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Digital Twin Synchronization Strategies for Real-Time Control of Distributed Production Networks

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KEYWORDS

Digital twin synchronization; Distributed production networks; Real-time control; Edge-cloud computing; multi-agent coordination.

ABSTRACT

Digital twin synchronization is central to reliable real-time control in distributed production networks, yet current implementations remain constrained by latency, state inconsistency, heterogeneous data structures, limited scalability, cybersecurity exposure, and weak industrial validation. This review critically examines the conceptual foundations, architectures, performance metrics, synchronization strategies, control mechanisms, applications, and research gaps associated with physical–virtual alignment across geographically dispersed manufacturing systems. The reviewed strategies comprise time-driven, event-driven, hybrid, edge–cloud coordinated, AI-driven predictive, and blockchain-based synchronization. Their suitability depends on the required balance among update frequency, state accuracy, communication delay, computational burden, data consistency, security, and control criticality. Evidence from manufacturing, robotics, logistics, energy-aware production, and multi-plant coordination shows that effective synchronization can support closed-loop control, adaptive scheduling, predictive maintenance, resource allocation, energy optimisation, and disturbance response. However, no single strategy performs optimally under all operating conditions. Fixed updates may waste resources, event-triggered methods may overlook gradual drift, predictive approaches remain vulnerable to model error, and secure consensus mechanisms may introduce unacceptable delay. The review therefore positions synchronization as a first-class control and systems-engineering problem rather than a secondary data-management function. Future research should prioritise self-adaptive and uncertainty-aware synchronization, deterministic low-latency communication, causal and federated twin architectures, energy-efficient computing, secure governance, standardised metrics, shared benchmarks, and long-term industrial field validation. These advances are required to move digital twins from passive monitoring tools to dependable operational intelligence systems for distributed manufacturing.

1. Introduction

Manufacturing systems have undergone a significant structural shift over the past two decades. Production no longer takes place within a single facility. Instead, modern manufacturing environments span multiple geographically dispersed sites, connected through digital infrastructures that support real-time monitoring, coordination, and control (Li et al., 2022; Kabir & Ray, 2023). This transformation aligns with the broader push toward Industry 4.0, where cyber-physical systems, industrial Internet of Things (IIoT) technologies, and data-driven decision-making frameworks form the backbone of intelligent production (Dai, 2025; Nwamekwe et al. 2025). The digitization of the shop floor has led to more accurate and timely information flow, enhancing reporting times, reducing errors, and increasing process planning flexibility (Liu et al., 2022). Distributed production networks now require integration between factory floor automation and enterprise resource planning systems, with manufacturing

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execution systems serving as intermediaries to manage production lines aligned with business strategies (Liu et al., 2022; Monek & Fischer, 2024). In this context, the need for virtual representations that mirror physical operations in real time has become pressing, as enterprises seek to maintain competitiveness through rapid response capability and flexible manufacturing operations (Wang et al., 2025).

Digital twins have emerged as a central component in this transformation. A digital twin is a dynamic virtual representation of a physical system that continuously updates using real-time data (Li et al., 2023; Wang et al., 2024; Perno & Hvam, 2020). The concept, first introduced by Grieves in the early 2000s as a paradigm for product lifecycle management (Zhang et al., 2021; Liu et al., 2024), has since expanded to encompass entire production lines, supply chains, and distributed manufacturing networks (Zhang et al., 2024; Gao et al., 2024). In distributed settings, digital twins enable system-wide visibility, predictive analytics, and coordinated control across multiple production nodes (Monek & Fischer, 2024; Hart & Shakir, 2025). Real-time capable dynamic simulation has made it possible for simulation models to run in parallel and simultaneously with operating machinery, and state observer techniques such as Kalman filtering have enabled synchronization between simulation and the real world (Piras & Agostinelli, 2023). Companies increasingly use digital twins to enhance operational flexibility and gain a view of their performance and operating conditions based on real-time data, which supports condition monitoring, function simulation, dynamic scheduling, predictive maintenance, and quality control (Piras & Agostinelli, 2023; Gao et al., 2022). The establishment of digital twin models of automated production line manufacturing processes characterizes and maps the manufacturing process in real time, which holds practical significance for enterprise production process optimization, cost reduction, and quality improvement (Li et al., 2022; Harrison et al., 2021). Digital twins describe system operation from both virtual and real perspectives and provide robust support to customized design, rapid reconstruction, distributed integration, transparent monitoring, and virtual operation of workshop production lines (Wang et al., 2025).

1.1 Problem Statement

Despite their potential, digital twin systems in distributed networks often suffer from synchronization limitations. Real-time information interaction, virtual-reality synchronization, and mutual control remain open problems in digital twin systems for the industrial Internet (Sheraz et al., 2024). These include delays in data transmission, inconsistencies between physical and virtual states, and asynchronous updates across different nodes (Pater & Stadnicka, 2021; Zhou et al., 2022). Traditional digital twin implementations often fall short of meeting the requirements of modern manufacturing environments because static modelling approaches lack the flexibility to adapt to real-time changes or disruptions in operations (Dai, 2025). Delays in data synchronization compromise the effectiveness of representations, leading to inefficient decision-making; for instance, an industrial digital twin network aiming to synchronize real-time data from various IoT devices and machines to monitor and optimize production processes faces the risk that delays in synchronizing critical parameters could result in sub-optimal outcomes (Pater & Stadnicka, 2021). Challenges arise when sensors from different manufacturers use varying communication protocols and data structures, leading to interoperability issues and transmission errors during data parsing (Song et al., 2022). The construction of digital twin workshops faces multiple challenges during implementation, including real-time synchronization of virtual and physical workshop data, as well as processing and analysing large amounts of data (Juneja et al., 2021). In real-time control applications, even minor synchronization errors propagate through the system, affecting scheduling, resource allocation, and process stability (Liu et al., 2022; Monek & Fischer, 2024). The lack of consistent synchronization mechanisms therefore represents a fundamental barrier to achieving reliable and scalable distributed control. During the operation phase within the lifecycle of a cyber-physical production system, any occurring changes in the physical system should be fed

into the digital twin so that it is always synchronized to the current state, yet achieving this consistently across distributed nodes remains a significant technical challenge (Monek & Fischer, 2024).

1.2 Research Motivation

Existing research has primarily focused on digital twin modelling and analytics, with limited attention given to synchronization as a control-enabling mechanism. Most digital twins in the literature synchronously represent the real system without any control elements despite the bidirectional data link (Liu et al., 2022). Studies have addressed aspects such as product design frameworks (Wang et al., 2025), process monitoring (Li et al., 2022; Harrison et al., 2021), and scheduling optimization (Hart & Shakir, 2025; Gao et al., 2022), but few have treated synchronization itself as a first-class design concern for distributed control. There is a clear need for frameworks that explicitly integrate synchronization strategies with control theory, ensuring that digital twins support real-time, high-precision decision-making. The digital twin requires three main characteristics: synchronization with the real asset, active data acquisition from the real environment, and the ability of simulation (Monek & Fischer, 2024). Frequency of synchronization is related to the digital twin use case, available resources, real-world asset type, and real-time data acquisition methods; regular updates are necessary to prevent the virtual representation from becoming obsolete and limiting the usefulness of the digital twin (Piras et al., 2024). Without proper monitoring and maintenance of synchronization frequency, confidence in the digital twin's ability to meet requirements and provide benefits decreases (Piras et al., 2024). Research on real-time synchronization in specific domains, such as robotic digital twins achieving latency of approximately 20 milliseconds (Yan et al., 2022), and edge computing integration for reducing latency in workshop digital twins (Juneja et al., 2021), points toward promising directions. Yet a unified treatment that connects synchronization strategies to control performance across distributed production networks remains absent from the literature.

1.3 Objectives of the Review

This review is structured to achieve four objectives. First, it aims to classify existing digital twin synchronization strategies, drawing on the range of approaches reported in the literature, from event-driven and time-driven synchronization to hybrid methods integrating edge computing and deep learning (Juneja et al., 2021), physics-based state estimation (Piras & Agostinelli, 2023), and distributed communication architectures (Wang et al., 2025). Second, it seeks to establish the relationship between synchronization mechanisms and control performance, recognizing that synchronized models enable insights from physics-based simulation to be used directly to assess loads and system damage (Piras & Agostinelli, 2023), and that real-time data-driven virtual monitoring supports the virtual control of operation processes from both physical and geometric levels (Li et al., 2022). Third, it identifies technical challenges limiting current implementations, including interoperability of heterogeneous communication protocols (Song et al., 2022), latency in virtual-real synchronization (Sheraz et al., 2024), and the gap between digital twin technology and the described real-physical entity in manufacturing workshops. Fourth, it proposes future research directions for scalable and adaptive synchronization, informed by emerging trends such as AI-enabled digital twin networks (Pater & Stadnicka, 2021), reinforcement learning for adaptive optimization (Dai, 2025), and connective frameworks supporting the lifecycle of cyber-physical production systems (Monek & Fischer, 2024). By addressing these objectives, this review provides a structured foundation for advancing synchronization as a core enabler of real-time control in distributed production networks.

2. Conceptual Foundations

2.1 Digital Twin Architecture in Distributed Systems

A distributed digital twin system operates through a layered architecture where each layer performs a distinct function in bridging the physical production environment with its virtual counterpart. The physical layer comprises machines, sensors, actuators, and production assets distributed across multiple facilities (Li et al., 2022; Wang et al., 2024; Zhang et al., 2021) proposed a refined nine-layer intelligent digital twin model framework, subdividing the physical evaluation into an entity layer, an auxiliary layer, and an interface layer to manage physical resources and coordinate the overall system scientifically. The data acquisition layer captures real-time operational data from the physical layer through multi-sensor data acquisition methods and standardized communication protocols such as OPC UA (Li et al., 2022; Zhou et al., 2022; Li et al. Li et al., 2023) described how sensors perform data collection to provide data support for real-time mapping of digital space to physical space, with Express server setups and routing file integration accomplishing data collection, transmission, and processing. The twin modelling layer processes and simulates system behaviour. Wang et al. (2024) demonstrated this through a digital twin platform integrating finite element modelling for real-time process parameter simulation, enabling monitoring of parameters such as surface deformation during machining. Kurvinen et al. (2022) showed how physics-based simulation models run in parallel and simultaneously with operating machinery, forming the computational core of this layer. The control interface layer enables decision-making and system actuation. Monek and Fischer (2024) presented an "Expert Twin" framework where a fuzzy-based decision-making module generates and selects alternatives for smart manufacturing, increasing production line utility by up to 28%. Harrison et al. (2021) emphasized the need for a connective framework supporting the lifecycle of cyber-physical production systems, ensuring digital twins remain consistent with the real system throughout all phases. The interaction between these layers defines the overall performance of the digital twin system, and the quality of data flow between them directly affects synchronization fidelity and control responsiveness (Zhang et al., 2021; Liu et al., 2024).

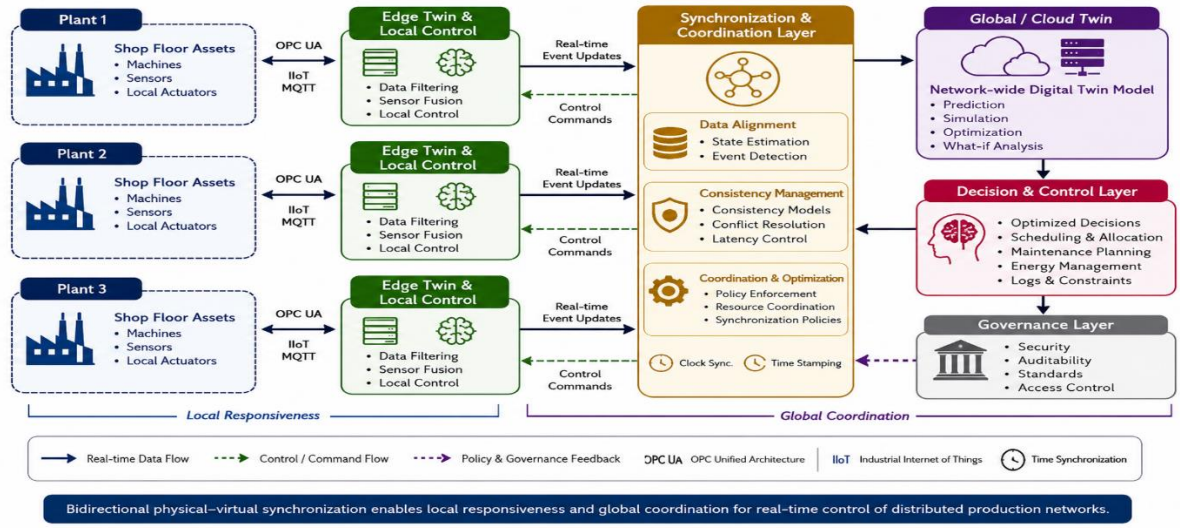


Figure 1. Digital twin synchronization architecture for distributed networks

2.2 Definition of Synchronization

Synchronization refers to the process of maintaining consistency between the physical system and its digital representation over time. Kurvinen et al. (2022) described synchronization as the alignment achieved through state observer techniques such as Kalman filtering, enabling simulation models to track the real-world state of operating machinery. Piras et al. (2024) noted the frequency of synchronization is related to the digital twin use case, available resources, real-world asset type, and real-time data acquisition methods. Three

primary categories of synchronization exist in the literature. Temporal synchronization involves the alignment of timestamps across distributed systems. In distributed production networks, sensors from different manufacturers use varying communication protocols and data structures, creating interoperability issues and timing inconsistencies during data parsing (Li et al., 2022; Song et al., 2022). Zhou et al. (2022) addressed this by combining multi-sensor data acquisition with OPC UA information models to achieve multi-source heterogeneous virtual and real data fusion with high real-time performance. State synchronization concerns the consistency of system variables between the physical and virtual domains. Wang et al. (2024) validated state synchronization in a machining digital twin, demonstrating satisfactory performance in synchronization between physical and virtual models with minimal latency. Harrison et al. (2021) specified the requirement for the digital twin to remain synchronized to the current state during the operation phase, with any occurring changes in the physical system fed into the digital twin. Event-driven synchronization triggers updates based on system changes rather than fixed time intervals. Monek and Fischer (2024) implemented this approach in their Expert Twin framework, where unexpected events in the production line trigger re-scheduling decisions through fuzzy logic control. Liu et al. (2024) proposed an edge computing integration where the edge computing layer preprocesses heterogeneous data from multiple sources and makes rapid response decisions, effectively supporting event-driven synchronization in digital twin workshops.

2.3 Real-Time Control Requirements

Effective real-time control in distributed production networks demands three core capabilities: low latency communication, deterministic system response, and stable feedback loops. Low latency communication is essential because delays in data synchronization compromise the effectiveness of digital twin representations, leading to inefficient decision-making (Pater & Stadnicka, 2021). Hart and Shakir (2025) quantified latency requirements in a body tracking digital twin system, achieving optimal results with latency within 30 to 50 milliseconds on high-end hardware, while simulated low-end configurations revealed challenges in latency and accuracy. Liu et al. (2024) addressed latency reduction through edge computing integration in digital twin workshops, where the edge computing layer handles preprocessing close to the data source to enable rapid response decisions. Deterministic system response requires the control system to produce predictable outputs within bounded time frames. Zhang et al. (2021) emphasized the importance of timeliness, stability, and reliability in workshop manufacturing systems, noting these properties are significantly restricted due to lack of real-time communication. Dai (2025) demonstrated how reinforcement learning algorithms optimize key manufacturing parameters including throughput, energy efficiency, and system reliability, achieving an 18% improvement in production throughput and a 15% decrease in system downtime. Stable feedback loops form the third requirement. The bidirectional data link between physical and virtual systems enables closed-loop control (Monek & Fischer, 2024; Wang et al., 2024). Wang et al. (2024) established dual-directional data communication between a physical machine tool and its virtual counterpart based on TCP/IP protocol, achieving real-time visualization, monitoring, and control of the entire working process. Failure to meet these requirements leads to degraded system performance and instability, as even minor synchronization errors propagate through the system, affecting scheduling, resource allocation, and process stability (Monek & Fischer, 2024; Harrison et al., 2021).

2.4 Core Synchronization Metrics

Synchronization performance is evaluated using four primary metrics. The first is synchronization delay, defined as the time lag between physical and digital states. Hart and Shakir (2025) measured this directly, reporting latency values ranging from 30 to 50 milliseconds under optimal conditions to over 100 milliseconds on lower-end hardware. Wang

et al. (2024) confirmed minimal latency in their machining digital twin, validating synchronization between physical and virtual models through preliminary experiments. The second metric is state deviation error, representing the difference between actual and simulated states. Kurvinen et al. (2022) applied state estimator techniques to estimate unmeasured quantities, also referred to as virtual sensing, and to enhance the quality of measured signals, directly reducing state deviation. Hart and Shakir (2025) quantified this through mean squared error (MSE), achieving an MSE of 0.008 on high-end setups. The third metric is updating frequency, the rate at which synchronization occurs. Piras et al. (2024) stressed regular updates are necessary to prevent the virtual representation from becoming obsolete and limiting the usefulness of the digital twin. Without proper monitoring and maintenance of synchronization frequency, confidence in the digital twin's ability to meet requirements and provide benefits decreases (Piras et al., 2024). Zhang et al. (2021) addressed this by dividing the data evaluation into a data layer and a processing layer to improve flexible response ability and ensure synchronization of real-time data. The fourth metric is the data consistency index, measuring the degree of alignment across system nodes. Zhou et al. (2022) tackled this through multi-source heterogeneous virtual and real data fusion using OPC UA information models, ensuring consistent data representation across distributed sensors and virtual models. Li et al. (2022) established a unified architecture and standardized communication protocol based on OPC UA technology to solve the problem of difficult data perception and interaction caused by nonuniform communication interface protocols of different devices on automated production lines. Together, these four metrics provide a quantitative basis for assessing and comparing synchronization strategies in distributed digital twin systems.

3. Taxonomy of Digital Twin Synchronization Strategies

3.1 Time-Driven Synchronization

Time-driven synchronization updates the digital twin at fixed, predetermined intervals regardless of whether the physical system has changed. This approach provides predictability and simplicity in implementation, making it a common choice for systems where periodic monitoring suffices (Nwamekwe et al. 2025; Wang et al., 2024). Kurvinen et al. (2022) demonstrated this principle through physics-based simulation models running in parallel with operating machinery, where state observer techniques such as Kalman filtering synchronize the simulation with the real world at regular time steps. Wang et al. (2024) implemented a similar strategy in their machining digital twin, establishing dual-directional data communication between a physical machine tool and its virtual counterpart based on TCP/IP protocol at fixed update cycles. Zhang et al. (2021) divided the data evaluation in their nine-layer framework into a data layer and a processing layer specifically to improve flexible response ability and ensure synchronization of real-time data at consistent intervals. Piras et al. (2024) noted the frequency of synchronization is related to the digital twin use case, available resources, and real-world asset type, implying time-driven approaches require careful calibration of the update interval. The primary limitation of this strategy is redundant data transmission. When the physical system remains stable between update cycles, the digital twin still receives and processes data, increasing computational load without adding informational value (Liu et al., 2024; Pater & Stadnicka, 2021). In distributed production networks with hundreds of sensors, this redundancy compounds quickly. Li et al. (2023) addressed part of this problem by setting up Express servers and integrating routing files to handle data collection, transmission, and processing efficiently, avoiding a decrease in operational efficiency due to excessive data read and write operations. Still, the fixed-interval approach struggles to balance responsiveness with resource consumption, particularly in systems where changes occur sporadically or unpredictably (Monek & Fischer, 2024; Zhang et al. (2021).

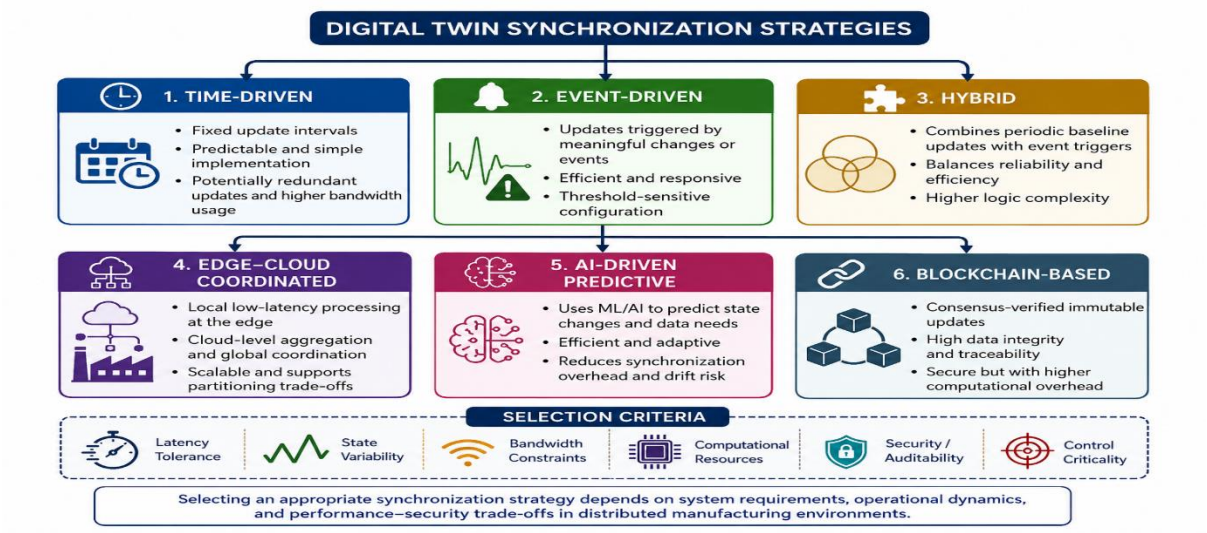


Figure 2. Taxonomy of synchronization strategies

3.2 Event-Driven Synchronization

Event-driven synchronization triggers updates only when meaningful changes occur in the physical system, reducing unnecessary data transmission and processing. Monek and Fischer (2024) implemented this approach in their Expert Twin framework, where unexpected events in the production line trigger re-scheduling decisions through fuzzy logic control, increasing production line utility by up to 28%. Zhou et al. (2022) combined multi-sensor data acquisition with OPC UA information models to detect and respond to state changes in port crane operations, enabling synchronous mapping simulation and remote control based on detected events. This strategy improves efficiency by concentrating computational resources on moments of actual change (Liu et al., 2024; Zhou et al., 2022). The event detection mechanism itself becomes a design consideration. Li et al. (2022) established a unified architecture and standardized communication protocol based on OPC UA technology to solve the problem of difficult data perception and interaction caused by nonuniform communication interface protocols across different devices. Zhang et al. (2024) applied event-driven principles in their IGBT production line, where real-time data transmitted from the physical line to the digital line trigger storage and analysis processes based on quality events during each packaging process. The weakness of event-driven synchronization lies in its potential to miss subtle, gradual variations occurring between discrete events (Zhang et al., 2021; Piras et al., 2024). Piras et al. (2024) warned regular updates remain necessary to prevent the virtual representation from becoming obsolete. A slow drift in a machine parameter, for instance, might not trigger an event threshold but still accumulate into a significant state deviation over time. Defining appropriate event thresholds therefore requires domain knowledge and careful tuning to avoid both excessive triggering and missed state changes (Monek & Fischer, 2024; Zhou et al. (2022).

3.3 Hybrid Synchronization Models

Hybrid models combine time-driven and event-driven approaches to balance accuracy and efficiency. These systems adaptively switch between periodic updates during stable operation and event-triggered synchronization during periods of change (Liu et al., 2024; Harrison et al., 2021). Harrison et al. (2021) envisioned a connective framework for cyber-physical production systems where digital twins remain consistent with the real system throughout its lifecycle, requiring adaptive synchronization strategies responsive to different operational phases. Liu et al. (2024) proposed a multi-layered, modular framework structure achieving real-time synchronous mapping and interaction between physical workshops and virtual workshops, where the edge computing layer handles rapid response decisions while deep learning algorithms conduct in-depth analysis and optimization of the production process. Zhang et al.

(2021) designed their intelligent digital twin model framework with both periodic data layer updates and event-responsive processing layer functions, enabling the system to maintain baseline synchronization while responding to production anomalies. Yan et al. (2022) described a digital twin-driven production line variant design where the system maintains continuous synchronization during normal operation but switches to intensive update modes during line reconfiguration and commissioning of new equipment. Dai (2025) demonstrated a reinforcement learning approach where the optimization algorithm interacts with the real-time manufacturing environment, effectively creating a hybrid synchronization pattern where the learning agent determines when additional state updates are needed based on prediction confidence. The primary advantage of hybrid models is their adaptability to varying operational conditions (Dai, 2025; Liu et al., 2024). The primary challenge is the added complexity of managing switching logic between synchronization modes, which demands robust decision rules and sufficient computational overhead to monitor the system state continuously (Zhang et al., 2021; Harrison et al., 2021).

3.4 Edge-Cloud Coordinated Synchronization

This strategy distributes computational tasks between edge devices located near the production floor and cloud platforms providing centralized coordination. Liu et al. (2024) proposed this approach directly, with the edge computing layer responsible for preprocessing heterogeneous data from multiple sources and making rapid response decisions, while deeper analysis and optimization occur at higher computational tiers. Li et al. (2023) built a web-based digital twin system using a Chrome V8 engine and Three.js for 3D visualization, where users log in through a browser at any time and place while the Express server handles data processing, effectively separating local data handling from remote access and coordination. Edge computing enables low-latency synchronization by processing time-sensitive data close to the source (Liu et al., 2024; Juneja et al., 2021). Juneja et al. (2021) proposed a cyber-twin architecture for 6G technology where the cyber-twin maintains a log record of network data and manages digital assets, distributing processing between local and network layers to improve reliability and adaptability. Cloud systems provide global coordination and data aggregation across distributed production nodes (Sheraz et al., 2024; Pater & Stadnicka, 2021). Sheraz et al. (2024) discussed AI-enabled digital twin networks in 6G where cloud-level intelligence manages resource allocation, caching, and data offloading across the network. Zhou et al. (2022) demonstrated a practical implementation where local OPC UA servers handle real-time data fusion from multiple sensors on port cranes while the monitoring system provides centralized visualization and remote-control capabilities. The trade-off in edge-cloud coordination involves determining which computations to perform locally and which to offload (Liu et al., 2024; Sheraz et al., 2024). Bandwidth constraints, data privacy requirements, and latency tolerances all influence this partitioning decision. Zhang et al. (2021) noted the importance of scientifically managing physical resources and coordinating the overall system, a principle directly applicable to edge-cloud task distribution in distributed production networks.

3.5 AI-Driven Predictive Synchronization

Artificial intelligence models predict system states between synchronization points, reducing the need for continuous data transmission while maintaining an accurate digital representation. Dai (2025) presented a framework integrating reinforcement learning with digital twin systems, where RL algorithms optimized key manufacturing parameters by interacting with real-time manufacturing environments, improving production throughput by 18% and reducing energy consumption by 12%. Kurvinen et al. (2022) applied state estimator techniques, including Kalman filtering, to estimate unmeasured quantities through virtual sensing, enhancing the quality of measured signals and reducing reliance on direct sensor readings. Liu et al. (2024) employed deep learning algorithms to conduct in-depth analysis, forecasting, and optimization

of the production process within their digital twin workshop framework. Gao et al. (2022) combined digital twin and machine learning to tackle AGV path planning problems in time-changing operation environments, where the digital twin provides real-time data and machine learning generates path planning schemes validated in the virtual environment before deployment. Sheraz et al. (Sheraz et al., 2024; surveyed AI-enabled digital twin networks in 6G, identifying AI's role in effective network management, optimal resource allocation, and precise behaviour prediction. The predictive approach enhances efficiency by filling gaps between actual synchronization events with model-based estimates (Dai, 2025; Nwamekwe et al. 2020). Hart and Shakir (2025) demonstrated AI-driven pose estimation achieving frame rates of 55 to 60 FPS with mean squared error of 0.008 on high-end setups, showing the precision achievable through AI-based state prediction in real-time digital twin applications. The risk of this strategy lies in prediction drift. When the AI model's assumptions diverge from actual system behaviour, the predicted states accumulate errors until the next physical synchronization corrects them (Nwamekwe et al. 2024; Gao et al., 2022). Maintaining prediction accuracy requires periodic retraining and validation against ground truth data from the physical system (Dai, 2025; Liu et al., 2024).

3.6 Blockchain-Based Synchronization

Blockchain technologies ensure secure and tamper-proof data synchronization across distributed systems by creating immutable records of state updates shared among network participants. Song et al. (2022) discussed the convergence of computing and communications in networked AI systems, highlighting the importance of transparency, accountability, and security in data exchange across distributed intelligent systems. In distributed production networks, multiple stakeholders and facilities share digital twin data, creating vulnerabilities to data tampering, unauthorized access, and inconsistent records (Sheraz et al., 2024; Song et al., 2022). Sheraz et al. (2024) identified data security as a driving advancement in 6G digital twin networks, noting the need for secure mechanisms in resource allocation, caching, and data offloading across distributed nodes. Blockchain addresses these concerns by requiring consensus among network nodes before accepting state updates, ensuring all participants maintain a consistent and verified view of the system (Sheraz et al., 2024; Song et al., 2022). Harrison et al. (2021) emphasized the existing divide in information technology and operational technology and the ad hoc integration practices resulting in inconsistent data and data models at various levels of manufacturing processes. Blockchain-based synchronization offers a structural solution to this inconsistency by enforcing data integrity at the protocol level. The primary limitation is computational overhead. Each transaction requires consensus verification across participating nodes, introducing latency incompatible with the millisecond-level response times required in real-time control applications (Hart & Shakir, 2025; Sheraz et al., 2024). Piras et al. (2024) noted the importance of maintaining synchronization frequency to preserve confidence in the digital twin's ability to meet requirements. Blockchain's consensus mechanisms slow this frequency, particularly as the number of distributed nodes increases. Current research explores lightweight consensus protocols and permissioned blockchain architectures to reduce this overhead while preserving data integrity guarantees (Sheraz et al., 2024; Song et al., 2022). The applicability of blockchain-based synchronization is strongest in scenarios where data auditability and cross-organizational trust matter more than sub-second update rates, such as supply chain coordination and regulatory compliance across distributed production networks (Harrison et al., 2021; Song et al., 2022).

4. Synchronization Mechanisms for Real-Time Control

4.1 Data Assimilation Techniques

Data assimilation integrates real-time measurements into digital twin models to correct and update the virtual representation continuously. Kurvinen et al. (2022) demonstrated this through Kalman filtering applied to physics-based digital twins of mobile log cranes and rotating

machines, where state observer techniques synchronized simulation models with operating machinery in real time. The Kalman filter estimates unmeasured quantities through virtual sensing and enhances the quality of measured signals, directly reducing the gap between physical and digital states (Nwamekwe et al. 2025). Particle filtering offers an alternative for nonlinear systems where Gaussian assumptions do not hold. Wu et al. (2023) discussed state synchronization as the real-time updating of the virtual model in response to the physical entity's state, noting the ongoing challenge of dynamically compensating for errors and reducing model state synchronization delay. Multi-sensor fusion represents a third approach. Li et al. (2022) applied information fusion technology based on D-S evidence theory, fusing multisensory data and information from other channels to more accurately describe diagnostic objects and make correct judgments for complex fault diagnosis. Zhou et al. (2022) combined multi-sensor data acquisition methods with OPC UA information models and plug-in programming to realize multi-source heterogeneous virtual and real data fusion in port crane monitoring systems. Wang et al. (2024) integrated finite element modelling into their digital twin platform for real-time process parameter simulation, enabling monitoring of surface deformation during machining. Okpala et al. (2024) applied advanced data assimilation techniques using a Variational Bayesian Recurrent Neural Network model, demonstrating how the model dynamically predicted signals reflecting real-time latent states by sequentially updating latent variables through data assimilation from observed measurements. These methods improve model accuracy and reduce synchronization errors across different application domains (Li et al., 2022; Nwamekwe et al. 2026; Zhou et al., 2022).

4.2 Latency Management Strategies

Latency represents a primary obstacle to real-time synchronization in distributed digital twin systems. Three principal strategies address this challenge. Edge computing deployment places computational resources close to the data source, reducing round-trip communication times. Liu et al. (2024) proposed an edge computing layer responsible for preprocessing heterogeneous data from multiple sources and making rapid response decisions in digital twin workshops. Chen et al. (2024) formulated a joint digital twin migration, communication, and computation resource management problem to minimize data synchronization latency, proposing a multi-agent reinforcement learning algorithm that reduced data synchronization latency by 23% to 30% compared to benchmark schemes. Data compression and efficient communication protocols form the second strategy. Li et al. (2023) set up Express servers and integrated routing files to accomplish data collection, transmission, and processing, avoiding a decrease in operational efficiency due to data read and write operations. Li et al. (2022) established a unified architecture and standardized communication protocol based on OPC UA technology to address the problem of nonuniform communication interface protocols across different devices on automated production lines. Asynchronous communication protocols constitute the third approach. Wang et al. (2023) described how a synchronized private link enables real-time data transmission between the digital twin and its physical entity or other twins, with digital twins deployable within cloud or edge servers. Hart and Shakir (2025) quantified the hardware dependency of latency, reporting optimal latency of 30 to 50 milliseconds on high-end setups but significant degradation on lower-end configurations. Zhang et al. (2021) emphasized the importance of dividing data evaluation into separate data and processing layers to improve flexible response ability and ensure synchronization of real-time data, a structural approach to latency management at the architectural level.

4.3 Feedback Loop Integration

Synchronization enables closed-loop control systems in which the digital twin continuously informs control decisions and receives updated state information from the physical system. Monek and Fischer (2024) presented the Expert Twin framework, combining traditional process simulations with real-time communication and data acquisition using programmable

logic controllers designed to control automated systems. Their approach reduced the reaction time of production to unexpected events and increased decision support efficiency, with production line utility increasing by up to 28% (Monek & Fischer, 2024). Wang et al. (2024) established dual-directional data communication between a physical machine tool and its virtual counterpart based on TCP/IP protocol, achieving real-time visualization, monitoring, and control of the entire working process. Model predictive control frameworks benefit significantly from accurate synchronization. Dai (2025) demonstrated a reinforcement learning approach where the optimization algorithm interacts with the real-time manufacturing environment, improving production throughput by 18%, reducing energy consumption by 12%, and decreasing system downtime by 15% compared to conventional methods. Novák and Vyskočil (2022) emphasized the digital twin must be synchronized with the real twin during every operation, proposing a new generation of manufacturing execution systems to provide this synchronization. At the start, the digital twin begins with a problem specification corresponding exactly to the initial state of the real production system, and after both are running, the digital twin keeps the current global state based on communication with the MES (Novák & Vyskočil, 2022). Suhail et al. (2022) described the closed-loop process where simulation data are fed back to the physical object to calibrate operations and enhance system performance, characterizing this bidirectional mapping between physical and virtual space as the defining feature of a digital twin. Harrison et al. (2021) reinforced this point by envisioning a connective framework where digital twins remain consistent with the real system throughout its lifecycle, supporting continuous feedback rather than one-time design validation.

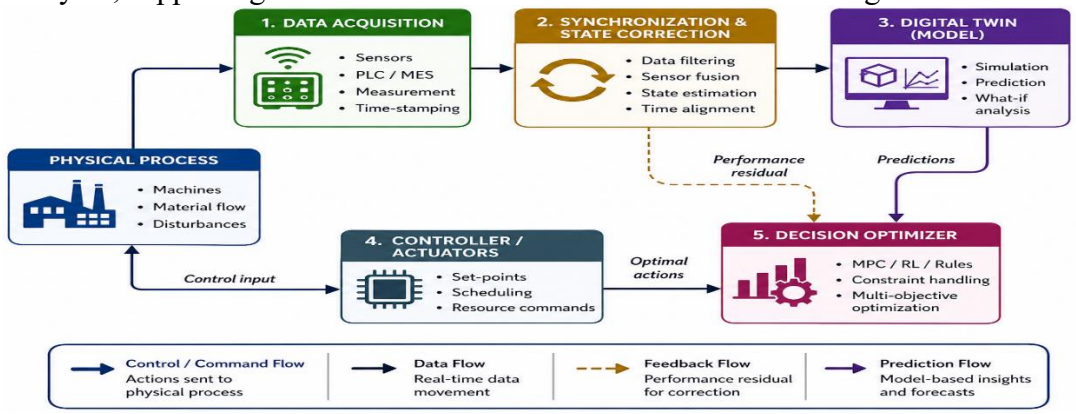


Figure 3. Closed-loop control with synchronized digital twin

4.4 Multi-Agent Coordination

In distributed production networks, multiple digital twins operate across geographically dispersed facilities and must coordinate their actions to maintain system-wide consistency. Chen et al. (2024) addressed this directly by transforming the digital twin migration problem between different servers as a decentralized partially observable Markov decision process, proposing a novel agent-contribution-enabled multi-agent reinforcement learning algorithm where the counterfactual baseline method characterizes the contribution of each agent and facilitates cooperation among agents. Consensus algorithms form a foundational coordination mechanism. Wang et al (2023) discussed the Internet of Digital Twins where massive physical entities and their virtual twins interconnect through inter-twin and intra-twin communications, enabling free data exchange, dynamic mission cooperation, and efficient information aggregation across vast physical and virtual entities. Suhail et al. (2022) described how Digital Twin Aggregate represents the combination of Digital Twin Instances to mirror the bigger picture of the physical world, requiring coordination protocols to maintain consistency across sub-components. Distributed control protocols represent a second coordination mechanism. Gao et al. (2022) combined digital twin and machine learning to tackle AGV path planning in time-changing operation environments, where the digital twin-based scheduling approach obtains real-time data from the physical automated container terminal and path planning

schemes solved by machine learning serve as input to the virtual terminal for validation and optimization. Okeagu et al. (2024) discussed shared digital twins in collaborative distributed systems, noting many stakeholders will technically not be able to synchronize the shared digital twin in a fully automated way, requiring both real-time synchronization and synchronization on demand as design principles. Conflict resolution strategies address situations where different digital twins produce contradictory recommendations. Zhang et al. (2021) proposed an intelligent workshop manufacturing system model framework driving deep information integration among the physical entity, data collection, and information decision-making, with the scheduling layer developing flexible manufacturing plans to resolve competing resource demands. Wu et al. (2023) noted random resource distribution in real environments results in inadequate resource allocation for placing digital twins in various regions, suggesting splitting the digital twin of the same physical entity into multiple sub-digital twins distributed to nearby resource-rich areas as a resolution strategy.

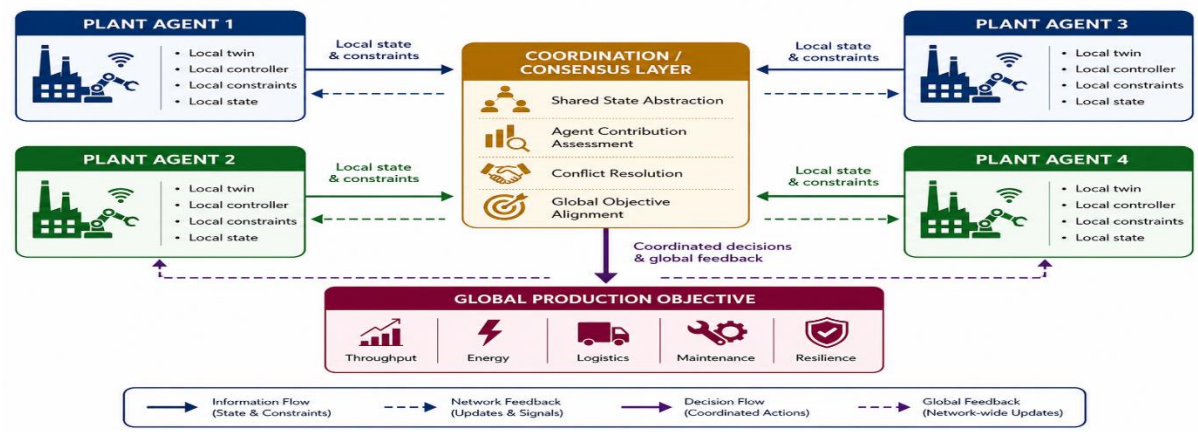


Figure 4. Multi-agent synchronization across distributed plants

5. Applications in Distributed Production Networks

5.1 Multi-Plant Manufacturing Systems

Synchronization enables coordinated production across multiple facilities by maintaining consistent digital representations of each plant's operational state. Zhang et al. (2021) proposed an intelligent workshop manufacturing system model framework based on digital twin, driving deep information integration among the physical entity, data collection, and information decision-making across production nodes. Their nine-layer framework refined the physical evaluation into entity, auxiliary, and interface layers to scientifically manage physical resources and coordinate the overall system, increasing production efficiency by 34.46% in a textile workshop (Zhang et al., 2021). Song et al. (2023) presented a digital twin-based self-organizing manufacturing system where decentralized digital twin models interconnect smart workpieces and smart resources, establishing a decentralized self-organizing network to achieve intelligent collaboration between tasks and resources across distributed shop floors. Their implementation case demonstrated synchronized online intelligence in the configuration of resources and response to disturbances (Song et al., 2023). Yi et al. (2023) described a synchronized decision-making framework for digital twin-enabled production logistics systems, where the information architecture based on digital twin realizes dynamic accurate perception and real-time feedback control among production logistics units across multiple facilities. The framework maps total factor data of multi-dimensional real-time production logistics from multiple sources to corresponding digital twins, providing data support for precise control and synchronized decision-making (Yi et al., 2023). Harrison et al. (2021) addressed the existing divide in information technology and operational technology across manufacturing levels, proposing the SIMPLE framework to support consistent data models throughout the engineering lifecycle of cyber-physical production systems spanning multiple plants. Tang et al. (2022) described how

edge computing based smart manufacturing with distributed control structure enables physical entities to act as edge devices, with local digital twins achieving local control and decision making while a global digital agent connected to a global digital twin globally controls the network of manufacturing nodes for optimization of production order and logistics. Chen et al. (2024) formulated a joint digital twin migration, communication, and computation resource management problem to minimize data synchronization latency as users roam between edge servers, reducing latency by 23% to 30% compared to benchmark schemes. These contributions collectively demonstrate the value of synchronized digital twins in enabling multi-plant coordination, though challenges remain in maintaining consistency across heterogeneous systems with varying communication protocols and data structures (Zhang et al., 2021; Song et al., 2023).

5.2 Smart Supply Chains

Digital twin synchronization supports real-time inventory tracking, demand forecasting, and logistics optimization across supply chain networks. Gao et al. (2022) combined digital twin and machine learning to tackle AGV path planning problems in the time-changing operation environment of automated container terminals. Their digital twin-based AGV scheduling approach obtains real-time data from the physical terminal, formulates a mathematical model to minimize transportation time, and validates path planning schemes solved by machine learning in the virtual terminal before deployment (Gao et al., 2022). Yi et al. (2023) introduced a synchronized decision-making architecture for digital twin-enabled production logistics consisting of three parts: digital twin information architecture, opti-state control mechanism, and a mathematical model for "production-in-plant logistics-storage" optimization. By analysing and constructing the production logistics operation logic flow of production workshops and warehouse units, physical entities and their dependency relationship data feed the virtual-real mapping driven by digital twin (Yi et al., 2023). Corallo et al. (2021) noted the digital twin technology allows for analysing, monitoring, and predicting the behaviour of a system, controlling its status in real time, and supporting the management of the product and service lifecycle in a sustainable way. At the object level, the manufacturing status including ID, attribute, status, and service is captured, mapped, and converged on a real-time basis (Corallo et al., 2021). Wu et al. (2023) described how a digital twin network of a physical space is constructed in information space, where the twin entity selects a target base station for migration based on its physical entity's real-time location to maintain continuous low-latency information exchange. The physical entity and its corresponding twin entity maintain state synchronization through real-time data interaction (Wu et al., 2023). Okpala et al. (2025) proposed a digital twin construction framework and scheme for inputting data derived from IoT into simulation models, enabling real-time tracking of production status and inventory levels across the supply chain. The effectiveness of supply chain digital twins depends on the synchronization frequency and data consistency across nodes, as delays in synchronizing critical parameters result in sub-optimal logistics decisions (Chen et al., 2024; Yi et al., 2023).

5.3 Autonomous Production Lines

Real-time synchronization allows adaptive scheduling, fault detection, and automated system adjustments on autonomous production lines. Zhang et al. (2024) proposed a modular intelligent IGBT production line based on digital twin, where real-time data transmit from the physical line to the digital line for storage and analysis. The digital line is visualized, and an intelligent management platform containing multiple functions addresses quality issues arising during each packaging process using a problem-solving approach based on digital twin methodology (Zhang et al., 2024). Igbokwe et al. (2024) proposed DigTwinOps, a digital twin framework for runtime verification of cyber-physical production systems, featuring a Digital Twin Execution Engine that manages digital twin models to synchronize states of real machines in the production environment. Their framework enables a human worker to observe the states

of production objects and verify the effectiveness of control commands before applying them to the real production environment (Igbokwe et al., 2025). Song et al. (2023) designed a mechanism of job-machine optimal assignment and adaptive optimization control to improve the capabilities of reconfiguration and responsiveness in their digital twin-based self-organizing manufacturing system. Real-time manufacturing data synchronized with the digital twin model allows a comprehensive simulation application containing process simulation, disturbance recognition, and adaptive optimization modules (Song et al., 2023). Monek and Fischer (2024) presented the Expert Twin framework combining traditional process simulations with real-time communication and data acquisition using programmable logic controllers, reducing the reaction time of production to unexpected events and increasing production line utility by up to 28%. Liu et al. (2024) addressed the challenges of real-time data synchronization and big data processing in digital twin workshops, proposing an edge computing and deep learning integration where case studies demonstrated significant improvement in equipment utilization and optimized workpiece scheduling. Novák and Vyskočil (2022) emphasized the digital twin must be synchronized with the real twin during every operation, proposing a formal description of production resources and related operations from which an executable digital twin is automatically derived and enhanced with operation duration times obtained through process mining methods. Groshev et al. (2021) implemented an Edge Robotics Digital Twin system enabling real-time applications such as visualization and remote control, achieving 5G-enabled remote control latency of 20 milliseconds and average synchronization of 95% as the threshold below which impact on robotic arm operation becomes noticeable.

5.4 Energy-Aware Manufacturing Networks

Synchronization enables real-time energy monitoring and optimization across distributed manufacturing systems. Dai (2025) demonstrated a reinforcement learning framework integrated with digital twin systems that reduced energy consumption by 12% while simultaneously improving production throughput by 18% and decreasing system downtime by 15% compared to conventional methods. Groshev et al. (2021) analysed the capability of their Edge Robotics Digital Twin system to offer potential savings by means of computation offloading, showing 16% CPU and 34% memory savings achieved by virtualizing and offloading software components to the edge, directly reducing the energy footprint of digital twin operations. The manufacturing sector, as the largest world energy consumer accounting for 55% of the world's energy, is in a constant search for energy efficient optimization strategies to reduce consumption (Groshev et al., 2021) Zhang et al. (2021) proposed a framework where the scheduling layer develops flexible manufacturing plans to shorten production cycles and reduce logistics costs, with the optimized production system achieving a 34.46% increase in production efficiency, which carries direct implications for energy use per unit of output. Igbokwe et al. (2025b) compared production strategies in their digital twin framework, measuring travelling distance and comprehensive energy consumption as key performance indicators, demonstrating the digital twin's role in selecting energy-optimal control commands. He and Bai (2020) reviewed digital twin-based sustainable intelligent manufacturing, noting manufacturing systems monitor physical processes, create a digital twin in the physical world, receive real-time information for simulation analysis, and make informed decisions through real-time communication. The combination of digital twin and intelligent manufacturing makes production more efficient, with real-time monitoring of product and equipment status enabling timely prediction of possible failures (He & Bai, 2020). Tang et al. (2022) described how digital twin edge networks enable continuous monitoring of network status, with networking schemes such as resource management studied from a centralized perspective to optimize energy allocation across distributed nodes. These applications show synchronized digital twins provide the data foundation for energy-aware decision-making, though the energy cost of maintaining the synchronization infrastructure itself remains an open consideration (Groshev et al., 2021; He & Bai, 2020).

6. Key Challenges and Research Gaps

6.1 Scalability Issues

Large-scale distributed production networks require synchronization across numerous nodes, and this requirement introduces significant complexity as the number of connected assets grows. Chen et al. (2024) identified the scalability issue directly, noting high dimensional state spaces emerge when multiple edge servers and mobile users interact in multi-tier computing systems. They addressed this by utilizing embedding matrices to code agents' actions and states, releasing the scalability constraint under high dimensional conditions in their multi-agent reinforcement learning algorithm (Chen et al., 2024). Wu et al. (2023) observed random resource distribution in real environments results in inadequate resource allocation for placing digital twins in various regions, suggesting splitting the digital twin of the same physical entity into multiple sub-digital twins distributed to nearby resource-rich areas as a workaround. Zhang et al. (2021) proposed a nine-layer framework to manage the complexity of workshop manufacturing systems, but the framework was validated on a single textile workshop rather than across a multi-plant network. Stadtmann et al. (2023) identified scalability as one of the main challenges hindering the realization of highly capable digital twins, categorizing the barriers into standards-related, data-related, model-related, and industrial acceptance-related issues. Tang et al. (2022) discussed digital twin edge networks where networking schemes such as resource management are studied from a centralized perspective, but acknowledged the difficulty of scaling such centralized approaches to large distributed systems. Vogel-Heuser et al. (2023) measured delay times in a multi-agent system for gearbox assembly, noting cloud-based digital twin solutions face communication delays that become bottlenecks in terms of real-time communication as the number of agents increases. The core tension remains: adding more production nodes increases the state space, communication overhead, and coordination burden, and current frameworks have not demonstrated consistent performance at the scale of full distributed production networks (Chen et al., 2024; Wu et al., 2023; Stadtmann et al., 2023).

6.2 Data Heterogeneity

Integration of diverse data sources remains a significant challenge in distributed digital twin systems. Wang et al. (2025) noted challenges arise when sensors from different manufacturers use varying communication protocols and data structures, leading to interoperability issues and transmission errors during data parsing. Li et al. (2022) addressed this problem by establishing a unified architecture and standardized communication protocol based on OPC UA technology to solve the difficulty of data perception and interaction caused by nonuniform communication interface protocols of different devices on automated production lines. Zhou et al. (2022) combined multi-sensor data acquisition methods with OPC UA information models and plug-in programming to realize multi-source heterogeneous virtual and real data fusion in port crane monitoring. Liu et al. (2024) described the edge computing layer as responsible for preprocessing heterogeneous data from multiple sources, acknowledging the variety of data formats and structures present in manufacturing environments. Chen et al. (2024) summarized multiple data transmission approaches used in digital twin systems, including RS485 protocol, IoT-based collection, edge computing gateways, and TCP/IP communication through client/server architectures, illustrating the fragmented state of data acquisition methods. Kabir and Ray (2023) discussed how several industries employ various types of prototyping technologies with individual needs for development, creating heterogeneous data environments when these systems need to interoperate. Stadtmann et al. (2023) characterized data challenges through the 10 Vs of big data, including volume, velocity, variety, veracity, value, validity, variability, venue, vocabulary, and vagueness, all of which compound the heterogeneity problem. Harrison et al. Harrison et al. (2021) attributed much of this difficulty to the existing divide in information technology and operational technology and ad hoc integration practices resulting in inconsistent data and data models at various levels of manufacturing processes.

Without standardized data models spanning the full production network, each integration effort becomes a custom engineering task (Li et al., 2022; Wang et al., 2025).

6.3 Cybersecurity Risks

Synchronized digital twin systems are vulnerable to cyber threats that compromise data integrity and disrupt control operations. Siddique et al. (2023) explored cybersecurity concerns arising from the convergence of physical and virtual systems in digital twin applications, emphasizing secure data transmission, access control, encryption, and threat detection as elements that must be ensured for digital twin systems in the industrial sector. Chidiebube et al. (2025a) proposed implementing digital twins equipped with intrusion detection algorithms, noting their novel algorithm detects attacks in a timely manner and diagnoses the type of attack by classification. They identified synchronization between digital twins and real systems as a specific vulnerability, observing prior research missed the synchronization aspect of security (Chidiebube et al., 2025b). Wang et al. (2023) surveyed security and privacy threats in the Internet of Digital Twins, noting severe known and unknown security flaws and privacy invasions hinder wide deployment, with the decentralized structure and information-centric routing of digital twin networks entailing critical challenges for security service provisioning. Coppolino et al. (2023) proposed an architecture for cybersecurity monitoring in smart grids, converting a Common Information Model-compliant system into a digital twin and incorporating a Security Information and Event Management solution. Suhail et al. (2022) described how blockchain-based digital twins address key challenges of disparate data repositories and untrustworthy data dissemination, with cross-validated data stored on the blockchain to maintain integrity and trustworthiness. Sheraz et al. (2024) identified data security as a driving concern in 6G digital twin networks, discussing the need for secure mechanisms in resource allocation and data offloading across distributed nodes. The fundamental tension is that synchronization requires open and frequent data exchange between nodes, which simultaneously expands the attack surface available to adversaries (Wang et al., 2023; Siddique et al., 2023; Chidiebube et al., 2025c).

6.4 Latency vs Accuracy Trade-off

Higher synchronization frequency improves the accuracy of the digital twin representation but increases computational cost and network bandwidth consumption. Piras et al. (2024) stated the frequency of synchronization is related to the digital twin use case, available resources, real-world asset type, and real-time data acquisition methods, and regular updates are necessary to prevent the virtual representation from becoming obsolete. At the same time, without proper monitoring and maintenance of synchronization frequency, confidence in the digital twin's ability to meet requirements decreases (Piras et al., 2024). Hart and Shakir (2025) quantified this trade-off directly, reporting optimal latency of 30 to 50 milliseconds and mean squared error of 0.008 on high-end hardware, while simulated low-end configurations revealed significant degradation in both latency and accuracy, emphasizing hardware dependency. Vogel-Heuser et al. (2023) measured delay times in multi-agent systems and noted modelling delay times before implementation leads to a more efficient approach to elaborating on complex systems' hard and soft real-time capabilities. Groshev et al. (2021) reported 16% CPU and 34% memory savings achieved by virtualizing and offloading software components to the edge, demonstrating the computational cost of maintaining high-fidelity synchronization. Chen et al. Chen et al. (2024) formulated the trade-off as a joint optimization problem minimizing data synchronization latency while managing communication and computation resources, achieving 23% to 30% latency reduction through multi-agent reinforcement learning. Tilbury (2019) identified the synchronization of time between the simulation model and the physical process as the most challenging part of enabling real-time monitoring, since most simulation models run either much faster or much slower than real time. Emeka et al. (2025) noted a digital twin may capture state data only at distinct times, process numerous types of events frequently,

capture sensor readings at fixed intervals, or sample high-resolution time series, with each approach carrying different accuracy and cost implications. No universal guideline exists for selecting the optimal synchronization frequency for a given application (Piras et al., 2024; Chen et al., 2024; Tilbury, 2019).

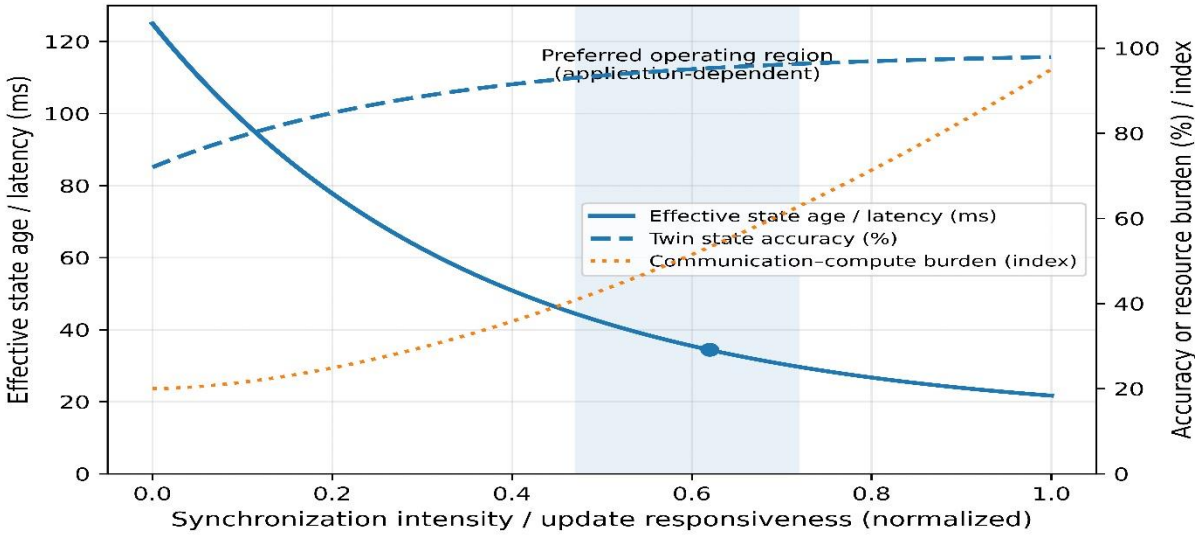


Figure 5. Latency–accuracy trade-off curve

6.5 Lack of Standardized Frameworks

There is no unified standard for digital twin synchronization across distributed production networks. Stadtmann et al. (2023) identified standards-related challenges as one of the four main categories hindering the realization of highly capable digital twins, noting user cases need to demonstrate value for the industry to invest time and money, and documentation and standardization are required for the industry to accept digital twins. Chen et al. (2024) observed academia and industry have used a variety of interpretations, and the scientific literature lacks a unified and consistent definition of the digital twin term itself, let alone standardized synchronization protocols. Nwamekwe et al. (2025) derived requirements for digital twin platforms based on literature and multi-year research projects, identifying bidirectional synchronization and convergence as core requirements, but noted existing platforms address these requirements unevenly. Ezeanyim et al. (2025a) proposed using the Asset Administration Shell as a technology-neutral meta-model for implementing digital twins, aiming to enhance interoperability and availability of properties and services of any asset within value creation networks. Harrison et al. (2021) attributed the lack of consistency to the existing divide in information technology and operational technology and ad hoc integration practices at various levels of manufacturing processes, proposing the SIMPLE framework as one possible solution. Vitalis et al. (2024) demonstrated how to design shared digital twins for collaborative distributed systems, noting many stakeholders will technically not be able to synchronize the shared digital twin in a fully automated way, requiring both real-time synchronization and synchronization on demand as design principles. Wang et al. (2025) emphasized universal standardization of communication protocols is essential for ensuring effective communication between sensors in digital twin systems. The absence of a common framework forces each implementation to develop custom synchronization solutions, limiting interoperability and reuse across different production networks (Stadtmann et al., 2023; Chen et al., 2024; Ezeanyim et al., 2025b).

6.6 Validation and Benchmarking

Limited real-world datasets and testing environments hinder performance validation of digital twin synchronization strategies. Novák and Vyskočil (2022) tested and validated their

digital twin approach in an Industry 4.0 Testbed equipped with four robots and a transport system, but acknowledged this controlled laboratory setting differs from full-scale production environments. Igbokwe et al. (2024) applied their DigTwinOps framework to a cyber-physical production system prototype, demonstrating effectiveness in controllability verification of control commands, but the prototype scale limits generalization to larger distributed networks. Groshev et al. (2021) implemented an Edge Robotics Digital Twin system as a prototype to gradually validate and optimize digital twin solutions, recognizing prototyping is required because designing and implementing a system that integrates all emerging technologies and meets connectivity requirements is an ambitious task. Vogel-Heuser et al. (2023) measured delay times in a gearbox assembly use case under academic conditions, noting the system is not restricted by either hard or soft real-time boundaries, with the primary focus on examining real-time capabilities rather than meeting production-grade constraints. Chen et al. (2024) validated their digital twin migration scheme using two real-world taxi mobility trace datasets, providing more realistic conditions but still outside the manufacturing domain. Okpala et al. (2025) proposed a digital twin construction framework and verified its effectiveness by constructing a simulation model for an IoT-aided manufacturing system, but the verification remained at the simulation level. Perno and Hvam (2020) noted the process of scoping digital twin projects proves daunting for process manufacturing companies given the novelty of the concept and the broad range of technologies upon which it is built. The field lacks standardized benchmarks, shared datasets, and agreed-upon evaluation criteria for comparing synchronization strategies across different production network configurations (Novák & Vyskočil, 2022; Igbokwe et al., 2025; Groshev et al., 2021).

7. Future Research Directions

The reviewed literature confirms that digital twin synchronization has moved beyond simple physical–virtual state updating. It is now becoming a major control requirement for distributed production networks. However, present approaches still struggle with fixed synchronization intervals, communication delay, heterogeneous data structures, limited scalability, prediction drift, cybersecurity exposure, and the absence of common validation standards. Future research should therefore focus on synchronization mechanisms that are adaptive, resource-aware, secure, interoperable, and directly linked to measurable control performance. The priority should not be to increase synchronization frequency blindly. Rather, future systems should determine when, where, and how synchronization is required to maintain an acceptable level of state fidelity without imposing unnecessary communication and computational burden.

7.1 Self-Adaptive Synchronization Systems

Future digital twins should move from fixed synchronization rules to self-adaptive mechanisms that adjust update frequency, communication mode, and model-correction intensity according to the operational condition of each production node. The reviewed evidence shows that time-driven synchronization provides predictable updates but generates redundant data traffic during stable operation. Event-driven synchronization reduces this burden but may fail to detect slow process drift. Hybrid approaches offer a better balance, although their switching logic remains difficult to design and validate. Future work should therefore develop synchronization policies that continuously assess state deviation, event severity, prediction uncertainty, network condition, process criticality, and available computational resources before deciding whether an update is required. Reinforcement learning, adaptive control, Bayesian uncertainty estimation, and change-point detection provide useful foundations for this direction. An intelligent synchronization controller could increase update frequency when a machine enters an unstable condition, when uncertainty exceeds a specified threshold, or when a critical production event occurs. It could then reduce the update rate during steady operation. This would help address the latency–accuracy trade-off identified in the manuscript while avoiding excessive bandwidth consumption. Nevertheless, adaptive

policies must operate within defined safety constraints. An algorithm should not delay an update where stale data may lead to unsafe actuation, production loss, or equipment damage. Future studies should therefore integrate hard synchronization limits, fail-safe fallback modes, and application-specific criticality levels into adaptive synchronization algorithms. Their performance should be evaluated using synchronization delay, state deviation error, update frequency, data consistency, control response time, resource utilization, and synchronization confidence.

7.2 Integration with Ultra-Low-Latency Networks

The effectiveness of synchronized digital twins in real-time control depends strongly on the communication infrastructure connecting physical assets, edge twins, cloud services, and distributed production agents. Current studies have reported promising latency values in robotics and high-performance computing environments. However, these results are not yet sufficient to guarantee deterministic performance across large multi-plant networks. Future research should investigate the joint design of digital twin synchronization and emerging communication technologies, including private 5G, future 6G networks, time-sensitive networking, deterministic Ethernet, software-defined networking, network slicing, and ultra-reliable low-latency communication. The key research issue is not merely achieving low average latency. Distributed production control requires bounded end-to-end delay, low jitter, reliable packet delivery, accurate clock alignment, and rapid recovery from communication failure. A network may report acceptable mean latency while still producing occasional delay spikes that destabilize a closed control loop. Future studies should therefore model the complete synchronization path from sensing and timestamping to edge processing, model correction, optimization, and physical actuation. Communication delay, processing delay, queuing delay, model execution time, and actuator response should be assessed jointly. Edge–cloud task allocation should also become synchronization-aware. Time-critical state estimation and local control should remain close to the physical process, while computationally intensive prediction, long-horizon scheduling, and network-wide optimization may be performed at higher computing layers. Future frameworks should dynamically decide which twin functions are executed locally and which are migrated or offloaded. This decision should consider bandwidth availability, energy consumption, data privacy, process urgency, and the cost of twin migration. Such research will be important for production environments in developing economies, where industrial connectivity may be unstable and computing resources may differ considerably across plants.

7.3 Causal and Uncertainty-Aware Digital Twins

Most existing synchronized digital twins depend on correlation-based prediction, state estimation, or machine-learning models. These approaches can identify patterns but may not reliably explain whether a predicted intervention will produce the intended physical outcome. This limitation becomes serious when the digital twin is connected directly to scheduling, maintenance, quality, energy, or resource-allocation decisions. Future research should therefore integrate causal inference into synchronized digital twin systems. A causal digital twin should distinguish between variables that merely move together and variables that directly influence process behaviour. This would allow the system to estimate the likely consequence of changing a machine set-point, reallocating a production order, modifying a maintenance schedule, or shifting energy demand between plants. Structural causal models, causal graphs, counterfactual reasoning, and intervention analysis could improve the reliability of digital twin recommendations. They would also support conflict resolution where different plant twins propose competing actions. Causal reasoning should be combined with uncertainty quantification. AI-driven predictive synchronization can reduce communication demand by estimating physical states between confirmed updates. However, prediction error may accumulate when the production environment changes, sensors degrade, or the model operates

outside its training range. Future systems should attach calibrated uncertainty values to predicted states, synchronized measurements, and control recommendations. Synchronization should be triggered when uncertainty becomes unacceptable, rather than only when a fixed time interval expires. Research should also distinguish between measurement uncertainty, communication uncertainty, model uncertainty, and process variability. This will allow the digital twin to determine whether an apparent physical–virtual mismatch is caused by actual process change, sensor error, delayed transmission, or model drift.

7.4 Federated and Decentralized Twin Architectures

Distributed production networks often involve separate plants, suppliers, logistics providers, service companies, and regulatory bodies. These participants may need coordinated digital twin synchronization but may be unwilling or legally unable to share raw operational data. Centralized synchronization architectures also create scalability constraints, communication bottlenecks, and single points of failure. Federated and decentralized twin architectures therefore represent an important future research direction. A federated architecture should allow local twins to retain sensitive plant data while sharing model parameters, state summaries, uncertainty measures, resource requests, or encrypted synchronization updates. This can support network-wide optimization without exposing proprietary production records. Future work should develop federated synchronization protocols that address non-identically distributed data, unequal computing capacity, unreliable participation, communication dropouts, and differences in local update frequency. The system must also prevent a poorly calibrated or compromised local twin from degrading the shared global state. Multi-agent coordination should form a major part of this research. Plant-level agents should negotiate production capacity, maintenance priority, inventory position, logistics availability, and energy demand while maintaining local autonomy. Consensus mechanisms should account for the reliability and contribution of each agent rather than treating all updates as equally trustworthy. Future studies should also explore hierarchical coordination in which machine-level twins synchronize with line-level twins, line-level twins synchronize with plant twins, and plant twins contribute to a network-level twin. Such a structure may reduce communication load and improve scalability. However, clear rules will be required for conflict resolution, model ownership, update authority, synchronization responsibility, and recovery when different twins hold inconsistent states.

7.5 High-Performance and Energy-Aware Computing Integration

Large-scale digital twin synchronization involves continuous sensor ingestion, multi-source data fusion, state estimation, simulation, optimization, visualization, and control. The computational burden grows rapidly as the number of machines, production lines, plants, and synchronized variables increases. Future research should therefore investigate high-performance computing architectures that can sustain real-time synchronization without introducing unacceptable energy demand. Graphics processing units, distributed computing clusters, field-programmable gate arrays, neuromorphic processors, cloud–edge accelerators, and parallel simulation methods can improve model execution and state-correction speed. However, the use of more powerful computing resources should not be treated as a complete solution. The manuscript already establishes that synchronization infrastructure has its own CPU, memory, communication, and energy costs. Future work should therefore optimize synchronization quality and computing efficiency together. Energy-aware synchronization frameworks should determine whether the improvement obtained from an additional update justifies its communication and computational cost. For non-critical variables, model-based prediction or lower-frequency updating may be sufficient. Critical safety, quality, and control variables may require continuous or high-rate synchronization. Future studies should formulate this allocation as a multi-objective optimization problem involving state accuracy, control performance, latency, bandwidth, computing load, and energy consumption. Research should

also examine carbon-aware workload placement, particularly where cloud and edge resources operate under different energy conditions.

7.6 Secure and Trustworthy Synchronization

Cybersecurity should become an integral part of synchronization design rather than an additional protection layer introduced after implementation. Frequent bidirectional data exchange increases the attack surface of distributed digital twins. An attacker may alter timestamps, inject false sensor data, delay control commands, manipulate state estimates, compromise local agents, or create inconsistency between physical and virtual states. Such attacks may remain undetected where monitoring focuses only on the accuracy of the digital model. Future research should develop synchronization-specific threat models and intrusion-detection mechanisms. These mechanisms should identify replay attacks, false-data injection, clock manipulation, communication delay attacks, model poisoning, unauthorized twin migration, and malicious agent updates. Physical invariants, process constraints, redundancy checks, state-estimation residuals, and cross-twin consistency tests can be combined to detect abnormal synchronization behaviour. Blockchain and distributed ledger technologies may improve traceability and cross-organizational trust, but their use should be selective. Conventional consensus mechanisms may introduce delays that are unsuitable for millisecond-level control. Future research should investigate lightweight permissioned ledgers, off-chain processing, selective logging, and risk-based verification. Critical state changes and governance records may be stored immutably, while high-frequency control data remain within faster local channels. Trustworthy synchronization should also include authentication, role-based access, data provenance, explainability, uncertainty disclosure, and clear human override procedures.

7.7 Standardization, Benchmarking, and Industrial Validation

The absence of common definitions, benchmark datasets, synchronization interfaces, and evaluation procedures currently limits comparison across studies. Future research should establish standardized test environments that represent realistic distributed production conditions. These environments should include heterogeneous sensors, multiple communication protocols, different update rates, variable network delays, missing data, machine disturbances, cyberattacks, and competing production objectives. Benchmarking should evaluate more than prediction accuracy or average network latency. A comprehensive assessment should include synchronization delay, jitter, state deviation, consistency across nodes, update efficiency, control-response time, closed-loop stability, fault-recovery time, communication overhead, computational cost, energy demand, security resilience, and economic benefit. The same synchronization strategy should be tested under stable operation, gradual drift, sudden disruption, communication failure, sensor degradation, and multi-agent conflict. More importantly, future studies should move beyond small laboratory prototypes and simulation-only validation. Long-term industrial field studies are required across multi-plant manufacturing, autonomous production lines, logistics networks, process industries, and energy-intensive facilities. These studies should report the hardware configuration, communication architecture, number of synchronized variables, update policy, network conditions, failure scenarios, and operational constraints clearly. Shared datasets and reproducible experimental protocols would improve comparison and accelerate industrial adoption. Standardized frameworks should also support OPC UA, Asset Administration Shells, manufacturing execution systems, enterprise resource planning platforms, and existing industrial control infrastructure. Overall, the next stage of digital twin synchronization research should treat synchronization as an intelligent, closed-loop, and safety-critical control function. Progress will depend on the joint development of adaptive algorithms, deterministic communication, causal and uncertainty-aware models, federated coordination, energy-efficient computing, cybersecurity, and rigorous industrial benchmarking. These directions will enable

digital twins to progress from passive virtual representations to dependable decision and control systems for large-scale distributed production networks.

8. Conclusion

This review establishes digital twin synchronization as a core requirement for dependable real-time control in distributed production networks. The evidence examined shows that synchronization is no longer limited to updating a virtual model from physical measurements. It now supports closed-loop control, predictive decision-making, multi-agent coordination, adaptive scheduling, maintenance planning, energy management, logistics optimization, and system-wide resilience. Time-driven, event-driven, hybrid, edge–cloud coordinated, AI-driven predictive, and blockchain-based strategies each offer distinct benefits, but none provides a universal solution across all industrial conditions. The central finding is that synchronization performance depends on achieving a practical balance among latency, state accuracy, update frequency, data consistency, computational demand, communication overhead, and control criticality. High-frequency updating can improve virtual–physical fidelity, yet it may also increase bandwidth usage, energy consumption, and processing burden. Conversely, reduced updating can conserve resources but may produce stale states, delayed responses, and unstable control actions. This confirms that synchronization policies must be selected according to process dynamics, risk level, available infrastructure, and required response time. The review also identifies persistent barriers to industrial deployment. These include heterogeneous data structures, nonuniform communication protocols, scaling difficulties, cybersecurity exposure, prediction drift, limited interoperability, and inadequate real-world benchmarking. Most reported implementations remain confined to prototypes, testbeds, single workshops, or simulation environments. Therefore, stronger industrial validation across multi-plant systems is still required. Future progress should prioritise self-adaptive and uncertainty-aware synchronization, deterministic ultra-low-latency communication, causal digital twins, federated and decentralised coordination, energy-efficient high-performance computing, and secure governance mechanisms. Standardised metrics, shared datasets, interoperable architectures, and reproducible validation protocols are equally necessary. Overall, synchronized digital twins can become reliable operational intelligence systems for distributed manufacturing, but this will require treating synchronization as a measurable, safety-conscious, and control-enabling engineering function rather than a secondary data-management activity. Its success will depend on aligning technical sophistication with industrial affordability, workforce readiness, regulatory expectations, and long-term maintainability.

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