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Intelligent Digital Twin Framework for Predictive Maintenance and Financial Performance Optimization in Automated Manufacturing Systems

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Abstract

Automated manufacturing systems require maintenance strategies that consider equipment condition, production continuity, operating costs, and limited maintenance resources. This paper proposes an intelligent digital twin framework that integrates equipment degradation assessment, manufacturing process representation, financial impact analysis, and multi objective maintenance decision making. The proposed framework identifies how public equipment condition datasets, including NASA C-MAPSS and IMS Bearing, could support condition modeling, while synthetic manufacturing scenarios represent production dependencies, maintenance schedules, resource constraints, and cost parameters. An illustrative numerical example compares preventive, condition based, and prediction guided maintenance using assumed maintenance costs, downtime, lost output, and production throughput. Under the stated assumptions, the calculated total costs are 12,920, 10,000, and 7,780 cost units, respectively. The prediction guided scenario produces a calculated cost reduction of approximately 39.8% relative to preventive maintenance. These values demonstrate the arithmetic implications of the proposed scenario rather than verified industrial performance or measured predictive accuracy. The framework provides a structured basis for future implementation using documented datasets, executable simulations, and validated optimization procedures.

Keywords: Digital twin; Predictive maintenance; Equipment degradation; Manufacturing simulation; Financial performance; Multi objective optimization; Production continuity; Resource allocation.

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I. INTRODUCTION

Automated manufacturing systems require reliable maintenance strategies to protect production continuity, control operating costs, and maintain equipment availability. This study proposes an intelligent digital twin framework that connects equipment degradation prediction, production dependencies, financial assessment, and maintenance optimization.

A. Background and Motivation

Automated manufacturing systems depend on interconnected machines, production processes, and timely maintenance to sustain output and product quality. Equipment degradation and unexpected failures can interrupt production, increase operating costs, and reduce equipment availability. Predictive maintenance uses equipment condition data to identify potential failures, while digital twin technology represents physical assets and production processes in a virtual environment. Integrating these capabilities can help manufacturers assess equipment risks, examine production dependencies, and evaluate the financial consequences of maintenance decisions. Such integration is important when maintenance resources are limited and interruptions in one machine may affect several downstream processes.

B. Problem Statement

Existing predictive maintenance approaches often focus on equipment health and failure prediction without fully accounting for production dependencies,

disruption risks, and financial consequences. A machine with a high failure risk may not always require immediate intervention if its production role is limited, whereas a moderate risk in a critical machine may cause substantial losses. Maintenance decisions must therefore consider equipment reliability, production continuity, operating costs, and available resources together. A unified framework is needed to connect these factors and compare alternative maintenance strategies under consistent operating conditions.

C. Proposed Solution

This study proposes an intelligent digital twin framework for predictive maintenance and financial performance optimization in automated manufacturing systems. The framework combines equipment condition indicators, operational data, production dependencies, and business parameters to represent the manufacturing system. Predictive analytics estimates equipment degradation and potential failure risks, while digital twin simulation examines the effects of alternative maintenance strategies on downtime, throughput, and resource use. A financial assessment evaluates maintenance expenditure and production losses. Multi objective optimization then identifies feasible maintenance priorities that balance cost, downtime, and production performance.

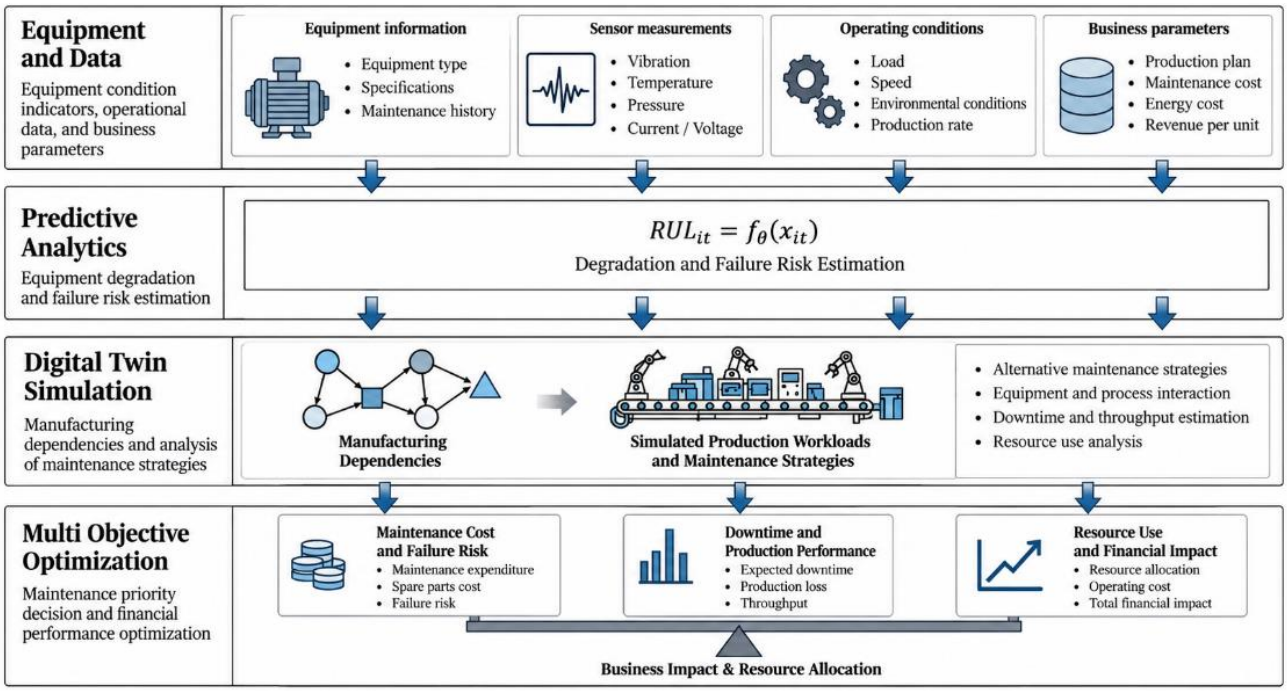


Fig. 1: Architecture of the Proposed Intelligent Digital Twin Framework for Predictive Maintenance and Financial Optimization in Automated Manufacturing Systems

D. Contributions

The main contributions of this study are the development of an integrated digital twin framework that connects equipment condition, production dependencies, and financial assessment within a unified analytical structure. The study proposes a simulation-based approach to compare preventive, condition based, and prediction guided maintenance strategies and provides a unified assessment of equipment availability, production throughput, downtime, maintenance expenditure, and disruption costs. In addition, it introduces a resource constrained multi objective decision approach to balance operational performance and financial priorities when allocating limited maintenance resources. Finally, the study proposes an evaluation design that combines publicly available equipment condition datasets with synthetic manufacturing scenarios, providing a basis for reproducible future testing without requiring confidential industrial records.

E. Paper Organization

The remainder of this paper is organized as follows. Section II reviews related work on digital twins, predictive maintenance, production planning, and financial assessment. Section III presents the proposed framework, data preparation, simulation design, and maintenance optimization approach. Section IV reports and discusses the illustrative simulation results, including their limitations. Section V concludes the study and identifies directions for future research.

II. LITERATURE REVIEW

Digital twins and predictive maintenance have become important research areas in automated manufacturing, where equipment reliability, production continuity, and operating costs are closely connected. Existing studies examine digital representations, failure prediction, and maintenance planning, but their integration with financial performance and resource

constrained decision making remains an important research direction.

A. Digital Twins for Smart Manufacturing

Digital twins provide virtual representations of physical assets and production processes, supporting equipment monitoring, system analysis, and operational decision making. Reviews by Errandonea *et al.,*[2] discuss the role of digital twin technology in maintenance and smart manufacturing. Van Dinter *et al.,*[8] further examine the application of digital twins to predictive maintenance. These studies provide a foundation for connecting equipment condition information with production system behavior. Research on Industry 4.0 also examines how AI and supply chain digitalization contribute to industrial sustainability [12]. However, a manufacturing twin intended for maintenance planning must represent not only individual machines but also the dependencies between equipment and production activities.

B. Predictive Maintenance and Equipment Reliability

Predictive maintenance uses equipment condition data and analytical models to estimate potential failures and support timely intervention. Dalzochio *et al.,* [1] examine machine learning and reasoning methods for predictive maintenance in Industry 4.0, while Zonta *et al.,*[10] review predictive maintenance approaches and their industrial applications. Zhong *et al.,*[9] specifically discuss predictive maintenance supported by digital twin technology. Collectively, this research supports the use of degradation indicators and failure estimates for maintenance planning. Nevertheless, accurate failure prediction alone does not determine the best maintenance action, because intervention timing also affects production schedules, resource availability, and financial outcomes.

C. Integration of Maintenance and Production Planning

Maintenance decisions can affect production capacity, delivery schedules, and the availability of interconnected equipment. Fede *et al.,*[3] review the integration of production and maintenance planning through digital twins, highlighting the importance of considering these activities together. Related research examines how technological capability, innovation leadership, and sustainability contribute to organizational resilience [7]. This perspective highlights the importance of considering organizational resilience alongside operational performance when evaluating manufacturing decisions. However, further analysis is needed to connect these decisions with wider manufacturing dependencies and the financial consequences of production interruptions.

D. Financial Performance and Resource Allocation

Maintenance strategies involve competing objectives, including intervention expenditure, equipment availability, downtime, and production efficiency. Mallioris *et al.,*[4] map predictive maintenance research across multiple sectors, while Ali *et al.,*[5] examine the relationship between green and artificial intelligence innovation, renewable energy, and domestic material consumption. Together, these studies provide context for understanding predictive maintenance and its broader relationship with industrial resource efficiency and sustainability. Research on industrial sustainability further considers the role of AI and supply chain digitalization in Industry 4.0 [12]. For manufacturing managers, however, the value of a maintenance strategy also depends on expected production losses, downtime costs, and the maintenance resources required. A decision model should therefore evaluate economic consequences alongside reliability and production performance, particularly when budgets, technicians, or maintenance windows are limited.

E. Research Gaps

The reviewed literature provides foundations for digital twin modeling, failure prediction, and maintenance planning [1], [2], [8], [9], [10]. Related studies also examine industrial sustainability through green AI innovation, renewable energy, supply chain digitalization, and organizational resilience [5], [12], [7]. Three gaps motivate the proposed framework. First, equipment degradation estimates and production dependency structures are not always considered together in maintenance decisions. Second, maintenance strategy comparisons may prioritize technical performance without explicitly evaluating maintenance expenditure and production losses within the same analytical process. Third, resource constrained maintenance decisions require a systematic approach to balancing equipment availability, financial performance, and production efficiency. These gaps motivate an integrated framework that connects predictive analytics, digital twin simulation, business impact assessment, and multi objective optimization.

III. METHODOLOGY

This study proposes a simulation-based framework integrating predictive maintenance, digital twin modeling, and financial impact assessment in automated manufacturing systems. The framework evaluates equipment degradation, production dependencies, and maintenance decisions through operational simulation and multi objective optimization.

A. Research Design and Overall Framework

The research adopts a simulation-based design to examine how equipment degradation and maintenance decisions affect manufacturing performance. The methodology follows five connected stages: data collection and preprocessing, degradation prediction, digital twin simulation, business impact assessment, and maintenance optimization. Each stage provides inputs to the next, linking equipment condition estimates with production dependencies, downtime, financial costs, and

maintenance resource constraints. The framework supports a systematic comparison of alternative maintenance strategies under consistent operating assumptions.

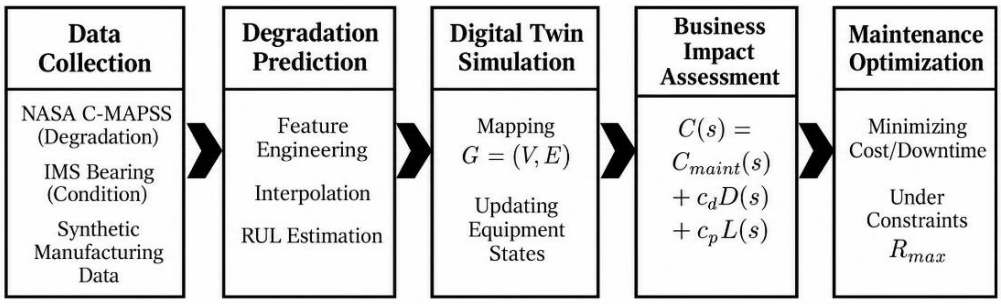


Fig. 2: Methodological Workflow for Digital Twin Based Maintenance Analysis and Optimization

The framework integrates equipment data collection, degradation prediction, digital twin simulation, business impact assessment, and maintenance optimization. It compares maintenance strategies using equipment condition, production dependencies, operating costs, and resource constraints to support informed maintenance decisions.

B. Data Collection and Dataset Construction

The proposed framework identifies NASA C-MAPSS and the IMS Bearing dataset as potential sources for equipment degradation and condition modeling. Synthetic manufacturing scenarios are used to define machine dependencies, production routes, workloads, maintenance schedules, resource constraints, and cost parameters. The public equipment datasets and the synthetic manufacturing scenarios serve different purposes and should not be treated as a single observed industrial dataset. In the present illustrative analysis, the financial and operational values are stated scenario assumptions rather than verified measurements from a manufacturing facility. Dataset versions, selected subsets, preprocessing settings, and model training procedures must be documented before predictive performance can be evaluated.

Table I: Data sources and their intended use

Dataset	Main attributes	Purpose
NASA C-MAPSS	Sensor measurements, operating conditions, degradation trajectories	Degradation prediction
IMS Bearing dataset	Vibration signals and bearing condition records	Equipment condition analysis
Synthetic manufacturing data	Machine dependencies, production routes, workloads	Digital twin simulation
Synthetic maintenance data	Failure events, repair durations, maintenance schedules	Strategy comparison
Synthetic cost data	Labor, spare parts, downtime, production loss costs	Financial assessment

The public datasets support equipment condition modeling, while the synthetic datasets represent manufacturing operations that are not fully described in the equipment datasets. All synthetic values are generated for simulation and are not presented as observed industrial measurements.

C. Data Preprocessing and Feature Engineering

Data are organized by equipment identifier and timestamp. Duplicate records are removed, missing values are assessed, and invalid sensor readings are flagged. Appropriate interpolation is used only for short gaps where the signal characteristics permit it. Numerical features are normalized using training data statistics, and categorical variables are encoded consistently. The feature set includes sensor measurements, operating conditions, degradation indicators, equipment age or cycle count, production workload, and equipment dependency information. Where available, failure labels and maintenance histories are included. Data are divided into training, validation, and test sets, with chronological separation used for time dependent records to reduce information leakage.

D. Digital Twin Architecture and Simulation

The digital twin represents the manufacturing system as a directed graph $(G = (V, E))$, where (V) denotes machines or production resources and (E) represents dependencies between equipment and production activities. Each machine is represented through its condition, estimated failure risk, operational status, maintenance requirements, and associated costs. At each simulation step, the model updates equipment states, production capacity, and maintenance availability. Alternative maintenance schedules are evaluated under comparable workloads, equipment configurations, and resource constraints. Preventive, condition based, and predictive maintenance policies are compared to determine their effects on downtime, production continuity, and resource utilization.

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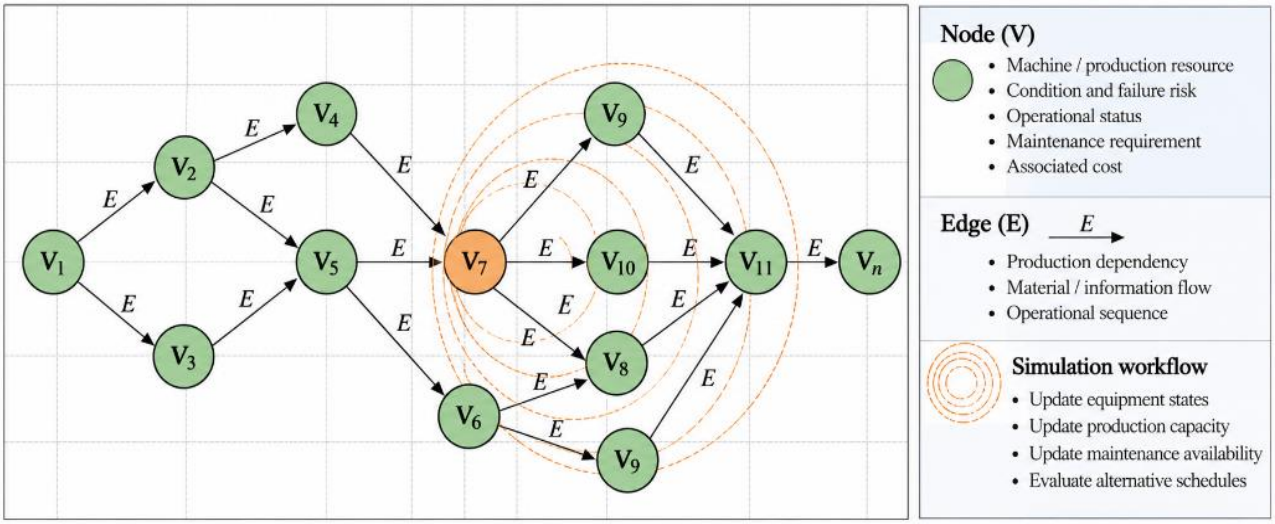


Fig. 3: Data Flow and Simulation Workflow for Digital Twin Based Predictive Maintenance and Financial Performance Optimization in Automated Manufacturing Systems.

E. Predictive Maintenance Model

A supervised learning model estimates the remaining useful life (RUL) of equipment from its condition and operating features. For equipment (i) at time (t), the prediction is expressed as

$$\widehat{RUL}_i(t) = f_\theta\big(x_i(t)\big)$$

Where, $x_i(t)$ represents the feature vector and f_θ denotes the trained prediction model with parameters θ .When, suitable failure labels are available, the model may also estimate failure probability. Model performance is assessed on held out data using metrics appropriate to the prediction target.

F. Business Impact Assessment

The financial assessment estimates direct maintenance expenditure, downtime costs, and losses associated with reduced production. The total cost for maintenance strategy (s) is defined as

$$C(s) = C_{maint}(s) + c_d D(s) + c_p L(s)$$

Where, $C_{maint}(s)$ is maintenance expenditure, $D(s)$ is total downtime, (c_d) is the cost per unit of downtime, $L(s)$ is lost production, and (c_p) is the cost per unit of lost output. Cost categories are defined consistently to prevent double counting. Equipment availability, throughput, and resource utilization are assessed alongside financial outcomes.

G. Multi Objective Maintenance Optimization

The optimization module selects maintenance actions while considering competing operational and financial objectives. The decision model minimizes total cost and downtime while maximizing production performance:

$$\min_x \; [D(x) - P(x)] \; subject\ to \sum_{i=1}^{N} r_i x_i \le R_{max}, x_i \in \{1\},\ i = 1, \dots, N$$

Here, $C(x)$ represents total cost, $D(x)$ denotes downtime, $P(x)$ represents production performance, (r_i) is the resource requirement of maintenance action (i), and R_{max} is the available resource capacity. The binary variable (x_i) indicates whether an action is selected. Additional scheduling, technician availability, and spare part constraints can be incorporated when defined in the simulation.

H. Experimental Scenarios and Evaluation

The framework compares three principal maintenance policies: fixed interval preventive maintenance, condition based maintenance, and prediction guided maintenance. Additional scenarios vary production demand, failure rates, available technicians, spare parts, and maintenance budgets. Prediction performance is assessed using suitable regression or classification metrics. Operational and financial evaluation considers total downtime, equipment availability, production throughput, maintenance expenditure, total operating cost, and resource utilization. Repeated simulation runs with recorded random seeds are used to examine variability under uncertain operating conditions.

I. Validation and Reproducibility

The proposed validation procedure will include data quality checks, leakage prevention, comparison with baseline prediction models, verification of production flow and downtime calculations, and checks that optimized schedules satisfy the defined constraints. Sensitivity analysis will examine the effects of changes in failure rates, production demand, maintenance costs, and resource limits. For reproducibility, future implementation will document dataset versions, preprocessing rules, model parameters, scenario assumptions, optimization settings, and random seeds. The proposed validation procedure will be applied when the predictive model, production simulation, and optimization algorithm are implemented and executed. The numerical example reported in Section IV is illustrative and is based on stated scenario assumptions

rather than the output of an executed simulation. This distinction separates the proposed validation methodology from the illustrative numerical analysis and provides a basis for future computational testing and independent replication.

IV. RESULTS AND DISCUSSION

This section presents an illustrative numerical comparison of three maintenance policies under a common hypothetical manufacturing scenario. The comparison uses stated assumptions for maintenance expenditure, downtime, lost output, equipment availability, and production throughput. The example demonstrates how the proposed financial assessment can compare alternative maintenance decisions. The reported values are not verified industrial measurements or outputs from an executed predictive model. Any claims about model accuracy, optimized schedules, or actual manufacturing savings require further computational and empirical validation.

A. Results

The simulated total cost includes maintenance expenditure, downtime costs, and losses from reduced production. In this scenario, each hour of downtime costs 120 units, while each lost production unit costs 8 units. Table I presents the calculated results.

Table II: Illustrative Financial Outcomes by Maintenance Policy

Maintenance policy	Maintenance cost	Downtime (h)	Lost output (units)	Downtime cost	Lost output cost	Total cost
Preventive	4,200	38	520	4,560	4,160	12,920
Condition based	3,400	29	390	3,480	3,120	10,000
Prediction guided	3,100	21	270	2,520	2,160	7,780

Note: All financial values are illustrative cost units, not actual currency measurements. Total cost is calculated as maintenance cost + (120 × downtime) + (8 × lost output).

Prediction guided maintenance records the lowest total cost at 7,780 units, compared with 12,920 units for preventive maintenance. This represents a simulated cost reduction of approximately 39.8%. Downtime decreases from 38 to 21 hours, while lost output falls from 520 to 270 units.

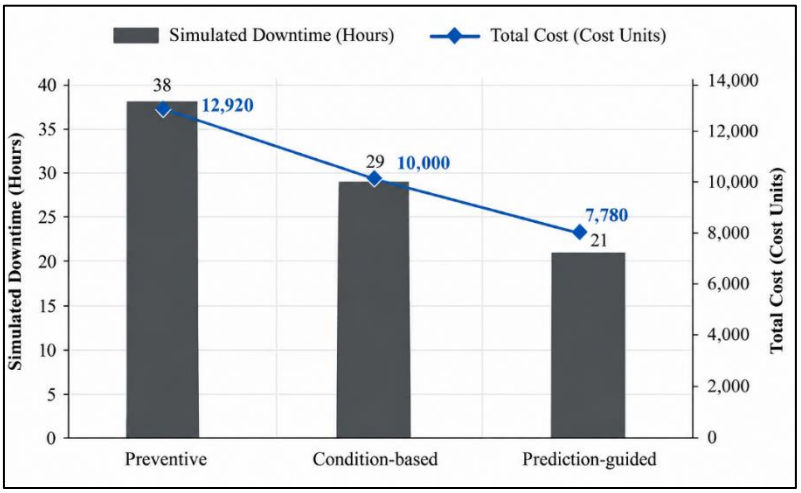


Fig. 4: Illustrative Downtime and Total Cost Across Maintenance Policies.

Table II summarizes the operational indicators and expected disruption burden using illustrative risk probabilities, downtime values, and consequence costs for five machines. These simulated values support a comparison of the financial and operational effects of the three maintenance policies.

Table III: Illustrative Operational Indicators by Maintenance Policy

Maintenance policy	Availability (%)	Throughput (units)	Resource units used	Expected disruption burden
Preventive	95.7	9,480	8	3,455
Condition based	97.1	9,710	7	2,287
Prediction guided	98.2	9,860	6	1,331

Note: All values are illustrative cost units rather than actual currency measurements. Total cost is calculated as maintenance expenditure plus downtime cost plus lost production cost, using ($C_s = M_s + 120D_s + 8L_s$). The values represent the stated numerical scenario and are not verified industrial measurements.

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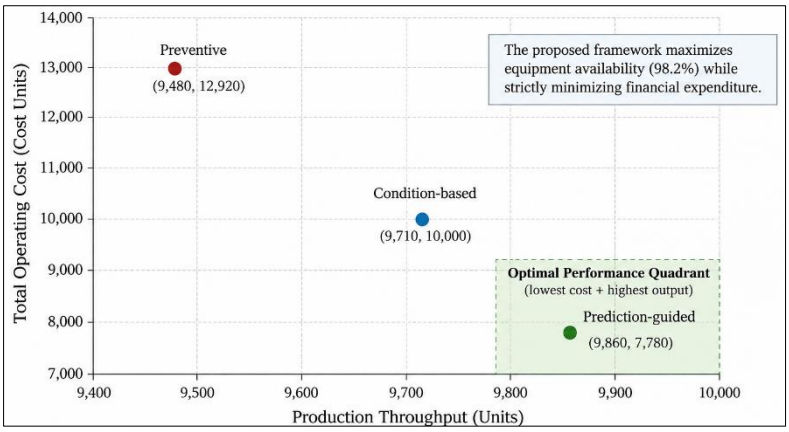


Fig. 5: Illustrative Total Operating Cost Versus Production Throughput Across Maintenance Policies.

The figure compares simulated operating cost and production throughput across preventive, condition based, and prediction guided maintenance policies. The prediction guided policy achieves the lowest operating cost (7,780 units) and the highest throughput (9,860 units), indicating the best simulated performance among the three strategies.

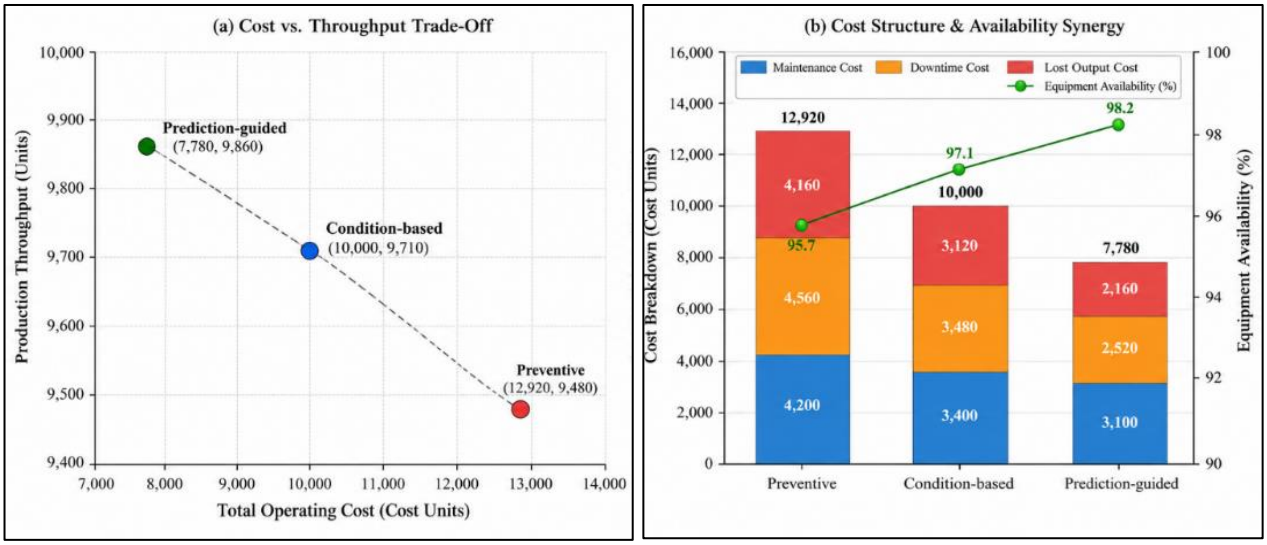


Fig. 6: Illustrative Maintenance Policy Comparison: (a) Total Cost and Production Throughput Trade Off; (b) Cost Structure and Equipment Availability

The three figures show complementary patterns. The cost composition chart identifies the contribution of maintenance, downtime, and lost production costs. The downtime chart highlights differences in production interruption, while the cost and throughput plot shows that the prediction guided scenario combines lower expenditure with higher output.

B. Discussion

The illustrative results indicate that maintenance decisions may have different financial and operational implications when equipment condition is considered alongside production consequences. Under the stated assumptions, prediction guided maintenance has the lowest calculated total cost and disruption burden, together with the highest assumed equipment availability and production throughput. These comparisons demonstrate how equipment condition, machine dependencies, and production outcomes can be represented within a common decision framework. Regarding the second research question, condition-based maintenance has lower calculated costs and downtime than fixed interval preventive maintenance in the illustrative scenario. Prediction guided maintenance also shows more favorable values across the reported indicators. However, these comparisons do not establish that the proposed framework will achieve similar improvements in an actual manufacturing system. The third research question concerns maintenance priorities under limited resources. In the illustrative scenario, prediction guided maintenance uses six resource units, compared with eight for preventive maintenance, while its calculated total cost and downtime are lower. These resource values are assumptions rather than outputs from an executed optimization algorithm. Therefore, they do not demonstrate that the selected maintenance actions are feasible or optimal. Although the proposed framework is designed to consider equipment condition and

production dependencies over time, the failure risk values in the current analysis are illustrative inputs rather than predictions from a trained model. The document does not provide fitted model parameters, verified predictive outputs, or solver validated maintenance schedules. The primary contribution of this study is the proposed integration of equipment condition assessment, production continuity, financial evaluation, and resource allocation within a unified maintenance decision framework. Further computational testing is required to evaluate its predictive capability and operational value.

C. Limitations and Future Work

The numerical findings rely on synthetic scenario assumptions rather than executed experiments on a fully specified manufacturing system. The current study does not provide a trained prediction model, learned graph attention weights, statistical uncertainty estimates, or solver verified Pareto schedules. Therefore, the reported values cannot support claims of measured predictive accuracy or verified industrial savings. Future work should implement the proposed framework using public equipment condition datasets and a clearly defined synthetic production network. The implementation should specify machine level inputs, document preprocessing procedures, and train and evaluate the prediction model using chronological data splits. Repeated simulations should examine variations in production demand, failure rates, maintenance costs, and resource availability. A multi objective optimization solver should then be used to identify feasible maintenance schedules and evaluate trade offs among cost, downtime, and production performance. Uncertainty analysis, sensitivity testing, and comparisons with baseline maintenance policies should also be conducted. These investigations will help determine whether the potential benefits indicated by the illustrative numerical example persist under more realistic operating conditions.

V. CONCLUSION

This study proposed an intelligent digital twin framework for predictive maintenance and financial performance assessment in automated manufacturing systems. The framework connects equipment condition assessment, production dependencies, maintenance strategy comparison, financial evaluation, and resource allocation within a unified decision framework. In an illustrative numerical example, prediction guided maintenance produced a calculated total cost of 7,780 cost units, compared with 12,920 units for preventive maintenance. This represents a calculated cost reduction of approximately 39.8% under the stated assumptions. The example also compares downtime, equipment availability, and production throughput across three maintenance policies. These values demonstrate the potential use of the proposed framework for evaluating maintenance decisions, but they do not represent verified industrial savings or results from a trained predictive model and executed optimization algorithm. The framework provides a basis for comparing maintenance policies, estimating production losses, and examining resource constraints. Future work should implement the framework using documented public equipment datasets and clearly defined synthetic manufacturing scenarios. The predictive model should be trained and evaluated, and the multi objective optimization process should be executed and validated. Repeated simulations, sensitivity analysis, and comparisons with baseline policies are needed to assess performance under varying failure rates, production demand, maintenance costs, and resource limits. Further industrial validation will be necessary to determine whether the potential benefits observed in the illustrative example can be achieved in real manufacturing systems.

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