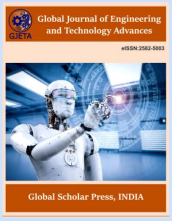
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TEMPORAL GRAPH LEARNING FOR CASCADING FAILURE PREDICTION, BUSINESS IMPACT ASSESSMENT, AND RECOVERY OPTIMIZATION IN SMART MANUFACTURING SYSTEMS

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ABSTRACT

Smart manufacturing systems contain interconnected machines, production processes, and operational resources. A failure in one component may affect dependent components, increase downtime, and create additional business losses. This paper presents a conceptual framework for temporal graph learning, cascading failure risk assessment, business impact estimation, and recovery optimization in smart manufacturing systems. The framework consists of five stages: synthetic data specification and preprocessing, temporal graph construction, cascading failure prediction, business impact assessment, and recovery optimization with explainability. A six component illustrative numerical example is used to demonstrate the business impact and resource constrained recovery decision. Under a resource capacity of five units, the example selects components M2 and M4 for recovery. The calculated total modeled cost decreases from $5,552.50 to $2,442.50, representing a 56.01% reduction under the specified assumptions. These values are analytical example results rather than outputs from a trained model or an experimentally validated simulation. The proposed framework provides a basis for future evaluation using real industrial data, repeated simulation trials, and comparative experiments.

Keywords: Smart Manufacturing, Temporal Graph Learning, Cascading Failures, Business Impact Assessment, Recovery Optimization, Explainable Artificial Intelligence.

1 INTRODUCTION

Smart manufacturing systems are increasingly interconnected, creating opportunities for efficient production while increasing exposure to cascading disruptions. This study proposes an integrated framework linking temporal graph

learning, business impact assessment, and resource constrained recovery optimization to support operational resilience.

1.1 Background and Motivation

Smart manufacturing integrates production equipment, industrial communication networks, automated controllers, and interconnected processes. These relationships support coordinated operations but also allow localized failures to spread across dependent components, causing production delays, service interruptions, and financial losses. Although predictive maintenance and graph learning support failure detection, identifying equipment faults alone does not establish how disruptions propagate or which recovery actions provide the greatest business benefit. An integrated analytical approach is therefore needed to connect technical risk with operational consequences and recovery planning [1]-[6].

1.2 Problem Statement

Existing approaches face three related challenges. First, static or component level models may not capture evolving dependencies among equipment, controllers, and production processes. Second, predicted failures are rarely connected systematically to measurable downtime, production losses, and financial exposure. Third, recovery planning must account for failure propagation, component criticality, maintenance costs, and limited resources. These limitations motivate a unified framework that predicts cascading disruptions, quantifies their business consequences, and prioritizes recovery actions under operational constraints [4], [7], [8].

1.3 Proposed Solution

This study proposes a temporal graph learning framework that combines cascading failure prediction, business impact assessment, and resource constrained recovery optimization. Industrial components and their dependencies are represented as a time varying graph,

$(G_t = (V, E_t, X_t))$. A temporal graph neural network estimates component failure probabilities and potential propagation pathways. The business impact layer converts predicted risks into expected downtime, production losses, and financial exposure, while a mixed integer optimization model selects recovery actions according to expected losses, recovery costs, and resource availability. Explainability analysis identifies influential components and pathways, and simulation based evaluation examines predictive performance, impact estimation error, and recovery efficiency.

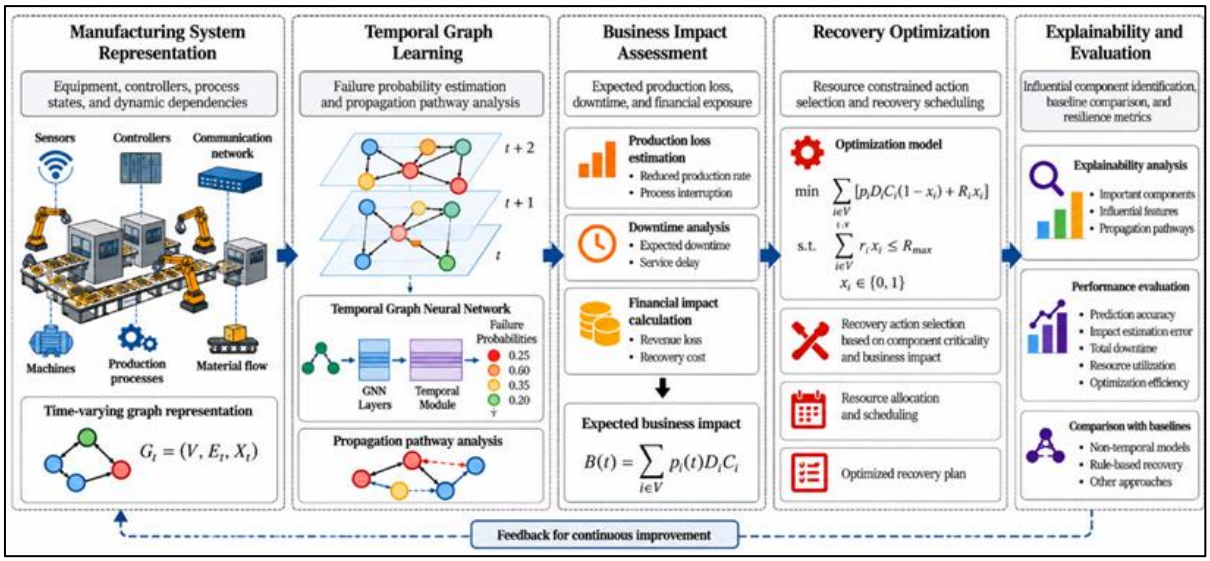


Figure 1: Integrated framework for cascading failure prediction and recovery optimization.

The framework integrates temporal graph learning to predict cascading failures and assess their operational and financial impacts in smart manufacturing systems. It uses explainable, resource constrained optimization to prioritize recovery actions, allocate resources, and evaluate system resilience.

1.4 Contributions

The principal contributions of this study are the development of a temporal graph learning approach to represent evolving industrial dependencies and estimate cascading failure risks, the formulation of a systematic method for connecting predicted technical failures with their expected operational and financial consequences, and the design of a

mixed integer optimization model to prioritize recovery actions under limited maintenance resources. In addition, the study proposes an integrated decision support framework that combines explainability and simulation based evaluation to examine failure risks, business impacts, and recovery performance within a common analytical structure. The distinctive contribution lies in integrating these components into a unified decision framework rather than treating them as separate analytical tasks. However, the predictive accuracy, optimization effectiveness, and practical benefits of the proposed framework require systematic experimental validation.

1.5 Paper Organization

The remainder of this paper is organized as follows. Section II reviews related studies and identifies research gaps. Section III describes the methodology, including simulated data generation, temporal graph modeling, business impact estimation, and recovery optimization. Section IV presents the simulation results and discusses their implications and limitations. Section V concludes the study and outlines future research directions.

2 LITERATURE REVIEW

Smart manufacturing systems depend on interconnected equipment, production processes, and industrial communication networks. Existing research addresses temporal graph learning, predictive maintenance, cyber physical system resilience, and production scheduling, but connecting failure propagation with financial impact and resource constrained recovery remains the central motivation for this study [1]-[10].

2.1 Temporal Graph Learning for Industrial Dependencies

Dynamic graph neural networks model relationships that change over time, while graph based time series methods support forecasting, classification, and anomaly detection [1], [2]. Spatiotemporal graph research further provides methodological foundations for learning evolving interactions among connected system components [3]. However, applying these methods to manufacturing requires more than identifying abnormal behavior. Models must estimate how an initial equipment failure may propagate through dependent machines, controllers, and production processes. This study therefore focuses on temporal dependency modeling for cascading disruption prediction.

2.2 Predictive Maintenance and Failure Propagation

Predictive maintenance uses intelligent sensors and data driven techniques to identify equipment deterioration and anticipate failures [9]. Although these methods support maintenance planning, component level prediction alone cannot fully represent the consequences of interconnected failures. Research on cascading failures in collaborative manufacturing networks provides a closer foundation for examining disruption propagation and resilience improvement [4]. The remaining challenge is to connect evolving failure probabilities with explicit propagation pathways and operational dependencies.

2.3 Cyber Physical System Resilience

Resilience research examines how cyber physical systems respond to disruptions and maintain or restore their intended functions [6]. Smart manufacturing resilience also involves organizational and operational capabilities that influence disruption response [5]. These perspectives support the need for a system level assessment rather than isolated equipment reliability measures. Nevertheless, the proposed framework requires a direct analytical connection between predicted technical disruptions, production consequences, and recovery priorities.

2.4 Business Impact Assessment

Manufacturing disruptions can affect production capacity, delivery commitments, service continuity, and financial performance. Smart manufacturing scheduling research examines production planning under operational constraints [8], while adaptive rescheduling methods address unforeseen disruptions [7]. Digital twin research offers additional foundations for representing manufacturing systems and supporting industrial decision making [10]. However, the proposed study focuses specifically on translating predicted failures into measurable production losses, downtime, recovery urgency, and estimated financial exposure.

2.5 Recovery Optimization and Resource Allocation

Production rescheduling and manufacturing network optimization provide foundations for responding to disruptions under operational constraints [4], [7], [8]. Recovery decisions must account for equipment criticality, dependency relationships, maintenance capacity, and the consequences of delayed restoration. Mixed integer optimization offers a suitable approach for selecting recovery actions subject to limited resources. This study extends the decision process conceptually by using predicted business impact and cascading risk to prioritize recovery activities rather than relying solely on equipment condition or fixed maintenance priorities.

2.6 Research Gaps

The reviewed literature supports dynamic graph modeling, predictive maintenance, resilience analysis, and disruption responsive scheduling [1]–[10]. However, the available references do not independently demonstrate a single validated framework that integrates all these elements into a unified approach. Several research gaps remain, including the limited integration of failure prediction, business impact estimation, and recovery optimization, which are often addressed as separate analytical tasks. In addition, evolving dependencies among equipment and production processes require explicit modeling to identify and assess cascading risks. Another important gap concerns the translation of predicted technical failures into measurable business consequences, such as production losses, downtime, and estimated financial exposure. Recovery decisions also need to account for both failure propagation risks and business consequences while considering resource constraints. Furthermore, interpretable explanations of influential components and propagation pathways are needed, alongside reproducible simulation scenarios to evaluate the performance of an integrated framework. These gaps provide the motivation for the proposed study; however, they should not be interpreted as evidence that previous research has failed to address any of these individual components.

3 METHODOLOGY

The proposed methodology integrates temporal graph learning, business impact assessment, and resource constrained recovery optimization. A simulated manufacturing environment is used to study how equipment failures propagate, affect production and financial performance, and influence recovery decisions under limited resources.

3.1 Overall Research Framework

The framework contains five connected stages: data generation and preprocessing, cascading failure prediction, business impact assessment, recovery optimization, and explainability with performance evaluation.

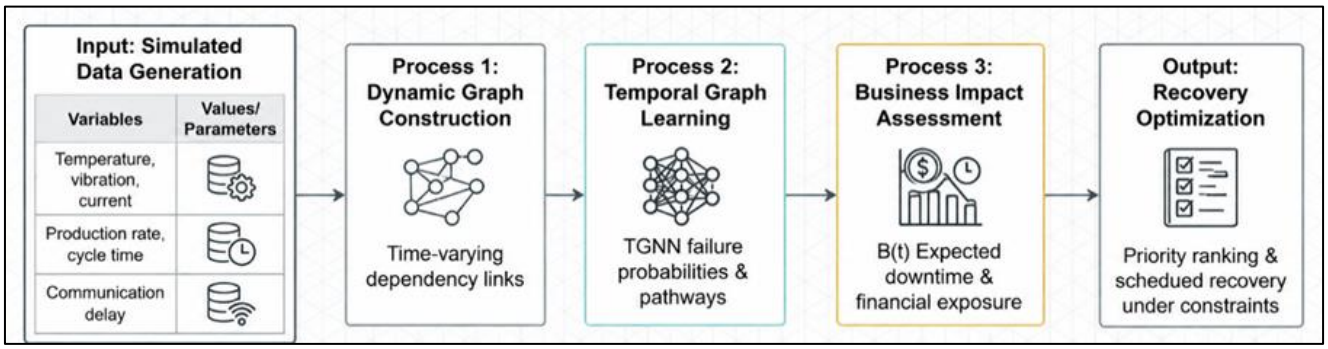


Figure 2: Overall framework and data flow

The figure illustrates the complete simulation pipeline, from manufacturing data generation and dynamic graph construction to temporal graph learning and business impact assessment. The final stage prioritizes recovery actions based on expected downtime, financial losses, and resource constraints.

3.2 Simulated Data Collection and Scenario Design

Table 1: Simulated dataset specification

Data category	Variables	Generation method	Purpose
Equipment data	Temperature, vibration, current, operating state	Synthetic time series with normal and fault states	Predict component failure
Process data	Production rate, cycle time, queue length	Process flow simulation	Estimate operational loss
Network data	Communication delay, packet loss, controller state	Simulated communication conditions	Model cyber physical dependencies
Dependency data	Machine links, process links, controller relationships	Directed graph from a predefined system topology	Identify propagation pathways
Failure scenarios	Failure type, start time, duration, affected nodes	Monte Carlo sampling and predefined fault scenarios	Evaluate cascading risk

Business parameters	Production value, downtime cost, repair cost, delay penalty	Explicit simulation assumptions	Estimate financial exposure

Since confidential industrial records are unavailable, the study uses a synthetic smart manufacturing environment. The simulated system represents machines, production processes, controllers, communication links, and material flows. Each component receives time indexed operational attributes and a state label. Sensor values and process conditions are generated under normal operation, while fault scenarios introduce abnormal states, component failures, and dependency driven disruptions. Monte Carlo simulation generates alternative failure sequences and disturbance conditions. Production loss, repair duration, and recovery cost are represented through explicit simulation parameters.

For reproducibility, the final experimental protocol must specify the number of components, simulation horizon, sampling interval, random seeds, failure distributions, scenario count, and cost assumptions. These settings must be selected and reported before performance evaluation; the table above describes data categories rather than claiming that a dataset has already been generated.

3.3 Data Preprocessing and Dynamic Graph Construction

Numerical features are checked for invalid values and normalized using parameters estimated from the training period. Categorical states are encoded consistently, timestamps are ordered, and duplicate or inconsistent records are handled according to predefined rules. Missing sensor values are flagged and imputed only where justified; failure labels and event times are preserved. The manufacturing system is represented as a time varying graph:

$$(G_t = (V, E_t, X_t)).$$

Where, V denotes equipment, process, and controller nodes; E_t denotes the active dependency links at time t; and X_t contains their observed features. Edge attributes represent dependency strength or operational influence. Graph snapshots preserve changes in system state and dependency relationships over time.

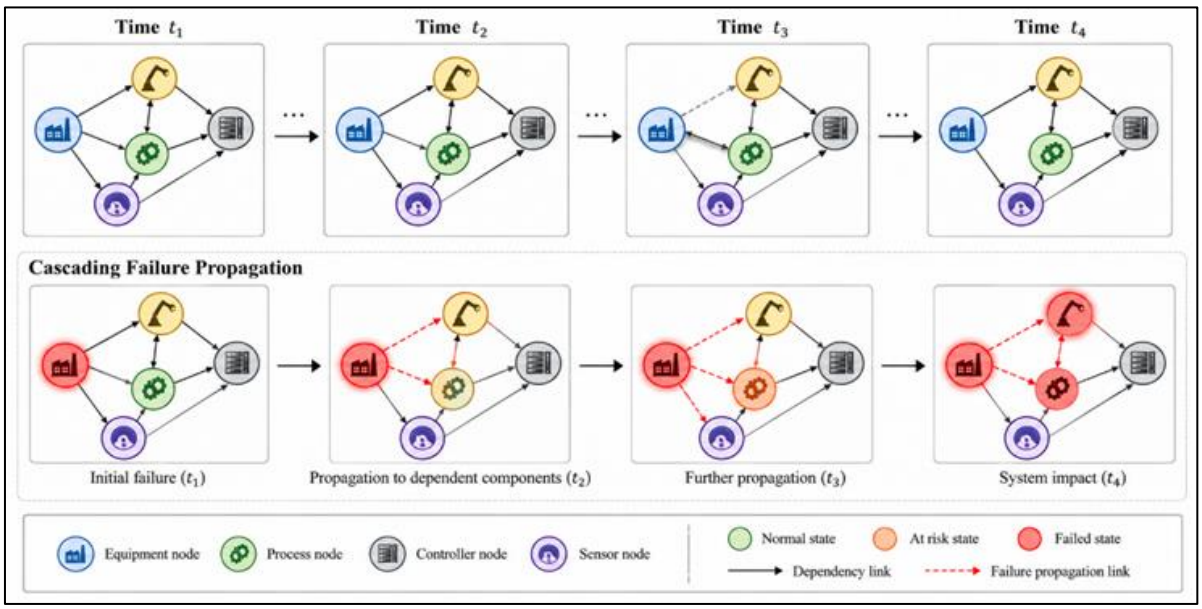


Figure 3: Temporal graph and cascading failure propagation

The figure traces how manufacturing system dependencies evolve over time and how an initial equipment fault can spread to connected components. Different node colors distinguish normal, at risk, and failed states, while directional links illustrate dependency relationships and the progression of cascading failures.

3.4 Temporal Graph Learning for Failure Prediction

A temporal graph neural network (TGNN) is designed to represent changes in component states and dependency relationships over time. At each time step, the model combines current node features with information from neighboring components and previous graph states. Its intended output is the estimated failure probability of each component within the next prediction window. The failure probability is expressed as

$$p_i(t+1) = \sigma(\, W_h h_i(t) + \, W_m \sum_{j \varepsilon N(i)} \alpha_{ij}\,(t) h_j(t) + b$$

Where, $h_i(t)$is the learned representation of component i, $N(i)$is its set of neighboring components, α_{ij} represents the learned influence of neighbor j, W_h and W_m are trainable weights, b is a bias term, and σ is the sigmoid function. The temporal representation may incorporate information from neighboring components and previous graph states through a suitable graph learning architecture. The predicted probabilities can be combined with graph connectivity to identify plausible failure propagation pathways. These pathways represent model inferred relationships and do not establish physical causation. In this study, the TGNN is a proposed component of the framework; its parameters have not been trained or empirically validated. The predictive formulation therefore describes the intended modeling approach rather than an experimentally verified prediction system.

3.5 Business Impact Assessment

The impact layer converts component level predictions into estimated operational and financial consequences. For each component, the simulation defines expected downtime, production loss per unit of time, and any applicable service interruption cost. Dependency relationships determine which processes may be affected when a component fails.

3.5.1 The expected business impact is estimated as

$$B(t) = \sum_{i \in V} p_i(t) D_i C_i$$

Where, $p_i(t)$ is the predicted failure probability, D_i is the expected downtime, and C_i is the estimated business loss per unit of downtime. The resulting $B(t)$ represents expected loss for the specified assessment horizon, provided the cost estimates and impact assumptions are consistent. Overlapping losses must be accounted for to avoid double counting.

3.6 Recovery Optimization

A mixed integer optimization model selects recovery actions under limited maintenance resources. Each candidate action has a resource requirement, recovery cost, and expected reduction in business loss. The optimization prioritizes actions that reduce expected disruption while respecting resource capacity and operational dependencies. The objective is

$$\begin{aligned} \min_{x} \; & \sum_{i \in V} [p_i D_i C_i (1 - x_i) + R_i x_i] \\ \text{subject to } & \sum_{i \in V} r_i \, x_i \leq R_{\max}, \\ & x_j \leq x_i, \; (i, j) \in P, \\ & x_i \in \{0, 1\}, \; i \in V. \end{aligned}$$

Here, $x_i = 1$ indicates that recovery action i is selected within the planning horizon, R_i is its recovery cost, r_i is its resource requirement, and R_{max} is the available resource capacity. Additional precedence constraints should be included where one repair depends on another. The objective balances expected unrecovered loss against recovery expenditure; the relative cost assumptions must be stated explicitly.

3.7 Explainability and Validation

Explainability analysis identifies the component attributes, neighboring nodes, and propagation pathways that contribute most to predicted failures. Feature attribution and pathway analysis are used to interpret model decisions, while causal relationships are not claimed without supporting evidence. The evaluation protocol assesses prediction performance using precision, recall, F1 score, and area under the receiver operating characteristic curve. Impact estimation is evaluated using mean absolute error or root mean squared error against simulated ground truth. Recovery performance is assessed through total simulated downtime, residual business loss, resource utilization, and recovery cost, while optimization efficiency is examined in terms of computation time, solution feasibility, and objective value. The validation process includes chronological separation of training, validation, and test data, prevention of future information leakage, repeated simulation runs with different random seeds, and comparisons against non temporal prediction models and rule based recovery baselines. All methods are evaluated under the same simulated scenarios and resource constraints to maintain comparability. Ablation tests are also conducted to examine the individual contributions of temporal information, impact assessment, and optimization to the overall framework. No performance values should be reported until the corresponding experiments have been executed and their results verified.

4 RESULTS

This section examines an illustrative simulated manufacturing environment to evaluate failure propagation, expected business losses, and resource constrained recovery. The analysis uses component level failure probabilities, equation based loss estimates, and an exhaustive search of feasible recovery decisions to demonstrate the proposed framework.

Table I presents six simulated manufacturing components with their failure probabilities, expected downtime, financial loss rates, and recovery requirements. The probability trajectories in Fig. 5 illustrate increasing failure risk over successive time steps, while Fig. 4 shows the resulting differences in expected business loss.

Table 2: Simulated component data and calculated expected losses

Component	p_i at $(t+3)$	D_i (h)	C_i ($/h)	Expected loss ($)	Recovery cost ($)	Resource units
M1	0.30	2	500	300	200	1
M2	0.45	4	700	1,260	350	2
M3	0.25	3	600	450	250	1
M4	0.60	5	900	2,700	500	3
M5	0.35	3	650	682.50	300	2
M6	0.20	2	400	160	150	1
Total	—	—	—	5,552.50	—	—

Expected loss was calculated using $p_i D_i C_i$. For example, M4 produces an expected loss of $0.60 \times 5 \times 900 = \$2{,}700$, the largest among the six components. The values represent illustrative simulation inputs and calculations, not measured factory performance.

Figure 4 highlights the concentration of expected loss in M4 and M2. Together, these components account for approximately 71.3% of the total modeled loss. This pattern suggests that recovery priorities should reflect the magnitude of potential business consequences, rather than treating all equipment failures equally.

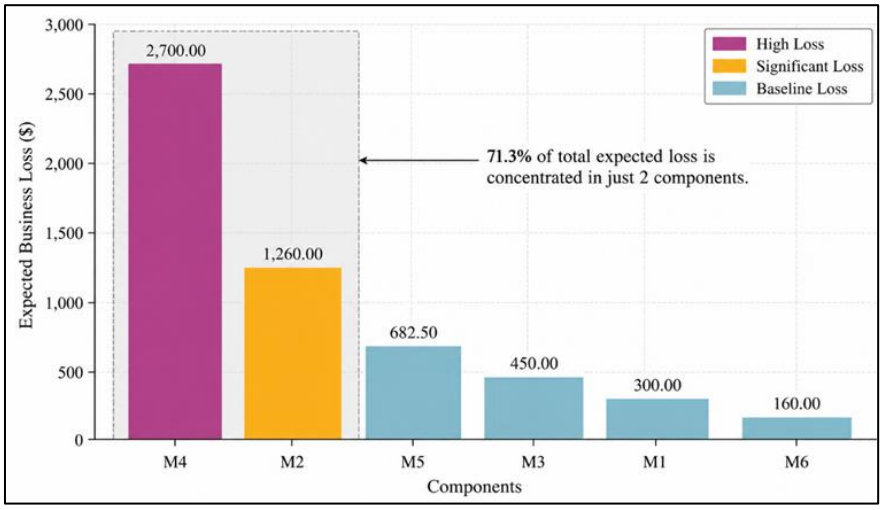


Figure 4: Component level expected business loss

Figure 4 compares the expected business losses across six simulated manufacturing components. M4 and M2 contribute approximately 71.3% of the total expected loss, indicating that these components should receive priority during recovery planning.

The simulated probability trajectories in Fig.5 show that risk increases across the four time steps for all six components. M4 reaches a probability of 0.60 at $t+3$, followed by M2 at 0.45. These values provide the inputs for the component level impact calculations in Table II.

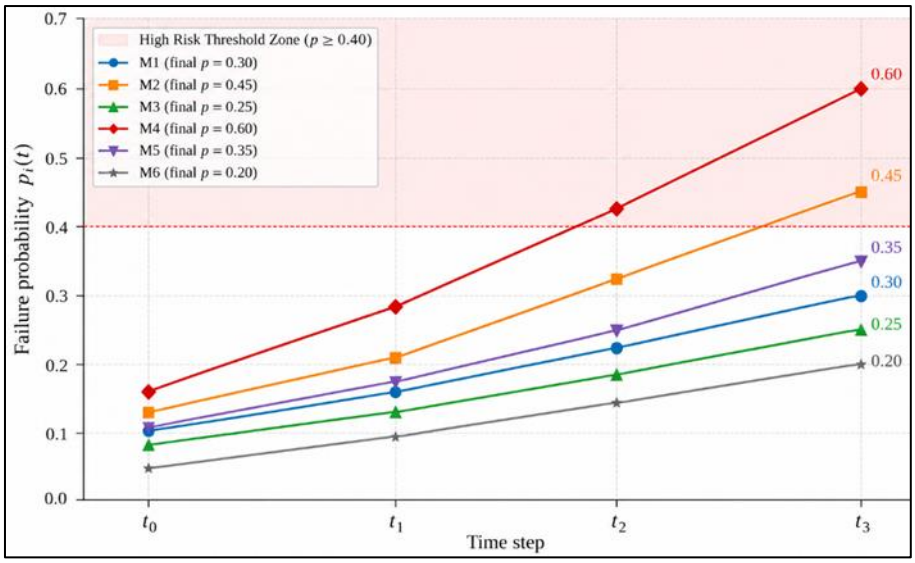


Figure 5: Illustrative evolution of component failure probabilities

The trajectories are prescribed simulation outputs for this example, not predictions produced by a trained temporal graph neural network. A completed experiment would need to establish whether the TGNN can recover such patterns from generated features and dependency graphs.The mixed integer objective was evaluated across all feasible binary recovery combinations under a resource capacity of five units. The optimal solution selects M2 and M4, consuming all five units. Their combined expected loss is $3,960, while their combined recovery cost is $850. The optimized strategy therefore leaves an expected unrecovered loss of $1,592.50 and a total modeled cost of $2,442.50.

Table 3: Comparison of simulated recovery strategies

Metric	No recovery	Optimized recovery
Expected unrecovered loss	$5,552.50	$1,592.50
Recovery expenditure	$0	$850.00
Total modeled cost	$5,552.50	$2,442.50
Resource units used	0	5 of 5
Reduction in total modeled cost	0%	56.01%

The total modeled cost is the sum of expected unrecovered loss and recovery expenditure, as specified in Equation (3). Relative to the no recovery baseline, the optimized plan reduces this cost by $3,110, or 56.01%.

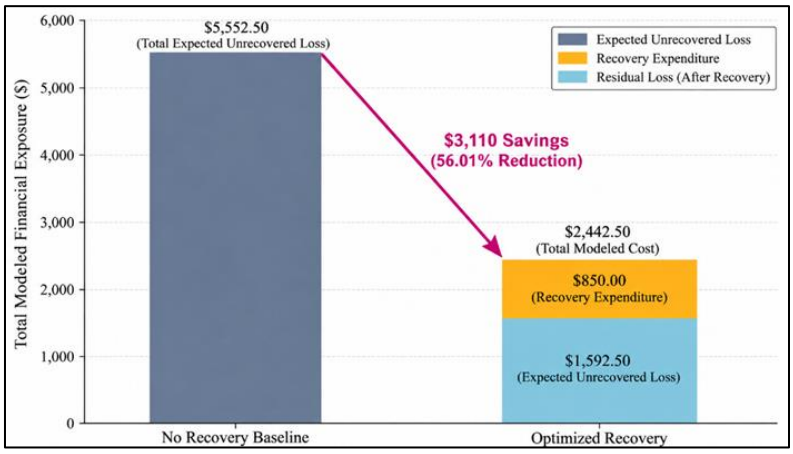


Figure 6: Expected loss and recovery expenditure by strategy.

Figure 6 compares the baseline financial exposure with the total modeled cost under the optimized recovery strategy. The optimized plan reduces total modeled cost by $3,110 (56.01%), with $850 in recovery expenditure and $1,592.50 in residual loss.

5 DISCUSSION

The illustrative results demonstrate how temporal risk estimates can be connected to business impact and recovery decisions in a single analytical framework. The largest predicted risks do not automatically determine the optimal schedule; the decision also depends on recovery cost and resource requirements. In this example, M4 and M2 provide the greatest combined reduction in modeled cost within the available capacity. This supports the study's central contribution: integrating technical failure intelligence with financially informed recovery planning. The business impact equation translates failure probabilities into comparable expected losses, while the optimization model selects actions according to their modeled economic benefit. The temporal graph component provides a mechanism for representing changing dependencies and potential propagation pathways. However, the results establish only the internal consistency of this illustrative calculation. They do not demonstrate that a TGNN outperforms conventional prediction models, that the estimated probabilities are well calibrated, or that the optimized schedule improves performance in a real manufacturing system. Those claims require executed experiments and comparisons against defined baselines.

Limitations and Future Work

The analysis uses six illustrative components, prescribed failure probabilities, assumed downtime and cost values, and a small binary optimization problem. It does not include trained model outputs, repeated Monte Carlo trials, statistical uncertainty intervals, or observed industrial records. The probability trajectories also do not establish causal propagation between components. Future work should generate a larger synthetic manufacturing network with documented random seeds, explicit dependency rules, and repeated failure scenarios. A trained TGNN should be compared with non temporal baselines using precision, recall, F1 score, and AUROC. Business impact estimates should be evaluated against simulated ground truth, and recovery strategies should be compared using downtime, residual loss, resource utilization, and computation time. Sensitivity analysis should examine changes in failure probability, recovery cost, and resource capacity before testing the framework against real industrial data.

6 CONCLUSION

This study proposed an integrated framework for predicting cascading failures in smart manufacturing systems, estimating their operational and financial consequences, and prioritizing recovery actions under resource constraints. The illustrative numerical example shows that the assigned expected losses are concentrated in components M4 and M2. Under the specified objective function and a five unit resource capacity, the example selects both components for recovery. This calculation demonstrates how business impact estimates can inform recovery decisions, but it does not establish the performance of a trained temporal graph neural network or a completed simulation system. The resulting modeled cost decreased from $5,552.50 to $2,442.50, representing a 56.01% reduction compared with the no recovery scenario. These results illustrate the potential value of linking temporal failure risk with business impact assessment and recovery planning. The framework could support maintenance prioritization, production continuity planning, and resource allocation in interconnected manufacturing environments. However, the numerical findings are simulation based and do not establish predictive superiority or real world effectiveness. Future work should implement and validate a trained temporal graph neural network, conduct repeated Monte Carlo experiments, compare the framework with established baselines, and examine sensitivity to failure probabilities, recovery costs, and resource availability. Testing with industrial data would provide further evidence of its practical value and generalizability.

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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