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TITLE: FUNCTIONAL REQUIREMENTS OF DATA ANALYTIC TOOLS AND SOFTWARE FOR METAL ADDITIVE MANUFACTURING

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ABSTRACT

Additive manufacturing's (AM's) transition to an accepted production technology has led to increasing demands on data requirements. Many of these advances have been made possible by an increase in in-situ sensing and ex-situ measurement devices. These new devices are rapidly increasing the volume, variety, and value of AM data. The number of software tools used to measure, model, simulate, and manage AM material, part, and process is increasing to take advantage of emerging customer needs and market opportunities. However, the capabilities and accessibility of these tools, which are being used by both practitioners and researchers, vary greatly. Software tools for AM users should be able to handle ex-situ needs as well as address emerging in-situ requirements, including 1) process the different types of measured data, 2) understand defect formation, geometric variation, surface roughness, and 3) run fast enough for the layer-by-layer, scanning process. To better understand both the current capabilities and future needs, this paper provides an AM product-lifecycle landscape of software tools. The landscape includes tools for product design, design analysis, process planning, process monitoring, process modeling, process simulation, and production management. A preliminary set of functional requirements are identified, and requirements that if supported will further data analytics capabilities in AM. Furthermore, this paper identifies opportunities to develop new data-analytics tools that can improve product quality and reduce production time.

Keywords: additive manufacturing, data analytics, functional requirements, product lifecycle engineering, software.

1. INTRODUCTION

Fabricating metal AM parts can create many challenges when considering data management. For metals, challenges come from both the amount of data that can be associated with the material and the amount of data associated with the processing of the material. The material processing information is critical to improvements in the metal AM (MAM) part production. Complex metal parts fabricated by additive manufacturing technology can be difficult to experimentally measure [38] [61], and thus difficult to quantitively characterize and record the status of process. Four main reasons are as follows. First, instability in Laser-Based Powder Bed Fusion of Metals (PBF-LB/M) [29] processes, which primarily contributes to the part variations [19] [20], creates significant measurement challenges. Second, the relationships among design, material, process, and property are difficult to formulate, model, or describe [2] [10] [11]. Third, even using currently available physics-based models, a quantitative understanding of AM cause-and-effect relationships is difficult to achieve [27] [31]. Fourth, the factors that determine the full state of the PBF-LB/M system are not well understood. Using software tools to curate and model the instability and variations in PBF-LB/M processes has become a critical need to ensure the MAM part quality [67].

This paper focuses on data-management software tools. There are three main challenges related to data management tools that have also been discussed in MAM data-related workshops [39, 44]. First, there is a lack of an integrated suite of tools for data management, analysis, monitoring [64], and control of PBF-LB/M processes, including melting, solidification [27], microstructure analysis, and material properties [39] [50] [54]. Second, there is a lack of software tools for process planners to determine process planning parameters for PBF-LB/M processes. Third, there is a lack of software tools that enable users to correlate data from different sensors. As a result, there are few tools available to meet these challenges when industrial users need to 1) specify design rules and allowables to ensure manufacturability, 2) monitor and control these processes, and 3) analyze production scenarios to optimize future production.

MAM technology users have shown a tremendous need for an integrated suite of software tools for data analytics and physics-based modeling and simulation [38]. Specific software capabilities include data analytics for defect characterization and identification [14] [56] [71] [72], physics-based modeling and simulation [70], microstructural changes versus temperature changes, mechanical property prediction, and part validation[1] [24]. Furthermore, software tools for PBF-LB/M process monitoring for decision-making for in-process control are also needed by industries. Note that the scope of this paper is PBF-LB/M for AM, including AM part design, powder spreading, powder bed fusion, melting [43], solidification [50], grain growth [32], phase transition, mechanical property estimation, and residual stress calculations. Also, software capabilities on data modeling, processing, and fusion are within the scope of this paper.

This paper consists of the following sections. Section 2 reviews related publications in software tools that are used in design, production management, and data analytics areas. Section 3 identifies preliminary functional requirements for product data-driven analytic tools for ensuring the quality of MAM parts. Section 4 associates available software capabilities with identified data management requirements and discusses gaps and opportunities in data analytics tools for MAM. Section 5 concludes the outcomes of the paper and future works.

2. REVIEW OF SOFTWARE TYPES AND FUNCTIONS

This section reviews the capabilities of currently available software tools that support the five aspects of MAM: design, powder, process, property, and product. In the design aspect, design modeling and analysis take place. Activities include the product's shape and properties (features, materials, datums, tolerances, dimensions, surface roughness, among others) are selected and analyzed. In the powder aspect, powder material properties are defined for procurement. In the process aspect, part building activities, such as determining process parameters, selecting physical resources, setting up machine and workpiece, defining scan paths, and monitoring the process, take place. In the property aspect, microstructural analysis and post-processing activities take place. Those activities include grain structure and phase analysis, heat treatment, porosity reduction, machining, and polishing. In the product aspect, product lifecycle management and validation [65] take place. Those activities include product data management, material property testing, part inspection, nondestructive evaluation, and surface roughness measurement. Software tools, with varied capabilities, are available to support these five aspects of MAM (see Table 1).

Design modeling focuses on creating models of the part's geometry, features, and geometric dimensioning and tolerancing (GD&T). Design analysis decides whether the proposed design will meet the required specifications. Design analysis for AM investigates design features, including lattice structures and support structures. Material selection software is commonly used to find appropriate powder material for making parts. Process planning selects the powder material, part setup, including support structure location on the built platform, the slicing the setup part into layers, and the process parameters. Physics-based modeling and simulation represent powder spreading, melt-pool formation, melt-pool solidification, grain growth, phase transition, property modeling, and residual stress estimation [60]. Production management tools are used to monitor the chamber environment, including its current temperature and inert gas flow rate. Process monitoring relies on a variety of different sensors. Commonly used PBF-LB/M sensors include optical, thermal, and acoustic. These sensors use different setups to collect data, which can be used collectively to determine the state of the PBF-LB/M process. Microstructural and post-process analysis reports analyzed material properties of parts using scanning electron microscope (SEM) images, such as electron back-scattered diffraction (EBSD) scanning electron microscopy, or dimensional, surface and volumetric measurements such as those from an ex-situ X-ray computed tomography (XCT) or coordinate measuring machines (CMM). Material management is a function of managing material data for material selection, traceability on part performance, and process validation. Product lifecycle management is a function of managing the product lifecycle data for design, planning, quality, and delivery. Part validation may include contributions from the previously identified stages as well as additional requirements. Generally, it is a process of validating the material, equipment, and production process for the quality of MAM parts.

Major sources of data include the many types of in-situ and ex-situ measuring equipment, including sensors that have been used for PBF-LB/M process monitoring by researchers and manufacturers. Types of equipment include photogrammetry, thermography, XCT, and CMM. In-situ sensors collect data in different setups, such as coaxial with the laser axis and off-axis (staring). They can be used collectively to determine the state of the PBF-LB/M process and defect [24]. The data from these sensors need to be correlated as an integrated suite of data for analytics and decision-making.

Today, determining the state of the build is done using a variety of data analytics (DA) tools. The use of DA tools can lead to new insights and knowledge – both of which can help enhance quality, increase productivity, and reduce costs. Artificial Intelligence (AI)-based DA models or tools, such as machine learning (ML), can make predictions, optimize performance, detect defects, and perform classification, regression, or forecasting [69]. Razvi et al. [53] present a

[1] Process of providing evidence that the output from AM will meet specified requirements.

literature review of ML or DA applications in additive manufacturing (AM). The review identifies areas in the AM lifecycle, including design, process plan, build, post-process, and test and validation, that have been researched using ML. Currently, software modules from the research are available, such as defect detection for PBF-LB/M using in-situ images coupled with ex-situ XCT scan model, see Petrich et al. [47] and Gobert et al. [21] for more details.

Table 1 MAM Software Tools and Their Capabilities[2]

Capability		General-purpose tool	MAM-Specialized tool
Design	Design modeling	Netfabb [8], Siemens NX [46], Solidworks [59], Creo [12]	nTopology [45], Altair Inspire Print3D [5]
	Design analysis	Abaqus [3], Ansys [7], MSC Software [42], Comsol [13]	nTopology, 3DXpert [1], Flow-3D [18]
Powder	Material selection	Granta Design Selector [23]	Material Selection and Analysis Tool [37], Senvol Database [57], and Granta MI:additive manufacturing [22], AMMD [4]
Process	Process planning		Materialise Magics [35], Materialise e-Stage [34]
	Process analysis, modeling, and simulation	Abaqus, Ansys, Comsol	MSC Software, Materialise Magics
	Process monitoring		Streamics [36], ifiniAM Spectral [60], Printrite3D [49], infiniAM Sonic [28]
Property	Microstructural and post-process analysis	APEX [8], MTEX [38], Aztec [47], CALYPSO [73], Avizo [64], Dragonfly [15], Simpleware [58], VGSTUDIO MAX [67]	Dream.3D [15]
Product	Material management	Siemens Teamcenter, Dassault Systems Enovia	Material Selection and Analysis Tool, Senvol Database, and Granta MI:additive manufacturing, AMMD
	Product lifecycle management	Siemens Teamcenter, Dassault Systems Enovia [17]	
	Part validation		AMMD

We believe that to truly benefit from available analytics methods and software tools, it is important to understand their functional requirements with the context of MAM [31].

3. FUNCTIONAL REQUIREMENTS OF METAL AM SOFTWARE TOOLS

This section presents a preliminary set of the various lifecycle and functional requirements that DA tools should meet to capitalize on analytics opportunities for a given application. Function is the relation between input and output and is commonly unknown. The format of each function is as follows: (Output_Data) = **Function** (Input_Data), where Input_Data includes data for the function to generate Output_Data. In some cases, Input_Data can include coefficients that control the behavior of the function. Functional requirement is the specification of input data and output data of the function, as in ISO/IEC/IEEE 31320-1 [30].

3.1 Design Modeling

Design Modeling-related functions are used to develop an optimized design. The functional requirements are as follows.

[2] No guarantee that it is a complete list of available tools.

(Design_Rules) = GenerateDesignRules(Part_Model, Material_Properties, AM_Machine_Capabilities, Design_Requirements)

This function guides designers to create functional parts with optimized lattice structures, tolerances, and datums. The input parameters to the GenerateDesignRules function are Part_Model (i.e., the CAD model), Material_Properties (e.g., material composition, physical properties, powder shapes and size distributions), AM_Machine_Capabilites (e.g., maximum power, work volume, maximum speed, and the range of layer thickness), and Design_Requirements (e.g., maximum porosity, tensile strength, grain orientation, and tolerances). The output parameter is Design_Rules (e.g., rules, including constraints, that designer can use to optimize the design model).

(Design_Allowables) = GenerateDesignAllowables (Part_Model, Material_Properties, AM_Machine_Capabilities, Part_Properties)

This function specifies the range of allowed deviations from the design parameters. Examples include mechanical properties, size, feature tolerances, and costs. The range constrains the magnitude of those deviations. The input parameters to the function are Part_Model, Material_Properties, AM_Machine_Capabilites, and Part_Properties (e.g., tensile strength, and hardness). The output parameter is Design_Allowables (e.g., ranges of specific design parameters, such as size, strength, fatigue life, hardness, materials, and costs).

(Design_Model) = GenerateDesignModel(Design_Rules, Design_Requirements)

This function uses the design rules to create a design model that includes Design_Allowables. The input parameters are the Design_Rules and Design_Requirements. The output parameter is Design_Model (an enhanced Part_Model that is generated using design rules and allowables).

(Lattice_Model) = LatticeDesign(Objective_Function, Design_Model)

This function creates a lattice structure that reduces part weight without compromising the part's functions. The input parameters are Objective_Function (the function for design optimization) and Part_Model. The output parameter is Lattice_Model (a part of the CAD model that replaces some portion of solid regions in the part).

3.2 Design Analysis

Design analysis functions include the following MAM-specific functions and builds on many of the concepts introduced in Section 3.1.

(Analysis_Report) = AnalyzeDesignModel(Objective_Function, Part_Model, Design_Requirements)

This function analyzed the Design_Model based on the Objective_Function. For example, consider an Objective_Function that optimizes product performance. Doing so would involve three types of Part_Model analyses. A structural (i.e., stress-strain) analysis ensures that the designed part can meet the expected loads when the part is in use. A tolerance analysis ensures that the AM part is within the specified tolerances. A fluid-flow analysis ensures that the designed part meets all requirements of fluid mechanics. The input parameters to the function are Part_Model, Objective_Function (the function of product performance vs. design parameters), and the Design_Requirements. The output parameter is the Analysis_Report (report of estimated product performance and design parameters).

(Optimized_Model) = OptimizeDesign(Objective_Function, Part_Model, Design_Requirements)

This function optimizes the part design given a collection of constraints, including topology, weight, size, materials, shrinkage warpage and costs, external loads, air resistance, and production time. The input parameters are Part_Model, Objective_Function, and Design_Requirements. The output parameter is an optimized CAD model.

3.3 Material Selection

Material selection functions are as follows.

(Material_Type) = SelectMaterialType(Design_Rules, Part_Model)

This function selects a specific material type based on the part model and design rules. Material type is a specific type of metal powder, such as a specific type of steel, titanium alloy, or nickel alloy.

(Powder_Parameters) = DefineMaterialProperties(Material_Type, Part_Model)

This function selects the powder material parameters based on the selected Material_Type and the current Part_Model. Powder_Parameters include powder particle size distribution, shape distribution, thermal properties, chemical composition, physical properties, and mechanical properties.

3.4 Process Planning

MAM process planning is a pre-process activity to prepare for the PBF-LB/M operations. Process planning functions are as follows.

(Setup_Rules) = GenerateSetupRules(Part_Model, Material_Type, Powder_Parameters, Process_Capability)

This function generates setup rules based on the part model, material type, powder parameters, and process capability. Process capability includes the maximum laser power, the minimum laser spot size, the maximum scanning speed, and the build platform size. The output parameter is a set of setup rules that can be used to specify how a part can be set up on a build platform.

(Setup_Model) = SpecifySetup(Part_Model, Setup_Rules, Design_Requirements)

This function specifies part setup on the build platform based on the part model, setup rules, and design requirements. The output parameter is a setup model that indicates the location and orientation of the part on the build platform.

(Support_Model) = SupportDesign(Setup_Model)

This function designs the support structure for overhangs using Setup_Model as the input parameter. The output parameter is the Support_Model that has necessary support structures to support overhangs.

(Sliced_Model) = GenerateSlicedModel(Support_Model)

This function generates the Sliced_Model based on the Support_Model. The output parameter is a Sliced_Model that includes the slices needed to fabricate the various layers in the part.

(Scanning_Commands) = GenerateScanningCommands (Sliced_Model, Scanning_Strategy, Scanning_Parameters)

This function generates scanning commands for the galvanometer(s), based on the sliced model, scanning strategy, and scanning parameters. The output is a set of Scanning_Commands needed to scan powder layers for building a part.

3.5 In-situ and Ex-situ Monitoring Planning

In-situ, ex-situ monitoring planning is a pre-monitoring activity to prepare for measuring PBF-LB/M process and part parameters. The in-situ, ex-situ monitoring planning function is as follows.

(Monitoring_Methods) = GenerateInSituExSituMonitoringMethods (Scanning_Commands, Sensor_Capabilities)

This function generates in-situ, ex-situ monitoring methods, based on Scanning_Commands and Sensor_Capabilities. The latter defines the characteristics of each sensor, including resolution, measurement ranges, sampling speed, sensitivity, and magnification. The output parameter is a set of Monitoring_Methods to monitor the process and part.

3.6 Process Analysis

In the PBF-LB/M process, it is important to analyze in-process phenomena, such as melt pool temperature variation, geometric variation, acoustic emission, plume, and spatter, for monitoring and control. Some requirements for in-process analysis software tools are as follows.

(Thermal_Characteristics) = AnalyzeMeltPoolThermalCharacteristics(Melt_Pool_Thermal_Images, Pyrometry_Data)

This function analyzes melt-pool thermal characteristics, such as temperature and energy intensity. The input parameter is a set of Melt_Pool_Thermal_Images and Pyrometry_Data. Note that Pyrometry_Data is a point measurement of meltpool temperature using a single or a multiple color pyrometer. The output is a set of Thermal_Characteristics, including melt pool temperature variation, spectrum in the infrared range. The thermal characteristics are used to analyze melting conditions, such as normal, over-melting, or under-melting.

(Geometric_Characteristics) = AnalyzeMeltPoolGeometricCharacteristics(Melt_Pool_Images, Melt_Pool_Single_Track_Images)

This function analyzes melt-pool geometric characteristics, such as size and width, based on in situ Melt_Pool_Images and ex situ track images. These images can be either gray-scale or thermal. The output parameter is a set of Geometric_Characteristics, including melt pool sizes and shapes, size and shape variation trends, and tail shape variations, needed for downstream analyses.

(Layer_Characteristics) = AnalyzeLayerCharacteristics(Layer_Images)

This function analyzes layer characteristics for possible defects, such as over melting, under melting, and overhang powders. The input parameter is a set of Layer_Images from imagers, such as staring and video camera. The output parameter is a set of Layer_Characteristics, including balling, discontinuities, voids, and unmelted powders for downstream analyses.

(Acoustic_Analysis_Results) = AnalyzeAcousticEmissions(Acoustic_Signals)

This function analyzes acoustic emissions for abnormal sparking or cracking, based on the measured Acoustic_Signals collected from an acoustic-emission sensor. The output parameter is a set of Acoustic_Analysis_Results, including signals in both time and frequency domains, which are used for downstream analyses.

(Plume_Characteristics) = AnalyzePlumeCharacteristics (Plume_Images, Thermal_Characteristics)

This function analyzes plume characteristics based on Plume_Images and Thermal_Characteristics. The input parameter is a set of images of the plume from a staring camera and a set of thermal characteristics. The output parameter is a set of Plume_Characteristics, including plume density, plume shape, and moving direction.

(Spatter_Characteristics) = AnalyzeSpatterCharacteristics (Spatter_Images, Thermal_Characteristics)

This function analyzes spatter characteristics, such as particle size distribution and spatter locations. The input parameters are a set of Spatter_Images and Thermal_Characteristics. The output parameter is a set of Spatter_Characteristics, including spatter size, velocity, flying distance, and the number. They are used for downstream analyses.

3.7 Process Modeling and Simulation

To model the physical phenomena in PBF-LB/M processes requirements for physics-based process modeling [39] and simulation software tools are as follows.

(Melt_Pool_Model) = ModelMeltPool(Material_Properties, Scanning_Commands)

This function builds models of powder melting, heat transfer, fluid flow, and solidification. Input parameters include sets of Material_Properties and Scanning_Commands (e.g., scan speed, laser power, and spot size). The output is a physics-based Melt_Pool_Model that can be used as input to a simulation tool.

(Grain_Growth_Model) = ModelGrainGrowth (Melt_Pool_Model, Material_Properties)

This function builds models of grain growth after solidification using Melt_Pool_Model and Material_Properties as inputs. The output is a Grain_Growth_Model.

(Track_Formation_Model) = ModelTrackFormation (Grain_Growth_Model, Melt_Pool_Model, Material_Properties, Powder_Parameters, Thermal_Characteristics)

This function builds models of track formation during cooling and solidification. The input parameters are Grain_Growth_Model, Melt_Pool_Model, Material_Properties, Powder_Parameters, and Thermal_Characteristics. The output is a Track_Formation_Model.

(Material_Phases_In_Part) = ModelPhaseTransitions (Grain_Growth-Model, Thermal_Characteristics)

This function models phase transitions of the metal material in solidification. The input includes a Grain_Growth_Model and Thermal_Characteristics in solidification. The output is a Material_Phases_In_Part model.

(Stress_Model) = ModelThermalStresses (Material_Phases_in_Part, Grain_Growth_Model, Thermal_Characteristics)

This function models thermal stresses in the part with three inputs: Material_Phases_in_Part, Grain_Growth_Model, and Thermal_Characteristics. The output is a Stress_Model of the part.

(Pore_Model) = ModelPores(Thermal_Characteristics, Powder_Parameters)

This function models pores in the part as inputs of Powder_Parameters that determine fluid flow in the melt pool along with Thermal_Characteristics during solidification. Given the powder material properties and the machine condition, we assume that pore formation depends on fluid characteristics in the melt pool, and the fluid characteristics are determined by the thermal characteristics (i.e., maximum temperature, heat-up rate, and cooling rate) [24, 50]. The output is the Pore_Model.

(Mechanical_Properties) = PredictThePartMechanicalProperties(Grain_Growth_Model, Thermal_Characteristics)

The function models and predicts mechanical properties of the part [5]. Mechanical properties include material strength, fatigue life, and hardness. The input includes the Grain_Growth_Model and the Thermal_Characteristics during solidification. The output includes the estimated Mechanical_Properties of the part.

3.8 Microstructural Analysis

Microstructural analysis reports material properties of additively manufactured parts based on measured data, e.g., images, obtained from measurement instruments, such as a back-scattered scanning electron microscope.

(Microstructural_Analysis_Report) = AnalyzeMicrostructures (Sample_Data)

This function is used for grain structure (size, orientation, and phase) analysis and microstructural defect detection, including abnormal residual stress concentrations. The input to this function is Sample_Data, e.g., images and three-dimensional model (built from a stack of two-dimensional images). The output is a microstructural analysis report.

3.9 Part Property Analysis

Part property analysis reports mechanical, dimensional, and surface properties of the part based on measured data obtained from measurements and mechanical tests. Mechanical properties include tensile strength, torsional strength, fatigue life, and hardness. Dimensional measurements are used to verify if part features meet tolerance requirements specified in design. Surface properties are primarily from surface roughness measurements. Additionally, pore analysis is a part of the report from the porosity measurement.

(Part_Mechanical_Property_Analysis_Report) = AnalyzePartMechanicalProperties (Mechanical_Measured_Data)

This function analyzes a post-processed part. The input is Mechanical_Measured_Data. The output is a Part_Mechanical_Property_Analysis_Report on the measured mechanical properties, such as tensile strength, torsional strength, fatigue life, and hardness.

(GD&T_Analysis_Report) = AnalyzeCMMData (Point_Cloud)

This function analyzes CMM data for feature analysis with the input of Point_Cloud, which is the set of measured points. The output is a GD&T_Analysis_Report, including the analysis of if measured features are within specified tolerances.

(Surface_Roughness_Analysis_Report) = AnalyzeSurfaceRoughnessData(Surface_Topography_Data)

This function analyzes surface roughness with the input of a Surface_Topography_Data measured with a surface roughness measuring instrument. The output is a Surface_Roughness_Analysis_Report on the measured surface roughness of all the features.

(Porosity_Analysis_Report) = AnalyzePorosityMeasurement(Porosity_Data)

This function analyzes the porosity of an AM fabricated part. The measured data can be generated from nondestructive measurement, such as XCT [64]. The output is a Porosity_Analysis_Report.

3.10 Data Registration

Data registration is a function to register measured data for validation as follows.

(Registered_Data) = RegisterData(Measured_Data, Meta_Data)

This function supports the data registration process that has three major sub-processes: (1) couple sensor-related data and build-related data with the measured data, (2) transforms coupled data related from each local coordinate systems to a single, common coordinate system, and (3) assign an identifier (ID) to the data for future reference and validation. Since data registration is a complex process, only the main function of data registration is included in this paper. The inputs to this function include Measured_Data and its associated Meta_Data. The output is the Register_Data, which can now be used in downstream applications.

3.11 Material Management

Material management is a process for managing material-related data for material selection, traceability in part performance, and process validation.

(Organized_Material_Data) = MaterialManagement (Material_Data)

Since data management is a complex activity, only the main function is shown. The input is the Material_Data of material types and properties and the administrative data. The output is the Organized_Material_Data related to the build.

3.12 Product Lifecycle Management

Product lifecycle management (PLM) is a process to manage MAM product lifecycle data for design, planning, quality, and delivery. Since PLM is a complicated process, only the main function of PLM is shown as follows.

(Product_Lifecycle_Data) = ProductLifecycleManagement (Data_From_Product_Lifecycle)

The input are data from activities in the product lifecycle, such as design, design analysis, process planning, process modeling, production management, material management, and part properties, as described above. The output is the organized Product_Lifecycle_Data that can be referenced or applied for data analytics.

3.13 Production Management

This function manages the MAM build process. It is a function for monitoring the chamber environmental factors, such as temperature and inert gas flow. The purpose is to ensure the quality and productivity of successful builds.

(Chamber_Environment_Monitoring_Data) = ProductionManagement(Sensor_Data)

Again, we show only one of many production-management functions: build chamber monitoring. This input is a collection Sensor_Data, including gas pressure, airflow, and air temperature. The output Chamber_Environment_Monitoring_Data, which is an organized version of the build-related data. The purpose is to ensure a successful build.

3.14 Part Validation

This function validates the quality of the final MAM part. Currently, selecting the "right" validation criteria is still a research subject. The inputs to the validation functions will be based on preceding outputs.

(Validation_Report) = PartValidation (Chamber_Environment_Monitoring_Data, Organized_Material_Data, Microstructural_Analysis_Report, Part_Mechanical_Property_Analysis_Report, Porosity_Analysis_Report, GD&T_Analysis_Report, Surface_Roughness_Analysis_Report, Layer_Characteristics, Registered_Data, Optimized_Model)

This function checks the following data as input for part validation: the Chamber_Environment_Monitoring_Data, Organized_Material_Data, Microstructural_Analysis_Report, Part_Mechanical_Property_Analysis_Report, Porosity_Analysis_Report, GD&T_Analysis_Report, Surface_Roughness_Analysis_Report, Layer_Characteristics, Registered_Data, and Optimized_Model. The purpose is to ensure the quality of MAM parts. The output is a Validation_Report.

4. OPPORTUNITIES/DISCUSSIONS

The previous section explored dependencies between different data types. These mappings provide necessary insight into how different data sources are and can be related to support DA opportunities. While Section 3 provides what is still a preliminary mapping, cross-links between functions clearly require careful considerations on how data is curated.

This section associates available software capabilities with identified functional requirements and discusses gaps and opportunities. Most of the existing tools that support the MAM product-lifecycle activities have been described in Section 2. Based on Table 1 (MAM software tools) and the functional requirements described in Section 3, this paragraph provides an analysis and identification of some gaps in the current technology (see Table 2 in Annex).

Table 2 (a) shows capabilities of different types of software related to design, material, and process, as listed in Table 1 and described in Section 2. The software types are in the top row of Table 2 (a). Functional requirements are listed in the left column. These functional requirements have been described in Section 3. A software type that can meet a requirement will be indicated as "H" – highly capable. A software type that can moderately meet a requirement will be indicated as "M" – moderately capable. A software type that can somewhat meet a requirement will be indicated as "L" – somewhat capable. A blank cell means not available.

From our review, the design modeling area is well covered by existing software, including lattice structure generation; however, areas of design rules and allowables generation are not. The design analysis, material selection, and process planning areas are well covered. In-situ process monitoring planning capability is moderately covered by mainly research software. More general and robust software tools are needed for sensor selection, melt pool image processing, and defect detection. Process analysis capability is well covered, except plume and spatter characteristics analyses. A small number of research results have been published, but robust software tools are needed. Process modeling and simulation capability is well covered, except pores modeling and mechanical properties prediction. Robust software tools that can analyze pores and predict mechanical properties are needed.

The rest of the software types and functional requirements are in Table 2 (b). Those software types have been also described in Section 2, and the functional requirements have been also described in Section 3. Microstructural Analysis capability is well covered. Part-property-analysis capabilities are covered, except part mechanical properties and X-ray Computed Tomography (XCT) data analyses. A small number of research results have been published, but more robust software tools are needed. Data-registration capability is not covered and needs to be developed. Material-management capability is well covered by the available software tools. Product-lifecycle management capability is moderately covered by the currently available software tools. Specific MAM-related data objects and functions are not well addressed in currently available software tools. Production-management capability is well covered by the currently available MAM software systems. Part-validation capability is not covered since part validation is too complex for the scope of the paper. Further research and development are needed.

Challenges remain in meeting industry needs. For example, the needs for data collection, sensor capabilities modeling, data analytics for monitoring and validating AM processes are still in a research stage. Suite of software tools fast and powerful enough for AM technology users to make better products are needed to support high-quality measurement and measured data analytics and enable fabricating improved quality products. Further, an overall software architecture of AM data analytics is needed to support users to apply tools for AM process modeling, storing knowledge, and data. Software tools need the support from the following mechanisms: (1) database to access needed data, (2) information models to ensure workflow and software integration, (3) workflow templates such as functions, data, analysis results, and decision makings will be accessible for analyzing relations among design, material, process, property, and performance of an additively manufactured part, and (4) uncertainty analysis and quantification in the measured data [40] for more robust data analytics.

5. CONCLUSIONS

The demands on new software tools for PBF-LB/M have increased as the variety, volume, and value of data are rapidly increasing. Some existing software tools meet corresponding demands in various functional categories. This paper describes what those categories are and their relationships to data analytics. These categories closely relate to the main functions for the lifecycle of AM products. The software tool functional requirements in this paper address the emerging issues in performing data analytics in additive manufacturing. We identified gaps in currently available software tools. Enhanced in the current tools and new tools are needed to provide functionality for data analytics in AM in general. The paper identified a preliminary set of functional requirements of AM-related software tools used in the design modeling, design analysis, material selection, process planning, process analysis, modeling and simulation, process monitoring, microstructural analysis, material management, product lifecycle management, and part validation. AM industry is facing challenges related to data collection, sensor capabilities modeling, data analytics, and AM process validation.

For future work, some input-output data objects are very complex, such as powder material property parameters, pore growth model, scanning strategy, tessellated model, grain growth model, and XCT model. The complex models must be developed as industry demands new, versatile, and integrated software tools.

DISCLAIMER AND ACKNOWLEDGEMENT

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Annex

Table 2 (a) Examples of Software Tools for Lifecycle Applications

Functional Requirement		Design modeling software	Design analysis software	Material selection software	Process planning software	Process analysis software	Process modeling, & simulation software
Design modeling	Generate design rules	L					
	Generate design allowables	L					
	Generate design model	H					
	Lattice design	H					
Design analysis	Analyze design model		H				
	Optimize design		H				
Material selection	Select material Type			H			
	Define material properties			H			
Pro ces s	Generate part setup rules				H		

	Specify setup				H		
	Design support structures				H		
	Generate tessellated model				H		
	Generate build model				H		
In-situ process monitoring planning	Generate in-situ monitoring methods				M		
Process analysis	Analyze melt pool thermal characteristics					M	
	Analyze melt pool geometric characteristics					M	
	Analyze layer characteristics					L	
	Analyze acoustic emissions					L	
	Analyze plume characteristics					L	
	Analyze spatter characteristics					L	
Process modeling and simulation	Model melt pool						H
	Model grain growth in solidification						H
	Model track formation						M
	Model phase transitions						H
	Model thermal stresses						M
	Model pores						L
	Predict the part mechanical properties						L

Legend: H-highly capable, M-moderately capable, L-somewhat capable, blank space–not available

Table 2 (b) Examples of Software Tools for Lifecycle Applications

Functional requirement \ Software type		Micro-structural analysis Software	Part Property Analysis Software	Data Registration Software	Material Manage-ment Software	Product Lifecycle Manage-ment Software	Pro-duction Manage-ment	Part Vali-dation Software
Micro-structural Analysis	Analyze Micro-structures	H						
Part property analysis	Analyze part mechanical properties		L					
	Analyze 3D model from XCT data		M					
	Analyze CMM data		M					
	Analyze surface roughness data		M					
Data regis-tration	Register data							
Material management	Manage material				H			
Product lifecycle management	Manage product lifecycle					M		
Production management	Manage production						H	
Part validation	Validate part							L

Legend: H-highly capable, M-moderately capable, L-somewhat capable, blank space–not available