Proceedings of the ASME 2024
International Design Engineering Technical Conferences and Computers and Information in Engineering Conference
IDETC/CIE2024
August 25-28, 2024, Washington, DC

DETC2024-138090

ONTOLOGY-BASED CONTEXT-AWARE DATA ANALYTICS IN ADDITIVE MANUFACTURING

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ABSTRACT

Recent advances in Additive Manufacturing (AM), particularly in production scenarios, have been largely driven by insights achieved through data analytics. AM has greatly benefited from the increasingly large amounts of data generated during the design to product transformation. Despite the large amounts of data that can be generated from each build, the variations that can occur between builds create challenges in data reuse.

Advances in data analytics are coming in the form of advanced machine learning algorithms, and often associated with deep learning, where large amounts of data are analyzed and interpretations are made. While such algorithms are increasingly adept at solving complex problems, solutions are highly dependent on the data used to train the algorithms and thus often subject to unwanted bias. Contextualization of data can help limit unintended bias and improve the probability of attaining viable results.

Data contextualization often comes through domain context. This work describes the development of an AM ontology to support context-aware data analytics. The Additive Manufacturing Data Analytics Ontology, or AMDA Ontology, is developed to facilitate the contextualization of AM data through the representation of explicit AM concepts throughout the design to product transformation and the encoding of inhering relationships within. The AM concepts are accompanied by a suite of concepts representative of the necessary modeling, simulation, and analytics terms necessary to create links between AM data, AM data analytics opportunities, and appropriate machine learning algorithms. The early results indicate that AMDA ontology has the ability to facilitate key correlations between AM data and the analytic opportunities to enhance the design to product transformation of AM parts.

Keywords: Context-aware Analytics, Data Analytics, Ontology, Additive Manufacturing

1. INTRODUCTION

Additive manufacturing (AM) technologies offer the capability to build complex and customized three-dimensional (3D) geometries by layering material layer-by-layer according to a digital model. [1] These technologies offer enhanced design freedom, material efficiency, and customized production compared to traditional subtractive manufacturing technologies, facilitating rapid growth in various industries. [2] AM depends on precise process control to produce repeatable, reliable, and quality-ensured parts, necessitating the extensive use of sensors that generate a substantial volume of data. [3]

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The data-intensive characteristics of AM processes present strong research opportunities to support AM decision-making through various data analytics (DA) techniques. [4] Data analytic opportunities exist throughout the entire AM workflow, encompassing design optimization, process planning, build phase, and post-processing activities. [5] By leveraging data analytics at each step, AM data can be transformed into actionable and insightful information to better control AM processes. [6]

Due to the inherent complexities of AM process and the proliferation of AM data [7], there lies a substantial opportunity to better manage and analyze the data generated throughout the AM process. AM data is collected at every stage of the AM process flow, implying that AM data inherently reflects the content and context of the AM process. The digital nature of AM processes serves as an opportunistic backbone for deriving analytical solutions aimed at improving and optimizing AM processes. Recent progress in analytical technologies, including machine learning (ML), modeling and simulation (M&S), and deep learning (DL), has provided advantages in managing vast volumes of AM data, creating new opportunities for data-driven decision-making.

Advanced analytical models excel in capturing complex patterns within AM data, often sacrificing context for its capability. The "black box" nature of recent data analytics approaches presents challenges in interpreting data analytics results within the intricate context of AM process and AM data. [8] The capability to effectively capture and utilize the context of AM data can provide transformative data analytics discovering deeper insights.

The context of AM data analytics can be defined by integrated knowledge from use cases, data analytics, AM data specifics, and the AM domain, all of which are interrelated to enhance the understanding and implementation of data analytics within the AM field. [9] Furthermore, the contextual framework can be expanded to include machine, temporal, and spatial contexts to realize data analytics for improving the AM process. [10] Diverse and extensive representations of AM context can create complex connections, resulting in interrelations that AM data analytics needs to manage. Consequently, recognizing and integrating these contexts is important for leveraging data analytics to reach its full potential in enhancing AM processes.

This study addresses context-aware data analytics in AM through the development of an application-oriented ontology. We define the two specific domain contexts that are used for AM data analytics and detail the concepts within each domain, mapping the relationships between these concepts. The Additive Manufacturing Data Analytics (AMDA) ontology is developed to support the application of context-aware data analytics in AM processes.

This paper is structured as follows. Section 2 provides the background of the methodology, addressing AM process and AM data, context-aware data analytics, and data analytics for AM projects. In Section 3, we detail the requirements that drive the development of the ontology. Section 4 presents the AMDA ontology, including the classes and properties to facilitate context-aware data analytics in AM. Section 5 provides a case study to illustrate the application and its effectiveness. The paper concludes in Section 6, summarizing our contributions and outlining future works.

2. BACKGROUND

2.1 AM Process and AM Data

The inherent complexity of AM processes, and the core physics they rely on, provide unique data-driven opportunities compared to traditional manufacturing methods. [11] AM processes involve complex interactions among the intricacies of geometry design, feedstock materials, finely tuned machine settings and parameters, variations in build environment conditions, and the often-necessitated post-processing considerations. [12] Furthermore, the process conditions have significant variability depending on different AM technologies, with the combination of all often leading to variations in the final product. [11]

AM data includes all relevant data captured, utilized, generated, and shared throughout an AM design-to-product transformation. [13] The data generated and utilized throughout the AM process is as complex as the process itself, capturing a wide array of information from design specifications to final quality assessment, characterized by its volume, variety, velocity, and intricate interconnections within the AM process. [6] Moreover, AM data comprises a range of data formats, standards, and methods, including 3D models, 2D slices, and specific types of AM data utilized throughout the AM process. This variety complicates data interoperability, which leads to difficulties in data integration. [14]

Considerations for successful data analytics include transparency and interoperability throughout the design-to-product transformation. Siloed data limits opportunities for capitalizing on analytics opportunities. Systematically organizing and structuring these complex relationships and concepts of AM process and data can support AM context management which leads to enhanced interoperability, precise data analytics, improved decision support, and knowledge sharing.

2.2 Context-aware Data Analytics

Context-aware data analytics involves analyzing data within the framework of its context to improve comprehension, interpretation, and practical insights derived from data. [15] This approach is increasingly applied in complex domains such as AM, due to the ability to account for situational and environmental context of the data in a repeatable manner. [16]

Within the AM domain, the integration of contextual data into analytics is an emerging area, with significant opportunities and relatively few studies. Recent studies have explored the utilization of knowledge graphs to apply both design and process context constraints to construct design rules for AM [17]. Additionally, there has been research applying explainable artificial intelligence for detecting defects in AM processes. [18] Despite the potential benefits of these advanced analytical

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techniques, their application within the AM domain remains relatively limited, highlighting a significant area for further exploration and development.

To implement context-aware analytics, several advanced technologies and methodologies are available including ML, natural language processing (NLP), semantic web technologies, knowledge graphs, and ontology. [15] Among these methods, ontology plays a pivotal role by providing a structured and machine-interpretable representation of complex, domain-specific contexts. Ontologies can facilitate a deep semantic understanding by defining concepts with properties and relations between them. [19] This semantic foundation enables sophisticated analysis and interpretation, considering the relationships that are crucial in complex AM domains.

2.3 Data Analytics in Additive Manufacturing

Throughout the entire AM lifecycle, from design to validation, DA methods are available to support decision-making applications. These methods are deployed for a variety of purposes, including; optimizing design, optimizing process and machine performance, monitoring and controlling in-situ processes, regulating post-processing activities, and conducting testing and validation. [6] In AM projects, regression models like neural networks (NN) and Gaussian processes (GP) play a crucial role in optimizing process parameters, predicting part properties, controlling geometric deviations, and implementing closed-loop control systems. Meanwhile, classification models, including decision trees (DT), support vector machines (SVM), and convolutional neural networks (CNN), are widely applied for detecting defects and predicting the quality of manufactured parts. Additionally, clustering models such as the self-organizing map (SOM) and elastic net (EN) are utilized for accurate cost estimation. [20]

While these methods operate well in their respective silos, these DA methods in larger AM projects often fall short due to their limited ability to interpret complex relationships and dependencies inherent in AM processes. [8] Without un-siloing the data, these traditional approaches may not adequately explore and account for the dynamic interactions between material properties, machine parameters, and environmental conditions, leading to suboptimal decision-making. Without incorporating the context in which data is generated, these DA methods can miss critical details, resulting in less accurate analytics. [16] Context-aware DA can provide a more detailed understanding by guiding data usage and considering the specific situations and variables influencing the AM process, resulting in more reliable and actionable insights.

3. METHODOLOGY

3.1 Identifying Domain-Specific Context

Perhaps the primary consideration during the development of the AMDA ontology is the identification of relevant domain concepts. Given that the AMDA ontology borrows from the AM domain, the data science domain, and peripheral domains presented in Figure 1, the ontology must represent a diverse set of concepts to achieve the desired functionality. Specifications and specializations are key to achieving a desired balance of available information context.

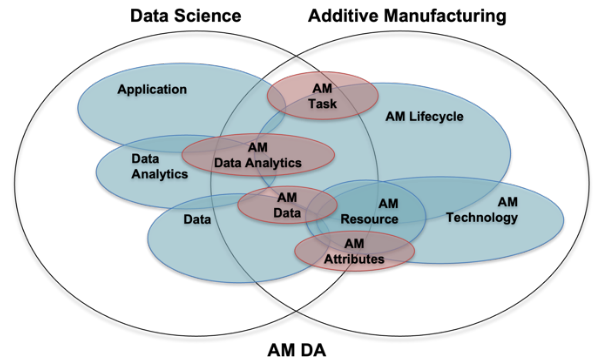

FIGURE 1: PRIMARY DOMAINS TO CONTEXTUALIZE AMDA

In the development of the AMDA ontology, considerations must be for the domains to be represented and the granularity they should be represented in. While the high-level domain concepts of data science and additive manufacturing are apparent, how these domains are decomposed requires substantial consideration. As the goal of AMDA is to contextualize data to facilitate AM data analytics opportunities, the domains must be properly scoped and granularized so that meaningful connections can be made between ontology classes and properties.

From AM, contextualize should happen at each phase of the AM lifecycle, allowing for contextualization of data for feedforward and feedback analytics. The different types of AM data are driven by the phases and the equipment used to handle the data at each phase, such as in-process monitoring sensors, non-destructive evaluation equipment, and mechanical testing equipment. The different software used to process data at each stage, and the different formats used to represent the data, must also be considered. Finally, the fundamental physics that governs the processing technologies provides a key context in which AM data can be normalized.

Data science is a vast field, and the contextualization of this domain is very much application driven. As the goal of AMDA is to facilitate analytics opportunities, contextualization focuses on problem formulation, particularly for ML and AI. Additional scoping must be performed at this stage due to the wide range of analytic methods available. The level of granularity must be able to facilitate analytics at different scales, depending on the desired application.

3.2 Framework for Context-aware AMDA

Context-aware data analytics begins by addressing the DA opportunities [21] that are present throughout the entire AM lifecycle. In the journey toward developing data-driven solutions for DA opportunities, referred to as “AM Tasks”, it is advantageous to have a prior understanding of the underlying context of the tasks, which provides a valuable foundation for the analysis.

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This Section explores the foundational concepts behind AMDA contextualization and, by leveraging these concepts, outlines a framework designed for context-aware AMDA. The framework aims to facilitate and support AMDA solutions for AM tasks, providing a contextual understanding of AM tasks. This is achieved through the integration of contextual factors from the interconnected domains associated with AMDA, enriching the analytical process with a deeper AM domain-specific insight.

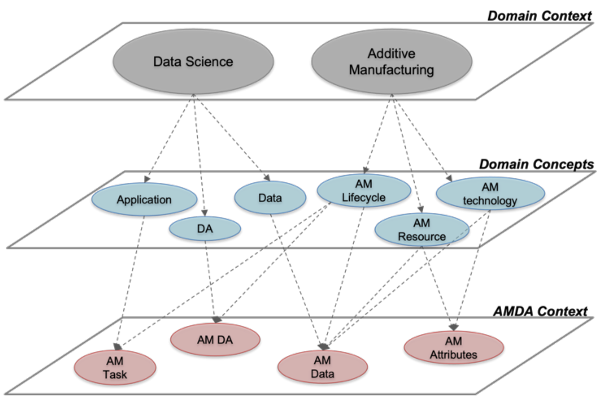

FIGURE 2: AMDA CONTEXTUALIZATION

The foundational concepts of AMDA contextualization are presented in Figure 2. The AMDA process requires an understanding of both AM process and AM data prior to the implementation of DA solutions [9]. Building on this groundwork, the AMDA can be contextualized by defining the integration mapping between the data science context and the AM context. This integration plays a key role in facilitating an in-depth understanding of both AM process and AM data.

AMDA contextualization consists of three layers: the domain context layer, the domain concept layer, and the AMDA context layer. The top layer, defined as the domain context layer, includes the broad domains of data science and AM. Placing the two domains at a high level gives a holistic understanding of AMDA, necessitating an integrative perspective encompassing both data science and AM capabilities.

The intermediate layer referred to as the domain concept layer, represents the essential concepts from each domain context that contribute to the AMDA context. On the data science front, this includes application, DA, and Data. Meanwhile, the AM side includes AM lifecycle, AM resource, and AM technology. Domain concepts represented in this layer are pivotal in bridging the gap between data-driven insights and real-world AM processes.

The bottom layer defined as the AMDA context layer integrates the concepts from the data science context and the AM context in the layer above. This integration is designed to enhance the contextual understanding to support DA solutions aimed at addressing AM tasks. Within the AMDA context layer, several components including AM Task, AMDA, AM Data, and AM Attributes are defined using concepts from both data science and AM domains. AM Task is contextualized by leveraging application and AM lifecycle concepts to describe specific tasks within AM, guiding tailored applications. The AMDA context is supported by DA and AM lifecycle concepts, emphasizing an analytical approach informed by the stages of AM processes. AM data is contextualized by integrating concepts of data, AM lifecycle, and AM technology, providing context for understanding data generated in the stages of AM processes with the resources and technologies applied. Lastly, the AM attribute provides critical characteristics of AM to be analyzed in the AMDA process, describing the relevant concepts of AM resource and AM technology.

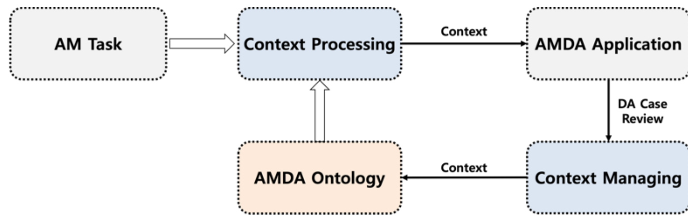

FIGURE 3: CONCEPTUAL FRAMEWORK FOR CONTEXT-AWARE AMDA

Building upon the contextualization of AMDA, we have developed AMDA ontology, detailed further in Section 4. Figure 3 illustrates a conceptual framework for context-aware AMDA by utilizing the developed AMDA ontology. The AMDA ontology provides two functions, context managing and context processing, which support the implementation of the AMDA application to provide data-driven solutions for AM tasks. Employing the ontology enables us to engage in context management by analyzing cases from previously developed AMDA applications. Additionally, the ontology allows us to furnish the specific AMDA context by referencing the details of the AM task through the context processing function.

4 DEVELOPMENT OF THE AMDA ONTOLOGY

4.1 Design of the Ontology

The AMDA ontology is designed with a focus on representing the AMDA context within the realm of established domain contexts and domain concepts. This ontology is structured to provide a pivotal framework for representing AMDA by strategically mapping the interrelations among the data science context, the AM context, and the AMDA context itself. Moreover, the ontology development process follows the three layers of the AMDA conceptualization.

First, the domain context layer branches into two principal classes: the *Data Science Context*, and the *Additive Manufacturing Context*. Subsequently, the domain concept layer acts as a supporting structure, offering subclasses for each of the two principal classes. Within the *Data Science Context*, the subclasses are *Application*, *Data Analytics*, and *Data*. Concurrently, the *Additive Manufacturing Context* is further detailed into subclasses including *AM Lifecycle*, *AM Resource*, and *AM Technology*. Following that, the AMDA context layer is defined as *AMDA Context* class with subclasses including *AM*

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Task, *AMDA*, *AM Data*, and *AM Attributes*. This structure leverages the interplay and relationships between the subclasses of both *Data Science Context* and *Additive Manufacturing Context* to enrich the understanding and application of AMDA.

Classes and properties within the ontology are structured to articulate the AMDA context. Figure 4 illustrates the relations between the high-level classes of the ontology, showing how they interrelate to represent the context of AMDA. First, the subclasses of *Data Science Context* are employed to detail the subclasses within the *AMDA Context*. Specifically, the *Application* subclass is utilized to interpret the *AM Task*, the *Data Analytics* is applied to explain the *AMDA*, and the *Data* is used for clarifying the *AM Data* aspect. Furthermore, the interaction between the subclasses of both the *Additive Manufacturing Context* and the *AMDA Context* plays a crucial role in supporting the interpretation of the AMDA process. This interaction ensures that insights from both additive manufacturing and data science are integrated, enriching in-depth understanding and application of the AMDA process. The *AM Attributes* are characterized by features from the *AM Resource* and the *AM Technology*, offering a reference for interpreting the *AM Data*. The data source of the *AM Data* is specified within the comprehensive scope of the *Additive Manufacturing Context*, including the *AM Lifecycle*, the *AM Resource*, and the *AM Technology*. Moreover, the *AM Data* serves as an input to the *AMDA*, providing support in deploying solutions for the *AM Task*, which in turn facilitates the enhancement of the *AM Lifecycle*.

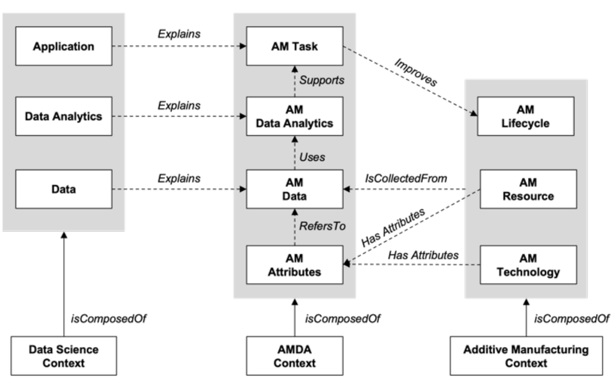

FIGURE 4: RELATIONS BETWEEN THE AMDA ONTOLOGY

Guided by the relations and interaction among the ontology's high-level classes, a comprehensive structure of the AMDA ontology was developed. This structure presents an organized hierarchy of classes and their associated properties, as shown in Figure 5.

The detailed subclasses under the *Additive Manufacturing Context* class are addressed, providing a breakdown of the components within each subclass. The *AM Lifecycle* class is specified into the sequential stages of the AM process, ranging from the initial *Design* class to the final *Evaluation* class. [6] Within the subclasses of *AM Lifecycle*, instances represent specific activities or actions that occur at each stage of the process. The *AM Resource* class includes subclasses such as *Material*, *Equipment*, *Machine*, and *Software* that are utilized during the AM process. The *AM Technology* class refers to the specific print methods utilized for the AM process, with instances such as "*Laser Power Bed Fusion*" representing the technologies that are employed.

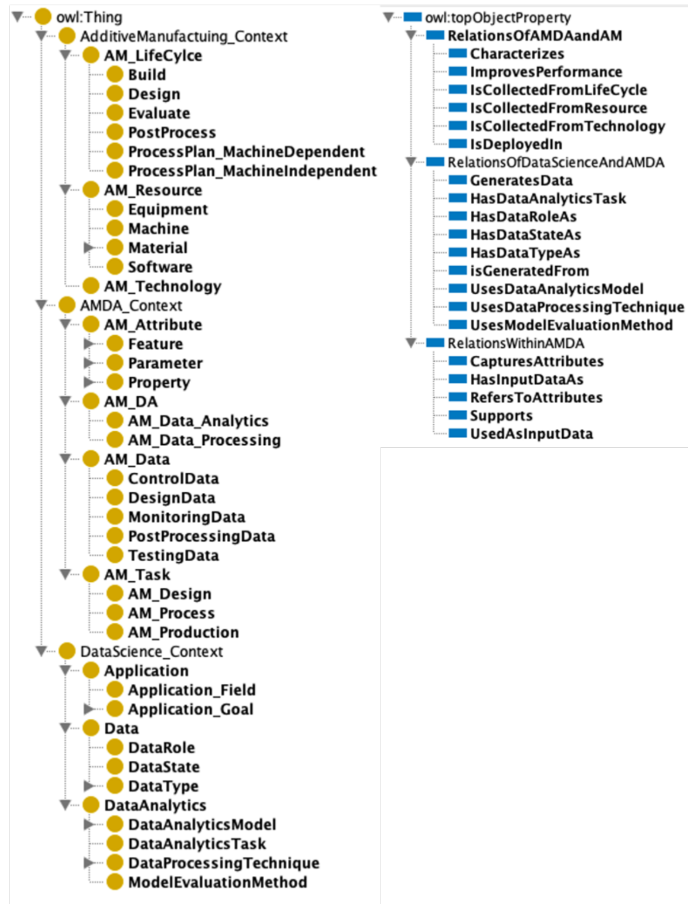

FIGURE 5: THE STRUCTURE OF AMDA ONTOLOGY

For the *AMDA Context* class, the specific classes are defined for *AM Task*, *AMDA*, *AM Data*, and *AM Attributes*. The *AM Task* contains classes such as *AM Design*, *AM Process*, and *AM Production*, describing areas where data-driven support systems are implemented in AM. [22] The *AMDA* has two subclasses, the *AM Data Processing* class and the *AM Data Analytics* class. The instances within these classes are elaborately defined, incorporating the domain concepts of the *Additive Manufacturing Context* and the *Data Science Context*. The AM Data is classified into *Control Data*, *Design Data*, *Monitoring Data*, *Postprocessing Data*, and *Testing Data*. These classes include both predefined data set up prior to the AM process and data generated during the process. The *AM Attribute* is composed of the *Feature*, *Parameter*, and *Property* classes, that explain the AM context influencing AM data. Subclasses within the *AM Attribute* are organized to provide detailed insights; for instance, the *Feature* class encompasses subclasses such as *Design Feature*, *Process Feature*, and *Material Feature*.

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The detailed subclasses under the *Data Science Context* are structured. The *Application* is defined to include subclasses that offer specific details such as the *Application Goal* and the *Application Field*. Meanwhile, the *Data Analytics* class is categorized into subclasses that are utilized for clarifying the *AMDA* class, with subclasses including *Data Processing Technique*, *Data Analytics Model*, *Model Evaluation Method*, and *Data Analytics Task*. The *Data* class is specified with subclasses including *Data Role*, *Data State*, and *Data Type*, providing detailed description of data involved in the AMDA process, such as raw data, generated data, and input data. These components facilitate a comprehensive understanding of the data science elements crucial for AMDA.

Lastly, object properties and data properties are defined to specify the connections among classes, instances, and data values. Object properties elucidate the interactions between the AMDA context and the AM context, the relationships between the data science context and the AMDA context, and the interactions within the AMDA context itself. Figure 5 shows a detailed list of the object properties employed within the ontology, providing clarity on the structured interconnections.

4.2 Using the AMDA Ontology

The AMDA ontology can be used for managing and processing the context of AMDA. In terms of context management, the ontology provides a logic for representing the context with a common structure, enabling dynamic updating and maintenance of contextual information. Also, the AMDA ontology ensures that the contextual semantics of AMDA are well-captured and systematically organized, improving the efficiency and effectiveness of data-driven decision-making in AM. Moreover, context processing takes the context of an AM task and processes it with the AMDA context utilizing the ontology to generate contextual insights for implementing an AMDA solution tailored to the given task. By analyzing the contextual layers and their interrelations within the ontology, context processing enhances the applicability of AMDA, addressing challenges and details of each AM task.

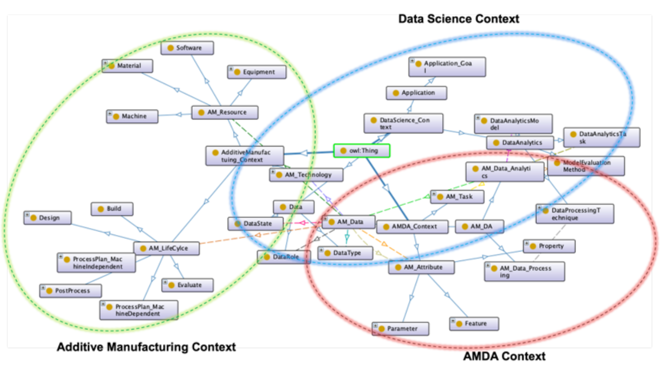

FIGURE 6: OVERVIEW OF THE AMDA ONTOLOGY

As shown in Figure 6, the AMDA ontology can be transformed into a graphical format, unveiling various opportunities. This transformation enables the AMDA ontology to act as a blueprint for constructing a knowledge graph that represents the complex relationships and entities within the domain of additive manufacturing and data analytics. Converting the ontology into a knowledge graph enables the assessment of concept relatedness, enhancing the comprehension of the interplay between various aspects of the AM process and data science. This relational structure promotes the contextualization of data, providing effective data mapping and enriching AMDA with deeper insights.

5 CASE STUDY

In this section, we demonstrate the utility of the AMDA ontology in facilitating context-aware AMDA through case studies. The case studies exemplify how AMDA ontology can provide the common structure of the AMDA context and contextualize the AM data effectively. We focus on two distinct AMDA applications: case 1) Melt pool size classification [23] and case 2) Structure prediction for topology optimization [24], to demonstrate the AMDA ontology.

The AMDA ontology is designed to provide a unified structure that encapsulates the context of AMDA, enhancing the capability for sharing, reutilizing, updating, and maintaining contextual information efficiently. Figure 7 visually shows the AMDA context of two cases: case 1 is described on the left, focusing on melt pool size classification, while case 2 is shown on the right, focusing on the structure prediction for topology optimization. Each instance; "DA1" for case 1, and "DA2" for case 2, adheres to a consistent structure, detailing the context of AM data, DA model, evaluation methodology, DA Task, and AM Task, exemplifying the ontology's role in providing a coherent and comprehensive structure for contextualizing AMDA process.

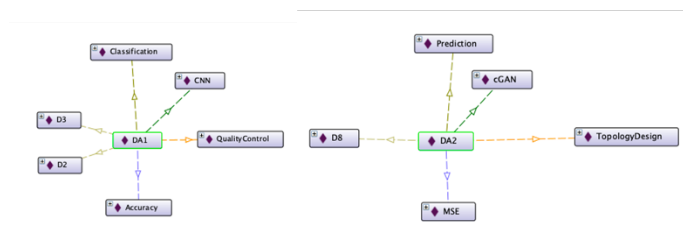

FIGURE 7: THE COMMON STRUCTURE OF THE AMDA CONTEXT

Furthermore, the AMDA ontology facilitates the contextualization of AMDA components, providing a deeper understanding of the AMDA process. This improvement in understanding supports navigating the complexities of AMDA by ensuring that each element is considered within its relevant context, leading to more informed decision-making. Figure 8 and Figure 9 illustrate the AM data contexts from the perspective of AMDA for each respective case.

Figure 8 outlines the data context of case 1, describing how the data is utilized throughout the analysis. The figure uses red arrows to depict the flow and sequence of the context. In this case, "DA1" known as "melt pool classification model" represents the DA model that incorporates "D2" and "D3" as

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input data. Both “D2” and “D3” are derived from the original dataset “D1” through specific preprocessing steps. “D2” is generated by applying the data processing method “DP1”, which conducts “boundary detection” and “labeling” with the original data “D1”. Similarly, “D3” is the product of “DP2”, a data processing method tasked with “resizing” the original data “D1”. According to Figure 8, within the context of “DA1”, “D2” serves as the “Descriptive Data” providing features for analysis, while “D3” is used as “Target Data”, the variable that the DA model seeks to classify.

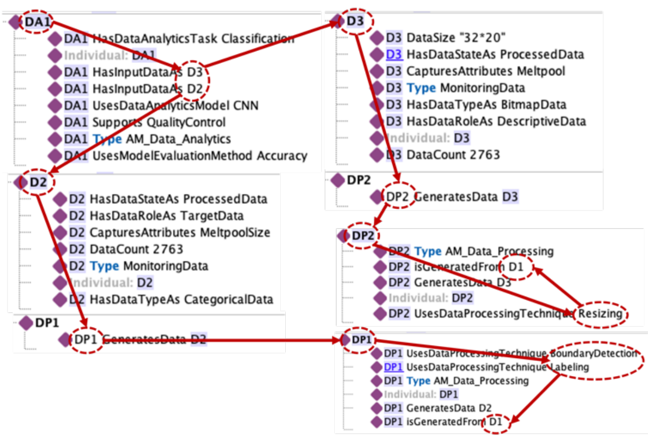

FIGURE 8: AM DATA CONTEXTUALIZATION FOR CASE 1

Figure 9 provides a visualization of the data context for case 2, which focuses on "DA2", known as "structure prediction for topology optimization". The pathway from raw data through to the predictive modeling used in topology optimization is mapped, offering insight into the application of DA. “DA2” employs “D8” as the input data for the “cGAN” model to develop the “prediction” model. The input data “D8” is generated by executing the data processing method “DP3”, which involves “Normalization” of datasets “D4”, “D5”, “D6”, and “D7”. This process underlines the crucial step of preparing and transforming data to ensure it is suitably conditioned for use in sophisticated modeling techniques, such as cGAN, for achieving accurate and effective structure prediction in topology optimization.

FIGURE 9: AM DATA CONTEXTUALIZATION FOR CASE 2

The case studies show how the AMDA ontology supports context-aware AMDA, emphasizing its role in structuring and contextualizing the AMDA context. It is meaningful that we can capture the contextual information of AMDA by referring to the ontology’s standardized structure. This supports the consistent management of contextual information, enhancing the ability to share, update, and maintain the context within AMDA. Moreover, AMDA ontology enables us to trace the flow of contextual information, understand the connections between data-related contexts, and leverage this knowledge within the AMDA process. While the ontology has shown its effectiveness, there is a necessity for future research to focus on the expansion of the ontology’s structure and the actualization of its functions. By doing so, the ontology will not only serve as a conceptual framework but also as a practical tool in the implementation of AMDA systems.

6 CONCLUSION

This paper outlines the development and utilization of the Additive Manufacturing Data Analytics (AMDA) Ontology, enabling context-aware data analytics in AM. The AMDA ontology offers a comprehensive structure that encapsulates the intricate relationships between AM processes, data, and analytics, providing opportunities for enhancing data-driven decision-making in AM. Primary domains essential for contextualizing AMDA were defined, providing the foundation for the AMDA contextualization process.

The development of the AMDA ontology was guided by the three layers of AMDA contextualization. Furthermore, a framework for context-aware AMDA was introduced, leveraging AMDA ontology with functions that facilitate context managing and context processing. Through the transformation of the ontology into a knowledge graph, we have unveiled the potential for advanced analysis and interpretation, enabling stakeholders to better navigate the intricacies of AM and DA.

Further efforts will be focused on refining the ontology, exploring its integration with advanced ML techniques, and validating its effectiveness through additional case studies.

ACKNOWLEDGEMENTS

This work was supported by the Additive Manufacturing Program at the National Institute of Standards and Technology (NIST), U.S. Department of Commerce. Such commercial systems identified in this article do not imply recommendation or endorsement by NIST. Moreover, the contents of this article do not reflect the views of NIST or any other U.S. government.

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