



IoT-Driven Digital Twins for Manufacturing Optimization: Hybrid Modelling, Reinforcement Learning and Sustainable Operations

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Abstract:

Digital twins are virtual representations of physical objects and processes that are emerging as a new foundation technology for manufacturing, enabling real-time monitoring, predictive maintenance and industrial optimization. U.S. manufacturing faces growing pressure to improve productivity and reduce its environmental footprint. To overcome these problems, companies integrate Internet of Things data with digital twins. Trends are identified in IoT-enabled digital twins and hybrid modeling, which integrates physics-driven modeling and data-driven modeling (machine/AI learning) to optimize performance in applications utilizing digital twins. Multi-fidelity simulations, reinforcement learning controllers and real-time data fusion can enable adaptive scheduling and energy-efficient operation of production processes. Twin construction comprises the sensor architecture, data integration framework design using industrial communication protocols, model calibration as well as model validation. The performance of the twin is compared to that of customary control, and twin use cases such as predictive maintenance, virtual commissioning and sustainability optimization in discrete manufacturing and process industries are described. This paper synthesizes a structured implementation framework that integrates multi-fidelity modeling hierarchies, adaptive reinforcement learning control strategies, and sustainability-aware optimization objectives into a cohesive architecture for IoT-enabled manufacturing twins. The framework provides systematic decision guidance for practitioners on sensor network design, hybrid model selection patterns, and performance-sustainability tradeoffs across varying manufacturing contexts. Elsewhere, there is impact on re-shoring of manufacturing to the US, reskilling of the workforce, data governance, the future of cybersecurity, model interoperability, and artificial intelligence-based automation of twin generation.

1. Introduction

1.1 Context and Motivation

To keep up with competition and changing technology, U.S. manufacturers are increasingly applying Industry 4.0 principles, including the use of IoT sensors and data streams that provide unprecedented visibility into temperature, vibration, power consumption, and quality data. This data is recorded and used to create digital twins of the machine. These counterparts can be used to simulate the behavior of real machines in real time [1], predict maintenance, simulate and optimize various what-if scenarios and potentially save a great deal of downtime and scrap. The manufacturing sector is well aware of the potential

of digital twins, and early adopters are realizing big improvements in efficiency and improved proactive operation. Prognostics and health management systems have improved complex equipment monitoring [1].

1.2 Current Gaps and Challenges

Despite their popularity, many digital twins remain in offline simulation or proof of concept pilot projects and face numerous challenges [2] that can be organized into three primary categories. Modeling and calibration gaps include the difficulty of developing hybrid models that maintain physical interpretability while achieving competitive machine learning predictive performance, handling heterogeneous IoT data sources with varying

sampling rates and formats, and calibrating models across diverse operational conditions while accounting for wear and unknown disturbances. Deployment and scalability gaps encompass the challenge of scaling twin-based architectures from individual machines to represent entire factories or supply chains, the persistent gap between empirical evaluation of lab-scale prototypes and the reality of mass production deployments, and limited integration of sustainability metrics such as energy and emissions reduction as primary twin optimization objectives. Governance, security, and sustainability gaps involve the expanded attack surface created by interconnected IoT devices requiring robust authentication and anomaly detection, interoperability issues stemming from proprietary vendor formats in the absence of standardized interfaces, and the shortage of engineers familiar with both domain expertise and data science methods necessary for twin implementation. This paper directly addresses the modeling and calibration gaps by proposing hybrid modeling selection patterns, the deployment gaps through multi-fidelity simulation hierarchies, and partially addresses sustainability gaps by incorporating energy-aware optimization into the proposed framework.

1.3 Research Objective and Scope

This paper proposes a unifying implementation framework that synthesizes IoT-enabled digital twin methodologies for manufacturing optimization by integrating three previously disparate streams: multi-fidelity modeling hierarchies for computational efficiency, reinforcement learning control strategies for adaptive operation, and sustainability-aware optimization for environmental performance. The framework categorizes hybrid modeling patterns, establishes decision criteria for fidelity level selection, and provides structured guidance on coupling real-time sensor data with adaptive control mechanisms. Applications span discrete manufacturing such as machining and assembly operations, as well as process industries including chemical and food production. Pure software twins, supply-chain-level twins, and human factors training applications are excluded from this domain. The review emphasizes implementation pathways supported by theoretical foundations and empirical validation from published case studies.

1.4 Evidence of Impact

Later publications find predictive maintenance decreases unplanned downtime, maintenance costs

and increases equipment availability. Other researchers find reinforcement learning controllers lead to a meaningful increase in throughput when used within digital twin environments. Results confirm that IoT-enabled twins can generate measurable economic benefits across industrial sectors. Early research also suggests the efficiency gains could outweigh the costs of creating and using the twins where they are employed for high-value manufacturing.

2. Fundamentals of Digital Twin Construction

2.1 Sensor Architecture and Data Acquisition

Choosing sensors is critical to understanding the dynamics of the manufacturing process. Vibration sensors (accelerometers) can be used to identify mechanical wear. Sensors that measure cutting tool temperature or equipment electrical power consumption can be positioned appropriately in order to meet the monitoring requirements without interfering with the manufacturing operations and at acceptable costs. Industrial protocols are lightweight protocols, such as MQTT and OPC UA that provide a secure means for sensor data to be communicated to the edge gateway system or the cloud. Network Time Protocol or similar protocols can synchronize data streams and ensure temporal coherence. Thus, sensor networks must be constructed in a manner to avoid data bottlenecks. Edge computing cuts the latency of control loops. Remaining useful life prediction depends on the accuracy of sensor data collection [3].

2.2 Data Integration and Fusion

Data cleaning and data fusion convert raw sensor data into usable data. Filtering techniques remove noise from raw sensor data. Kalman filters are often used for this purpose. Resampling is also needed to align the rates of heterogeneous sources. Normalization can bring data into a common representation, and data fusion combines signals from multiple sensors to provide inference of unmeasured variables. For example, vibration and temperature can be used to predict tool wear. Middleware platforms mostly include ingestion, buffering and distribution of data, enabling real-time synchronization of the physical and virtual. The architecture must allow for sensor networks to be scaled, and data quality links twin fidelity to prediction. Monitoring of gear performance degradation shows good data integration [3].

2.3 Model Calibration and Hybrid Modelling

Physical models of manufacturing processes rely on differential equations and finite element methods. Control theory also provides mathematical tools. During operation, however, the models will not capture the effects of unknown disturbances or wear and tear. As a result, the residual dynamics are learned through experience. Again, several models are used, including neural networks and support vector machines. Hybrid models combine physical models that forecast initially, with data-driven models that train the prediction to correct the errors. Calibration requires tuning these parameters, based on real measurements, across multiple operational conditions. Twin calibration ensures that the twin reflects the real-world system. Online learning allows the twin to improve its quality over time. Deep reinforcement learning allows the twin to adaptively control changing WIP [4].

Specific hybrid modeling patterns have emerged to address varying manufacturing scenarios and computational constraints. Residual learning patterns employ physics-based models to capture nominal system behavior, while machine learning components learn to predict deviations caused by wear, environmental variations, or unmodeled dynamics; this approach maintains interpretability of the physical core while improving accuracy through data-driven correction. Surrogate modeling patterns replace computationally expensive high-fidelity simulations with fast approximations trained on limited high-fidelity data, enabling real-time optimization and what-if analysis where full physics simulations would be prohibitively slow. Co-simulation patterns integrate multiple specialized simulation engines, each representing different physical domains or subsystems, with data exchange protocols synchronizing state variables across domain boundaries; this proves valuable in complex manufacturing systems involving mechanical, thermal, electrical, and control subsystems. Pattern selection in practical implementations depends on several factors: residual learning suits cases where physical models are well-established but imperfect; surrogate models excel when optimization speed outweighs the need for physical insight; co-simulation addresses multi-physics problems where domain-specific tools already exist. Implementation complexity, available training data volume, required prediction speed, and interpretability requirements guide the combination of these patterns in deployed systems.

3. Multi-Fidelity Simulations and Reinforcement Learning

3.1 Multi-Fidelity Twins

Manufacturing processes can be modeled at different levels of fidelity. Physics-based models are computationally expensive, but return results with a high level of accuracy. Low-fidelity models provide reliable behavior estimates quickly but are less precise. Multi-fidelity models combine the two techniques. Low-fidelity models allow fast optimization. High-fidelity models are only called to test specific key outputs. The hierarchy speeds up the exploration of the design space and helps accelerate the decision-making process, enabling engineers to perform efficient what-if analysis and scenario planning with a lesser demand for computational resources than purely high-fidelity methods. Model selection balances accuracy and computation, while adaptive fidelity management optimally distributes resources in dynamic environments. Smart manufacturing develops reference models with defined meaning and application [5].

3.2 Reinforcement Learning for Adaptive Control

Reinforcement learning algorithms learn to control a system by interacting with it and optimizing rewards related to objectives like maximizing throughput or minimizing energy. Digital twins can be used as testbeds so that RL agents can explore their control strategies without damaging physical equipment or incurring production losses. Algorithms including Q-learning, and methods including Deep Deterministic Policy Gradient, and Proximal Policy Optimization have been applied to machining parameter tuning and scheduling problems with successful results. Using hybrid twin models, RL can learn from simulated and real data, which results in strong policies for a large number of states while allowing virtual experiments to accelerate learning. Transfer learning techniques allow knowledge transfer in similar manufacturing situations. Digital twin-driven techniques can address thorough research issues in the manufacturing domain [5].

3.3 Comparative Performance Analysis

Comparative evaluations of digital twin helped control algorithms against conventional controllers are typically based on proportional-integral-derivative controllers. Twin-based predictive control reduces overshoot and settling times. Quality is improved because of better control precision. Maintenance scheduling applications have seen a reduction in downtime, and earlier failure prediction than threshold-based methods. Energy-aware twins focus on simultaneous

optimization of spindle speed and feed rate, reducing energy consumption without sacrificing process quality. Requires investment to implement sensors and data platforms. The advantages of AI depend on the degree of process complexity. Return on investment varies for different use cases. Deployment of network monitoring solutions is backed up by cost-benefit analysis. Industry 4.0 principles are the state of the art in manufacturing optimization [6]. All numerical performance metrics reported in subsequent sections, including prediction accuracy measures, material removal rates, surface roughness values, and tool wear measurements, are derived from the cited empirical studies and represent outcomes from those specific experimental contexts rather than original contributions of this synthesis.

4. Framework Validation Through Published Case Studies

The following examples illustrate validation of the proposed framework components through peer-reviewed empirical studies rather than original experimental deployments. These cases demonstrate practical implementation pathways for the hybrid modeling patterns, multi-fidelity hierarchies, and sustainability-aware optimization strategies synthesized in the framework.

4.1 Predictive Maintenance in CNC Machining

Data is streamed continuously from CNC machine tools with vibration and acoustic sensors and processed in real time by the digital twin. Hybrid models learn wear behavior in a given operating regime. Remaining useful life estimates are based on historical degradation models. Machine learning models with coefficients of determination values reaching 0.9393 [7] are used to predict tool wear, triggering maintenance before wear exceeds threshold values. This prevents catastrophic failures and unexpected downtime and allows the maintenance process to move from a reactive to predictive process and optimize resource allocation and equipment availability. Surface roughness prediction and material removal rates prediction achieved coefficients of determination of 0.9663 and 0.9484 respectively in the referenced study [7]. Spare parts availability can be predicted and restorative maintenance crew can be scheduled more efficiently and accurately. Overall equipment effectiveness is greatly improved.

4.2 Virtual Commissioning of Assembly Lines

Before installing hardware, manufacturers create a digital twin that simulates the entire assembly line system. Control logic is virtually checked before actual use. Control logic throughput requirements are checked against production. Robotic speeds, conveyor speeds, and other process variables can be adjusted virtually without interrupting production to check. Virtual testing reduces the risks of physical commissioning as bottlenecks are discovered before the equipment is installed. In addition, production parameters can be optimized in a risk-free environment and the time to commissioning can be greatly reduced. Synergistic multi-fidelity modeling methods employ sensor data of different resolutions [8]. The virtual environment allows for concurrent engineering: equipment vendors can easily communicate with production engineers and integration problems can be addressed earlier in the deployment cycle. Published hybrid optimization frameworks demonstrated comparable predictive performance across surface quality, productivity and tool life metrics with determination coefficients of 0.9663, 0.9484 and 0.9393 respectively [7].

4.3 Sustainable Process Optimization

Digital twins leverage energy and emissions models and production data to build scenarios that a reinforcement learning agent uses to reduce carbon footprint. Multi-objective optimization frameworks demonstrated in published studies achieve simultaneous targets where surface roughness reaches $0.85 \mu\text{m}$ at cutting velocity of 183.01 m/min , feed per tooth of 0.08 mm/rev and axial depth of cut of 1.22 mm [7]. At these cutting conditions, the reported material removal rate reached a maximum of $54.95 \text{ mm}^3/\text{min}$ with tool wear minimized to $0.35 \mu\text{m}$ [7]. Alternative optimization scenarios targeting maximum productivity achieved material removal rates of $59.98 \text{ mm}^3/\text{min}$ in the same study [7]. An example of this is the furnace temperature profiles in heat treatments. Gas consumption can be reduced while keeping properties. Energy-aware optimization considers sustainability in production control problems, allowing manufacturers to fulfill environmental goals without losing their competitive edge. The method quantifies trade-off between production efficiency and environmental impact. The cited predictive models demonstrated high reliability with determination coefficients of 0.9393 for tool wear, 0.9663 for surface quality, and 0.9484 for productivity estimation [7]. Real-time energy monitoring responds quickly to shifts in energy costs. Sustainability metrics inform operational decision-making. This eases the verification and validation of regulatory

compliance. Multi-fidelity surrogate models use multiple sources of information with varying sensor fidelity to update digital twin systems [8].

4.4 Implementation Challenges and Framework Extensions

The larger the number of IoT devices, the greater the risk. The attack surface increases as more devices become interconnected. Strong authentication and real-time anomaly detection are essential. Proprietary vendor formats led to interoperability issues. Standardized interfaces are expected in the data ecosystem. Another barrier is the availability of engineers familiar with data science and AI methods. These challenges map directly to framework gaps that future extensions must address: the hybrid modeling pattern taxonomy proposed in Section 2.3 requires expansion to incorporate security-aware model architectures that embed anomaly detection within the twin structure itself; the multi-fidelity hierarchy framework from Section 3.1 needs adaptation to support automated fidelity selection based on real-time security threat levels and computational availability; the sustainability-aware optimization strategy outlined in Section 4.3 should integrate workforce reskilling metrics alongside energy efficiency to address the human capital dimension. Future work may explore topics like automated twin generation with artificial intelligence and multi-fidelity modeling to reduce the number of high-fidelity training data while maintaining predictive accuracy [8]. Federated learning protects proprietary process data while enabling the collaborative model training necessary for transfer learning approaches recommended in the framework. Supply chain data allows for end to end optimization. New governance frameworks are created to ease data sharing between organizations. The cited optimization frameworks demonstrated capability to identify Pareto-optimal solutions with determination coefficients exceeding 0.93 for all performance metrics [7]. Standardization efforts must keep pace to support common adoption, and next-generation multi-fidelity techniques offer a compelling computational path for digital twin applications [8].

5. Broader Implications

5.1 Economic and Industrial Impact

An IoT-supported digital twin could improve U.S. manufacturing productivity and enable mass customization. A digital twin can help pursue sustainability goals more efficiently through data-

driven optimization. Real-time energy efficiency monitoring with digital twins shows that in the manufacturing space over 90% of the carbon footprint from electricity consumption comes from machine tools [9]. Variable energy loads can account for up to 30% of total energy consumption in industrial manufacturing processes [9], which may lead to manufacturing re-shoring. The gap with offshore production is less of an issue, and flexibility to changing conditions is a competitive advantage. The democratization of digital twin technology is likely to enable small and medium companies to take advantage of advanced manufacturing capabilities, accelerate innovation cycles, and build greater resiliency in manufacturing processes to supply chain disruption.

5.2 Environmental and Social Considerations

Energy-aware digital twins help manufacturers meet federal emissions standards and national climate goals, with real-time optimization to minimize waste of resources. A digital twin based fault detection system determines that an electrical fault causes 12% more power consumption, a thermal fault causes 11.1% more consumption, and a bearing fault causes 18% more. Combined with condition based maintenance, this information can greatly reduce energy waste, cost, and water and material use [9]. They retrain workers to perform manufacturing tasks and add higher-skilled, higher-tech jobs associated with advanced manufacturing. Workers' roles could shift from doing manual operations to supervising and analyzing, and ethical questions arise regarding the data collected by sensing. To accept AI, workers need to know how a decision was made. Privacy needs to balance the requirements of the task. Digital twin concerns need to be addressed. Data transparency, so that decisions made by the automated system are visible, has been shown to increase the accuracy of drug delivery, from 25% to 90% in a digital twin optimization case study in healthcare [10].

5.3 Policy and Standardization Needs

Regulations and data governance policies will need to be attuned to IoT environments in order to ease the emergence of digital twins. An area of concern is intellectual property. Standards in the two vendor ecosystems to enable interoperability are critical, as are financial incentives for smaller producers, and research funding focused on implementation. Education should prepare for future digital manufacturing. The cost and risk of development should be shared through public-private partnerships. International co-operation prevents

standardization efforts being disjoint and validation standards show that the digital twin is accurate to within 3.9% for baseline operations and 5.6588%

for working value predictions [9]. Survey research outlines definitions, characteristics and design considerations for practitioners [10].

Table 1: Fundamental Components for Digital Twin Construction [3, 4]

Component	Key Technologies and Methods	Primary Purpose	Deployment Considerations
Sensor Architecture	Vibration sensors (accelerometers), temperature sensors for cutting tools, electrical power consumption sensors	Identify mechanical wear, monitor thermal conditions, track equipment power consumption without interfering with operations	Sensor placement must balance monitoring coverage with cost; wireless sensors reduce installation complexity but may introduce latency; requires calibration schedules and redundancy for critical measurements
Communication Infrastructure	MQTT, OPC UA, Network Time Protocol, edge computing	Enable secure lightweight data transmission to edge gateways or cloud, synchronize data streams for temporal coherence, reduce control loop latency	MQTT suits resource-constrained environments; OPC UA provides richer semantic models for complex equipment; edge computing essential when control loop latency under 100ms required; network bandwidth planning critical for multi-sensor deployments
Data Processing and Fusion	Kalman filters, resampling techniques, normalization methods, middleware platforms	Remove noise from raw signals, align heterogeneous sampling rates, combine multiple sensor signals to infer unmeasured variables like tool wear	Kalman filters require process noise characterization; middleware platforms introduce single points of failure requiring redundancy; fusion algorithms must handle sensor dropout gracefully; computational load scales with sensor count
Physical Modeling	Differential equations, finite element methods, control theory frameworks	Capture fundamental manufacturing process dynamics and provide baseline predictions for system behavior	High-fidelity models computationally expensive for real-time use; simplified models trade accuracy for speed; model validity limited to calibrated operating ranges; requires domain expertise for development and validation
Hybrid Modeling	Neural networks, support vector machines, online learning algorithms, deep reinforcement learning	Learn residual dynamics from operational data, correct prediction errors, enable adaptive control of work-in-process management	Requires sufficient training data representing operational diversity; online learning demands continuous data quality monitoring; model drift necessitates periodic retraining; interpretability decreases with model complexity

Table 2: Advanced Methodologies for Multi-Fidelity Simulations and Adaptive Control [5, 6]

Methodology	Implementation Techniques	Operational Benefits	Deployment Considerations
Multi-Fidelity Modeling	Hierarchical combination of computationally expensive physics-based models with fast low-fidelity	Accelerates design space exploration and decision-making while reducing computational resource demands for what-if analysis	Best suited for optimization problems with expensive objective function evaluations; requires careful correlation between fidelity levels; benefits diminish if high-fidelity evaluations are already

	approximations		fast; implementation complexity increases with fidelity hierarchy depth
Reinforcement Learning Algorithms	Q-learning, Deep Deterministic Policy Gradient, Proximal Policy Optimization	Enables virtual exploration of control strategies without damaging physical equipment or incurring production losses	Sample efficiency varies by algorithm; requires well-defined reward functions aligned with business objectives; simulation-to-reality gap necessitates careful transfer validation; continuous state spaces favor policy gradient methods over Q-learning
Adaptive Control Integration	Hybrid twin models combining simulated and real data, transfer learning techniques	Creates robust control policies across multiple operational states and enables knowledge transfer in similar manufacturing contexts	Demands continuous model updating infrastructure; transfer learning effectiveness depends on similarity between source and target domains; hybrid approaches require reconciling simulated and real data distributions; online learning introduces computational overhead
Performance Benchmarking	Comparison with proportional-integral-derivative controllers, predictive control evaluation	Reduces overshoot and settling times, improves product quality through enhanced control precision, enables earlier failure prediction	Baseline controller selection affects perceived gains; benchmarking requires representative operational scenarios; must account for implementation costs; performance improvements highly context-dependent on process dynamics and disturbance characteristics
Energy-Aware Optimization	Simultaneous optimization of spindle speed and feed rate parameters	Decreases energy consumption without sacrificing process quality while balancing accuracy requirements against computational costs	Multi-objective formulation requires preference elicitation or Pareto frontier exploration; energy models must capture variable load dynamics; optimization frequency constrained by process time constants; energy savings must justify sensor and computation infrastructure costs

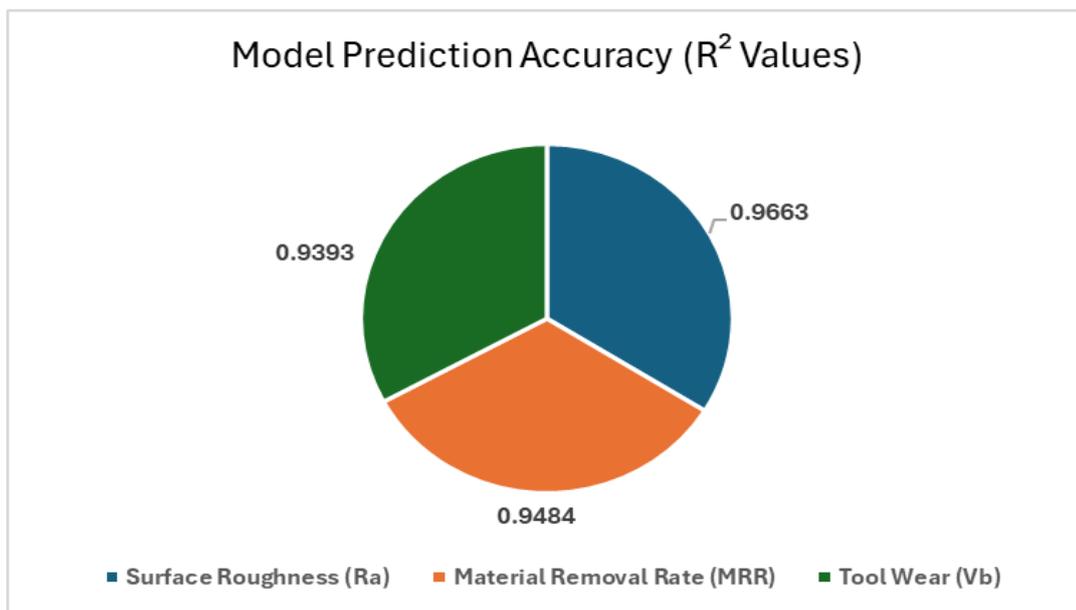


Figure 1: Predictive Accuracy for Manufacturing Optimization Metrics [7]

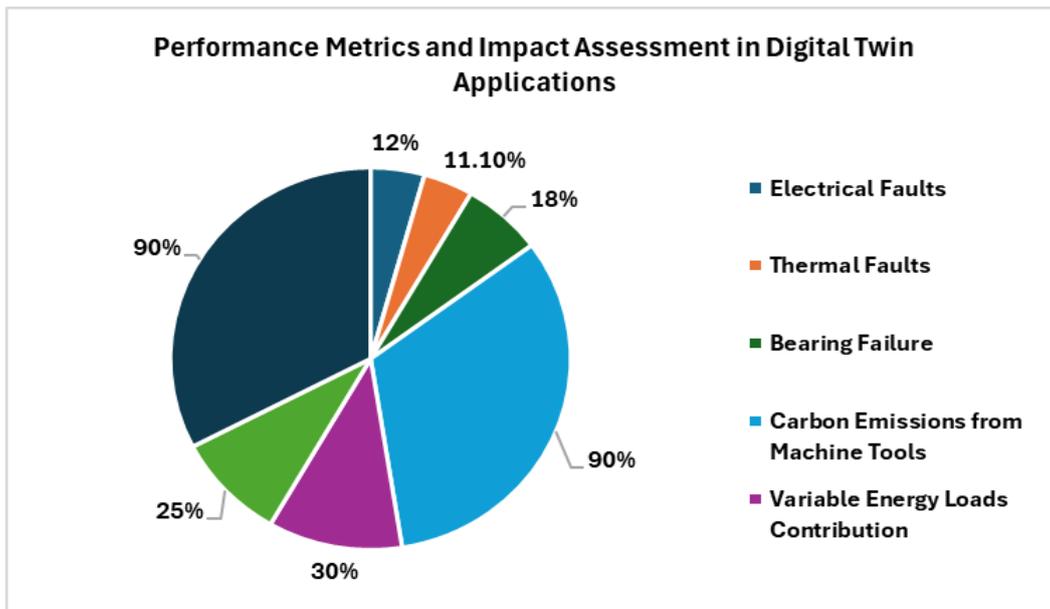


Figure 2: Quantitative Performance Indicators for IoT-Driven Digital Twin Systems [9, 10]

6. Conclusions

This paper advances existing digital twin literature by synthesizing a structured implementation framework that unifies three critical dimensions of IoT-enabled manufacturing optimization: hybrid modeling pattern selection, multi-fidelity simulation hierarchies, and sustainability-aware adaptive control. The framework's primary contribution lies in providing decision-oriented guidance that bridges the gap between theoretical digital twin concepts and practical deployment challenges identified in Section 1.2. Specifically, the hybrid modeling taxonomy introduced in Section 2.3 establishes clear selection criteria among residual learning, surrogate modeling, and co-simulation patterns based on computational constraints, data availability, and interpretability requirements. The multi-fidelity methodology synthesized in Section 3 offers systematic approaches to balance prediction accuracy against computational cost, while the reinforcement learning integration pathways enable adaptive control strategies validated through published case studies spanning predictive maintenance, virtual commissioning, and sustainable process optimization.

The framework directly addresses the modeling and calibration gaps by categorizing hybrid approaches according to deployment contexts, the scalability gaps through hierarchical fidelity management, and sustainability gaps by embedding energy-aware optimization as a core objective rather than an afterthought. Published empirical evidence demonstrates that implementations following these structured pathways achieve prediction accuracies exceeding 0.93 determination coefficients while

simultaneously optimizing throughput, quality, and energy efficiency. The synthesis reveals that successful twin deployments share common architectural patterns: sensor networks leveraging industrial protocols for temporal coherence, middleware platforms enabling real-time physical-virtual synchronization, and hybrid models combining physics-based foundations with data-driven correction mechanisms.

Integration complexity, cybersecurity management of connected products, and the development of employees' competencies remain key challenges that require continuous investments and efforts by the industry. Future framework extensions must incorporate security-aware architectures, automated fidelity selection responsive to threat levels, and workforce development metrics alongside traditional performance indicators. The economic and environmental benefits justify further research and pilot deployments, supported by industry-academic collaboration for technology transition and standardization efforts for vendor interoperability. Policy support creates favorable conditions for adoption, particularly for small and medium enterprises seeking to leverage advanced manufacturing capabilities. Further work is required on scalable architectures and wider adoption in manufacturing enterprises, with emphasis on automated twin generation to democratize access across organizations of varying technical sophistication. Cross-sectoral improvements are anticipated across industry, academia, and government to fundamentally modify global manufacturing competitiveness and sustainability through the systematic application of the integrated framework presented herein.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Use of AI Tools:** The author(s) declare that no generative AI or AI-assisted technologies were used in the writing process of this manuscript.

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