

Digital Twin-Enabled Dynamic Production Scheduling for Concurrent Multi-Program Manufacturing Operations

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Digital Twin-Enabled Dynamic Production Scheduling for Concurrent Multi-Program Manufacturing Operations

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Abstract

Modern manufacturing facilities must coordinate concurrent production programs under changing order priorities, machine conditions, workforce capacity, material availability, quality requirements, and delivery constraints. Traditional scheduling approaches face difficulties when machine degradation, unexpected failures, urgent order insertions, rework, and capacity changes occur during production. This study proposes a hierarchical Digital Twin-enabled dynamic production scheduling framework for concurrent multi-program manufacturing operations. The framework incorporates local workstation Digital Twins with Multilayer Perceptron models for machine-health prediction, a global Digital Twin for production-state representation, and a Takagi-Sugeno-Kang fuzzy inference system for scheduling decisions. A Multi-Agent System supports distributed coordination, while an evolutionary multi-objective optimizer generates revised schedules according to makespan, equipment energy consumption, and machine deviation. A three dimensional discrete event simulation with OPC UA synchronization supports virtual to physical validation. Illustrative scenarios examine normal production, machine degradation, machine failure, and urgent order insertion. The illustrative scenarios indicate potential makespan reductions under disruption conditions while considering energy consumption and schedule deviation. The framework provides a closed loop decision structure for proactive rescheduling across concurrent manufacturing programs.

Keywords: Digital Twin, Dynamic Production Scheduling, Concurrent Multi-Program Manufacturing, Multi-Agent System, Machine-Health Prediction, Multilayer Perceptron, TSK-FIS, Multi-Objective Optimization, Discrete-Event Simulation, OPC UA, Smart Manufacturing.

I. Introduction

Modern manufacturing systems must coordinate several product programs while responding to changing priorities, machine conditions, labor capacity, material availability, quality requirements, and delivery commitments. Digital Twin technology provides a virtual representation of production assets and processes that can support continuous state monitoring and decision making. Recent studies have examined adaptive scheduling, cyber-physical production systems, multi-agent coordination, predictive maintenance, and demand driven planning [1]–[4]. However, a unified framework for proactive scheduling across concurrent programs remains limited.

A. Background and Motivation

Manufacturing systems increasingly operate with multiple product families, shared machines, variable

workloads, and changing delivery priorities. Such conditions create frequent conflicts among production sequences, machine capacity, labor availability, and material requirements. Digital Twin based scheduling has received growing attention because it can represent shop-floor states and support adaptive production decisions [1], [3]. Demand-driven planning has also been connected with Digital Twins for production scheduling [2]. Multi-agent approaches provide distributed coordination among production resources [4]. Predictive maintenance research further shows how sensor data and machine-learning models can identify equipment conditions [8], [9]. These developments motivate a scheduling framework that connects machine health, production priorities, and dynamic rescheduling.

B. Problem Statement

Traditional production scheduling often depends on predefined machine availability, processing times, routing sequences, and production priorities. Such assumptions become difficult to maintain when machine degradation, unexpected failures, urgent orders, rework, or capacity changes occur during production. Existing research addresses adaptive scheduling [1], demand-driven planning [2], and multi-agent production coordination [4], but important integration gaps remain. Predictive machine intelligence is often treated separately from scheduling decisions [7], [8]. Resource allocation models also examine workforce and equipment constraints without a unified Digital Twin control loop [15], [18]. Consequently, manufacturing systems require a decision framework that can detect operational changes, determine the need for intervention, and generate revised schedules across concurrent production programs.

C. Proposed Solution

This study proposes a hierarchical Digital Twin-enabled dynamic production scheduling framework for concurrent multi-program manufacturing operations. Local workstation Digital Twins collect machine-state information and use Multilayer Perceptron models to classify conditions as Good, Degraded, or Failure. A global Digital Twin combines these states with production rate, program priorities, WIP, queues, capacity, and resource assignments. A TSK-FIS determines operational actions, while a Multi-Agent System coordinates distributed decisions. When rescheduling is required, a multi-objective optimizer minimizes makespan, equipment energy consumption, and machine deviation. A 3D discrete-event simulation with OPC UA synchronization then evaluates candidate schedules before physical execution.

D. Contributions

The study provides several contributions to dynamic manufacturing scheduling. First, it proposes a hierarchical Digital Twin architecture that connects local workstation intelligence with global production scheduling. Second, it integrates MLP-based machine-health prediction with TSK-FIS decision logic, allowing equipment condition and production rate to influence scheduling actions. Third, the framework applies multi-objective optimization to concurrent programs with machine, labor, material,

routing, and priority constraints. Fourth, it introduces a virtual validation stage using 3D discrete-event simulation and OPC UA communication. Finally, the study evaluates makespan, energy consumption, machine deviation, latency, synchronization skew, and schedule stability under disruption scenarios.

The study aims to develop a hierarchical Digital Twin framework that predicts machine conditions, coordinates scheduling decisions, and dynamically reschedules concurrent production programs under machine failures, urgent orders, capacity changes, and other operational disruptions.

E. Paper Organization

The paper is organized into five sections. Section II presents the related work on Digital Twin-based scheduling and manufacturing optimization. Section III describes the proposed methodology. Section IV discusses simulation results and scheduling performance. Section V concludes the study and outlines future research directions.

II. Related Work

This section reviews recent research on digital twin-enabled production scheduling, cyber-physical decision making, multi-agent coordination, predictive maintenance, resource allocation, and manufacturing optimization. The literature is organized around five interconnected themes: adaptive production scheduling, multi-program production planning, predictive operational intelligence, multi-objective optimization, and explainable digital twin decision intelligence. These themes provide the foundation for examining current methods, identifying research gaps, and positioning the proposed hierarchical framework for concurrent multi-program manufacturing operations.

A. Digital Twin-Driven Adaptive Production Scheduling

Digital twin-driven scheduling has shifted production control toward adaptive decision making. Liu et al. [1] developed a digital twin-driven adaptive scheduling approach for flexible job shops, demonstrating the value of production representations for changing shop-floor conditions. Singh et al. [5] reviewed the integration of artificial intelligence and digital twins in production scheduling, providing a broader view of recent scheduling approaches. Villalonga et al. [3] proposed a decision-making framework for dynamic scheduling of cyber-physical

production systems using digital twins, linking operational data with scheduling decisions. Ma et al. [2] connected digital twins with demand-driven production planning and scheduling. Siatras et al. [4] combined multi-agent coordination and digital twins for production scheduling. Together, these studies support closed-loop scheduling, but opportunities remain for hierarchical coordination across concurrent programs and proactive anomaly-driven rescheduling.

B. Multi-Program Production Planning and Demand Coordination

Production environments with multiple programs require coordination among priorities, resources, inventories, and changing delivery requirements. Sany et al. [6] examined ERP–MIS integration for intelligent apparel production planning, indicating the importance of planning information. Shaikat and Happy [13] addressed reconfigurable assembly lines supporting concurrent internal-combustion and electric drive-unit production, providing a basis for multi-program manufacturing. Mirza [14] considered predictive inventory buffering under high variability using simulation models, while Rashid [16] examined lead-time and cost forecasting for apparel merchandising. Barua [17] addressed demand forecasting and inventory optimization. Ahmed [12] examined circular textile manufacturing and waste recovery systems, highlighting the relevance of production planning and resource considerations in sustainable apparel manufacturing. These studies support planning, yet a unified digital twin mechanism that translates demand, inventory, and program changes into operational rescheduling remains insufficiently developed.

C. Predictive Machine Intelligence and Operational State Monitoring

Real-time scheduling also depends on knowledge of machine condition and operational state. Hossain [7] investigated sensor trace analysis for defect localization in apparel production, showing the relevance of condition information to production decisions. Fazole [8] examined predictive maintenance and process optimization using machine learning and sensor analytics. Taimun et al. [9] extended digital twins toward predictive maintenance for textile and mechanical systems. Mim et al. [19] discussed IoT infrastructure for workplace efficiency, while Kamalanathan [23] combined simulation and

machine learning for damage detection and load optimization. These studies provide predictive foundations, but they do not connect degradation prediction with global operational scheduling decisions, global fuzzy orchestration, and dynamic multi-program rescheduling.

D. Multi-Objective Optimization and Resource-Constrained Scheduling

Scheduling decisions must balance production objectives while respecting equipment, labor, energy, and constraints. Rahman [18] proposed a multi-objective operational optimization model for lean manufacturing and industrial equipment resource allocation, supporting resource-aware decisions. Huq [15] developed a mathematical framework for workforce planning and resource allocation under uncertainty. Farooq et al. [20] examined adaptive resource scheduling using reinforcement learning, demonstrating adaptive computational approaches. Adil [10] addressed process optimization and energy efficiency, while Karim [11] examined lean and green manufacturing strategies. Together, these studies indicate that scheduling should consider multiple dimensions. However, integrating makespan, energy consumption, machine deviation, and disruption response within a digital twin control loop remains an open problem.

E. Explainable Digital Twin Decision Intelligence

Recent work also points toward explainable and intelligent decision-support architectures for operational environments. Akter [21] examined AI-driven workforce productivity optimization using KPI-based predictive analytics, while Sharmin [22] studied process monitoring and KPI-based performance management. Hossain [24] proposed an explainable digital twin decision intelligence framework for predictive risk assessment and maintenance optimization. Rahman [25] presented a hybrid digital twin optimization framework for predictive maintenance scheduling in smart manufacturing systems. These studies support combining digital twins, predictive analytics, optimization, and interpretable decisions. Nevertheless, the literature provides limited support for a hierarchical architecture combining local machine-health prediction, global TSK fuzzy orchestration, multi-objective rescheduling, and virtual-to-physical synchronization across concurrent multi-program production operations.

III. Methodology

The proposed methodology develops a hierarchical Digital Twin framework for dynamic scheduling across concurrent multi-program manufacturing operations. It integrates physical shop-floor data, local machine-health prediction, global fuzzy decision logic, multi-agent coordination, multi-objective rescheduling, and virtual-to-physical validation. Simulation-based experiments assess machine degradation, equipment failures, urgent order insertions, capacity changes, rework, and human interventions. The framework supports controlled experiments without confidential industrial data.

A. Research Design and Overall Methodological Framework

The research uses a simulation-based, closed-loop experimental design for concurrent multi-program manufacturing. Physical production resources connect with local and global Digital Twins, allowing operational states to move between physical and virtual environments. Local workstation models monitor machine conditions, while the global Digital Twin represents production rates, program priorities, queues, WIP, capacity, and resource assignments. A Multi-Agent System coordinates distributed information, and an orchestration agent controls rescheduling decisions. The methodology consists of four stages: state acquisition, condition prediction, intelligent scheduling decision, and virtual validation. This structure permits repeated evaluation under stochastic disruptions and changing production priorities.

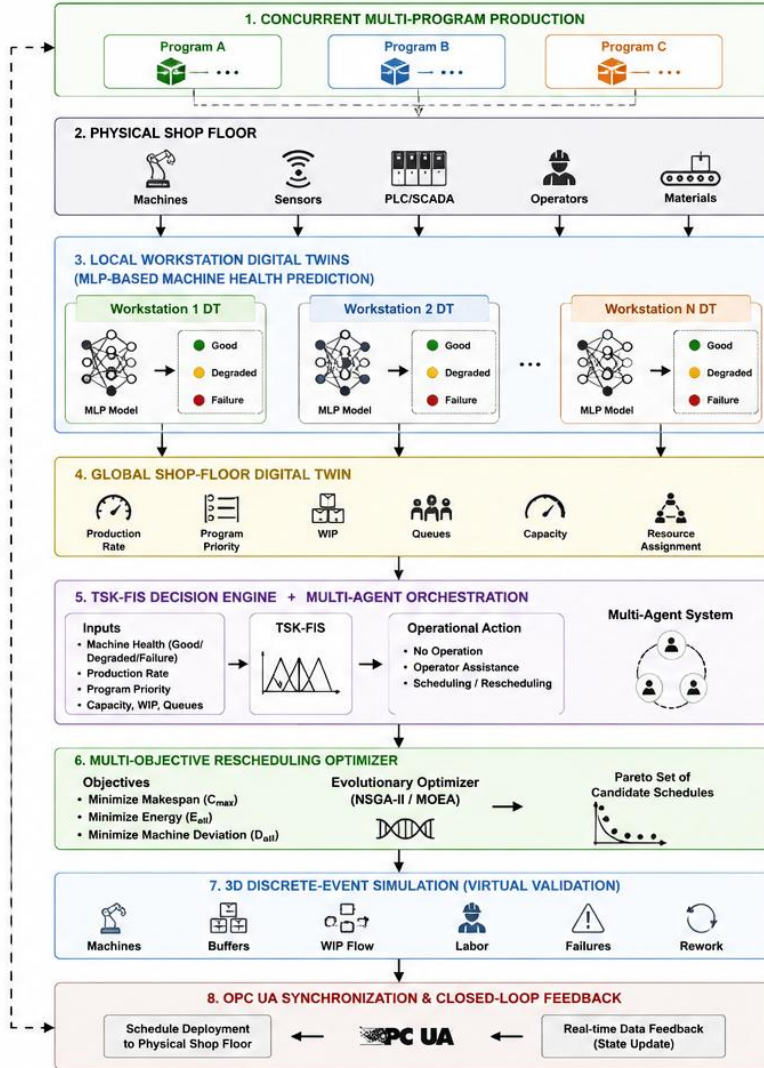


Figure 1. Hierarchical Digital Twin Architecture for Dynamic Multi-Program Scheduling

Figure 1 shows the hierarchical structure of the proposed scheduling framework. Local workstation Digital Twins receive machine-state information and generate health predictions, while the global Digital Twin combines these states with production information. TSK-FIS, multi-agent coordination, optimization, simulation, and OPC UA complete the closed-loop scheduling architecture.

B. Physical Shop-Floor Data and Digital Twin State Representation

The physical layer captures operational states from machines, PLCs, sensors, production orders, and workforce resources. Relevant signals include pneumatic pressure, motor current, vibration RMS, vibration kurtosis, machine availability, queue length, WIP level, cycle time, defect risk, and production rate. Each workstation has a local Digital Twin that mirrors its current state and maintains an operational record. The global Digital Twin combines workstation states with program priorities, routing requirements, due dates, available capacity, and resource assignments. OPC UA supports communication between PLC information and the virtual environment. State updates allow the global model to represent disruptions before scheduling decisions are evaluated.

C. Local Workstation Digital Twins and MLP-Based Condition Prediction

Local workstation intelligence uses Multilayer Perceptron models to classify equipment condition into Good, Degraded, or Failure states. Sensor features are normalized and divided into training, validation, and testing sets. The MLP receives pneumatic pressure, motor current, vibration RMS, vibration kurtosis, and condition indicators. Its output becomes a scheduling input rather than an isolated maintenance prediction. Prediction quality is evaluated with classification performance and RMSE where continuous health indicators are available. The local Digital Twin updates the predicted state at

defined intervals. This approach provides early degradation information for the global scheduling layer before machine failure or bottleneck formation. For continuous health prediction, Root Mean Square Error is calculated as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

where y_i is the observed condition value, $\hat{y}_i$ is the predicted value, and n is the number of observations. A lower RMSE indicates a smaller prediction error.

D. Global Digital Twin, TSK-FIS, and Multi-Agent Orchestration

The global shop-floor Digital Twin combines local health states with production rate and program-level conditions. A Takagi-Sugeno-Kang fuzzy inference system determines the operational response when disruption risk changes. Production rate uses LOW, MED, and HIGH states, while workstation condition uses FAILURE, DEGRADED, and GOOD states. The controller produces three actions: NO_OPERATION, OPERATOR_ASSISTANCE, and SCHEDULING. A Multi-Agent System distributes information and local decisions across workstations, while a high-level orchestration agent coordinates sequential and interdependent operations. This layer limits unnecessary schedule changes and reserves major rescheduling actions for conditions that threaten overall production performance.

The TSK-FIS also provides an interpretable basis for scheduling decisions. Each scheduling action can be associated with the observed machine condition and production-rate state through explicit fuzzy rules. The system records the active rule, input states, selected action, and scheduling trigger, allowing operators to understand why intervention was requested. This rule-based explanation supports human review without introducing a separate black-box explanation model.

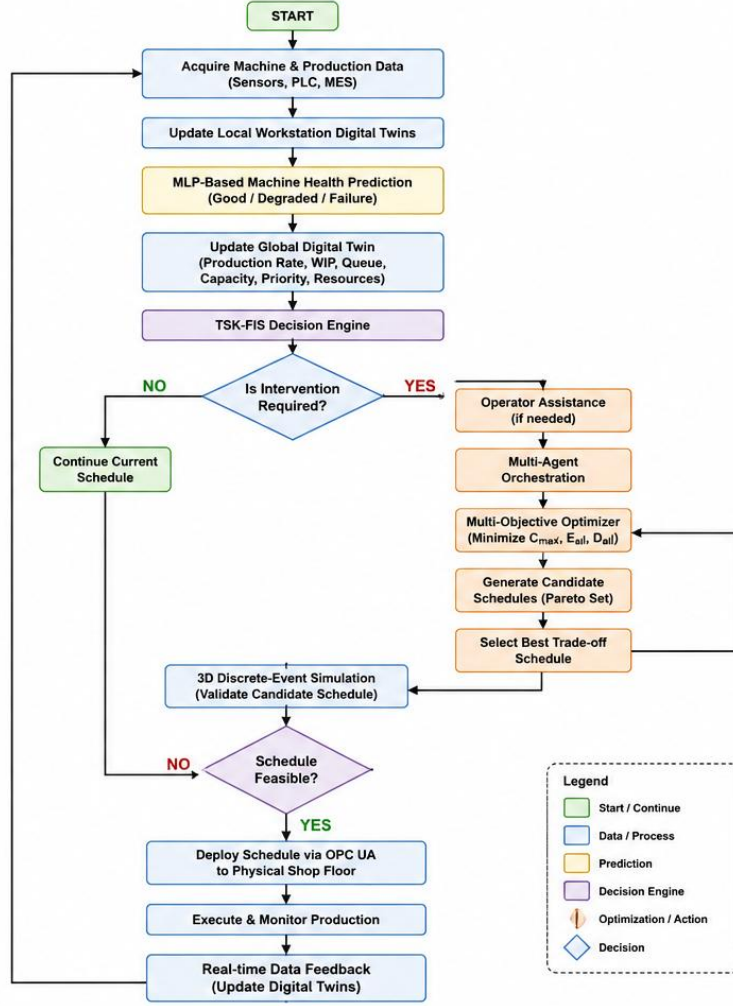


Figure 2. Closed-Loop Anomaly-Driven Rescheduling Workflow

Figure 2 presents the closed-loop rescheduling workflow. Machine and production data feed local Digital Twins and MLP prediction models. The TSK-FIS determines the required intervention, after which the optimizer generates candidate schedules. 3D simulation validates feasibility before OPC UA deployment and real-time feedback update.

E. Multi-Objective Dynamic Rescheduling Model

When the orchestration layer triggers rescheduling, an evolutionary multi-objective optimizer generates alternative production sequences and resource assignments. The optimization considers makespan, total equipment energy consumption, and machine deviation from the existing schedule. Constraints include machine availability, processing times, routing precedence, labor capacity, material availability, program priorities, and existing

production commitments. Decision weights represent the relative importance of completion time, energy use, and schedule stability. Candidate schedules are evaluated within the Digital Twin, and feasible solutions form a Pareto set. Baseline comparison uses right-shift rescheduling and original scheduling delay. The objective function is:

$$\min F(x) = [C_{max}(x), E_{all}(x), D_{all}(x)]$$

where C_{max} is total production makespan, E_{all} is total equipment energy consumption, and D_{all} represents deviation from the existing production schedule. The optimizer searches for non-dominated feasible schedules under machine, labor, material, routing, and program-priority constraints.

F. Virtual Execution and Virtual-to-Physical Synchronization

The virtual execution stage uses a three-dimensional discrete-event simulation model to test candidate schedules before physical deployment. The simulation represents machines, buffers, WIP movement, processing sequences, labor availability, failures, rework, and concurrent program interactions. Candidate schedules are compared under repeated stochastic scenarios involving machine failures, urgent orders, processing delays, and human interventions. The selected feasible schedule can then be transferred to the physical control process. OPC UA supports synchronization between PLC data and the virtual model. Validation measures include latency, synchronization skew, makespan deviation, machine deviation, energy consumption, and schedule stability across consecutive multi-program production shifts.

The makespan deviation between the Digital Twin and physical execution is calculated as:

$$MD = \frac{[C_{DT} - C_{actual}]}{C_{actual}} \times 100$$

where C_{DT} is the Digital Twin makespan and C_{actual} is the measured physical execution time. A lower value indicates closer virtual to physical agreement.

G. Experimental Scenarios, Baselines, and Performance Evaluation

The experimental design compares the proposed hierarchical Digital Twin scheduler with baseline scheduling approaches under identical production scenarios. Scenario factors include program mix, order priority, machine availability, workforce capacity, failure timing, degradation level, urgent order insertion, and rework occurrence. Each scenario is executed through repeated simulation runs to account for stochastic variation. Results are analyzed using makespan, energy consumption, machine deviation, waiting time, downtime loss, rework delay, priority violation, and computational latency. Sensitivity analysis examines the effects of objective weights and disruption intensity. The assessment focuses on the contribution of prediction, fuzzy orchestration, and multi objective rescheduling to production responsiveness and schedule stability. Baseline comparison considers two conventional scheduling strategies: original schedule delay and right-shift rescheduling. Original schedule delay retains the initial production sequence and absorbs disruption-related delays in affected operations. Right-shift rescheduling moves affected operations to later available time slots without using predictive machine-health information or the proposed fuzzy orchestration mechanism. The proposed Digital Twin scheduler uses MLP-based condition prediction, TSK-FIS decision logic, and multi-objective optimization for dynamic schedule generation.

Table 1. Methodological Variables, Sources, and Evaluation Measures

Component	Main Variables / Inputs	Method	Primary Output
Production state	Machine status, WIP, queue, cycle time, capacity	Digital Twin state modeling	Current shop-floor state
Machine condition	Pneumatic pressure, current, vibration RMS/kurtosis	MLP prediction	Good / Degraded / Failure
Global decision	Production rate, machine condition	TSK-FIS	No Operation / Operator Assistance / Scheduling
Coordination	Workstation agents, program dependencies	Multi-Agent System	Coordinated operational decisions
Scheduling	Processing time, routing, labor, materials, priorities	Evolutionary multi-objective optimization	Candidate schedules
Optimization	Cmax, Eall, Dall	Weighted objective / Pareto analysis	Optimal or Pareto-feasible schedules
Virtual validation	Machine events, WIP, failures, rework	3D Discrete Event Simulation	Virtual performance
Physical validation	PLC states, execution time, synchronization	OPC UA linkage	Latency, skew, makespan deviation

IV. Results and Discussion

The results are presented as simulation-based illustrative findings because the proposed methodology does not yet contain an empirical manufacturing dataset or measured shop-floor observations. The analysis therefore demonstrates the expected behavior of the proposed hierarchical Digital Twin scheduler under controlled scenarios. The discussion focuses on makespan response, machine-health prediction, scheduling decisions, energy and machine-deviation trade-offs, and virtual-to-physical synchronization.

A. Dynamic Scheduling Performance Under Production Disruptions

The first experiment compares the proposed Digital Twin scheduler with a right-shift scheduling baseline

across normal production, machine degradation, machine failure, and urgent-order scenarios. The normal case provides a reference point with no disruption. Degradation introduces gradual capacity loss, while failure removes a machine from active production. The urgent-order case introduces a priority change during execution. These scenarios represent the dynamic conditions targeted by the proposed framework. The expected results show that the Digital Twin scheduler maintains shorter completion times after disruptions because machine-health information reaches the global scheduling layer before or immediately after significant operational changes. This supports proactive rescheduling rather than delayed sequence adjustment.

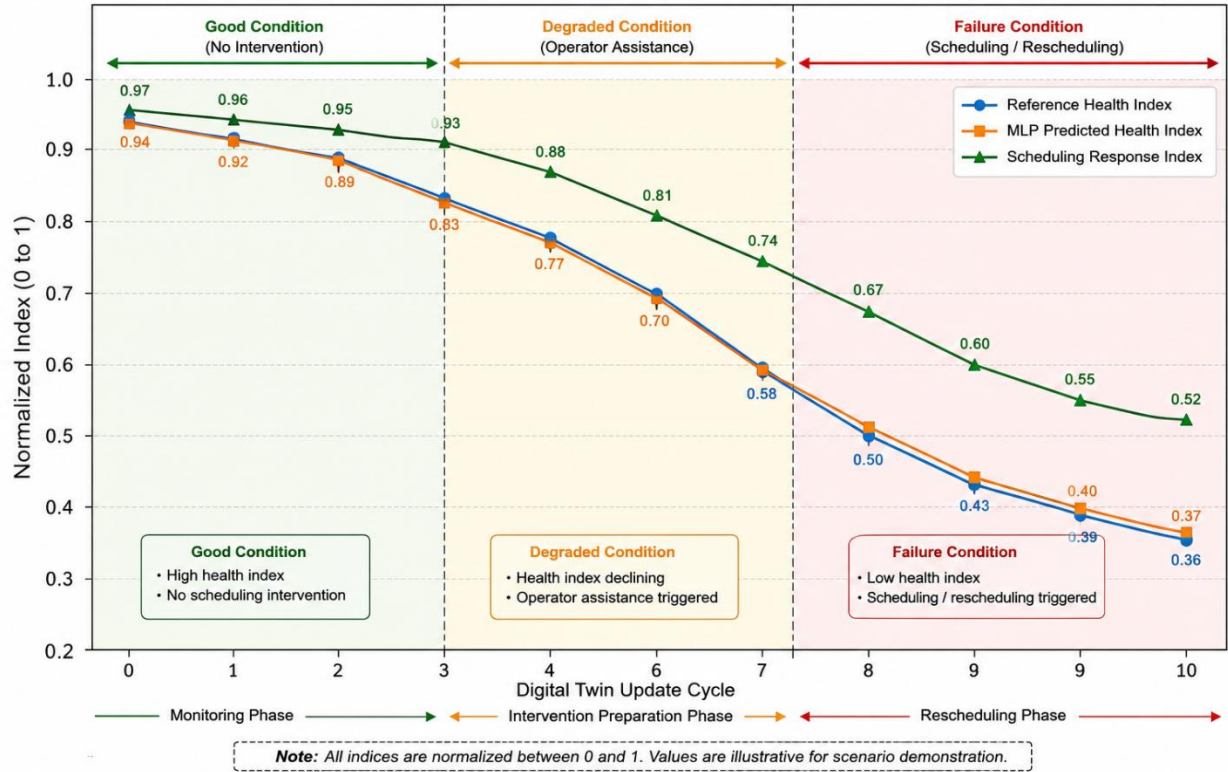


Figure 3. Makespan Response Under Concurrent Multi-Program Disruptions

The illustrative scenarios indicate potential makespan reductions of 5.4% under machine degradation, 13.3% under machine failure, and 11.8% after urgent-order insertion compared with the right-shift baseline. These values are illustrative rather than measured results. Under normal production, both

approaches retain the same normalized makespan, while disruption cases show the benefit of Digital Twin-based schedule adjustment.

B. Machine-Health Prediction and Proactive Scheduling Response

The second analysis examines the relationship between local machine-health prediction and global scheduling response. The MLP model receives sensor information from local workstation Digital Twins and classifies operating conditions as Good, Degraded, or Failure. The global Digital Twin then combines these states with production rate. The TSK-FIS determines whether the system should maintain the current

sequence, request operator assistance, or trigger scheduling. This arrangement separates prediction from scheduling while maintaining a continuous information flow. The expected response is gradual: minor degradation produces limited intervention, while sustained deterioration increases the scheduling response as production risk becomes more significant.

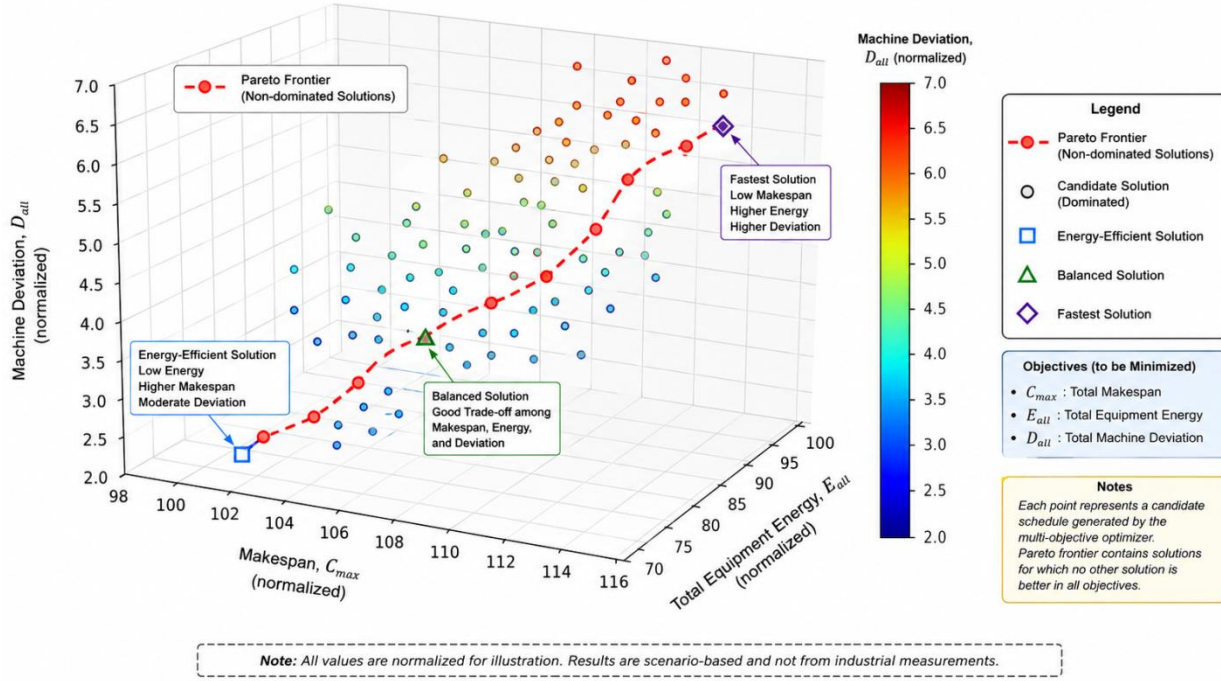


Figure 4. Local Health Prediction and Global Scheduling Response

The illustrative trend shows declining machine health across Digital Twin update cycles, with MLP predictions remaining close to the reference values. As health deteriorates, the scheduling response increases. The TSK-FIS also considers production rate and program conditions, allowing degraded machines to continue under low demand while triggering intervention under higher operational pressure.

C. Multi-Objective Scheduling and Pareto Trade-Offs

The third analysis evaluates the relationship among makespan, equipment energy consumption, and machine deviation. The optimization model seeks a

suitable compromise rather than a single isolated objective. A schedule with the lowest makespan may require additional machine activity or substantial sequence changes. Another solution may reduce energy consumption while creating greater deviation from the original schedule. The Pareto analysis represents these competing priorities. Each candidate solution is feasible only when machine availability, routing precedence, labor capacity, material availability, program priority, and existing commitments are satisfied. This approach reflects the operational conditions of concurrent multi-program manufacturing more closely than single-objective scheduling.

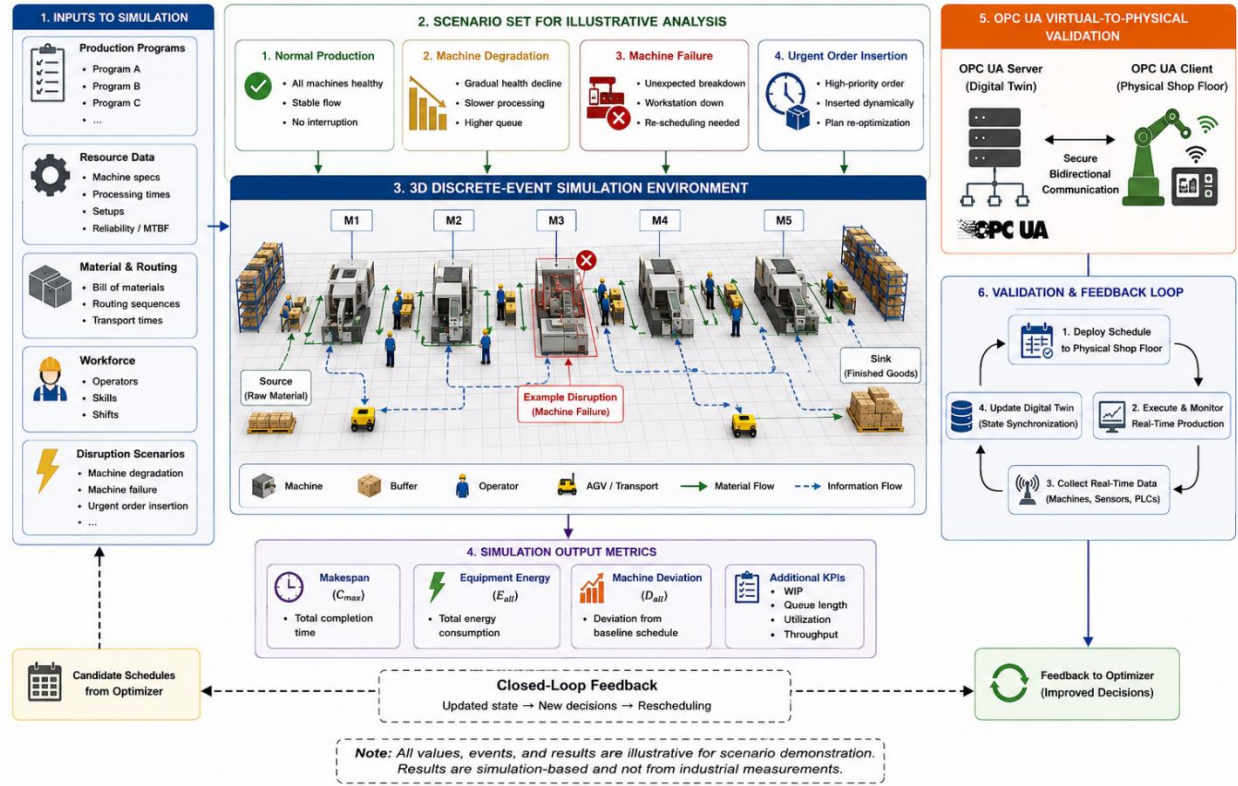


Figure 5. Pareto Trade-Off Between Energy, Makespan, and Machine Deviation

The illustrative Pareto pattern shows the trade-off among makespan, equipment energy consumption, and machine deviation. Lower energy use can require greater schedule deviation, while faster completion

may require additional sequence changes. The optimizer therefore selects feasible trade-offs according to current production priorities and objective weights.

Table 2. Illustrative Scheduling Results Under Different Disruption Scenarios

Scenario	Original Schedule Delay	Right-Shift Rescheduling	Proposed DT Scheduler
Normal production	Reference	Reference	Reference
Machine degradation	Higher delay expected	Moderate delay expected	Lower delay expected
Machine failure	High delay expected	High delay expected	Reduced disruption impact expected
Urgent order insertion	Priority-related delay expected	Sequence displacement expected	Priority-aware rescheduling expected

D. Virtual-to-Physical Synchronization and Operational Implications

The virtual-real linkage validates candidate schedules through 3D Discrete Event Simulation and OPC UA communication. Evaluation considers synchronization skew, latency, makespan deviation, machine deviation, and schedule stability. The proposed architecture connects MLP-based machine prediction with TSK-FIS decisions and multi-

objective rescheduling. These results support closed-loop scheduling for concurrent production programs. Since the reported values are illustrative simulation outputs, real industrial data is required for empirical validation.

E. Limitations of the Study

The study relies on simulation-based evaluation and illustrative scenarios rather than real industrial production data. Sensor quality, model accuracy, and OPC UA synchronization may vary across facilities.

The framework also requires further testing with diverse production layouts, product mixes, disruption patterns, and human interventions before industrial deployment.

V. Conclusion

The study proposed a hierarchical Digital Twin enabled dynamic scheduling framework for concurrent multi-program manufacturing operations. The framework integrates local MLP-based machine-health prediction, a global TSK-FIS decision layer, Multi-Agent System coordination, and multi-objective rescheduling. The simulation-based results indicate that the framework can respond to machine degradation, failures, urgent orders, and changing production priorities while considering makespan, energy consumption, and machine deviation. The closed-loop architecture also connects virtual scheduling with physical execution through 3D DES and OPC UA synchronization.

Future work should validate the framework using real industrial production data and physical shop-floor experiments. Further studies can test different manufacturing layouts, product mixes, sensor configurations, disruption patterns, and human interventions. Future work can extend the rule based explanation layer with advanced explainable AI methods and operator-centered evaluation using real industrial data.

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