

Digital Twin-Enabled Adaptive Production and Asset Coordination for Resilient Industrial Operations Under Dynamic Disruptions

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Abstract

Industrial production systems face disruptions caused by machine failures, material delays, workforce shortages, and changing production requirements. Conventional scheduling and maintenance practices often operate separately, limiting coordinated responses to changing operational conditions. This study proposes a Digital Twin enabled adaptive production and asset coordination framework that integrates machine degradation, Remaining Useful Life (RUL), workforce capacity, material availability, and disruption states within a virtual production environment. A co-simulation layer represents machine workforce interactions, while an adaptive multi-objective scheduling layer considers makespan, schedule deviation, energy consumption, material waste, recovery time, and operating cost. An Adaptive Twin-Reinforcement Learning (ATRL) layer incorporates carbon and waste considerations into disruption recovery decisions. A hierarchical edge cloud architecture supports local schedule repair and cloud-based policy updates. The framework is evaluated through synthetic simulation scenarios involving machine failures, demand surges, supply delays, workforce shortages, and simultaneous resource disruptions. Results show that the proposed framework reduces makespan from 120 h to 94 h and recovery time from 34 h to 17 h compared with static scheduling. Lower energy consumption and material waste are also observed across the evaluated scenarios. The findings indicate that Digital Twin-based adaptive coordination can support resilient production planning, asset management, sustainability-aware recovery, and operational decision-making under dynamic industrial conditions.

Keywords: Digital Twin, Adaptive Production Scheduling, Predictive Maintenance, Remaining Useful Life (RUL), Workforce Coordination, Disruption Recovery, Reinforcement Learning, Sustainable Manufacturing, Edge-Cloud Computing, Resilient Industrial Operations.

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I. INTRODUCTION

Industrial production systems operate under changing machine conditions, material constraints, workforce limitations, and uncertain production requirements. Equipment failures, supply delays, workforce shortages, and urgent orders can interrupt planned operations and create cascading effects across production activities. Digital Twin technology provides a virtual representation of physical operations, but current applications often treat production scheduling, asset maintenance, and resource planning as separate functions. This study addresses that integration problem through a closed loop adaptive decision framework.

A. Background and Motivation

Digital Twins have become an important approach for representing production systems and supporting adaptive scheduling. Recent studies have applied DTs to flexible job shops, demand-driven planning, cyber-physical production systems, and multi-agent scheduling [1-5]. At the same time, predictive maintenance uses sensor and condition information to assess machine health and availability [7-9]. Production continuity, however, also depends on workforce capacity, material availability, energy use, and waste. These factors create a need for coordinated operational decisions under dynamic disruptions.

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B. Problem Statement

Conventional production scheduling often assumes relatively stable machine availability, while maintenance activities operate through fixed or reactive procedures. A sudden machine failure, material delay, workforce shortage, or urgent order can therefore create schedule deviations and longer recovery periods. Existing DT-based approaches provide improved visibility, but machine degradation, workforce capacity, material flows, and disruption recovery are not sufficiently connected within one decision loop. Sustainability factors such as energy, carbon impact, and material waste also receive limited integration with real-time recovery decisions. [1,-5,8,9]

C. Proposed Solution

This study proposes a Digital Twin-enabled adaptive production and asset coordination framework that connects machine condition, RUL, workforce capacity, material availability, job requirements, and disruption states. The framework uses co-simulation to represent machine–workforce interactions, while an adaptive multi objective scheduling layer evaluates production, recovery, cost, energy, and waste objectives. An Adaptive Twin-Reinforcement Learning (ATRL) layer introduces carbon and waste considerations. A hierarchical edge-cloud architecture supports local schedule repair and cloud-based optimization and policy updates.

D. Contributions

The study provides four main contributions. First, it integrates machine degradation and workforce capacity within a common Digital Twin decision model. Second, it introduces carbon, energy, and material waste into adaptive disruption-recovery decisions through ATRL. Third, it incorporates hierarchical edge cloud execution for low-latency rescheduling and policy management. Fourth, it evaluates the framework through synthetic disruption scenarios covering machine failures, demand surges, supply delays, workforce shortages, and simultaneous resource disruptions. The framework therefore connects production continuity, asset coordination, sustainability, and computational responsiveness.

E. Paper Organization

The remainder of the paper is organized as follows. Section II reviews research on Digital Twin-based production scheduling, predictive maintenance, workforce and inventory coordination, sustainability, and intelligent resource scheduling. Section III presents the proposed methodology, including system modeling, disruption representation, multi objective scheduling, ATRL, and edge-cloud execution. Section IV reports synthetic simulation results and discusses production, recovery, sustainability, and computational performance. Section V concludes the study and outlines future research directions.

The objective is to develop and evaluate a Digital Twin-based framework that coordinates machine condition, workforce, materials, scheduling, sustainability, and disruption recovery under dynamic industrial conditions.

II. RELATED WORK

Digital twin research has increasingly connected virtual representations with adaptive production planning, equipment monitoring, resource coordination, and intelligent decision-making. Recent studies address scheduling, predictive maintenance, workforce allocation, inventory planning, sustainability, and reinforcement learning from different perspectives. However, these areas remain fragmented, leaving opportunities for an integrated framework that coordinates asset condition, production resources, disruptions, recovery, and operational performance within one adaptive industrial system.

A. Digital Twin-Based Adaptive Production Scheduling

Digital twins provide synchronized virtual representations that support production planning under changing operational conditions. Liu *et al.*, [1] proposed digital twin-driven adaptive scheduling for flexible job shops, demonstrating how updated production information can support dynamic decisions. Ma *et al.*, [2] developed a conceptual digital twin framework for demand-driven production planning and scheduling, connecting changing requirements with production decisions. Villalonga *et al.*, [3] examined digital twin-based decision-making for dynamic scheduling in cyber-physical production systems. Siatras *et al.*, [4] combined digital twins with multi-agent scheduling in bicycle manufacturing. Singh *et al.*, [5] reviewed artificial intelligence and digital twin applications for production scheduling. These studies establish the foundation for adaptive scheduling, but integrated disruption recovery remains comparatively limited.

B. Asset Condition and Predictive Maintenance Integration

Asset health is an important factor in production continuity because machine availability can change during operations. Fazle [8] examined machine learning and sensor analytics for predictive maintenance and process optimization, supporting condition-based operational decisions. Hossain [7] explored sensor trace analysis for defect localization, showing how operational data can support equipment and process diagnosis. Taimun *et al.*, [9] investigated digital twin-enabled predictive maintenance for textile and mechanical systems, connecting asset monitoring with maintenance-oriented intelligence. These studies demonstrate the value of sensor-driven asset intelligence. However, predictive maintenance is commonly addressed as a separate activity from production rescheduling. A stronger approach should translate degradation and availability information into scheduling decisions while

considering disruption timing, recovery requirements, and competing resource constraints.

C. Workforce, Inventory, and Multi-Resource Coordination

Industrial resilience depends on more than machine availability because workforce capacity, materials, and inventory can also restrict production continuity. Sany *et al.*, [6] examined ERP–MIS integration for intelligent apparel production planning, demonstrating the value of integrated operational information. Mirza [14] investigated predictive inventory buffer optimization for high-variability manufacturing supply chains using statistical and simulation models. Huq [15] proposed a mathematical framework for workforce planning and resource allocation under uncertainty, highlighting workforce constraints in organizational decision making. Barua [17] addressed demand forecasting and inventory optimization for supply chain performance. Rahman [18] examined multi objective operational optimization for manufacturing equipment and resource allocation. These contributions provide separate resource perspectives, but simultaneous coordination of machines, workers, materials, and disruptions remains insufficiently integrated.

D. Sustainability, Energy, and Circular Production

Sustainable production requires operational decisions to consider energy use, emissions, waste, and resource efficiency alongside productivity. Adil [10] investigated energy efficient and low-emission manufacturing through process optimization and reactor control. Karim [11] discussed lean and green manufacturing as combined strategies for economic and environmental performance. Ahmed [12] examined circular textile manufacturing and waste recovery within sustainable apparel supply chains. Mim *et al.*, [19] studied smart IoT infrastructure for workplace efficiency and energy savings. These studies indicate that environmental performance can be incorporated into industrial decision systems. However, sustainability variables are often examined independently from real-time disruption recovery and asset coordination. The proposed research therefore considers throughput, utilization, lateness, recovery time, operating cost, energy, and material waste within adaptive operational decision-making under uncertain disruptions.

E. Intelligent Resource Scheduling and Reinforcement Learning

Artificial intelligence and reinforcement learning provide mechanisms for adaptive resource decisions when production conditions change. Farooq *et al.*, [20] investigated reinforcement learning for adaptive resource scheduling in cloud-connected IoT networks, demonstrating the potential of learning-based approaches for dynamic resource allocation. Singh *et al.*, [5] identified artificial intelligence as an expanding component of digital twin-based production scheduling.

Shaikat and Happy [13] reviewed architectural flexibility in reconfigurable assembly systems, highlighting the need to accommodate changing production configurations. Rashid [16] examined AI-based lead time and cost forecasting for global apparel merchandising, showing how predictive intelligence can support delay and cost management. These studies support intelligent adaptation, but low-latency decision-making, novel disruption generalization, and coordinated asset-resource recovery remain open challenges for industrial digital twin environments.

Research Gap and Positioning

The reviewed studies demonstrate meaningful progress across digital twin scheduling, predictive maintenance, enterprise information integration, inventory management, workforce planning, sustainability, reconfigurable production, and reinforcement learning. Nevertheless, these contributions largely address individual components rather than a closed-loop operational framework. Existing work does not sufficiently integrate continuously changing machine condition, workforce capacity, material availability, disruption risk, production scheduling, and recovery decisions within one virtual operational representation. Sustainability factors such as energy consumption and material waste also require stronger integration with resilience-oriented decisions. In addition, learning based approaches require consideration of computational responsiveness and performance under previously unseen disruption patterns. These gaps motivate the proposed digital twin enabled framework for adaptive production and asset coordination under dynamic disruptions.

III. METHODOLOGY

This methodology presents a Digital Twin-based decision framework for production and asset coordination during dynamic disruptions. It connects machine condition, workforce capacity, material availability, production schedules, disruption states, and recovery actions within one operational model. Simulation experiments assess adaptive decisions against conventional scheduling methods using production, resilience, sustainability, and computational measures linked directly to the three research questions defined here.

A. Digital Twin-Based System Modeling

The production system is represented as a virtual operational model containing machines, jobs, workers, materials, task dependencies, and available capacity. Machine records include operating state, effective efficiency, condition indicators, and remaining useful life (RUL). Worker records contain availability, shift assignment, and qualification status. Material records describe inventory and supply conditions. Job records include processing requirements, precedence relations, and due dates. At each decision point, current

information updates the twin before a scheduling action is selected.

The system state is expressed as
 $S_t = \{M_t, W_t, I_t, J_t, D_t\}$

where M_t, W_t, I_t, J_t , and D_t the terms denote machine, workforce, inventory, job, and disruption states, respectively. This representation supports operational state assessment.

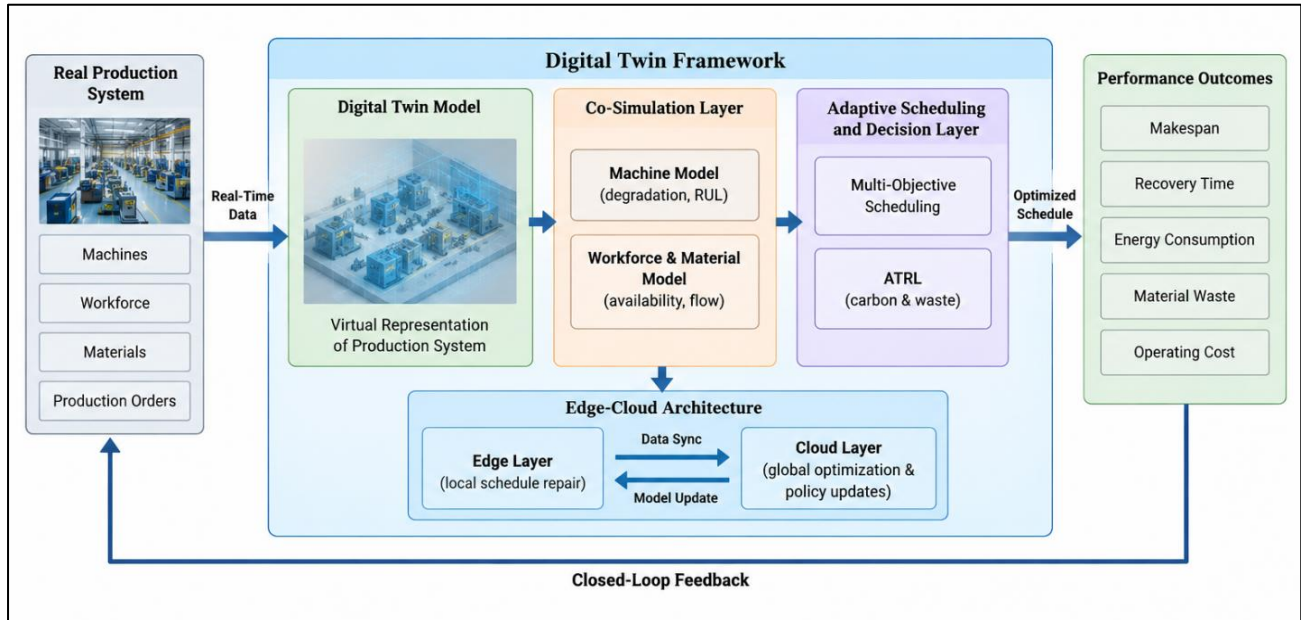


Figure 1: Digital Twin-Enabled Adaptive Production and Asset Coordination Architecture

Figure 1 presents the proposed architecture as a closed operational loop. Physical production information updates the Digital Twin, while its current state informs disruption assessment and scheduling decisions. Machine condition, workforce capacity, material availability, and job requirements are considered together. The edge-cloud structure separates immediate schedule repair from computationally intensive optimization and policy updating.

B. Asset, Workforce, and Disruption Modeling

Machine degradation enters the scheduling process through condition indicators and RUL estimates. The model therefore does not assume fixed machine availability. Workforce capacity includes shift schedules, worker availability, and qualifications, while material capacity reflects inventory and supply delays. Disruption scenarios are defined through occurrence time T_d , recovery duration T_r , machine efficiency η_m , demand surge volume, and resource severity. These factors define experimental conditions. For RQ1, machine and workforce states are updated together so task assignments can change after failures or workforce shortages. The resulting decisions are assessed through

makespan, schedule deviation, recovery time, and continuity under disruptions across simulation runs.

C. Adaptive Multi-Objective Scheduling

The adaptive scheduling layer selects job sequences, machine assignments, workforce allocation, material allocation, and recovery actions from the current twin state. Its objectives cover production speed, schedule stability, energy use, material waste, recovery time, and operating cost. The formulation is expressed as:

$$miF = \{C_{max}, D_{all}, E_{all}, W_{all}, R_t, C_{op}\}$$

Here, C_{max} denotes makespan; D_{all} denotes schedule deviation; E_{all} denotes energy consumption; W_{all} denotes material waste; R_t denotes recovery time; and C_{op} denotes operating cost. The model permits trade-offs among competing objectives rather than using a single cost criterion under uncertainty. Feasibility remains subject to machine capacity, worker qualifications, material availability, task precedence, and disruption conditions.

Table I: Key Variables and Evaluation Measures

Category	Variables / Measures
Scheduling decisions	Job sequence, X_{ijk} , machine/workforce allocation
Asset condition	RUL, η_m , machine availability
Workforce	Availability, shifts, qualification
Materials	Inventory, supply delay, material availability
Disruptions	T_d , T_r , failure severity, demand surge

Category	Variables / Measures
Production	CmaxC {max}, utilization, lateness, throughput
Recovery	Recovery time, DallD {all}
Sustainability	Energy, carbon impact, material waste
Computation	Latency, synchronization skew
Learning	Generalization accuracy/error

D. Sustainability and Adaptive Twin-Reinforcement Learning

The sustainability component incorporates carbon impact, energy consumption, and material waste into disruption-recovery decisions. The Adaptive Twin-Reinforcement Learning (ATRL) layer receives the updated twin state and evaluates scheduling actions under changing production conditions. Its decision structure considers completion performance, schedule deviation, recovery time, energy or carbon impact, and material waste. A fuzzy satisfaction parameter λ represents preferences among competing objectives. Synthetic demand-surge scenarios are used to examine trade-offs among operating cost, energy consumption, and material waste. Exact mathematical programming is identified as a potential reference method for future comparative validation.

E. Edge-Cloud Decision and Simulation Evaluation

The computational layer uses an edge cloud arrangement. Edge nodes receive production states and execute local schedule repairs, while cloud resources handle longer horizon optimization, data processing, and policy updates. Experimental scenarios include machine failures, demand surges, supply delays, workforce shortages, and simultaneous resource disruptions. The method is compared with static scheduling, rule-based right shift rescheduling, and cost minimization scheduling under same conditions. RQ1 focuses on degradation and workforce coordination, RQ2 examines energy, material waste, and sustainability-related trade-offs, and RQ3 examines the proposed separation of local schedule repair and cloud based computational tasks. Simulation replications support comparison across scenarios, using throughput, utilization, lateness, recovery time, cost, energy, waste, and computational measures.

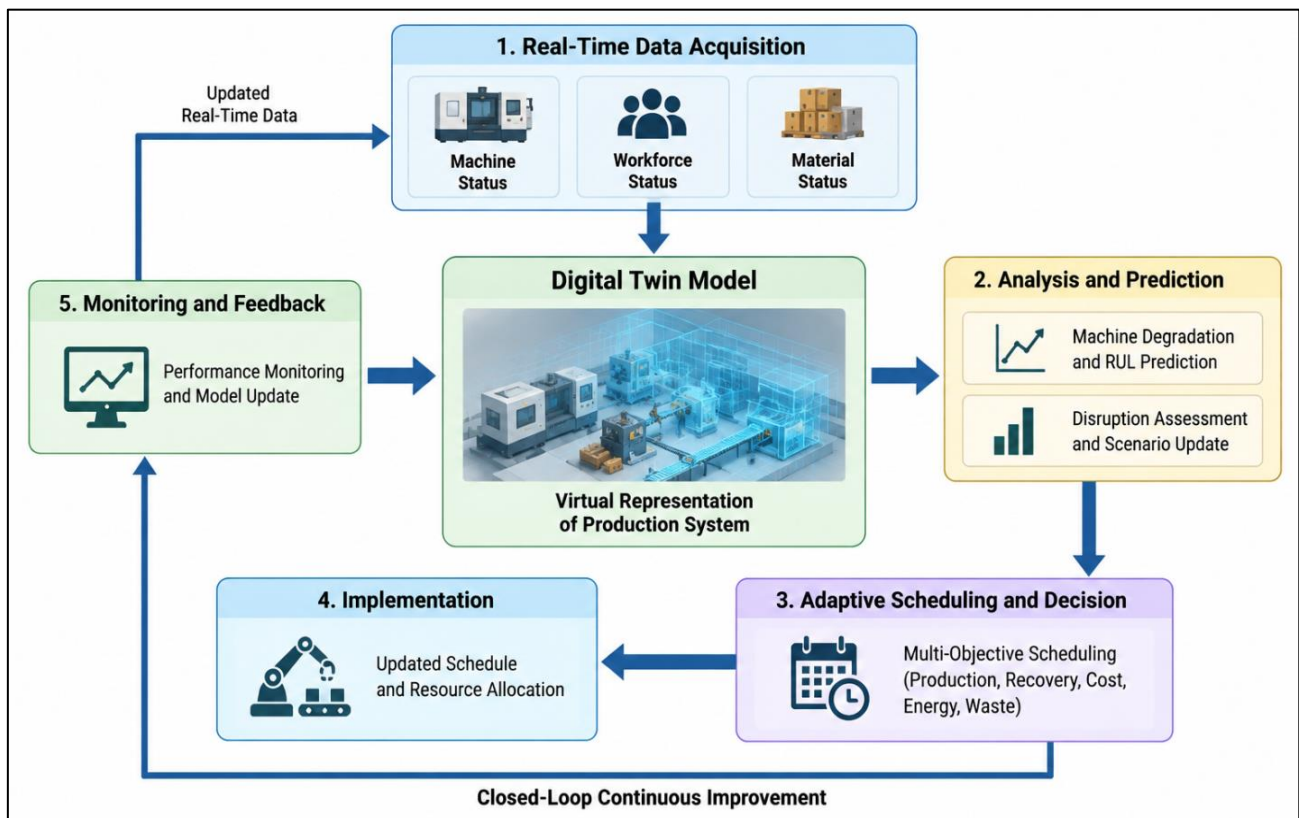


Figure 2: Closed-Loop Disruption Recovery and Experimental Evaluation

Figure 2 illustrates the closed loop experimental process. Disruptions update the Digital Twin state and trigger condition assessment, adaptive scheduling, implementation, and performance monitoring. The

process supports machine workforce coordination, sustainability-related decisions, and local schedule repair under changing conditions.

IV. RESULTS AND DISCUSSION

The proposed framework was evaluated through synthetic simulation scenarios designed around machine degradation, workforce constraints, material availability, disruption recovery, sustainability, and computational responsiveness. The evaluation follows the three research objectives and examines production performance, coordinated recovery, environmental trade-offs, and edge-cloud execution. Since no proprietary industrial dataset is available, the numerical results are illustrative simulation outputs rather than measurements from an operating manufacturing facility.

A. Production Performance Under Dynamic Disruptions

The first experiment evaluates the effect of coordinated Digital Twin decisions under a representative machine disruption. The scenario includes machine degradation, temporary resource unavailability, and dependent production tasks. The Digital Twin updates machine condition, workforce availability, material status, and job dependencies before each scheduling decision. Four strategies are compared: static scheduling, right-shift rescheduling, cost-minimization recovery, and the proposed framework. The evaluation focuses on makespan and recovery time, which directly correspond to RQ1 and the machine workforce coordination objective.

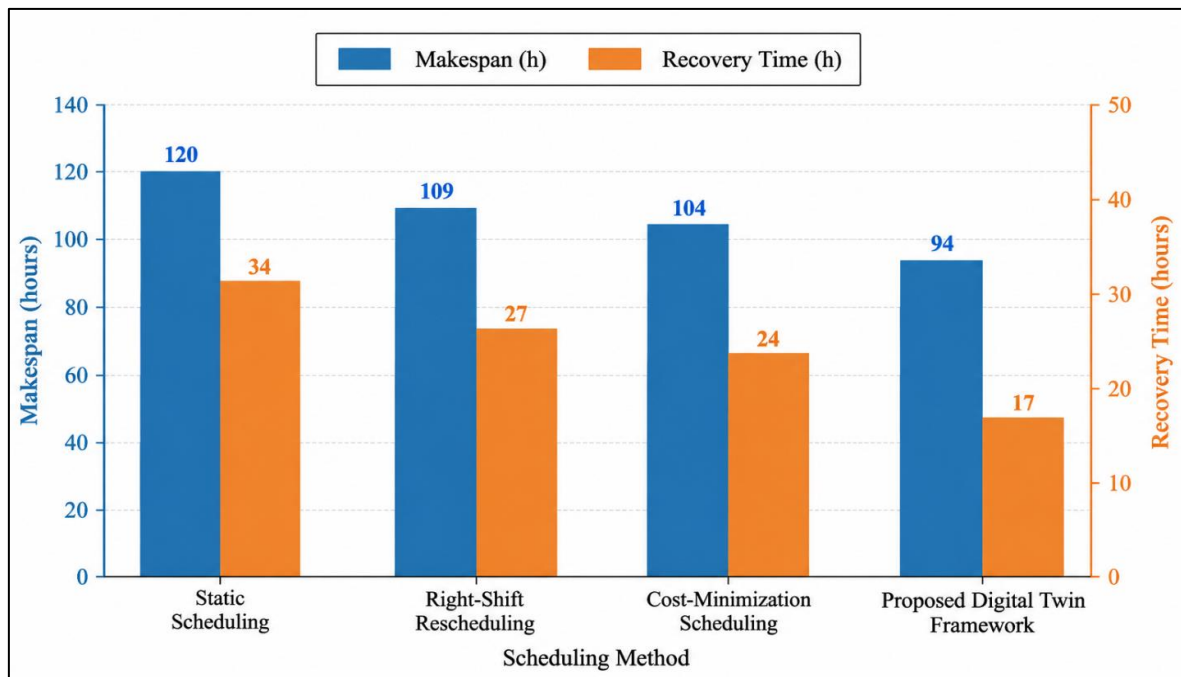


Figure 3: Digital Twin-Based Production and Recovery Performance Under a Representative Disruption

Figure 3 shows that static scheduling produces a makespan of 120 h and recovery time of 34 h. Right-shift rescheduling reduces these values to 109 h and 27 h, while cost-minimization reaches 104 h and 24 h. The proposed Digital Twin framework records 94 h and 17 h. Relative to static scheduling, these illustrative results represent reductions of approximately 21.7% in makespan and 50% in recovery time. The result suggests that continuous machine-state and workforce information can support earlier resource reassignment and reduce propagation of disruption across dependent tasks.

B. Machine Workforce Coordination and Recovery Behavior

The second experiment examines recovery behavior under different disruption severities. Four levels low, moderate, high, and severe represent increasing disturbance to machine availability and production capacity. The experiment reflects the Human in the Loop angle, where qualified workforce availability is considered together with machine degradation and RUL information. Instead of treating equipment and operators as independent resources, the scheduling layer considers their joint effect on task assignment and recovery. This evaluation provides a direct test of the first research gap concerning multi-resource coupling.

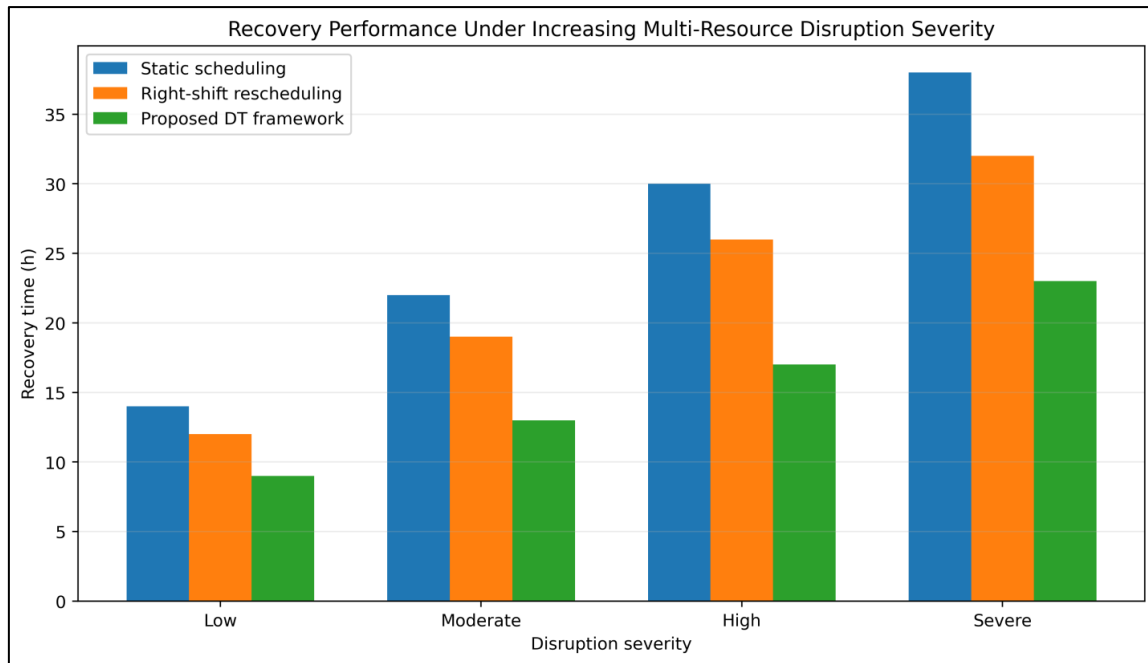


Figure 4: Recovery Time Under Increasing Disruption Severity

Figure 4 indicates recovery times of 9, 13, 17, and 23 h for the proposed framework under low, moderate, high, and severe disruptions, respectively. Static scheduling requires 14, 22, 30, and 38 h, while right-shift rescheduling requires 12, 19, 26, and 32 h. The difference becomes more pronounced at higher disruption levels. This pattern indicates that coordinated consideration of machine condition, operator availability, and task requirements can limit cascading schedule changes. The result supports RQ1 by showing how the proposed co-simulation concept can maintain shorter recovery paths as disruption severity increases.

C. Carbon-, Energy-, and Waste Aware Decision Trade-Off

The third experiment evaluates the sustainability resilience component associated with RQ2. The ATRL layer treats environmental indicators as active decision variables rather than secondary reporting measures. Four scheduling methods are compared across operating cost, energy consumption, and material waste. The analysis demonstrates the expected trade-off between economic expenditure and environmental performance. Carbon-aware decision logic can also incorporate changing grid emission factors within the reward structure, while waste limits constrain feasible production decisions.

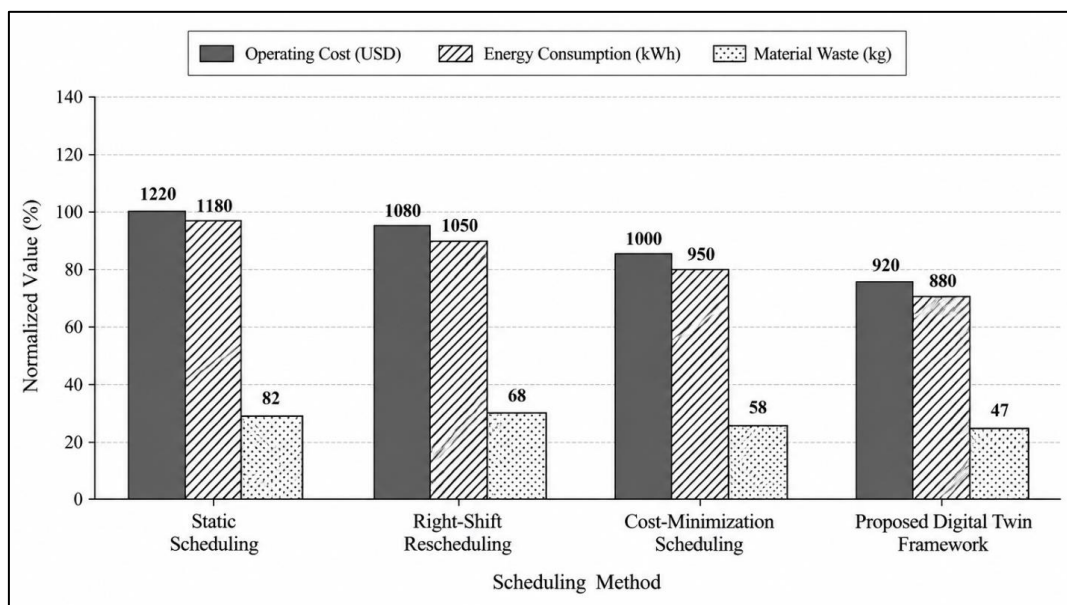


Figure 5: Synthetic Multi-Objective Trade-Off Between Operating Cost, Energy, and Material Waste

Figure 5 shows the synthetic trade-off among operating cost, energy consumption, and material waste across four scheduling methods. The proposed Digital Twin framework records lower energy consumption and material waste while maintaining the lowest operating cost among the evaluated methods.

D. Comparative Performance Assessment

Table I consolidates the main synthetic results for the representative disruption scenario. The comparison considers makespan, recovery time, energy

consumption, and material waste. These indicators connect the production-resilience and sustainability objectives within a single evaluation. The proposed framework produces the lowest values across all four measures. The results are intended to demonstrate framework behavior rather than report empirical industrial performance. They also provide a common basis for comparison among conventional scheduling, reactive rescheduling, cost-oriented recovery, and the proposed Digital Twin approach.

Table 2: Synthetic Comparative Performance Under a Representative Disruption

Scheduling Strategy	Makespan CmaxC_{max} (h) ↓	Recovery Time (h) ↓	Energy Consumption ↓	Material Waste ↓
Static Scheduling	120	34	1240	86
Right-Shift Rescheduling	109	27	1180	74
Cost-Minimization	104	24	1110	69
Proposed DT Framework	94	17	980	51

Note: Values are synthetic simulation outputs created for framework-level evaluation and do not represent measurements from a real industrial facility.

The proposed framework reduces makespan from 120 to 94 h and recovery time from 34 to 17 h relative to static scheduling. Energy consumption decreases from 1240 to 980 units, while material waste decreases from 86 to 51 units. The combined pattern indicates that disruption recovery and sustainability objectives do not need to operate as separate decision processes. Machine condition, workforce availability, material status, and environmental indicators can instead contribute to a common scheduling decision.

E. Edge-Cloud Responsiveness and Overall Discussion

The final assessment examines the proposed hierarchical edge-cloud architecture from a computational design perspective. Edge nodes are assigned rapid local schedule repair, while cloud resources support longer-horizon optimization, data processing, policy training, and model updates. The architecture allows computational responsibilities to vary according to disruption severity, network conditions, and edge processing capacity. End-to-end latency, synchronization skew, and policy generalization are identified as future quantitative evaluation measures for validating the architecture under larger and more diverse industrial scenarios.

The overall framework addresses the three identified research gaps at the design level. The machine workforce component represents multi-resource coupling; ATRL incorporates carbon, energy, and waste considerations into disruption decisions; and the edge-cloud structure provides a basis for low-latency local repair and cloud-based computational management. The synthetic results provide a controlled basis for examining relationships among RUL, workforce capacity, material availability, disruption severity, scheduling decisions, recovery, and sustainability. Quantitative validation of

latency, synchronization, and policy generalization remains a topic for future empirical evaluation.

Limitations of the Study

The study relies on synthetic simulation values rather than real industrial datasets, so empirical validation remains limited. Machine degradation, workforce fatigue, carbon intensity, and edge-cloud performance are represented through modeled parameters. Future research should test the framework with real production, sensor, workforce, energy, and material flow data.

V. CONCLUSION

This study proposed a Digital Twin-enabled adaptive production and asset coordination framework for resilient industrial operations under dynamic disruptions. The framework integrates machine degradation and RUL, workforce capacity, material availability, disruption conditions, adaptive scheduling, sustainability objectives, and recovery decisions within a closed loop structure. Synthetic simulation results showed lower makespan, recovery time, energy consumption, and material waste than static scheduling, right shift rescheduling, and cost-minimization approaches. The framework also incorporates carbon and waste factors through Adaptive Twin Reinforcement Learning (ATRL) and supports rapid local rescheduling through hierarchical edge cloud coordination. These results indicate the potential of integrated Digital Twin decision support for production continuity and coordinated resource management under uncertain operating conditions.

Future work will focus on validation with real industrial datasets containing machine sensor data, RUL indicators, workforce availability, production schedules, material flows, energy use, and disruption records.

Further research will examine operator fatigue, real-time carbon intensity, material waste limits, unseen disruption patterns, and multi-site edge-cloud deployment. Comparative experiments can assess ATRL against exact optimization and other reinforcement learning methods under standardized manufacturing scenarios. These studies can provide empirical evidence on recovery performance, computational latency, policy generalization, and practical application in asset-intensive production systems.

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