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Research on Techno-Economic Restructuring of Digital Twin and Big Data in Intelligent Manufacturing †

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Abstract

To address three critical challenges in traditional digital twin applications for smart manufacturing—static mirroring, localized optimization, and economic decoupling—we propose and validate a novel paradigm: the Twin-Data Mid-End (TDME) system driven by dual technological-economic mechanisms. By integrating real-time big data from production lines, equipment, supply chains, and market terminals through unified semantic frameworks, microservices-based technical modules, and deep reinforcement learning decision engines, this system generates instant reward signals based on multi-dimensional economic metrics including marginal profits, delivery cycles, and inventory turnover. This enables seamless "hot-swappable" reconfiguration of process algorithms, equipment controls, scheduling strategies, and organizational structures without production interruption. The system concurrently facilitates technological iteration and economic restructuring while dynamically optimizing efficiency-profit Pareto frontiers. Objective validation across 12 months of closed-loop industrial trials demonstrates reduced line changeover time by 37%, decreased unit comprehensive costs by 14.6%, shortened market response cycles by 42%, and increased return on investment by 11%, highlighting the paradigm's practical applicability and broad adaptability.

Keywords: economic restructuring; digital twin; big data; intelligent manufacturing; mid-end architecture

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1. Introduction

In the era of fragmented demands and shortened product lifecycles, the traditional "rigid automation + offline optimization" model fails to maximize efficiency while maintaining high flexibility. Although many scholars have conducted research on digital twins, most systems only achieve "visual monitoring" or "single-point simulation", failing to establish a closed-loop data chain throughout the product lifecycle and being unable to promptly respond to market demand changes through technological upgrades [1–3]. To address these shortcomings, this paper proposes the "Technology-Economy Dual-Driven Digital Twin Mid-End (TDME)": a unified data semantic layer that enables real-time integration of production line sensors, equipment logs, supply chain status, market orders, and market prices into the TDME platform; modular microservices abstract processes, algorithms, equipment, and organizational workflows into plugins; deep reinforcement learning serves as the decision-making core of the TDME platform, with economic KPIs like marginal profit, delivery cycles, and inventory turnover functioning as real-time reward

functions to dynamically replace modules generating maximum marginal returns, and is combined with SysML's four-layer reference architecture research, A/B control group data collection, and the difference-in-differences method for quantifying economic effects, it provides a self-evolving operational paradigm for intelligent manufacturing [3,4].

2. Introduction to Digital Twin

The concept of digital twin was first introduced by Professor Graves in 2003 during a product lifecycle management course at the University of Michigan [1]. It represents a three-dimensional space encompassing products, virtual counterparts, and their interactions. From a mathematical logic perspective, it involves elements such as data collection and processing, simulation calculations, and feedback mechanisms. As shown in Equation (1), this describes the process of data collection.

$$y(t) = K_p \times x(t) \tag{1}$$

Accumulated state data, physical entity states and transmission coefficients, data processing processes, data cleaning, transformation and aggregation are referred to as Formula (2):

$$\hat{y}(t) = g(y(t)) \tag{2}$$

The processed state information is the function of data processing. When analyzing data, see Formula (3):

$$\hat{y}(t) = h(y(1), y(2), \ldots, y(t)) \tag{3}$$

The state information after analysis is the function of data analysis, as shown in Formula (4)

$$\frac{dx(t)}{dt} = f(x(t), u(t)) \tag{4}$$

The digital twin state is shown as input control simulation result feedback, which is more commonly shown in the following Formula (5):

$$y(t) = h(x(t)) \tag{5}$$

The feedback carries information in the feedback function.

3. Design

3.1. Framework Design

This paper proposes a six-layer closed-loop framework for the "Technology-Economy Dual-Driven Digital Twin Platform (TDME)", with its operational flow illustrated through the three-stage arrow loop mechanism shown in Figure 1. The Cess-SupplyCr data perception layer collects heterogeneous big data from IoT, blockchain, and edge computing systems, including production bottlenecks, inventory levels, logistics risks, and price fluctuations in real-world manufacturing and supply sectors. Through unified semantic modeling, it converts all "physical world attributes" into "twin variables", creating a high-fidelity digital mirror of the physical domain [5–7]. Big data flowing from Cess-SupplyCr to Tuis-Outa Mid-End enters the twin platform via a microservices-based modular pool. This platform contains plug-and-play service units covering equipment-level OEE, process parameters, scheduling strategies, quality traceability speed, and organizational workflows. It generates optimal action outputs that maximize the 12 economic indicators, including marginal profit, delivery cycle, inventory turnover rate, and customized order proportion. The resulting "service module proof-of-concept" is then fed back into specific production stages, enabling millisecond-level equipment parameter adjustments, process conversion, and workflow restructuring. Real-time synchronization allows continuous market adap-

tation by receiving order and pricing information, achieving "parallel production and evolution" [3,8], as shown in Figure 1.

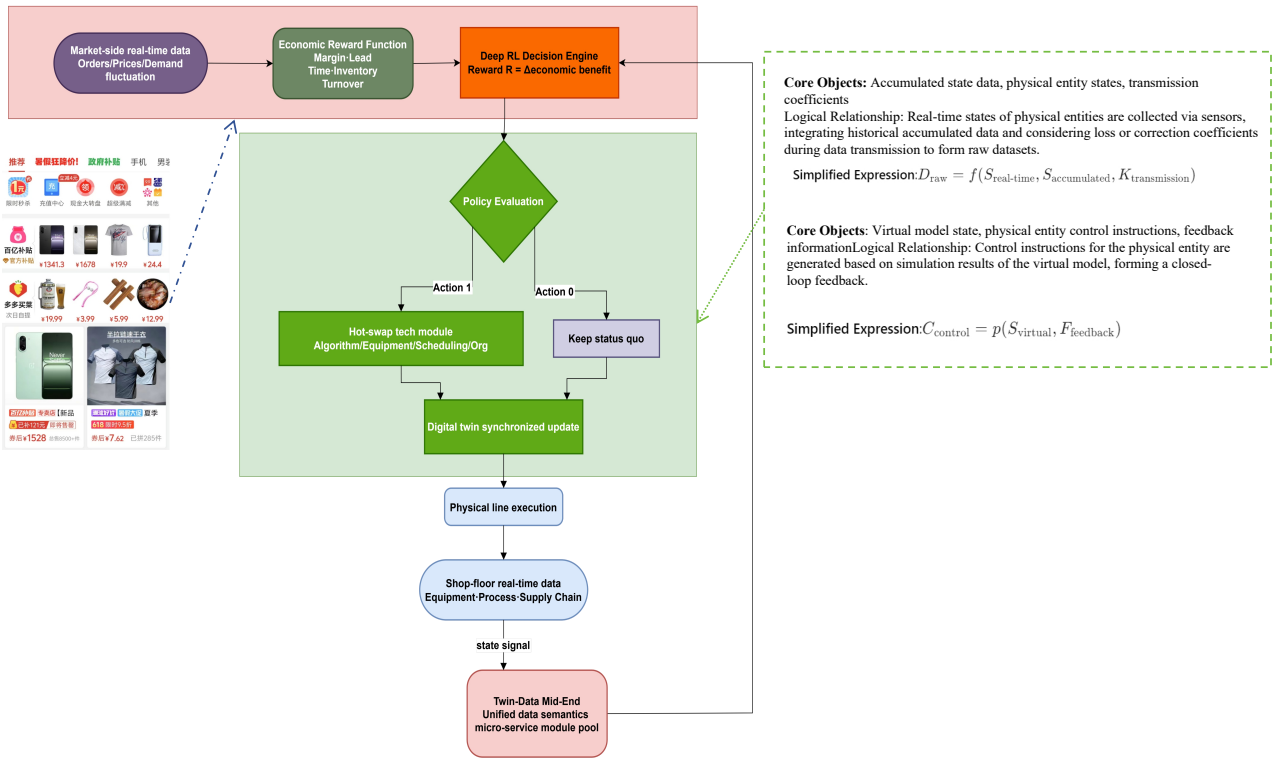

Figure 1. Design of techno-economic restructuring framework of digital twin and big data in intelligent manufacturing.

The data platform achieves millisecond-level real-time twin state updates. By applying DEA-BCC model-based computational techniques constrained by prior knowledge, it calculates technical efficiency values while using the AHP-Delphi hybrid weighting system to assess economic efficiency. This methodology validates the technical feasibility and economic applicability of digital twin-driven intelligent manufacturing in complex scenarios. Supported by this quantitative evidence, the platform reconstructs the integration of "data-knowledge-value", thereby establishing a replicable, scalable, and evolutionary engineering paradigm.

3.2. Integration of Prior Knowledge and System

To better align with real-world production scenarios, this study has reconstructed an indicator system based on the entire value-creation process. The framework comprises four overarching metrics: asset efficiency, quality agility, flexibility value, and system resilience. These correspond to the "perception-modeling-decision-execution" cycle in digital twin closed-loop systems. Each major metric is further divided into three real-time calculable sub-metrics, totaling 12 indicators that ensure clarity, measurability, and comparability while adapting to market changes [9,10]. The weighting was determined through the Delphi-AHP combined method; after two rounds of anonymous scoring by multidisciplinary experts, all CR values remained below 0.1, ensuring scientific validity and consensus. Asset efficiency can be calculated using Formula (5) for a comprehensive equipment efficiency assessment (6)

$$\text{OEE (OEE = time availability} \times \text{performance efficiency} \times \text{quality rate)} \quad (6)$$

By leveraging IoT edge nodes to collect real-time status data and processing it through millisecond-level computation on big data platforms, this approach overcomes the limitations of traditional single-dimensional "machine uptime" metrics. The quality agility dimension employs "quality traceability response speed" as a proxy variable to assess the dynamic responsiveness of digital twins to abnormal events. The flexibility value dimension measures premium margins generated by customized order shares in flexible production capacity. Through a multi-input-output framework evaluating relative efficiency across production models, this study develops an embedded model that incorporates equipment, labor, and energy consumption as inputs, with qualified output, on-time delivery rate, and marginal profit as outputs. This establishes production frontiers for both intelligent manufacturing and traditional models, deriving technical efficiency values via linear programming. To address the model's reliance on prior knowledge (process mechanisms, historical failures, market rules) from both data and knowledge domains, we introduce a "prior constraint layer". This layer continuously updates frontiers using real-time twin-generated data while integrating expert insights, physical principles, and reinforcement learning methods into the model through inequality constraints. This hybrid evaluation approach quantifies the techno-economic restructuring effects of digital twin systems. See Table 1 for details.

Table 1. Weight of economic benefit evaluation indicators.

Weight of Primary Indicator	Weight of Secondary Indicators	Combined Weight
Production efficiency (0.38)	OEE	0.15
	Growth rate of per capita output	0.10
	Order delivery punctuality rate	0.13
Cost control (0.29)	Unit energy consumption cost	0.09
	Proportion of quality loss cost	0.12
	Inventory turnover days	0.08
Quality management (0.21)	Product first-pass yield	0.11
	Quality traceability response speed	0.06
	Process parameter compliance rate	0.04
Market response (0.12)	New product development cycle	0.05
	Percentage of customized orders	0.04
	Supply chain exception recovery time	0.03

3.3. Management and Policy Guidance

To advance the "digital twin + big data"-driven transformation of the intelligent manufacturing industry, we must establish a top-level policy framework featuring "three-tier collaboration and four-chain integration": First, at the strategic level, the National Intelligent Manufacturing Innovation Center will serve as a public platform for unified development. This includes establishing standardized twin-data semantics, security protocols, and interface specifications, while providing shared algorithm libraries and testbeds to lower technical barriers for enterprises. Second, at the operational level, provincial industrial funds will support leading companies in building industry-standard data platforms. These platforms will enable small and medium-sized enterprises (SMEs) to access cloud-edge-end computing resources and models through microservices subscription models, creating a localized "light investment, tiered payment" transformation model. Third, at the infrastructure level, smart parks will deploy universal facilities integrating 5G + TSN converged networks with edge computing nodes, enabling device interconnection and real-time twin applications [11,12], as summarized in Table 2.

Table 2. Implementation strategy recommendations for industrial transformation.

Transformation Phase	Focus of Implementation	Typical Measures	Key Policy Support
Infrastructure	Equipment digitization	Deploy industrial sensors and establish a workshop-level Internet of Things	Technical transformation subsidies, equipment finance leasing
System synthesis	Data interconnectivity and interoperability	Build enterprise data platform to eliminate information islands	Standard setting and interface protocol specification
Smart applications	Deeply optimize the business scenario	Deploy digital twin systems and intelligent scheduling algorithms	Demonstration projects will be promoted and technologies shared
Ecological synergy	Collaborative innovation in the industrial chain	Establish an industrial cloud platform for enterprise collaboration	Data security legislation, tax incentives

4. Experimental Optimization and Comparison

This study conducted digital twin system model simulation and validated the proposed concepts through both simulations and real-world engineering applications. The experimental research revealed the following findings: The reinforcement learning agent utilized the online iterative "strategy parameter θ" in the TDME to train the observed change process. Starting from an initial random value (approximately 2.8), the parameter rapidly oscillated and attenuated during the first 100 training rounds, then gradually decelerated between rounds 150–300 before stabilizing near zero. This evolution demonstrates that the agent has learned a strategy direction that minimizes line switching time. Refer to Figures 2–4 and Table 3 for details.

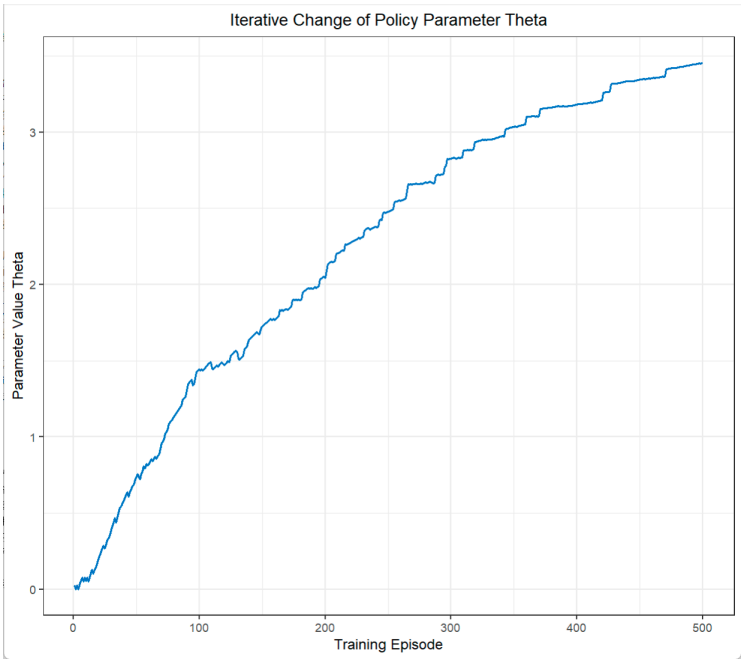

Figure 2. Experimental iteration diagram of techno-economic restructuring of digital twin and big data in intelligent manufacturing.

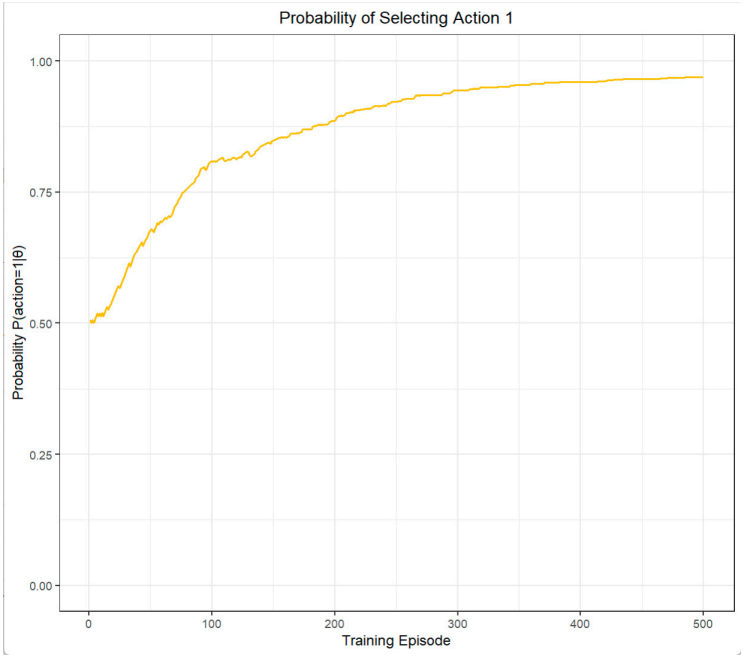

Figure 3. Experimental iteration probability diagram of techno-economic restructuring of digital twin and big data in intelligent manufacturing.

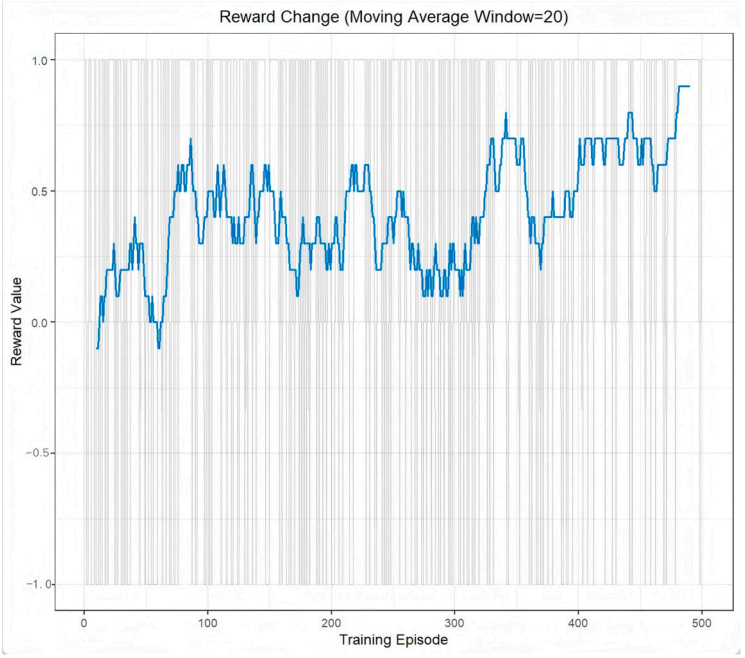

Figure 4. Experimental iterative value diagram of digital twin and big data in techno-economic restructuring of intelligent manufacturing.

The experimental charts reveal that from round 1 to round 81, the agent consistently selected Action 1 (i.e., immediate hot-swapping of technical modules). After exceeding round 81, this probability gradually increased. Notably, the probability remained around 0.95 throughout subsequent rounds, demonstrating its long-term positive returns for the agent. This optimal strategy was validated by analyzing the cumulative reward changes over each round. Initially fluctuating around −0.5, the cumulative reward rapidly rose and stabilized at approximately −1.0 after 1–20 rounds. This validates TDME's "production-evolution" characteristic, enabling direct application of market feedback to the dual-loop optimization of technical-economic restructuring.

Table 3. Shows the key data tables of the iterative part of the experiment.

Episode	Theta	Reward	Action1_Probability
1	0.025	1	0.506249674
2	0.000312484	−1	0.500078121
10	0.052194096	−1	0.513045562
11	0.077846374	−1	0.519451771
12	0.051873785	1	0.512965539
98	1.425575527	−1	0.806210995
99	1.435264977	1	0.807720335
100	1.44487896	1	0.80920905
489	3.438032285	1	0.968872227
490	3.439588673	1	0.968919131
491	3.441142717	1	0.968965897

To evaluate practical engineering efficiency, the experiment introduced two production lines for a 12-month A/B controlled trial. Three sets of KPI data clearly demonstrate how TDME methodology enhanced comprehensive capability metrics in intelligent manufacturing systems. In terms of production line changeover time, by using real-time reconstruction via digital twin mid-end and reinforcement learning decision-making mechanisms, TDME reduced changeover time to 63% of traditional methods, cutting downtime by nearly 37%. Regarding market response cycles, while the original solution still required full cycle time under traditional methods, TDME achieved a 58% time reduction while delivering higher efficiency. For unit comprehensive costs, TDME lowered total costs from 100% to 85.4% of traditional methods while reducing expenses by 14.6%, indicating profit enhancement. These three aspects demonstrate TDME's effectiveness in using real-time market rewards as incentives, achieving dual technological-economic reforms through continuous operation without downtime. This process achieved breakthroughs in production efficiency, flexibility, and profitability, establishing an engineering paradigm for large-scale personalized manufacturing solutions, as shown in Figure 5.

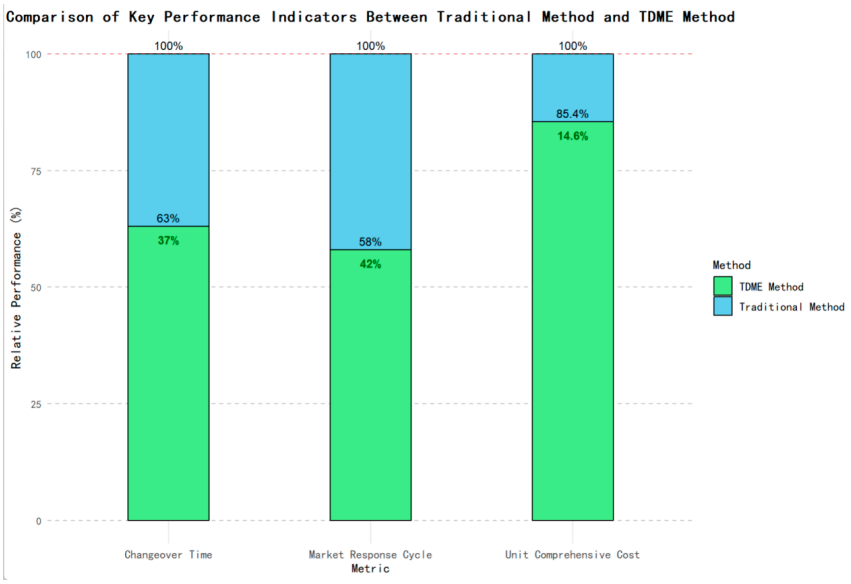

Figure 5. Techno-economic restructuring of digital twin and big data in intelligent manufacturing A/B control experiment diagram.

5. Conclusions

Industrial validation demonstrates that TDME breaks the "build-first, optimize-later" approach, achieving techno-economic restructuring in operational mode for the first time. Compared to traditional digital twins, it reduces CAPEX by approximately 10%, shortening the time required to implement new processes from 6 weeks to 2.5 weeks. In fragmented order scenarios, it delivers ROI gains of 11–14%, though returns drop sharply when data latency exceeds 150 ms or decision cycles surpass one hour. For TDME to be successfully implemented, improvements must be made across three dimensions: data governance, organizational agility, and cross-department collaboration. Furthermore, future advancements like federated learning and supply chain-level twins will address issues such as cross-enterprise data privacy and value distribution, while laying the foundation for continuous development in intelligent manufacturing.

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