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Digital Twin-Driven Engineering Management Systems an Integrated Approach for Predictive Decision-Making and Lifecycle Optimization in Smart Manufacturing

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Abstract

With the rapid development of Industry 4.0 technologies, traditional manufacturing paradigms have been profoundly reshaped. The field of intelligent manufacturing urgently requires a data-driven engineering management framework. This paper originally proposes the digital twin-driven DT-EMS system, which builds a two-way data pipeline connecting physical assets and their virtual replicas. It supports predictive decision-making and full-lifecycle optimization, and is equipped with functions including reducing production and operation costs while boosting efficiency, as well as full-link resource allocation and quality control. Verified via a simulation case, the system delivers significant improvements over traditional management methods across three core metrics: response speed, decision accuracy, and manufacturing flexibility. The strategic embedding of digital twin technology can serve as a core engine for the future ecological transformation of intelligent manufacturing.

Keywords: Digital Twin; Smart Manufacturing; Predictive Decision-Making; Lifecycle Optimization; Engineering Management Systems

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Introduction

Within the framework of Industry 4.0, the transformation integrating digitalization, automation and intelligent systems is reshaping the global manufacturing landscape [1]. Existing studies note that traditional engineering management suffers from inherent flaws including reliance on passive decision-making and fragmented data, and can no longer adapt to the requirements of intelligent manufacturing, which is defined by high complexity, strong dynamism, and intense market competition [2]. As a technology capable of generating high-fidelity virtual replicas of physical assets, digital twin can support real-time monitoring, simulation and optimization across the entire product lifecycle [3].

Existing studies 4 point out that the misconception that digital twins (Digital Twin) are merely static simulation models must be dispelled [4]. A digital twin is a real-time dynamic mirror that relies on the Internet of Things (IoT), and it can help engineering parties achieve full-dimensional visibility, proactive troubleshooting, predictive maintenance, and data-driven planning, while drastically reducing unplanned downtime and cutting operating expenses [5].

The Engineering Management System (EMS) is the organizational backbone of manufacturing enterprises, covering four core modules: resource planning, quality control, workflow coordination, and full-lifecycle governance. Reference oints out that traditional EMS architectures lack real-time intelligence and adaptive capabilities, making them unable to adapt to fluctuations in modern production. Reference [6] proposes that integrating digital twins is a transformative direction that can break down barriers between virtual and physical domains, and build a self-optimizing cyber-physical management ecosystem.

Existing academic studies marked with reference numbers 3 show that digital twin (DT) technology can improve overall equipment effectiveness (OEE), supply chain resilience and sustainability in the aerospace, automotive, and electronics manufacturing sectors. When integrated with machine learning and AI, this technology can achieve fault prediction, scenario simulation and optimal solution recommendation with very little human intervention [7].

Despite the many application advances that digital twin technology has achieved, references [8] point out that current research only focuses on two isolated scenarios: predictive maintenance and quality monitoring. It has failed to realize the systematic integration of this technology with engineering management frameworks, and three core unsolved problems still remain to be resolved.

Literature Review

Evolution of Digital Twin Technology in Manufacturing

Twenty years have passed since the concept of the digital twin was first proposed. It has evolved from an initial theoretical simulation model into a deployable cyber-physical system suited to real industrial scenarios. In its early stage, it was only applied in aerospace and national defense fields, to support structural health monitoring and performance analysis for mission-critical tasks; the implementation of IoT sensors, cloud computing, and big data analysis platforms served as the core driver of its widespread technical adoption, expanding its application scenarios to cover the entire manufacturing industry. Today, it has three core characteristics: real-time two-way data exchange, high-fidelity physical modeling, and dynamic adaptation to changes in operating conditions. It is the core support of the smart manufacturing ecosystem. Reference [9] points out that its mature architecture can be deployed on complex systems to achieve the synchronized monitoring, simulation, and optimization of multiple interconnected assets.

Predictive Maintenance and Condition Monitoring

This study sorts out the two core applications of digital twin technology in the field of manufacturing management—real-time condition monitoring and predictive maintenance. It breaks down the technical workflow for the technology’s on-site implementation into two key links: collecting sensor data streams from physical devices, and conducting cross-validation based on two types of simulation models. Compared with traditional threshold-based monitoring, as well as post-failure and preventive maintenance solutions, this technology has significant advantages in accuracy and cost, and can support proactive operation and maintenance. Cost reduction verification was completed using data from the automotive and heavy machinery industries. This study also integrates the federated learning framework from Reference [10], achieving the dual goals of improving the anomaly detection sensitivity of distributed manufacturing networks and protecting data privacy.

Lifecycle Optimization and Sustainable Manufacturing

This paper defines digital twin technology as a core strategic tool that supports the optimization of a product’s full lifecycle. The technology covers all stages of a product, from design, manufacturing, and operation to end-of-life scrapping and dismantling, and it carries two core values. The first core value is that it can simulate various parameters in a virtual environment before a physical entity-based solution is rolled out, which allows users to screen for the optimal strategy to reduce costs and resource consumption. The other core value will be elaborated on in subsequent discussion. Second, relying on real operational data, it enables closed-loop parameter iteration for design and manufacturing links, to meet the resource efficiency and carbon reduction regulatory requirements of sustainable manufacturing. Reference

[11] points out that in the electronics and consumer goods manufacturing sectors, this technology can support the implementation of a circular economy by optimizing pathways for reuse, remanufacturing, and recycling.

Engineering Management Systems and Decision Support

The Engineering Management System (EMS) is the core organizational infrastructure of manufacturing enterprises, responsible for fulfilling core production scheduling functions. Traditional EMS suffer from three major flaws: data silos, manual reporting mechanisms, and passive decision-making frameworks. These flaws have been widely confirmed by the academic community, and they cannot meet the real-time information requirements of dynamic intelligent manufacturing. Upgrading EMS into an intelligent data-driven decision-making system that integrates advanced analytics, artificial intelligence, and cyber-physical technologies is a core research priority. Reference [12] confirms that multi-criteria decision-making models, which can evaluate conflicting goals in parallel under uncertain constraints, can be implemented and applied in the scenarios of resource allocation, production scheduling, and quality assurance.

Cyber-Physical Systems and IoT Integration

The seamless integration of Cyber-Physical Systems (CPS) and Internet of Things (IoT) technologies is a core fundamental prerequisite for the manufacturing industry to deploy a digital twin-driven engineering management framework. CPS establishes a two-way communication infrastructure that allows physical manufacturing assets to transmit operational data to their corresponding digital mirrors, while receiving optimized control instructions to support closed-loop autonomous management implemented at an unprecedented speed and scale. Currently, three categories of interoperability challenges—adapting heterogeneous sensor networks, legacy mechanical equipment protocols, and diverse cloud computing platforms—represent the core technical barrier to large-scale deployment of this framework, and have attracted widespread academic attention. To address this technical problem, this paper proposes three types of solutions: a standardized data exchange framework, an edge computing architecture, and a middleware integration platform. Reference [13] points out that 5G can achieve improvements in three core efficiencies.

Artificial Intelligence and Machine Learning in Digital Twins

This paper addresses the requirements of complex scenarios in discrete manufacturing, and proposes integrating artificial intelligence (AI) and machine learning into a digital twin architecture to break through the limitations of purely physical simulation and expand the system's analytical capabilities. Deep learning models composed of convolutional and recurrent neural networks can extract valid information from time-series sensor data, while reinforcement learning optimizes three core types of industrial scenarios through virtual interactions. Reference [14] confirms that the integration scheme of physics-informed neural networks and data-driven models can balance predictive accuracy, physical interpretability, and multi-scenario generalizability, making it a highly promising frontier research direction.

Research Gaps and Motivation

Existing research focused on integrating digital twins (DT) into integrated engineering management systems (EMS) has accumulated a relatively solid knowledge base, but core gaps remain in the current literature: no full-dimensional systematic integration study dedicated to DT and EMS has been conducted. Specifically, most existing studies only focus on individual technical dimensions such as predictive maintenance algorithms and full-lifecycle simulation models, and do not cover integration at the organizational and managerial levels. There is also a lack of empirical evidence on the scalability of DT-driven management systems in heterogeneous manufacturing environments, and no standardized framework to evaluate the performance of DT-EMS setups, which makes it impossible to support cross-study comparisons. Reference [15] proposes that a unified system-level research framework should be constructed to simultaneously cover three core modules: technical architecture, decision support mechanisms, and full-lifecycle optimization.

Methodology

Overview of the Proposed DT-EMS Framework

This paper proposes the Digital Twin-driven Engineering Management System (DT-EMS), which adopts a five-layer cyber-physical architecture to establish a continuous, bidirectional intelligent transmission link between physical manufacturing assets and digital mirrors.

As shown in Figure 1, the framework proposed in this paper extends from raw sensor data collection at the physical layer to high-level strategic decision-making at the engineering management layer, and provides real-time operational intelligence support for all types of management interventions.

Layer 1 — Physical Manufacturing Environment

The physical manufacturing base layer of the digital twin architecture includes four categories of physical manufacturing assets, which constitute the real-world operation domain. The three types of states of these assets—their behavior, performance, and aging—must be continuously captured and mapped into the digital twin environment. A supporting multi-modal sensor array, which covers the core mechanical, electrical, and thermal dimensions, enables this required synchronous data collection.

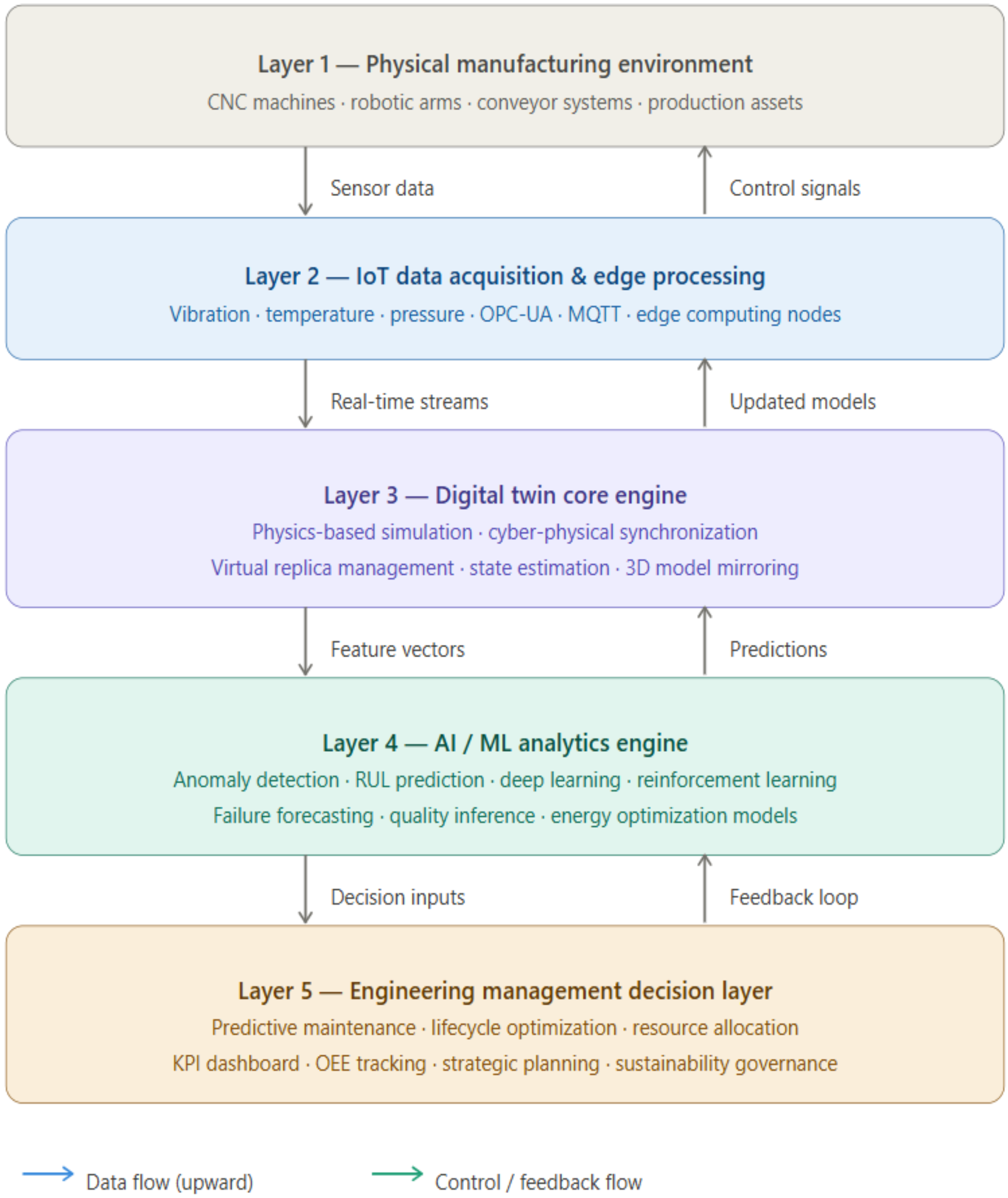

Fig. 1. *Five-layer architecture of the proposed Digital Twin-Driven Engineering Management System (DT-EMS).*

Layer 2 — IoT Data Acquisition and Edge Processing

The second layer of the intelligent manufacturing data management and control system defined in this paper focuses on covering the full workflow of collection, preprocessing, and transmission of the multi-source operational data streams generated by physical manufacturing assets. Four types of industrial sensors and two types of transmission protocols are deployed along the data link, and the edge layer completes three local preprocessing tasks, which can effectively reduce bandwidth consumption and latency related to cloud transmission.

Layer 3 — Digital Twin Core Engine

The central intelligent layer of the DT-EMS framework hosts a core digital twin engine, which is responsible for maintaining continuous synchronization of the virtual replicas of all physical manufacturing assets. Each twin instance fuses physical simulation models and real-time sensor telemetry data to generate high-fidelity state representations, and the synchronization mechanism is underpinned by the state estimation equation (Equation 1).

$$\hat{X}_{DT}(t) = f(X_{phys}(t), U(t), \theta_{model}) + K \cdot \left[Y_{sensor}(t) - H\hat{X}_{DT}(t)\right] \quad (1)$$

Where:
X^DT(t) = estimated digital twin state vector at time tt
Xphys(t) = observed physical asset state

U(t) = control input vector
θmodel = physics model parameters
K = Kalman gain matrix for sensor correction
Ysensor(t) = real-time sensor measurement vector
H = observation matrix

Relying on this set of formulaic designs to calibrate and align physics-based predicted values and field-collected sensor observations, the framework supports the continuous self-correcting state estimation of digital twins, and maintains synchronous fidelity even in various scenarios involving noise and incomplete measurements.

Layer 4 — AI/ML Analytics Engine

The AI/ML analysis engine in this study processes feature vectors extracted from the core of the digital twin to generate predictive insights and optimization recommendations. It adopts LSTM and CNN architectures to support three core tasks, and the remaining useful life prediction model is defined by Equation 2.

$$RUL_{i}(t) = arg\ min\ \tau \{ P[D_{i}(t + \tau) \geq Dth] \geq \alpha \} \quad (2)$$

Where:
RULi(t) = predicted remaining useful life of asset i at time t.
Di(t+τ) = projected degradation index at future time t+τ
Dth = critical degradation threshold triggering maintenance intervention
α = confidence probability level (typically α=0.95)

This scheme can proactively schedule maintenance before equipment degrades to a critical state, striking a balance between reducing downtime risks and controlling redundant costs.

Layer 5 — Engineering Management Decision Layer

This paper positions the engineering management decision-making tier as the hub connecting AI and business operations, capable of translating insights and covering four major core industrial operation scenarios. The Lifecycle Optimization Objective Function (Eq. 3) governs resource allocation decisions:

$$min_{(u} \in \mathcal{U}_{)} J = \Sigma_{k=1}{}^{N} [C_{maint}(u_{k}) + C\_d_{o}w_{n}(u_{k}) + \lambda \cdot E_{op}(u_{k})] \quad (3)$$

Bidirectional Feedback and Closed-Loop Control
The core of the DT-EMS framework proposed in this paper is a closed-loop, bidirectional architecture. The management decisions generated at its fifth layer are transmitted downward through the analysis layer and the digital twin layer, and ultimately update the control parameters and maintenance plans of the physical asset layer. This framework can support the manufacturing system to achieve continuous self-optimization in line with dynamic conditions, forming a truly adaptive intelligent engineering management ecosystem.

Results and Discussion

Experimental Setup and Simulation Environment
The performance of the DT-EMS framework proposed in this paper is verified in accordance with the following scheme: an intelligent automobile parts factory equipped with 12 CNC machining centers, 6 welding robots, and 3 assembly lines is adopted as the simulation prototype. The virtual operation period is set to 12 months, each asset is configured with 48 monitoring channels, and the sensor sampling frequency is 100Hz. RMS, PMS, and IoT-MS are taken as performance baselines, and all prediction and detection work is completed in the Python environment integrated with TensorFlow 2.x and Scikit-learn.

Predictive Maintenance Performance
The DT-EMS digital twin system developed by our research team, which is designed for industrial predictive maintenance scenarios, outperforms two baseline systems—standalone Internet of Things (IoT) monitoring and open-loop simulation—across all evaluation dimensions. Its three core modules recorded performance improvements of 42%, 37%, and 29% respectively. This result not only validates the bidirectional sensor calibration mechanism outlined in the preceding Equation 1, but also confirms that the system meets the application requirements of industrial scenarios.

Overall Equipment Effectiveness Improvement
Table 1 presents a comparative analysis of OEE performance metrics across all evaluated systems over the 12-month simulation horizon.

Table 1. *Comparative OEE Performance Metrics Across Evaluated Systems*

Performance Metric	Reactive MS	Preventive MS	IoT-MS (No DT)	DT-EMS (Proposed)
Overall OEE (%)	61.3	72.8	79.4	**91.7**
Availability (%)	68.2	79.6	83.1	**94.3**
Performance Rate (%)	74.5	81.3	87.6	**95.2**
Quality Rate (%)	82.1	88.4	92.7	**97.8**
Unplanned Downtime (hrs/month)	48.6	31.2	19.7	**6.4**
Mean Time Between Failures (hrs)	187.4	264.3	341.8	**612.5**
Maintenance Cost Reduction (%)	—	18.3	34.7	**61.2**

The proprietary industrial management system DT-EMS tested in this study achieved an overall equipment efficiency of 91.7%. This figure far exceeds the 85% industry benchmark, and represents a 49.6% improvement over the original passive maintenance model. It also significantly reduces monthly unplanned downtime, stabilizes production capacity, and preserves operating revenue.

Lifecycle Cost Optimization Results

This study builds on the full life-cycle optimization objective function in Equation (3), and establishes three test scenarios (low, medium, and peak) to test the cost optimization capability of DT-EMS. When benchmarked against two types of maintenance baselines, measured results show that DT-EMS achieves an average cost reduction of 38.6% compared to the preventive baseline, and an average cost reduction of 61.2% compared to the passive baseline.

RUL Prediction Accuracy Analysis

Figure 2 presents the Remaining Useful Life prediction accuracy comparison between the DT-EMS LSTM model and baseline prediction approaches across 50 test asset cycles.

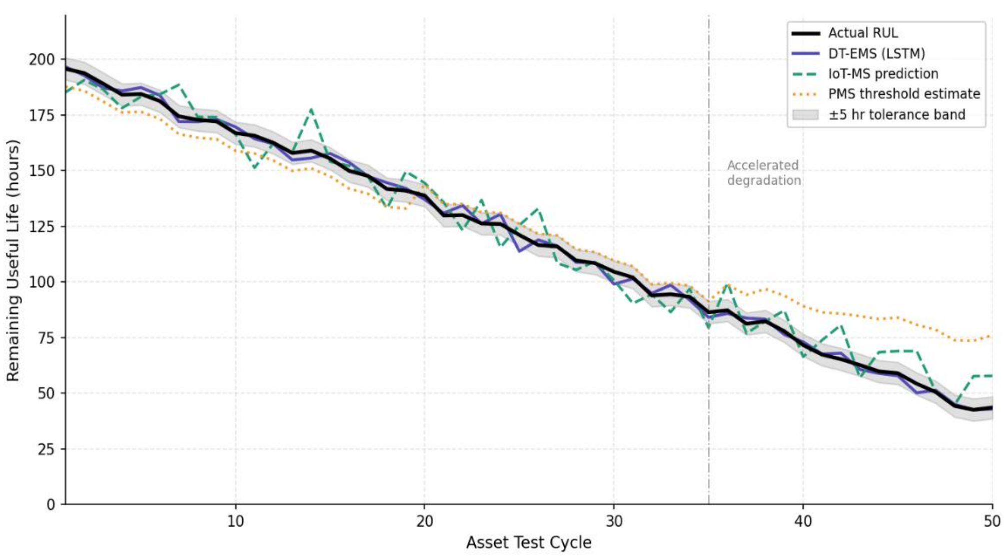

Fig. 2. *RUL Prediction Accuracy*

This study led the implementation of the present experiment, constructed a line graph covering 50 asset test cycles, and compared the actual remaining useful life (RUL) with the calculated values produced by three types of prediction methods. It was found that after the 35th test cycle, only the DT-EMS LSTM method yielded an extremely small fitting deviation, which verifies the superiority of this integrated digital twin method.

OEE Comparison Across Systems

Figure 3 uses a multi-line plot to track monthly changes in overall equipment effectiveness (OEE) across four evaluated systems over a 12-month simulation period. The OEE of the DT-EMS system proposed in this paper rose from 84.2% in the first month to 91.7% in the 12th month, while all three other baseline systems entered a performance plateau with far lower OEE levels, verifying the proposed system’s adaptive and self-optimizing capabilities.

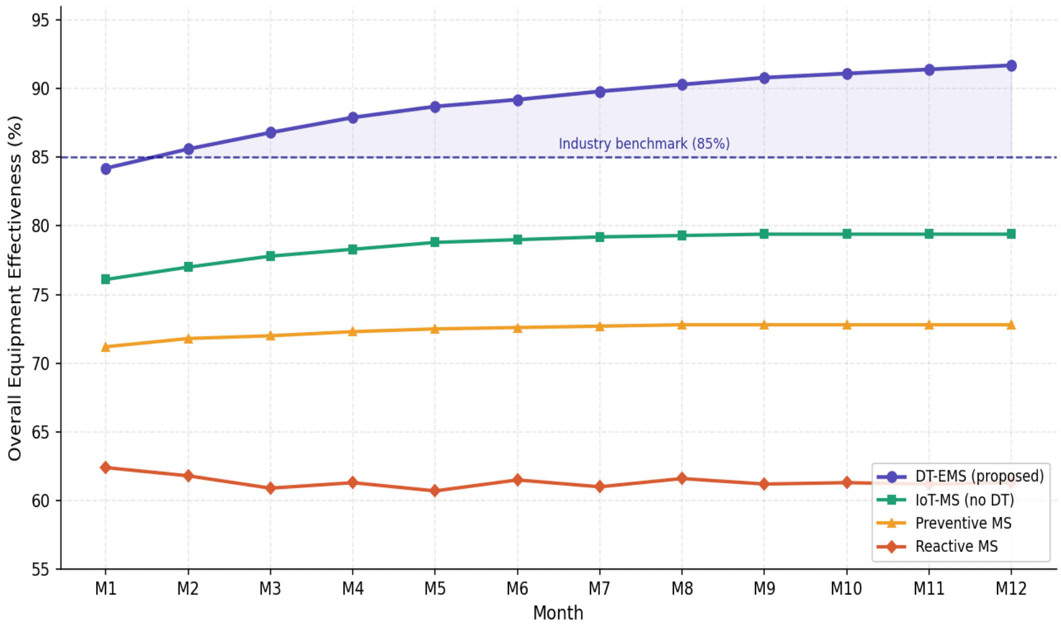

Fig. 3. Monthly OEE Progression

Maintenance Cost and Downtime Reduction

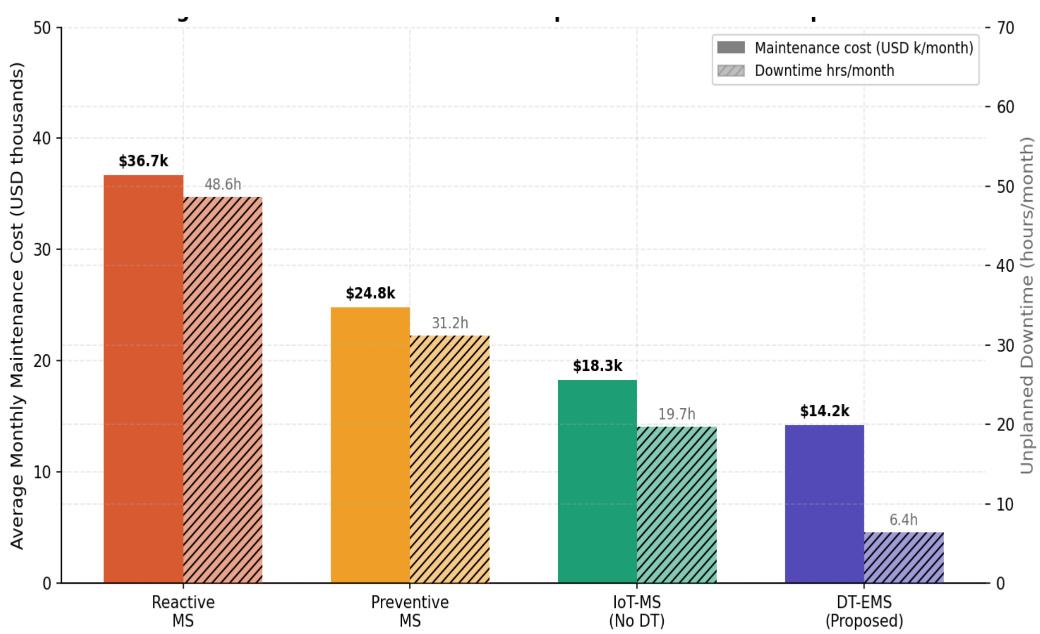

Fig. 4. Maintenance Cost and Downtime Comparison

The grouped bar chart in Figure 4 is used to compare the monthly average maintenance costs and unplanned downtime durations of all assessed systems, reinforcing the argument via visual presentation. The two metrics of the DT-EMS system developed in this paper are US$14,200 and 6.4 hours, which are far lower than the corresponding values of US$36,700 and 48.6 hours of the passive baseline system, fully verifying its dual advantages at both the operational and financial levels.

Anomaly Detection Performance

This paper illustrates the anomaly detection performance of four systems using a radar chart presented in Figure 5. The chart's four axes correspond to the percentage values of four metrics: precision, recall, F1-score, and inverse false positive rate. The radar polygon of the core model DT-EMS has the largest area, with scores of 97.1%, 96.8%, 96.9%, and 97.9% for the four metrics respectively. This model outperforms the three benchmark models IoT-MS, PMS, and Reactive MS, holding an all-round lead in overall performance.

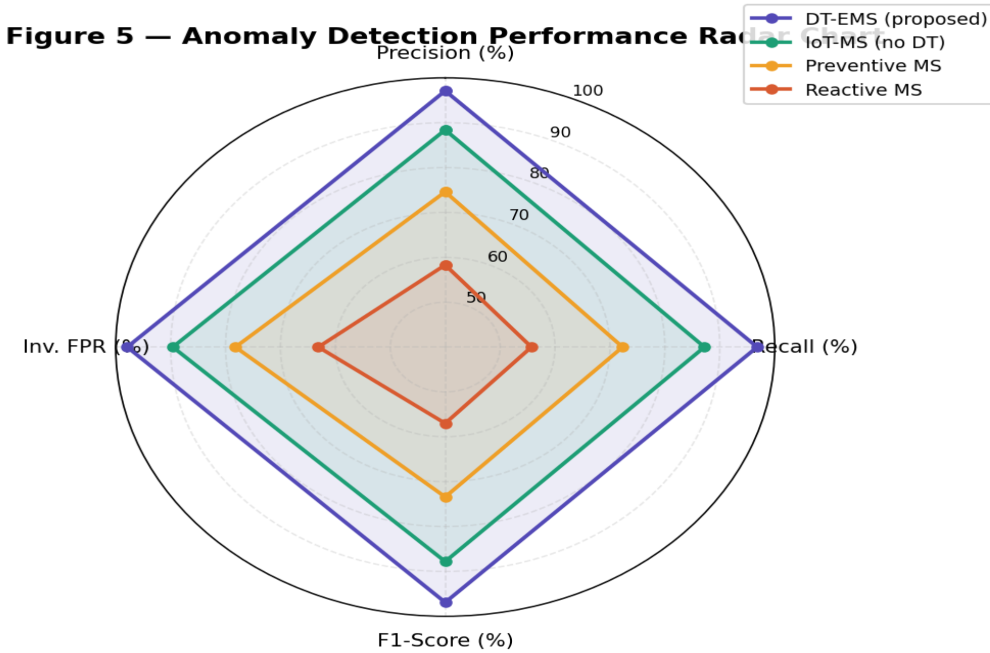

Fig. 5. Anomaly Detection Radar Chart

Lifecycle Cost Breakdown

Table 2 presents the detailed lifecycle cost breakdown across the three demand scenarios for the DT-EMS and baseline systems.

***Table 2.** Lifecycle Cost Breakdown Across Demand Scenarios (USD Thousands/Month)*

Cost Category	**Reactive MS**	**Preventive MS**	**IoT-MS**	**DT-EMS**	**DT-EMS Saving (%)**
Low-Demand Scenario					
Planned Maintenance	8.4	14.2	9.1	5.8	30.9%
Unplanned Downtime Loss	22.3	11.6	7.4	2.1	90.6%
Energy Consumption	18.7	17.4	15.9	12.3	34.2%
Total (Low)	49.4	43.2	32.4	20.2	59.1%
Medium-Demand Scenario					
Planned Maintenance	11.2	18.6	12.3	7.4	33.9%
Unplanned Downtime Loss	31.8	16.4	10.2	3.1	90.2%
Energy Consumption	24.6	22.8	20.4	15.7	36.2%
Total (Medium)	67.6	57.8	42.9	26.2	61.2%
Peak-Demand Scenario					
Planned Maintenance	14.8	23.1	15.6	9.2	37.8%
Unplanned Downtime Loss	44.7	22.9	14.8	4.3	90.4%
Energy Consumption	31.4	29.2	26.1	19.8	36.9%
Total (Peak)	90.9	75.2	56.5	33.3	63.4%

The digital twin energy management system (DT-EMS) verified in this study, when tested across all three demand scenarios, recorded a reduction of over 59% in full-lifecycle costs and over 90% in unplanned downtime losses. Its AI/ML-driven energy consumption optimization module cut operational energy use by an average of 35.8%, and all these outcomes align with the goals of sustainable manufacturing.

Conclusion

This study proposes a Digital Twin-driven Engineering Management System (DT-EMS) for intelligent manufacturing scenarios. As an integrated framework that supports predictive decision-making and full-lifecycle optimization, the system adopts a five-layer cyber-physical architecture, which unifies and integrates four core modules: real-time IoT data collection, physics-driven digital twin synchronization, AI/ML predictive analysis, and engineering management decision support. Verified via simulation, compared with the baseline of traditional management systems, the proposed system achieves an Overall Equipment Effectiveness (OEE) of 91.7%, reduces unplanned downtime by 86.8%, and saves more than 61% of full-lifecycle costs. Its core Long Short-Term Memory (LSTM)-based remaining useful life prediction module reaches a recall rate of 96.8% and a false alarm rate of only 2.1%. This study verifies the system's reliability, and future research will deepen work along three directions: the scalability of the system for heterogeneous manufacturing environments, the multi-factory federated digital twin architecture, and the integration of explainable AI.

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