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Modeling Network Evolution and Underload Cascading Failure in Multi-Tier Strategic Supply Chain Networks under a Just-in-Case Strategy

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Abstract: In the context of escalating geopolitical tensions and increasing supply uncertainty, global supply chains are increasingly shifting from the efficiency-oriented just-in-time (JIT) paradigm to a more redundancy-based just-in-case (JIC) strategy. The primary objective of this study is to examine the topological and functional implications of this strategic shift. To achieve this, this study first develops a directed and weighted five-tier supply chain network evolution model that incorporates dynamic compensation mechanisms, including multi-source substitution and internal inventory reserves. The model shows that the JIC strategy alleviates the "rich get richer" effect, leading to more balanced resource allocation. Based on this model, we investigate underload cascading failures triggered by supply shortages and evaluate network robustness using the order fulfillment rate. The results show that the evolved network has obvious dual characteristics of robustness and vulnerability. It can relatively resist small random disturbances, but it is particularly vulnerable to targeted attacks on key enterprises, and the system will fail rapidly due to bidirectional load propagation. In addition, although the JIC strategy improves the resilience to severe disturbances, excessive hoarding costs increase the threshold for the network's survival and operation, and may also lead to early underload cascading failures under slight shocks. Managerially, this implies that focal enterprises must dynamically optimize, rather than blindly maximize, their strategic reserves to balance resilience with capital lock-up costs. These findings offer a theoretical basis for understanding the trade-off between resilience and cost in strategic supply chain design and provide managerial insights for focal enterprises seeking to build more resilient supply networks under uncertainty. A limitation of this study is its reliance on numerical simulations and future research should empirically validate these mechanisms using real-world industry data.

Keywords: supply chain resilience; just-in-case strategy; supply chain network; underload cascading failure; strategic inventory

1. Introduction

In recent years, escalating geopolitical tensions increase the risk of severe disruptions in global supply chains. Events expose the limitations of the just-in-time (JIT) model, such as the U.S.-China trade dispute, the Russia-Ukraine conflict, and the Red Sea shipping crisis. This model has dominated global production and logistics systems. The JIT model emphasizes lean inventory and efficiency-oriented operations, but it still remains highly vulnerable to external shocks. Disruption at a single enterprise may spread across the entire supply chain network, thereby reducing system performance. In response to growing geopolitical risk and supply uncertainty, many economies are shifting from JIT toward a more redundancy-oriented just-in-case (JIC) strategy. Rather than maintaining only minimal commercial inventories, firms and governments are increasingly building strategic reserves of critical raw materials, semiconductors, energy resources, and other essential commodities to reduce the risk of conflict-related disruptions, transport blockages, and supply shortages. This shift has important implications for the topology, operating mechanism, and resilience of supply chain networks (SCN).

A strategic supply chain refers to a supply network designed to ensure continuity in the supply of critical resources and to improve system resilience under uncertainty. Unlike traditional JIT supply chains, which are primarily driven by cost minimization and efficiency, strategic supply chains place greater emphasis on security, resilience, and continuity. A strategic supply chain system uses buffer inventory, redundant production capacity, alternative supplies and multi-source sourcing to enhance buffering capacity, and can adapt to changes and recover from disruptions. The essence is to rebalance efficiency and security so as to enhance supply chain resilience, dynamically optimize operating costs and improve risk mitigation capabilities.

However, these methods need to make a trade-off between flexibility and cost. While redundancy improves risk resistance, it also increases operational costs and structural complexity, and strengthen the interdependence among critical enterprises. This imparts distinct robustness and vulnerability characteristics to supply chain networks. On one hand, moderate redundancy and strategic reserves buffer stochastic disturbances and suppress the propagation of local disruptions. On the other hand, targeted attacks at core enterprise may still trigger bidirectional load transfer and underload cascading failures through upstream and downstream interdependencies. This process may significantly weaken network performance and even cause widespread functional breakdown. Therefore, measuring and enhancing the dynamic robustness of strategic supply chain networks under extreme disturbances has become an important issue in both theory and practice.

To address the aforementioned gaps, the overarching research question guiding this study is: How does the shift to a JIC strategy, characterized by strategic reserves, impact the topological evolution and dynamic robustness of multi-tier supply chain networks under extreme disruptions? To answer this, we formulate three specific sub-research questions:

RQ1: How do multi-factor competitive advantages and strategic reserve behaviors reshape the evolution and topological structure of supply chain networks?

RQ2: How do underload cascading failures propagate bidirectionally when considering multi-source substitution and internal reserve compensation?

RQ3: What is the optimal balance between strategic reserve levels and network resilience under different disruption scenarios?

Methodologically, these questions are explicitly mapped to our analytical steps. RQ1 is addressed by constructing a multi-tiered network evolution model that incorporates node competitive advantage and reserve intensity (Section 3.1). Specifically, we introduce node competitive advantage and reserve intensity into the evolution process and design a network formation mechanism with dynamic node entry and exit, cross-tier connections, and multi-factor weighted preferential attachment and removal rules. RQ2 is tackled by developing a bidirectional underload cascading failure model driven by dynamic capacity constraints (Section 3.2). Different from the conventional focus on unidirectional overload failures, our model captures the underload propagation process triggered by supply shortages from the perspective of the minimum fixed-cost threshold required for firm survival. Finally, RQ3 is answered through numerical simulations that evaluate dynamic robustness via order fulfillment rates under both random and targeted attack scenarios (Section 4).

The main contributions of the paper are outlined as follows: It advances research on supply chain network evolution by incorporating strategic reserve behavior into a multi-tier directed and weighted network framework. The Multi-tiered Evolutionary Model fully accounts for node heterogeneity, cross-layer connectivity, and dynamic node entry and exit mechanisms. Therefore, this provides a more practical evolutionary framework for the supply chain structure. This study constructs a bidirectional load propagation mechanism driven by external subsystems and internal resources, as well as a “many-to-many” dynamic compensation mechanism. These mechanisms enrich the relevant literature on cascading failures and supply chain resilience. The proposed research framework provides a new perspective for revealing the impact of strategic resource strategies on interrupt risk transmission and dynamic recovery in multi-layer supply chain networks.

The rest of this paper is organized as follows. Section 2 reviews the literatures on network evolution and cascading failures. Section 3 elaborates the construction and evolution mechanism of the multi-layer supply chain networks and constructs the underload cascading failure model and the framework for dynamic robustness evaluation. Section 4 conducts simulation analysis under different reserve strengths and attack scenarios. Section 5 proposes key insights such as prioritizing the protection of core nodes, selecting partners based on competitiveness and moderate reserves, and dynamically optimizing inventory to balance efficiency and risk. Finally, Section 6 summarizes the main research findings, and also discusses future research directions.

2. Literature Review

In recent years, complex network theory has been applied to study supply chain network topology evolution, cascading failure mechanisms and recovery strategies. The formation and evolution of supply chain networks in the real world is a dynamic process driven by various internal factors. Early studies relied on classic random network (ER), small-world network or scale-free network (BA) models to describe supply chain topologies [1–7]. As research deepens, more scholars have incorporated real-world industry characteristics into evolution rules. Fang et al. [8] propose a manufacturing-centered network evolution model to test the impact of external market demand and internal competition–cooperation dynamics on network topology reconstruction. Sun et al. [9] construct a multi-tier supply chain complex network evolution model based on node degree preference attachment and competitive advantage coefficient, and reveal the evolution pattern of the network's statistical characteristics. Zhang et al. [10] incorporated the element of "trust" as edge weights into a directed, weighted complex network, thereby mitigating the over-concentration of node influence caused by the dominance of a single indicator. Furthermore, Wang et al. [11], drawing on Complex Adaptive Systems (CAS) theory, designed an evolutionary model incorporating adaptive strategies for enterprise edge growth and rewiring.

The interdependence of supply chain networks is quite obvious. Local small disturbances can cause cascading failures due to material flows and information flows. When early developing supply chain cascading failure models, scholars used systematic analysis methods from power grids, transportation networks, communication networks and other aspects to build overload cascading failure models [12–14]. Geng [15] and Zeng [16] built a cascading failure model focusing on cluster supply chain networks, providing a theoretical basis for local control and resilience optimization within the clusters. Tang [17] and Zhou [18] analyze the dependency characteristics and recovery strategies of interdependent systems in a network system to explore the robustness of the network. For example, in the logistics networks of the distribution industry, Chen [19] proposed a load redistribution mechanism, considering the impact of traffic and node failures and Lu [20] introduced a multilayer supply chain network overload cascading failure detection model, accounting for delay probabilities and investigating the influence of initial load and node capacity on failure propagation. Under geopolitical conflicts, "underload cascading failure" [21–25] has become the focus of recent research. External shocks cause upstream and downstream enterprises to fail first due to reduced demand or interrupted material supply. Interference spreads between network nodes, leading to large-scale "underload cascade failure" of the entire network [26,27]. Studies show that initial node load and capacity lower limit are key parameters for the propagation range of cascade failure [26,28]. In practical applications, underload cascading failure models have been widely used for network analysis across various industries. In manufacturing supply chains, underload nodes arising after load redistribution are the primary drivers of network resilience degradation, and the importance of core manufacturers far exceeds that of general suppliers [29,30]. In analyses of global commodity trade networks, this theory not only quantifies the asymmetric impact of core node failures on global transmission efficiency but also reveals network resilience characteristics when facing financial crises and public health emergencies [31,32]. In recent years, researchers have been growing interested in the modeling of mixed cascading failures (MCF). For instance, Shi [33] proposed a generic Interdependent Supply Network (ISN) model to evaluate hybrid cascading failures (HCF) caused by simultaneous over-load and loss-dependency. Building upon this structural foundation, Zhang [34] expanded the scope to Cyber-Physical Supply Chain Networks (CPSCNs) by formalizing four mixed failure modes. Most recently, Zhang [35] further enhanced the realism of mixed cascading failure (MCF) modeling by introducing failure delay-time dynamics into ISCNs.

To address these problems, researchers have shown considerable interest in exploring different recovery strategies. Moving beyond traditional, Jiang [36] proposed a multidirectional recovery strategy for interdependent networks unilateral node restoration. Focusing on relational dynamics within specific industries, Li [37] explored the disruption propagation in agri-food supply chains. More recently, Zhang [35] advanced the field by incorporating realistic operational constraints into interdependent supply chain networks (ISCNs). Collectively, these studies highlight a clear progression in recovery strategies from topology-centric reinforcement and relationship building to dynamic, resource-optimized interventions. Network robustness plays a critical role in enhancing supply chain resilience to disturbances and reducing risk. Currently, most scholars use node centrality measures such as node degree and betweenness centrality to assess network robustness. For example, Sun et al. [9] characterize structural robustness using average node degree and the maximum distance within the largest connected component. Li et al. [38] define robustness metrics including the number of healthy nodes, the size of the largest connected component, and network efficiency, thus quantifying supply chain robustness from multiple dimensions. Han and Shin [39] considered network elements and used average path length, node in-degree and out-degree to evaluate network performance. On the contrary, few scholars evaluate the robustness of SCN from a functional perspective. Tang [40] used capacity loss to evaluate the robustness of assembly SCN. Adenso-Díaz et al. [41] proposed a new method, focus on the impact of transportation link damage on service level, how do transportation disruptions affect supply network performance now.

Overall, existing studies have made great contributions to SCN evolution, underload cascading failure model and robustness evaluation. However, several limitations remain. (1) The supply chain evolution models rarely consider the impact of strategic stockpiling on node capacity and connection preferences. (2) The compensation mechanisms for substitute nodes in underload cascading failure models remain underdeveloped, and modeling for many-to-many compensation scenarios is insufficient. (3) The robustness assessments primarily rely on static topological metrics and lack descriptions of dynamic failure processes from a functional perspective. To address these limitations, this study develops a multi-tiered supply chain network evolution model that integrates strategic reserve behavior and designs an underload cascading failure model incorporating a many-to-many compensation mechanism. The study evaluates network robustness from a functional perspective, using order fulfillment rate as the core measure, with the aim of providing theoretical support for enhancing supply chain resilience under the new paradigm.

3. Model Building

3.1. A Multi-tiered Evolutionary Model of Strategic Supply Chain Networks

3.1.1. Evolutionary Mechanisms

Given the large scale of real-world supply chain, the number of enterprises and the significant challenges in obtaining actual data, researching actual supply chains directly often spends prohibitively high costs. So, many scholars adopt complex network approaches, generating supply chain networks according to specific evolutionary mechanisms. This method conceptualizes the formation of real-world supply chain systems as network evolution rules and formalizes them into corresponding evolutionary algorithms. The formation and evolution of real-world supply chain networks constitute a dynamic process driven by multiple factors, including market demand, technological advancement, and geopolitical dynamics. As strategic stockpiling behavior becomes increasingly prevalent, enterprises must consider not only short-term profitability but also long-term risk resilience in decision-making. Drawing on existing research and real-world observations, this study builds the following evolutionary mechanisms.

(1) Node entry and exit rule. Supply chain networks are not static but evolve dynamically. As market demand expands or new enterprises enter, the network size increases; conversely, when enterprises exit due to poor performance, policy changes, or unexpected shocks, the network contracts. The network evolution state of the model is determined by the growth-recession threshold H_0 plus randomness.

(2) Tier heterogeneity rule. The supply chain has multi-level situations, from third-tier suppliers (L1) to final customers (L5). The number of enterprises at different levels and the entry thresholds are not the same. The number of L1 and L5 nodes is large and the entry threshold is low, the number of core manufacturing layer (L4) nodes is small and the entry threshold is high. This leads to the formation of a typical "dumbbell-shaped" network structure.

(3) Cross-level connections rule. To improve supply reliability and shorten time, enterprises often bypass the traditional interaction method and establish direct cooperation with high-level or low-level nodes (such as manufacturers directly cooperating with secondary suppliers). This cross-level connection fundamentally embodies the practice of strategic reserve behavior.

(4) Preferential attachment rule. They prefer to become partners with enterprises that have strong competitiveness and sufficient reserves when the nodes enter the network. Competitiveness is determined by node degree, competitive advantage, and strategic reserve level. Node degree indicates the breadth of a enterprise's collaborations. Competitive advantage is quantified by the competitiveness coefficient, reflecting firm size, technology, and market position. Reserve level is measured by the strategic reserve coefficient, which represents the enterprise's buffering capacity against disruptions.

(5) Preferential removal rule. In contrast to preferential attachment, enterprises with low competitiveness and insufficient strategic reserves are more likely to exit the network. Enterprises with a high strategic reserve

coefficient possess strong risk resilience and can maintain operations using internal reserves even during short-term shocks, resulting in a lower probability of exit.

3.1.2. Mathematical modeling

This paper abstracts the multi-tier strategic supply chain network into a 5-tier directed, weighted network, denoted as a graph structure G(N, E, C, S, W), with the initial network structure illustrated in Figure 1.

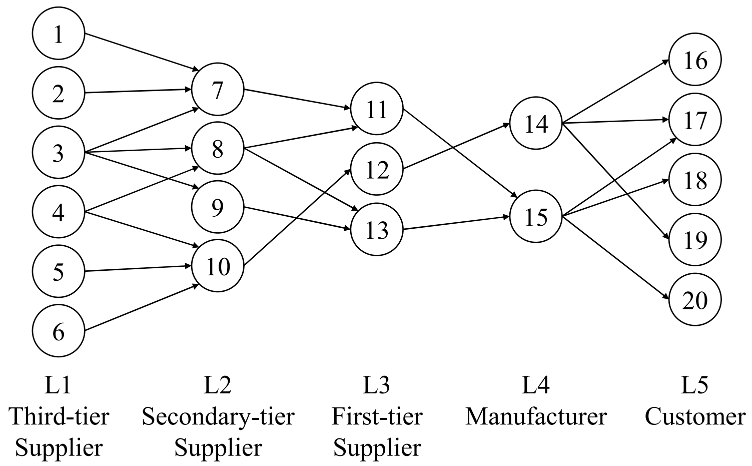


Figure 1. Schematic diagram of supply chain network structure.

In this model, the basic network structure and node attributes are defined as follows. The node set N represents enterprise entities in the network, functionally divided into five levels: third-tier suppliers (L1), secondary-tier supplier (L2), first-tier supplier (L3) supplier, manufacturer (L4), and end customer (L5). The directed edge set E characterizes the direction of supply-demand relationships among enterprises within the supply chain. The competitiveness coefficient $C_i \in (0,1]$ indicate the competitiveness for the enterprise node. The strategic reserve coefficient $S_i \in (0,1]$ is used to measure production capacity or inventory redundancy, and reflects the node's buffering capacity against supply disruptions. In actual situations, it is related to hierarchical characteristics. Manufacturers and upstream nodes affected by geopolitics obtain higher values, while other nodes obtain lower values. The weight set W quantify the strength of supply-demand relationships between enterprises. Empirical research has revealed the correlation between the weight of an edge connecting two nodes in a weighted network and the degrees of those two nodes, with the calculation formula as follows.

$$W(i,j) = [k(i) \times k(j)]^{\lambda} \tag{1}$$

where, $W(i,j)$ represents the edge weight between node i and node j; $k(i)$ and $k(j)$ denote the node degrees of node i and node j, respectively; and $\lambda \in (0,1)$ is the edge weight adjustment coefficient, utilized to calibrate the strength of the cooperative relationship between nodes.

3.1.3. Evolutionary Steps

The evolution of the supply chain network comprises two fundamental processes: node entry and exit. The basic evolutionary rules for the supply chain network proposed in this study are detailed as follows:

(1) Initial network state configuration. The supply chain network is configured with $N_0 = 20$ initial nodes, and its network topology is illustrated in Figure 1; the competitive advantage coefficient C_i of the nodes is randomly generated, and the strategic hoarding coefficient S_i is randomly generated based on the distribution of its corresponding tier.

(2) Parameter configuration. Establish the probability threshold for node entry and exit as $H_0 \in (0,1)$, constants Q_1, Q_2, Q_3, Q_4 satisfying $0 < Q_1 < Q_2 < Q_3 < Q_4 < 1$, and R_1, R_2, R_3, R_4 satisfying $0 < R_1 < R_2 < R_3 < R_4 < 1$. In each evolutionary iteration, generate random real numbers $H, Q, R \in (0,1)$ alongside the number of edges m for new nodes.

(3) When $H < H_0$, a new node is added to the network. Depending on the value of Q, the following five scenarios may occur:

   (i) If $Q < Q_1$, a new L1 node is added, and the local world available for its connection consists of L2 and L3.

(ii) If $Q_1 < Q < Q_2$, a new L2 node is added, and the local world available for its connection consists of L1, L3, and L4.
(iii) If $Q_2 < Q < Q_3$, a new L3 node is added, and the local world available for its connection consists of L2 and L4.
(iv) If $Q_3 < Q < Q_4$, a new L4 node is added, and the local world available for its connection consists of L2, L3, and L5.
(v) If $Q_4 < Q < 1$, a new L5 node is added, and the local world available for its connection consists of L4.

After determining the specific tier and local world scope of a node entering the network, a tier connectivity constraint is introduced to prevent intermediate-tier nodes from devolving into an isolated state during evolution. If the newly added node belongs to an intermediate tier (L2, L3, or L4), it is mandated to select at least one node from both its upstream and downstream local worlds to establish connections. This paper comprehensively incorporates the target node's degree, competitive advantage coefficient, and strategic hoarding coefficient to guide preferential attachment. Consequently, the probability of node *i* connecting with the new node is formulated as:

$$P_i = \lambda_1 \frac{k_i}{\sum_{j\in\Omega} k_j} + \lambda_2 \frac{C_{\mathrm{i}}}{\sum_{j\in\Omega} C_j} + \lambda_3 \frac{S_i}{\sum_{j\in\Omega} S_j} \tag{2}$$

where, Ω represents the set of nodes within the local world, and λ_1, λ_2, and λ_3 are the weight coefficients satisfying $\lambda_1 + \lambda_2 + \lambda_3 = 1$. When geopolitical risks escalate, λ_3 can be appropriately increased to reflect the heightened emphasis enterprises place on reserve levels. Directed edges are established between the newly added node and the target nodes.

(4) When $H > H_0$, a node is removed from the network. Depending on the value of R, the following five scenarios may occur:
(i) If $R < R_1$, an L1 node and its connected edges are removed.
(ii) If $R_1 < R < R_2$, an L2 node and its connected edges are removed.
(iii) If $R_2 < R < R_3$, an L3 node and its connected edges are removed.
(iv) If $R_3 < R < R_4$, an L4 node and its connected edges are removed.
(v) If $R_4 < R < 1$, an L5 node and its connected edges are removed.

Similar to preferential attachment, lower attractiveness and fewer strategic reserves in the local world correspond to a higher probability of exit after existing nodes exit. Therefore, the exit probability of each node is associated with its preferential attachment probability P_i, and the calculation formula is given by:

$$Z_i = \frac{1 - P_i}{\sum_{j\in\Omega}(1 - P_j)} \tag{3}$$

Prior to the formal removal of the designated node and all its incident edges, an isolation risk assessment is executed. First, all neighboring nodes connected to the targeted node are traversed. If a neighboring node's in-degree or out-degree is projected to become zero following the edge deletion—indicating that the enterprise faces a localized chain disruption risk—an isolated node reconnection mechanism is triggered. In accordance with the preferential attachment rules, the affected node subsequently searches its corresponding local world to establish an alternative connection. Finally, the designated exit node, along with its residual edges, is removed from the network.

(5) Simulation termination condition. Following the aforementioned evolutionary rules, steps (3) and (4) are repeated iteratively until the time step reaches a predetermined threshold, at which point a 5-tier supply chain network comprising a specific number of nodes is obtained.

3.2. Underload Cascade Failure Model

3.2.1. Underload Cascade Failure Mechanism

Confronted with the vulnerability and cascading failure characteristics exhibited by supply chain systems under extreme shocks, this paper employs the classic load-capacity model from complex networks as the mathematical foundation to characterize the evolution of failures. Most existing studies research network node failures based on the overload assumption. In contrast, this study adapts traditional models to align with the global trend of supply chains shifting toward strategic reserves. it maps the minimum fixed costs required for enterprises to maintain basic operations to the "capacity lower bound" of network nodes. then, this study builds a dynamic cascading failure model triggered by "underload".

(1) Bidirectional Load Propagation Mechanism

In globalized supply chains, the deep coupling between enterprises increases operational efficiency but also heightens network vulnerability. From a logistics perspective, cascading failure in supply chains manifests as bidirectional chain reactions. Upstream enterprises fail due to a decline in product demand, while downstream enterprises fail due to inadequate material supply. Both decreased product demand and insufficient material supply can be regarded as reductions in load. Unlike overload cascading failure in most infrastructure networks, the underload failure cascading more accurately characterizes cascading failures in supply chain network. Under severe geopolitical shocks, the disruption of any enterprise often causes related enterprises to fall below the minimum production requirements and incur losses. Consequently, these enterprises incur financial losses and ultimately exit the market, thereby triggering an underload failure.

As shown in Figure 2, the propagation of underload cascading failures is bidirectional. Upon the disruption of a node due to a sudden event, it concurrently triggers supply shortages for downstream nodes and a loss of demand for upstream nodes. If the residual load of the affected neighboring nodes falls below the lower-bound constraint required to sustain fundamental enterprise operations (i.e., the minimum cost), these nodes will experience new failures, subsequently propagating the disruption throughout the entire system.

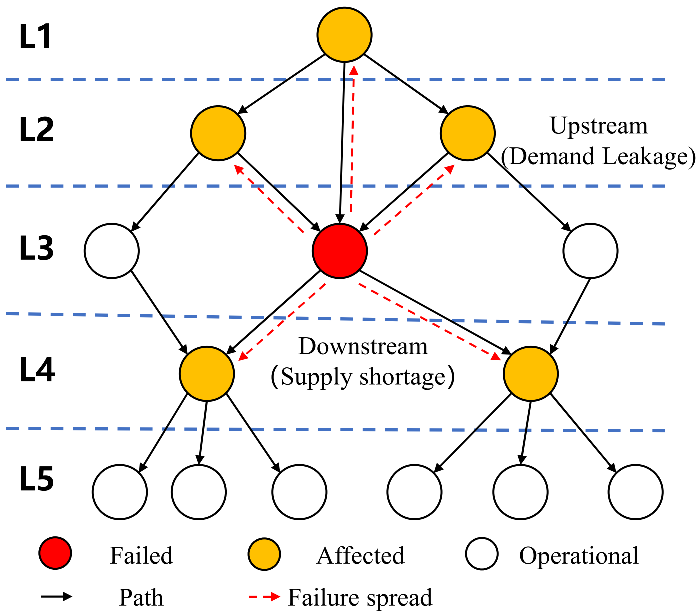


Figure 2. Diagram of Bidirectional Load Propagation in a Supply Chain.

(2) Strategic Reserve Compensation Mechanism

During the evolution of the supply chain network's response to underload cascading failures, enterprises do not passively accept load losses. To withstand geopolitical shocks or the risk of supply disruptions, enterprises are gradually shifting from the Just-in-Time (JIT) paradigm to the Just-in-Case (JIC) strategic hoarding model. Consequently, an internal strategic reserve compensation mechanism, predicated on resource allocation and self-recovery, exists within the system. This mechanism aims to mitigate the failure pressure triggered by load deficits at nodes through the dual pathways of external coordination and internal hedging.

The system first initiates load redistribution in the SCN when the nodes detect a load reduction. Affected nodes conduct "many-to-many" procurement in the network, obtaining redundant capacity support from adjacent nodes. This stage is a self-organizing response of the network structure. The system reallocates logistics resources to offset the initial fault interference, so that the remaining load of the node is above the survival threshold. After load redistribution, if the external compensation of the manufacturer is insufficient to offset the cost, the system initiates an internal strategic reserve compensation mechanism. Enterprises use well-preserved strategic resources to fill the gaps. This mechanism relies on consuming internal inventory to maintain liquidity, and is also a key defensive measure against shocks.

The final evolutionary state of the system is related to computing resources and insufficient load. If impaired enterprises without resource reserves cannot obtain sufficient computing resources from neighbors after load redistribution, the system considers that an insufficient load fault has been triggered and then exits. When the enterprise exhausts its resource reserves and still cannot fill the insufficient load situation after internal calculation, the system also considers that an insufficient load fault has been triggered and exits permanently. This logic identifies key nodes, which here causes cascading failures to shift from local distribution to system collapse, and also mentions the vulnerability of the support chain network after buffer exhaustion.

3.2.2. Development of the Underload Cascading Failure Model

Based on the mechanisms described above, the 5-tier supply chain network graph, denoted as G = (*N*, *E*, *C*, *S*, *W*), constructed in this study is integrated with the underload propagation model. The specific mathematical model evolution and computational steps are formulated as follows:

(1) Definition of Initial Load and Constraints

Distinct from the degree-based static load allocation typical of conventional networks, the load in real-world supply chains is driven by final demand. Assuming the network consists of T = 5 tiers, the initial total demand load of the L5 (customer) tier is known. The network edge weight reflects the strength of business connections between enterprises. The initial allocation proportion of the physical flow through the edges is determined by the business intensity weights between a node and its upstream or downstream partners. Reflecting the actual balance of supply and demand, the flow F_{ij} allocated by node *j* to supplier *i* is calculated as follows:

$$F_{ij}(0) = L_j(0) \cdot \frac{W_{ij}}{\sum_{k\in\Gamma_j^U} W_{kj}} \tag{4}$$

where, Γ_j^U represents the set of all upstream adjacent nodes to node *j*. Accordingly, by recursively calculating backwards tier by tier, the initial loads of nodes across all tiers are determined. The initial load $L_i(0)$ of node *i* is equal to the sum of the flows on all its out-edges:

$$L_i(0) = \sum_{j\in\Gamma_i^D} F_{ij}(0) \tag{5}$$

The downstream L5 customer tier serves exclusively as the demand end with no downstream nodes; thus, it only possesses inbound loads and lacks outbound loads, with its total loads volume equal to the initial total demand. Conversely, the upstream L1 tier serves exclusively as the supply end with no upstream nodes; therefore, it only possesses outbound loads and lacks inbound loads, with its initial load derived entirely in reverse from downstream demand. Except for nodes at both terminal tiers, other nodes have equal in-edge and out-edge logistics, which reflects the supply-demand balance observed among enterprises in real-world supply chains.

In practical networks, a node's capacity to handle load is constrained by factors such as cost. An enterprise's supply capacity, manufacturing capacity, or sales capacity is limited by its scale. Therefore, each enterprise has an upper bound on load in the supply chain network. When an enterprise operates at full capacity, its load reaches but does not exceed this upper limit. The overarching objective of a supply chain network is to deliver products to end customers; for individual enterprises at each node, the ultimate goal is profitability. If an enterprise's product demand or raw material supply falls below a specific threshold, it cannot sustain normal operations and may even face bankruptcy due to a lack of profitability.

Therefore, the load required to maintain normal enterprise operations must exceed a certain limit; an excessively low load will precipitate enterprise failure. This paper defines this limit as the lower bound of an enterprise's load capacity, which is associated with operational costs (e.g., labor costs, machinery costs). The formulas for calculating the upper and lower load limits of a node (such as node *i*) are as follows:

$$A_i = (1+\alpha)L_i(0) \tag{6}$$

$$B_i = \delta L_i(0) \tag{7}$$

where, α represents the capacity redundancy upper bound adjustment coefficient ($0 < \alpha$), and δ represents the minimum load lower bound parameter ($0 < \delta < 1$). To incorporate the "strategic hoarding" behavior, each node enterprise is endowed with an additional strategic reserve capacity H_1. Concurrently, due to the increased capital lock-up and warehousing costs associated with maintaining this reserve, its lower load bound must be correspondingly elevated:

$$H_i(0) = S_i A_i(0) \tag{8}$$

$$B_i = (\delta + \mu)L_i(0) \tag{9}$$

$$\mu = \gamma S_i \tag{10}$$

where, μ represents the reserve penalty coefficient ($\mu > 0$), denoting the elevation in the survival threshold induced by maintaining the additional reserves; γ represents the unit holding cost parameter ($\gamma > 0$). The formulation (10) dynamically elevates the survival threshold B_i. As an enterprise increases its strategic reserve S_i, the associated capital and warehousing costs scale proportionally, thereby requiring a higher minimum load to sustain operations. Initially, the lower bound is determined by the baseline operational cost parameter δ, as formalized in Formulation (7). However, under the JIC paradigm, establishing a strategic reserve capacity incurs additional capital lock-up and warehousing costs. To incorporate this into the model, the lower-bound constraint is dynamically adjusted. As shown in formulation (9), the survival threshold is elevated by the reserve penalty coefficient μ. Mathematically, during the cascading failure process, if the residual load of node i satisfies $L_i(t) < B_i$ after compensation mechanisms are exhausted, the node is formally classified as failed at time $t+1$.

(2) Multi-Directional Load Loss Propagation

When an initial attack or perturbation occurs, the load of the failed node and the flow on its connected edges instantaneously drop to zero. The failed node *i* simultaneously inflicts load losses upon both its upstream set Γ_i^U and its downstream set Γ_i^D. For an affected upstream node *m*, its lost demand load $\Delta_{m,i}^-(t)$ is allocated in accordance with the original proportion of the supply-demand flow:

$$\Delta_{m,i}^-(t) = L_i(t)\frac{F_{mi}(t-1)}{\sum_{p\in\Gamma_i^U} F_{pi}(t-1)} \tag{11}$$

Simultaneously, the current load of the upstream node *m* is updated:

$$L_m(t) = L_m(t-1) - \Delta_{m,i}^-(t) \tag{12}$$

For an affected downstream node *s*, its lost supply load $\Delta_{s,i}^-(t)$ is similarly allocated in accordance with the original proportion of the supply flow:

$$\Delta_{s,i}^-(t) = \Delta_i^-(t)\frac{F_{is}(t-1)}{\sum_{g\in\Gamma_i^D} F_{ig}(t-1)} \tag{13}$$

Simultaneously, the current load of the downstream node *s* is updated:

$$L_s(t) = L_s(t-1) - \Delta_{s,i}^-(t) \tag{14}$$

This loss propagates tier by tier both upstream and downstream along the network's connectivity. When a given node is simultaneously impacted by multiple failed nodes, its lost loads must be cumulatively summed.

(3) Strategic Reserve Compensation Mechanism and State Determination

Following the propagation of load loss, the impaired node initiates a compensation mechanism for self-recovery. Introducing the dynamic residual load capacity of node *i*, which represents the maximum production capacity of the company:

$$RL_i(t) = A_i - L_i(t) \tag{15}$$

During the compensation phase, the impaired node initially searches for residual capacity RL among its originally connected, surviving upstream or downstream nodes to offset the deficit. The specific compensation amount, denoted as $\Delta_{k,i}^+(t)$, cannot exceed the dynamic residual capacity RL of the node providing assistance. Assuming that following the failure of node *i*, its downstream node *j* opts to strengthen its existing relationship with another upstream node *k*. Nodes possessing substantial redundant capacity are preferentially selected; consequently, the probability of node *k* being selected and its corresponding increase in load are formulated as:

$$P_k = \frac{RL_k(t)}{\sum_{r\in\Gamma_k^U} RL_r(t)} \tag{16}$$

$$\Delta_{k,i}^+(t) = \min(RL_k(t), \Delta_j^-(t)) \tag{17}$$

The node *j* can strengthen supply-demand relationships with multiple upstream enterprises at the same time until the lost load is compensated or all upstream enterprises exhaust their remaining capacity. During the "many-to-many" compensation process, a critical scenario arises when multiple affected downstream nodes simultaneously request capacity from the same upstream node *k* within a single time step. To resolve this concurrent competition for the finite residual capacity $RL_k(t)$, the model employs a proportional allocation rule based on edge weight. Specifically, the available capacity of node *k* is distributed among the competing downstream nodes in proportion to their initial edge weight W_{kj} ($j \in \Gamma_k^D$). This ensures priority is logically aligned with the historical strength of the supply-demand relationship. If $L_j(t) < B_j$, node *j* fails at time $t + 1$. For core enterprises, they have strategic reserve capacity. If their reserves are sufficient, they can utilize the internal reserves to fill the load deficit. In this case, these enterprises remain operational, but their internal reserve resources decrease.

$$E_j(t) = E_j(t-1) - [B_j - L_j(t)] \tag{18}$$

Conversely, if their reserves are insufficient, their load in the Supply chain network still below the lower bound. At this time, the node *j* is judged as failed and fails at time $t + 1$. At time *t*, if some enterprises in the supply chain network fail, a new round of cascading failure propagation occurs at time $t + 1$. This process repeats until no additional enterprises fail in the network.

3.2.3. Cascade Failure Evaluation Metrics

In current literature, cascading failure models predominantly employ post-failure network robustness metrics, such as the network robustness index or the network efficiency index, for evaluation. Specifically, network robustness is typically measured by the average avalanche size or the relative size of the maximum connected component, while network efficiency is quantified using the average reciprocal shortest path length or the average shortest path length. However, these traditional metrics are ill-suited for evaluating the robustness of supply chain networks. Following a disruption, very few nodes are entirely removed from such networks; the majority of affected nodes remain interconnected. To address this limitation, this paper introduces the demand fulfillment rate, denoted as *RI*, as a novel evaluation metric based on node load. Utilize *RI* to assess the dynamic robustness of the supply chain network against underload cascading failures triggered by either random perturbations or targeted attacks. It is expressed as follows:

$$RI = \frac{\sum_{k\in\Omega_1} L_k(t)}{\sum_{k\in\Omega_1} L_k(0)} \tag{19}$$

where, Ω_1 denotes the set of all customer nodes (L5) within the supply chain network, $L_k(t)$ represents the final load borne by node *k* after the cascading failure process, and $L_k(0)$ represents the initial load borne by node *k*. To provide a more comprehensive assessment of the system's internal resilience, this study introduces a supplementary metric: the Intermediate Node Survival Ratio (INSR):

$$INSR = \frac{N_{surviving}(t)}{N_{initial}} \tag{20}$$

where $N_{initial}$ is the total number of intermediate nodes (L1–L4) prior to the cascading failure, and $N_{surviving}(t)$ is the number of operational intermediate nodes after the cascading failure concludes.

4. Simulation Analysis

To evaluate the effectiveness of the theoretical framework, this section adopts numerical simulation to validate both the network evolution model incorporating strategic reserves and the underload cascading failure model with "many-to-many" compensation. The study primarily utilizes complex network analysis tools to simulate and analyze the dynamic evolution of the network and the failure propagation process under abrupt disruptions.

4.1. Simulation and Analysis of Strategic Supply Chain Networks

Based on the network structure of manufacturing supply chains in the real world, the initial simulation parameters are set as follows.

(1) Time steps *T*. The initial number of nodes N_0 is set to 20. The initial network structure is distributed according to a five level structure in Figure 1. To ensure the network evolves to a stable and statistically significant scale, the evolutionary time step *T* is set to 2000.

(2) Entry and exit probabilities. To simulate a market environment in an expansionary phase, the threshold value for network growth and decline H_0 is set to 0.9. The tier-specific probability distribution for newly added nodes is set as $Q_1 = 0.3$, $Q_2 = 0.5$, $Q_3 = 0.7$, $Q_4 = 0.85$, $R_1 = 0.3$, $R_2 = 0.5$, $R_3 = 0.7$, and $R_4 = 0.85$. These specific probability thresholds are not entirely arbitrary but are calibrated to empirically reflect the hierarchical topology of real-world manufacturing supply chains, such as the automotive or electronics industries. In these sectors, raw material suppliers (L1) and end customers (L5) constitute the vast majority of network entities, while core original equipment manufacturers (L4) are highly concentrated with high entry barriers. Consequently, Q_1 and Q_4 are set to higher cumulative probability intervals to ensure a prolific generation of peripheral nodes, while the narrow interval for Q_3 to Q_4 restricts the number of L4 nodes. This deliberately generates the steady-state "dumbbell-shaped" topology observed in empirical studies.

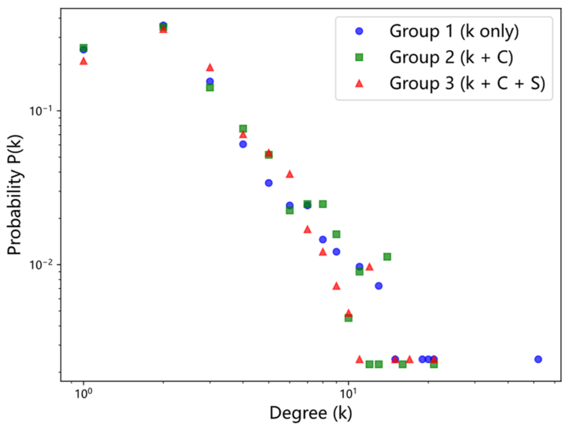
(3) Node properties. For parameter settings of node attributes, the competitive coefficient is assigned according to a uniform distribution within the interval (0, 1). Additionally, to account for differentiation in reserve willingness and capacity among enterprises at different tiers due to geopolitical factors, this study assigns the strategic reserve coefficient S_i only to L4-tier nodes. The value of this parameter is also generated as a random number within the interval (0, 1).

This study use the controlled variable method to analyze and verify the actual impact of the proposed "multi-factor preferential attachment and exit mechanism" on the evolution of supply chain networks. Three simulation experiments are designed for comparative analysis, as summarized in Table 1.

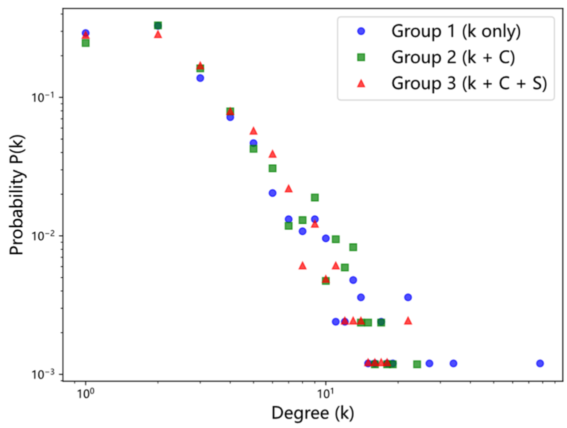
Table 1. Table of Weight Coefficient Settings for Three Comparative Experiments.

Group	Role Description	Range
Group 1	Node degree only	$\lambda_1 = 1$ $\lambda_2 = 0$ $\lambda_3 = 0$
Group 2	Node degree competitive advantage	$\lambda_1 = 0.57$ $\lambda_2 = 0.43$ $\lambda_3 = 0$
Group 3	Node degree competitive advantage strategic reserve	$\lambda_1 = 0.4$ $\lambda_2 = 0.3$ $\lambda_3 = 0.3$

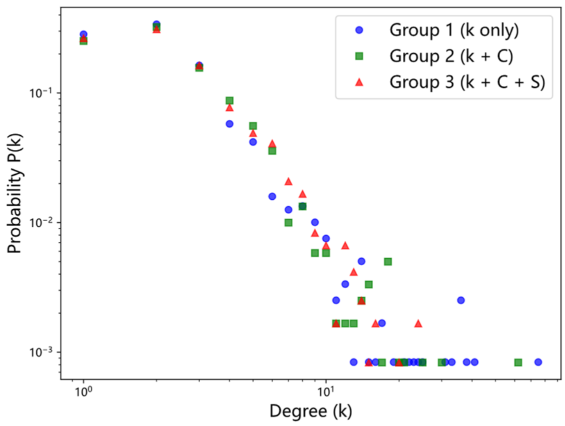
The formation of real-world supply chain networks is driven by the interplay of multiple complex factors. It is difficult to delineate the specific roles of each variable in reshaping network topology in the outcome of multifactor evolution. Therefore, this experimental is design to progressively introduce three evolutionary driving variables. They include the node degree, the competitive coefficient and the strategic reserve coefficient. The simulation results are shown in Figure 3.



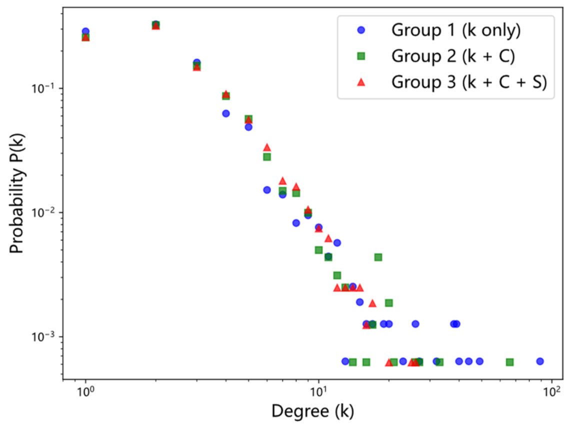
(**a**) Degree Distribution Comparison at Step 500



(**b**) Degree Distribution Comparison at Step 1000



(**c**) Degree Distribution Comparison at Step 1500



(**d**) Degree Distribution Comparison at Step 2000

Figure 3. Evolution of degree distribution in supply chain networks across three experimental groups. (**a**–**d**) depict the network topological states at simulation steps 500, 1000, 1500, and 2000, respectively, illustrating the gradual expansion of network scale and the rightward shift of degree distribution points as the system reaches a stable scale-free state.

The four following conclusions can be drawn by observing the degree distribution maps at different simulation step sizes.

(1) In three experimental groups, the degree distributions approximate a downward-sloping straight line in the logarithmic coordinate. This indicates that the evolved supply chain networks exhibit scale free feature. Regardless of the number of evolutionary driving variables considered, the preferential attachment mechanism consistently ensures that the resulting supply chain networks have scale free characteristics.

(2) In the Group 1, the first mover advantage is highly pronounced. The super hub node with the maximum degree typically dominates the supply chain network. This result reflects a quintessential rich-get-richer effect.

(3) The figures show that the slope of the long tail is different after introducing competitive advantage (Group 2) and strategic reserve (Group 3). The new nodes no longer attach blindly to the nodes with the highest degree but instead consider the overall influence of potential connections. As a result, some enterprises with relatively low degree but high operational efficiency, strong competitive and substantial strategic reserves still attract many connections. The degrees of the 2nd and 3rd groups are more evenly distributed. This mechanism can prevent excessive concentration of supply chain resources on a small number of nodes, and improve the stability of the network and the fairness of resource allocation at the macro level.

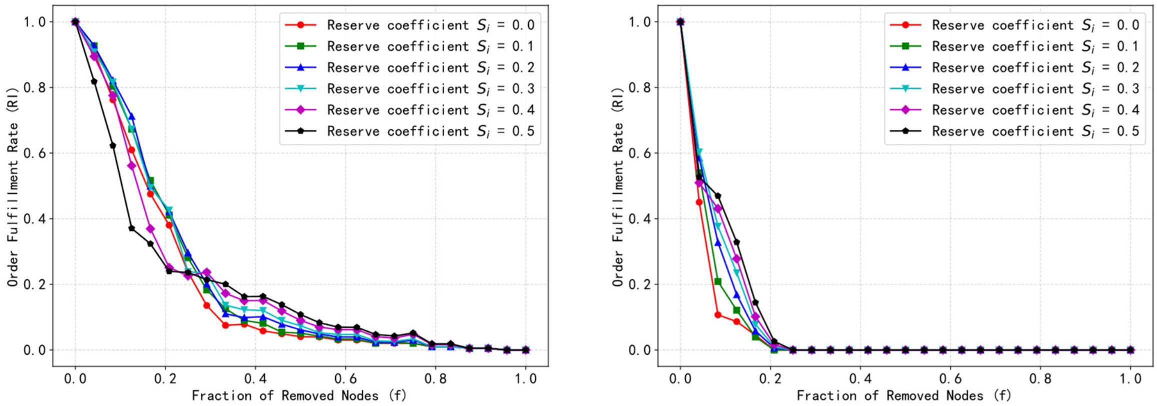
(4) The evo steps range from 500 to 2000, the network scale gradually expands, and the degree distribution points shift to the right. When the steady state is reached at 2000 steps, the topological differences of the three models are more obvious. The attributes of internal nodes such as the strategic reserve coefficient have an impact on the reshaping of the network topology during the long-term evo process.

4.2. Robustness Analysis of Underload Cascading Failure

Based on the supply chain network generated by the aforementioned evolution model, this subsection validates the underload cascading failure model and evaluates the enhancement effect of the reserve compensation mechanism on the network's dynamic robustness from a functional perspective. To evaluate how the strategic hoarding mechanism under the "Just-in-Case" (JIC) paradigm enhances the resilience of multi-tier supply chain networks, we conduct comparative experiments on underload cascading failures under varying strategic reserve coefficients. These experiments are performed on a stable network—comprising 1590 nodes and 2310 edges—generated after 2000 evolutionary time steps. The experiments employ two disruption modes: random attacks and targeted attacks. By plotting the fraction of removed nodes (f) on the horizontal axis and the order fulfillment rate (RI) on the vertical axis, we quantitatively assess the network's dynamic robustness. The simulation results are presented in Figure 4.

A comparison of simulation results under the two attack modes clearly shows that the supply chain network exhibits robust resilience to random attack but exhibits highly susceptible to targeted attack. Under the random attacks, as the proportion of removed nodes increases, the demand fulfillment rate exhibits a relatively gradual linear decline. When 60% of the nodes are removed, the network still maintains a low demand fulfillment rate. This resilience arises from the inherent properties of scale free networks. In the random attack scenario, the peripheral nodes are likely to be attacked. So, most of the core enterprises are retained to minimize the destruction on the functionality of the network. In contrast, under the targeted attacks, the demand fulfillment rate experiences a cliff-like drop. In the base group, removing less than 5% of nodes reduces the demand fulfillment rate to below 40%, triggering large-scale systemic paralysis. This finding confirms the extreme vulnerability of supply chain networks characterized when facing deliberate disruptions of key nodes, such as those caused by geopolitical conflicts.

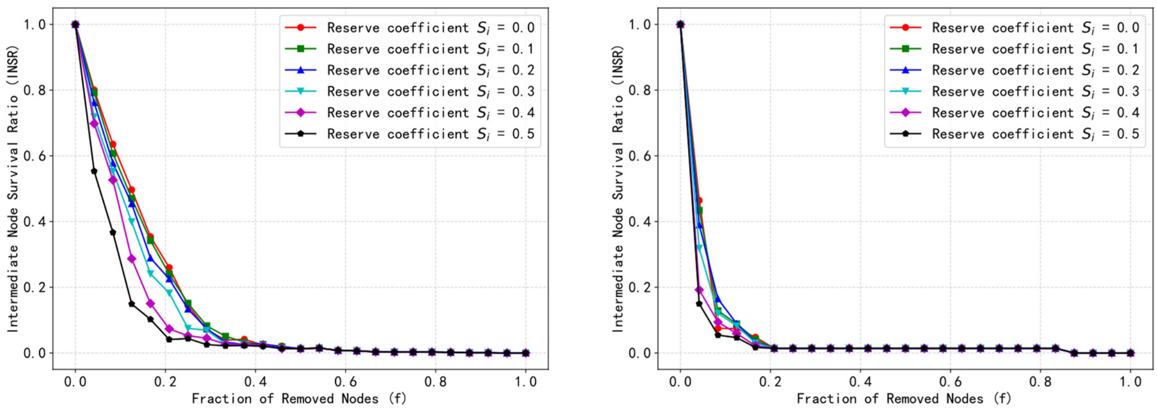
The variations in the strategic reserve coefficient clearly illustrate how stockpiling behavior alters the dynamics of cascading failures. When core enterprises do not set strategic reserves, the interruptions of their upstream or downstream partners directly affect their operational status. If a core enterprise fails due to underload, the supply chain network will lose a large portion of load. Other small and medium-sized enterprises are unable to compensate for this large gap, which triggers catastrophic cascading failures. When S_i reaches 0.5, supply chain network resilience will change due to targeted attacks. Strategic reserves have a buffering effect. Core enterprises adjust internal reserves to supplement loads and reduce failure probabilities. In Figure 4, high reserve levels substantially suppress the cliff-like drop in the demand fulfillment rate. At the same time, introducing a reserve mechanism also increases cost. When the removed node part is at a low level, excessive strategic reserves may cause the demand satisfaction rate to be lower than zero, and the corresponding situation also exists when the reserve level is low. High reserves tie up capital and also bring storage and operating costs, all to enable enterprises hard to survive. So the elevated survival threshold raises the risk of premature failure due to underload in the presence of minor disruptions.



(**a**) Robustness of supply chain network under random attack (**b**) Robustness of supply chain network under targeted attack

Figure 4. The results of supply chain robustness under cascading failures. Subgraph (**a**) shows the network's resilience to random attacks, characterized by a gradual linear decline in performance; (**b**) highlights the network's extreme vulnerability to targeted attacks, illustrating how strategic reserves buffer cliff-like performance drops, while also revealing that excessive hoarding can raise survival thresholds and cause premature failures.

To further uncover the internal structural degradation, this experiments also evaluate the Intermediate Node Survival Ratio (INSR) under both random and targeted attacks, as depicted in Figure 5.



(**a**) The INSR of supply chain network under random attack (b) The INSR of supply chain network under targeted attack

Figure 5. The INSR of supply chain robustness under cascading failures. Subgraph (**a**) reveals the degradation under random attacks, highlighting a resilience paradox where higher strategic reserves (S_i) inadvertently accelerate intermediate node failures due to elevated capital lock-up costs; (**b**) demonstrates the extreme vulnerability of intermediate tiers to targeted attacks, where the removal of core nodes triggers a rapid and massive systemic collapse.

Consistent with the RI findings, the INSR exhibits extreme vulnerability to targeted attacks. Removing less than 10% of the nodes causes the survival ratio of the intermediate tiers (L1–L4) to plummet below 20%, triggering a rapid systemic collapse. Conversely, under random attacks, the structural degradation is relatively more gradual. Unlike the RI, a higher S_i paradoxically accelerates the failure of intermediate nodes. In Figure 5, the network with the highest reserve level ($S_i = 0.5$) experiences the steepest decline in INSR, where the baseline network ($S_i = 0.0$) maintains a comparatively higher survival rate. As formalized in the dynamically scaled lower-bound constraint (B_i), maintaining high strategic reserves significantly inflates capital lock-up and warehousing costs. This elevated operational threshold means that minor reductions in load can push enterprises below their financial survival baseline, causing premature underload failures. When core manufacturers (L4) mobilize their internal strategic reserves to compensate for downstream supply deficits, they essentially substitute external procurement with internal inventory consumption. While this successfully shields terminal customers (L5) from supply shocks, it simultaneously cuts off demand to upstream suppliers (L1–L3). This demand starvation intensifies the underload propagation upstream, leading to a massive die-off of intermediate nodes. These findings explicitly demonstrate that excessive hoarding inadvertently hollows out the intermediate supply base, ultimately compromising the long-term structural integrity of the supply chain network.

5. Discussion and Managerial Implications

The simulation results reveal several critical insights that extend the current understanding of supply chain resilience. (1) One finding that the evolved supply chain network is robust to random attacks but highly vulnerable to targeted attacks is consistent with classic complex network theories regarding scale-free topologies (e.g., Zhao, Z.-g [7] and Sun, J [9]). However, we extend this by demonstrating that the introduction of multi-factor preferential attachment (incorporating competitive advantage and strategic reserves) softens the "rich-get-richer" effect, distributing risk more evenly than traditional degree-based models. (2) The bidirectional underload cascading failure model provides a novel counter-narrative to traditional overload failure models. While recent studies highlight the dangers of capacity bottlenecks under demand surges, the results emphasize that supply shortages (mapped as a failure to meet the lower-bound cost constraint) are equally catastrophic. (3) The analysis of the strategic reserve coefficient (S_i) contrasts with the prevailing assumption that "more redundancy equals more resilience". While previous studies advocate for robust buffering, our findings reveal a "resilience paradox": excessive strategic reserves introduce high holding costs (represented by μ), which artificially inflate the firm's survival threshold. Consequently, under low-intensity disruptions, firms with excessive reserves may fail prematurely due to liquidity exhaustion rather than physical supply disruption. This highlights the necessity of dynamically optimizing JIC strategies rather than treating redundancy as a universal method.

The simulation results of the multi-tier supply chain network provide several actionable insights for managers navigating the transition from a Just-in-Time (JIT) to a Just-in-Case (JIC) paradigm. First, the network's demonstrated resilience to random disruptions, contrasted with its extreme vulnerability to targeted attacks, indicates that managers must prioritize the protection and redundancy of core enterprise nodes. Relying solely on a few high-degree hub nodes poses a catastrophic systemic risk during geopolitical conflicts. Second, the network evolution simulations reveal that when forming partnerships, enterprises should look beyond conventional scale; prioritizing connections with firms that possess strong competitive advantages and adequate strategic reserves leads to a more balanced and robust supply network. Finally, the findings regarding the strategic reserve coefficient highlight a critical cost-resilience trade-off. While higher strategic reserves provide a vital buffer during severe disruptions by suppressing cliff-like drops in demand fulfillment, blindly maximizing inventory can be detrimental. Excessive reserves increase capital lock-up and storage costs, thereby raising the minimum operational threshold for the enterprise. Consequently, under minor or low-intensity shocks, over-hoarding can trigger premature underload cascading failures. Therefore, managers must dynamically optimize their strategic reserve levels to carefully balance operational efficiency with risk mitigation, rather than pursuing maximum inventory.

6. Conclusions and Future Research Direction

The simulation experiment of Section 4.1 demonstrates that the proposed multi-factor preference attachment mechanism successfully reshapes supply chain network structures while maintaining their essential scale-free characteristics, which integrates node degree, competitive advantage, and structural resistance. Simulation results show that the three experimental groups have approximately linear degree distribution under logarithmic scale, which confirms the scale-free property of the network. Compared with the basic group, the model with competitive advantage and structural resistance has a more balanced degree distribution, which finding indicates that the proposed network evolution model can allocate network resources more fairly, which is in line with the actual situation. After 2000 steps, the network has 1590 nodes and 2310 edges. The network structures evolved under different models are different, which confirms that strategic reserves have a continuous impact on long-term network evolution. Furthermore, the evolved supply chain networks exhibit a distinct dual nature regarding robustness. Under random attacks, the demand satisfaction rate gradually decreases. When 60% of the nodes are removed, the network still maintains a low demand satisfaction rate. However, in targeted attacks, the network performance deteriorates sharply. In the baseline group, less than 5% of the nodes are quickly removed, and the demand satisfaction rate quickly drops below 40%. This result shows that scale-free properties enable networks to withstand random interference, but the networks remain vulnerable to targeted attacks. Adopting a strategic reserve under the Just-in-Case (JIC) paradigm significantly enhances the network's ability to withstand these targeted disruptions by providing an effective buffer for core enterprises. When the strategic reserve coefficient reaches 0.5, the situation where the demand satisfaction rate drops sharply is effectively controlled. This shows that the strategic reserve creates an effective buffer for the core enterprise. However, in the case of low-intensity target attacks, excessive reserves will cause the order satisfaction rate to decline more severely. High inventory will increase capital and storage costs, thereby raising the threshold for enterprise survival. Reserve elastic income needs to balance operating costs; The goal of an enterprise is to obtain the optimal reserve quantity, not just the maximum inventory quantity.

According to the research findings, the researchers put forward suggestions: first, turn the enterprise reserve strategy into dynamic decision-making to adapt to the changing geopolitical risks, market fluctuations and financial conditions; second, use the real data of strategic implementation industries such as semiconductors, critical minerals and new energy to verify the proposed framework; third, add additional resilience encoders, such as recovery time, interruption cost, service continuity and so on, to conduct a more comprehensive assessment of supply chain resilience.

Author Contributions

Y. G.: conceptualization, methodology, writing. F.Z.: supervision, conceptualization, proof-reading. K.D. and F.T.S.C.: writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

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Given the conceptual nature of study, this study does not use any quantitative data.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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