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Digital-Twin-Enabled Industrial IoT: Vision, Framework, and Future Directions

Qihao Li, Qiang (John) Ye, Ning Zhang, Wei Zhang, and Fengye Hu

Abstract

Building digital twins (DTs) in industrial Internet-of-Things (IIoT) is challenging, especially considering complex and large-scale network architectures, real-time data requirements, and computational demands. Traditional modeling-based approaches, relying on either small datasets with physics-based models or large datasets processed through artificial intelligence (AI) techniques, face limitations in adaptability and accuracy. In this article, we propose a hybrid DT framework to address these challenges, which integrates both physics-based models and AI techniques. The physics-based models, grounded in communication, computing, and caching (3C) resources, ensure alignment with known system behaviors and predetermined assumptions, while the AI components dynamically adapt to real-time network environments, allowing the DT to learn from the evolving environments. The proposed DT framework incorporates layers that support real-time data acquisition, data processing, and decision-making through continuous feedback, enhancing system performance and enabling proactive maintenance, quality control, and optimization. A hybrid model-based case study demonstrates that the proposed framework can reduce packet queuing size and improve network performance under varying network load and outage conditions. Finally, open research issues for DT in IIoT are discussed.

Introduction

The industrial Internet-of-Things (IIoT), as one of the major technological advancements toward industrial automation, focuses on an integration of interconnected devices across multiple sectors to boost efficiency, reliability, and data-driven decision-making [1]. Leveraging cyber-physical systems, advanced data analytics, and cloud computing, IIoT enhances production processes and product quality through continuous monitoring and predictive maintenance [2, 3]. To accommodate the extensive data generated by sensors and devices, IIoT relies on robust connectivity solutions that enable rapid data transfer across the industrial environment, from on-site machinery to centralized cloud-based analytics. These networks require high reliability, minimal latency, and stringent security measures to protect sensitive industrial data.

However, the challenges of IIoT are manifold, caused by the intricate dynamics of large-scale network architectures, real-time data demands, and advanced computational requirements [4, 5]. Compounding these challenges, IIoT is vulnerable to various bias issues, including observation, inductive, and learning biases, which arise during data collection and processing stages, as shown in Fig. 1. As IIoT grows increasingly complex, characterized by ultra-dense and heterogeneous architectures involving a large number of devices, managing such complex structures becomes exceedingly difficult [5]. First, this complexity can lead to observation bias caused by measurement inaccuracies or sampling limitations, leading to data that poorly reflects the actual network state. As these networks generate vast amounts of real-time data, any inaccuracies in data collection can compromise the quality of information available for analysis and decision-making [6]. Moreover, the necessity for rapid data processing in IIoT intensifies the issue of inductive bias, which refers to the assumptions or predefined rules that artificial intelligence (AI) algorithms use to make predictions about future data patterns. Challenges arise with inductive bias in IIoT due to the variability of industrial environments. If the training data used by machine learning models does not fully represent the diverse conditions in large-scale IIoT, the inductive bias can lead to incorrect generalizations. This is particularly critical in applications requiring real-time data, such as autonomous vehicles, where erroneous predictions can have severe consequences. Furthermore, learning bias within AI-driven network management systems can lead to resource allocations that favor suboptimal solutions, misaligning with real-world operational needs [7, 8]. For instance, in IIoT, learning bias may result in resource allocation strategies that prioritize specific data patterns while ignoring others or may favor responses that work well with historical data but become ineffective under new conditions. Consequently, as IIoT continues to grow in complexity, traditional models struggle to balance accuracy with computational feasibility, rendering them less effective for real-time service provisioning and network deployment.

Digital twins (DTs) offer a potential way of bridging the gap between complex physics-based models and intelligent, data-driven models to tack-

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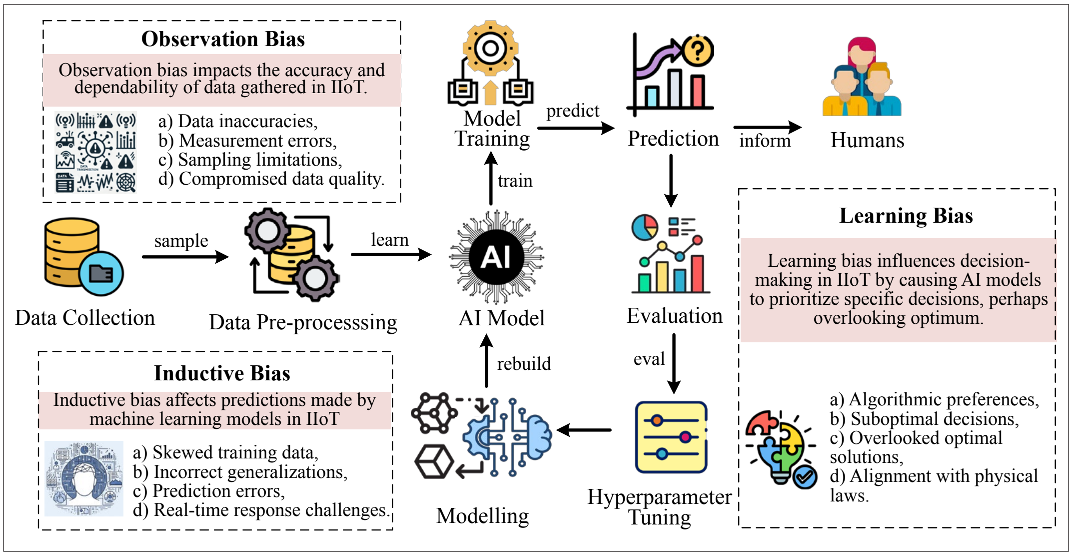

FIGURE 1. The influence of observation, inductive, and learning biases affecting decision-making in IIoT.

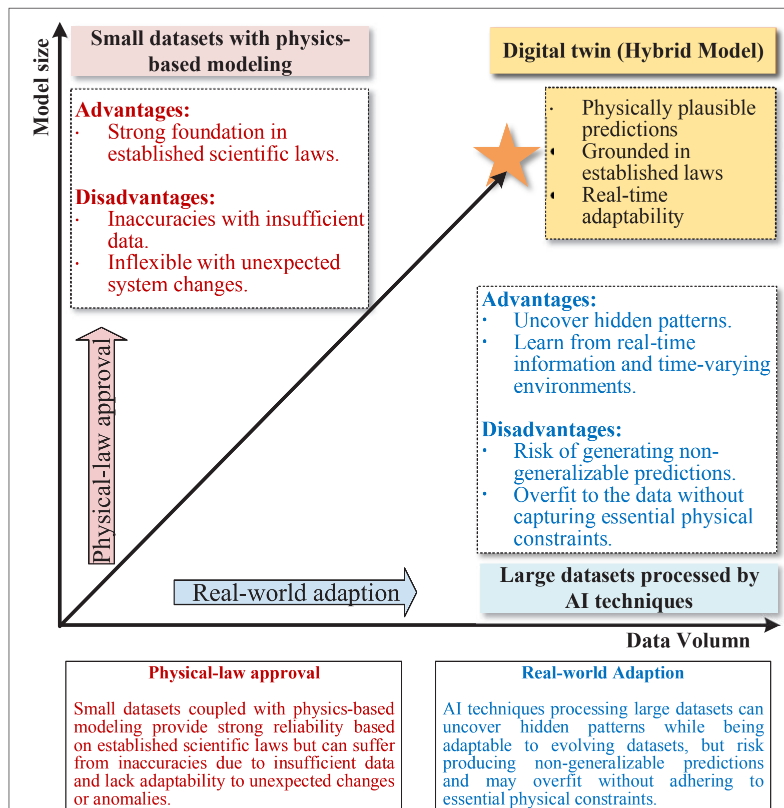

FIGURE 2. Comparison of modeling approaches and the benefits of the hybrid DT Model. The hybrid DT model combines physics-based models and AI techniques to achieve physically plausible predictions with real-time adaptability.

le IIoT challenges and bias issues [4]. As a virtual counterpart of a physics-based system, process, or service, a DT enables real-time predictions and informed decision-making without impacting physical operations. In the IIoT domain, DTs can optimize industrial operations, anticipate maintenance needs, and guide decision-making processes. Recent research has explored DT applications in IIoT. Tao *et al*. reviewed DT use cases across industries, emphasizing their role in smart manufacturing and outlining future integration challenges [9]. Okegbile *et al*. highlighted AI and blockchain's role in advancing DT capabilities for real-time monitoring and predictive maintenance, introducing AI techniques such as transfer and federated learning [10]. Yu *et al*. proposed digital twin edge networks (DTENs), utilizing federated learning to enhance privacy and address resource constraints in DT models of IoT devices [11]. These studies primarily focus on advancing DT capabilities with AI, blockchain, and refined network architectures to better align virtual models with physical counterparts. The scalability issues of their proposed solutions can be further investigated in real-world industrial environments, which often involve diverse system configurations that may not align perfectly with the theoretical models. New modeling of DTs needs to be established by developing dynamic virtual representations of physics-based systems or services and, through the integration of AI techniques to improve prediction accuracy, resource management, and decision-making, thereby facilitating continuous learning and adaptation to address the diversity and dynamics in IIoT services.

However, existing methodologies are insufficient to meet the modeling requirements of DTs, much less overcome the aforementioned challenges, particularly the limitations arising from relying on small datasets coupled with extensive physics-based modeling and large datasets processed by AI techniques, as shown in Fig. 2. First, physics-based models developed with predefined rules and parameters frequently demonstrate limitations in accuracy when operational data is insufficient. This constraint presents challenges in effectively monitoring system variations and responding to unforeseen operational events, including system anomalies, mechanical faults, and component failures. Second, AI techniques that process vast amounts of data without incorporating fundamental physics can identify patterns and correlations but risk producing results that are physically implausible or inconsistent with specific rules and assumptions, leading to non-generalizable decisions. The proposed hybrid DT model combining physics-based models with AI techniques can overcome the aforementioned challenges by ensuring physical plausibility and

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enhancing the overall system performance. Specifically, the physics-based model, built on communication, computing, and caching (3C) resources, provides a structured framework that adheres to known physical laws and system behaviors. Meanwhile, AI components enable DTs to dynamically adjust to real-time data, learning from new network information and adapting to unforeseen environment changes. This integration can allow DTs to accurately model complex systems even when data is incomplete and the physics rules are partially understood, providing robust and adaptive solutions that harness the strengths of physics-based models and AI techniques.

By integrating data-driven AI techniques with physics-based principles, DTs can mitigate observation, inductive, and learning biases that typically compromise predictive model accuracy in complex IIoT environments. DTs mitigate this by continuously assimilating data from multiple sources and sensors and ensuring a comprehensive and precise representation of the physical system. By incorporating fundamental physics laws and domain knowledge into AI techniques, DTs provide strong theoretical constraints that guide the learning process, ensuring predictions remain consistent with known physical behaviors and enhancing generalization performance. In essence, DTs harmoniously blend data-driven AI with physics-based models, ensuring that system learning and predictions are both informed by empirical data and grounded in physical reality, leading to more accurate, reliable, and robust outcomes in managing the complexities of IIoT environments.

In this article, we specify the generation of DT for services in IIoT and investigate the hybrid model to build the specific DT framework by integrating both physics-based models and AI techniques. The proposed IIoT DT framework presents a sophisticated solution to the complexities of the IIoT, primarily by linking intricate physical systems with intelligent, data-driven models. This hybrid model can facilitate ongoing learning and adaptation, effectively addressing the diversity and dynamic aspects of IIoT services. Furthermore, we provide a case study to demonstrate the effectiveness of the proposed hybrid DT framework for IIoT services.

The Generation of DT

Generating DTs for a specific service in IIoT using a hybrid modeling approach involves a strategic integration of physics-based models and AI techniques. Initially, network virtualization technology is applied to pool 3C resources essential for constructing the DT's physics-based part, which forms the foundation of the digital representation and simulates the known physical and engineering principles governing the system [12]. The generated physics-based model ensures that DT adheres to the theoretical constraints of the physical world, providing a reliable baseline from which more detailed analyses can be derived. Concurrently, data-driven AI techniques process large volumes of data generated within the IIoT environment, detecting patterns, identifying anomalies, and predicting future states based on historical and real-time data. These adaptive AI techniques are crucial for responding to the frequent and unpredictable changes in complex IIoT systems. The integration of AI techniques with the physics-based model allows the DTs to dynamically update and refine their predictions and simulations, thus enhancing their accuracy and utility. This hybrid DT model combines the robustness of 3C-based physical modeling with the adaptability of AI-driven methods to improve performance in dynamic industrial settings.

Physics-Based Model for DT Generation

The use of 3C resources (i.e., communication, computing, and caching) is essential in generating DTs for effective support of network services within IIoT environments. These resources form the foundation of the DT's physics-based model, enabling the simulation and dynamic management of network operations. Network virtualization technology plays a critical role by abstracting, pooling, and efficiently allocating these resources to meet the specific demands of DT generation. This virtualization enables flexible pre-reservation and dynamic allocation of resources, promoting a scalable and adaptable DT deployment model that allows efficient resource reallocation based on fluctuating operational needs.

Specifically, communication resources are important for ensuring continuous and efficient data flow across the IIoT [13]. It involves the transmission of industrial data between devices and from devices to central servers. Computing resources refer to the processing power required to handle and analyze incoming data streams. In IIoT, computing resources are generally distributed with edge devices processing data locally to reduce response time and the load on central servers. Caching resources involves temporarily storing data at strategic points within the network to minimize access time and reliance on constant communication with the central database. This is especially beneficial in environments where data needs to be accessed frequently or quickly, as it significantly reduces latency and bandwidth usage, which are critical for the performance of real-time applications.

In a hybrid DT model, the physics-based model is constructed based on the state and availability of virtualized 3C resources, represented as variables in service-oriented objectives. For example, Communication resources are modeled by bandwidth, latency, and data transfer rates, which guarantee that data flow between devices and central servers stays within network constraints. Computing resources are modeled as processing capacity at various nodes, with objective functions distributing tasks across edge and cloud resources to minimize response time and optimize throughput, constrained by processing capacity and energy consumption. Caching resources are optimized by modeling the cache size and data access frequency, positioning frequently accessed data closer to the edge, thereby reducing communication overhead. The physics-based model of DT can then be formulated as a constrained optimization problem, balancing the utilization of communication, computing, and caching resources to meet real-time operational demands. By solving this problem, the DTs can dynamically adjust their physics-based model in response to changing 3C resource conditions, ensuring efficient, real-time operation and accurate reflection of the physical system.

Additionally, container technology is implemented in conjunction with virtualized 3C resources to facilitate DT development. The containerization approach effectively segregates DT resources from the underlying infrastructure, facilitating consistent deployment across multiple environments. This architectural strategy enhances system scalability and flexibility through streamlined updates and modifications while fostering seamless integration across various IIoT platforms. Through the strategic utilization of virtualized resources and containerization methodologies, the DT framework can effectively model the operational characteristics and conditions of the requisite IIoT services, thereby enabling enhanced operational decisions and efficiency improvements.

AI Techniques for DT Generation

Physics-based models derived from virtualized 3C resources rely on predefined parameters and rules grounded in physics laws. Consequently, these models are typically static and lack adaptability to unforeseen changes or anomalies in the operational environment, making them less effective in dynamic or complex scenarios where rapid adjustments are essential. To address these limitations, integrating AI techniques, such as deep reinforcement learning (DRL) or machine learning (ML), into the physics-based model is critical.

AI techniques process historical and real-time data, continuously learning and refining their understanding of the system [14, 15]. This AI integration enables a DT not only to represent the current state of the system but also to forecast future behaviors, make autonomous decisions, and prescribe actions that enhance performance. In IIoT, optimal service decisions are learned through environmental interactions where the DT receives feedback (rewards or penalties) based on its actions. This continuous learning process strengthens the DT's ability to manage complex systems effectively, particularly in dynamic and unpredictable industrial settings. The feedback loop between real-world conditions and the DT allows AI to refine its decision-making, making it valuable for applications such as resource allocation, predictive maintenance, and operational optimization.

Integrating AI algorithms into a DT physics-based model requires a structured approach for seamless data processing and predictive capability refinement. A commonly used AI method for this integration is deep reinforcement learning (DRL), as it learns optimal strategies through trial and error and adapts to changing conditions. For example, a deep Q network (DQN) can be incorporated into the DT physics-based model to support continuous improvement. The integration process begins with data collection and preprocessing, where data from real-world conditions, including sensor readings, resource usage, network traffic, and operational metrics, is gathered. Both historical data (for training) and real-time data (for updates) are collected. Preprocessing steps involve cleaning, normalizing, and structuring the data, addressing outliers and missing values to ensure model accuracy. Feature extraction identifies critical attributes that define the system's state. Next, a virtual environment is created in which the DQN can operate, replicating the DT operational conditions and resources, such as communication, computing, and caching, enabling real-time interaction and learning. Within this environment, the DT's current state, including resource usage, latency, and network performance, is represented, forming the basis for AI-based state representation.

The framework incorporates action space definition and reward mechanisms, establishing specific learning actions such as resource reallocation and caching adjustments. These actions are evaluated based on performance metrics, including latency reduction and operational efficiency improvements. Through systematic exploration and observation, the AI algorithm develops its understanding of optimal policies by implementing learning methodologies and analyzing outcome-based rewards. The DT's evolution encompasses comprehensive model refinement and deployment processes, utilizing controlled testing environments to validate AI model performance and ensure operational alignment with physical systems. A feedback mechanism facilitates real-time adaptation of the AI model, incorporating current system data to maintain precise synchronization between the DT and actual operations, particularly during periods of variable system demands and network conditions. This advanced integration enables the DT to conduct precise simulations, generate accurate predictions, and implement optimized decision-making protocols, thereby enhancing operational efficiency in complex operational environments.

Hybrid Model for DT Generation

Integrating data-driven insights with domain-specific knowledge enables a robust hybrid model for DT development, which is particularly valuable for enhancing accuracy, stability, and adaptability in the demanding context of IIoT. This hybrid model addresses traditional model limitations by combining physics-based models, initialized from virtualized 3C resources, with AI techniques. The physics-based model establishes structure and adherence to established physics laws, while the AI component allows the DT to dynamically adjust to real-time data, improving predictions, optimization, and decision-making within complex IIoT environments. The physics-based model captures known physics laws, constraints, and system behavior, making it deterministic and reliable for well-understood processes. The AI techniques extend the DT capabilities by overcoming the static limitation of physics-based models, allowing us to learn from both historical and real-time data and adapt to dynamic and unpredictable changes in industrial scenarios. Feedback mechanisms within the AI layer refine the model predictions, transforming the DT from a descriptive tool into a prescriptive one capable of autonomous decision-making to optimize operations, minimize downtime, and adjust to the complexities of IIoT systems. The following steps outline the construction of the hybrid DT model, as shown in Fig. 3.

Step 1: Build the physics-based model. Start by constructing the physics-based model using virtualized 3C resources, incorporating known physics-based rules, system constraints, and operational principles.

Step 2: Integrate AI techniques. Incorporate AI techniques to process historical and real-time data, which can support the DT learning from

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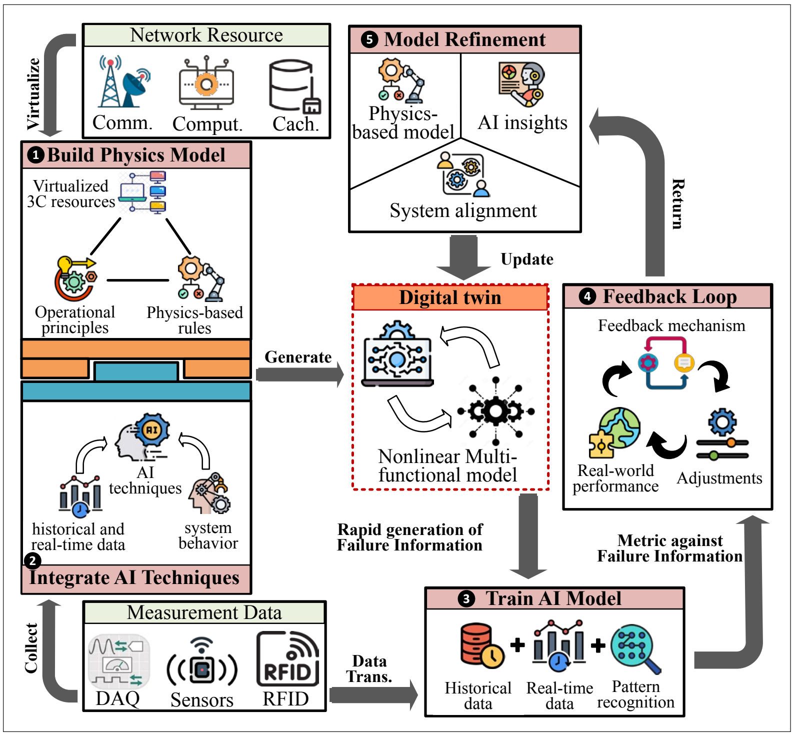

FIGURE 3. DT Generation in IIoT. A hybrid DT model with the integration of virtualized 3C resources, AI techniques, and continuous feedback for model refinement and alignment with real-world conditions.

past and ongoing events, refining its understanding of the system's behavior dynamically.

Step 3: With both the physics-based model and AI techniques in place, the DT model is constructed. This hybrid model combines the structured, physics-based foundation of the physics-based model with the adaptive, learning-based approach of AI techniques.

Step 4: Train the AI model. Train the overall physics-based model with embedded AI techniques using both historical data (to establish baseline patterns) and real-time data (to adapt to current conditions), in which allows the DT to become proficient in recognizing complex patterns and making decisions.

Step 5: Continuous feedback loop. Establish a continuous feedback mechanism where the AI learns from the real-world performance of the system, feeding that knowledge back into the model. The AI component adjusts its predictions and recommendations as the physical system evolves.

Step 6: Model refinement. Continuously update both the physics-based model and AI-driven insights, ensuring that the DT is always aligned with the current state of the physical system.

Proposed DT Framework for IIoT

The proposed DT framework for services in IIoT enables real-time monitoring, simulation, and optimization of industrial processes by integrating physics-based models derived from 3C resources with AI techniques. The DT framework, as shown in Fig. 4, consists of multiple layers, starting with the physical and data acquisition layer, followed by the communication layer. Data is then stored and processed by the data management layer, which then feeds into the DT core, where physics-based models are integrated with AI techniques. The framework is completed by the application layer and security layer, which enables communication with external systems to ensure effective monitoring, control, optimization, and protection.

Specifically, the physical layer forms the foundation of the DT framework, comprising industrial assets equipped with embedded 3C resources that enable intelligent operations. Here, computing resources manage data processing; communication resources facilitate information exchange and control resources support autonomous functionality, collectively establishing the base for DT operations. The data acquisition layer captures real-time data through sensors and IoT devices, which track critical operational metrics such as temperature, pressure, and vibration. Local edge computing devices then preprocess this data to reduce transmission loads, enhancing responsiveness in time-sensitive applications. The communication layer ensures reliable data flow across the system through networks and protocols, utilizing wired and wireless connections like Ethernet, WiFi, and 5G, alongside standardized communication protocols such as message queuing telemetry transport (MQTT) and OLE for process control unified architecture (OPC UA), to enable interoperability within the IIoT ecosystem. The data management layer oversees the lifecycle of collected data, employing data storage solutions (databases, data warehouses, data lakes) to retain historical and real-time data. Data processing tools handle tasks like cleaning, filtering, and aggregating, preparing data for accurate modeling and analysis. The physics-based model layer leverages virtualized 3C resources to implement mathematical models that predict system behavior across various scenarios. This layer incorporates system dynamics modeling to analyze component interactions, ensuring adherence to fundamental physics principles. The AI techniques layer enhances system adaptability through the strategic implementation of machine learning, deep learning, and reinforcement learning algorithms. These advanced technologies enable sophisticated data analysis, pattern recognition, and iterative decision optimization. The AI components demonstrate particular effectiveness in monitoring real-time network conditions through the analysis of continuous sensor data streams. Through systematic integration of physical system feedback, these AI components maintain precise digital twin synchronization with actual network conditions, even during dynamic fluctuations in bandwidth or node performance. The integration of physics-based parameters with empirical data analysis enables the AI components to deliver consistent performance adaptation in variable IIoT environments while maintaining computational precision. The DT core layer serves as the central integration point, combining physics-based models with artificial intelligence capabilities through an advanced hybrid integration engine. This integration establishes a sophisticated environment for conducting virtual experimentation and scenario analysis within a controlled simulation framework. The system's real-time analytics capabilities deliver actionable insights that enable informed, forward-looking decision-making. Finally, the application layer functions as the interface between humans and the DT, featuring user interfaces like dashboards and control panels, decision support systems, and alert mechanisms, making operational insights actionable for predictive maintenance, quality control, and process optimization. The security layer fortifies the DT framework by implementing authentication, encryption, and intrusion prevention to safeguard data integrity and compliance, ensuring system reliability.

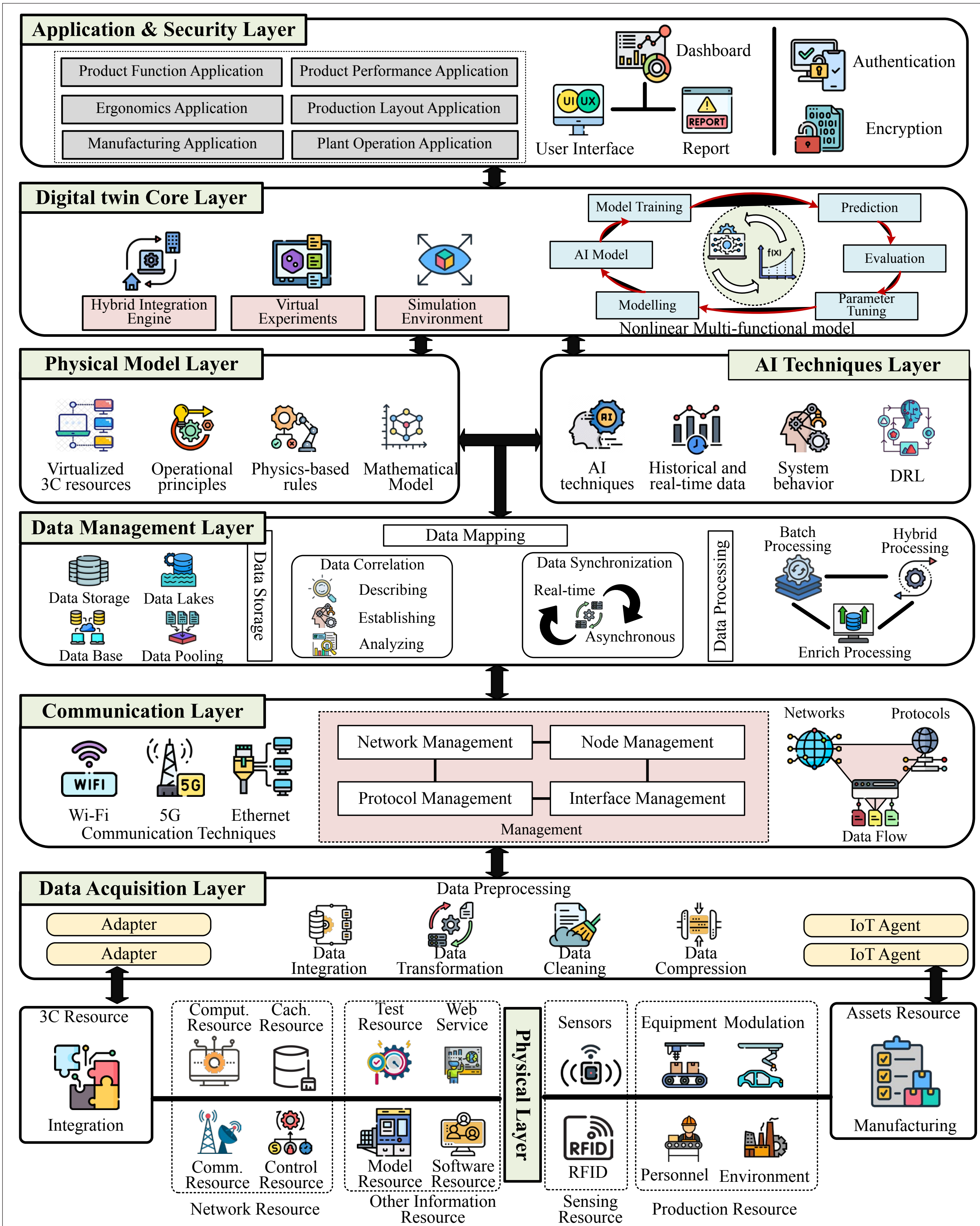

FIGURE 4. Layered DT framework for IIoT with the sequential flow and interactions between physical assets, data acquisition, communication, data management, physics-based and AI models, the DT core, and application and security layers to ensure comprehensive monitoring, control, and optimization in IIoT environments.

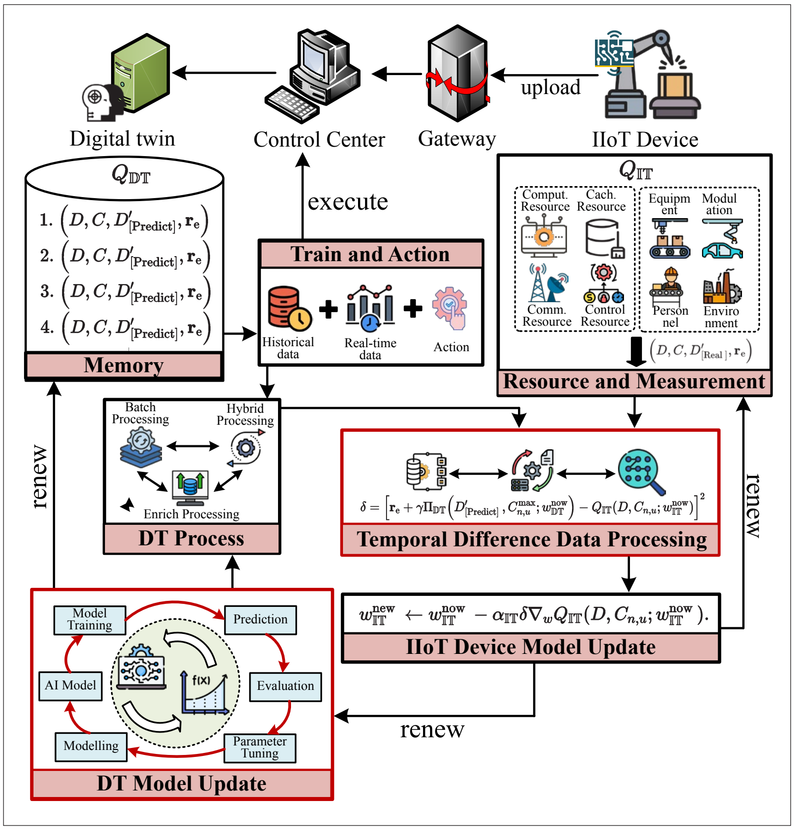

FIGURE 5. The PLO scheme for IIoT channel access management with process flow for updating and learning for IIoT devices, showcasing the interactions between the DT, control center, gateway, and IIoT devices through data collection, model training, temporal difference calculations, and continuous updates for optimal decision-making and adaptation.

The DT framework operates through a sequential flow across these layers to create a comprehensive virtual representation of industrial systems. Starting with the physical layer, industrial assets equipped with 3C resources generate real-time data via embedded sensors and actuators. This data is collected and locally processed by sensors and edge computing devices in the data acquisition layer to reduce latency and perform preliminary analysis. The processed data is then transmitted over wired or wireless networks using standard protocols in the communication layer. Then, in the data management layer, the data is stored in databases or data lakes and processed to be suitable for modeling and analysis. The physics-based model layer uses this data to feed mathematical models and simulations based on physics laws, while the AI techniques layer concurrently analyzes the data to detect patterns and optimize control strategies using machine learning, deep learning, and reinforcement learning. The DT Core merges output from the physics-based models and AI techniques to run virtual experiments and provide real-time analytics. Users interact with the digital twin through dashboards and decision support systems in the application layer, receiving actionable insights and alerts. Throughout this process, the security layer protects data and system access with authentication, encryption, and intrusion detection. Through this synergistic interplay, each layer not only performs its function but also enhances the capabilities of the others, leading to improved efficiency, real-time responsiveness, and proactive decision-making.

Case-Study: DT-Enabled Channel Access Control for IIoT

The network consists of a single access point (AP) connected to multiple IoT devices in a star topology, where each device communicates directly with the central AP. There are scatterers uniformly distributed in this industrial environment, leading to significant multipath fading due to signal reflections, which affect data packets transmitted from devices to the AP. This network includes a DT that acts as a virtual counterpart to the physical IoT devices, replicating their functions and gathering data transmitted through a gateway to the network controller. The DT employs a parallel learning and optimization (PLO) scheme that utilizes memory recall techniques to bolster real-time decision-making and optimize channel access management, effectively reducing transmission latency.

In building the DT, key components such as IoT devices, data collection systems, and a control center are integrated. IoT devices gather real-time data, which is transmitted to the control center via a gateway. Here, the DT processes this data using advanced algorithms to predict outcomes and suggest operational adjustments. This setup supports not only real-time monitoring and simulation but also predictive maintenance and decision support. The continuous data loop from IoT devices to the DT and back to the devices forms the DT core, allowing dynamic adjustments based on real-time data. This DT leverages the strengths of physics-based models, which provide structured, law-based predictions, and AI techniques, which adapt to new data and evolving conditions, enhancing the system's capacity to manage complex and changing industrial IoT environments.

The proposed PLO scheme, as shown in Fig. 5, is structured to optimize operations through a continuous cycle that updates knowledge of physical IoT devices based on the outcomes of prior actions. This cycle begins with data collection from IoT devices, which is then analyzed and transformed into actionable knowledge. This knowledge guides subsequent actions, generating new data that refines and expands the knowledge base, enabling ongoing operational adaptation and improvement. This scheme ensures that both the physical IoT devices and their DT counterparts operate autonomously yet interactively, based on distinct yet complementary principles. Here, knowledge acts as a bridge, assimilating data to dynamically adjust operations. It is structured around an inverse model that uses revised policies to guide decisions, establishing a feedback loop with the real-world environment. As shown in Fig. 6, this synthesis of components and methods results in a resilient, efficient, and adaptive DT framework with the PLO scheme that significantly improves the performance and reliability of IIoT systems.

Challenges and Open Research Issues

Current Challenges

Implementing DTs for IIoT environments presents several challenges across technical, organizational, and operational domains. These challenges impact multiple layers within the DT framework, from data acquisition to integration. Below, we specify the possible challenges in DT implementation for IIoT, highlighting their impact on each layer.

Data Integration and Management: The integration and management of data in IIoT environments present significant challenges due to diverse data streams originating from multiple devices with distinct formats and protocols, which creates complexity in establishing standardized formats for DTs. The management of data quality becomes particularly challenging when addressing the requirements of high-velocity data generation, system scalability, and real-time processing capabilities, particularly in scenarios involving data inconsistencies or gaps. To address these challenges, organizations can implement several strategic solutions: ETL tools facilitate data standardization processes, data federation enables efficient cross-source queries, semantic integration ensures meaningful data interpretation, and edge computing architecture optimizes performance through localized processing.

Interoperability Issues: The diverse protocols and standards implemented across IIoT devices and systems present challenges for communication and integration initiatives. Communication infrastructure must effectively manage multiple protocols, including MQTT, OPC UA, HTTP, and Modbus, while integration processes address compatibility limitations with legacy systems that lack contemporary API functionality. To enhance system interoperability, organizations are implementing strategic solutions such as open standards adoption (OPC UA and MQTT), protocol-bridging middleware deployment, and the development of modular frameworks incorporating abstraction layers and API-driven architectures.

Computational and Storage Requirements: DT implementations require substantial computing and storage resources to execute sophisticated physical simulations, conduct real-time analytics, and facilitate AI model training, particularly for advanced deep learning frameworks. To effectively address scalability considerations related to hardware constraints and associated costs, organizations can leverage cloud computing solutions that provide flexible, cost-effective resource allocation. Additionally, implementing strategic algorithm optimization approaches, including model compression methodologies, optimized code structures, and distributed processing frameworks, can significantly enhance operational efficiency while managing computational requirements.

Model Accuracy and Maintenance: Maintaining model accuracy in dynamic industrial environments is challenging, as physics-based models become outdated due to equipment upgrades, process changes, and parameter drift, while AI techniques face data drift and obsolescence without regular retraining. Hybrid models combining physics-based and AI techniques require continuous validation through performance monitoring, feedback loops, and anomaly detection, alongside automated retraining with adaptive algorithms and robust version control to ensure alignment with real-world conditions.

Addressing these challenges requires a combination of innovative technological solutions. Effectively tackling these issues will enhance DT efficiency, predictive capabilities, and provide a competitive advantage in the evolving IIoT landscape.

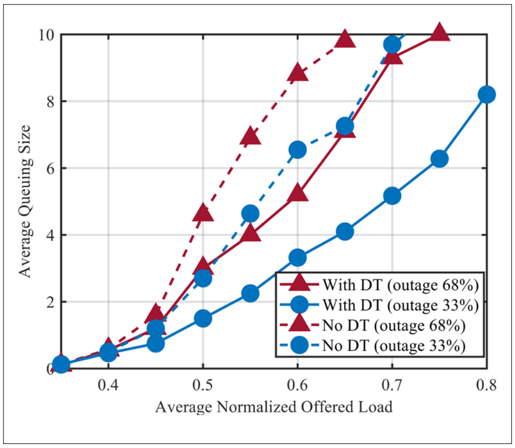

FIGURE 6. Impact of DT on average queue size under varying network load and outage conditions, demonstrating that the implementation of DT significantly reduces queuing delays across different outage levels (33 %, 51 %, and 68 %) compared to scenarios without DT support.

Open Research Issues

Future research directions for DTs in IIoT focus on addressing current challenges and exploring new avenues for innovation.

First, seamless multi-source data fusion will be prioritized to develop advanced algorithms for integrating data from diverse sources, such as sensors, edge devices, and cloud systems, to support smooth real-time operations. Cognitive DTs represent another critical direction, advancing beyond asset simulation to autonomously interpret and analyze data, generating actionable insights and recommendations. The development of self-learning DTs will leverage AI, particularly deep reinforcement learning (DRL), to transition from reactive to proactive systems, optimizing operations in response to dynamic conditions. Emphasis will also be placed on creating green DTs, which prioritize energy efficiency by minimizing power consumption across devices and infrastructure, thus aligning with sustainability goals. Research on lifecycle DTs will expand to provide continuous monitoring and optimization across an asset's entire lifecycle—from design to disposal. Integrating AR/VR-enhanced DTs is expected to offer immersive interfaces, enabling users to interact with and control IIoT systems remotely. Cross-domain DTs will facilitate inter-industry collaboration, spanning fields such as manufacturing, healthcare, and logistics, to optimize operations through shared data and synchronized performance. Efforts will also target the development of intuitive user interfaces, making DTs accessible to non-expert users to broaden adoption. Lastly, establishing interoperability standards will be essential, with research directed toward universal protocols and open communication standards to support seamless cross-platform integration and foster collaboration across diverse systems and manufacturers.

Research in these areas will establish DTs as a critical component of IIoT and a driver of innovation and transformation across industries.

Conclusion

In this article, we investigated the potential of DTs as a solution to address the challenges posed by the increasing complexity of future IIoT, particular-

With our scheme, IIoT can achieve improved reliability, performance, and adaptability to evolving industrial scenarios, addressing the challenges posed by ultra-dense, heterogeneous network architectures.

ly in network management, data processing, and latency reduction. Accordingly, within the proposed hybrid DT framework, we proposed a PLO scheme that integrates physics-based models with advanced AI techniques to dynamically and accurately model the channel access optimization services. The proposed scheme enables continuous learning and adaptation, enhancing decision-making and operational efficiency in highly dynamic and heterogeneous IIoT environments. With our scheme, IIoT can achieve improved reliability, performance, and adaptability to evolving industrial scenarios, addressing the challenges posed by ultra-dense, heterogeneous network architectures.

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