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Digital Twin for Industrial Control: High-Fidelity Mapping, Closed-Loop Optimization, and Embodied Intelligence Evolution

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Abstract: Digital twin technology is undergoing a paradigm shift from static reproduction to dynamic closed-loop control in industrial control. Following the logic of "high-fidelity mapping-state deduction-closed-loop optimization-embodied evolution", this paper systematically reviews the technical system, application paradigms, and frontier trends. It analyzes the implementation and bottlenecks of virtual-real dynamic mapping from multi-dimensional modeling, data fusion, and low-code visualization; elaborates the value of hybrid-driven state deduction in predictive maintenance and anomaly warning; reveals the closed-loop optimization mechanisms for single-equipment online tuning, multi-agent scheduling, and reinforcement-learning-based control; and proposes the enabling paradigm of digital twin as a virtual sandbox for embodied intelligence with a closed-loop evolution path. Current challenges in real-time performance, standardization, generalization, and security are summarized, and future directions including hybrid modeling, edge-cloud architecture, generative AI integration, and unified data governance are outlined. This paper provides a systematic reference and roadmap for digital twin transitioning from an auxiliary tool to an autonomous intelligent core engine.

Keywords: Digital twin, Industrial control, Virtual-real mapping, Closed-loop optimization.

1. Introduction

Industrial control systems face increasing demands for global state perception, high-precision closed-loop regulation, and intelligent decision-making under complex multi-physical-field coupling and dynamic conditions [1]. Traditional mechanism modeling and offline simulation suffer from unidirectional mapping, poor real-time performance, and weak adaptability, failing to support next-generation control systems [2]. Digital twin technology, with its core of multi-physical, multi-scale, and full-lifecycle bidirectional dynamic mapping, enables real-time data interaction, simulation deduction, and decision optimization, making it a key enabler for industrial control [3]. Its concept originated from the Apollo 13 rescue mission, was formalized by NASA in 2010, and has since expanded from aerospace to manufacturing, energy, and mining [4]. Recent advances in IoT, 5G, edge computing, and AI have accelerated its engineering adoption [5].

Existing reviews predominantly focus on general frameworks or single-domain applications [6], lacking systematic integration for industrial control closed-loop scenarios. Tao et al. [7] proposed a five-dimensional model but did not address closed-loop control; Rasheed et al. [8] analyzed modeling enablers without covering real-time optimization; Wu et al. [9] reviewed power system applications but omitted embodied intelligence fusion. No existing work has systematically synthesized the technical architecture, application paradigms, core bottlenecks, and frontier directions specifically for industrial control, nor has it tackled key practical issues such as modeling accuracy, virtual-real synchronization, and industry standards [10].

Taking "high-fidelity mapping-state deduction-closed-loop optimization-embodied evolution" as a new logical thread, this paper systematically reviews domestic and international literature, focuses on industrial control to fill the research gap, integrates key technologies and application paradigms, analyzes technical bottlenecks, and proposes future directions. The aim is to provide rigorous academic support for the theoretical development, technological breakthroughs, and large-scale deployment of digital twins in industrial control.

2. High-fidelity Dynamic Mapping of Industrial Digital Twins

Virtual-real mapping is the foundational capability of digital twins for industrial control. It enables bidirectional mapping from physical entities to virtual models through model construction, data acquisition, and visualization, supporting higher-order functions like prediction, optimization, and embodied intelligence [11]. This process centers on four-layer integrated modeling (geometry-physics-behavior-association), integrates multi-source heterogeneous data, and delivers visual presentation via 3D and low-code construction [12]. The CPS framework reinforces this mapping by emphasizing closed-loop feedback, which positions virtual-real mapping as central to industrial digital twin systems [13].

2.1. Multi-dimensional Modeling: Geometric-Physical-Behavioral-Relational Coupling Representation Method

Modeling is the core of virtual-real mapping. Research has evolved from early geometric modeling to a four-layer integrated paradigm covering geometry, physics, behavior, and association, applied across scenarios like discrete manufacturing, precision equipment, construction, mining, and shipbuilding [14]. Theoretical efforts have produced staged construction methods, evolution frameworks from reality to digital twins [15], and multi-dimensional evaluation

systems [16]. Figure 1 shows the multi-scale, multi-scenario staged modeling method proposed by Jia et al. [17], which progresses from simple twin to complex twin by gradually introducing multi-physics coupling and scene adaptation.

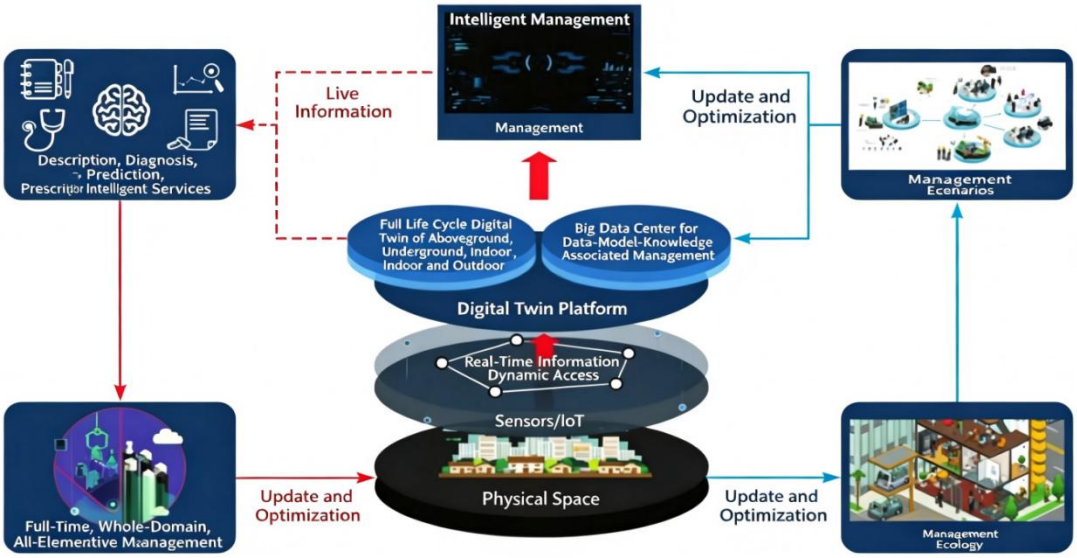

Figure 1. Digital twin modeling for sustainable iteration

Cross-domain modeling relies on domain-specific methods with clear scene differentiation. BIM+IoT is used for prefabricated construction [18], BIM+GIS+IoT for hydraulic structures [19], dynamic modeling for coal mines [20], and multi-scale models for gas turbines and aerospace [21]. These have also extended to geophysics [22] and tailings pond safety [23]. This diversity reflects strong knowledge dependence and technology fragmentation in the industry.

Despite progress, three bottlenecks remain for closed-loop industrial control: (1) insufficient multi-physics coupling accuracy under time-varying conditions, with unclear boundary transfer mechanisms and rapid model degradation during nonlinear extrapolation; (2) severe lack of model standardization and reusability, forming "model chimneys" that block large-scale adoption. Future research should focus on online adaptive multi-physics coupling, model reduction for real-time solving, and open-model standardization, driving modeling from "visible" to "controllable".

From the perspective of modeling granularity, MBSE-Modelica suits system-level design, UE5 lightweight suits equipment-level real-time rendering, and additive manufacturing suits process-level multi-physics coupling. From the scenario perspective, complex R&D emphasizes multi-disciplinary collaboration, intelligent construction focuses on BIM-site data fusion, and smart manufacturing stresses human-machine-object integration. Each method has its strengths, but no unified industrial modeling standard exists.

2.2. Multi-source Heterogeneous Data Deep Fusion and Millisecond Level Virtual and Real Synchronization Mapping

Data fusion integrates multi-source data to ensure the digital twin accurately reflects physical objects. Industrial sites now collect data via IoT, lidar, and UAV tilt photography, gradually breaking down data silos. Case studies include watershed twin driving mechanisms [24], virtual PV power acquisition [25], transparent mine platforms [26], hydraulic support attitude mapping [27], and real-time data-driven workshops. These efforts build a data foundation from point collection to full-scene integration. Figure 2 shows the overall architecture of Wei et al.'s [28] digital twin workshop system, defining data flow across acquisition, mapping, and application layers as a deployment reference for shop-floor implementation.

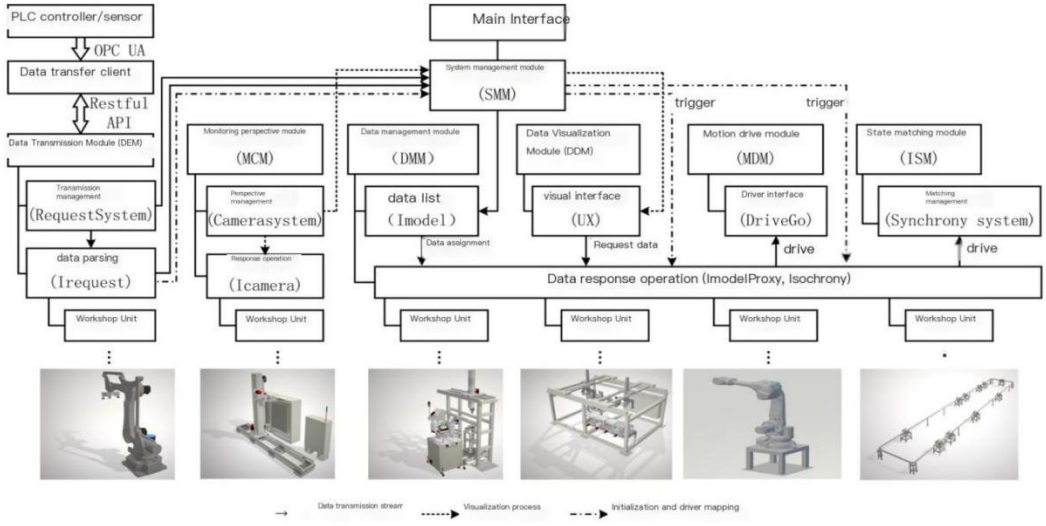

Figure 2. Overall architecture of digital twin workshop system

Virtual-real synchronization couples physical and virtual spaces via real-time data exchange. Protocols like MQTT, 5G, OPC UA, and TSN now support millisecond-level interaction. Xu et al. [29] used adaptive Kalman and complementary filters to keep robot joint angle estimation error below 0.1°. Wang et al. [30] built an indoor propagation calibration model to ensure deterministic industrial wireless communication. Scenario validations cover IoT-driven ship synchronization [31] and 6G-enabled millisecond interaction [32].

Despite millisecond-level progress, data governance remains challenging: multi-source consistency is hard to guarantee, edge computing power struggles with real-time demands, and data security risks grow. Song [33] noted the lack of lifecycle integrity verification for twin data, threatening credibility; Wang et al. [34] proposed architecture-level security solutions. Future work should integrate TSN with OPC UA, develop end-edge-cloud lightweight processing, and enforce full-lifecycle data security [35], pushing data links from "connectivity" to "stability" and "security".

2.3. 3D Visualization and Low-Code Scene Construction for Human-Computer Integration

Visualization renders digital twin models for intuitive display and human-machine interaction, with Unity3D and UE5 as core engines. Applications span environmental wind tunnels, trackless rubber-wheel vehicle monitoring, grain scraper control [36, 37], workshop-level multi-layer monitoring [38], discrete manufacturing [39], and production processes [40], expanding from single-point to multi-level panoramic presentation.

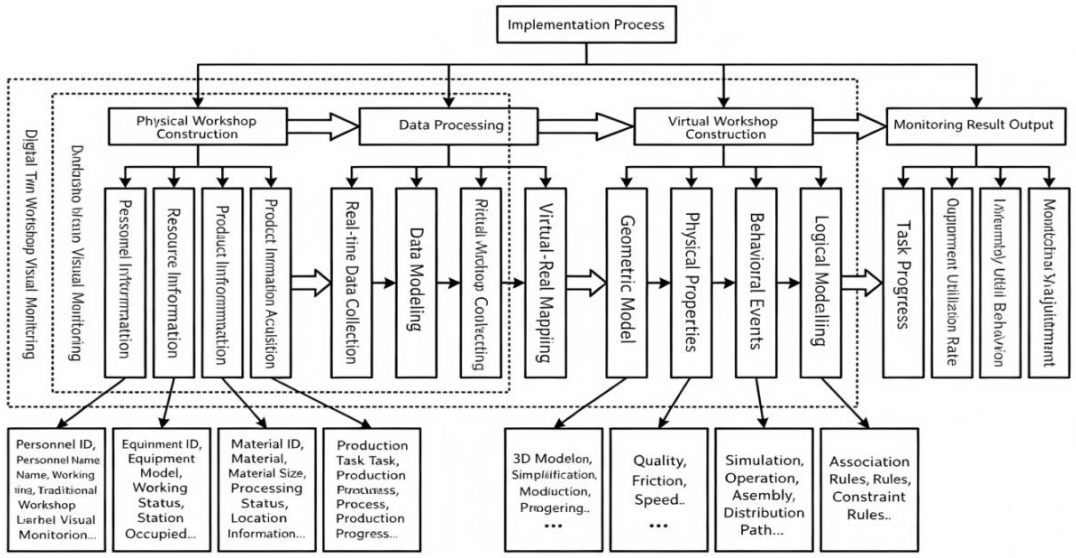

Figure 3. Key implementation process of visual real-time monitoring

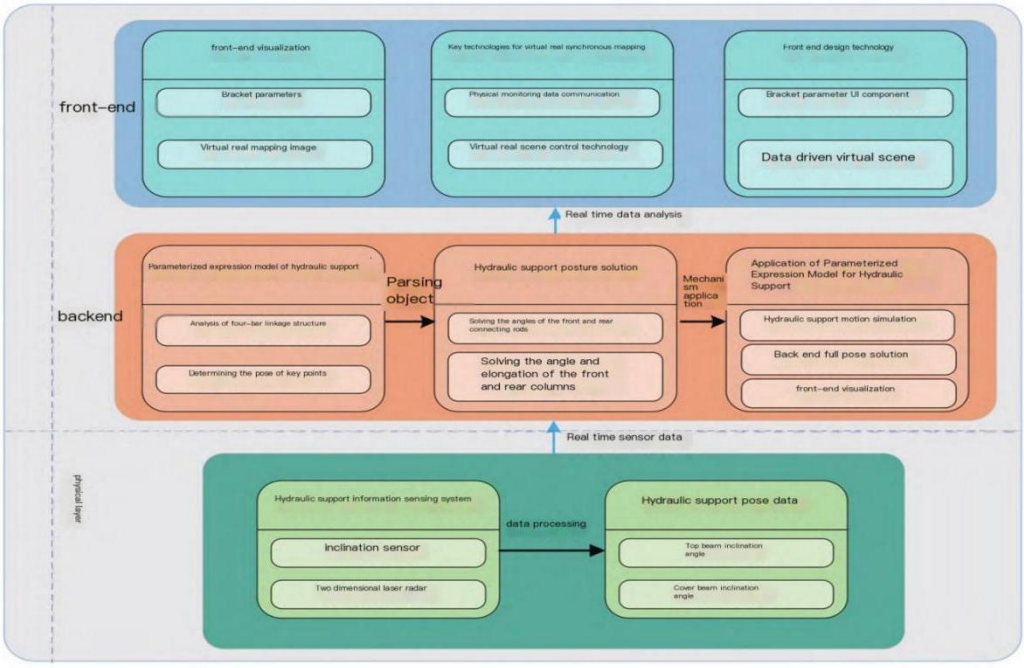

Figure 4. Overall framework of virtual and real mapping of hydraulic support

Visualization handles display; low-code handles rapid construction. Figure 3 shows Zhao et al.'s 3D visualization real-time monitoring workflow, from CAD analysis to dynamic rendering. The color-coded framework in Figure 4

maps hydraulic support attitude deviation from numerical to visual deviation, demonstrating the engineering effectiveness of virtual synchronization for equipment monitoring. Low-code tools, using standardized scene description and multi-engine compatibility, reduce development costs [41]. Chen et al. [42] validated this approach for beam yard production control; Liu et al. [43] cut scene construction cycles from weeks to hours. Low-code is shifting digital twin development from professional programming to scenario configuration.

Current visualization still faces three bottlenecks: large-scale scene rendering performance, multi-engine data interaction barriers, and trade-offs between lightweight and high-fidelity models. Peter et al. [44] demonstrated real-time visualization for welding robots but struggled to maintain 30 fps in complex scenes. Future work should target adaptive rendering, unified cross-engine interfaces, and dynamic balance between lightweight and fidelity.

3. Digital Twin Industrial Control State Deduction and Prediction Warning

Virtual prediction, powered by bidirectional synchronous data and mechanism-data hybrid models, enables state deduction, remaining life prediction, and fault warning [45]. It shifts industrial maintenance from reactive "after-the-fact repair and scheduled maintenance" to proactive "predictive and intelligent maintenance", reducing unplanned downtime [46].

3.1. Predictive Maintenance and Equipment Health Management of Digital Twin Enabling

Predictive maintenance uses digital twins for equipment health assessment, remaining life prediction, and maintenance strategy optimization [47]. It has evolved from pure data-driven to mechanism-data hybrid approaches, with proven effectiveness in rotating machinery, energy, aerospace, and precision equipment [48, 49]. Figure 5 shows Chen et al.'s [50] centrifugal compressor digital twin system, which integrates data acquisition, virtual-real mapping, and fault diagnosis into a closed-loop predictive maintenance framework.

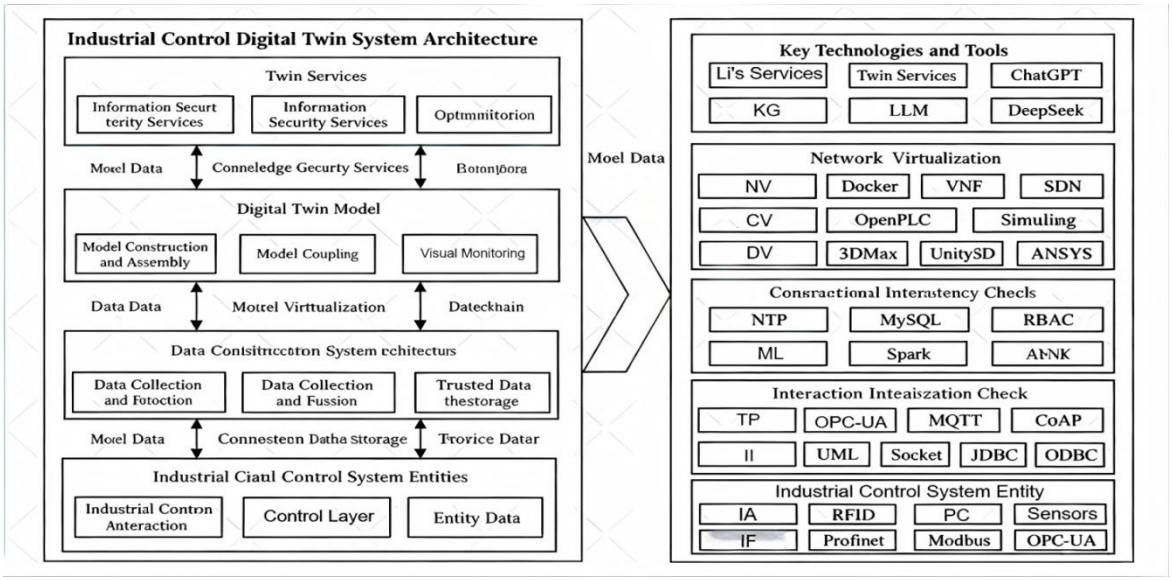

Figure 5. Digital twin architecture of industrial control system

Methodologically, hybrid-driven prediction and sample enhancement have advanced beyond traditional data-driven approaches. Li et al. generated fault samples via twin simulation and used a Transformer-LSTM-XGBoost network for hydraulic robot fault identification. Sha et al. [51] combined digital twin with model predictive control for disc brake pad wear prediction and closed-loop feedback maintenance.

In industrial applications, rotating machinery and energy equipment are the most active areas. Jiang et al. [52] built a digital-analog fusion twin for multi-stage centrifugal compressor health monitoring. Li et al. developed a gas turbine twin for metal temperature prediction and lifecycle management. Aviation, power equipment [53], planetary gearbox fault diagnosis [54], and shearer health prediction [55] have also adopted twin-based predictive maintenance.

Current challenges include insufficient model generalization under complex conditions, limited online self-calibration, and difficulty in multi-equipment collaborative modeling [56]. Predictive maintenance integrated with energy saving and carbon reduction also remains underexplored [57]. Future work should focus on online hybrid algorithm iteration, multi-equipment collaborative health management, and green O&M optimization.

3.2. Multi-level Anomaly Detection and Real-Time Warning Mechanism for Industrial Control Safety

Industrial anomaly warning uses real-time twin data with time-series comparison, physical consistency verification, and anomaly scoring to identify deviations, data distortion, cyber-attacks, and structural degradation. Physical consistency checking-comparing physical responses against twin model predictions-distinguishes twin-based detection from pure data-driven methods.

For equipment state anomaly detection, few-shot learning and motion state recognition are key research focuses. Asaf et al. [58] achieved >90% detection accuracy on a cogeneration system with only 5% abnormal samples using twin models.

Xu et al. applied adaptive filtering to fuse twin data for accurate abnormal motion recognition in industrial robots. These approaches address the challenges of scarce abnormal samples and insufficient identification accuracy.

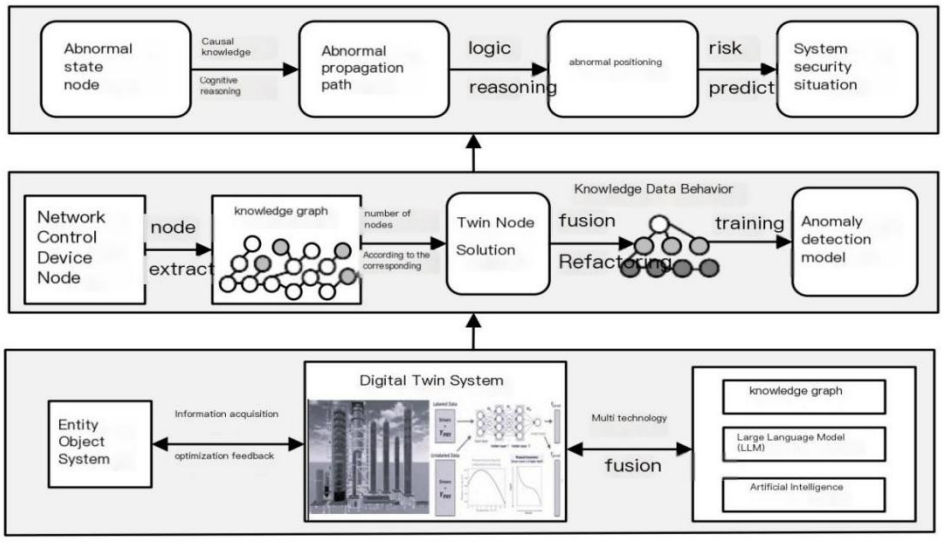

Figure 6. Safety situation assessment of industrial control system integrating emerging technologies

Anomaly warning also applies to industrial network security and structural health. Song applied digital twins to coal mine industrial control networks for real-time attack monitoring and integrated abnormal warning. Gehrmann et al. built an active defense system using twin-based virtual isolation and attack simulation, enabling threat identification and response in information space without affecting physical production (Figure 6). Wang et al. proposed a three-layer warning framework of "twin data reference-real-time behavior comparison-anomaly scoring". For structural health, Liu et al. combined twin and AI for early warning of structural damage; Lu et al. [59] integrated twin with domain-adaptive feature transfer for cable-stayed bridge damage detection.

Current challenges include weak cross-domain anomaly correlation analysis, lack of adaptive threshold mechanisms under dynamic conditions, and insufficient edge-side real-time performance. Future work should address multi-source correlation reasoning, dynamic threshold self-tuning, and lightweight edge inference. Meanwhile, the trade-off between false positive and false negative rates remains critical-static thresholds often miss real faults or trigger frequent false alarms; dynamic threshold tuning must balance detection rate with false positive reduction.

3.3. Enlightenment of Multi-Domain Digital Twin State Deduction for Industrial Control

Digital twin capability extends beyond industrial control to medical, agriculture, power, transportation, water conservancy, smart city, and aerospace domains. These applications share a common four-stage closed-loop-virtual mapping, real-time synchronization, deduction prediction, and strategy iteration-which offers cross-domain reference for industrial control.

Cross-domain applications of digital twin state deduction have been widely reported, spanning smart agriculture [60, 61] (e.g., precision irrigation and moisture prediction), intelligent transportation [62] (e.g., traffic congestion and passenger flow forecasting), water conservancy [63, 64] (e.g., flow state and flood risk prediction), smart cities, and aerospace. These achievements demonstrate the transferability of common methods to different physical systems, providing methodological reserves for industrial control.

However, direct transplantation faces adaptability challenges. Industrial control differs from other fields in its hard real-time requirements, high security demands, and strong physical coupling. General deduction methods cannot easily meet millisecond-level decision-making and closed-loop control needs. Data standardization, model commonality, and deduction interpretability-already mature elsewhere-are more difficult under industrial constraints. A credibility evaluation framework for virtual deduction results is still lacking [65]. Future work should develop real-time deduction engines for industrial constraints, uncertainty quantification, and credibility assessment, moving from "available" to "credible."

4. Self-adaptive Regulation Optimization of Pseudo-Real Iterative Drive

Closed-loop optimization follows virtual-real mapping and state prediction, relying on bidirectional iteration, multi-objective optimization, and real-time feedback to achieve global process optimization and autonomous control. Its closed-loop mechanism—data acquisition, virtual mapping, deduction optimization, and real-world counter-control—distinguishes digital twins from traditional simulation models [66]. The core value is transforming virtual-space information gains into physical-space efficiency improvements [67].

4.1. On-line Dynamic Optimization and Adaptive Control of Single Point Equipment

Online real-time optimization uses high-fidelity digital twin models with edge computing and real-time algorithms for millisecond-level parameter iteration [68], now common in precision manufacturing, process industry, and high-end equipment control. Liu et al. [69] verified this approach in power distribution cyber-physical systems.

Methodologically, research follows two lines: multi-model fusion optimization and real-time data-driven calibration. In fusion optimization, Yang et al. integrated geometric, physical, and behavioral models for additive manufacturing process

optimization; Yang et al. [70] optimized a multi-source heating system, cutting energy consumption by >18%; a full-lifecycle data-driven framework provides systematic support. In data-driven calibration, Zhang built a ship digital twin for online navigation parameter calibration; mine geology-equipment matching and hydraulic support attitude mapping demonstrate real-time calibration effectiveness in mining scenarios.

Current bottlenecks include insufficient computational efficiency under multi-physics coupling, lack of lightweight edge algorithms, and imperfect model calibration mechanisms. Poor online self-calibration causes optimization failure under long-term variable conditions [71]. Future work should target lightweight optimization engines, end-edge-cloud collaborative inference, and online adaptive model calibration to make online optimization reliable.

4.2. Multi-Agent Cooperative Scheduling and Distributed Optimization for Complex Systems

Collaborative scheduling optimization uses digital twin-based global data fusion to build cross-agent, multi-objective, distributed scheduling models for optimal allocation of production resources, energy flows, and logistics, overcoming information silos, local optima, and low efficiency in traditional scheduling [72].

Industrial applications span energy-water systems, mining, transportation logistics, and power systems. Zhang et al. built a Bayesian-based hydraulic twin for reservoir-pumping station-channel collaborative scheduling. Shang et al. optimized coal mining, ventilation, and transportation coordination. In transportation, 5G-R-based railway communication scheduling, underwater excavation path optimization [73], and grain delivery line scheduling demonstrate feasibility. Figure 7 shows Wu et al.'s multi-sensor network for FDM additive manufacturing, integrating temperature, vibration, and displacement sensors for process optimization. He et al. developed a demand-side resource scheduling framework for source-grid-load-storage coordination under peak shaving, also addressing cross-regional data consistency and multi-timescale coupling [74]. Collaborative scheduling is evolving from single production lines to cross-system, cross-regional global optimization.

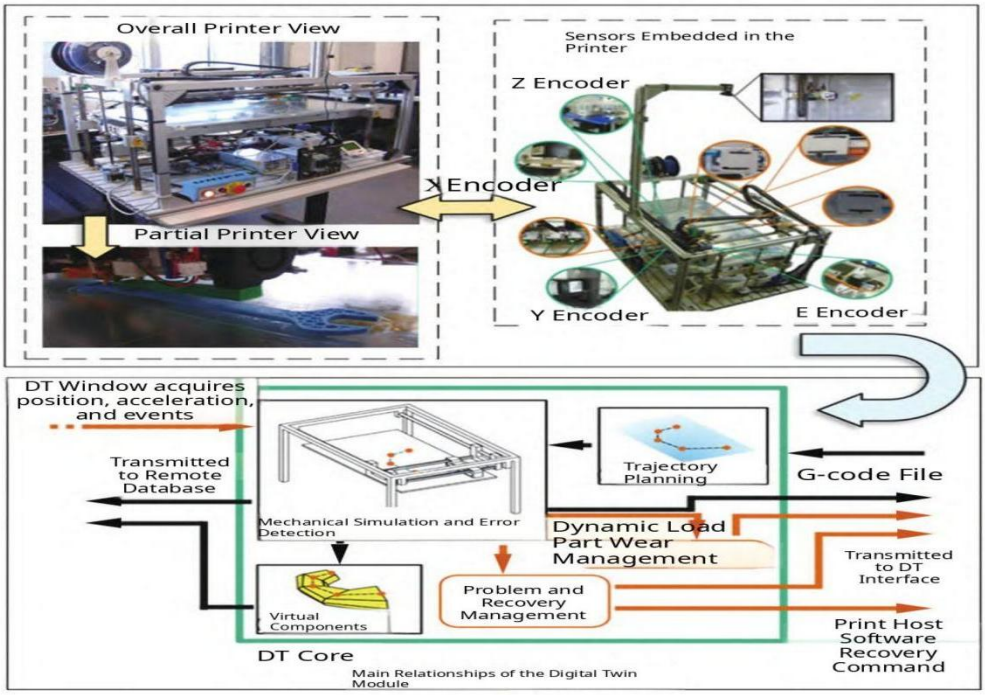

Figure 7. Multi-source sensing network for FDM system

Current obstacles include non-uniform cross-domain data standards and a lack of multi-objective conflict resolution mechanisms [75]. Semantic interoperability via unified ontology modeling is a prerequisite for large-scale scheduling [76], enabling systems with different protocols and formats to share data meaning for cross-device collaboration. Future work should target cross-domain semantic alignment, multi-objective dynamic game coordination, and distributed real-time solving.

4.3. Digital Twin Model-Free Adaptive Control Based on Deep Reinforcement Learning

Digital twin–reinforcement learning fusion provides a safe, reusable virtual training environment with infinite trial-and-error capacity, enabling autonomous decision-making and optimal policy output for industrial control. This eliminates the high risk and sample scarcity of traditional RL training. Agents accumulate millions of virtual interactions without physical trial-and-error costs, shifting the paradigm from "substitute human" to "enhance human".

Validation spans mechanical equipment, power systems, and architecture. Genetic-algorithm-optimized digital twin robot trajectory planning [77] and autonomous path planning [78] have demonstrated feasibility. Pu et al. proposed an intelligent scheduling architecture integrating digital twin and deep RL for model-free adaptive control. In building and city applications, semantic digital twins with RL achieved autonomous O&M optimization [79], and smart city frameworks verified autonomous resource scheduling. These efforts expand fusion control from single machines to systems and from industry to city scale. Figure 8 shows a cluster robot collaborative manufacturing twin framework, supporting collaborative perception, task allocation, and motion planning for multi-robot trajectory optimization via genetic algorithm.

Current challenges include the Sim-to-Real migration gap, slow training convergence, and weak decision interpretability. Seamless policy migration requires addressing virtual environment fidelity, parameter uncertainty, and sensor noise consistency. Future work should focus on high-fidelity simulation, transfer learning with domain randomization, and interpretable RL to move from simulation verification to industrial real-time decision-making.

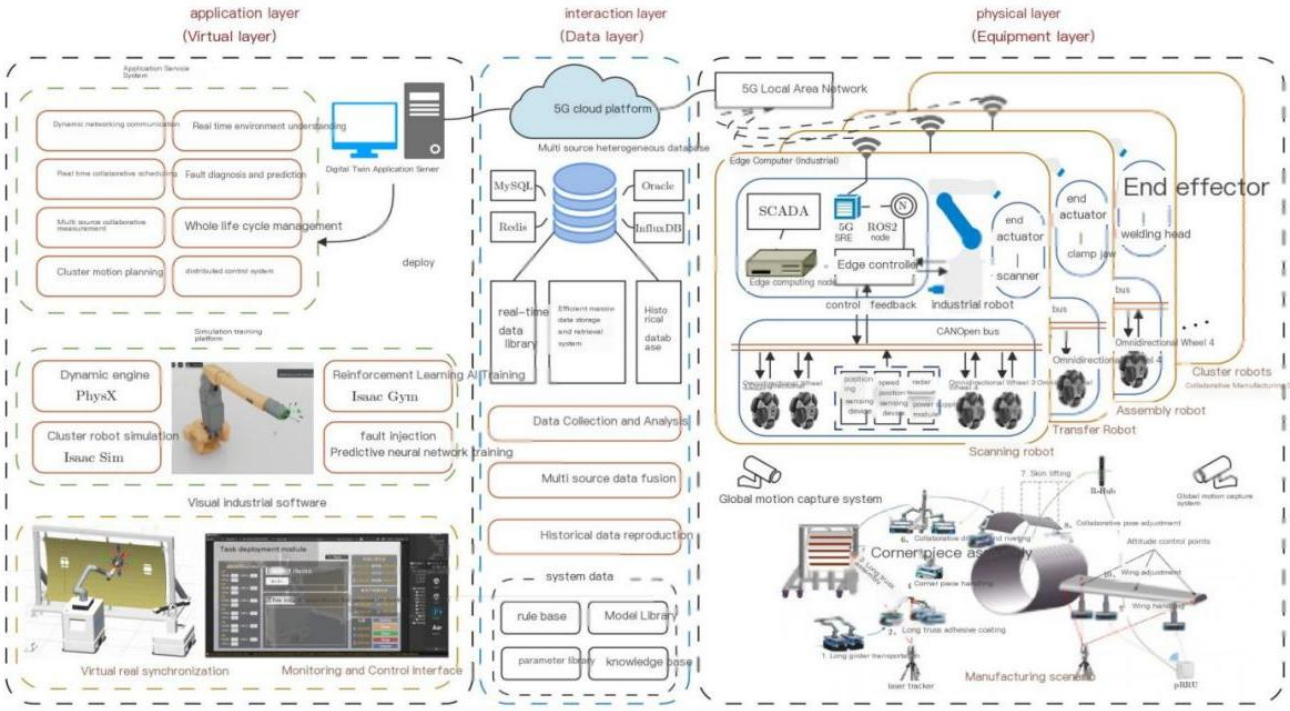

Figure 8. A Framework of Digital Twin System for Collaborative Manufacturing of Cluster Robots

5. Digital Twin Enabling Industrial Intangible Intelligence: Virtual Training and Security Deployment

Embodied intelligence enables autonomous decision-making through physical interaction. Digital twins lack physical bodies, but their high-fidelity virtual environments provide a zero-risk pre-training sandbox. The fusion follows a three-stage closed loop: virtual training → Sim-to-Real policy migration → real-data feedback for Real-to-Sim iteration, driving virtual data into physical embodied evolution [80]. This framework positions autonomous dynamic interaction as the highest maturity level of digital twins, with engineering feasibility already demonstrated [81].

5.1. Digital Twins as Enabling Engines for Efficient Training of Embodied Intelligence

Embodied intelligence Embodied Intelligence emphasizes that agents perceive, make decisions, and act through real-time interactions with the physical environment, and its core lies in the shaping of intelligence by the perception-action closed-loop. Although digital twins do not have physical entities themselves, the high-fidelity virtual environment they provide just simulates a large number of physical interactions required for this closed-loop-including contact dynamics, sensor noise, actuator delays, etc. -enabling agents to complete strategy pre-training with zero risk. Therefore, the essence of digital twin-enabled embodied intelligence is to transform trial-and-error costs in physical space into computational overhead in information space. This section explains this fusion path from four aspects: virtual training data generation, multimodal physical simulation, Sim-to-Real migration, and continuous evolution.

Training efficiency improvements focus on perception accuracy, scene efficiency, and security. Wang et al. improved perception accuracy via indoor propagation calibration; Liu et al. integrated low-code scene construction with Qi et al.'s path planning to accelerate environment building and decision efficiency; Yu et al. [84] provided security constraints for energy-scene embodied intelligence, and Liu et al. [85] enhanced safety through virtual pre-training of human-robot cooperation strategies.

Current shortcomings include the lack of virtual-physical dynamic adaptation, insufficient multi-modal training data fusion, and immature physical parameter modeling, causing performance degradation during strategy transfer [86]. Future work should focus on high-fidelity physics simulation, multi-modal joint representation, and seamless Sim-to-Real migration, pushing digital twins from training platforms to industrial deployment with physical intelligence.

5.2. High-fidelity Virtual Training Environment: Full Working Condition Coverage and Zero Risk of Trial and Error

High-fidelity virtual environments are the foundation for embodied intelligence perception, decision-making, and action debugging. Digital twins offer reusable, full-condition, zero-risk training environments, with multi-scale modeling supporting layered construction.

Applications now span single equipment to complex systems. Li et al. [87] built an offshore ISAC twin for marine embodied intelligence. Wind tunnel twins support aerodynamic training for transportation. Xie et al. [88] developed a mining equipment twin, verifying collaborative training under three-machine coal-cutting conditions. Campus visualization and reconfigurable combat platforms

extend training to public services and cluster coordination. Figure 9 shows equipment posture monitoring via a color-coded framework for visual status validation.

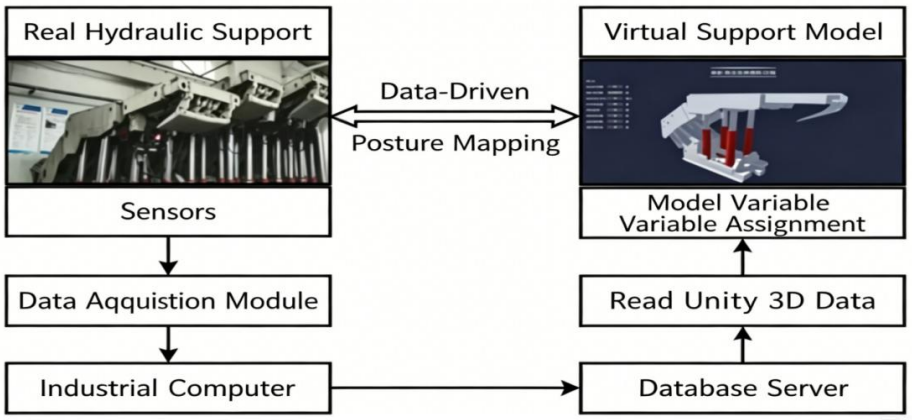

Figure 9. Virtual Real-time Monitoring of Equipment Attitude

Current bottlenecks include insufficient large-scene rendering performance and limited multi-physics coupling accuracy [89]. Fidelity and decision validity are nonlinearly related—the priority should be modeling causally relevant physical features rather than pursuing all-element high fidelity. For example, in robotic arm grasping, end-effector position accuracy matters most, while secondary factors like joint temperature can be simplified. This "task-driven adaptive fidelity" principle should guide modeling. Future work should address adaptive fidelity, multi-physics online coupling, and large-scene real-time rendering to shift from "high fidelity" to "high utility."

5.3. Closed-Loop Paradigm of "Virtual Pretraining-Physical Deployment-Iterative Feedback"

"Virtual pretraining–physical deployment–iterative feedback" is the core paradigm for digital twin and embodied intelligence fusion. Its logic: complete full-scene training and policy verification in a high-fidelity virtual environment, safely deploy the policy to physical entities, and iterate continuously via virtual-real closed-loop feedback. The essence is transforming physical-space execution risk into information-space computational cost, fundamentally changing intelligent-system trial-and-error patterns.

Engineering validation spans single equipment, human-robot collaboration, and industrial systems. Zhang et al. [90] improved UAV deployment success by 40% and reduced flight incidents by 82%, with domain randomization reducing virtual-to-real performance degradation. Jin et al. [91] increased water treatment O&M efficiency by 35% via virtual training. The paradigm also shows potential in medical support [92]. Figure 10 shows Huang et al.'s [93] three-level distributed multi-agent architecture ("single-machine autonomy-cluster collaboration-global scheduling"), providing a scalable deployment path for industrial embodied intelligence.

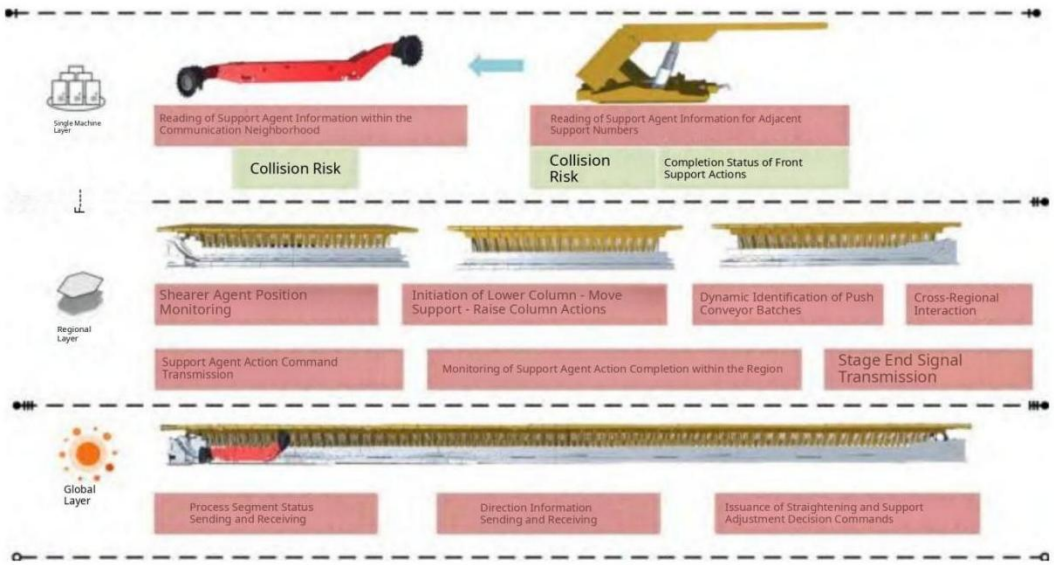

Figure 10. Three-level distributed multi-agent decision architecture

Current constraints include policy deviation in real-scene execution and lack of online iterative optimization. Without closed-loop virtual-real feedback, the virtual model will diverge from the physical entity over time. Establishing bidirectional data paths and model update triggers is essential for long-term operation. Future work should address Sim-to-Real migration adaptation, online policy adaptive updating, and multi-scene generalization to move from "landing" to "trustworthiness."

6. Conclusions and Prospects

6.1. Conclusions

This paper systematically reviews the technical system and

evolution of digital twins for industrial control along the logic of high-fidelity mapping, state deduction, closed-loop optimization, and embodied evolution, revealing a four-stage progression from "sensible" to "knowable" to "controllable" to "walkable". Key bottlenecks identified include insufficient multi-physics coupling and standardization, poor data consistency and security, lack of lightweight edge algorithms and online self-calibration, non-uniform cross-domain standards, Sim-to-Real migration gaps, and limited attention to green O&M. Despite these challenges, the technologies for mapping and deduction have reached large-scale verification, closed-loop optimization is at a key breakthrough stage, and embodied intelligence fusion remains in concept exploration. The proposed full-chain framework offers a valuable reference for both theoretical advancement and engineering deployment. Future research should focus on hybrid mechanism-data modeling, edge-cloud collaborative lightweight architectures, generative AI integration for interpretable decisions, unified data governance and standards, transfer learning for seamless policy migration, and energy-saving collaborative optimization, thereby driving digital twins from auxiliary tools to autonomous intelligent engines for industrial control.

6.2. Prospects

Future research should address six key areas: (1) modeling-insufficient multi-physics coupling accuracy and lack of standardization, forming "model chimneys"; (2) data-poor multi-source consistency and incomplete lifecycle security governance; (3) optimization-insufficient edge lightweight algorithms and online self-calibration, hindering real-time regulation; (4) collaboration-non-uniform cross-domain standards and missing multi-objective conflict resolution, limiting large-scale scheduling; (5) intelligence-significant Sim-to-Real migration gap and weak decision interpretability, restricting RL deployment; (6) sustainability-insufficient attention to green low-carbon and energy-saving collaborative optimization.

6.2.1. Hybrid Drive and Autonomous Dynamic Optimization Modeling Technology Breakthrough

At present, the coupling precision of multi-physical fields is insufficient, the model standardization is less, the traditional model is inaccurate in extrapolation under time-varying conditions, and the pure data-driven model lacks physical interpretability. This problem is especially prominent in the residual life prediction of complex equipment such as gas turbine and centrifugal compressor. Integrating physical prior and industry knowledge into data-driven modeling and developing mechanism-data hybrid driving method is a feasible way. At the same time, online self-calibration and self-evolution algorithms need to be developed to dynamically modify the virtual model using real-time operational data. The ultimate goal is to enable the twin model to achieve efficient internal module interaction and model dynamic optimization based on expert knowledge.

6.2.2. Lightweight Digital Twin Deployment Architecture for Edge-Cloud Collaboration

Industrial site computing power is limited and bandwidth is insufficient. It is difficult to balance real-time rendering and data transmission of existing high-fidelity twin models. This contradiction is especially prominent in small and medium-sized factories or old equipment renovation scenarios. By building a lightweight twin architecture with end-edge-cloud layered collaboration, it is possible to realize real-time rendering of multiple data under limited hardware. The edge end is responsible for real-time perception and local optimization, while the cloud undertakes global scheduling and model training. In addition, model compression and lightweight rendering technologies need to be synchronized to strike a balance between fidelity and operational efficiency and accelerate the adoption of digital twins.

6.2.3. Fusion Evolution of Digital Twin and Generative AI

Despite progress in hybrid-driven prediction and anomaly detection, the "black box" problem—opaque fault attribution and uninterpretable policy generation—remains a concern for high-security industrial control. Future work should develop large language model functions for semantic interaction and policy generation, and build interpretable decision chains based on twin-data causal logic to make key control strategies transparent, meeting safety compliance and advancing human-machine integrated autonomous control.

6.2.4. Cross-domain Unified Standard System and Data Governance Mechanism

Multi-source data formats and communication protocols are not unified, limiting virtual-real synchronization efficiency. Multi-engine data interaction barriers hinder visualization system scaling. In collaborative scheduling, the lack of unified semantic models prevents efficient cross-device and cross-system optimization. Full-process industry standards for modeling, data, interfaces, and security are needed to unify geometric precision, data formats, protocols, and evaluation metrics, eliminating cross-level and cross-vendor barriers. Industrial-level data governance and quality control mechanisms should also be established to build a trusted, interoperable, and reusable digital twin data foundation.

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