A functional modeling approach for quality assurance in metal additive manufacturing

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Abstract

Purpose – Due to the complexity of and variations in additive manufacturing (AM) processes, there is a level of uncertainty that creates critical issues in quality assurance (QA), which must be addressed by time-consuming and cost-intensive tasks. This deteriorates the process repeatability, reliability and part reproducibility. So far, many AM efforts have been performed in an isolated and scattered way over several decades. In this paper, a systematically integrated holistic view is proposed to achieve QA for AM.

Design/methodology/approach – A systematically integrated view is presented to ensure the predefined part properties before/during/after the AM process. It consists of four stages, namely, QA plan, prospective validation, concurrent validation and retrospective validation. As a foundation for QA planning, a functional workflow and the required information flows are proposed by using functional design models: Icam DEFinition for Function Modeling.

Findings – The functional design model of the QA plan provides the systematically integrated view that can be the basis for inspection of AM processes for the repeatability and qualification of AM parts for reproducibility.

Research limitations/implications – A powder bed fusion process was used to validate the feasibility of this QA plan. Feasibility was demonstrated under many assumptions; real validation is not included in this study.

Social implications – This study provides an innovative and transformative methodology that can lead to greater productivity and improved quality of AM parts across industries. Furthermore, the QA guidelines and functional design models provide the foundation for the development of a QA architecture and management system.

Originality/value – This systematically integrated view and the corresponding QA plan can pose fundamental questions to the AM community and initiate new research efforts in the in-situ digital inspection of AM processes and parts.

Keywords Additive manufacturing, Quality assurance, Quality control, Functional design models

Paper type Conceptual paper

1. Introduction

Additive manufacturing (AM) is considered by many to be the next "disruptive manufacturing technology" with enormous potential to change the entire manufacturing landscape (Gao *et al.*, 2015; Debroy *et al.*, 2018). However, several barriers must be overcome before AM is widely adopted across different industries. Based on analysis from roadmaps (Bourell *et al.*, 2009; NIST, 2013) and review papers (Frazier, 2014; Sames *et al.*, 2016; Rodrigues *et al.*, 2019), these barriers can fall into seven categories, namely, lack of knowledge, capability and/or limitations in:

1 standards and guidelines;
2 modeling and simulation tools;

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3 AM design tools;
4 data information management;
5 number of available materials;
6 build capacity and processing time; and
7 certification and qualification.

This paper focuses on the qualification of the AM products, which is essential to survive in a competitive market. Qualification can mean that AM technologies must produce high-quality parts at the same or lower cost than their traditional counterparts. The quality and cost of AM parts vary considerably. For example, in the aerospace industry, complete qualification of new AM materials and processes often requires thousands of individual tests, costs millions of dollars and takes 5 to 15 years to complete (Brice, 2011; Najmon *et al.*, 2019; Russell *et al.*, 2019). In the orthopedic-implant industry, on the other hand, AM technologies can fabricate low-cost, high-quality knee and hip joints routinely in a few months (Nakano and Ishimoto, 2015).

Our approach to qualification begins with quality assurance (QA). In ISO 9000, QA is defined as "part of quality management focused on providing confidence that quality requirements will be fulfilled" (ISO 9000, 2005). In this paper, we redefine QA for AM, as "all planned and systematic activities necessary to consistently and reliably assure the predefined qualities both during and at the end of the AM process." This new definition is necessary because QA in AM has to deal with two issues not usually found in traditional manufacturing processes:

1 Increased uncertainty, complexity and variability during the AM processes.
2 Information flows across the various stages of product realization.

Both of these issues can deteriorate the repeatability, reliability and reproducibility in AM (Kim *et al.*, 2017).

To better illustrate these issues and their impacts, AM processes are compared with turning processes. First, input material in the turning process is solid, but the input material of AM is typically a powder or a wire. Accordingly, properties of the final turned-part are almost the same as those of the input work-piece. The properties of the final AM part, on the other hand, are different from those of the input materials. Second, the layer-by-layer stacking mechanisms in AM have inherently more uncertainty than turning processes. Third, AM process parameters are more complex and critical than those of the turning process (e.g. depth of cut, spindle speed and feed rate). For example, a powder bed fusion (PBF) system can include more than 200 parameters (Mani *et al.*, 2015). Fourth, the correlation between parameter settings and final part properties is well-understood in turning, but this is not the case in AM. To address these issues, many research and development (R&D) efforts are underway. While each R&D effort is making progress, focus on integration and interoperability in a systematically integrated view is lacking. With the possible exception of Mazumder (2015) and Huang *et al.* (2015), who have coined the phrase "certify-as-you-build," only a few R&D efforts are underway to develop a comprehensive framework and methodology of QA for AM.

In this paper, a systematically integrated view is presented to ensure the predefined part properties before, during and after the AM process. Then, we discuss four topics, namely, QA plan, prospective validation, concurrent validation and retrospective validation. The foundation for this discussion includes a functional model developed with Icam DEFinition for Function Modeling (IDEF0), a workflow and a collection of information models. This paper reflects on the need for systematic integration, management and analysis of the data/information generated during the different phases of AM design-to-product transformations in terms of QA plans. It investigates the AM digital spectrum, from design to final part/product, for general adoption in the manufacturing industry from the perspective of QA. The outline in this paper is as follows: Section 2 explains related work and its gaps and needs, Section 3 presents a holistic view for QA, Section 4 presents the workflow and the information models and Section 5 demonstrates the feasibility of the proposed holistic view using an operational scenario. Directions for research to address the current bottlenecks are discussed in Section 6 and a conclusion is presented in Section 7.

2. Background

Based on roadmaps (Bourell *et al.*, 2009; NIST, 2013) and review papers (Frazier, 2014; Sames *et al.*, 2016; Kok *et al.*, 2018; Rodrigues *et al.*, 2019), we discovered the following relevant R&D efforts necessary for QA planning:

- Modeling/simulation for fundamental understanding.
- Process planning and optimization.
- Correlations among process, structure and property.
- In-situ monitoring and control.
- Non-destructive evaluation (NDE).

Each of these are discussed in this section with a discussion on the gaps and needs in the end.

2.1 Related work

2.1.1 Modeling and simulation for fundamental understanding

Modeling/simulation techniques have been extensively used to better predict part behavior, properties and process performance (Keller *et al.*, 2017). For example, Loh *et al.* (2015) used a finite element analysis (FEA) to predict volume shrinkage and material evaporation in a selective-laser-melting (SLM) process. They established relationships between process parameters and various thermal phenomena, melting and evaporation of powder and cooling rate. Beuth *et al.* (2013) presented a process-mapping approach for qualification that identified five primary process variables, namely, heat source power, travel speed, feed rate, existing temperature of the part and feature geometry. Using actual process parameters taken from the literature, Thomas *et al.* (2016) presented a method for the construction of a process map for metal AM application. They investigated the correlation between process parameters, microstructure and defects. Ganeriwala *et al.* (2019) estimated residual stress of Ti-6Al-4V samples from a PBF process and validated the elastic strain in the parts with the synchrotron X-ray diffraction measurements.

For a fundamental understanding of the AM processes, multi-scale modeling/simulation techniques have been used to create a part with optimal geometry, composition and functionality (Bandyopadhyay and Traxel, 2018). However, due to the high computation costs of multi-scale simulations, AM design capability is still limited to a particular scale in length. Also, controlling complex physical phenomena remains a challenge due to a lack of understanding of process-microstructure-property correlations. Although current modeling tools and techniques have not been fully integrated at different scales, AM models coupled with multi-scales enable solutions to issues associated with melt pool, thermal cycle and part geometry. For example, three-dimensional mesoscopic models (e.g. particle and melt pool scale) have been developed to simulate the PBF process (Körner *et al.*, 2011; Khairallah and Anderson, 2014; Khairallah *et al.*, 2016; Lee and Zhang, 2015, 2016). As those simulations are able to track melt-pool-free-surface, they are used for predicting and correlating the formation of undesired defects, such as balling, with various manufacturing conditions. Additionally, the melt-pool-scale model has been combined with microstructure to provide insight into part solidification pattern (Wei *et al.*, 2015). The solidification microstructure is determined by the competition between maximum heat flow direction and preferred crystallographic growth direction. Using numerical modeling, the heat flow direction in an AM part can be calculated based on the thermal gradient (G) and solidification rate (R). At the scale of the liquid-solid interface, phase-field modeling has been used to predict solidification morphology and size and quantify microstructure evolution (Sahoo and Chou, 2016).

2.1.2 Process planning and optimization

Process planning activities provide the key link between design and fabrication (Majeed *et al.*, 2019). These activities are crucial because they affect the part properties, which are directly related to quality. Optimization of parameters is an example of a process planning activity. Sun *et al.* (2013) and Kim *et al.* (2015) used several statistical methods, such as the design of experiments (DOE), Taguchi methods and analysis of variance (ANOVA), to determine the near-optimal parameters. In addition to laser power and scan speed, they also determined values for layer thickness, hatching distance and scanning strategy. Casalino *et al.* (2015) used DOE and ANOVA to determine laser power and scan speed to optimize the part density of 18Ni300 maraging steel in SLM. Raghavan *et al.* (2016) also used ANOVA to quantify the effect of input parameters on the solidification microstructure. They found that preheat is the most influential input parameter to control the volume of equiaxed grains in electron-beam melting (EBM). Recently, Kim (2019) presented a systematic approach using data from disparate analytical, experimental and informational sources to compose predictive models that can manage multi-criteria decision-making in PBF.

2.1.3 Correlations among process, structure and property

Understanding relationships between process, structure and property can provide the foundation for developing predictive models and generating new knowledge (Smith *et al.*, 2016). In the case of SLM using Ti-6Al-4V, Song *et al.* (2012) found that the process parameters were closely correlated to the microstructures and material properties. Bauereiß *et al.* (2014) sought to understand the correlation between defect formation and the speed of an EBM process. They found that increasing the speed of the melting process caused wetting and capillary forces, which lead to defects. Dehoff *et al.* (2015) demonstrated the capability of site-specifically controlling microstructure in EBM by changing the melting pattern from raster to point heat source melting. Kirka *et al.* (2017) also proposed a point heat source melting strategy to control microstructure. They demonstrated the ability to transition from columnar to equiaxed grain structures in Inconel 718. The equiaxed structure was formed using the point heat source melting strategy and yielded an isotropic tensile property that fell between the horizontal and vertical tensile strength of columnar grained material. Chauvet *et al.* (2018) demonstrated the possibility of creating a single crystal structure in Ni-based superalloy and pointed out that the fabrication of a single crystal requires tight control of the melting process parameters. Lee *et al.* (2018) showed that scan patterns and part geometry affect cracking behavior. Controlling the tilting angle and scan pattern can mitigate the inhomogeneity in a temperature distribution so that the cracking in an AM part is potentially reduced. Recently, Zhang *et al.* (2019) have used a machine learning-based predictive modeling method to predict material properties.

2.1.4 In-situ monitoring and control

In metal AM, robust in-situ monitoring and control systems are desired to detect part imperfections and reduce the uncertainty of part performance. Recent advances in AM offer the ability to minimize undesired defects such as balling, porosity, cracking and other anomalies (Kim and Moylan, 2018). Mireles *et al.* (2013) proposed an automatic, feedback-control system for EBM equipped with an infrared (IR) camera to:

- achieve parameter modification for controlling grain size;
- attempt temperature stabilization by imaging process and automatic decision-making; and
- detect porosity to stop the process or to be used in post-build analysis.

Phillips *et al.* (2018) developed a feed-forward control system that can manage the temperature fluctuation for selective laser sintering by controlling laser influence, based on IR measurements. Raplee *et al.* (2017) developed a method for proper calibration of temperature and surface emittance between the metal powder and solidified part using thermographic data obtained from a mid-wave IR camera. Babu *et al.* (2018) showed that near-infrared image data obtained from an EBM process can be used to detect the location of porosities, cracks and surface abnormalities. This methodology can be coupled with deep neural nets to correlate the mechanical performance of the part with the region that has high porosity intensity (Yoder *et al.*, 2018). For more details, review papers are available (Tapia and Elwany, 2014; Everton *et al.*, 2016; Kim *et al.*, 2018).

2.1.5 Non-destructive evaluation

Metallic AM components are often used at high temperatures, stress and other harsh environmental conditions. Extensive part inspections are one of the compulsory activities done to ensure quality (Babu *et al.*, 2018). Waller *et al.* (2014) summarized the current state of the art in NDE methods and concluded that the NDE should be identified as a universal method for part qualification. Slotwinski *et al.* (2014) measured the porosity of Co-Cr AM samples using two NDE methods, namely, Archimedes and X-ray computed tomography (CT). Kroll *et al.* (2013) used a combination of CT and a three-dimensional scanning method for inspecting:

- the internal and external accuracy of geometry;
- the deformation during the cooling process;
- defects; and
- surface roughness.

Todorov *et al.* (2014) reviewed various NDE techniques to determine the most applicable techniques for AM. In the report, X-ray CT was selected as the most promising technique for a reliable inspection. However, 100% detection of defects in the part is not practical due to issues of scaling this technique in a production environment. Moreover, the limited number of studies on the utilization of NDE techniques for complex AM components can lead to unreliable detection of geometric and non-geometric anomalies.

2.2 Industrial gaps and future needs

As discussed in Sections 1 and 2.1, many different R&D efforts exist to verify/validate predictive models, part properties and process performances during AM process stages for ultimately achieving QA. However, many of them are researched and developed in a stand-alone way. Based on the current state of the art, major gaps for QA are summarized as follows:

- Even though many R&D efforts focus in-depth on each research area, a holistic view considering the whole AM process stages and experimental or numerical verification/validation for QA is lacking.
- Modeling and simulation techniques enable us to provide quality improvements and the possibility for manufacturers to move away from physical inspection. However, due to a lack of knowledge, it is achieved only with limited models under certain environments.
- Still, commercially available systems are mainly based on hand-tuned process parameters determined by experienced operator's trial and error for a limited set of metal powders, which is neither efficient nor optimal. Thus, the uncertainty in the AM process is significantly large.
- Destructive tests with coupons are not appropriate for inspecting AM parts. Even though the specimen (test coupon) satisfies stringent mechanical properties, the properties of the additively manufactured part may not satisfy the requirements due to the uncertainty from AM process variations.

The following are the future needs in terms of QA for metal AM.

- Traditional QA approaches are time-consuming and cost-intensive, thus a new paradigm to ensure QA with the industry-acceptable cost is needed.
- Because of the heterogeneity in data and protocols from AM processes, interoperability and integration issues are magnified. Thus, a generalized, integrated QA framework is required.
- Comprehensive predictive models are required at multi-scale and multi-stage, which can characterize the relationships among process, material, thermal analysis, microstructure, property and performance in the perspective of QA. The relationships provide the fundamental basis for QA achievement.
- QA is a critical point for mass customization, as the competitiveness of a company can be improved by making decisions with satisfying the different stakeholders' desires simultaneously.

Systematic integration of the previous R&D efforts into a federated QA view should provide the following synergistic effects, namely, it can reduce cost and lead-time for new product development, detect and prevent defects and satisfy stakeholders' desires. In the next sections, we introduce a functional model using IDEF0, which can lay the foundation for R&D efforts to address these gaps and needs.

3. A holistic view for quality assurance plan

National Institute of Standards and Technology (NIST) researchers (Kim *et al.*, 2015) decomposed the PBF process into eight phases and presented a digital thread (DT) concept to link these phases. The DT refers to the generation, storage and flow of the information needed to implement the eight phases in an AM process. In recent work (Kim *et al.*, 2017), they condensed the eight phases into six ones, as seen in Figure 1. The main functional activities of each phase are briefly explained as follows:

1. *(A1) Generate AM design*. This activity generates details from a conceptual design. This phase represents the "form" of the part and available design rationale. Geometry may exist as a computer-aided design (CAD) file from a three-dimensional scan. The output is a watertight model.
2. *(A2) Plan independent of process-machine*. This activity determines the process-machine independent process plans (e.g. part orientation and support structure).
3. *(A3) Plan depending on process-machine*. This activity determines the process-machine dependent process plans (e.g. slicing, process parameters and scan path strategy).
4. *(A4) Build part*. In this activity, a part is manufactured with respect to the determined plans.
5. *(A5) Post-process part*. This activity is needed to finish a part, depending on the requirements.
6. *(A6) Qualify part*. This activity includes mechanical testing or NDE on the AM part and the results. Results can be added to part pedigree, establishing a reference for future part quality inquiries.

In this context, the following higher-level activities for QA are integrated into the AM process (Figure 2):

- *QA plan*: determine key performance indicators (KPIs), objectives and any corresponding constraints based on the plans for the three consecutive validation activities and requirements dictated by stakeholders.
- *Prospective validation*: validate the generated three-dimensional model, the process plans and the generated machine codes before the actual manufacturing.
- *Concurrent validation*: inspect manufacturing status and thermal characteristics on the heat-affected zone (HAZ), minimize the occurrence of defects by adjusting variations, and validate performance during the AM process.
- *Retrospective validation*: analyze the signature measurements of the process, obtained from the concurrent validation stage, and digitally validate the results after manufacturing. It is also necessary to physically validate the properties of the part.

3.1 IDEF0 activities for quality assurance plan

Developing a QA plan begins with analyzing requirements from stakeholders. This analysis can provide the objectives, constraints and KPIs. The objectives and constraints help determine the materials, resources, machines, software, operator and budget cost. Meanwhile, the KPIs help determine various performance measures, including asset utilization, agility and sustainability (Roy *et al.*, 2014). Asset utilization is related to planning and maintenance activities. Agility is related

Figure 1 IDEF0 diagram of NIST digital thread for AM in a report (Kim *et al.*, 2017)

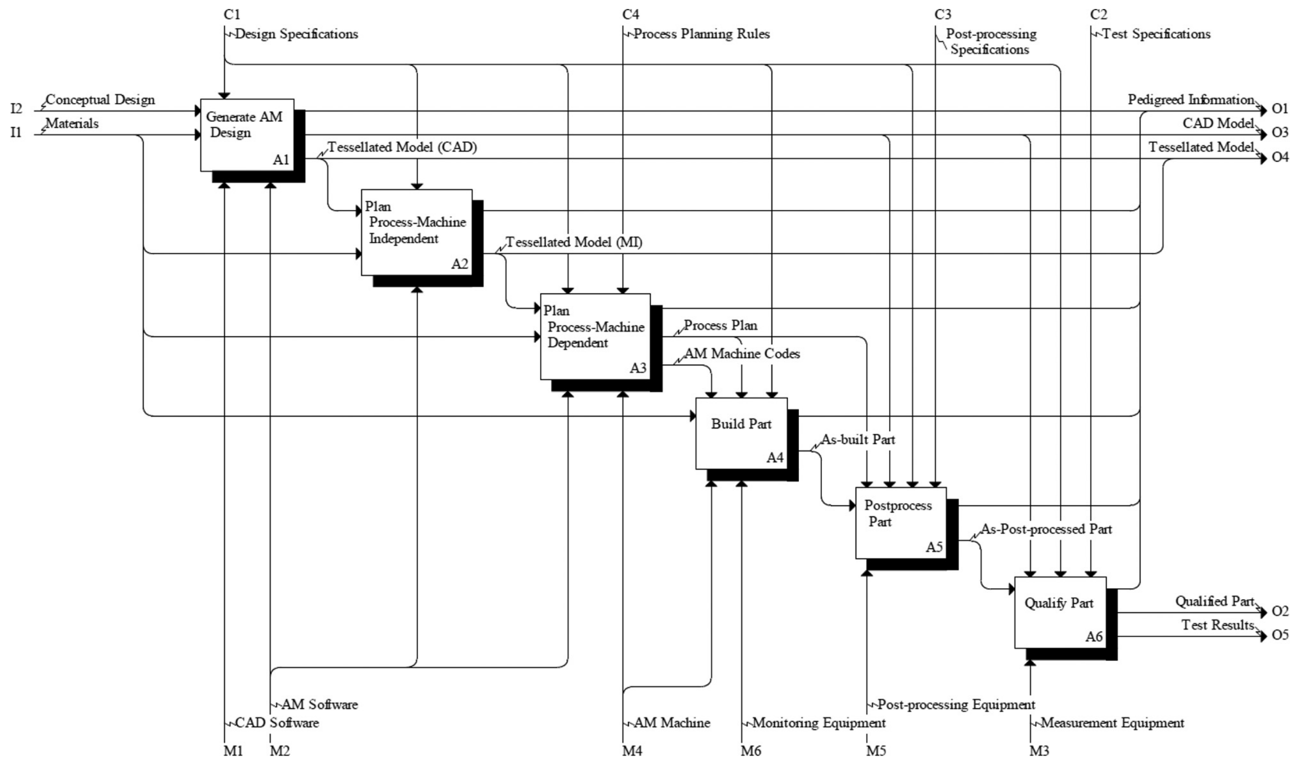
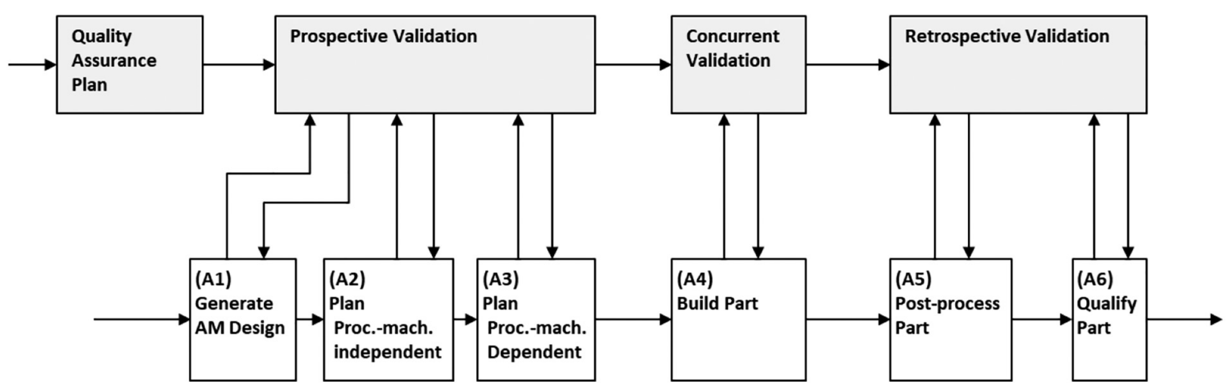


Figure 2 A holistic view of QA with the AM process activities



to the ability to adapt dynamically to changing manufacturing and market conditions. Sustainability is related to triple bottom lines: environmental, economic and societal factors. The QA plan provides the basic inputs into the following activities.

3.2 IDEF0 activities for prospective validation

Prospective validation is concerned with validating the "correctness" in the four pre-fabrication activities. The activities include the generated CAD design, the process-machine-independent plan, the process-machine-dependent plan and the machine code, as seen in Figure 3.

3.3 IDEF0 activities for concurrent validation

The goals of concurrent validation are to control the fabrication process and to validate each layer in real-time, as seen in Figure 4. Achieving these goals requires a complete understanding of the AM process, thermal analysis, microstructures and their relationships. Thermal analysis is especially critical for in-situ control, as it closely relates to microstructure and defect formation (King *et al.*, 2015; Schoinochoritis *et al.*, 2015). For example, microstructure characteristics (e.g. grain size and direction) can be controlled by the process mapping (Gockel and Beuth, 2013) between the scan speed and power.

Figure 3 IDEF0 model of prospective validation

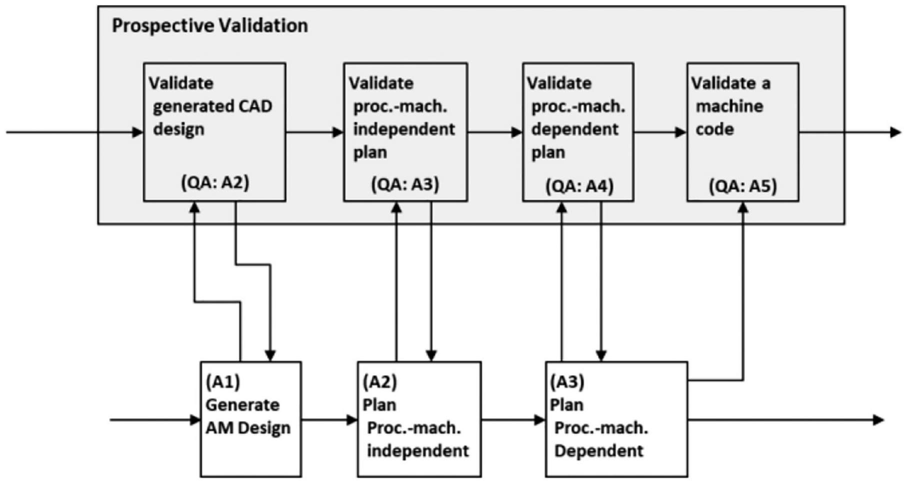


Figure 4 IDEF0 model of concurrent validation

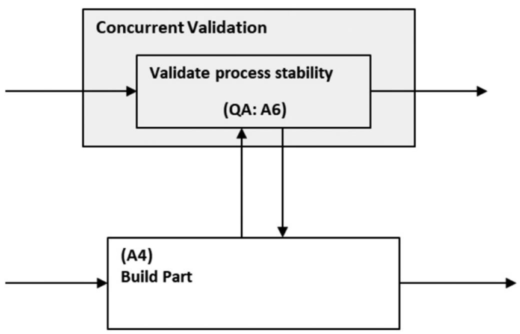
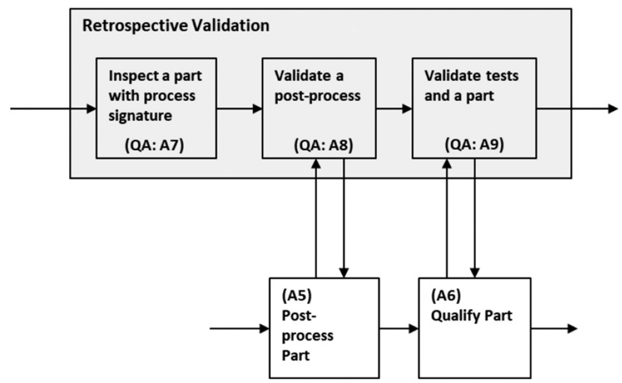


Figure 5 IDEF0 model of retrospective validation



3.4 IDEF0 activities for retrospective validation

The retrospective validation consists of three activities, namely, "inspect a part with process signature," "validate a post-process" and "validate tests and a part," as seen in Figure 5.

To "inspect a part with the process signature," it is necessary to validate the part by analyzing historically monitored data. The analysis produces process signatures of prior fabrications. Then, by investigating the quality of the AM parts, we can establish correlations between process signatures and part quality. As noted above, thermal conditions have the highest correlation with part quality. Rapid solidification, cooling direction and phase transformations induced by repeated non-equilibrium thermal cycles have a profound influence on the microstructures of the AM parts. Rapid solidification reduces elemental partitioning, extends solid solubility and can result in metastable phase formations. Directional heat extraction results in preferred directionality in grain growth.

In many cases, AM parts need post-processes to reduce the residual stress and satisfy certain design specifications such as surface roughness. Under the "validate a post-process" activity, post-processes are specified and completed. Post-processes can include support-material removal, surface-texture improvements (e.g. shot peening), accuracy improvements (e.g. machining) and heat treatments.

In the "validate tests and a part" activity, part properties and test methods are validated. AM processes are difficult to control, which causes part properties to vary from one build to the next. This means that each AM part will have slightly different properties, even though the parts are manufactured in the same conditions. In addition, inspection tests should be validated, due to the amount of uncertainty and current limitations inherent in AM.

4. Workflow and information models for quality assurance in additive manufacturing

The functional design models of the top and second levels are shown in Section 4.1. The third level models are shown in Section 4.2.

4.1 Functional design models (IDEF0) of the topmost and second level

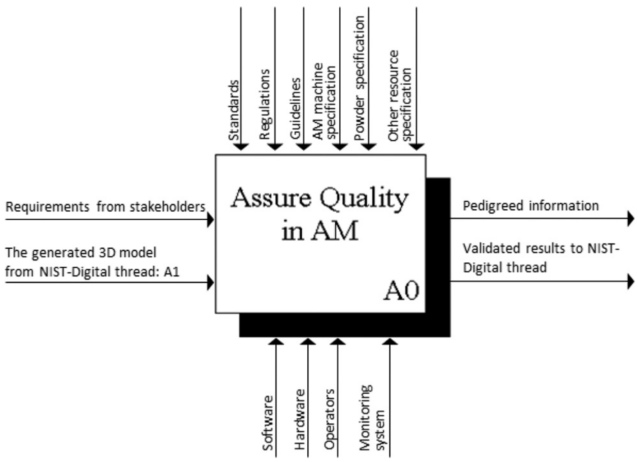
Figure 6 shows the top-level model (A0) for QA, which shows the function, inputs, outputs, controls and mechanisms. The inputs are transformed by a QA function to produce an AM part. The controls are the specifications (e.g. guidelines, standards, constraints, policies, knowledge, design rule and methods). The mechanisms are the supporting tools (e.g. hardware, software, operator and monitoring system). After performing a QA function, the outputs are the QA-related pedigreed information and the validated results given to NIST-

DT activities (A1–A6) for modifying the design/process plan/manufacturing/test or further processing.

The top function of QA (A0) can be achieved by nine functions, shown in Figure 7 and briefly described as follows:

- *(QA: A1) Plan QA*: identify objective/KPIs/constraints and creates a comprehensive description of the QA plan for the following activities. Each sub-activity is planned, based on requirements analysis, resource availability and QA level. The outputs are the QA plans for each activity (QA: A2–A9), as seen in Figure 8.

Figure 6 Topmost IDEF0 diagram of QA in AM



- *(QA: A2) Validate a three-dimensional design*: validate the integrity of the three-dimensional design generated from the NIST-DT: A1 phase. This includes robustness (e.g. duplicate nodes in triangle meshes) and completeness (e.g. check for the existence of holes) of the design. It also validates the compatibility (e.g. data format interoperability between CAD design, software for a process plan and machine) and manufacturability (e.g. manufacturable minimum feature size).
- *(QA: A3) Validate process-machine independent plan*: validate an independent process plan generated from the NIST-DT: A2 phase. For example, this includes validations of part orientation and support structure. The output is the validated independent process plan, given to NIST-DT: A3 phase for further processing.
- *(QA: A4) Validate process-machine dependent plan*: validate a dependent process plan generated from the NIST-DT: A3 phase. For example, this includes validations of slice, scan path and process parameters. The output is the near-optimal process plan, given to NIST-DT: A4 phase for further processing.
- *(QA: A5) Validate a machine code*: predict and validate the part quality and process performance before AM fabrication by using a simulation tool. In this step, the near-optimal process plan needs to be translated into machine code (e.g. STEP-NC).
- *(QA: A6) Validate process stability*: validate the status of the process, as well as the thermal characteristics of the melt pools and the layers. For quality control, unwanted

Figure 7 Second level of functional activities diagram for QA

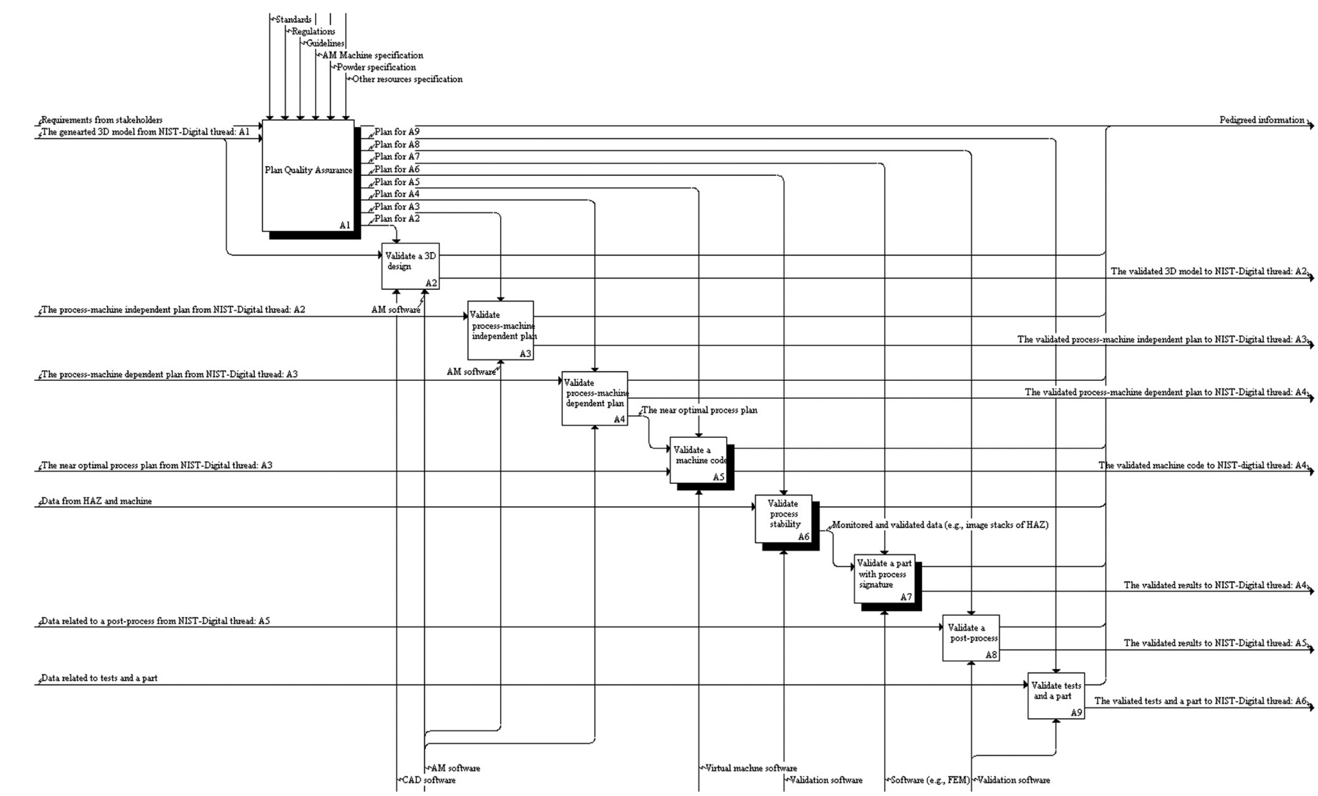
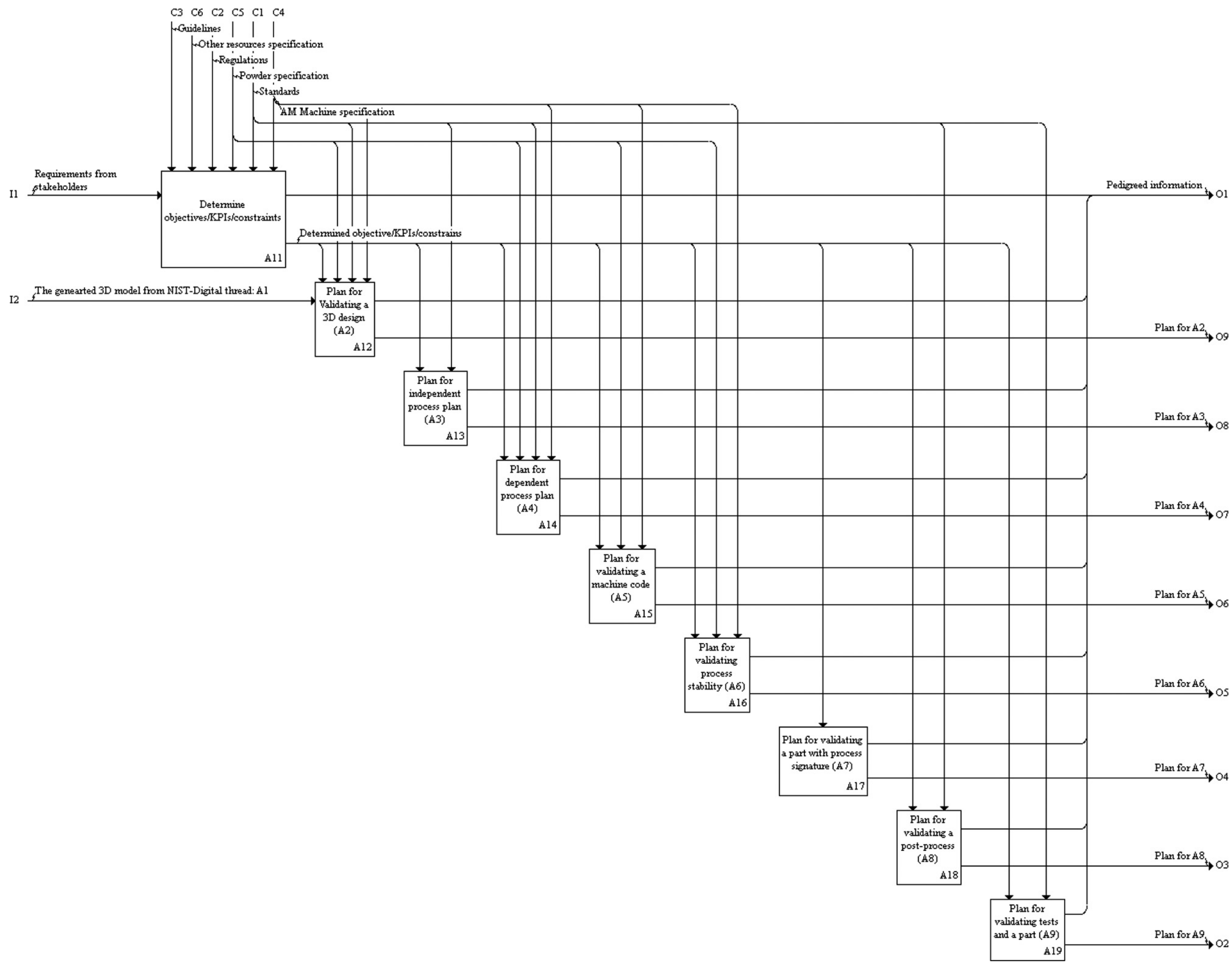


Figure 8 Third level functional activities for plan QA (QA: A1)



phenomena (e.g. balling effect) can be minimized by using a closed-loop control, as seen in Figure 10.

- *(QA: A7) Validate a part with process signature*: digitally validate the part properties by analyzing part properties and process performances. The input is the monitored data during the AM processing or validated data from the previous activity A6, as seen in Figure 11.
- *(QA: A8) Validate a post-process*: validate a post-process (e.g. support removal and heat treatment). The input is the data related to post-processes in NIST-DT: A5. The results are given to NIST-DT: A5 for further processing.
- *(QA: A9) Validate tests and a part*: validate whether inspection tests are performed correctly and whether the final part meets the stakeholders' requirements. The input is the data related to inspection tests and a part in NIST-DT: A5. The validated results are given to NIST-DT: A6.

4.2 Functional design (IDEF0) of the third level in A1/A5/A6/A7

Among nine functional models (QA: A1–A9), the important activities are A1, A5–A7. The details will be explained in the next sub-sections.

4.2.1 Third level of plan quality assurance (QA: A1)

The second-level function of "Plan QA (A1)" can be achieved by nine major activities, which are planned based on identified guidelines, standards and regulations. The output of each activity will be given to QA: A2–A9 as controls and mechanisms, as seen in Figure 8. Each activity is briefly explained as follows:

- *(A11) Determine objectives/KPIs/constraints*, based on requirements analysis, standards, guidelines, powder/machine specifications and regulations. Outputs will be the controls to the following sub-activities (A12–A19).
- *(A12) Plan for validating a three-dimensional design* for the manufacturability, robustness and completeness, based on machine/powder specification and determined objectives/KPIs/constraints. This also includes the software and methodologies that will be used in the validation.
- *(A13) Plan for validating independent process plan*, based on determined objective/KPIs/constraints, methods and software are specified for checking model orientation and support structure.
- *(A14) Plan for validating dependent process plan*, such as slicing, scan path and control parameters.

- *(A15) Plan for validating a machine code*, including which a simulator will be used for the checking.
- *(A16) Plan for validating process stability* with respect to the identified objective/KPIs/constraints and machine/powder specifications. A different set of sensors/analysis/control can be determined, based on the resource availability and QA level.
- *(A17) Plan for validating a part with process signature*, based on determined objective/KPIs/constraints, and it must be planned, which simulator (e.g. FEA) will be used for the validation.
- *(A18) Plan for validating a post-process*. For example, heat treatment is planned for resolving any residual stresses together with all the required parameter settings. In addition, an inspection plan should be determined on how to validate whether the post-processing was done correctly.
- *(A19) Plan for validating tests and a part*. For example, Eddy current test is planned for inspecting cracks in a part.

4.2.2 Third level of validate a machine code (QA: A5)
This second-level function can be achieved by five major activities, as seen in Figure 9. The details of each activity are explained as follows:

1 (A51) Translate near-optimal process plan into machine codes by inputting the NIST-DT: A3 or QA: A4 into a translator.
2 (A52) Analyze part properties by using simulation software (e.g. FEA) before real manufacturing. The analyzed results of part properties are given to A54 for predicting part properties.
3 (A53) Analyze process performance using simulation software or performance metrics. The analyzed results are given to A54 for predicting process performances.
4 (A54) Predict part properties and process performance, based on the previous analysis. The predicted results are given to A55 for validating them.
5 (A55) Validate predicted results with respect to the defined objectives/KPIs/constraints. The validated machine codes are given to NIST-DT: A4 for the actual manufacturing. If the predicted results do not satisfy the objectives/KPIs/constraints or process performance, a request query for modifying a process plan is given to NIST-DT: A3.

4.2.3 Third level of validate process stability (QA: A6)
This second-level function can be achieved by five major activities, as seen in Figure 10. Each activity is briefly explained as follows:

1 *(A61) Collect data from machine* (e.g. power and inert gas flow) with respect to the machine code. The collected data will be given to A63 for analysis. Sensors and its interfacing protocols (e.g. MTConnect) are necessary to communicate between a machine and a computer (Vijayaraghavan and Dornfeld, 2010).
2 *(A62) Collect data from HAZ.* Monitoring systems (e.g. IR imaging system) and interfacing protocols are necessary to communicate between a machine and a computer. The collected data will be used to analyze the process stability in A63.

Figure 9 Third level functional activities for validate a machine code (QA: A5)

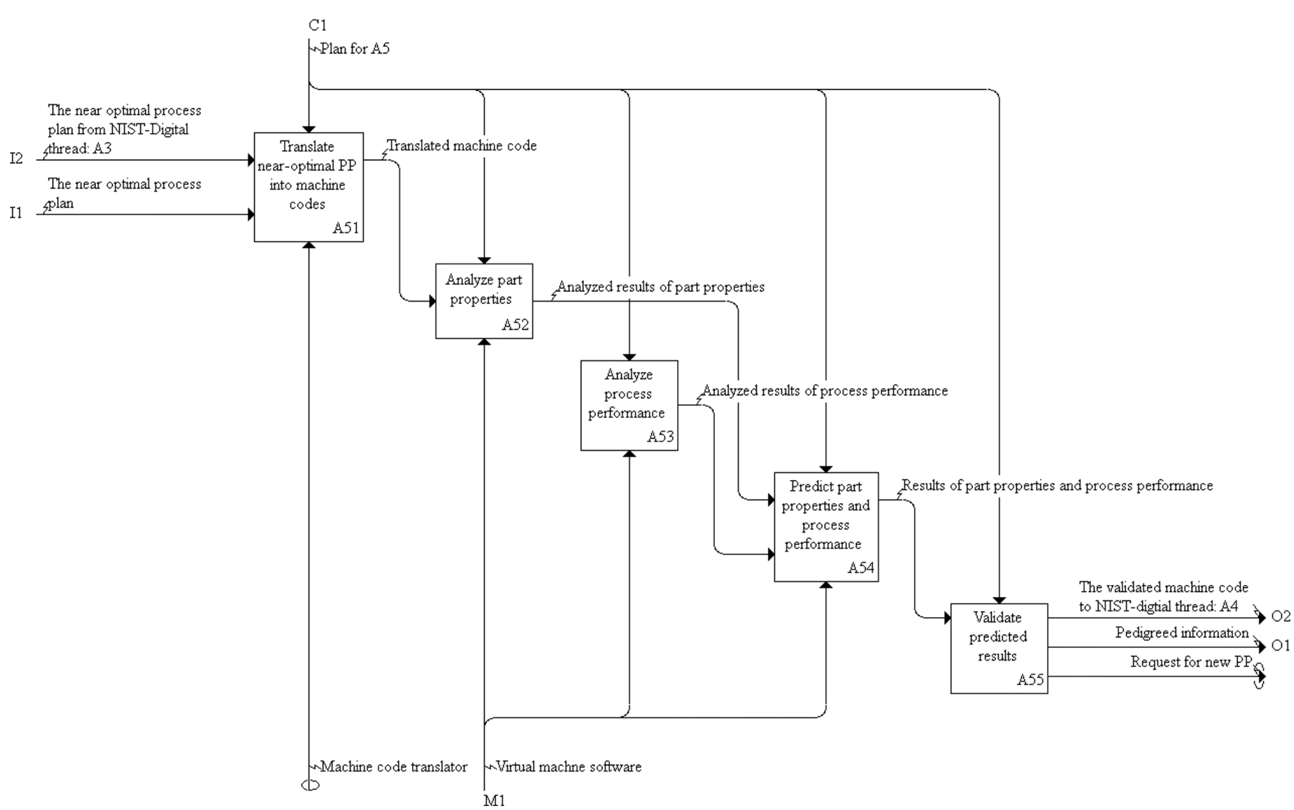
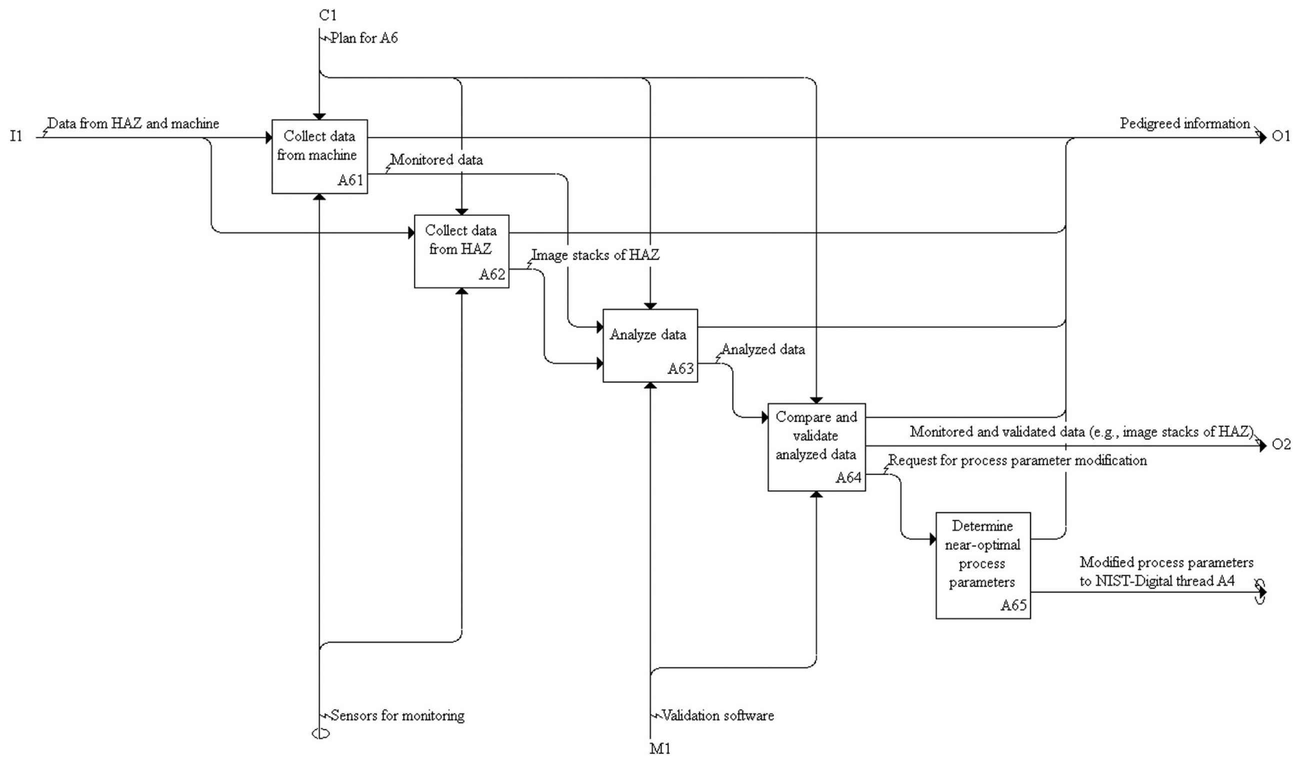


Figure 10 Third level functional activities for "validate process stability (QA: A6)"



3 *(A63) Analyze data* (e.g. melt pool characteristics) from A61 and A62 by using a simulator (e.g. FEA).
4 *(A64) Compare and validate analyzed data* with reference data/model and validates the melt pool and the layers. The outputs are the monitored and validated data (e.g. image stacks of HAZ), which are given to QA: A7 activity.
5 *(A65) Determine near-optimal parameters*, which control defects. The outputs are the modified process parameters (e.g. power and scan speed), given to NIST-DT: A4 for real-time control.

4.2.4 Third level of validate a part with process signatures (QA: A7)
This second-level function can be achieved by the five major functions, as seen in Figure 11. The details are explained as follows:
1 *(A71) Estimate residual stress of a part* by analyzing the historically monitored or validated data. Images stacks of HAZ have important information for thermal analysis. From the thermal analysis, the residual stress can be estimated by simulation software (e.g. FEA). The results are given to A75 for the validation.
2 *(A72) Estimate the microstructure* by analyzing the historically monitored data. For example, critical information (e.g. cooling rate and direction and solidification rate) can be extracted from the images stacks to estimate the microstructures by simulation software (e.g. FEA). The results are given to A75 for the validation.
3 *(A73) Estimate geometric distortion* from the residual stress analysis in A71 by using simulation software. The results are given to A75 for the validation.
4 *(A74) Estimate other properties* by analyzing the monitored and validated data from NIST-DT: A4 or QA: A7 and results from the residual stress (A71) and microstructure (A72). Other properties can be estimated by simulation software. The results are given to A75 for the validation.
5 *(A75) Compare and validate the properties* and performances with the objectives/KPIs/constraints. The results are given to NIST-DT: A4 for further processing.

5. Operational scenario

In this section, we describe how the functional models can be applied to an operational scenario in a PBF process. First, it is assumed that there are established databases, knowledge, predictive models and data that illustrate the relationships between the PBF process, materials, thermal analysis and resulting part microstructure, properties and performance. Second, it is assumed the QA management system has used this knowledge. The machine has the following properties: building capacity of 250 mm^3 * 250 mm^3 * 215 mm^3, power ranging up to 200 W, speed ranging up to 7 m/s and layer thickness between (20 μm–100 μm). The powder is Ti-6Al-4V. The part is a NIST test artifact with dimensions (100 mm * 100 mm * 17 mm) and volume (101,000 mm^3) (Moylan *et al.*, 2014), as seen in Figure 12. The operational scenario is performed via the nine functional activities described in Section 4. Each activity is explained in the following paragraphs.

5.1 (Qa: A1) plan quality assurance

American society for testing and materials (ASTM) F42 and ISO/TC 261 standards generally provide the guidelines for how to achieve QA of the part properties and process performances. The inputs for the A1 activity are a three-dimensional model with an

Figure 11 Third level functional activities for validate a part with process signatures (QA: A7)

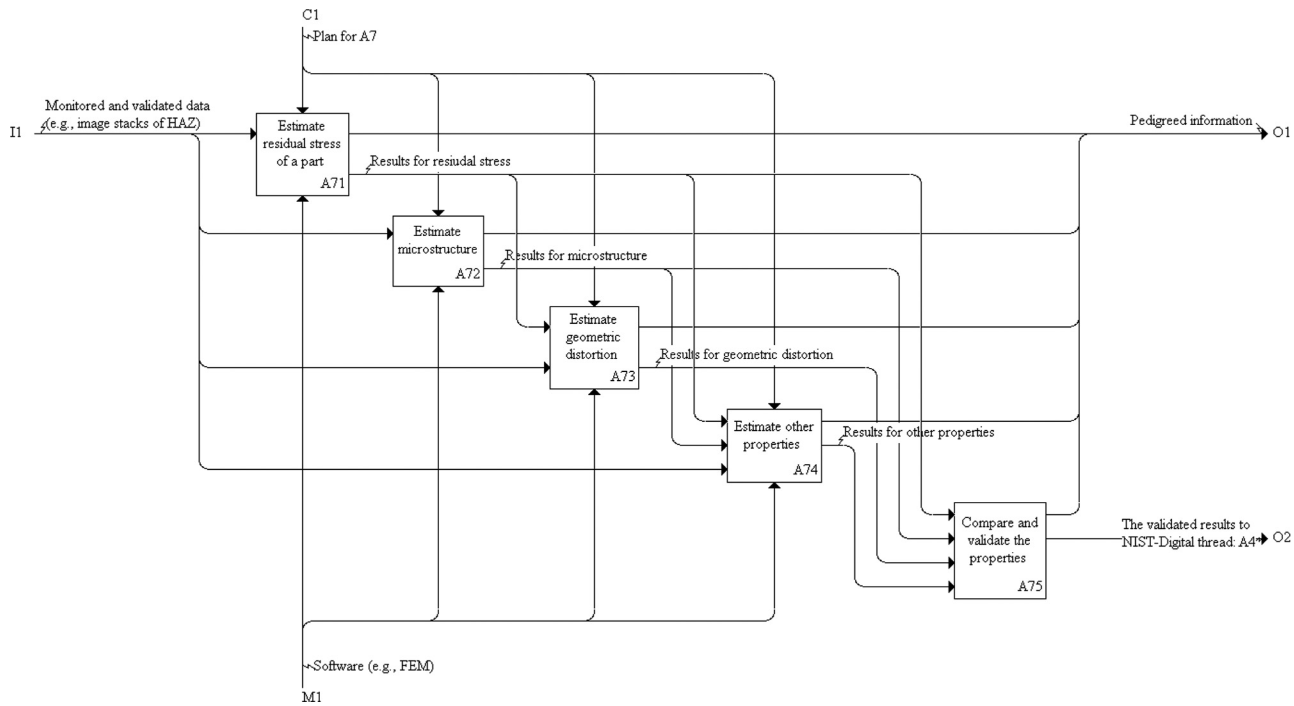
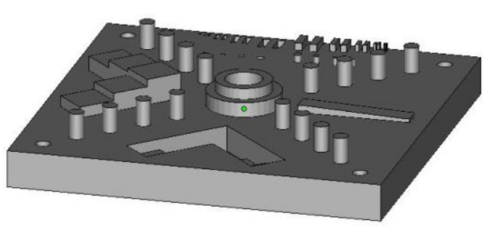


Figure 12 A solid model of a NIST test artifact



additive manufacturing format in ISO/ASTM 52915: 2016 and the requirements from stakeholders.

- *(A11) Determine objectives/KPIs/constraints.* Based on an analysis of requirements, the flatness and surface roughness are selected as KPIs in terms of geometric dimensioning and tolerancing (GD&T). The design requirement for the flatness is 50 μm (Z_a, average deviation) with 102 μm (Z_t, maximum deviation). The requirement of the surface roughness is 50 μm (R_a, average) with 100 μm (R_t, maximum).
- *(A12) Plan for validating a three-dimensional design.* This plan involves validating the defects (i.e. duplicate nodes in triangle meshes) and the manufacturability of the CAD design. The details of the plan are given to A2.
- *(A13) Plan for validating process-machine independent plan.* This plan involves validating orientation and support structure. The details of the plan are given to A3.
- *(A14) Plan for validating process-machine dependent plan.* This plan involves validating slicing and process parameters (i.e. power, laser and scan pattern). The details of the plan are given to A4.
- *(A15) Plan for validating a machine code.* This plan involves validating the machine codes and KPIs. The details of the plan are given to A5. It is assumed that the translator and its virtual AM machine are developed, based on the guidelines from STEP-numerical control.
- *(A16) Plan for validating process stability.* This plan involves monitoring parameters (e.g. power, scan speed), based on the approach described by Mireles *et al.* (2013). The details of the plan are given to A6.
- *(A17) Plan for validating a part with process signature.* MTConnect (Vijayaraghavan and Dornfeld, 2010), which establishes a communication protocol between a machine and a computer, is planned to be used to measure the process signatures. One of the analysis tools, ABAQUS, is planned to be used to simulate the surface roughness and flatness by analyzing the measured historical image stack of the HAZ. The details of this plan are given to A7.
- *(A18) Plan for validating a post-process.* Based on the guidelines from ASTM F2924-14, electron discharge machining (EDM) and hot isostatic pressing (HIP) are planned to be used for removing any unwanted structures (e.g. support structures) and for reducing the level of porosity, respectively. The details of this plan are given to A8.
- *(A19) Plan for validating tests and a part.* Based on the American Society of Mechanical Engineers Y14.5, a coordinate-measuring machine (CMM) and stylus profilometer are chosen to measure the flatness and surface roughness. In total, 12 points of the top surface are planned to be measured: 8 points near the outer edges and four points near the center hole. The surface roughness is planned to be measured along a 25 mm line at the top

surface next to the ramp feature, collecting a point every 0.25 μm. The details of this plan are given to A9.

5.2 (Qa: A2) validate a three-dimensional design

The three-dimensional geometric model is inspected for water tightness. The radius of curvature of the NIST artifact is inspected to determine whether it is manufacturable with the given conditions.

5.3 (Qa: A3) validate process-machine independent plan

The manufacturability of the determined orientation and support structure is validated.

5.4 (Qa: A4) validate process-machine dependent plan

The predictive models for GD&T are developed as a second-order polynomial model, based on the DOE and response surface methodology (RSM), similar to Sun *et al.* (2013). Consequently, the near-optimal process parameters are determined with respect to four exposure types, namely, pre-contour, core, skin and post-contour. For the pre-contour and post-contour, the laser power and scan speed are 60 W and 700 mm/s. For the core, the laser power, scan speed and hatching distance are 195 W, 1,000 mm/s and 100 μm. For the skin, there are three process parameters, namely, 195 W, 1,000 mm/s and 100 μm are determined for a side-skin, 195 W, 3,000 mm/s, 40 μm and 20 μm are determined for a down-skin and 160 W, 500 mm/s, 100 μm and 20 μm are determined for an up-skin.

5.5 (Qa: A5) validate a machine code

The near-optimal process plan is translated into STEP-NC (ISO, 10303 AP-238) format. As the machine codes have ultimately determined the values of the selected KPIs, we build a simulation model to predict those values. First, the translated machine codes are validated via error detections (e.g. scan path integrity) and the identified KPIs are estimated and validated by using a simulation tool. The flatness and surface roughness are estimated as Z_a: 50 μm with Z_t: 102 μm and R_a: 8.8 μm with R_t: 45.6 μm.

5.6 (Qa: A6) validate process stability

Based on the plan, monitoring systems are used to detect defects and provide the thermal characteristics for the analysis. It then reduces and fixes defects using an in-situ control approach.

5.7 (Qa: A7) validate a part with process signature

Based on the validation plan, the GD&T are estimated, analyzed and validated based on the analysis of process signatures. The acquired images have the necessary information to analyze the flatness and surface roughness. It is estimated that the flatness and surface roughness are Z_a: 48 μm with Z_t: 98 μm and R_a: 6.9 μm with R_t: 52.4 μm, respectively.

5.8 (Qa: A8) validate a post-process

EDM is used to remove the support structure and HIP is performed to reduce the porosity with a setting of 100 MPa pressure at 900°C for 2 h from the guidelines in ASTM F2924-14.

5.9 (Qa: A9) validate tests and a part

A CMM and stylus profilometer are used to measure the flatness and surface roughness. It is estimated that the flatness and the surface roughness are measured as Z_a: 50 μm with Z_t: 100 μm and R_a: 5.56 μm with R_t: 43.89 μm. Thus, all KPIs are satisfied.

6. Discussions and implementation challenges

We proposed an IDEF0 functional model as the foundation for developing QA plans. We also showed how this plan could be implemented using a simple operational scenario. However, these functional models should be further specified in terms of QA plans. For example, detail QA plans for powdery materials should be specified, as it can significantly affect the final AM part. In addition, implementing QA for metal AM processes and parts is challenging for several reasons. The following are the discussions about these.

The characteristics of powder materials, such as powder size, distribution, morphology (e.g. dimensional, spherical, roundness and perimeter), chemical composition, density (e.g. apparent density, tap density and skeletal density), thermal properties (e.g. conductivity and diffusivity) of powder, are the key elements for the powder quality (Slotwinski *et al.*, 2014; Vock *et al.*, 2019). In addition, the powder material is recycled, thus the number of recycling time is another key element for the powder quality (Sutton *et al.*, 2020). Accurate characteristics of a powder material can give the corresponding modeling and analysis of part properties or melt pool characteristics and ensure the part quality. Thus, functional design models of powdery materials in prospective and concurrent validation stages are necessary in terms of QA plans.

Due to the complexities that arise from the multi-physics, multi-scale and multi-criteria aspects of AM (Yan *et al.*, 2018), it is not easy to understand the relationships between the AM process, material, thermal analysis and the resulting part's microstructure, properties and performance. One possible solution is to use a semantic ontology mapping method. NIST researchers have developed methods for understanding the relationships between porosity, process variables and powder specifications, which include semantic relationships (Mani *et al.*, 2015; Roh *et al.*, 2016). Based on the semantic maps, the need for various predictive models becomes clear. For example, empirical models can be generated by combining of DOE with RSM or machine learning methods. Although these models require numerous physical experiments, they have advantages in customization and practicality. The time-consuming and cost-intensive physical experiments can potentially be reduced by using high fidelity modeling methods.

High-fidelity models can be generated from the fundamental understandings of the AM processes. Examples include a set of highly complex physics models, high-order empirical models or hybrids of both models. They are frequently used in welding and the AM community. Nevertheless, the application of the models is limited to controlled scales and conditions. Developing and implementing these models often requires high performing computing, which enables high accuracy but significantly increases computational cost. To address this burden, surrogate (low-fidelity) models are being created by reducing high-order models into lower-order approximations (Meckesheimer *et al.*, 2002; Lee *et al.*, 2017; Plotkowski *et al.*, 2017). These models can make use of existing knowledge and can produce more powerful predictive models with robust decision-making support and stronger predictive capability. Because of the considerably higher computational efficiency compared to high-fidelity models, these surrogate models can be used for in-situ control. In addition, real-time data collection and analytics can be combined with the surrogate models to improve model accuracy. One common approach in data analytics is to use the thermal characteristics (e.g. melt pool shape and size) to train a set of process parameters in a neural network model, which then produces a solution that reduces and/or fixes any unwanted defects (Scime and Beuth, 2019). By taking advantage of simulation techniques, training data sets can be also generated without running numerous real experiments.

To assure quality, a large amount of data is generated, especially in retrospective validation. In Berumen *et al.* (2010), the total size of the acquired data is 1.08 PB. This large number is based on an 8-bit grayscale image taken with a resolution of 2,200 * 2,200 pixels and 16,666 fps over a building time of 4 h. For another example, Slotwinski *et al.* (2014) used X-ray CT with a resolution of 1,000 * 1,000 * 1,000 and two-byte integer to generate approximately 2 GB of data. To manage the huge amount of data, innovative techniques, such as big data and data mining, are needed (Majeed *et al.*, 2019).

The architecture and management system will be developed in the near future. However, it requires several different types of techniques/methods/tools/systems. This results in integration and interoperability issues. For the integration issues, the system will be developed by considering the tightly and loosely coupled integration for the development efficiency. For the interoperability issues, a neutral and standardized format for design/build/test should be established. In addition, the workflow and information models should be seamlessly integrated to those of NIST-AM DT architecture (Kim *et al.*, 2015; Kim *et al.*, 2017).

7. Conclusion

This paper summarized previous related work and the gaps and needs in QA planning literature. Based on these, it is concluded each research issue in AM can be integrated to ultimately achieve QA. For the initial step, a systematically integrated view is proposed, consisting of four stages, namely, QA plan, prospective validation, concurrent validation and retrospective validation. Then, a workflow and information models were developed by using the IDEF0 models. This work provides the foundations for capturing the background and requirements of QA architecture and framework development, logically relating them to the NIST-DT. An operational scenario was included to demonstrate how these functional models could be applied. Through the operational scenario, we showed how the performances can be assured via nine functional design models. After that, challenging research issues were discussed in terms of semantic ontology mapping, predictive model and knowledge, design rule, surrogate model, real-time control and big data management. Through this research work, the authors can conclude with several findings and highlights:

- The systematically integrated functional modeling approach can ensure the predefined part properties before/during/after AM processes.
- The functional design model of the federated QA view provides the systematically integrated view that can be the basis for inspection of AM processes for the repeatability and qualification of AM parts for reproducibility.
- The functional modeling approach can provide the following synergistic effects, namely, it can reduce cost and lead-time for new product development, detect and prevent defects and satisfy stakeholders' desires.
- This work provides an innovative and transformative methodology that can lead to greater productivity and improved quality of AM parts across industries. Furthermore.
- The functional design models provide the foundation for the development of a QA architecture and management system.

In the near future, the research team will establish an in-situ inspection method for process repeatability and a digital twin-driven qualification framework for part reproducibility of a wire + arc additively manufactured part, based on the proposed QA plan scheme and the NIST-DT concept (Tanvir *et al.*, 2019; Mukherjee and Debroy, 2019; Ahsan *et al.*, 2020).

References

Ahsan, M.R.U., Tanvir, A.N.M., Seo, G., Bates, B., Hawkins, W., Lee, C., Liaw, P.K., Noakes, M., Nycz, A. and Kim, D.B. (2020), "Heat-treatment effects on a bimetallic additively-manufactured structure (BAMS) of the low-carbon steel and austenitic-stainless steel", *Additive Manufacturing*, Vol. 32, p. 101036.

Babu, S.S., Raghavan, N., Raplee, J., Foster, S.J., Frederick, C., Haines, M., Dinwiddie, R., Kirka, M.K., Plotkowski, A., Lee, Y. and Dehoff, R.R. (2018), "Additive manufacturing of nickel superalloys: opportunities for innovation and challenges related to qualification", *Metallurgical and Materials Transactions A*, Vol. 49 No. 9, pp. 3764-3780.

Bandyopadhyay, A. and Traxel, K.D. (2018), "Invited review article: metal-additive manufacturing-modeling strategies for application-optimized designs", *Additive Manufacturing*, Vol. 22, pp. 758-774.

Bauereiß, A., Scharowsky, T. and Körner, C. (2014), "Defect generation and propagation mechanism during additive manufacturing by selective beam melting", *Journal of Materials Processing Technology*, Vol. 214 No. 11, pp. 2522-2528.

Berumen, S., Bechmann, F., Lindner, S., Kruth, J.P. and Craeghs, T. (2010), "Quality control of laser-and powder bed-based additive manufacturing (AM) technologies", *Physics Procedia*, Vol. 5, pp. 617-622.

Beuth, J., Fox, J., Gockel, J., Montgomery, C., Yang, R., Qiao, H., Soylemez, E., Reeseewatt, P., Anvari, A., Narra, S.P. and Klingbeil, N. (2013), "Process mapping for qualification across multiple direct metal additive manufacturing processes", *24th*

International Solid Freeform Fabrication Symposium – An Additive Manufacturing Conference, *Austin, TX*, pp. 655-665.

Bourell, D.L., Leu, M.C. and Rosen, D.W. (2009), *Roadmap for Additive Manufacturing*, University of TX, Austin, TX.

Brice, C.A. (2011), "Unintended consequences: how qualification constrains innovation", in Allison, J., Collins, P. and Spanos, G. (Eds), *Proceedings of the 1st World Congress on Integrated Computational Materials Engineering (ICME)*, John Wiley & Sons Inc., Hoboken, NJ, pp. 241-246.

Casalino, G., Campanelli, S.L., Contuzzi, N. and Ludovico, A.D. (2015), "Experimental investigation and statistical optimisation of the selective laser melting process of a maraging steel", *Optics & Laser Technology*, Vol. 65, pp. 151-158.

Chauvet, E., Tassin, C., Blandin, J.J., Dendievel, R. and Martin, G. (2018), "Producing Ni-base superalloys single crystal by selective electron beam melting", *Scripta Materialia*, Vol. 152, pp. 15-19.

Debroy, T., Wei, H.L., Zuback, J.S., Mukherjee, T., Elmer, J.W., Milewski, J.O., Beese, A.M., Wilson-Heid, A., De, A. and Zhang, W. (2018), "Additive manufacturing of metallic components – process, structure and properties", *Progress in Materials Science*, Vol. 92, pp. 112-224.

Dehoff, R.R., Kirka, M.M., Sames, W.J., Bilheux, H., Tremsin, A.S., Lowe, L.E. and Babu, S.S. (2015), "Site specific control of crystallographic grain orientation through electron beam additive manufacturing", *Materials Science and Technology*, Vol. 31 No. 8, pp. 931-938.

Everton, S.K., Hirsch, M., Stravroulakis, P., Leach, R.K. and Clare, A.T. (2016), "Review of in-situ process monitoring and in-situ metrology for metal additive manufacturing", *Materials & Design*, Vol. 95, pp. 431-445.

Frazier, W.E. (2014), "Metal additive manufacturing: a review", *Journal of Materials Engineering and Performance*, Vol. 23 No. 6, pp. 1917-1928.

Ganeriwala, R.K., Strantza, M., King, W.E., Clausen, B., Phan, T.Q., Levinec, L.E. and NHodgea, E. (2019), "Evaluation of a thermomechanical model for prediction of residual stress during laser powder bed fusion of Ti-6Al-4V", *Additive Manufacturing*, Vol. 27, pp. 489-502.

Gao, W., Zhang, Y., Ramanujan, D., Ramani, K., Chen, Y., Williams, C.B., Wang, C.C.L., Shin, Y.C., Zhang, S. and Zavattieri, P.D. (2015), "The status, challenges, and future of additive manufacturing in engineering", *Computer-Aided Design*, Vol. 69, pp. 65-89.

Gockel, J. and Beuth, J. (2013), "Understanding Ti-6Al-4V microstructure control in additive manufacturing via process maps", *24th International Solid Freeform Fabrication Symposium – An Additive Manufacturing Conference*, *Austin, TX*, pp. 666-674.

Huang, Y., Leu, M.C., Mazumder, J. and Donmez, M.A. (2015), "Additive manufacturing: current state, future potential, gaps and needs, and recommendations", *Journal of Manufacturing Science and Engineering*, Vol. 137 No. 1, pp. 014001-1-10.

ISO 9000 (2005), "Quality management systems – fundamentals and vocabulary".

Keller, T., Lindwall, G., Ghosh, S., Ma, L., Lane, B., Zhang, F., Kattner, U.R., Lass, E.A., Heigel, J., Idell, Y., Williams, M.E., Allen, A.J., Guyer, J.E. and Levine, L.E. (2017), "Application of finite element, phase-field, and CALPHAD-based methods to additive manufacturing of Ni-based superalloys", *Acta Materialia*, Vol. 139, pp. 244-253.

Khairallah, S.A. and Anderson, A. (2014), "Mesoscopic simulation model of selective laser melting of stainless steel powder", *Journal of Materials Processing Technology*, Vol. 214 No. 11, pp. 2627-2636.

Khairallah, S.A., Anderson, A., Rubenchik, A. and King, W.E. (2016), "Laser powder-bed fusion additive manufacturing: physics of complex melt flow and formation mechanisms of pores, spatter, and denudation zones", *Acta Materialia*, Vol. 108, pp. 36-45.

Kim, D.B. (2019), "An approach for composing predictive models from disparate knowledge sources in smart manufacturing environments", *Journal of Intelligent Manufacturing*, Vol. 30 No. 4, pp. 1999-2012.

Kim, F.H. and Moylan, S.P. (2018), "Literature review of metal additive manufacturing defects", Advanced Manufacturing Series (NIST AMS), Report No. 100-16.

Kim, D.B., Denno, P. and Jones, A. (2015), "A model-based approach to refine process parameters in smart manufacturing", *Concurrent Engineering Research Engineering*, Vol. 23 No. 4, pp. 365-376.

Kim, H., Lin, Y. and Tseng, T.B. (2018), "A review on quality control in additive manufacturing", *Rapid Prototyping Journal*, Vol. 24 No. 3, pp. 645-669.

Kim, D.B., Witherell, P., Lipman, R. and Feng, S.C. (2015), "Streamlining the additive manufacturing digital spectrum: a systems approach", *Additive Manufacturing*, Vol. 5, pp. 20-30.

Kim, D.B., Witherell, P., Lu, Y. and Feng, S. (2017), "Toward a digital thread and data package for metals-additive manufacturing", *Smart and Sustainable Manufacturing Systems*, Vol. 1 No. 1, pp. 75-99.

King, W., Anderson, A.T., Ferencz, R., Hodge, N.E., Kamath, C. and Khairallah, S.A. (2015), "Overview of modelling and simulation of metal powder bed fusion process at Lawrence Livermore national laboratory", *Materials Science and Technology*, Vol. 31 No. 8, pp. 957-968.

Kirka, M.M., Lee, Y., Greeley, D.A., Okello, A., Goin, M.J., Pearce, M.T. and Dehoff, R.R. (2017), "Strategy for texture management in metals additive manufacturing", *The Journal of the Minerals, Metals & Materials Society (TMS)*, Vol. 69 No. 3, pp. 523-531.

Kok, Y., Tan, X.P., Wang, P., Nai, M.L.S., Loh, N.H., Liu, E. and Tor, S.B. (2018), "Anisotropy and heterogeneity of microstructure and mechanical properties in metal additive manufacturing: a critical review", *Meterials & Design*, Vol. 139, pp. 565-586.

Körner, C., Attar, E. and Heinl, P. (2011), "Mesoscopic simulation of selective beam melting processes", *Journal of Materials Processing Technology*, Vol. 211 No. 6, pp. 978-987.

Kroll, J., Botta, S., Breuninger, J. and Verl, A.W. (2013), "Adaptive quality assurance of the product development process of additive manufacturing with modern 3D data evaluation methods", *Proc. SPIE 8650, Three-Dimensional Image Processing (3DIP) and Applications*.

Lee, Y.S. and Zhang, W. (2015), "Mesoscopic simulation of heat transfer and fluid flow in laser powder bed additive manufacturing", *International Solid Free Form Fabrication Symposium*, *Austin*, pp. 1154-1165.

Lee, Y.S. and Zhang, W. (2016), "Modeling of heat transfer, fluid flow and solidification microstructure of nickel-base superalloy fabricated by laser powder bed fusion", *Additive Manufacturing*, Vol. 12, pp. 178-188.

Lee, Y.S., Kirka, M.M., Raghavan, N. and Dehoff, R.R. (2017), "Simulation of spot melting scan strategy to predict columnar to equiaxed transition in metal additive manufacturing", *International Solid Free Form Fabrication Symposium*, *Austin*, pp. 1005-1017.

Lee, Y.S., Kirka, M.M., Kim, S., Sridharan, N., Okello, A., Dehoff, R.R. and Babu, S.S. (2018), "Asymmetric cracking in Mar-M247 alloy builds during electron beam powder bed fusion additive manufacturing", *Metallurgical and Materials Transactions A*, Vol. 49 No. 10, pp. 5065-5079.

Loh, L.E., Chua, C.K., Yeong, W.Y., Song, J., Mapar, M., Sing, S.L., Liu, Z.H. and Zhang, D.Q. (2015), "Numerical investigation and an effective modelling on the selective laser melting (SLM) process with aluminium alloy 6061", *International Journal of Heat and Mass Transfer*, Vol. 80, pp. 288-300.

Majeed, A., Lv, J. and Peng, T. (2019), "A framework for big data driven process analysis and optimization for additive manufacturing", *Rapid Prototyping Journal*, Vol. 25 No. 2, pp. 308-321.

Mani, M., Donmez, M.A., Feng, S.C., Moylan, S., Fesperman, R. and Lane, B. (2015), "Measurement science needs for real-time control of powder bed fusion processes", NISTIR 8036.

Mazumder, J. (2015), "Design for metallic additive manufacturing machine with capability for 'certify as you build'", *Procedia Cirp*, Vol. 36, pp. 187-192.

Meckesheimer, M., Booker, A.J., Barton, R.R. and Simpson, T.W. (2002), "Computationally inexpensive metamodel assessment strategies", *Aiaa Journal*, Vol. 40 No. 10, pp. 2053-5060.

Mireles, J., Terrazas, C., Medina, F. and Wicker, R. (2013), "Automatic feedback control in electron beam melting using infrared thermography", *24th International Solid Freeform Fabrication Symposium – An Additive Manufacturing Conference*, *Austin, TX*, pp. 708-717.

Moylan, S., Slotwinski, J., Cooke, A., Jurrens, K. and Donmez, M.A. (2014), "An additive manufacturing test artifact", *Journal of Research of the National Institute of Standards and Technology*, Vol. 119, pp. 429-459.

Mukherjee, T. and DebRoy, T. (2019), "A digital twin for rapid qualification of 3D printed metallic components", *Applied Materials Today*, Vol. 14, pp. 59-65.

Najmon, J.C., Raeisi, S. and Tovar, A. (2019), "Review of additive manufacturing technologies and applications in the aerospace industry", *Additive Manufacturing for the Aerospace Industry*, pp. 7-31.

Nakano, T. and Ishimoto, T. (2015), "Powder-based additive manufacturing for development of tailor-made implants for orthopedic applications", *KONA Powder and Particle Journal*, Vol. 32 No. 0, pp. 75-84.

NIST (2013), *Measurement Science Roadmap for Metal-Based Additive Manufacturing*, National Institute of Standards and Technology, Department of Commerce.

Phillips, T., Fish, S. and Beaman, J. (2018), "Development of an automated laser control system for improving temperature uniformity and controlling component strength in selective laser sintering", *Additive Manufacturing*, Vol. 24, pp. 316-322.

Plotkowski, A., Kirka, M.M. and Babu, S.S. (2017), "Verification and validation of a rapid heat transfer calculation methodology for transient melt pool solidification conditions in powder bed metal additive manufacturing", *Additive Manufacturing*, Vol. 18, pp. 256-268.

Raghavan, N., Dehoff, R., Pannala, S., Simunovic, S., Kirka, M., Turner, J., Carlson, N. and Babu, S.S. (2016), "Numerical modeling of heat-transfer and the influence of process parameters on tailoring the grain morphology of IN718 in electron beam additive manufacturing", *Acta Materialia*, Vol. 112, pp. 303-314.

Raplee, J., Plotkowski, A., Kirka, M.M., Dinwiddie, R., Okello, A., Dehoff, R.R. and Babu, S.S. (2017), "Thermographic microstructure monitoring in electron beam additive manufacturing", *Scientific Reports*, Vol. 7 No. 1.

Rodrigues, T., Duarte, V., Miranda, R.M., Santos, T.G. and Oliveira, J.P. (2019), "Current status and perspectives on wire and arc additive manufacturing (WAAM)", *Materials*, Vol. 12 No. 7, p. 1121.

Roh, B.M., Kumara, S.R.T., Simpson, T.W., Michaleris, P., Witherell, P. and Assouroko, I. (2016), "Ontology-based laser and thermal metamodels for metal-based additive manufacturing", *ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, p. V01AT02A043.

Roy, U., Li, Y. and Zhu, B. (2014), "Building a rigorous foundation for performance assurance assessment techniques for 'smart' manufacturing systems", *2014 IEEE International Conference on Big Data*, pp. 1015-1023.

Russell, R., Wells, D., Waller, J., Poorganji, B., Ott, E., Nakagawa, T., Sandoval, H., Shamsaei, N. and Seifi, M. (2019), "Qualification and certification of metal additive manufactured hardware for aerospace applications", *Manufacturing for the Aerospace Industry*, pp. 33-66.

Sames, W.J., List, F.A., Pannala, S., Dehoff, R.R. and Babu, S.S. (2016), "The metallurgy and processing science of metal additive manufacturing", *International Materials Reviews*, Vol. 61 No. 5, pp. 315-360.

Schoinochoritis, B., Chantzis, D. and Salonitis, K. (2015), "Simulation of metallic powder bed additive manufacturing processes with the finite element method: a critical review", *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, Vol. 231 No. 1, pp. 96-117.

Scime, L. and Beuth, J. (2019), "Using machine learning to identifying in-situ melt pool signatures indicative of flaw formation in a laser powder bed fusion additive manufacturing process", *Additive Manufacturing*, Vol. 25, pp. 151-165.

Slotwinski, J.A., Garboczi, E.J. and Hebenstreit, K.M. (2014), "Porosity measurements and analysis for metal additive manufacturing process control", *Journal of Research of the National Institute of Standards and Technology*, Vol. 119, pp. 494-528.

Slotwinski, J.A., Garboczi, E.J., Stutzman, P.E., Ferraris, C.F., Watson, S.S. and Peltz, M.A. (2014), "Characterization of metal powders used for additive manufacturing", *Journal of*

Research of the National Institute of Standards and Technology, Vol. 119, pp. 460-493.

Smith, J., Xiong, W., Yan, W., Lin, S., Cheng, P., Kafka, O.L., Wagner, G.J., Cao, J. and Liu, W.K. (2016), "Linking process, structure, property, and performance for metal-based additive manufacturing: computational approaches with experimental support", *Computational Mechanics*, Vol. 57 No. 4, pp. 583-610.

Song, L., Bagavath-Singh, V., Dutta, B. and Mazumder, J. (2012), "Control of melt pool temperature and deposition height during direct metal deposition process", *The International Journal of Advanced Manufacturing Technology*, Vol. 58 Nos 1/4, pp. 247-256.

Sun, J., Yang, Y. and Wang, D. (2013), "Parametric optimization of selective laser melting for forming Ti6Al4V samples by Taguchi method", *Optics & Laser Technology*, Vol. 49, pp. 118-124.

Sutton, A.S., Kriewall, C.S., Karnati, S., Leu, M.C. and Newkirk, J.W. (2020), "Characterization of AISI 304L stainless steel powder recycled in the laser powder-bed fusion process", *Additive Manufacturing*, Vol. 32, p. 100981.

Tanvir, A.N.M., Ahsan, M.R.U., Ji, C., Hawkins, W., Bates, B. and Kim, D.B. (2019), "Heat treatment effects on Inconel 625 components fabricated by wire+ arc additive manufacturing (WAAM) – part 1: microstructural characterization", *The International Journal of Advanced Manufacturing Technology*, Vol. 103 Nos 9/12, pp. 1-14.

Tapia, G. and Elwany, A. (2014), "A review on process monitoring and control in metal-based additive manufacturing", *Journal of Manufacturing Science and Engineering*, Vol. 136 No. 6, p. 060801.

Thomas, M., Baxter, G.J. and Todd, I. (2016), "Normalised model-based processing diagrams for additive layer manufacture of engineering alloys", *Acta Materialia*, Vol. 108, pp. 26-35.

Todorov, E., Spencer, R., Gleeson, S., Jamshidinia, M. and Kelly, S.M. (2014), "America makes: national additive manufacturing innovation institute: project 1: nondestructive evaluation (NDE) of complex metallic additive manufactured (AM) structures", AFRL-RX-WP-TR-2014-0162, Interim Report.

Vijayaraghavan, A. and Dornfeld, D. (2010), "Automated energy monitoring of machine tools", *CIRP Annals Manufacturing Annals*, Vol. 59 No. 1, pp. 21-24.

Vock, S., Klöden, B., Kirchner, A., WeißGärber, T. and Kieback, B. (2019), "Powders for powder bed fusion: a review", *Progress in Additive Manufacturing*, Vol. 4 No. 4, pp. 383-397.

Waller, J.M., Parker, B.H., Hodges, K.L., Burke, E.R. and Walker, J.L. (2014), "Nondestructive evaluation of additive manufacturing state-of-the-discipline report", *NASA Langley Research Center*, Hampton, VA.

Yan, W., Lin, S., Kafka, O.L., Lian, Y., Yu, C., Liu, Z., Yan, J., Wolff, S., Wu, H., Ndip-Agbor, E., Mozaffar, M., Ehmann, K., Cao, J., Wagner, G.J. and Liu, W.K. (2018), "Data-driven multi-scale multi-physics models to derive process–structure–property relationships for additive manufacturing", *Computational Mechanics*, Vol. 61 No. 5, pp. 521-541.

Yoder, S., Morgan, S., Kinzy, C., Barnes, E., Kirka, M., Paquit, V., Nandwana, P., Plotkowski, A., Dehoff, R.R. and Babu, S.S. (2018), "Characterization of topology optimized Ti-6Al-4V components using electron beam powder bed fusion", *Additive Manufacturing*, Vol. 19, pp. 184-196.

Zhang, J., Wang, P. and Gao, R.X. (2019), "Deep learning-based tensile strength prediction in fused deposition modeling", *Computers in Industry*, Vol. 107, pp. 11-21.

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