IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 September 2023, accepted 17 October 2023, date of publication 23 October 2023, date of current version 8 November 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3327054

RESEARCH ARTICLE

Ensuring Quality in Metal Additive Manufacturing Through a V-Model Framework

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This work was supported in part by the U.S. Department of Commerce under Grant 70NANB15H016, in part by the National Institute of Standards and Technology (NIST) under Grant 2019-NIST-MSE-01, and in part by The University of Oklahoma Libraries Open Access Fund.

ABSTRACT Metal Additive Manufacturing (MAM) produces complex, part geometries from a variety of materials in powder and wire form. Due to complexities of MAM processes that create those geometries, especially powder bed fusion, quality assurance, and qualification remain an ongoing challenge. Quality assurance involves assessing the quality of a part's geometry, surface finish, and mechanical properties. Currently, quality assurance is not easily achieved due to variations in the powder inputs, the MAM process itself, and environmental factors, such as temperature. Many efforts are underway to develop a new quality system that includes 1) planning, measuring, and qualifying parts and 2) enhancing quality through a processing-monitoring-qualifying framework. Creating this new system requires building the complex relationships between requirements, processes, and quality. These relationships are needed to specify, measure, analyze, and optimize variables to ensure final part quality. Thus, a processing-monitoring-quality framework could provide critical steps to identify those relationships and help meet stakeholder needs. The paper describes how to adapt the ''software and systems engineering'' V-model to a ''metal AM quality assurance'' V-model that can provide a framework for quality assurance in MAM.

INDEX TERMS Metal Additive Manufacturing (MAM), Quality Assurance, V-Model, System Verification, System Validation, Cyber-Physical Systems.

I. INTRODUCTION

To ensure the metal AM quality, the Metal Additive Manufacturing (MAM) process involves a series of steps that must be taken to ensure that the parts produced meet the required specifications. These steps include design validation, material selection, process optimization, inspection, and post-processing. Each of these steps must be carefully monitored and controlled to ensure that the parts produced are of the highest quality [1], [2]. By following a rigorous quality assurance and control process, metal AM can be used to produce parts with the highest level of reliability and performance [31], [32].

Due to the development of sensors, real-time metal AM monitoring became a new way to ''see'' the part quality. Real-time monitoring allows for the detection of any anomalies in the process, allowing for quick corrective action to be taken [3]. This can help to reduce scrap and improve product quality. Additionally, real-time monitoring can provide valuable data that can be used to optimize the process and improve efficiency. However, there are still some limitations in using metal AM real-time monitoring to qualify the part as-built qualities. For example, it can be difficult to integrate with existing systems, and it may not be suitable for many types of metal AM processes. Finally, the collected data

The associate editor coordinating the review of this manuscript and approving it for publication was Nikhil Padhi.

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from the real-time monitoring still requires a heavy amount of manual work to correlate to the ultimate performance, such as mechanical strength and fatigue. To detect and qualify the as-built quality, it is still necessary to have manual inspections [33].

The current process prediction models for the metal additive manufacturing process are mainly based on the finite element method (FEM). This method is used to simulate the entire process, from the initial powder deposition to the final product. It is used to predict the temperature, stress, strain, and other parameters during the process. This helps to identify potential problems and optimize the process parameters. Other models such as artificial neural networks (ANNs) and support vector machines (SVMs) can also be used to predict the process parameters. These models are used to identify the optimal parameters for a given set of conditions and can be used to optimize the process.

However, these models have some limitations. For example, they cannot accurately predict the behavior of multiple physics or their interactions and dynamic evolution with complex microstructures. Additionally, they are limited in their ability to predict the effects of process parameters on the final product. Finally, these models are not able to account for unexpected events or changes in the environment that could affect the process.

The V-model is a visual depiction of the software development process. It can also aim to ensure quality assurance by deconstructing user requirements into components that are easy to understand. [4]. The V-model is a type of software development model that follows a sequential path from the initial stages of requirements gathering and analysis, through design, coding, testing, and finally to maintenance. The V-model is a representation of the process that helps to ensure that all aspects of the software development process are addressed. It also helps to ensure that all stakeholders are involved in the process, from the initial requirements gathering to the final maintenance phase. The V-model helps to ensure that all aspects of the software development process are addressed in an organized and systematic manner.

The V-model is a quality assurance system used in metal additive manufacturing (AM) that helps ensure the quality of the parts produced. It is based on the concept of verifying the design and production process at each stage of the process. The V-model begins with the design phase, where the part is designed and verified for accuracy and manufacturability. This is followed by the production phase, where the part is produced and inspected for quality. Finally, the post-production phase involves testing and validating the part to ensure that it meets all requirements. The V-model helps to ensure that all parts produced are of high quality and meet all customer requirements.

The proposed V-model works by having each stage of the AM process evaluated and tested for quality assurance. This includes the design, pre-processing, build, post-processing, and inspection stages. At each stage, the review of the process is enabled and make sure that all requirements are met. This includes checking for any potential defects or errors that could lead to a failed part. Once all stages have been evaluated and approved, the part is ready for production. The V-model helps to ensure that all parts produced are of the highest quality and meet all customer requirements.

FIGURE 1. Workflow of metal AM.

To successfully adapt AM to high-precision technology for highly precise applications, a generic understanding of how to execute a quality inspection of AM parts is both essential and needed. Since AM technology is very complex, developing such an understanding will require solutions to three fundamental, quality-assurance-related problems.

(1) Design characteristics such as complex surface geometry, lattice, and internal features create challenges in monitoring AM process characteristics and updating AM process parameters. These features are difficult to measure and monitor due to their intricate nature, making it difficult to accurately assess the quality of the part being produced. Additionally, the process parameters used in AM processes are highly sensitive and require frequent updates to ensure optimal performance. This is especially true for lattice structures, which require precise control of the laser power and speed to ensure the desired results. As a result, monitoring and updating AM process parameters can be a time-consuming and costly process, making it important for manufacturers to have a reliable system in place for monitoring and updating these parameters.

(2) Process characteristics are the parameters that define the process of manufacturing a part. These characteristics include the type of material used, the tooling used, the cutting speed, and the feed rate. These parameters create the local geometric features of a part, such as the shape, size, and surface finish. If the process parameters are not changed, these characteristics can lead to internal part defects, such as burrs, chips, or cracks. These defects can affect the quality and performance of the final part. Thus, it is important to monitor and adjust process parameters to ensure that parts are produced with high quality and performance.

(3) Process complexities often make it challenging to adjust the right process-parameter changes in order to ensure the quality and performance of the current and future parts. Measuring the current AM part's quality and performance and predicting its future quality and performance based on its current ones are still in their research phases. This is because accurately measuring the required metastable phases, microstructural instability, residual stress, and the dynamics of mechanical behaviors are part of the AM-part testing, research phase. As a result, there are very few commercial, quality-assurance products available on the market today.

TABLE 1. Overview of AM modeling and simulation capabilities in metal AM qualification.

References / Model	Design	Process parameters	Physical phenomenon	Monitoring	Quality
[13,14]	✓				
[15,16]	✓		✓		
[17-19]			✓	✓	✓
[20,21]		✓			✓
[22,23]		✓	✓		

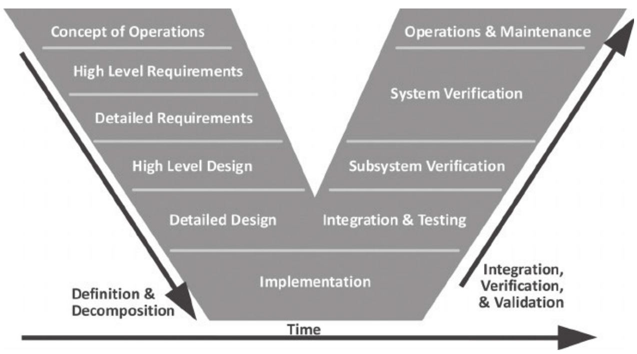

FIGURE 2. V-model in system & software engineering [5].

Frequently, the execution of each AM lifecycle process, when diagrammed, forms a V-shaped sequence of steps. Steps like those used to verify and validate the Systems Engineering hardware/software process (see Figure 2) [28]. In AM V-model, the hardware part comprises both the AM process and the AM part. The hardware sequence (the RHS) demonstrates the real relationships between each step in the fabrication, testing, and validation of the AM part. In AM V-model, the software part (the LHS) comprises applications that start with design and modeling and ends with process parameters and NC-code [5].

II. BACKGROUND AND LITERATURE REVIEW OF MODELING, SIMULATION, AND QUALITY ASSURANCE

A. LITERATURE REVIEW

Many modeling and simulation tools have been deployed for thermal-distribution and melt-pool analysis during Metal Additive Manufacturing (MAM) fabrication process [29], [30]. These tools generate disparate computational results that have yet to be fully leveraged to provide feedback and improve control of that process. To be useful, those computational results must be integrated into a cohesive framework for monitoring, diagnosing, qualifying, and meeting design, material, and process requirements. To construct such a framework, an understanding of the various modeling and simulation capabilities is critical to improve quality assurance. The following paragraphs review past work on modeling, simulation, and quality assurance. Table 1 provides a summary overview of AM modeling and simulation capabilities that other researchers have closely examined for metal AM quality assurance. Experimental studies have been conducted to identify melt pool anomalies, such as a keyhole, and powder spatter during the fabrication process. Gibson et al. [6] investigated melt-pool-size measurements via infrared thermography in Directed Energy Deposition (DED). They focused on demonstrating consistent, melt-pool-size measurements and characterizing interactions between the process variables and the measurements. Cheng et al. [7] analyzed melt pool geometry in powder-bed fusion by monitoring the change in melt pool shape.

Kiss et al. [8] studied laser-induced, keyhole defects in the powder bed fusion process by 1) emphasizing the importance of understanding processing parameters and 2) developing a reliable defect-mitigation method using empirically validated models. They measured vapor-depression dynamics, keyhole-void formation, and vapor-bubble dynamics using high-speed X-ray imaging. Guo et al. [9] focused on the transient dynamic behavior of powder spattering during the laser powder bed fusion process using an x-ray imaging technique, providing a potential method to mitigate powder spattering in the AM process.

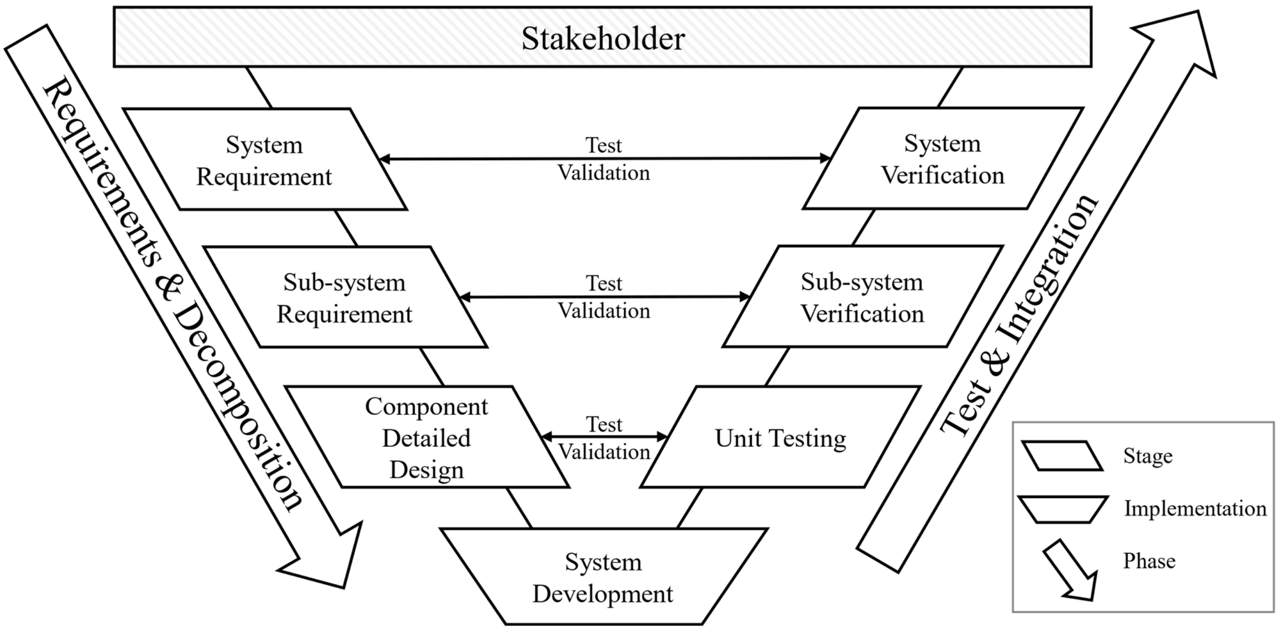

FIGURE 3. Schematic representation of V-model structure for systems engineering.

Using real-time, AM process data as inputs to use machine learning (ML) models for defect detection has become popular. Li et al. [10] proposed measuring part quality using image data collected during the process to build a deep learning-based quality identification method. Mohammadi et al. [11] studied reliable product quality through dimensional error prediction, investigating the performance of several different ML methodologies to detect defects in real-time. Aminzadeh et al. [12] researched the inspection of a parts' dimensional accuracy during the build process through the development of machine-vision-based, dimensional-inspection techniques.

Ponche et al. [13] investigated a new design for AM parts using a new numerical chain approach. Chu et al. [14] studied opportunities in design for AM by using the process-structure–property behavior model. Ríos et al. [15] studied an analytical process model for predicting layer height in wire + arc AM. Lei et al. [16] introduced an AM process model for product family design, incorporating AM into the design process. Grasso et al. [17] investigated data-fusion-based, monitoring methods using support-vector, data descriptions. Rao et al. [18] studied failure and anomalies using a sensor data-driven approach. Shevchik et al. [19] investigated in-situ monitoring for the formation and concentrations of different types of pores in AM. Das et al. and Matos et al. [20], [21] investigated an optimal, build orientation for minimizing part errors by reducing support structures, meeting tolerance requirements, and decreasing printing time.

Raghavan et al. [22] developed heat-transfer simulation models to refine electron beam melting. Yao et al. [23] simulated temperature variation by controlling process parameters in DED. Balaji et al. [24] compared the waterfall model to the V-model to guide the development of software solutions. Sheffield [25] investigated systemic knowledge and the V-model by adding considerable details to the concepts sketched in the V-model. He explained the V-model generation from general systems concepts of a deceptively simple but robust model that is demonstrated via recursion. Clark [26] studied the system of systems engineering to develop system engineering standards using the V-model and dual V-model. Graessler et al. [27] proposed a design methodology for V-model and validation for mechanics systems.

B. QUALITY ASSURANCE FOR METAL AM

Quality assurance for Metal AM is an important consideration for any stakeholder that is looking to use this technology. Quality assurance is the process of certifying that a product meets certain standards of quality and performance. In the case of AM, quality assurance involves ensuring that the parts produced are accurate, consistent, and reliable. The first step in quality assurance for AM is to assure that the design and build process is properly documented. This includes documenting the design parameters, build parameters, and post-processing parameters. This documentation should keep update and should be reviewed regularly to ensure that the parts produced are meeting the desired specifications. The second step in quality assurance for AM is to ensure that the materials used are of the highest quality. This includes ensuring that the materials used are certified and meet the required standards. It is also essential to ensure that the materials used are compatible with the AM process and that they are properly stored and handled. The third step in quality assurance for AM is to ensure that the parts produced are inspected and tested, including visual inspection,

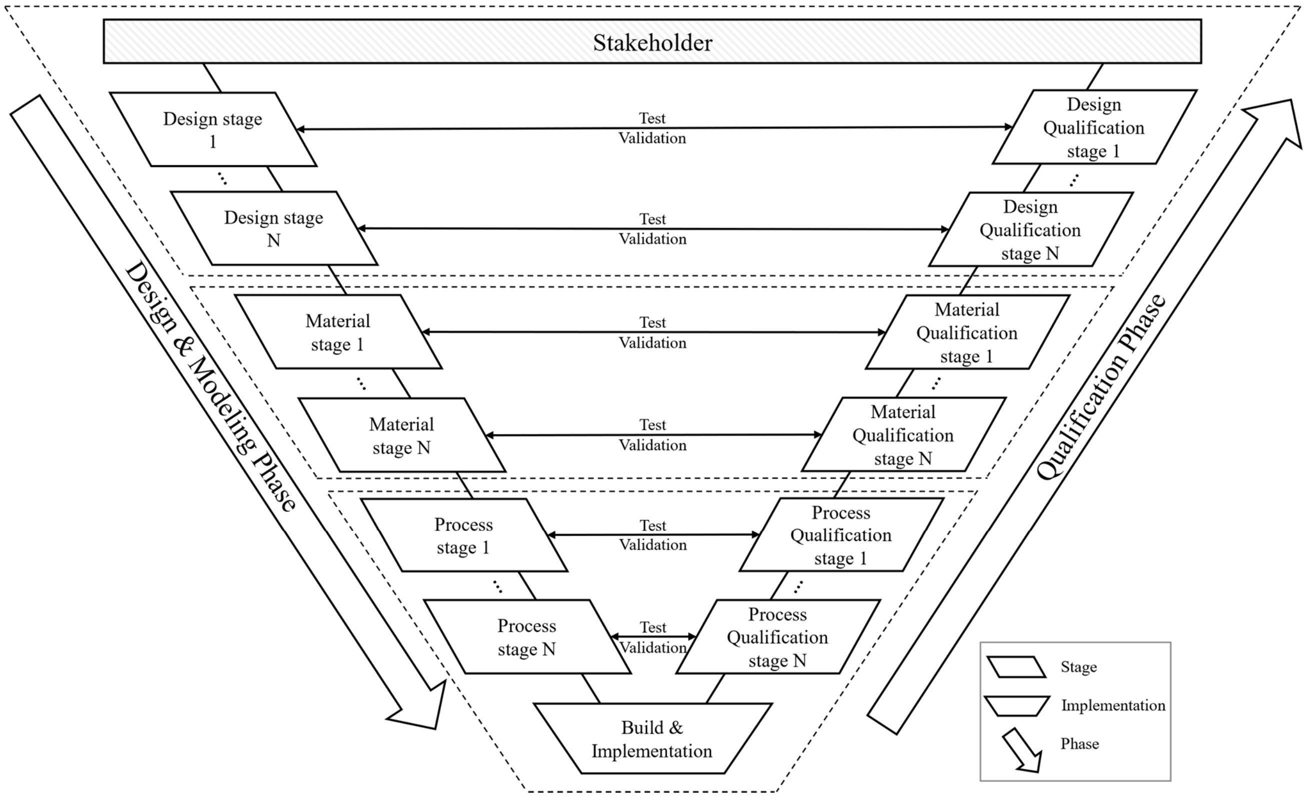

FIGURE 4. **Schematic representation of V-model structure for design and qualification.**

dimensional inspection, and functional testing. It is critical to ensure that the parts produced meet the desired specifications and that any defects are identified and corrected. Finally, it is important to secure that the AM process is properly monitored and maintained. This includes ensuring that the machines are properly calibrated and maintained, that the process parameters are regularly reviewed, and that any changes to the process are documented.

C. BACKGROUND OF THE V-MODEL

The V-model framework is an approach model where the process executes in a sequential manner to describe verification and validation activities, associated with a testing phase for each corresponding requirements stage, as part of the system development process. The requirements of each stage are directly connected with the testing phase. The V-model captures the interconnections between each requirement phase and corresponding test activity to systems development.

1) STRUCTURE AND COMPONENTS OF THE V-MODEL

Figure 3 illustrates a generalized V-model for systems Engineering, which can be described as follows:

- **Stage:** One of the three distinct, process stages – System, Sub-system, Component – with the following sequence:
  - ➢ System: The process of realizing and decomposing, when possible, the system-level requirements needed to meet stakeholders.
  - ➢ Sub-system: The process of defining the Sub-system requirement that includes a part of the system.
  - ➢ Component: This stage is to create a set of detailed components related to the Sub-system requirement.
- **Phase:** There are two phases: the Requirements & Decomposition Phase and the Test & Integration Phase
- **Level:** The two phases are linked using the horizontal stages
- **Process flow:** Transition from one stage to the next in the development process from the requirement to test
- **Test & Validation:** In the V-model, each stage in the Requirements & Decomposition Phase is linked to a corresponding stage in the Test & Integration Phase. These links implement testing and validation procedures which are used to prove that the developed system meets its design requirements.

V-model has advantages in representing complex system engineering activities that decompose stakeholder's needs into small, manageable pieces that are easily understandable with their related testing activities in a logical manner.

In our AM V-model, corresponding "Requirements & Decomposition" and "Test & Integration" steps are also linked. Technical aspects of the product cycle in the V diagram start with the needs and requirements at the upper left and, breaking down the design requirements into sequential design phases, end with the acceptance testing and

TABLE 2. Components of design requirements & measurement and qualification at level of scale.

	Level of scale					
	Quality	**Part**	**Micro/Coupon**	**Nano/Micro/Meso**	**Physics & Signature**	**Parameters & Signal**
Design Requirements	***Quality requirements***	***Part specification***	***Mechanical property***	***Microstructural property***	***Process phenomenon***	***Process parameter***
	Size, Weight, Low porosity, High strength	GD&T, Features	Tensile strength, Fatigue, Elongation	Phase, Crystal structure, Microstructural orientation	Melting, Solidification, Heat & mass transfer, Vaporization	Laser power, Scan speed, Layer thickness, Spot size
Measurement and Qualification	***Quality management***	***Part inspection***	***Mechanical testing***	***Microstructural characterization***	***Process signature***	***In-process signals***
	QC/QA	CMM, Dimensional metrology	Fatigue testing, Tensile testing	SEM, TEM, EBSD, XRD, XPS	Melt pool, Scan track, powder bed & printed slice, Crack formation	Radiation, Photon level, Pressure, Pulse, Acoustic emission, Wavelength, Frequency

verification phases (each of which corresponds with a design phase on the left side of the diagram) to meet requirements at the upper right. We propose such a V-model framework as a basis for metal AM quality assurance. To address rule-based MAM quality assurance, a V-model part qualification framework is adopted to provide a systematic, rigorous method for robust guidance in measurement and testing based on part requirements.

III. REQUIREMENTS FOR AM V-MODEL

This section proposes a framework for translating requirements from the part level to associate definition states with verification stages in metal AM quality assurance. The framework is modeled after the "Systems V" popularized by NASA for systems engineering [28].

Manufacturing complex systems such as metal AM requires generic systems engineering methods for quality assurance. One important role of the V-model is to correctly translate quality requirements (design, material, process) to corresponding necessary qualifications (design, material, process) to test and validate design requirements and qualify part quality (See Figure 4). The left side of the V-model constitutes the decomposition of requirements in AM design, material, and process. The right side shows how decomposed requirements are qualified by corresponding measurement activities.

A. STRUCTURE AND COMPONENTS OF THE V-MODEL

Figure 4 illustrates a generalized AM V-model, which can be described as follows:

- **Stage:** One of the four distinct, process stages - Design, Materials, Fabrication, and Qualification - with the following sequence:
  - ➢ Design stage: The process of realizing and decomposing, when possible, the design requirements needed to meet stakeholder. The result is a "Design", which includes the CAD Model and its associated documentation, that will meet those requirements.
  - ➢ Material stage: The process of defining the material requirements that include the specific material, its internal structure, and its mechanical properties. Requirements needed to fabricate a product based on "Design".
  - ➢ Process Stage: This stage using the design and materials to create a set of interrelated tasks and activities at the AM process level. The result is an AM part.
  - ➢ Qualification stage: The process of comparing the design AM part to the fabricated one.
- **Phase:** There are two phases. the Design and Modeling Phase and the Qualification Phase
- **Level:** The two phases are linked using the horizontal, physical Process Stage
- **Process flow:** Transition from one stage to the next in the development process from design to qualification
- **Test & Validation:** In the V-model, each stage of the Design and Process Modeling Phase is linked to a corresponding stage in the Qualification Phase. These links implement testing and validation

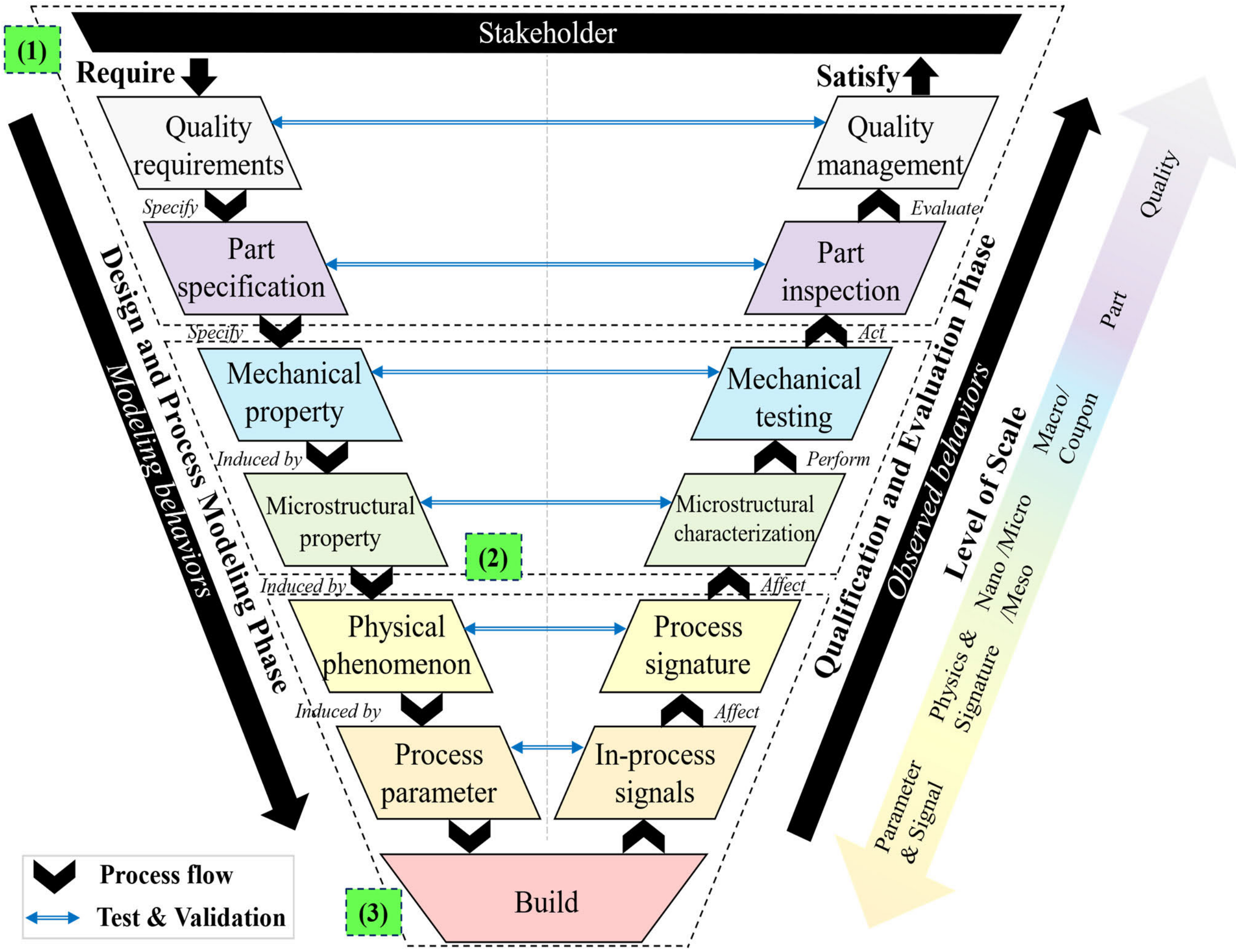

FIGURE 5. V-model for quality assurance in metal AM.

procedures which are used to prove that the fabricated AM part 1) meets its design requirements, 2) accomplishes its intended purpose in the intended environment, and 3) satisfies the expectations of the original stakeholders.

B. DESIGN QUALIFICATION FOR METAL AM

We target building a quality assurance framework to include design, structure, properties, and quality combinations to make the comprehensive quality assurance guidance based on the process–structure-property relationships. To build a framework, it is required to consider links of design-process-structure-property-quality, integrating design requirements, process variables, monitoring, material structure, mechanical properties, and inspection, as well as employing the V-model to construct the life cycle of design and qualification. Table 2 provides details that connect the different scales associated with the design and qualification phases of the V-model.

To extensively understand quality relationships and qualify the fabricated AM part, it is required to consider components of Design Requirements and Measurement and qualification at different levels as outlined in table 2. Levels constitute 1) Quality, 2) Part, 3) Micro/Coupon, 4) Nano/Micro/Meso, 5) Physics & Signature, 6) Parameters & Signal. **Quality** level identifies the expected condition based on a stakeholder's needs and its physical qualification activities. **Part** level sets down stakeholder needs in formal document statement of material, design, and product and inspection activities to detect flaws so that a part will perform to its intended design specification. **Micro/Coupon** is tested to measure the mechanical property and induced physically by the evolution of microstructure. **Nano/Micro/Meso** describes how a material structure is formed by the physical deposition process and tested to identify the microstructural state and determine its experimental characterization. **Physics & Signature** level includes a physics-based model, including the physical phenomenon of metallic power melting and solidifying into a 3D physical part. At this level, process signature to capture corresponding physical phenomenon is traced to monitor observable signature and help gather sensing data for testing and validation. **Parameters & Signal** requires consideration of the physical effects of interest to specify the associated process parameters before the physical printing process. During the build process, an embedded sensor can capture process emissions and collect observed data for real-time quality monitoring to provide timely information about part quality by directly processing the data collected, enabling rapid response to address quality deviation and potential defects.

IV. V-MODEL FRAMEWORK FOR METAL AM

To improve the metal AM workflow, we propose creating an AM V-model (See Figure 5) to monitor and guide both the AM process and the AM part quality. The V-model starts from the desired process quality and guides to tracking the optimal real-time monitoring zone; the acceptable printable zone includes optimal selections of process parameters. Component requirements in the V-model should contain the acceptable domain of the component's quality monitoring, measurements, and qualification as well as its specifications.

A. DESIGN AND PROCESS MODELING PHASE

The V-model provides stakeholders with the confidence needed to verify that quality requirements - such as strength, density, roughness, and porosity - are fulfilled. From the given quality requirements, desired part properties and specifications are determined. Material characteristics such as ductility, conductivity, and plasticity are induced by physical phenomena and are affected by the final part properties. Each process parameter impacts those phenomena, which can be validated by process signals such as radiation and wavelength during the testing and qualification (or evaluation or verification) process.

A comprehensive description of specific components in the design and process-modeling phase is followed by:

- *Quality requirements:* Elicit stakeholders' quality expectations, such as regarding part size, weight, surface roughness, porosity, strength, and measurement tolerance (allowable variation)
- *Part specifications:* Establish stakeholder expectations in statements of acceptability, such as regarding geometric dimensioning and tolerancing (GD&T)
- *Mechanical properties:* Define acceptable mechanical properties, e.g., tensile strength, fatigue, elongation
- *Microstructural properties:* Define acceptable microstructural properties, e.g., phase, crystal structure, microstructural orientation
- *Physical phenomenon:* Determine relevant physical phenomenon, e.g., melting, solidification, heat and mass transfer, vaporization
- *Process parameters:* Select suitable process parameters to operate a given AM machine, e.g., laser power, scan speed, layer thickness, spot size

Six stages between a stakeholder's specification of part quality requirements and the Build stage in the Design and Process Modeling Phase are shown in Figure 6. The objective of this phase is to decompose high-level, design requirements into low-level, manageable components that of the fabrication process, can produce. The stages of this phase are implemented mainly by researchers and engineers with end-user and stakeholder participation.

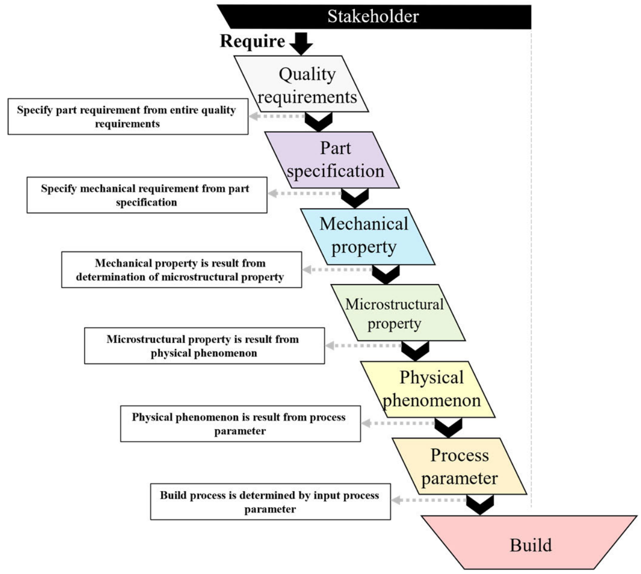

FIGURE 6. Process flow in the design and process modeling phase in metal AM.

B. QUALIFICATION AND EVALUATION PHASE

The right-hand side of the V-model represents the components associated with qualification and evaluation to guide testing and validating the AM parts (see Figure 7). Process signals are emitted in response to process signatures. A process signature refers to a unique observation in manufacturing science of a physical phenomenon, such as melt pool geometry or plume behavior, which proves the phenomenon during printing processing. For example, microstructure formation by a melt pool in a process signature affects the mechanical properties of strength and fatigue, which are measured by tensile and fatigue (mechanical) testing to validate part properties. The next stage, part-inspection, is based on dimensional and mechanical properties to satisfy given quality requirements, followed by the quality assurance stage, which determines whether the measured quality satisfies given requirements. Definition of a specific component is followed by these stages:

- *In-process signals:* During the build process, signals (e.g., radiation, photon level, pressure, pulse, acoustic emission, wavelength, frequency) are measured to collect, analyze, and report objective data and other information to effectively guide and demonstrate process quality
- *Process signature:* Capture observations (e.g., regarding melt pool, scan track, powder bed or printed slice, crack

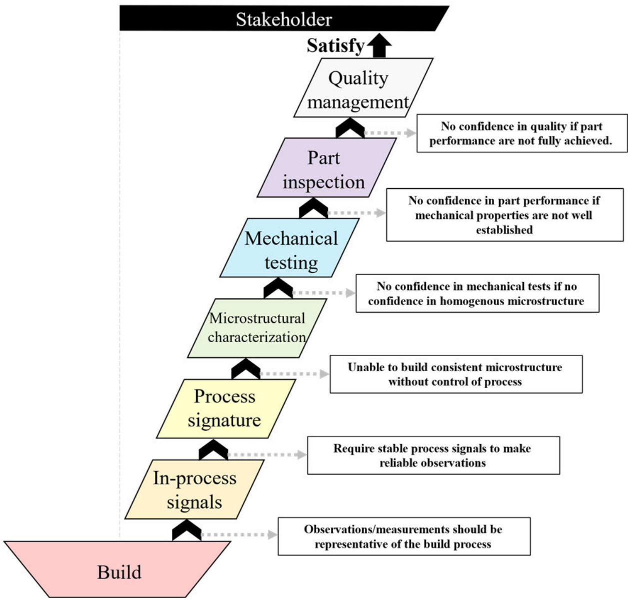

FIGURE 7. **Process flow in the qualification and evaluation phase in metal AM.**

formation) to analyze relative to expectations, as measures of process effectiveness

- *Microstructural characterization:* Determination of crystal structure, grain size, size distribution, and phase volume fraction by evaluating micrographs (e.g., SEM, TEM, EBSD, XRD, XPS)
- *Mechanical testing:* Validate (e.g., by fatigue testing, tensile testing) that defined mechanical expectations reflect bidirectional traceability
- *Part inspection:* Obtain stakeholder commitment to order, fund, or otherwise support research for or development of parts that meet the validated (e.g., by CMM, dimensional metrology) set of stakeholder expectations
- *Quality assurance:* Evaluate (e.g., by QC/QA methods) parts to confirm that baseline stakeholder expectations are met

Qualification and Evaluation Phase activities begin after initiation of the Build stage to ensure that fabricated part quality will meet functional and performance requirements under anticipated environmental conditions. Many performance criteria are tested and validated while measurements and analyses are updated, as test data are acquired from real-time monitoring, in-situ and ex-situ measurements through the series of stages.

C. V-MODEL FRAMEWORK FOR METAL ADDITIVE MANUFACTURING HAS 3 LEVELS

There are 3 levels in our proposed, AM, V-model framework. These levels are based on a classification system we developed. This classification system has six, distinct, processing components: Quality, Part, Macro/Coupon, Nano/Micro/Meso, Physics & Signature, and Parameter & Signal. Collectively, these components capture real-time AM process-and-part, monitoring data collected by in-situ and ex-situ sensors. Pairwise, components are linked into the 3 levels, which are described below.

1) THE "QUALITY/PART PAIRWISE" LEVEL

Figure 8 shows the V-model framework's topmost level, Quality/Part process component.

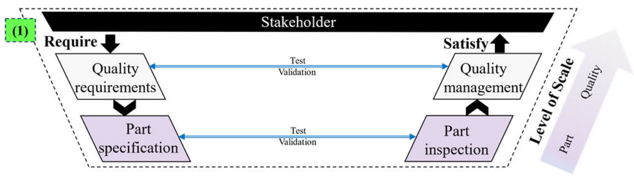

FIGURE 8. **"Quality and part" level in V-model for metal AM.**

The former has two Quality Stages: Requirements and Management. The Quality requirements stage of the V-model is the first step in part development. This stage identifies the anticipated condition or capability, based on a stakeholder's defined needs, providing sufficient information for build guidance, constraints, and requirements to execute the build by deploying a product quality plan for fabricating and manufacturing the product to meet stakeholder requirements. The Quality management stage refers to the physical, qualification activities needed to test and validate AM parts against the Quality requirements. Those activities essentially compare gathered outcome measures against given quality requirements to ensure that a part meets requirements.

The later has two Part Stages: Specification and Inspection. The Part specification stage sets down stakeholder needs in formal documentation containing a textual statement of materials, design, and product. Part specification includes general requirements for materials, workmanship, and quality, and describes materials, products, equipment, and tolerances to be inspected. The Part inspection stage detects flaws and defect issues to avoid so a part will perform to its intended design specification. This stage also details all measurable part levels of inspection to support testing and validation of a part's specifications.

2) NANO/MICRO/MESO AND MACRO/COUPON LEVEL

Figure 9 shows the Nano/Micro/Meso and Macro/Coupon Level, sometimes called the "Mechanical and Microstructural" quality-assurance level.

The "Mechanical" part of the quality assurance level has a bi-directional link between Mechanical Properties stage and Mechanical Testing stage. Mechanical Properties are calculated from AM part-quality requirements, which are determined by the Design and Modeling Phase described above.

Each desired property, in the Mechanical Property stage is measured using a physical AM coupon. An AM coupon is a relatively inexpensive sample produced in sufficient quantity to be statistically significant, is used to determine static or

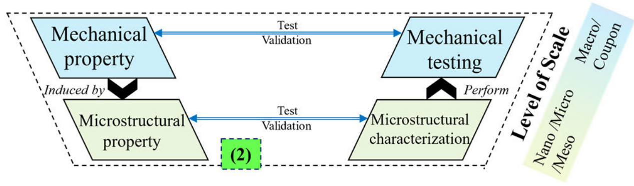

FIGURE 9. Level of nano/micro/meso and macro/coupon in V-model for metal AM.

dynamic mechanical properties. Properties that will be representative of the full, prototype, AM part. The mechanical testing done at this stage is a destructive examination to understand a coupon's real properties, including, for example, its material behavior or its performance under different loading conditions. Examples of the former include phase change, grain size, and crystal structure. Examples of the latter include tension, bending, peeling, crashing, applying pressure, and fracturing. Currently, Mechanical testing verifies only macro-level, mechanical properties, which are induced physically by the AM part's microstructure.

The microstructural stage describes how a material's microstructure is affected by the physical, AM-process. That microstructure property part of this stage determines several, desired physical properties. The microstructure characterization property part of this stage provides evidence regarding the real material structure and those real material properties. Properties are seen at the Nano/Micro/Meso level in MAM, as revealed by atomic force microscopy (AFM), scanning electron microscopy (SEM), transmission electron microscopy (TEM), and/or electron backscatter diffraction (EBSD). Identifying the microstructural state and determining its experimental characterization provides verification that the intended microstructure has been generated.

3) THE PARAMETER & SIGNAL AND PHYSICS & SIGNATURE LEVEL

Figure 10 shows three stages: the Physical stage, the AM ''Build'' stage, and Process stage. And real-time AM monitoring, distinguishing each stage from the others and providing an explanation of what justifies proceeding to the next stage in the level of Parameter & Signals and Physics & Signature.

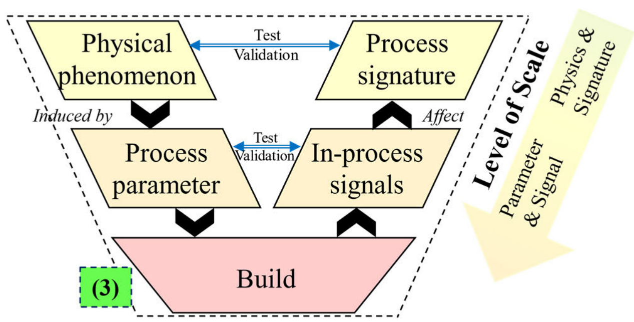

FIGURE 10. The third level in AM V-model.

The Physical phenomenon part of this Physical stage includes a physics-based model which addresses the physical phenomenon of metallic powder melting and solidifying into a 3D physical object. This model can be used to 1) trace the required physical phenomenon of concern to select correlated process parameters on AM processing machines and 2) monitor any observable process signature for testing and validation. The inputs to such a physics-based model are based on the results of the Process signature part. This part involves observations of the material transformation build stage. Process signatures represent observable changes to material depositions as detected by sensors, providing underlying physical information.

Proceeding from the Physical phenomenon stage to the Process parameter stage requires considering the physical effects of interest and specifying the associated process parameters before the physical printing process.During the build process, an embedded sensor can capture process emissions and collect observed data for real-time quality monitoring to provide timely information about part quality by directly processing the data collected, enabling rapid response to address quality deviation and potential defects.

During the Build stage, metal powders are deposited layer-by-layer and melted layer-by-layer until the complete three-dimensional geometry of the part is fabricated. This stage can also be used for simulations and physics-based models to predict geometry accurately.

V. CASE STUDIES

This section shows an application of proposed approaches and examines the results of their implementation. Figure 11 provides a more detailed and hierarchical view of the top two levels summarized above. This figure covers the network connection from stakeholders' quality requirements and specifies detailed specifications and properties to meet those requirements in the design and process stage for fabrication.

During the last and lowest level, where the build and measurement process takes place, the previous network connection guides what to collect and how to measure physical events and data. That network connection also enables those events and data to be communicated to later stages of the V-model. For example, to estimate a mechanical property called tensile strength, the mechanical testing will be affected by grain size, microstructural orientation, and grain structure, which results from the microstructural characterization.

We now apply the V-model in Figure 11, including those network connections, to an example case study: in-situ monitoring and qualification. This case study requires in-situ measurements from a sensor to be embedded in the AM fabrication system. These measurements directly capture in-process signals that vary as the input process parameters vary during the build.

TABLE 3. **V-model case studies.**

Phase / Level of scale	Design and Process Modeling Phase	Qualification and Evaluation Phase	Case 1
Physics & Signature	Physical phenomenon	Process signature	✓
Parameter & Signal	Process parameter	In-process signals	✓
	Build		✓

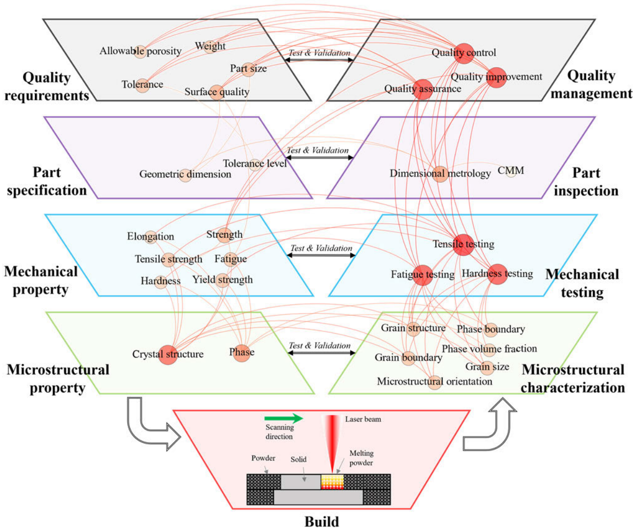

FIGURE 11. **Hierarchical network from the quality requirement to microstructure and build.**

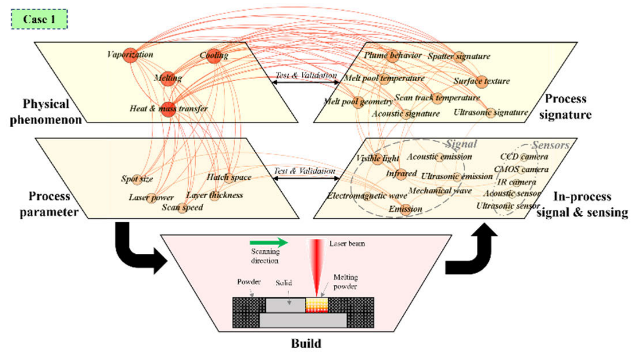

FIGURE 12. **Case1: In-situ monitoring and qualification.**

Table 3 summarizes similarities and differences in the context of a case study.

The V-model for this AM Case Study as shown in Figure 12, where process inputs cause physical behavior and signatures. The signatures generate various emissions and signals, which are captured by sensors, and they help determine the final part quality. Therefore, the V-model framework helps lead to real-time sensors for defect identification and ultimately increases the assurance of fabricated parts. Case 1 is used to explain the structured abstraction of in-situ monitoring and qualification in which this structured approach provides the capability to trace measurable physical phenomenon for monitoring and optimal sensor selection.

VI. CONCLUSION AND FUTURE WORK

This paper introduces a V-model framework to facilitate part qualification in metal AM. The V-model framework addresses two critical, guiding steps for part qualification: quality assurance and process maintenance. The major contributions include the ability 1) to contextualize the AM qualification process with a proven, step-by-step, model, 2) to provide the foundations for testing and validating the design, material, and process requirements of V-model architecture. To enhance functionality of printed part quality, the proposed framework provides an underlying platform for in-situ sensor measurements and real-time guidance for characterizing printing defects, as well as from AM diagnostics and process quality indication.

Future work will include the implementation of V-models to facilitate data-driven, real-time prediction, control, and connection with a digital twin in metal additive manufacturing. Developments in prediction and control can leverage the use of a digital twin in AM simulation to aid ICME (integrated computational materials engineering) for product design, simulation, measurement, and qualification, as well.

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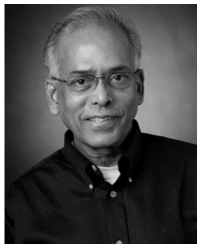

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