

Digital Twin Tools for Smart Manufacturing: A Paradigm Shift for Industry 4.0

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ABSTRACT The convergence of digital twin (DT) technology with Internet of Things-driven smart manufacturing is driving a paradigm shift in Industry 4.0 and beyond. By enabling real-time cyber-physical integration, data-centric decision-making, and closed-loop optimization, DTs are becoming central to the evolution of manufacturing systems. This perspective article explores foundational concepts, emerging trends, and the market trajectory of DTs in manufacturing. We provide insights into the landscape of current tools and platforms supporting DT development, highlighting their capabilities and limitations. We also discuss the role, practical challenges, and future opportunities of the ISO 23247 standard in supporting interoperable and scalable DT frameworks in manufacturing. Finally, we discuss case studies with practical implementations, emphasizing the need for higher autonomy, artificial intelligence-enabled predictive analytics, robust lifecycle governance, and resilience in next-generation manufacturing ecosystems.

INDEX TERMS Digital twin (DT), Industrial Internet of Things (IIoT), ISO 23247, semiconductor fabrication, smart manufacturing.

I. INTRODUCTION

Industry 4.0 represents a transformative era characterized by the convergence of cyber-physical systems, pervasive connectivity through the Industrial Internet of Things (IIoT), advanced analytics, and increased automation in manufacturing environments [1], [2]. At the core of this revolution lies the digital twin (DT), an advanced technology that creates high-fidelity digital replicas of physical assets, processes, and systems [3]. Unlike conventional static simulation models, DTs maintain dynamic, real-time synchronization with their physical counterparts, enabling seamless cyber-physical integration. This capability supports manufacturers in achieving real-time monitoring, predictive insights, and proactive optimization, fundamentally reshaping traditional manufacturing paradigms [4].

DTs represent a significant paradigm shift, transitioning manufacturing from a reactive, historically data-driven approach toward predictive, autonomous, and resilient operational strategies. This shift is crucial as manufacturers increasingly grapple with complexity in global supply chains, sustainability requirements, and demand for rapid product innovation [5]. Modern DT tools and platforms leverage

extensive IIoT integration, cloud computing, and advanced visualization technologies, facilitating comprehensive lifecycle management and optimized resource allocation across complex manufacturing ecosystems [6]. A pivotal component accelerating the effectiveness and adoption of DTs is their integration with artificial intelligence (AI) and machine learning (ML) technologies [7]. AI and ML significantly enhance DT capabilities, providing powerful tools for anomaly detection, predictive maintenance, and real-time decision-making processes [8]. More recently, large language models (LLMs) have emerged as a novel means of interacting with DT environments. LLMs facilitate natural language-based querying, reporting, and scenario analysis, greatly enhancing accessibility and interpretability of complex DT data for decision-makers [9]. By embedding these intelligent methodologies, DTs transcend basic monitoring functionalities and evolve into fully interactive and autonomous systems capable of dynamic adaptation and learning.

Given the rapid evolution and growing complexity of DT technologies, there is a need for practical guidance on assembling production-grade toolchains and aligning them with emerging standards. This perspective critically reviews

state-of-the-art DT tools for manufacturing—mapping strengths, limitations, and adoption patterns. We examine how the ISO 23247 framework supports interoperable, scalable twins while identifying practical challenges and near-term opportunities. We illustrate these points with a semiconductor manufacturing case study, which illustrates how multilayer twins integrate with AI/ML to deliver early yield prediction and closed-loop recipe optimization. The insights provided through this perspective are valuable for researchers, practitioners, and industry stakeholders seeking to effectively leverage DT technologies within modern manufacturing settings. Highlighting both current capabilities and future opportunities, this article underscores the strategic importance of DTs as critical enablers of Industry 4.0 and beyond.

The rest of the article is organized as follows. Section II discusses foundational DT concepts and situates DTs within the Industry 4.0 landscape. Section III discusses practitioner-oriented commercial DT tools, highlighting capabilities and limitations. Section IV presents an overview of generalized DT development tools. Section V analyzes the ISO 23247 framework, outlining its architectural roles, interoperability gaps, and near-term opportunities. Section VI details a semiconductor manufacturing case study, demonstrating multilayer twins, early yield prediction, and closed-loop recipe optimization. Finally, Section VII concludes this article with priorities for increased autonomy, robust lifecycle governance, and resilient operations.

II. DT IN MANUFACTURING: CONCEPTS AND ROLE

A. DT DEFINITIONS

The concept of a DT refers to a virtual representation of a physical system, product, or process that enables real-time monitoring, simulation, and optimization throughout its lifecycle. Initially introduced by Grieves and Vickers [10] in 2003, and later refined by NASA [11], the DT has become a cornerstone of smart manufacturing and cyber-physical integration. A DT integrates multiphysics simulation, real-time sensor data, historical information, and analytics to replicate the behavior and performance of its physical counterpart with high fidelity. What makes DTs powerful is their ability to pull in real-time data and use tools, such as ML and simulation to predict how things might unfold—whether that is identifying issues before they happen or finding ways to improve performance. In manufacturing, for example, this means that a production line can be tested and optimized virtually before making any physical changes, saving both time and money. As industries from automotive to energy embrace DTs, they are becoming an increasingly vital part of how businesses make smarter, faster decisions [11].

B. INDUSTRY 4.0, IIOT, AND BEYOND

Industry 4.0 represents the broader transformation of manufacturing through advanced digital technologies, often referred to as the “Fourth Industrial Revolution” [12]. It follows



FIGURE 1. Global DTs in manufacturing market size (2023–2032). The market is projected to grow from US\$ 10.27 billion in 2023 to US\$ 714.01 billion in 2032, reflecting a CAGR of 60.20%.

previous waves of industrial change—mechanization, mass production, and automation—and aims to create smart, autonomous, and highly efficient production systems. At the heart of Industry 4.0 are technologies, such as IIoT, cyber-physical systems, DTs, AI, cloud computing, 3-D printing, and Big Data analytics [13].

Among these, IIoT plays a foundational role by connecting industrial devices, such as machines, sensors, and controllers, enabling them to communicate and share data in real time. Unlike traditional industrial automation, IIoT brings a new level of connectivity and intelligence by collecting vast amounts of real-time data from physical assets and making it accessible for analysis and decision-making. When integrated with DTs, IIoT allows for continuous monitoring and deeper insights into system behavior, enabling predictive maintenance, process optimization, and improved product quality. For manufacturers, this means fewer unexpected breakdowns, more efficient use of resources, and faster response to changing conditions. Ultimately, IIoT serves as the digital backbone of smart manufacturing, helping industries move toward more agile, responsive, and data-driven operations.

C. DT MANUFACTURING MARKET

To better understand the growing relevance and impact of DT technology in smart manufacturing, it is useful to examine key market trends, investment dynamics, and technological adoption patterns. Fig. 1 illustrates the explosive growth of the global DTs market within the manufacturing sector. Valued at US\$ 10.27 billion in 2023, the market is projected to reach approximately US\$ 714.01 billion by 2032, driven by a staggering compound annual growth rate (CAGR) of 60.20% [14]. The exponential rise reflects increasing adoption across industries to enhance operational efficiency, product quality, and predictive capabilities. The chart clearly demonstrates a shift from early adoption to widespread deployment as DTs become foundational to smart manufacturing strategies.

Fig. 2 compares the estimated implementation costs with the projected benefits, using market size as a proxy, over a ten-year span. While implementation costs increase steadily (e.g., from US\$ 8 billion in 2023 to US\$ 30 billion in 2032),

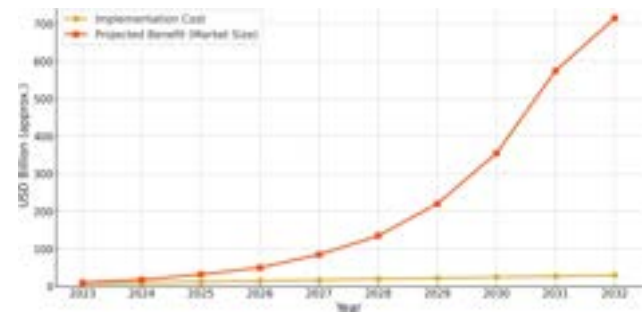


FIGURE 2. Cost versus benefit of DT in manufacturing. While implementation costs increase steadily, the benefits, represented by market value, grow exponentially, indicating a strong return on investment.

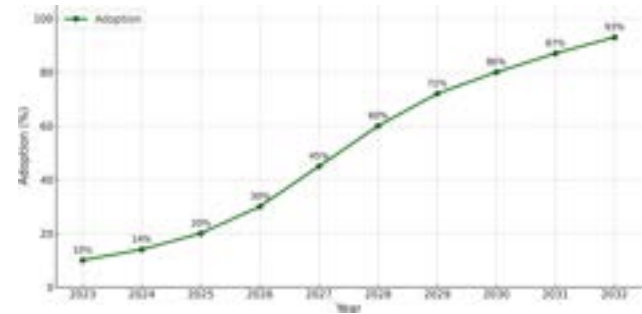


FIGURE 3. IIoT-DT integration adoption (2023–2032).

the associated benefits grow exponentially, mirroring the market value trend. This highlights a strong return on investment for early adopters, especially as the technology matures and economies of scale reduce deployment costs.

The trend line, as shown in Fig. 3, shows the percentage of manufacturers integrating IIoT with DTs over time. Starting at just 10% in 2023, the adoption is expected to surpass 90% by 2032, reflecting a rapidly growing reliance on real-time data connectivity and sensor-driven analytics.¹ This integration is crucial for enabling continuous monitoring, predictive maintenance, and system optimization—core pillars of Industry 4.0.

III. COMMERCIAL DT TOOLS AND SOFTWARE PLATFORMS

To bring order to the crowded DT landscape, we group the tools most commonly encountered in smart-manufacturing projects into three functional categories (i.e., C1, C2, and C3) that mirror the typical life cycle of a factory asset. The taxonomy is shown in Fig. 4.

To ensure transparency in the review scope, the selection of commercial DT tools followed a structured set of criteria. Tools were included based on 1) publicly documented industrial adoption of at least ten deployments or equivalent case studies, 2) availability of developer APIs or open integration interfaces supporting IIoT and simulation workflows, and 3) relevance to recent manufacturing applications reported. Bibliographic sources were gathered from IEEE Xplore and

¹Figs. 2 and 3 are produced from the authors’ own analysis based on aggregated market data found from source [14].

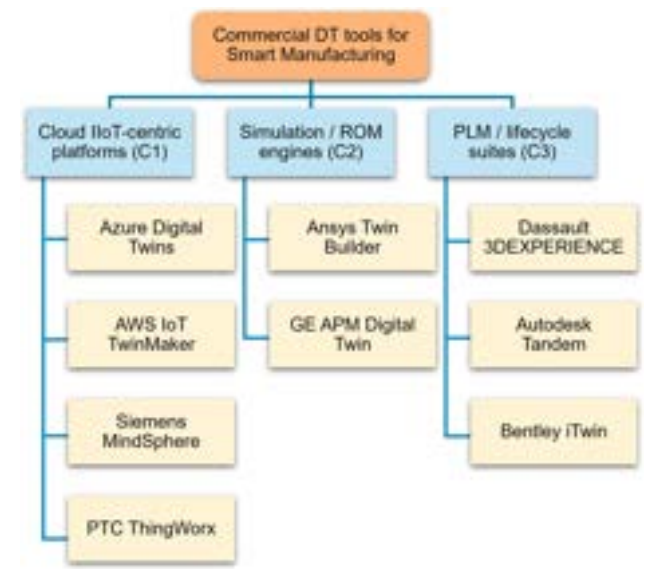


FIGURE 4. Taxonomy of commercial DT tools for smart-manufacturing in functional categories.

ScienceDirect using search terms, such as “digital twin manufacturing” and “digital twin commercial tools” along with the tool names.

A. CLOUD IIOT-CENTRIC PLATFORMS

Cloud IIoT-centric platforms serve as the backbone of scalable DT ecosystems by integrating IIoT data with cloud computing capabilities. These platforms enable real-time data acquisition, edge-to-cloud processing, and remote monitoring of physical assets, allowing manufacturers to visualize, analyze, and optimize operations from anywhere. By providing built-in support for device connectivity, time-series databases, and interactive dashboards, platforms in this category (e.g., AWS IoT TwinMaker and Azure Digital Twins) empower smart manufacturing with agility and responsiveness.

1) MICROSOFT AZURE DIGITAL TWINS

Microsoft Azure Digital Twins [15] is a fully managed platform-as-a-service that enables the construction of rich, live digital replicas of physical environments—ranging from individual machines to entire smart cities. Using the open digital twins definition language (DTDL), users define entities and their relationships, which are then stored as a graph that can be queried in real time. The platform integrates seamlessly with Azure IoT Hub and other data sources, allowing telemetry to stream directly into the DT graph, where event routing, time series insights, functions, and AI tools can be employed for analysis or automated decision-making. With support for multiple development environments (i.e., C#, Python, Java, and JavaScript) and fine-grained access control, Azure Digital Twins facilitates the development of secure, data-driven DT solutions across domains, such as manufacturing, smart buildings, and urban infrastructure.

Several studies discuss the use of Azure Digital Twins within manufacturing-related scenarios, often highlighting practical implementations or case studies across different sectors. For example, Parle et al. [16] performed a comparative analysis of several DT platforms, including Azure Digital Twins, emphasizing its potential for achieving net-zero manufacturing through cloud-native scalability and integration flexibility. Similarly, Fahim et al. [17] presented a practical demonstration of a wind turbine DT model utilizing Azure's IoT capabilities and DTDL for predictive modeling and operational optimization. Lu et al. [18] provided a broader review of DT applications in smart factories, identifying cloud services, such as Azure Digital Twins as key enablers for scalable, real-time cyber-physical integration. In another study, Picone et al. [19] proposed a flexible edge-to-cloud architecture where Azure Digital Twins plays a central role in managing distributed twin instances and facilitating modular deployment strategies. Finally, Lehner et al. [20] explored model-driven engineering approaches for DTs, explicitly mentioning Azure Digital Twins Explorer as a reference implementation for managing data models generated from system transformations.

2) SIEMENS MINDSPHERE (INSIGHTS HUB)

As part of Siemens' Xcelerator portfolio, NX and MindSphere (now known as Insights Hub) form a powerful ecosystem for implementing closed-loop DT solutions. Siemens NX is a comprehensive, cloud-enabled CAD/CAM/CAE platform that supports generative design, simulation, and manufacturing planning—all within a single, model-driven environment. MindSphere extends this digital workflow into the physical world by connecting industrial assets via IIoT. It collects real-time data from sensors and machines, either at the edge or in the cloud, and applies analytics to monitor performance, detect anomalies, and drive improvements. Together, NX creates the virtual model, while MindSphere brings in real-world data, enabling a continuous feedback loop. This integration helps manufacturers accelerate design iterations, improve quality, and develop new service-oriented business models.

A case study [21] of Siemens MindSphere explored how boundary resources such as application programming interfaces (APIs) and software development kits (SDKs), facilitate the development of IIoT ecosystems by enabling third-party integration and innovation. The study highlights that MindSphere's openness and provision of technical resources support a growing network of partners, driving platform-based end-to-end industrial solutions. This work extends the theoretical understanding of boundary resources in the B2B domain, emphasizing their critical role in shaping ecosystem emergence and value creation within IIoT platforms.

3) AWS IOT TWINMAKER

AWS IoT TwinMaker [22] provides a distinctive approach to DT development by seamlessly integrating disparate data

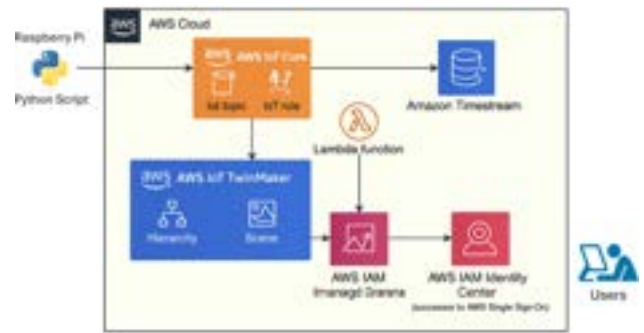


FIGURE 5. High-level architecture of AWS IoT TwinMaker solution.

sources—including IoT sensor streams, video feeds, and enterprise databases—into cohesive, real-time 3-D visualizations. Its flexible architecture enables developers and engineers to construct detailed virtual representations without relocating underlying data, thereby enhancing scalability and responsiveness in industrial monitoring and control tasks. By facilitating real-time insight and predictive analytics, AWS IoT TwinMaker plays a transformative role in sectors ranging from manufacturing facilities to intelligent infrastructure management. Fig. 5 shows a generic architecture for the AWS IoT TwinMaker approach.

4) PTC THINGWORX

PTC ThingWorx is more than just another IoT platform—it is a powerful engine for bringing DTs to life. Its robust integration capabilities with sensors, control systems, and analytical tools allow precise modeling of complex industrial processes and products. ThingWorx's ability to deliver real-time predictive insights significantly enhances operational decision-making, promoting efficiency, and proactive maintenance strategies across industries, such as automotive, aerospace, and industrial manufacturing [23]. The majority of its applications have been in IIoT factory optimization and platform development [24], [25], but its use in creating DTs is still in its infancy. For instance, Bellalouna [26] relied on estimated loading data and high safety factors during product design, which often leads to overdimensioning and inefficient material use. They aimed to apply the DT approach to accurately capture real operational loads, enabling more precise and sustainable load-oriented product design.

B. HIGH-FIDELITY SIMULATION ENGINES

High-fidelity simulation engines specialize in creating accurate virtual replicas of physical systems through advanced physics-based modeling and numerical methods. These tools support multidomain simulations to replicate mechanical, electrical, thermal, and control dynamics with high precision. By enabling scenario testing, predictive maintenance, and system optimization, they play a critical role in the design and validation of complex manufacturing systems before deployment.

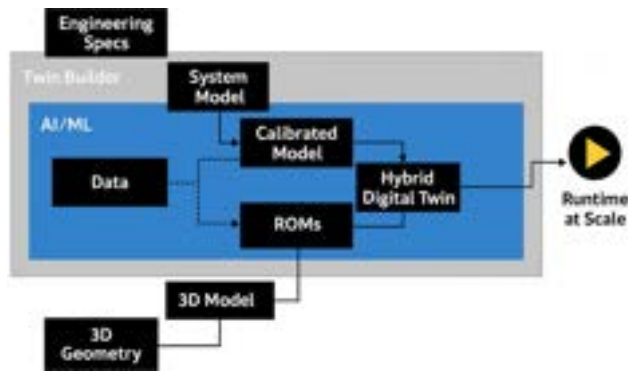


FIGURE 6. Ansys Twin Builder workflow for hybrid DT deployment.

1) ANSYS TWIN BUILDER

Ansys Twin Builder [27] is a powerful engineering simulation platform designed to create and deploy high-fidelity DTs of physical assets. By integrating real-world data with physics-based modeling and simulation, Twin Builder enables engineers to design, validate, and optimize systems throughout their operational lifecycle. It supports seamless cosimulation with various tools and allows for real-time monitoring, predictive maintenance, and performance optimization. With its strong foundation in multiphysics modeling and system-level simulation, Ansys Twin Builder accelerates the development of robust DTs for industries, such as aerospace, automotive, energy, and manufacturing. Fig. 6 depicts a workflow for hybrid DT deployment by Ansys Twin Builder.

A couple of studies [28], [29] highlighted the use of ANSYS Twin Builder for induction motor control. One developed a vector field oriented control system using reduced-order modeling and coupled simulations with ANSYS Maxwell. The other focused on stabilizing a synchronous generator's rotor speed via scalar control of an induction motor using a proportional–integral–differential (PID)-regulated inverter. Both studies showcased Twin Builder's ability to simulate high-fidelity motor control systems using built-in libraries and imported field-based models. Tietieriev et al. [30] focused on a synchronous generator with permanent magnets in a wind power plant and explored two methods for stabilizing its rotational speed: one using a PID-controlled electromagnetic clutch and the other using a squirrel-cage induction motor controlled by scalar law via an inverter. The complete energy conversion and transmission process is simulated using ANSYS Electromagnetics, with the generator modeled in ANSYS Maxwell and integrated into Twin Builder for cosimulation.

2) GE VERNOVA PREDIX

GE Vernova's Predix [31] stands apart as a DT platform tailored specifically for heavy industries aiming for sustainability and efficiency. By embedding advanced analytics and ML into its core, Predix provides organizations with proactive visibility into their assets—spotting operational risks and inefficiencies before they occur. From reducing energy

consumption in industrial plants to ensuring reliability in renewable energy operations, Predix is the digital backbone for transformative, predictive asset management.

C. PRODUCT LIFECYCLE MANAGEMENT AND LIFECYCLE-DRIVEN VIRTUAL TWINS

Product Lifecycle Management (PLM) and lifecycle-driven platforms focus on maintaining digital continuity across a product's lifecycle—from conceptual design and engineering to manufacturing and maintenance. Tools, such as Dassault 3DEXPERIENCE, Autodesk Tandem, and Bentley iTwin, provide robust data management, collaboration features, and traceability, ensuring that the DT evolves in sync with its physical counterpart.

1) DASSAULT 3DEXPERIENCE

Dassault Systèmes' 3DEXPERIENCE platform uniquely integrates sophisticated DT modeling with collaborative innovation tools, effectively bridging virtual simulations with physical operations. The platform's extensive simulation and visualization capabilities enable engineers and stakeholders to collaboratively design, validate, and optimize complex products and systems in a virtual environment. Widely adopted in automotive, aerospace, and smart manufacturing domains, the 3DEXPERIENCE platform accelerates sustainable innovation by streamlining decision-making processes and enhancing resource efficiency [32].

2) BENTLEY ITWIN PLATFORM

Bentley System's iTwin platform [33] provides a specialized cloud-based infrastructure DT solution, which converts static engineering data into dynamic, interactive DTs of physical assets. Its open architecture, complemented by comprehensive APIs, facilitates real-time collaboration, lifecycle asset management, and seamless integration of multidisciplinary data sources. The iTwin platform significantly advances infrastructure project planning, construction, and operational management, offering transformative efficiency and enhanced transparency for urban development and infrastructure projects. Parle et al. [16] presented a comprehensive case study demonstrating the application of the Bentley iTwin platform in a manufacturing context. They developed a DT framework that integrates real-time sensor data with engineering models to monitor and optimize manufacturing processes. This approach facilitated enhanced decision-making, predictive maintenance, and operational efficiency within the manufacturing environment.

3) AUTODESK TANDEM

Autodesk Tandem [43] introduces a distinct building information modeling (BIM)-centric approach to DT technology, enabling detailed virtual representations of built environments. By integrating static BIM data into dynamic operational models, Tandem empowers facility managers and engineers to

TABLE 1. Commercial DT Tools in Manufacturing: Public Adoption, Typical Use Cases, and Limitations

Category	Platform	Public industrial footprint	Typical manufacturing use-case	Limitations
C1	Siemens MindSphere	> 1100 industrial customers (Siemens exec interview, 2019; customer base still growing) [34]	Cloud + edge IIoT PaaS, asset monitoring, predictive maintenance, bridging to Siemens automation stack	Siemens-centric; interoperability with non-Siemens hardware may require extra integration
C1	AWS IoT TwinMaker	No aggregate figure yet; AWS showcases early adopters Invista, Carrier, Belden, and construction giant John Holland	Cloud-native, low-code twins combining SiteWise data, 3D/BIM, and video for asset dashboards, connected-worker apps, and production monitoring [35]	Early maturity, dependent on AWS ecosystem, limited built-in simulation support
C1	PTC ThingWorx + Kepware Edge	More than 1,200 customers and partners have selected PTC as their IoT solutions provider [36]	Production performance roll-ups, KPI boards, and predictive maintenance initiatives—particularly in plants utilizing Kepware PLC connectors or Rockwell/DeM validated edge stacks.	Reliance on PTC/Kepware stacks for optimal integration, moderate learning curve for advanced setups
C1	Microsoft Azure Digital Twins	Tech-intel scan shows 50 + named enterprises (theirstack) and marquee deployments (e.g., Mars runs ADT in 160 factories) [37]	Hyperscale PaaS for twin graphs, event routing, AI at scale; flexible when paired with Ansys, PTC, Unity, etc.	Cloud-dependent, complex setup, limited built-in physics modeling
C2	Ansys Twin Builder	Case-study driven; dozens of high-end engineering firms (e.g., Wärtsilä, Skagerak Kraft) publicly documented [38]	Physics-based hybrid twins, ROMs, HIL/SIL validation, heavy CAE co-simulation	Requires advanced simulation knowledge, limited real-time IoT analytics capabilities without external platforms
C2	GE Vernova Predix	Tech-stack census shows ~ 104 companies publicly using Predix as a PaaS [39]	Hybrid physics + ML twins for rotating equipment (turbines, compressors, generators), driving maintenance and optimization across multi-site fleets.	Narrow industry focus (heavy industry, energy), high complexity for setup and maintenance
C3	Dassault Systèmes 3DEXPERIENCE	~ 350,000 paying customers across all industries (platform URD, 2024) [40]	End-to-end product lifecycle, immersive “virtual twin” factories, quality planning, MES/ERP integration	Heavyweight, high-complexity solution with expensive deployments, best suited for enterprises over SMEs
C3	Bentley iTwin	WSP Australia alone operates the platform on 150 active projects with 2,000 users; similar large-scale deployments in Shell Deepwater and Asian infrastructure projects [41]	Federated “evergreen” twins of factories, plants, and logistics sites—tracking change across CAD/BIM, reality-capture scans, and IoT to coordinate design-build-operate workflows [42]	Focused heavily on infrastructure and civil engineering, limited IoT analytics capabilities
C3	Autodesk Tandem	Still in early commercial rollout; public pilots include Autodesk’s own Toronto tech-centre floors and client proofs-of-concept such as NV5 wastewater facilities	Data-rich handover twins for new or retro-fitted industrial buildings—tagging equipment, linking O&M manuals, and visualizing space utilization for facilities teams.	Still early maturity in industrial contexts, limited built-in simulation and predictive analytics

monitor, manage, and optimize building performance effectively. This approach transforms facility management practices by providing actionable insights throughout the building lifecycle, thereby improving operational efficiency and sustainability outcomes in commercial and industrial properties. Autodesk Tandem has been used primarily in other domains (e.g., energy management, healthcare facility, smart city, etc.). In the case of manufacturing, Elias et al. [44] proposed using DTs to enhance facilities and asset management by transforming static BIM data into dynamic, actionable models. They demonstrated this approach through Autodesk Tandem, which is designed to support real-time collaboration and data integration in the architecture, engineering, construction, and operations (AECOs) industry.

D. COMPARATIVE ANALYSIS

To contextualize the diverse roles that DT platforms play in smart manufacturing, we present a comparative analysis of their industrial adoption and typical applications. Table 1 categorizes leading tools based on their core functionality—ranging from cloud-based IIoT platforms (C1)

and simulation-driven engines (C2) to PLM suites (C3). For each platform, we report publicly disclosed customer counts or flagship deployments, outline representative use cases, and limitations that illustrate how these tools are deployed on factory floors. This overview highlights not only the maturity and scope of each solution but also the varying depths of integration with production systems, simulation tools, and enterprise architectures.

IV. GENERALIZED DT DEVELOPMENT TOOLS

A. MATHEMATICAL MODELING AND SIMULATION

1) MATLAB/SIMULINK

MATLAB/Simulink is a popular software tool used by engineers to build, simulate, and analyze dynamic systems. Its easy-to-use graphical interface allows users to quickly create digital models that closely mimic physical systems, making it highly suitable for developing DTs. By connecting sensor data, implementing control algorithms, and performing real-time predictions, MATLAB/Simulink effectively bridges the gap between virtual simulations and real-world applications. With specialized toolboxes for IoT integration, ML, and data

analytics, it has become an essential platform for engineers developing DTs in fields, such as manufacturing, automotive, aerospace, and healthcare.

Kombaya et al. [45] presented a DT design and simulation model for reconfigurable manufacturing systems (RMSs) using MATLAB and Simulink. Their approach combines data-driven and physics-based modeling to enable prediction, anomaly detection, and hypothesis testing within a dynamic, multi-station manufacturing setup. By leveraging tools like SimEvents and Stateflow, they simulate both continuous and discrete behaviors, aiming to automate system reconfiguration and improve adaptability to changing production demands. Cimino et al. [46] explained how MATLAB/Simulink enables the development of high-fidelity DTs in manufacturing by combining physics-based modeling, real-time data integration, and predictive analytics. Simulink is used to replicate machine behavior, while tools like Stateflow and SimEvents simulate control logic and discrete workflows. Data-driven toolboxes assist in fault detection, model validation, and system optimization, making the platform well-suited for smart, RMSs.

2) PYTHON SCIENTIFIC LIBRARIES

Python scientific libraries (i.e., *NumPy*, *SciPy*, and *SimPy*) provide a versatile, open-source framework for developing DTs in manufacturing and industrial applications. *NumPy* enables efficient numerical computation and large-scale data handling essential for real-time data processing, while *SciPy* offers advanced mathematical algorithms for optimization, signal processing, and system modeling. *SimPy* complements these capabilities by facilitating discrete-event simulations, which are crucial for modeling manufacturing workflows, scheduling, and logistics. Together, these libraries create a flexible and accessible ecosystem, allowing developers and engineers to rapidly prototype and implement customized DT solutions tailored to specific industrial challenges. For example, Mattera et al. [47] proposed a reinforcement learning workflow for industrial manufacturing control, specifically applied to a wire arc additive manufacturing (WAAM) process, where a process-based reward function, reduced order model, and deep deterministic policy gradient controller were developed. Using *NumPy* for numerical computation, they integrated a realistic WAAM simulator to enable sim-to-real transfer and automatic code generation for deployment on the motion platform controller.

B. AI, ML, AND NATURAL LANGUAGE INTERACTION

1) ML FRAMEWORKS

Industrial ML is increasingly central to Industry 4.0, enabling predictive maintenance, anomaly detection, and quality control while facing challenges of reproducibility, scalability, and reliability. Against this backdrop, the following frameworks illustrate how such capabilities are being realized within DTs [48]. ML frameworks, such as TensorFlow [49], PyTorch [50], and scikit-learn [51], are increasingly critical

in the development of intelligent DTs in smart manufacturing. TensorFlow and PyTorch enable deep learning-based predictive modeling, anomaly detection, and dynamic optimization through neural network architectures, while scikit-learn provides robust algorithms for classical ML tasks, such as clustering, regression, and classification [52], [53]. Perno et al. [54] presented a framework for developing ML-based DTs to predict critical process parameters in real time within the process manufacturing industry. The framework was validated through a case study at an international manufacturing company, demonstrating improved prediction accuracy and highlighting both the potential benefits and challenges of implementing DT-ML systems in industrial settings. Furthermore, multiple studies [55], [56], [57], [58] extensively discussed the role of DT within ML, deep learning, and comprehensive frameworks.

2) LARGE LANGUAGE MODELS

LLMs, such as ChatGPT and GPT-4, present transformative potential for DT applications by enabling advanced natural language interaction, knowledge integration, and reasoning capabilities. These generative AI models facilitate intuitive human-machine collaboration, help interpret complex data insights, and automate report generation and decision recommendations. Recent studies [9], [59] highlighted their capacity to improve the usability of DTs, particularly in contexts where nonexpert stakeholders must understand sophisticated manufacturing insights, perform guided troubleshooting, or conduct scenario analyses through conversational interfaces.

Twin Talk GPT, by Embassy of Things (EOT) [60], is a generative AI solution designed to enhance DTs at the industrial edge. It combines advanced AI models with EOT's edge controllers, enabling real-time simulation and analytics of operational data for predictive maintenance, anomaly detection, and process optimization. Integrated within EOT's Industrial Data Fabric, Twin Talk GPT supports secure and seamless data exchange between industrial equipment, control systems, and analytics platforms, making industrial processes smarter, more responsive, and easier to manage. A conceptual architecture for an industrial DT by Twin Talk GPT is depicted in Fig. 7.

3) CLOUD AI PLATFORMS

Cloud-based AI platforms (e.g., Azure AI, Amazon SageMaker, Google AI, etc.) are reshaping how manufacturers build and manage DTs by offering powerful, flexible tools that go beyond traditional software capabilities. With built-in tools for training sophisticated ML models, deploying them quickly at scale, and running real-time analytics, these platforms streamline the integration of AI into everyday operations. This means manufacturers can swiftly turn massive amounts of data into actionable insights, monitor their operations globally in real time, and anticipate problems before they occur—making their processes smarter, more adaptive, and more competitive on a global stage [3], [18].

Industrial Digital Twin Functional Architecture



Industrial Digital Twin Logical Architecture

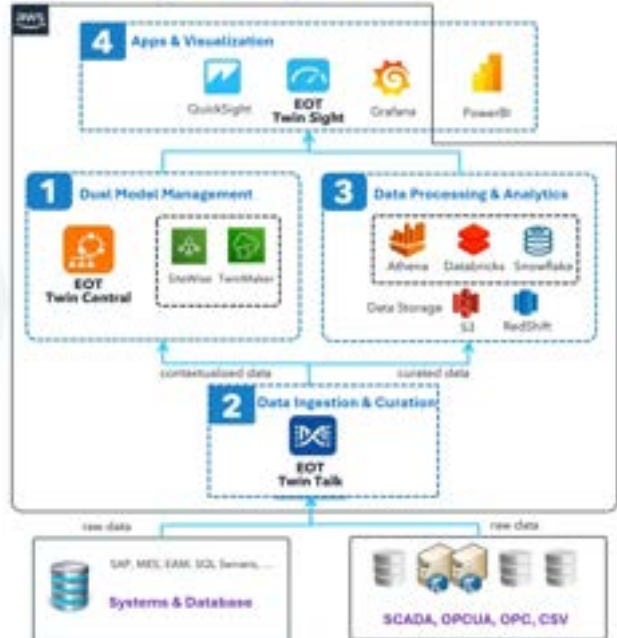


FIGURE 7. Twin Talk GPT Conceptual Architecture for DT.

V. ISO 23247 STANDARD FOR DT IN MANUFACTURING

A. ROLE AND SIGNIFICANCE IN CURRENT PRACTICES

ISO 23247 is an emerging international standard that defines a DT framework for manufacturing, providing common terminology and a multilayer reference architecture for implementing DTs on the factory floor. It partitions a DT system into distinct layers and entities, from observable manufacturing elements (OMEs) (e.g., personnel, equipment, materials, processes, and products) up to user applications, ensuring a consistent structure across implementations. The standard's reference architecture includes an entity-based data model and a set of functional building blocks for DT systems, adapted from general IoT architecture but specialized for manufacturing needs. This structured approach is significant because it offers manufacturers a unified blueprint: by aligning with ISO 23247, organizations can develop DTs with interoperability and scalability in mind, rather than using ad hoc or proprietary architectures.

In current practice, ISO 23247 is increasingly used as a guiding framework in research and pilot applications of manufacturing DTs. For example, Kim et al. [61] implemented a DT architecture for a WAAM process based on ISO 23247, demonstrating how the standard's layered model helps address integration of sensors, machine controllers, and analytics for real-time monitoring and anomaly detection. Likewise, industry projects have begun aligning their DT platforms with ISO 23247; Erdal et al. [62] demonstrated a drone factory assembly line integrating IoT and DT-compliant software, enabling real-time control, virtual reality (VR)-assisted operations, and scenario simulations. Other applications include automotive assembly lines [63], industrial metaverse [64], and modular production systems [65]. This adoption across diverse

manufacturing scenarios underscores ISO 23247's role as an organizational backbone, helping teams and vendors achieve consistency, interoperability, and comprehensive operational context. A summary of ISO 23247's core architectural components, along with their functions, benefits, and limitations, is presented in Table 2 to provide a consolidated view of the standard's structure and practical implications.

B. LIMITATIONS AND PRACTICAL CHALLENGES

Despite its promise, the ISO 23247 standard faces several limitations in practical adoption across industrial settings. To reflect both architectural and governance considerations, these challenges can be grouped into two broad categories: 1) implementation and interoperability issues and 2) security, privacy, and data-governance challenges.

1) IMPLEMENTATION AND INTEROPERABILITY CHALLENGES

- 1) *Early adoption and awareness:* ISO 23247 adoption remains limited, as many DT implementations were developed independently. Ferko et al. [66] noted that industry often emphasizes only parts of the standard, reflecting low awareness and reluctance to overhaul existing architectures.
- 2) *Complexity and implementation effort:* The standard is broad and abstract, requiring significant interpretation and design effort. Implementing ISO 23247 fully—especially in SME settings—can be resource-intensive due to the need to map entities and data flows without supporting tools.
- 3) *Gaps in specificity and interoperability:* ISO 23247 avoids prescribing specific technologies or protocols, which offers flexibility but causes ambiguity. The lack

TABLE 2. ISO 23247 DT Framework: Key Components, Functions, Benefits, and Limitations

Architecture components	Core functions / Entities	Key Benefits	Known Limitations
OME	Real-world assets (machines, people, and materials) that generate sensor data and receive control inputs.	Enables complete, contextual digital modeling of factory operations.	Not formally modeled in ISO 23247; requires domain-specific standards (e.g., OPC UA and MTConnect) for representation.
Device communication entity	Interfaces between physical systems and the DT; manages data collection and control signals.	Enables modular integration of sensors and actuators; promotes plug-and-play connectivity.	Lacks mandated protocols or interfaces; implementers must handle integration and interoperability challenges.
DT entity	Maintains and updates digital representations; runs simulations, analytics, and management services.	Centralizes twin logic and analytics; supports scalable, fit-for-purpose implementations.	Abstract design; lacks guidance on version control, persistence, and lifecycle validation.
User entity	Interfaces with users and enterprise systems (e.g., ERP and MES) for visualization, control, and decision support.	Facilitates enterprise integration and stakeholder access to twin insights.	No standardized APIs or user interaction models; requires custom integration.
Cross-system entity	Provides support services, such as data translation, security, and assurance across components.	Enhances interoperability and security; supports twin integration across domains.	High-level guidance only; lacks concrete tools or reference ontologies.
Traditional (nonstandardized) DT (for comparison)	Ad hoc architectures with tightly coupled, case-specific components and interfaces.	Faster to implement for narrow use-cases; high design flexibility.	Poor scalability, reusability, and interoperability; difficult to maintain or integrate.

of guidance on data exchange, storage, and model versioning can lead to inconsistent and fragmented implementations.

- 4) *Limited tooling and templates*: Few platforms or SDKs directly support ISO 23247, forcing users to manually integrate its concepts. For example, Kim et al. [61] had to custom-build an entire WAAM architecture due to the absence of turnkey solutions.
- 5) *Scope gaps*: The standard lacks depth on DT lifecycle management and validation practices. Wallner et al. [67] highlights that while it covers product lifecycle aspects, it overlooks how twins themselves evolve or maintain fidelity over time.

2) SECURITY, PRIVACY, AND DATA-GOVERNANCE CHALLENGES

- 1) *Fragmented security guidance*: Although ISO 23247 designates “*security and assurance*” within the cross-system entity, the guidance is high-level [68]. Implementers must independently define concrete controls for encryption, authentication, and access management across heterogeneous vendor systems.
- 2) *Expanded attack surface*: Distributed DT ecosystems connect sensors, controllers, cloud platforms, and AI services, increasing exposure to threats, such as data exfiltration, model tampering, and supply-chain compromise.
- 3) *Authentication and authorization*: Robust, mutually authenticated links between device communication entities and DT services are needed, complemented by fine-grained role-based access control and attribute-based access control for simulation models, telemetry topics, and APIs.

- 4) *Data ownership and governance*: Cross-vendor DT deployments blur data boundaries. Clear policies must define ownership, residency, retention, and sharing of process data, test patterns, and virtual-lab imagery to prevent intellectual-property leakage.
- 5) *Privacy preservation*: When DT data involve operators or production workflows, anonymization and federated-learning techniques can protect sensitive information while maintaining analytic utility.
- 6) *Operational hardening*: DT systems require continuous security posture management—secure-by-default protocol profiles, signed model packages, software bill of materials, and tested incident-response procedures—to ensure resilience throughout the twin lifecycle.

In summary, while ISO 23247 provides an invaluable high-level framework, its effective deployment depends equally on robust security and governance practices that ensure trust, accountability, and safe data exchange across the DT ecosystem.

C. FUTURE DIRECTIONS AND OPPORTUNITIES

Looking ahead, there are several opportunities for evolving ISO 23247 to better support real-world manufacturing needs and to ease its adoption.

1) REFINEMENT OF THE REFERENCE ARCHITECTURE

The standard could be expanded or revised to address the identified gaps in its current architecture. Continuous evolution is already recognized as necessary—for example, Latsou et al. [69] argued that the ISO 23247 framework should be refined to include specifications for data storage, model versioning, and other implementation details that are currently omitted. Future editions of the standard (or companion technical reports) could provide more concrete guidelines or

modules for these aspects, thereby reducing ambiguity. Incorporating guidance on how to verify and validate DTs (perhaps by defining quality metrics or compliance checkpoints within the framework) would help ensure that implementations maintain fidelity over time.

2) IMPROVED INTEROPERABILITY AND INTEGRATION GUIDELINES

To tackle interoperability challenges, ISO 23247 could explicitly reference or incorporate other standards and technologies. One opportunity is to define standardized interfaces or data models for common manufacturing scenarios. For instance, aligning with data exchange standards (such as ISO 21597 for linked data containers or AutomationML) and industrial communication protocols (OPC UA, MQTT, etc.) in an official capacity would give implementers a clearer path to achieving interoperability. In addition, developing an ontology or reference data schema for the “*OME*” would allow different DT systems (even from different vendors) to understand each other’s core concepts. Such enhancements would make it easier to plug components together and realize the “*digital thread*” across the four layers. Kim et al. [61] demonstrated this need in an additive manufacturing context by using an open platform with socket communication to connect robots and applications, and they highlighted that further integration is still a work in progress.

3) DEVELOPMENT OF TOOLS AND REFERENCE IMPLEMENTATIONS

An important opportunity is for the community (standards bodies, researchers, and industry consortia) to create reference implementation blueprints, software libraries, and toolkits aligned with ISO 23247. These might include open-source middleware that implements the standard’s functional entities or reference DT models for typical manufacturing equipment following the ISO 23247 data structures. If manufacturers can download a basic ISO 23247-compliant DT template (e.g., a computer numerical control (CNC) machine or a robotic cell [70]) and adapt it to their needs, then the barrier to adoption would drop significantly. Similarly, certification programs or testbeds could be established to validate that vendor products (e.g., an IoT platform or a simulation software) conform to ISO 23247’s interoperability requirements. Such ecosystem support would transform ISO 23247 from a paper specification into a practical foundation that companies can readily build upon.

4) ENHANCING SUPPORT FOR LIFECYCLE AND EVOLUTION:

To ensure longevity and relevance, the standard should consider the entire lifecycle of DT systems. This means guiding how to manage updates to the twin as the physical system changes (new sensors, machine upgrades, and process modifications) and how to decommission or replace twin components gracefully. One future direction is to introduce a

TABLE 3. Conceptual Mapping of ISO 23247 Entities to RAMI 4.0 Functional Layers

ISO 23247 entity / Layer	RAMI 4.0 layers
OME	Asset layer
Device communication entity	Integration layer
Cross-system entity (Data translation, security, and assurance)	Communication layer
DT entity (Simulation, analytics, and control)	Functional layers
User entity (Visualization and decision support)	Business layer
DT lifecycle management (Future ISO 23247 extension)	Lifecycle and value stream axis

formal notion of a “*DT lifecycle*” within ISO 23247, possibly as a new part of the series. This could define states of a DT and standard procedures for data handover between states. By doing so, ISO 23247 would help practitioners plan for the evolution of their DTs in parallel with the physical assets’ lifecycle, thereby maintaining the twins’ accuracy and usefulness over the years. Wallner et al.’s proposal of a lifecycle meta-layer to handle DT updates is an example of the kind of concept that could be standardized [67]. Embracing such ideas would empower the standard to not only facilitate initial implementation but also long-term sustainability of DT deployments.

D. ALIGNMENT WITH REFERENCE ARCHITECTURE MODEL FOR INDUSTRY 4.0 (RAMI 4.0)

While ISO 23247 provides a domain-specific framework for manufacturing DTs, it can be conceptually aligned with RAMI 4.0, which defines a broader multilayer structure for cyber-physical systems [71], [72]. Table 3 illustrates how ISO 23247 entities correspond to the hierarchical layers defined in RAMI 4.0, highlighting their complementary roles in interoperability and lifecycle management.

This alignment highlights that ISO 23247 focuses primarily on operational interoperability within the factory domain, while RAMI 4.0 introduces a lifecycle and organizational dimension extending from design to decommissioning. A combined perspective enables manufacturers to design DT solutions that are both standards-compliant and lifecycle-aware, bridging shop-floor data exchange (ISO 23247) with enterprise-level business processes (RAMI 4.0). In parallel, the NIST smart manufacturing framework (SMF) can also offer a complementary perspective by defining functional domains (e.g., connectivity, analytics, and decision support) that operationalize these architectural layers [73]. Future revisions of ISO 23247 may benefit from formally referencing RAMI 4.0 and harmonizing with frameworks, such as NIST SMF to achieve greater international coherence in DT architectures.

VI. CASE STUDIES AND PRACTICAL IMPLEMENTATIONS: SEMICONDUCTOR MANUFACTURING

The semiconductor fabrication case study presented in this work is a conceptual example illustrating how multilayer DTs can enable early yield prediction and process optimization.² Semiconductor fabrication, one of the most complex and capital-intensive manufacturing domains, is ideal for demonstrating the value of DTs that integrate sensor-rich process data, physics-based simulations, and AI/ML models. The following subsections highlight representative implementations and the potential of DTs in semiconductor manufacturing.

A. MULTILAYER DTs FOR YIELD AND PROCESS CONTROL

Semiconductor manufacturing demands fast time-to-market, high-volume output, and high yield to remain profitable. Traditionally, fabs rely on statistical process control and advanced process control (APC) techniques to monitor and adjust fabrication steps [74]. These methods use real-time data and statistical models to keep processes within spec, but they operate with limited scope (often per tool or step). A DT can greatly enhance this by providing an integrated, physics-rich simulation of the entire process flow, synchronized with sensor data across all tools. In fact, a DT can act as a replacement for conventional standalone simulations in process development, offering a continuously updated “virtual fab” that mirrors the real fabrication line. By aligning with the emerging ISO 23247 architecture, semiconductor fabs can develop these twins on a robust, interoperable blueprint.

In a semiconductor fabrication plant (fab), DT implementations can be envisioned in multiple layers or scales, each providing insights at different granularities. For example, at the process-tool level, a fab can maintain a “chamber-level” twin for equipment, such as etchers or deposition tools (including detailed physics models of plasma or chemical reactions), and a feature-level twin that simulates the patterning results on wafers. Building on these, a fab-wide twin integrates data from all tools and process stages. We describe this stratification as follows.

- 1) Discrete process simulation for predicting the yield of new process recipes from test wafers.
- 2) Cluster tool monitoring to calibrate and compare performance across tools from different vendors.
- 3) A comprehensive virtual fab that emulates each process step in sequence.
- 4) Continuous integration of module and process performance data to optimize yield in real time.

In practice, this means that each tool (e.g., each lithography scanner or etcher) could have a localized twin that monitors its specific parameters and drifts. Such a twin can run virtual “experiments” for that tool, allowing engineers to fine-tune settings to minimize variation. At the next level, the comprehensive fab twin aggregates live data from all these tools

and process steps—from wafer start to final sort—enabling prediction of final yield before the lot has even completed fabrication. This early visibility is crucial: if the DT forecasts a yield drop or systematic defect before final testing, then engineers can intervene sooner (reworking or adjusting later steps) to avoid scrapping large batches of wafers. Crucially, the integration of module-level and end-of-line data in a twin forms a feedback loop to continually improve the process “recipe” for high-volume manufacturing. By the time real wafers reach end-of-line tests, the twin (fed with in-line metrology and equipment data) has already projected potential failure modes, allowing engineers to adjust process parameters on-the-fly. Fig. 8 shows an illustration of multilayer DTs and closed-loop yield control.

B. AI-AUGMENTED FAULT PREDICTION AND DEFECT CLASSIFICATION

After fabrication, semiconductor wafers undergo rigorous postsilicon testing and failure analysis to ensure that only good chips ship to customers. This typically includes the following.

- 1) *In-line metrology inspections*: Performed during and after key process steps to detect structural or dimensional deviations.
- 2) *Wafer-level electrical testing*: Used to evaluate electrical characteristics and isolate failing dies.
- 3) *Detailed failure analysis*: Applied to suspect dies using optical, e-beam, or nanoprobe techniques.

Identifying the root cause of defects is incredibly challenging, given modern chips pack billions of transistors across dozens of layers [75]. Here, AI/ML models integrated into a DT can radically accelerate fault analysis and even predict issues before the final test. By embedding ML into the twins’ analytical toolkit, the system can correlate patterns from manufacturing data and testing results to probable defect mechanisms. For instance, a DT that monitors comprehensive process parameters layer-by-layer can retain a “signature” of each wafer’s journey; if a die fails at end-of-line, then the twin can trace back through its simulated history to pinpoint which process step or tool setting likely introduced the flaw. Moreover, a “virtual lab” twin that aggregates automated test equipment data, scan test patterns, and high-resolution images can use AI to predict the defect mode (e.g., electrical open, particle contamination, and lithography error) before physical failure analysis is even performed. A recent study demonstrated a real-to-sim automatic simulation model generator for a DT in semiconductor manufacturing, validated across two operational fabrication facilities. The resulting DT simulations closely matched actual factory key performance indicators, with throughput and uptime deviations within 7.5% across machine groups during 300-day validation runs [76].

In parallel, inline defect classification during fabrication is being supercharged by AI. Modern fabs generate immense image data from optical wafer inspectors and metrology tools.

²This case study is a conceptual synthesis based on publicly available studies and the coauthor’s industrial experience in semiconductor process. No proprietary fab data were used; rather, representative process and AI-integration steps are outlined to enable methodological reproducibility.

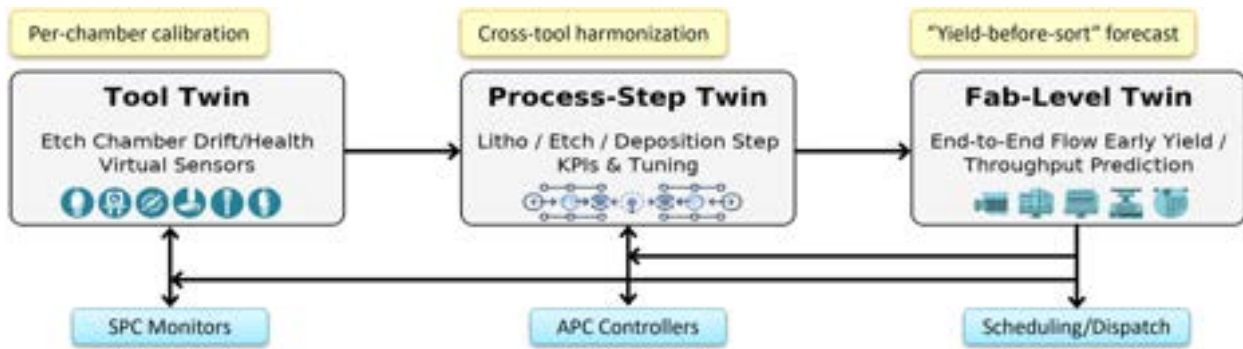


FIGURE 8. Multilayer twins and closed-loop yield control.

TABLE 4. Practical Examples of AI/DT Integration for Defect Detection and Prediction

Use Case	Approach / Technology	Example / Source
Inline defect classification	Vision-based classification of wafer inspection images with anomaly detection	TSMC deployed advanced AI vision models within its DT/AI toolkit, accelerating automated wafer defect classification and root-cause pinpointing [78].
Lot-level anomaly detection	ML models learn “normal” wafer signatures and flag deviations in real time	Modern fabs integrate ML into DTs to stop lots mid-flow or reroute wafers predicted to have catastrophic defects.
Synthetic defect generation for ML training	Physics-based DT simulations generate rare/what-if failure scenarios	Lithography or etch twins simulate misalignment or equipment glitches, producing synthetic defect data to improve ML robustness.
Cross-domain demonstration	DT-simulation fused with real-time sensor data to predict failures in advance	Phoenix Contact engineers used <i>Ansys Twin Builder</i> with sensor fusion for predictive failure analysis in relays, showing transferability to fabs.

ML can learn the “normal” pattern of a wafer and automatically flag anomalies in real time. Unsupervised anomaly detection algorithms, for example, build a profile of what a defect-free wafer should look like and then identify any deviations without needing explicit training on every defect type. Embedding these capabilities in a DT means the twin is not just passively receiving data—it is actively interpreting it. In practical terms, an AI-infused twin can stop a lot mid-flow if it predicts that a catastrophic defect is occurring, or route wafers to rework based on defect patterns.

Another powerful synergy is using high-fidelity simulations to generate synthetic data for ML—essentially the twin helping to train AI. Many fatal defect modes in chips are rare and not represented well in historical data, which limits supervised learning. A DT can fill that gap by simulating “what-if” scenarios or rare failure conditions (e.g., lithography misalignment and brief equipment glitches), producing virtual defect patterns. These simulated defects can be added to the ML training set, greatly improving the model’s ability to recognize and diagnose them in real production [77]. By augmenting real data with twin-generated data, manufacturers gain a more robust defect prediction model that is prepared for even novel failure mechanisms. The practical examples of these approaches are summarized in Table 4.

C. CLOSED-LOOP FEEDBACK AND RECIPE OPTIMIZATION

DTs in semiconductor manufacturing are progressing from simple monitoring tools into autonomous control systems. The vision is a fully optimized, closed-loop fab where the twin not only forecasts outcomes but also adjusts recipes

and tool parameters in real time, effectively self-optimizing production. For example, a twin monitoring an etch process can detect drift in etch rate via virtual sensors and immediately recalibrate gas flow or RF power on the next wafer—without human intervention. This closed-loop approach extends traditional APC by combining AI/ML-driven predictions with physics-based simulation. Platforms, such as Siemens MindSphere (linked with Siemens NX), Microsoft Azure Digital Twins, and plasma-etch twins have shown how IoT telemetry and calibrated models can reduce costly trial-and-error cycles [79]. Instead of repeatedly fabricating test wafers, adjustments are simulated virtually, providing faster-than-real-time recipe feedback and accelerating process qualification.

A key enabler is a cloud infrastructure, which allows supervisory twins to aggregate data across hundreds of tools and multiple fabs. Services, such as AWS IoT TwinMaker or Azure enable cross-fab comparisons, flagging out-of-spec behavior, and harmonizing recipes across equipment fleets. Parle et al. [16] highlighted how cloud-native scalability supports not only operational uniformity but also sustainability goals, such as energy efficiency. Closed-loop twins also implement feedforward control: issues detected early (e.g., lithography focus errors) are used to fine-tune downstream steps for specific wafers. This wafer-level personalization is impossible to do manually but achievable with algorithmic twins, leading to significant yield and throughput gains. As Moyne et al. [80] noted, run-to-run optimization twins can even be coupled with scheduling twins to optimize lot routing across the fab.

VII. CONCLUSION

DTs are moving from isolated pilots to the backbone of smart manufacturing. This article has mapped that progression across three layers: 1) the tools landscape spanning cloud IIoT platforms, high-fidelity simulation, and PLM/virtual-twin suites; 2) the ISO 23247 framework that enables compatible and scalable system implementations; 3) semiconductor case studies that demonstrate multilayer twins for yield prediction, AI-assisted defect classification, and closed-loop process optimization. Together, these threads show that the combination of continuous telemetry, physics-based models, and AI/ML transforms DTs from dashboards into predictive, prescriptive systems capable of real-time decision support and recipe tuning on the fab floor. At the same time, practical gaps remain. Industrial teams still face interoperability friction, limited out-of-the-box support for ISO 23247 entities, and uneven lifecycle governance of twin fidelity. Data quality, labeling effort for AI, and the scarcity of rare-defect examples are persistent barriers—although hybrid twins and synthetic data help to close those gaps.

Looking forward, we see three priorities. First, deeper standardization—including reference models, testbeds, and conformance tooling for ISO 23247—will reduce time-to-value and improve portability. Second, higher autonomy via closed-loop control (from tool-level up to fab-wide scheduling) will push DTs toward self-optimizing operations. Third, human-centered interfaces, including LLM-enabled copilots, will make complex diagnostics and “what-if” exploration accessible to cross-functional teams. With these advances, DTs will not only mirror factory reality but also continuously improve it, delivering resilient, energy-efficient, and economically compelling manufacturing at scale. By closing the loop, DTs convert manufacturing into a self-correcting system. They bring to life the Industry 4.0 vision of a smart fab that not only detects problems and diagnoses them (diagnostic and predictive analytics) but also prescribes and implements solutions autonomously. Achieving this at scale will require continued adherence to standards (to ensure that all these moving parts interoperably share data) and robust validation, but the payoff is transformative: near-zero excursions, adaptive processes, and maximal yield and throughput.

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