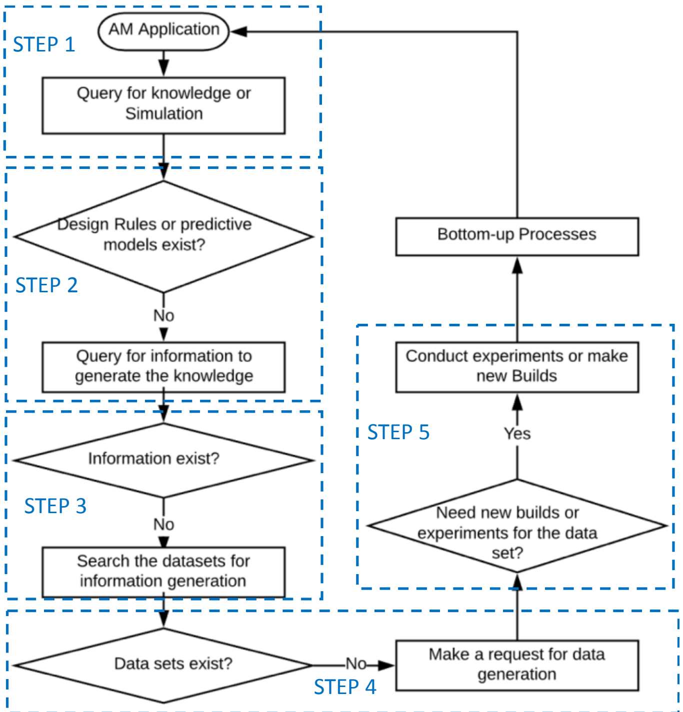

Figure 7: A typical top-down process

By far, few research activities on streamlining goal-oriented AM data generation process exist. In information fusion for combat system command and control, a user directed information discovery method has been proposed to manage intelligence products for mission objectives [12]. A similar methodology can be developed for AM information systems.

3.3 Closed-loop Knowledge Management

As shown in both Figure 6 and Figure 7, the bottom-up process and the top-down process are naturally connected with each other at the end, which forms a closed loop AM knowledge lifecycle. The closed-loop system, consisting of the bottom-up adaptive knowledge engineering and the top-down data generation process, if automated, will not only accelerate AM knowledge acquisition, and also reduce AM data generation cost dramatically. Data and information sharing is critical to implement an automated self-improving knowledge management system. Collaborative AM development platforms built on a shared knowledge base will further shorten the AM product, machine, material and process development lifecycle. Service-oriented architecture has the potential to integrate all the tiers and the links into an organic eco-system. For those links involving human-in-the-middle, a publish/subscribe mechanism can improve human response to knowledge changes and new data generation requests.

4 A CASE STUDY: A METAL AM PROCESS MODEL ADAPTATION

A case study demonstrates a manual process for bottom-up adaptive AM knowledge management. A predictive metamodel was adapted for this purpose and deployed with empirical data from a metal AM process. This approach uniquely combines a previously established metamodel of the process with newly ingested data to complete a self-improving process. The general workflow deployed here is shown in Figure 8.

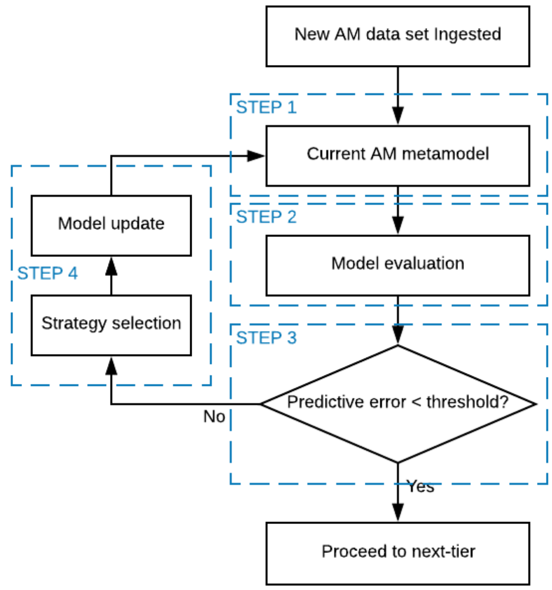

Figure 8. General workflow of data-driven metamodel updating

As shown in Figure 8, newly ingested data triggers an evaluation of the current metamodel for prediction accuracy. The prediction error of the metamodel on the new data set is used for decision making for model update. If the prediction error is within a predefined threshold, the metamodel is considered effective, and no modification is needed. Otherwise, the model has to be improved using the new data and with the best available update strategy. In this case study, the predefined threshold value is generated from the average relative error magnitude (AREM) of the current metamodel based on the leave-one-out (LOO) cross-validation method [21, 22]. Three update strategies were designed for model updating, including 1) Direct data combination – assuming that the existing metamodel was trained and validated using the data generated under the same experimental condition as the new one, new data points are just added to optimize the model parameters. 2) Grey-box modeling [11], which is applied if the new experimental conditions are different, but the design spaces are highly overlapped. 3) Interpolation modeling strategy, which can be chosen for any cases. Here again, AREM [10][21] is selected to evaluate the predictive accuracy:

$$AREM = \frac{1}{n}\left(\frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{y_i}\right)$$

where y is the observed value, $\hat{y}$ is the value predicted by the metamodel and n is the total number of new data points.

For our study, data sets were collected from two independent experiments conducted for a laser melting powder bed fusion metal AM process [23]. The first experiment melted the powder directly on a bare build plate. This set of data is used to build an initial metamodel. The second experiment was conducted on a single layer of powder and the data generated is considered as a new data set. Laser power (LP) and scanning speed (SS) are the input variables, and melt-pool width is the output variable of the metamodel. Both experiments used the fractional factorial design of experiments (DOE) method, with the laser power ranging from 100W to 250W and the scan speed ranging from 200 μm/s to 1400 μm/s. Two data points were left out because of infeasible builds at low energy intensity. The remaining 26 data points are listed in Table 2. The melt-pool width was measured along a 1mm section near the center of the scan trace and the measurement method is detailed in Fox et al [25]. The mean value is listed in the table.

Table 2. Results of laser melting experiments

LP (W)	SS (mm/s)	Melt-pool width (μm)	
		Bare build plate	On powder
100	200	134.57	127.77
100	400	114.75	112.43
100	800	80.52	97.98
100	600	87.58	86.64
100	1000	75.35	64.43
150	200	181.44	162.65
150	400	126.50	149.24
150	600	124.70	129.07
150	800	106.39	119.95
150	1000	103.50	101.26
150	1200	99.28	97.98
150	1400	99.40	95.95
195	200	235.94	225.16
195	400	178.07	150.01
195	600	150.52	153.05
195	800	129.57	151.04
195	1000	122.86	119.19
195	1200	115.38	125.60
195	1400	112.40	114.83
250	200	247.39	253.57
250	400	227.55	254.10
250	600	159.31	150.13
250	800	160.85	175.71
250	1000	141.34	141.05
250	1200	134.58	137.31
250	1400	126.69	124.42

To generate an appropriate metamodel update strategy, we manipulated and divided the original data points into several sub data sets to represent various data-model matching scenarios. Table 3 summarizes four sub data set partitions covering four possible data-model matching scenarios. For scenarios 1 and 2, both the initial data set and the new data set are sampled from Experiment 1. For scenario 1, 15 out of 26 data points from the first experiment were sampled by space filling to construct the initial metamodel. The other 11 points are treated as newly ingested data. In scenario 2, the design space of the initial metamodel and the domain of the new data set are manipulated to be only partially overlapped. Scenarios 3 and 4 assume data from the first experiment for the initial metamodel construction and select data from the second experiment to form a new data set. Scenarios 3 and 4 consider different design space overlapping conditions.

Table 3. Test problem scenarios

No.	Overlapping condition				Experimental consistency
	Initial		New		
	LP	SS	LP	SS	
1	100-250	200-1400	100-250	200-1400	Yes
2	100-150	800-1400	195-250	200-1000	Yes
3	100-250	200-1400	100-250	200-1400	No
4	195-250	200-1400	100-195	200-1400	No

Polynomial regression was selected to build a metamodel in this example considering the linearity observed between the inputs and the output. If a grey-box modeling strategy is applied, Kriging method [24] is combined with the initial polynomial model. Table 4 lists the model update results for all test scenarios. The initial AREM was measured using the LOO cross-validation method. Predictive AREM refers to the prediction error on the new data points. Final AREM, however, is calculated differently for different scenarios. Scenarios 1, 2 and 4 use the LOO cross-validation method since there is no third data set available within the given design space. Scenario 3 used a third data set to evaluate the updated AREM beyond the initial LOO cross-validation. The third data set is extracted from the second experiment result, which covers those points not selected to construct the newly ingested data (with results shown in parenthesis). A star symbol marks the best update strategy and corresponding AREM.

Table 4. Results from model updating after ingesting new data

No.	Initial AREM	Predictive AREM	Updating strategy	Final AREM
1	0.0783	0.0626	Direct combination	0.0528
2	0.0520	0.3614	Direct combination	0.0760
			Interpolation modeling*	0.0743*
3	0.0528	0.0700	Direct combination	0.0564 (0.0749)
			Grey-box modeling*	0.0001* (0.0670*)
			Interpolation modeling	0.0822 (0.0852)

4	0.0672	0.2074	Direct combination*	0.0585*
			Interpolation modeling	0.0598

For Scenario 1, the predictive AREM on the new data set is 0.0626 which is less than the initial AREM. This observation indicates that it might be unnecessary to update the current metamodel further since the model can accurately predict the new data points. However, it is observed that after the model updating using the direct data combination strategy, the final AREM is further reduced to 0.0528. Scenario 2, however, requires a major update for the initial metamodel since it generates very large predictive AREM (0.3614) on the new data set. Both applicable strategies provided model improvement at a similar level. Though the AREM of the direct combination method is slightly higher than that of the interpolation strategy, it fundamentally increases the design space. For scenario 3, 13 data points are picked from the second experiment to form the new data set. The rest of the data is available to validate the model since the two data sets are in the same design space. In this case, the interpolation strategy is not optimal as the updated model generated has higher AREM. Instead, grey-box updating results in the greatest improvement. Scenario 4 represents the most complex situation among these test scenarios. Both design space and experimental conditions are inconsistent between the initial model and the new data set. Thus, any strategy that can utilize more information to update the metamodel would become useful. After strategic updating, the AREM was reduced from 0.2074 to 0.0585.

The case study demonstrates a valid approach to updating an existing metamodel using new data. It sheds a little light on a general metamodel update approach. However, the case study only illustrates a manual process for model updating. Further research is needed to discover an automated and more effective way for metamodel updating following emergence of new data sets in the AM domain.

5. CONCLUSIONS

As AM matures into a production-ready technology, greater emphasis will continue to be placed on rapid design-to-product transformations. AM will continue to become a more viable alternative for applications such as supply chain logistics and customized parts. To this end, this paper outlined a closed-loop data-information-knowledge-application framework that will support the functionalities necessary to realize rapid, customizable, design-to-product transformations through a self-improving knowledge management system.

The proposed analytic framework defines a bottom-up knowledge engineering process and a top-down data generation process to leverage individual efforts of conducting experiments and deriving knowledge from data. The streamlined bottom-up knowledge engineering process plus the application driven data generation process are connected by operators and engineers. As new data is ingested, it will be infused to the existing information system. The contextualized new data could trigger a metamodeling process where predictive models are updated to reflect PSP more accurately. Sequentially, the new knowledge will be integrated into the AM application to improve AM engineering decisions. Conversely, if the engineer receives some alarm caused by inconsistency between design decisions and design rules, he/she can perform engineering analysis by querying the knowledge. If knowledge is missing, information needs will be generated, and the demand will be passed to the information system, and ultimately design-of-experiments can be prescribed for the researchers and manufacturers. Thus additional experiments, builds, and tests can be performed in a cost effective fashion.

The integrated and automated workflow illustrated in this paper is comprehensive enough to cover and manage the whole development lifecycle of AM knowledge with continuous improvement. It was also discovered that to automate and streamline the workflow, further research on AM informatics is needed to build the links still missing, especially those in the top-down goal-oriented data generation processes.

Our future work will be focused on the integration of knowledge-based adaptive data-driven knowledge engineering and goal-oriented adaptive data sampling design. Specifically, we will investigate how ontology can potentially address the aforementioned need to learn from the experience of AM parts produced successfully or unsuccessfully. This would reduce requirements to simulate or analyze each new job fully. Approaches will be proposed to adaptively learn and enrich the knowledge base to enable continuous improvements. The two-way concept introduced in Section 3 provides the foundation to methodically adapt data and knowledge to improve the quality, reliability, and usefulness of both for improved understanding of the complexity of PSP relationships. This approach can help move toward a reusable knowledge base that improves with experience. A reference ontology can be developed and standardized to enable easy integrations of heterogeneous AM information systems.

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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