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A Hierarchical V-Network Framework for Part Qualification in Metal Additive Manufacturing

Byeong-Min Roh[1,2*], Hui Yang[2], Timothy W. Simpson[2*], Albert T. Jones[3], Paul Witherell[3]

[1]The University of Oklahoma, Norman, OK 73019
[2]The Pennsylvania State University, University Park, PA 16802
[3]National Institute of Standards and Technology, Gaithersburg, MD 20899

*Corresponding Authors: leonroh86@gmail.com, tws8@psu.edu

Abstract

Advances in metal additive manufacturing (AM) technologies have enabled greater design freedoms than subtractive manufacturing has afforded. The design freedoms and flexibilities offered by a metal AM system, however, dramatically increase process uncertainties that may also increase part-quality variabilities. Any metal AM part must be tested, validated, and verified to meet quality, safety, and performance requirements. Common qualification methodologies rely on destructive testing, which is neither cost-effective nor efficient. Much research, which has been conducted on sensing-based, part qualification in AM systems, attempts to maximize the reduction of destructive testing by closely monitoring the fabrication process in real-time. So much "big data" is generated by this increased use of sensors and available measurement sources. However, the use of the data is still hindered by 1) scale & size and 2) uniformity. We propose a hierarchical, V-network framework of quality assurance with the corresponding translation from ex-situ to in-situ part qualifications. This framework offers an innovative, Cyber-Physical System (CPS) that accurately ties models, processes, and measurements together to interpret the sensor data. The framework also supports and guides translation from ex-situ to in-situ quality measurements, thereby providing a systematic structure and focusing on interrelationships between key observations that influence AM part quality. Ultimately the sensor data can support the detection of process anomalies, thus providing a more streamlined and more efficient qualification process than is otherwise possible.

1. Introduction

1.1 Background

Metal additive manufacturing (AM) technologies allow greater design freedom and manufacturability than traditional manufacturing technologies [1-2]. A wide selection of metallic, powder materials is available for different purposes and applications. However, parts made from metal AM technologies usually require secondary post-processing or destructive measuring to qualify the part's performance. Based on different needs and process stages, quality assurance and control methods include many different activities with varying perspectives. Examples include ensuring the correctness of the design model, the mechanical properties, the material structure, the process signatures, and the sensor signals [3-4].

Much research has been conducted on quality assurance and control processes in additive manufacturing systems, such as simulation software [5-9], or in-situ failure awareness systems [10-14]. These researches are relevant to 1) computational techniques such as physical simulation, 2) contact coordinate computing [15-16], 3) geometric design [17-18], measurement and analysis [19-20] using optical computing systems, and 4) geometric accuracy analyses using volume-based methods, including computed tomography [21-22]. The computation and simulation techniques are utilized to test products, systems, processes, and concepts. However, current computational simulations for part qualification have

difficulties in producing optimum results and dealing with uncertainties, specifically for complex geometries. The three requirements for a simulation are listed below:

(1) Reliability: It is essential to simplify the physics equations and iteratively solve them to simulate gas and melt-pool flow in metal AM for a specific environment.
(2) Prediction: Real physics derivatives from the predicted models because simulation heavily depends on underlaying physical equations
(3) Complexity: Computational complexity in the surrogate model requires a powerful and intensive computational capability in the simulation.

1.2 Our Proposed Framework

We propose a V-network framework to address those limitations using what we call "compositional models. It does so by building, testing, validating, verifying the individual models and and composing them as implied in the V-network Framework. We view this framework as a foundation that is created to accurately reflect the existing, AM cyber and physical infrastructure. The physical infrastructure includes sensors that produce data during the Metal AM process. Gathered sensor data is then relayed to a processing system and applied to the digital network model. That digital network model used to quantify different aspects of the part's performance. This digital model does so by executing simulations, calculating current performance, and analyzing potential improvements. The outputs from those models can be used as feedback to the actual physical AM.

In our view, this virtual infrastructure can also be applied to non-physical objects, processes and systems, what are commonly called digital twins (DTs). These DTs twins "mirror" the actual AM objects, processes and systems. But, these DTs can be used as inputs to simulations that can operate on real-time data. Today, creating such DTs is leveraged by both the Internet of Things (IoT) and embedded sensors technologies. They can capture high-level information that can then be integrated into the virtual model. The V-network Framework is, in effect, a virtual environment where ideas can be tested with few limitations. When connected to a real-time, a monitoring platform, the model becomes an integrated, closed-loop system. A system that can be used to inform and drive a real AM-based Cyber-Physical System,

Table 1. Comparison of AM simulation and V-network

	AM Simulation	V-network
Data interaction	·	✓
Real-time	·	✓
Feedback	·	✓
Simulation basis	Potential parameters input for testing	Real-time feedback from a specific product/process
Scope	Narrow – primarily design	Wide

1.3 Applying the Framework to an AM-based, Cyber-Physical System

The convergence of the cyber and physical parts of AM manufacturing is related to a broader concept of technological-manufacturing convergence. The result of this convergence is a "state" with boundaries between design and qualification. Physical components in this "state" extensively interact with cyber components through sensing, monitoring, and computing methods. These methods enable the monitoring

of the gathered, "big" sensing data and the analysis of that big data to understand the physical behavior of AM manufacturing better.

However, in this paper we focus on the more fundamental question, "How do cyber components and AM physical components actually converge? Answering this question requires the integration of computational processes with the physical processes in additive manufacturing. Integration, on the other hand, requires 1) translating cyber components into physical components for data interpretation and 2) physical components into cyber components for monitoring.

Conceptually, there are five, major, physical AM components: input, process, structure, property, and performance. There are no generic details on how these components are physically interconnected in metal AM systems. The RHS in Figure 1 shows how these individual physical components are, conceptually at least, physically interconnected. The LHS of Figure 1 shows the individual, cyber components and their interconnections. The LHS component side starts with Design Requirements and ends with the Build Parameters.

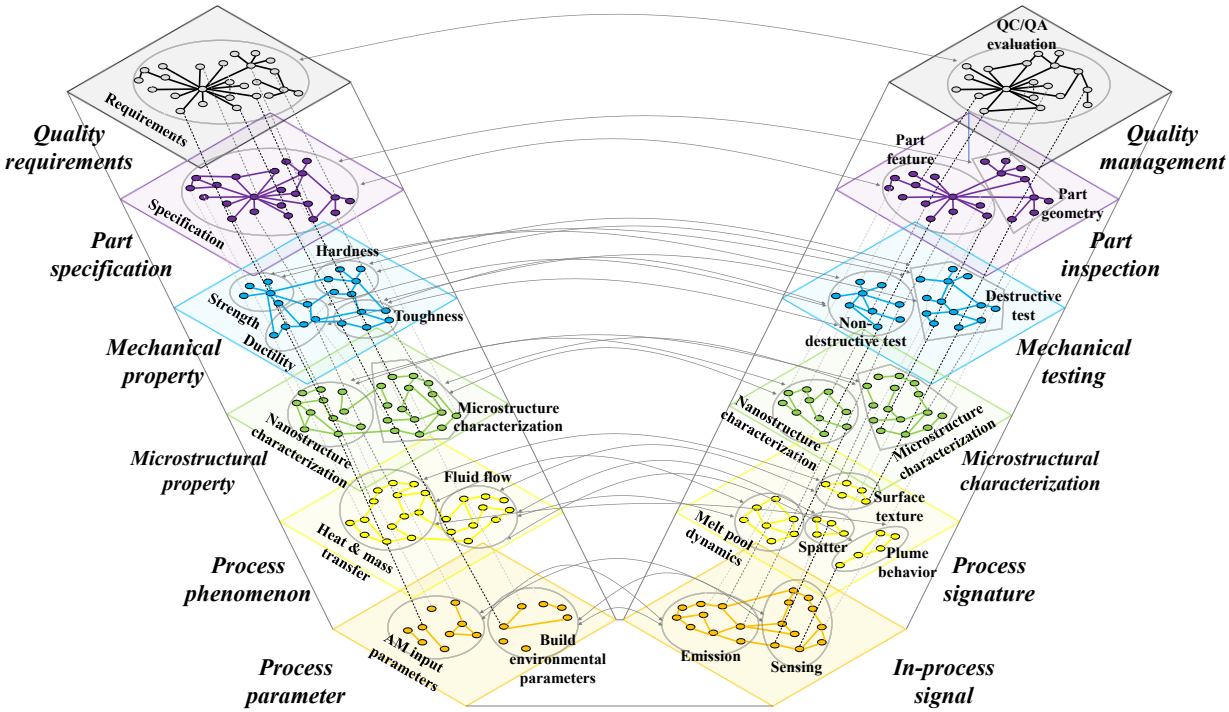

Figure 1. Overview of Hierarchical Structure for Part Qualification in Metal AM

Figure 1 also shows the different feedforward/feedbackward links between the LHS Virtual components and RHS Physical components. For example, the V-network structure shows interactions between Design & Process requirement (left phase) and Measurement & Qualification (right phase) physical phenomenon along with vertical levels such as quality, part, micro/coupon, nano/micro/meso, physics & signature, and parameters & signal using node (variable) and link (connection). Physical interactions, induced by inputs, cause physical behaviors, dynamic phenomena, and process signatures, creating various emissions, and affect the evolution of microstructure, determining the final mechanical property.

1.4 The Benefit of Our Proposed Framework

The major benefit of our proposed framework is to boost the performance and efficiency of designing, printing, monitoring, testing, and qualifying AM parts. It does this by creating a Cyber-Physical System

(CPS) model for metal AM (See the top left part of Figure 2). The P part of that CPS model provides the systematic approach needed to trace measurable, physical AM phenomena and signatures and link them to process monitoring and quality testing. The results from the process monitoring are used to control the AM process parameters. Therefore, the P part of the V-network assumes the existence of a guideline, including test & validation methods, for physically qualifying complex AM parts.

The top RHS part of Figure 2, shows a multi-layer architecture for physically qualifying AM parts. AM qualification typically focuses on identifying and monitoring defects in those parts. In metal AM processes, input process parameters play a key role in determining fabricated part quality and performance. The reason is there is a causal chain in metal AM is a sequence of events in which any single new input in the chain effects the next link, and every other link, leading up to a final effect (See Figure 2). For example, the change of laser power and scan speed affects process phenomena, determining the microstructure and property formation. However, understanding the cause and effect chain between different levels in metal AM is very complicated because input parameters affect process phenomenon, determining microstructure and the following mechanical property and performance of the part. Although some recent research progresses in the modeling approaches can help correlate input-process-structure-property-performance, the interconnections between this architecture have yet to be fully established.

By implementing this architecture, we are using an assurance model to increase the quality of fabricated AM parts. These results from the quality assurance model quality link the Physical part of the CPS to the Cyber part of the CPS. This quality assurance model is utilized to allow designer and manufacturer to focus on fabrication and part qualification based on their design requirements. The results of the model are 1) compared with the initial, part-quality, design requirements 2) used to determine whether the actual, part-quality results meet those design requirements.

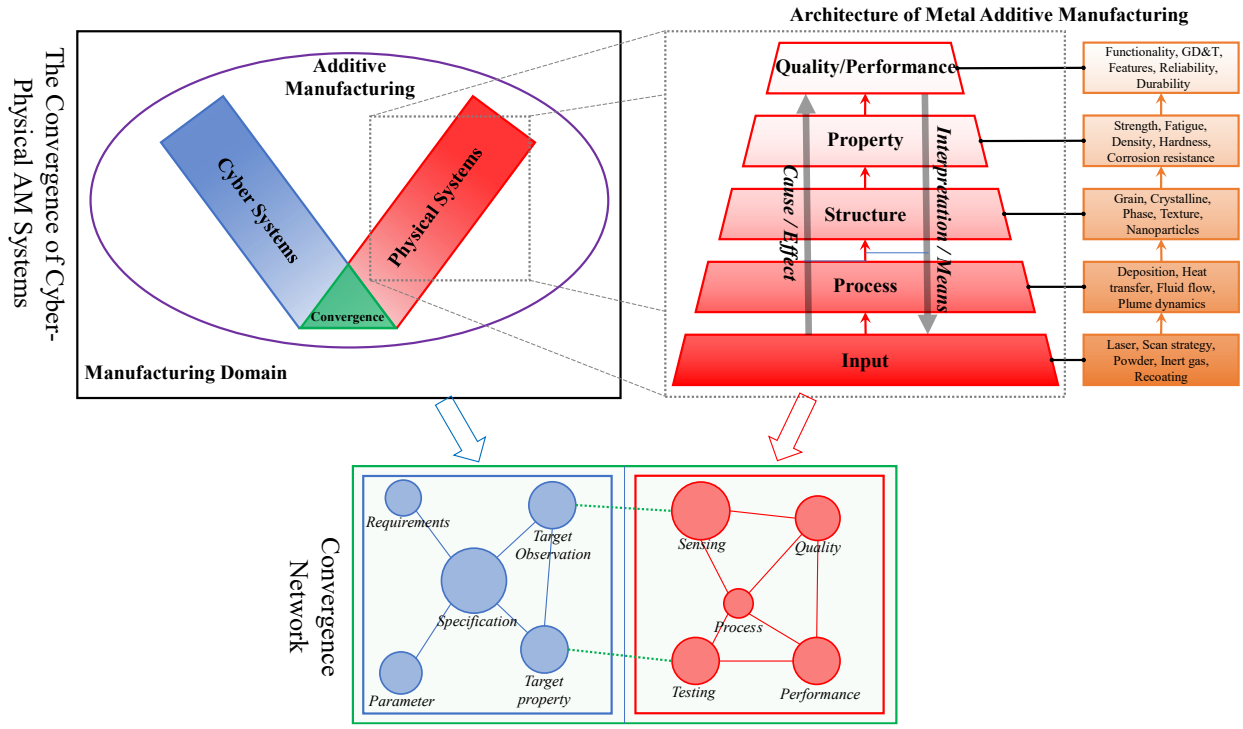

Figure 2. Convergence of Cyber and Physical Components in Additive Manufacturing

A convergence network enables the integration of cyber and physical components by node and link connections. These connections combine several components of different natural processes in metal AM to

control a physical process through sensor monitoring data and feedback mechanisms that adapt themselves to new conditions in real-time.

1.5 Paper Outline

The paper is organized as follows: Sec. 2 reviews a framework for cyber-physical system and uncertainty quantification and part certification in Additive Manufacturing. Next, Sec. 3 presents the formal hierarchy method, ontology, and V-model to illustrate the structure of the V-network. Next, the structured V-network framework is explained to clarify the applications and results in Sec. 4. The article concludes by offering insights and future direction in Sec. 5.

2. Review of Past Work

Many types of cyber-physical frameworks have been developed - mainly for design and control - by incorporating machine learning techniques in metal additive manufacturing (AM). Different frameworks serve different purposes while each creates duplicate features and generates disparate results [23]. The current frameworks have yet to be fully leveraged to provide comprehensive guidance for the monitoring of, measurement of, detection of, and feedback to the physical additive process. That guidance, which will be based on real-time, sensor and measurement data, must be integrated into a cohesive, cyber-physical framework for monitoring, diagnosing, testing (the Physical part) and meeting QC/QA requirements (the Cyber part). To build such an integrated framework, it is critical to understand the various AM quality assurance and control components that may interact with each other in the framework. They can interact at the same level or across different levels in the framework. The following sections review past work in a framework for cyber-physical systems, uncertainty quantification, and part certification for metal additive manufacturing.

2.1. Frameworks for Cyber-Physical Systems

Building a framework for an AM cyber-physical system can help integrate and simulate cyber and physical components with new functionalities in additive manufacturing. Griffor et al. [24] used a broad range of CPS experts to develop the generic CPS framework and applied it to the four application domains: manufacturing, transportation, energy, and healthcare. Their proposed CPS framework integrates and reorganizes components based on cohesive guidance about the identified concepts of “facets” and “aspect”. Concepts that satisfy the need for a reference CPS description language where standards, and documented applications can be based. The CPS framework targets controlling the process using changing knowledge, integrating research across sectors, and supporting CPS development with new functionalities. Zheng et al. [25] developed a Cyber-Physical Systems (CPS) system architecture that focuses on building and linking digital twins in smart manufacturing. The authors used a tri-model-based approach to concurrently simulate real-world, physical behavior and update the characteristics of the digital twin. These efforts primarily focused on a conceptual, rather than technical, description of the digital twins and their possible applications without the working details.

Dillon et al. [26] developed a framework of Web-of-things, which is a set of web standards for the interoperability of different Internet of things (IoT), for cyber-physical systems for integration of digital computation and communication with physical monitoring and control, enabling robust and flexible systems. Nagar et al. [27] investigated the cyber-physical additive manufacturing model by developing a machine learning module to reduce and replace the common defects and reduce the data overload via wireless networks. Lhachemi et al. [28] reviewed augmented reality, cyber-physical systems, and feedback control for additive manufacturing to provide information on feedback control in additive manufacturing and applied feedback theory to enable users to interact better with AM machines. Mahan et al. [29] studied simulating cyber-physical systems for design for additive manufacturing to provide a digital testbed for

future research to characterize the vulnerabilities of manufacturing and develop new methods to effectively identify compromised parts.

2.2. Uncertainty Quantification and Part Certification in Additive Manufacturing

Uncertainty quantification for additive manufacturing is studied by using statistical and computational methods to make predictions. Wang [30] developed an uncertainty quantification method to optimize composition for improving the mechanical property, expanding the choice of alloy in metal additive manufacturing. They analyzed the process-structure-property relationship for 450,000 compositions around the nominal composition of steel alloy and improved the probability of successful AM builds by 44.7%. Xie [31] studied mechanistic, data-driven prediction using wavelet transforms and convolutional neural networks to predict location-dependent mechanical properties over printed parts based on process-induced thermal history in metal additive manufacturing. The data-driven prediction helps multiresolution analysis and importance analysis to find the dominant, mechanistic features underlying the process. Tapia [32] investigated uncertainty propagation analysis of computational models in metal Additive Manufacturing and proposed a generalized polynomial chaos expansion framework to finite element model to quantify distributions of melt pool dimension.

Uncertainty analysis is needed for real-time, process certification, which is leveraged by in-situ sensor measurements and data-driven analytics. Together, they permit real-time, estimation and characterization of defects. Waller et al. [33] summarized the non-destructive method to meet materials, design, and test requirements during process optimization, real-time process monitoring, finished part qualification, and certification in additive manufacturing. Petrich et al. [34] conducted real-time quality monitoring using multi-modal sensor fusion, facilitating data-driven defect detection in AM. Lu et al. [35] researched compressive sensors for measuring temperature fields; they used them as inputs to heat transfer models and other numerical methods in AM. Spears et al. [36] conducted a review of in-process sensing and monitoring for selective laser melting, specifying significant challenges from multiple input variables that affect part quality. Salama et al. [37] applied the industrial internet of things(IoT) technique to facilitate real-time monitoring and optimize system parameters such as nozzle temperature and filament breakage/runout, leading to reduced maintenance time.

Pandiyan et al. [38] studied a semi-supervised approach to differentiate the defect-free regime and anomalies with acoustic signatures. Nassar et al. [39] examined sensor-based defect detection in the directed energy deposition process using optical emission spectroscopy and data acquisition to research the formation of defects during the build process. However, these research efforts do not directly guide the part certification in different levels of scales(e.g., GD&T, mechanical property, microstructure, phenomenon, signal, and emission) in metal additive manufacturing to support a systematic part certification strategy to qualify part requirements at different levels of scale and monitoring [40]. The main contribution of the current research is conducting the systematic cyber-physical framework for guiding test & validation based on QC/QA requirements at different levels. Specifically, this article considers 1) selection of sensors and data collection based on quality requirements, 2) capability map of a multi-purpose sensor to detect specific defects and then adjust process inputs, 3) guidance of data fusion to integrate Hierarchical data from multiple sensors to produce an essential dataset for ML.

3. Methodology

In this section, we introduce an overview for the construction of the V-model to build a quality assurance framework with corresponding part requirements. The development and integration of hierarchy

models are then proposed along with the detailed, hierarchical information in the network, starting from the requirement to design and testing.

3.1. V-Model Development

3.1.1. V-Model Framework

V-model framework is an extension of the waterfall model. This framework provides a development process that results in a general verification and validation model for software and systems engineering [41]. The V-model helps visualize the relationships between each phase of the development life cycle and its associated test and validation. The horizontal and vertical axes indicate time or task completeness (left-to-right) and level of hierarchical step (coarsest to fine-grain abstraction), respectively. The process steps move downwards on the LHS and upwards on the RHS to form the systematic V shape.

The V-model facilitates a rigorous, structured method, where each phase can be implemented by the detailed connections of the previous phase. The objective of the V-model is to improve the efficiency and effectiveness of the software and system development process. It does this by reflecting the relationship between test activities and development activities. That development process is decomposed into understanding stakeholders' requirements, performing requirements analysis, designing the initial outline, designing advanced details, and describing required tests in the fundamental development process from left to right on each other counterparts. Software and system testing are necessary to incorporate testing activity into the entire software and system development life cycle. The V shape proceeds down and then up, from left to right delineating the sequential development and testing activities. The model highlights the existence of different testing levels and depicts how each relates to a different development phase.

3.1.2. Hierarchical Network

A hierarchical network involves decomposing the complex 3D network into discrete planar levels. Each planar level has it own 2D network topology – it can be drawn on the two-dimensional plane (See Figure 3). Each level, or layer, in the hierarchy, provides specific functions that define its role within the overall network. The hierarchical structure helps understand horizontal and vertical interactions among different levels and provides a mathematical representation of connections, optimizing modeled process features to perform specific roles for the domain network layer. The benefit of dividing a planar network into smaller, more meaningful decomposition is deploying lower-level steps to understand complex problems

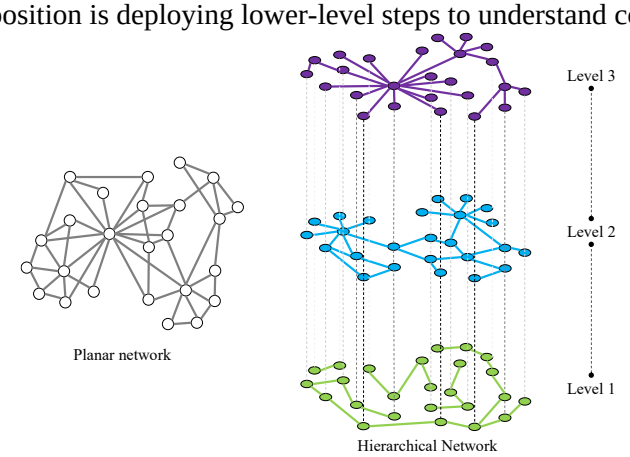

Figure 3. Planar Network and Hierarchical Network

3.2. Design Hierchaical Structure in V-Model Framework

The V-network framework is represented as an ontology hierarchy that describes all design requirements and criteria in Figure 4. The ontological hierarchy includes Quality requirement & management (A, A′), Part specification & inspection (B, B′), Mechanical property & testing (C, C′), Microstructural property & characterization (D, D′), Process phenomenon & signature (E, E′) – defined as follows (See Table 2):

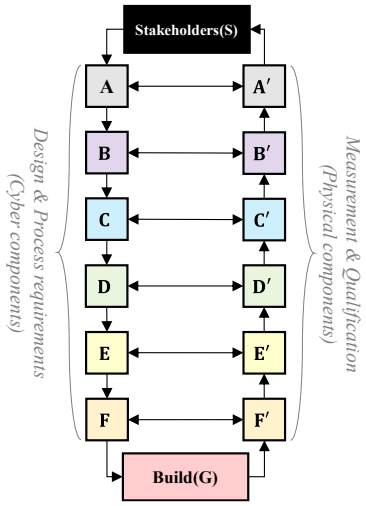

Figure 4. Schematic of Hierarchy Structure of V-network Framework in Metal AM

Quality requirement & management (A, A′): Elicit stakeholders' quality expectations (e.g., size, weight, low surface roughness, low porosity, high strength, tolerance requirement) and evaluate the baseline of stakeholder expectations (e.g., QC/QA).

Part specification & inspection (B, B′): Establish stakeholder expectations in acceptable statements. (e.g., GD&T) and obtain stakeholder commitments to the validated set of expectations (e.g., CMM, dimensional metrology).

Mechanical property & testing (C, C′): Define acceptable mechanical property (e.g., tensile strength, fatigue, elongation and validate that defined mechanical expectations reflect bidirectional traceability (e.g., fatigue testing, tensile testing).

Table 2. Definition of Design Requirements & Measurement and Qualification

CPS	Symbol	Definition
Design requirements (Cyber requirements)	**A**	Quality requirements
	B	Part specification
	C	Mechanical property
	D	Microstructural property
	E	Process phenomenon
	F	Process parameter
Measurement and Qualification (Physical measurements)	**A′**	Quality management
	B′	Part inspection
	C′	Mechanical testing
	D′	Microstructural characterization
	E′	Process signature
	F′	In-process signals

Microstructural property & characterization (D, D′): Define acceptable microstructure property (e.g., phase, crystal structure, microstructural orientation) and Determine grain size, size distribution, and phase volume fraction by evaluation of micrographs (e.g., SEM, TEM, EBSD, XRD, XPS).

Process phenomenon & signature (E, E′): Determine relevant physical phenomenon (e.g., melting, solidification, heat & mass transfer, vaporization) and capture and analyze expectation observations for measures of effectiveness(e.g., melt pool, scan track, powder bed & printed slice, crack formation).

Process parameter & In-process signals (F, F′): Select process parameter to operate AM machine (e.g., laser power, scan speed, layer thickness, spot size) and measure signals during the build process (e.g., radiation, photon level, pressure, pulse, acoustic emission, wavelength, frequency).

Stakeholders and Build are defined as follows:

Stakeholders (S): individual or group that has an interest and expectation in any decision or outcome of a product, including suppliers, clients, and organizations.

Build (G): fabrication activity based on stakeholder requirements and expectations.

To translate design requirements to measurement and qualification, the representation of a matrix of the V-network framework is essential.

$$
\begin{array}{c|c}
 & \begin{matrix} S & A' & B' & C' & D' & E' & F' & G \end{matrix} \\
\begin{matrix} S \\ A \\ B \\ C \\ D \\ E \\ F \\ G \end{matrix} &
\begin{pmatrix}
0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 & 0
\end{pmatrix}
\end{array}
$$

Figure 5. Matrix of V-network framework

In Figure 5, the matrix is transformed from network connections of the V-model. The matrix highlights which of the design or process steps have an impact on meeting the requirements. This benefit allows the product and quality users to focus on the critical measurement and qualification, which flow down into a specific requirement level and find a corresponding measurement method for further examination.

3.3. Translation in V-model for Verification

The V-network framework described in the previous sections is utilized in scenarios of 1) Verification of Part Level, 2) Verification of Coupon & Physical Signature Level, and 3) Verification of Signal Level. This section provides the applications of proposed approaches and examines how V-model can help multiple cases. Descriptions of each scenario are presented below:

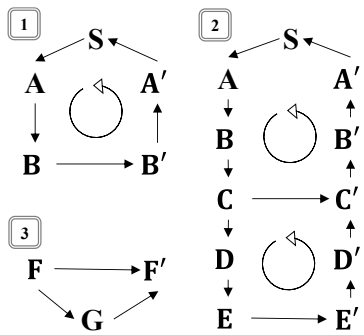

Figure 6. Scenario of V-network: (1) Verification of Part Level, (2) Verification of Coupon & Physical Signature Level, (3) Verification of Signal Level

Scenario 1 (Verification of Part level): To verify the quality of the set of stakeholder (S) requirements in part level, Figure. 6-(1) shows the hierarchical process of verification of part specification using V-network. Quality (A) aspect of requirements can be extracted from stakeholder (S) needs and then decomposed into the part specification (B). The part specification (B) can be tested and validated to determine whether it meets the requirements by inspection (B'). The part inspection (B') results are used to evaluate the performance of quality management (A') and then make the quality decision by stakeholders (S).

Scenario 2 (Verification of coupon and physical signature level): In Figure. 6-(2), the quality requirement (A) and part specification (B) are identified from stakeholder's needs (S), and then required mechanical property (C), microstructural property (D), process phenomenon (E) are examined to meet the quality requirement (A) and specification (B) to be tested and validated by correlating physical measurement. The figures provide guidance for the test and validation step of mechanical property (C) and process phenomenon (E) by mechanical testing (C') such as tensile test and sensoring signatures (E') such as melt pool and plume. Collected measurement data are used to evaluate inspection (B') and quality (A') of the part and then make the decision from stakeholders (S).

Scenario 3(Verification of signal level): Figure. 6-(3) illustrates how process signals (F') change by the parameter (F) on the build (G) stage. In order to verify constant process parameter (F), capturing process signal (F') and emission from build (G) is required.

4. Results

Section 4 demonstrates how our proposed methodology can 1) support and guide in-situ, ex-situ, destructive, and non-destructive, quality measurements, 2) provide a systematic structure, and 3) focus on the interrelationship between those measurements. Measurements that influence the quality of parts produced using metal AM processes. The results of our methodology show how a multi-level, hierarchical, V-network can be used to facilitate accurate part qualification in metal AM.

4.1. Implementation of V-model

This section provides a critical implementation and use case, of the V-network framework, which is based on the test, validation, and subsequent qualification, of the complex, metal, AM parts. The result of this use case sequentially presents a guidance for AM part qualification. This guidance creates a two-way bridge. The forward way links design requirements to the actual part requirements. The reverse way links

relevant measurement procedures and their real-part measurements to determine if those real measurements achieve the desired part quality. This determination is based on an analytical interpretation of the measured quality that is correlated to the desired quality. The major quality focus in this example, is porosity.

4.2. Final Systems of V-model

Figure 7 illustrates a more comprehensive look at our proposed V-model framework for metal AM quality assurance. The framework represents the convergence of AM cyber systems and AM physical systems that comprise metal AM part qualification. The cyber system starts at the top left by first identifying the design requirements from the stakeholders, then understanding process requirements, and finally ending by creating digital twins of next, actual, physical, process parameters. The physical system starts at the bottom by using those process parameters to build, monitor, test, and measure the AM part. Those physical measurements are then used as inputs to cyber components that do the final inspection. The inspection results can help to determine whether the measurement results satisfy the stakeholders' requirements.

The entire V-model framework includes a causal chain to guide the test and validate quality requirements at each level in determining as-built part quality and performance, providing the direct translation between input-process-structure-property-performance, guiding the better quality performance.

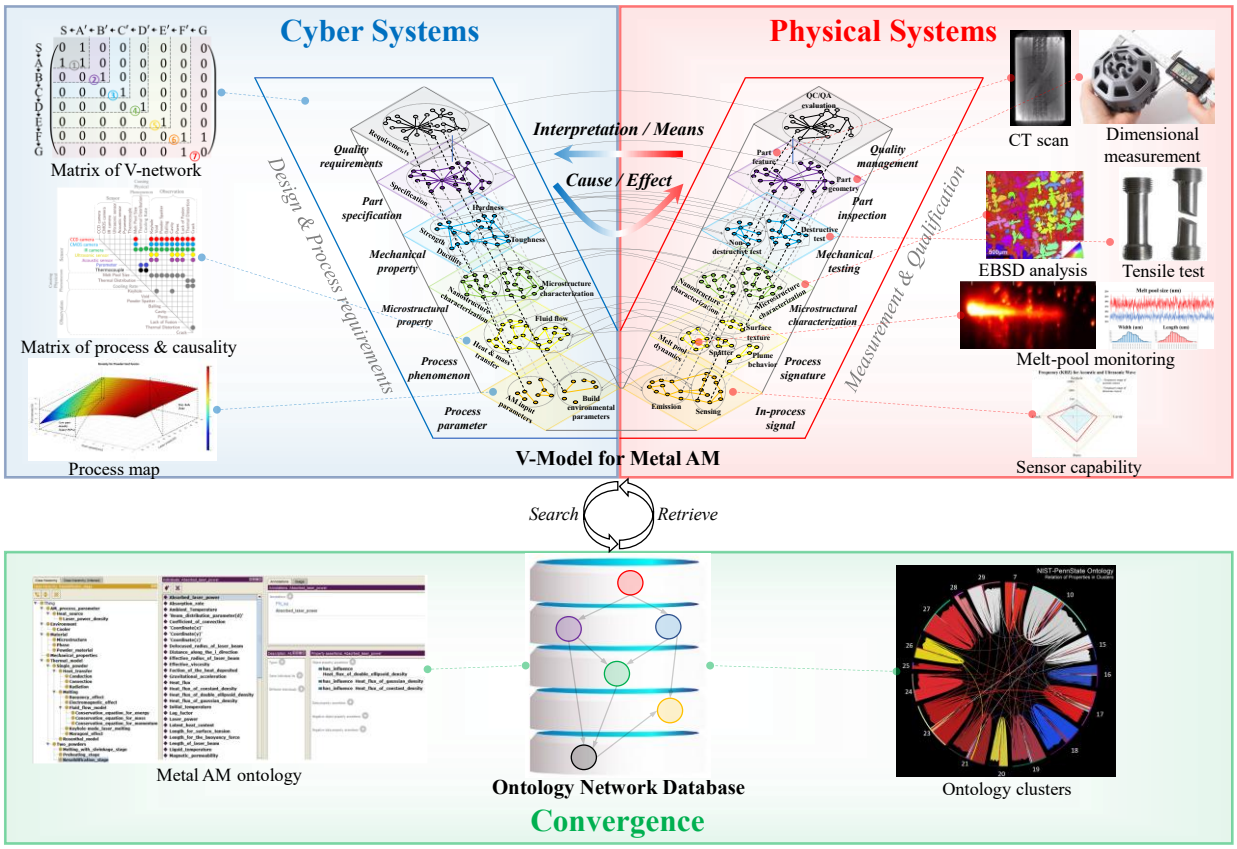

Figure 7. Convergence of Cyber and Physical System on V-model in Metal Additive Manufacturing Part Qualification

Convergence of the AM cyber systems and the AM physical system is needed to complete the V-model framework. To support this convergence, we have created a Convergence layer that has three components: a Metal AM Ontology, Ontology Network Database, and Ontology Clusters.

- *Cyber Systems*

Cyber Systems involve computational components in the V-model for metal AM, interacting network of a computational matrix, multi-dimensional process & causality, semantic map, and process map. Requirement of design & process is included

- *Physical Systems*

Physical Systems consider physical measurement & qualification by gathering physical data to monitor observations and test part for part qualification. Sensor capability is guided to select associated signatures and monitoring. Signature (e.g., melt-pool) is captured during the printing process and material test(e.g., EBSD) and tensile test. CT scan and dimensional measurements are conducted for inspection and quality management.

- *Convergence*

The convergence layer enables components of the V-model to search for relevant information when making decisions. The convergence includes ontology data, analytics clusters for AM process, and hierarchy knowledge information.

5. V-Model Case Study of Qualification

This case study starts with a stakeholder's requirements. These requirements will impact how the target, and final, design variables are affected, and possibly correlated. These design variables will determine which physical measurements will be made to successfully estimate the physical quantities needed to satisfy design requirements at different levels of abstraction. Implementing the AM V-model translates design requirements into those physical measurements. This implementation leverages the management of and processing of captured data, which can used to identify defects and anomalies. By doing so, the V-model makes the measurements and computations needed for performance monitoring, process control, and part qualification more manageable and more efficient.

Figure 8 provides a user's perspective on capturing the system's behavior as it responds to stakeholder's quality requirements. A use case is represented as hierarchical iterative steps in sequence processing of part qualification, beginning with a quality goal of "Towards Fully Solid Part" from stakeholder and ending when that goal is fulfilled by repeated, multiple, processes at distinct levels.

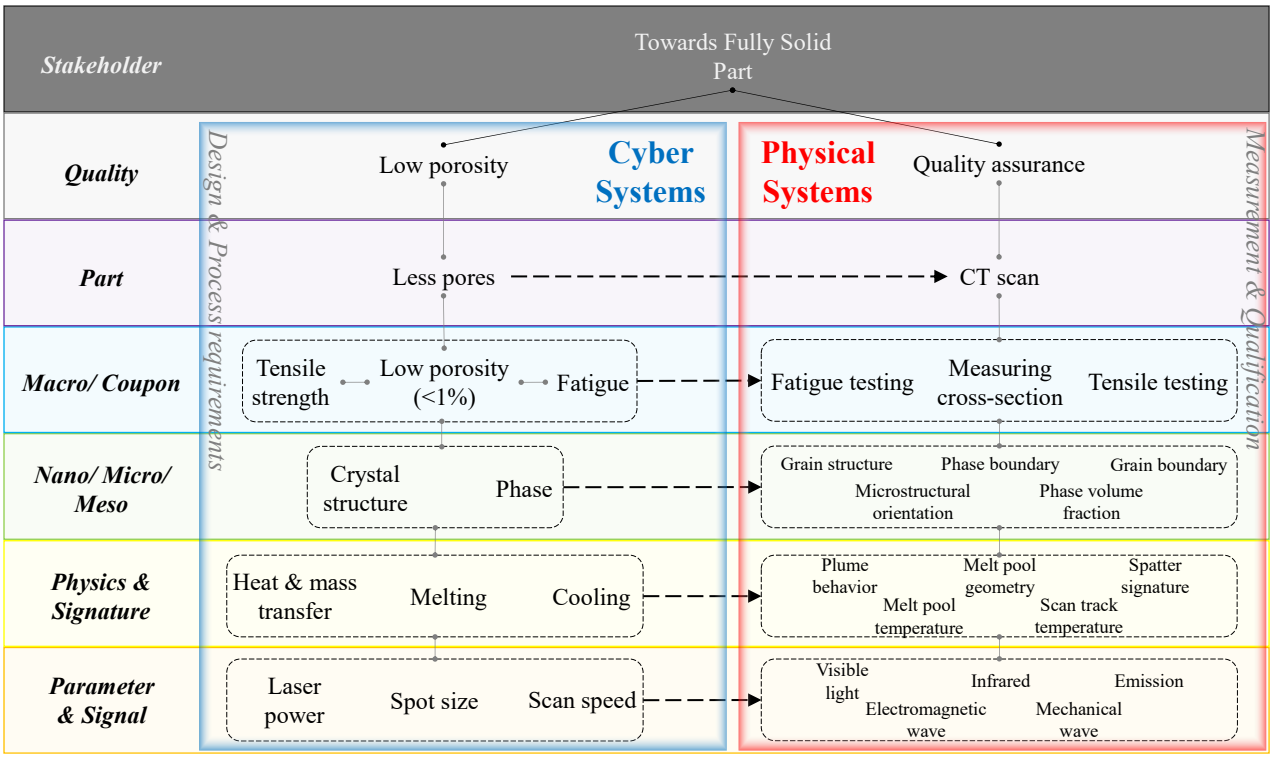

Figure 8. Case Study of V-Model: "Avoid void space in solidified part"

The "Towards Fully Solid Part" requirement is decomposed into the Quality, Part, … Parameter & Signal levels of the Cyber System. In this example, Quality is translated into low porosity; Part is translated into less pores; and, Parameter & Signal is translated into laser power, spot size, and scan speed. Each of these six cyber levels is linked directly to a corresponding level of physical phenomena.

In Section 4, we illustrated our three proposed ideas. First, we demonstrated our hierarchical structure of each side of our V-model framework. The LHS is a hierarchical cyber system and the RHS is hierarchical, physical system; an AM-based, part-qualification system. Second, we demonstrated the convergence of two individual systems into cyber-physical systems. We used this system for tracing & searching relevant quality information through the three proposed "convergence compoents". Third, we showed an interactive, multi-layer, by-directional relationship that links the different cyber and physical components. These illustrations, when combined, enabled us to identify, correlate and qualify parts by comparing design requirements to the actual physical measurements for the AM.

This "quality assurance" V-model will allow designers and manufacturers to focus on fabrication and part qualification based on their design requirements. Thus, this advantage provides insights into what can be performed with given design criteria and will prioritize measurement capabilities for determining whether AM qualification is fulfilled.

6. Conclusion, Discussion & Future Work

In this work, we proposed a hierarchical, V-network framework for quality assurance and control in metal additive manufacturing. The framework comprises two systems: a cyber-based design system and a physical-based measurement system. Each system has six, linked, hierarchical levels. Each level defines its role in quality assurance, test and validation; and each level exists at a relative, scale size in the framework.

Each level is linked physically based on the network connections at each level. These six, connected levels and two systems make up our proposed AM, our V-network, cyber-physical system.

This research underpinning this framework included guidance in modeling, testing, validating, and verifying methods in cyber-physical systems. The V-network framework guides quality measurement from the requirement for part certification, providing a rigorous hierarchy structure of quality management. Networked interrelationship describes the connection between requirement, observation, measurement, and quality elements, guiding quantification of quality uncertainty by collecting correct sensing data and processing data fusion. In this paper, the framework was used to measure, to test, and to validate the quality of AM parts: quality in this paper was based on the number of pores in the part.

V-network combines the dynamics of the physical processes with those of the sensors, network, machine, and tools, providing description and modeling, simulation, design, process, and analysis techniques for the integrated whole. Our V-network paves the path for virtual modeling structured physical process, sensor, data, and interconnection to integrate physical components (e.g., sensors, machine, and physical process) and cyber components (e.g., information, data, and computation) for advanced digital twin.

Future work includes 1) conducting experiments to implement the V-network framework to expand the types of quality problems such as cracks, under fusion, and over fusion, 2) process modeling to build extensible systems interacting with sensors, data, processes, and quality in additive manufacturing. Our proposed work will coordinate sensing, computing, and controlling physical AM manufacturing systems and infrastructures, connecting them to the AM cyber system, and reflecting the changes in each other.

As this work evolves, we believe that our V-network framework can be leveraged to implement data-driven, real-time, prediction and control approach in the AM industry. An approach that collects sensor data, observes physical behavior based on that data, uses that behavior to drive various measurement methods.

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