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Research on the evolution law of supply chain disruption based on Complex Adaptive System

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Abstract
The increasing complexity of global supply chain networks has led to frequent disruptions, resulting in massive economic losses, while traditional linear management approaches fail to address their nonlinear propagation. This study employs Complex Adaptive System theory and develops a multi-agent simulation model using NetLogo, based on supply chain data from 1,105 listed automotive manufacturing enterprises in China, analyze the propagation law of supply chain disruption over time and the adaptive strategy of enterprises. The analysis reveals that: Supply chain disruptions exhibit significant ripple effects, with an average node failure rate of 83.6% without adaptive strategies, and low-resilience enterprises showing markedly higher failure rates than high-resilience counterparts. Adaptive strategies temporarily reduce node failure rates to 34.2%, but cannot fully counteract long-term disruption spread. Network hierarchy modulates disruption propagation paths—long-distance delays initially buffer core enterprises, yet ultimately lead to over 80% node failure. This research provides theoretical and practical tools for identifying vulnerable nodes and designing tiered resilience strategies, offering critical insights for global supply chain risk management.

Keywords Complex Adaptive System · Supply chain disruption · Evolution law · Multi-agent simulation · Supply chain resilience

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1 Introduction

With the acceleration of globalization, supply chains have become highly interconnected and dynamically complex systems. Traditional linear supply chain management faces challenges such as the increasing complexity of industrial division of labor, economic uncertainty, decoupling policies, trade frictions, and natural disasters. These challenges not only increase the complexity of supply chain management but also raise the risk of supply chain disruptions. A disruption can lead to a series of problems for businesses, such as raw material shortages, production halts, logistics delays, order cancellations, and even cause supply chain-wide instability and significant economic losses. For instance, during the COVID-19 pandemic, the global manufacturing sector experienced a “chain-breaking trend.” The chip shortage severely impacted the automotive industry. According to the IMF, in 2021 alone, global automobile production decreased by 11.3 million units due to chip supply disruptions, resulting in direct economic losses of $210 billion (Pianta 2021). In March 2021, the blockage of the Suez Canal caused the Ever Given container ship to run aground, disrupting global trade for six days. Lloyd’s estimated that global trade lost $400 million per hour (Thakur 2023). This event triggered a “butterfly effect,” forcing European auto factories to halt production due to delayed Asian parts deliveries. These supply chain disruptions highlight the fragility of traditional supply chains.

In recent years, research on supply chain disruptions has made significant progress in areas such as resilient network design (Hosseini and Ivanov 2022), disruption cause analysis (Ovezmyradov 2022), and emergency response strategies (Moosavi et al., 2021). However, a literature review reveals three critical methodological disconnects that limit the ability of existing theories to explain issues like the non-linear transmission of supply chain disruption impacts and adaptive corporate games.

Firstly, mainstream studies rely on static optimization models that are based on preset risk scenarios. For example, Lotfi et al. (2021) developed a two-stage robust stochastic programming model that can handle multi-objective optimization problems, but it is essentially a proactive decision-making framework and cannot capture real-time adaptive interactions between supply chain nodes. Similarly, Namdar et al. (2021) proposed a hybrid stochastic model that incorporates business continuity indicators, but it fails to explain how micro-level adaptive behaviors like inventory restructuring and order rerouting trigger macro-level resilience emergence. This static flaw is particularly evident in Yaroson et al.’s (2021) pharmaceutical supply chain study. Although semi-structured interviews identified 31 resilience factors, the methodology couldn’t quantify the dynamic coupling effects between these factors. These limitations make existing models struggle to depict path-dependent phenomena during disruption propagation and explain self-organized recovery mechanisms observed in real-world cases.

Secondly, existing literature generally studies network topology features (such as node centrality and clustering coefficients) and disruption propagation mechanisms (such as cascading failures and risk diffusion) in isolation. Parast and Subramanian’s (2021) empirical study on 315 Chinese enterprises confirmed the correlation between network density and performance loss, but it didn’t reveal how topological features affect disruption propagation thresholds through non-linear dynamics. This disconnect causes significant deviations between theoretical predictions and real-world observations. For instance, supply chains with similar topological indicators may show completely different disruption impact patterns, as seen in the 2011 Tohoku earthquake in Japan triggering a four-level cascading failure (Zhou et al. 2021; Son et al. 2021) versus the 2021 Suez Canal blockage having only localized effects (Yang 2024; Wan et al. 2023). These two cases are similar in terms of centrality indices and network density. However, the supply chain disruption caused by the Japan earthquake spread from the earthquake - affected area to the Asia - Pacific region, then to North America and Europe, and finally had a global impact. In contrast, the supply chain disruption due to the Suez Canal blockage was mainly concentrated in the Asia - Europe trade sector. Current mainstream models, such as Matsuno et al.'s (2021) capacity reservation model, worsen this problem by assuming node homogeneity and ignoring the key modulating effect of firm heterogeneity (like inventory flexibility and supplier diversification) on propagation paths.

Lastly, there is a significant paradigm gap in the theory of supply chain network modeling. Operations research models (Foroozesh 2022) oversimplify real-world complexities to maintain computational feasibility and are constrained by low-dimensional solution spaces. Fuzzy analytic hierarchy process methods (like the one proposed by ALI et al. 2021) lack temporal resolution and can't capture phase-transition critical points during disruption evolution. Case studies (like Butt's,2021, multi-case analysis) can generate context-specific insights, but their conclusions are hard to generalize to other industrial settings. This fragmentation traps research in a scalability dilemma—either sacrificing real-world complexity for analytical solutions or relying on qualitative induction to produce conclusions lacking quantitative verification.

The above research has greatly enriched the relevant research on supply chain disruption, but there are still the following deficiencies: Firstly, when designing resilient supply chain models and studying supply chain disruption issues, most scholars use operations research and case study methods, failing to fully consider the adaptability, proactiveness, and complexity of supply chain entities. Secondly, there are relatively few articles studying the laws of supply chain disruption propagation and ripple effects. Thirdly, most current research focuses on simple supply chain structures, unable to fully grasp the interaction between network structure and disruption propagation.

To address the aforementioned limitations, this study first constructs a novel analytical framework based on Complex Adaptive Systems theory, incorporating dimensions such as multi-agent interactions and dynamic evolution mechanisms. Second, transcending traditional static optimization paradigms, it focuses on real-world automotive manufacturing supply chains. By utilizing upstream and downstream relationship data from actual automotive enterprises, we develop a multi-level network simulation model. Leveraging the NetLogo simulation platform, we replicate supply chain network disruption scenarios. Finally, through analyzing simulation results, we investigate how disruption impacts propagate through real-world supply chains, the varying severity of effects across different enterprises, and how adaptive corporate behaviors respond to disruptions. These findings aim to provide decision-making support for enhancing supply chain management efficiency and resilience.

2 Complexity analysis of supply chain from the perspective of CAS

2.1 The relationship between supply chain system and CAS

Complex Adaptive Systems (CAS) originated from complexity theory and refer to systems composed of many interacting intelligent agents (Choi et al. 2001). Under internal model regulation and external environmental stimuli, these agents can exhibit adaptive and self-organizing behaviors (Braz and Mello 2022). Moreover, they can "continuously learn" and "accumulate experience" through interactions with other agents and the environment, ultimately altering their own and the organization's behavior and structure, driving the evolution and optimization of the entire system (Azadegan and Dooley 2021).

Supply chains consist of multiple interconnected individuals and organizations. Their interactions are nonlinear and can lead to complex adaptive behaviors as time and the environment change (Wieland and Durach 2021). Information flows, logistics, and capital flows within supply chains undergo unpredictable changes over time. Also, connections between enterprises may appear or disappear due to adaptation or lack of adaptation to the external environment (Guo et al. 2022). Given these characteristics, supply chains and CAS are logically compatible. Table 1 provides a more detailed comparison of the main features of CAS and supply chains.

The comparison in Table 1 reveals significant similarities between CAS and supply chains, particularly in key aspects such as adaptability, self-organization, emergence, non-linearity, and diversity. These aspects show a high fit with supply chain disruption scenarios. Therefore, this paper treats the supply chain network as a CAS and uses CAS theory to explore the emergence patterns of supply chain disruptions. This perspective helps better grasp the dynamic characteristics of supply chains and formulate more effective management strategies.

2.2 Construction of conceptual framework of supply chain disruption evolution

In supply chains, entities exhibit significant autonomy, responsiveness, interaction, independence, and adaptability, resulting in complex dynamics and variability (Surana et al. 2005). For instance, companies can adjust production and sales strategies in response to market changes, while consumers choose products and services based on their needs and market information, leading to numerous game-theoretic behaviors (Li et al. 2020). However, traditional mathematical modeling methods, which rely on numerous assumptions, struggle to accurately capture the dynamic interactions and autonomous decision-making between supply chain companies and between companies and consumers. Similarly, when external environmental shocks cause supply chain disruptions, these traditional methods fail to fully capture the complexity of interactions between supply chain entities and their environment. For example, when external factors disrupt a supply chain, companies must react quickly, adjusting their supply chain strategies to minimize disruptions' impacts, which involves reconfiguring resources and coordinating with suppliers, distributors, and other partners (Zhang et al. 2023).

Table 1 Comparison of CAS characteristics with supply chains

Feature	CAS	Supply chain
Self-organization	Individuals form complex global patterns through local rules and interactions, without a central control guiding the entire system.	Coordination is decentralized. Each link makes autonomous decisions based on its situation and market information, forming the overall supply chain network structure.
Self-adaptation	Individuals adjust their behavior through learning and experience accumulation to better adapt to environmental changes, thus influencing the system's evolution.	Companies need to constantly adjust their strategies and operations in response to market signals, cost changes, technological progress, etc.
Chaos	The system's evolution may be unpredictable.	It's hard to fully predict the system's evolution when facing market fluctuations, sudden events, etc.
Edge complexity	The system operates at the edge of order and disorder.	The supply chain seeks balance between stability and change to adapt to changes.
Environmental interactivity	Interaction between individuals and the external environment affects system evolution.	It is influenced by external factors like market trends, policy changes, and technological progress.
Emergence	The system's macro-behavior is the result of individual interactions, which are unpredictable at the individual level.	The overall performance and efficiency result from interactions among links, which a single company can't independently control.

In their research, Nair and Reed (2019) categorized the components of CAS into three key dimensions: internal mechanisms, external mechanisms, and co-evolution, as shown in Table 2. These dimensions offer a basic framework for understanding and analyzing behaviors and dynamics in complex systems. Internal mechanisms are the core of CAS, involving interactions and communication between agents (which can be individuals, teams, or organizations) within the system. External mechanisms emphasize the interaction between the system and its external environment, focusing on how the system perceives and responds to environmental changes such as market demand fluctuations, policy changes, or technological advancements. Co-evolution describes how the system evolves and adapts through the interaction of internal and

Table 2 The three important dimensions framework of CAS elements

Components of CAS	Characteristics
Self-organization	Agent behavior patterns, rules, interactions, and nonlinearity.
Self-adaptation	System-environment interactions, such as market demand fluctuations, policy changes, and financial crises.
Co-evolution	Adaptability, chaos, self-organization, and emergent behavior.

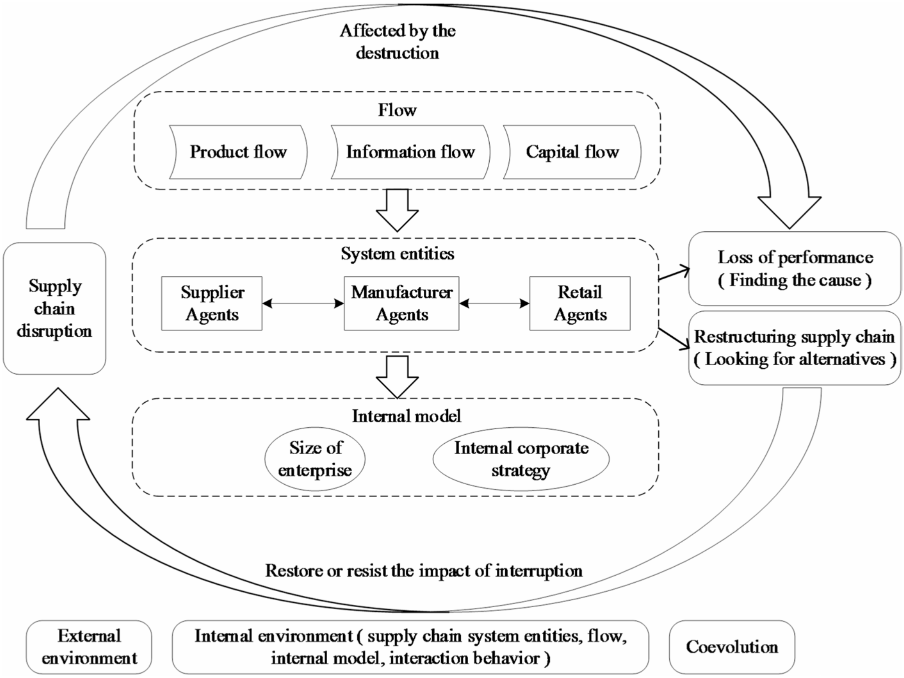


Fig. 1 Conceptual framework of supply chain disruption evolution based on CAS

external factors. However, this framework lacks a more detailed breakdown of internal mechanisms.

Based on this, this paper refines the internal mechanisms by integrating supply chain characteristics into three levels: flow, system entities, and internal models. Flow, the most basic level, involves the movement of products, information, and funds. System entities encompass all supply chain participants, including suppliers, manufacturers, distributors, retailers, and end-users. Given each entity has its own objectives, strategies, and operations, they are mapped to adaptive Agents. Internal models consist of the internal operation models and decision-making processes of supply chain participants. The conceptual model of supply chain disruption evolution is shown in Fig. 1.

At the macro level, the autonomous interactions between Agents in this conceptual model fully demonstrate the dynamic and complex characteristics of the supply chain. Specifically, the interactions between Agents not only reflect the supply chain's response speed and adjustment ability to external environmental changes but also reveal the interdependencies and cooperation methods between different parts of the supply chain. Furthermore, the interaction between Agents and the environment further showcases the supply chain's flexibility and stability. Through continuous feedback and adjustment with the environment, the supply chain can maintain high stability and adaptability in the face of various uncertainties and unexpected events.

At the micro level, this model delves into the internal models and specific behaviors of Agents, showing the coordination of internal resources within the supply chain. For instance, the decision-making processes, resource allocation methods, and specific operational steps within Agents can be intricately depicted and analyzed through the model. This detailed representation not only aids in understanding the operational mechanisms of each link in the supply chain but also enhances the interpretability of the supply chain's complex behaviors. By simulating and analyzing the behavior of Agents, we can better anticipate the supply chain's performance in different scenarios, optimize supply chain management and decision-making, and ultimately boost the efficiency and effectiveness of the entire supply chain.

3 Construction of supply chain disruption simulation model

3.1 Data sources and network construction

The automotive supply chain not only embodies the fundamental characteristics of supply chains but also features product complexity and a trend towards globalization (Belhadi et al. 2021). It frequently faces various disruption risks and is internationally recognized as one of the most complex supply chains.

Therefore, this study constructs a supply chain network using real-world data on upstream and downstream relationships in the automotive supply chain. It selects companies listed in the A-share market within the automotive manufacturing industry from 2018 to 2023 as seed nodes, collecting data from the CSMAR database, Wind database, and annual reports of these companies. This includes data on the first and second-tier suppliers and customers of automotive manufacturing companies, as well as customers of the first and second-tier suppliers. Besides supplier-customer relationship data among all companies, data on the number of employees, year-end assets, and inventory turnover rates were also collected. The upstream and downstream relationship data of automotive manufacturing companies were then imported into Gephi software. Non-listed companies, financial institutions, and discrete nodes were excluded, ultimately resulting in a network diagram of the automotive manufacturing supply chain (Fig. 2).

Figure 2 includes 1,105 enterprise nodes and 1,504 unidirectional edges, involving 65 different industries. The top three industries with the strongest representation are Computer, Communications and Other Electronic Equipment Manufacturing (9.05%), Software and Information Technology Services (8.14%), and Electrical Machinery and Equipment Manufacturing (7.96%). The average distance between two nodes in the supply chain network is 10.961, with the maximum distance between any two

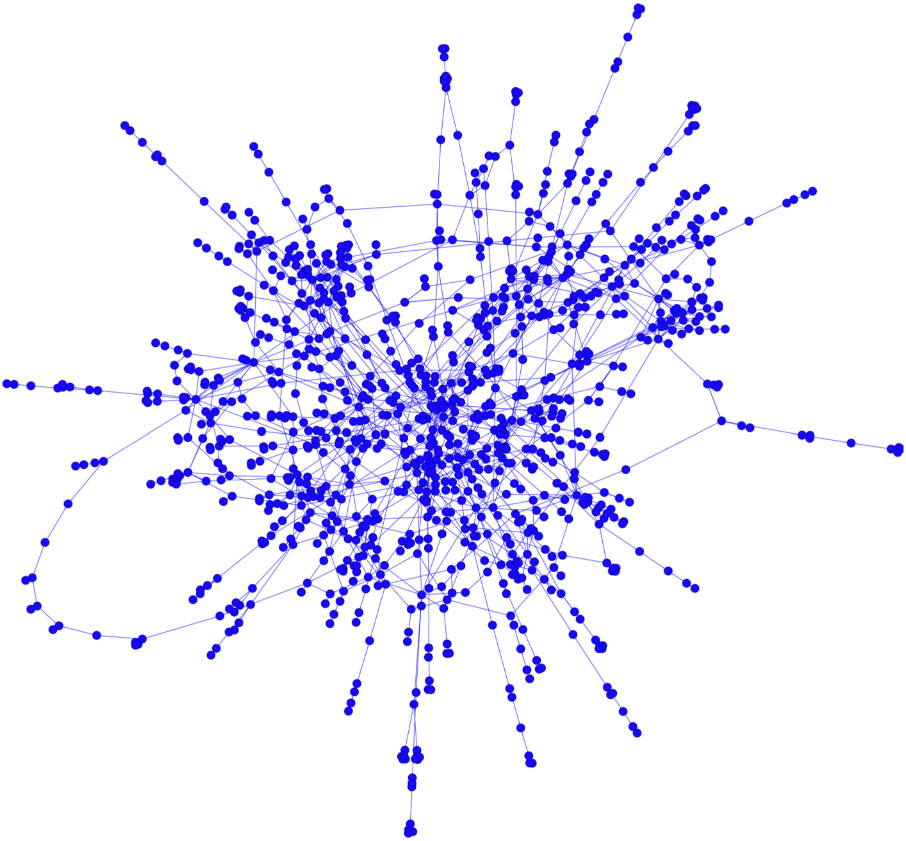


Fig. 2 Automobile manufacturing supply chain network diagram

nodes not exceeding 32. Moreover, real-world supply chain network data reveal that an enterprise can simultaneously act as both an upstream supplier and a downstream customer within the entire supply chain network. This not only highlights the high degree of complexity in the supply chain network but also underscores the necessity of establishing a large-scale, enterprise-level supply chain network using real-world data, as synthetic networks struggle to reveal this level of complexity.

3.2 Subject attributes and variable interpretation

To better understand the complex characteristics and behaviors of various entities within the supply chain, we map each node enterprise on the supply chain into adaptive Agents, where each enterprise Agent possesses two main attributes: SCR and Performance (P).

In conjunction with the aforementioned definition of SCR and referring to the research of Han et al. (2020), we categorize SCR into three dimensions based on the supply chain's response to external shocks over time: preparation, response, and recovery. It employs a composite index method to measure SCR, with a detailed index system shown in Table 1. The preparation aspect primarily considers the inherent attributes and historical accumulation of the enterprise, reflecting the robustness of the supply chain before being subjected to external shocks, including enterprise size, business revenue, assets-liability ratio, and total profit (Zidi et al. 2022). The response aspect mainly considers the efficiency of responding to disruptions and the efficiency of completing supply chain processes, reflecting the flexibility of the supply chain when facing external shocks, including the flow of capital, products, and information. Supply chain efficiency, following the approach of Fu et al.(2023), is measured by the number of days of inventory turnover. The recovery aspect mainly considers the efficiency of returning to normal and the reconstruction of the supply chain, reflecting the supply chain's vulnerability and adaptability, including current ratio, operating profit margin, and investment and financing activities.

Through the enterprise SCR index system illustrated in Table 3, the paper uses the entropy weight method to calculate the SCR level of each enterprise. To assess and compare the SCR of enterprises with varying degrees of supply chain robustness in the face of supply chain disruptions, we have employed the K-Means clustering algorithm to automatically categorize enterprises into three levels of SCR: high, medium, and low. This is an efficient unsupervised learning method that begins by randomly selecting initial cluster centers, assigns data points to the nearest cluster, and iteratively updates the cluster centers until they stabilize.

$$p_i = \frac{(c_i - a_i)(d_i - b_i)}{a_i b_i} \tag{1}$$

In the equation, p_i stands for the performance of the i-th enterprise, while a_i and b_i denote its initial in-degree and initial out-degree, respectively. Additionally, c_i and d_i signify the current in-degree and current out-degree of the enterprise.

3.3 Adaptive strategy design

In reality, when a supplier halts production, the affected firm won't just wait for the supplier to restart operations. Instead, it will seek alternative suppliers and may ask to establish a new connection with one of them to resume normal business(Mukherjee et al. 2022). When alternative suppliers receive such requests, they'll decide whether to accept them.

Therefore, this paper designs an adaptive strategy for firms in a supply chain network disruption scenario. Core to this strategy is that when a supplier suddenly stops operating, the firm won't passively wait for its recovery but will take adaptive actions to maintain normal operations. Specifically, it will assess the capabilities of potential alternative suppliers and send requests to establish new partnerships. The alternative suppliers will then decide whether to accept these requests based on their own situations. This adaptive strategy design better demonstrates a firm's proactiveness and adaptability during supply chain disruptions. Through this strategy, firms can quickly adjust their supply relationships when a supply chain network disruption occurs, thus minimizing the impact on their operations.

Table 3 SCR index system of enterprise

Goal layer	First grade indexes	Second grade indexes	Third grade indexes	Indicator description
SCR	Preparation	Eobustness	Enterprise size	Ln(Year-end total assets)
			Eusiness revenue	Total operating income (billions)
			Assets-liability ratio	Total liabilities / total assets (%)
			Total profit	Operating profit (billion)
	Response	Flexibility	Capital flow	Operating expenses (billion)
			Product flow	Supply chain efficiency ln (365 / inventory turnover)
			Information flow	Ln (total number of enterprise digital word frequency + 1)
	Recovery	Vulnerability	Current ratio	Current assets / current liabilities (%)
			Operating profit margin	Operating profit / operating income (%)
		Adaptability	Investment activities	Cash flow of investment activities (billion)
			Financing activities	Cash flow of financing activities (billion)

Poor corporate performance, a common impact of supply chain disruptions, can lead to business shutdown when the performance indicator P-value falls below a critical threshold (Hamidu et al. 2023). Thus, this paper uses P-value to evaluate a firm's performance in the supply chain network and determine if it should be removed. However, assessing P-value changes due to disruptions is challenging with composite-indicator methods, which fall short in accuracy. In contrast, graph theory offers a dynamic way to monitor supply chain network changes during disruptions, such as node/edge fluctuations and structural evolution (Agarwal et al. 2022). Therefore, this paper uses graph theory to measure P-value changes in the supply chain network. The computation is delineated in Eq. (1):

3.4 Design of subject interaction rules

To accurately simulate the response of automotive manufacturing firms to supply chain network disruptions, the enterprise Agents in this model are endowed with proactiveness and adaptability similar to real-world companies. The model runs through multiple iterations to simulate the complex interactions among enterprise Agents. Specifically, it simulates supply chain disruptions by removing specific enterprise nodes, forcing the affected Agents to actively seek alternative suppliers and establish new connections to meet their performance requirements. If a firm fails to meet the minimum performance standard, it will be removed from the supply chain network. Notably, considering that large firms generally have greater resilience to supply chain risks than small firms in reality (Sabahi and Parast 2020). In the model, enterprises with different SCR levels are set different minimum performance requirements, that is, P1, P2 and P3 are set as the minimum performance requirements of enterprise nodes with high, medium and low resilience respectively, so as to reflect the reality more realistically. The interaction mechanism of each subject when the supply chain is interrupted is shown in Fig. 3.

Figure 3 mainly consists of three parts: removal of enterprise nodes, affected enterprises searching for alternative suppliers, and alternative suppliers establishing connections with affected enterprises.

Before the simulation model runs, focus enterprises are selected for different resilience levels. Specifically, the automotive manufacturing enterprises with the highest total in-degree and out-degree and with high, medium, and low SCR are designated as Enterprise A, Enterprise B, and Enterprise C, respectively. Enterprise A is the largest passenger vehicle manufacturer listed on the Chinese A-share market, with

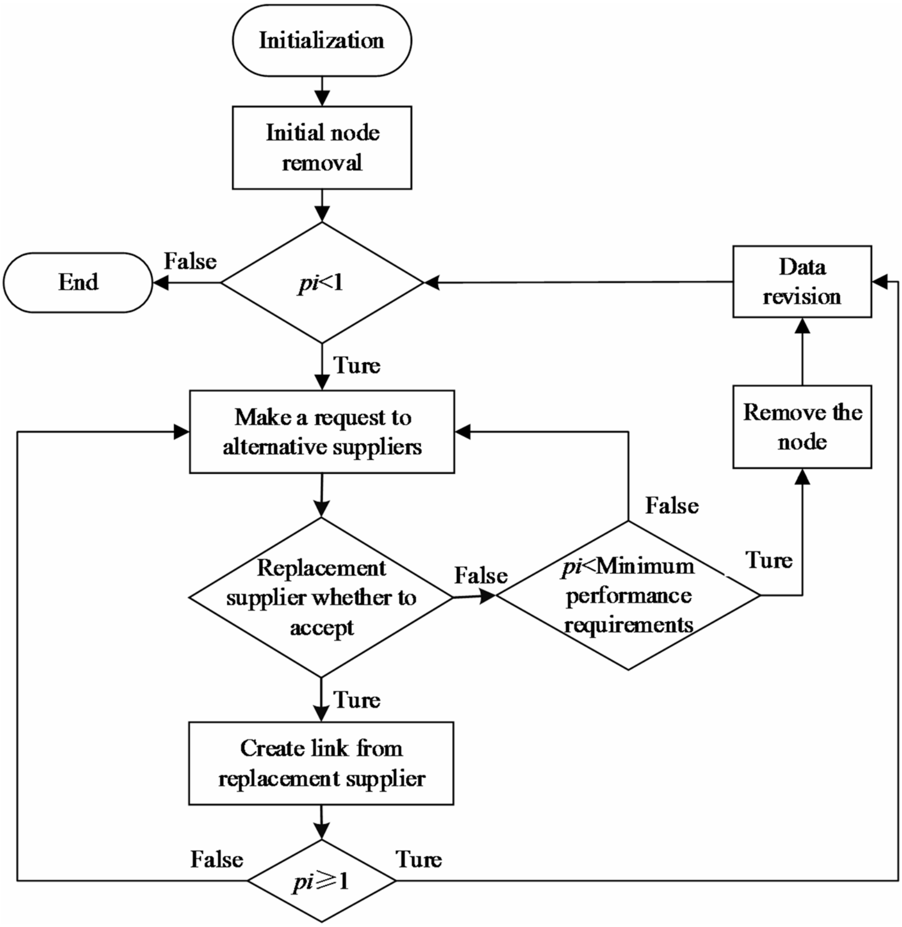


Fig. 3 The interaction mechanism of each subject when the supply chain is interrupted

a business scope covering the research and development, production, and sales of passenger and commercial vehicles, as well as automotive parts (engines, transmissions, etc.) and automotive service trade. Its passenger vehicle sales have ranked first nationwide for 16 consecutive years. Enterprise B is a leading player in the automotive parts field, mainly producing automotive parts and new energy power systems. The company's products include body parts, chassis parts, and interior and exterior parts, and it has established long-term cooperative relationships with many well-known automotive manufacturers. Enterprise C is an important player in the domestic automotive electronic and electrical parts sector, focusing on the research and development, production, and sales of automotive electronic and electrical parts. It is an important member of the supplier system for new energy vehicle manufacturers such as NIO and Li Auto, playing a significant role and exerting considerable influence in the new energy vehicle field.

The removal of enterprise nodes is divided into initial node removal and node removal during the interaction process. Randomly removing nodes connected to Enterprise A, B, and C, whether they are close-range or long-range nodes, is referred to as initial node removal. The purpose is to observe the extent to which automotive manufacturing enterprises with different levels of SCR are affected by supply chain disruptions. During the interaction process, if a high-SCR enterprise's performance falls below P1 within a certain number of time steps (the average network diameter), the model will automatically remove that enterprise node. Similarly, medium-SCR enterprises will be removed if their performance drops below P2, and low-SCR enterprises will be removed if their performance falls below P3.

After the initial nodes in the supply chain network are removed, the enterprises affected by the disruption will initiate adaptive strategies to restore their supply relationships. The implementation of this strategy involves two key steps (affected enterprises searching for alternative suppliers and alternative suppliers establishing connections with affected enterprises):

First, the enterprises affected by the disruption will identify potential alternative suppliers based on two criteria: (1) the affected enterprise's current in-degree must be less than its initial in-degree ($c_i < a_i$), indicating that its supply relationship has not yet been fully restored; and (2) the potential alternative supplier's current out-degree must be less than its initial out-degree ($d_i < b_i$), indicating that it still has the capacity to accept new connections.

Second, after identifying potential alternative suppliers, the affected enterprises will send connection requests to them and await responses. If the alternative supplier accepts the request, a one-way connection will be established between the two parties. If the request is rejected, the enterprise will continue to send requests to other potential alternative suppliers. If the enterprise fails to meet the minimum performance requirement after multiple attempts, it will be removed from the network. For alternative suppliers, when receiving a single request, they will directly establish a connection with the requesting enterprise. When receiving multiple requests simultaneously, they will rank the candidate enterprises by size and prioritize establishing connections with the top (d_i-b_i) enterprises. Once the current out-degree reaches the initial out-degree (d_i=b_i), they will stop accepting new connection requests.

As shown in Fig. 2, some enterprises in the supply chain network can act as both upstream suppliers and downstream customers. Based on this characteristic, this study does not strictly distinguish between traditional roles such as suppliers, manufacturers, and retailers in the simulation design. Instead, the supply chain network is divided into a three-tier structure according to the initial in-degree and out-degree of the enterprise nodes. The first tier consists of enterprise nodes with an initial in-degree of 0, which are set as terminal nodes that do not actively seek alternative suppliers in network interactions. The second tier includes enterprise nodes with both initial in-degree and out-degree not equal to 0, which have bidirectional interaction capabilities and can both actively seek alternative suppliers and accept connection requests from alternative customers. The third tier is composed of enterprise nodes with an initial out-degree of 0, which are restricted to the supplier role and cannot accept connection requests from alternative customers.

4 Simulation results and analysis

4.1 Problem description and assumptions

The supply chain of publicly listed automotive manufacturing companies is known. By simulating supply chain disruptions through the removal of enterprise nodes, the changes in the number and performance of enterprises with different resilience levels are observed to summarize the evolution pattern of supply chain disruptions.

The simulation model is based on the following assumptions: no new enterprise agents are generated during entity interactions; enterprise agents failing to meet performance requirements during entity interactions will cease operations and be removed; all connections are one-way connections from suppliers to their customers.

4.2 Simulation design

This simulation is based on the NetLogo simulation platform. After importing the upstream and downstream relationship data of relevant enterprises in the automotive manufacturing industry and the basic information data of each enterprise into the NetLogo platform, the code is written according to the entity interaction rules mentioned earlier. Parameters P1, P2, and P3, which represent the enterprise scale, in-degree, and out-degree of enterprises with different resilience levels, are set to 0.5, 0.6, and 0.75, respectively. For intuitive operation and data statistics during the model's runtime, the number of enterprises with different resilience levels and the performance of Enterprises A, B, and C are visualized. The simulation interface is designed as shown in Fig. 4.

In Fig. 4, the "Setup" button serves as the model initialization button, while "Go" initiates the simulation. Enterprises with high, medium, and low resilience levels are respectively identified by the colors red, yellow, and green. "Ticks" represent the time steps of the model's execution, with each increment indicating one iteration of the model. The number of enterprise nodes and their performance change according to the variation in ticks.

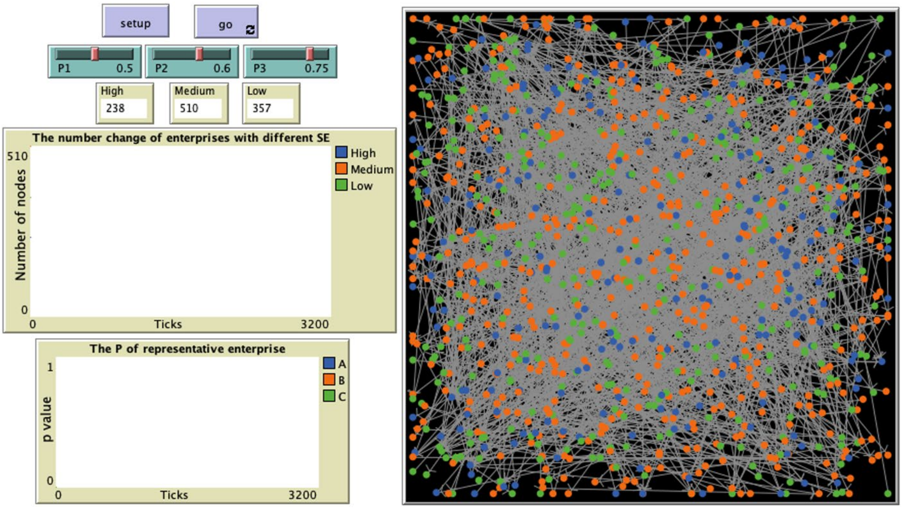


Fig. 4 Supply chain disruption evolution simulation interface design

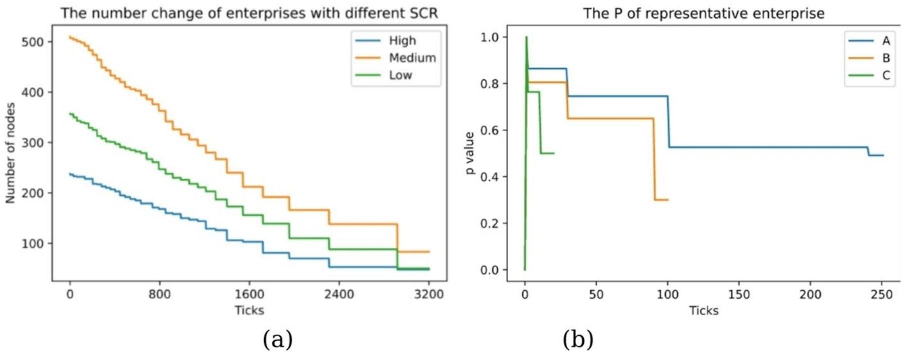


Fig. 5 Simulation of short-distance interruption without considering adaptive strategy

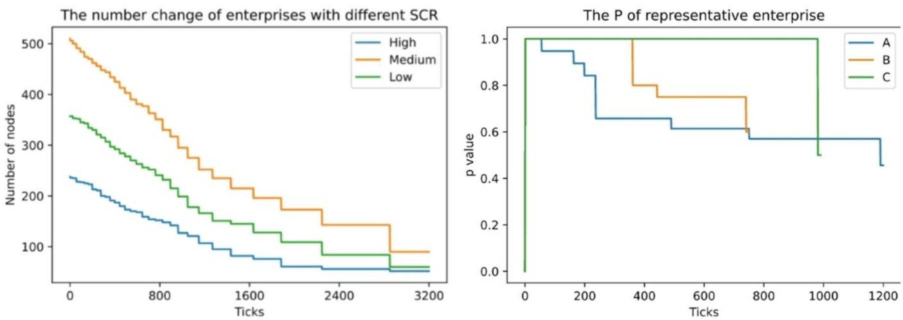
4.3 Simulation result

The simulation is based on the following three scenarios: short-distance disruption without adaptive strategies, long-distance disruption without adaptive strategies, and short-distance disruption with adaptive strategies. Short-distance disruption refers to the disruption of first-tier suppliers, that is, the deletion of enterprise nodes directly connected to the focal enterprise. Long-distance disruption refers to the deletion of enterprise nodes that are two or more steps away from the focal enterprise.

Taking Enterprise A, Enterprise B, and Enterprise C in the automotive manufacturing industry as the focal enterprises with high, medium, and low SCR respectively, we randomly remove the short-distance enterprise nodes connected to Enterprise A, B, and C, and observe the changes in the number of enterprise nodes with different SCRs and the performance changes of Enterprise A, B, and C. Figure 5 shows the simulation results. As shown in Fig. 5(a), after 3,200 iterations, the number of enterprise nodes with high, medium, and low SCR decreased from the initial 238, 510, and 357 to 48, 83, and 50, respectively. The failure rates of the nodes were 79.83%, 81.76%, and 85.99%, with an average failure rate of 83.62%. Figure 5(b) shows that after the short-distance enterprise nodes were disrupted, the performance of Enterprise A, B, and C declined. With the removal of the initial nodes, Enterprise C was removed in the second iteration due to performance falling below the minimum requirement. Enterprise B and A were removed in the 100th and 251st iterations, respectively.

To simulate the impact of long-distance enterprise node disruptions and their propagation in the supply chain, in the initial node removal phase, nodes outside the second tier of the supply chain for Enterprises A, B, and C were removed. The simulation results are shown in Fig. 6. Figure 6(a) shows that after 3,200 iterations, the remaining number of enterprises with high, medium, and low SCR were 52, 90, and 60, respectively. The node failure rates were 78.15%, 82.35%, and 83.19%, with an average failure rate of 81.72%, which is not much different from the results of Fig. 5(a). Figure 6(b) shows that Enterprise A was affected first, with its performance starting to decline at the 55th iteration and continuing to drop until it was removed at the 1,200th iteration for failing to meet the minimum performance standard. Enterprise B's performance began to decline at the 360th iteration and was removed at the 750th iteration. Enterprise C's performance declined at the 980th iteration and was removed 10 iterations later. This shows that Enterprise A has a greater ability to withstand disruption risks than Enterprises B and C.

Considering the adaptive behavior of enterprises affected by disruptions, when short-distance enterprise nodes are removed, the behavior of searching for alternative suppliers is added for the enterprises, and the simulation situation is shown in Fig. 7. In Fig. 7(a), after 3,200 iterations, the remaining number of nodes for the three types of enterprises was 170, 342, and 215, respectively. The node failure rates were 28.57%, 32.94%, and 39.78%, with an average failure rate of 34.21%, which is significantly lower than that in Fig. 5(a) and Fig. 6(a). After the disruption, the performance of Enterprises A, B, and C gradually declined with fluctuations. Enterprises B and C were eventually removed at the 750th and 100th iterations, respectively,



(a) (b)

Fig. 6 Simulation of long-distance disruption without considering adaptive strategy

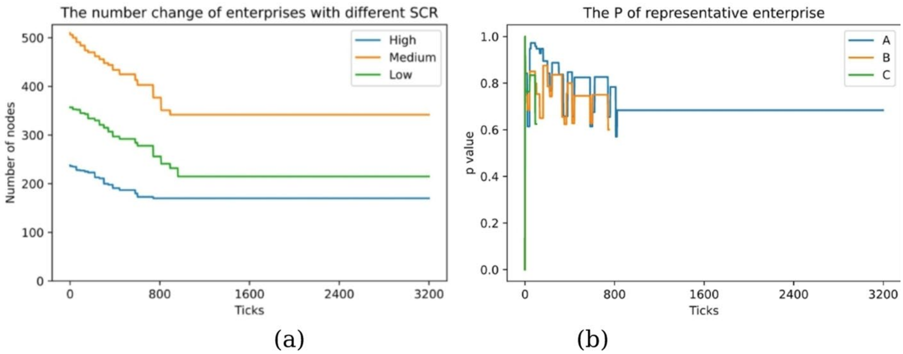


Fig. 7 Short-distance disruption simulation considering adaptive strategy

due to failure to find new alternative suppliers and thus failing to meet the minimum performance requirement. In contrast, Enterprise A's performance stabilized at 0.68 after 820 iterations.

4.4 Analysis of effect

The simulation results show that supply chain network disruptions have a ripple effect, causing a gradual decline in corporate performance and a reduction in the number of enterprise nodes. This is especially true for the automotive manufacturing sector, where supply chains are highly complex and globalized, involving multiple tiers of suppliers and partners. Consequently, disruptions can affect not only the original equipment manufacturers but also upstream parts suppliers and downstream dealers. Thus, automotive manufacturers must recognize and address the propagation effects of supply chain disruptions.

From Figs. 5(a) and 6(a), it is evident that both short-distance and long-distance disruptions to Enterprises A, B, and C can lead to the removal of over 80% of nodes in the supply chain network. Comparing Figs. 5(b) and 6(b) reveals that long-distance disruptions do not immediately affect Enterprises A, B, and C. However, as the disruption spreads, Enterprise A is impacted first. Notably, Enterprise A can continue operating for a longer period than Enterprises B and C after being affected, indicating that a higher SCR enhances a firm's ability to withstand supply chain disruptions.

After implementing adaptive strategies, the simulation of short-distance disruptions shows a node failure rate of 34.21%, a significant 49.41% reduction compared to not considering adaptive behaviors. High-SCR enterprises still show stronger resilience against disruptions. This indicates that adaptive strategies can reduce the likelihood of firms being removed, thus enhancing their ability to withstand disruptions. However, low-SCR enterprises, often smaller in scale, less efficient in supply chain operations, and with fewer partners, struggle to find suitable alternatives quickly and face a higher risk of being removed. Although high-SCR enterprises are less likely to be removed, the disruption still significantly impacts the performance of all enterprises.

5 Discussion

5.1 Research contributions

This study provides innovative insights at both theoretical and practical levels.

Theoretically, it advances supply chain disruption research by systematically integrating Complex Adaptive Systems theory, proposing a conceptual framework that captures multi-agent interactions and dynamic evolution across three dimensions (internal mechanisms, external mechanisms, co-evolution) and three hierarchical levels (flow, system agents, internal models). This framework transcends traditional static models by elucidating nonlinear disruption propagation mechanisms—such as the path-dependent nature of cascading failures—and self-organizing recovery behaviors like dynamic supplier substitution. These insights bridge a critical gap in existing literature by demonstrating how micro-level adaptive behaviors drive the emergence of macro-level resilience, while offering methodological advancements for applying CAS principles to supply chain management.

Practically, the development of a multi-tiered simulation model using automotive industry data enables quantitative assessment of resilience variations. The findings reveal that supply chain disruptions propagate through tightly coupled enterprise networks, generating systemic ripple effects that extend beyond individual firms. While organizations with higher resilience exhibit stronger disruption mitigation capabilities, adaptive strategies alone prove insufficient as cascading effects amplify operational impacts over time. These results underscore the strategic imperative for building robust information-sharing systems and enhancing systemic efficiency to counteract disruption escalation.

5.2 Recommendations

The adaptive behaviors examined in this study primarily reflect reactive post-disruption strategies. However, advancing digital capabilities could empower firms to adopt proactive approaches, such as real-time disruption detection and preventive interventions, which may significantly reduce impact severity and contain propagation across supply networks. Enterprises must adopt tiered strategies aligned with their resilience levels.

High-resilience firms should focus on dynamic optimization during response phases through technologies like digital twins and IoT-enabled inventory monitoring, which could reduce decision latency by 40–60% when combined with machine learning for supplier matching. Medium-resilience organizations require enhanced data integration during preparedness phases, exemplified by blockchain-based platforms that automate contingency protocols—as demonstrated by Toyota's blockchain-driven 14-day early warning system for chip shortages (Cai et al. 2022). Low-resilience entities must prioritize foundational digitalization, employing lightweight SaaS tools for supplier risk mapping while cultivating strategic partnerships to share resources and risks, thereby strengthening systemic recovery capacity.

5.3 Research limitations and prospects

This research has several limitations that warrant consideration. The analysis omits external environmental variables such as transportation networks and customs policies by focusing solely on tier-2 suppliers, while the exclusion of inter-firm competitive dynamics (e.g., supplier bidding) may underestimate market restructuring effects. Additionally, the static weighting of supply chain resilience indicators fails to account for industry-specific priorities, such as response speed in electronics versus recovery stability in agriculture.

Future studies should address these gaps through multi-agent reinforcement learning models to simulate long-term adaptive strategy evolution, cross-industry resilience benchmarking frameworks with sector-specific criteria, and integrated risk forecasting systems that combine climate projections and geopolitical data. Such advancements could shift disruption management from reactive response to pre-emptive immunity, enabling enterprises to refine contingency strategies and ensure operational sustainability in increasingly volatile global contexts.

Data availability The data that support the findings of this study are openly available in CSMAR at https://data.csmar.com/.

Declarations

Competing interests No potential conflict of interest was reported by the authors.

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