

Digital Twin in Manufacturing

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Abstract:

Digital Twin (DT) technology has developed from a primarily representational idea into a manufacturing-oriented digital system that can connect physical equipment, production data, models, analytics and decision services. The reviewed work shows a clear progression: early studies concentrated on distinguishing Digital Models, Digital Shadows and Digital Twins, while later work increasingly addresses practical deployment, real-time data integration, simulation, artificial intelligence, robotics, predictive maintenance, edge computing, federated learning, generative AI and automated decision support. The papers also reveal that the central difficulty is no longer only creating a virtual representation; it is maintaining a reliable connection between heterogeneous physical systems and useful digital services. Across the papers, sensors and industrial communication provide the data foundation, simulation supplies virtual experimentation, AI supplies prediction or optimization, and increasingly intelligent architectures support autonomous or human-guided decisions. The survey compares the methods, technologies, applications and reported outcomes and identifies recurring gaps in scalability, interoperability, model fidelity, latency, data quality, security and explainability.

Keywords — Smart Manufacturing; Industry 4.0; IoT; IIoT; Sensors; Simulation; Artificial Intelligence; Machine Learning; Edge AI; Federated Learning; Robotics; Predictive Maintenance; Process Mining; Generative AI; Manufacturing Optimization.

I. INTRODUCTION

Manufacturing systems are becoming increasingly connected, data-intensive and responsive. The papers reviewed in this survey describe Digital Twins as a way of linking the physical manufacturing world with a digital representation so that current conditions can be observed, alternative situations can be examined and operational decisions can be improved. The central idea is therefore not simply a three-dimensional model. A useful manufacturing DT depends on data acquisition, synchronization, modelling, analytics and a mechanism through which digital insights can influence manufacturing activities [1–15]. The earliest paper in the supplied set, Kritzinger et al.

(2018), is important because it separates three levels of integration: Digital Model, Digital Shadow and Digital Twin. The distinction is based on how information moves between physical and digital representations. Their review found that fully integrated Digital Twin implementations were comparatively scarce at that stage, while Digital Models and Digital Shadows were more common [2]. This provides a useful baseline for understanding the later papers, many of which attempt to move from representation and monitoring toward prediction, optimization and closedloop interaction.

A. Previous / Existing Methods

Traditional manufacturing optimization commonly depends on offline planning, fixed rules, manual

parameter tuning, isolated simulation models or feedback controllers. The supplied literature shows why these approaches become restrictive when the physical process is dynamic. In roll-to-roll manufacturing, for example, conventional feedback control can suffer from response delay and measurement error, while model-predictive control depends on an accurate model and can impose a high computational burden [8]. In production simulation, manually constructed discrete-event models can require substantial expert effort and may not adapt quickly when process behaviour changes [12]. Other limitations occur when a DT is introduced into an existing factory. Renard et al. report that legacy equipment may contain different sensors, PLC states, communication protocols and data structures, making standardized DT deployment difficult [11]. Li et al. identify a related problem at the model level: CAD, finite-element and Modelica representations can describe the same physical quantities in incompatible ways, creating semantic and transformation barriers [7]. Thus, the existing-method problem has two sides: manufacturing methods can be too static for changing environments, while DT implementations can themselves be difficult to integrate and maintain.

B. Results of Existing Approaches

- Early DT literature established the need for a synchronized physical–digital relationship rather than a static digital description [2].
- Sensor and communication studies demonstrate that reliable data collection and contextualization are prerequisites for useful twins [11].
- Simulation-oriented studies show that DTs can test production alternatives without immediately disturbing the physical process [12,13].
- AI-enabled studies move DTs toward prediction, optimization and autonomous control, but introduce new requirements for model quality, computation and trust [8,9,15].
- Recent work on robotics and manufacturing emphasizes the combination of DTs with IIoT, cloud/edge computing, 5G, modelling and simulation, and AI [3].
- The newest papers increasingly treat interoperability, explainability, decentralized learning and automated model generation as core

DT capabilities rather than optional additions [1,5,6,7,12,15].

II. EVOLUTION OF DIGITAL TWIN TECHNOLOGY IN MANUFACTURING

The fifteen supplied papers collectively show an evolution from conceptual classification to application-specific and increasingly intelligent manufacturing systems. The progression is useful because it explains why current DT implementations contain a much larger technology stack than early manufacturing DT studies.

A. From Digital Model to Digital Twin

Kritzinger et al. established a categorical view in which a Digital Model is primarily a digital representation, a Digital Shadow incorporates an automated physical-to-digital information flow, and a Digital Twin adds a stronger integrated relationship between physical and digital entities [2]. This distinction remains relevant in the later papers because a system may contain a sophisticated virtual model but still fail to provide continuous synchronization or actionable interaction.

B. From Frameworks to Deployment Methodologies

The 2024 sensor-oriented study by Renard et al. shifts attention toward deployment in existing manufacturing systems. Its iterative approach starts from sensors and contextualized data and progressively develops DT services. OPC-UA is highlighted as an important communication technology because it can support industrial interoperability and information modelling [11]. The 2025 and 2026 papers then broaden the problem. Aurich et al. propose the Digital Twin–Manufacturing Application Taxonomy (DT-MAT), classifying applications by manufacturing level, purpose and model type [10]. Villegas et al. similarly seek a unified conceptual view across product, production and service domains, linking application maturity with technological capabilities [14]. Aznar Lapuente et al. focus specifically on methodologies for DT design, development and implementation and report that many earlier contributions remain theoretical or are tied to narrow use cases [1].

C. Increasing Intelligence and Autonomy

The newest papers show DTs becoming computational decision environments. AI-driven control uses probabilistic optimization [8]; Edge AI and Federated Learning reduce dependence on centralized cloud processing [9]; process mining can automatically construct simulation environments from manufacturing event data [12]; generative AI can assist DT design [5]; and interpretable machine learning plus large language models can make scheduling recommendations easier for human users to understand [15]. Integration levels used to distinguish Digital Model, Digital Shadow and Digital Twin is shown in Fig 1.

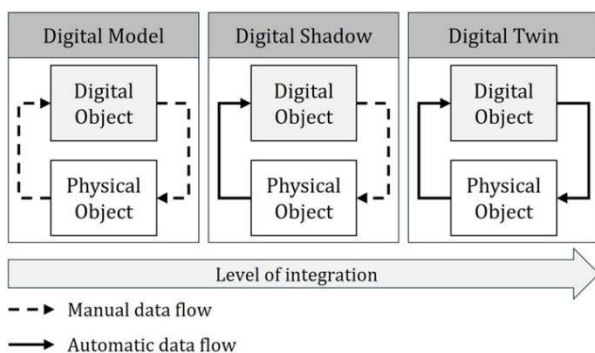


Fig. 1. Integration levels used to distinguish Digital Model, Digital Shadow and Digital Twin

III. DIGITAL TWIN ARCHITECTURE AND SURVEY METHODOLOGY

A. Common Architecture Observed in the Papers

Although the fifteen papers use different terminology, their systems can be interpreted through a common sequence: physical manufacturing entities generate observations; a connection layer transports and contextualizes information; digital models reproduce relevant behaviour; analytics or simulation services interpret the state; and an application or control layer delivers decisions. Fu explicitly uses five levels—physical entity, data interaction, virtual model, functional service and system application—for mechanical manufacturing optimization [13]. Qin et al. use a four-layer robot DT architecture consisting of physical, connection, virtual and supporting layers [3]. The exact labels differ, but the functional logic

is similar. Layered manufacturing Digital Twin framework is shown in Fig 2.

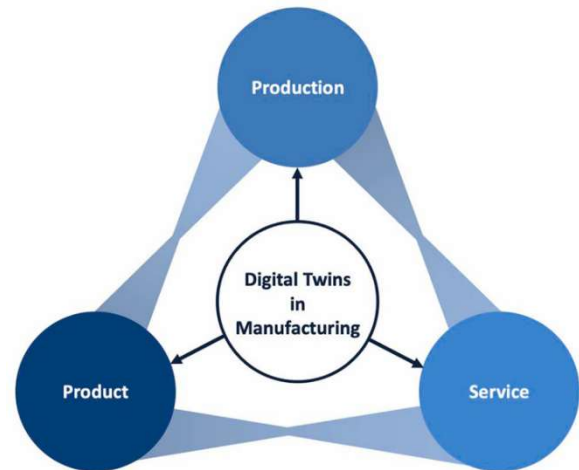


Fig. 2. Layered manufacturing Digital Twin framework

B. Literature-Survey Method Used for This Report

- 1) The fifteen uploaded papers were treated as the only evidence base for the survey.
- 2) Each paper was reviewed for title, publication year, objective, methodology, technologies, application area and reported findings.
- 3) The papers were grouped chronologically to show the development of manufacturing DT research.
- 4) Technologies recurring across the papers were synthesized into thematic groups: sensing/connectivity, modelling/simulation, AI/ML, edge and distributed intelligence, robotics, process analytics, and human-centred decision support.
- 5) Results were compared qualitatively rather than inventing a common numerical benchmark, because the supplied studies use different processes, datasets, models and evaluation criteria.

C. Research Questions for the Survey

- How has the role of the Digital Twin changed across the supplied manufacturing literature?
- Which technologies are repeatedly used to build the physical-to-digital connection?
- How are simulation and AI being combined with DTs for prediction, optimization and control?
- What practical benefits and implementation barriers are reported by the supplied studies?

- What direction does the literature suggest for scalable, intelligent and human-centred manufacturing DTs?

IV. TECHNOLOGIES PRESENT IN MANUFACTURING DIGITAL TWINS

A. Sensors, PLC Data and IoT/IIoT

The data connection is the foundation of a manufacturing DT. Renard et al. describe sensor values, PLC internal states and IoT information as essential inputs when converting an existing manufacturing system into an evolutive twin [11]. The challenge is that devices can operate with different refresh rates, power constraints and communication protocols. The study therefore emphasizes contextualized data and OPC-UA communication. In practical terms, the sensor layer is responsible for observing machine condition, process variables, material movement or other measurable states; the communication layer then makes these observations understandable to the digital representation. The robot focused review by Qin et al. extends this foundation to smart robotic systems, where sensors, IoT connectivity, cloud or edge computing and adaptive control operate together [3]. The implication is that a DT cannot be separated from its data acquisition environment. Poor sensor coverage, inconsistent semantics or delayed transmission directly limits the fidelity and usefulness of the virtual model.

B. Communication and Interoperability

Interoperability is a repeated theme in the supplied papers. Renard et al. identify heterogeneous protocols as a barrier to large-scale deployment [11]. Li et al. address interoperability at a deeper semantic level: heterogeneous engineering models may use different data structures and descriptions even when they represent the same physical system [7]. Their proposed meta-model therefore combines ontology association, domain mapping and automated model transformation. This indicates that interoperability is not only a networking problem; it is also a modelling and semantic problem.

C. Modelling and Simulation

Simulation gives a DT the ability to explore behaviour beyond direct observation. The supplied

papers include discrete-event simulation, physics-based modelling, finite element modelling, Modelica-based multi-physics modelling and hybrid model approaches [3,7,9,12,13]. DES is especially important for manufacturing analytics because it can represent workflows, queues, resource use and bottlenecks. Namaki-Araghi et al. show that manually building DES models is expensive and difficult to keep aligned with changing processes; their WEFTSIM approach instead extracts simulation structures from event data [12]. Physics based modelling offers another advantage: it embeds known relationships between process variables. The Edge AI paper combines physics-based co-simulation with the Functional Mock-up Interface so that physical and virtual behaviour can be synchronized across nodes [9]. Li et al. note that finite element and Modelica models can provide detailed physical behaviour, but computational cost can restrict their direct use in fast real-time control [7].

D. Artificial Intelligence and Machine Learning

AI changes the role of a DT from a descriptive model into a predictive and optimization-oriented system. The supplied papers contain supervised learning, Bayesian optimization, Gaussian-process modelling, deep reinforcement learning, interpretable decision trees, process-mining methods and other data-driven techniques [1,3,8,9,12,15]. The key benefit is that a DT can use accumulated process data to estimate future states, identify abnormal behaviour or search for better operating conditions.

E. Bayesian Optimization and Gaussian Processes

Gafurov et al. demonstrate an AI-driven DT for roll-to-roll web-tension control [8]. Conventional feedback control depends on measured error, while model-based control can be computationally demanding. Their approach uses Bayesian optimization with a Gaussian-process surrogate model to search for proportional and integral control parameters efficiently. The important technology principle is sample efficiency: the optimizer can learn useful control settings without requiring a large number of physical experiments. The reported

experiments showed reduced tension variation and improved stability.

F. Edge AI and Federated Learning

Padmavathi et al. address the latency and privacy limitations of cloud-centric DT architectures [9]. Edge AI moves inference and selected computation closer to the manufacturing assets, reducing dependence on distant cloud resources. Federated Learning allows multiple factory-side nodes to contribute to model learning without directly pooling their production data. Their FMI-based co-simulation framework reported up to 35.

G. Generative AI and Large Language Models

Mata et al. introduce generative AI into the design of manufacturing DTs [5]. Their framework combines S4 features, a Morphological Matrix and Fuzzy TOPSIS to select a suitable DT structure while incorporating human knowledge. A reconfigurable micromachine case study is used to demonstrate the approach. The technology is significant because DT development itself can become a complex design problem when many devices, data sources and possible functions must be considered. Genetti et al. take a different route by combining interpretable machine learning and Large Language Models for production scheduling [15]. Instead of relying only on black-box predictions, their framework produces decision-tree policies and uses language models to explain those policies in natural language. This places human understanding inside the DT decision loop and addresses a major adoption issue: users need to understand why a recommendation is being made before trusting it in an industrial setting.

V. APPLICATIONS AND REPORTED RESULTS

A. Robotics and Human–Robot Collaboration

Qin et al. review Robot Digital Twins and show how DT technology supports assembly, machining, grasping, material handling, human–robot interaction, predictive maintenance and additive manufacturing [3]. The review emphasizes the convergence of IIoT, cloud/edge computing, 5G,

virtual reality, modelling and simulation, and AI. Robot DTs are particularly useful where the physical robot must adapt to changing tasks because the virtual environment can be used for analysis and decision support before or alongside physical execution.

B. Predictive Maintenance and Root-Cause Analysis

Hassan and Björzell extend DT use from individual machines to systems and systems-of-systems [6]. Their industrial ring-rolling case deployed multiple DTs in parallel with operation and combined them into a higher-level DT for process-wide analysis. Principal Component Analysis was used to reduce the complexity of high-dimensional data. The study identified a processing-tool problem and showed that early anomalies could support root-cause identification. It also reported practical challenges involving monitoring complexity, real-time data management, false alarms and computation near edge devices.

C. Process Optimization and Dynamic Scheduling

Fu's mechanical-manufacturing study integrates state mapping, data fusion and multi-objective optimization within a five-level DT architecture [13]. The experimental flexible manufacturing unit included CNC machines, industrial robots and an AGV. Compared with traditional simulation optimization and rule-based scheduling, the reported DT method reduced average production cycle time by 18.7.

D. Automated Simulation and Process Mining

Namaki-Araghi et al. propose WEFTSIM, which combines a Process Discovery Engine and a Process Simulation Engine in a closed loop [12]. Event logs are used to discover workflow structures, after which simulation models are generated for forward-looking analysis. In the reported evaluation, the automatically derived models reached about 80.

E. Small-Batch and Additive Manufacturing

Munhoz et al. investigate AI, DTs and additive manufacturing for small-batch production [4]. Their layered datacentric architecture includes a Digital Process Twin and progressive fault-management cases, moving from operatorsupervised intervention

to automated calibration and finally toward closed-loop in-process adjustment. The study emphasizes synchronization, latency, human oversight and the need for reusable integration, particularly when SMEs have limited data and technical resources.

VI. COMPARATIVE LITERATURE ANALYSIS

The comparative analysis technology is shown in Table 1.

Table 1. Comparative analysis of technology

Year	Paper focus	Main Technology	Result DT classification in manufacturing [2]
2018	DT classification in manufacturing [2]	Digital Model / Shadow / Twin classification	Established an integration-based classification; fully integrated DT studies were comparatively scarce.
2024	Sensors-to-DT deployment [11]	Sensors, PLC, IoT, OPC-UA	Iterative path for scaling DT services on existing manufacturing systems.
2025	Roll-to-roll control [8]	Bayesian optimization , Gaussian process	Adaptive controller tuning; reduced tension variation and improved stability.
2025	Edge smart factories [9]	Edge AI, Federated Learning, FMI	Up to 35% latency reduction, 28% lower cloud usage, 13.2% throughput gain.
2025	Manufacturing taxonomy [10]	Meta-analysis / DT-MAT	Classified DTs by factory/machine/process, purpose and model type.
2025	Unified DT framework [14]	Application and technology-capability frameworks	Connected applications, maturity and technological capabilities across manufacturing domains.

2025/26	Generative-AI DT design [5]	Morphological Matrix, Fuzzy TOPSIS, LLM	Structured DT design with human knowledge and generative AI.
2026	Methodologies review [1]	Systematic methodology analysis	Identified lack of structured, validated and reusable DT implementation methodologies.
2026	Robot DT review [3]	IIoT, 5G, edge/cloud, AI, simulation	Four-layer RDT architecture and broad manufacturing application landscape.
2026	SoS predictive maintenance [6]	Multiple DTs, PCA, real-time analytics	System-level root-cause analysis; exposed edge and false-alarm challenges.
2026	Multi-domain DT integration [7]	Ontology, meta-model, M2M/M2C	Improved cross-domain semantic consistency and automated transformation.
2026	Automated DES [12]	Process mining, DDS, DES	80% activity coverage and 90% trace similarity in reported validation.
2026	Mechanical optimization [13]	Five-level DT, data fusion, multi-objective optimization	18.7% cycle reduction and 22.3% utilization improvement.
2026	AI + DT for small-batch AM [4]	Digital Process Twin, AI, AM	Progressive fault management toward closed-loop adjustment.
2026	Interpretable intelligent DT [15]	Decision trees, LLM, simulation-optimization	Human-centred, explainable scheduling support.

A. Major Technology Pattern

A clear pattern emerges from the comparison. The physical layer is increasingly instrumented; the connection layer is becoming more standardized and semantically rich; models are moving from static

representations toward hybrid and data-driven forms; analytics are moving from monitoring toward prediction and optimization; and the application layer is moving toward autonomous or human-guided control. The technological stack therefore becomes progressively more integrated as the literature advances.

B. Recurring Limitations

- Heterogeneous data and communication protocols complicate deployment across existing equipment [11].

- Different model representations create semantic and transformation problems across engineering domains [7].

- High-fidelity physical simulation can be computationally expensive and may not satisfy strict real-time constraints [7,9].
- Cloud-only architectures can introduce latency, scaling and privacy limitations [9].

- False alarms, high-dimensional data and edge computation remain practical maintenance challenges [6].

- Many DT methodologies are still conceptual, narrow in scope or insufficiently validated in industrial environments [1,14].

- Opaque AI models can reduce trust, motivating interpretable and human-in-the-loop approaches [15].

VII. DISCUSSION

The supplied literature indicates that manufacturing DT research is shifting from the question “How can a physical asset be represented digitally?” toward the broader question “How can a synchronized digital environment continuously support manufacturing decisions?” This shift is visible in the increasing importance of analytics, optimization, autonomy and human interaction.

A. Current Technology Landscape

At the data level, sensors, PLCs and IoT/IIoT provide observations. At the connectivity level, industrial protocols and contextual information help make heterogeneous data usable. At the model level, geometric, physics-based, discrete-event, hybrid and data-driven models provide different balances between fidelity and computational speed. At the

intelligence level, machine learning, Bayesian optimization, process mining, edge AI, federated learning and generative AI extend DT capabilities. Finally, decision-support interfaces and interpretable models connect these capabilities to people and manufacturing operations [1,3,5,7–15].

B. What the Literature Suggests for Future Manufacturing DTs

The fifteen papers collectively point toward several directions. First, DT development needs reusable and systematic methodologies rather than isolated demonstrations [1]. Second, interoperability must cover not only data transport but also model semantics and automated transformations [7,11]. Third, real-time performance will increasingly depend on distributing computation across edge and cloud resources rather than placing every function centrally [9]. Fourth, simulation should become more data-driven and adaptive so that virtual models can keep pace with physical process changes [12]. Fifth, AI should be combined with DTs in ways that preserve safety, human oversight and explainability [5,15].

C. Overall Literature Synthesis

The papers do not support a single universal DT implementation because manufacturing systems differ in physical behaviour, data availability, control requirements and application objectives. Instead, the strongest common lesson is modularity. A DT should be assembled from a physical representation, reliable data connections, suitable models, analytics and services selected for a defined manufacturing purpose. This interpretation is consistent with the application and technology taxonomies of Aurich et al. and Villegas et al. [10,14], the implementation methodology emphasis of Aznar Lapuente et al. [1], and the application-oriented architectures of the more recent case studies [4,6,7,9,12,13,15].

VIII. CONCLUSION

This literature survey reviewed fifteen supplied papers on Digital Twins in manufacturing and arranged their contributions chronologically. The literature begins with the classification of Digital Model, Digital Shadow and Digital Twin and

develops toward connected, intelligent and increasingly autonomous manufacturing systems. Sensors, PLCs and IoT form the data foundation; industrial communication and semantic modelling enable interoperability; simulation supports virtual experimentation; AI and machine learning enable prediction and optimization; and edge, federated and generative technologies expand the speed, scalability and intelligence of the twin. The reported studies demonstrate practical gains, including improved control stability, lower latency, better throughput, improved equipment utilization, reduced production cycle time, automated simulation construction and more explainable decision support. At the same time, the survey identifies persistent issues involving heterogeneous data, model transformation, computational cost, synchronization, security, false alarms, validation and user trust. Therefore, the future of manufacturing Digital Twins depends not only on more powerful algorithms but on integrated, interoperable, maintainable and human-centred architectures. This conclusion is derived only from the fifteen supplied papers and does not introduce external literature.

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