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Cascading Failure Resilience of Dual-layer Supply Chain Networks under Enterprise Competition with Incomplete Information

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Abstract

Cascading failures are a critical factor affecting the operation of supply chain systems and have received widespread attention. In real-world cases, when an enterprise fails, resources are not evenly distributed to nearby similar enterprises. Instead, they are indirectly allocated through adjustments based on the competition and cooperation among enterprises. Moreover, enterprises often withhold complete information during competition in order to gain more benefits. These factors all influence cascading failures in supply chains. Therefore, we investigate the resilience of cascading failures in dual-layer supply chain networks under enterprise competition with incomplete information. We propose a supply-sales dual-layer network model that takes into account product similarity and enterprise competitiveness. Based on this model, we develop a cascading failure mechanism that includes node competition, replacement, and indirect neighboring load redistribution. Additionally, we incorporate the concept of enterprise information transparency to align with real-world supply chains. Experimental results indicate that 1) increased enterprise transparency can enhance the network's resilience to cascading failures; 2) for suppliers, focusing on the quality rather than the quantity of cooperative sales enterprises is more critical for resisting cascading failures; 3) compared to the sales network, attacks on the supply network can result in a larger scale of cascading failures.

Keywords: cascading failures; supply chain; resilience; competitiveness; information transparency

1. Introduction

The supply chain is a networked system made up of various business entities that collaborate with one another. Its core activities, including the production and sale of products, are closely linked to the socio-economic environment and people's daily lives [1]. With the development of global trade and the integration of emerging technologies into traditional supply and marketing models, the connections between enterprises within the supply chain have become increasingly tighter. Due to the dynamic nature of the supply chain network and the strong interdependencies among its members, a disruption at any point in the network can quickly spread from one enterprise to another, potentially leading to a widespread collapse of the entire system [2]. This "avalanche" effect of continuous failure is known as cascading failure [3].

Cascading failure is a common risk propagation mechanism in complex systems. It refers to the phenomenon where, after a node fails due to a disturbance or shock, its original functions or loads are redistributed to other nodes. If these nodes are unable to bear the additional burden, they may also fail in succession, ultimately triggering a chain reaction that leads to large-scale systemic collapse. In supply chain systems, this mechanism is typically manifested

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as the disruption of one enterprise’s operations affecting its upstream and downstream partners, thereby impacting otherwise unaffected enterprises. The disruption then spreads continuously through the network structure, impairing the normal operation of the supply chain. In recent years, cascading failure events in supply chains have been on the rise. For example, in 2023, armed attacks along the Red Sea shipping route forced many international cargo vessels to reroute, resulting in significant delays. This led to port congestion and container shortages worldwide, especially affecting the Asia–Europe supply chain cycle, delaying production schedules and causing large-scale order cancellations. In 2024, the collapse of the Francis Scott Key Bridge in Baltimore, USA, blocked a critical port, disrupting industries such as automotive, energy, and logistics. The incident led to delivery delays for companies like General Motors and Ford, and hindered coal imports to India. Furthermore, according to the 2024 report by the United Nations Conference on Trade and Development (UNCTAD)[4], the global supply chain pressure index has remained at a high level in recent years, and many key industries have shown weak resilience. Therefore, the issue of cascading failure resilience in supply chain networks has become a widely discussed and critical topic.

In real-world scenarios, many supply chain systems exhibit a distinct hierarchical structure. A typical configuration consisting of two primary stages—supply and sales—is referred to as a two-tier supply chain. The upper tier is the supplier network, responsible for providing raw materials or components, while the lower tier is the sales network, which delivers finished products to the market. These two tiers are connected through the flow of products, resources, and capital, forming upstream and downstream relationships that jointly support the coordinated operation of the supply chain. This structure reflects clear functional division and close collaboration. Although enterprises at different tiers are organizationally independent, they are functionally interdependent; at the same time, enterprises within the same tier often engage in both competition and cooperation. The division of labor and coordination mechanism improves resource allocation efficiency. However, due to the tight coupling between layers, the failure of any single component can rapidly propagate along the upstream or downstream paths, resulting in broader systemic disruptions. Therefore, while two-tier supply chains benefit from enhanced coordination, they also bear the inherent risk of system-wide cascading failures, posing significant challenges to resilience.

Existing research assumes that when an enterprise node in a supply chain fails, its load is directly redistributed to adjacent, similar enterprises, allowing the network to continue operating. However, current studies often focus on the occurrence and recovery of cascading failures at the network level, with limited attention given to the unique market environment—characterized by intense competition—and its impact on supply chains. In real-world supply chains, when an enterprise fails, resources are not simply redistributed to nearby similar enterprises. Instead, they are indirectly allocated through competition and cooperation among multiple enterprises. In reality, when a supplier fails, the impact is first directly transmitted to its downstream cooperating sales enterprises: the originally supplied resources can no longer be maintained, causing supply disruptions for the associated sales enterprises. If these sales enterprises fail to find alternative sources in time, they may suffer losses due to stockouts and fall into operational crises. In this way, failures at upstream nodes propagate downstream through the flow of products. During this process, the diversity of products and demand compels sales enterprises to consider not only the supply-demand relationship but also the competitiveness of other suppliers in the market. Consequently, they may choose to strengthen cooperation with the remaining suppliers or seek new ones to meet actual demand. A similar dynamic occurs when a sales enterprise fails. Therefore, an enterprise’s ability to obtain redistributed resources from a failed partner depends not only on its own competitiveness but also on the strength of its relationships with cooperating partners. Moreover, in a real market, for reasons such as business competition, enterprises may not provide accurate information about their operational

status. As a result, resources released by failed enterprises during cascading failures may not be precisely allocated based on actual conditions. Therefore, the transparency of enterprise information has a significant impact on the cascading failure process within the supply chain.

Based on the aforementioned characteristics of real-world supply chains, we propose a cascading failure model for dual-layer supply chains that incorporates enterprise information transparency, node replacement, and node competition. The specific contributions of this work are as follows:

- 1) We construct a dual-layer supply chain network model based on product similarity and enterprise competitiveness. In this model, supplier and sales enterprises form separate supply and sales networks, with resources flowing between the layers according to supply-demand cooperation relationships. The competitiveness of enterprise nodes influences the selection of substitute nodes and the redistribution of resources during the cascading failure process, thereby shaping the overall failure propagation within the system;
- 2) Considering the heterogeneous demand and multi-supplier competition in real supply chain networks, we propose an “indirect neighboring” redistribution mechanism and design a realistic cascading failure model for supply chains. In this mechanism, when an enterprise node fails, its upstream and downstream partners will seek new substitute nodes to form new links or strengthen their ties with existing cooperative enterprises, and the system possesses a dynamic adaptive reconfiguration capability consistent with practical supply-demand logic;
- 3) We introduced the concept of enterprise information transparency to describe the perception bias of enterprises regarding system status under incomplete information environments. This factor affects the selection of substitute nodes and the redistribution paths of loads, thereby influencing failure propagation patterns and the system’s resilience to cascading failures. This concept aligns with the common reality of information incompleteness in competitive supply chain markets, enabling us to assess the impact of enterprise information transparency on overall network performance from a system-level perspective.

The remainder of this work is organized as follows: Section 2 reviews existing research; Section 3 introduces the dual-layer supply chain model; Section 4 provides a detailed description of the cascading failure model; Section 5 presents the experimental results and case studies; and, finally, Section 6 concludes the work.

2. Literature review

Currently, many scholars have conducted research on cascading failures in supply chains with various structures and types. For instance, Wei et al.[5] proposed a link addition strategy based on ternary closure structures to enhance the cascading resilience of supply chain networks under disruption propagation and interruption risks. Khakifirooz et al.[6] constructed a scale-free supply chain network model and introduced entropy-based metrics and value-at-risk analysis to examine the cascading impacts and risk diffusion processes in disruption scenarios. Zhang et al.[7] introduced a cascading failure model based on underload failure to analyze the influence of node enterprises’ production capacity on the propagation of cascading failures in supply chains. Yue et al.[8] proposed a cascading failure model of global supply networks from both static structural and dynamic propagation perspectives, identifying the effects of critical enterprise nodes on systemic risk. Luo et al.[9] developed a cascading failure propagation model for hierarchical supply chains, analyzing how disruptions propagate through both vertical supply-demand relations and horizontal enterprise connections. Hossain et al.[10], based on

dependency theory, constructed a supply chain model to study the cascading effects of Industry 4.0 technology disruptions on supply chain analytics systems. Habibi et al.[11] developed a multi-layer supply chain network model to investigate the role of network hierarchy and connectivity in disruption propagation and their impact on resilience. Chen et al.[12] proposed a cascading failure model that considers node heterogeneity, exploring the risk transmission mechanisms under multi-attribute differences. Gervais et al.[13] established a multi-layer supply chain model based on the photovoltaic industry, analyzing how disruption propagation paths and product diversification influence system resilience.

Based on the above literature review, it is clear that existing research primarily focuses on the effects of network topology and node capacity, analyzing cascading failure behavior in different types of supply chains. However, in real-world scenarios, factors such as competition among enterprises and the level of information transparency also influence cascading failure behavior. Therefore, in this work, we propose a cascading failure model for supply chains that incorporates both enterprise competition and information transparency. To illustrate this more clearly, Table 1 compares and summarizes the differences between our proposed model and existing models across several aspects.

Reference	Network topology structure	Node tolerance threshold	Multiple failure strategies	Dynamic node state	Heterogeneous demand	Node replacement	Multi-node competition	Information transparency
[5]	✓		✓					
[6]	✓	✓	✓					
[7]	✓	✓						
[8]	✓	✓	✓	✓				
[9]	✓	✓	✓	✓				
[10]	✓	✓	✓					
[11]	✓	✓	✓	✓				
[12]	✓	✓			✓			
[13]	✓				✓	✓		
Our work	✓	✓	✓	✓	✓	✓	✓	✓

Table 1: Comparison of the proposed model and existing models.

3. Network model

In a supply chain, the production and sale of products fully reflect the cooperative and competitive relationships among multiple enterprises. Therefore, we adopt a classic supply-sales structure to study the cascading failure resilience of the supply chain under enterprise competition with incomplete information. We divide the supply chain into two parts—supply network and sales network—based on product flow, and construct a dual-layer supply chain model that integrates both supply and sales, grounded in complex network theory.

3.1. Supply network

Suppliers are the group of enterprises in the supply chain network that produce or provide products for sales enterprises, and the supply network is the actual network formed by this group of suppliers. In the supply chain network, enterprises not only have cooperative relationships with upstream and downstream enterprises for product supply and sales, but also establish competitive and cooperative relationships with similar enterprises within the same market. We represent supplier enterprises as nodes in the supply network, forming the node set $V^S = \{v_i^S \mid i = 1, 2, 3, \dots, N^S\}$, where N^S represents the number of suppliers. The competitive-cooperative relationships among suppliers are represented as edges between nodes, forming the edge set $E^S = \{e_{i,j}^S \mid i, j = 1, 2, 3, \dots, N^S, i \neq j\}$. The strength of the competitive relationships between enterprises is represented by the edge weight set $W^S = \{w_{i,j}^S \mid i, j = 1, 2, 3, \dots, N^S, i \neq j\}$. Thus, the supply network can be represented as $G^S = (V^S, E^S, W^S)$.

147 In the supply network, the similarity of the main products among enterprises can directly
 148 reflect the strength of the competitive-cooperative relationships between them. From the per-
 149 spective of product characteristics, even for the same type of product, the products offered
 150 by different suppliers may exhibit slightly different features. However, the primary struc-
 151 tural features that determine the basic functional attributes of the product are the same and
 152 are shared by products within the same category. For a given product category, we denote
 153 the product produced by enterprise i as H_i , with its structural attribute feature set defined
 154 as $\mathcal{F} = \{F_1, F_2, F_3, \dots, F_{N^F}\}$, where F_k ($1 \leq k \leq N^F$) represents the k -th structural at-
 155 tribute feature of this category (e.g., material), and N^F is the total number of structural
 156 attribute features. Each structural attribute feature F_k of product H_i is defined by a vector
 157 $F_k^i = \{f_{k,1}^i, f_{k,2}^i, f_{k,3}^i, \dots, f_{k,N^{F_k}}^i\}$, where $f_{k,r}^i$ ($1 \leq r \leq N^{F_k}$) denotes the r -th element that de-
 158 fines the structural attribute feature F_k of product H_i (e.g., the proportion of various materials
 159 in the product), and N^{F_k} denotes the total number of elements in feature F_k . A weight set
 160 $W^F = \{w^{F_1}, w^{F_2}, w^{F_3}, \dots, w^{F_{N^F}}\}$ is assigned to the structural attribute features to indicate the
 161 importance of each feature in determining the product's functional characteristics. To calcu-
 162 late the weighted similarity of the product concerning its structural attributes, the similarity of
 163 each structural attribute feature should be weighted. The similarity of each specific structural
 164 attribute feature is determined by the feature elements within the sets of these features, as
 165 shown in Figure 1.

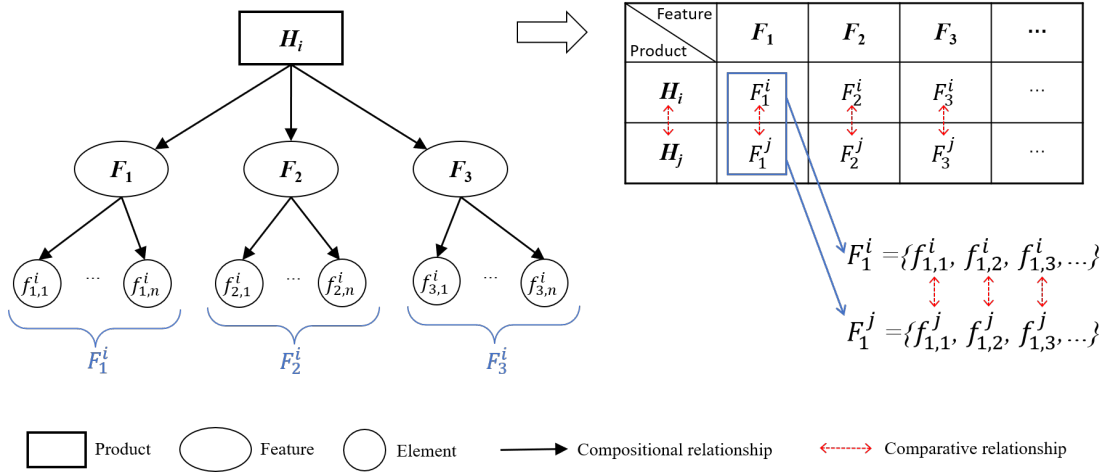


Figure 1: Product feature decomposition.

166 Based on the similarity calculation methods in [14], [15], and [16], we define a similarity
 167 metric for structural attribute features, denoted as $\text{SIM}(H_i, H_j, F_k)$:

$$\text{SIM}(H_i, H_j, F_k) = \frac{\alpha_{i,j}}{\alpha_{i,j} + \lambda_{i,j}} \times 100\%, \quad (1)$$

168 where $\text{SIM}(H_i, H_j, F_k) \in [0, 1]$ represents the similarity between products H_i and H_j with
 169 respect to the structural attribute feature F_k . A similarity of 100%, i.e., $\text{SIM}(H_i, H_j, F_k) =$
 170 1, indicates that the two products share the same structural feature and possess identical
 171 structural functional attributes; a similarity of 0%, i.e., $\text{SIM}(H_i, H_j, F_k) = 0$, indicates that
 172 the two products do not share any similarity in that feature. $\alpha_{i,j} \in [0, 1]$ can be viewed as the
 173 baseline similarity value, which reflects the similarity of common structural attribute elements
 174 between the two products, and $\lambda_{i,j}$, a binary parameter, represents the difference in the products
 175 concerning this structural attribute feature. The detailed calculation rules for (1) are as follows:

- 176 1) If the feature element sets of products H_i and H_j for the structural attribute feature F_k
 177 are equal, i.e., $F_k^i = F_k^j$, then set $\lambda_{i,j} = 0$; consequently, $\text{SIM}(H_i, H_j, F_k) = 1$.

2) If $F_k^i \neq F_k^j$, then $\lambda_{i,j} = 1$, and the similarity of the structural attribute feature is calculated as

$$\text{SIM}(H_i, H_j, F_k) = \frac{|F_k^i \cap F_k^j|}{|F_k^i \cap F_k^j| + \gamma_{i,j,k}^F |F_k^i \setminus F_k^j| + (1 - \gamma_{i,j,k}^F) |F_k^j \setminus F_k^i|} \times 100\%, \quad (2)$$

where $\gamma_{i,j,k}^F \in [0, 1]$ is a tunable parameter that indicates the importance of the differences in feature F_k between products H_i and H_j ; the term $|F_k^i \cap F_k^j|$ represents the number of common elements between F_k^i and F_k^j ; $|F_k^i \setminus F_k^j|$ represents the number of elements in F_k^i that are not shared with F_k^j , and $|F_k^j \setminus F_k^i|$ represents the number of elements in F_k^j that are not shared with F_k^i .

Considering various structural attribute features of the products, the weighted similarity of structural attribute features between product H_i and product H_j can be calculated as

$$\text{SIM}_{\text{Total}}^F(H_i, H_j) = \frac{\sum_{k=1}^{N^F} (w_{F_k} \times \text{SIM}(H_i, H_j, F_k))}{\sum_{k=1}^{N^F} w_{F_k}}, \quad (3)$$

where $\text{SIM}_{\text{Total}}^F(H_i, H_j) = 1$ indicates that the structural attributes of the main products of enterprises i and j are identical, and $\text{SIM}_{\text{Total}}^F(H_i, H_j) = 0$ signifies that there are no similarities in the structural attributes of the main products of enterprises i and j , implying no competitive or cooperative relationship between the enterprises producing these two products. We use the weighted similarity of the structural attributes of the main products from supplier enterprises as the edge weights between the nodes of supplier enterprises, i.e., $w_{i,j}^S = \text{SIM}_{\text{Total}}^F(H_i, H_j)$. Given the symmetry of similarity, where $\text{SIM}_{\text{Total}}^F(H_i, H_j) = \text{SIM}_{\text{Total}}^F(H_j, H_i)$, the edges of the supply network can be represented by a symmetric adjacency matrix $\mathbf{M}^S$, expressed as

$$\mathbf{M}^S = \begin{pmatrix} w_{1,1}^S & \cdots & w_{1,N^S}^S \\ \vdots & \ddots & \vdots \\ w_{N^S,1}^S & \cdots & w_{N^S,N^S}^S \end{pmatrix}, \quad (4)$$

where

$$w_{i,j}^S \begin{cases} > 0, & \text{if enterprise } i \text{ and } j \text{ have a competitive-cooperative relationship} \\ = 0, & \text{if enterprise } i \text{ and } j \text{ have no competitive-cooperative relationship} \end{cases}. \quad (5)$$

3.2. Sales network

The sales network consists of enterprises that procure products from suppliers and sell them to consumers through various channels such as distribution, wholesale, retail, and others. Similar to suppliers, sales enterprises also engage in both cooperation and competition with each other due to differences in market conditions and primary products. We model the sales enterprises as nodes in the sales network, forming the node set $V^A = \{v_i^A \mid i = 1, 2, 3, \dots, N^A\}$, where N^A represents the total number of sales enterprises. The competition and cooperation relationships among the sales enterprises are represented as edges between the nodes, forming the edge set $E^A = \{e_{i,j}^A \mid i, j = 1, 2, 3, \dots, N^A, i \neq j\}$. The intensity of these competitive and cooperative relationships is represented by the edge weight set $W^A = \{w_{i,j}^A \mid i, j = 1, 2, 3, \dots, N^A, i \neq j\}$. Thus, the sales network can be represented as $G^A = (V^A, E^A, W^A)$.

Unlike suppliers, sales enterprises directly cater to a diverse range of consumers. Due to the diversity and personalization of consumers in the market, the products in the sales network should not only fulfill basic functional attributes but also address the heterogeneous demands

of consumers that extend beyond these attributes. Therefore, customer demand features are introduced. Structural attribute features define the basic functionality of the product, while customer demand features address diverse consumer needs and can be adjusted without affecting the core performance of the product.

For a product category, let the product operated by sales enterprise i be denoted as H_i . The set of customer demand features for this product category is represented as $\mathcal{D} = \{D_1, D_2, D_3, \dots, D_{N^D}\}$, where D_k ($1 \leq k \leq N^D$) denotes the k -th specific customer demand feature for this category (e.g., product color composition). Similarly, each customer demand feature D_k can be represented by a corresponding set $D_k^i = \{d_{k,1}^i, d_{k,2}^i, d_{k,3}^i, \dots, d_{k,N^{d_k}}^i\}$, where $d_{k,r}^i$ ($1 \leq r \leq N^{d_k}$) denotes the r -th element that defines the customer demand feature D_k of product H_i (e.g., specific color), and N^{d_k} represents the total number of elements in feature D_k . A weight set $W^D = \{w^{D_1}, w^{D_2}, w^{D_3}, \dots, w^{D_{N^D}}\}$ is introduced to the customer demand features to represent the importance of each feature in meeting the heterogeneous demands of consumers.

Similarly, following the similarity calculation methods in [14], [15], and [16], we compute the similarity of customer demand features, denoted as $\text{SIM}(H_i, H_j, D_k)$:

$$\text{SIM}(H_i, H_j, D_k) = \frac{\beta_{i,j}}{\beta_{i,j} + \mu_{i,j}} \times 100\%, \quad (6)$$

where $\text{SIM}(H_i, H_j, D_k) \in [0, 1]$ represents the similarity between products H_i and H_j with respect to the customer demand feature D_k . A similarity of 100%, i.e., $\text{SIM}(H_i, H_j, D_k) = 1$, indicates that the customer demand features D_k of the two products are identical; a similarity of 0%, i.e., $\text{SIM}(H_i, H_j, D_k) = 0$, indicates that there is no similarity in the customer demand features D_k of the two products. $\beta \in [0, 1]$ can be viewed as the baseline similarity value that considers the similarity of common customer demand elements between the two products, and $\mu_{i,j}$, a binary parameter, represents the variance in customer demand features for the products. Therefore, the detailed calculation rule for (6) is as follows:

- 1) If the feature element sets of products H_i and H_j for the customer demand feature D_k are equal, i.e., $D_k^i = D_k^j$, then set $\mu_{i,j} = 0$; consequently, $\text{SIM}(H_i, H_j, D_k) = 1$.
- 2) If $D_k^i \neq D_k^j$, then set $\mu_{i,j} = 1$; the customer demand similarity calculation method is:

$$\text{SIM}(H_i, H_j, D_k) = \frac{|D_k^i \cap D_k^j|}{|D_k^i \cap D_k^j| + \gamma_{i,j,k}^D |D_k^i \setminus D_k^j| + (1 - \gamma_{i,j,k}^D) |D_k^j \setminus D_k^i|} \times 100\%, \quad (7)$$

where $\gamma_{i,j,k}^D \in [0, 1]$ is a tunable parameter that indicates the importance of the differences in feature D_k between products H_i and H_j ; the term $|D_k^i \cap D_k^j|$ represents the number of common elements between D_k^i and D_k^j ; $|D_k^i \setminus D_k^j|$ represents the number of elements in D_k^i minus the number of elements that D_k^j shares with D_k^i .

Considering multiple customer demand features, the weighted customer demand similarity $\text{SIM}_{\text{Total}}^D$ between products H_i and H_j is calculated as

$$\text{SIM}_{\text{Total}}^D(H_i, H_j) = \frac{\sum_{k=1}^{N^D} (w^{D_k} \times \text{SIM}(H_i, H_j, D_k))}{\sum_{k=1}^{N^D} w^{D_k}}, \quad (8)$$

where $\text{SIM}_{\text{Total}}^D(H_i, H_j) = 1$ indicates that the customer demand features of the main products of enterprises i and j are identical, and $\text{SIM}_{\text{Total}}^D(H_i, H_j) = 0$ indicates that there are no similarities in the customer demand aspects of the main products of enterprises i and j .

When determining the edge weights between sales enterprise nodes, both the structural attribute similarity and the customer demand similarity of the products are considered. The weighted similarity between products H_i and H_j can be calculated as

$$\text{SIM}_{\text{Total}}(H_i, H_j) = \delta \times \text{SIM}_{\text{Total}}^{\text{F}}(H_i, H_j) + (1 - \delta) \times \text{SIM}_{\text{Total}}^{\text{D}}(H_i, H_j), \quad (9)$$

where $\delta \in [0, 1]$ is a tunable weight coefficient that reflects the relative importance of structural attribute features and customer demand features in determining the overall similarity of the products.

Using weighted product similarity to represent the edge weights in the sales network, we have $w_{i,j}^{\text{A}} = \text{SIM}_{\text{Total}}(H_i, H_j)$. The edge weights in the supply network can also be represented by a symmetric adjacency matrix $\mathbf{M}^{\text{A}}$, expressed as

$$\mathbf{M}^{\text{A}} = \begin{pmatrix} w_{1,1}^{\text{A}} & \cdots & w_{1,N^{\text{A}}}^{\text{A}} \\ \vdots & \ddots & \vdots \\ w_{N^{\text{A}},1}^{\text{A}} & \cdots & w_{N^{\text{A}},N^{\text{A}}}^{\text{A}} \end{pmatrix}, \quad (10)$$

where

$$w_{i,j}^{\text{A}} = \begin{cases} > 0, & \text{if enterprises } i \text{ and } j \text{ have a competitive-cooperative relationship} \\ = 0, & \text{if enterprises } i \text{ and } j \text{ have no competitive-cooperative relationship} \end{cases}. \quad (11)$$

The indicator SIM measures the similarity between enterprises based on the structural attributes and customer demand features of their main products, thereby reflecting the degree of homogeneity and the potential strength of cooperative relationships between them. In this study, it is also used as the basis for determining the edge weights between nodes of the same type. To intuitively demonstrate the calculation process and practical significance of this indicator, a home appliance supply chain in a specific region is selected as an example. Three enterprises, A, B, and C, are selected, all of which primarily operate refrigerators. Among them, A and B are production suppliers, while C is a sales enterprise. Although all three enterprises are engaged in the refrigerator business and may have multiple types of connections, we focus specifically on the similarity among their main refrigerator products. The structural attributes of refrigerators are categorized into three types: cooling method, compressor type, and energy efficiency level. Customer demand is mainly reflected in color preference and control mode. Table 2 presents the characteristic information of the main refrigerator products operated by enterprises A, B, and C.

Taking enterprises A and C as an example, the similarity of each structural attribute of their products is calculated as follows:

$$\text{SIM}(A, C, F_1) = \frac{0.5 \times 1 + 0.5 \times 1}{0 + 0.5 \times 1 + 0.5 \times 1} = 0,$$

$$\text{SIM}(A, C, F_2) = \frac{1}{1 + 0.5 \times 1 + 0.5 \times 1} = 0.5,$$

$$\text{SIM}(A, C, F_3) = \frac{1}{1 + 0 + 0.5 \times 2} = 0.5.$$

Accordingly, the structural attribute similarity between A and C is

$$\text{SIM}_F^{\text{Total}}(A, C) = \frac{0.5 \times 0 + 0.2 \times 0.5 + 0.3 \times 0.5}{1} = 0.250.$$

Similarly, the demand similarity between A and C is $\text{SIM}_D^{\text{Total}}(A, C) = 0.667$. According to (9),

Enterprise	Main Product	Structural Feature F1: Cooling Method (Weight 0.5)	Structural Feature F2: Compressor Type (Weight 0.2)	Structural Feature F3: Energy Efficiency Level (Weight 0.3)	Demand Feature D1: Color Preference (Weight 0.4)	Demand Feature D2: Control Function (Weight 0.6)
A	H_A	{Air cooling}	{Inverter, Dual inverter}	{Level 1}	{White, Black, Dark gray}	{Touch screen, Buttons, Voice control, APP remote control, WiFi smart connection}
B	H_B	{Direct cooling}	{Inverter, Fixed-frequency}	{Level 2, Level 3}	{White, Black, Floral}	{Buttons, Remote control, APP remote control}
C	H_C	{Direct cooling}	{Inverter, Fixed-frequency}	{Level 1, Level 2, Level 3}	{White, Black, Floral}	{Touch screen, Buttons, Remote control, APP remote control}

Table 2: Feature information and corresponding weights of main refrigerator products of enterprises A, B, and C.

when $\delta = 0.6$, the overall similarity between A and C is:

$$\text{SIM}^{\text{Total}}(A, C) = 0.6 \times \text{SIM}_F^{\text{Total}}(A, C) + (1 - 0.6) \times \text{SIM}_D^{\text{Total}}(A, C) \approx 0.417.$$

The structural attribute similarity $\text{SIM}_F^{\text{Total}}(B, C)$, customer demand similarity $\text{SIM}_D^{\text{Total}}(B, C)$, and overall similarity $\text{SIM}^{\text{Total}}(B, C)$ between B and C can be calculated using the same method. The similarity indicators between each pair of enterprises are shown in Table 3. As can be seen, the main products of B and C are more similar, and thus B is more likely to be selected as a cooperation partner for C.

Enterprise pair	Structural attribute similarity	Customer demand similarity	The weighted similarity
(A, C)	0.250	0.667	0.417
(B, C)	0.940	0.914	0.930

Table 3: Similarity metrics of main products between enterprise pairs.

3.3. Supply-sales dual-layer network model

The cooperative and competitive relationships among similar enterprises are reflected by the similarity of their main products, while the connections between suppliers and sales enterprises are established through product-based supply-demand relationships, as illustrated in Figure 2. The supplier network and the sales network together form a two-tier structure, in which circular nodes represent suppliers and square nodes denote sales enterprises. Different colors indicate variations in the core products operated by each enterprise. The colored pentagons represent product features, with each product defined by a combination of multiple features. Due to the heterogeneity of product features, enterprises may exhibit varying degrees of similarity or difference in their primary business focus.

In practice, the cooperative relationship between suppliers and sales enterprises can be summarized as a supply-demand relationship. From a market perspective, this cooperative relationship is the result of bilateral selection:

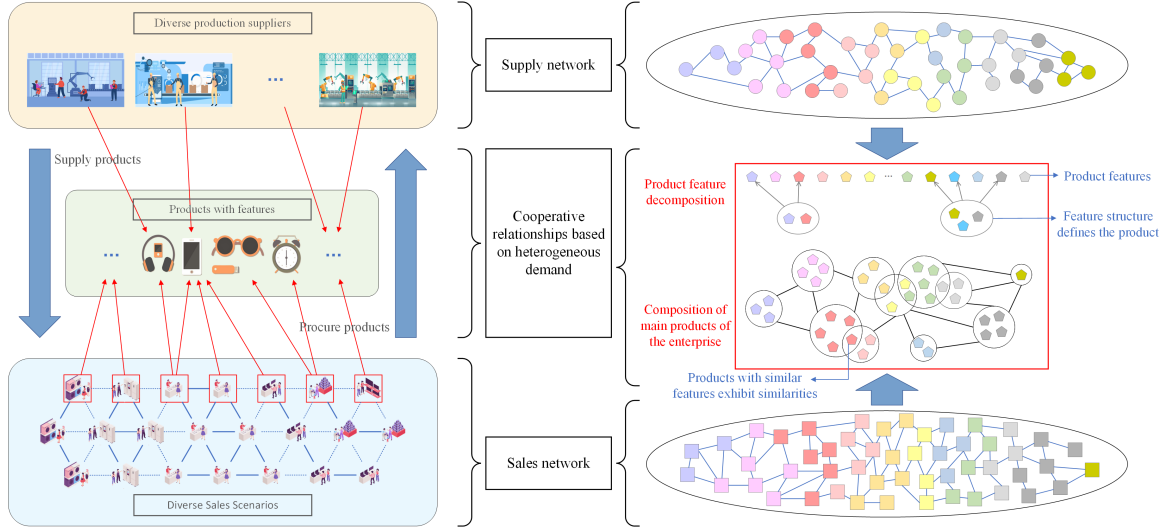


Figure 2: Supply-demand relationships for products in supply-sales dual-layer supply chains. (Note: Circular nodes represent suppliers, square nodes denote sales enterprises, and node colors indicate differences in their core product features.)

Suppliers, as product providers in this relationship, prioritize collaboration with sales enterprises that are large, influential, and high-status. For sales enterprises, a broader product range, larger customer base, and more sales channels indicate stronger market survival and greater influence. Therefore, we use the sum of product similarities between a sales enterprise and other sales enterprises to represent the influence of a sales enterprise, defining the influence of sales enterprise i as

$$IF_i = \sum_{j \in \Omega_i} w_{i,j}^A, \quad (12)$$

where Ω_i is the set of intra-layer neighboring nodes of node i .

As the consumer side of this cooperative relationship, sales enterprises have different value assessments for different collaborating enterprises. In this context, how to develop profit strategies and select high-quality cooperative customers, based on internal structural costs and external market demands, to enhance overall competitiveness is a critical issue that suppliers need to consider. We categorize the production and operational processes of supplier enterprises into two main types: recycling and remanufacturing, and traditional production processes. We introduce decision variables and parameters related to these processes.

The recycling and remanufacturing process is primarily divided into two steps:

Step 1: Recovering products from customers and extracting the usable quantity of raw materials, denoted as IN_j , from the recovered products.

Step 2: Transporting TQ_j quantity of recovered materials to the production center for secondary use.

The production process consists of four steps:

Step 1: Procuring the necessary raw materials j from raw material suppliers, with a procurement quantity of S_j .

Step 2: Selecting a specific production mode k to produce a quantity $MQ_{k,p}$ of product p at the production center.

Step 3: Transporting a portion of the produced SI_p quantity of products from the production center to the warehouse.

Step 4: After the products are sold, transporting them from the warehouse to customers, with an outgoing product quantity of SO_p and a remaining raw material inventory of M_j .

The production and operational process of supplier enterprises is illustrated in Figure 3.

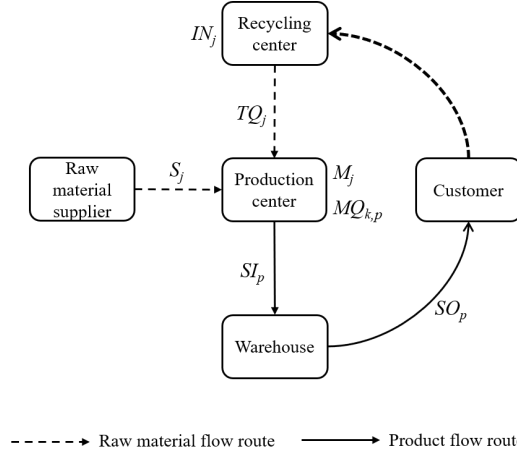


Figure 3: The production and operational process of supplier enterprises.

Assuming that the total quantity of products is P , the total quantity of materials is J , the total quantity of production modes is K , the market demand for product p is D_p , the selling price of product p is SL_p , the unit procurement cost of raw material j is CP_j , the unit production cost of product p using production mode k is $C_{k,p}$, the unit transportation cost from the production center to the warehouse for product p is TC_p , the unit conversion cost of material j from the recycling center to the production center is TM_j , the unit storage cost of material j at the recycling center is HO_j , the unit inventory storage cost for product p is HW_p , and the average cost of work-in-process (WIP) for the enterprise is HC_j .

Based on the above variables, the enterprise's profit and various costs can be calculated as follows:

- Sales Revenue: $SA = \sum_{p=1}^P SL_p \times D_p$
- Production Cost: $PC = \sum_{p=1}^P \sum_{k=1}^K C_{k,p} \times MQ_{k,p}$
- WIP Cost: $HC = \sum_{j=1}^J HC_j \times M_j$
- Inventory Cost: $HW = \sum_{p=1}^P HW_p \times SO_p$
- Procurement Cost: $CP = \sum_{j=1}^J CP_j \times S_j$
- Transportation Cost: $TC = \sum_{p=1}^P TC_p \times SI_p$
- Conversion Cost: $TM = \sum_{j=1}^J TM_j \times TQ_j$
- Recycling Storage Cost: $HO = \sum_{j=1}^J HO_j \times IN_j$

By deducting various costs from the revenue, the profit of the supplier enterprise can be calculated as

$$PF = SA - PC - HC - HW - CP - TC - TM - HO. \quad (13)$$

For supplier enterprises, improving comprehensive competitiveness requires not only increasing profits but also enhancing the quality and quantity of cooperative customers, which is

positively correlated with their stability in the supply chain network. Based on this, we define the supply competitiveness of an enterprise i as

$$CM_i = \eta \left(\frac{PF_i}{\sum_{j \in V^S} PF_j / N^S} \right) + \xi \left(\frac{\sum_{k \in \Gamma_i} IF_k / N_{\Gamma_i}}{\sum_{k \in V^A} IF_k / N^A} \right) + (1 - \eta - \xi) \left(\frac{Q_i}{\sum_{j \in V^S} Q_j / N^S} \right), \quad (14)$$

where CM_i represents the supply competitiveness of supplier enterprise i , PF_i denotes the profit of supplier enterprise i , Γ_i represents the set of cross-layer neighboring nodes of node i , IF_k indicates the influence of sales enterprise k , and Q_i signifies the number of sales enterprises with which supplier enterprise i has a cooperative relationship. $\eta \in [0, 1]$ and $\xi \in [0, 1]$ are tunable parameters, representing the supplier's emphasis on its own profit and the quality of cooperative sales enterprises, respectively.

The cooperative relationships between supplier and sales enterprises are represented as cross-layer edges, with weights reflecting the cooperation strength, positively correlated with the influence of sales enterprises and the supply competitiveness of suppliers. The cross-layer edge weight is defined as

$$w_{i,j}^C = \begin{cases} CM_i \times IF_j, & \text{if enterprise } i \text{ and } j \text{ have a cooperative relationship} \\ 0, & \text{if enterprise } i \text{ and } j \text{ have no cooperative relationship} \end{cases}. \quad (15)$$

The cross-layer edges between the supply network and the sales network can be represented by a symmetric adjacency matrix $\mathbf{M}^C$, expressed as

$$\mathbf{M}^C = \begin{pmatrix} w_{1,1}^C & \cdots & w_{1,N^A}^C \\ \vdots & \ddots & \vdots \\ w_{N^S,1}^C & \cdots & w_{N^S,N^A}^C \end{pmatrix}. \quad (16)$$

Since both the similarity that determines edge weights and the strength of cooperative relationships are symmetric, we assume that edges in this dual-layer network are undirected. For clarity, Figure 4 provides an example of a dual-layer supply chain network model, and Table 4 summarizes the notations used in the network model and the cascading failure model.

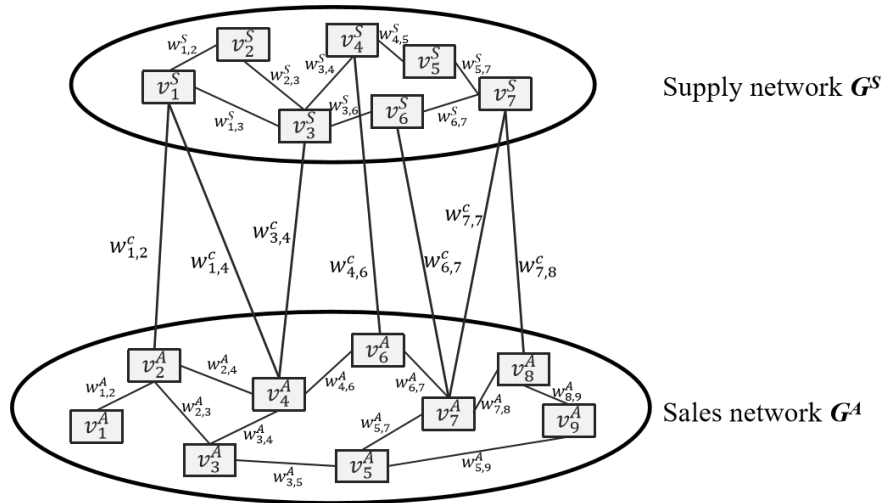


Figure 4: Example of a dual-layer supply chain network model.

Notations	Descriptions
$G^S; G^A$	Supply network; sales network
$V^S; V^A$	Set of supplier nodes; set of sales enterprise nodes
$E^S; E^A$	Set of edges between supplier nodes; between sales enterprise nodes
$W^S; W^A$	Set of edge weights between supplier nodes; between sales enterprise nodes
$N_S; N_A$	Total number of nodes in the supply network; in the sales network
$\mathcal{F}; \mathcal{D}$	Set of product structural attribute features; set of customer demand features
$N^F; N^D$	Number of product structural attribute features; number of customer demand features
$f; d$	Structural attribute features element; customer demand feature element
$W^F; W^D$	Set of weights for structural attribute features; set of weights for customer demand features
$\alpha; \beta$	Weight of structural similarity; weight of demand similarity
$\lambda_{i,j}; \mu_{i,j}$	Edge stability between nodes i and j ; cooperation strength between nodes i and j
$M^S; M^A; M^C$	Adjacency matrix of the supply network; adjacency matrix of the sales network; cross-layer adjacency matrix of the dual-layer supply chain network
$w_{i,j}^C$	Cross-layer edge weight between supplier enterprise i and sales enterprise j
δ	Weight of structural similarity in the total similarity score
$CM_i; PF_i; IF_k; Q_i$	Supply competitiveness of supplier i ; profit of supplier i ; influence of sales enterprise k ; number of cooperative sales enterprises of supplier i
$IN_j; TQ_j; S_j;$ $MQ_{k,p}; SI_p; SO_p;$ M_j	Recovered raw materials; quantity of transported recovered materials; procured raw material j ; product p under mode k ; quantity to warehouse; quantity sold; remaining inventory of raw material j
$P; J; K; D_p; SL_p;$ $CP_j; C_{k,p}; TC_p;$ $TM_j; HO_j; HW_p;$ HC_j	Total number of products; raw materials; production modes; market demand and selling price of product p ; unit procurement cost of raw material j ; unit production cost of product p under mode k ; unit transportation cost of product p to warehouse; unit conversion and storage cost of material j ; unit inventory cost of product p ; average work-in-process cost for material j
$SA; PC; HC;$ $HW; CP; TC;$ $TM; HO$	Total sales revenue; total production cost; work-in-process cost; inventory cost of products; procurement cost of raw materials; transportation cost of products to warehouse; conversion cost of recovered materials; storage cost of recovered materials
$\eta; \xi$	Weight of supplier's own profit; weight of cooperative sales enterprise quality
$\Omega_i; \Gamma_i; \Phi_j; \Psi_j; \Pi_{j,i}$	Set of intra-layer neighbors of node i ; cross-layer neighbors of node i ; same-layer indirectly failed neighbors of node j ; cross-layer failed suppliers of sales node j ; replacement suppliers found by node j for failed supplier i
$\varphi_i; \psi_i$	Eigenvector centrality of node i in the intra-layer and cross-layer network, respectively
$z^S; z^C$	The largest eigenvalue of the intra-layer adjacency matrix $\mathbf{M}^S$; the largest eigenvalue of the cross-layer adjacency matrix $\mathbf{M}^C$.
$C_i^{\max}; C_i^{\min}$	The upper limit of the load that node i can withstand; the lower limit of the load that node i can withstand.
$\sigma; \tau$	Tunable parameters indicating an enterprise's tolerance for overload risk; tunable parameters indicating an enterprise's tolerance for underload risk.
$RA_i; L_i$	Load loss ratio of node i ; actual load of node i
$HCCI_{i,j}$	Horizontal Competition-Cooperation Index between enterprise j and i
$P_{i,j}^S; P_{i,j}^A$	Probability of selecting node j as a replacement for failed node i in the supply network; in the sales network
$\Delta L_{i,j,k}; \Delta L_{i,j};$ $L_{i,k}$	Additional load received by same-layer node j from failed node i via node k Load to be redistributed from node i through intermediary node k
$\Delta L_j^{\theta_S}; \Delta L_{i,j}^{\theta_S};$ $\Delta L_{i,j,k}^{\theta_S}$	Total additional load on node j from all same-layer indirectly adjacent failed nodes; from node i to node j ; from node i to node j via node k , all considering supplier information transparency

Table 4: Notations in the system model and cascading failure model.

4. Cascading failure model

In this Section, we introduce the details of the cascading failures in the proposed dual-layer supply chain model.

4.1. Initial load

In a supply chain, the flow of products and the operations of enterprises are influenced by the combined effects of material flow, capital flow, and information flow. Therefore, similar to most studies on supply chain resilience, we refer to these flows as “resource flows.” For enterprises, the higher the quality of their partners and the better the cooperation, the more significant their role becomes in the network, meaning they bear a greater flow of resources. This is consistent with the concepts of node degree and eigenvector centrality. Hence, we propose a definition of initial load that integrates both node degree and eigenvector centrality:

$$L_i(0) = \sum_{j \in \Omega_i} (k_i^{\text{in}} k_j^{\text{in}})^{\varphi_i} + \sum_{j \in \Gamma_i} (k_i^{\text{C}} k_j^{\text{C}})^{\psi_i}, \quad (17)$$

where $L_i(0)$ denotes the initial load of node i ; k_i^{in} is the intra-degree of node i , representing the number of edges within the same layer; k_i^{C} is the cross-degree of node i , representing the number of edges connecting different layers; and φ_i and ψ_i represent the eigenvector centrality of node i in the intra-layer and cross-layer network dimensions. In the context of the supply chain network, the eigenvector centrality of an enterprise can be understood as reflecting the positive impact of its cooperative partners’ resources on its own resources. For supply network node i as an example, the value of φ_i is calculated by

$$\varphi_i = \frac{1}{z^{\text{S}}} \sum_{j \in \Omega_i} w_{i,j}^{\text{S}} \varphi_j, \quad (18)$$

where z^{S} is the largest eigenvalue of the edge adjacency matrix $\mathbf{M}^{\text{S}}$ for node i within the supply network. For sales network nodes, a similar calculation applies. The eigenvector centrality of node i in the cross-layer dimension is calculated as

$$\psi_i = \frac{1}{z^{\text{C}}} \sum_{j \in \Gamma_i} w_{i,j}^{\text{C}} \psi_j, \quad (19)$$

where z^{C} is the largest eigenvalue of the cross-layer edge adjacency matrix $\mathbf{M}^{\text{C}}$ for node i in the dual-layer network.

4.2. Load capacity

In the proposed dual-layer supply chain network model, we consider both overload and underload failure scenarios. For suppliers, receiving orders that exceed their production capacity can lead to failure due to factors such as insufficient capacity, goods accumulation, or cash flow issues. For sales enterprises, purchasing quantities that exceed their sales capacity may result in failure due to insufficient market demand or inventory backlog. We refer to these situations as overload failures. On the other hand, suppliers may face failure risks due to cash shortages caused by insufficient orders, while sales enterprises may experience operational issues from product shortages if their procurement quantities are too low. We refer to these situations as underload failures. This implies that the load on enterprise nodes must remain within an acceptable range, and deviations above or below this range will lead to failure. We assume that an enterprise’s load-bearing capacity is positively correlated with its scale, meaning the upper and lower load limits of a node are proportional to its initial load. Based on this assumption,

we define the upper and lower load capacity limits for nodes in the network as follows:

$$C_i^{\max} = (1 + \sigma)L_i(0), \quad (20)$$

$$C_i^{\min} = (1 - \tau)L_i(0), \quad (21)$$

where $C_i^{\max}$ represents the upper limit of the load that the node can withstand, and $C_i^{\min}$ represents the lower limit; $\sigma \in [0, 1]$ and $\tau \in [0, 1]$ are tunable parameters that reflect an enterprise's ability to withstand risks arising from fluctuations in its load.

Existing research on node-level cascading failures mostly assumes that nodes operate normally within an acceptable load threshold and fail immediately when their load exceeds or falls below a certain range [17, 18]. However, this work argues that enterprises typically possess a certain level of self-regulation to cope with operational fluctuations. For example, when experiencing poor performance, an enterprise does not immediately cease operations. Instead, it may scale down its activities—such as by rejecting some orders or reducing its purchasing volume of raw materials—to maintain basic functionality. In our model, node states are dynamic, referred to as *dynamic node state*, which aligns with the gradual failure characteristics exhibited by enterprises during the cascading failure process. Unlike the traditional binary classification of node states as either “functional” or “failed,” the model developed in this paper allows nodes to adjust their operational scale in response to load fluctuations, thereby delaying or avoiding complete failure. In this framework, node state transitions are not instantaneous but evolve dynamically based on load levels. A node remains functional as long as its load stays within its upper and lower capacity limits. As the load approaches these thresholds, the enterprise begins to experience partial performance degradation, manifested as weakened ability to absorb or release load. A node only completely fails—and loses all functional capacity—when its load fully exceeds the tolerable range. Based on this mechanism, we define the load loss ratio of node i as calculated by

$$RA_i(t) = \begin{cases} 1, & L_i(t) < C_i^{\min} \text{ or } L_i(t) > C_i^{\max} \\ \frac{C_i^{\max} - L_i(t)}{C_i^{\max} - C_i^{\min}}, & C_i^{\min} \leq L_i(t) \leq C_i^{\max} \end{cases}, \quad (22)$$

where $L_i(t)$ denotes the load of node i at time t . (22) captures the evolutionary process of the node state as a function of load: within the tolerable range, the load loss rate dynamically adjusts with variations in the load; once the load exceeds the acceptable bounds, the node fails immediately, and the load loss rate reaches 100%.

4.3. Cascading failure mechanism

4.3.1. Failure process considering indirectly adjacent failures

In real-world supply chain scenarios, when an enterprise shuts down or loses orders, the resource flow may not directly pass to all its competing and cooperating enterprises. Instead, it first affects its downstream partners, and through adjustments in the new cooperation model by these downstream enterprises, the impact is indirectly transmitted to other similar enterprises, as shown in Figure 5. To address this, we propose a cascading failure mechanism that considers indirectly adjacent failures. In this mechanism, the load redistribution caused by cascading failures in the supply chain network takes into account cross-layer connections, with the path of load redistribution determined by the neighboring nodes of the failed node.

In our proposed cascading failure mechanism, the process unfolds as follows: when a supplier enterprise fails, the sales enterprises that have a cooperative relationship with it will lose part of their product supply. To maintain their operational scale, they will increase orders from other cooperating suppliers or choose new suppliers. In this way, the load from the failed enterprise is transferred to similar enterprises, leading to an increase in their load. This process

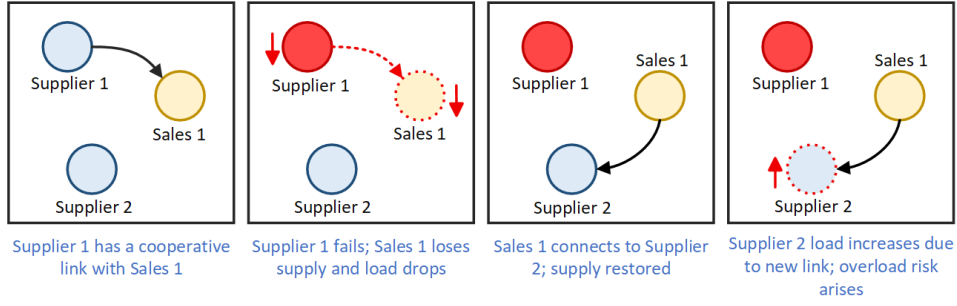


Figure 5: Failure propagation process among indirectly adjacent nodes.

continues until the sales enterprise cannot find a suitable new supplier and is forced to reduce its product operations in accordance with the supply ratio, entering an underloaded state. The process is similar when a sales node fails. As this process repeats, it continues until a large-scale node failure occurs within the network, leading to a loss of network functionality, or until the propagation of failures is absorbed by the network and stops, concluding the cascading failure.

According to the cascading failure process described above, we propose that when enterprise node i fails at time t for certain reasons, the load originally carried by it will be redistributed to other nodes at the same layer, but in a manner different from traditional approaches. We introduce the concept of same-layer indirect adjacency: if node i has a cross-layer adjacent node k , and node k 's cross-layer adjacent node j is at the same layer as node i , then node i and node j are considered indirectly adjacent. The proposed load redistribution mechanism includes two components: intra-layer indirect adjacency redistribution and cross-layer proportional adjustment redistribution. The flowchart of the cascading failure mechanism is shown in Figure 6.

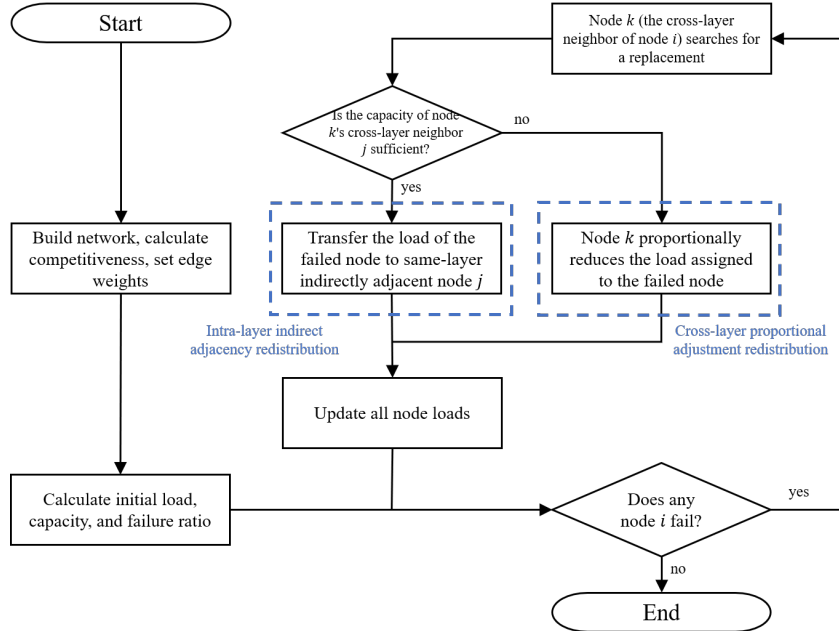


Figure 6: Cascading failure mechanism of dual-layer supply chain under enterprise competition.

4.3.2. Replacement node selection

In the case of supply shortages, sales enterprises will choose new suppliers to replace the original failed supplier and establish new cooperative relationships. When selecting a replacement supplier, the primary consideration for the sales enterprise is to compensate for the products

that share similar structural attributes. Therefore, we introduce the Horizontal Competition-Cooperation Index ($HCCI$) to measure the resource proportion of enterprises operating similar products to those of the already failed enterprises. The $HCCI$ of enterprise j relative to the failed enterprise i is defined as

$$HCCI_{i,j} = \frac{\text{SIM}_{\text{Total}}^F(H_i, H_j)}{\sum_{j \in \Omega_i} \text{SIM}_{\text{Total}}^F(H_i, H_j) / N_{\Omega_i}}, \quad (23)$$

where N_{Ω_i} denotes the number of nodes in Ω_i .

In a market environment characterized by heterogeneous demand and multi-supplier competition, in addition to the $HCCI$, the remaining load margin that supplier t can bear at time t and its own competitiveness will also influence the sales enterprise's choice of replacement suppliers. Sales enterprises tend to prefer collaborating with suppliers that have sufficient load capacity and strong competitive abilities. Therefore, the probability $P_{i,j}^S$ of selecting supply network node j as a replacement for the failed supply network node i is defined as

$$P_{i,j}^S = \frac{RL_j}{\sum_{k \in V^S} RL_k / N^S} \times \frac{CM_j}{\sum_{k \in V^S} CM_k / N^S} \times HCCI_{i,j}. \quad (24)$$

Similarly, the probability $P_{i,j}^A$ of selecting sales enterprise node j as a replacement for failed sales enterprise node i is defined as

$$P_{i,j}^A = \frac{RL_j}{\sum_{k \in V^A} RL_k / N^A} \times \frac{IF_j}{\sum_{k \in V^A} IF_k / N^A} \times HCCI_{i,j}. \quad (25)$$

The remaining load capacity of node i at time t , denoted as $RL_i(t)$, is calculated as

$$RL_i(t) = C_i^{\max} - L_i(t). \quad (26)$$

4.3.3. Cascading failure propagation within the same-layer network

Assume that at time t , supply network node i fails. At time $t+1$, the cross-layer neighboring node k of node i must find a new supplier node. If a suitable replacement node j is found, a new edge is established between node k and j ; otherwise, no new edge is formed. The load lost by node i will be redistributed through node k to its cross-layer adjacent nodes, namely the indirectly adjacent nodes of node i . Furthermore, the stronger the collaboration between node k and its neighbors, and the greater the proportion of similar resources shared with node i , the more load will be redistributed to those nodes. Thus, the additional load $\Delta L_{i,j,k}$ received by the same-layer indirectly adjacent node j of the failed node i , via node i 's cross-layer neighboring node k , is given by

$$\Delta L_{i,j,k} = \frac{w_{k,j}^C}{\sum_{r \in \Gamma_k} w_{k,r}^C} \times L_{i,k}, \quad (27)$$

where $L_{i,k}$ denotes the amount of load redistributed from node i via node k , which can be calculated as

$$L_{i,k} = \frac{w_{i,k}^C}{\sum_{r \in \Gamma_i} w_{i,r}^C} \times L_i \times RA_i. \quad (28)$$

Finally, the total additional load $\Delta L_{i,j}$ received by node j from node i is given by

$$\Delta L_{i,j} = \sum_{k \in \Gamma_i} \Delta L_{i,j,k}. \quad (29)$$

In actual supply chain networks, when enterprises compete, they may not provide accurate information about themselves in order to gain cooperative benefits. Since the information provided by the enterprises directly affects the cooperative relationships between them, we introduce the concept of transparency in enterprise information within both the supply and sales networks, denoted as θ_S and θ_A , respectively. These variables measure the impact of the incomplete information provided by enterprises on the network during competition in the supply chain. Specifically, information transparency reflects the degree to which an enterprise truthfully discloses its operational status in the context of competition and cooperation. This includes, but is not limited to: current load levels, remaining capacity (such as inventory and production capability), cost-benefit information of products and services, delivery performance capability, and the strength of historical cooperation with upstream and downstream enterprises. A higher level of information transparency enables enterprises to identify suitable substitute nodes based on more accurate and comprehensive information, thereby facilitating rational load redistribution and effectively mitigating the impact of node failures. In contrast, lower transparency may lead to biased perceptions, resulting in erroneous substitution decisions and imbalanced resource allocation, which in turn amplifies the failure effect. Building on this, we propose a method for calculating load distribution under conditions of incomplete information:

$$\Delta L_{i,j,k}^{\theta_S} = \frac{(w_{k,j}^C)^{\theta_S}}{\sum_{r \in \Gamma_k} (w_{k,r}^C)^{\theta_S}} \times L_{i,k}, \quad (30)$$

where $\theta_S \in [0, 1]$ represents the transparency of supplier enterprise information. $\Delta L_{i,j,k}^{\theta_S}$ denotes the additional load that the same-layer indirect adjacent node j receives from node i via node k after considering the transparency of enterprise information. When $\theta_S = 1$,

$$\Delta L_{i,j,k}^{\theta_S} = \Delta L_{i,j,k}. \quad (31)$$

This indicates that the enterprise information is completely transparent, resulting in the same distribution outcome as when the transparency of enterprise information is not considered. When $\theta_S = 0$,

$$\Delta L_{i,j,k}^{\theta_S} = \frac{1}{N_{\Gamma_k}} \Delta L_{i,j,k}, \quad (32)$$

where N_{Γ_k} represents the number of cross-layer neighboring nodes of node k , and (32) indicates that when the information required by the enterprise is completely missing, the load loss of node i is evenly distributed among its indirectly adjacent nodes via cross-layer neighboring nodes. Finally, the total additional load $\Delta L_{i,j}^{\theta_S}$ received by node j from node i , considering enterprise information transparency, is calculated by

$$\Delta L_{i,j}^{\theta_S} = \sum_{k \in \Gamma_i} \Delta L_{i,j,k}^{\theta_S}. \quad (33)$$

Thus, considering incomplete enterprise information, the additional load ΔL_j received by node j from all its same-layer indirectly adjacent failed nodes at time t is calculated as

$$\Delta L_j^{\theta_S}(t) = \sum_{i \in \Phi_j} \Delta L_{i,j}^{\theta_S}(t), \quad (34)$$

where Φ_j denotes the set of same-layer indirectly adjacent failed nodes of node j . Furthermore, the load of node j at time $t+1$ is the sum of the load from the node at time t and the additional load it receives, defined as

$$L_j(t+1) = L_j(t) + \Delta L_{i,j}^{\theta_S}(t). \quad (35)$$

At this point, if $L_j > C_j^{\max}$, meaning that the load on node j exceeds its capacity limit, the node will become overloaded and fail, entering a new round of load redistribution. Such cascading failures will spread throughout the network. The cascading failure process in the sales enterprise network, along with redistribution and the use of the transparency of sales enterprise information θ_A , follows similar rules to those mentioned above, so it will not be elaborated upon here.

The redistribution mechanism defined in (30)–(35) indicates that the proposed model accounts for the resource reallocation process under conditions of information opacity, exhibiting a disturbance amplification pattern similar to the bullwhip effect. Traditionally, the bullwhip effect refers to the phenomenon where downstream demand information is progressively amplified as it propagates upstream in a supply chain, ultimately causing severe fluctuations for upstream enterprises. Although the cascading failure in this study shares certain similarities, its root cause does not lie in inaccurate market demand forecasts. Instead, it arises from irrational redistribution of the failed node's load under incomplete information. When a node fails, its remaining load is allocated to candidate substitute nodes within the network. Under low transparency, enterprises may misjudge the capabilities and status of their partners, resulting in the formation of suboptimal connections and inefficient redistribution. Such misallocations distort the balance of resource allocation, amplifying what could otherwise have been a locally absorbable disturbance, and triggering further node failures that eventually lead to cascading failures. Therefore, the “bullwhip-like effect” demonstrated in this model is not a result of traditional supply-demand volatility, but rather a structurally induced amplification mechanism caused by information opacity and misallocation of resources.

4.3.4. Cascading failures between dual-layer networks

After a node fails in the supply network G^S , the corresponding load changes will be transmitted to the sales network G^A through cross-layer connections, due to the product supply and demand relationship. Assuming that supplier node i fails at time t , if its cross-layer neighboring node j cannot find a new supplier to provide similar products, or if the replacement cannot fully compensate for the amount previously provided by node i , i.e., $\sum_{m \in \Pi_{j,i}} RL_m(t) < L_{i,j}(t-1)$, where $\Pi_{j,i}$ represents the set of replacement nodes that node j has found for the failed node i . If no suitable replacement supplier is found, sales enterprise node j must adjust its product operating volume based on the current situation, leading to a decrease in load. The amount of load lost by node j is related to the proportion of products provided by various suppliers and is calculated by

$$\Delta L_{i,j}(t) = \left(\frac{w_{i,j}^C}{\sum_{k \in \Gamma_j(t-1)} w_{k,j}^C} - \frac{\sum_{m \in \Pi_{j,i}(t)} w_{m,j}^C}{\sum_{k \in \Gamma_j(t)} w_{k,j}^C} \right) \times L_j(t), \quad (36)$$

where $\Delta L_{i,j}(t)$ represents the change in load for node j at time t ; $\Gamma_j(t)$ represents the set of cross-layer neighboring nodes of node j at time t ; $\Pi_{j,i}(t)$ is the set of replacement nodes that node j seeks to replace node i at time t . When $\Delta L_{i,j}(t) > 0$, sales node j experiences a decrease in load due to the loss of sufficient supply cooperation relationships. However, when $\Delta L_{i,j}(t) \leq 0$, the cooperation relationship established between sales node j and replacement supplier node m may even be stronger than the original cooperation relationship with the failed supplier node i . In this case, node j can be considered to have occupied some of the other cooperative resources of replacement node m , and as a result, the load on node j does not decrease but may even increase. Thus, the load ΔL_j lost by node j due to all its cross-layer

failed nodes at time t is calculated as

$$\Delta L_j(t) = \sum_{i \in \Psi_j} \Delta L_{i,j}(t), \quad (37)$$

where Ψ_j denotes the set of cross-layer failed nodes of node j . Similarly, the load of node j at time $t + 1$ is updated by subtracting the lost load, expressed as

$$L_j(t + 1) = L_j(t) - \Delta L_j(t). \quad (38)$$

At this point, if $L_j < C_j^{\min}$, meaning that the load on node j is below its capacity threshold, the node will experience an underload failure and enter a new round of load redistribution. Such cascading failures will then spread within the dual-layer network. The process of cascading failure propagation from the sales network to the supply network is similar and will not be elaborated upon here.

4.4. Example of cascading failure process

To facilitate understanding of the specific process of cascading failures in the dual-layer supply chain, this section presents the cascading failure propagation process of a dual-layer supply chain network through Figures 7(a) to (f). The upper-tier supply network consists of 12 nodes, while the lower-tier sales network consists of 9 nodes. The cascading failure process in this network occurs as follows: Assume that the upper-tier supplier node v_5^S fails, as shown in Figure 7(a). After v_5^S fails, its cooperating nodes v_3^A and v_5^A will transfer the relevant resources to other suppliers. This means that v_5^S 's load is passed through its cross-layer adjacent cooperating nodes v_3^A and v_5^A to their suppliers, v_4^S and v_6^S , resulting in an increase in the loads of v_4^S and v_6^S . At the same time, v_2^A and v_5^A will search for new suppliers to replace v_5^S . Suppose v_5^A finds a replacement node, v_8^S , and establishes a new cross-layer cooperation edge (blue arrow). v_8^S , as the new supplier for v_5^A , will also receive part of the load, leading to an increase in v_8^S 's load, as shown in Figure 7(b). At this point, node v_6^S receives too much load, exceeding its capacity limit, and enters overload failure. This failure will affect its cross-layer adjacent cooperating nodes, v_3^A and v_5^A . Since no suitable replacement node can be found to compensate for the load, v_3^A and v_5^A are forced to reduce their loads, as shown in Figure 7(c). Due to the underload failure of v_3^A and v_5^A , their cooperating nodes, v_4^P and v_8^P , experience a decrease in load, as shown in Figure 7(d). v_4^S and v_8^S undergo underload failure. As the remaining suppliers cannot compensate for the load, the load on v_1^A also decreases proportionally. Meanwhile, v_6^A finds a replacement node, v_9^S , and transfers its load to cooperating supplier nodes v_7^S and v_9^S , resulting in an increase in the loads of v_7^S and v_9^S . v_7^A also transfers part of its load to v_{10}^S , causing v_{10}^S 's load to increase, as shown in Figure 7(e). v_1^A experiences underload failure, while v_7^S and v_{10}^S experience overload failure. At this point, node v_4^A has difficulty finding a replacement for its only supplier node, v_7^S , and is on the verge of failure. v_2^S also struggles to find a replacement sales node for its only sales node, v_1^A , and is about to fail. v_9^S also experiences a decrease in load due to supplier failures. However, v_1^S finds a replacement sales node, v_2^A , which causes v_2^A 's load to increase, as shown in Figure 7(f). At this point, only 6 fully functioning nodes remain in the network, and we consider the supply chain network to be severely damaged.

5. Experimental results

5.1. Experimental setup

The data used to construct the dual-layer supply chain topology is derived from a real-world automotive supply chain case [19, 20, 21]. Based on this, we construct a dual-layer supply chain network consisting of 30 supplier nodes and 55 sales enterprise nodes, with average node

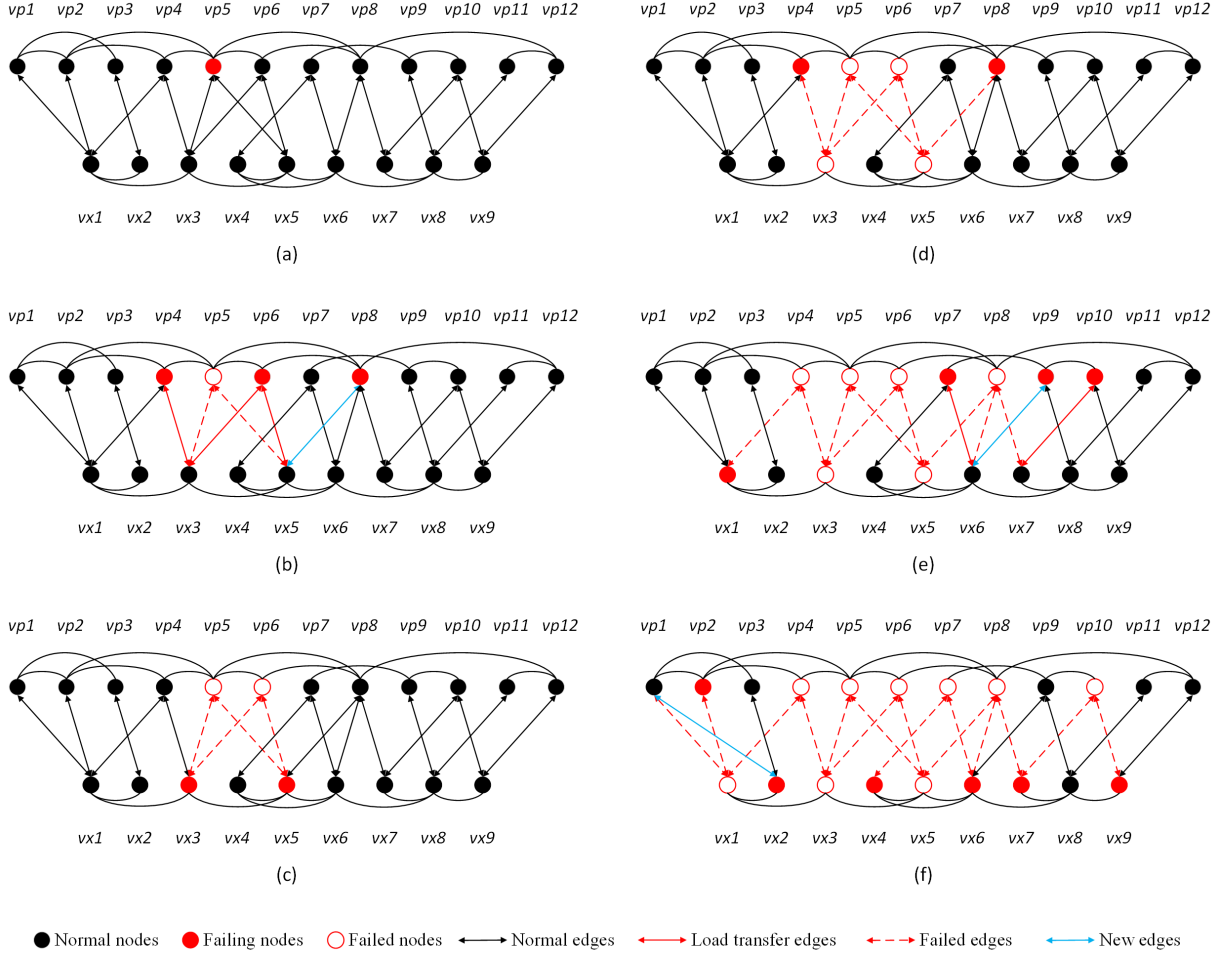


Figure 7: Example of cascading failure process in a dual-layer supply chain under enterprise competition.

degrees of 4.3 in the supplier network and 5.5 in the sales network. The product feature set for each enterprise node is generated from publicly available business data [22, 23], enabling the calculation of product similarity and the determination of edge weights among same-layer nodes. Figure 8 shows the network structure, where yellow and blue circles represent supplier and sales nodes, respectively. We further conducted a structural analysis of the network and performed comparative validation against similar real-world cases, which confirmed the practicality and representativeness of the constructed model as a dual-layer supply chain network.

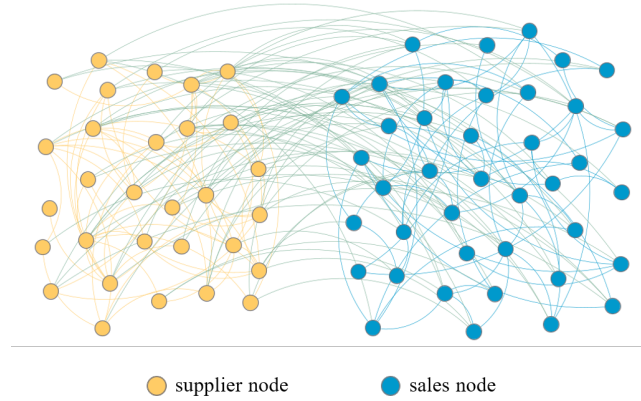


Figure 8: Experimental case network structure.

5.2. Cascading resilience metrics

In the simulation experiments, we introduce two triggering strategies for cascading failures: single-point attacks and multi-point attacks. In the single-point attack strategy, we sequentially select individual nodes from the network to attack and observe the resulting changes in the network. By normalizing all possible single-point attack scenarios in both the supply network and the sales network, we define the cascading reliability of the supply chain system under the single-point attack strategy as follows:

$$R_S^{\text{Single}} = \frac{\sum_{i \in V^S} (N_S^i + N_A^i)}{N^S(N^S + N^A)}, \quad (39)$$

$$R_A^{\text{Single}} = \frac{\sum_{i \in V^A} (N_S^i + N_A^i)}{N^A(N^S + N^A)}, \quad (40)$$

where R_S^{Single} represents the cascading resilience of the dual-layer supply chain network under single-point attacks in the supply network; N_S^i and N_A^i denote the number of surviving nodes in the supply network and sales network, respectively, after the removal of enterprise node i from the network. R_S^{Single} quantifies the average node survival rate of the supply chain network under single-node failure scenarios in the supplier network. Its value reflects the cascading resilience of the system. Specifically, a higher R_S^{Single} indicates that most nodes in the network remain functional under single-point attacks, suggesting that the system possesses strong resistance to disturbances and cascading failures, i.e., high cascading resilience. In contrast, a lower R_S^{Single} implies that node failures trigger wider cascading failures, indicating a more fragile system. Similarly, the cascading resilience of the sales network under single-point attacks is measured by R_A^{Single} , which follows the same definition logic. We use R_S^{Single} and R_A^{Single} as resilience indicators to assess the two-tier supply chain system's ability to maintain overall functionality under single-node failure scenarios. Under this attack strategy, there is no need to consider the selection of specific attack targets; therefore, we adopt single-point attacks to explore the impact of various modeling parameters on the network's cascading resilience.

In the multi-point attack strategy, we select multiple nodes in the network, accounting for a proportion q , to render them ineffective and observe the cascading failure process of the network. Specifically, considering the characteristics of both intra-layer and cross-layer relationships in the constructed dual-layer supply chain network model, we adopt the following three attack strategies:

- Intra-layer Degree Attack (IDA): Nodes are removed from the network in descending order based on their intra-layer degree.
- Cross-layer Degree Attack (CDA): Nodes are removed from the network in descending order based on their cross-layer degree.
- Load-based Attack (LA): Nodes are removed from the network in descending order based on their load.

We define the cascading resilience of the supply chain system under the multi-point attack strategy as follows:

$$R_S^{\text{Multi}} = \frac{N_{S,S}^q + N_{A,S}^q}{N^S + N^A}, \quad (41)$$

$$R_A^{\text{Multi}} = \frac{N_{S,A}^q + N_{A,A}^q}{N^S + N^A}, \quad (42)$$

where $N_{S,A}^q$ denotes the number of surviving nodes in the supply network after removing a proportion q of nodes from the sales network. Similarly, $N_{S,S}^q$, $N_{A,S}^q$, and $N_{A,A}^q$ are defined

following the same logic. R_S^{Multi} and R_A^{Multi} represent the cascading resilience of the dual-layer supply chain network following multi-point attacks on the supply network and the sales network, respectively. This indicator evaluates the system's ability to maintain its original functionality in the event of simultaneous node failures. A higher value of R_S^{Multi} indicates that the system retains a larger number of surviving nodes even under large-scale disturbances, suggesting stronger resistance to cascading failures. In contrast, a lower value implies that the system is more sensitive to multi-point shocks, structurally fragile, and more prone to widespread cascading failures. Unlike single-point attacks, multi-point attacks simulate simultaneous node failures within the system, thereby more accurately reflecting the complex impacts of real-world disruptive events. In this study, we adopt multi-point attacks to analyze the cascading resilience characteristics of the network under different attack strategies.

5.3. Rationality of the system model

Figure 9 presents the distribution of intra-layer degree, cross-layer degree, and load among nodes in the network. It can be observed that both intra-layer degree and cross-layer degree are positively correlated with node load. This suggests that companies with a broader range of main products and stronger competitive relationships tend to occupy a significant portion of market resources. Additionally, on average, the intra-layer degree among suppliers is relatively low, indicating strong heterogeneity in the products operated by supplier enterprises. Figure 10 shows the distribution of node loads in the supply network and the sales network. A comparison of the two networks clearly reveals significant differences in the distribution of node loads. The load distribution in the supply network roughly follows a power law, meaning that a small number of nodes bear a large portion of the network load. This aligns with the characteristic observed in real-world supply chains, where a few large suppliers occupy pivotal positions. In fact, the scale-free property of the supply network has been widely verified and studied in many research efforts [6, 24]. On the other hand, the load distribution indicates a more balanced load among nodes.

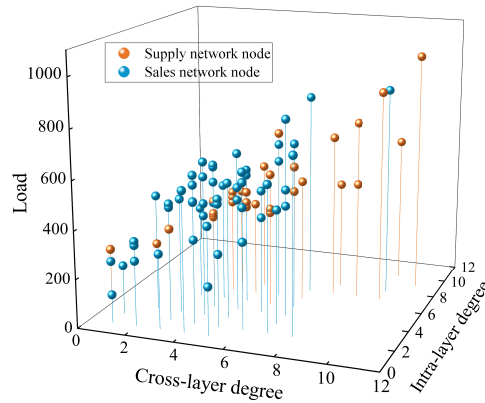


Figure 9: The relationship between the degree and load distribution of nodes in the network.

5.4. The impact of modeling parameters

5.4.1. The impact of load capacity parameters

As shown in Figure 11(a), as the lower limit of node load capacity, τ , increases, the cascading resilience of the network is significantly enhanced. Additionally, we can observe a critical threshold $\tau = 0.6$. When τ is less than 0.6, an increase in τ effectively improves the cascading resilience of the network. However, when τ exceeds 0.6, further increases in the lower limit of node capacity no longer impact the cascading resilience of the network. Figure 11(b) demonstrates that as the upper limit of node load capacity, σ , increases, the cascading resilience of

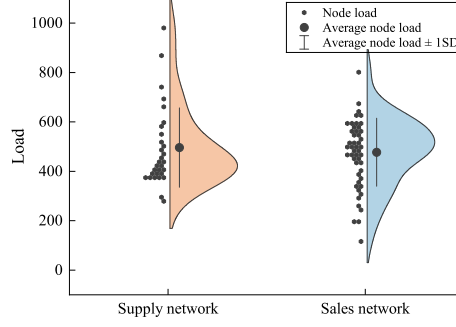
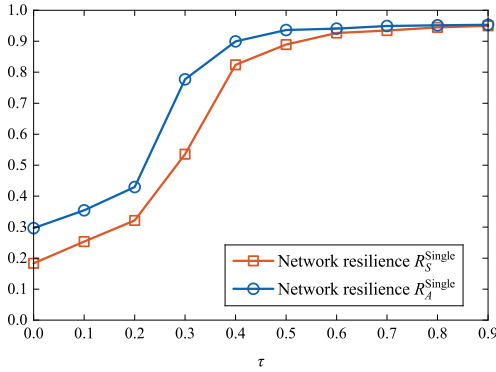


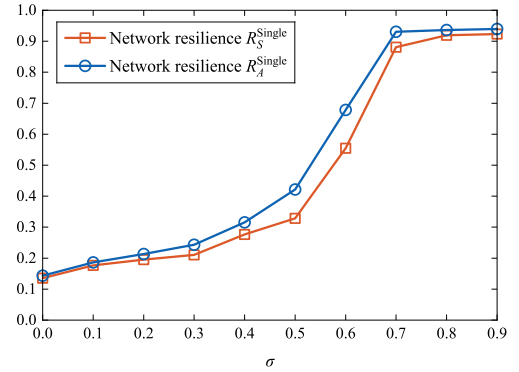
Figure 10: Load distribution of nodes in the network.

the network is significantly enhanced. It can also be observed that when σ exceeds 0.2, further increases in σ effectively improve the cascading resilience of the network. However, when σ surpasses the critical threshold of 0.8, increasing σ further no longer provides additional benefits.

By comparing Figures 11(a) and 11(b), we observe that the network resilience curve obtained from attacking the supply network lies below the curve obtained from attacking the sales network. This indicates that the failure of supplier nodes leads to more widespread cascading failures compared to the failure of sales network nodes, thereby having a more pronounced impact on the overall resilience of the network. This is because, in the supply chain network, there are fewer supplier enterprises than sales enterprises, and, on average, each supplier has more cross-layer cooperative relationships. Consequently, their failure is more likely to propagate and affect a larger number of salespeople, resulting in more extensive cascading failures.



(a)



(b)

Figure 11: Network resilience under different node capacity parameters. (a) Network resilience with varying lower capacity bound τ ; (b) Network resilience with varying upper capacity bound σ .

To further validate the above analysis, we expanded the parameter range to investigate the impact of the dual parameters of node capacity limits on network cascading resilience. As shown in Figures 12, under conditions of limited enterprise redundancy, $\tau = 0.6$ and $\sigma = 0.8$ represent the optimal input ratio. Additionally, when $\tau > 0.6$ and $\sigma > 0.8$, the network resilience stabilizes at a relatively high value with no significant changes. This suggests that, in scenarios where enterprises have a certain level of basic load redundancy, it is more crucial to increase the upper capacity limit proportionally rather than further lowering the lower capacity limit to enhance network resilience. This is because, in a supply chain network, when some enterprises fail due to overloaded business volumes, the business does not disappear immediately. Instead,

it is redistributed to other enterprises in the market. This characteristic of network failure means that other nodes may bear a heavier load, thus requiring more load redundancy to improve the overall risk resistance capability.

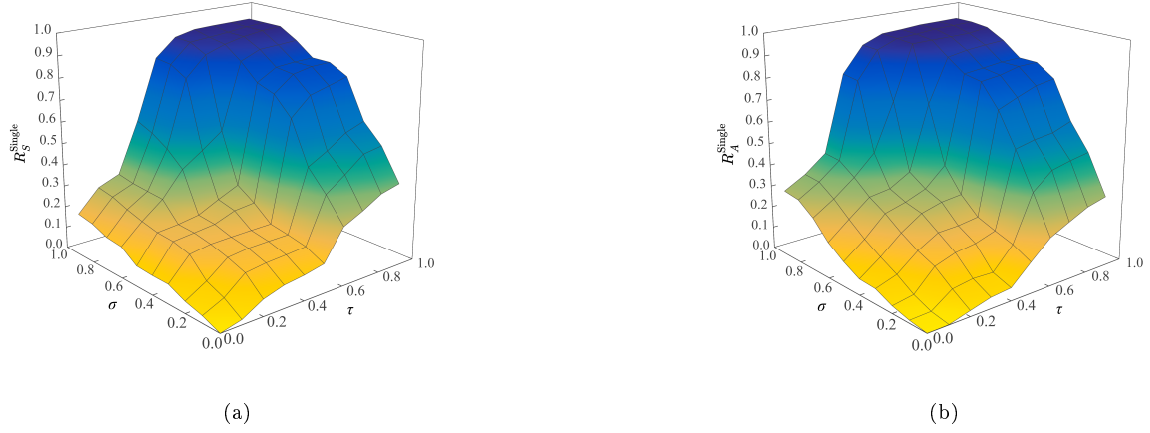


Figure 12: Network resilience under different node capacity parameters. (a) Resilience R_S^{Single} of the supply network with varying τ and σ ; (b) Resilience R_A^{Single} of the sales network with varying τ and σ .

5.4.2. The impact of information transparency

As shown in Figures 13, the information transparency of enterprises is generally positively correlated with the resilience of the supply chain network. In Figure 13(a), for suppliers, when $\theta_S < 0.6$, the network resilience remains at a low level with no significant changes. After $\theta_S > 0.6$, an increase in θ_S significantly enhances the cascading resilience of the network. In Figure 13(b), for sales enterprises, when $\theta_A > 0.3$, the network resilience begins to improve noticeably as θ_A increases. Once $\theta_A > 0.8$, the network resilience reaches a high level, and further increases in θ_A lead to only marginal improvements in network resilience. Comparing Figures 13(a) and 13(b), it is notable that both suppliers and sales enterprises exhibit low network resilience when enterprise information transparency is low. Only after reaching a certain threshold does improving information transparency significantly enhance network resilience. This is because lower transparency prevents enterprises from making clear decisions regarding resource allocation; as a result, the overall load redistribution becomes indifferent to the differences among enterprises, approaching a state of “equal distribution.”

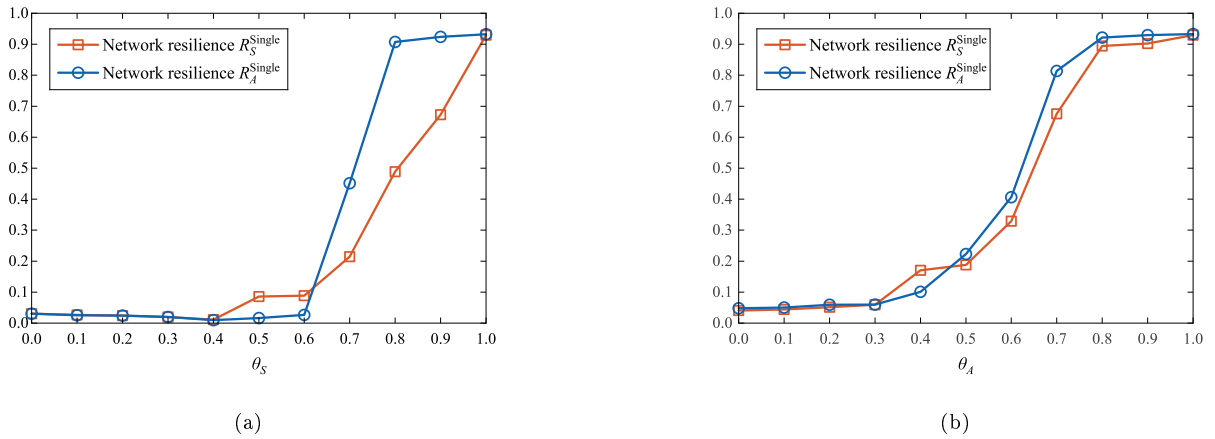


Figure 13: Figure 12: Network resilience R_S^{Single} and R_A^{Single} with varying enterprise information transparency. (a) Resilience with varying supply network transparency θ_S ; (b) Resilience with varying sales network transparency θ_A .

To further investigate the relationship between enterprise information transparency and supply chain network resilience, we examine the changes in the network resilience evaluation index R under the dual parameters θ_S and θ_A . As shown in Figures 14, whether in the supply network or the sales network, the resilience of the network significantly improves with increased information transparency among enterprises. This finding highlights an important conclusion: regardless of whether enterprises act as suppliers or sales entities, greater information transparency within the supply chain leads to better overall resilience performance of the network.

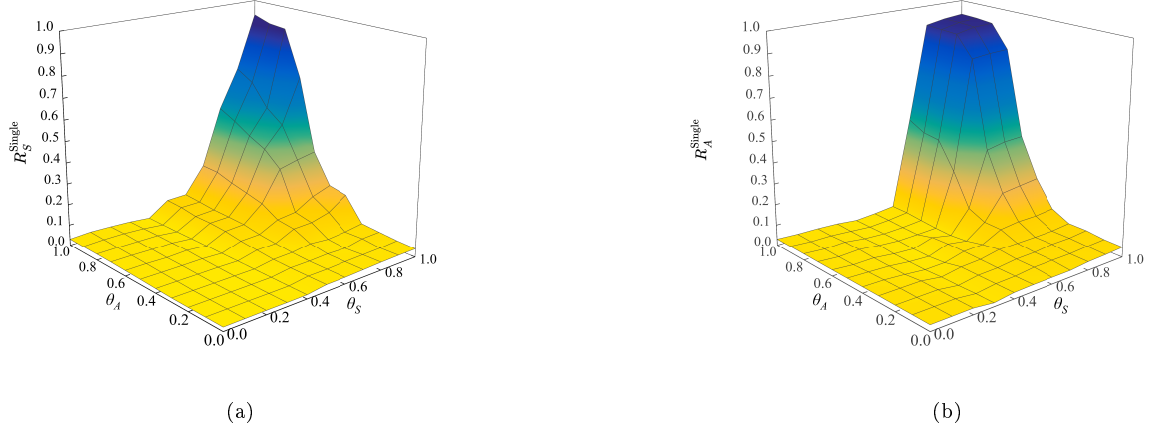


Figure 14: Network resilience with varying enterprise information transparency. (a) Resilience R_S^{Single} with varying θ_S and θ_A ; (b) Resilience R_A^{Single} with varying θ_S and θ_A .

5.4.3. The impact of supplier competitiveness

Figure 15(a) shows the variations in supplier competitiveness under the dual parameters η and ξ , where η and ξ represent the extent to which suppliers prioritize profit and the quality of their cooperating enterprises, respectively. It can be observed that when suppliers consider both their own operational benefits and the quality and quantity of their cooperating sales enterprises, the range marked by the red circle represents the optimal investment ratio. Furthermore, we found that when an enterprise prioritizes profit, a larger ξ enhances its competitiveness. This suggests that supplier enterprises should prioritize the quality of their cooperating sales enterprises over their quantity when forming partnerships. Higher-quality sales enterprises possess better survival capabilities, which can effectively buffer risks for cooperating suppliers when the network system faces pressure. Additionally, the upper-left region marked by the black circle in the figure indicates a sub-optimal yet favorable ratio, showing that when ξ is fixed and non-zero, a higher value of η leads to a greater competitiveness index for suppliers. This suggests that, given a certain level of cooperation quality with sales enterprises, increasing profit levels is more beneficial for suppliers than merely expanding the number of partnerships at the expense of profitability.

Many studies have demonstrated that when competition among horizontally homogeneous enterprises is strong, there is a greater likelihood of similar types of resources existing among these enterprises [25, 26]. This similarity makes it easier for them to become substitutes, thereby reducing the risks borne by both upstream and downstream enterprises, as well as themselves, thus enhancing the network's cascading resilience to risks. To explore the impact of competitive strategies on the cascading resilience of the network, we examined the network resilience R_S^{Single} under the influence of profit emphasis η and partner quality ξ . As shown in Figure 15(b), the range of network resilience closely corresponds to the range of enterprise competitiveness. Additionally, we observed that when η and ξ are within the range marked by the red circle, the resilience of the network reaches its peak. This peak aligns well with the region of highest

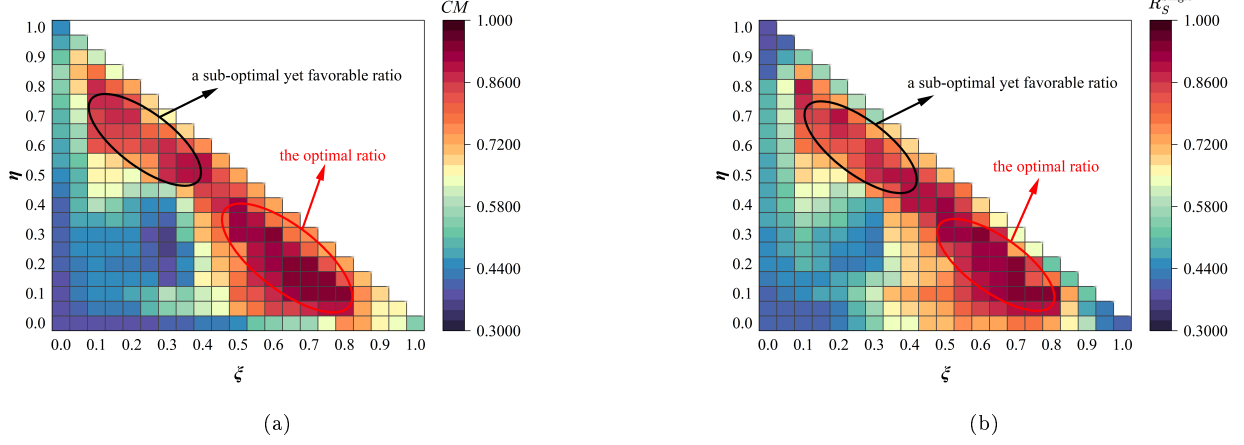


Figure 15: Supplier competitiveness and network resilience with varying profit emphasis η and partner quality ξ . (a) Supplier competitiveness CM with varying η and ξ ; (b) Resilience R_S^{Single} with varying η and ξ .

supplier enterprise competitiveness. These results reasonably verify that strong horizontal competition among supplier enterprises enhances the network's resilience against attacks on the supply network.

5.5. Cascading failures under deliberate attacks

From Figure 16, it can be observed that for different attack strategies, network resilience tends to decrease as the proportion of initially failed nodes increases. By comparing the three attack strategies, we find that the most harmful multi-point attack strategies to the network are, in order: load-based priority attack, cross-layer degree priority attack, and intra-layer degree priority attack. This is understandable because, in our model, the initial load of the nodes, based on the concept of vector centrality, comprehensively reflects both intra-layer and cross-layer degrees of the nodes.

Additionally, it can be observed that when the proportion of failed nodes is relatively small, the curve for cross-layer degree priority attacks is closer to that of intra-layer degree priority attacks. However, as the proportion of failed nodes increases, the curve for cross-layer degree priority attacks gradually approaches that of load-based priority attacks. This is due to the interdependence between the supply and sales networks in the supply chain. When subjected to small-scale disruptions, other enterprises in the network can re-establish cooperative relationships based on market demand. However, in the case of large-scale disruptions, the collapse of certain major suppliers or sales enterprises leads to a fundamental mismatch in the circulation of product resources within the market. As a result, the supply and sales relationships among enterprises within the entire system are severely affected.

By comparing Figures 16(a) and 16(b), it can be seen that multiple-point attacks on the supply network cause less damage than those on the sales network. This contrasts with the network changes observed in Section 5.4, where single-point attacks produced different effects. The difference arises from the fact that the number of sales enterprises exceeds that of suppliers. A single supplier typically occupies a larger scale within its network than a single sales enterprise, and is connected to more sales enterprises, making its resources harder to replace. As a result, the impact of single-point attacks is greater on the supply network than on the sales network. However, in scenarios where the same proportion of nodes are targeted by multiple-point attacks, suppliers can distribute the risk across more entities due to their connections with more sales enterprises. Therefore, under the same attack proportion, the supply network exhibits higher resilience compared to the sales network.

Figure 17 shows the composition of failed nodes in the supply and sales networks under different attack scenarios, with each subfigure corresponding to a specific combination of attack

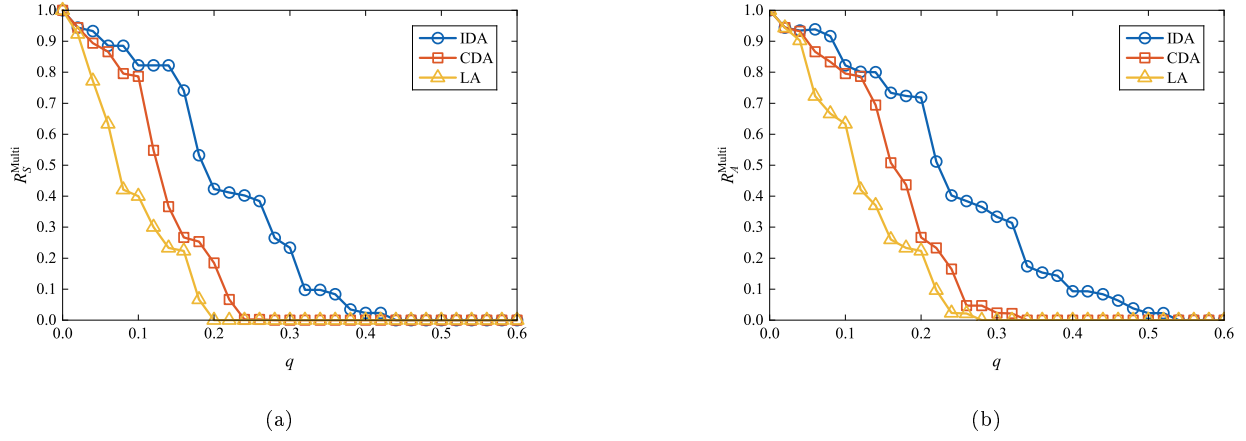


Figure 16: Network resilience under different multi-point attack strategies. (a) Attacks on the supply network; (b) Attacks on the sales network.

and affected layers. A comparison reveals that in the supply network, the proportion of overload failures is the highest, followed by underload failures, and finally isolated failures. In the sales network, the proportions of overload and underload failures are similar, with isolated failures being the lowest. Additionally, the failure rate of sales enterprise nodes is significantly higher than that of supplier nodes. It is known that in the supply and sales cooperative relationship, if either the supplier or the sales enterprise fails, the business will seek new alternative partners to maintain operations. Due to the extensive proprietary technology and specialized production capacity held by suppliers in many industries, finding replacement suppliers is more challenging. Therefore, when a supplier fails, sales enterprises face greater difficulty in finding alternative suppliers. Conversely, in the modern market, the diversification of sales enterprises increases the flexibility of suppliers, making it easier for suppliers to find alternative sales enterprises when a sales enterprise fails. This is why the proportion of failed sales enterprise nodes is higher than that of supplier nodes. This result indicates that, in our model, sales enterprises are more dependent on suppliers, and the network needs to allocate more resources to protect suppliers to ensure network stability. Furthermore, it is noteworthy that as the proportion of initial failed nodes q increases, the proportion of isolated failed nodes also rises. This reflects that widespread cascading failures impair the connectivity among nodes within the network.

5.6. Case study

In this section, we analyze the resilience of different real-world supply chain cases [27, 28, 29, 30, 31]. The specific steps for the simulation experiment are as follows:

- 1) Based on different supply chain scenarios, construct a dual-layer supply chain network model for simulation using case data.
- 2) Trigger cascading failures in the network using two representative multi-point attack strategies: LA, which targets high-load nodes and causes the most severe failures, and CDA, which targets cross-layer hubs and captures inter-layer dependency in dual-layer supply chains.

Referring to the trend of system resilience with respect to the attack ratio q in Figure 16, we select two multi-point attack ratios— $q = 7\%$ and $q = 15\%$ —to simulate the cascading failure performance of the network under mild and moderate-to-high levels of disturbance. Specifically, $q = 7\%$ falls within the sensitive region where system resilience begins to decline significantly, capturing the failure characteristics under mild disturbances. In contrast, $q = 15\%$ lies in the relatively smooth transition zone where the overall functionality of the system is still

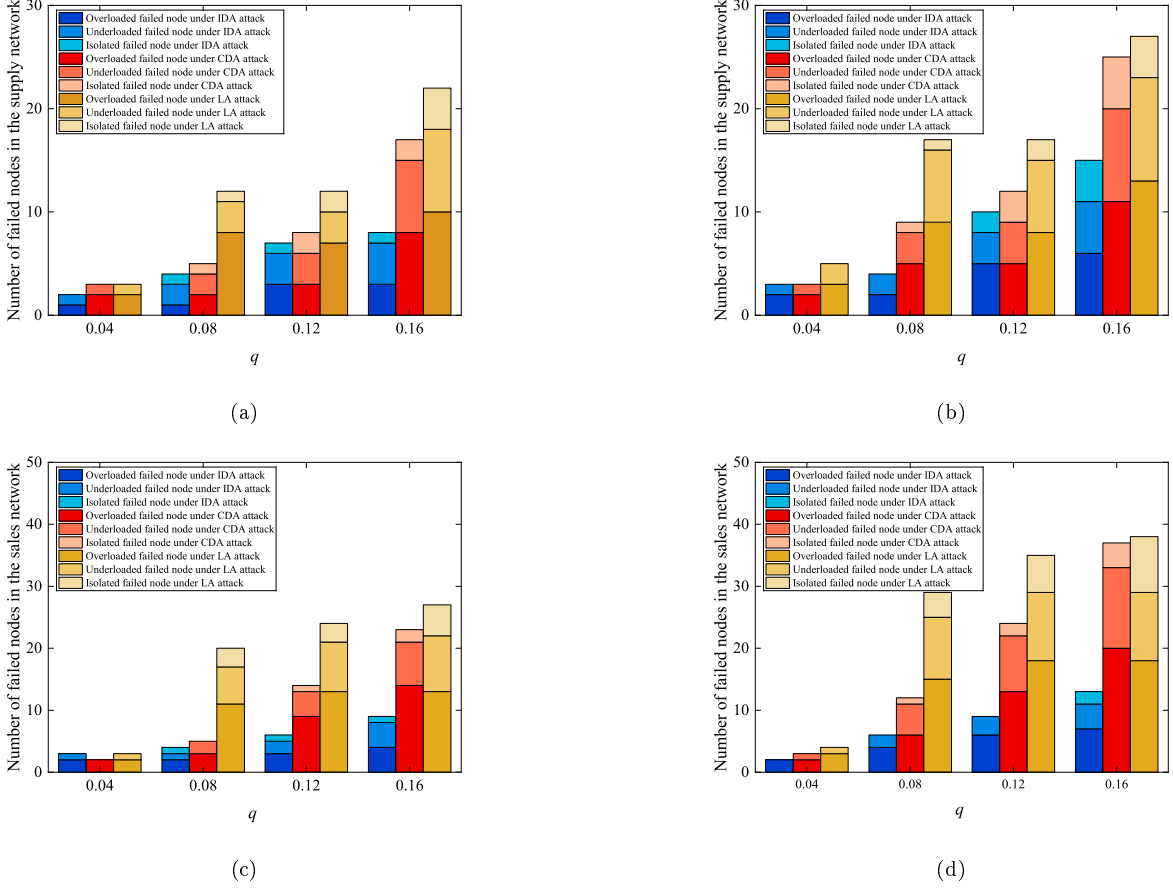


Figure 17: Composition of failed nodes in the supply and sales networks under different multi-point attack strategies. (a) Failed nodes in the supply network under attacks on the sales network; (b) Failed nodes in the supply network under attacks on the supply network; (c) Failed nodes in the sales network under attacks on the sales network; (d) Failed nodes in the sales network under attacks on the supply network.

maintained but approaching collapse, representing a moderate-to-high disturbance scenario in the transition from stability to widespread failure.

We selected four types of supply chain networks: agricultural product supply chain, apparel supply chain, household appliance supply chain, and medical device supply chain. These networks exhibit significant differences in terms of enterprise scale and connection density. Specifically:

- The agricultural product supply chain is a small-scale network with a total of 33 nodes, including 17 supplier nodes and 16 sales enterprise nodes. It has a lower connection density between the nodes.
- The apparel supply chain is a medium-scale network with 54 nodes, comprising 20 supplier nodes and 34 sales enterprise nodes. This network has a moderate connection density.
- The household appliance supply chain is a large-scale network with 225 nodes, which include 70 supplier nodes and 155 sales enterprise nodes. It features a higher connection density among the nodes.
- The medical device supply chain is an ultra-large-scale network with 416 nodes, consisting of 200 supplier nodes and 216 sales enterprise nodes. This network exhibits an extremely high connection density between the nodes.

837 Tables 5 and 6 illustrate the cascading failure propagation across four different supply chain
838 scenarios, revealing notable disparities. Among them, the agricultural product supply chain
839 network suffers the most severe cascading failures and demonstrates the weakest resilience,
840 while the medical device supply chain network is the least affected. This difference is typically
841 attributed to the relatively small scale and limited interconnectivity in the agricultural product
842 supply chain, resulting in lower load redundancy and weaker risk resistance, thereby making
843 the entire system more vulnerable to cascading failures.

Attack strategy		Agricultural product supply chain	Clothing supply chain	Home appliance supply chain	Medical device supply chain
Initial state					
LA	$q = 7\%$ Attacks on the sales network				
	$q = 7\%$ Attacks on the supply network				
	$q = 15\%$ Attacks on the sales network				
	$q = 15\%$ Attacks on the supply network				
CDA	$q = 7\%$ Attacks on the sales network				
	$q = 7\%$ Attacks on the supply network				
	$q = 15\%$ Attacks on the sales network				
	$q = 15\%$ Attacks on the supply network				

Table 5: The network states of four typical supply chain systems after cascading failures.

844 It is worth noting that under the LA strategy, the household appliance and medical device
845 supply chains exhibit a high sensitivity to attacks on the supply network, where such attacks
846 trigger significantly more widespread cascading failures than those targeting the sales network.
847 This is due to the bottleneck effect in high-tech industries, where suppliers with proprietary
848 technologies often occupy critical positions in the overall product market. These suppliers tend
849 to create strong customer dependence and are difficult to replace quickly. Under the CDA
850 strategy, this trend is not only sustained but becomes even more pronounced in certain scenar-
851 ios. In particular, the medical device supply chain experiences more extensive failures under
852 CDA attacks on the supply network than under LA, indicating that the stable operation of this

Attack strategy	Removal ratio of nodes	The attacked network	Agricultural product supply chain	Clothing supply chain	Home appliance supply chain	Medical device supply chain
LA	$q = 7\%$	the sales network	45%	37%	29%	19%
	$q = 7\%$	the supply network	44%	42%	38%	30%
	$q = 15\%$	the sales network	100%	78%	70%	55%
	$q = 15\%$	the supply network	100%	81%	79%	67%
CDA	$q = 7\%$	the sales network	42%	31%	27%	15%
	$q = 7\%$	the supply network	42%	33%	33%	30%
	$q = 15\%$	the sales network	100%	72%	51%	48%
	$q = 15\%$	the supply network	100%	73%	59%	70%

Table 6: Failure ratios of different supply chain systems under LA and CDA strategies with node removal ratios $q = 7\%$ and $q = 15\%$.

supply chain heavily relies on a few key suppliers. When these suppliers fail, their products cannot be easily substituted, leading to system-wide functional breakdowns. In contrast, the agricultural product and apparel supply chains show relatively small differences in resilience between attacks on supplier nodes and sales enterprise nodes under both LA and CDA strategies. This is because these industries are characterized by lower technological barriers and faster product turnover, and their internal structures are more balanced, with no strongly dependent cross-layer bottleneck nodes.

6. Conclusion and future work

In this work, we propose a dual-layer cascading failure model for supply chains, considering enterprise competition and incomplete information. This model introduces a mechanism for load redistribution among indirectly adjacent nodes and simulates the changes in supply and sales cooperation relationships within the actual supply chain network through enterprise node competition and replacement. Through extensive experiments, we validate the feasibility of the model and examine the impact of key factors such as node capacity, enterprise competitiveness, and information transparency on network resilience. Additionally, we examine the network's cascading failure performance under single-point and multiple-point attack strategies. Finally, using the proposed model, we analyze cascading failures in four typical real-world supply chain scenarios. The experimental results yield several insightful observations that enhance our understanding of network resilience and cascading failures in supply chains. The experimental results yielded several insightful observations:

- 1) The resilience of the supply chain network against cascading failures is significantly influenced by the load capacity of enterprises, with enterprise load capacity positively correlated with network cascading resilience. Failures due to node overload are notable, making it necessary for enterprises to remain vigilant against high loads.
- 2) The higher the transparency of enterprise information, the better the cascading resilience of the supply chain network. Therefore, enterprises should be encouraged to provide comprehensive information required by the market when participating in supply chain competition.
- 3) While ensuring their own operational profits, supplier enterprises should focus more on the quality rather than the quantity of cooperating sales enterprises. This approach is beneficial for enhancing supplier competitiveness and the network's ability to withstand cascading failures.

4) Among the three attack strategies analyzed, load-based attacks have the greatest impact on network cascading failures. Therefore, targeted protective measures should be implemented for large enterprises within the supply chain.

5) In high-tech industries, supplier enterprises play a crucial role in cascading failures. Attacks on the supply network trigger more extensive cascading failures within the supply chain network than those on the sales network. Therefore, protective measures should be established for supplier enterprises possessing proprietary technology.

In this work, we primarily focus on the cascading failure modeling of dual-layer supply chain networks under enterprise competition with incomplete information. We have found that the competition and cooperation relationships both within the same level of enterprises and across different levels have a significant impact on the cascading failure resilience of the entire system. Therefore, in the next step of our work, we will focus on how to improve the cascading failure resilience of the entire supply chain by optimizing the competition and cooperation relationships between enterprises.

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