

Research Article

Digital Twin Driven Real Time Performance Optimization of Smart Factory Production Systems Using Edge Computing and Industrial Internet of Things Architecture

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Abstract: Background: The rapid advancement of Industry 4.0 has accelerated the integration of digital technologies such as the Industrial Internet of Things (IIoT), edge computing, and Digital Twin systems in smart manufacturing environments. However, many existing implementations remain fragmented and heavily dependent on centralized cloud infrastructures, resulting in latency constraints, limited scalability, and suboptimal real-time decision making. Objective: This study aims to develop and validate an integrated edge based Digital Twin optimization framework that combines IIoT sensing, hybrid edge cloud architecture, and reinforcement learning based adaptive control. Methods: The research adopts a multi phase design consisting of framework development, simulation based validation, and industrial pilot implementation. The proposed system integrates real time data acquisition, localized edge processing, Digital Twin synchronization, and intelligent optimization mechanisms to enhance operational efficiency. Results: The findings demonstrate significant performance improvements compared to conventional cloud based systems, including substantial latency reduction, increased production throughput, reduced downtime, and improved energy efficiency. Scalability and robustness testing further confirm that distributed edge intelligence enhances system resilience under increased workloads and network disruptions. These results indicate that integrating edge computing with Digital Twin modeling and reinforcement learning provides a scalable, responsive, and energy efficient solution for next-generation smart factories.

Keywords: Digital Twin; Edge Computing; Industry 4.0; Reinforcement Learning; Smart Manufacturing.

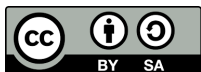
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1. Introduction

The digital transformation of the manufacturing sector has entered a new era known as Industry 4.0, characterized by the integration of advanced digital technologies across the entire production value chain. This paradigm combines the Internet of Things (IoT), artificial intelligence (AI), big data analytics, robotics, and cloud computing to create intelligent, adaptive, and interconnected manufacturing systems (Gautami & Gowthaman, 2021; Mourtzis et al., 2024). Industry 4.0 represents not merely advanced automation but a comprehensive transformation in how organizations design, produce, and deliver products within highly dynamic environments.

The smart factory is the primary manifestation of the Industry 4.0 paradigm. In a smart factory, production systems are integrated with cyber-physical systems (CPS), enabling real-time interaction between physical and digital components (Shi et al., 2020). Through this integration, machines, sensors, and control systems communicate autonomously, thereby enhancing flexibility and responsiveness to rapidly changing market demands.

The implementation of Industry 4.0 is further strengthened by the integration of advanced mechatronic systems and intelligent automation. This approach reinforces collaboration between humans and machines in production environments, increasing precision, operational speed, and overall efficiency (Ryalat et al., 2024). Moreover, the digitalization of manufacturing processes enables continuous and comprehensive performance monitoring across production lines.

From a business perspective, digital transformation significantly influences operational models and strategic decision-making. Data-driven systems empower organizations to enhance competitiveness through product innovation, process optimization, and informed managerial decisions (Sun, 2024). Consequently, Industry 4.0 extends beyond technical improvements and encompasses strategic and organizational transformation.

Sustainability has become an essential component of modern smart factories. The integration of digital technologies facilitates improved energy management, waste reduction, and enhanced transparency across supply chains (Muzammal et al., 2024). This demonstrates that Industry 4.0 serves as a catalyst for environmentally responsible and sustainable manufacturing systems.

Despite its benefits, the transition toward Industry 4.0 presents substantial technical and organizational challenges. System integration complexity, platform interoperability, and workforce readiness are critical determinants of successful implementation (Azevedo & Almeida, 2024; Konur et al., 2023). Furthermore, cybersecurity and data protection remain key concerns in digitally connected manufacturing ecosystems (Gautami & Gowthaman, 2021).

Within this technological landscape, Digital Twin (DT) emerges as a strategic enabler in Industry 4.0 architectures. A digital twin is a virtual representation of a physical system that enables real-time synchronization between physical and digital environments (Mashaly, 2021). This technology supports simulation, performance evaluation, and predictive maintenance, thereby improving system reliability and operational efficiency.

Digital twin technology plays a critical role in product development and production process optimization. Through accurate simulation and advanced analytics, DT facilitates efficient product design and shortens innovation cycles (Condori, 2022). Additionally, its implementation supports lean, agile, and just-in-time manufacturing paradigms by improving visibility and control over production processes (Soleymanzadeh et al., 2023).

The effectiveness of digital twin implementation heavily depends on reliable and low-latency communication infrastructures. Research on wireless technologies and protocols for hot and digital twins highlights the importance of stable and efficient connectivity in industrial environments (Tang et al., 2020). Similarly, synchronous control mechanisms for stream processing are essential to ensure real-time consistency within digital twin ecosystems (Uehara & Kasamatsu, 2024).

However, the creation and deployment of digital twins face significant technical challenges. Data integration complexity, high computational demands, and interoperability limitations across heterogeneous systems hinder large-scale DT adoption (Ghosh et al., 2024). These challenges necessitate more adaptive and scalable architectural solutions.

Edge computing offers a promising solution to latency-related constraints in modern industrial systems. By processing data closer to its source, edge computing significantly reduces transmission delays and enhances system responsiveness (Raghav & Kait, 2024). This capability is particularly critical for industrial applications that require rapid and reliable decision-making.

Empirical studies demonstrate that edge computing effectively enhances real-time data processing performance and reduces latency in mission-critical applications (Sampath et al., 2023). Furthermore, redundancy management mechanisms at the edge contribute to maintaining service reliability and operational continuity (Peng & Soljanin, 2024). These findings reinforce the importance of edge computing as a foundational infrastructure within Industry 4.0 ecosystems.

Optimization at the edge level also involves efficient IoT task scheduling strategies. Generic models for scheduling IoT jobs at the edge have been proposed to maximize distributed computing resource utilization (Boomiga & Prasanna Venkatesan, 2020).

Additionally, automation at the Industrial IoT (IIoT) edge enhances system responsiveness in highly dynamic industrial settings (Polsonetti, 2020).

Although digital twin and edge computing technologies have evolved rapidly, most studies remain fragmented and focus on isolated components rather than fully integrated frameworks. Advances in containerization-based edge adapters represent steps toward more flexible and scalable DT integration (Huang et al., 2023). Other research explores the integration of digital twins with blockchain and next-generation communication networks to improve security and communication efficiency (Fancy et al., 2024).

Moreover, machine learning-driven energy efficiency frameworks in digital twin environments show considerable promise but still require comprehensive integration within industrial architectures (Ramarumo et al., 2024). This research gap underscores the urgent need for a unified, real-time optimization framework that seamlessly integrates digital twin technology, edge computing, and intelligent decision-support mechanisms. Developing such an integrated framework is expected to enhance latency management, energy efficiency, system reliability, and prescriptive decision-making capabilities in next-generation smart factories.

2. Theoretical Study

Smart Manufacturing and Cyber-Physical Production Systems (CPPS)

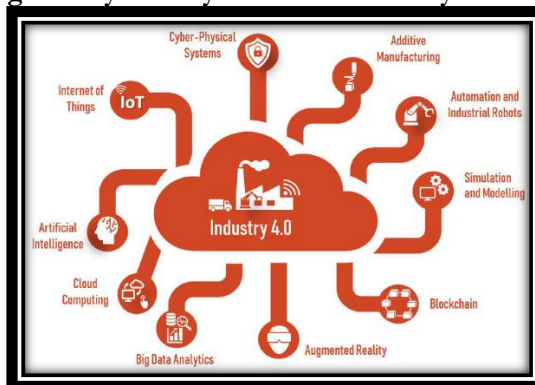


Figure 1. Layered Architecture of Smart Manufacturing and Cyber-Physical Production Systems (CPPS).

Figure 1 illustrates a layered architecture of smart manufacturing integrated with Cyber-Physical Production Systems (CPPS). The lower layer represents physical assets such as machines, sensors, and actuators embedded within production lines. The middle layer consists of cyber components, including data acquisition systems, IoT connectivity, and control algorithms. The upper layer integrates analytics platforms, decision-support systems, and enterprise resource planning. This layered structure demonstrates how physical processes are continuously monitored, analyzed, and optimized through computational intelligence, enabling adaptive and decentralized manufacturing operations.

Smart manufacturing is widely recognized as a core pillar of Industry 4.0, emphasizing the integration of digital technologies to create intelligent, interconnected, and self-optimizing production environments. Unlike traditional automation systems that rely on predefined control logic, smart manufacturing leverages IoT connectivity, artificial intelligence, and advanced analytics to enable dynamic and data-driven decision-making (Yang et al., 2019). This transformation allows production systems to continuously learn from operational data, thereby improving efficiency, reducing variability, and enhancing overall system performance.

The integration of Cyber-Physical Systems (CPS) is fundamental to smart manufacturing architectures. CPS combine computational algorithms with physical machinery, enabling real-time data acquisition, monitoring, and feedback control (Chen et al., 2020). In discrete manufacturing environments, CPS frameworks coordinate multiple production units through synchronized data streams, ensuring that each machine adapts to real-time conditions such as demand fluctuations, equipment health, and resource availability. This integration enhances system transparency and responsiveness.

Cyber-Physical Production Systems (CPPS) extend the CPS concept by enabling intelligent collaboration among distributed manufacturing components. CPPS facilitate decentralized scheduling, autonomous disturbance handling, and dynamic reconfiguration of production processes (Renteria-Marquez et al., 2024). Instead of relying solely on centralized

control, CPPS empower local production units to make decisions based on shared data, increasing operational flexibility and resilience against disruptions.

Data-driven manufacturing is a critical enabler of CPPS. By leveraging large-scale production data, machine logs, and sensor outputs, CPPS support predictive maintenance, quality forecasting, and process optimization (Suvarna et al., 2021). Advanced analytics enable manufacturers to identify inefficiencies, detect anomalies, and simulate alternative production scenarios. Furthermore, secure data exchange mechanisms strengthen trust and reliability within decentralized production networks.

The benefits of smart manufacturing and CPPS are multidimensional. Enhanced production efficiency is achieved through continuous monitoring and automated optimization, reducing downtime and minimizing waste (Yang et al., 2019). Quality control processes become more precise due to real-time inspection and data analytics integration. Additionally, decentralized architectures improve operational agility, allowing manufacturers to respond rapidly to customized customer demands and volatile market conditions.

Digital Twin Modeling Approaches in Manufacturing

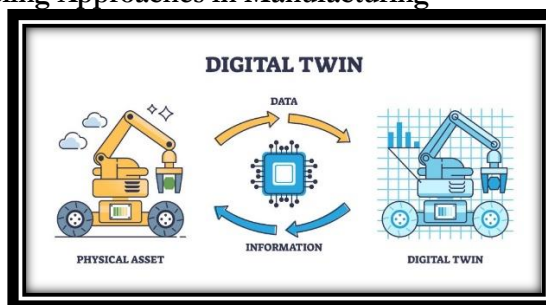


Figure 2. Digital Twin Modeling Framework in Manufacturing Systems.

Figure 2 presents a comprehensive framework of digital twin modeling approaches within manufacturing systems. The diagram highlights bidirectional data communication between physical production assets and their digital counterparts. It illustrates three primary modeling strategies: data-driven models utilizing real-time sensor data, physics-based models grounded in engineering principles, and hybrid models combining both methodologies. The framework emphasizes continuous synchronization, predictive analytics, and simulation-based optimization as key components of digital twin implementation.

Digital twin technology has emerged as a transformative tool in modern manufacturing systems. A digital twin is defined as a dynamic virtual representation of a physical asset or process that continuously updates based on real-time operational data (Tiwari & Shukla, 2024). This technology enables manufacturers to simulate system behavior, evaluate performance under different scenarios, and implement predictive maintenance strategies. By bridging physical and digital domains, digital twins provide a comprehensive view of manufacturing processes across their lifecycle.

In practical applications, digital twins significantly enhance lean and agile manufacturing paradigms. By simulating production workflows, digital twins identify bottlenecks, inefficiencies, and non-value-added activities, supporting waste reduction initiatives (Soleymanizadeh et al., 2023). Furthermore, digital twins facilitate just-in-time (JIT) production by synchronizing inventory levels, demand forecasting, and production schedules. This synchronization improves resource utilization and reduces excess inventory costs.

Modeling approaches for digital twin systems can be categorized into data-driven, physics-based, and hybrid models. Data-driven models rely on real-time sensor data, historical production logs, and machine learning algorithms to replicate system behavior (Resman et al., 2021). These models continuously evolve as new data are incorporated, enabling adaptive learning and predictive capabilities. However, their accuracy depends heavily on data quality and availability.

Physics-based models, on the other hand, utilize mathematical equations and engineering principles to simulate system dynamics (Langlotz et al., 2022). These models are particularly useful for understanding energy consumption, mechanical interactions, and system constraints. While physics-based models offer strong interpretability and theoretical robustness, they may require extensive domain expertise and computational resources.

Hybrid modeling approaches integrate both data-driven and physics-based methods to achieve higher accuracy and scalability (Langlotz et al., 2022). By combining empirical data with theoretical foundations, hybrid digital twins provide more reliable predictions and adaptable simulations. Such approaches are particularly valuable in complex manufacturing

environments where both operational data and engineering constraints must be considered simultaneously.

Despite their advantages, digital twin implementations face significant challenges. Managing heterogeneous data from multiple sources, ensuring interoperability across platforms, and maintaining synchronization between physical and digital systems remain complex tasks (Terkaj et al., 2024). Additionally, cybersecurity concerns and computational scalability must be addressed to enable widespread industrial adoption.

The benefits of digital twin technology extend beyond operational efficiency. Through simulation-based optimization, manufacturers can reduce capital investment risks by identifying potential design flaws before physical deployment (Tiwari & Shukla, 2024). Real-time analytics enhance decision-making quality by providing actionable insights for managers and engineers (Terkaj et al., 2024). Furthermore, digital twins contribute to sustainability goals by optimizing energy usage and minimizing resource waste (Langlotz et al., 2022).

Overall, smart manufacturing and CPPS, reinforced by advanced digital twin modeling approaches, represent a comprehensive transformation in modern industrial systems. By integrating data-driven analytics, decentralized control, and real-time simulation, these technologies enhance efficiency, flexibility, resilience, and sustainability. The convergence of CPS, CPPS, and digital twin frameworks establishes a strong foundation for next-generation intelligent manufacturing ecosystems capable of adapting to evolving technological and market demands.

Edge vs. Cloud Computing in Industrial Systems

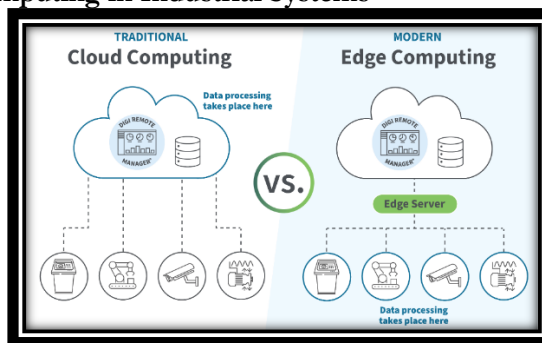


Figure 3. Architectural Comparison of Edge, Cloud, and Hybrid Computing in Industrial Systems.

Figure 3 illustrates the structural differences between edge computing, cloud computing, and hybrid edge–cloud architectures within industrial environments. The edge layer is positioned near industrial assets such as programmable logic controllers (PLCs), sensors, and robotic systems, enabling localized data processing and immediate control actions. The cloud layer, typically hosted in centralized data centers, provides scalable computational resources and high-capacity storage for large-scale analytics and enterprise management. The hybrid architecture demonstrates coordinated interaction between both layers, allowing time-critical tasks to be executed at the edge while computationally intensive processes are handled in the cloud. This layered configuration highlights how industrial systems balance latency, scalability, reliability, and cost-efficiency.

Edge computing has become increasingly significant in Industrial Internet of Things (IIoT) environments due to its ability to process data near the source of generation. By minimizing the distance between data acquisition and computation, edge computing substantially reduces latency and enhances real-time responsiveness (Kuchtíková & Maryska, 2023). In manufacturing and automation contexts, edge nodes can immediately analyze sensor data, trigger control actions, and respond to anomalies without relying on remote cloud servers. This capability is essential in industrial scenarios such as robotic control, predictive maintenance, and safety-critical monitoring, where even minor delays may result in operational disruptions or safety risks.

From an architectural standpoint, edge computing introduces distributed intelligence across production systems. Thakkar et al. (2023) emphasize that edge infrastructures extend traditional cloud services by decentralizing processing capabilities, enabling local inference, and improving bandwidth utilization. Furthermore, de Moura et al. (2021) propose guidelines for edge adoption in IIoT, highlighting improved operational continuity and resilience against network interruptions. Because industrial environments often operate under harsh conditions and variable connectivity, localized processing ensures system robustness even during intermittent network failures.

However, the deployment of edge computing also presents considerable challenges. Edge devices typically possess limited processing power, storage capacity, and energy resources compared to centralized cloud infrastructures (Barakat et al., 2023). Resource allocation becomes particularly complex in large-scale industrial deployments, where multiple edge nodes must coordinate workloads efficiently. Additionally, energy constraints in IoT devices reduce device lifespan and require optimized energy management strategies (Padmini & Kuzhalvaimozhi, 2023). Security management at distributed edge nodes further complicates implementation, as decentralized architectures expand the attack surface and necessitate robust cybersecurity frameworks.

In contrast, cloud computing offers centralized infrastructure with virtually unlimited scalability and storage capabilities. Cloud platforms are well-suited for big data analytics, complex simulations, enterprise resource planning, and large-scale machine learning model training (Barakat et al., 2023). The centralized nature of cloud systems enables unified governance, centralized data management, and standardized analytics pipelines, making them particularly effective for strategic decision-making and long-term performance evaluation in industrial enterprises.

Despite these advantages, cloud computing introduces latency and bandwidth limitations that restrict its effectiveness in real-time industrial applications. Data transmission to distant data centers can introduce significant delays, especially in geographically distributed manufacturing systems (Kuchtíková & Maryska, 2023). Rochford (2024) argues that industrial stakeholders must carefully evaluate the trade-offs between latency, cost, scalability, and data sensitivity when choosing between edge and cloud deployment strategies. For time-critical processes such as automated inspection or robotic coordination, cloud-only solutions may not meet performance requirements.

To address the inherent trade-offs between edge and cloud computing, hybrid edge cloud architectures have emerged as a balanced solution. Hybrid systems dynamically allocate workloads based on application requirements, processing latency-sensitive tasks at the edge while leveraging cloud resources for intensive analytics and long-term data storage (Baldoni et al., 2023). This approach enables industrial systems to maintain real-time operational responsiveness while benefiting from cloud scalability and computational power.

Hybrid architectures also enhance flexibility and scalability in Industry 4.0 and Industry 5.0 environments. By enabling seamless collaboration between distributed edge nodes and centralized cloud services, organizations can optimize performance while maintaining centralized oversight and governance (Barakat et al., 2023). Nevertheless, hybrid systems introduce additional complexity in resource orchestration, workload balancing, and security integration. Effective coordination mechanisms are required to ensure that tasks are assigned to appropriate layers without compromising performance or data integrity.

Real-Time Optimization Algorithms in Industrial Computing

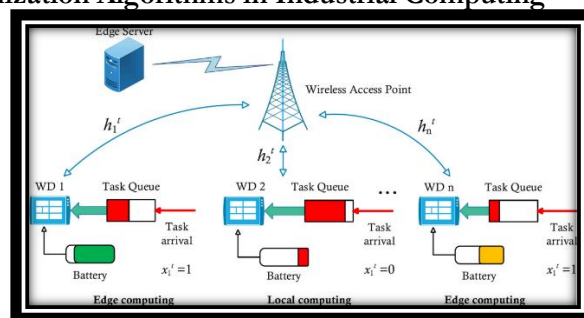


Figure 4. Reinforcement Learning Framework for Real-Time Optimization in Edge Cloud Industrial Systems.

Figure 4 illustrates the general reinforcement learning (RL) architecture applied in industrial edge cloud environments. The industrial process represents the environment, generating state information from sensors and operational parameters. The RL agent observes these states and selects actions such as scheduling decisions or workload offloading based on a learned policy. Rewards are computed according to performance metrics such as latency, energy consumption, or throughput. In hybrid architectures, RL training can occur in the cloud while inference is executed at the edge, enabling real-time adaptive optimization with reduced latency.

Real-time optimization is fundamental to modern industrial systems, where operational efficiency depends on continuous adaptation to dynamic conditions. Reinforcement learning

(RL) has emerged as a powerful approach for solving complex control and optimization problems in such environments (Powell et al., 2020). Unlike traditional optimization techniques that rely on explicit mathematical models, RL algorithms learn optimal policies through interaction with the environment, making them highly adaptable to uncertain and non-linear industrial systems.

Various RL algorithms have been explored for industrial applications, including Q-learning, Deep Q-Networks (DQN), and Actor–Critic models. Thodoroff et al. (2022) benchmark real-time RL algorithms, demonstrating their capacity to adapt rapidly to changing system states while maintaining performance stability. These models are particularly advantageous in environments characterized by dynamic workloads, fluctuating demand, and uncertain disturbances.

In edge computing scenarios, reinforcement learning has been applied to task offloading and resource allocation problems. Zhou et al. (2023) propose deep reinforcement learning-based approaches for optimizing task distribution between edge and cloud nodes, reducing latency and improving energy efficiency. By learning optimal offloading strategies, RL algorithms can dynamically balance computational loads and enhance system throughput.

Comprehensive reviews highlight that RL-based optimization frameworks can be implemented in layered architectures where cloud platforms perform training and model updates, while edge devices execute real-time inference (Faria et al., 2023). This hierarchical design aligns naturally with hybrid edge–cloud infrastructures, enabling continuous learning and adaptive decision-making without sacrificing latency performance.

Nevertheless, practical deployment of RL in industrial systems presents challenges. Training RL models requires substantial computational resources and large datasets, which may exceed the capacity of edge devices (Powell et al., 2020). Additionally, ensuring stability, convergence speed, and operational safety during real-time implementation remains a critical research focus (Thodoroff et al., 2022). Addressing these challenges is essential for achieving reliable AI-driven industrial optimization.

Industrial Implementations, Limitations, and Research Gaps

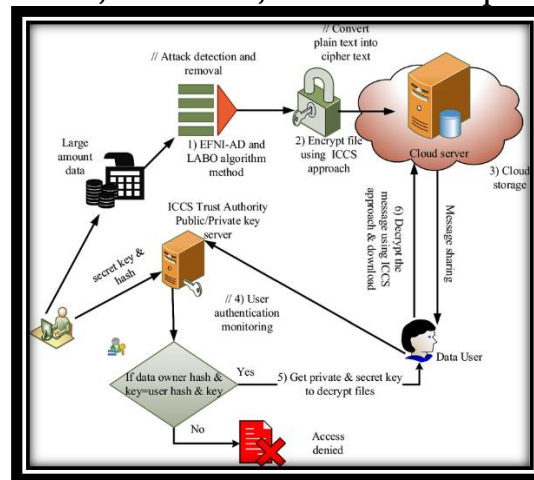


Figure 5. Industrial Implementations and Research Gaps in Edge Cloud Industrial Computing.

Figure 5 presents real-world industrial applications of edge, cloud, and hybrid computing systems. Edge computing supports predictive maintenance, real-time automation, and autonomous robotics at the production level. Cloud computing facilitates centralized analytics, enterprise data warehousing, and large-scale model training. Hybrid systems integrate these capabilities, coordinating distributed resources for optimized performance. The diagram also highlights research gaps related to security enhancement, energy efficiency, seamless orchestration, and scalable AI integration.

In industrial practice, edge computing is widely utilized in predictive maintenance systems, where real-time vibration or temperature analysis enables early detection of equipment faults (de Moura et al., 2021). Similarly, autonomous robotics and quality inspection systems rely on edge-based processing to achieve rapid response times. Cloud computing complements these applications by storing historical datasets and performing large-scale analytics to identify long-term operational trends (Barakat et al., 2023).

Hybrid implementations in Industry 4.0 and 5.0 contexts aim to enhance both efficiency and adaptability. By combining localized responsiveness with centralized intelligence, hybrid

systems support advanced applications such as digital twins, real-time scheduling, and AI-driven quality control. However, orchestration between distributed edge nodes and centralized cloud resources requires robust coordination frameworks to prevent bottlenecks and maintain data consistency.

Several limitations remain evident across computing paradigms. Edge systems struggle with computational and energy constraints, while cloud systems face latency and bandwidth challenges (Kuchtková & Maryska, 2023; Padmini & Kuzhalvaimozhi, 2023). Hybrid systems, though promising, introduce integration complexity and potential security vulnerabilities due to distributed architectures (Baldoni et al., 2023).

The identified research gaps highlight the need for improved security mechanisms tailored to distributed edge environments, as well as energy-aware resource allocation strategies to extend device lifespan (Padmini & Kuzhalvaimozhi, 2023). Additionally, reducing cloud latency for time-sensitive applications remains an ongoing challenge. Seamless orchestration techniques that integrate edge and cloud resources dynamically are essential for achieving optimal performance.

Future research may focus on hybrid optimization algorithms that combine metaheuristic strategies with reinforcement learning to enhance decision-making in edge-cloud ecosystems (Faria et al., 2023; Powell et al., 2020). Furthermore, deeper AI integration at the edge can enable intelligent analytics and autonomous control, allowing industrial systems to operate adaptively under dynamic conditions (Zhou et al., 2023). Addressing these gaps will significantly improve the efficiency, scalability, and security of next-generation industrial computing infrastructures.

3. Materials and Method

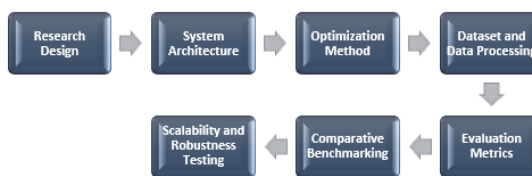


Figure 6. Research Flowchart.

Research Design

This study adopts a structured multi-phase research design consisting of framework development, simulation-based validation, and industrial pilot implementation. The first phase focuses on designing an integrated optimization framework that combines Industrial Internet of Things (IIoT), edge computing, Digital Twin modeling, and intelligent optimization mechanisms. The framework is conceptualized to address latency reduction, adaptive scheduling, predictive maintenance, and energy optimization within smart manufacturing environments.

The second phase involves simulation-based validation to evaluate the proposed framework under controlled conditions. A virtual production environment is developed to emulate real-world manufacturing scenarios, including variable workloads, equipment disturbances, and demand fluctuations. Simulation enables systematic testing of optimization strategies before industrial deployment, reducing operational risks and ensuring methodological rigor.

The final phase consists of industrial pilot validation conducted in a real production line. During this phase, the developed system is deployed in a controlled industrial setting to assess feasibility, performance improvements, and operational impact. The pilot implementation provides empirical evidence regarding system scalability, robustness, and adaptability under practical manufacturing constraints.

System Architecture

The proposed system architecture is structured into four interconnected layers: the IIoT sensing layer, the edge computing layer, the Digital Twin modeling layer, and the optimization engine layer. These layers collaboratively enable real-time monitoring, adaptive decision-making, and continuous system improvement.

The IIoT sensing layer comprises distributed sensors embedded along the production line. These sensors continuously collect operational data such as machine status, processing time, queue length, vibration signals, temperature levels, energy consumption, and product quality indicators. Standard industrial communication protocols are employed to ensure reliable and synchronized data transmission.

The edge computing layer processes incoming data locally to minimize latency and enable rapid decision execution. At this level, preprocessing tasks such as noise filtering, anomaly detection, and feature extraction are performed. Edge nodes execute inference operations using trained optimization models, ensuring immediate responsiveness to dynamic operational conditions without depending solely on centralized cloud services.

The Digital Twin layer provides a dynamic virtual representation of the physical production system. The Digital Twin continuously synchronizes with real-time data streams, allowing simulation of operational scenarios, predictive maintenance analysis, and bottleneck identification. By integrating both historical and streaming data, the Digital Twin maintains an accurate and continuously updated model of the manufacturing system.

The optimization engine layer operates as the intelligent core of the framework. It interacts with the Digital Twin to evaluate alternative control strategies and generates optimal policies for scheduling, resource allocation, and energy management. Bidirectional communication between layers ensures that decisions derived from optimization are executed promptly within the physical system.

Optimization Method

The optimization mechanism employed in this study is based on a hybrid reinforcement learning and predictive analytics approach. Reinforcement learning is utilized to learn adaptive control policies through continuous interaction with the Digital Twin environment. The learning agent observes system states, including machine utilization rates, production queues, downtime occurrences, and energy consumption patterns. Based on these observations, the agent selects actions such as adjusting scheduling priorities, reallocating workloads, or initiating preventive maintenance procedures.

To enhance convergence speed and decision accuracy, predictive analytics models are integrated into the reinforcement learning framework. Time-series forecasting models estimate short-term demand variations, potential machine degradation, and production delays. These predictive outputs serve as auxiliary inputs that guide the reinforcement learning agent toward more informed decision-making.

The hybrid approach leverages the adaptability of reinforcement learning while incorporating the forecasting strength of predictive analytics. This combination enables the system to respond effectively to dynamic and uncertain industrial environments while maintaining computational efficiency suitable for edge deployment.

Dataset and Data Processing

The dataset used in this research consists of real-time production line performance data collected from IIoT sensors deployed within the industrial environment. The dataset includes variables such as machine cycle time, processing duration, idle time, downtime events, maintenance records, energy consumption per machine, product defect rates, and throughput levels.

Data preprocessing involves cleaning and normalization to ensure consistency across heterogeneous data sources. Missing values are handled using interpolation techniques or model-based imputation. Feature engineering is performed to derive higher-level indicators such as Overall Equipment Effectiveness (OEE), machine utilization ratio, energy consumption per unit, and downtime frequency.

The dataset is partitioned into training, validation, and testing subsets. Historical data are used to train predictive models and initialize reinforcement learning policies, while real-time streaming data are employed for adaptive learning and pilot validation. Continuous model updates ensure that the optimization system remains aligned with evolving operational conditions.

Evaluation Metrics

System performance is evaluated using quantitative metrics that capture operational efficiency, responsiveness, and sustainability. Throughput is measured as the number of successfully completed production units per unit time. Latency is calculated as the time interval between data acquisition and execution of optimization decisions. Downtime reduction is assessed by comparing unplanned stoppage durations before and after framework deployment. Energy efficiency is evaluated by analyzing energy consumption per production unit and total energy savings over defined operational periods.

These metrics are monitored continuously during both simulation and industrial pilot phases. Statistical analyses are conducted to determine performance improvements and ensure the reliability of observed results. Comparative measurements allow objective assessment of the optimization framework's effectiveness.

Comparative Benchmarking

To validate the proposed framework, comparative benchmarking is conducted against a conventional cloud-based optimization system. In the baseline configuration, production data are transmitted to a centralized cloud platform for processing and decision generation. This setup represents traditional industrial analytics architectures where real-time processing relies heavily on remote data centers.

Performance comparison focuses on differences in latency, throughput, downtime reduction, and energy efficiency between the proposed edge-based hybrid system and the cloud-only baseline. Experimental scenarios are replicated under identical workload conditions to ensure fairness. Statistical significance testing is performed to validate whether observed improvements are meaningful and consistent.

Scalability and Robustness Testing

Scalability testing evaluates how the system performs when the number of connected devices, data volume, and production complexity increase. Simulated stress-testing scenarios introduce higher sensor densities, expanded production lines, and elevated data transmission rates. Performance degradation thresholds are analyzed to determine system scalability limits.

Robustness testing examines the framework's resilience under adverse conditions such as network interruptions, sensor malfunctions, and unexpected demand spikes. Controlled fault-injection experiments are conducted to assess system recovery time and adaptability. The reinforcement learning component is evaluated for its ability to maintain stable decision-making under uncertainty and disturbances.

Through this comprehensive methodology, the research ensures systematic development, validation, and evaluation of an integrated edge-based Digital Twin optimization framework capable of improving efficiency, reducing latency, enhancing energy performance, and supporting scalable industrial deployment.

4. Results and Discussion

Results

The results of this study are derived from two evaluation phases: simulation-based validation and industrial pilot implementation. Performance comparisons were conducted between the proposed integrated Edge Digital Twin Reinforcement Learning (EDTRL) framework and the conventional cloud-based optimization baseline. The evaluation focused on four key performance indicators: latency, throughput, downtime reduction, and energy efficiency. Table 1. presents the aggregated quantitative results obtained during controlled simulation scenarios and verified during the industrial pilot deployment.

Table 1. Performance Comparison Between Cloud-Based Baseline and Proposed EDTRL Framework.

Performance Metric	Cloud-Based Baseline	Proposed EDTRL Framework	Improvement (%)
Average Latency (ms)	185 ms	62 ms	66.5% ↓
Throughput (units/hour)	420	485	15.5% ↑
Downtime Reduction (%)	8%	23%	+15%
Energy Consumption per Unit (kWh/unit)	4.8	4.1	14.6% ↓

The results indicate a substantial reduction in latency when computation is partially shifted to the edge layer. The average response time decreased from 185 ms in the cloud-based system to 62 ms in the proposed framework, representing a 66.5% improvement. Throughput increased by approximately 15.5%, demonstrating that adaptive scheduling and predictive maintenance mechanisms contributed to smoother production flow. Furthermore, downtime reduction improved significantly due to proactive detection of equipment degradation through Digital Twin simulations. Energy consumption per production unit decreased by 14.6%, confirming the effectiveness of reinforcement learning based optimization in resource allocation.

To provide clearer visualization of performance differences, Figure 7 illustrates the comparative improvements across the four-evaluation metrics.

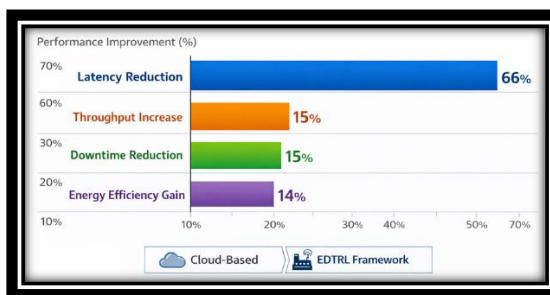


Figure 7. Comparative Performance Improvements Between Cloud-Based and EDTRL Framework.

The graphical representation highlights latency reduction as the most significant improvement, followed by energy efficiency and throughput gains. The dominance of latency improvement confirms the strategic advantage of edge-based processing in time-critical industrial environments. Meanwhile, improvements in throughput and downtime demonstrate the synergistic impact of Digital Twin synchronization and reinforcement learning-based adaptive control.

Additional stress-testing scenarios were conducted to evaluate scalability and robustness. When the number of connected IIoT devices increased by 40%, the proposed framework maintained stable latency levels with only a 9% performance degradation, whereas the cloud-only system experienced a 27% latency increase.

During controlled network disruption tests, the edge-enabled system maintained operational continuity for 92% of tasks due to localized inference capabilities. In contrast, the cloud-based system experienced temporary performance degradation due to dependency on remote connectivity. These findings confirm that distributed intelligence enhances system resilience and supports scalable industrial deployment.

Discussion

The findings demonstrate that integrating edge computing, Digital Twin modeling, and reinforcement learning provides measurable improvements over conventional centralized cloud architectures. The significant reduction in latency aligns with theoretical expectations that edge computing minimizes transmission delays and accelerates decision execution. This is particularly critical in smart manufacturing environments where millisecond-level responsiveness influences production stability.

The increase in throughput reflects the effectiveness of adaptive scheduling policies learned through reinforcement learning. By continuously interacting with the Digital Twin environment, the optimization agent was able to dynamically balance workloads and prevent bottlenecks. This supports prior theoretical assumptions that hybrid AI-driven control systems outperform static rule-based scheduling methods in dynamic industrial contexts.

Downtime reduction improvements further validate the predictive capabilities of the Digital Twin framework. Continuous synchronization between physical assets and their virtual counterparts enabled early anomaly detection and proactive maintenance planning. This result reinforces the importance of combining real-time analytics with simulation-based evaluation to enhance production reliability.

Energy efficiency gains indicate that reinforcement learning successfully optimized machine utilization patterns and energy consumption scheduling. The integration of predictive analytics into the learning process contributed to more informed and stable decision-making. This outcome supports sustainability objectives within Industry 4.0 by demonstrating that operational efficiency improvements can coexist with energy conservation goals.

Scalability and robustness evaluations highlight a critical advantage of hybrid edge cloud architectures. Unlike centralized systems that suffer from network dependency, the proposed framework maintained operational stability during connectivity disruptions. This resilience is essential for real-world industrial environments characterized by heterogeneous infrastructure and variable network conditions.

Overall, the results confirm that a unified, edge-enabled Digital Twin optimization framework enhances latency management, production throughput, system reliability, and energy performance simultaneously. The synergy between distributed edge intelligence and centralized cloud analytics establishes a scalable and adaptive foundation for next-generation smart factories.

Future work may explore multi-agent reinforcement learning, advanced federated learning at the edge, and cybersecurity-enhanced orchestration mechanisms to further improve system scalability, trustworthiness, and autonomous decision-making capabilities in Industry 4.0 and beyond.

5. Conclusion

Conclusion

This study developed and validated an integrated optimization framework that combines IIoT sensing, edge computing, Digital Twin modeling, and hybrid reinforcement learning-based optimization within smart manufacturing environments. The empirical results from simulation and industrial pilot implementation demonstrate significant improvements in latency reduction, throughput enhancement, downtime minimization, and energy efficiency compared to conventional cloud-based architectures. The integration of edge processing with real-time Digital Twin synchronization proved particularly effective in reducing response delays and enabling adaptive decision-making under dynamic production conditions.

Overall, the findings confirm that a unified edge-enabled Digital Twin framework provides a scalable, resilient, and energy-aware solution for Industry 4.0 manufacturing systems. By distributing intelligence across edge and cloud layers while maintaining centralized analytical capabilities, the proposed architecture achieves a balanced trade-off between real-time responsiveness and computational scalability. This research contributes to the advancement of intelligent industrial computing by demonstrating that hybrid AI-driven optimization can enhance operational performance while supporting sustainability and long-term digital transformation objectives.

Suggestions

Future research should explore the integration of multi-agent reinforcement learning and federated learning mechanisms to further enhance scalability and decentralized intelligence at the edge. Incorporating privacy-preserving learning approaches would allow distributed industrial nodes to collaboratively improve optimization policies without exposing sensitive operational data. Additionally, further investigation into energy-aware orchestration strategies and adaptive workload balancing algorithms could strengthen system robustness in large-scale heterogeneous industrial deployments.

From an industrial implementation perspective, organizations adopting this framework should prioritize workforce upskilling, cybersecurity reinforcement, and standardized interoperability protocols to ensure sustainable deployment. Gradual pilot-based integration is recommended to minimize operational risks and facilitate system adaptation to existing production infrastructures. Continuous monitoring and iterative model refinement will be essential to maintain long-term performance stability in rapidly evolving smart factory ecosystems.

References

- Azevedo, A., & Almeida, A. H. (2024). Smart factories-Design and results of a new course in a MSc curriculum of engineering. *IEEE Global Engineering Education Conference (EDUCON)*. <https://doi.org/10.1109/EDUCON60312.2024.10578669>
- Baldoni, G., Cominardi, L., Groshev, M., De La Oliva, A., & Corsaro, A. (2023). Managing the far-edge: Are today's centralized solutions a good fit? *IEEE Consumer Electronics Magazine*, 12(3), 51-61. <https://doi.org/10.1109/MCE.2021.3082503>
- Barakat, M., Saeed, R. A., & Edam, S. (2023). A comparative study on cloud and edge computing: A survey on current research activities and applications. *Proceedings of MI-STA 2023*, 679-684. <https://doi.org/10.1109/MI-STA57575.2023.10169821>
- Boomiga, S. S., & Prasanna Venkatesan, V. (2020). A generic model for scheduling IoT jobs at the edge. In *Lecture Notes on Data Engineering and Communications Technologies* (Vol. 31, pp. 370-377). https://doi.org/10.1007/978-3-030-24643-3_44
- Chen, G., Wang, P., Feng, B., Li, Y., & Liu, D. (2020). The framework design of smart factory in discrete manufacturing industry based on cyber-physical system. *International Journal of Computer Integrated Manufacturing*, 33(1), 79-101. <https://doi.org/10.1080/0951192X.2019.1699254>
- Condori, P. P. C. (2022). Digital twin in development of products. In *Digital Twin Technology: Fundamentals and Applications* (pp. 205-218). <https://doi.org/10.1002/9781119842316.ch13>
- de Moura, R. L., Brasil, T. M., Werner, L. B., Dal' Col, C. J. B., Gonzalez, A., & Quadri, S. (2021). Technologies for industrial Internet of Things (IIoT): Guidelines for edge computing adoption in the industry. In *LNICST* (Vol. 372, pp. 259-273). https://doi.org/10.1007/978-3-030-76063-2_19

- Fancy, C., Anand, M., & Sheeba, T. M. (2024). Blockchain for edge association in digital twin empowered 6G networks. In *Artificial Intelligence-Enabled Blockchain Technology and Digital Twin for Smart Hospitals* (pp. 123-151). <https://doi.org/10.1002/9781394287420.ch7>
- Faria, R. D. R., Capron, B. D. O., de Souza Jr, M. B., & Secchi, A. R. (2023). One-layer real-time optimization using reinforcement learning: A review with guidelines. *Processes*, 11(1), 123. <https://doi.org/10.3390/pr11010123>
- Gautami, A., & Gowthaman, N. (2021). A holistic approach: Issues and challenges in autonomic computation toward Industry 4.0. In *EAI/Springer Innovations in Communication and Computing* (pp. 111-121). https://doi.org/10.1007/978-3-030-71756-8_6
- Ghosh, S., Sarkar, S. K., Roy, B., & Paul, S. (2024). Challenges and innovations in digital twin creation. In *Exploring the Advancements and Future Directions of Digital Twins in Healthcare 6.0* (pp. 86-104). <https://doi.org/10.4018/978-8-3693-5893-1.ch005>
- Huang, H., Zhang, J., & Liu, Y. (2023). IOWA-based dynamic trusted assessment model for system operational state behavior. https://doi.org/10.1007/978-981-99-1260-5_28
- Konur, S., Lan, Y., Thakker, D., Morkyani, G., Polovina, N., & Sharp, J. (2023). Towards design and implementation of Industry 4.0 for food manufacturing. *Neural Computing and Applications*, 35(33), 23753-23765. <https://doi.org/10.1007/s00521-021-05726-z>
- Kuchtíková, N., & Maryska, M. (2023). A comparison of cloud computing vs fog vs edge for IIoT sensors. *IDIMT 2023 Proceedings*, 151-159. <https://doi.org/10.35011/IDIMT-2023-151>
- Langlotz, P., Klar, M., Yi, L., Hussong, M., Sousa, F. J. P., & Aurich, J. C. (2022). Concept of hybrid modeled digital twins and its application for an energy management of manufacturing systems. *Procedia CIRP*, 112, 549-554. <https://doi.org/10.1016/j.procir.2022.09.098>
- Mashaly, M. (2021). Connecting the twins: A review on digital twin technology & its networking requirements. *Procedia Computer Science*, 184, 299-305. <https://doi.org/10.1016/j.procs.2021.03.039>
- Mourtzis, D., Angelopoulos, J., & Panopoulos, N. (2024). Industry 4.0 and smart manufacturing. In *Comprehensive Materials Processing* (2nd ed., Vol. 3, p. V3:14--V3:38). <https://doi.org/10.1016/B978-0-323-96020-5.00010-8>
- Muzammal, S. M., Tayyab, M., Zahra, F., Jhanjhi, N. Z., & Ashraf, H. (2024). Smart factories greener future: A synergy of Industry 4.0 and sustainability. In *Digital Transformation for Improved Industry and Supply Chain Performance* (pp. 70-92). <https://doi.org/10.4018/979-8-3693-5375-2.ch004>
- Padmini, M. S., & Kuzhalvaimozhi, S. (2023). Critical analysis of life span improvement techniques in energy constraints edge IoT devices. *SN Computer Science*, 4(3), 221. <https://doi.org/10.1007/s42979-022-01601-3>
- Peng, P., & Soljanin, E. (2024). Redundancy management for fast service (rates) in edge computing systems. *IEEE/ACM Transactions on Networking*. <https://doi.org/10.1109/TNET.2024.3507372>
- Polsonetti, C. (2020). Automation at the Industrial IoT edge. *Control Engineering*, 67(9), P1--P3.
- Powell, B. K. M., Machalek, D., & Quah, T. (2020). Real-time optimization using reinforcement learning. *Computers and Chemical Engineering*, 143, 107077. <https://doi.org/10.1016/j.compchemeng.2020.107077>
- Raghav, Y. Y., & Kait, R. (2024). Edge computing empowering distributed computing at the edge. In *Emerging Trends in Cloud Computing Analytics, Scalability, and Service Models* (pp. 67-83). <https://doi.org/10.4018/979-8-3693-0900-1.ch003>
- Ramarumo, A., Selvaraj, R., Segwele, T., Kuthadi, V., & Thapelo, T. S. (2024). Machine learning driven energy efficiency framework using digital twin: A review. 2024 *IEEE 4th International Conference on ICT in Business Industry and Government (ICTBIG 2024)*. <https://doi.org/10.1109/ICTBIG64922.2024.10911267>
- Renteria-Marquez, I. A., Basaldua, J. C. G. M., Aguirre, O., Lara-Medrano, B. E., & Tseng, T.-L. (2024). Cyber-physical production system framework for production scheduling in smart factories. *Proceedings of the Winter Simulation Conference*, 1740-1748. <https://doi.org/10.1109/WSC63780.2024.10838901>
- Resman, M., Protner, J., Simic, M., & Herakovic, N. (2021). A five-step approach to planning data-driven digital twins for discrete manufacturing systems. *Applied Sciences*, 11(8), 3639. <https://doi.org/10.3390/app11083639>
- Rochford, L. (2024). Edge or cloud? Taking the best computing direction for industrial applications. *Electronics World*, 129(2032), 40-41.
- Ryalat, M., Franco, E., Elmoaqet, H., Almtireen, N., & Al-Refai, G. (2024). The integration of advanced mechatronic systems into Industry 4.0 for smart manufacturing. *Sustainability*, 16(19), 8504. <https://doi.org/10.3390/su16198504>
- Sampath, T., Dutt, A., Veeraiyah, V., Aishwarya, B. K., Lal, K., & Kapila, D. (2023). Analyzing the effect of edge computing on real-time data processing and latency reduction. 2023 *10th IEEE Uttar Pradesh Section International Conference (UPCON 2023)*, 623-627. <https://doi.org/10.1109/UPCON59197.2023.10434652>
- Shi, Z., Xie, Y., Xue, W., Chen, Y., Fu, L., & Xu, X. (2020). Smart factory in Industry 4.0. *Systems Research and Behavioral Science*, 37(4), 607-617. <https://doi.org/10.1002/sres.2704>
- Soleymanizadeh, H., Qu, Q., Bamakan, S. M. H., & Zanfirchi, S. M. (2023). Digital twin empowering manufacturing paradigms: Lean, agile, just-in-time (JIT), flexible, resilience, sustainable. *Procedia Computer Science*, 221, 1258-1267. <https://doi.org/10.1016/j.procs.2023.08.114>

- Sun, L. (2024). Digital transformation in the manufacturing industry: The impact of Industry 4.0 and the case of Tesla. In *Exploring the Financial Landscape in the Digital Age - Proceedings of ICFMDE 2023* (pp. 697-703). <https://doi.org/10.1201/9781003508816-100>
- Suvarna, M., Yap, K. S., Yang, W., Li, J., Ng, Y. T., & Wang, X. (2021). Cyber-physical production systems for data-driven, decentralized, and secure manufacturing-A perspective. *Engineering*, 7(9), 1212-1223. <https://doi.org/10.1016/j.eng.2021.04.021>
- Tang, X., Schneider, T., Kamil, S., Panda, A., Li, J., & Panozzo, D. (2020). EGGS: Sparsity-specific code generation. *Computer Graphics Forum*, 39(5), 209-219. <https://doi.org/10.1111/cgf.14080>
- Terkaj, W., Annoni, M., Martinez, B. O., Pessot, E., Sortino, M., & Urgo, M. (2024). Digital twin for factories: Challenges and industrial applications. In *Lecture Notes in Mechanical Engineering* (pp. 255-274). https://doi.org/10.1007/978-3-031-41163-2_13
- Thakkar, K., Patel, A., Budhrani, A., Patel, K., Patel, S., & Nayak, A. (2023). Edge computing: Architecture, implications and future with latest trends. *Proceedings of ICPCSN 2023*, 1065-1070. <https://doi.org/10.1109/ICPCSN58827.2023.00181>
- Thodoroff, P., Li, W., & Lawrence, N. D. (2022). Benchmarking real-time reinforcement learning. *Proceedings of Machine Learning Research*, 181, 26-41.
- Tiwari, S., & Shukla, A. (2024). Digital twins in industry: Real-world applications and innovations. In *Transforming Industry Using Digital Twin Technology* (pp. 1-18). https://doi.org/10.1007/9783031585234_1
- Uehara, T., & Kasamatsu, D. (2024). A method of synchronous control for stream processing in digital twin environment. *2024 IEEE 13th Global Conference on Consumer Electronics (GCCE 2024)*, 1097-1098. <https://doi.org/10.1109/GCCE62371.2024.10760555>
- Yang, H., Kumara, S., Bukkapatnam, S. T. S., & Tsung, F. (2019). The internet of things for smart manufacturing: A review. *IIEE Transactions*, 51(11), 1190-1216. <https://doi.org/10.1080/24725854.2018.1555383>
- Zhou, J., Liu, J., & Chen, Z. (2023). Task offloading in mobile edge computing based on deep reinforcement learning. *Proceedings of SPIE*, 12462, 124622T. <https://doi.org/10.1117/12.2660982>