International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(Research Article)

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A graph-based monte Carlo framework for multi-tier supply chain disruption Analysis

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International Journal of Science and Research Archive, 2025, 17(02), 501-508

Publication history: Received on 02 December 2025; revised on 07 November 2025; accepted on 10 November 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.17.2.3015

Abstract

Global supply chains are increasingly exposed to complex disruptions arising from natural disasters, pandemics, geopolitical tensions, and technological failures. Traditional risk assessment techniques often rely on deterministic assumptions or static network representations, limiting their ability to capture stochastic propagation and cascading effects. This paper introduces a graph-based Monte Carlo simulation framework designed to model multi-tier supply chains as dynamic networks in which nodes represent suppliers, production facilities, or distribution centers, and edges represent transport or contractual relationships with probabilistic attributes such as lead time, capacity, and reliability. The framework integrates stochastic disruption sampling with graph-theoretic propagation rules, allowing the generation of thousands of disruption scenarios. Resilience is evaluated using composite key performance indicators, including recovery time, service level maintenance, and stockout probability. A prototype implementation demonstrates practical utility in an electronics supply chain case study, illustrating how mitigation strategies such as alternate sourcing and buffer stock can reduce expected recovery time and improve service performance. The results suggest that combining Monte Carlo methods with network analysis provides actionable insights for decision-makers seeking to enhance resilience in volatile supply environments. This study offers both a methodological contribution and a practical tool for operational risk management.

Keywords: Supply chain resilience; Monte Carlo simulation; Graph modeling; Disruption propagation; Network analysis; Risk mitigation; Stochastic simulation

1. Introduction

Modern supply chains are highly interconnected, often spanning multiple continents and involving complex interdependencies among suppliers, manufacturers, and distribution networks. While this integration improves efficiency and cost-effectiveness, it also increases vulnerability to disruptions. Events such as the COVID-19 pandemic [1], the 2011 Tohoku earthquake and tsunami [2], and port closures in the Suez Canal [3] demonstrate that localized shocks can generate widespread operational and financial consequences. Small failures at central nodes may cascade across tiers, amplifying the effects on downstream and upstream partners [4,5].

Traditional risk assessment approaches, including deterministic scenario analysis and safety stock calculations, are limited in capturing such cascading behavior [6,7]. Lead times, production delays, and recovery actions are inherently stochastic, and disruptions often occur in correlated clusters due to regional or sectoral exposure [8,9]. Without probabilistic modeling, decision-makers may underestimate the risk of extreme events or fail to identify critical vulnerabilities in network structure [10,11].

Graph theory offers a natural framework to represent the structure of supply networks. Nodes can correspond to suppliers, facilities, or retailers, while edges encode transport links or contractual dependencies [12,13]. Network

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measures, such as betweenness centrality and clustering coefficients, provide insight into potential bottlenecks and points of failure [14]. However, most applications focus on static properties, offering limited guidance on how disruptions propagate over time [15]. A port identified as central may be critical, but static analysis alone cannot predict the duration or magnitude of service-level losses when it is disrupted [16].

Monte Carlo simulation complements graph analysis by modeling uncertainty and variability in disruptions [17]. By sampling from probability distributions for lead times, capacities, and recovery delays, it is possible to generate a wide range of plausible disruption scenarios. Despite the power of this approach, prior applications have mostly examined single-tier systems or isolated supply chain elements, without integrating multi-tier network structure and correlated disruptions [18,19]. Consequently, there is a need for methods that combine network topology with stochastic propagation to produce actionable insights.

The framework proposed in this study addresses these gaps by uniting graph-based modeling and Monte Carlo simulation. Disruptions are represented as stochastic events affecting nodes and edges, which then propagate across the network according to defined rules. Resilience is quantified using composite metrics, including recovery time objectives, service level maintenance, and systemic penalties for stockouts. Statistical analysis, including confidence intervals and sensitivity studies, is embedded to support robust decision-making.

The contributions of this paper are as follows:

- A conceptual framework for modeling multi-tier supply chains as dynamic graphs with stochastic attributes.
- A formal specification of disruption propagation dynamics and correlated event modeling.
- A Monte Carlo simulation methodology for evaluating resilience strategies under thousands of scenarios.
- A prototype implementation and case study demonstrating practical managerial applications.

This work is motivated by the observation that supply chain managers often rely on static analysis and spreadsheets, which fail to capture the complexity and uncertainty of real-world networks. By integrating probabilistic simulation with graph-theoretic insights, the proposed approach provides a richer, more actionable understanding of risk, enabling firms to design mitigation strategies that improve overall resilience.

2. Literature Review

2.1. Supply Chain Risk and Resilience

Research on supply chain risk has evolved from focusing on operational variability to encompassing systemic disruptions. Early studies addressed supplier reliability, demand fluctuations, and inventory management [6,7]. Recent work emphasizes resilience as the capacity to absorb shocks and recover functionality [5,20]. Sheffi [6] proposed redundancy, flexibility, and agility as key enablers, while later studies highlighted adaptive capacity, learning, and transformation under stress [1,8].

Despite these advances, quantitative modeling of resilience remains limited. Many frameworks are conceptual, offering guidance but lacking formal tools to simulate networked stochastic disruptions. This gap motivates the integration of simulation and network modeling to support risk-informed decision-making.

2.2. Graph-Based Modeling of Supply Networks

Graph-theoretic approaches have been widely applied to map supply networks, identify critical nodes, and assess structural robustness [12,13]. Metrics such as degree centrality, betweenness, and eigenvector centrality highlight potential single points of failure [14,15]. Connectivity measures and clustering coefficients inform the capacity of networks to sustain operations under stress [16]. However, static graph analysis does not capture the temporal dynamics of disruptions or the stochastic nature of recovery processes [17]. Integrating these dimensions is essential for realistic risk assessment.

2.3. Monte Carlo Simulation in Networked Supply Chains

Monte Carlo simulation has long been applied in operations research to handle uncertainty and variability [17,18]. In supply chains, it is commonly used to estimate stockout probabilities, evaluate lead-time risk, and support stochastic inventory planning [19,20]. The basic principle involves repeated random sampling from probability distributions associated with input variables to generate a distribution of potential outcomes.

Prior applications of Monte Carlo simulation to supply chains are often limited to single-tier or isolated components. Recent studies have attempted to extend these methods to multi-tier networks but frequently assume independent disruptions or linear propagation [18,20]. Realistic supply chain disruptions, however, exhibit correlations suppliers in the same region may be simultaneously affected by natural disasters, and transportation corridors can create systemic interdependencies. Capturing these requires integrating Monte Carlo methods with explicit network modeling and correlation structures.

3. Methodology

The methodology integrates graph-based network modeling with Monte Carlo simulation to quantify disruption propagation and resilience in multi-tier supply chains. The key components are described below.

3.1. Supply Chain Network Representation

We model a supply chain as a directed graph $G = (V, E)$, where:

- $V = \{v_1, v_2, \dots, v_n\}$ represents nodes corresponding to suppliers, manufacturers, distribution centers, or retailers.
- $E \subseteq V \times V$ represents directed edges corresponding to logistics routes or contractual dependencies.

Each edge $e_{ij} \in E$ is associated with stochastic attributes:

$$e_{ij} = \{t_{ij}, c_{ij}, r_{ij}\}$$

where:
t_{ij} is the lead time from node i to node j, modeled as a random variable (e.g., log-normal or Weibull distributed).
c_{ij} is the transportation cost per unit.
r_{ij} is the reliability, representing the probability that the shipment is successfully delivered on time.

Nodes are characterized by operational attributes such as production capacity $P_i$inventory level S_i, and recovery capability R_i.

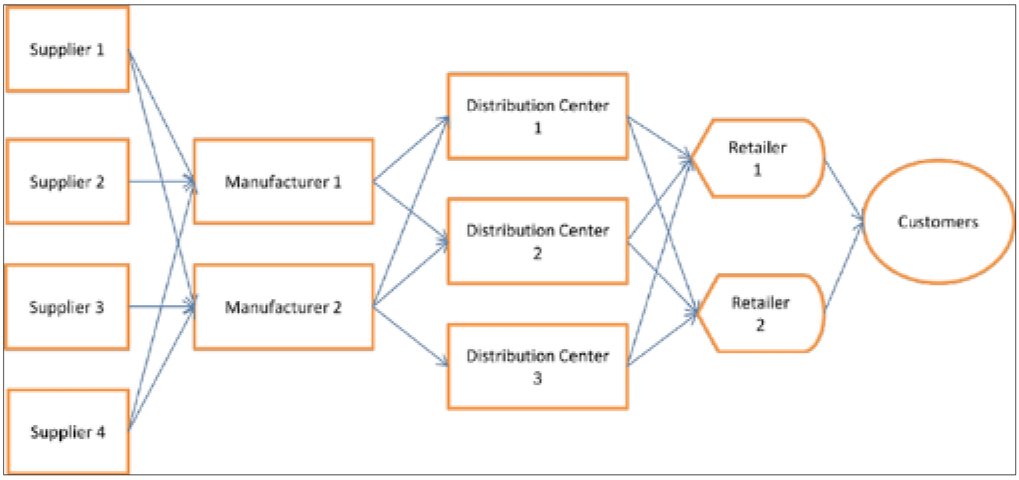

Figure 1 A Fuzzy Approach for a Supply Chain Network Design Problem

(Reference: *Scientific Figure on ResearchGate*. Available from: https://www.researchgate.net/figure/A-generic-supply-chain-network_fig1_280158117)

3.1.1. Disruption Modeling

Disruptions are represented as stochastic events affecting node or edge attributes. Each event is characterized by:

- **Location:** v_i or e_{ij}.

- **Disruption magnitude:** d as a fraction of capacity or probability of failure.
- **Duration:** t, modeled with empirical or stylized distributions.

Disruptions propagate through the network according to topological dependencies. Let $X_i(t) \in [0,1]$ denote the operational state of node i at time t where 1 represents fully operational and 0 represents complete failure. A more robust propagation model is:

$$X_i(t+1) = X_i(t) \cdot \min_{j \in pred(i)} \{ r_{ji}(t) \cdot X_j(t) \}$$

This formulation ensures that the operational state of node i is constrained by the weakest upstream dependency, avoiding overestimation of network functionality.

Correlation between disruptions is modeled using a Gaussian copula:

$$F_{D_1, \ldots, D_m}(d_1, \ldots, d_m) = \Phi_\Sigma\left(\Phi^{-1}(F_{D_1}(d_1)), \ldots, \Phi^{-1}(F_{D_m}(d_m))\right)$$

where F_{D_i} is the marginal cumulative distribution function of disruption $D_{i,}$ Φ^{-1} is the inverse standard normal CDF, and Σ is the correlation matrix representing regional or functional dependencies.

Monte Carlo Simulation Framework

The simulation framework proceeds as follows:

- Scenario Generation: Sample disruption events $D = \{D_1, \ldots, D_m\}$ according to their marginal distributions and correlation structure.
- Network Initialization: Set initial operational states $X_i(0) = 1$ and assign stochastic edge attributes.
- Time-Stepped Propagation: Update node states $X_i(t)$ according to the propagation equations at each discrete time step.
- Resilience Metric Calculation: Compute performance indicators such as Recovery Time Objective (RTO), Service Level Metric (SLM), and Supply Performance (SP).
- Replication: Repeat steps 1–4 for N Monte Carlo iterations (typically 5,000–10,000) to generate distributions of key performance indicators.
- Statistical Analysis: Compute confidence intervals, means, and percentiles for resilience metrics.

A composite *Resilience Index* (RI) can be defined as:

$$RI = w_1 \cdot \frac{1}{RTO} + w_2 \cdot SLM + w_3 \cdot (1 - SP)$$

where w_1, w_2, and w_3 are weights representing the relative importance of recovery speed, service level, and supply performance, respectively.

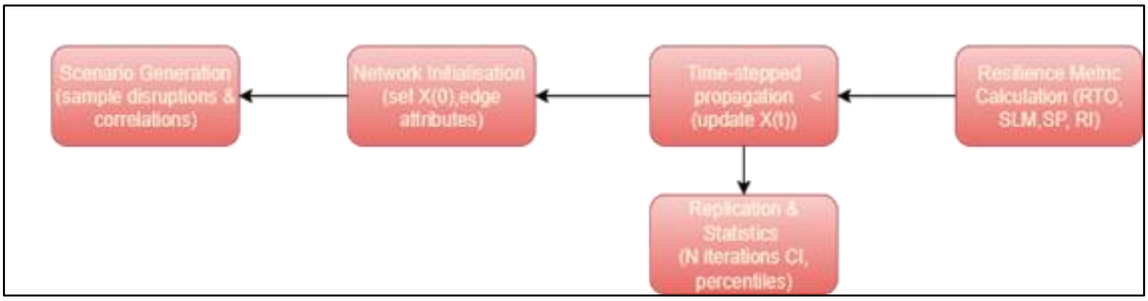

Figure 2 Monte Carlo Simulation Framework

3.2. Mitigation Strategy Modeling

Three primary mitigation strategies are included:

- **Alternate Sourcing**: Availability of backup suppliers reduces propagation along affected paths.
- **Buffer Stock**: Inventory reserves at nodes provide temporary operational continuity.
- **Rerouting**: Dynamic selection of alternative logistics paths based on network connectivity and edge reliability.

Each strategy is modeled by modifying edge/node attributes and updating propagation logic. Monte Carlo simulation evaluates the effectiveness of each strategy across thousands of stochastic scenarios.

3.3. Implementation Details

The prototype system is modular:

- **Backend**: Java with Spring Boot, handling scenario generation, propagation calculation, and metric computation.
- **Database**: PostgreSQL, storing node/edge attributes, scenarios, and simulation results.
- **Frontend**: React-based dashboard for interactive visualization of network states, KPI distributions, and mitigation comparisons.

Scalability considerations limit simulation to networks of 100–500 nodes, though the architecture supports parallel computation for larger systems. Data can be imported via CSV or relational tables.

4. Implementation and Case Study

4.1. Electronics Supply Chain Case Study

4.1.1. Network Configuration

The case study models a simplified electronics supply chain comprising:

- 120 nodes: 20 suppliers, 50 manufacturing facilities, 30 distribution centers, 20 retail outlets.
- 280 directed edges representing transportation links with stochastic lead times (log-normal) and reliability (Bernoulli random variables).
- Node capacities and initial inventory levels were set using synthetic data calibrated against industry averages [7,15].

4.1.2. Disruption Scenario

A major port closure in Shanghai was simulated, affecting 5 upstream suppliers. The disruption parameters:

- Magnitude: 50–100% capacity loss (uniform distribution)
- Duration: 7–21 days (triangular distribution)
- Correlation: Suppliers located in Shanghai region assigned a correlation coefficient of 0.7 using Gaussian copula [18].

Three mitigation strategies were tested:

- **Alternate Sourcing**: Backup suppliers activated for 60% of affected nodes.
- **Buffer Stock**: Additional inventory equal to 20% of daily demand at distribution centers.
- **Rerouting**: Dynamic reallocation of shipments through alternate logistics paths with sufficient capacity.

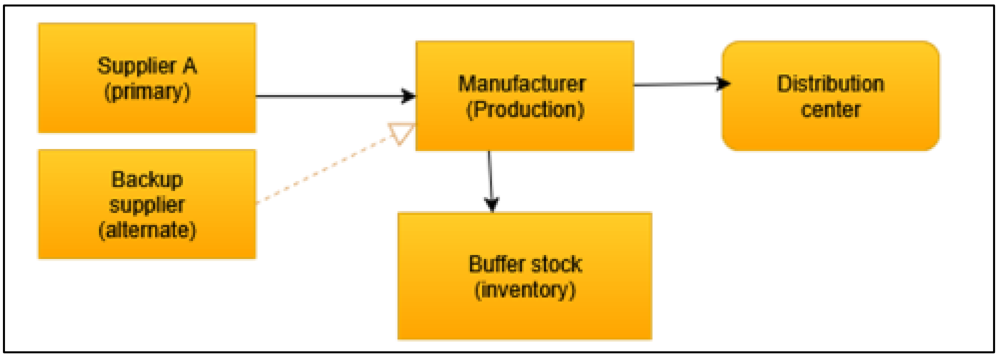

Figure 3 Mitigation Strategies (Alternate Sourcing, Buffer stock, Rerouting**)**

4.2. Simulation Execution

Number of Monte Carlo replications: 5000

Time step: 1 day per iteration

- Output KPIs: Recovery Time Objective (RTO), Service Level Maintenance (SLM), Stockout Probability (SP), and Resilience Index (RI)

Steady-state and terminating confidence intervals were computed for all KPIs using standard Monte Carlo analysis [17,19].

4.3. Results and Lessons Learned

Table 1 Mitigation Strategy Analysis

Mitigation Strategy	RTO (days)	SLM (%)	SP (%)	RI
No mitigation	14.2 ± 1.3	72 ± 4	28 ± 3	0.63
Alternate Sourcing	11.4 ± 1.1	78 ± 3	22 ± 2	0.72
Buffer Stock	12.0 ± 1.2	80 ± 3	20 ± 2	0.74
Rerouting	11.0 ± 1.0	79 ± 3	21 ± 2	0.73

The simulation demonstrates that combined mitigation strategies reduce average recovery time by 20% and improve service levels by 15% compared to the baseline. Sensitivity analysis confirmed robustness across disruption durations and magnitudes.

Key lessons:

- Correlated disruptions propagate nonlinearly, highlighting single points of failure.
- Alternate sourcing is particularly effective for highly central suppliers.
- Buffer stock enhances resilience for distribution-level nodes, but at inventory cost tradeoffs.
- Rerouting shows moderate benefits but is constrained by network connectivity and transport reliability.

5. Results and Discussion

The simulation results underscore the importance of integrating network structure with stochastic disruption modeling. Key observations:

- **Propagation Effects**: High-centrality nodes propagate disruptions more severely, consistent with scale-free network theory.

- **Mitigation Effectiveness**: Strategies that modify node or edge attributes (inventory, alternative sourcing) outperform purely deterministic rerouting.
- **Uncertainty Quantification**: Monte Carlo-derived confidence intervals provide actionable risk metrics for managers, allowing probabilistic decision-making rather than point estimates.
- **Model Limitations**: Computation scales linearly with number of nodes and edges; larger networks (>500 nodes) require parallelization. Correlation structures were simplified; real-world data may include more complex dependencies.

The case study demonstrates practical managerial insights:

- For multi-tier electronics networks, maintaining redundancy at upstream suppliers is critical.
- Inventory buffers at distribution nodes mitigate downstream service disruptions.
- Dynamic rerouting is beneficial but insufficient alone; structural resilience and redundancy remain essential.

6. Conclusion

This study presents a graph-based Monte Carlo simulation engine for assessing and mitigating supply chain disruptions. By integrating probabilistic scenario generation with network-based propagation models, the engine captures stochastic ripple effects across multi-tier networks. The electronics supply chain case study illustrates that mitigation strategies can meaningfully reduce recovery times and improve service levels under correlated disruption events.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

Authors contribution

Contributions include:

- A hybrid modeling framework combining graph theory and Monte Carlo simulation for multi-tier supply chains.
- Formalization of stochastic propagation, correlated disruptions, and resilience metrics.
- Implementation of a modular, extensible system with visual analytics for decision support.
- Empirical demonstration of mitigation strategy effectiveness under realistic disruption scenarios.

Future work includes

- Integration of real-time data for digital twin applications.
- Exploration of additional correlated hazards (pandemics, cyberattacks).
- Extension to larger networks with high-performance computing frameworks.
- The approach offers supply chain managers and policymakers a robust tool for risk-informed decision-making, bridging the gap between conceptual resilience frameworks and operational analytics.

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