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IN-SITU OBSERVATION SELECTION FOR QUALITY MANAGEMENT IN METAL ADDITIVE MANUFACTURING

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ABSTRACT

Metal additive manufacturing (MAM) provides a larger design space with accompanying manufacturability than traditional manufacturing. Recently, much research has focused on simulating the MAM process with regards to part geometry, porosity, and microstructure properties. Despite continued advances, MAM processes have many variables that are not well understood with respect to their effect on the part quality. With the common use of in-situ sensors - such as CMOS cameras and infrared cameras – numerous, real-time datasets can be captured and analyzed for monitoring both the process and the part.

However, currently, real-time data predominantly focuses on the build failure and process anomalies by capturing the printing defects (cracks/peel-off). A large amount of data - such as melt pool geometries and temperature gradients - are just beginning to be explored, along with their connections to final part quality. Towards investigating these connections, in this paper we propose models that capture numerous sensor capabilities and associate them with the corresponding, real-time, physical phenomena. These sensor models lay the foundation for a comprehensive, knowledge framework that forms the basis for quality monitoring and management of MAM process outcomes.

Using our previously developed process ontology model [1-3], which describes the relationship between process variables and process outcomes, we can discover the relationship between the real-time, physical phenomena and the deviations in the targeted, build quality. For example, statistically significant sensor data that predicts deviations from targeted process qualities can be detected and used to control the process parameters. Case studies that scope the physical phenomena and sensor data are provided for verifying the effectiveness and efficiency of the proposed qualification and certification models.

Keywords: additive manufacturing, sensor systems, quality management, in-situ monitoring, ontology

1. INTRODUCTION

Currently, producing parts with metal additive manufacturing technologies relies heavily on additional post-processing to satisfy functionality needs and design requirements [4]. Post-processing requirements can be potentially reduced by taking advantage of real-time sensor data - such as melt pool geometry and cooling rate - captured via in-situ monitoring systems [5-7]. Currently, however, sensor data is primarily used in a more passive manner to monitor build failures or to predict deviations in the build qualities. This research presents a foundation for a more active approach to monitoring and feedback, using prognostic and diagnostic process models based on real-time process phenomena to improve monitoring and predict failure indicators.

Metal AM processes expand design freedom from traditional manufacturing. However, users need to manually determine the process parameters such as build orientation, the scan pattern, and the layer thickness before executing the build [8-10]. Choosing the optimal

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combination of process parameters is critical to both achieving successful builds and establishing acceptable part qualities. [11- 14].

Figure 1 shows a current AM workflow from process setup to the quality estimation. This workflow incorporates simulation as a decision support tool. However, "simulation" in this workflow often relies on physics-based models without incorporating feedback from real-time empirical measurements.

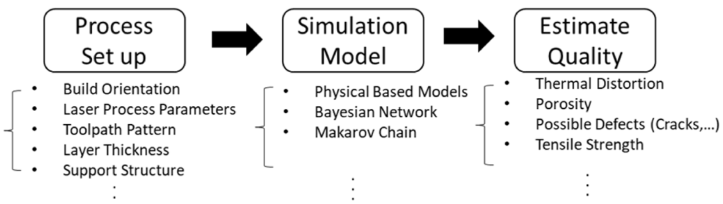

Figure 1. Process estimation on metal AM

Ongoing research is investigating the relationships between the system input (process parameters) and the outputs (print quality – shape, GD&T, functionality) by leveraging models and simulation. Observed limitations and drawbacks to many of these approaches are listed below:

1. Simulation results for the metal AM process are constrained mostly to geometric distortion and porosity prediction.
2. Predictive physical models do not include most of the process parameters, and comprehensive quantitative models for the metal AM process are still lacking.
3. Build failure can only be detected during the physical fabrication process; however, most modes of build failure prevention are currently unachievable.
4. The mechanical properties are crucial for determining the functionality of the parts; however, properties vary from one build to the next and lack a standardized certification methodology.

New smart configurations for sensoring and monitoring are needed to acquire real-time insight during the MAM fabrication. Such a system could support repeatability through observations made during part fabrication. For example, collected in-situ data could be used as a reference to indicate anomalies in future builds.

To gain a better understanding of the overall metal AM process, we propose a framework that relates process parameters to desired build and mechanical properties. In this paper, we use ontology-based metamodels as a foundation for this framework. These models capture the overall process variables, in-situ physical phenomenon, sensor information, and process outcomes. This information is categorized into five models: Input models, Thermal models, Physical models, Microstructure models, and Mechanical models.

Input models consist of all AM processing parameters, including machine variables and user process planning variables [15-17]. Thermal models use those inputs to characterize the thermal properties associated with the generated physical phenomenon. Physical models then use sensor data to generate process signatures at the melt-pool or layer-wise scales. The sensor ontology can be used with the process ontology to relate process physics and final part quality. In addition, microstructure and mechanical property models are represent characteristics of the final part quality that are produced by different scenarios of the thermal models.

Metamodels are capable of generalizing correlations among the datasets used in these models [18,19]. These correlations can be used to help 1) monitor and categorize decision making and reasoning processes, and 2) highlight resultant variables during the metal AM process.

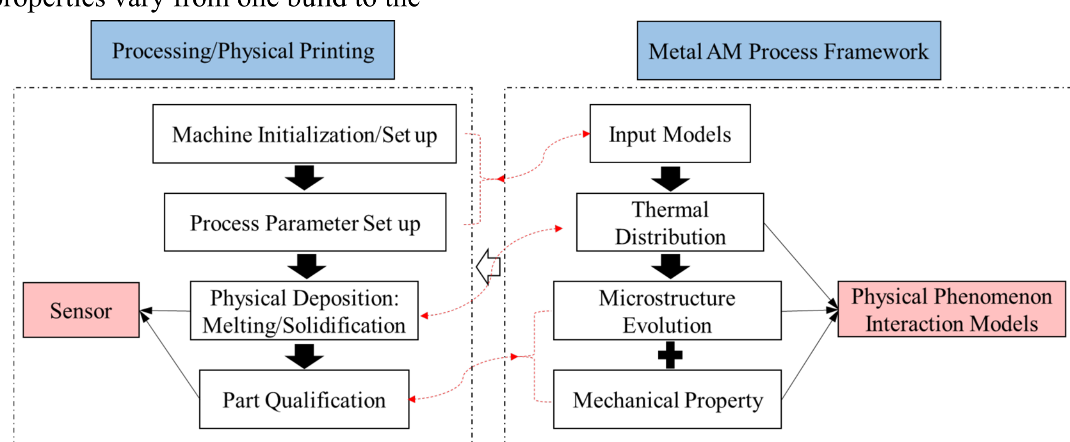

Figure 2. Metal AM process workflow interaction with real-time data

In this paper, a process and sensor framework are leveraged to develop a feasible working zone of quality assurance by assigning a set of optimal process variables for achieving a satisfactory build. The feasible working zone provides proper monitoring guidance of the physical phenomenon to adequately regulate print quality. This research proposes a real-time, aspect-driven model to anticipate issues in quality and automatically identify the responsible parameters.

2. REVIEW OF PAST WORK

Numerous types of sensors are available and have been deployed for in situ monitoring during MAM fabrication. These sensors are generating disparate sets of data that have yet to be fully leveraged to provide feedback to the MAM process at the system and part levels. The data from these sensors must be integrated into a cohesive knowledge and information framework for monitoring, diagnosing, and meeting QC/QA requirements. To build an integrated model of AM sensor data, it is critical to understand the various sensor capabilities. The following sections review past work in sensors, sensor classification, data fusion, and in-situ monitoring.

2.1 Sensors for real-time process monitoring

Real-time process monitoring is empowered by in-situ sensor measurements and data-driven analytics both of which permit real-time estimation and characterization of defects. Rao et al. [20] conducted real-time, quality monitoring with heterogeneous sensors, facilitating data-driven defect detection in AM. Lu et al. [21] studied compressive sensors for capturing temperature fields; they used them as inputs to heat transfer models and other numerical methods in AM. Spears et al. [22] reviewed in-process sensing for selective laser melting (SLM), enumerating significant challenges from multiple input variables that impact part quality. Salama et al. [23] applied the industrial internet of things to facilitate real-time monitoring and to optimize system parameters - such as nozzle temperature and filament breakage/runout- thus reducing maintenance time. Shevchik et al. [24] studied AM quality monitoring using acoustic emissions as inputs to a spectral, convolution neural network to differentiate the acoustic features of dissimilar quality. Nassar et al. [25] investigated sensor-based, defect detection for directed energy deposition (DED). They used optical emission spectroscopy and data acquisition to study the formation of defects during the process.

2.2 Knowledge representation for AM

Despite the continued growth of AM technologies, there has been only limited work focusing on building a reliable, comprehensive, coherent, knowledge base for an AM system. Such a knowledge base could be used to improve AM design and fabrication. Ko et al. [26] presented a framework for Design for AM (DfAM) that uses a knowledge base and machine learning techniques to extract design knowledge from structured data. Also, they applied ontology with graph representation as a knowledge base for updating AM knowledge, reasoning about the AM knowledge for leveraging data-driven AM design rules. Kim et al. [27] proposed an ontological framework for DfAM to provide structured information on AM design, considering manufacturability constraints imposed by AM processes. Hagedorn et al. [28] studied a knowledge-based method for AM design ideation by developing a suite of modular, formalized ontologies to capture information about new uses of AM. The ontology helps to expedite innovative deployment of AM by associating an archive of business, manufacturing, and product realization relevant to previous AM products with an assortment of knowledge representations delineating different AM processes' functional capabilities. Dinar et al. [29] developed a formalized knowledge framework for DfAM with reusability and integration into CAD tools.

Many investigators have conducted countless experiments in modeling and simulation to help understand the complex physics of AM processes [30-32]. The knowledge gained has been expressed in guidance and support, quantitatively addressing what aims to be achieved for a successful build without any defects. Roh et al. [2, 33] investigated the interactive relationship between process parameters and thermal models to build a knowledge-based metal AM model. Michopoulos et al. [34] conducted ontological multiphysics modeling of metal AM to tailor functional part performance. Ali et al. [35] developed a product life cycle ontology for AM, encouraging the development of an ontology for reusability, shareability, and extensibility. Feng et al. [36] investigated the use of meta-data as a base for new interface and exchange standards, which also promote the use of in-situ sensors for in-situ monitoring in laser powder bed fusion processes. These efforts mainly focus on improving accuracy, repeatability, and fabrication reliability to avoid build uncertainty in AM. In general, existing knowledge management efforts are not well

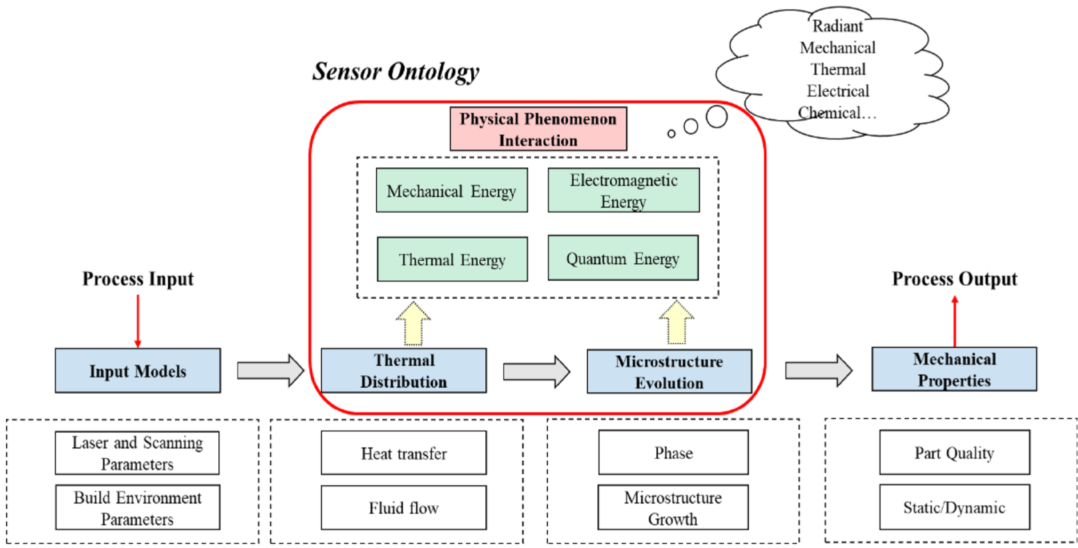

Figure 3. Ontology model overview

classified, and relations among sensors, emissions, physical phenomenon, and mechanical properties are often not well formed.

3. METHODOLOGY

In this section, we first present an overview for the construction of AM ontology models. The development and integration of a sensor-specific ontology is then proposed along with the detailed, hierarchical information in the ontology models. Starting from the comprehensive input models, Figure 3 provides an overview of the sensor ontology model, which follows the build physics of the AM process. The thermal distribution and the microstructure evolution represent thermal behaviors in the material deposition process, which can also be observed through the real-time monitoring system. The process outputs include the mechanical properties that need to satisfy the user quality and control requirements.

Figure 3 presents the sensor ontology "family" and its connection to the process inputs and outcomes. The sensor ontology captures physical phenomenon interactions from thermal and micro-scale behaviors and captures their relationships and high interconnectedness. The objective of the sensor ontology is to produce a dynamic, controlled vocabulary for capturing information attained through sensors. The thermal behaviors, physical phenomena, process outcomes and mechanical properties are derived from the performance of the real-time data.

3.1 Ontology development

To create the sensor ontology, we first identified its scope, contents, objectives, and requirements. To meet the requirements, the target ontology should capture knowledge from different sensors and describe their capabilities. Understanding how various sensors can be classified and what physical phenomenon is captured by each sensor is essential. The resulting knowledge base should support different levels of abstraction and criteria. For example, the sensor ontology should represent domain knowledge as well as empirical knowledge gathered from benchmark studies. The following steps are used to construct the sensor ontology in this paper:

(1) Specify the entities representative of sensors for metal AM.
(2) Define and link potential object properties in semi-natural sentences.
(3) Enumerate subclasses of entities.
(4) Populate with individuals and instances.
(5) Evaluate the model and iterate through the previous steps.

The ontology framework is built using Protégé [37], which offers a graphical interface for constructing hierarchical ontology based on RDF (Resource Description Framework), OWL (Web Ontology Language), and XML (Extensible Markup Language) format [38].

3.2 Integration of ontology

The sensor ontology aims to align process inputs and outputs using purposefully grouped physical phenomena and corresponding sensors. Additionally, the sensor ontology targets in-situ monitoring for quality assurance through real-time data. Accordingly, adopting this sensor ontology approach increases the capability of detecting and guiding the metal AM process at a controllable level. A detailed sensor capability map, which conveys connections between sensors, physical phenomena, and part quality does not currently exist. The integrated sensor model development is a crucial, first of its kind contribution for codifying AM processes to support quality assurance and process control through optimal sensor selection.

We developed five, local, ontology models involving sensing features, physical emissions, causes and results of physical phenomena, and part quality. The shared nodes in these five models are then integrated into a larger, quantitative, ontology model. Details of constructing the integrated ontology are presented in Figure 4.

The first layer of the sensor ontology contains the detailed definitions of additional components, features, and classifications, as well as the capability to link the physical emissions and phenomena. In this regard, this layer provides a bridge to related research on a process-ontology-development method, which focuses on the process input, the thermal behavior, the evolution of microstructure, and the final mechanical properties [2].

The physical emission layer refers to the transition of molecules and atoms, which results from a spectrum of frequencies, energy levels, and electromagnetic radiation wavelengths that occur during the process. Emissions are part of the physical process. They occur when the higher energy of quantum particles is converted to lower-level energy. The conversion causes light emissions with a specific frequency and wavelength.

The causing physical phenomenon layer uses the range of emitted wavelengths by an atom, captured by a sensor, to quantify and measure physical activity. For example, the melt-pool dynamics and solidification are detected by the emission of reflected light. Obtained sensor images provide geometric information of the melt pool and temperature distribution through the captured emission levels.

The physical phenomenon layer connects the causing physical phenomena with part quality. Consequently, this layer helps the framework to observe levels and variations of part quality. For example, the causing physical phenomena of melt pool affects the formation of defects observed in the deposition process, including unintended keyholes, cracks, and pores. These physical defects of the build process deteriorate part performance.

Finally, the part quality layer explains the final part quality and mechanical properties induced by the physical phenomena. This layer explains how defects and physical phenomena cause variations in part quality.

4. SENSOR ONTOLOGY FRAMEWORK

The use of broad and specific terms in the ontology is required to characterize and identify sensor capabilities in metal AM. Some transducer characterizations, both static and dynamic, exist in the literature, but without considering the uniqueness of metal AM. Our sensor ontology includes the inherent characteristics of metal AM

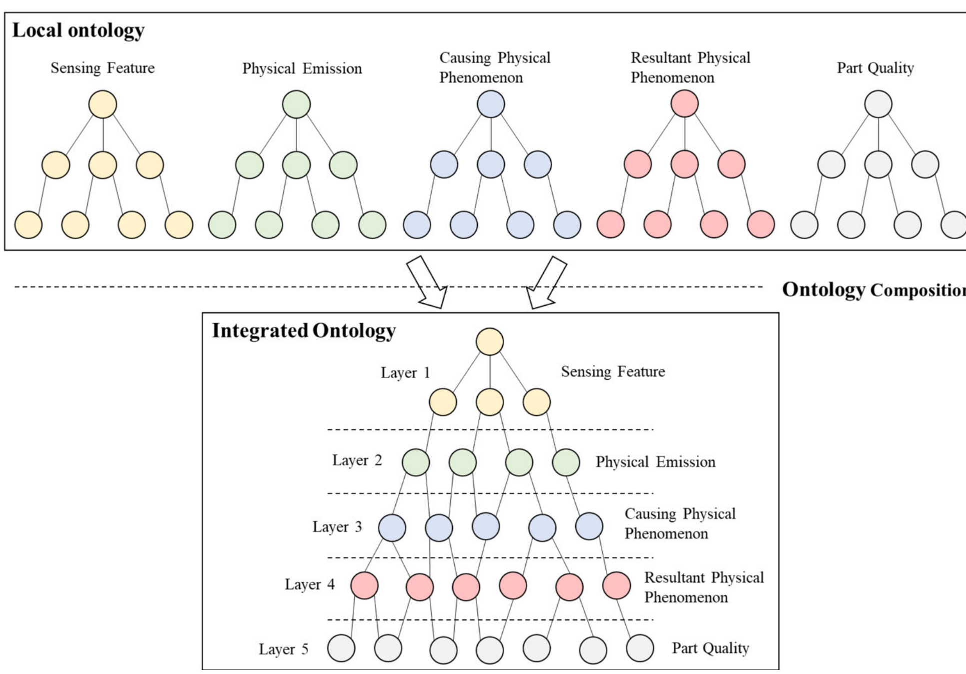

Figure 4. Structure of sensor ontology

physics. Those inherent capabilities are described in greater detail in the next sections.

4.1 Hierarchy of sensor ontology

The sensor ontology is created with a set of high-level classifications based on the essential knowledge identified in a general fabrication scenario. In this scenario, a fabrication event occurs when 1) the AM process, pre-set up, material, and process parameters are chosen, 2) the physical phenomena and process signatures are observed, and 3) the resultant physical phenomena such as balling, spattering, pores, and crack, are identified.

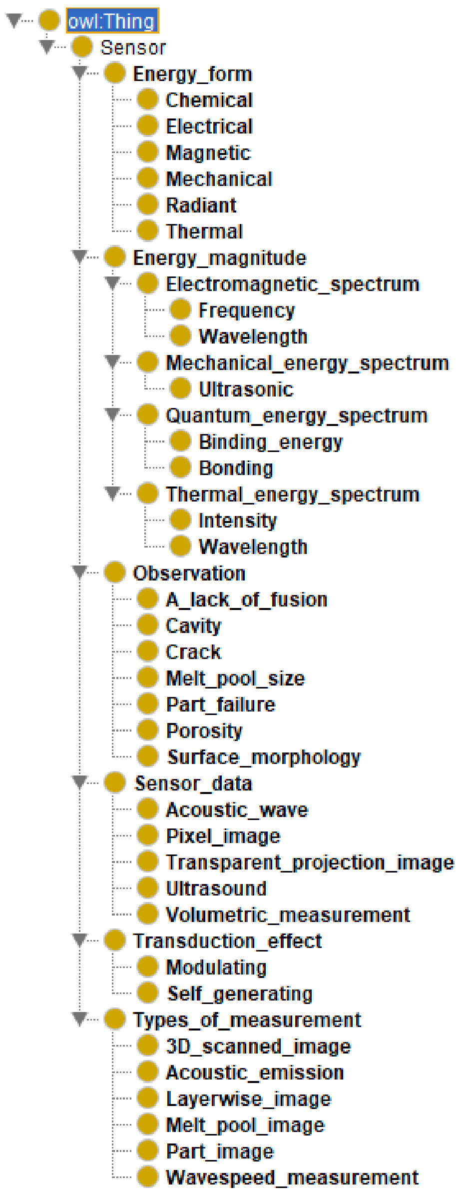

Figure 5. The hierarchical structure of AM sensor ontology

There are advantages of utilizing a sensor ontology as a bridge between real-time monitoring data and part quality data. By leveraging the ontology during a build, a researcher does not have to focus on every process signature and relevant sensor data because the ontology helps identify then subsets of knowledge needed to meet multiple QC/QA requirements.

$$\text{Sensor Ontology} \supseteq \left\{ \begin{array}{c} \text{Observation} \\ \text{Sensor data} \\ \text{Type of measurement} \\ \text{Transduction effect} \\ \text{Energy magnitude} \\ \text{Energy from} \end{array} \right\}$$

Figure 5 shows the hierarchical class structure of our proposed sensor ontology. The taxonomy shown is a simplified, high-level, class structure, with some entities hidden because of the limited space. The sensor ontology is governed by the main classes of **Observation**, **Sensor data**, **Types of measurement**, **Transduction effect**, **Energy magnitude**, and **Energy form**. **Observation** is a superclass related to measurable objects such as a lack of fusion, cavity, porosity, and melt pool in AM. **Sensor data** represents a sensor output observation, which detects and responds to some type of input from the physical phenomenon and environment.

For example, sensor data includes an acoustic wave, a pixel image, a transparent projection image, ultrasound, and a volumetric measurement. **Types of measurement** refers to the types of measurements that result from measured physical emissions that include classes of 3D scanned images, acoustic emissions, layer-wise images, melt pool images, part images, and wave speed measurements.

Transduction effect means converting a signal in one form of energy to a signal in another. Electrical signals are converted from a quantity of physics such as energy, light, motion, temperature, force, and position. The transduction effect is classified by modulating and self-generating.

Energy form classifies sensors into six energy forms or signal domains. **Chemical energy** includes oxidation and reduction potential, pH, composition, reaction rate, and concentration. **Radiant energy** has transmittance, reflectance, wavelength, intensity, phase, and refractive index. **Magnetic energy** involves permeability, flux density, magnetic moment, and field intensity. **Electrical energy** encompasses dipole moment, polarization, voltage, current, inductance, resistance, and capacitance. **Thermal energy** is composed of the state of matter, entropy, temperature, heat flow, and specific heat. **Mechanical**

energy covers volume, area, length, force, acoustic wave, angular velocity/ acceleration, linear velocity/acceleration, mass flow, pressure, and acoustic intensity. **Energy magnitude** captures sensor sensitivity and the correlations between the form of the sensor signal and sensor sensitivity, based on the magnitude of the energy change detected. Electrical and magnetic signals require the detection of energy in the relevant parts of the electromagnetic spectrum.

4.2 Properties in sensor ontology

The object-type properties are defined in Table 1. These properties are labeled as passive and active verbs that identify the relations between entities. Similar relations indicate a common terminology; for example, *captures* relate Sensor to Observation, which means "Sensor *captures* Observation." Table 1 presents the object properties established in the current high-level, sensor ontology. Each pair of classes and entities (in bold font) that are related from the first column to the first row are defined. A *has* object property is defined to accommodate such relations of **Sensor** to **Types of measurement**, **Transduction effect**, **Energy magnitude,** and **Energy form**. The direction of interpretation in the table is always linked from the first column class to the class of the first row with corresponding object properties. The *affects* object property allows defining connection of influence **Types of measurement**, **Transduction effect** on the result of **Sensor data** and captures the quantity of **Energy magnitude**.

The sensor ontology reflects the technical classification of the sensor. This includes its capability to measure physical phenomenon and to monitor part quality. Both capabilities indicate how to link and identify sensor types to functionality using knowledge networks. The sensor's place in the hierarchical structure should also be defined. Furthermore, the sensor ontology should include comprehensive information about the role the sensor plays in the AM solutions.

Hence, the sensor ontology provides sets of sensor, process, manufacturing, and quality alternatives to connect sensor and part quality by using an ontology framework. In addition, when measuring information of multi-process defects through energy forms, identifying the best combination of sensors is critical to finding QC/ QA solutions.

4.3 Summary

This section introduced a detailed explanation of the knowledge model of the proposed sensor ontology. Section 5 will illustrate an example implementation that includes both the physical phenomena and sensor selection, which are based on the QC/QA requirements. The sensor network, relational diagram, quality map, and sensor map will be introduced. The structured and formalized sensor knowledge representation for sensor capabilities, physical phenomenon, and part quality will also be presented.

5. RESULTS

This section demonstrates how the proposed methodology can leverage part quality, sensor data, and

Table 1. Relations among high-level of sensor ontology (reading direction ⮥, e.g., Sensor *obtains* Sensor data)

	Sensor	Observation	Sensor data	Types of measurement	Transduction effect	Energy magnitude	Energy form
Sensor		*captures*	*obtains*	*has*	*has*	*has*	*has*
Observation	*is captured by*		*Transform into*	*is captured by*	*is changed to signal*	*produces*	*produces*
Sensor data	*is obtained by*	*has information of*		*is result of*	*has*	*is output of*	*is transformed from*
Types of measurement	*belongs to*	*captures*	*affects*		.	*affects*	*affects*
Transduction effect	*belongs to*	*changes signal from*	*affects*			.	*transforms signal of*
Energy magnitude	*belongs to*	*is produced by*	*produces*	*is captured by*			*has type of*
Energy form	*belongs to*	*is produced by*	*produces*	*is captured by*	*change signal by*	*has level of*	

sensor selection through knowledge representation. The results show how the high-level, hierarchical, sensor ontology can use taxonomic identification to facilitate accurate analyses in metal AM.

5.1 High-level sensor ontology

The sensor ontology provides a hierarchical network of variables and parameters that can help identify differences and similarities between quality requirements. The network representation also functions as a knowledge graph, providing a means to navigate forward and backward. And, to explore information resources and the relationships between process variables and physical phenomena in the ontology.

Graphical network visualization results in this section are based on Gephi [39]. Gephi helps to visualize complex knowledge-based systems, combining the complementary advantages from handling large datasets, statistical analysis, algorithms, and matrices.

The high-level, sensor ontology in Figure 6 represents classes of **Sensor**, **Types of measurement**, **Sensor data**, and **Observation**, which show the composition of sensor features and relations. Lager and smaller nodes are marked as red and blue, respectively; the size of the node is proportional to its connection. The sensor network map provides opportunities to improve sensor selection, data acquisition, in-situ monitoring, and part quality. Those opportunities can be found by forward and backward tracing to the related quality requirement variables.

Classes (nodes) and their interrelationships highlight abstract knowledge, while each class and classification indicate empirical knowledge of specific AM sensor types. The next section 1) provides insight into both the abstract and detailed sensor relationships and 2) uses different application scenarios to demonstrate the interconnectivity between each sensor, each physical phenomenon, and each part-quality requirement.

5.2 Quality and sensor network

This section will show a hierarchical, network graph highlighting sensor features, physical phenomena, and part quality. The AM sensor ontology generates this graph that can be used to 1) look for the previously mentioned similarities and differences and 2) determine new, critical, connected relationships between sensors, phenomena, and quality. Three examples are illustrated in Figure 7-9. Each node is based on the hierarchical classification of sensing, physical emission, causes/results of physical phenomena, and, QC/QA layers.

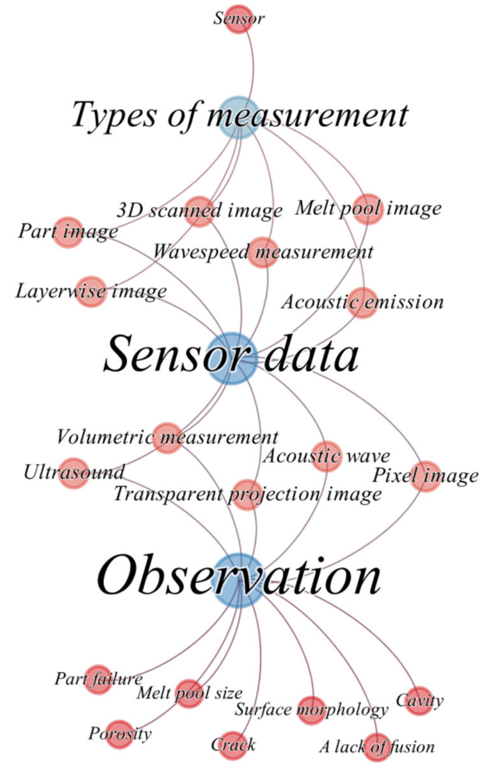

Figure 6. Visualization of sensor ontology

Figure 7 shows the network chain from sensor type to the fatigue. The graph has the capability to trace the measurable physical phenomena to provide insight into the fatigue qualities of a part. For example, we can measure melt-pool geometry, cooling rate, and thermal distribution in the graph and correlate them to the part's fatigue. Likewise, the graph gives guidance to understand how the measured physical phenomena affect different mechanical properties based on different quality requirements including part fatigue, tensile strength, yield strength, elongation, Vickers hardness, and surface roughness

Figure 8 shows an example of how to leverage the sensor ontology and navigate the network graph in reverse. This approach can be used to identify what types of physical phenomena and sensor data should be captured to help assure that a requirement is satisfied. In this example, the tensile strength of the part is the requirement. We navigate the knowledge graph backward until we find measurable physical phenomena that we might be able to sense, and the corresponding sensor set to be captured from these the physical phenomena. While we may not be able to measure the level of tensile strength directly during the build process, this nonetheless supports the decision of what physical phenomena we might want to sense and what sensors we can use to gather the data.

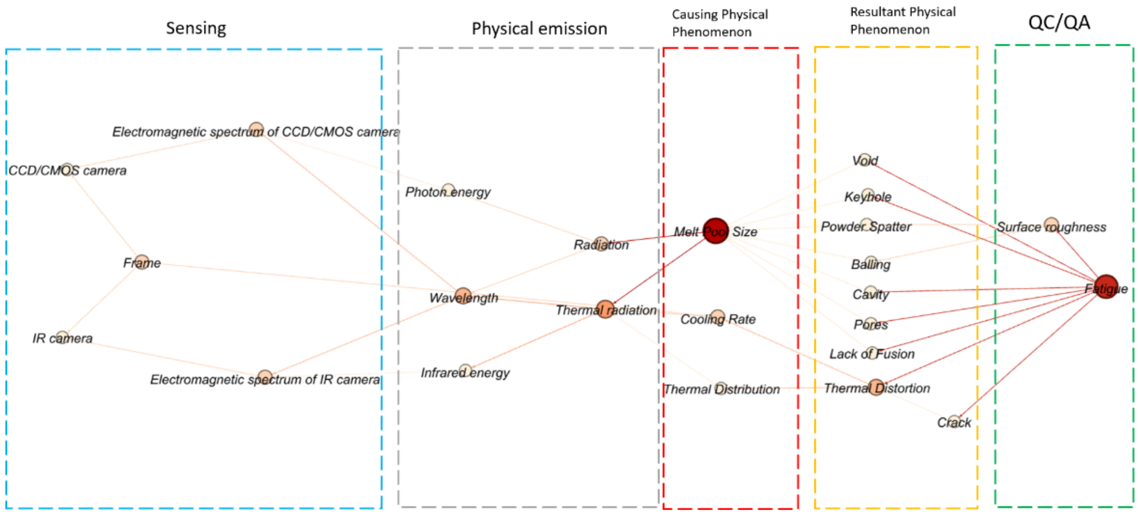

Figure 7. Quality and sensor map of fatigue

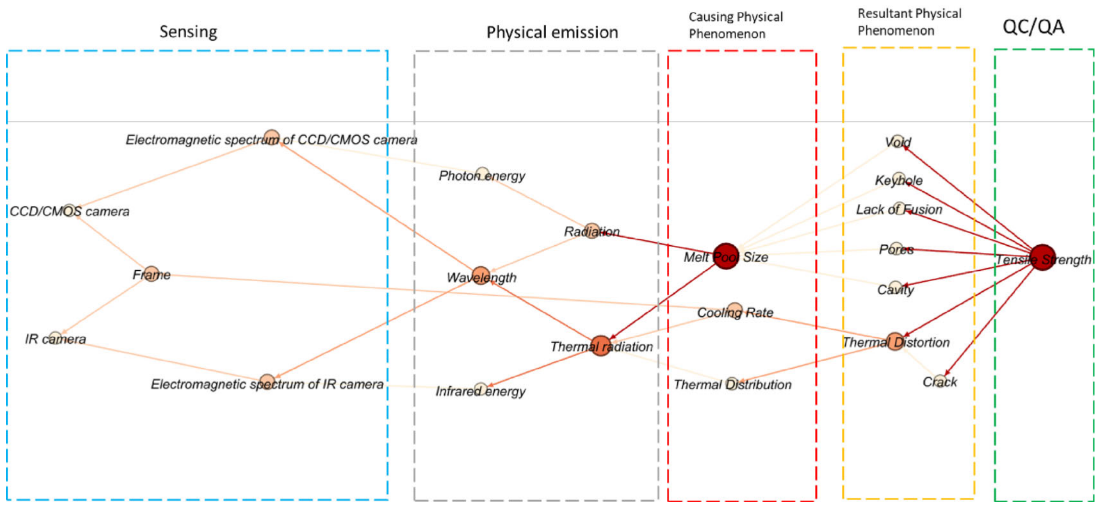

Figure 8. Quality and sensor map of tensile strength

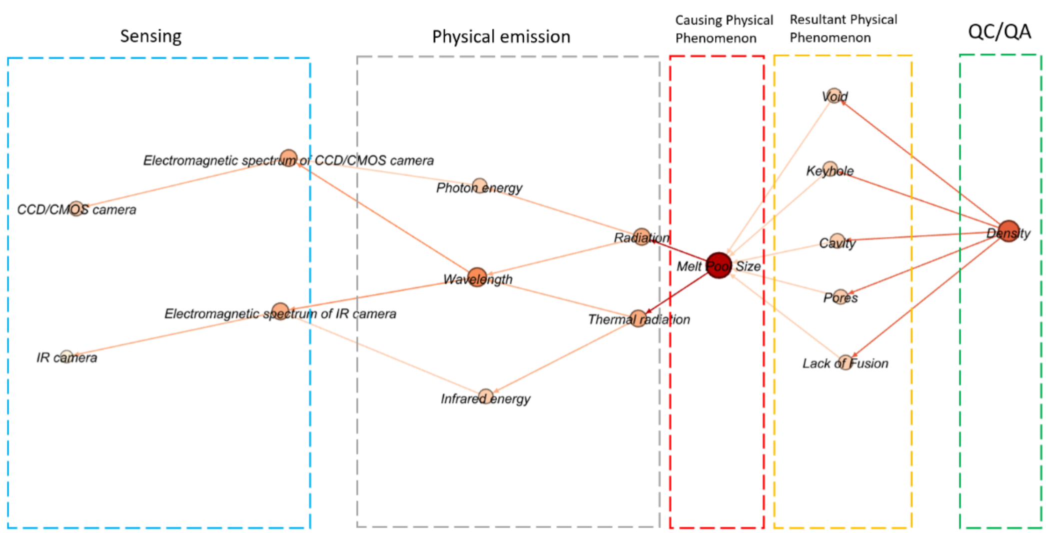

Figure 9. Quality and sensor map of density

Figure 9 illustrates the quality and sensor map for satisfying a density requirement by correlating the quality of density, sensor, and physical phenomena. Density is affected by multiple resultant physical phenomena related to voids, keyholes, lack of fusion, pores, and cavities, which are also classified as observed defects. These defects are the results of the fusion-based process and limit various mechanical properties. During the build process, these defects can occur by a change of melt-pool size, which is significantly affected by the heat source and other process variables in real-time. The heat source emits thermal radiation and the melt pool emits electromagnetic energy levels and wavelengths, characteristic captured in Figure 9.

5.3 Relational diagram for monitoring

The radar plot is a useful method to explore the complex, multidimensional relationships among the data using the sensor ontology [40].

This two-dimensional radar diagram 1) gives a graphical representation of multivariate data from the ontology and 2) provides a way of comparing multiple, quantitative variables in complex systems. Each variable is provided with an axis that starts from the center. All axes are arranged radially, with equal distances between each other, while maintaining the same scale between all axes. Gridlines that connect from axis to axis are often used as a guide. A variable is plotted along an axis, and all the variables from the ontology are connected to form a polygon.

As shown in Figure 10, the radar graph highlights multi-relational features and connections to various causal physical phenomena. This graph shows how the melt pool, cooling, and thermal distribution correlate to multiple defects during the process and overcomes the limitations of the network graph described in Sec 5.2.

Figure 11 shows a detailed mapping of sensor capabilities to the physical phenomena – such as the melt pool, thermal behavior, crack, and cooling - providing a process monitoring strategy. Therefore, the results illustrate a sensor capability and mapping combined with the methods developed in the ontological, network graph. These results can be used to integrate and navigate the AM process and sensing capability.

In Section 5, we described 1) a hierarchical structure of sensors for AM, 2) a quality and sensor network, and 3) an interactive relation of physical phenomena and sensor capability to QC/QA requirements. Together, these help us investigate an AM system network to identify correlated physical phenomena and the minimum set of sensors for maximum coverage of a given set of multiple requirements for process monitoring. Conversely, they help us identify, for a given set of sensors, the best subset of requirements that can be met. Thus, this advantage provides insights into what can be performed with an existing sensor suite and will prioritize new sensor capabilities for in-situ monitoring.

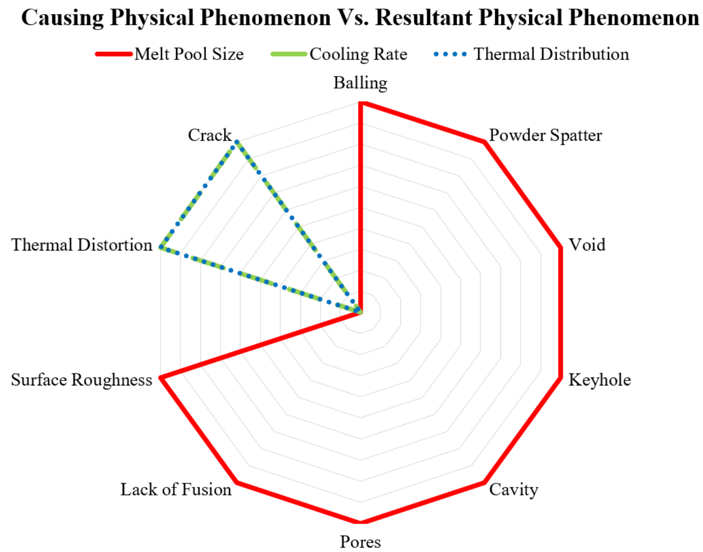

Figure 10. Relational diagram between Causing Physical Phenomenon and Resultant Physical Phenomenon

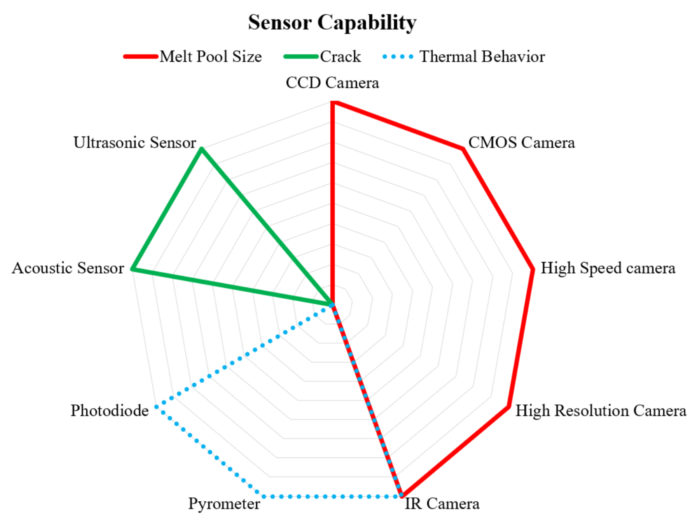

Figure 11. Diagram of sensor capability

6. CLOSING REMARKS AND FUTURE WORK

This research investigates the relationship between AM process inputs, physical phenomena, and process outputs by considering different sensors, their capabilities, physical emissions, and mechanical properties. The minimal selection of sensors is targeted to cover a given set of quality requirements by detecting and tracking feature deviations during the AM build process. The selection uses a sensor capability map based on information captured in the AM process ontology. An essential and necessary outline for understanding and identifying in-situ sensing capabilities and process monitoring is developed.

In addition, a hierarchical structure is embedded in the sensor ontology, which is relevant to the AM process models. Towards better insight into the large data sets from AM processes, the multi-physics in metal-based AM technology is characterized. Furthermore, the sensor framework can aid advanced process control and help predict potential changes of a specific parameter and physical phenomenon. This is done by monitoring and diagnosing process problems in the metamodel.

Novel, framework development is necessary to enhance repeatability, fidelity, and functional integrity of experimentation. Thus, the proposed ontology-based sensor framework offers an underlying platform for in-situ sensor measurements, real-time guidance for characterizing printing defects, AM diagnostics, and process quality indication.

Future work includes the development of models to facilitate the data-driven, real-time prediction and control of metal additive manufacturing. The real-time prediction and control model can facilitate the analysis of the process, measurements, and data-driven formulation to achieve closed-loop control.

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