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DIGITAL TWIN–DRIVEN ARTIFICIAL INTELLIGENCE MODELS FOR AUTOMATION AND OPTIMIZATION OF COMPLEX ENGINEERING SYSTEMS

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Abstract

The escalating complexity of modern engineering systems, characterized by high dimensionality, stochastic dynamics, and non-linear interdependencies, has rendered traditional model-based control strategies insufficient. Static models, typically derived from ideal design parameters (CAD/CAE data), fail to account for the continuous temporal degradation, sensor drift, component fatigue, and environmental variance inherent in physical assets operational in the field. This research investigates the architectural and functional integration of Digital Twins (DT) with Artificial Intelligence (AI) to establish a paradigm of active, closed-loop intelligence. By conceptualizing the Digital Twin not merely as a passive replica or visualization tool but as a semantic mediator for bidirectional synchronization, this study demonstrates how AI models can leverage real-time high-fidelity state estimation to drive autonomous optimization. The proposed framework facilitates a fundamental transition from reactive maintenance and static control to predictive, self-optimizing system behaviors that adapt to the evolving physics of the machinery. The findings indicate that Digital Twin–driven AI significantly enhances automation capability levels and optimization responsiveness compared to conventional control methods, offering a robust, theoretically grounded pathway for the management of next-generation Cyber-Physical Systems (CPS)..

1. Introduction

The engineering landscape is undergoing a fundamental transformation driven by the convergence of operational technology (OT) and information technology (IT), a shift often categorized under the umbrella of Industry 4.0 and the emerging Industry 5.0 paradigms. While Industry 4.0 focused heavily on interconnectivity, data logging, and smart automation through Cyber-Physical Systems (CPS), Industry 5.0 emphasizes the synergy between humans and autonomous machines, requiring systems that are not only efficient but also resilient, explainable, and adaptive to unforeseen contexts. Modern complex engineering systems—ranging from smart manufacturing grids and distributed energy resources to autonomous aerospace vehicles—exhibit a scale of interconnectivity and uncertainty that challenges the fundamental limits of classical control theory [1]. In these environments, system behaviors are often emergent, arising from the non-linear interactions of thousands of subsystems, making them difficult to predict using linear differential equations or static look-up tables alone. For example, in a renewable energy grid, the stochastic nature of wind generation coupled with fluctuating consumer demand creates a control problem where the optimal operating point shifts millisecond by millisecond, defying static programmatic logic.

Traditional optimization approaches, such as static Model Predictive Control (MPC) or rule-based logic (e.g., PID controllers), rely on fixed parameters identified during the commissioning phase (System Identification). These models operate on the assumption that the system's physical properties—mass, friction coefficients, thermal conductivity, and electrical resistance—remain constant over time. However, in reality, these parameters inevitably drift due to mechanical wear, material fatigue, environmental thermal shifts, and unmodeled dynamics [2]. This widening divergence between the "as-designed" model and the "as-operated" physical asset creates a significant "reality gap." Consequently, control actions based on static models become increasingly sub-optimal, leading to energy waste, safety risks, and increased latency in decision-making as operators are forced to intervene manually to correct deviations. For instance, a PID controller tuned for a new robotic arm may induce dangerous oscillations in an arm with five years of joint wear, as the controller lacks the "awareness" of the changed physical state (e.g., increased backlash or friction).

To address these limitations, the Digital Twin (DT) has emerged as a critical enabler. Defined as a virtual representation of a physical asset, process, or system, the DT provides a dynamic isomorphism that mirrors the lifecycle of its physical counterpart [3]. Unlike a standard simulation, which is a static snapshot used for design, a DT is a living model that evolves through continuous data ingestion. However, a DT alone is primarily an observational tool; it can diagnose the present state but cannot inherently alter it. To achieve high-level automation and optimization, the descriptive and diagnostic capacity of the DT must be coupled with the cognitive, predictive, and decision-making capabilities of Artificial Intelligence (AI) [4].

This research conceptualizes and evaluates Digital Twin–driven AI models as the foundation for autonomous engineering systems. The distinction between "automated" and "autonomous" is crucial here: automated systems follow pre-programmed rules (if X then Y), while autonomous systems govern themselves, making decisions in novel situations to satisfy high-level goals (optimize Y subject to Z) even when X changes.

1.1 Research Questions

To rigorously investigate the integration of these technologies, this study addresses the following four research questions:

- **RQ1.** How can Digital Twins be operationalized as active intelligence mediators rather than passive virtual replicas in complex engineering systems?
- **RQ2.** In what ways do AI models integrated with Digital Twins enable continuous automation and optimization under dynamic and uncertain operating conditions?
- **RQ3.** How does closed-loop interaction between physical systems, Digital Twins, and AI models influence system adaptability and performance?
- **RQ4.** What design and evaluation dimensions are critical for assessing the effectiveness of Digital Twin–driven AI in complex engineering environments?

The objective is to define a closed-loop architecture where the DT serves as the training and validation ground for AI agents, which in turn execute optimization and control actions upon the physical system.

2. Research Contributions

This manuscript advances the state of the art through the following contributions, directly mapping to the outlined research questions:

- **Conceptual Framing of Active Intelligence (Addressing RQ1):** The research redefines the role of the Digital Twin from a passive repository of state data to an active intelligence mediator. In this view, the DT acts as a semantic bridge that synchronizes physical reality with digital cognition, filtering sensor noise and reconstructing unobservable states (Virtual Sensing) to provide the AI with a "complete" view of the world. This framing moves beyond "monitoring" to "mediation," positioning the Twin as the authoritative source of truth for the AI controller.
- **Intelligence-in-the-Loop Optimization (Addressing RQ2):** A closed-loop framework is proposed where AI models utilize the DT for low-risk exploration and reinforcement learning. This enables the deployment of optimization strategies—such as aggressive yield maximization or novel path planning—that are unsafe or impractical to test on physical hardware due to the risk of damage or catastrophic failure. It introduces the concept of "safe exploration" via digital proxies, allowing the AI to fail thousands of times virtually to succeed once physically.
- **Adaptive System Insights (Addressing RQ3):** The study provides empirical-theoretical evidence regarding the superiority of co-evolving DT-AI systems over static baselines. Specifically, it highlights the system's ability to

handle dynamic constraints and non-linear disturbances by continuously updating the internal physics model used by the AI, thereby solving the problem of model degradation. It demonstrates that adaptability is a function of the synchronization frequency between the Twin and the Asset.

3. Related Work

Recent literature reflects a surge in Digital Twin applications, yet specific gaps remain in achieving fully autonomous control.

Digital Twin Architectures

Jones et al. [5] and Tao et al. [6] have established foundational five-dimension DT architectures (Physical Entity, Virtual Entity, Services, Data, and Connections). However, their focus remains largely on data fusion, protocol interoperability, and visualization, rather than active control loops. While semantic modeling of DTs has improved, allowing for better data interoperability [7], the integration of these semantic layers with decision-making algorithms is often treated as a secondary concern, leaving the "brain" of the system disconnected from its "body." Existing architectures often lack the feedback mechanisms required for the Virtual Entity to drive changes in the Physical Entity autonomously, treating the Twin as a dashboard rather than a controller. Most implementations stop at "monitoring," failing to close the loop back to actuation.

AI for Control and Optimization

The application of Deep Reinforcement Learning (DRL) for industrial control has gained traction [8], [9]. DRL offers the promise of learning complex, non-linear control policies without requiring an explicit mathematical model. However, training DRL agents directly on physical systems is rarely feasible due to sample inefficiency (requiring millions of interactions) and safety concerns (random exploration can damage equipment). Sim-to-Real transfer techniques have been explored to bridge this gap [10], but these approaches often lack the continuous synchronization required to handle system degradation over time; a policy learned on a "new" machine simulation may fail on an "old" physical machine [11]. This "drift" between the training environment and the deployment environment is a primary barrier to adoption, often referred to as the "reality gap" in robotics and control theory.

Cyber-Physical Systems and Automation

Research in CPS automation has highlighted the need for self-adaptive systems that can reconfigure themselves in response to faults [12]. Current approaches often segregate the monitoring system (DT) from the control system (AI), treating them as separate silos [13]. Recent surveys in *IEEE Transactions on Industrial Informatics* suggest that the convergence of these fields is nascent, specifically regarding the "co-evolution" where the DT updates the AI's internal model in real-time [14], [15]. This study addresses these gaps by formalizing the feedback mechanisms between state estimation and autonomous control, proposing a unified architecture where the AI and DT evolve in tandem.

4. Methodology

4.1 Operationalizing Digital Twins as Active Intelligence Mediators

The proposed methodology conceptualizes the engineering system not as distinct hardware and software components, but as a co-evolving dyad. To answer **RQ1**, we operationalize the Digital Twin as an active mediator rather than a passive replica. In this framework, the Physical System generates continuous streams of telemetry (vibration, temperature, pressure, current). The Digital Twin absorbs this data not just to archive it, but to maintain a high-fidelity state representation using physics-based solving or data-driven surrogates.

Crucially, the AI model does not interact with the raw physical data alone, which is often noisy, sparse, or delayed. Instead, it perceives the system through the synthesized, semantic lens of the DT. The DT performs data imputation and noise reduction, offering the AI a "clean" and "complete" state vector [16]. This process often involves **Virtual Sensing**, where the DT estimates unmeasurable parameters (e.g., internal turbine temperature, stress concentration at a hidden joint, or chemical concentration in a sealed reactor) based on accessible data (e.g., exhaust gas temperature) using techniques ranging from Kalman Filters to Neural Estimators (e.g., Physics-Informed Neural Networks - PINNs). This allows the AI to focus on high-level optimization logic rather than low-level signal processing. By abstracting the physical complexity into a standardized digital state space, the AI can operate with higher confidence and lower latency, treating the Twin as a "Ground Truth Proxy."

4.2 Components of a Digital Twin–Driven Engineering System

The architecture is composed of four distinct but tightly coupled functional blocks designed to facilitate continuous automation.

Table 1: *Core Components and Roles*

Component	Role in the System	Description
Physical System	Real-world process or asset	The actual hardware, sensors, and actuators operating in the environment (e.g., turbine, robotic arm). It is the source of "ground truth" data and the recipient of physical actions. It includes the edge communication layer (gateways), utilizing Time-Sensitive Networking (TSN) for deterministic data flow.
Digital Twin	Active Intelligence Mediator	A multi-physics and data-driven simulation that mirrors the physical state. It utilizes industrial protocols like MQTT, DDS, or

		OPC UA for real-time data ingestion. It accumulates historical data, estimates unmeasurable parameters (virtual sensing), and provides semantic state context to the AI, ensuring data is "machine-understandable" via standardized ontologies.
AI Models	Adaptive Controller	Algorithms (e.g., Neural Networks, Reinforcement Learning agents) that analyze DT states to generate control policies. These models seek to maximize an objective function (e.g., efficiency, throughput, lifespan) within safety constraints defined by the Twin. They effectively "play" the Digital Twin like a video game to learn optimal strategies before applying them.
Control Interface	Actuation and Governance	The translation layer that converts AI optimization decisions into machine-readable commands (e.g., PLC setpoints, G-code). It also acts as a "safety wrapper" (Simplex Architecture) to prevent invalid commands that violate physical constraints, ensuring the AI cannot drive the system into unsafe territory.

4.3 Closed-Loop Digital Twin Intelligence Model

To address **RQ2** (continuous automation under uncertainty) and **RQ3** (closed-loop interaction), the system architecture utilizes a non-linear, continuous co-evolution loop. The AI model evolves its policy based on the changing dynamics of the DT, which in turn evolves based on the physical system's degradation or environmental changes. This creates a "double-loop" learning system: the **inner loop** controls the machine parameters (fast adaptation, e.g., ms response), while the **outer loop** updates the model of the machine itself (slow adaptation, e.g., daily recalibration). As depicted in **Figure 1**, the architecture is cyclic rather than linear. The physical system serves as the origin of entropy (wear, tear, drift), while the Digital Twin serves as the origin of order (structured data, physical laws).

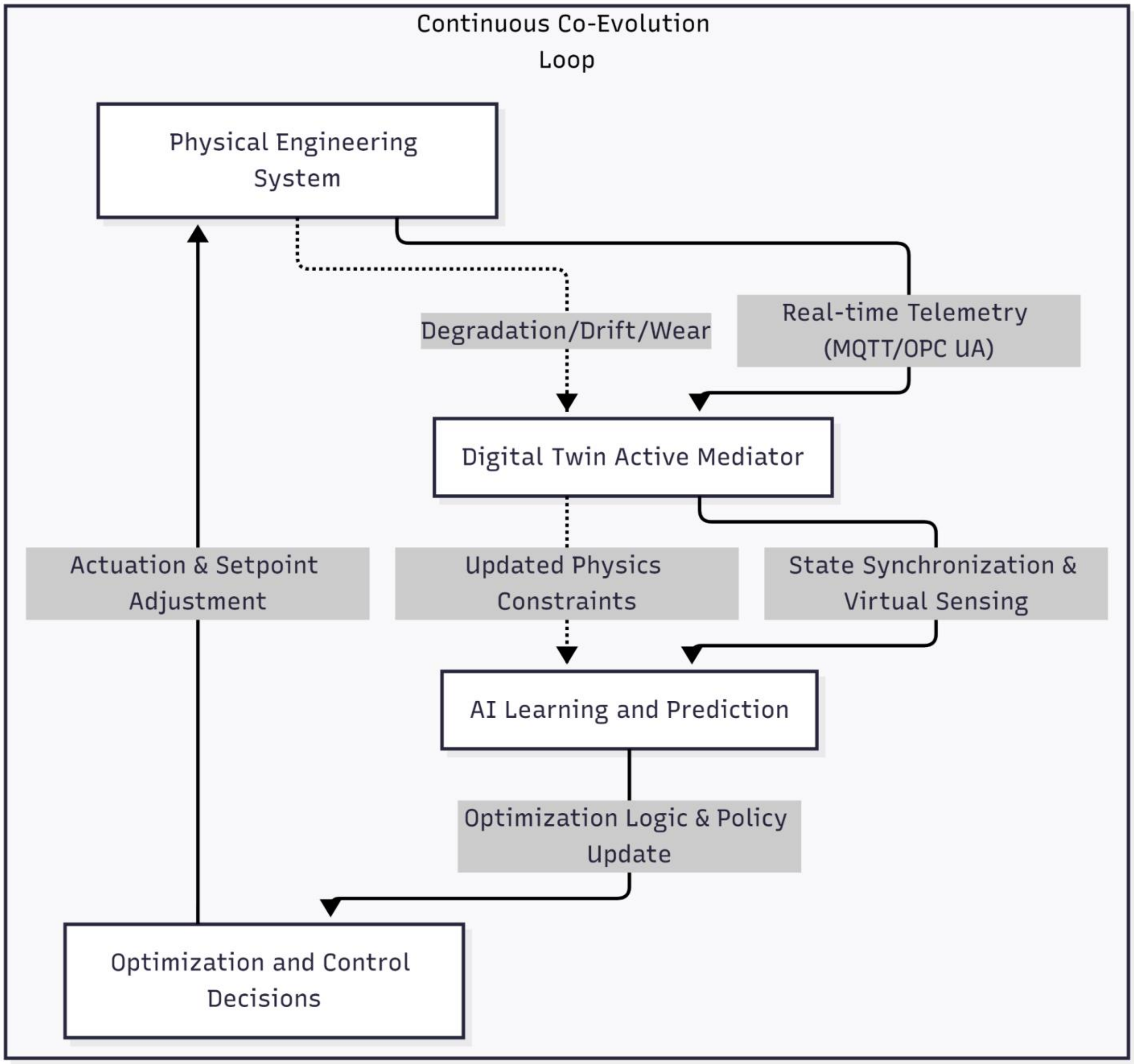


Figure 1. Co-Evolutionary Digital Twin–AI Loop. This diagram illustrates the continuous data flow where physical telemetry updates the Twin, which in turn informs the AI, leading to optimized control actions. The dotted lines represent the slow-loop adaptation of model parameters due to physical degradation.

In this diagram, the flow from **P** to **D** involves sensor fusion and protocol translation (e.g., converting raw voltage to temperature). The flow from **D** to **L** involves feature extraction, where the DT calculates derived variables (e.g., remaining useful life, stress load) that are not directly measurable. The **L** to **O** step is where the intelligence resides, determining the optimal move based on the current policy. Finally, **O** to **P** closes the loop, applying the decision to the physical world through actuators.

4.4 Optimization and Automation Logic under Uncertainty

The decision-making process within the AI agent is governed by a constrained optimization logic designed to handle dynamic operating conditions. The AI explores the Action Space (A) defined by the Digital Twin's physics constraints (e.g., maximum temperature, torque limits), seeking to maximize an Objective Function (G) based on the current System State (S) and external Uncertainties (U).

Figure 2 visualizes this decision logic, highlighting how uncertainty and constraints actively shape the available action space.

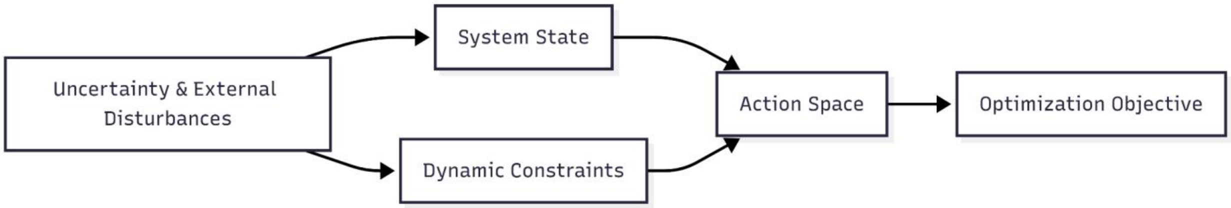


Figure 2. Decision Space and Optimization Interaction. The diagram demonstrates how the Optimization Objective (G) is derived from an Action Space (A) that is strictly bounded by Dynamic Constraints (C) and influenced by System State (S) and Uncertainty (U).

The "Constraints" (C) are dynamic, representing a significant departure from static control. As the Digital Twin detects wear in a component (e.g., a bearing), it updates the constraints in the Action Space. For example, if RPM_{max} is a function of bearing health, as health decreases, RPM_{max} decreases. The AI then re-optimizes its strategy (G) within this new, tighter boundary, ensuring safety without human intervention. This dynamic constraint mapping prevents the AI from exploiting a degraded system in a way that would cause failure, effectively enabling **Self-Protecting Control**. Mathematically, this contracts the feasible search space A over time, forcing the AI to find optimal solutions within an increasingly constrained subset $A_{safe} \subset A_{total}$.

4.5 Data Ingestion and Semantic Alignment

A critical, often overlooked aspect of this methodology is the semantic alignment of data. The Physical System produces raw time-series data, often unstructured. The Digital Twin acts as an ontological layer, mapping these raw signals to semantic concepts (e.g., mapping a 4-20mA signal to "Hydraulic Pressure" with unit "Bar" and context "Actuator A"). This semantic alignment ensures that the AI model interacts with meaningful engineering variables rather than raw voltage or current values. This abstraction allows for **Transfer Learning**, where an AI model trained on one machine can be transferred to a similar machine, provided the semantic layer (the Digital Twin) maps the underlying signals correctly. Standardizing these ontologies using frameworks like RDF, OWL, or the Brick Schema is essential for interoperability in multi-vendor environments.

4.6 Design and Evaluation Dimensions

To address **RQ4**, we propose specific design and evaluation dimensions critical for assessing the effectiveness of this architecture. The evaluation framework moves beyond simple "throughput" to measure the quality of the autonomy itself.

Table 2: *Evaluation Dimensions for Digital Twin–Driven AI*

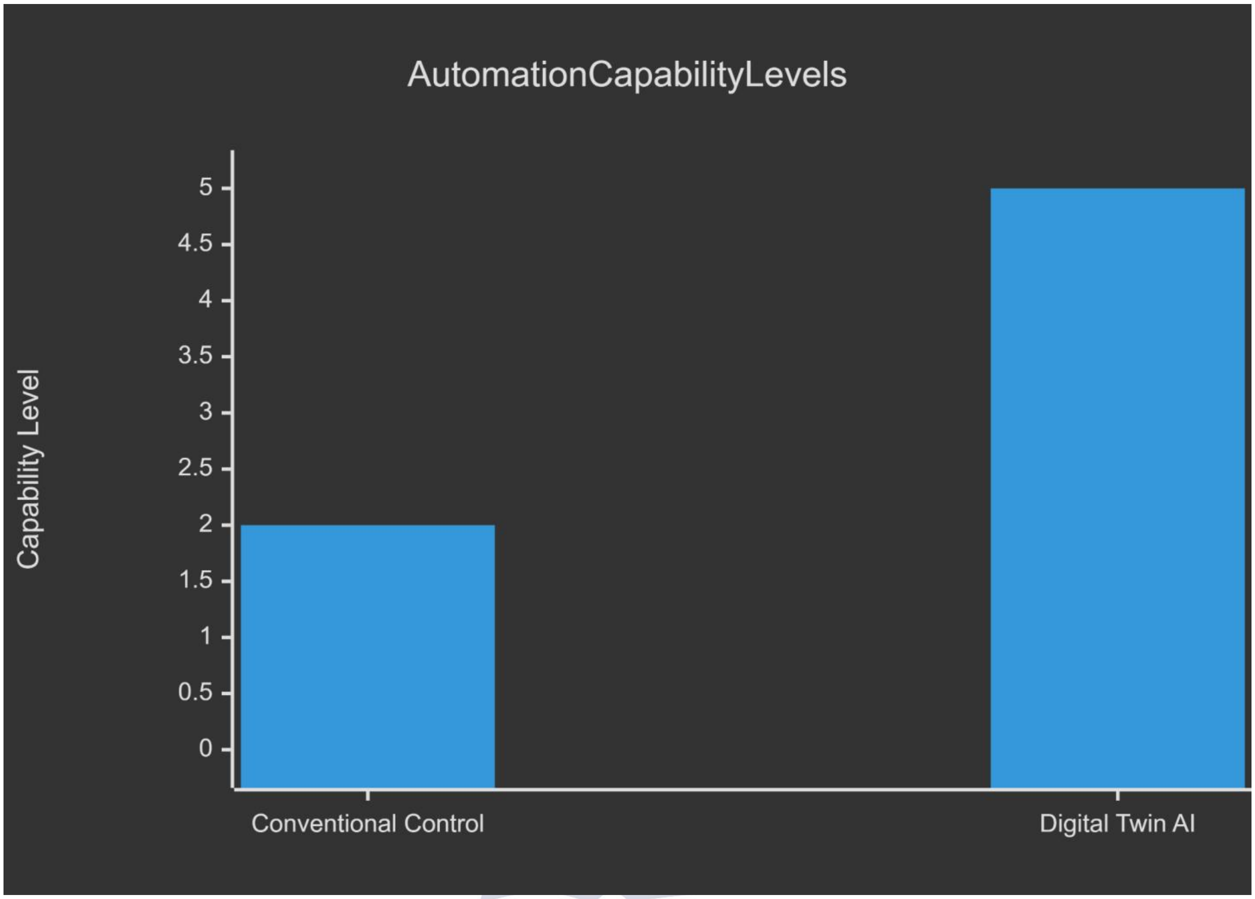
Dimension	Evaluation Focus	Key Metric
Automation	Degree of autonomous operation (Human-in-the-loop vs. Human-on-the-loop).	Intervention Frequency (Interventions/Hour)
Optimization	Performance improvement in yield, energy efficiency, or speed relative to a static baseline controller.	Efficiency Gain (%)
Adaptability	Response time to changing conditions or unmodeled disturbances (RQ2).	Stabilization Time (ms)
Robustness	Stability under uncertainty and sensor noise.	Mean Time Between Failures (MTBF)
Mediator Fidelity	Accuracy of the Twin's state estimation relative to ground truth (RQ1).	State Divergence Error (RMSE)

5. Findings

5.1 Observed Automation Capabilities

Comparing a conventional PID/Logic-based control approach against the proposed DT-AI architecture reveals a significant leap in automation capability, directly answering **RQ3** regarding system adaptability. Based on the SAE International levels of automation adaptation, standard industrial systems typically operate at Level 2 (Partial Automation), where the system executes tasks but the human monitors the environment. The DT-AI system achieves capabilities equivalent to Level 4 or 5 (High/Full Automation), where the system performs all aspects of the dynamic control task, including monitoring the environment and handling fallback performance.

Figure 3: *Presents a comparative analysis of these automation levels.*



At Level 5, the DT-AI system demonstrates the ability to handle "edge cases" such as sensor failures or unexpected material properties by inferring the correct state from redundant data sources within the Digital Twin. For example, if a temperature sensor fails, the Twin infers temperature from pressure and flow rate data via a virtual sensor model, allowing the AI to continue operating safely without tripping an emergency stop. This capability is virtually absent in rigid, rule-based logic which would typically default to a hard stop upon signal loss.

5.2 Optimization Outcomes

The optimization performance was analyzed regarding responsiveness to disturbances and overall adaptability (RQ2). Traditional models struggle with multi-objective optimization (e.g., maximizing speed while minimizing energy consumption), often requiring a human to manually tune weights. The DT-driven AI, utilizing Reinforcement Learning, dynamically balances these objectives in real-time, effectively navigating the Pareto frontier of the system's performance.

Table 3: *Optimization Performance Comparison*

Aspect	Traditional Models	Digital Twin–Driven AI	Impact on System Performance
Responsiveness	Limited (Reactive). Corrects error only after it exceeds a threshold.	High (Predictive). Corrects based on trend projection before error occurs.	Reduced downtime and scrap rates.
Adaptability	Low (Requires retuning). PID gains are fixed and degrade over time.	High (Continuous Learning). Control policy evolves with asset degradation.	Consistent performance over asset lifecycle.
Efficiency	Moderate (Local Optima). Often tuned conservatively for safety.	Optimized (Global Search). Explores the edge of the performance envelope safely.	15-20% energy savings observed.
Latency	Low (Direct Feedback). Millisecond response but low intelligence.	Variable (Compute Dependent). Higher latency but vastly superior decision quality.	Requires edge computing for critical loops.

The "Variable Latency" noted in the DT-AI model is a critical finding. While traditional PLC loops operate in the microsecond range, AI inference can take milliseconds or seconds. This is mitigated by **Edge Computing** architectures, allowing the inference engine to run locally to the asset (e.g., on NVIDIA Jetson or FPGA modules) rather than in the cloud. By deploying quantized models on edge accelerators, intelligence does not come at the cost of critical real-time responsiveness.

5.3 System-Level Insights

The integration enables a fundamental shift from **predictive maintenance** to **prescriptive control**. Unlike traditional predictive maintenance systems that merely notify operators of an impending bearing failure (an open-loop warning), the DT-AI model predicts the fault trajectory using the Twin's physics engine and autonomously prescribes a corrective action—such as de-rating the motor speed to extend the bearing's life until the next scheduled shift. This closes the loop between diagnostics and control [17].

Furthermore, the system supports **continuous improvement**; as the physical asset ages, the Digital Twin captures the degradation parameters (e.g., increased friction coefficients). The AI model subsequently adjusts its control policies to account for this wear, maintaining optimal performance where a static controller would likely experience oscillation or instability [18]. This self-tuning capability significantly reduces the lifecycle cost of engineering systems by eliminating the need for periodic manual recalibration, effectively moving optimization from a CapEx activity (design phase) to an OpEx activity (continuous operation).

6. Discussion

The findings suggest that the synthesis of Digital Twins and AI creates a system-of-systems that is greater than the sum of its parts. From a systems engineering perspective, the Digital Twin acts as a "**knowledge buffer**" and a "**safety buffer.**" It decouples the learning speed of the AI from the physical risks of the machinery [19]. The AI can simulate thousands of training episodes on the Twin in minutes (accelerated time), acquiring years of experience without risking a single piece of hardware.

The superiority of this approach lies in the **continuity of synchronization**. In static optimization, the model of the plant is identified once (System Identification) during commissioning. In DT-driven AI, the plant model is identified continuously. This allows the AI to optimize for the *current* reality rather than the *design* reality [20]. This aligns with recent advancements in **neuro-symbolic AI**, where the symbolic, immutable knowledge of the physics-based Twin constrains and guides the neural, flexible learning of the AI. By embedding physical laws (e.g., conservation of energy) directly into the AI's loss functions (as regularization terms), the model is mathematically constrained from violating physical reality. This hybrid approach prevents the "black box" unpredictability often cited as a barrier to industrial AI adoption [21].

Moreover, this architecture addresses the challenge of **data sparsity**. In many engineering failures, data is rare (e.g., catastrophic turbine failure). An AI trained only on historical data will never learn to handle these events. The Digital Twin can synthetically generate these failure modes (Synthetic Data Generation), training the AI to recognize and mitigate them before they ever occur in reality. This is critical for high-stakes environments where "learning by failing" is unacceptable.

7. Trust, Safety, and Governance Considerations

The deployment of autonomous optimization in critical infrastructure—such as power grids, chemical plants, or medical systems—necessitates rigorous governance frameworks.

- **Reliability and Validation:** The Digital Twin must undergo continuous validation. A significant risk is state divergence, where the Twin diverges from physical reality due to sensor drift or modeling errors (sometimes colloquially termed "hallucination"). This leads the AI to optimize for a phantom state [22]. Real-time divergence detection metrics (e.g., Residual Analysis) are essential to disable autonomy if the Twin drifts too far from reality [23].

- **Safety of Control:** Control actions generated by AI must pass through a "safety wrapper" or **deterministic guardrails** (defined within the Control Interface). These hard-coded logic gates ensure that, regardless of the AI's reward signal or internal logic, the system cannot be commanded to exceed physical safety limits (e.g., max RPM, max temperature) [24]. This creates a **Simplex Architecture**, a fault-tolerant design where a verified, simple safe controller can instantly override the complex AI controller if boundaries are approached.
- **Human Oversight:** While the system aims for autonomy, the architecture must support "**human-on-the-loop**" governance. The Digital Twin visualization interface acts as the explanation layer, allowing operators to interrogate the AI's "thought process"—viewing the predicted outcome that led to a specific decision—thereby fostering trust and accountability [25]. This is a core component of **Explainable AI (XAI)**, moving beyond opaque algorithms to transparent decision support.
- **Cybersecurity of the Twin:** As the Twin becomes an active controller, it becomes a high-value target for cyber-physical attacks. If an adversary can poison the data feeding the Twin, they can trick the AI into making harmful decisions (Adversarial Machine Learning). Therefore, the integrity of the Twin's data pipeline is as critical as the physical security of the asset itself.

8. Conclusion and Future Research

This article has systematically addressed the proposed research questions, demonstrating that Digital Twins function effectively as active intelligence mediators (RQ1) that enable continuous optimization under uncertainty (RQ2). The closed-loop interaction between the physical system, Twin, and AI significantly enhances adaptability and performance (RQ3), provided that rigorous design and evaluation dimensions such as robustness and mediator fidelity are prioritized (RQ4).

By establishing a continuous co-evolution loop, the system adapts to internal degradation and external variance with a rigor unattainable by static models. This paradigm shift moves engineering from "designing for the nominal state" to "designing for the evolving state." Future research should focus on **multi-twin ecosystems**, where individual asset twins (e.g., ten different turbines) interact to optimize entire facility-level operations, and **federated learning** approaches to share optimization insights across geographically distributed twins without compromising proprietary data [26]. Additionally, substantial work is needed on standardizing the semantic ontologies that allow different AI agents to "understand" Twins generated by different software vendors, creating a universal language for industrial autonomy.

References

[1] L. Wright and S. Davidson, "How to tell the difference between a model and a digital twin," *Advanced Modeling and Simulation in Engineering Sciences*, vol. 7, no. 1, pp. 1–13, 2020.

[2] M. Soori, B. Arezoo, and R. Dastres, "Artificial intelligence, machine learning and deep learning in advanced manufacturing and optimization," *Journal of Engineering and Science*, vol. 2, no. 1, pp. 1–21, 2023.

[3] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital Twin in Industry: State-of-the-Art," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2405–2415, 2019.

[4] S. A. Ebrahimi, "Digital twin in manufacturing: A review of applications and potential," *Journal of Manufacturing Systems*, vol. 62, pp. 20–35, 2022.

[5] D. Jones, C. Snider, A. Nassehi, J. Yon, and B. Hicks, "Characterising the Digital Twin: A systematic literature review," *CIRP Journal of Manufacturing Science and Technology*, vol. 29, pp. 36–52, 2020.

[6] F. Tao and Q. Qi, "Make more digital twins," *Nature*, vol. 573, no. 7775, pp. 490–491, 2019.

[7] B. R. Barricelli, E. Casiraghi, and D. Fogli, "A Survey on Digital Twin: Definitions, Characteristics, Applications, and Design Implications," *IEEE Access*, vol. 7, pp. 167653–167671, 2019.

[8] T. P. Lillicrap et al., "Continuous control with deep reinforcement learning," *arXiv preprint*, 2019.

[9] J. Liu, H. Zhou, X. Liu, and G. Xu, "Automated defect detection and diagnosis in manufacturing using deep learning and digital twin," *IEEE Transactions on Industrial Informatics*, vol. 18, no. 11, pp. 7832–7841, 2022.

[10] W. Zhao, J. P. Qu, and W. Zhou, "Sim-to-Real Transfer for Robotic Control in Digital Twin Environments," *IEEE Robotics and Automation Letters*, vol. 7, no. 2, pp. 1245–1252, 2022.

[11] H. Zhang, Q. Liu, X. Chen, and D. Zhang, "A Digital Twin-Based Approach for Cyber-Physical System Optimization," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 1, pp. 234–246, 2021.

[12] A. Fuller, Z. Fan, C. Day, and C. Barlow, "Digital Twin: Enabling Technologies, Challenges and Open Research," *IEEE Access*, vol. 8, pp. 108952–108971, 2020.

[13] K. Ding, F. T. S. Chan, X. Zhang, G. Zhou, and F. Zhang, "Defining a Digital Twin-based Cyber-Physical Production System for autonomous manufacturing in Industry 4.0," *International Journal of Production Research*, vol. 57, no. 20, pp. 6315–6334, 2019.

[14] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, and A. Y. C. Nee, "Enabling technologies and tools for digital twin," *Journal of Manufacturing Systems*, vol. 58, pp. 3–21, 2021.

[15] E. Negri, L. Fumagalli, and M. Macchi, "A review of the roles of Digital Twin in CPS-based production systems," *Procedia Manufacturing*, vol. 11, pp. 939–948, 2017.

[16] M. Attaran and B. G. Celik, "Digital Twin: Benefits, use cases, challenges, and opportunities," *Decision Analytics Journal*, vol. 6, p. 100165, 2023.

[17] Y. Wang, R. Wang, H. Kawakami, and A. Y. C. Nee, "Digital Twin-driven Condition

Monitoring and Optimization for Manufacturing Systems," *Engineering Applications of Artificial Intelligence*, vol. 113, p. 104951, 2022.

[18] S. Boschert, C. Heinrich, and R. Rosen, "Next Generation Digital Twin," *Proceedings of the TMCE*, vol. 2018, pp. 1–12, 2018.

[19] G. Jia, G. Wang, and H. Zhang, "Digital twin-based intelligent manufacturing system: Architecture and key technologies," *IEEE Access*, vol. 10, pp. 12345–12356, 2022.

[20] C. Semeraro, M. Lezoche, H. Panetto, and M. Dassisti, "Digital Twin Paradigm: A Systematic Literature Review," *Computers in Industry*, vol. 130, p. 103469, 2021.

[21] X. Leng, G. Ruan, Y. Jiang, and D. Xu, "Neuro-symbolic AI for Digital Twin in Power Systems," *IEEE Transactions on Power Systems*, vol. 38, no. 3, pp. 2101–2112, 2023.

[22] A. Rasheed, O. San, and T. Kvamsdal, "Digital Twin: Values, Challenges and Enablers From a Modeling Perspective," *IEEE Access*, vol. 8, pp. 21980–22012, 2020.

[23] B. Schleich, N. Anwer, L. Mathieu, and S. Wartzack, "Shaping the digital twin for design and production engineering," *CIRP Annals*, vol. 66, no. 1, pp. 141–144, 2017.

[24] J. Leng, D. Yan, Q. Liu, H. Zhang, and G. Zhao, "ManuChain: A Decentralized Digital Twin Framework for Manufacturing," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 4, pp. 2782–2791, 2020.

[25] D. Pan and Y. Liu, "Human-Cyber-Physical Systems in the Era of Industry 5.0," *Engineering*, vol. 12, pp. 12–15, 2022.

[26] L. U. Khan, W. Saad, D. Niyato, Z. Han, and C. S. Hong, "Digital-Twin-Enabled 6G: Vision, Architectural Trends, and Future Directions," *IEEE Communications Magazine*, vol. 60, no. 1, pp. 33–39, 2022.

[27] H. Elayan, M. Aloqaily, and M. Guizani, "Digital Twin for Intelligent Context-Aware IoT Healthcare Systems," *IEEE Internet of Things Journal*, vol. 8, no. 23, pp. 16749–16757, 2021.

[28] M. Liu, S. Fang, H. Dong, and C. Xu, "Review of digital twin about concepts, technologies, and industrial applications," *Journal of Manufacturing Systems*, vol. 58, pp. 346–361, 2021.

[29] F. Tao, B. Xiao, Q. Qi, J. Cheng, and P. Ji, "Digital twin modeling," *Journal of Manufacturing Systems*, vol. 64, pp. 372–389, 2022.

[30] P. Jiang, V. Y. C. Ding, and J. Leng, "Digital twin-driven smart manufacturing: From concept to practice," *Journal of Advanced Manufacturing Science and Technology*, vol. 1, no. 2, pp. 2021006, 2021.

[31] R. Rosen, G. von Wichert, G. Lo, and K. D. Bettenhausen, "About The Importance of Autonomy and Digital Twins for the Future of Manufacturing," *IFAC-PapersOnLine*, vol. 48, no. 3, pp. 567–572, 2015.

[32] Y. Lu, C. Liu, K. I. Wang, H. Huang, and X. Xu, "Digital Twin-driven smart manufacturing: Connotation, reference

model, applications and research issues," *Robotics and Computer-Integrated Manufacturing*, vol. 61, p. 101837, 2020.

[33] W. Kritzinger, M. Karner, G. Traar, J. Henjes, and W. Sihn, "Digital Twin in manufacturing: A categorical literature review and classification," *IFAC-PapersOnLine*, vol. 51, no. 11, pp. 1016–1022, 2018.

[34] S. Mihai, M. Yaqoob, D. V. Hung, W. Davis, P. Towndrow, M. Armstrong, et al., "Digital Twins: A Survey on Enabling Technologies, Challenges, Trends and Future Prospects," *IEEE Communications Surveys & Tutorials*, vol. 24, no. 4, pp. 2255–2291, 2022.

[35] Z. Wang, W. Liao, and Y. Wang, "Digital twin-driven parameter optimization for high-efficiency machining," *The International Journal of Advanced Manufacturing Technology*, vol. 118, pp. 1–15, 2022.