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Enhancing the topological robustness of supply chain networks against dynamic disruptions: A complex adaptive system perspective ☆

Jiepeng Wang [a] [ID], Peng Qin [b] [ID], Li Chen [a] [ID],*, Changgui Gu [a] [ID], Yufei Yuan [c] [ID], Hong Zhou [d] [ID]

[a] Business School, University of Shanghai for Science and Technology, Shanghai 200093, PR China
[b] Faculty of Data Science, City University of Macau, Macau 999078, PR China
[c] Department of Transport & Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Stevinweg 1, 2628CN, Delft, The Netherlands
[d] School of Economics and Management, Beihang University, Beijing 100191, PR China

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ABSTRACT

With growing disruptions, uncertainties, and complex risks like pandemics, natural disasters, and geopolitical tensions, firms must ensure supply chain continuity, quick recovery, and agility in responding to market needs. As a result, designing resilient supply chain networks (SCNs) has become both essential and highly important. To address this problem, based on the complex adaptive system (CAS) theory and by modifying the Barabási and Albert (BA) model, a supply chain network evolving (SCNE) model with adaptive strategies is designed, which considers firms' edges growth and rewiring strategies. Utilizing mean-field theory, the SCNE model is analyzed and subjected to simulation studies to verify its scale-free properties. It also examines the structural characteristics of SCN evolution under different adaptive strategies. Subsequently, a case study of Acura automobile SCN is conducted for topological robustness analysis. Finally, the results of the simulation are validated using an ordinary least squares (OLS) regression model, demonstrating the effectiveness of adaptive strategies in enhancing the topological robustness of SCNs. We find that the enhancement of SCN topological robustness can be achieved through firms' edges growth and rewiring strategies in response to node removal disruptions. Quantitatively, firms' edges growth strategies improve SCN topological robustness approximately 2.1 times more than rewiring strategies, as indicated by the coefficients of 0.81 and 0.75 for largest connected component size and network efficiency, respectively, compared to 0.38 and 0.37 for rewiring strategies. These findings underscore the critical role of adaptive strategies in enhancing the resilience of SCNs.

1. Introduction

1.1. Background

A supply chain network (SCN) emerges when organizations collaborate to share resources, services, and information, aiming to enhance efficiency and cost-effectiveness. SCNs are inherently large-scale, dynamic, and complex systems, evolving under the influence of internal coordination mechanisms and external environmental pressures [1–6]. However, in today's highly uncertain environment, SCNs are increasingly exposed to disruptions, uncertainties, and systemic risks, including pandemics, natural disasters, geopolitical tensions, and economic instability. For instance, the COVID-19 pandemic severely disrupted global supply chains, causing factory shutdowns, logistics bottlenecks,

labor shortages, and infrastructure failures, which hampered global manufacturing and trade flows [7,8]. Geopolitical tensions, such as the U.S.-China trade war and sanctions on critical industries, have further fractured global supply chains, particularly in sectors like semiconductors, pharmaceuticals, and technology, forcing firms to reconsider their sourcing and operational strategies.[1] Additionally, climate change and natural disasters — including floods, hurricanes, and earthquakes — have heightened supply chain vulnerabilities, while geopolitical conflicts (e.g., the Russia-Ukraine war) have led to severe energy price fluctuations and supply shortages.[2] These cascading disruptions underscore the fragility of global SCNs, highlighting the urgent need for resilient and adaptive supply chain networks that can withstand and recover from external shocks.
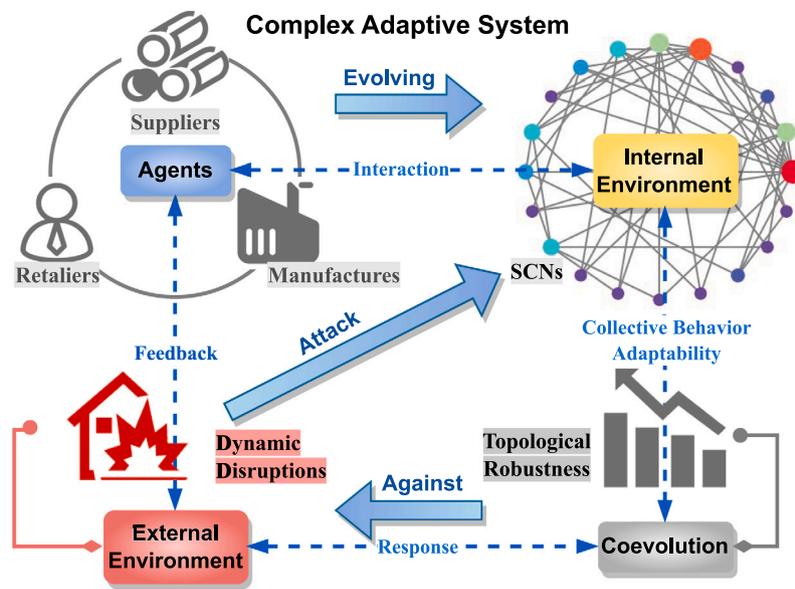
Fig. 1. An overview of supply chain network dynamics under disruptions, adaptation, and topological robustness.

1.2. Research challenges and gaps

Given the increasing complexity of supply chain risks, enhancing SCN robustness has become a critical research challenge [4,6]. Traditional SCN modeling approaches — such as operations research (OR), game theory, and system dynamics — have provided valuable insights into network optimization and risk management [9]. However, these methods often assume static network structures and struggle to capture the self-organizing, dynamic, and adaptive nature of real-world SCNs. Complex adaptive system (CAS) theory offers a more comprehensive and dynamic perspective, allowing researchers to model nonlinear interactions, emergent behaviors, and evolutionary dynamics in SCNs [1,2,10–13]. Within network science, complex network theory has been widely used to analyze SCN topology and resilience [3]. The Barabási–Albert (BA) model, which captures scale-free properties, has been applied to study SCN structural characteristics [14–16]. However, most existing studies focus on static resilience assessments rather than proactive adaptation mechanisms. Few studies have systematically examined how SCN structures evolve in response to disruptions and how firms' adaptive strategies — specifically, edge growth and rewiring — affect network robustness.

Moreover, while previous research has evaluated SCN robustness under various risk scenarios, there is limited empirical validation of adaptive strategies in real-world settings [17]. The lack of quantitative verification through statistical models such as ordinary least squares (OLS) regression restricts the generalizability of prior findings. Additionally, as illustrated in Fig. 1, SCNs operate in a coevolutionary environment, where firms interact, adapt, and collectively respond to dynamic disruptions through self-organizing behaviors, network adaptability, and structural adjustments. Yet, existing models fail to adequately capture this complex interplay between internal mechanisms, external risks, and network resilience strategies.

1.3. Aim and innovation of the study

To address these challenges, this study aims to enhance the topological robustness of supply chain networks against dynamic disruptions by integrating CAS theory with adaptive network evolution strategies. Specifically, we develop a supply chain network evolving (SCNE) model, incorporating adaptive edge growth and rewiring strategies to improve SCN resilience. By modifying the BA model, this study systematically explores how SCNs evolve in response to disruptions and

identifies effective adaptation mechanisms for firms to mitigate risks and enhance network stability.

This study introduces several key innovations:

1. A dynamic, adaptive SCN evolution model: While previous studies have applied CAS theory to SCNs, this study presents an advancement by introducing an adaptive evolution model that incorporates specific adaptive strategies (i.e., edge growth and rewiring) to reflect the dynamic nature of SCN resilience. Unlike traditional models that often assume static or fixed supply chain structures, our model accounts for the evolution of SCNs in response to disruptions, offering a more realistic and context-sensitive representation of SCN adaptability and robustness.
2. Integration of adaptive edge growth and rewiring strategies: Previous studies have primarily focused on static resilience assessments. This research introduces adaptive edge growth and rewiring mechanisms, demonstrating how firms' structural adjustments enhance SCN robustness against dynamic disruptions.
3. A multi-method validation framework: Few studies have systematically validated SCN adaptation strategies using quantitative methods. This study integrates mean-field theory, simulation experiments, and an empirical case study of the *Acura* automobile SCN, offering a multi-method validation approach. Additionally, it employs OLS regression to quantify the impact of adaptive strategies on SCN resilience, improving the generalizability and practical applicability of the findings.

To achieve these objectives, this study seeks to answer the following key research questions (RQs):

- RQ1: In today's highly uncertain environment, how can the robustness of supply chain systems be enhanced?
- RQ2: How can a supply chain network be designed from the perspective of a CAS?

By addressing these questions, this study contributes both theoretically and practically to the design, adaptation, and resilience enhancement of supply chain networks. The proposed SCNE model offers new insights into SCN evolution, equipping businesses and policymakers with strategies to improve supply chain robustness in an increasingly volatile global environment.

2. Literature review

This section covers the literature related to the modeling of supply chain networks (SCNs), SCNs as complex adaptive systems (CAS), and risk propagation, evolution, and control in SCNs. Last, we highlight the knowledge gap.

2.1. Modeling of supply chain networks

There are various methods for modeling supply chain networks (SCNs), including operations research(*OR*) methods [18,19], game theory [20], nonlinear dynamics methods [21,22], and agent-based methods(ABMs) [12,23,24]. Models based on OR primarily focus on optimization, including linear programming models, integer programming models, and mixed-integer programming models [9] [19] proposed a supply chain network design model using OR methods, considering the trade-off between total cost and feasibility performance under facility and transportation disruptions. They employed the Lagrangian relaxation algorithm, integrating the subgradient method and an improved genetic algorithm, to solve problems of various scales. Both OR and game theory approaches primarily involve using mathematical tools for model construction and description. However, these models are often challenging to intuitively represent supply chain networks. Furthermore, models built using OR and game theory typically assume *a static supply chain network topology*, which may not be suitable for dynamic supply chain network modeling. Since ABMs emphasize agent adaptability and learning capabilities, scholars and researchers often approach this field from the perspective of complex adaptive systems(CAS) [10–13] .

2.2. Supply chain networks as complex adaptive systems

Studying supply chain networks from the perspective of CAS has become a significant research area. This is because, on one hand, supply chain networks are constrained by both internal mechanisms (e.g., inter-organizational collaboration, human factors, financial management) and external environments (e.g., natural conditions, international politics, cultural differences, infrastructure). On the other hand, supply chain networks exhibit characteristics such as *self-organization, non-linearity, emergence, and evolution* [10]. [25] pioneered the conceptualization of supply chain networks as CAS by providing a detailed mapping of CAS properties, i.e., internal mechanisms, co-evolution, and environment, to supply chain networks. Based on ABMs, [12] constructed a supply chain network using real-world data to investigate firms' adaptive strategies in response to supply chain disruptions. [26] developed an ABM-based model to explore the relationship between supply chain network topology and its ability to recover from disruptions through inventory mitigation and rerouting, revealing the impact of network topology on the effectiveness of risk management strategies. [11] using the CAS framework, conducted empirical studies demonstrating the benefits of modular network structures and the functional similarity among process components. [27] applied CAS research methodologies, integrating nonlinear dynamics, statistical physics, and information theory to characterize and model supply chain networks. [28] expanded on [25], further developing the concept of complex adaptive supply chain networks, emphasizing their complexity and adaptability. [2] underscored the importance of viewing supply chains as complex adaptive systems (CASNs), using modeling and simulation based on fitness landscape theory to reveal evolutionary complexities such as emergence, chaos, and quasi-equilibrium, while highlighting external environmental factors and internal firm mechanisms as key drivers of CASN evolution. With the advancement of complex network theory [29–32], a growing number of researchers have studied supply chain networks from the *complex network perspective* [3]. Complex supply chain networks evolve from linear supply chains and network structures, making their characteristics, i.e., dynamism, complexity, and interconnectivity, more pronounced [33]. These factors also pose greater challenges in the modeling, risk evolution, and control of complex supply chain networks [16,34,35].

In complex network theory, the *topological structure* reveals how nodes are connected through edges. For example, in random network models, new edges between nodes are added randomly [36]. In scale-free network models, new edges follow a preferential attachment mechanism, meaning high-degree nodes are more likely to gain additional connections [30]. Network topological robustness focuses on analyzing the resilience of networks from a structural perspective, identifying vulnerability, failure conditions, and evolutionary patterns. Robustness is a structural concept, i.e., a network is *robust* if it can maintain its core functions despite internal and external failures. A resilient network, however, can adapt its operation to absorb and recover from shocks, disasters, or crises without losing its functional capacity [32]. A highly robust/resilient network can continue operating despite small-scale disruptions. Different network topologies exhibit varying degrees of robustness/resilience under different failure or attack types. That is, under targeted node attacks, random networks show greater robustness than scale-free networks. Under random node failures, scale-free networks exhibit stronger robustness, but they are highly vulnerable to targeted attacks.

2.3. Risk propagation, evolution, and control in SCNs

In the research on supply chain risk management(SCRM), most of the current literature focuses on the *adverse effects* of supply chain risks, typically represented as losses or potential losses [37,38]. Disruption risks are often viewed as *unplanned or unforeseen events* that disrupt the normal flow of goods and materials in the supply chain [39–42], or events that suddenly cut off supply [43], which pose significant threats to the normal operation of firms [44], potentially leading to increased costs, profit losses, and a decline in corporate reputation [40, 45,46]. Risk events (such as natural disasters, supplier bankruptcies, quality issues, etc.) can propagate or spread through the supply chain network, moving from one firm to another, from one link to another, thereby affecting the capability and stability of the entire supply chain system [47–51]. Among these, *local disruptions* in SCN firms spread through the network to adjacent firms, triggering a chain reaction that can even lead to a network-wide phenomenon known as the "ripple effect" [23,52–54].

In terms of risk propagation mechanisms, numerous studies have focused on the relationship between supply chain risk propagation mechanisms and supply chain network topology. For example, [47] used industry and enterprise logistics data to construct supply chain networks and explored how network structure regulates the economic impact on industry or enterprise sales. [55] quantified the extent of financial risk propagation in supply chain networks, finding that sub-network structures are an important source of risk for core firms, and the degree of subnetwork sharing is a major regulatory factor. [49,50] considered the impact of network structure and established a epidemic model to analyze the risk propagation mechanisms and evolution in supply chain networks. Furthermore, [56] studied the bullwhip effect from the supply chain network perspective, finding that the customer–supplier relationship in the management network can help mitigate the bullwhip effect. Additionally, firms in the network engage in game relationships through competition or cooperation, affecting the equilibrium and evolution of the supply chain system. For instance, [20] studied the evolution of game theory among upstream and downstream firms in supply chain networks under disruption risks.

Building resilient/robust supply chain network structures to counter disruption risks is another direction of research on risk propagation and evolution. Related studies can be broadly divided into three categories:

1. Modeling and Topological Structure Analysis of Supply Chain Networks. [51] studied the topological structure of the TFT-LCD supply chain network and the propagation of COVID-19-related risks from a dynamic perspective, analyzing the evolution of the constructed supply chain network topology and hidden risk sources. [57] designed and constructed a green logistics network based on the inherent attributes of ecological industrial systems, modifying the BA model and analyzing its topology.

2. Interaction Between Network Topology and Its Robustness in Mitigating Disruption Risks. [58] extended linear supply chains to a supply chain network and studied the relationship between network topology and its robustness against supply interruptions in the case of random failures and targeted attacks. [59] used a combination of empirical and simulation methods to study the robustness of manufacturing networks and found that a network science perspective can verify the interdependencies in large-scale supply chain network data. [15,17,60–62] analyzed the robustness of complex supply chain networks under disturbance events using simulation methods, finding that network topology robustness plays an important role in mitigating the impact of disruptions.

3. Network Resilience Metrics, Design, and Optimization. [22] selected "alternatives" for vendor nodes in different scale regions of the supply chain network based on the self-similarity of geographic structures during supply chain network evolution, aiming to reconfigure the supply chain and enhance network resilience. [63] proposed a resilience evaluation mechanism for supply chain structures, measuring the resilience of supply chain structures to disruptions. [64] proposed a decision support system based on re-wiring strategies for analyzing the robustness of supply chain networks against disruptions through topological structure analysis and network optimization. [24] studied the resilience of the logistics network in the express delivery industry to node failures caused by network disruptions. By considering the flow capacity between nodes and the impact of each node failure, they proposed a load redistribution mechanism in the case of cascading failures and various adjustment strategies to enhance resilience.

In the field of risk control in complex supply chain networks, the concept models in *qualitative analysis* mainly offer strategic recommendations to address supply chain risks from the network perspective [65–68]. For example, [68] combined grey theory and directed graph methods to introduce a framework combining various methods. [69–71] proposed general supply chain risk management approaches: Construct supply chain network → Identify risks and their current position → Assess risks → Manage risks → Form collaborative supply chain risk strategies → Implement supply chain risk strategies. In *quantitative analysis*, [21] studied event-triggered control protocols for supply chain finance nonlinear multi-agent systems, designing event-based control methods using a decreasing time threshold function to manage the dynamics of supply chain systems. [72] proposed an improved susceptible-infected-susceptible (SIS) model, combining complex network models and optimized risk control strategy selection methods to explore risk control strategy selection in cross-border supply chains. [73] combined case studies and simulation models and found that during catastrophic events, certain network configuration strategies (such as collaboration and multi-sourcing) are more effective than others. By adopting strategies that mix active and passive elements, small and medium-sized enterprises (SMEs) can avoid suffering more damage than large competitors.

2.4. Knowledge gap

Despite the extensive research on SCN modeling, risk propagation, and resilience enhancement, several critical gaps remain unaddressed. First, while traditional modeling approaches—such as OR, game theory, and system dynamics, have provided valuable insights into supply chain network optimization and decision-making, these methods often assume static network topologies and struggle to capture the dynamic, self-organizing, and adaptive nature of real-world SCNs. The CAS framework, which better represents the nonlinear, evolutionary, and emergent properties of SCNs, has been underutilized in SCN robustness studies.

Second, although complex network theory, particularly the BA model, has been applied to study supply chain topology and resilience, existing research rarely integrates adaptive strategies into SCN evolution modeling. Most studies focus on either static resilience assessments or reactive risk mitigation strategies, neglecting the *proactive adaptation mechanisms* that firms employ to restructure their networks under disruptions, uncertainties, and cascading failures. Consequently, the role of firms' adaptive strategies in shaping SCN robustness — specifically, how edge growth and rewiring strategies influence SCN resilience — remains insufficiently explored.

Third, while prior studies have examined SCN robustness under various risk scenarios, including random and targeted disruptions, there is limited empirical validation of how adaptive strategies quantitatively enhance SCN robustness. Existing research lacks systematic simulation analyses that integrate both mean-field theoretical approaches and empirical case studies to validate network resilience strategies. Furthermore, the lack of statistical validation methods, such as ordinary least squares (OLS) regression analysis, in SCN robustness studies limits the generalizability of previous findings.

To bridge these gaps, this study proposes a supply chain network evolving (SCNE) model, incorporating adaptive edge growth and rewiring strategies within the CAS framework to analyze SCN topological robustness under disruptions. By modifying the BA model and integrating mean-field theory, simulation studies, and empirical validation through an *Acura* automobile SCN case study, this research seeks to provide a more comprehensive and dynamic perspective on SCN resilience enhancement.

3. Model

This section presents model assumptions in Section 3.1, elements of an SCN based on the CAS theory in Section 3.2, the SCNE model in Section 3.3 (consisting of model algorithm in Section 3.3.1, and analysis of the SCNE model in Sections 3.3.2 and 3.3.3 both from the aspects of theoretical and simulation levels), the dynamic disruption model in Section 3.4 and the topological robustness measuring in Section 3.5. For ease of reference, we summarize the notations and definitions in Table 1.

3.1. Model assumptions

SCNs are large-scale, dynamic, complex systems [10,16,27,49,61], comprising different types of business entities (e.g., suppliers, manufacturers, distributors, retailers), as well as intricate flows, connections, and associations (e.g., material flow, information exchange, contractual relationships, cash flow) [34,49,74]. As new firms continuously enter the SCN to maintain its operational functions, the topological structure of the SCN evolves over time [4,15,17,57]. [75] define an SCN as a network of exchange relationships among suppliers, customers, and their partner enterprises, considering these relationships essential for the production and provision of goods and services to the market. In our model, nodes represent the firms within the supply chain network, while the edges between nodes represent the exchange relationships between firms (e.g., cooperation, business association).

We consider the scenarios studied in this article mainly revolve around the industrial ecosystems formed around core firms in the SCN, which are generally of a large scale. Compared with past studies, for example, the SCN in [57] consists of 82 nodes; [74] construct an SCN with 70 nodes; [58] describe an SCN with 18 nodes; [76] model an

Table 1
The notations and definitions in the SCN models.

Notation	Definition
V	The set of nodes in the SCN;
E	The set of edges in the SCN;
G	An SCN, undirected network graph with V nodes and E edges, $G = (V, E)$;
e_{ij}	The edge between the node i and the node j, $e_{ij} \in E$;
v_i	The node i, $v_i \in V$;
k_i	The degree of node i;
$P(k_i)$	The degree distribution of the SCN;
Model 1	**SCN Evolving Model**
m_0	The number of the nodes in the SCN at the initial time;
e_0	The number of the edges in the SCN at the initial time;
m	The number of the edges varied (grow, rewire, or added with a node) in the SCN at each time step;
p_1	The probability of edges growing, $p_1 \in [0, 1)$;
p_2	The probability of the edges rewiring, $p_2 \in [0, 1)$;
p_3	The probability of the edges with a node adding in the SCN, $0 < p_3 = 1 - p_1 - p_2$;
N	The total number of the nodes in the SCN;
t/T	Time step;
$\prod_{i,j}$	The probability of connection between the node i and the node j.
Model 2	**Dynamic Disruption Model**
$D(i)$	Degree centrality of node i;
$EB(e_{ij})$	Betweenness centrality of an edge e_{ij} in an SCN;
$\sigma(s, t)$	The total number of shortest paths between node s and node t in an SCN;
$\sigma(s, t \mid e_{ij})$	The number of shortest paths between node s and node t that pass through edge e_{ij} in an SCN;
q	The proportion of nodes (edges) removed at each time step t;
$R(q)$	The relative size of the largest connected component in the SCN;
$E(q)$	The relative network efficiency of the SCN.

SCN comprising 106 nodes; [64] report on an SCN with 184 nodes; and [53] present an SCN involving 250 nodes while 250 is considered a conventional size for an SCN; in [60], the number of nodes in the SCN is set to 600; in [14] ; [15,77], the number of nodes in the SCN is set to 1000, indicating relatively large scales for SCNs.

3.2. Elements of an SCN based on the CAS theory

From the perspective of CAS theory, an SCN can be regarded as a complex adaptive system [10,25,27,28]. CAS theory emphasizes the interactions between internal and external environments as well as the interdependencies and adaptive capabilities of various actors within the system (as shown in Fig. 1).

Based on the CAS theoretical framework, supply chain networks exhibit the following characteristics

- Dynamic Evolution. Actors within an SCN (such as suppliers, retailers, and manufacturers) gradually form a complex supply chain network through a long-term, dynamic, and intricate evolutionary process. These actors interact, depend on, and influence each other, continuously adjusting and adapting their behaviors in response to these interactions. According to CAS theory, supply chain networks function as adaptive systems that evolve through continuous trial-and-error, learning, and adjustment [20,24,78]. Over time, these adaptive processes shape the structural and behavioral patterns of SCNs, allowing them to align with market demands and external environmental changes.

- Adaptive Strategy: Business Cooperation. CAS theory highlights adaptability within systems, where SCNs leverage adaptive mechanisms to manage risks and uncertainties. Business cooperation between firms is a crucial component of supply chain networks [79], as it fosters information sharing, resource integration, and collaborative innovation. Close partnerships among firms facilitate efficient communication and knowledge exchange, enhancing the network's overall responsiveness [16,27]. By sharing market intelligence, demand forecasts, and supply chain data, firms can jointly address market fluctuations and risks, allowing them to adjust operational strategies in a timely manner and improve their adaptive capabilities [20,49].

In other words, strengthening business collaborations and increasing the frequency of cooperation helps SCNs adapt to external changes and mitigate risks. *Within the SCNE model, this phenomenon is captured by the idea that even without new firms entering the network, existing firms can still establish new exchange relationships. The corresponding modeling step is adding new edges to the network.*

- Adaptive Strategy: Rewiring Business Partnerships. Actors within a SCN may need to reassess their cooperation strategies in response to external changes. CAS theory posits that actors within the system possess autonomy and adaptability, allowing them to adjust their behaviors and collaboration models based on environmental changes. When facing significant external shifts — such as market demand fluctuations, technological advancements, or competitive landscape transformations — firms may need to reevaluate their partnerships. Through learning from past experiences, they can identify new partners, adjust collaboration models, and optimize operational processes to better adapt to these changes [33,80,81].

Adaptability enables firms to flexibly modify their cooperation strategies to meet new market demands, thereby enhancing the resilience and robustness of the system. *Within the SCNE model, this phenomenon is reflected in how firms reconfigure their exchange relationships, such as manufacturers switching suppliers [80]. The corresponding modeling step is rewiring existing edges within the network.*

- Emergence of Collective Behavior. The CAS framework suggests that collective behaviors within an adaptive system can be strengthened through a coevolutionary process. In a supply chain network, firms engage in *business cooperation* and *rewire business partnerships*, allowing actors to jointly learn and adapt to market changes, thereby enhancing system robustness and adaptability [10,13].

As supply chain actors co-evolve and enhance collective behaviors, the system becomes better equipped to handle risks and uncertainties, maintaining both stability and flexibility over time.

3.3. Supply chain network evolving model

3.3.1. Model algorithm

Based on the above model assumptions and theoretical background, combined with [30,64,82,83], we propose the supply chain network evolving (SCNE) model for the evolution of SCNs with adaptive strategies. The algorithm is as follows:

- Step 1 - Initial state: Time step $t = 0$, the SCN G_0 begins to evolve, generating a network with m_0 initial nodes with e_0 initial edges.
- Step 2 - Adaptive mechanism selection for the SCN: Let the time step $t = t + 1$, the supply chain network evolution will choose the following three mechanics with a certain probability:
  (1) Edge Growth Mechanism(Adaptive Strategy p_1, $p_1 \in [0, 1)$): Add m ($m < m_0$) new edges to the network, representing new business collaborations or associations in the SCN. The origin of the edge follows a random attachment(RA) mechanism, while the destination follows a preferential attachment(PA) mechanism.
  (2) Rewiring Mechanism(Adaptive Strategy p_2, $p_2 \in [0, 1)$): Select m ($m < m_0$) edges in the network to rewire. Similarly, the origin of the edge follows a RA mechanism, while the destination follows a PA mechanism.
  (3) Node Growth Mechanism(p_3, $p_3 = 1 - p_1 - p_2$): [30] indicate that node growth is fundamental to network evolution, hence we have $p_3 > 0$. Considering the phenomenon of new firms continuously entering the SCN, add a new node with m ($m < m_0$) edges to the network, representing a new firm in the SCN. The edges follow a PA mechanism.

The preferential probability of PA is defined as

$$\Pi(k_i) = \frac{k_i}{\sum_j k_j}, \tag{1}$$

where k_i is the node degree. Formula (1) indicates that in SCNs, firms are more inclined to cooperate with firms that have a higher degree, in order to access more abundant operational resources and reduce potential risks.

- Step 3 - Iteration: Repeat the aforementioned Step 2 until the supply chain network G reaches the specified size N.

After T time steps, according to the evolutionary rules of the SCNE model, an SCN can be generated with $N = m_0 + p_3 T$ nodes and $e_0 + m(1 - p_2)T$ edges. Fig. 2 is a simplified schematic diagram of the SCNE model. In this example, $m = 2$, meaning that at each time step t, the SCN changes by 2 edges. At $t = 0$, the SCN begins its evolution from an initial network with $m_0 = 5$ nodes (labeled $1 - 5$) and $e_0 = 5$ edges (gray). When $t = 1$, the SCN has 3 evolutionary strategies to choose from: (1) Edge growth with probability p_1 (adding new green edges e_{24} and e_{35} with preferential probability (1)); (2) Rewiring with probability p_2 (rewiring gray edge e_{23} to red edge e_{24}, and gray edge e_{15} to red edge e_{13} with preferential probability (1)); (3) Node growth with probability p_3 (orange node 6 enters the network, adding new orange edges e_{64} and e_{63} with preferential probability (1)). As more nodes are added, a SCN will complete its evolution when it reaches the expected size N.

3.3.2. Theoretical analysis

According to the mean-field theory [84], for any node (firm) i in the supply chain network, there is an assumption of a continuous distribution of node degrees. Therefore, the processes $(1) - (3)$ of the SCNE model contribute to the rate of change of degree k_i for the node (firm) i within a unit time step t, satisfying the following formula:

$$\left(\frac{\partial k_i}{\partial t}\right)_{(1)} = p_1 m \frac{1}{N} + p_1 m \frac{k_i}{\sum_j k_j}, \tag{2}$$

$$\left(\frac{\partial k_i}{\partial t}\right)_{(2)} = -p_2 m \frac{1}{N} + p_2 m \frac{k_i}{\sum_j k_j}, \tag{3}$$

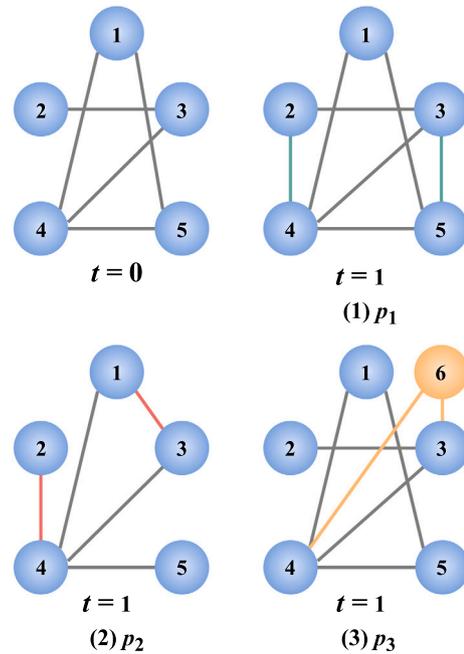$$\left(\frac{\partial k_i}{\partial t}\right)_{(3)} = p_3 m \frac{k_i}{\sum_j k_j}. \tag{4}$$

Fig. 2. An example of the SCNE model.

According to the formula (2)–(4), we have

$$\frac{\partial k_i}{\partial t} = (p_1 - p_2) m \frac{1}{N} + m \frac{k_i}{\sum_j k_j}. \tag{5}$$

According to complex network theory, it can be derived that: $N = m_0 + (1 - p_1 - p_2)t$, $\sum_j k_j = 2e_0 + 2(1 - p_2)mt$. Let $t \to \infty$, we have $N = (1 - p_1 - p_2)t$, $\sum_j k_j = 2(1 - p_2)mt$. Therefore, formula (5) can be rewritten as:

$$\frac{\partial k_i}{\partial t} = (p_1 - p_2) m \frac{1}{(1 - p_1 - p_2)t} + m \frac{k_i}{2(1 - p_2)mt}. \tag{6}$$

By applying the standard solution of a first-order linear ODE:

$$\frac{dy}{dx} + p(x)y = g(x) \to y(x) = \frac{1}{\exp\left(\int^x p(t)dt\right)} \left[\int^x g(\xi)\exp\left(\int^\xi p(t)dt\right)d\xi + C'\right] \tag{7}$$

We can solve differential Eqs. (6), that is,

$$k_i(t) = \frac{C}{1 - p_1 - p_2} \left(2t(1 - p_1 - p_2)(1 - p_2)\right)^{\frac{1}{2(1-p_2)}} - \frac{2m(1 - p_1)(p_1 - p_2)}{1 - p_1 - p_2}. \tag{8}$$

With initial condition $k_i(t_i) = m$, we have $C = \frac{m(1-p_1-p_2)+2m(1-p_1)(p_1-p_2)}{(2t_i(1-p_1-p_2)(1-p_2))^{\frac{1}{2(1-p_2)}}}$. By substituting C into formula (8), we can obtain:

$$k_i(t) = \left(m + \frac{2m(1 - p_2)(p_1 - p_2)}{1 - p_1 - p_2}\right) \left(\frac{t}{t_i}\right)^{\frac{1}{2(1-p_2)}} - \frac{2m(p_1 - p_2)(1 - p_2)}{1 - p_1 - p_2}. \tag{9}$$

Therefore, in the SCN, the probability that the degree $k_i(t)$ of node i is less than k is

$$p(k_i(t) < k) = p\left(t_i > \left(\frac{\frac{2m(p_1 - p_2)(1 - p_2)}{1 - p_1 - p_2} + m}{\frac{2m(p_1 - p_2)(1 - p_2)}{1 - p_1 - p_2} + k}\right)^{2(1 - p_2)} t\right). \tag{10}$$

In the SCNE model, new nodes are added to the SCN at equal time intervals, therefore the arrival time t_i of node i has a constant

probability density:

$$p(t_i) = \frac{1}{m_0 + t}. \tag{11}$$

By substituting formula (11) into formula (10), we obtain

$$p(k_i(t) < k) = 1 - \frac{t}{m_0 + t} \left(\frac{\frac{2m(p_1 - p_2)(1 - p_2)}{1 - p_1 - p_2} + m}{\frac{2m(p_1 - p_2)(1 - p_2)}{1 - p_1 - p_2} + k} \right)^{2(1 - p_2)}. \tag{12}$$

Based on this, the degree distribution $p(k)$ of nodes in the supply chain network can be calculated as

$$p(k) = \frac{\partial p(k_i(t) < k)}{\partial k}$$

$$= \frac{t}{m_0 + t} \left(\frac{\frac{2m(p_1 - p_2)(1 - p_2)}{1 - p_1 - p_2} + m}{\frac{2m(p_1 - p_2)(1 - p_2)}{1 - p_1 - p_2} + k} \right)^{2(1 - p_2)} \times 2(1 - p_2) \tag{13}$$

$$\times \left(\frac{2m(p_1 - p_2)(1 - p_2)}{1 - p_1 - p_2} + k \right)^{-1 - 2(1 - p_2)}.$$

k is a continuous random variable representing the degree of nodes in the SCN. Therefore, we have:

$$P(k) \propto \left(\frac{2m(p_1 - p_2)(1 - p_2)}{1 - p_1 - p_2} + k \right)^{-1 - 2(1 - p_2)}. \tag{14}$$

Therefore, the degree distribution of the SCN is determined by m, p_2, and p_1, and by adjusting these parameters, supply chain networks with different topological structures can be obtained. Based on theoretical analysis, the following properties can be derived.

Proposition 1. *The SCNE model can generate supply chain networks with scale-free characteristics. Specifically, when $p_1 = p_2 = 0$, the supply chain network becomes a BA network.*

Proof. According to the generation algorithm of the SCNE model, theoretical analysis yields the degree distribution of the SCN as $P(k) \propto \left(\frac{2m(p_1 - p_2)(1 - p_2)}{1 - p_1 - p_2} + k \right)^{-1 - 2(1 - p_2)}$, and when $p_1 = p_2 = 0$, $P(k) \propto k^{-3}$. The degree exponent distribution is $\gamma = 3$. According to [30], this result indicates that the SCNE model can generate SCNs with scale-free characteristics, and when $p_1 = p_2 = 0$, the supply chain network becomes a BA network. □

In fact, when $p_1 = p_2 = 0$, that is, when the evolution of the SCN does not consider the two adaptive strategies of firm edge growth and rewiring, the SCNE model naturally degenerates into the BA model.

3.3.3. Simulation analysis

On one hand, computational experiments are conducted to validate the theoretical analysis. On the other hand, actual operational data of supply chain firms are typically confidential and not publicly available, making it difficult to obtain [85,86]. Therefore, this section employs *computational experiments* for numerical simulation to explore the structural characteristics of supply chain network evolution under different adaptive strategies. First, based on *Proposition* 1, when $p_1 = p_2 = 0$, the supply chain network follows the *BA model*, denoted as *SCN-J*. Additionally, we set the parameters as follows[3]: $N = 500$, $m = 3$, $m_0 = 5$, and $e_0 = 5$, while selecting nine other parameter groups, corresponding

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[3] $N = 250$ is considered a typical supply chain network size [53]. In contrast, [60] set $N = 600$, [14,77] set $N = 1000$, indicating relatively large supply chain networks. Here we set $N = 500$ to construct a large-scale supply chain network.

Based on [30,60], the number of firms in the initial supply chain network is relatively small, thus $m_0 = 5$ is set.

Following the same rationale as m_0, $e_0 = 5$ is set.

According to [60,87], and [30], it is assumed that each newly added node connects with $m = 3$ edges.

Table 2
SCNE model initial parameter settings.

The SCN	p_1	p_2	m	N	m_0	e_0
SCN-A	0.3	0	3	500	5	5
SCN-B	0.3	0.3	3	500	5	5
SCN-C	0	0.3	3	500	5	5
SCN-D	0.6	0	3	500	5	5
SCN-E	0.6	0.3	3	500	5	5
SCN-F	0	0.6	3	500	5	5
SCN-G	0.9	0	3	500	5	5
SCN-H	0.3	0.6	3	500	5	5
SCN-I	0	0.9	3	500	5	5
SCN-J	0	0	3	500	5	5

to *SCN-A* to *SCN-I*. Among them: Three SCNs consider only firms' edge growth ($p_2 = 0$). Three SCNs consider only firms' rewiring ($p_1 = 0$). Three SCNs incorporate both adaptive strategies. The initial parameter settings are detailed in Table 2. The simulation experiment steps are as follows:

- Degree Distribution Analysis: (1) Generate the degree distribution of the supply chain networks based on the given parameter settings. (2) Conduct a comparative analysis of the results.
- Network Topology Visualization: (1) Select four networks: *SCN-B*, *SCN-E*, *SCN-H*, and *SCN-J*. Except for *SCN-J*, the other three networks incorporate both firms' edge growth and firms' rewiring adaptive strategies. (2) To better observe the structural characteristics of the supply chain networks, adjust the parameter to $N = 50$ while keeping all other parameters unchanged. (3) Generate the network topology diagrams and conduct a comparative analysis.

Fig. 3 presents the degree distribution histograms for the supply chain networks from *SCN-A* to *SCN-J*. The horizontal axis represents the degree k of firms (nodes) in the network, while the vertical axis indicates the proportion of firms with a given degree in the SCN. It can be observed that the SCNs generated by the SCNE model exhibit a clear *scale-free characteristic*, where high-degree nodes are relatively few, while low-degree nodes are abundant. This result aligns with most existing studies on complex supply chain networks [16,34,49,58,75]. Notably, *SCN-J* exhibits a distinct power-law distribution, as it essentially follows the BA scale-free network model.

By comparing *SCN-J*, *SCN-A*, *SCN-D*, and *SCN-G*, which do not incorporate the firms' rewiring strategy, it can be observed that as p_1 increases ($0 \rightarrow 0.3 \rightarrow 0.6 \rightarrow 0.9$), i.e., as the firms' edge growth adaptive strategy strengthens, two key trends emerge: (1) Increase in Maximum Node Degree: The highest-degree firms in the SCN increase from approximately 40 to 80, then to 120, and eventually to 200. This suggests that exchange relationships within the SCN become more frequent as the adaptive strategy intensifies. (2) Reduction in Network Heterogeneity: The probability of low-degree firms decreases, while the probability of high-degree firms increases. This indicates that the firm-edge growth strategy enhances the degree centrality (*DC*) of hub firms, making the SCN more centralized around key firms.

Next, comparing $SCN-J$, $SCN-C$, $SCN-F$, and $SCN-I$, which do not incorporate the firms' edge growth strategy, we observe that as p_2 increases ($0 \rightarrow 0.3 \rightarrow 0.6 \rightarrow 0.9$), i.e., as the firms' rewiring adaptive strategy strengthens, the degree distribution exhibits a *Poisson-like* evolution trend: The number of high-degree firms decreases, reducing the heterogeneity of the SCN. This suggests that the firms' rewiring strategy reduces both high-degree and low-degree firms, leading to a more evenly distributed network structure. In *SCN-B*, *SCN-E*, and *SCN-H*, where both adaptive strategies are considered, the degree distribution exhibits a combined effect of both strategies. To better compare these nine SCNs, their degree distributions are logarithmically transformed and plotted together in Fig. 4.
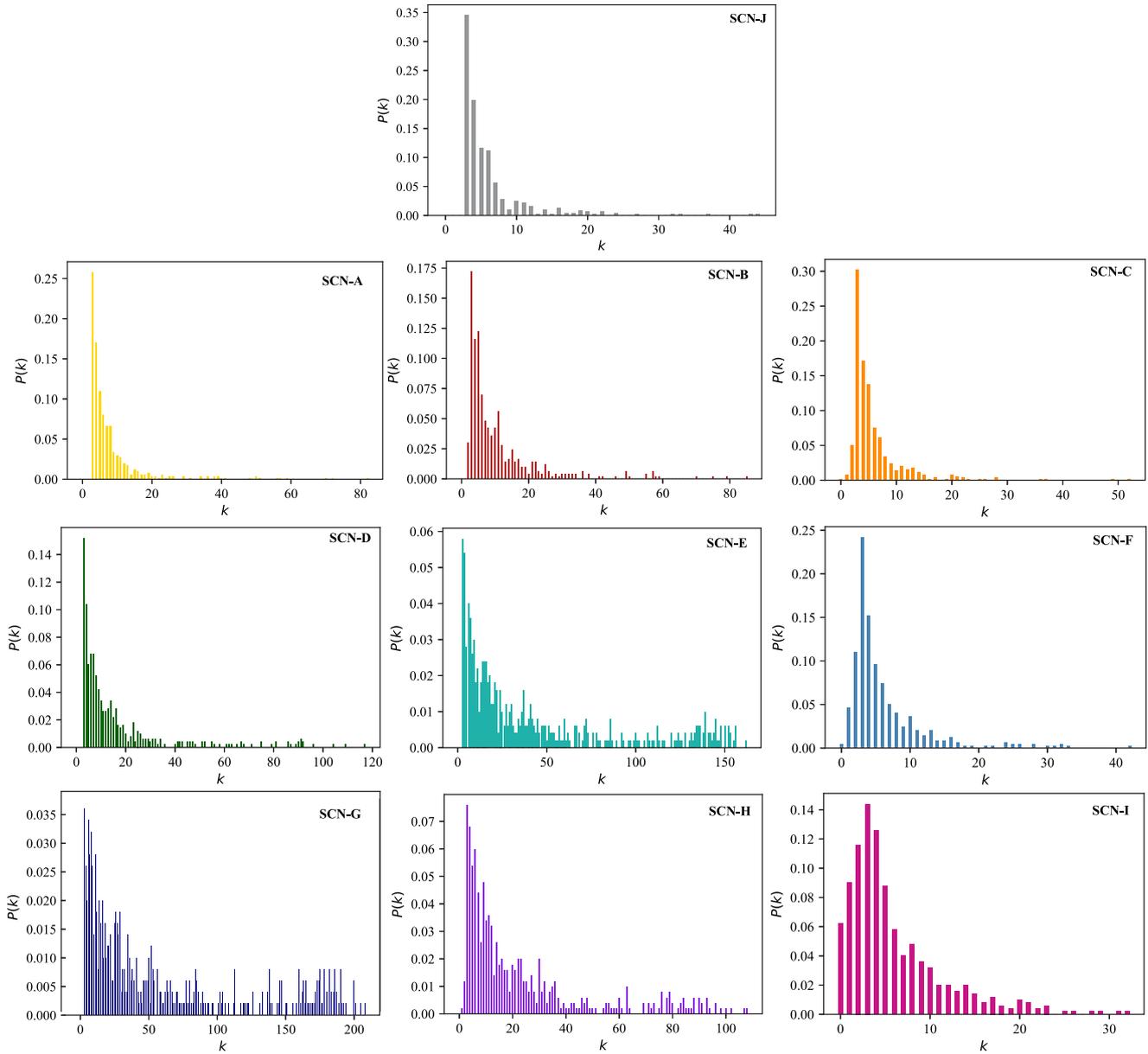
Fig. 3. Degree distribution histogram of the SCNE model.

Fig. 4 presents the scatter plot of degree distributions for the nine SCNs generated by the SCNE model. The figure not only demonstrates the scale-free nature of the networks but also illustrates how different adaptive strategies shape the heterogeneity of SCNs. For example, *SCN-G* has lower heterogeneity than *SCN-E*, while networks such as *SCN-C*, *SCN-F*, *SCN-I*, *SCN-H*, and *SCN-B* exhibit *Poisson-like* network characteristics. *Poisson-like* supply chain networks can be generated by modifying adaptive strategies (e.g., *SCN-C*, *SCN-F*, *SCN-I*, *SCN-H*, *SCN-B*).

Fig. 5 visualizes the network topology of SCNs under different adaptive strategies. The simulation results indicate that:

- Strengthening the firms' edge growth adaptive strategy (*SCN-B* vs. *SCN-E*)
- Strengthening the firms' rewiring adaptive strategy (*SCN-B* vs. *SCN-E*)
- Strengthening both adaptive strategies (*SCN-J* vs. *other SCNs*)

All of the above lead to an increase in the number of key firms (i.e., higher-degree nodes) and the number of network edges, making the SCN more complex. Notably, in *SCN-E*, firms have the highest number of edges, and the largest number of high-degree firms, since it applies the strongest adaptive strategy.

Based on the above analysis, we propose the following property:

Proposition 2. *The firms' edge growth adaptive strategy enhances the degree of core firms (hubs) in the supply chain network. The firms' rewiring adaptive strategy promotes a Poisson-like degree distribution in the SCN. By adjusting different firm adaptive strategies, it is possible to generate SCNs with varying degrees of heterogeneity.*

3.4. Dynamic disruption model

In the context of supply chain networks based on complex network theory, simulation methods are commonly used to model supply chain
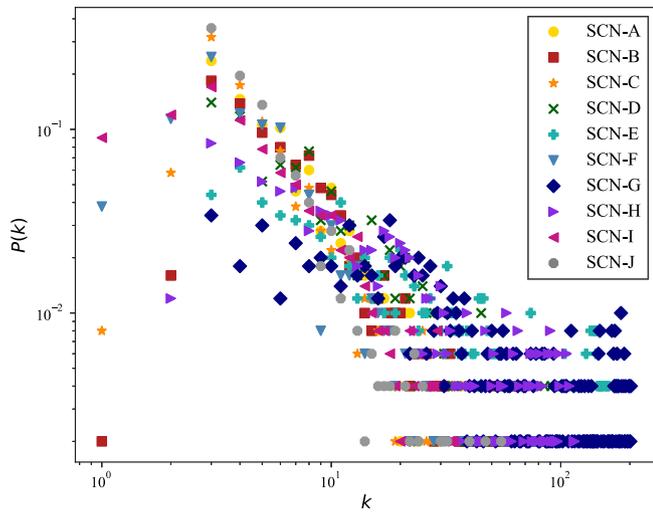
Fig. 4. SCNE model degree distribution scatter plot.

disruption risks. Traditionally, supply chain disruption risks can be divided into two types: random disruptions and targeted disruptions [15, 17,58,60,64].

1. Random Disruptions: In the supply chain network, each node (edge) has an equal probability of being removed. This simulates numerous external environmental shock events that are less likely to occur but have a significant impact on the SCN, such as natural disasters (i.e., floods, earthquakes, hurricanes), contagious diseases (i.e., COVID-19), factory fires, and economic or financial crises.
2. Targeted Disruptions: In the supply chain network, important nodes (edges) are more likely to be removed. This simulates a large number of man-made political upheavals (i.e., war, labor disputes, regulations), terrorism, terrorist attacks, and economic sanctions. These events can greatly damage the SCN, even dismantling the entire supply chain network.

Based on this, the dynamic disruption model for supply chain networks is described as follows:

- Step 1: Initialization. $t = 0$, given an initial supply chain network $G_0 = (V, E)$ with n_0 nodes and e_0 edges.
- Step 2: Removal of nodes (edges) in the supply chain network. Depending on different types of disruptions, nodes (edges) are removed from the given supply chain network G_t. It is assumed that the proportion of nodes (edges) removed at each time step t is q_N (q_E).
  (1) In the case of random disruptions, at each time step t, nodes i (edges e_{ij}) within the SCN are removed with equal probability, meaning randomly selecting $n_0 \cdot q_N$ nodes ($e_0 \cdot q_E$ edges) for removal.
  (2) In the case of targeted disruptions, initially rank the nodes i(edges e_{ij}) within the SCN by importance $d = [d_1, d_2, \ldots, d_n]$. And then, based on their level of importance, remove the top $n_0 \cdot q_N$ nodes ($e_0 \cdot q_E$ edges). $t = t + 1$, update SCN G_{t+1}. Re-rank the importance of nodes (edges) to $d' = [d_1, d_2, \ldots, d_m]$ and repeat the removal process.
- Step 3: Repeat. Continuously repeat the removal strategy of Step 2 until there are no nodes (edges) left in the SCN.

For targeted disruptions, in the complex network theory, there are numerous metrics and methods for measuring the importance of nodes(edges) within the SCN. For node importance, metrics such as

degree centrality, betweenness centrality, and closeness centrality are used; for edge importance, metrics such as edge weight and edge betweenness are used [15,34,53,59,74,88]. Next, we introduce two metrics for measuring the importance of nodes and edges in supply chain networks.

1. Degree Centrality, D [53,88]. D measures the number of direct neighboring nodes a node has. In complex supply chain networks, nodes with high degree centrality typically represent firms that play a crucial role in commercial cooperation activities. This implies that the disruption of such a firm could significantly impact the performance of the complex supply chain network.
   D is defined as follows:

$$D(i) = \sum_{i \neq j} e_{ij} \tag{15}$$

   where $e_{ij} = 1$ indicates the presence of an edge between node i and node j;otherwise, $e_{ij} = 0$.

2. Edge Betweenness Centrality, EB [88,89]. EB measures the proportion of shortest paths in the network that pass through a given edge. In complex supply chain networks, edges with high betweenness centrality are those that appear in numerous shortest paths, playing a crucial role in facilitating efficient information exchange, business collaboration, and operational connectivity.
   EB is defined as follows:

$$EB(e_{ij}) = \sum_{s,t \in V} \frac{\sigma(s, t \mid e_{ij})}{\sigma(s, t)} \tag{16}$$

   where V represents the set of nodes in the complex supply chain network, $\sigma(s, t)$ is the total number of shortest paths between nodes s and t, and $\sigma(s, t \mid e_{ij})$ is the number of shortest paths between s and t that pass through edge e_{ij}.

Fig. 6 illustrates the schematic diagram of the SCN dynamic disruption model, which includes two strategies: node removal and edge removal. The upper part of the figure presents an example of node disruption under targeted disruption risk [15,90]: At each time step t, the supply chain network is attacked by removing the red node with the highest degree centrality ($D = 5$) along with its edges. At time t_1, a single node is deliberately disrupted from the SCN (i.e., nodes are sorted by degree centrality D, and the highest-degree node is removed). The vertical axis also shows the changes in SCN robustness metrics over time t. The lower part of the figure illustrates an example of edge disruption under random disruption risk: At each time step t, the supply chain network is attacked by randomly removing blue edges.

3.5. Topological robustness measuring

In complex supply chain networks, *topological metrics* can serve as effective indicators of network performance [15,34,59]. Specifically, when nodes or edges in a supply chain network are attacked, both the topological structure and efficiency of the network undergo changes. Therefore, the size of the largest connected component (LCC), denoted as S, and network efficiency, denoted as E_{ffi}, can be used to measure the topological robustness of supply chain networks under disruption risks. Here, we define two topological robustness metrics:

1. $R(q)$: The relative size of the largest connected component. According to percolation theory [91], the robustness of an SCN can be measured by finding out the size of the LCC. Based on that, the relative size of the LCC $R(q)$ is expressed as
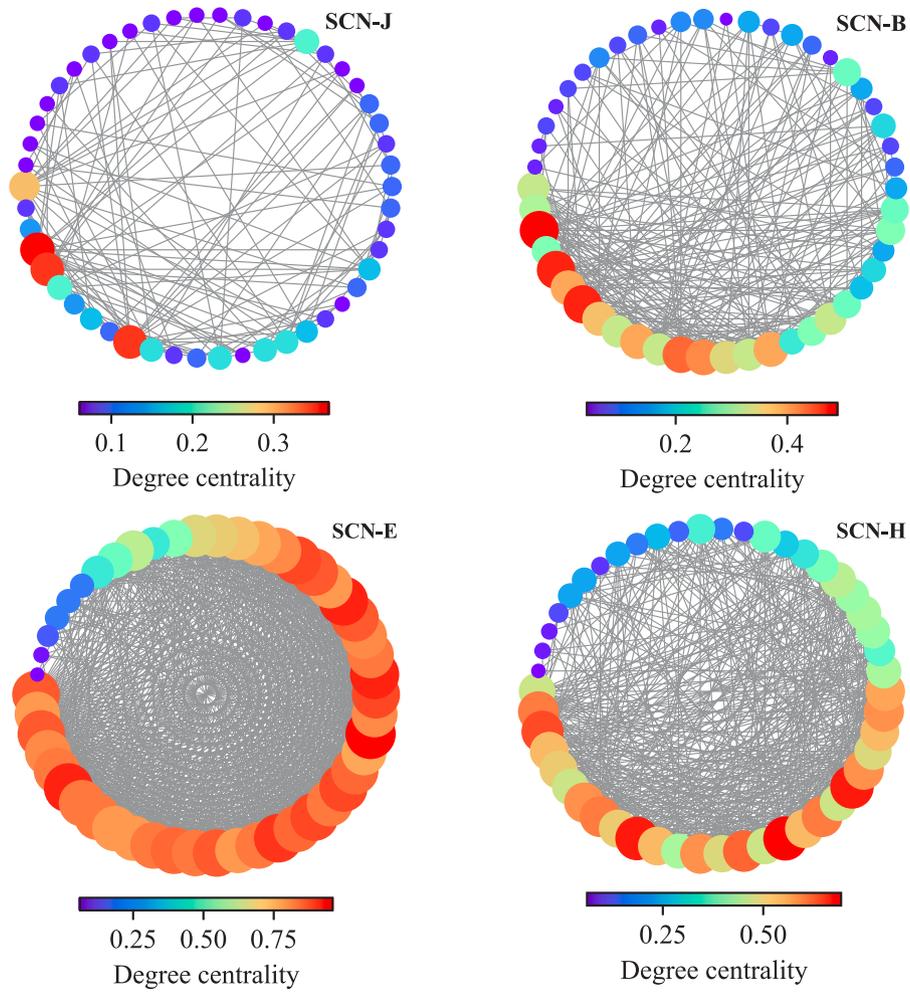
$$R(q) = \frac{S(q)}{S(0)}, \tag{17}$$

Fig. 5. SCNE network topology under different adaptive strategies.
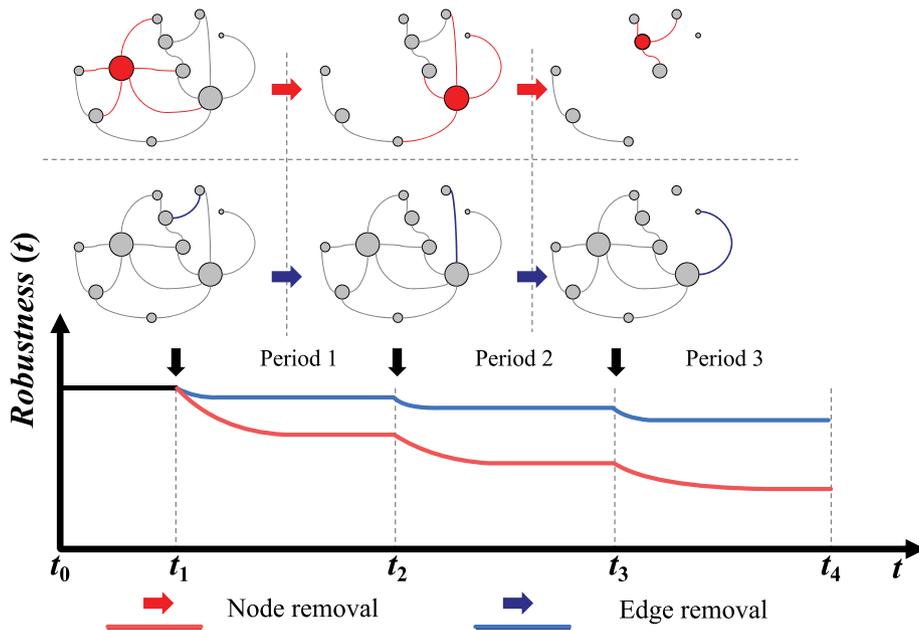

Fig. 6. Schematic diagram of the dynamic disruption model in supply chain networks.
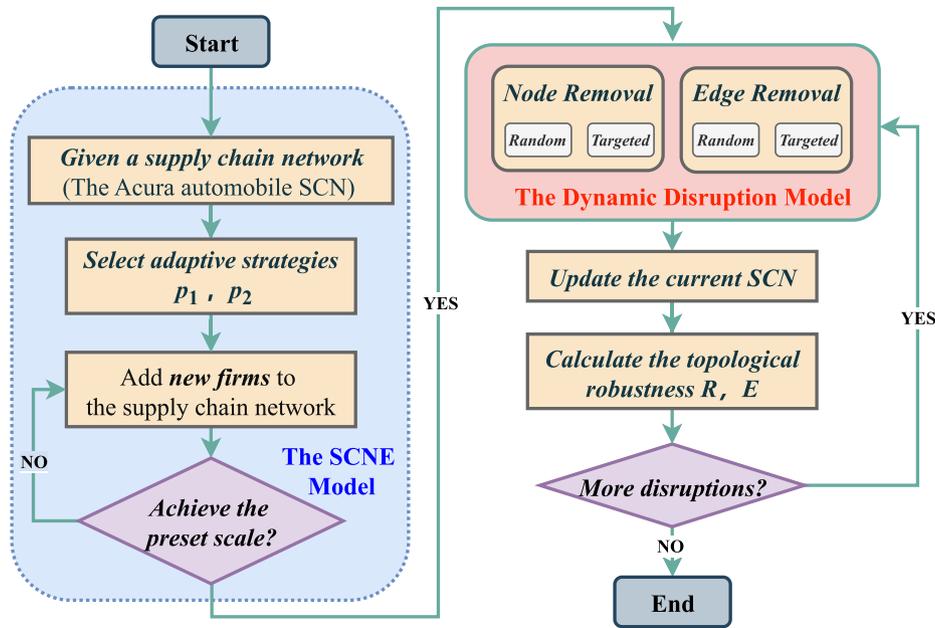
Fig. 7. Flowchart of the case study.

where $S(q)$ is the number of nodes in the LCC of the SCN after the repeated disruptions, and $S(0)$ refers to the number of nodes in the initial SCN.

2. $E(q)$: Relative network efficiency. Network efficiency (E_{ffi}) was first proposed by [84] to characterize small-world networks. This metric evaluates the propagation capability of a complex network by computing the inverse of the shortest path lengths between all node pairs and taking their average. E_{ffi} is defined as follows:

$$E_{ffi} = \frac{1}{N(N-1)/2} \sum_{i \neq j} \frac{1}{d_{ij}} \tag{18}$$

where N represents the number of nodes in the supply chain network. d_{ij} is the shortest path length between node i and node j. A shorter average shortest path length indicates higher efficiency in terms of business cooperation, exchange relationships, and information flow within the supply chain network. The network efficiency metric measures the extent to which the supply chain network can continue to function effectively over time and serves as an indicator of network robustness. $E(q)$ is defined as:

$$E(q) = \frac{E_{ffi}(q)}{E_{ffi}(0)} \tag{19}$$

where $E_{ffi}(q)$ is the network efficiency after removing a proportion q of nodes or edges. $E_{ffi}(0)$ is the initial network efficiency before any disruptions.

In the Appendix A, we provide four additional importance measurement metrics or algorithms for supply chain networks (abbreviated as B, C, KC, and CI). Under the node removal strategy, we select four supply chain networks (*SCN-B*, *SCN-E*, *SCN-H*, and *SCN-J*) for analysis. Among them, *SCN-B*, *SCN-E*, and *SCN-H* incorporate both firms' edge growth and firms' rewiring adaptive strategies, whereas *SCN-J* does not. We analyze six disruption strategies in the dynamic disruption model: *Random*, $D-D$, $D-B$, $D-C$, $D-KC$, and $D-CI$. Among these, *Random* represents a random disruption strategy, while the other five strategies are dynamic targeted disruption strategies, where the importance of nodes is determined based on different metrics or algorithms. Here we have:

Proposition 3. *Targeted disruptions are far more destructive to supply chain networks than random disruptions. Moreover, under targeted disruptions, the topological robustness of the supply chain network experiences a rapid decline within a specific node removal proportion range.*

Proposition 4. *Under an appropriately strong adaptive strategy, the topological robustness of the supply chain network decreases sequentially under different disruption risks. The destructiveness ranking of disruption strategies is as follows:* $Random < D-KC < D-D < D-C < D-B < D-CI$.

4. A case study for supply chain network topological robustness enhancement analysis

To validate the effectiveness of the proposed model, we first select a real-world case, *Acura's automotive supply chain network*, as the initial network for a case study analysis. Note that the Acura's automotive SCN is inherently complex, involving numerous suppliers, manufacturers, and distributors [24]. Also, Acura's supply chain, being part of the global automotive industry [59], represents a large and intricate network, which is ideal for studying robustness and adaptive strategies in SCNs. Based on the SCNE algorithm, adaptive strategies p_1 and p_2 are chosen to generate a large-scale SCN of preset size. Then we simulate real-world disruption risks (where targeted disruption follows the $D-D$ strategy) to explore the changes in the robustness of the SCN under different adaptive strategies, thereby designing and enhancing the robustness of the SCN. The experimental design is shown in Fig. 7.

4.1. The case study

As shown in Fig. 8(a), the topological structure of the Acura's automotive SCN, with data sourced from [74,92], is modeling by contractual relationships among firms. It can be observed that the core firms (Hubs) in this SCN are *Intek*, *Honda*, *Arkay*, and *Select Ind*. Clearly, this SCN evolves over time, with new firms entering the network and forming a complex supply chain network [5,6]. Therefore, based on the simulation experiment design process, we construct a large-scale SCN under different adaptive strategy combination (with a scale of $N = 500$). Fig. 8(b) illustrates the scenario where the adaptive strategies are $p_1 = 0.3$, $p_2 = 0.6$. We further simulate real-world disruption risks
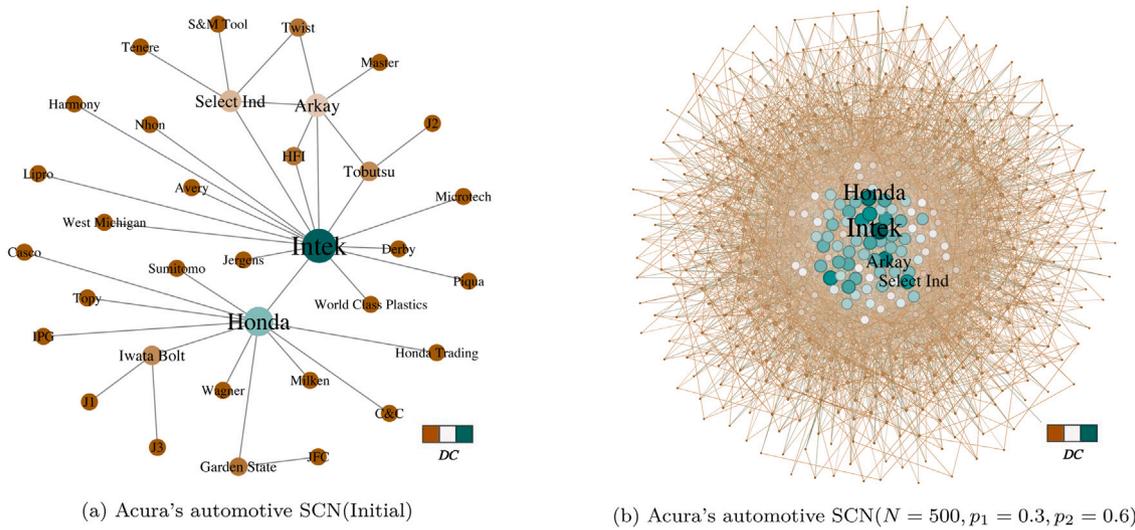
(a) Acura's automotive SCN(Initial)

(b) Acura's automotive SCN($N = 500, p_1 = 0.3, p_2 = 0.6$)

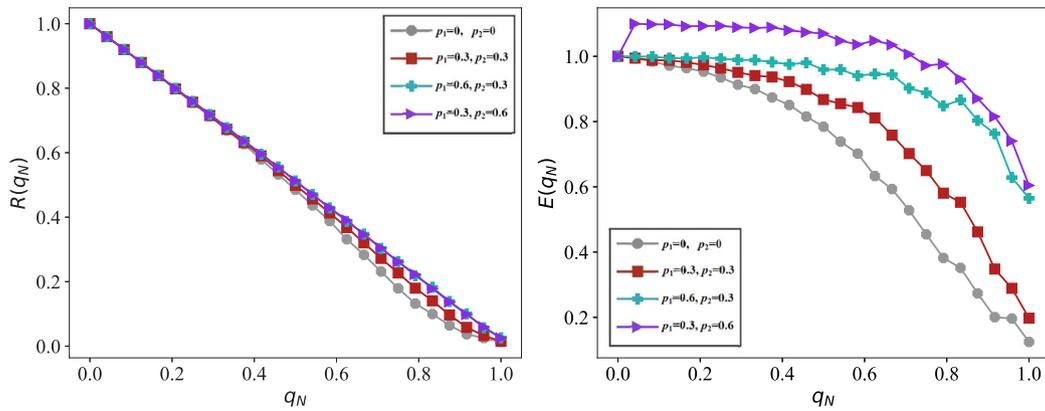**Fig. 8.** Acura's automotive supply chain network.

Fig. 9. Topological robustness variation of SCN with different adaptive strategies under random disruption risk (node removal).
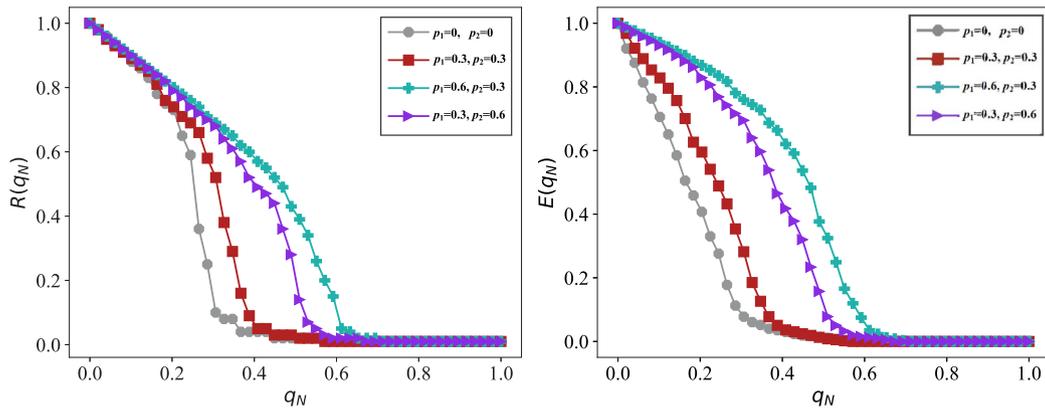

Fig. 10. Topological robustness variation of SCN with different adaptive strategies under targeted disruption risk (node removal).

(where targeted disruption follows the $D - D$ strategy) and calculates the changes in the topological robustness of the SCN. The simulation results are presented in Figs. 9–12.

4.2. Results

4.2.1. Node-level

In the node removal strategies (as shown in Figs. 9 and 10), comparing four combinations of adaptive strategies (without adaptive strategy:

$p_1 = 0, p_2 = 0$. with adaptive strategies: $p_1 = 0.3, p_2 = 0.3$; $p_1 = 0.6, p_2 = 0.3$; $p_1 = 0.3, p_2 = 0.6$.), regardless of whether under random or targeted disruption risk, enhancing the firms' edge growth adaptive strategy p_1 (comparing $p_1 = 0.3, p_2 = 0.3$ with $p_1 = 0.6, p_2 = 0.3$) or enhancing the firms' rewiring adaptive strategy p_2 (comparing $p_1 = 0.3, p_2 = 0.3$ with $p_1 = 0.3, p_2 = 0.6$) can both improve the topological robustness of the supply chain network. A more intuitive explanation is that the cooperative exchange relationships formed by firms' growth in the supply chain
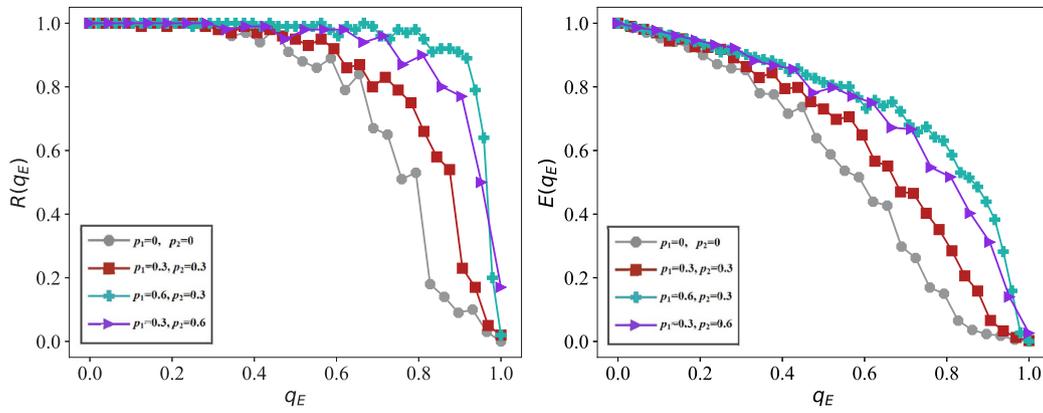
Fig. 11. Topological robustness variation of SCN with different adaptive strategies under random disruption risk (edge removal).
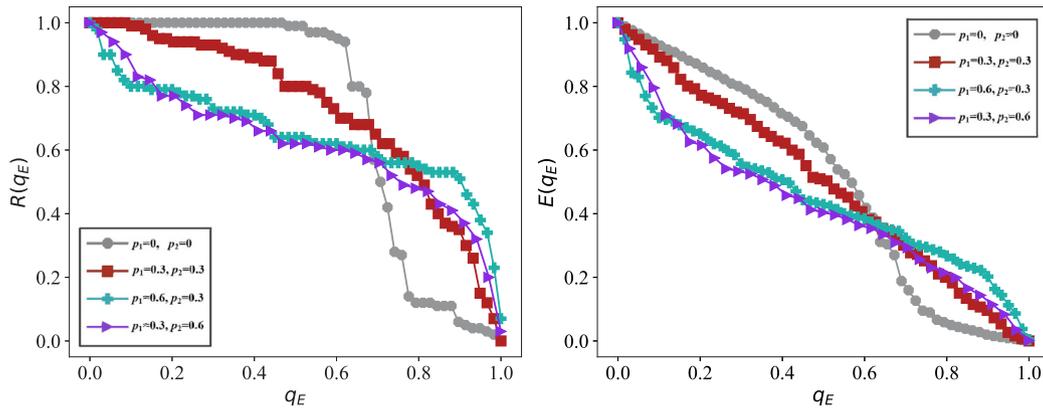

Fig. 12. Topological robustness variation of SCN with different adaptive strategies under targeted disruption risk (edge removal).

network make the SCN more interconnected. Firms' rewiring enables high-degree firms in the network to reestablish exchange relationships, thereby dispersing part of the risk. Both adaptive strategies alter the network topological structure of the SCN, ultimately enhancing its topological robustness. Under targeted disruption, the supply chain network generated by the adaptive strategy $p_1 = 0.6, p_2 = 0.3$ exhibits the highest topological robustness. This indicates that the firms' edge growth adaptive strategy is more effective in enhancing SCN robustness compared to the firms' rewiring adaptive strategy. However, under random disruption, the robustness of SCNs generated by the adaptive strategies $p_1 = 0.3, p_2 = 0.6$ and $p_1 = 0.6, p_2 = 0.3$ shows little difference. In fact, the relative network efficiency E of the SCN generated by $p_1 = 0.3, p_2 = 0.6$ even exceeds 1, which occurs because the removed nodes do not affect the shortest paths in the SCN. According to the efficiency expression (19), as the number of nodes decreases while the shortest paths remain unchanged, the SCN's network efficiency increases.

In practice, decision-makers in the *Acura* automotive supply chain network should carefully consider both adaptive strategies to help supply chain firms establish diverse exchange relationships. This approach can effectively disperse risks when supply chain disruptions occur, thereby improving overall system performance and resilience.

4.2.2. Edge-level

In the edge removal strategy (Figs. 11 and 12), under random disruption risk, both enhancing the firms' edge growth adaptive strategy p_1 (comparing $p_1 = 0.3, p_2 = 0.3$ with $p_1 = 0.6, p_2 = 0.3$) and enhancing the firms' rewiring adaptive strategy p_2 (comparing $p_1 = 0.3, p_2 = 0.3$ with $p_1 = 0.3, p_2 = 0.6$) can improve the topological robustness of the supply chain network. Among them, the SCN generated under the adaptive strategy $p_1 = 0.3, p_2 = 0.6$ exhibits the highest robustness. However, under targeted disruption risk, an interesting phenomenon is observed:

There exists an edge removal threshold $q_E^* \approx 0.7$. Before this threshold ($q_E < 0.7$), considering adaptive strategies actually accelerates SCN collapse, whereas beyond this threshold ($q_E > 0.7$), stronger adaptive strategies lead to higher SCN robustness. This phenomenon can be explained as follows: The essence of adaptive strategies is to alter the importance of edges within the SCN, thereby enhancing its robustness against node removal. In the case of targeted edge removal, when the most critical edges (those with high EB) are removed first, the robustness of the SCN declines rapidly. Moreover, the stronger the adaptive strategy, the faster the network collapses. However, as the key edges continue to be removed, the rate of robustness decline slows down, eventually surpassing the robustness of SCNs without adaptive strategies.

In practice, decision-makers in the *Acura* automotive supply chain network should carefully consider the edge removal threshold q_E^*. If the destructive impact of targeted edge disruption is sufficiently high, employing adaptive strategies becomes crucial for enhancing SCN robustness.

4.3. OLS regression analysis

To rigorously validate the impact of adaptive strategies p_1 and p_2 on enhancing the robustness of supply chain networks (under the node removal strategy), we conduct an Ordinary Least Squares (OLS) regression analysis using Model (20) and Model (21) [12,23,85]. The dependent variables, the relative size of the largest connected component (LCC) $R(0.4)_{\text{Targeted}}$ after removing 40% of the nodes and the relative network efficiency $E(0.4)_{\text{Targeted}}$ after removing 40% of the nodes, are logarithmically transformed to satisfy OLS regression assumptions. To mitigate multicollinearity caused by interaction effects, all independent variables are standardized in the analysis. Variance

Table 3
OLS regression results.

Dependent variable	$R(0.4)^{Targeted}$	$E(0.4)^{Targeted}$
	Model(20)	Model(21)
p_1	0.808535***	0.751706***
	(0.078615)	(0.091141)
p_2	0.384313***	0.365706***
	(0.078615)	(0.091141)
Constant	−0.169833***	−0.184719***
	(0.045161)	(0.052357)
Obs.	1080	1080
Adj.R^2	0.663406	0.555856
F − Stat	53.22979***	34.16534***

(   ) is Standard Error.

*** $p < 0.001$.

Inflation Factor (VIF) analysis indicates that all variables, including interaction terms, have VIF values below 4 (specifically, 1.417824), which is well below the critical threshold of 10[93], confirming the absence of multicollinearity. The subscript i represents each observation, and a total of 54 different combinations of p_1 and p_2 are considered. The results of the OLS analysis are presented in Table 3.

$$R(0.4)_i^{Targeted} = \alpha_0 + \alpha_1 * p_{1i} + \alpha_2 * p_{2i} + \varepsilon_i, i = 1, 2, \dots, 20 \quad (20)$$

$$E(0.4)_i^{Targeted} = \beta_0 + \beta_1 * p_{1i} + \beta_2 * p_{2i} + \varepsilon'_i, i = 1, 2, \dots, 20 \quad (21)$$

According to the regression results in Table 3, the findings further confirm that both the firms' edge growth adaptive strategy and the firms' rewiring adaptive strategy enhance the robustness of the generated SCN. Moreover, the firms' edge growth adaptive strategy has a stronger impact on fostering a robust SCN compared to the firms' rewiring adaptive strategy, as indicated by the larger coefficient of p_1 relative to p_2. Based on the above analysis, we propose the following Propositions:

Proposition 5. *For node removal strategies, enhancing both the firms' edge growth adaptive strategy and the firms' rewiring adaptive strategy can improve the topological robustness of the supply chain network. However, the firms' edge growth adaptive strategy is more effective than the firms' rewiring adaptive strategy in enhancing the topological robustness of the network.*

Proposition 6. *For random edge removal, strengthening both the firms' edge growth adaptive strategy and the firms' rewiring adaptive strategy can improve the topological robustness of the supply chain network. However, for targeted edge removal, there exists a critical edge removal threshold q_E^*. Before this threshold, considering adaptive strategies actually accelerates the collapse of the supply chain network; however, beyond this threshold, the stronger the adaptive strategy, the higher the topological robustness of the supply chain network.*

5. Conclusions

As modern supply chain networks expand in scale, their exchange relationships have become increasingly complex and interdependent. Consequently, SCNs should be studied as integrated systems rather than isolated components. This study addresses this issue by integrating CAS theory with network science and proposing the SCNE model, which modifies the BA model to incorporate adaptive edge growth and rewiring strategies. Through theoretical analysis and simulation experiments, this study provides new insights into SCN evolution, robustness, and adaptability under dynamic disruptions.

5.1. Theoretical contributions

This study makes several key theoretical contributions to the supply chain resilience and complex network literature:

1. Integration of CAS Theory and Complex Network Models

   - Unlike traditional SCN models that assume static topologies, this study introduces a dynamic evolutionary framework by incorporating adaptive strategies into network formation and restructuring.
   - The SCNE model advances CAS-based SCN modeling by illustrating how SCNs evolve in response to disruptions and self-organize to enhance resilience.

2. Understanding Adaptive Strategies in SCN Resilience

   - The study systematically examines the effects of edge growth and rewiring strategies on SCN robustness.
   - Results show that edge growth strategies are more effective in strengthening SCN resilience compared to rewiring strategies, particularly under node removal disruptions.
   - Additionally, the study identifies a threshold effect in intentional edge removals, where adaptive strategies can either accelerate SCN collapse or enhance robustness, depending on the proportion of removed edges.

3. Network Robustness under Different Disruption Risks

   - This study highlights that targeted disruptions cause significantly greater damage to SCNs than random disruptions.
   - The robustness ranking of different disruption strategies follows the order: $Random < D - KC < D - D < D - C < D - B < D - CI$

These findings contribute to the growing body of literature on network resilience and disruption propagation by providing a quantitative assessment of SCN robustness under various attack scenarios.

5.2. Managerial implications

This research provides practical insights for supply chain managers, policymakers, and industry practitioners aiming to enhance SCN resilience:

1. Proactive Risk Mitigation through Adaptive Strategies

   - Firms should proactively adopt adaptive edge growth and rewiring strategies to strengthen SCN robustness.
   - While both strategies enhance resilience, edge growth (establishing new partnerships) is more effective than rewiring (switching existing partners) in mitigating disruptions.
   - Managers should prioritize strengthening ties with key partners rather than simply reconfiguring existing relationships.

2. Identifying Critical Nodes and Edges for Resilience Planning

   - Given that targeted disruptions disproportionately impact SCNs, firms should identify and protect critical nodes and links that serve as central hubs in the network.
   - Investing in redundant pathways and alternative suppliers can prevent cascading failures and reduce vulnerability to targeted attacks.

3. Balancing Adaptation and Stability in SCN Design

   - While adaptive strategies enhance resilience, firms must carefully balance adaptation with stability.
   - In intentional edge removal scenarios, the study identifies a critical threshold (q_E^*), below which adaptation accelerates SCN collapse rather than mitigating risks.

- Managers should carefully evaluate the intensity of adaptive strategies and ensure they do not inadvertently increase systemic fragility.

By integrating CAS theory, network science, and adaptive strategies, this study provides a comprehensive framework for understanding SCN resilience in complex, uncertain environments. The SCNE model offers a practical and theoretical tool for analyzing network robustness and designing adaptive SCN strategies. Future research could extend this model to multi-layer SCNs [32], industry-specific disruptions [6], or empirical validation using real-world supply chain data [12], further enhancing our understanding of supply chain adaptability and resilience.

CRediT authorship contribution statement

Jiepeng Wang: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Peng Qin:** Visualization, Validation, Software, Formal analysis. **Li Chen:** Formal analysis, Data curation, Conceptualization. **Changgui Gu:** Writing – review & editing, Conceptualization. **Yufei Yuan:** Writing – review & editing. **Hong Zhou:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript.

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Appendix A

A.1. Four metrics for SCN

1. Betweenness centrality, B [53,88]. B measures the extent to which a node lies on the shortest paths between other nodes. The shortest path represents the most efficient route between two nodes in the network. In complex supply chain networks, firms with high betweenness centrality are considered to have greater control over the flow of materials, information, and capital passing through them [53,59]. Consequently, if such a firm is disrupted, it can significantly impact the performance of the supply chain network. The betweenness centrality is defined as:

$$B(i) = \sum_{j<k} \frac{t_{jk}(i)}{t_{jk}} \tag{A.1}$$

where t_{jk} represents the total number of shortest paths between nodes j and k. $t_{jk}(i)$ represents the number of shortest paths between nodes j and k that pass through node i.

2. Closeness centrality, C [53,88]. C measures how close a node is to all other nodes in the network. Nodes with high closeness centrality typically have shorter average distances to all other nodes. In complex supply chain networks, firms with high closeness centrality play a vital role in efficient communication and
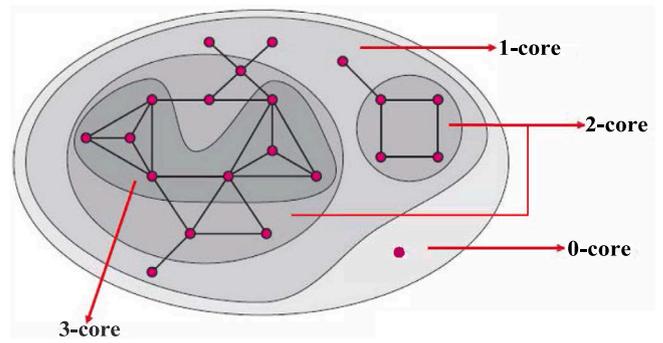

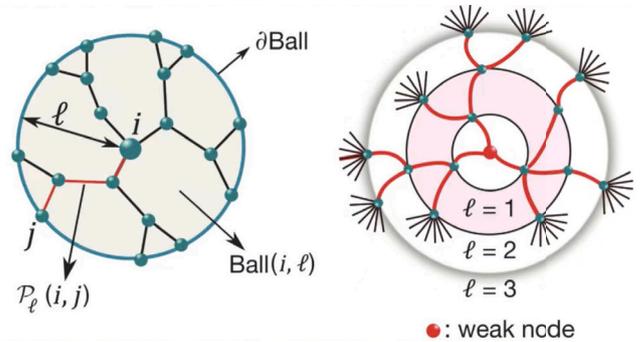**Fig. A.13.** An example of the $k-core$.

Fig. A.14. An example of CI [95].

resource distribution. If such a firm is disrupted, the average shortest path length in the network may increase, reducing overall network efficiency.
The closeness centrality is defined as:

$$C(i) = \frac{1}{\sum_{i \neq j} d_{ij}} \tag{A.2}$$

where d_{ij} represents the shortest path length between nodes i and j.

3. $k-Core$ Algorithm, KC [94]. KC is obtained by iteratively removing nodes with a degree less than k along with their edges. The remaining subgraph after this process is called the $k-core$, and its size represents the core depth of firms within the supply chain network. In complex supply chain networks, a firm's $k-core$ value can reflect its integration depth in the supply chain. The maximum $k-core$ value corresponds to the firms located in the most central part of the SCN. Fig. A.13 illustrates an example of the $k-core$ structure.

4. Collective Influence, CI [95]. As shown in Fig. A.14, a ball of radius ℓ, denoted as $Ball$, is first defined. For each node i, all other nodes within a shortest path distance of ℓ from node i are identified, forming the set $\partial Ball(i, \ell)$. Then, solving Eq. (A.3) yields the CI value of node i at a given radius ℓ. By iterating over all nodes in the complex supply chain network, the CI values for all nodes can be obtained. CI is defined:

$$CI(i) = (k_i - 1) \sum_{j \in \partial Ball(i, \ell)} (k_j - 1) \tag{A.3}$$

where k_i represents the degree of node i. In complex supply chain networks, a firm's CI value represents its collective influence within the network. Higher CI values indicate firms with greater influence over the network's structure and connectivity.
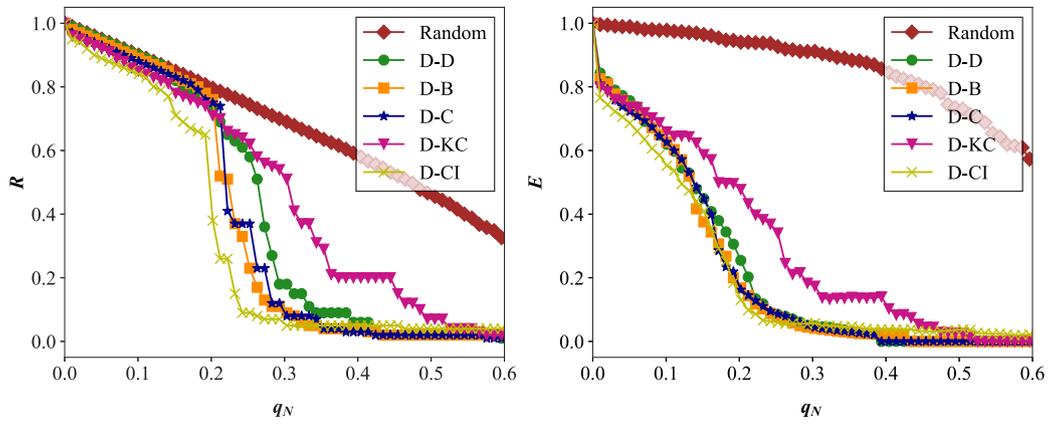
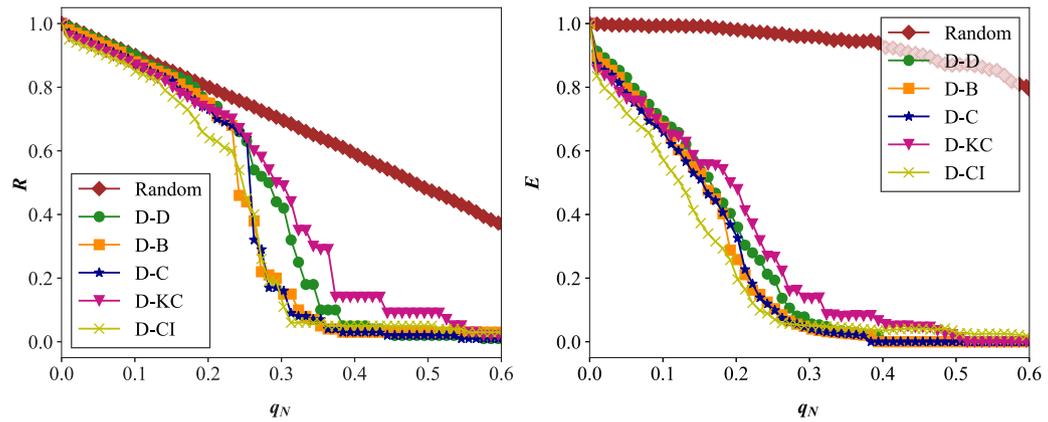**Fig. A.15.** Topological robustness variation of supply chain network under dynamic disruption risk (SCN-J).

Fig. A.16. Topological robustness variation of supply chain network under dynamic disruption risk (SCN-B).
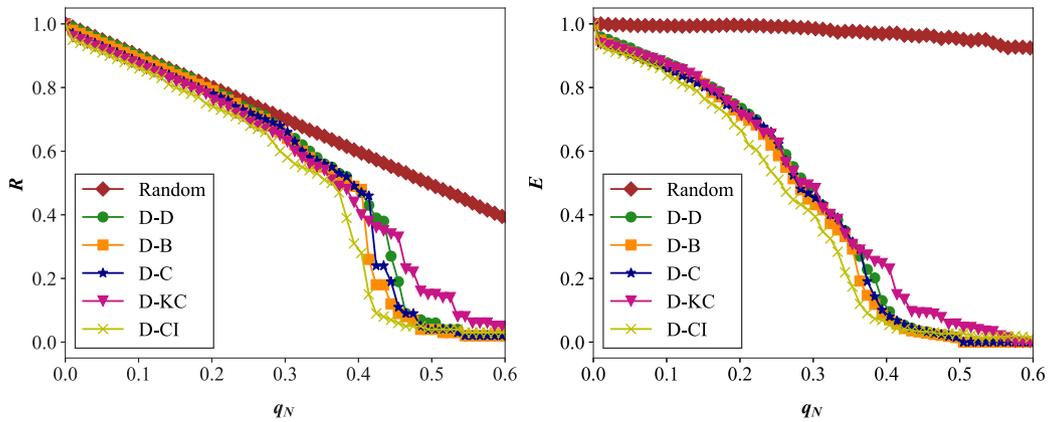

Fig. A.17. Topological robustness variation of supply chain network under dynamic disruption risk (SCN-H).

A.2. Simulation experiments on dynamic disruption strategies

We present simulation experiments analyzing six disruption strategies (node removal) for the same supply chain networks: *SCN-B*, *SCN-E*, *SCN-H*, and *SCN-J*. The simulation results are shown in Figs. A.15 and A.18.

In the four figures, the relative size of the largest connected component (LCC, denoted as R) and the relative network efficiency (denoted as E) decrease as node removal increases, exhibiting different trends under various dynamic disruption risks. The topological robustness indicators of the four SCNs perform best under random disruption risk. The R shows an almost linear decline, while E decreases gradually. Specifically, when 60% of nodes are removed, the network efficiency values are as follows: $E(0.6)_{\text{SCN-J}} \approx 0.6$, $E(0.6)_{\text{SCN-B}} \approx 0.8$, $E(0.6)_{\text{SCN-H}} \approx 0.95$, $E(0.6)_{\text{SCN-E}} \approx 1$. Under different targeted disruption risks, the topological robustness of *SCN-J* (Fig. A.15), *SCN-B* (Fig. A.16), and *SCN-H* (Fig. A.17) decreases sequentially, following the order: $D - KC > D - D > D - C > D - B > D - CI$. This suggests that the $D - CI$ removal strategy is the most destructive, as it targets the most critical firm nodes in the SCN. The simulation results further confirm that targeted disruptions are significantly more damaging than random disruptions.
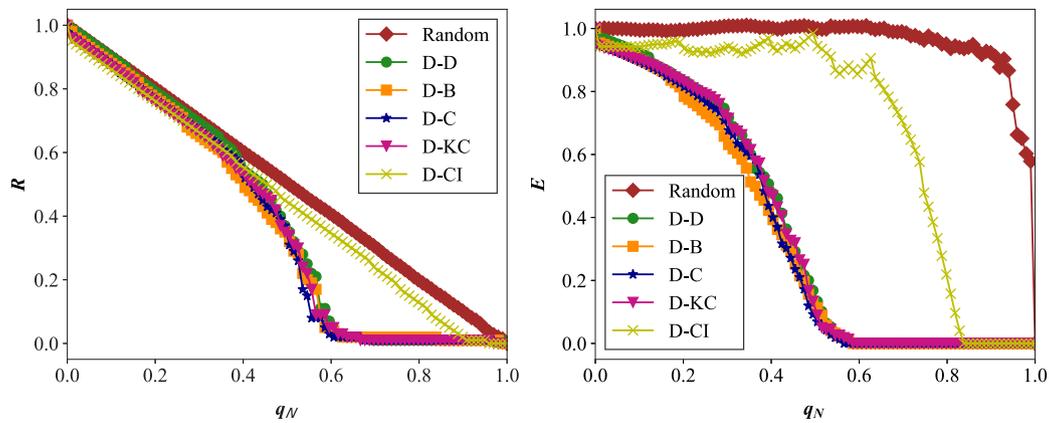
Fig. A.18. Topological robustness variation of supply chain network under dynamic disruption risk (SCN-E).

However, in the case of *SCN-E*, the $D - CI$ disruption strategy is less destructive than the other four targeted disruption strategies. The underlying reason for this phenomenon is shown in Fig. 5, which indicates that SCN-E has a large number of redundant edges (exchange relationships). The $D - CI$ algorithm (Fig. A.14) specifically targets low-degree nodes that play a crucial role in network connectivity. However, such nodes are relatively scarce in *SCN-E*, making the $D - CI$ strategy behave similarly to random disruption. Additionally, under targeted disruption strategies, the topological robustness of the four supply chain networks experiences a rapid decline within a specific node removal proportion range $q_N^* \in \left[\underline{q_N}, \overline{q_N}\right]$, as shown below: *SCN-J*: Five targeted disruptions result in $q_N^* \in [0.2, 0.4]$. *SCN-B*: Five targeted disruptions result in $q_N^* \in [0.25, 0.35]$. *SCN-H*: Five targeted disruptions result in $q_N^* \in [0.4, 0.5]$. *SCN-E($D - CI$ disruption)*: $q_N^* \in [0.75, 0.8]$. This suggests that before reaching the critical threshold q_N^*, managers and decision-makers should proactively implement protective measures for key firm nodes under targeted disruptions to prevent SCN degradation or system collapse.

Data availability

Data will be made available on request.

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