Proceedings of the ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference
IDETC/CIE 2016
August 21-24, 2016, Charlotte, North Carolina

DETC2016-60392

DIGITAL SOLUTIONS FOR INTEGRATED AND COLLABORATIVE ADDITIVE MANUFACTURING

Yan Lu, Paul Witherell
National Institute of Standards and Technology
Gaithersburg, MD 20899
Email: [yan.lu, paul.witherell]@nist.gov

Felipe Lopez
University of Texas at Austin
Austin, TX 78712
Email: felipelopez@utexas.edu

Ibrahim Assouroko*
Université de Technologie de Compiègne
Compiègne, France
Email: ibrahim.assouroko@nist.gov

ABSTRACT

Software tools, knowledge of materials and processes, and data provide three pillars on which Additive Manufacturing (AM) lifecycles and value chains can be supported. These pillars leverage efforts dedicated to the development of AM databases, high-fidelity models, and design and planning support tools. However, as of today, it remains a challenge to integrate distributed AM data and heterogeneous predictive models in software tools to drive a more collaborative AM development environment. In this paper, we describe the development of an analytical framework for integrated and collaborative AM development. Information correlating material, product design, process planning and manufacturing operations are captured and managed in the analytical framework. A layered structure is adopted to support the composability of data, models and knowledge bases. The key technologies to enable composability are discussed along with a suite of tools that assist designers in the management of data, models and knowledge components. A proof-of-concept case study demonstrates the potential of the AM analytical framework.

Keywords: additive manufacturing, analytical framework.

1 INTRODUCTION

Additive manufacturing (AM) builds a part layer-by-layer directly from a 3D model. 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 in an emerging manufacturing paradigm characterized by mass-customization, personalization and new business models and supply chain models.

While the last several years have already observed an increase of the relative share of AM use for end-product manufacturing (mainly in automotive, medical and aerospace applications) [1], limitations have also been observed by both researchers and practitioners [2–4]. Such limitations may manifest either physically or digitally. For instance, some physical limitations observed in these processes include the maximum size of AM-produced components, the low build speed and the limited spectrum of materials available for use in AM. While physical limitations are well known among process engineers, digital limitations are gaining more and more attention. To some extent, digital limitations originate from the lack of an effective development environment to enable repeatable and reproducible builds and low cost qualification [5]. As of today, design, process planning, part building, testing and value chain activities (material and machine development) are commonly conducted separately and in fragmented environments.

First of all, there is a lack of a digital thread to integrate the supply chain of data from product conception to building and testing. Limited connectivity exists between AM lifecycle activities. For instance, the STL (STereoLithography) file format - the de facto standard used to connect CAD (Computer-aided design) to part building - is not well suited for the representation of most of the optimized shapes used in AM [6]. During fabri-

*Currently employed as Associate Guest Researcher at NIST.

cation, AM machines work with proprietary build file formats, vendor specific configuration languages and encoded monitoring logs. Though some effort [7–9] has been committed to homogenizing AM data, these efforts have been limited in scope and implemented primarily in research environments. The lack of shareable information across the AM lifecycle not only complicates process and part qualification at the machine level [10, 11] but also leads to large implementation gaps.

Secondly, there is limited understanding of the relationships between geometry, processing, structure, and properties, which could help predict the characteristics of AM final products. AM models, along with other sources of knowledge, play critical roles in the development of such products, from the selection of a process and material, lattice and support structure design, process parameter optimization to in-situ process control. However, given the different AM technologies, and the numerous variables associated with each technology (i.e., process and material parameters), AM modeling and knowledge mining efforts are currently not well coordinated, limiting their adoption. Models are usually developed for specific scenarios, and they are often subject to unique constraints. Moreover, these modeling results are usually proprietary due to the nature and purpose for which such models are often developed. To better utilize AM models and knowledge, a structured approach is necessary to move toward more composable and reusable solutions [12].

Last but not the least, the current AM software environment is far from being mature and tools are disconnected from each other. CAD vendors provide tools for conventional manufacturing and export STL files for AM machines. Some AM software companies (e.g., Materialise, Nettfab) offer STL fixing functions, and allow structure modification, support design and even slicing for a set of machines. However, both traditional CAD systems and AM process planning software do not possess the desired tools (i.e. design rules, modeling and simulation engines) to fully support informed AM design. In rare cases when those tools are available, meta-information (including process knowledge) is incorporated into the tools as black boxes [1].

The fragmentation of today's AM development environment is illustrated with the three pillars shown in Figure 1. Software tools, models and knowledge base, and data are drawn as three supports for AM applications, but in a disconnected fashion. As a large amount of AM data has already been generated and considerable effort has been dedicated to the development of AM models and knowledge bases, the data and models are ultimately expected to be used by AM software tools to enable a collaborative AM development environment, where a fully-integrated design optimization can be conducted for development cycle and

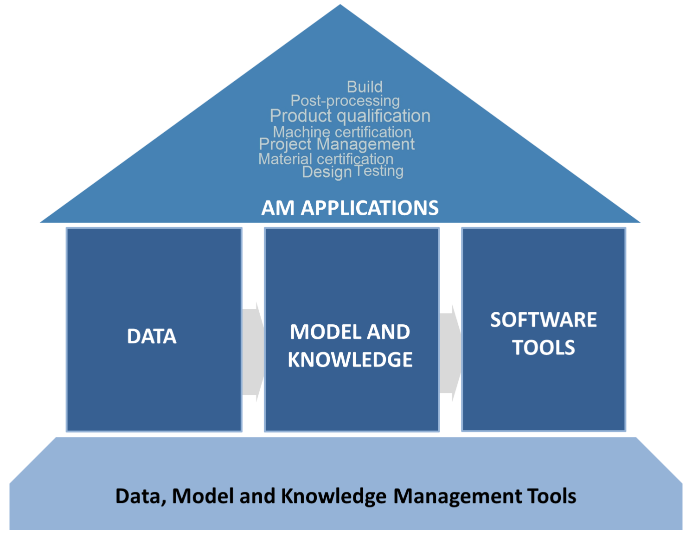

FIGURE 1: Three pillars for AM development.

cost minimization and with greater confidence in part quality. In order to achieve that goal, there is a need for a systems approach to bring together all the distributed data and necessary models and knowledge, and make them work in an integrated manner. Therefore, a foundation consisting of a suite of data, model and knowledge management tools is added under the three pillars to achieve the ability to retrieve the data, build predictive models and obtain design knowledge quickly and at low cost, as shown in Figure 1.

In this paper, a layered AM analytical framework is outlined as a solution to address the digital limitations and enable rapid AM part development. Within the framework, AM-specific traits are considered, yet general enough so that these traits can be specialized. AM-specific information and knowledge management opportunities exist in relation to production and lifecycle [13], material information [9], data analytics and predictive modeling [12], and process planning [14], among others. It is with these considerations in mind that the framework is designed to support the representation, curation, facilitation, and management of AM data, information, and knowledge across distributed environments.

Section 2 of the paper provides a description of the conceptual analytical framework. Section 3 focuses on the key technology of the analytical framework. Section 4 shows a case study of the application of such an analytical framework to AM material informatics; and Section 5 concludes the paper.

2 AN AM ANALYTICAL FRAMEWORK

A multi-layered, analytical framework (Figure 2) will enable the integration of data, models and a knowledge base and software tools for the rapid development and deployment of AM-destined parts. In the fully functional framework, the data, model

[1] Certain commercial equipment, instruments, or materials are 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.

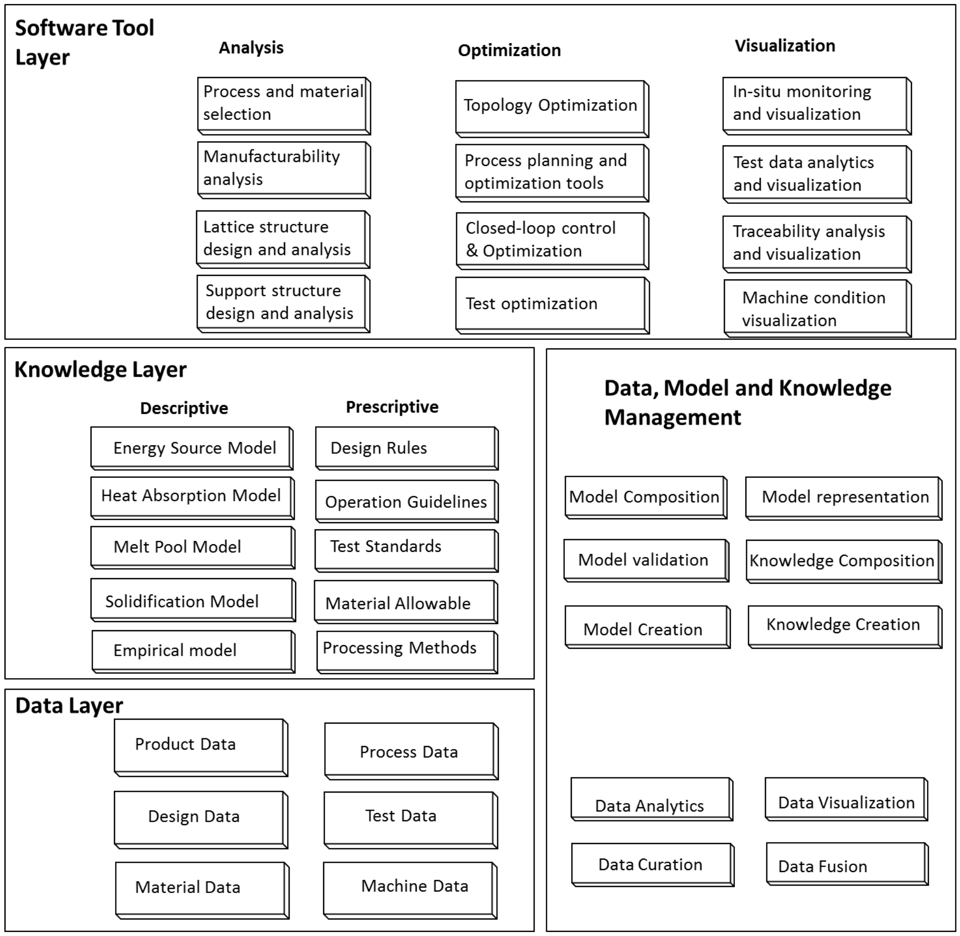

FIGURE 2: A layered structure of AM analytical framework

and knowledge, and software tools are structured in a quasi-hierarchy. The Data Layer sits at the bottom, while the Software Tool Layer is positioned on the top, providing mechanisms that directly serve the requests from AM stakeholders. In the middle sits the Knowledge Layer, bridging the Data Layer with the Software Tool Layer. Depending on the nature of an activity, models can directly interact with the data to support software tools or AM queries. A cross-layer set of Data, Model and Knowledge Management Functions facilitate the interactions between the three layers. Descriptions of the layers and rules of design follow.

(a) **Software tool layer**: Software tools throughout the AM lifecycle and value chain may include: CAD design, CAE tools, lattice design, support structure design, process planning tools, process control and monitoring, material intelligence, machine qualification, test results analysis and part qualification tools. Interoperability is key to integrating software applications, highlighting the importance of standard data exchange formats. Software tools should be constructed to allow for the incorporation of reusable models and knowledge bases. In addition, in collaborative environments, it is preferable to use software tools that are designed as services and accessible by all the AM stakeholders.

(b) **Knowledge layer**: Effective software tools should possess decision support functions driven by knowledge. Two categories of knowledge are included: descriptive and prescriptive. Descriptive knowledge describes things as they are, while prescriptive knowledge prescribes how thing should be for a desired goal [15, 16]. This layer maintains libraries of unit AM models and customizable knowledge bases. For instance, AM process models include both physics-based models and data driven empirical models. The model elements can be built at different length- and time scales. These model units should be composed and reconfigured based on desired outputs, such as dimensional accuracy, surface roughness, residual stress, microstructure and mechanical properties.

In addition to models, knowledge bases are also included at Knowledge Layer. For instance, the Knowledge Layer may contain a knowledge base for reconfigurable constructs for design rules. Dedicated AM design rules are necessary for both CAD tools and AM process planning tools. Strong dependencies of AM process outputs on part geometry makes the standardization and representation of material properties for AM very challenging, a challenge potentially addressed with customizable material database interfaces.

A key criterion in designing the Knowledge Layer is the incorporation of principles that support modularity. Modularity and composability support customization and federation within and between implementations. Models should be designed in modules, and represented in standard formats accompanied by semantic descriptions for automatic orchestration in software tools.

(c) **Data layer**: The Data Layer provides the foundation of the AM development environment and supports both the Knowledge Layer and the Software Layer. Data is necessary to derive and validate models and knowledge bases through machine learning techniques. Newly added data can be fed into the Data Layer to enhance the models and knowledge bases continuously.

AM data is directly used in different software tools by AM stakeholders as inputs, controls and resources. All of the AM data generated and used during the build of a part should be stored for effective traceability analysis, establishing a digital thread that is critical for part qualification. In addition, the interfaces to support experimental data generated by material vendors and equipment builders are included in the framework.

The data components must be inclusive enough to cover material data, equipment data, product data, design models, process data and test data. A common data access interface is critical for federation and consistent data query results among different stakeholders. Since a central data repository is not feasible for an AM collaborative environment, data should be structured appropriately to support federation and easy mapping between the common data access interface and distributed data sources.

(d) **Data, Model and Knowledge Management Functions**: Modularity, composability and compositionality are the foundation of the proposed AM analytical framework. These traits are fundamental to achieving sharable data, reusable models and knowledge bases. Sets of management functions are necessary for data curation and the fusion between data analytics and visualization. Support functions are needed for model and knowledge creation and composition, for instance to derive or validate models through data.

Development of these functions requires understanding the types of data to be curated, the structure which with this data is best supported, and the applications most likely to access this data.

A fully realized AM development environment, based on the integrated analytical framework, is expected to support complete, end-to-end digital processing during the AM product lifecycle. Such a capability can greatly streamline how AM products are developed, from understanding design considerations to employing predictive analytics. For instance, the predictive models, representing the relationship between design variables and process parameters and part properties, as well as the knowledge base specifying design constraints, allow engineers to investigate, through design rules or numerical simulation, “what if” scenarios. A realized architecture allows answers to be supported by the data collected through experiments, tests and previous builds. Through the integrated use of software tools, predictive models and AM lifecycle data, greater confidence can be instilled in part quality. Using the framework for early parallelization of AM activities can significantly reduce development and qualification costs. The key technologies enabling the analytical framework will be discussed in next section.

3 KEY TECHNOLOGIES

The theoretical foundation for building the data, model and knowledge management functions lies in five areas: (1) information modeling, (2) model representation, (3) model ontologies, (4) surrogate modeling, and (5) modular design rules. The rules that lead the development of these technologies are specified in this section along with some early work in these fields.

3.1 A common information model

A comprehensive, and AM-specific, information model is required to link activities to a digital spectrum, and implement an integrated information system to support data sharing. Such a model must provide:

(a) Full coverage of AM lifecycle and value chain activities.
(b) Information necessary to verify and validate an AM part throughout design-to-product transformations.
(c) Multi-discipline data analytics to develop in-depth AM knowledge bases, including process-material-property relationships, AM design allowables, and AM design rules.
(d) Schema support for different AM file formats (including STL, 3MF, and AMF).
(e) Information federation among distributed data sources.
(f) A modular structure to the model to facilitate the continued maintenance and development of the model.

Our previous work resulted in a conceptual integrated data model for the AM lifecycle [9]. The model was based on a classical PLM information modeling methodology named the Product-Process-Resource (PPR) model. Based on the PPR model, we

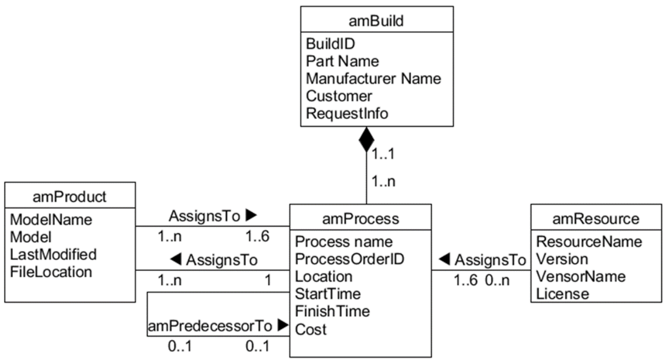

FIGURE 3: Core schema of an integrated AM data model [9].

were able to classify AM information into three domains: Product, Process, and Resource. Product domain information includes any component-related information, from specifications to as-designed and as-built product information. Process domain information records the AM activity governance data (e.g., process control) as well as dynamic data generated during the activities. Resource domain information can be further categorized into material, equipment, personnel, and software tools. The three types of AM information define a core schema to establish the most general layer within the data model (Figure 3). Entities defined in this layer can be referenced and specialized by other entities. The conceptual data model may be applicable to different types of AM technologies (e.g., powder bed fusion, directed energy deposition, binder jetting, etc.).

3.2 Model representation

Model implementations are often dependent on platform and language, limiting their capabilities to be reused and shared. Reusability in models can be improved with the separation of the model implementation and representation. There are various XML-based predictive model interchange formats. As an example, Figure 4 shows a regression model schema defined in PMML [17, 18].

PMML is limited to data-driven predictive models. Physics-based models, more common in the AM literature, are usually developed in vendor-specific finite element analysis software. Limited work has been found on defining a standard representation [19, 20]. In such scenarios, surrogate modeling could be an approach to converting physics-based models to data-driven predictive models, which can be represented using PMML.

3.3 An ontology for AM models

Physics-based models have been developed to determine the influence of processing parameters in the overall quality of an AM-produced-part [21–24]. Given the complexity of the physical processes involved in AM processes, simplifications and as-

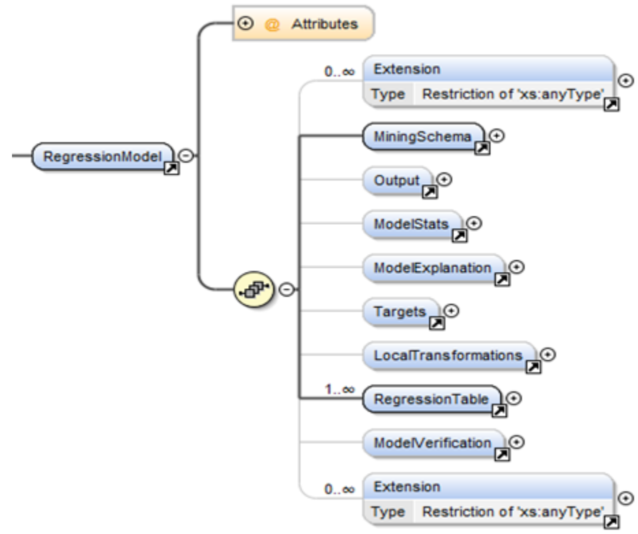

FIGURE 4: Regression model schema in PMML [18].

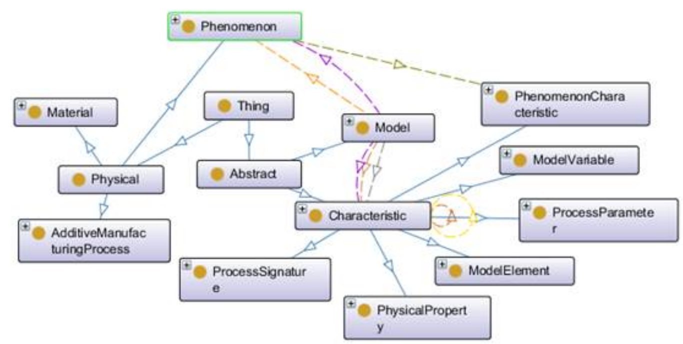

FIGURE 5: OWL ontology used to represent modeling assumptions and predictive capabilities.

sumptions are often necessary. Specific models are often developed for particular applications, such as providing means for thermal predictions, studying residual stresses, analyzing microstructural predictions, etc. Reusability in AM models is challenged by a users limited understanding of the assumptions and approximations made in the development of a model.

An AM model-driven ontology is being developed by NIST (see Figure 5) to capture key component attributes defining the modeling of the different physical phenomena involved in AM processes, as well as the underlying assumptions that set limitations on the models. The proposed model ontology, along with a set of instances of some available models, will help understand in a more structured manner which modeling concepts are appropriate for a given physical phenomenon, and which assumptions are playing important roles in the characterization and usage of a given modeling concept.

Our AM ontology is expected to play a key role in model composition and integration, as it can help identify commonalities between models, and provide understanding of their degree of compatibility by verifying that they predict the same physical phenomena, use consistent inputs, and return consistent outputs.

3.4 Surrogate modeling

Physics-based models for AM are developed for different applications and predict different variables with different degrees of uncertainty. The result of each AM model is a data set of predictions that explore user-defined regions of the space of processing conditions. Model predictions are often used for process optimization, for which it is necessary to explore the entire space of processing parameters (e.g. material, power, speed) to find the most appropriate combination for a given goal. The search for an optimum requires invoking computationally-expensive simulations numerous times, which in the case of the complex models used in AM is either time consuming or infeasible.

As an alternative, surrogate models (also known as metamodels or "models of models") are being explored as methods to merge predictions (information) from different computational models. In the field of additive manufacturing, surrogate models can serve two goals: 1) work as computationally-inexpensive tools for process optimization, and 2) merge information (data) from different models which explore different regions of the parameter space, creating global models.

The first goal of surrogate models has been the motivation of numerous disciplines, such as design optimization [25]. The second goal, however, is relatively new and a result of the high value of data obtained from AM simulations. This approach involves two new challenges: 1) determining what makes models compatible for comparison and aggregation (see section 3.3), and 2) measuring prediction uncertainty in each individual model to ensure the fidelity of the data set. The first challenge involves knowledge of each individual model, as captured by the ontology, while the second requires that each model be validated before being used [26].

3.5 Design rules for AM

Design rules are designated as a component of the Knowledge Layer. It is critical to synthesize the model element for design rules with elements from the Data and Data Management Layers. Design rules in AM are not clear-cut constraints, but instead provide baselines from which design constraints can be tailored on a case-by-case basis.

Modular design rules can support a configuration-based approach to their development (Figure 6). Elements of design rule modules can be classified based on the data and information they represent, and how this data is used. By decomposing design rules and properly classifying their constructs, the ability to reuse these rules can be increased, and customization can be built in. Related work at the National Institute of Standards and Technology [14] explored the formalization of design rules and their constructs. An approach based on "primitives" and "modules" was proposed to capture design rule fundamentals and their relationships. These same formalized fundamentals can be used as a foundation for reusable and customizable design rules in the proposed framework.

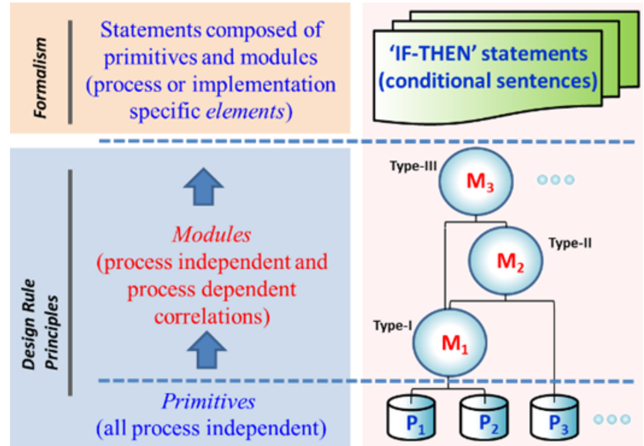

FIGURE 6: Proposed approach for design rule principles [14].

4 A CASE STUDY: MATERIALS INFORMATICS SYSTEM

To demonstrate the utility of the proposed analytical framework, we partially applied the structure and implementation rules of the analytical framework to building a material information system (Figure 7). The basic implementation details are described below.

(a) **Data Layer**: Complete process history, test data of AM builds from NIST MSAM projects [27] are captured and stored in a MongoDB database [28]. An XML-based AM data schema was developed based on the conceptual model presented in Section 3.1. Currently, the data is scoped to metal powder bed fusion processes. The database is wrapped with a REST API provided by the NIST Material Data Curation System (MDCS) [29].
(b) **Knowledge Layer**: Empirical Models capturing the relationship between laser power, layer thickness and mechanical properties are represented in PMML and stored in the NoSQL (non relational) database as well.
(c) **Data and Model Management Tools**: A web-based data curation system is provided by MDCS and used for the AM data population. A similar model creation tool is used to create regression models and save them into the database. Data Analytics can be performed directly from R or MATLAB through their MongoDB interfaces, and the results are manually captured and imported into the Model Creation tool. A Model Update tool can also be programmed to conduct au-

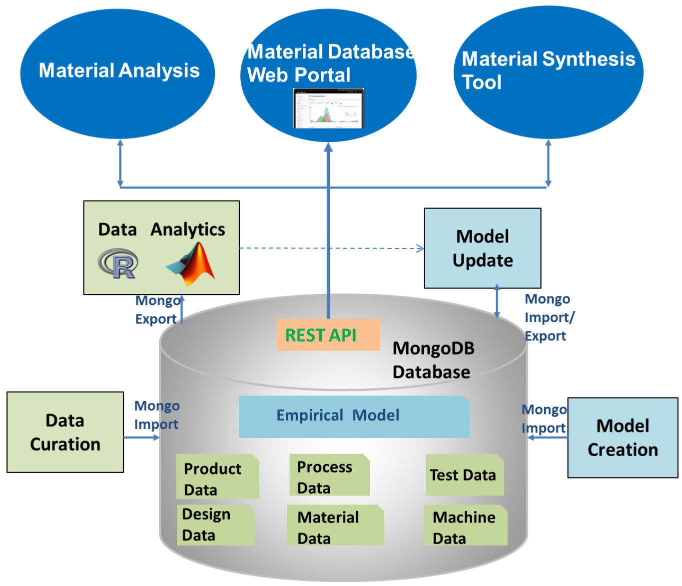

FIGURE 7: A material informatics system based on the AM analytical framework.

tomatic model adaptation upon the arrival of new data sets.

(d) **Software Tool Layer**: Three software tools are built to conduct a material informatics study. A web-based Material Database Web Portal is built to query and view AM data. A Material Analysis tool can query models by material type. The material-part property relationship can be imported into the software for selected material types. Comparisons can be made through plots and figures. Using the Material Synthesis tool, users can access the database and search for models that relate chemical composition to material properties (e.g., thermal properties), and models that relate material properties (e.g., thermal conductivity, absorptivity, powder size) to microstructure/part properties. Since both models are represented as surrogate input/output relationship models, they can be composed sequentially to compose the relationship between chemical composition and part properties. The new predictive model can be used to optimize the material chemical composition design.

5 CONCLUSIONS

Current AM production approaches rely on the generation of large amounts of trial-and-error data and proven, set configurations of processes and materials for a given product design. 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 reducing inventory in supply chain logistics and customized parts. To this end, this paper outlined an AM-dedicated analytical framework that will support the functionalities necessary to realize rapid, customizable, design-to-product transformations.

Significant efforts have been dedicated to the development of AM data management, high-fidelity models and design support tools for AM. These efforts are specialized based on the data they are developed to support. None of the current works are comprehensive enough to cover and manage the diversity of AM activities discussed in the proposed framework. As of today, it's still a great challenge to bring together all the distributed data and necessary models in AM domain and make them work together properly for diverse software applications.

We outline a layered analytical framework aimed to support rapid design-to-product transformations of AM parts. AM process model components, representing the relationship between process parameters, structure and part properties, as well as individual knowledge bases of AM material, product design, process planning and manufacturing operations, are captured and managed by the architecture. Configuring and reconfiguring model components and knowledge bases in software tools will allow engineers to explore "what if" analysis for decision making through AM lifecycle. A streamlined information flow supports increased confidence in part quality while reducing build times and costs.

The proposed framework for reusable data, models and knowledge bases relies on modularity and composability principles. The key technologies enabling the composability are discussed in the paper. These technologies can provide a suite of tools to assist designers to create, select and assemble data and knowledge components in various combinations into software applications in AM development environments.

REFERENCES

[1] Cotteleer, M. J., 2014. "3D opportunity for production: Additive manufacturing makes its (business) case". *Deloitte Review*(15).

[2] Leandri, A., 2015. Key design considerations for metal additive manufacturing. GrabCAD Blog, http://blog.grabcad.com/blog/2015/11/02/key-design-considerations-for-metal-additive-manufacturing/. Accessed: 04-05-2016.

[3] Royal Academy of Engineering, 2013. Additive manufacturing: opportunities and constraints. Tech. rep., Royal Academy of Engineering. http://www.raeng.org.uk/publications/reports/additive-manufacturing, Accessed: 04-05-2016.

[4] Ford, S. L., 2014. "Additive manufacturing technology: Potential implications for us manufacturing competitiveness". *Journal of International Commerce and Economics*, September.

[5] Scott, J., Gupta, N., Weber, C., Newsome, S., Wohlers, T., and Caffrey, T., 2012. Additive manufacturing: status and

opportunities. Tech. rep., Science and Technology Policy Institute, March.

[6] Lipman, R., and McFarlane, J., 2015. "Exploring model-based engineering concepts for additive manufacturing". In Proceedings of the 2015 Annual International Solid Freeform Fabrication Symposium, pp. 385–400.

[7] Lipson, H., 2013. "Standard specification for additive manufacturing file format (AMF) version 1.1". *ASTM International,* **10**.

[8] Nassar, A. R., and Reutzel, E. W., 2013. "A proposed digital thread for additive manufacturing". In Proceedings of the 2013 Annual International Solid Freeform Fabrication Symposium, pp. 19–43.

[9] Lu, Y., Choi, S., and Witherell, P., 2015. "Towards an integrated data schema design for additive manufacturing: Conceptual modeling". In ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, American Society of Mechanical Engineers.

[10] ASTM Standard E-8. Standard test methods for tension testest of metallic materials. Active Standard ASTM E8 / E8M, http://www.astm.org/COMMIT/SUBCOMMIT/E2804.htm. Accessed: 04-05-2016.

[11] ISO 77.040.10. Mechanical testing of metals. http://www.iso.org/iso/iso_catalogue/catalogue_ics/ catalogue_ics_browse.htm?ICS1=77&ICS2=040&ICS3=10. Accessed: 04-05-2016.

[12] Witherell, P., Feng, S., Simpson, T. W., Saint John, D. B., Michaleris, P., Liu, Z.-K., Chen, L.-Q., and Martukanitz, R., 2014. "Toward metamodels for composable and reusable additive manufacturing process models". *Journal of Manufacturing Science and Engineering,* **136**(6), p. 061025.

[13] Kim, D. B., Witherell, P., Lipman, R., and Feng, S. C., 2015. "Streamlining the additive manufacturing digital spectrum: A systems approach". *Additive Manufacturing,* **5**, pp. 20–30.

[14] Jee, H., Lu, Y., and Witherell, P., 2015. "Design rules with modularity for additive manufacturing". In Proceedings of the 2015 Annual International Solid Freeform Fabrication Symposium, pp. 1450–1462.

[15] Lelas, S., 2000. *Science and Modernity: Toward an integral theory of science*. Springer Netherlands.

[16] Birkhofer, H., 2011. *The future of design methodology*. Springer.

[17] Pechter, R., 2009. "What's PMML and what's new in PMML 4.0?". *ACM SIGKDD Explorations Newsletter,* **11**(1), pp. 19–25.

[18] Data Mining Group. PMML 4.0 - mining schema. http://dmg.org/pmml/v4-0-1/MiningSchema.html. Accessed: 02-20-2016.

[19] Michopoulos, J., Mast, P., Chwastyk, T., Gause, L., and Badaliance, R., 2001. "FemML for data exchange between FEA codes". In ANSYS Users Group Conference.

[20] Michopoulos, J., Martin, R., and Anto, B., 2005. "Advances of the finite element modeling markup language". In ASME 2005 International Mechanical Engineering Congress and Exposition, American Society of Mechanical Engineers, pp. 181–189.

[21] Li, R., Shi, Y., Liu, J., Yao, H., and Zhang, W., 2009. "Effects of processing parameters on the temperature field of selective laser melting metal powder". *Powder Metallurgy and Metal Ceramics,* **48**(3-4), pp. 186–195.

[22] Yin, J., Zhu, H., Ke, L., Lei, W., Dai, C., and Zuo, D., 2012. "Simulation of temperature distribution in single metallic powder layer for laser micro-sintering". *Computational Materials Science,* **53**(1), pp. 333–339.

[23] Hussein, A., Hao, L., Yan, C., and Everson, R., 2013. "Finite element simulation of the temperature and stress fields in single layers built without-support in selective laser melting". *Materials & Design,* **52**, pp. 638–647.

[24] Roberts, I. A., 2012. "Investigation of residual stresses in the laser melting of metal powders in additive layer manufacturing".

[25] Simpson, T. W., Poplinski, J., Koch, P. N., and Allen, J. K., 2001. "Metamodels for computer-based engineering design: survey and recommendations". *Engineering with computers,* **17**(2), pp. 129–150.

[26] Lopez, F., Witherell, P., and Lane, B., 2016. "Identifying uncertainty in laser powder bed fusion models". In Proceedings of the ASME 2016 Manufacturing Science and Engineering Conference.

[27] National Institute of Standards and Technology. Measurement science for additive manufacturing program. http://www.nist.gov/el/isd/sbm/msam.cfm. Accessed: 02-20-2016.

[28] MongoDB. https://www.mongodb.com. Accessed: 02-20-2016.

[29] National Institute of Standards and Technology. Material data curation system. https://mgi.nist.gov/materials-data-curation-system. Accessed: 02-20-2016.