

Received 13 November 2025, accepted 3 December 2025, date of publication 8 December 2025, date of current version 12 December 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3641205

## RESEARCH ARTICLE

# Toward a Digital Ecosystem for Additive Manufacturing Driven by Standards-Based Digital Thread and Digital Twins

EFRAIN RODRIGUEZ<sup>1</sup> AND ALBERTO J. ALVARES<sup>2</sup>

<sup>1</sup>Department of Mechanical and Mechatronics Engineering, The Technological University of Bolívar, Campus Tecnológico, Cartagena, Bolívar 131001, Colombia

<sup>2</sup>Department of Mechanical Engineering, University of Brasilia, Campus Darcy Ribeiro, Brasília 70910-900, Brazil

Corresponding author: Efrain Rodriguez (efrainrg2009@gmail.com)

This work was supported in part by the National Council for Scientific and Technological Development (CNPq), in part by the Foundation for Research Support of the Federal District (FAPDF), and in part by the Deanship of Research and Innovation/University of Brasilia (DPI/UnB).

**ABSTRACT** The ongoing digitalization of manufacturing is transforming how products are designed, produced, and optimized, driven by the convergence of the Digital Thread (DTh) and Digital Twin (DTw) paradigms. However, achieving seamless integration across these technologies remains a major challenge due to persistent issues of data interoperability, consistency, collaboration, and intelligent data exchange throughout the product lifecycle. Moreover, the limited intelligence at the machine level and the fragmentation of data across heterogeneous systems hinder the realization of fully connected, autonomous manufacturing environments. To address these challenges, this work conducts a comprehensive review of the literature on DTh and DTw technologies, focusing on their application in additive manufacturing (AM) and their alignment with international standards for data exchange and system interoperability. Building on this foundation, a unified digital ecosystem for contextualized intelligence is proposed, aiming to integrate DTh and DTw through standardized, semantically rich, and interoperable data flows. Furthermore, a standards-based DTh–DTw framework is presented, leveraging key industrial standards, including STEP/STEP-NC, MTConnect, QIF, OPC UA, MQTT, and ISO 23247, to ensure traceability, real-time synchronization, and data-driven decision-making across the AM lifecycle. Two implementation scenarios validate the proposed approach: (i) an FDM-based AM process using STEP-NC and MTConnect for integrated process planning and monitoring, and (ii) a robotic wire-based LMD cell featuring three DTw implementations compliant with ISO 23247 for real-time simulation, predictive maintenance, and process visualization. These implementations demonstrate the feasibility of constructing interoperable, data-centric manufacturing workflows using open standards. The results underscore the potential of the proposed ecosystem to enhance interoperability, data consistency, and intelligence across manufacturing processes, while also revealing current limitations in AM-specific standardization and cross-platform integration. Although focused on AM, the framework is inherently extensible to other manufacturing domains, paving the way toward standards-driven, intelligent, and generative manufacturing ecosystems.

**INDEX TERMS** Additive manufacturing, digital thread, digital twin, STEP-NC, ISO 23247, ISO 10303-238, data integration, interoperability, industry 4.0, laser metal deposition.

### NOMENCLATURE

<b>AI</b>	Artificial Intelligence.	<b>AP</b>	Application Protocol.
<b>AM</b>	Additive Manufacturing.	<b>API</b>	Application Programming Interface.
		<b>CAD</b>	Computer-Aided Design.
		<b>CAI</b>	Computer-Aided Inspection.
		<b>CAIP</b>	Computer-Aided Inspection Planning.

The associate editor coordinating the review of this manuscript and approving it for publication was Zhiwu Li<sup>1</sup>.

<b>CAM</b>	Computer-Aided Manufacturing.
<b>CAPP</b>	Computer-Aided Process Planning.
<b>CMM</b>	Coordinate Measuring Machine.
<b>CNC</b>	Computer Numerical Control.
<b>CPS</b>	Cyber-Physical System.
<b>DCDCE</b>	Data Collection and Device Control Entity.
<b>DTw</b>	Digital Twin.
<b>DTwE</b>	Digital Twin Entity.
<b>DTUE</b>	Digital Twin User Entity.
<b>DTh</b>	Digital Thread.
<b>DThE</b>	Digital Thread Entity.
<b>FDM</b>	Fused Deposition Modeling.
<b>GD&amp;T</b>	Geometric Dimensioning and Tolerancing.
<b>IoT</b>	Internet of Things.
<b>ISO</b>	International Organization for Standardization.
<b>LMD</b>	Laser Metal Deposition.
<b>MBSE</b>	Model-Based Systems Engineering.
<b>MQTT</b>	Message Queuing Telemetry Transport.
<b>MTConnect</b>	Manufacturing Technology Connect.
<b>NIST</b>	National Institute of Standards and Technology.
<b>OME</b>	Observable Manufacturing Element.
<b>OPC UA</b>	Open Platform Communications Unified Architecture.
<b>PLM</b>	Product Lifecycle Management.
<b>QIF</b>	Quality Information Framework.
<b>SOM</b>	System-Oriented Modeling.
<b>STEP</b>	Standard for the Exchange of Product Model Data.
<b>STEP-NC</b>	Standard for the Exchange of Product Model Data – Numerical Control.

## I. INTRODUCTION

In today's fast-paced and increasingly interconnected world, digitalization has emerged as a transformative force, changing not only how people live, but also the socio-economic and industrial sphere worldwide [1]. Digitalization can be referred to as the "integration of digital technologies into everyday life by the digitization of everything that can be digitized", according to the Business Dictionary (2015) [2]. However, this digital transformation goes beyond just digitizing analog processes (digital enablement) or improving existing digital ones (digital optimization) [3]. It represents a complete paradigm shift that utilizes cutting-edge digital technologies to generate value for new products/processes, organizations, and businesses. By embracing this transformation, modern companies can unlock new sources of revenue, improve profitability, and create innovative opportunities to better serve their customers across a wide range of sectors, including the manufacturing industry.

This highly impactful degree of digitalization is triggering an authentic renaissance in the realm of manufacturing, manifesting in the form of the fourth industrial revolution, the so-called Industry 4.0. Industry 4.0 aims to transform traditional industrial production systems into a new generation of Smart Factories for the future that are characterized by increased intelligence, flexibility, reconfigurability, and sustainability [4]. To achieve this, Industry 4.0 emphasizes the integration of advanced manufacturing systems and new generation information technologies (new IT) such as Cyber-Physical Systems (CPS), Internet of Things (IoT), Cloud Computing, Artificial Intelligence (AI), and Big-Data Analytics [5]. Various Industry 4.0 initiatives have emerged globally, all aiming to enhance industrial efficiency and competitiveness through intelligent and autonomous manufacturing systems, paving the way for Smart Manufacturing [6]. Recently, marking a decade since the inception of Industry 4.0, the European Commission unveiled Industry 5.0, an evolved paradigm that prioritizes a value-driven approach, focusing on human-centric, resilient, and sustainable manufacturing systems [7]. This trajectory indicates a shift toward Generative Manufacturing Systems (GMS), where human-centered oversight and generative AI converge to manage complexity in dynamic industrial environments [8].

At the forefront of this digitalization wave, Digital Thread (DTh) and Digital Twins (DTw) are pivotal technologies for Industry 4.0, enabling the realization of smart manufacturing. These concepts thrive on data, which serve as the lifeblood flowing through the veins of advanced information systems in the modern manufacturing environments. The DTh enables a continuous and traceable flow of data across all phases of a product's lifecycle, from design and manufacturing to operation and end-of-life, supporting systems interoperability and informed decision-making. In contrast, DTws are dynamic, virtual representations of physical assets that can exist at any point along the DTh, serving as real-time mirrors to analyze, predict, and optimize performance across the lifecycle. In essence, the DTh aligns more closely with lifecycle management, while the DTw resonates with advanced simulation, real-time monitoring and operational intelligence. Both technologies are crucial for companies to extract maximum value from the extensive data generated across the product development lifecycle, offering cohesive and intelligent approaches to integrate data, knowledge, and processes. However, achieving their full implementation poses significant challenges, especially for manufacturing systems in small and medium-sized enterprises, where constraints in financial resources, infrastructure, and technological expertise hinder their seamless adoption and integration.

According to a study [9], companies are missing up to 65% of the potential value of their DTws by relying on the development of standalone DTws for a single purpose. To unlock this value, there should be a systematic integration and interoperability between DTh and DTws. The

conventional “throw it over the wall” approach to department handovers involves disjointed processes, from 3D model creation to production, leading to data silos and inefficiencies [10]. These problems are primarily attributed to the heterogeneity of: data itself, file formats for data exchange, communication protocols, and existing implementation frameworks.

In particular, in additive manufacturing (AM) processes, its DTh traditionally encounters multifaceted challenges that impede seamless data integration, sharing, and interoperability across its various stages. These challenges contribute to inefficiencies and bottlenecks in the AM process. Information isolation and loss hinder a holistic understanding of the manufacturing context, leading to suboptimal decision-making. Redundant information and diverse file formats increase the complexity of data management and sharing, creating barriers to effective collaboration. The unidirectional data flow restricts the establishment of feedback loops essential for real-time adjustments and optimizations. Moreover, the limited intelligence of machine CNC controllers limits adaptive and intelligent control over the manufacturing process [11]. Reproducibility also remains a significant hurdle, as inconsistencies in data handling can lead to variations in the final product quality, undermining reliability and repeatability in production [12].

To address these challenges, this work envisions the development of a comprehensive digital ecosystem for AM grounded in a high-level, standards-based DTh seamlessly integrated with DTws. Through the adoption of standardized and semantically rich data models, the proposed ecosystem enables consistent information flow across design, manufacturing, and inspection stages. This integration fosters interoperability, data coherence, and real-time feedback to support informed decision-making throughout the AM lifecycle. By leveraging standards such as STEP, STEP-NC, QIF, MTConnect, OPC-UA, MQTT, ISO 23247 and ISO 23704, the envisioned ecosystem aims to establish a digitally connected environment that promotes interoperability, collaboration, and intelligent automation, ultimately aligned with the principles of Industry 4.0.

The subsequent contents of this paper are as follows. Section II reviews research on DTh in AM, focusing on lifecycle integration and data exchange formats. Section III surveys DTw frameworks and reference models for manufacturing. Section IV presents a comparative analysis between DTh and DTw concepts. Section V introduces the proposed Unified Framework for Contextualized Intelligence, addressing the systematic integration of DTh and DTw. Section VI presents a Standards-Based Ecosystem Framework grounded in open industrial standards such as STEP, STEP-NC, MTConnect, and ISO 23247. Section VII illustrates two implementation scenarios, one for FDM and another for LMD, developed under the proposed framework. Finally, Section VIII concludes the paper and outlines future research perspectives.

## II. SURVEY ON DTH IN AM

AM, or 3D printing, encompasses a family of technologies that build three-dimensional objects by adding material layer by layer directly from digital models. According to ISO 52900, AM is defined as the “process of joining materials to make parts from 3D model data, usually layer upon layer, as opposed to subtractive and formative manufacturing methodologies” [13]. This approach enables the creation of complex geometries without dedicated tooling, minimizing waste and production costs while allowing for greater design flexibility and customization. Over the past decade, AM has evolved from a prototyping tool into an established manufacturing method, widely adopted in aerospace, automotive, biomedical, and construction industries. Its contribution to sustainability and digital transformation aligns closely with the principles of Industry 4.0, promoting reduced material use, distributed production, and more responsive supply chains. As noted by Butt [14], integrating DTh concepts into AM reinforces these advantages by improving traceability and enabling smarter, data-driven manufacturing workflows.

AM processes can be applied across four main production domains, as illustrated in Figure 1: i) rapid prototyping, for fast and cost-effective validation of designs; ii) re-manufacturing, which enables component repair and refurbishment without traditional recycling; iii) on-demand production, reducing inventories and logistical constraints; and iv) direct manufacturing of end-use parts, supported by advanced materials and machine capabilities. Managing the data generated across these domains is essential for improving efficiency and product quality. In this context, the DTh and DTw provide the digital infrastructure needed to connect design, production, and inspection activities. The DTh links process and product data across stages, while the DTw interprets this information in real time to monitor conditions, support decision-making, and adjust process parameters when necessary. Their combined use strengthens data continuity and process understanding, contributing to more reliable and efficient AM operations.

### A. STATE OF THE ART ON THE DTH IN AM

The objective of this review is to synthesize how the DTh has been conceptualized and implemented in manufacturing, with particular attention to its application in AM. Beyond a descriptive overview, the review seeks to identify coherent trends and gaps in how data standards, information models, and integration patterns contribute to lifecycle continuity, interoperability, and DTw readiness. In doing so, a complementary goal was to determine whether systematic methodologies or frameworks have been proposed to guide the practical integration of DTh and DTw, an aspect often mentioned in theory but rarely articulated through explicit and replicable approaches. To this end, the selection of sources focused on works that (i) propose or validate DTh architectures for AM; (ii) map open standard

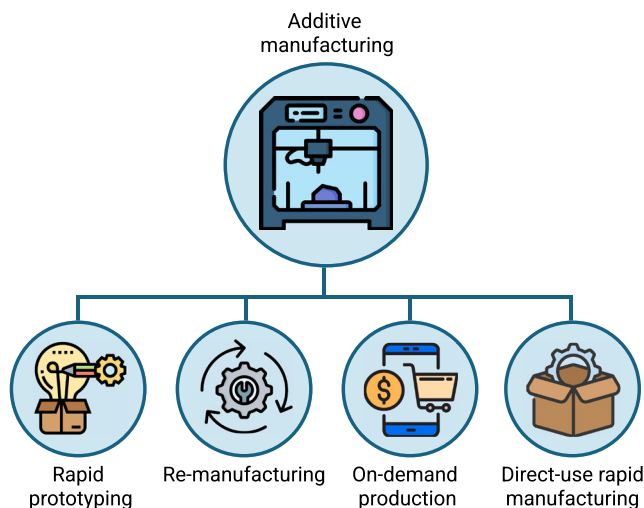


FIGURE 1. Production domains of AM processes.

technologies to specific lifecycle stages; and (iii) demonstrate implementation or validation evidence through software tools, datasets, or industrial case studies.

The notion of DTh was first introduced by Cohen in 2010 in the context of aerospace composites manufacturing, where it was envisioned as an end-to-end digital backbone interlinking design, production, and lifecycle management [15]. Later formalized through initiatives such as the U.S. Air Force Global Horizons report [16] and NIST definitions [17], the DTh evolved into a cross-domain framework supporting real-time assessment and decision-making throughout the product lifecycle.

NIST’s research has been instrumental in shaping this vision through cyber-physical testbeds, graph-based data linkage methods, and multi-layered architectures balancing interoperability with intellectual property protection [18], [19], [20]. The vision of the NIST Smart Manufacturing Systems (SMS) Test Bed for the DTh centers on integrating data across the as-designed, as-planned, as-executed, and as-inspected phases of the product lifecycle, as illustrated in Figure 2. This integration relies on open standards such as STEP AP242, G-code, MTConnect, and QIF (Quality Information Framework) to enable consistent data exchange across domains. Building on this foundation, Kwon et al. [21] extended the concept toward automated quality assurance by combining STEP (as-designed) and QIF (as-inspected) data through ontologies and knowledge graphs. Their approach generates linked knowledge representations, aligns them via semantic mappings, and enables rule- and query-based reasoning to enhance traceability and decision-making in product qualification. Collectively, these initiatives promote structured provenance across the “as-designed, as-planned, as-executed, and as-inspected” stages, forming the foundation of the modern DTh. More recent work expands this toward DTw-oriented implementations that combine design optimization, process monitoring, and predictive

simulation [22]. Overall, the DTh has evolved from an abstract digital backbone into an implementable, standards-based infrastructure supporting lifecycle completeness and interoperability across heterogeneous systems.

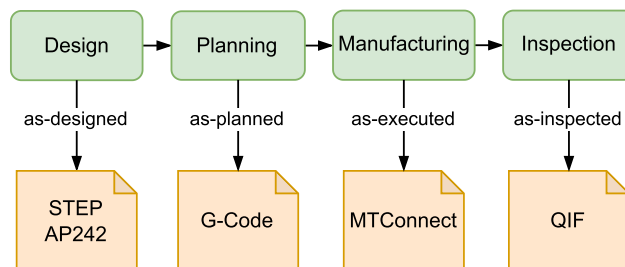


FIGURE 2. The vision of a standards-based DTh from the NIST SMS test bed. Adapted from [21].

In AM, the DTh represents the continuous and contextualized flow of information describing the what, how, where, who, when, and why of each process step [23]. Early approaches such as those by Nassar and Reutzel [24] structured this flow into four main phases (blue boxes in Figure 3): design, process planning, execution, and verification; later expanded by Kim et al. [23] into eight granular stages (purple boxes in Figure 3) ranging from CAD geometry to validated part, and further extended by Bonnard et al. [25] and Rodriguez et al. [11] to include delivery and end-of-life (orange box in Figure 3) activities such as maintenance, repair, and remanufacturing (green box in Figure 3). These feedback loops create circular data flows, reinforcing traceability, process efficiency, and innovation across the AM value chain, including feedback mechanisms that enable re-entry of components into earlier stages for repair or reuse.

A systematic search in Scopus retrieved 75 publications between 2013 and 2025 that address the DTh in AM. The growing number of studies after 2018 reflects the strong convergence between DTh concepts and Industry 4.0 trends. Figure 4 shows the annual distribution of publications, highlighting the consistent growth of this topic and the consolidation of research activity in the most recent years. From this broader corpus, 29 works were identified as making substantial contributions, summarized in Table 1, which categorizes each study according to its purpose, technological scope, standards employed, and relevance to DTh–DTw integration.

Early works centered on file-based data exchange, such as the XML-based extensions of the AMF format proposed by Nassar and Reutzel [24] (AMSF, AMPF, AMQF, and AMVF), which enabled a consistent but lightweight representation of slicing, path, and qualification data. While these structures ensured readability and portability, they offered limited semantic richness and weak coupling with DTw integration. In contrast, the federated architectures proposed by NIST introduced standardized interfaces and information maps designed to overcome

TABLE 1. Summary of reviewed works on DTh in AM.

Reference	Purpose	Stage/Work Type	Technologies/Standard	Key Highlights
Nassar and Reutzel [24]	Define a unified paradigm for data exchange in AM.	Proposal	XML, ASTM F291, AMF extensions (AMSF, AMPF, AMQF, AMVF).	Early comprehensive AM DTh vision covering full lifecycle.
Kim et al. [23], [26]	Develop a federated information systems architecture and certification for AM.	Proposal	Federated architecture, information map.	Streamlines design-to-product transformations through interoperability and certification.
Bonnard et al. [25], [27]–[29]	Propose a STEP-NC based high-level digital DTh for AM	Proposal, Review, Implementation	STEP-NC, Object-oriented modeling	Proposes a hierarchical object-oriented model based on STEP-NC to support the AM DTh.
Mies et al. [30]	Introduce AM Informatics for lifecycle data management.	Review	Data mining, simulations.	Emphasis on reproducibility, qualification, and innovation.
Belkadi et al. [31]	Model AM value chain for semantic interoperability.	Proposal	Business Process Modelling Notation.	Connects design and production processes across stakeholders.
Xiao et al. [32], [33]	Review AM data formats for GD&T and PMI.	Review, Proposal	STL, AMF, STEP.	Advocates STEP-AM as basis for standardized geometry and tolerances.
Pei et al. [34]	Evaluate AM standards for redistributed manufacturing.	Review/Survey	STL, AMF, 3MF, STEP, STEP-NC.	Identifies key features for RDM; highlights AMF and STEP-NC.
Mahan et al. [35]	Study scan-to-print errors with low-cost scanners.	Experiment, Implementation	S2P workflows, HMM.	Identifies acquisition errors; manual corrections ineffective.
Bonham et al. [36]	Implement DTh for customized kayak production.	Case study	PLM systems, collaborative tools.	Demonstrates remote AM and user-driven customization.
Gupta et al. [37]	Analyze AM supply chains and cybersecurity risks.	Proposal/Analysis	Cyber-physical systems, risk models.	Links DTh with supply chain security and attack vectors.
Sjarov et al. [38]	Propose digitally integrated process chains for PBF.	Proposal, Architecture	Semantic technologies, integration patterns.	Provides building blocks for cost/quality transparency.
Xiong et al. [39]	Define intelligent AM and design (IAMD).	Proposal, Conceptual	Triple-layer model: DTh, CPS, services.	Positions DTh as enabler of AI-driven AM ecosystems.
Knapp et al. [40], [41]	Connect DTh with multiscale simulations.	Implementation, Software	Myna platform, PBF datasets.	Automates simulation workflows for digital twin validation.
Karadgi et al. [42]	Conceptualize end-to-end data integration.	Proposal, Framework	Real-time monitoring, adaptive control.	Maps AM data streams into DTh for predictive quality.
Feng et al. [43]	Identify requirements for DT–DTh integration.	Case study	Sensors, monitoring systems.	Highlights barriers to reliable part qualification with DTs.
Poka et al. [44]	Create unified file format for PBF-LB/M workflows.	Implementation, Case study	Advanced formats, CAD–CAM integration, DT.	Eliminates metadata loss; ensures cross-machine portability.
Xiao et al. [45]	Extend STEP-NC for knowledge discovery in AM.	Review/Proposal	STEP-NC, OntoSTEP.	Proposes semantic-rich extensions for AM DTh.
Furferi [46]	Discuss GD&T challenges in AM.	Perspective/Proposal	GD&T frameworks, MBD.	Calls for AM-specific tolerancing standards and inspection methods.
Research from our lab [11], [47]–[50]	Propose to advance toward a DTh integrated with DTws, grounded in standards for data exchange and the management of contextualized information and closed-loop feedback with inspection data in AM	Review, Proposal, Implementation	STEP-NC, MTConnect, MQTT, OPC-UA, Digital Twins, ISO 23247, FDM, LMD	Emphasizes on standards-based DTh and DTws for AM and closed-loop feedback from inspection

proprietary silos, fostering reproducibility, certification, and traceability across the design-to-product workflow [23], [26].

Subsequent research advanced model-based and semantically enriched frameworks grounded in open standards such as STEP and STEP-NC. Bonnard et al. [28], [29] developed hierarchical object-oriented models (HOOM) that integrate CAD, CAPP, CAM, and CNC data into a single digital chain, while Xiao et al. [32], [45] proposed extensions such as OntoSTEP-NC, incorporating semantic layers, PMI, and GD&T information to support knowledge-driven interoperability and automated reasoning. Parallel studies explored distributed and cloud-based integration strategies: Pei et al. [34] examined AM standards for redistributed manufacturing, Bonham et al. [36] implemented user-driven DTh

workflows for customized production, and Knapp et al. [41] linked DTh data to multiscale simulations using the Myna platform. Complementary works by Feng et al. [43] and Furferi [46] addressed barriers in DT–DTh synchronization and challenges in AM-specific tolerancing and inspection standards.

From this analysis, three main technological lines can be distinguished. The AMF/XML stream provides simplicity and portability but limited semantic capacity. The STEP/STEP-NC-based line ensures feature-level continuity and traceability throughout the lifecycle, supporting DTw synchronization and model-based certification. Finally, semantic and distributed frameworks, often relying on ontologies, cloud computing, and real-time data transport protocols such as MQTT, OPC UA, or MTConnect, bridge

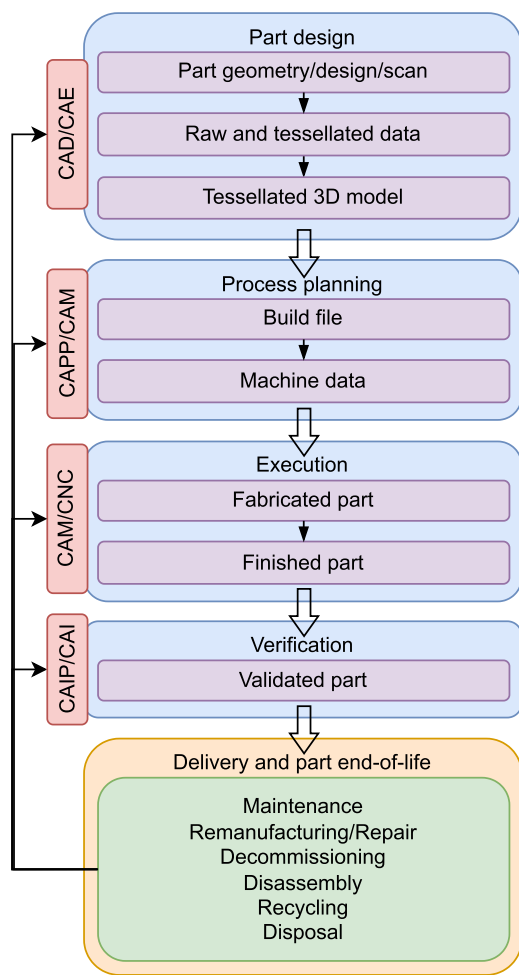


FIGURE 3. Overview of the AM digital thread.

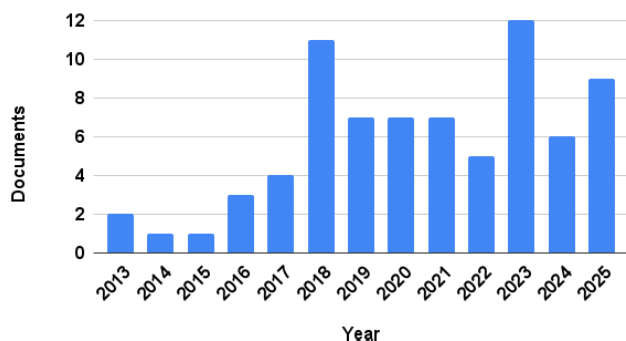


FIGURE 4. Publications by year on DTh in AM using the query TITLE-ABS-KEY (“additive manufacturing” OR “3D printing” OR “rapid prototyping”) AND (“Digital Thread” OR “Digital Chain”).

the gap between static data exchange and dynamic, context-aware monitoring.

Despite these advances, the review reveals a persistent lack of systematic methodologies explicitly guiding the integration between DTh and DTw. Most studies discuss interoperability conceptually but stop short of formalizing

concrete workflows or implementation patterns that ensure consistent synchronization between physical and virtual entities. This observation reinforces the motivation for the framework proposed in this work, which formalizes such integration through standards-based mechanisms and feedback loops across multiple manufacturing domains.

**B. FILE FORMATS ENABLING DATA EXCHANGE IN THE AM DTH**

Efficient data exchange across the AM lifecycle depends on interoperable file formats capable of linking geometry, materials, and process data within a consistent digital framework. Several studies have compared existing representations, highlighting both their diversity and fragmentation. Qin et al. [51] conducted one of the most comprehensive evaluations, classifying over twenty formats used for 2D and 3D representation in AM. Their analysis emphasized criteria such as data coverage, geometric accuracy, reparability, interoperability, and practical applicability, revealing that no single format yet provides full lifecycle integration. Kumar et al. [52] later reinforced these findings, comparing 3D model and 2D slice-based representations and underscoring the persistent trade-off between simplicity and expressiveness.

Table 2 summarizes the most relevant AM file formats and their suitability for supporting the DTh. Early standards such as STL (Standard Tessellation Language), AMF (Additive Manufacturing File Format), 3MF (3D Manufacturing Format), OBJ (Wavefront Object), and CLI (Common Layer Interface) remain widely used but are mostly geometry-centric. They describe shapes through tessellations or slices and include limited metadata, often lacking material, tolerance, or process information, making them unsuitable for lifecycle traceability. Because they do not represent semantic or contextual relationships among product, process, and inspection data, they fall short of enabling the interoperability and feedback loops required in a high-level DTh. Newer formats like OVF (Open Vector Format) [53] improve efficiency and data compactness for metal AM but still lack standardized semantics for full end-to-end data integration.

Within this landscape, the STEP [58] and STEP-NC [59], [60] standards stand out as the most promising enablers of a high-level, standardized DTh for AM [11], [28], [50]. STEP provides a comprehensive, semantically rich structure for representing geometry, tolerances, and manufacturing features, while STEP-NC extends these capabilities down to the machine-control level by embedding process, operation, and resource information. This dual structure bridges CAD, CAM, CAPP, and CNC domains, enabling seamless data continuity from design to production. Several authors noted the potential of STEP-NC to support redistributed, cloud-based and robotic manufacturing environments [28], [34], [61], integrating product and process data within a single, machine-interpretable model.

As highlighted in recent work from our lab [11], extending STEP-NC to include layer-based operations, process

**TABLE 2.** Comparative benchmark of most common AM file formats.

Format	Standardization / Origin	Data Representation	Strengths	Limitations	Relevance to DTh / CNC-level support
STL [54]	3D Systems (1987), industry de facto standard.	Tessellated geometry using triangular facets.	Simple, robust, widely adopted; easy conversion from CAD.	Redundant data, no support for color, materials, or tolerances; prone to errors in normals and intersections.	Foundational format for AM but limited to geometry; does not support high-level process lifecycle data.
AMF [55]	ISO/ASTM 52915 (2013), XML-based.	Tessellated geometry, materials, color, metadata.	Standardized, extensible, supports multiple attributes, open development.	Issues with normals and slicing; adoption not universal.	Recognized format for DTh proposals; enables partially lifecycle data integration.
3MF [56]	3MF Consortium (Microsoft-led), XML-based.	Triangular meshes, with material and property segments.	Compact, unambiguous, human-readable, open access.	Limited adoption; lacks curved triangles, reducing accuracy.	Designed to overcome STL/AMF gaps; facilitates CAD-AM interoperability.
OBJ [57]	Wavefront Technologies (1990s), open-source.	Tessellations, free-form curves/surfaces; material template library for textures/colors.	Supports multi-color and multi-material; flexible encoding.	Complex repair/editing; requires paired MTL files.	Useful for color/texture-rich AM applications; less suited for full DTh workflows.
CLI [51]	Commission of the European Communities.	2D slice-based data (layer thickness, contours, hatches).	Machine-independent, efficient for slicing phase.	Restricted to layer data; lacks lifecycle or semantic information.	Relevant to slicing stage in DTh, but not suitable for complete chain integration.
OVF [53]	RWTH Aachen University and Fraunhofer ILT (2024), open-source.	Binary, process-oriented vector data using Protocol Buffers; includes geometry, laser parameters, and scan data.	Compact and efficient; supports distributed data processing and networked control; open-source and manufacturer-independent.	Still in early adoption; primarily validated in research environments; limited software integration.	Designed for LPBF and metallic AM; supports CNC-level control, process monitoring, and interoperability within Industry 4.0 architectures.
STEP / STEP-NC [58], [59]	ISO 10303 (STEP), ISO 14649 (STEP-NC).	Semantic-rich product and process data; integrates CAD, CAM, CAPP, CNC, CMM.	Standardized, interoperable, supports geometry, tolerances, and process planning.	Complex implementation; adoption in AM slower than in machining.	Strong candidate for full high-level DTh; explicitly designed for supporting the entire product/process lifecycle including CNC-level interoperability.

parameters, and material behaviors represents an important step toward a more integrated digital ecosystem for AM. Incorporating these elements into future revisions of the standard would enhance interoperability and allow DTWs to access richer, standardized process data. Such integration is essential to support adaptive and feedback-driven manufacturing, improving process stability and part quality while helping to detect and correct machine deviations that affect production accuracy and consistency [62].

As illustrated in Figure 5, several entities for representing AM process information have already been proposed for inclusion in the latest revision of ISO 10303-238 [60], [63], establishing a foundation for the standardized description of AM operations within the STEP-NC data model. Building on this progress, Milaat et al. [64] introduced entities to capture key parameters in PBF processes, including beam diameter, path mode, laser power, powder flow, scan speed, and scan strategy, while Rodríguez et al. [11] proposed data entities to cover process parameters and machine functions related to FDM and LMD processes. These

additions define process- and machine-specific data such as deposition parameters, operational functions, and layer-based behaviors. Overall, these developments demonstrate growing momentum toward extending STEP-NC beyond subtractive manufacturing, reinforcing its potential as a unifying data model for AM. By enabling a consistent and semantically rich representation of process information, STEP-NC provides a practical foundation for integrating AM workflows within a high-level DTh and for future alignment with DTW architectures.

### III. SURVEY ON DTW IN AM

#### A. THE DTW CONCEPT

The concept of DTWs has emerged as one of the most transformative innovations in modern manufacturing. First introduced by Dr. Michael Grieves in 2003 within the context of product lifecycle management (PLM) [65], DTWs are built on the integration of a physical entity, its virtual counterpart, and the continuous bidirectional flow of data between them. Over time, advances in IoT, cloud computing, big data,



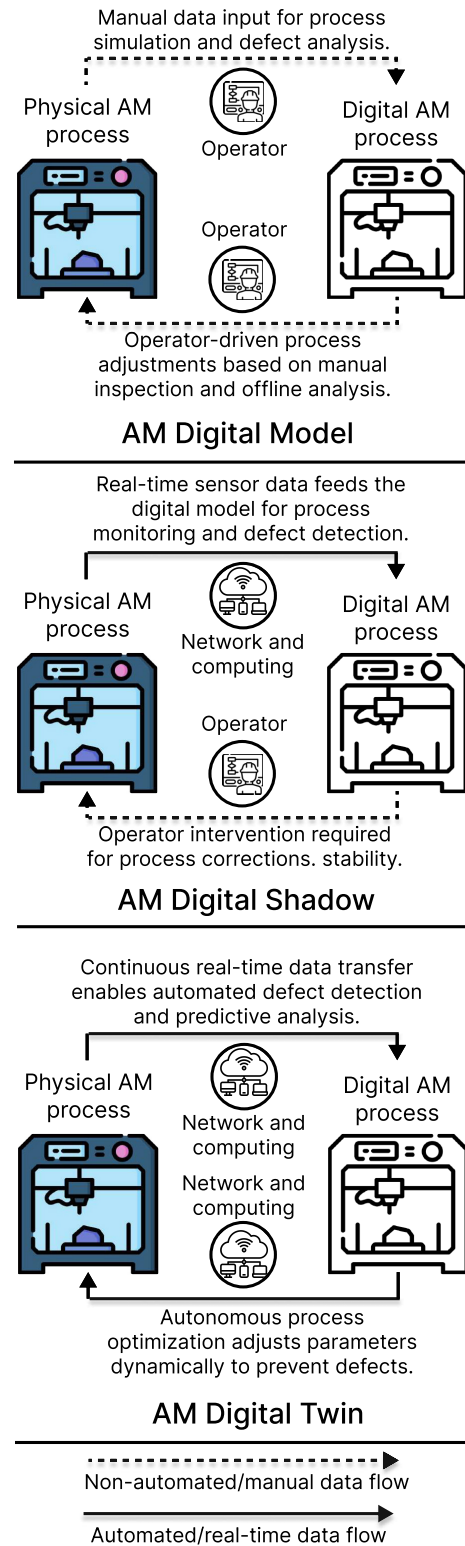
Kritzinger et al. [70] distinguish between a digital model (manually updated), a digital shadow (real-time, one-way data flow from physical to virtual), and a digital twin (bidirectional synchronization). Chen et al. [71] further refine this view by highlighting autonomy: whereas models and shadows rely on human intervention, full twins enable autonomous information exchange and adaptive control, with humans acting mainly as supervisors. Figure 6 illustrates how these levels of integration manifest in AM processes, exemplifying their progressive role in monitoring and defect control. At the digital model level, analysis and defect detection are performed offline through simulation or inspection. The digital shadow enables real-time monitoring by streaming sensor data from the process, allowing early detection of anomalies. A fully developed DTw closes the loop, dynamically adjusting process parameters based on live feedback, thereby improving quality, efficiency, and process stability with minimal human intervention.

**B. REFERENCE MODELS FOR DTWS**

Several reference models have been proposed to conceptualize and structure the DTw framework in manufacturing. The three-dimensional model, first introduced by Grieves [65] and shown in Figure 7(a), defines the DTw as an interconnected system composed of a physical entity, its virtual counterpart, and the bidirectional data flow between them. Building on this idea, Lu et al. [72] proposed an extended three-component model for smart manufacturing (Fig. 7(b)), comprising an information model for mapping physical assets, a data processing module to generate digital representations, and a two-way communication layer that enables synchronization between physical and digital spaces.

Tao et al. [73] advanced this concept through a five-dimensional DTw model that integrates physical and virtual components with data, connections, and service layers. This holistic structure supports simulation, decision-making, and real-time control, reinforcing DTws as key enablers of smart manufacturing. In the machining domain, STEP Tools, Inc. [74] developed an interoperable DTw framework (Figure 8) that demonstrates closed-loop manufacturing through integration of design, process planning, and inspection data. The system uses standards such as STEP-NC (ISO 14649), MTConnect, and QIF to facilitate data interoperability across CAD/CAM/CNC stages, enabling real-time monitoring and feedback via standardized communication protocols.

Beyond these efforts, various researchers have explored complementary DTw architectures. Alam and El Saddik [75] introduced a cloud-based CPS model (C2PS) incorporating intelligent control through fuzzy logic and Bayesian networks. Similarly, Aheleroff et al. [76] proposed a DTw-as-a-Service (DTaaS) framework for Industry 4.0 applications, demonstrating its utility in predictive maintenance, real-time monitoring, and remote operation. Additional works [77],



**FIGURE 6.** DTw categories for AM processes.

[78], [79], [80] further enrich the field, presenting diverse perspectives that collectively contribute to shaping the evolving landscape of DTw frameworks in manufacturing.

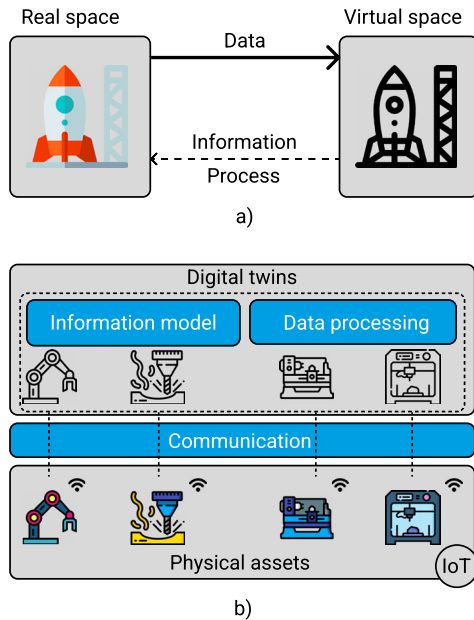


FIGURE 7. Three-dimensional reference models for DTs: (a) adapted from [65]; (b) adapted from [72].

- **Part 2 – Reference architecture [82]:** presents a generic architecture model for manufacturing DTws, outlining interactions among system domains.
- **Part 3 – Digital representation of manufacturing elements [83]:** identifies the physical elements to be represented within the DTw environment.
- **Part 4 – Information exchange [84]:** specifies requirements for data synchronization and communication across DTw components.
- **Part 5 – Digital Thread for Digital Twin (draft) [85]:** describes how the Digital Thread enables DTw creation, connectivity, and lifecycle management through standardized principles and methodologies.
- **Part 6 – Digital twin composition (draft) [86]:** specifies digital twin composition in manufacturing by defining principles, showing methodologies, and providing use case examples of configuration, communication, combination and collaboration between digital twins during manufacturing.

Figure 9 illustrates the ISO 23247 Part 2 reference framework [82], which defines four core domains. The Observable Manufacturing Elements (OME) domain includes machines, sensors, materials, and processes requiring monitoring and control. The Data Collection and Device Control Entities (DCDCE) domain manages the acquisition of sensor data and actuator control, ensuring synchronization between physical and digital entities. The DTw domain provides services for simulation, management, analysis, and optimization, functioning as the core of the framework. Finally, the DTw User domain comprises the human or system entities that consume DTw services. A cross-system layer complements these domains by providing essential services such as information exchange, data assurance, and cybersecurity, ensuring robust interoperability and coordinated operation across the DTw ecosystem.

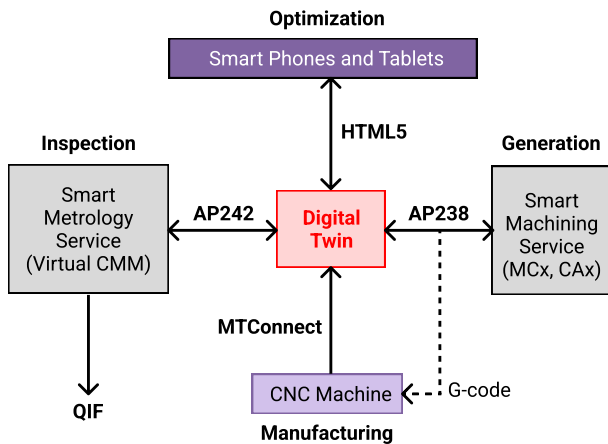


FIGURE 8. Digital Twin framework for machining proposed by STEP Tools, Inc. Adapted from [74].

### C. ISO 23247: DTW REFERENCE FRAMEWORK FOR MANUFACTURING

Published in 2021 by ISO TC 184/SC 4, the ISO 23247 standard [68] establishes a comprehensive reference framework for developing DTws in industrial manufacturing within the context of Industry 4.0. Its main objective is to guide the design, implementation, and integration of DTw systems, promoting interoperability, data consistency, and the seamless synchronization of information between physical and digital domains [81]. The framework is structured into four published parts, with a fifth and sixth currently under development:

- **Part 1 – Overview and general principles [68]:** defines key concepts, requirements, and general guidelines for DTw development.

### D. RESEARCH ON DTW IN AM

This section reviews research on DTw technologies in AM, emphasizing how these systems extend the DTh into real-time, model-driven process intelligence. The goal is not only to trace the growth of this research area but also to identify how DTw implementations, particularly those aligned with the ISO 23247 standard, are shaping standards-based, interoperable digital ecosystems for AM. A systematic search in Scopus was conducted using the keywords “additive manufacturing,” “3D printing,” and “digital twin.” The results show an exponential increase in related publications, reflecting the strategic relevance of DTws in AM. As illustrated in Figure 10, the number of studies rose from a single paper in 2016 to more than 225 in 2024, and 2025 already shows high momentum with 167 publications. This trend demonstrates how DTws are consolidating as key enablers of intelligent, data-driven manufacturing, supporting predictive control, closed-loop feedback, and virtual commissioning.

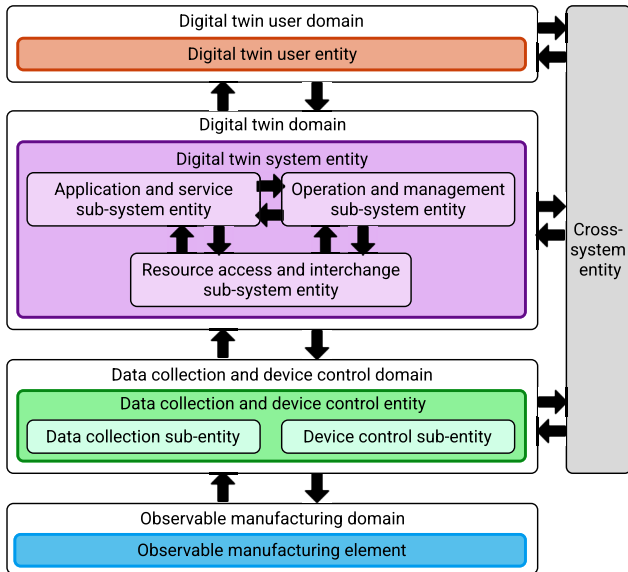


FIGURE 9. DTw reference framework for manufacturing from ISO 23247. Adapted from [68].

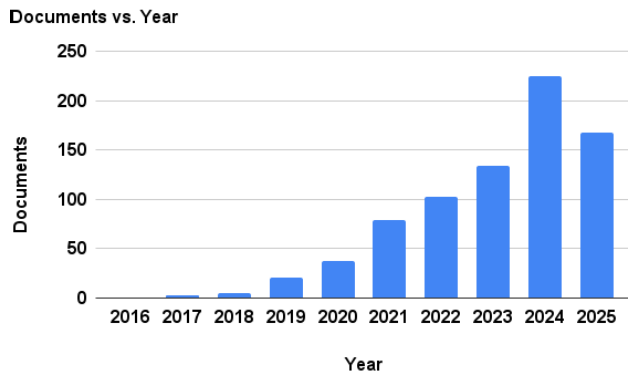


FIGURE 10. Publications by year on DTW in AM using the query TITLE-ABS-KEY (“additive manufacturing” OR “3D printing”) AND (“Digital Twin”).

Early DTw studies in AM laid the foundation for physics-based and data-driven simulations aimed at replacing trial-and-error experimentation [87], [88], [89]. These works established the DTw as an integrated cyber-physical construct combining process modeling, sensing, and adaptive feedback [90]. Subsequent reviews [91], [92] and case studies extended this vision toward multi-sensor data fusion, machine-learning-based defect detection, and intelligent process optimization. Diverse implementations now demonstrate DTws across AM processes, including distortion prediction and process monitoring in Wire + Arc AM (WAAM) [93], [94], parameter optimization in Powder Bed Fusion (PBF) [95], and adaptive control in Directed Energy Deposition (DED) [96]. Collectively, these efforts show a clear evolution from simulation-driven control toward self-learning, closed-loop DTws that enhance process stability, part quality, and lifecycle traceability.

A growing portion of this research adopts the ISO 23247 framework as a reference model for standardized DTw development. Initially conceptualized as a general manufacturing reference architecture, ISO 23247 has matured into a practical foundation for interoperable DTw implementations. Within the NIST Smart Manufacturing Systems (SMS) Test Bed, it has been used for machine monitoring, scheduling, and virtual commissioning [97]. Building on this, several works have demonstrated ISO 23247-based DTws for AM and machining. Kim et al. [98] implemented the framework in WAAM for anomaly detection and real-time decision-making, while Kang et al. [99] introduced edge-computing architectures to reduce latency and improve responsiveness. Cabral et al. [100], [101] applied it to CNC and robotic metal AM systems, leveraging MTConnect and MQTT for real-time telemetry and cloud-based analytics. Additional studies have explored its applicability to modular manufacturing [102], [103], precision assembly [104], and immersive human-machine interaction [105], confirming its versatility across domains.

Recent developments demonstrate how ISO 23247 can serve as a common interoperability layer connecting multiple standards. Rodríguez et al. [11] proposed a cyber-physical architecture that aligns ISO 23247 with STEP/STEP-NC, QIF, MTConnect, OPC UA, and MQTT to form a unified digital ecosystem for DTh-DTw integration. Alvares et al. [106] further extended this concept through three DTw implementations for robotic wire-based Laser Metal Deposition (LMD), addressing real-time motion simulation, predictive maintenance, and adaptive process control. Together, these studies highlight a transition from isolated DTws toward standards-based, interoperable DTw ecosystems capable of real-time collaboration and adaptive optimization.

Table 3 summarizes the most representative ISO 23247-based DTw implementations, outlining their domains, objectives, and key contributions to the evolution of standards-driven DTw frameworks in manufacturing. While these efforts demonstrate significant progress toward standardized digital integration, the convergence of DTh and DTw concepts in AM remains largely unexplored, situating the present work within this emerging research direction.

#### IV. COMPARATIVE ANALYSIS OF DTH AND DTW

Although DTh and DTw are closely related within the paradigm of modern digital manufacturing, they encapsulate distinct conceptual and functional domains. The DTh, which originates from aerospace and defense applications, serves as an integrated and contextually rich information flow that spans the entire product lifecycle, ensuring data continuity from design to deployment. In contrast, DTw, first introduced in the context of PLM [65], represents a dynamic, high-fidelity virtual counterpart of a physical asset or system, using multi-physics simulation, real-time sensor data, and historical records to enable predictive analysis, monitoring, and optimization [66]. Table 4 delineates the primary

**TABLE 3. Comparative analysis of DTw implementations based on ISO 23247.**

Reference	AM Process	Technologies Used	Main Contribution
[98]	WAAM (Wire+Arc AM)	Machine learning, Anomaly detection	DTw for real-time decision-making in WAAM.
[99]	WAAM (Wire+Arc AM)	Edge computing, Data fusion	Reduces latency, optimizes data flow in DTws.
[100]	CNC machining	MQTT, MTConnect, React.js	DTw for real-time monitoring and 3D simulation.
[101]	Metal AM robotic cell	Cloud-based monitoring	Online and post-process quality analysis.
[102]	Flexible manufacturing	ISO 21597, ITU-T Y.3090	Lifecycle meta-layer for DTw maintenance efficiency.
[104]	Automotive assembly	RAMI 4.0, Defect detection	DTw to prevent defect propagation in production.
[105]	Flexible manufacturing	Augmented reality, Gesture tracking	Enhances interaction and real-time monitoring.
[107]	Machine tending (robotics)	OPC UA, ROS, UR10e cobot	AI-based monitoring for process repeatability.
[103]	Modular production	Web services, Databases	Real-time optimization of industrial processes.
[108]	Aging cranes	Ansys Twin Builder	Predictive maintenance and risk assessment.
[109]	Battery systems	Reconfigurable, Software-defined batteries	Enhances runtime adaptability and efficiency.
[110]	Aerospace (LEO collision avoidance)	ISO 23247 adaptation	DTw for space debris tracking and avoidance.
[11]	AM processes	ISO 10303, STEP, STEP-NC, QIF, MTConnect, MQTT, OPC-UA	STEP-NC cyber-physical architecture
[106]	Wire-based LMD	ISO 23247, Kuka IIQoT, MQTT, NodeRed, RoboDK, Meltio, FireStore Cloud, Faster R-CNN, YOLO, FCN, Python library	Real-time process monitoring, 3D simulation, and defect detection

differentiating aspects of these two concepts, including their historical origins, formal definitions, functional scope, and associated technological frameworks.

**TABLE 4. Conceptual and technological differentiation of DTh and DTw.**

	DTh	DTw
<b>Origin</b>	2013 - Global Horizons, U.S. Air Force [16]	2003 - Dr. Grieves, PLM course at the University of Michigan [65]
<b>Definition</b>	“Digital Thread a digital linkage between materials, design, processing, and manufacturing that provides the agility and tailorability needed for rapid weapon system development and deployment” [16]. “... is an integrated information flow that connects all the phases of the product lifecycle” [111].	“Digital Twin is an integrated multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system that uses the best available physics models, sensor updates, fleet history, etc., to mirror the life of the corresponding flying twin” [66]
<b>Akin to</b>	Product/process lifecycle digitization	Specific asset/system digitization
<b>Related technological concepts</b>	PLM, MBSE, OOM, SOM	Cyber-Physical Systems, IoT, Simulation, Surrogate Models

Conceptually, the DTh acts as the information backbone of digital manufacturing, ensuring that data generated throughout the product lifecycle remain connected, contextualized, and reusable. The DTw, on the other hand, represents the intelligence layer, transforming that connected data into actionable insights through modeling, simulation, and analytics. While the DTh emphasizes continuity and traceability, the DTw focuses on representation and prediction. The distinction extends to their technological relation with other concepts: DTh is closely linked to concepts such as PLM, Model-Based Systems Engineering

(MBSE), Object-Oriented Modeling, and System-Oriented Modeling (SOM), whereas the DTw is deeply integrated with CPS, IoT, and advanced simulation and surrogate modeling techniques. Their relationship is therefore complementary. When these mechanisms are aligned under shared standards, they enable consistent data flow and feedback between physical and digital systems, supporting more coherent and reliable manufacturing processes.

### V. UNIFIED DIGITAL ECOSYSTEM FOR CONTEXTUALIZED INTELLIGENCE

This work proposes a unified digital ecosystem for contextualized intelligence, aimed at progressively integrating DTh and DTws through standardized data models, interoperable communication protocols, and structured data management. In this framework, the DTh provides a consistent backbone for organizing lifecycle information, while DTws act as interactive layers that use and update this data in real time. The approach relies on open standards such as STEP/STEP-NC, QIF, OPC UA, MQTT, and ISO 23247 to ensure compatibility and seamless information exchange among connected systems. By linking process, product, and machine data within their operational context, the ecosystem promotes gradual DTh–DTw convergence and supports reliable data sharing, improved traceability, and better use of information for process monitoring and optimization in manufacturing environments.

Each stage, ranging from design to inspection, and beyond, produces a wealth of information, encapsulating everything from geometrical specifications and process parameters to real-time performance metrics and quality assurances. This interconnected data stream, conceptualized in Figure 11, not only enables a comprehensive understanding of the

manufacturing process but also creates opportunities for integrating DTw at every phase.

The power of a DTw lies in its ability to replicate and augment the physical counterpart it represents, performing functions that range from real-time monitoring to predictive simulations. When tied to a specific phase of the DTh, a DTw can optimize processes within that phase. For instance, in the design phase, the DTw can analyze geometry, material properties, and manufacturability constraints, providing feedback on potential design flaws or improvements. During process planning, a DTw could simulate tool paths, optimize process parameters, and predict bottlenecks, improving overall efficiency. In the manufacturing phase, the DTw can monitor production in real-time, detect deviations from planned processes, and adapt operations to prevent defects. Finally, in the inspection phase, a DTw can compare actual quality metrics with design specifications, identify anomalies, and guide corrective measures.

The true potential of DTw can be unlocked when they draw on contextualized data across the entire DTh. A Design DTw, enriched with insights from manufacturing and inspection, could recommend design alterations to enhance manufacturability and ensure quality compliance. Similarly, an Inspection DTw, armed with data on design intent and manufacturing conditions, could perform root-cause analysis of defects, enabling closed-loop quality improvements. By transcending phase-specific applications, these interconnected DTws drive holistic advancements across the manufacturing lifecycle.

Building upon the integration of DTh and DTws, advanced manufacturing systems often feature multiple DThs (See Figure 12). These threads originate from diverse products, processes, or organizational units, each encapsulating distinct lifecycles, contexts, and objectives. Although independent, its convergence within a unified analytical framework can unlock unprecedented insights and efficiencies.

A multi-threaded architecture enables DTws to analyze and synthesize data across these threads, enhancing contextual understanding and cross-lifecycle optimization. To formalize this concept, consider a system comprising multiple DThs,  $DTh_1, DTh_2, \dots, DTh_n$ , each representing a distinct product, process, or organizational context. These DThs feed data into a shared set of DTws associated with different lifecycle stages (e.g., design, planning, manufacturing, inspection), facilitating integrated decision-making across domains.

Let  $DTh_i(t)$  denote the  $i$ -th DTh at time  $t$ , where  $i \in \{1, 2, \dots, n\}$ . In manufacturing environments, data are best represented as streams composed of time-series measurements and event logs. Each DTh encapsulates time-dependent data streams (vector or record containing parameters, measurements, and metadata relevant to that stage) corresponding to different lifecycle phases, such as design (d), planning (p), manufacturing (m), and inspection (q), which can be represented as:

$$DTh_i(t) = \{d_i(t), p_i(t), m_i(t), q_i(t)\}$$

A contextual filter operator,  $\Pi_{c_i}[\cdot]$ , selects, aligns, and processes relevant lifecycle information from each DTh according to the analysis or decision required. Each DTw, denoted by  $DTw_j$ , dynamically aggregates and interprets filtered data from one or more DThs:

$$DTw_j = f_j\left(\bigsqcup_{i=1}^n \Pi_{c_i}[DTh_i(t)]\right), \quad \forall j \in \{1, 2, \dots, m\}$$

where:

- $DTw_j$ : the  $j$ -th DTw that synthesizes and contextualizes data from several DThs to perform monitoring, simulation, optimization, or control.
- $f_j(\cdot)$ : a mapping function describing how multi-source data are fused and transformed into actionable knowledge.
- $\Pi_{c_i}[\cdot]$ : the contextual filter or projection operator that extracts relevant lifecycle subsets from  $DTh_i(t)$ .
- $\bigsqcup$ : a fusion operator representing temporal and semantic merging of data streams.

Each DTw maintains an internal state  $x_j(t)$  that evolves based on the contextualized inputs, producing estimated outputs and possible control actions:

$$\begin{aligned} x_j(t+1) &= \Phi_j\left(x_j(t), \bigsqcup_{i=1}^n \Pi_{c_i}[DTh_i(t)]\right), \\ y_j(t) &= \Psi_j(x_j(t)), \quad u_j(t) = \Gamma_j(x_j(t)), \end{aligned}$$

where  $y_j(t)$  are the DTw outputs (e.g., performance estimates or defect diagnostics), and  $u_j(t)$  are control or advisory actions enabling closed-loop adaptation with the physical system. The total set of DTws within the ecosystem is therefore defined as:

$$\{DTw_1, DTw_2, \dots, DTw_m\} = \bigcup_{j=1}^m f_j\left(\bigsqcup_{i=1}^n \Pi_{c_i}[DTh_i]\right)$$

This formulation captures the unification of DTws and their interaction with multiple DThs to perform targeted analyses and operations. For example, consider a manufacturing scenario that involves two DThs:  $DTh_A$ , representing an additive manufacturing process, and  $DTh_B$ , representing a subtractive manufacturing process.  $DTh_A$  contains layer-by-layer deposition rates and thermal profiles, while  $DTh_B$  includes toolpath efficiency and cutting forces. A manufacturing DTw ( $DTw_M$ ) can synthesize data from  $DTh_A$  and  $DTh_B$  to predict scheduling conflicts, identify material interactions, and suggest parameter adjustments for optimized workflow. Simultaneously, an inspection DTw ( $DTw_Q$ ) could leverage defects data from both threads to diagnose systemic issues, propose corrective measures, and improve quality control.

This multi-threaded approach exemplifies the transformative potential of DTw when contextualized across interconnected DThs. By integrating and analyzing data

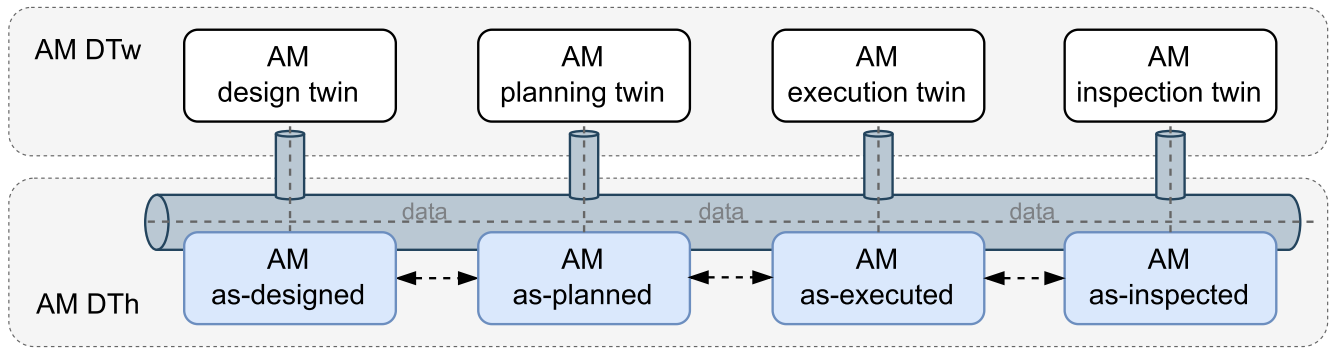


FIGURE 11. Concept of an AM DTh connected with DTWs.

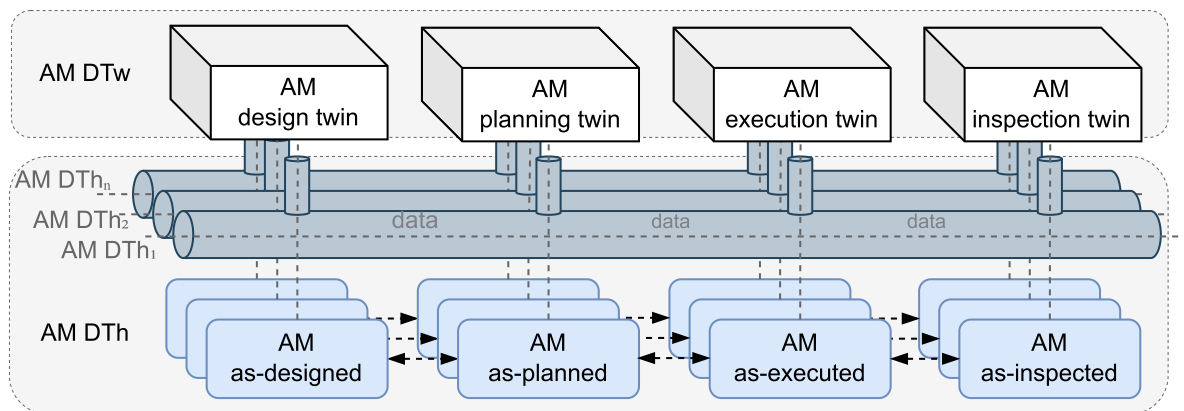


FIGURE 12. Concept of multi-threaded data flow interconnected with DTWs for cross-context lifecycle analysis.

streams from diverse lifecycles, DTw drive holistic optimization, enabling advanced predictive capabilities, adaptive decision-making, and enhanced efficiency throughout the manufacturing ecosystem. This vision naturally leads to the proposition of a unified digital ecosystem for contextualized intelligence, where seamlessly integrated DThs and DTWs, underpinned by standardized technologies and frameworks, provide a cohesive foundation for smarter, more adaptive manufacturing processes.

In the unified framework, data management plays a practical role in ensuring that information generated along the product lifecycle remains connected, consistent, and usable. Each DTh should capture and relate data from design, manufacturing, and inspection stages in a way that supports both historical traceability and current decision-making. This requires storage architectures capable of handling structured information together with time-dependent data, enabling DTWs to access contextual and up-to-date inputs. However, implementing such integration still poses challenges, including the coexistence of different data models, synchronization across systems, and the need for secure and standardized data exchange. Relying on established technologies such as STEP/STEP-NC, QIF, MTCConnect, OPC UA, MQTT, and ISO 23247 helps address these issues, fostering more reliable and transparent information flow across the DTh.

## VI. PROPOSAL OF A DIGITAL ECOSYSTEM FOR AM DRIVEN BY STANDARDS-BASED DTH AND DTW

This work proposes a standards-driven digital ecosystem that harnesses the combined potential of the DTh and DTw to achieve seamless integration between the physical and digital manufacturing domains, as illustrated in Figure 13. Based on the comprehensive literature review presented earlier, several key standards have been identified as foundational pillars of this ecosystem. Their integration not only enhances data quality, traceability, and reliability but also strengthens interoperability and collaboration across the industrial value chain. Through adherence to established standards and frameworks, the proposed architecture aims to accelerate the advancement and adoption of AM technologies while addressing current digitalization challenges and promoting best practices. Although this proposal focuses on AM, its structure is inherently adaptable to broader manufacturing environments.

The concept aligns with the vision of the ISO 23247 framework, which defines a comprehensive architecture for DTw implementation in manufacturing. This standard structures DTw systems around four domains, beginning with the physical space—corresponding to the Observable Manufacturing Elements (OMEs), where traditional tools such as CAD systems, CAPP/CAM platforms, CNC machines, and

maintenance systems operate as the foundation of production. The real value, however, emerges when these elements are interconnected through the DTh: a continuous, standards-based flow of data that captures each stage of the production lifecycle. This corresponds to the Digital Thread Entity (DThE) defined in the draft Part 5 of ISO 23247 [85].

The manufacturing process of an AM part begins with the definition of customer requirements, which are translated by design engineers into a CAD model. This model integrates geometric and non-geometric information, including 3D or 2D geometry, point clouds from scanned parts, GD&T requirements, and material specifications. These “as-designed” data constitute the foundation for subsequent stages and are transmitted through the design thread. In this ecosystem, the design thread is supported by model-based standards such as STEP, particularly AP203 [112], AP214 [113], and the more comprehensive AP242 [114], which facilitates AM design by representing tessellated and curved tessellated geometries.

The “as-designed” information then feeds into the process planning stage (CAPP/CAM), where the engineer generates a complete process plan. This stage makes use of feature-based manufacturing descriptions defined in STEP AP224 [115], combined with STEP-NC (ISO 14649 [116] or ISO 10303 AP238 [60]). In this phase, process planners select the appropriate AM technology, configure process parameters, determine optimal build orientation, and select support materials where needed. The resulting process simulation validates the plan and generates the “as-planned” data, transmitted through the process planning thread—also supported by STEP and STEP-NC within this ecosystem.

In the execution stage (CAM/CNC), the validated process plan is executed on the AM CNC system, following the workplan structure defined in STEP-NC, where each workstep corresponds to a specific AM feature or operation, as described in ISO 14649 Part 17 [117]. Toolpaths may either be precomputed during planning or generated dynamically by the machine controller. The resulting “as-executed” data populate the manufacturing thread, primarily governed by the STEP-NC data model. Throughout this stage, process and machine condition monitoring are performed through data acquisition from sensors and controllers, transmitted via communication protocols such as MTConnect [118], OPC UA [119], or MQTT [120]. These same protocols can also facilitate bidirectional control between the physical and digital systems. The outcome of this phase is a completed AM part, ready for subsequent post-processing and inspection.

Within the CAIP/CAI system, the inspection phase uses a variety of measurement tools, including Coordinate Measuring Machines (CMM), to ensure that the manufactured part meets both GD&T requirements and surface finish specifications. This meticulous inspection process is performed on the basis of a comprehensive inspection plan crafted by a dedicated inspection engineer. Using the feature-based inspection methodology outlined in STEP AP

219 [121] and STEP-NC standards, the engineer ensures a thorough examination. Furthermore, to effectively represent the inspection plan and manage the inspection results, the industry-standard QIF [122] and DMIS formats can be employed. Real-time transmission of measurement results across the network is facilitated by communication protocols such as MTConnect, OPC UA, or MQTT. These are the “as-inspected” data. The culmination of this phase is the generation of a comprehensive inspection report through the CAI system. Should adjustments be necessary, such as refining dimensions, tolerances, or surface finishes, the part may proceed to a subsequent phase of process planning for postprocessing.

Other several crucial phases of the AM process lifecycle can relate “as-maintained,” “as-repaired,” and “as-disposed” data. In the “as-maintained” stage, data tracks the ongoing condition and performance of the product during its usage, managed by maintenance professionals who ensure its optimal functionality. Transitioning to the “as-repaired” phase, the data record any maintenance or repair activities undertaken to address issues or failures, facilitated by maintenance or repair specialists. Hybrid manufacturing techniques can play a pivotal role in this phase, particularly in the context of remanufacturing. This approach combines traditional repair methods with advanced AM processes to restore components to their original specifications or even enhance their performance. By leveraging hybrid manufacturing in the “as-repaired” phase, remanufacturers can achieve greater flexibility, efficiency, and sustainability in the restoration of components, ultimately prolonging their lifecycle and reducing overall waste. These activities are often guided by standards such as ANSI RIC001.2, ISO 55000 for asset management, ISO 14000 for environmental management, and ISO 15270 for recycling management. Subsequently, in the “as-disposed” phase, data oversees the recycling or disposal of the product at the end of its lifecycle, overseen by professionals in logistics or product management, ensuring environmentally responsible practices are upheld throughout the process, from delivery to disposal.

Table 5 provides an overview of the key standards grouped by their application within the DTh stages and their relevance to DTw and CPS frameworks. These standards could collectively enable efficient data exchange, real-time monitoring, and enhanced decision-making across the manufacturing lifecycle. In addition to these standards, the Reference Architectural Model for Industry 4.0 (RAMI 4.0) [123] offers a conceptual framework for positioning manufacturing systems across three dimensions: hierarchy levels, life-cycle/value-stream, and architecture layers. Its life-cycle axis, defined by IEC 62890, distinguishes between product-type and product-instance data, an approach that aligns well with the principles of DTh and DTws. While RAMI 4.0 is not a technology standard, it provides a useful reference model for situating the proposed architecture within a broader Industry 4.0 context. In this work, however, the

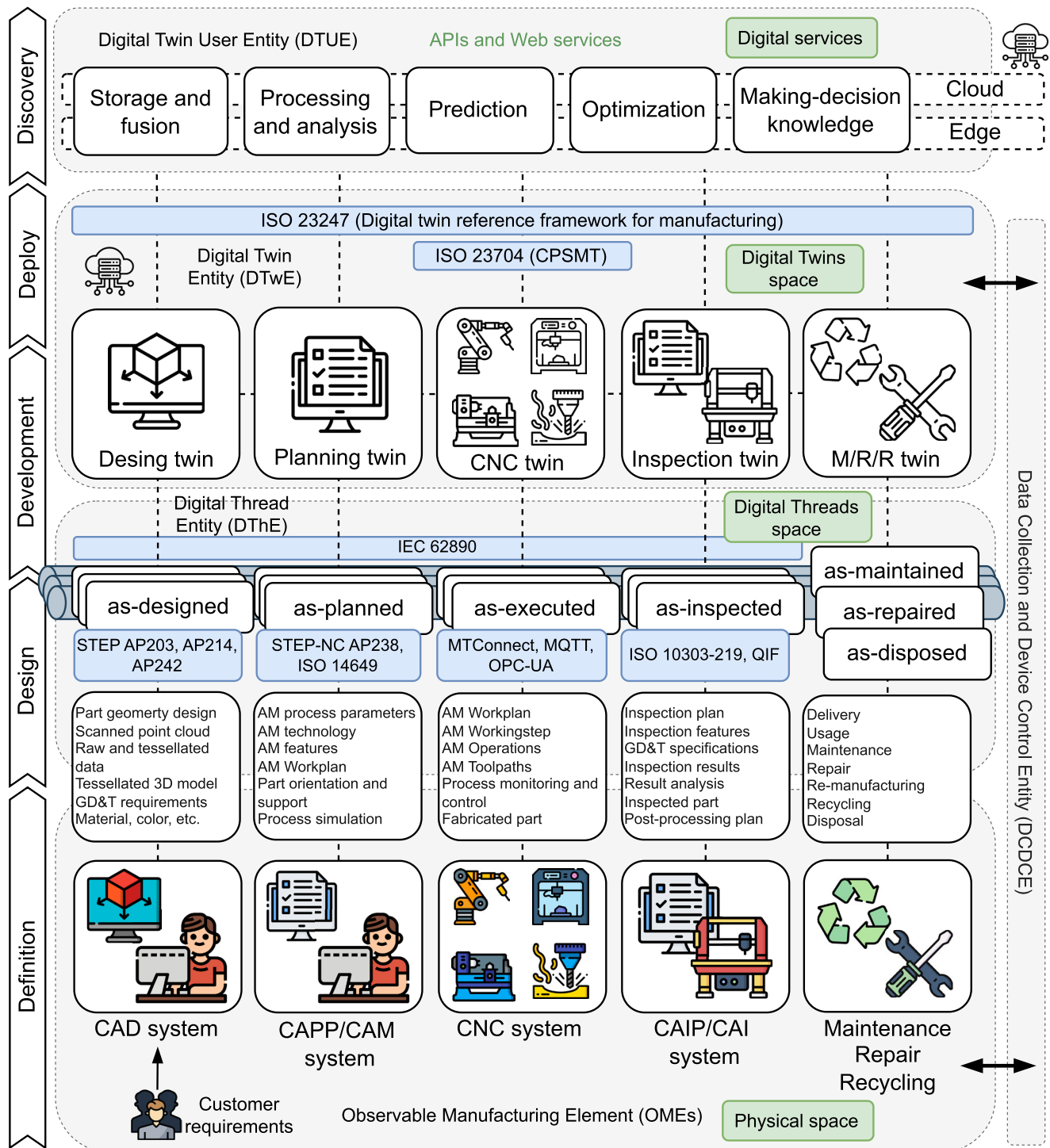


FIGURE 13. Digital ecosystem framework for AM driven by standards-based DTh and DTw.

focus remains on standards that directly define data structures and communication interfaces (such as ISO 23247 and STEP-NC), which serve as the practical foundation for implementing interoperable digital manufacturing systems.

A key advantage of this architecture is the role of STEP-NC models, which incorporate entities specifically

for AM, machining, or multi-process definitions. These models allow for detailed descriptions of AM operations and process parameters, ensuring that every aspect of the technology is captured. This data can be used not only to generate STEP-NC programs for machine controllers but also to provide an essential context for DTw. By combining

**TABLE 5.** Key standards for the proposed digital ecosystem.

Category	Description
<b>Design</b>	<b>STEP ISO 10303 - AP203, AP214, AP242:</b> Enable rich product data exchange, including geometric and model-based information for AM design processes.
<b>Process Planning</b>	<b>STEP-NC ISO 14649, ISO 10303 - AP238:</b> Support intelligent CNC programming, linking design and manufacturing through feature-based definitions and process plans.
<b>Manufacturing execution</b>	<b>MTConnect (ANSI/MT1.4), OPC-UA, MQTT (ISO/IEC 20922), ISO 14649, ISO 10303 AP238:</b> Facilitate real-time communication, process monitoring, and machine data collection during AM execution.
<b>Inspection</b>	<b>ISO 10303 - AP219, QIF (ISO 23952):</b> Ensure traceable quality control and inspection by linking measurement data to design specifications.
<b>DTw/CPS frameworks</b>	<b>ISO 23247, ISO 23704:</b> Provide reference architectures and frameworks for integrating DTw and CPS in manufacturing environments, supporting data synchronization and real-time monitoring.
<b>Lifecycle Management</b>	<b>IEC 62890:</b> Defines the type/instance distinction and lifecycle states foundational to semantic continuity.

real-time machine condition and process data gathered via MTConnect, MQTT, or OPC-UA, DTws are enriched, enabling deeper simulation, monitoring, and optimization of products and manufacturing systems. This creates a feedback loop where the physical and digital realms work together to drive continual improvement, enhance decision-making, and optimize performance across all stages of production. The Data Collection and Device Control Entities (DCDCE) module further enhances this integration by synchronizing the OMEs entities with DTw entities, effectively overseeing sensor data and managing actuated devices within the OME domain.

Each stage of the DTh (as-designed, as-planned, as-executed, as-inspected, as-maintained) is seamlessly mirrored in the cyber space by corresponding DTw, virtual replicas of their physical counterparts. The cyber space incorporates the DTw Entity (DTwE) as defined within the ISO 23247 framework, which is the core at this architecture. These twins, such as the design twin, process plan twin, CNC twin, and inspection twin, act as real-time reflections of their respective physical processes. This mirroring allows manufacturers to simulate, predict, and optimize outcomes long before committing physical resources, creating a digital ecosystem that ensures efficiency, flexibility, and resilience across the entire manufacturing lifecycle. For instance, the design twin serves as a virtual representation of the CAD model or design specifications of the part to be manufactured. It allows designers and engineers to simulate various design iterations, analyze structural integrity, and optimize geometries for AM processes. Furthermore, enables real-time collaboration and visualization of design changes, facilitating rapid prototyping and design validation leveraging integrated data from subsequent phases.

Similarly, the process planning twin encompasses the digital representation of the part's geometry, support structures,

and build orientation, optimized for AM. It enables process simulation, slicing, and toolpath generation, allowing operators to optimize build parameters, minimize material usage, and reduce build time. The DTw provides insights into the feasibility and manufacturability of the part, guiding decision-making during process planning activities.

The manufacturing twin operates as a virtual replication of the physical AM process, offering an immersive simulation of material layer construction, thermal behavior, and cooling dynamics throughout fabrication. This virtual environment enables real-time monitoring and precise control over AM parameters, ensuring strict adherence to quality standards while minimizing the occurrence of defects. Operators benefit from the ability to scrutinize process deviations, forecast potential build failures, and refine fabrication strategies, thereby enhancing both part quality and production efficiency. Furthermore, the manufacturing twin encompasses the monitoring of machine condition, leveraging data collected from the shop floor through communication protocols such as MTConnect, OPC UA, or MQTT. By amalgamating this real-time data with historical records, manufacturers can conduct sophisticated analyses utilizing machine learning and big data analytics, thereby improving overall process conditions and predicting machine behaviors with greater accuracy and foresight.

Moreover, the inspection twin is dedicated to monitoring and assessing the quality of AM parts throughout the production cycle. It integrates data from in-line sensors, non-destructive testing, and metrology equipment to track dimensional accuracy, surface finish, material properties, and defect detection. This twin enables real-time quality control, anomaly detection, and root cause analysis, empowering operators to identify and address quality issues proactively. Additionally, it supports traceability and documentation of quality metrics for compliance and certification purposes.

Furthermore, maintenance, repair, and recycling twins extends beyond the manufacturing phase to encompass the operational lifecycle of AM parts. It monitors part performance, usage conditions, and environmental factors affecting durability and reliability. It enables predictive maintenance, prognostics, and lifetime estimation, allowing stakeholders to optimize asset management strategies and maximize operational uptime. By capturing real-world operating conditions and feedback, this DTw facilitates continuous improvement and optimization of AM processes for enhanced lifecycle performance.

The ISO 23247 standard facilitates the systematic development of DTws, aligning their creation with established industry best practices. In addition, the ISO 23704 [124] series outlines critical requirements for smart machine tools, facilitating the advancement of smart manufacturing on the shop floor through a cyber-physical control framework. Notably, Part 3 of this series is dedicated to AM machines [125]. Collectively, these standards empower manufacturers to develop robust and effective DTws.

The final layer of this architecture is the digital services space, which includes the DTw User Entity (DTUE). Here, data from DTws is used for virtual monitoring, analytics, prediction, optimization, and decision-making. Through cloud-based APIs and Web platforms, manufacturers can integrate data from various sources to anticipate maintenance needs, optimize production schedules, and foster real-time innovation. This dynamic environment not only enhances operational efficiency but also empowers organizations to make data-driven decisions that drive growth, improve product quality, and maintain competitiveness in an ever-evolving market.

Finally, the left side of the Figure 13 illustrates the 5D product design process as proposed by Aheleroff et al. [76]. The first section, titled “Definition,” is situated entirely within the physical space, underscoring the critical role of establishing clear requirements and specifications at the project’s inception. Next, the “Design” section signifies the start of the DTh, marking the transition from tangible concepts to digital representations. The “Development” section extends from the DTh into the cyber space, emphasizing the integration of both physical and digital elements throughout the product’s evolution. Moving further into the cyber realm, the “Deploy” section concentrates on the effective implementation of these digital assets. Finally, the “Discovery” section, located within the digital services division, highlights the importance of leveraging data-driven insights and analytics to enhance product performance and drive innovation.

#### A. BENEFITS AND CHALLENGES OF THE PROPOSED ECOSYSTEM

The integration of DTh and DTw within the proposed ecosystem has the potential to reshape manufacturing practices fundamentally. Its benefits extend across several dimensions:

- **Data integration:** Seamless access to multi-source data (design, process, and performance) ensures continuity, coherence, and contextual understanding across the lifecycle.
- **Interoperability:** Adoption of open standards enables transparent communication between heterogeneous systems, enhancing collaboration and reducing vendor lock-in.
- **Bidirectional data flow:** The framework promotes both horizontal and vertical integration, linking shop-floor operations with higher-level management systems.
- **Closed feedback loops:** DTws provide real-time insights, linking performance data back to earlier lifecycle stages to drive continuous improvement.
- **Enhanced controller intelligence:** Integration of DTw with STEP-NC supports adaptive machining and process control, improving accuracy and responsiveness.
- **Model-based definition:** Unified, model-driven data reduces ambiguity, ensures precision, and minimizes manual rework.

- **Contextual enrichment:** DTws enhanced with lifecycle and domain-specific context improve predictive capability and adaptive decision-making.
- **Innovation and analytics:** Machine learning and big data analytics enable smarter optimization, informed design, and proactive process management.
- **Sustainability:** Predictive maintenance, hybrid repair, and recycling strategies contribute to circular economy goals and resource efficiency.

From an industrial standpoint, the adoption of the proposed standards-based digital ecosystem requires not only technological readiness but also organizational maturity. Integrating DTh and DTw infrastructures into established workflows involves tangible costs related to equipment sensorization, data management, and software interoperability. These initial investments can be significant, especially for small and medium enterprises. However, they can be progressively reduced through modular deployment strategies, introducing connectivity, monitoring, and traceability layers in stages, while leveraging open and vendor-neutral standards such as STEP-NC, MTConnect, MQTT, OPC UA, and QIF. These standards minimize integration risks and ensure that legacy assets can participate in the digital environment without full system replacement. Human and cultural factors also play a key role in industrial adoption. The successful deployment of this ecosystem depends on developing new digital skills among operators, engineers, and decision-makers. Early involvement of end-users, combined with training initiatives and clear demonstration of benefits such as reduced rework, improved part qualification, and faster decision cycles, can help overcome resistance to change. Adopting a human-centered approach, where technology supports rather than replaces the operator, fosters acceptance and long-term sustainability of digital transformation initiatives.

In terms of domain-specific applications, the proposed ecosystem, integrating the DTh and DTw, naturally aligns with the production modes and operational needs of high-value manufacturing sectors where traceability, data integrity, and lifecycle synchronization are critical. In the aerospace industry, the DTh establishes end-to-end traceability across design, process, and inspection stages, while the DTw continuously mirrors component behavior throughout fabrication and service life. Together, they enable a closed-loop certification process for additively manufactured parts, where process data, material provenance, and inspection results are linked within a unified digital representation. This approach not only supports direct-use manufacturing of lightweight, high-performance structures but also facilitates rapid prototyping of aerodynamic components and re-manufacturing of critical parts, extending their lifecycle and reducing waste in maintenance, repair, and overhaul operations.

In the biomedical sector, the integration of DTh and DTw connects patient-specific design data to process-aware DTws that simulate and monitor each production step in real time. This architecture supports rapid prototyping of anatomical

models and surgical guides for preoperative planning, as well as direct-use AM of implants and prosthetic devices under controlled, traceable conditions. The DTh maintains a continuous record of design intent, build parameters, and post-build validation, while the DTw ensures reproducibility and compliance with biocompatibility and medical quality standards.

Within the defense and military domains, the DTh–DTw ecosystem enables secure, distributed, and on-demand production of mission-critical components, often under resource-constrained or remote conditions. DTws support adaptive control and remote supervision of deployed additive systems, while the DTh ensures full traceability of process data, material batches, and part lineage. This combination enhances supply-chain resilience, allowing for in-field re-manufacturing and immediate replacement of essential components without dependence on centralized facilities.

Across these industries, the integration of DTh and DTw transforms AM from a standalone fabrication process into a connected, data-driven production paradigm. By supporting prototyping, re-manufacturing, direct-use, and on-demand production within a standards-based framework, the proposed ecosystem enables traceable, certifiable, and adaptive manufacturing practices tailored to the stringent requirements of regulated, high-value sectors. Additionally, it promotes interoperability, human-centered innovation, and incremental digitalization, helping bridge the gap between research-driven concepts and real-world manufacturing transformation.

## VII. IMPLEMENTATION SCENARIOS

This section presents two implementation scenarios developed to validate the contributions of this work within the proposed digital ecosystem for AM.

### A. SCENARIO 1: IMPLEMENTATION OF STEP-NC AND MTCONNECT IN AM USING AN FDM PROCESS

This implementation scenario focuses on an FDM-based AM process, utilizing the machining-oriented STEP-NC data model to encode the layer-by-layer toolpaths. Additionally, the scenario incorporates an implementation of MTConnect to monitor key process parameters during FDM operations. This system collects real-time data from the machine, including the status of process progress, the temperatures of the print bed and hotend, the X, Y, and Z positions of the machine, and the printing speed, making it accessible for visualization through a Web client and providing an effective way to remotely monitor the process.

The digital ecosystem framework proposed in this work serves as a reference for structuring the architecture of the implementation scenario, which is detailed in this section. The complete architecture, illustrating the interplay between STEP-NC and MTConnect within of the context of this scenario, is depicted in Figure 14. In the design phase, the 3D model of the part is created, followed by the planning phase,

where the model is sliced into layers, and deposition toolpaths for each layer are generated. These toolpaths are used to create a STEP-NC program containing workingsteps tailored for a FDM AM process. The workingsteps, along with their corresponding deposition toolpaths, are then simulated in the STEP-NC Machine environment, leveraging a kinematic 3D model of the machine to validate the operations. Finally, the part is manufactured on a real 3D printer. The simulation and manufacturing phases feed into DTw for simulation and process monitoring, respectively (highlighted with green boxes in the figure). The simulation DTw ensures toolpath feasibility, while the monitoring DTw tracks key parameters such as process progress, bed and hotend temperatures, the positions of the coordinate axes (X, Y, Z), and the printing speed, providing a comprehensive framework for data-driven oversight of the AM process.

The 3D model of the part to be printed originates from CAD software and is saved in the widely used STL format. This STL file serves as the input for a dedicated AM CAM software, Autodesk Netfabb, which is employed in this implementation scenario. Netfabb processes the STL model by slicing it into layers with a specified thickness, defining the FDM process parameters, and generating the corresponding toolpaths for each layer. The toolpaths are then exported in an XML-based AM layer format, encapsulating all necessary data to represent the sliced model.

The structure of the XML file, organizes the layer data within the <Layers> tag, which contains multiple <Layer> tags. Each <Layer> tag encapsulates one or more <Exposure> tags, representing individual toolpaths. The type of toolpath, such as contour or hatch, is specified by the “polylineType” property within each <Exposure> tag. Additionally, the <Exposure> tags contain <Segments> blocks, which further subdivide into <Segment> elements. Each <Segment> comprises <Point> tags with attributed x, y, and z properties, defining the coordinates of the polyline points as illustrated in the figure. The XML file, containing comprehensive toolpath data, is then passed to the next stage of the architecture, where it is converted into a STEP-NC program.

The generation of a STEP-NC program for AM constitutes a key outcome of this implementation [50]. A dedicated software adapter, developed in C, processes the XML file containing the sliced-layer toolpaths and automatically generates a STEP-NC program tailored for AM. The adapter, publicly available in [126], leverages the STEP-NC Machine DLL from STEP Tools Inc., enabling the creation, editing, and export of models in Part 21 or Part 28 formats within Visual Studio.

The software parses the XML structure, comprising layers, exposures, segments, and points, and maps these hierarchical elements to corresponding STEP-NC definitions. Each layer is converted into a workplan, while individual toolpaths are represented as workingsteps (contour or hatch). Toolpath coordinates are defined through the GoToXYZ function, and FDM process parameters, such as feedrate and

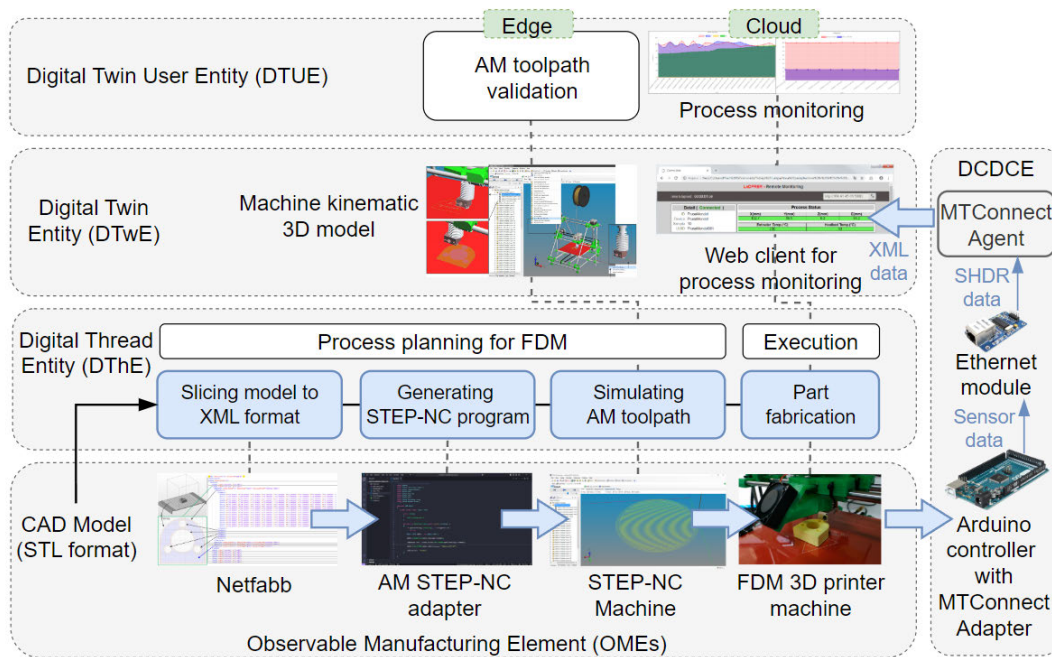


FIGURE 14. STEP-NC and MTConnect implementations in AM through digital ecosystem framework.

extruder temperature, are mapped to their machining analogs (Feedrate and SpindleSpeed).

Once generated, the STEP-NC model is serialized and visualized in the STEP-NC Machine environment, as shown on the left side of Figure 15. This enables detailed inspection of toolpaths, layer contours, and hatch structures, validating the correct translation of the XML data into the STEP-NC model. Overall, this approach demonstrates the feasibility of adapting the machining-oriented STEP-NC schema for AM processes, providing a foundation for extending the standard toward AM-specific entities and workflows.

To enable realistic simulation of the 3D printing toolpaths, the kinematic model of the RepRap Prusa Mendel i2 printer was integrated into the STEP-NC Machine environment (See Figure 15). This process begins with a STEP assembly file of the printer, used to generate an XML file defining its kinematic structure, organized into tool and workpiece sections that describe the motion axes (X, Y, Z) and fixed geometries of the machine. Optional sections, such as changer, can also be added to represent tool exchange systems.

The identification of assembly components (*shape\_eid*) and faces (*face\_eid*) required to build the XML model was performed using the visualization tools available in STEP-NC Machine. Once generated, both the STEP and XML files were placed in the machine directory of the software installation, with all resources made publicly available in [127]. Within STEP-NC Machine, the model is loaded via the Machine Tool interface, allowing the import of the printer's geometry and the simulation of both kinematic motion and toolpath execution. This configuration enables detailed verification of

process operations. Alternatively, the kinematic data could be embedded directly into the STEP file itself using the AP242 standard, which supports native definitions of geometric and kinematic relationships.

Beyond toolpath verification, the AP-238 STEP-NC program can be enriched with additional data, such as tool and part geometries, and geometric dimensioning and tolerancing (GD&T) information, leveraging integration capabilities with other STEP resources. This enrichment supports advanced functionalities such as quality checks and the assessment of surface finish requirements, offering opportunities for optimizing manufacturing processes and improving part quality.

The generated STEP-NC program was exported as G-code to operate on the RepRap 3D printer, powered by an Arduino Mega 2560 with Marlin firmware. Some process parameters, such as extruder and bed temperatures, had to be manually added, since the machining-oriented STEP-NC model could not directly represent FDM-specific attributes. This implementation demonstrates the feasibility of adapting STEP-NC for AM applications, using existing machining entities to define, simulate, and execute printing toolpaths. However, its limitations are also evident: the lack of dedicated AM entities requires manual interventions and indirect conversion to G-code, reducing automation and introducing potential inconsistencies. These findings highlight the need to extend the STEP-NC standard to fully capture FDM AM process characteristics and enable direct digital integration.

Although this mapping strategy proved useful to validate interoperability and workflow feasibility, it should be regarded as a temporary solution. The current edition of the

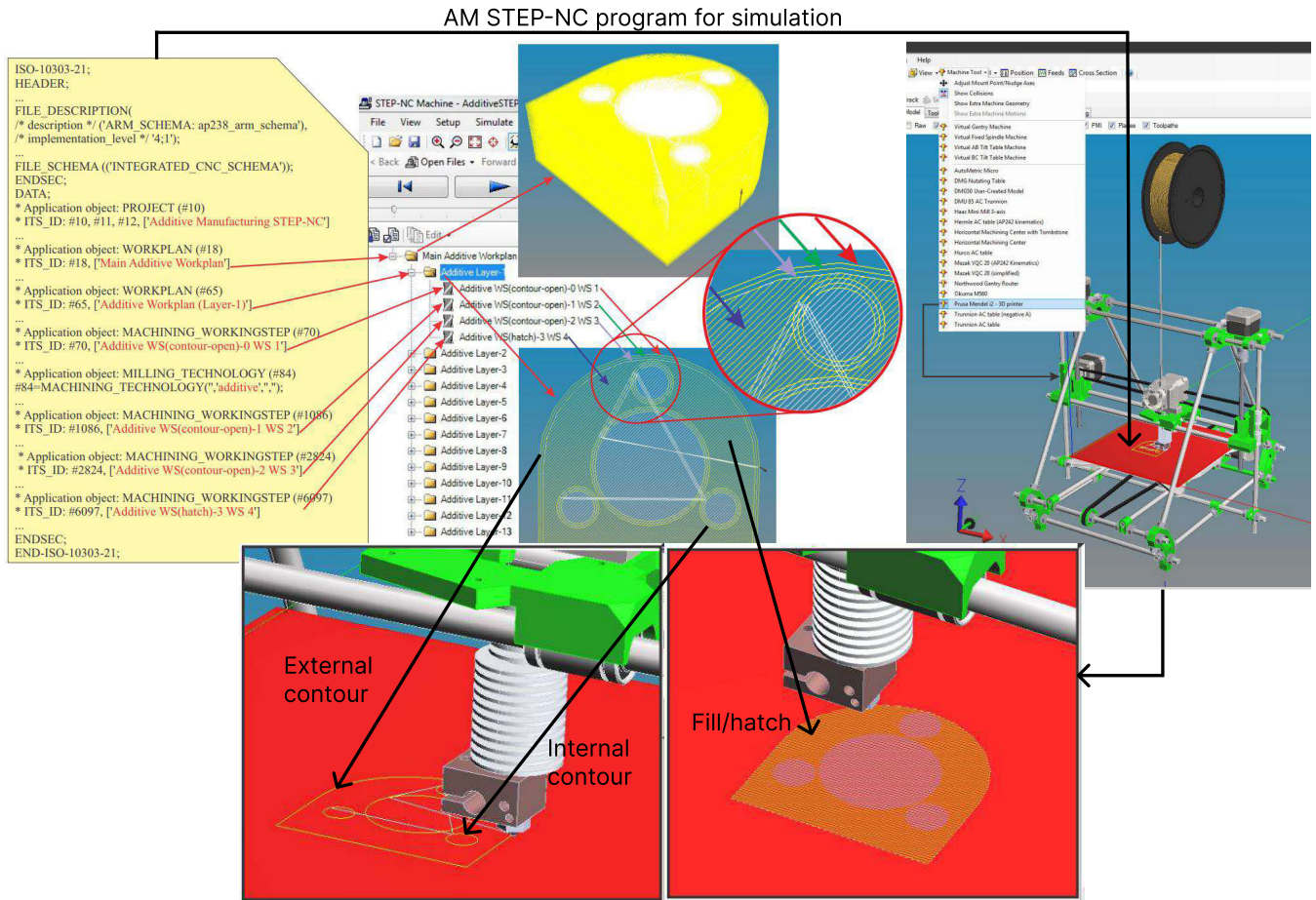


FIGURE 15. Simulation of the AM STEP-NC program in STEP-NC Machine software.

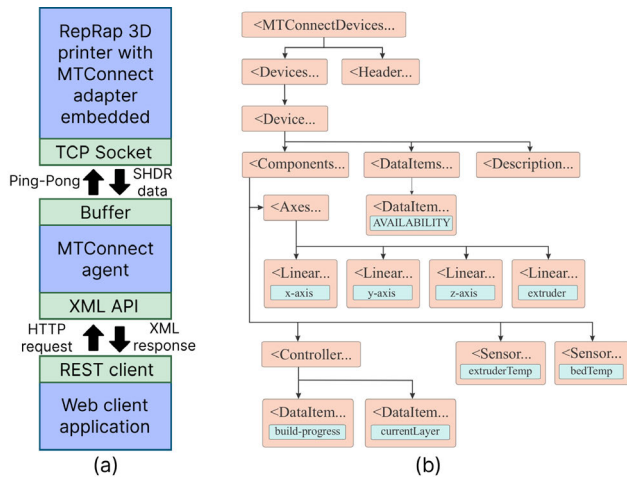
STEP-NC standard (ISO 10303-238, Edition 3) does not yet include entities capable of describing additive-specific process parameters for FDM or other AM technologies. Existing entities such as `am_workingstep`, `am_operation`, `am_workplan`, and `am_feature`, provide only a generic representation of AM operations and lack the expressiveness needed to capture key parameters such as extrusion temperature, heat bed temperature, nozzle diameter, extrusion feedrate, among others. As a result, adapting machining entities was, at this stage, the only practical way to encode FDM deposition operations within the available STEP-NC schema.

Ongoing research is actively addressing these limitations. Milaat et al. [64] have recently proposed a set of entities for Powder Bed Fusion processes that are being considered for inclusion in the forthcoming Edition 4 of ISO 10303-238. In parallel, our group has published a proposal outlining additional entities for FDM and LMD processes [11] as a call to the ISO 10303-238 working group to evaluate their potential adoption in future revisions of the standard. Once such AM-specific entities are formally incorporated into STEP-NC and implemented in existing tools such

as STEP-NC Machine and related software will be able to natively interpret AM operations, simulate them, and generate STEP-NC programs directly for FDM, LMD, and other AM technologies. This would eliminate the need for indirect mappings and manual edits, and would enable a more automated and consistent digital workflow for STEP-NC based AM.

As part of the implementation scenario described in this section, the integration of MTConnect was explored to enable real-time monitoring and data collection from the RepRap 3D printer [128]. MTConnect is a widely recognized standard for data exchange and communication in manufacturing environments. Figure 16a illustrates the architecture of the MTConnect implementation, which consists of three main components: the adapter, the agent, and the Web client. These components work together to establish a seamless data flow from the 3D printer to a cloud-enabled monitoring system.

The experimental setup was developed around an Arduino Mega 2560 controller, commonly used in RepRap machines, enhanced with an ENC28J60 Ethernet module to enable TCP/IP communication under the MTConnect protocol. A custom firmware extension was implemented within the



**FIGURE 16. MTConnect implementation: a) Architecture; b) 3D printer machine model.**

Sprinter firmware to collect key machine data, such as axis positions, hot-end and bed temperatures, build progress, and layer number, and transmit it in the Simple Hierarchical Data Representation (SHDR) format via TCP/IP. This lightweight integration eliminates the need for additional hardware, offering a cost-effective and efficient way to connect RepRap systems to a networked or cloud-based manufacturing environment.

A complementary element of this setup is the MTConnect-compliant machine information model, illustrated in Figure 16b. Structured in XML, it organizes data hierarchically under MTConnectDevices, including elements for machine metadata (Description), static attributes (DataItems), and dynamic operational data (Components). For the RepRap 3D printer, these include X–Y–Z positions, extruder and bed temperatures, build progress, and current layer information. This standardized model ensures compatibility with MTConnect Agents, enabling efficient real-time data exchange and monitoring across the digital manufacturing ecosystem.

Machine data acquisition tests were conducted by making various types of requests directly through a Web browser. The XML structure adheres to the MTConnect standard, including elements such as axis positions (X, Y, Z), extruder and heat-bed temperatures, build progress, and the current layer number. These standardized XML tags ensure compatibility with MTConnect-compliant client applications, enabling seamless data retrieval and real-time monitoring from a Web client.

To validate real-time monitoring capabilities, a lightweight Web client was developed using HTML, CSS, and JavaScript. As shown in Figure 17, the interface, accessible online at <https://efrainrodriguez.github.io/MTConnect-client/>, retrieves and processes XML data from the MTConnect Agent through “current” requests. The dashboard displays key machine parameters, including axis positions, temperatures, build progress, and current layer

number, allowing operators to intuitively monitor process status. Connectivity and performance tests confirmed stable communication between the MTConnect Agent and multiple browser-based clients, demonstrating reliable real-time data access for AM process supervision.

Figure 18 summarizes the monitoring results obtained from the RepRap 3D printer. As shown in Figure 18(a), the positional data of the X, Y, Z axes and extruder ensure accurate toolpath execution, while temperature readings for the hot-end and heat-bed (Figure 18(b)) confirm stable thermal conditions for consistent extrusion and layer adhesion. Additionally, historical data log for all monitored variables are stored in the database, supporting post-process analysis and quality assessment.

Performance evaluations validated the system’s reliability, with a maximum observed latency of approximately 700 ms over a 10 Mbit/s TCP/IP connection when tracking eight process variables. This delay, mainly due to HTTP overhead, SHDR data formatting, agent buffering, and XML rendering on the client side, remains well within acceptable limits for remote AM process supervision. Overall, the framework achieved near real-time data access, demonstrating its suitability for monitoring and quality control in 3D printing operations.

Although the observed latency of approximately 700 ms is acceptable for single-machine monitoring, the scalability of this MTConnect implementation is inherently constrained by the limited processing power and memory of the Arduino Mega 2560 controller (16 MHz clock speed, 8 KB of SRAM). These constraints limit the number of sensors, data refresh rate, and overall throughput that can be achieved. In multi-machine or high-frequency monitoring scenarios, network-related factors such as available bandwidth, transmission latency, and packet routing efficiency also play a decisive role in system performance. While these aspects fall beyond the scope of the present implementation, future work should include systematic performance benchmarking across different hardware configurations and network environments. To improve scalability, more powerful embedded systems or edge-computing nodes could aggregate and preprocess data locally before transmitting it to the MTConnect agent.

As a further improvement, the complementary use of asynchronous messaging protocol, such as MQTT, could enhance the data transport layer within the existing MTConnect framework. In this configuration, the MTConnect agent would operate as an MQTT publisher, transmitting machine-state updates in MTConnect XML or JSON format to a message broker. Client applications or edge nodes would then subscribe to specific topics (e.g., `mtconnect/machine1/temperature` or `mtconnect/machine1/position`) to receive real-time updates automatically, rather than issuing repeated HTTP requests through the standard current or sample commands. This publisher–subscriber mechanism offloads the agent from handling multiple polling requests and reduces overall network traffic. Consequently, updates are delivered to

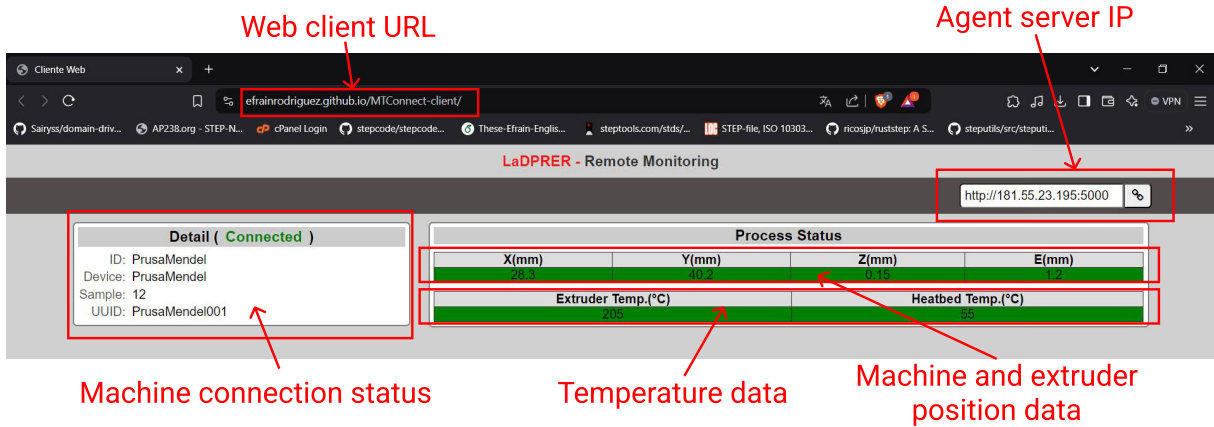


FIGURE 17. MTConnect Web client for FDM process monitoring.

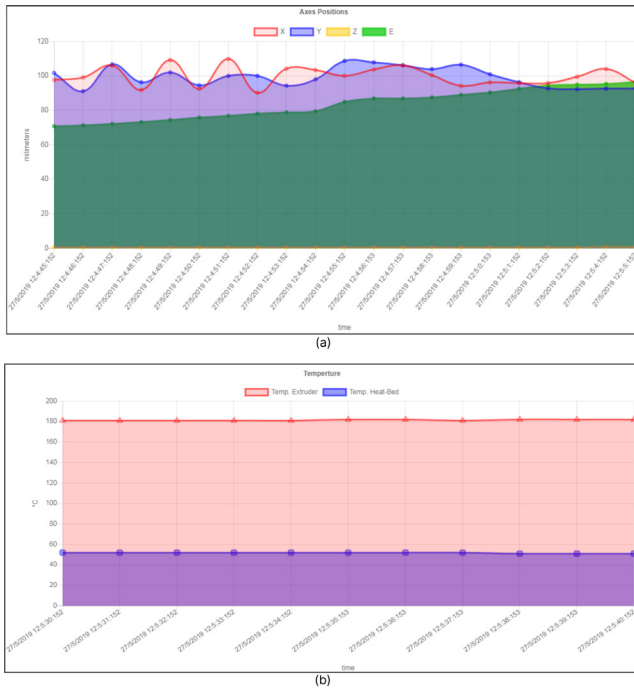


FIGURE 18. FDM process monitoring: a) Machine and extruder positions; b) Hotend and heatbed temperature [11].

clients only when new data is available, improving throughput and responsiveness as perceived by the user. While MTConnect continues to ensure semantic consistency and standardized communication, MQTT would serve as a lightweight, asynchronous transport layer that increases scalability and communication efficiency across distributed, factory-scale monitoring systems. It should be noted that this improved architecture, combining MTConnect for semantic interoperability and MQTT for asynchronous data transport, is proposed as a potential enhancement and was not implemented in the present study.

**B. SCENARIO 2: REAL-TIME PROCESS MONITORING FOR THE ROBOTIC LMD PROCESS**

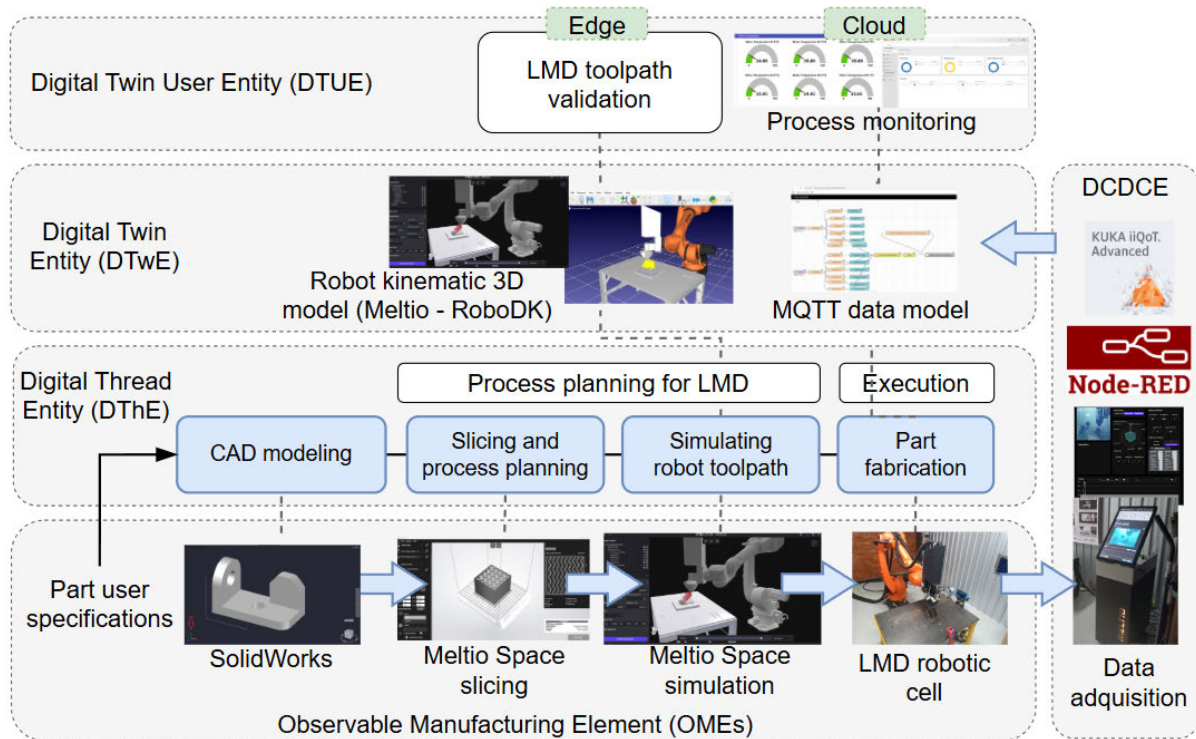
This scenario demonstrates the implementation of a DTw framework for process and condition monitoring in a robotic wire-based LMD cell, developed in alignment with ISO 23247 [106]. The study focuses on three core components: (i) the design of an ISO 23247-based architecture, (ii) the integration of multiple DTw implementations for real-time monitoring and predictive maintenance, and (iii) experimental validation in an industrial robotic AM environment.

Three DTws compliant with ISO 23247 were implemented. The first, a *real-time 3D simulation DTw*, was developed using RoboDK and CAD/CAM tools for process planning and collision detection. The second, an *Industrial IoT-driven DTw*, employs KUKA iiQoT to capture and analyze telemetry data for predictive maintenance. The third, the *Meltio Dashboard DTw*, supports remote monitoring and visualization of process parameters. Communication between the physical cell and the DTws is handled via MQTT and OPC UA, while Firestore Cloud enables historical data storage and analysis.

Figure 19 presents the proposed ISO 23247-based DTw architecture, integrating the five application domains, DThE, OME, DCDCE, DTE, and DTUE, as defined in ISO 23247-1 [68]. The synchronization among these domains enables seamless data flow from the physical to the digital layers, supporting both 2D process dashboards and 3D simulation of the robotic LMD cell.

In the OME domain, the physical setup comprises a KUKA KR70/2100 industrial robot equipped with a Meltio laser head, wire feeder, controller, chiller, and argon gas supply.

The DThE domain defines the digital workflow, integrating Rhino, Grasshopper, Meltio Space, and KUKA Sim for design, slicing, and toolpath generation. The resulting KUKA Robot Language (KRL) files ensure direct execution



**FIGURE 19.** Real-time process monitoring of a robotic LMD cell through digital ecosystem framework.

on the robot, maintaining digital continuity across the lifecycle.

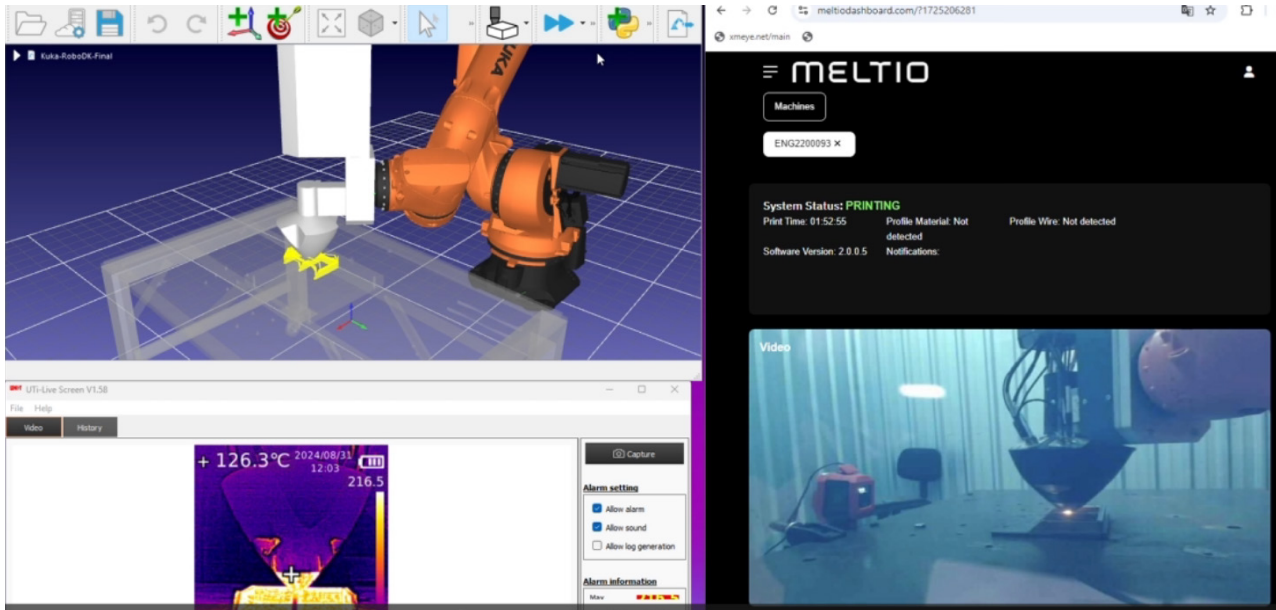
The DCDCE domain manages real-time data acquisition and communication using MQTT, OPC UA, and CAN Bus/USB. Dedicated servers and virtual machines handle data routing and processing, ensuring high-fidelity synchronization between physical operations and their digital counterparts along the DTh.

In the DTE domain, core DTw applications operate by combining real-time sensor streams with historical data for advanced monitoring, simulation, and diagnostics. RoboDK provides dynamic 3D visualization, KUKA iiQoT performs predictive maintenance analytics, and Meltio Dashboard and Node-RED enable process monitoring. Additionally, computer vision modules facilitate early defect detection and feedback propagation through the DTh, closing the information loop.

Finally, the DTUE domain offers a user interface through REST APIs and WebSocket-based applications for visualization, control, and AI-driven decision support. Operators can remotely monitor system performance, adjust parameters, and close the feedback loop. Firestore Cloud ensures scalable, synchronized data storage and persistent access to logs and DTw insights. Overall, this ISO 23247-compliant DTh-DTw implementation scenario demonstrates how integrated digital entities, supported by standardized communication and cloud infrastructures, can enhance the intelligence, resilience, and predictive capability of robotic AM systems.

The first DTw implementation focuses on real-time 3D simulation and process verification using RoboDK, as illustrated in Figure 20. This system creates a detailed virtual replica of the robotic wire-based LMD setup, allowing engineers to validate motion trajectories and process feasibility before execution. Integrated directly with CAD/CAM environments, RoboDK automatically generates and optimizes deposition paths to achieve precise material placement. Its collision detection and workspace analysis functions help identify interferences or reachability issues early in the workflow, improving safety and efficiency. Moreover, the simulation environment remains continuously linked to live data from the physical cell, enabling dynamic updates to motion commands and process parameters. Although the data flow operates primarily in one direction—from the physical system to its digital counterpart—it significantly enhances process understanding, reduces operational errors, and supports high-fidelity additive manufacturing outcomes.

The second DTw implementation centers on Industrial IoT-enabled monitoring and predictive maintenance using the KUKA iiQoT platform. This DT continuously collects telemetry data from the robot controller—such as joint temperatures, motor loads, and power consumption—to enable real-time diagnostics and performance assessment. Machine learning models analyze these data streams and historical trends to anticipate potential failures, supporting predictive maintenance that reduces downtime and extends system longevity. When deviations from normal behavior are



**FIGURE 20.** Real-time 3D simulation of the robotic cell during the material deposition using RoboDK.

detected, automated alerts and corrective recommendations are issued to operators. Hosted on a cloud infrastructure, KUKA iiQoT facilitates remote monitoring and long-term data analytics, fostering continuous process optimization and improved operational reliability.

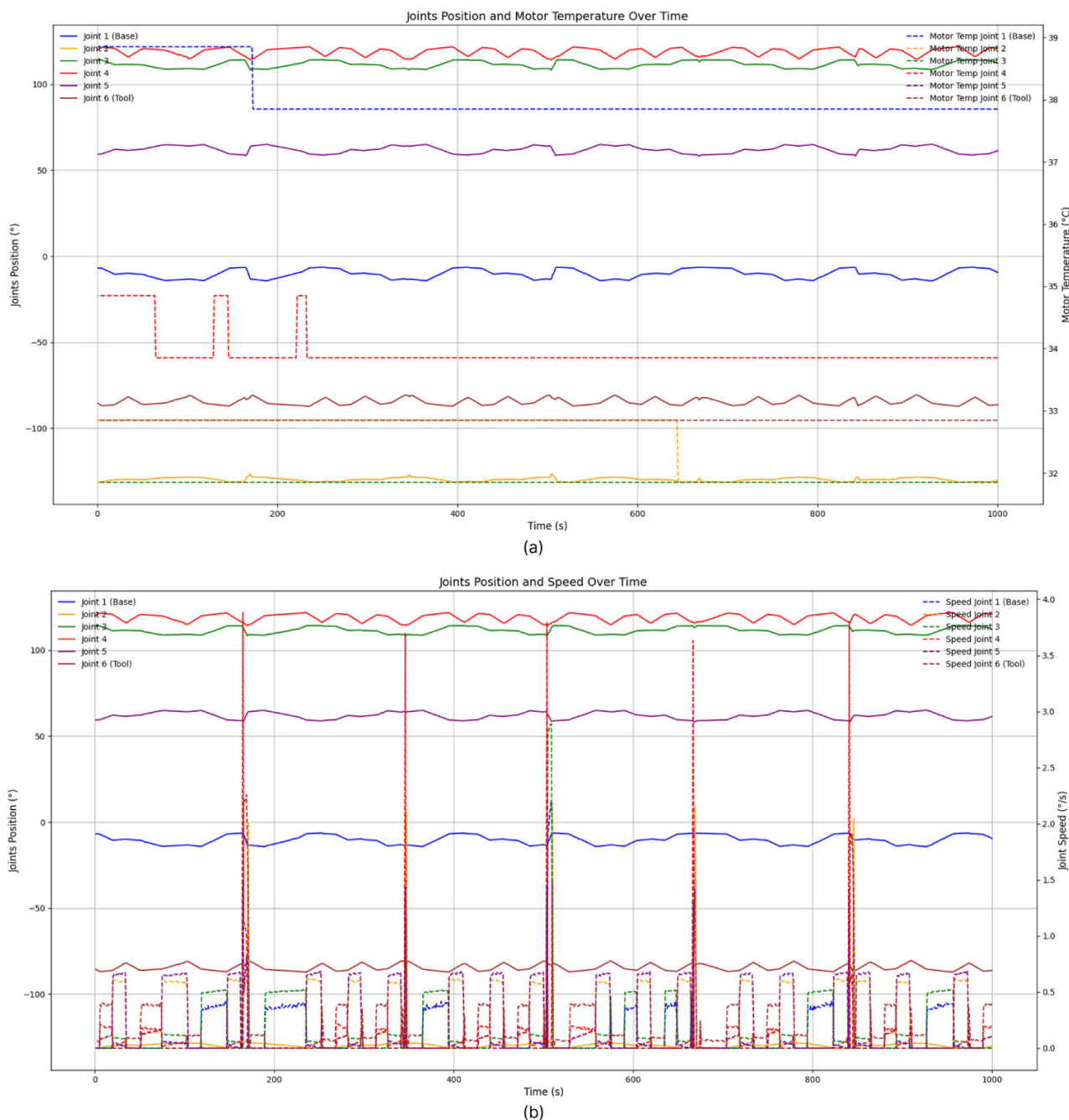
Figure 21(a) illustrates two overlaid time-series plots showing the evolution of the robot's joint positions and corresponding motor temperatures during the printing of the "Gravia" part. The data reveal a higher thermal rise in the base motor, reaching approximately 38C, compared to joint 3, which stabilizes around 32C. This temperature differential indicates uneven thermal loading among the robot's joints, potentially influencing motor performance, efficiency, and long-term durability under continuous operation.

Similarly, Figure 21(b) presents two overlapping plots depicting the time-series monitoring of the robot's joint positions and motor velocities. During deposition, the robot executes linear motion commands (KRL LIN) to perform material deposition, whereas the approach and retraction paths are carried out through point-to-point commands (KRL PTP). The observed variations in joint speeds result from the robot's serial kinematic configuration, which demands coordinated acceleration among all actuators. In particular, Joint 4 shows the highest velocity peaks and the largest positional changes, suggesting its pivotal role in sustaining deposition accuracy.

On the other hand, Figure 22 displays the time-series data of the stress exerted on the Meltio deposition head, measured via the load cell. Under stable operating conditions, the stress profile should remain low and approximately linear, with only slight oscillations. Pronounced peaks in the signal correspond to wire fusion or deposition irregularities, potentially resulting in defects in the manufactured part.

The integration of these sensor data streams within the DTw architecture follows the information flow defined by the ISO 23247 domains. Data from the load cell, together with temperature and power signals from the Meltio head and telemetry from the robot controller, are transmitted via MQTT and OPC UA through the DCDCE domain and stored in Firestore Cloud. These data are then made available to the DTw instances, where they are processed and used for both monitoring and optimization. In the KUKA iiQoT environment, aggregated sensor data support predictive maintenance and anomaly detection through trend analysis and machine learning routines. Simultaneously, the RoboDK DTw consumes historical load and temperature profiles to refine virtual deposition models and optimize process parameters such as feed rate or path spacing. This multi-level data integration creates a continuous improvement loop that strengthens the DTw's ability to diagnose deviations, recommend adjustments, and enhance overall process reliability.

Furthermore, analysis of the load-cell signal in conjunction with visual inspection and thermal imaging has revealed characteristic patterns associated with deposition anomalies. Sudden stress peaks were found to correlate with specific defect types, such as balling, dripping, or necking, each reflecting imbalances in laser alignment, wire feed, or heat distribution. By comparing timestamped sensor data with recorded video frames, these patterns enabled the identification of root causes and the implementation of corrective actions, such as recalibration of the collimator and fine-tuning of deposition parameters. This demonstrates how integrated sensor feedback within the DTw can support defect recognition and process optimization, reinforcing the role of the proposed ecosystem in achieving consistent and defect-free additive manufacturing outcomes [106].



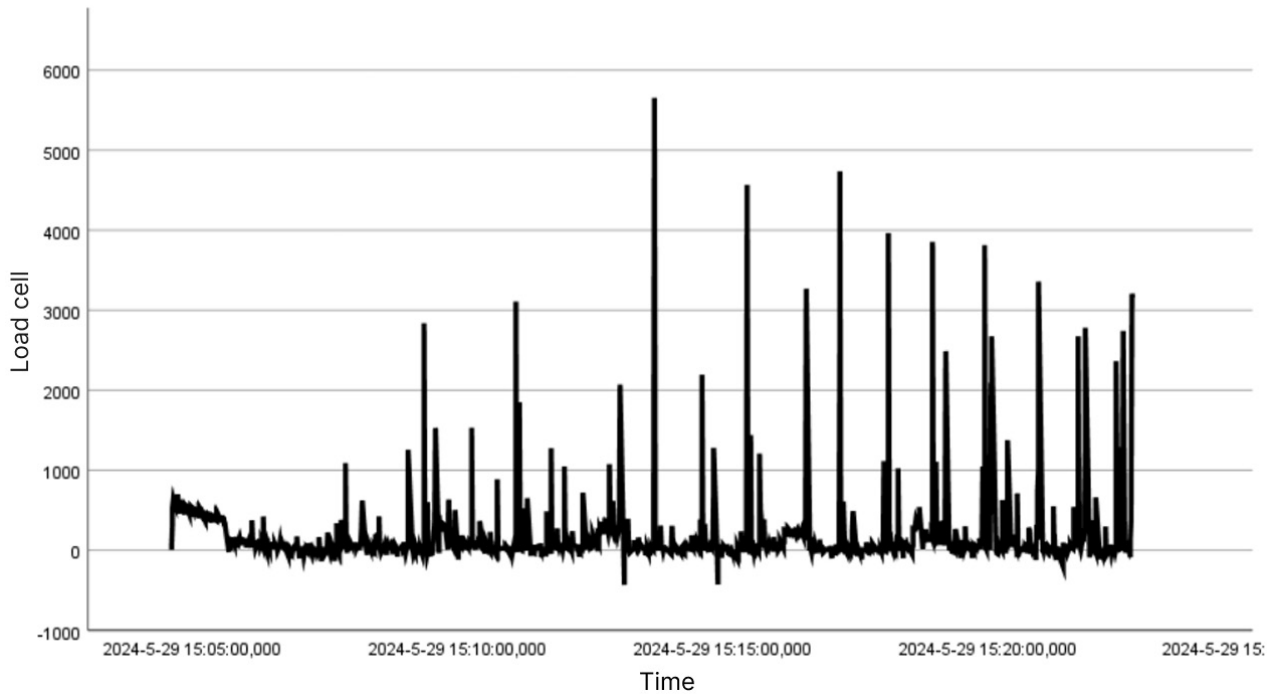
**FIGURE 21. Robot monitoring data: a) Joints position and motor temperature over time; b) Joints position and speed over time [106].**

The third DTw implementation employs the Meltio Dashboard for remote process monitoring, as illustrated in Figure 23. Through a TCP/IP socket connection, the system mirrors the Meltio controller interface, providing real-time visualization of key process variables such as diode laser temperatures, load cell forces, and wire feed tension, alongside live video of the deposition process. These data are displayed through an intuitive graphical interface that supports remote supervision and process analysis.

Collectively, these three DTw implementations constitute an integrated digital ecosystem that enhances the efficiency,

adaptability, and intelligence of the robotic LMD cell. Through the combination of real-time simulation, predictive maintenance, and interactive monitoring, the architecture embodies the principles of Industry 4.0 while laying a solid groundwork for the evolution of data-driven and intelligent manufacturing environments.

It is worth noting that the system operates under soft real-time conditions, which are adequate for robotic additive manufacturing processes. Although the communication protocols employed (MQTT and OPC UA) and the associated hardware are not intended for hard real-time control, they



**FIGURE 22.** Load cell data from the Meltio Engine Robot Integration head.

provide sufficiently reliable and responsive data exchange to ensure effective process supervision and coordination.

### C. ANALYSIS AND DISCUSSION OF IMPLEMENTATION SCENARIOS

The implementation scenarios presented in this study collectively demonstrate the practical relevance of the proposed standards-based digital ecosystem framework for manufacturing. Each implementation highlights how the combination of model-based data representations, standardized communication protocols, and reference frameworks can enhance interoperability, transparency, and contextualized data flow across the product lifecycle. Together, they reflect a gradual yet tangible movement toward the realization of intelligent, connected, and data-driven manufacturing systems.

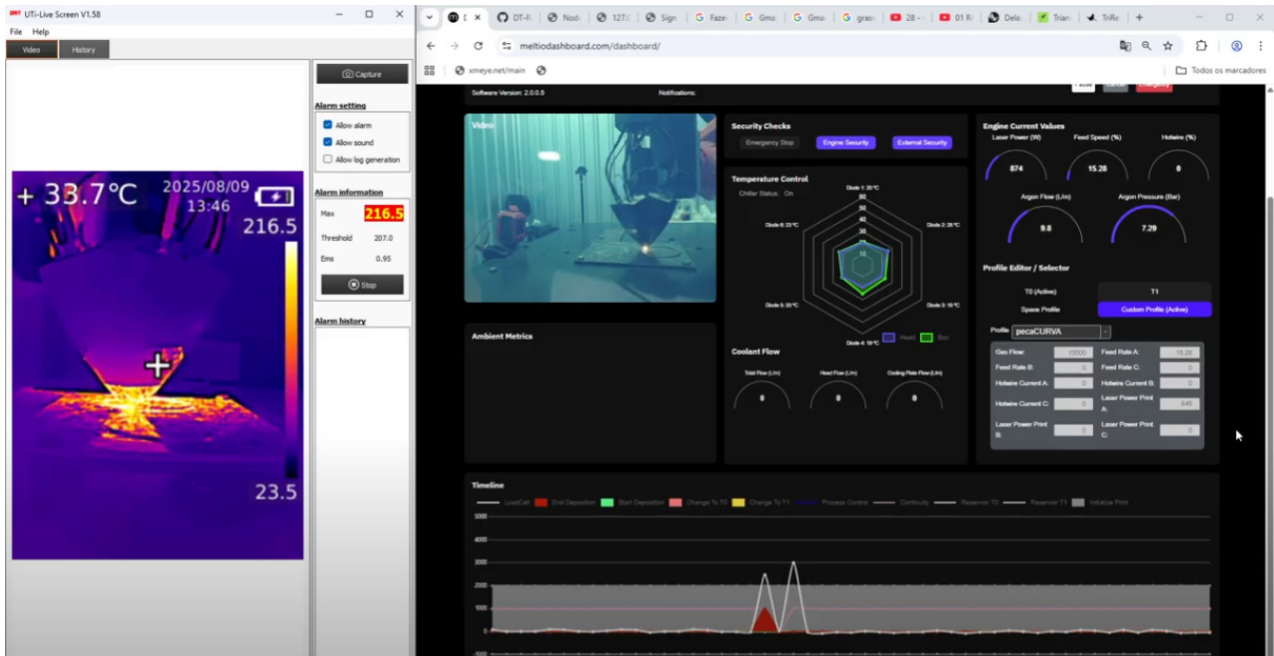
These implementations validate the pivotal role of open standards, such as STEP, STEP-NC, MTConnect, OPC UA, ISO 23704 and ISO 23247, in structuring communication and data exchange between heterogeneous systems. Their adoption ensures consistency, traceability, and interoperability while reducing dependence on proprietary software ecosystems. Moreover, by aligning with reference architectures such as ISO 23247, the systems demonstrate how DThs and DTws can coexist within a structured framework that supports simulation, monitoring, and decision-making across physical and cyber domains.

However, several challenges remain before these isolated implementations can evolve into a fully unified digital ecosystem. The current configurations, while effective within their specific contexts, still operate as independent systems rather than as interconnected components of a holistic digital continuum. Achieving the envisioned level of integration

requires substantial progress in harmonizing data models, ensuring semantic interoperability, and establishing bidirectional data flows across tools and lifecycle phases.

While the validation scenarios presented in this work focus on single-machine implementations, the proposed unified framework can be naturally extended to factory-level environments composed of multiple interconnected AM cells. In such a configuration, each AM system would maintain its own process-level DTw linked to a local DTh managing design, process, and inspection data. These individual DThs could then be integrated into a higher-level, plant-wide DTh that coordinates information flow across machines, enabling real-time synchronization of status, resource utilization, and production quality. For example, a set of laser metal deposition and fused deposition cells could share process and quality data through MTConnect and OPC UA, while higher-level DTws simulate global shop-floor performance and predict maintenance needs. Edge computing nodes would handle local synchronization and data aggregation, whereas cloud-based layers would support analytics and centralized monitoring. This hierarchical network of DThs and DTws would extend the framework's reach beyond single-machine validation, enabling scalable, collaborative, and continuously optimized manufacturing systems. Future work will focus on experimentally validating this multi-cell architecture and assessing its scalability, interoperability, and robustness under real industrial conditions.

A key limitation lies in the maturity of existing standards themselves. For example, the STEP-NC model remains largely oriented toward machining and lacks native entities to describe process parameters specific to additive manufacturing, such as extrusion flow rate or deposition temperature.



**FIGURE 23.** Real-time process monitoring using Meltio dashboard with thermal imaging showing temperature gradients during the material deposition.

This forces the adaptation of existing constructs, introducing semantic inconsistencies that limit automation and scalability. Similarly, while communication standards like MTConnect or OPC UA effectively enable data exchange, they do not inherently guarantee contextual consistency or synchronization across multiple DThs and DTws. In this regard, the implementations underscore both the progress achieved and the work still needed to realize a cohesive, standards-based digital ecosystem.

Beyond current interoperability and integration challenges, the next evolution of the proposed framework lies in its convergence with AI. The standardized and semantically rich data provided by interconnected DThs and DTws creates an ideal foundation for AI-driven analytics and decision support. Traditional DTws primarily serve as virtual mirrors of physical systems, focusing on visualization, monitoring, and predictive analysis. However, when augmented with generative and reasoning capabilities, they can evolve into Generative Digital Twins (GDTws), which are autonomous, self-adaptive entities capable of synthesizing new insights, optimizing processes, and even proposing design or control alternatives. These GDTws operate by continuously ingesting multimodal data from the DTh, learning correlations between parameters and outcomes, and generating novel solutions through generative models or reinforcement learning loops. Emerging Industrial Large Knowledge Models (ILKMs) [129] complement this paradigm by structuring domain-specific knowledge that allows GDTws to reason within the physical and process context. Together, they could enable manufacturing systems to transition from reactive to proactive behavior, where DTws not only reflect operations but also predict, adapt, and co-create alongside human decision-makers.

A particularly promising opportunity for integrating AI within the proposed framework arises from the robotic LMD scenario presented in this study. In the current implementation, the cell already operates under a condition-monitoring and predictive maintenance architecture, where telemetry from the robot and deposition head, such as joint loads, motor temperatures, and melt-pool stress, is continuously collected via MQTT and OPC UA. Building on this foundation, machine learning models could be trained using this standardized DTh data to correlate process parameters with deposition quality indicators, such as bead geometry or porosity levels. The associated DTw could then simulate the predicted process response and, through adaptive control routines, adjust parameters like laser power or wire feed rate in real time to stabilize the deposition. Over time, this closed-loop learning approach would enable the DTw to evolve from a passive monitoring layer into an intelligent, self-improving control entity within the ecosystem. Similar strategies could be extended to FDM processes, where layer-wise temperature and flow data could feed neural models to anticipate defects such as delamination or under-extrusion. In both cases, AI-driven reasoning embedded within the DTh–DTw framework would reinforce its capacity for predictive optimization, continuous adaptation, and autonomous decision-making, transforming DTws into proactive agents within a standards-based manufacturing ecosystem.

## VIII. CONCLUSION

This work has presented a comprehensive framework for developing a standards-based digital ecosystem that integrates the DTh and DTw to enable intelligent and interoperable AM. The preceding literature review showed

a clear movement toward standardization and data-driven integration in AM, but also revealed that many existing efforts remain isolated and lack a unified direction. From this analysis, the study identified fundamental elements, such as file formats, communication protocols, and reference implementation frameworks, that underpin digital continuity across AM processes. Building on international standards such as STEP-NC (ISO 14649 / ISO 10303-238), MTConnect, QIF (ISO 23952), OPC UA, MQTT and ISO 23247, the proposed ecosystem establishes a structured approach to achieving full digital continuity across the product lifecycle. By connecting design, process planning, manufacturing, and inspection phases through standardized data exchange, the framework promotes traceability, contextualized intelligence, and enhanced decision-making capabilities. Although centered on AM, the proposed approach is inherently generalizable and can be adapted to other manufacturing domains that rely on digital continuity and data-driven process integration.

Two implementation scenarios validated the feasibility of this approach. The first demonstrated the adaptation of the STEP-NC data model, originally conceived for machining, to represent toolpaths in a FDM process. This implementation, supported by the MTConnect protocol for real-time process monitoring, proved the capability of combining open standards to build a connected and transparent AM workflow. The second scenario focused on a robotic wire-based LMD system, where three DTw implementations were developed under the ISO 23247 framework. These included real-time 3D simulation, predictive maintenance using IIoT telemetry (KUKA iiQoT), and process visualization through the Meltio Dashboard. Together, they demonstrate the potential of DTw integration for adaptive, data-driven manufacturing environments.

The results highlight several key outcomes. First, the proposed framework effectively supports interoperability and data consistency through the unified use of open standards. Second, it demonstrates the practicality of extending STEP-NC beyond traditional machining, offering a viable foundation for standardizing AM workflows. Third, the integration of communication protocols such as MTConnect, MQTT and OPC UA shows that near real-time monitoring can be achieved even with low-cost hardware solutions, broadening the accessibility of smart manufacturing technologies.

However, notable challenges remain. The current STEP-NC model still lacks entities to fully describe AM-specific parameters such as extrusion rate, temperature control, or material properties, which limits its automation potential. Furthermore, while the presented implementations successfully address individual segments of the ecosystem, they do not yet constitute a fully unified architecture. Bridging these systems into a cohesive framework will require continued research into semantic interoperability, data governance, and cross-platform integration.

Future research should also explore the convergence of generative intelligence, Industrial Large Knowledge Mod-

els (ILKMs) [129], and DTh-DTw ecosystems. ILKMs, grounded in structured and human-interpretable knowledge libraries, can synthesize domain-specific insights from standardized DTh data streams. When enriched with generative AI, these models could give rise to Generative Digital Twins (GDTw), which could be autonomous, self-evolving virtual entities capable of learning from multi-modal manufacturing data to propose new designs, optimize process parameters, and predict system behaviors in real time. Within this vision, GDTws would act not merely as mirrors of physical assets but as co-creators, dynamically updating the DTh through bidirectional feedback and enabling self-improving workflows. This integration could ultimately transform AM into a cognitive ecosystem characterized by adaptive intelligence, closed-loop optimization, and continuous innovation.

## ACKNOWLEDGMENT

The authors would like to express their gratitude to CNPq (National Council for Scientific and Technological Development) and FAPDF (Research Support Foundation of the Federal District) for their financial support in developing this work. The authors also acknowledge the Graduate Program in Mechatronic Systems of the Department of Mechanical Engineering and the Faculty of Technology for covering the article processing charges (APC).

## REFERENCES

- [1] O. Kravchenko, M. Leshchenko, D. Marushchak, Y. Vdovychenko, and S. Boguslavskaya, "The digitalization as a global trend and growth factor of the modern economy," in *Proc. SHS Web Conf.*, vol. 65, May 2019, p. 07004. [Online]. Available: <https://www.shs-conferences.org/10.1051/shsconf/20196507004>
- [2] R. Rosen, G. von Wichert, G. Lo, and K. D. Bettenhausen, "About the importance of autonomy and digital twins for the future of manufacturing," *IFAC-PapersOnLine*, vol. 48, no. 3, pp. 567–572, 2015. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S2405896315003808>
- [3] C. Legner, T. Eymann, T. Hess, C. Matt, T. Böhm, P. Drews, A. Mädche, N. Urbach, and F. Ahlemann, "Digitalization: Opportunity and challenge for the business and information systems engineering community," *Bus. Inf. Syst. Eng.*, vol. 59, no. 4, pp. 301–308, Aug. 2017.
- [4] R. Y. Zhong, X. Xu, E. Klotz, and S. T. Newman, "Intelligent manufacturing in the context of industry 4.0: A review," *Engineering*, vol. 3, no. 5, pp. 616–630, Oct. 2017. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S2095809917307130>
- [5] F. Tao and Q. Qi, "New IT driven service-oriented smart manufacturing: Framework and characteristics," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 1, pp. 81–91, Jan. 2019.
- [6] P. Zheng, H. Wang, Z. Sang, R. Y. Zhong, Y. Liu, C. Liu, K. Mubarak, S. Yu, and X. Xu, "Smart manufacturing systems for industry 4.0: Conceptual framework, scenarios, and future perspectives," *Frontiers Mech. Eng.*, vol. 13, no. 2, pp. 137–150, Jun. 2018. [Online]. Available: <http://link.springer.com/10.1007/s11465-018-0499-5>
- [7] X. Xu, Y. Lu, B. Vogel-Heuser, and L. Wang, "Industry 4.0 and industry 5.0—Inception, conception and perception," *J. Manuf. Syst.*, vol. 61, pp. 530–535, Oct. 2021.
- [8] X. Li, A. Nassehi, H. Yang, F. Tao, J. Sutherland, L. Wang, and R. Gao, "Generative manufacturing systems," *SSRN Electron. J.*, 2025.
- [9] J. Warlick, R. Godziela, and D. Mitterbuchner. (2023). *Think Thread First: Surf the Wave of Product Data*. Accessed: Jan. 2, 2024. [Online]. Available: <https://www.ge.com/research/offering/digital-twin-creation>
- [10] C. Leiva. (2016). *Demystifying the Digital Thread and Digital Twin Concepts*. Accessed: Jan. 2, 2024. [Online]. Available: <https://www.industryweek.com/technology-and-iiot/systems-integration/article/22007865/demystifying-the-digital-thread-and-digital-twin-concepts>

- [11] E. Rodríguez, A. Alvares, and C. Riaño, "STEP-NC in additive manufacturing: A comprehensive review, architecture, and data model proposal," *Int. J. Adv. Manuf. Technol.*, vol. 137, nos. 11–12, pp. 5751–5787, Apr. 2025. [Online]. Available: <https://link.springer.com/10.1007/s00170-025-15290-8>
- [12] C. Liu, L. L. Roux, C. Körner, O. Tabaste, F. Lacan, and S. Bigot, "Digital twin-enabled collaborative data management for metal additive manufacturing systems," *J. Manuf. Syst.*, vol. 62, pp. 857–874, Jan. 2022, doi: [10.1016/j.jmsy.2020.05.010](https://doi.org/10.1016/j.jmsy.2020.05.010).
- [13] *Additive Manufacturing—General Principles—Fundamentals and Vocabulary*, Standard ISO/ASTM 52900, 2021.
- [14] J. Butt, "Exploring the interrelationship between additive manufacturing and industry 4.0," *Designs*, vol. 4, no. 2, p. 13, Jun. 2020.
- [15] L. Cohen, "The digital thread: Transformation to automation," *Composites World*, 2010. Accessed: Dec. 5, 2025. [Online]. Available: <https://www.compositesworld.com/columns/the-digital-thread-transformation-to-automation>
- [16] T. D. West and A. Pyster, "Untangling the digital thread: The challenge and promise of model-based engineering in defense acquisition," *INSIGHT*, vol. 18, no. 2, pp. 45–55, 2015.
- [17] T. D. Hedberg, M. Bajaj, and J. A. Camelio, "Using graphs to link data across the product lifecycle for enabling smart manufacturing digital threads," *J. Comput. Inf. Sci. Eng.*, vol. 20, no. 1, pp. 1–15, Feb. 2020, doi: [10.1115/1.4044921](https://doi.org/10.1115/1.4044921).
- [18] M. Helu and T. Hedberg, "Enabling smart manufacturing research and development using a product lifecycle test bed," *Proc. Manuf.*, vol. 1, pp. 86–97, Jan. 2015, doi: [10.1016/j.promfg.2015.09.066](https://doi.org/10.1016/j.promfg.2015.09.066).
- [19] T. D. Hedberg, M. Bajaj, and J. A. Camelio, "Using graphs to link data across the product lifecycle for enabling smart manufacturing digital threads," *J. Comput. Inf. Sci. Eng.*, vol. 20, no. 1, Feb. 2020, doi: [10.1115/1.4044921](https://doi.org/10.1115/1.4044921).
- [20] M. Helu, T. Hedberg, and A. B. Feeney, "Reference architecture to integrate heterogeneous manufacturing systems for the digital thread," *CIRP J. Manuf. Sci. Technol.*, vol. 19, pp. 191–195, Nov. 2017, doi: [10.1016/j.cirpj.2017.04.002](https://doi.org/10.1016/j.cirpj.2017.04.002).
- [21] S. Kwon, L. V. Monnier, R. Barbau, and W. Z. Bernstein, "Enriching standards-based digital thread by fusing as-designed and as-inspected data using knowledge graphs," *Adv. Eng. Informat.*, vol. 46, Oct. 2020, Art. no. 101102, doi: [10.1016/j.aei.2020.101102](https://doi.org/10.1016/j.aei.2020.101102).
- [22] L. Sun, Z. Jiao, S. Wang, F. Jiang, and X. Li, "A consistency evaluation method for digital twins in manufacturing," *IEEE Access*, vol. 13, pp. 109046–109056, 2025.
- [23] D. B. Kim, P. Witherell, R. Lipman, and S. C. Feng, "Streamlining the additive manufacturing digital spectrum: A systems approach," *Additive Manuf.*, vol. 5, pp. 20–30, Jan. 2015, doi: [10.1016/j.addma.2014.10.004](https://doi.org/10.1016/j.addma.2014.10.004).
- [24] A. R. Nassar and E. W. Reutzel, "A proposed digital thread for additive manufacturing," Dept. Mech. Eng., Appl. Res. Lab., Pennsylvania State Univ., 2013.
- [25] R. Bonnard, J.-Y. Hascoët, and P. Mognol, "Data model for additive manufacturing digital thread: State of the art and perspectives," *Int. J. Comput. Integr. Manuf.*, vol. 32, no. 12, pp. 1170–1191, Dec. 2019, doi: [10.1080/0951192x.2019.1690681](https://doi.org/10.1080/0951192x.2019.1690681).
- [26] D. B. Kim, P. Witherell, Y. Lu, and S. Feng, "Toward a digital thread and data package for metals-additive manufacturing," *Smart Sustain. Manuf. Syst.*, vol. 1, no. 1, pp. 75–100, Feb. 2017, doi: [10.1520/ssms20160003](https://doi.org/10.1520/ssms20160003).
- [27] R. Bonnard, P. Mognol, and J.-Y. Hascoët, "A new digital chain for additive manufacturing processes," *Virtual Phys. Prototyping*, vol. 5, no. 2, pp. 75–88, Jun. 2010, doi: [10.1080/17452751003696916](https://doi.org/10.1080/17452751003696916).
- [28] R. Bonnard, J.-Y. Hascoët, P. Mognol, and I. Stroud, "STEP-NC digital thread for additive manufacturing: Data model, implementation and validation," *Int. J. Comput. Integr. Manuf.*, vol. 31, no. 11, pp. 1141–1160, Nov. 2018, doi: [10.1080/0951192x.2018.1509130](https://doi.org/10.1080/0951192x.2018.1509130).
- [29] R. Bonnard, J.-Y. Hascoët, P. Mognol, E. Zancul, and A. J. Alvares, "Hierarchical object-oriented model (HOOM) for additive manufacturing digital thread," *J. Manuf. Syst.*, vol. 50, pp. 36–52, Jan. 2019, doi: [10.1016/j.jmsy.2018.11.003](https://doi.org/10.1016/j.jmsy.2018.11.003).
- [30] D. Mies, W. Marsden, and S. Warde, "Overview of additive manufacturing informatics: 'A digital thread,'" *Integrating Mater. Manuf. Innov.*, vol. 5, no. 1, pp. 114–142, Dec. 2016, doi: [10.1186/s40192-016-0050-7](https://doi.org/10.1186/s40192-016-0050-7).
- [31] F. Belkadi, L. M. Vidal, A. Bernard, E. Pei, and E. M. Sanfilippo, "Towards a unified additive manufacturing product-process model for digital chain management purpose," *Proc. CIRP*, vol. 70, pp. 428–433, Jan. 2018.
- [32] J. Xiao, N. Anwer, A. Durupt, J. Le Duigou, and B. Eynard, "Information exchange standards for design, tolerancing and additive manufacturing: A research review," *Int. J. Interact. Design Manuf. (IJIDeM)*, vol. 12, no. 2, pp. 495–504, May 2018, doi: [10.1007/s12008-017-0401-4](https://doi.org/10.1007/s12008-017-0401-4).
- [33] J. Xiao and Y. Lei, "Enriching semantics of geometry features and parameters for additive manufacturing peculiar structure based on STEP standards," *Crystals*, vol. 12, no. 8, p. 1154, Aug. 2022, doi: [10.3390/cryst12081154](https://doi.org/10.3390/cryst12081154).
- [34] E. Pei, M. Ressin, R. I. Campbell, B. Eynard, and J. Xiao, "Investigating the impact of additive manufacturing design data exchange standards for re-distributed manufacturing," *Prog. Additive Manuf.*, vol. 4, no. 3, pp. 331–344, Sep. 2019, doi: [10.1007/s40964-019-00085-7](https://doi.org/10.1007/s40964-019-00085-7).
- [35] T. Mahan, N. Meisel, C. McComb, and J. Menold, "Pulling at the digital thread: Exploring the tolerance stack up through automatic procedures and expert strategies in scan to print processes," *J. Mech. Design*, vol. 141, no. 2, pp. 1–12, Feb. 2019, doi: [10.1115/1.4041927](https://doi.org/10.1115/1.4041927).
- [36] E. Bonham, K. McMaster, E. Thomson, M. Panarotto, J. R. Müller, O. Isaksson, and E. Johansson, "Designing and integrating a digital thread system for customized additive manufacturing in multi-partner kayak production," *Systems*, vol. 8, no. 4, p. 43, Nov. 2020.
- [37] N. Gupta, A. Tiwari, S. T. S. Bukkapatnam, and R. Karri, "Additive manufacturing cyber-physical system: Supply chain cybersecurity and risks," *IEEE Access*, vol. 8, pp. 47322–47333, 2020.
- [38] M. Sjarov, N. Ceriani, T. Lechler, and J. Franke, "Building blocks for digitally integrated process chains in PBF-based additive manufacturing," in *Proc. Congr. German Academic Assoc. Prod. Technol.*, 2021, pp. 368–377.
- [39] Y. Xiong, Y. Tang, Q. Zhou, Y. Ma, and D. W. Rosen, "Intelligent additive manufacturing and design: State of the art and future perspectives," *Additive Manuf.*, vol. 59, Nov. 2022, Art. no. 103139.
- [40] G. L. Knapp, B. Stump, L. Scime, A. Márquez Rossy, C. Joslin, W. Halsey, and A. Plotkowski, "Leveraging the digital thread for physics-based prediction of microstructure heterogeneity in additively manufactured parts," *Additive Manuf.*, vol. 78, Sep. 2023, Art. no. 103861.
- [41] G. L. Knapp, S. T. Reeve, J. Coleman, M. Rolchigo, B. Stump, S. DeWitt, and A. Plotkowski, "Myna: Connecting powder bed fusion build data to simulation tools for digital twin applications," *Comput. Mater. Sci.*, vol. 258, Aug. 2025, Art. no. 114094.
- [42] S. Karadgi, P. M. Bhovi, A. Y. Patil, K. Ramaiah, K. Venkateswarlu, and T. G. Langdon, "A conceptual framework towards the realization of in situ monitoring and control of end-to-end additive manufacturing process," *Micro Nanosystems*, vol. 15, no. 2, pp. 92–101, Jun. 2023.
- [43] S. C. Feng, A. Jones, and G. Shao, "Data requirements for digital twins in additive manufacturing," in *Manufacturing Equipment and Automation; Manufacturing Processes; Manufacturing Systems; Nano/Micro/Meso Manufacturing; Quality and Reliability*. New York, NY, USA: American Society of Mechanical Engineers, 2023.
- [44] K. Poka, B. Merz, M. Epperlein, and K. Hilgenberg, "Integration of the whole digital chain in a unique file for PBF-LB/M: Practical implementation within a digital thread and its advantages," in *Proc. Int. Conf. Additive Manuf. Products Appl.*, 2024, pp. 91–114.
- [45] J. Xiao, N. Anwer, H. Huang, R. Bonnard, B. Eynard, C. Huang, and E. Pei, "Information exchange and knowledge discovery for additive manufacturing digital thread: A comprehensive literature review," *Int. J. Comput. Integr. Manuf.*, vol. 38, no. 8, pp. 1–26, Aug. 2025, doi: [10.1080/0951192x.2024.2387768](https://doi.org/10.1080/0951192x.2024.2387768).
- [46] R. Furferi, "Integrating geometric dimensioning and tolerancing with additive manufacturing: A perspective," *Appl. Sci.*, vol. 15, no. 6, p. 3398, Mar. 2025.
- [47] E. E. Rodríguez, R. Bonnard, and A. J. Alvares, "Proposal of an advanced data model for step-NC compliant additive manufacturing," in *Proc. 24th ABCM Int. Congr. Mech. Eng.*, 2017, pp. 1–16, doi: [10.26678/abcm.cobem2017.cob17-2435](https://doi.org/10.26678/abcm.cobem2017.cob17-2435).
- [48] E. Rodríguez, C. Riaño, A. Alvares, and R. Bonnard, "Design and dimensional synthesis of a linear delta robot with single legs for additive manufacturing," *J. Brazilian Soc. Mech. Sci. Eng.*, vol. 41, no. 11, pp. 1–16, Nov. 2019, doi: [10.1007/s40430-019-2039-6](https://doi.org/10.1007/s40430-019-2039-6).
- [49] C. Riaño, E. Rodríguez, and A. J. Alvares, "A closed-loop inspection architecture for additive manufacturing based on STEP standard," *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 2782–2787, 2019, doi: [10.1016/j.ifacol.2019.11.629](https://doi.org/10.1016/j.ifacol.2019.11.629).
- [50] E. Rodríguez and A. Alvares, "A STEP-NC implementation approach for additive manufacturing," *Proc. Manuf.*, vol. 38, pp. 9–16, Jan. 2019. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S2351978920300020>

- [51] Y. Qin, Q. Qi, P. J. Scott, and X. Jiang, "Status, comparison, and future of the representations of additive manufacturing data," *Comput.-Aided Design*, vol. 111, pp. 44–64, Jun. 2019, doi: [10.1016/j.cad.2019.02.004](https://doi.org/10.1016/j.cad.2019.02.004).
- [52] A. Kumar, P. Kumar, R. K. Mittal, and H. Singh, *Printing File Formats for Additive Manufacturing Technologies*. Amsterdam, The Netherlands: Elsevier, 2023, pp. 87–102, doi: [10.1016/B978-0-323-91834-3.00006-5](https://doi.org/10.1016/B978-0-323-91834-3.00006-5).
- [53] (2024). *New Open Data Format Simplifies 3D Printing Process*. Accessed: Oct. 5, 2025. [Online]. Available: <https://spaener.com/en/article/new-open-data-format-simplifies-3d-printing-process>
- [54] *Stereolithography Interface Specification*, 3D Systems, Rock Hill, SC, USA, 1989.
- [55] *Specification for Additive Manufacturing File Format (AMF)*, Standard ISO/ASTM-52915, 2020.
- [56] *3d Manufacturing Format (3MF)—The File Format for 3D Printing*, 3MF Consortium, San Francisco, CA, USA, 2014.
- [57] *Wavefront Advanced Visualiser Manual—appendix B1. Object Files (.obj)*, Wavefront Technologies, Coimbatore, India, 1995.
- [58] *Industrial Automation Systems and Integration—Product Data Representation and Exchange—Part 1: Overview and Fundamental Principles*, Standard 10303-1, 2024.
- [59] *Industrial Automation Systems and Integration—Physical Device Control—Data Model for Computerized Numerical Controllers*, Standard 14649-1, International Standard Organization, 2003.
- [60] *Industrial Automation Systems and Integration—Product Data Representation and Exchange—Part 238: Application Protocol: Model Based Integrated Manufacturing*, Standard 10303-238, International Standard Organization, 2022.
- [61] A. J. Alvares, E. Rodríguez, C. I. Riaño Jaimes, J. S. Toquica, and J. C. E. Ferreira, "STEP-NC architectures for industrial robotic machining: Review, implementation and validation," *IEEE Access*, vol. 8, pp. 152592–152610, 2020, doi: [10.1109/ACCESS.2020.3017561](https://doi.org/10.1109/ACCESS.2020.3017561).
- [62] C. I. R. Jaimes, A. J. Alvares, and C. A. Peña, "Kinematic compensation algorithm for reducing errors in a closed-loop manufacturing system," *IEEE Access*, vol. 12, pp. 89493–89505, 2024.
- [63] *STEP-NC Standard—Third Edition*, Standard ISO 10303-238, 2022. [Online]. Available: <https://ap238.org/ap238e3>
- [64] F. A. Milaat, P. Witherell, M. Hardwick, H. Yeung, V. Ferrero, L. Monnier, and M. Brown, "STEP-NC process planning for powder bed fusion additive manufacturing," *J. Comput. Inf. Sci. Eng.*, vol. 22, no. 6, pp. 1–11, Dec. 2022, doi: [10.1115/1.4055855](https://doi.org/10.1115/1.4055855).
- [65] V. B. P. RajratnaKharat, "Digital twin: Manufacturing excellence through virtual factory replication," 3MF Consortium, 3D Manufacturing Format (3MF), 3D Printing, San Francisco, CA, USA, 2014. Accessed: Dec. 5, 2025. [Online]. Available: <https://3mf.io>
- [66] E. H. Glaessgen and D. S. Stargel, "The digital twin paradigm for future NASA and U.S. Air force vehicles," p. 1818, 2012.
- [67] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital twin in industry: State-of-the-art," *IEEE Trans. Ind. Informat.*, vol. 15, no. 4, pp. 2405–2415, Apr. 2019, doi: [10.1109/TII.2018.2873186](https://doi.org/10.1109/TII.2018.2873186).
- [68] *Automation Systems and Integration—Digital Twin Framework for Manufacturing—Part 1: Overview and General Principles*, Standard 23247-1, International Standard Organization, 2021.
- [69] B. R. Barricelli, E. Casiraghi, and D. Fogli, "A survey on digital twin: Definitions, characteristics, applications, and design implications," *IEEE Access*, vol. 7, pp. 167653–167671, 2019, doi: [10.1109/ACCESS.2019.2953499](https://doi.org/10.1109/ACCESS.2019.2953499).
- [70] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital twin in manufacturing: A categorical literature review and classification," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, 2018, doi: [10.1016/j.ifacol.2018.08.474](https://doi.org/10.1016/j.ifacol.2018.08.474).
- [71] Z. Chen, K. Surendraarcharyagie, K. Granland, C. Chen, X. Xu, Y. Xiong, C. Davies, and Y. Tang, "Service oriented digital twin for additive manufacturing process," *J. Manuf. Syst.*, vol. 74, pp. 762–776, Jun. 2024, doi: [10.1016/j.jmsy.2024.04.015](https://doi.org/10.1016/j.jmsy.2024.04.015).
- [72] Y. Lu, C. Liu, K. I.-K. Wang, H. Huang, and X. Xu, "Digital twin-driven smart manufacturing: Connotation, reference model, applications and research issues," *Robot. Comput.-Integr. Manuf.*, vol. 61, Feb. 2020, Art. no. 101837. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S0736584519302480>
- [73] F. Tao and M. Zhang, "Digital twin shop-floor: A new shop-floor paradigm towards smart manufacturing," *IEEE Access*, vol. 5, pp. 20418–20427, 2017, doi: [10.1109/ACCESS.2017.2756069](https://doi.org/10.1109/ACCESS.2017.2756069).
- [74] (2016). *Digital Thread and Digital Twin Demonstrations at Future of Flight*. Accessed: Jan. 2, 2024. [Online]. Available: <https://www.steptools.com/blog/20161005digitalthreddemo/>
- [75] K. M. Alam and A. El Saddik, "C2PS: A digital twin architecture reference model for the cloud-based cyber-physical systems," *IEEE Access*, vol. 5, pp. 2050–2062, 2017, doi: [10.1109/ACCESS.2017.2657006](https://doi.org/10.1109/ACCESS.2017.2657006).
- [76] S. Aheleroff, X. Xu, R. Y. Zhong, and Y. Lu, "Digital twin as a service (DTaaS) in industry 4.0: An architecture reference model," *Adv. Eng. Informat.*, vol. 47, Jan. 2021, Art. no. 101225, doi: [10.1016/j.aei.2020.101225](https://doi.org/10.1016/j.aei.2020.101225).
- [77] Y. Zheng, S. Yang, and H. Cheng, "An application framework of digital twin and its case study," *J. Ambient Intell. Humanized Comput.*, vol. 10, no. 3, pp. 1141–1153, Mar. 2019, doi: [10.1007/s12652-018-0911-3](https://doi.org/10.1007/s12652-018-0911-3).
- [78] M. Bevilacqua, E. Bottani, F. E. Ciarapica, F. Costantino, L. Di Donato, A. Ferraro, G. Mazzuto, A. Monteriu, G. Nardini, M. Orteni, M. Paroncini, M. Pirozzi, M. Prist, E. Quatrini, M. Tronci, and G. Vignali, "Digital twin reference model development to prevent Operators' risk in process plants," *Sustainability*, vol. 12, no. 3, p. 1088, Feb. 2020, doi: [10.3390/su12031088](https://doi.org/10.3390/su12031088).
- [79] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, and A. Y. C. Nee, "Enabling technologies and tools for digital twin," *J. Manuf. Syst.*, vol. 58, pp. 3–21, Jan. 2021, doi: [10.1016/j.jmsy.2019.10.001](https://doi.org/10.1016/j.jmsy.2019.10.001).
- [80] A. Bárkányi, T. Chován, S. Németh, and J. Abonyi, "Modelling for digital twins—Potential role of surrogate models," *Processes*, vol. 9, no. 3, p. 476, Mar. 2021, doi: [10.3390/pr9030476](https://doi.org/10.3390/pr9030476).
- [81] G. Shao and M. Helu, "Framework for a digital twin in manufacturing: Scope and requirements," *Manuf. Lett.*, vol. 24, pp. 105–107, Apr. 2020, doi: [10.1016/j.mfglet.2020.04.004](https://doi.org/10.1016/j.mfglet.2020.04.004).
- [82] *Automation Systems and Integration—Digital Twin Framework for Manufacturing—Part 2: Reference Architecture*, Standard ISO 23247-2, 2021.
- [83] *Automation Systems and Integration—Digital Twin Framework for Manufacturing—Part 3: Digital Representation of Manufacturing Elements*, Standard ISO 23247-3, 2021.
- [84] *Automation Systems and Integration—digital Twin Framework for Manufacturing—Part 4: Information Exchange*, Standard ISO 23247-4, 2021.
- [85] *Automation Systems and Integration—digital Twin Framework for Manufacturing—Part 5: Digital Thread for Digital Twin*, Standard ISO 23247-5, 2024.
- [86] *Automation Systems and Integration—digital Twin Framework for Manufacturing—part 6: Digital Twin Composition*, Standard ISO 23247-6, 2024.
- [87] T. DebRoy, W. Zhang, J. Turner, and S. S. Babu, "Building digital twins of 3D printing machines," *Scripta Mater.*, vol. 135, pp. 119–124, Jul. 2017, doi: [10.1016/j.scriptamat.2016.12.005](https://doi.org/10.1016/j.scriptamat.2016.12.005).
- [88] G. L. Knapp, T. Mukherjee, J. S. Zuback, H. L. Wei, T. A. Palmer, A. De, and T. DebRoy, "Building blocks for a digital twin of additive manufacturing," *Acta Mater.*, vol. 135, pp. 390–399, Aug. 2017, doi: [10.1016/j.actamat.2017.06.039](https://doi.org/10.1016/j.actamat.2017.06.039).
- [89] T. Mukherjee and T. DebRoy, "A digital twin for rapid qualification of 3D printed metallic components," *Appl. Mater. Today*, vol. 14, pp. 59–65, Mar. 2019, doi: [10.1016/j.apmt.2018.11.003](https://doi.org/10.1016/j.apmt.2018.11.003).
- [90] H. L. Wei, T. Mukherjee, W. Zhang, J. S. Zuback, G. L. Knapp, A. De, and T. DebRoy, "Mechanistic models for additive manufacturing of metallic components," *Prog. Mater. Sci.*, vol. 116, Feb. 2021, Art. no. 100703, doi: [10.1016/j.pmatsci.2020.100703](https://doi.org/10.1016/j.pmatsci.2020.100703).
- [91] T. Shen and B. Li, "Digital twins in additive manufacturing: A state-of-the-art review," *Int. J. Adv. Manuf. Technol.*, vol. 131, no. 1, pp. 63–92, Mar. 2024, doi: [10.1007/s00170-024-13092-y](https://doi.org/10.1007/s00170-024-13092-y).
- [92] S. B. Amor, N. Elloumi, A. Eltaief, B. Louhichi, N. H. Alrasheedi, and A. Seibi, "Digital twin implementation in additive manufacturing: A comprehensive review," *Processes*, vol. 12, no. 6, p. 1062, May 2024, doi: [10.3390/pr12061062](https://doi.org/10.3390/pr12061062).
- [93] R. Reisch, T. Hauser, T. Kamps, and A. Knoll, "Robot based wire arc additive manufacturing system with context-sensitive multivariate monitoring framework," *Proc. Manuf.*, vol. 51, pp. 732–739, Jan. 2020, doi: [10.1016/j.promfg.2020.10.103](https://doi.org/10.1016/j.promfg.2020.10.103).
- [94] H. Mu, F. He, L. Yuan, H. Hatamian, P. Commins, and Z. Pan, "Online distortion simulation using generative machine learning models: A step toward digital twin of metallic additive manufacturing," *J. Ind. Inf. Integr.*, vol. 38, Mar. 2024, Art. no. 100563, doi: [10.1016/j.jii.2024.100563](https://doi.org/10.1016/j.jii.2024.100563).
- [95] S. Hartmann, O. Murua, J. I. Arrizubieta, A. Lamikiz, and P. Mayr, "Digital twin of the laser-DED process based on a multiscale approach," *Simul. Model. Pract. Theory*, vol. 132, Apr. 2024, Art. no. 102881, doi: [10.1016/j.simpat.2023.102881](https://doi.org/10.1016/j.simpat.2023.102881).
- [96] A. W. Malik, M. A. Mahmood, and F. Liou, "Digital twin-driven optimization of laser powder bed fusion processes: A focus on lack-of-fusion defects," *Rapid Prototyping J.*, vol. 30, no. 10, pp. 1977–1988, Nov. 2024, doi: [10.1108/rpj-02-2024-0091](https://doi.org/10.1108/rpj-02-2024-0091).

- [97] G. Shao, "Use case scenarios for digital twin implementation based on iso 23247," Adv. Manuf. Series (NIST AMS), Syst. Integr. Division, Eng. Lab., National Inst. Standards Technol., May 2021. [Online]. Available: <https://doi.org/10.6028/NIST.AMS.400-2>
- [98] D. Bong Kim, G. Shao, and G. Jo, "A digital twin implementation architecture for wire + arc additive manufacturing based on ISO 23247," *Manuf. Lett.*, vol. 34, pp. 1–5, Oct. 2022, doi: [10.1016/j.mfglet.2022.08.008](https://doi.org/10.1016/j.mfglet.2022.08.008).
- [99] M.-S. Kang, D.-H. Lee, M. S. Bajestani, D. B. Kim, and S. D. Noh, "Edge computing-based digital twin framework based on ISO 23247 for enhancing data processing capabilities," *Machines*, vol. 13, no. 1, p. 19, Dec. 2024, doi: [10.3390/machines13010019](https://doi.org/10.3390/machines13010019).
- [100] J. V. A. Cabral, E. A. R. Gasca, and A. J. Alvares, "Digital twin implementation for machining center based on ISO 23247 standard," *IEEE Latin Amer. Trans.*, vol. 21, no. 5, pp. 628–635, May 2023, doi: [10.1109/TLA.2023.10130834](https://doi.org/10.1109/TLA.2023.10130834).
- [101] J. V. A. Cabral, A. J. Alvares, and G. Caribé de Carvalho, "Digital twin implementation for an additive manufacturing robotic cell based on the ISO 23247 standard," *IEEE Latin Amer. Trans.*, vol. 22, no. 8, pp. 651–658, Aug. 2024, doi: [10.1109/TLA.2024.10620386](https://doi.org/10.1109/TLA.2024.10620386).
- [102] B. Wallner, B. Zwölfer, T. Trautner, and F. Bleicher, "Digital twin development and operation of a flexible manufacturing cell using ISO 23247," *Proc. CIRP*, vol. 120, pp. 1149–1154, Jan. 2023, doi: [10.1016/j.procir.2023.09.140](https://doi.org/10.1016/j.procir.2023.09.140).
- [103] G.-N. Le, T. V. Nguyen, V.-D. Tran, N.-T. Nguyen, X. Tang, and T. Hoang, "Multi-services digital twin for modular production system based on ISO 23247 and Web server," in *Proc. 1st Int. Conf. Sustainability Emerg. Technol. Smart Manufacturings*, 2025, pp. 679–689, doi: [10.1007/978-981-97-7083-0\\_68](https://doi.org/10.1007/978-981-97-7083-0_68).
- [104] V. Melo, J. Barbosa, G. Mota, F. D. L. Prieta, and P. Leitao, "Design of an ISO 23247 compliant digital twin for an automotive assembly line," in *Proc. IEEE 7th Int. Conf. Ind. Cyber-Phys. Syst. (ICPS)*, May 2024, pp. 1–6, doi: [10.1109/icps59941.2024.10640052](https://doi.org/10.1109/icps59941.2024.10640052).
- [105] G. Caiza and R. Sanz, "Immersive digital twin under ISO 23247 applied to flexible manufacturing processes," *Appl. Sci.*, vol. 14, no. 10, p. 4204, May 2024, doi: [10.3390/app14104204](https://doi.org/10.3390/app14104204).
- [106] A. J. Alvares, E. Rodriguez, and B. Figueroa, "Digital-twin-enabled process monitoring for a robotic additive manufacturing cell using wire-based laser metal deposition," *Processes*, vol. 13, no. 8, p. 2335, Jul. 2025.
- [107] T. B. Minh, D. X. Phu, Q. H. Nguyen, K. H. V. Nguyen, and T. T. T. Phan, "A digital twin implementation framework for a collaborative robot based on iso 23247," in *Proc. Int. Conf. Sustain. Energy Technol.*, 2024, pp. 747–755, doi: [10.1007/978-981-97-1868-9\\_74](https://doi.org/10.1007/978-981-97-1868-9_74).
- [108] A. Sobowale, L. Freitas, A. Lima, P. Marujo, F. Pereira, and H. Lopes, "Leveraging the ISO 23247 framework for the development of digital twins of stacker cranes," in *Innovations in Industrial Engineering III (Lecture Notes in Mechanical Engineering)*, J. Machado et al., Eds., Springer, 2024, pp. 36–50, doi: [10.1007/978-3-031-61582-5\\_4](https://doi.org/10.1007/978-3-031-61582-5_4).
- [109] J. Cederbladh, E. Ferko, and E. Lundin, "Towards adopting a digital twin framework (ISO 23247) for battery systems," in *Proc. 21st Int. Conf. Inf. Technology-New Generat.*, 2024, pp. 397–404, doi: [10.1007/978-3-031-56599-1\\_51](https://doi.org/10.1007/978-3-031-56599-1_51).
- [110] A. Shtofenmakher and G. Shao, "Adaptation of ISO 23247 to aerospace digital twin applications-on-orbit collision avoidance and space-based debris detection," *Aerosp. Res. Central*, vol. 2024, pp. 8–12, Jan. 2024.
- [111] M. Helu, A. Joseph, and T. Hedberg, "A standards-based approach for linking as-planned to as-fabricated product data," *CIRP Ann.*, vol. 67, no. 1, pp. 487–490, 2018, doi: [10.1016/j.cirp.2018.04.039](https://doi.org/10.1016/j.cirp.2018.04.039).
- [112] *Industrial Automation Systems and Integration—Product Data Representation and Exchange—Part 203: Application Protocol: Configuration Controlled 3D Design of Mechanical Parts and Assemblies*, Standard 10303-203, 2011.
- [113] *Industrial Automation Systems and Integration—Product Data Representation and Exchange—Part 214: Application Protocol: Core Data for Automotive Mechanical Design Processes*, Standard 10303-214, 2010.
- [114] *Industrial Automation Systems and Integration—Product Data Representation and Exchange—Part 242: Application Protocol: Managed Model-based 3D Engineering*, Standard 10303-242, International Standard Organization, 2022.
- [115] *Industrial Automation Systems and Integration—Product Data Representation and Exchange—Part 224: Application Protocol: Mechanical Product Definition for Process Planning Using Machining Features*, Standard 10303-224, International Standard Organization, 2006.
- [116] *Industrial Automation Systems and Integration—Physical Device Control—Data Model for Computerized Numerical Controllers - Part 10: General Process Data*, Standard 14649-10, International Standard Organization, 2004.
- [117] *Industrial Automation Systems and Integration—Physical Device Control—Data Model for Computerized Numerical Controllers—Part 17: Process Data for Additive Manufacturing*, Standard 14649-17, International Standard Organization, 2020.
- [118] *MTCconnect Standard*, AMT-The Assoc. Manuf. Technol., McLean, VA, USA, 2018.
- [119] *OPC Foundation—The Industrial Interoperability Standard*, OPC Unified Architecture, Scottsdale, AZ, USA, 2008.
- [120] *Information Technology—Message Queuing Telemetry Transport (MQTT)*, Standard 20922, International Standard Organization, 2016.
- [121] I. 10303-219, "Industrial automation systems and integration—Product data representation and exchange—Part 219: Application protocol: Dimensional inspection information exchange," *International Standard Organization*, 2007.
- [122] *Automation Systems and Integration—Quality Information Framework (QIF)—An Integrated Model for Manufacturing Quality Information*, Standard 23952, International Standard Organization, 2020.
- [123] (2015). *Reference Architecture Model Industrie 4.0*. [Online]. Available: <https://www.zvei.org/fileadmin/userupload/PresseundMedien/Publikationen/2016/januar/GMAStatusReportReferenceArchtitectureModelIndustrie4.0RAMI4.0/GMA-Status-Report-RAMI-40-July-2015.pdf>
- [124] I. 23704-1, "General requirements for cyber-physically controlled smart machine tool systems (CPSMT) - Part 1: Overview and fundamental principles," *International Standard Organization*, 2022.
- [125] *General Requirements for Cyber-physically Controlled Smart Machine Tool Systems (CPSMT)—Part 3: Reference Architecture of CPSMT for Additive Manufacturing*, Standard 23704-3, International Standard Organization, 2023.
- [126] E. Rodriguez. *STEP-NC Additive*. Accessed: Mar. 31, 2024. [Online]. Available: <https://github.com/EfrainRodriguez/additive-manufacturing-step-nc>
- [127] *RepRap Machine Model Prusa Mendel for STEP-NC Machine*. Accessed: Mar. 31, 2024. [Online]. Available: <https://github.com/StepNcLadpre/RepRap-machine-model-Prusa-Mendel-for-STEP-NC-Machine>
- [128] E. Rodriguez, J. P. Rodriguez, A. J. Alvares, C. Riaño, and L. E. D. Oliveira, "Developing a MTCconnect framework for RepRap additive manufacturing machines," *IFAC-PapersOnLine*, vol. 52, no. 13, pp. 2507–2512, 2019. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S2405896319315708>
- [129] J. Lee and H. Su, "A unified industrial large knowledge model framework in industry 4.0 and smart manufacturing," *Int. J. AI for Mater. Design*, vol. 1, no. 2, p. 41, Jul. 2024.



**EFRAIN RODRIGUEZ** received the Ph.D. degree in mechatronic systems from the University of Brasília, Brazil, in 2024. He is currently a Lecturer and a Researcher with The Technological University of Bolívar, Colombia. His research interests include advanced manufacturing systems, industrial robotics, STEP-NC-based digital thread, and digital twins in manufacturing.



**ALBERTO J. ALVARES** received the Graduate degree in mechanical engineering from the University of Brasília, in 1986, and the master's degree in mechanical engineering and the Ph.D. degree in mechanical engineering from the Federal University of Santa Catarina, in 1990 and 2005, respectively. He was a Postdoctoral Researcher at the University of Jaume, Spain, in 2017. He is currently a Full Professor with the University of Brasília, specializing in mechatronics engineering.