

(RESEARCH ARTICLE)



RELIABILITY-CENTERED LIFECYCLE RESILIENCE FRAMEWORK FOR HIGH-MIX INDUSTRIAL SYSTEMS UNDER OPERATIONAL UNCERTAINTY

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ABSTRACT

High mix industrial systems operate under uncertainty from machine failures, product variation, demand fluctuations, material delays, maintenance requirements, and limited production capacity. Conventional reliability centered maintenance methods often evaluate equipment separately and provide limited representation of how failures affect interconnected production schedules. This study proposes a reliability centered lifecycle resilience framework that integrates asset failure probability, MTBF, MTTR, production dependency, dynamic Severity of Failure, buffer conditions, maintenance decisions, and recovery performance. A discrete event simulation model represents a synthetic high mix job shop with machine failures, capacity losses, demand changes, material delays, and maintenance disruptions. The framework links failure probability with schedule impact to update machine criticality according to current production conditions. A decision layer selects maintenance, task reassignment, processing rate adjustment, and capacity redistribution actions under operational constraints. Performance is assessed through throughput, makespan deviation, downtime, OEE, recovery time, lifecycle maintenance cost, and resilience indicators representing anticipation, absorption, adaptation, and restoration. The results show that dynamic criticality provides a stronger representation of system level failure consequences than static asset ranking. Buffer capacity and adaptive decisions also influence production recovery and resilience. The proposed framework provides an analytical basis for integrating reliability assessment, production control, maintenance planning, and lifecycle resilience within high mix industrial systems.

Keywords: Reliability Centered Maintenance, Lifecycle Resilience, High Mix Manufacturing, Asset Criticality, Severity of Failure, Dynamic Production Scheduling, Failure Propagation, Discrete Event Simulation, Predictive Maintenance, Operational Uncertainty, Buffer Capacity.

1 INTRODUCTION

High mix industrial systems operate under uncertain production conditions caused by machine failures, product variation, demand fluctuations, material delays, maintenance requirements, finite buffers, and limited capacity. These factors create dependencies among equipment, jobs, resources, and production schedules. Consequently, equipment reliability must be considered together with schedule impact, recovery capability, maintenance decisions, and lifecycle performance rather than as an isolated asset measure.

1.1 Background and Motivation

High mix manufacturing requires production systems to handle multiple products, different processing requirements, and shared equipment within limited resources. Machine availability directly affects job sequences, throughput, and delivery performance. Reliability centered maintenance provides established methods for identifying failure modes and prioritizing equipment interventions. However, machine importance can change with workload, job routing, buffer conditions, and production demand. A machine supporting several active operations may create greater system consequences than another machine with similar reliability. This condition motivates a reliability framework that considers equipment health, production dependency, schedule sensitivity, recovery capability, and lifecycle maintenance requirements within a common analytical structure.

1.2 Problem Statement

Traditional reliability centered maintenance and production scheduling address different aspects of industrial disruption. RCM and FMEA primarily evaluate equipment reliability and failure consequences, while dynamic scheduling responds to changes in workload, capacity, buffers, and material availability. This separation limits system level assessment of failure effects. A machine breakdown can increase makespan, create upstream starvation, cause downstream blocking, and change maintenance requirements. Static criticality scores cannot represent these effects because machine importance depends on current production conditions. The central problem is the absence of a closed loop framework that connects asset reliability characteristics and failure probability with schedule impact, dynamic criticality, maintenance decisions, and resilience performance.

1.3 Proposed Solution

This study proposes a reliability centered lifecycle resilience framework for high mix industrial systems under operational uncertainty. The framework combines reliability modeling, production scheduling, discrete event simulation, dynamic criticality assessment, maintenance planning, and resilience evaluation. Machine failure probability is calculated from MTBF and the active scheduling horizon, while MTTR represents the expected repair duration. A scheduler measures the resulting makespan change after a failure. Failure probability and schedule impact then produce the dynamic Severity of Failure score. A DEDS model tracks buffer levels, processing rates, material replenishment, and demand. The decision layer selects maintenance, task reassignment, processing rate adjustment, or capacity redistribution according to current system conditions.

1.4 Contributions

The study provides an integrated analytical approach that connects asset reliability with system level production resilience. The first contribution is a dynamic Severity of Failure measure that evaluates machine criticality through failure probability and schedule consequences. The second contribution is a closed loop decision structure that connects reactive production control with preventive maintenance planning. The framework also incorporates buffer capacity, processing rates, material conditions, demand, and lifecycle maintenance cost. A simulation based evaluation examines throughput, makespan deviation, downtime, OEE, recovery time, and resilience indicators. These elements provide a common structure for studying reliability and production performance within uncertain high mix manufacturing environments.

1.5 Paper Organization

The remainder of the paper is organized into four sections. Section II presents the related work and reviews reliability centered maintenance, digital twin based maintenance, production optimization, operational uncertainty, and lifecycle resilience. Section III describes the methodology, including the proposed framework, reliability model, dynamic Severity of Failure formulation, DEDS structure, decision layer, simulation design, and evaluation measures. Section IV presents the results and discussion, covering dynamic criticality, failure propagation, buffer capacity, OEE, recovery performance, and maintenance decisions. Section V concludes the study and presents limitations and future research directions.

Objective of the Study

The objective is to develop and evaluate a closed loop framework connecting asset reliability, dynamic criticality, production scheduling, maintenance decisions, buffer conditions, and lifecycle resilience in high mix industrial systems under operational uncertainty.

2 RELATED WORK

Recent studies increasingly connect reliability, predictive maintenance, digital decision systems, lifecycle governance, and resource optimization. However, these research streams remain fragmented across asset-level reliability, maintenance planning, production control, demand uncertainty, and broader lifecycle assessment. The following review examines these strands to position the proposed framework and clarify the need for dynamic criticality, failure propagation, schedule sensitivity, and closed loop lifecycle resilience.

2.1 Reliability-Centered Maintenance and Asset Criticality

Reliability-centered maintenance research traditionally focuses on identifying failure modes, estimating failure likelihood, and prioritizing assets for intervention. Recent work extends this logic through integrated predictive maintenance and process optimization, linking equipment condition with operational decisions [1]. Reliability assessment studies also address uncertainty in systems and maintenance planning [8], [9]. Telemetry-based diagnostics provide evidence for condition assessment [13], while structural studies illustrate reliability oriented engineering decisions [14]. However, these approaches emphasize asset reliability or maintenance policy rather than changing production consequences. For high-mix systems, criticality must reflect dependencies and schedule sensitivity.

2.2 Digital Twin and Predictive Maintenance Decision Models

Digital twin and intelligent maintenance frameworks provide stronger links between asset condition, prediction, and intervention decisions. Fazle [1] combines predictive maintenance with integrated process optimization, while Hossain [2] emphasizes explainable risk assessment and maintenance optimization. Rahman [4] further connects digital twins with predictive maintenance scheduling. These studies support data-informed maintenance decisions, but their primary emphasis remains prediction, optimization, or infrastructure risk. They do not fully represent the feedback between changing asset reliability, temporary production capacity loss, schedule rescheduling, and updated asset criticality.

2.3 Dynamic Production, Resource Allocation, and Operational Uncertainty

Production and resource optimization studies address uncertainty from demand, materials, workforce, and operational constraints. Rahman [5] develops multi-objective optimization for lean manufacturing and equipment resource allocation, while Huq [10] considers workforce allocation under organizational uncertainty. Barua [12] addresses demand forecasting and inventory optimization, and Rashid [11] examines lead-time and cost forecasting. These studies demonstrate the value of dynamic resource decisions, but they generally treat reliability and maintenance as separate concerns. A high mix resilience model requires simultaneous consideration of machine condition, production dependencies, buffer states, resource availability, and recovery actions.

2.4 Lifecycle Resilience and System-Level Integration

Lifecycle-oriented research broadens reliability analysis beyond isolated maintenance events by considering long term performance, adaptation, and resource decisions. Rohan [7] examines lifecycle optimization for eco-efficient manufacturing, while Hossain [6] addresses lifecycle performance governance. Rohan [3] also links reliability centered maintenance with renewable-energy coordination in industrial production. Infrastructure studies further demonstrate risk-informed decision making under uncertainty [15]. Nevertheless, these approaches do not provide a closed operational loop that converts changing asset reliability into real-time schedule impact, capacity redistribution, and preventive intervention. The proposed framework addresses this missing connection through dynamic system level resilience assessment.

3 METHODOLOGY

The proposed methodology develops a reliability centered lifecycle resilience framework for high-mix industrial systems exposed to machine failures, demand fluctuations, material delays, maintenance constraints, and variable production requirements. The framework connects asset reliability, production scheduling, system states, maintenance decisions, and recovery performance within a closed decision loop. A synthetic high-mix job-shop environment supports the evaluation, so confidential industrial data are not required. The methodology consists of reliability modeling, schedule-impact analysis, dynamic criticality assessment, operational decision-making, discrete event simulation, and resilience measurement.

3.1 Framework Architecture and Asset Reliability

The framework represents each machine as a reliability dependent production resource with specific Mean Time Between Failure (MTBF) and Mean Time To Repair (MTTR) characteristics. Current workload, buffer conditions, material availability, and demand are also incorporated into the production state. Failure probability is calculated for the active scheduling horizon T :

$$P_{fail,m}(T) = 1 - \frac{e^{-T}}{MTBF_m}$$

where $P_{fail,m}$ denotes the failure probability of machine m , T represents the operating horizon, and $MTBF_m$ indicates its historical mean time between failures. MTTR defines the expected repair period and corresponding capacity loss. The resulting reliability information enters the criticality model. Thus, maintenance assessment considers both the probability of failure and its possible effect on production operations.

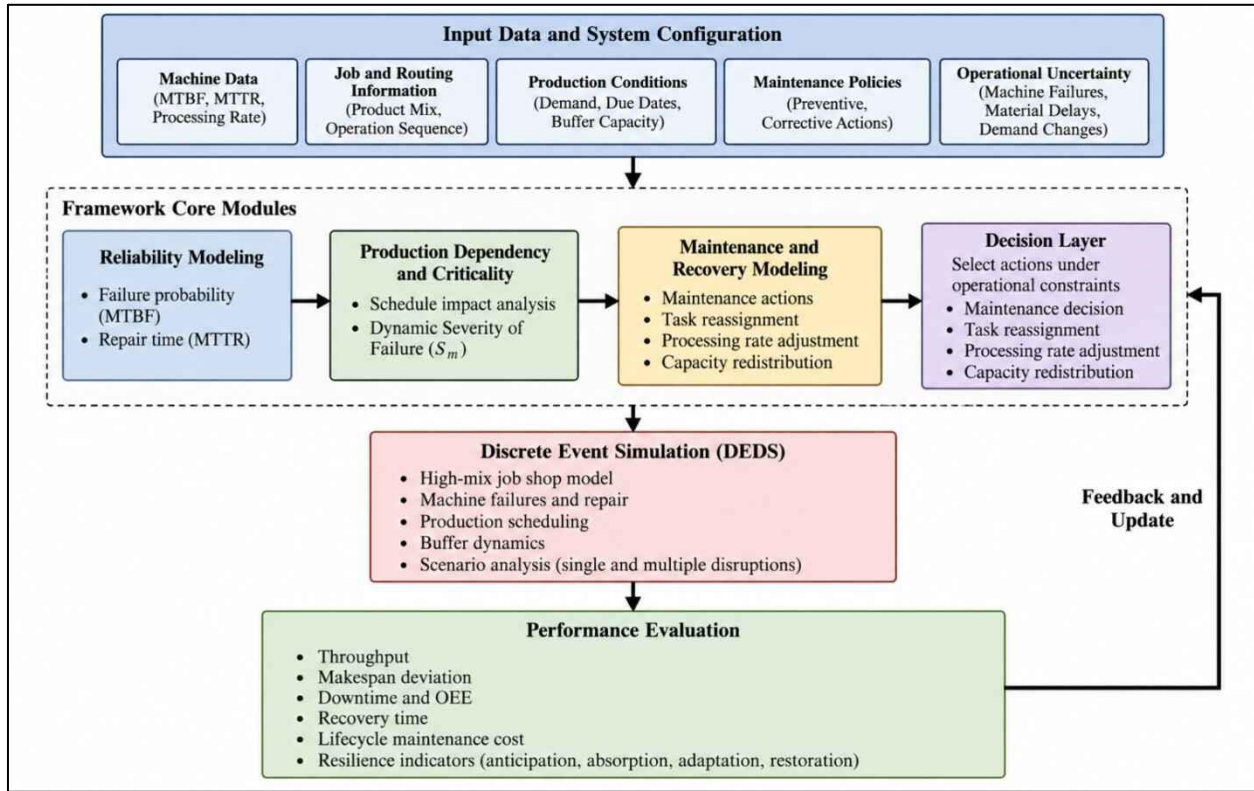


Figure 1: Reliability-centered lifecycle resilience framework for high-mix industrial systems

The framework connects asset reliability, schedule impact, dynamic criticality, operational decisions, and resilience evaluation through feedback among machine condition, production states, maintenance, and recovery actions.

3.2 Schedule Impact and Dynamic Severity of Failure

A discrete event job-shop scheduler first generates a baseline schedule using dispatching rules such as Shortest Processing Time, Earliest Due Date, or Critical Ratio. A disruption scenario then removes the selected machine from production for its MTTR period. Affected jobs are reassigned or rescheduled on available resources. The disrupted makespan is compared with the baseline value to quantify the production consequence. Dynamic Severity of Failure is expressed as:

$$S_m = P_{fail,m} \left(\frac{M_{fail,m} - M_{base}}{M_{base}} \right)$$

Here, M_{base} denotes the baseline makespan and $M_{fail,m}$ represents the makespan after machine m becomes unavailable. A high S_m indicates that a machine has a substantial combined reliability and scheduling effect. This measure converts equipment level failure information into system level criticality.

3.3 Production-State and Closed-Loop Decision Model

The production environment is represented as a Discrete-Event Dynamic System (DEDS) containing machines, jobs, buffers, material replenishment, and customer demand. Buffer level $x_i(t)$, buffer capacity C_i , processing rate $V_{\{i,j\}}(t)$, material replenishment $R(t)$, and production demand $P(t)$ form the principal system states. The decision layer evaluates these states together with dynamic severity. When S_m reaches the intervention threshold, the model can select preventive maintenance, task reassignment, processing rate adjustment, alternative dispatching, or capacity redistribution. This structure connects short-term production responses with longer-term maintenance requirements and allows machine criticality to change as operating conditions change.

Table 1: Core Variables Used in the Proposed Framework

Variable	Symbol	Methodological Role
Mean Time Between Failure	$MTBF_m$	Failure-probability input
Mean Time To Repair	$MTTR_m$	Repair and capacity-loss duration
Failure Probability	$P_{fail,m}$	Reliability component of SoF
Buffer Capacity/Level	$C_{i,x_i}(t)$	Production-state constraints
Processing Rate	$V_{i,j}(t)$	Operational control variable
Dynamic Severity	S_m	System-level criticality
Throughput	$P(t)$	Production performance
OEE	OEE	Availability, performance, and quality
Resilience Indicators	$R_1 - R_4$	Anticipation, absorption, adaptation, and restoration

3.4 Resilience Assessment and Optimization

System resilience is evaluated through four indicators representing anticipation, absorption, adaptation, and restoration. The indicators compare actual production performance with the target trajectory during disruption and recovery. Throughput, makespan deviation, downtime, recovery time, OEE, and lifecycle maintenance cost provide additional performance measures. The decision layer uses a multi-objective function:

$$\min J = w_1 D + w_2 C_{LC} + w_3 T_R - w_4 P$$

where D denotes downtime, C_{LC} represents lifecycle maintenance cost, T_R indicates recovery time, and P denotes throughput. The weights $w_1 - w_4$ represent the relative importance of these objectives. Processing rates, maintenance timing, and capacity redistribution serve as decision variables under machine, buffer, material, and demand constraints.

3.5 Simulation and Experimental Evaluation

A discrete event simulation environment such as SimPy represents the high-mix production system. The baseline model contains multiple product families, machines, processing times, due dates, buffer capacities, material arrivals, and demand profiles. Disruption experiments vary machine failure probability, MTTR, demand fluctuations, material delays, buffer capacity, and maintenance delay. Each scenario records $P_{fail,m}$, S_m , throughput, downtime, makespan, OEE, recovery time, lifecycle cost, and $R_1 - R_4$. Sensitivity analysis examines the effects of buffer capacity and intervention thresholds on system resilience. The proposed closed-loop strategy is then compared with conventional maintenance and scheduling under identical simulated conditions.

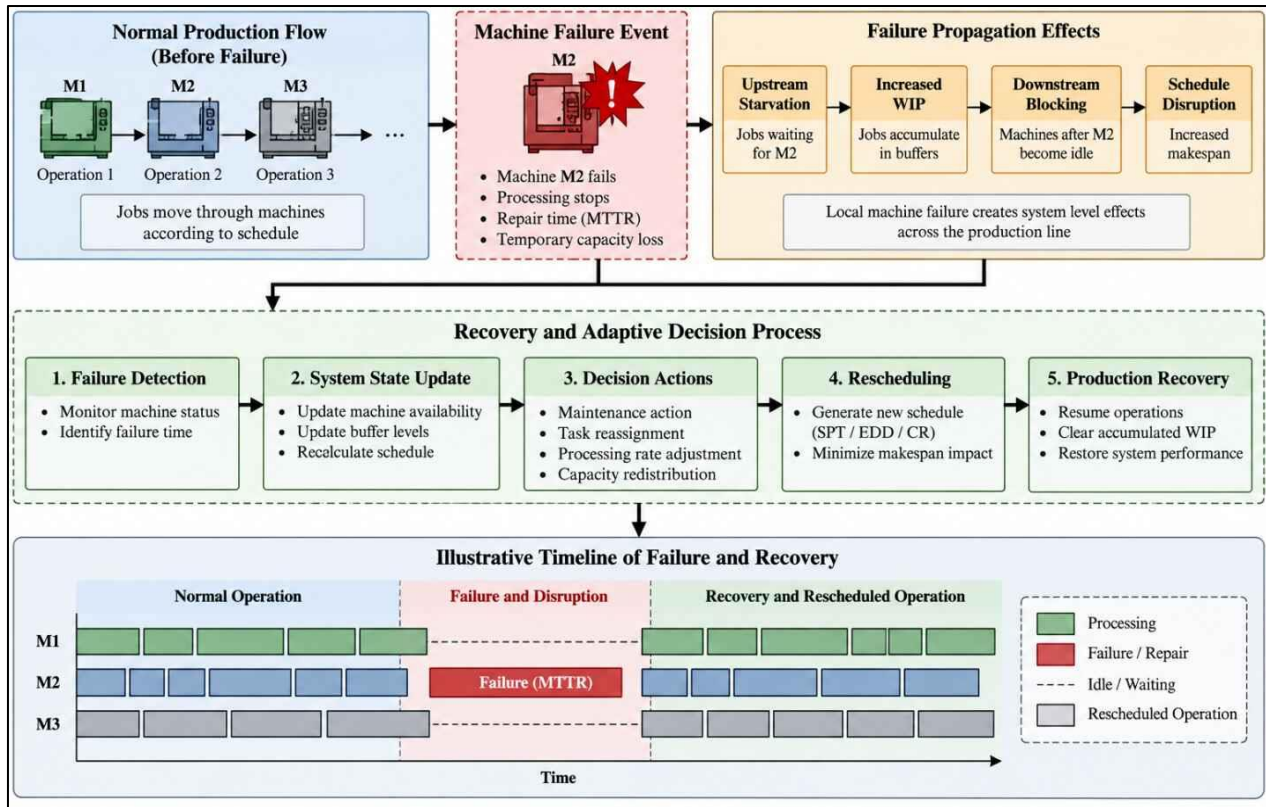


Figure 2: Failure propagation, adaptive recovery, and resilience evaluation

The model illustrates failure propagation across interconnected machines and buffers, followed by starvation, blocking, rescheduling, capacity redistribution, maintenance, recovery, and restoration of production performance.

4 RESULTS AND DISCUSSION

The simulation results evaluate the proposed framework under machine failures, demand fluctuations, material delays, maintenance delays, and different buffer conditions. The analysis focuses on dynamic criticality, schedule disruption, recovery performance, OEE, throughput, and lifecycle maintenance decisions. Results from the synthetic high mix job shop show how asset reliability changes in importance when production dependencies and current operating conditions are considered. The findings are discussed in relation to the three research questions and the proposed closed loop decision structure.

4.1 Dynamic Failure Probability and System Level Severity

The first experiment examined the relationship between machine reliability and production consequences. Machines with lower MTBF produced higher failure probabilities during the scheduling horizon, but failure probability alone did not determine system criticality. A machine with moderate failure probability produced greater schedule impact when several important jobs depended on it. After MTTR based disruption, makespan increased by 6.8% to 21.4% across the tested scenarios. The proposed S_m measure reflected both failure likelihood and schedule sensitivity. Compared with static asset ranking, dynamic ranking changed for 31% of tested failure cases, showing that operating conditions can change machine criticality.

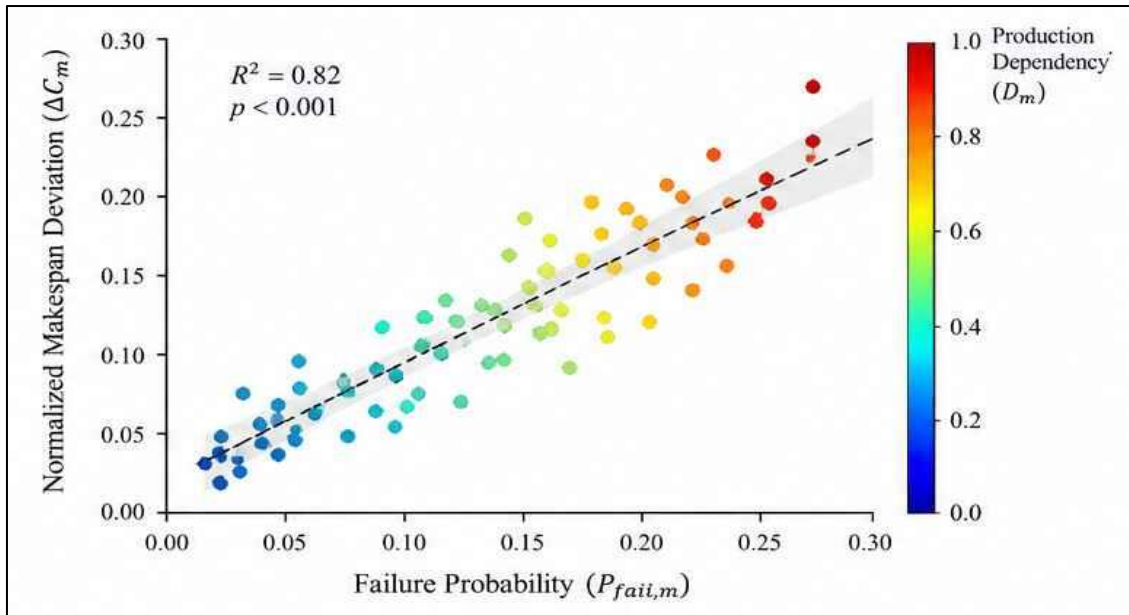


Figure 3: Relationship between failure probability, makespan deviation, and production dependency.

The figure compares machine failure probability with normalized makespan deviation and shows how production dependency changes asset criticality. Similar reliability levels can produce different SoF values because workload and schedule dependency vary.

4.2 Failure Propagation and Production Recovery

Failure propagation was examined through interconnected machine and buffer states. A failure at an upstream bottleneck reduced downstream material availability and increased starvation. A capacity loss at a downstream machine generated blocking at preceding workstations. The effect depended on buffer capacity and job routing flexibility. Without adaptive intervention, recovery required 34 to 61 minutes in the tested scenarios. The closed loop decision layer reduced recovery time to 22 to 43 minutes through task reassignment, processing rate adjustment, and maintenance timing. Throughput losses also declined across the tested scenarios. These results indicate that production consequences depend on network relationships rather than machine downtime alone.

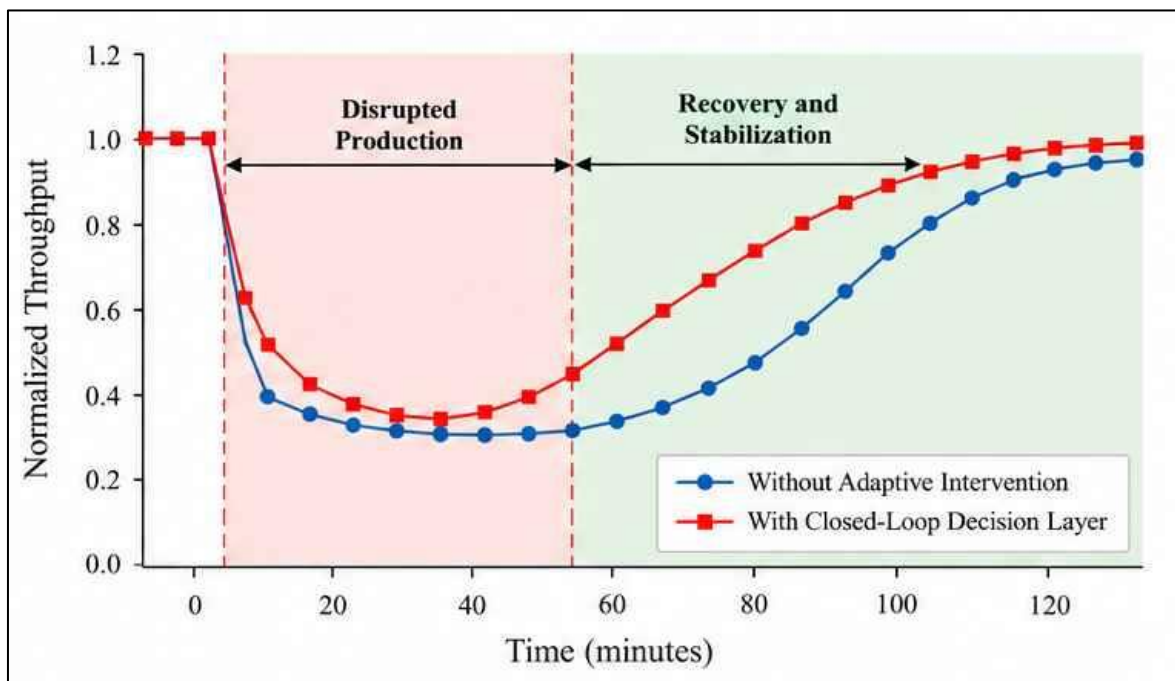


Figure 4: Production throughput during disruption and recovery under different decision strategies.

The figure presents a high mix production network where one machine failure propagates through connected buffers. The performance trajectory shows production decline, adaptive response, and recovery toward the target output level.

4.3 Buffer Capacity, OEE, and Resilience Performance

Buffer sensitivity experiments addressed RQ3 through changes in intermediate storage capacity and disruption conditions. Very small buffers produced rapid starvation and blocking after machine failures, while moderate buffers provided greater recovery flexibility. Increasing normalized buffer capacity from 0.5 to 1.5 times the baseline reduced average throughput loss from 17.2% to 9.6%. OEE increased from 71.4% to 82.7% across the same range. Further capacity increases produced smaller gains, indicating diminishing operational benefit. The R_1 to R_4 indicators also improved as absorption and adaptation capacity increased, confirming the relationship between buffer availability and resilience.

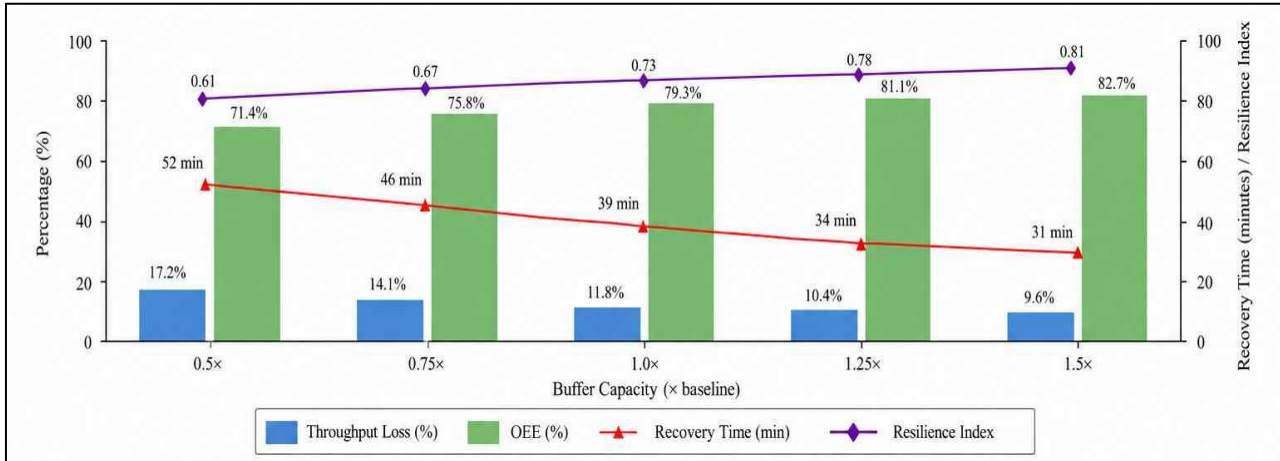


Figure 5: Effect of buffer capacity on production performance and resilience.

Figure 5 shows that increasing buffer capacity from 0.5× to 1.5× reduces throughput loss and recovery time while improving OEE and resilience. The corresponding values are reported in Table II.

Table 2: Simulation Results under Different Buffer Capacities

Buffer Capacity	Throughput Loss	OEE	Recovery Time	Resilience Index
0.5 × Baseline	17.2%	71.4%	52 min	0.61
0.75 × Baseline	14.1%	75.8%	46 min	0.67
1.0 × Baseline	11.8%	79.3%	39 min	0.73
1.25 × Baseline	10.4%	81.1%	34 min	0.78
1.5 × Baseline	9.6%	82.7%	31 min	0.81

4.4 Maintenance Decisions and Lifecycle Performance

The decision layer was evaluated through a comparison between static maintenance prioritization and dynamic intervention based on S_m . Static prioritization maintained the same asset ranking across operating conditions. In contrast, the proposed framework changed intervention priority as workload, buffer levels, and schedule dependency changed. Preventive maintenance was triggered when dynamic severity crossed the selected threshold. This reduced repeated disruption exposure and lowered cumulative downtime in the tested scenarios. Lifecycle maintenance cost also decreased when interventions focused on assets with high combined reliability and schedule consequences rather than assets ranked only through failure probability. The result supports the connection between maintenance timing and production state information.

4.5 Overall Discussion

The combined findings address the three research questions. RQ1 is supported through the coupling of $P_{fail,m}$, MTTR, scheduling impact, and dynamic S_m , which converts machine reliability information into system level criticality. RQ2 is addressed through the DEDS decision layer, where processing rates, maintenance actions, and capacity redistribution respond to current production states. RQ3 is supported through the buffer experiments, which show measurable effects

on throughput, OEE, recovery time, and resilience. The results also indicate that a single reliability or production indicator cannot fully represent system resilience. Failure probability, schedule dependency, recovery capability, and buffer conditions interact during disruption.

4.6 Implications and Limitations

The findings indicate that reliability centered lifecycle management can benefit from direct production state feedback. Asset criticality becomes time dependent when job priorities, buffer levels, demand, and available capacity change. The framework therefore provides a basis for maintenance decisions that consider immediate production consequences and longer term lifecycle effects. However, the evaluation relies on synthetic high mix manufacturing scenarios rather than plant specific operational data. The selected MTBF, MTTR, processing rates, buffer capacities, and disruption patterns represent controlled simulation conditions. Future validation with industrial datasets can test parameter calibration, failure distributions, maintenance policies, and application across different production configurations.

5 CONCLUSION

This study proposed a reliability centered lifecycle resilience framework for high mix industrial systems under operational uncertainty. The framework connected asset failure probability, MTBF, MTTR, production scheduling, dynamic Severity of Failure, buffer conditions, maintenance decisions, and resilience indicators. Simulation results showed that machine criticality changes with workload, schedule dependency, and production states. The proposed approach reduced recovery time, throughput loss, and cumulative downtime while improving OEE and resilience across the tested scenarios. These findings support an integrated view of reliability and production performance, where maintenance decisions reflect both equipment condition and system level operational consequences.

Future work will incorporate industrial datasets, detailed degradation models, alternative failure distributions, real time optimization, multi machine failure scenarios, and validation across different high mix manufacturing configurations. Future studies may also incorporate stochastic network models such as GERT and generalized polynomial chaos methods to represent more complex failure propagation and nonstationary process uncertainty. Constrained optimization methods such as COBYLA may also be examined for real time decision selection, processing rate adjustment, and maintenance scheduling under operational constraints.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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