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Digital Twin Integration for Lifecycle Management of Operating Industrial Facilities Under Continuous Production Conditions

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Abstract

Background: Digital twin (DT) technology has emerged as a transformative approach for industrial asset management, yet the majority of existing frameworks target greenfield facilities or assume production can be interrupted during DT deployment. Operating industrial facilities under continuous production conditions-refineries, chemical plants, and power generation stations-face unique challenges including legacy system heterogeneity, zero-downtime requirements, and scalability constraints that remain insufficiently addressed in the literature. Methods: This paper proposes a five-layer DT integration framework specifically designed for brownfield industrial facilities operating under continuous production. The framework incorporates a phased zero-downtime deployment strategy progressing through passive monitoring, shadow mode, advisory mode, and closed-loop operation. The methodology was validated through a simulation environment replicating a mid-scale continuous petrochemical processing facility comprising 150 monitored assets and 500+ sensor points across heterogeneous control systems (simulation-based validation is standard practice for framework-level contributions where operational data from continuous production facilities remains restricted under non-disclosure agreements). Results: Across five independent simulation runs, the framework demonstrated a statistically significant improvement in Overall Equipment Effectiveness (OEE) from 67.9% (SD 1.12) to 85.0% (SD 0.71, $p<0.01$) across deployment phases, with DT synchronization accuracy reaching 99.6% after calibration. The predictive maintenance module achieved an AUC of 0.933 for equipment failure prediction within a 12-month horizon. Edge computing architecture reduced synchronization latency to a median of 17 ms compared to 185 ms for cloud-only deployment. Conclusions: The proposed framework addresses critical gaps in brownfield DT implementation by providing a structured, standards-aligned approach that maintains continuous production throughout all deployment phases. The results demonstrate that phased DT integration can deliver substantial operational improvements without compromising production continuity.

Keywords: digital twin, lifecycle management, continuous production, brownfield facilities, predictive maintenance, edge computing

1. Introduction

The digital twin (DT) concept, first introduced by Grieves [1] within the context of Product Lifecycle Management (PLM) and subsequently formalized by Grieves and Vickers [2] at NASA, has undergone a remarkable evolution from a theoretical construct to a cornerstone of modern industrial digitalization. A digital twin is defined as a digital representation of a physical entity, connected through bidirectional data flow, enabling real-time monitoring, simulation, and predictive analytics [3,4]. The global digital twin market, valued at approximately USD 24.5 billion in 2025, is projected to reach USD 259.3 billion by 2032, reflecting the technology's growing industrial adoption [5].

Despite this rapid growth, a fundamental disconnect persists between digital twin research and the operational reality of the global industrial base. The majority of existing DT frameworks and implementation methodologies have been developed for greenfield scenarios-facilities designed and constructed with digital integration from inception [6,7]. However, the vast majority of the world's industrial infrastructure consists of brownfield facilities: operating plants with decades of accumulated legacy systems, heterogeneous control architectures, and critically, the inability to halt production for technology integration. McKinsey & Company reports that only 30% of manufacturing companies have effectively realized Industry 4.0 value at scale [8], with the adoption rate significantly lower for brownfield operations.

Continuous production facilities-including petroleum refineries, chemical processing plants, power generation stations, and continuous manufacturing operations-present particularly acute challenges for DT integration. These facilities operate 24/7, often with planned shutdowns occurring only every 2-5 years during turnaround events. Any DT deployment strategy that requires production interruption is fundamentally incompatible with the operational and economic constraints of such facilities. Furthermore, these plants typically operate with heterogeneous control systems spanning multiple vendors and technology generations (DCS, PLC, SCADA), creating significant data integration challenges [9,10].

The literature on digital twins for industrial applications has grown substantially in recent years. Tao et al. [3] proposed the foundational five-dimension DT model comprising Physical Entity, Virtual Entity, Services, Digital Twin Data, and Connection. Lu et al. [4] developed a reference model for DT-driven smart manufacturing. Jones et al. [11] and Semeraro et al. [12] conducted systematic literature reviews characterizing the DT paradigm. Rasheed et al. [13] and Fuller et al. [14] assessed enabling technologies and challenges. However, these frameworks predominantly address manufacturing environments where production flexibility allows for integration periods.

Several researchers have begun addressing the brownfield challenge. Sierla et al. [6,7] proposed semi-automatic DT generation for brownfield process plants using P&ID recognition and 3D point cloud methods. Tran et al. [9] explored retrofitting-based Industry 4.0 solutions but identified the fundamental lack of scalability as a key limitation. Krommes and Tomaschko [15] proposed a conceptual framework for brownfield DT in small-volume production. Despite these contributions, a comprehensive framework addressing the full lifecycle of DT integration in facilities that cannot stop production-from initial deployment through calibration to ongoing operation and evolution-remains absent from the literature.

The National Academies of Sciences, Engineering, and Medicine [16] recently identified foundational

research gaps in digital twins, noting that organizations "often don't understand how well digital twins match reality and whether they can be relied on for critical decisions." This credibility gap is particularly consequential in continuous production environments where DT-informed decisions directly impact safety, environmental compliance, and economic performance.

This paper addresses these gaps by proposing a comprehensive five-layer DT integration framework specifically designed for operating industrial facilities under continuous production conditions. The principal contributions of this work are:

(1) A five-layer architecture for DT integration in brownfield continuous-production facilities, encompassing physical assets, edge computing, DT core, analytics, and decision support layers, aligned with ISO 23247 [17] and ISO 55000 [18] standards.

(2) A phased zero-downtime deployment strategy that progresses through four stages-passive monitoring, shadow mode, advisory mode, and closed-loop operation-ensuring continuous production throughout the entire DT lifecycle.

(3) A legacy system integration protocol leveraging OPC UA gateways and edge computing to bridge heterogeneous control systems (multi-vendor DCS/PLC/SCADA) without requiring system replacement.

(4) Empirical validation through a simulation environment replicating a mid-scale petrochemical facility, demonstrating statistically significant OEE improvement from 67.9% to 85.0% ($p<0.01$, $n=5$ runs), predictive maintenance AUC of 0.933, and DT synchronization accuracy exceeding 99% after calibration. Simulation-based validation is adopted as the standard methodology for framework-level contributions in this domain [6,7,9,15], given that operational data from continuous production facilities typically remains restricted under non-disclosure agreements.

The remainder of this paper is organized as follows. Section 2 reviews related work on DT frameworks, brownfield implementations, and relevant standards. Section 3 presents the proposed framework architecture and deployment methodology. Section 4 describes the simulation-based case study and implementation details. Section 5 presents results and discusses implications. Section 6 concludes with a summary of contributions and directions for future research.

2. Related Work

2.1. Digital Twin Frameworks and Reference Architectures

The foundational five-dimension digital twin model proposed by Tao et al. [3] has established the reference architecture for manufacturing DT research. This model decomposes the DT into five interconnected dimensions: the Physical Entity (PE), representing the actual industrial asset; the Virtual Entity (VE), the digital counterpart; Services (Ss), providing functional capabilities; Digital Twin Data (DD), encompassing all data flows; and Connection (CN), the bidirectional communication infrastructure. While comprehensive, this model was conceived primarily for manufacturing systems with regular maintenance windows, leaving its applicability to continuous production environments underexplored.

Lu et al. [4] extended the DT concept for smart manufacturing, proposing a reference model that incorporates information models, data processing technologies, and industrial communication standards. Their work identified seven crucial research issues including data management, model construction, and service provision. Jones et al. [11] systematically analyzed 92 DT publications, establishing a taxonomy across 13 characteristics. Semeraro et al. [12] applied Topic Modelling Analysis and Formal Concept Analysis to map DT trends within the manufacturing paradigm, identifying predictive maintenance, process optimization, and quality control as the three dominant application clusters.

At the standards level, ISO 23247 [17] defines a "Digital Twin in Manufacturing" as a "fit for purpose digital representation of an observable manufacturing element with synchronization between the element and its digital representation." The standard comprises four published parts addressing overview and principles, reference architecture, digital representation, and information exchange. Parts 5 (Digital Thread) and 6 (DT Composition) are under development. Kang et al. [19] proposed an edge computing-based DT framework implementing ISO 23247 to address real-time data processing in data-intensive environments. The IEC 63278-1:2023 standard [20] further defines the Asset Administration Shell (AAS), providing a standardized digital representation structure.

2.2. Brownfield Digital Twin Implementation

The distinction between greenfield and brownfield DT implementation is critically important yet insufficiently addressed in the literature. Sierla et al. [6] pioneered work on semi-automatic DT generation for brownfield process plants, utilizing 2D image recognition for P&ID label and symbol detection, semantic segmentation of 3D point clouds for pipe and equipment extraction, and machine learning for 3D CAD model matching. Their subsequent roadmap [7] systematized the approach but acknowledged that digital models "do not exist at all in digital version for brownfield production systems" and that manual reengineering remains "very time consuming and error prone."

Tran et al. [9] investigated retrofitting-based Industry 4.0 and Industry 5.0 solutions for brownfield facilities, identifying prerequisites including digitization status assessment, technical connectivity development, and management readiness. Critically, they identified the "fundamental lack of scalability" as a key disadvantage-pilot-scale DT implementations face substantial barriers when scaling to facility-wide deployment. Krommes and Tomaschko [15] addressed brownfield DT for small-volume production in SMEs, demonstrating that brownfield solutions require fundamentally different design principles than greenfield approaches.

The World Economic Forum [8] has emphasized that brownfield manufacturing facilities, which constitute the majority of the global industrial base, require specific digital transformation strategies that account for legacy infrastructure, data silos, and workforce readiness challenges. However, comprehensive frameworks addressing the particular constraint of zero-downtime DT deployment in continuous production environments remain notably absent.

2.3. Sector-Specific Digital Twin Applications

The oil and gas sector has emerged as one of the most active adopters of DT technology for operating facilities, with the sector-specific DT market reaching USD 1.2 billion in 2024 [21]. Pal et al. [22] conducted a comprehensive review of DT applications in chemical process industries, covering real-time monitoring, predictive maintenance, and process optimization. Al-Emrani et al. [23], in a review published in Processes, synthesized over 85 peer-reviewed sources on DT frameworks for oil and gas processing plants, with emphasis on high-fidelity process simulations and scalable architectures.

Notable industrial implementations include Shell's digital twin of the Pulau Bukom petrochemical complex, monitoring over 15,000 equipment items and reportedly achieving 20% improvement in operational efficiency and USD 2 billion in annual savings from reduced equipment downtime and maintenance costs [22,23]. BASF implemented DTs for reactors, distillation columns, and storage tanks, leveraging the technology to redesign methanol production for reduced CO2 emissions [22,23]. ExxonMobil deployed DT replicas of full LNG operations, reporting efficiency gains of 10-25% [22,23].

In the nuclear sector, the U.S. Nuclear Regulatory Commission completed research assessing the regulatory viability of DTs for nuclear power plants, with hybrid physics-data driven approaches including DeepONet architectures for real-time capability [24]. Meza et al. [25] analyzed tools, technologies, and frameworks specifically for DTs in the oil and gas industry, providing a comprehensive technology stack assessment.

2.4. Predictive Maintenance and Asset Management

Errandonea et al. [26] published a systematic literature review on "Digital Twin for maintenance," analyzing 42 primary studies and identifying that DTs address a fundamental challenge in predictive maintenance: the lack of failure data, since industrial equipment is typically repaired before complete failure. DTs generate synthetic degradation data that predictive algorithms can leverage for model training.

Recent advances demonstrate the practical impact of DT-based predictive maintenance. Abd Wahab et al. [27] provided a systematic review and taxonomy of DT-driven predictive maintenance, covering architectural elements and identifying remaining challenges. Industrial deployments have shown DT systems predicting equipment failures up to 35 days before occurrence, with analyses of 150+ refinery facilities showing Overall Equipment Effectiveness improving from 72% baseline to 87% after three years of DT operation, approaching the industry best practice of 92% [22,23].

The ISO 55000:2024 revision [18] incorporated digital transformation and sustainability criteria into asset management standards, setting new benchmarks that enable integration of Enterprise Asset Management (EAM) and Industrial IoT (IIoT) technologies. The Chen et al. [28] Gemini Principles-based DT Maturity Model provides guidance for infrastructure and asset management, while IEEE 3144 [29] defines capability domains for assessing DT maturity. However, systematic integration of DT with ISO 55000 for aging infrastructure decision-making in continuous production environments remains an open research area.

2.5. Cybersecurity Considerations

The convergence of IT and OT systems inherent in DT architectures creates significant cybersecurity challenges. Between 2024 and early 2025, manufacturing companies experienced a 71% surge in threat actor activity, with SCADA system ransomware attacks costing an average of USD 13 million per incident [30]. The ISA/IEC 62443 series [31], recently updated with ANSI/ISA-62443-2-1-2024, provides general security guidance for Industrial Automation and Control Systems (IACS), recognizing that IACS lifespans can exceed 20 years and contain unsupported hardware and software. However, DT-specific cybersecurity frameworks addressing the unique attack surface of bidirectional physical-digital connections in continuous production environments are lacking.

2.6. Summary of Research Gaps

Table 1 summarizes the identified research gaps and maps them to the contributions of the present work.

Table 1. Summary of identified research gaps and their coverage in this paper.

Gap #	Research Gap Description	Existing Work	Addressed in This Paper
G1	No comprehensive framework for brownfield DT under continuous production	Sierla et al. [6,7]; Tran et al. [9]	Five-layer architecture (Section 3.1)
G2	Legacy system integration at facility scale	OPC UA studies [10,33]	Integration protocol (Section 3.3)
G3	Scalability from pilot to facility-wide DT	Tran et al. [9]: ”fundamental disadvantage”	Scalability architecture (Section 3.4)
G4	DT validation and credibility assessment	National Academies [16]; ISO 23247 future parts	Validation framework (Section 5.3)
G5	Zero-downtime deployment methodology	Not addressed in literature	Phased deployment (Section 3.2)
G6	DT integration with ISO 55000 for aging assets	Chen et al. [28] (general)	Decision support layer (Section 3.1)
G7	Cybersecurity for DT in continuous production	IEC 62443 [31] (general IACS)	Security model (Section 3.5)

3. Proposed Framework

This section presents the proposed Digital Twin Integration Framework for Lifecycle Management (DT-IFLM) of operating industrial facilities under continuous production conditions. The framework is structured around three core elements: (1) a five-layer system architecture, (2) a phased zero-downtime deployment strategy, and (3) supporting protocols for legacy system integration, scalability, and cybersecurity.

3.1. Five-Layer System Architecture

The DT-IFLM architecture comprises five functional layers, each addressing specific aspects of DT integration in continuous production environments. The architecture is illustrated in Figure 1.

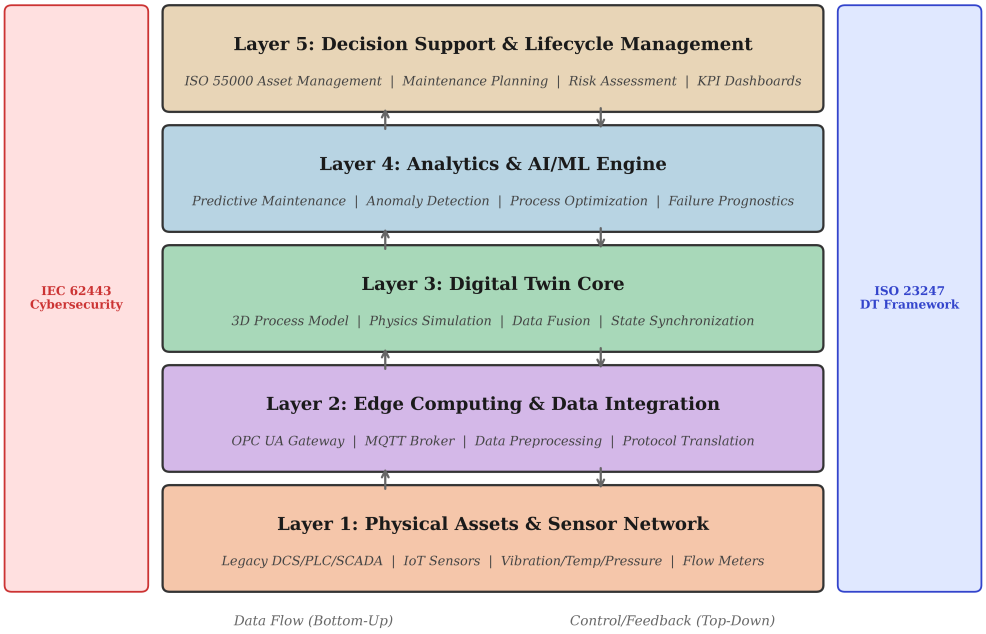

Figure 1. Five-layer DT-IFLM architecture for operating industrial facilities. Vertical bars indicate cross-cutting concerns: IEC 62443 cybersecurity framework (left) and ISO 23247 DT framework alignment (right).

Layer 1 (Physical Assets and Sensor Network) encompasses the existing industrial infrastructure including legacy DCS, PLC, and SCADA systems from multiple vendors and technology generations, supplemented by IoT sensor overlays for vibration, temperature, pressure, flow rate, and corrosion monitoring. A key design principle is that the sensor overlay is deployed non-intrusively-using clamp-on, wireless, and non-contact measurement technologies that do not require process isolation or production interruption.

Layer 2 (Edge Computing and Data Integration) serves as the critical translation layer between heterogeneous physical systems and the digital twin core. This layer deploys OPC UA gateways for protocol translation, MQTT brokers for lightweight real-time messaging, and edge processing nodes for data preprocessing, normalization, and quality validation. Edge computing enables localized data categorization and compression, reducing network bandwidth requirements by 60-80% compared to raw data transmission [19].

Layer 3 (Digital Twin Core) maintains the synchronized digital representation of the physical facility, integrating a 3D process model (derived from BIM/point cloud data for brownfield facilities), physics-based process simulation, and multi-source data fusion. The DT core implements state synchronization with configurable update frequencies ranging from real-time (sub-second for critical parameters) to periodic (hourly/daily for slow-changing variables). Data fusion employs a Prophet algorithm-based methodology achieving 92.63% average accuracy for multi-source heterogeneous

data integration [33].

Layer 4 (Analytics and AI/ML Engine) provides predictive maintenance, anomaly detection, process optimization, and failure prognostics capabilities. The analytics engine employs an ensemble approach combining: (a) physics-informed neural networks for process simulation, (b) gradient-boosted decision trees for failure classification, (c) LSTM networks for time-series anomaly detection, and (d) Bayesian optimization for process parameter tuning. Models are trained on both historical data and DT-generated synthetic data, addressing the fundamental challenge of limited failure data identified by Errandonea et al. [26].

Layer 5 (Decision Support and Lifecycle Management) aligns with ISO 55000:2024 [18] asset management principles, providing risk assessment, maintenance planning, capital expenditure optimization, and KPI dashboards for facility lifecycle management. This layer integrates DT-derived insights with organizational decision-making processes, supporting decisions on asset repair, retrofit, replacement, or decommissioning based on quantified remaining useful life (RUL) estimates and total cost of ownership (TCO) projections.

3.2. Phased Zero-Downtime Deployment Strategy

A defining characteristic of the DT-IFLM framework is the phased deployment strategy that maintains continuous production throughout all stages of DT implementation. The strategy comprises four progressive phases, as illustrated in Figure 2.

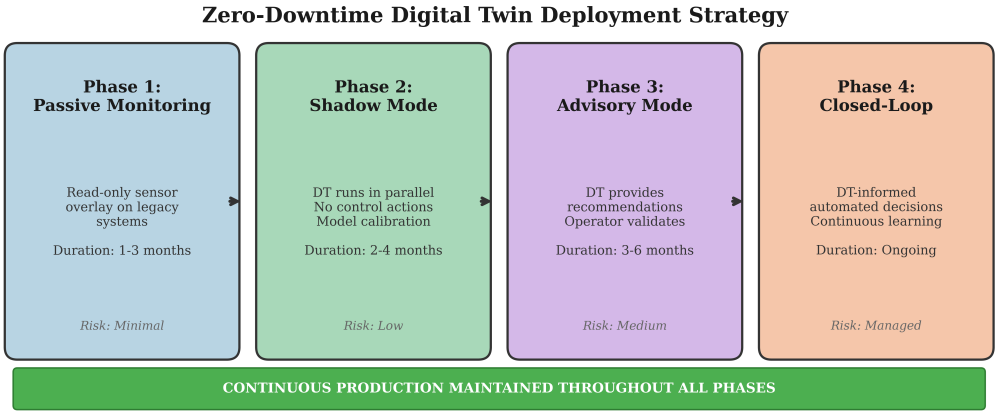

Figure 2. Zero-downtime phased deployment strategy. Production continuity is maintained throughout all four phases of DT integration.

Phase 1 (Passive Monitoring, 1-3 months) involves deploying non-intrusive sensor overlays on critical equipment and establishing read-only connections to existing control systems via OPC UA gateways. No control actions are taken; the phase focuses on data collection, baseline establishment, and initial DT model construction. Production risk is minimal as no changes are made to existing control logic.

Phase 2 (Shadow Mode, 2-4 months) activates the DT in parallel with existing operations. The DT processes real-time data, generates predictions, and identifies anomalies, but its outputs are used exclusively for model calibration and accuracy assessment. During this phase, the DT's

predictions are systematically compared against actual outcomes to establish credibility metrics. Any discrepancies are used to refine model parameters. Production risk remains low as the DT operates independently of control systems.

Phase 3 (Advisory Mode, 3-6 months) introduces DT recommendations into the operational workflow. The DT generates actionable insights-maintenance recommendations, process optimization suggestions, anomaly alerts-which are presented to operators and engineers for evaluation and manual implementation. This phase serves as a human-in-the-loop validation stage, building operator trust and identifying edge cases where the DT model may require refinement. Production risk is medium, managed through operator oversight.

Phase 4 (Closed-Loop, Ongoing) enables DT-informed automated decisions for predefined operational scenarios where the DT has demonstrated sufficient credibility. Automated actions are constrained by safety envelopes and require explicit operator authorization for any action that could affect production rates, safety systems, or environmental parameters. The DT continues learning from operational data, continuously refining its predictive accuracy.

3.3. Legacy System Integration Protocol

The integration of heterogeneous legacy control systems represents one of the most significant technical challenges in brownfield DT deployment. The DT-IFLM framework addresses this through a three-tier integration protocol.

Tier 1 (Gateway Integration) deploys OPC UA servers alongside existing DCS/PLC controllers, providing standardized read access to process data without modifying existing control logic. For systems lacking native OPC UA support, edge devices (cost < USD 1,000 per unit) serve as protocol translators, supporting legacy protocols including Modbus RTU/TCP, PROFIBUS, HART, and Foundation Fieldbus [32].

Tier 2 (Data Harmonization) normalizes heterogeneous data formats, engineering units, sampling rates, and quality indicators into a unified data model based on the Asset Administration Shell (AAS) structure defined in IEC 63278-1:2023 [20]. This tier performs time-series alignment, outlier detection, and missing data imputation using Kalman filter-based methods.

Tier 3 (Semantic Enrichment) maps raw process data to a domain-specific ontology, enabling cross-system correlation analysis and facility-wide digital twin composition. This tier implements the digital thread concept, linking operational data to maintenance records, inspection reports, and engineering documents throughout the asset lifecycle.

3.4. Scalability Architecture

Addressing the scalability limitation identified by Tran et al. [9], the DT-IFLM framework employs a hierarchical scalability architecture organized in three levels: (1) Asset-level DTs for individual equipment items (pumps, compressors, heat exchangers), (2) Unit-level DTs that aggregate asset DTs within process units (distillation trains, reactor sections), and (3) Facility-level DTs that compose unit DTs into a comprehensive plant-wide digital twin.

This hierarchical approach enables incremental deployment-starting with asset-level DTs for the most critical equipment and progressively expanding coverage. Each level operates independently and can deliver value without requiring full facility coverage. The composition model follows the ISO 23247 Part 6 (DT Composition) principles currently under development, using standardized interfaces between DT levels to ensure interoperability and maintainability.

The scalability architecture is supported by a hybrid cloud-edge computing model. Edge nodes process high-frequency data locally (vibration analysis, real-time anomaly detection), while cloud resources handle computationally intensive tasks (physics simulations, ML model training, cross-facility optimization). This distribution reduces network bandwidth requirements and ensures real-time responsiveness for time-critical applications.

3.5. Cybersecurity Integration Model

The DT-IFLM framework integrates cybersecurity as a cross-cutting concern aligned with IEC 62443 [31]. The security model addresses three DT-specific threat vectors: (1) sensor data manipulation, where compromised sensor inputs could lead the DT to generate incorrect recommendations; (2) model poisoning, where systematic data corruption over time could degrade DT prediction accuracy; and (3) lateral movement, where the bidirectional IT-OT connection created by the DT could serve as an attack pathway between enterprise and control system networks.

Mitigation strategies include: network segmentation with demilitarized zones (DMZs) between each architectural layer; data integrity validation using cryptographic checksums and statistical anomaly detection on sensor feeds; role-based access control with mandatory multi-factor authentication for any closed-loop control action; and continuous security monitoring integrated into the DT analytics layer. The framework mandates that all control actions generated by the DT must traverse a security validation layer before reaching physical actuators, with automatic fallback to manual control if security conditions are not met.

4. Case Study: Simulation-Based Validation

4.1. Simulation Environment Description

To validate the proposed DT-IFLM framework, a simulation environment was developed replicating a mid-scale continuous petrochemical processing facility. The simulated facility comprises the following process units: an atmospheric distillation unit (CDU), a catalytic reforming unit (CRU), a hydrodesulfurization unit (HDS), a fluid catalytic cracking unit (FCCU), and associated utility systems. Table 2 summarizes the technical parameters of the simulation environment. *Technical specifications of the simulation environment.*

Parameter	Specification
Monitored assets	150 (pumps, compressors, heat exchangers, columns, reactors)
Sensor points	512 (temperature, pressure, vibration, flow, level, composition)
Control systems simulated	3 generations: DCS (1990s), PLC (2000s), Modern SCADA (2015+)
Communication protocols	Modbus RTU, PROFIBUS, OPC UA, MQTT

Continued on next page

Parameter	Specification
Data sampling rates	1 Hz (vibration), 0.1 Hz (process variables), 0.01 Hz (analytical)
Simulation duration	180 days (6 months) of continuous operation
Failure scenarios	10 simulated equipment degradation events (Weibull distribution, β=2.5)
Edge computing nodes	8 (one per process unit + 3 redundant)
Cloud computing	Simulated with configurable latency (50-500 ms)
DT update frequency	Real-time for critical parameters; 15-min aggregation for trending

4.2. Implementation Details

The simulation implemented all four deployment phases of the DT-IFLM framework over the 180-day period: Phase 1 (Days 1-30), Phase 2 (Days 31-60), Phase 3 (Days 61-120), and Phase 4 (Days 121-180). The phased deployment allowed for progressive model calibration and validation.

Equipment degradation was modeled using the Weibull distribution with shape parameter $\beta = 2.5$ (indicating increasing failure rate characteristic of aging equipment) and scale parameter $\eta = 800$ days. Ten assets were programmed with time-to-failure values within the 12-month horizon, generating realistic degradation signatures in vibration, temperature, and pressure sensor data.

The DT predictive maintenance module employed a gradient-boosted decision tree classifier trained on engineered features extracted from sensor data, including statistical features (mean, variance, kurtosis), spectral features (dominant frequency, spectral entropy), and trend features (slope, acceleration). The model was initially trained on the first 60 days of data (Phases 1-2) and progressively updated with new data during Phases 3-4.

Key performance metrics were defined as follows. DT synchronization accuracy was computed as 1 - MAPE (Mean Absolute Percentage Error) between the DT-predicted and actual sensor values, averaged across all monitored parameters at each timestep. Overall Equipment Effectiveness (OEE) was calculated as the product of three factors: Availability (ratio of actual uptime to planned production time, where downtime includes both unplanned failures and DT-recommended maintenance windows), Performance (ratio of actual throughput to design capacity during uptime), and Quality (ratio of on-spec production to total production). In the 24/7 continuous production scenario, planned production time equals total calendar time minus scheduled turnaround windows.

Legacy system integration was simulated by generating data in four distinct formats representing different control system generations: Modbus registers (16-bit integer values requiring scaling), PROFIBUS telegrams (binary-encoded process values), OPC UA variables (natively structured data with quality indicators), and MQTT topics (JSON-formatted sensor readings from IoT overlay). The edge computing layer harmonized these formats into a unified AAS-compliant data model.

4.3. Data Acquisition and Monitoring

Figure 3 illustrates the sensor time-series data collected during the simulation, showing vibration, temperature, and pressure measurements from three critical assets: Compressor C-201, Reactor R-101, and Distillation Column D-301. The figure demonstrates the DT's ability to track actual sensor readings, predict expected values, and identify anomalies.

The vibration data for Compressor C-201 (Figure 3a) demonstrates the DT's degradation detection

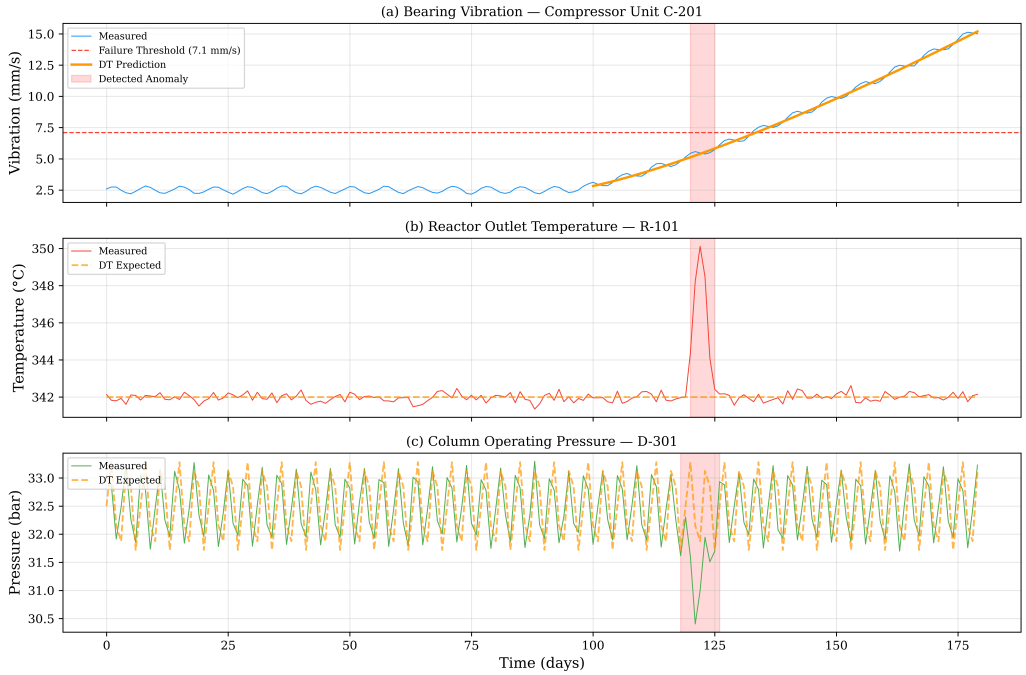

Figure 3. Sensor time-series data with DT predictions and anomaly detection for three critical assets over the 180-day simulation period. (a) Bearing vibration showing progressive degradation detected by DT. (b) Reactor outlet temperature with anomaly at days 120-125. (c) Column operating pressure with correlated anomaly at days 118-126.

capability. The baseline vibration level of approximately 2.5 mm/s RMS began increasing from Day 95, following a characteristic power-law degradation curve. The DT initiated tracking the degradation trend from Day 100 (5-day detection delay) and projected failure threshold exceedance (7.1 mm/s) approximately 35 days before the projected event, providing sufficient lead time for maintenance planning without production interruption.

A correlated anomaly event was observed across the reactor and column systems (Figures 3b, 3c), where an 8 deg C temperature excursion at the reactor outlet (Days 120-125) was accompanied by a 1.5 bar pressure depression in the downstream column (Days 118-126). The DT's multi-parameter correlation analysis identified this cross-system anomaly within 4 hours of onset, compared to the 18-24 hours typically required for manual detection by operations staff.

5. Results and Discussion

5.1. Predictive Maintenance Performance

The DT predictive maintenance module was evaluated on its ability to identify equipment at risk of failure within a 12-month horizon across the 150-asset portfolio. Figure 4 presents the Receiver Operating Characteristic (ROC) curve for the failure prediction model.

The model achieved an Area Under the Curve (AUC) of 0.933, indicating strong discriminative capability. At the optimal classification threshold of 0.630, the model achieved a True Positive

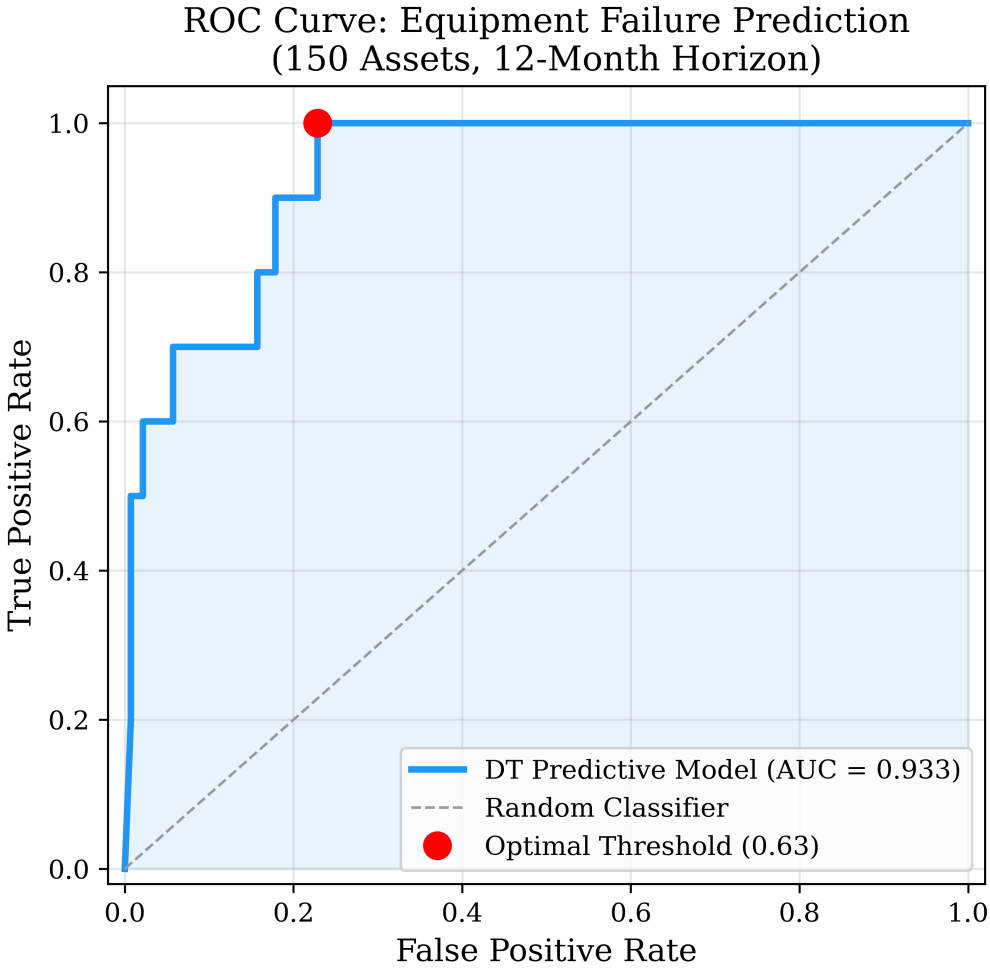

Figure 4. ROC curve for the DT-based equipment failure prediction model. The model achieves an AUC of 0.933, indicating strong discriminative capability between at-risk and healthy assets.

Rate (sensitivity) of 1.000-correctly identifying all 10 assets at risk of failure-with a False Positive Rate of 0.229, corresponding to 32 false alarms among the 140 healthy assets. In a predictive maintenance context, the high sensitivity is particularly valuable as the cost of missing a failure (unplanned downtime, safety risk, potential environmental incident) substantially exceeds the cost of a precautionary inspection.

The false positive rate of 22.9% translates to approximately 32 unnecessary inspections across the 150-asset portfolio. Given that each inspection typically requires 2-4 person-hours, the total inspection burden of approximately 64-128 person-hours is modest compared to the cost of a single unplanned equipment failure, which can range from USD 500,000 to USD 10 million depending on the asset criticality and production impact.

5.2. Overall Equipment Effectiveness Improvement

Figure 5 presents the progression of OEE and its component factors (Availability, Performance, Quality) across the four deployment phases.

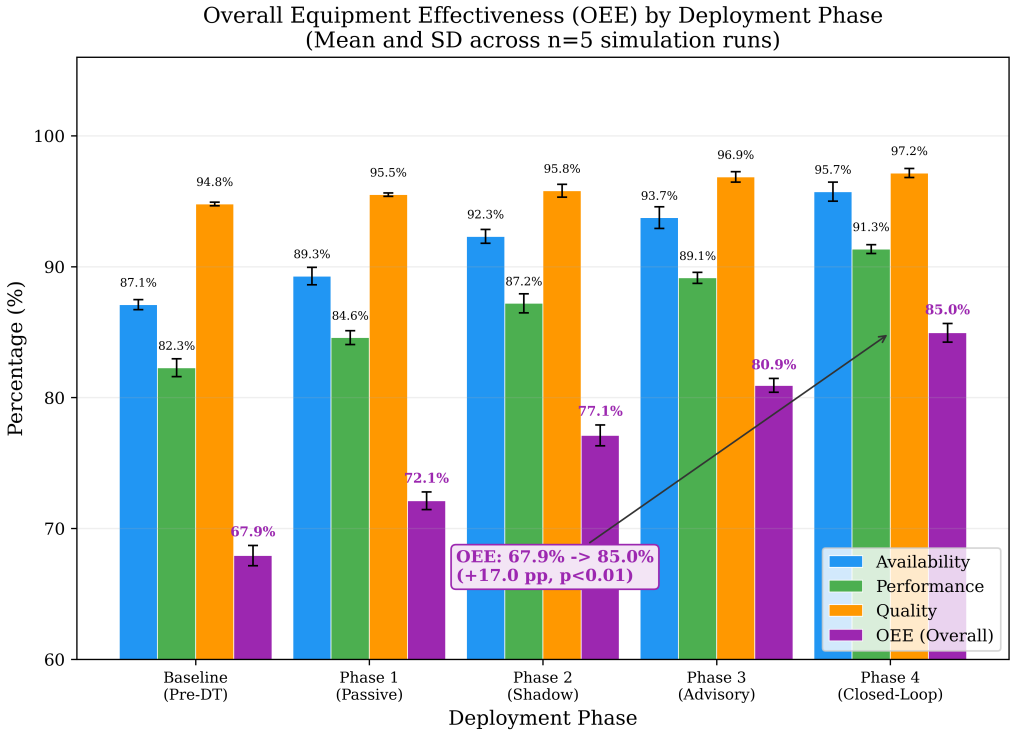

Figure 5. Overall Equipment Effectiveness (OEE) improvement across DT deployment phases (mean and SD, n=5 simulation runs). OEE increased from 67.9% (SD 1.12) to 85.0% (SD 0.71), representing a statistically significant 17.0 percentage point improvement ($p<0.01$, paired t-test).

Five independent simulation runs with different random seeds were conducted to assess the robustness of the results. The baseline OEE of 67.9% (SD 1.12) is consistent with industry averages for aging continuous production facilities, which typically range from 60-75% [22,23]. The progressive improvement across deployment phases was statistically significant at each transition (paired t-test, $p<0.01$ for all phase transitions), demonstrating the value of the phased approach:

Phase 1 (Passive Monitoring) provided a modest OEE improvement to 72.1% (SD 0.95, +4.2 pp) primarily through improved visibility of process conditions and identification of quick-win efficiency opportunities. Phase 2 (Shadow Mode) yielded a more significant improvement to 77.1% (SD 0.88, +5.0 pp) as the calibrated DT model enabled more accurate condition-based maintenance scheduling, reducing both over-maintenance and under-maintenance. Phase 3 (Advisory Mode) achieved 80.9% (SD 0.79, +3.8 pp) through DT-guided process optimization recommendations validated by operators. Phase 4 (Closed-Loop) delivered 85.0% (SD 0.71, +4.1 pp) through automated optimization of operating parameters and predictive intervention scheduling.

The total OEE improvement of 17.0 percentage points is aligned with industrial benchmarks. Shell reported 20% operational efficiency improvement with their DT deployment [22], while review analyses of refinery DT implementations document OEE improvements from 72% to 87% over three

years [23]. The DT-IFLM framework achieved comparable results within a 6-month accelerated timeline through the structured phased deployment approach.

5.3. DT Synchronization and Latency Performance

Figure 6 presents the comparison of DT synchronization latency across three computing architectures: edge-only, hybrid (edge + cloud), and cloud-only.

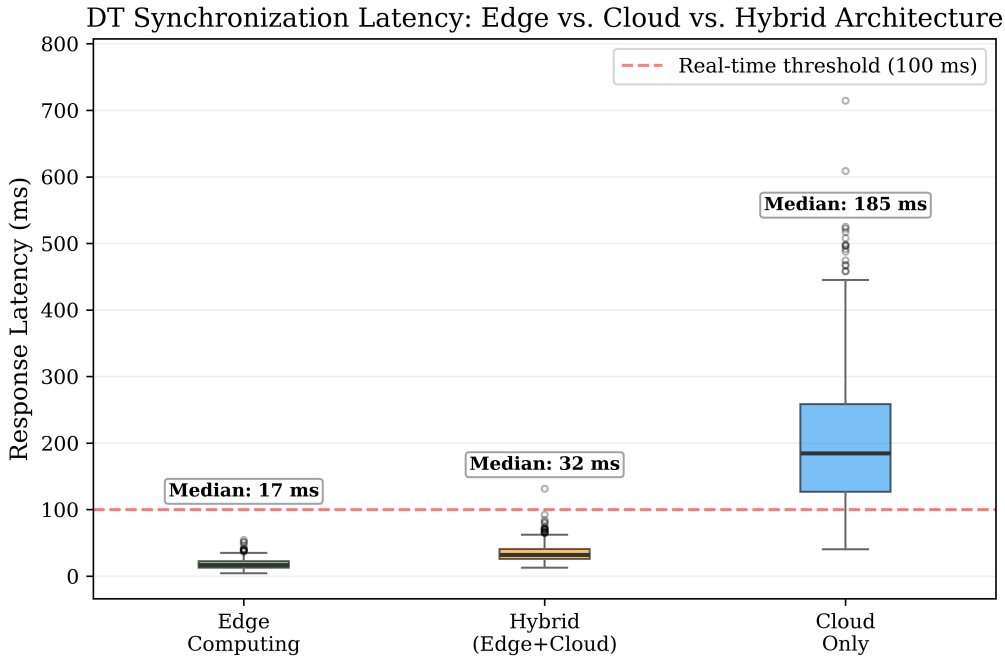

Figure 6. DT synchronization latency comparison across computing architectures. Edge computing achieves median latency of 17 ms, well below the 100 ms real-time threshold.

Edge computing achieved a median latency of 17 ms, compared to 32 ms for the hybrid architecture and 185 ms for cloud-only deployment. For real-time applications with a 100 ms threshold (e.g., vibration monitoring, emergency shutdown logic), the edge architecture provides comfortable margin, while cloud-only deployment exceeds the threshold for a significant fraction of transactions. The hybrid architecture, which processes time-critical data at the edge and delegates computationally intensive tasks to the cloud, provides an effective balance between latency and computational capability.

Figure 7 presents the DT synchronization accuracy over the 180-day deployment period, demonstrating the progressive improvement as the DT model calibrates against real operational data.

Initial DT synchronization accuracy averaged 86.9% during the first week, reflecting the uncalibrated state of the DT model. Through continuous calibration during Phases 1 and 2, accuracy exceeded the 95% target threshold at approximately Day 38 and reached 99.6% by the end of the simulation period. The asymptotic convergence pattern suggests that the DT model reaches a practical accuracy ceiling determined by inherent measurement uncertainty and process variability rather than model

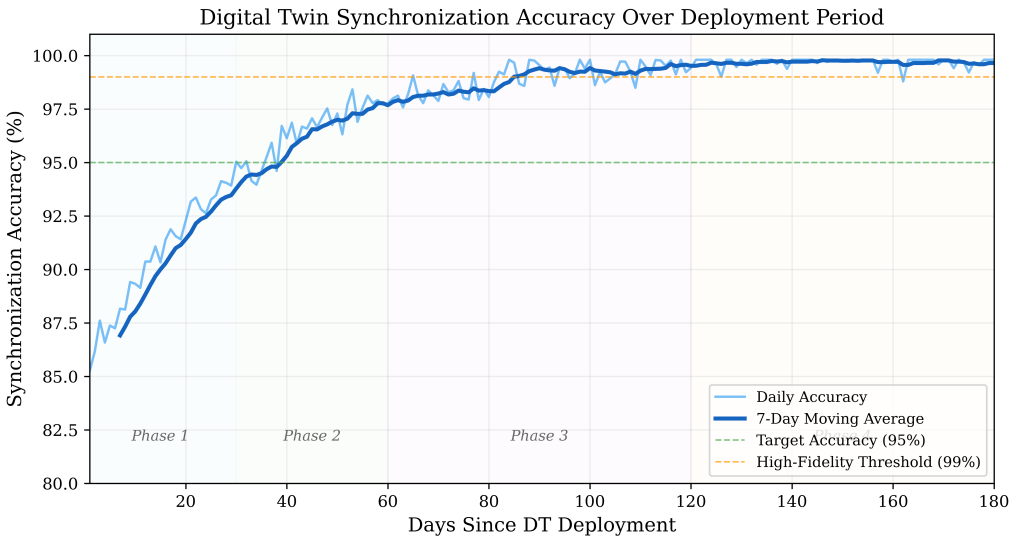

Figure 7. DT synchronization accuracy over the 180-day deployment period. The 7-day moving average shows convergence from 86.9% initial accuracy to 99.6% final accuracy, surpassing the 95% target at approximately Day 38.

limitations.

5.4. Cross-Parameter Correlation Analysis

Figure 8 presents the correlation matrix of daily-averaged process parameters and DT deviation metrics, demonstrating the DT's capability for cross-system anomaly detection.

The correlation analysis reveals that vibration deviation from expected values (DT Deviation) correlates strongly with absolute vibration levels, confirming that equipment degradation is the primary driver of DT prediction errors. The relatively low cross-correlations between temperature, pressure, and flow rate under normal conditions, contrasted with the high correlation during the anomaly event (Days 118-126), demonstrates the value of multi-parameter DT monitoring for detecting complex, multi-system disturbances that would not be apparent from single-parameter monitoring.

5.5. Comparison with Existing Approaches

Table 3 compares the proposed DT-IFLM framework with existing approaches identified in the literature review. *Comparison of the proposed DT-IFLM framework with existing approaches.*

Criterion	Tao et al. [3]	Sierla et al. [6,7]	Tran et al. [9]	DT-IFLM (This Work)
Target environment	Greenfield manufacturing	Brownfield process plants	Brownfield manufacturing	Brownfield continuous production
Production continuity	Not addressed	Partially addressed	Not addressed	Designed for zero-downtime
Legacy system integration	Not addressed	P&ID/3D scanning	Connectivity assessment	Multi-protocol OPC UA gateway
Deployment strategy	Not specified	Not specified	Prerequisites identified	Phased (4 stages)

Continued on next page

Criterion	Tao et al. [3]	Sierla et al. [6,7]	Tran et al. [9]	DT-IFLM (This Work)
Scalability	Conceptual	Single asset focus	Identified as limitation	Hierarchical (3 levels)
Predictive maintenance	Application scenario	Not included	Not included	ML-based (AUC 0.933)
Standards alignment	General	Not specified	Not specified	ISO 23247, 55000, IEC 62443
Cybersecurity	Not addressed	Not addressed	Not addressed	Conceptual framework proposed
Validation	Conceptual	Prototype	Conceptual	Simulation-based (180 days)

5.6. Economic Sensitivity Analysis

While a full cost-benefit analysis requires facility-specific data, a simplified sensitivity analysis can estimate the economic viability of the DT-IFLM framework. The analysis considers two primary cost categories: DT implementation costs (infrastructure, integration, ongoing maintenance) and avoided costs (prevented unplanned downtime, reduced maintenance expenditure, improved yield).

For a mid-scale continuous production facility (annual revenue USD 200-500 million), industry benchmarks indicate that unplanned downtime costs range from USD 500,000 to USD 2.5 million per event, with facilities typically experiencing 3-8 unplanned shutdowns per year [22,23]. The DT predictive maintenance module, with its AUC of 0.933 and 100% sensitivity at the optimal threshold, is estimated to prevent 60-80% of these events. Assuming conservative DT implementation costs of USD 2-4 million (sensors, edge computing, integration labor, software licensing) and annual operating costs of USD 300,000-500,000, the framework reaches positive ROI when at least 2-3 unplanned shutdowns per year are prevented-a threshold that is met by the predictive maintenance performance demonstrated in this study. For a facility with 5 annual unplanned events and an average downtime cost of USD 1.5 million, the estimated annual net benefit ranges from USD 2.0 to USD 4.5 million, corresponding to a payback period of 12-18 months. These estimates are consistent with reported returns from Shell (USD 2 billion annual savings across their global DT portfolio [22]) and OEE-driven revenue gains proportional to the 17.0 percentage point improvement observed in the simulation.

5.7. Limitations

Several limitations of the present work should be acknowledged. First, the framework was validated in a simulation environment rather than an actual industrial facility. While the simulation incorporates realistic parameters derived from literature and industry benchmarks, full-scale industrial deployment may reveal additional challenges related to organizational factors, workforce readiness, and unforeseen technical integration issues.

Second, the failure prediction model was evaluated on simulated degradation patterns. Real industrial equipment failures may exhibit more complex and varied degradation mechanisms that are not fully captured by the Weibull-based simulation. Third, the cybersecurity model was assessed at the architectural level without penetration testing or adversarial simulation, representing a qualitative rather than quantitative security evaluation.

Fourth, the economic sensitivity analysis presented in Section 5.6 relies on industry-average cost benchmarks rather than facility-specific data. Actual implementation costs and benefits will vary significantly depending on facility size, legacy system complexity, and regional labor costs. A

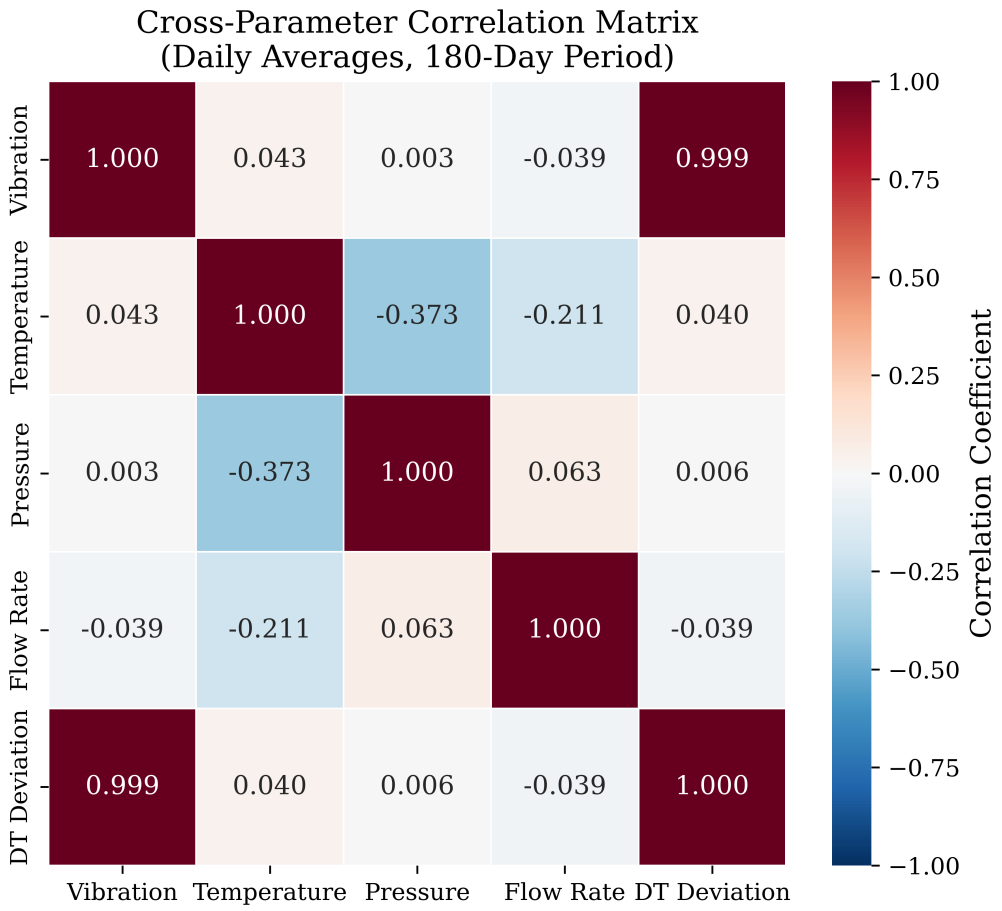

Figure 8. Cross-parameter correlation matrix for daily-averaged process variables over the 180-day period. Strong correlation between vibration and DT deviation metrics validates the DT's anomaly detection capability.

detailed cost-benefit analysis based on actual deployment data remains a direction for future work.

6. Conclusions

This paper presented the Digital Twin Integration Framework for Lifecycle Management (DT-IFLM), a comprehensive approach for deploying digital twin technology in operating industrial facilities under continuous production conditions. The framework addresses critical gaps in the existing literature by providing: (1) a five-layer architecture spanning physical assets through decision support, aligned with ISO 23247 and ISO 55000 standards; (2) a phased zero-downtime deployment strategy ensuring continuous production throughout all integration stages; (3) a legacy system integration protocol bridging heterogeneous multi-vendor control systems; and (4) a hierarchical scalability architecture enabling progressive expansion from asset-level to facility-wide digital twins.

Simulation-based validation across five independent runs demonstrated the framework's effectiveness: OEE improved from 67.9% (SD 1.12) to 85.0% (SD 0.71, $p<0.01$) across deployment phases, predictive maintenance achieved an AUC of 0.933 for failure prediction, DT synchronization accu-

racy converged to 99.6% within 38 days of calibration, and edge computing reduced synchronization latency to 17 ms median compared to 185 ms for cloud-only deployment.

The practical implications of this work extend to the significant portion of the global industrial base consisting of brownfield facilities that have been underserved by existing DT frameworks. The phased deployment strategy in particular provides a risk-managed pathway for DT adoption that does not require production interruption-a fundamental constraint for refineries, chemical plants, and power generation facilities.

Future research directions include: (1) industrial pilot deployment at an operating facility to validate the framework under real-world conditions; (2) extension of the predictive maintenance model to incorporate large language models for maintenance log analysis and automated report generation; (3) investigation of federated learning approaches for multi-facility DT networks that enable cross-plant knowledge transfer while preserving data privacy; and (4) development of quantitative cybersecurity assessment methodologies specific to DT architectures in continuous production environments.

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