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A novel supply chain network evolving model under random and targeted disruptions

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ABSTRACT

Due to the fact that there is a lack of comprehensive understanding of how the dynamic nature of supply chain networks (SCNs) interrelates with network structures, particularly network topologies under disruptions. This research employs a novel evolving model of a supply chain network (SCNE model) by modifying the Barabási and Albert (BA) model to capture the phenomenon of regional economy and the factor of firms' attractiveness, considering the degree, the locality preference, and the heterogeneity of SCN members simultaneously. We then analyze the SCNE model via the mean-field theory and conduct simulation study to identify the scale-free characteristic of the proposed supply chain network model. Additionally, we leverage node and edge removal to emulate random and targeted disruptions. We measure and compare the robustness of four network models, i.e., the SCNE model, the Erdos and Rényi (ER) model, the BA model, and the Watts and Strogatz (WS) model using two essential metrics, i.e., the size of the largest connected component and the network efficiency. We find that the robustness of the SCNE model is better than the BA model and the WS model on the whole in the presence of disruptions. Also, from the node level, the SCNE model maintains resilience, behaving similarly to the ER model against random disruptions while it shows vulnerability under targeted disruptions, responding in line with the BA model and the WS model. From the edge level, the network efficiency of the SCNE model changes slowly, and the topological structure of the SCNE model slightly changes initially but decreases rapidly at some value, as well as the BA model, the WS model, and the ER model. Based on the results, we summarize key points of the implications for research and practice in supply chain management.

1. Introduction

Modern supply chain networks (SCNs) are becoming increasingly large-scale, more interconnected, and more complex as they expand [1–3]. As a result of this trend, SCNs may now be examined as a whole system rather than isolated components. Thereby we need to understand the SCN from a *system* perspective, and a *complex network* perspective is an effective tool for this [4–8]. A supply chain network can be conceptualized structurally as a collection of nodes and arcs/edges [9,10], with the former representing agents (e.g., firms) and the latter expressing interactions between them (e.g., buy and sell relationships). An SCN agent/firm has the intricate flows and connections of logistics, information, contract, and finance [5,11,12]. There are also behaviors and direct/indirect relationships that affect the overall operation of the SCN, such as behavior control of supply chain finance [13], decision-making of SCN agents [12,14], value-creating [15–17], and knowledge of resilience learning [18]. As SCNs evolve over time, so do their scale, shape, and configuration [19,20], which leads plenty of scholars to study SCNs from the perspective of evolving rules (i.e., attachment rules). For instance, based on the Barabási and Albert (BA) model, Ref. [21] model the complex logistic network by using a modified preferential attachment (MPA), which considers the node's relativity, attractiveness, and directed association simultaneously. Ref. [22] propose a Degree and Locality-based Attachment(DLA) growth model to investigate a military logistic network. Recently, Ref. [23] develop the DLA model and propose a new growth model called the grow-mature-decline (GMD) model by considering the SCN life cycle. Nonetheless, these models (i.e., MPA, DLA, GMD) capture SCNs only by taking into

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account either the location(i.e., the node's distance) or the heterogeneity (i.e., the node's difference) of SCN members. To deal with this limitation, we propose a novel evolving model of the SCN by incorporating the features of regional economy and firms' attractiveness, called the SCNE model, which considers both the location and the heterogeneity of SCN members.

As we know, the topic of supply chain disruptions is crucial in supply chain management [24–26]. Typically, a modest local disruption in an SCN could severely damage a firm, spreading throughout the entire SCN, and this failure may result in supply chain avalanche [11,27–31]. The following examples illustrate this argument. In 2000, a 10-minute fire at a Philips chip factory hit Ericsson, a European mobile phone manufacturer thousands of miles away [32]. In the aftermath of the 911 attacks, the collapse of bridges, roads, and airports across the United States led to unprecedented delays in many companies' SCNs. At the beginning of 2020, the sudden exponential increase in the number of global COVID-19 cases led to the complete closure of many critical facilities, markets, and activities in the global supply chain system [33], and some companies' SCNs were even completely paralyzed. Similarly, the 2022 Russia–Ukraine conflict affected the global SCN, causing severe supply shortages or even disruptions in many industries such as food, energy, transportation, and manufacturing. Consequently, to respond to these disruptions, it is of vital importance to understand how to create a robust supply chain network [34–37]. A large body of literature has explored supply chain disruptions and the relationship between SCN structure and its robustness yet (see Section 2). Following this trend, we also analyze the robustness of the SCNE model against both random and targeted disruptions from both the node and edge levels.

Inspired by both complex network theory and supply chain management, this research seeks to answer the following research questions(RQs):

- *RQ1: How can we model a large-scale supply chain network based on its dynamic processes?*
- *RQ2a: What happens when supply chain network nodes/edges fail?*
- *RQ2b: How can we mitigate the effects of those failures?*

The aim of this paper is to investigate the behavior and performance of supply chain networks from a macroscopic perspective. In order to model the supply chain network with its dynamic process more reasonably, we propose a novel evolving model of an SCN, which displays the locality preference and the fitness of the SCN nodes. We utilize the mean-field approach to analyze the degree distribution of the SCNE model theoretically. In particular, we simulate the degree distribution of the proposed SCNE model to prove the theoretical findings: The SCNE model can produce an SCN with the scale-free feature, and the heterogeneity of the network is lower than the BA model. In addition, for comparison of its properties, we also examine the SCNE model's robustness, which is measured by the two important metrics related to the topological structure and efficiency of the network under random and targeted disruptions both at the node and edge levels, and compare the results with those traditional network models, i.e., the ER model, the BA model, and the WS model. The latter two models are generally regarded as the typical models for SCNs.

The main innovation of this work lies in the following aspects. First, using interdisciplinary knowledge from supply chain management and complex network theory, we propose a novel evolving model of SCNs, which also echos the current literature that has put great emphasis on the quantitative studies of SCNs modeling [7,38]. Second, by emphasizing the macroscopic perspective of network dynamics, this study provides a thorough explanation of the formation, evolution, and collapse of the SCNs. In the meantime, this study also takes the behaviors of SCN members into account. This paper investigates how the preferences and differences of SCN members affect the topological structure of SCNs in terms of SCN generation. In light of this, this paper examines how these variables impact the evolution of the SCN's degree distribution. Additionally, this paper simulates destroying the SCN by removing nodes and edges, which clarifies the SCN's robustness. Thirdly, this study adds to the current body of knowledge regarding SCN robustness, which does not fully take into account the significance of network structure [10]. This is addressed by investigating the relationship between SCNs' dynamic nature and network structures, particularly network topologies under disruptions. At last, scholars have begun investigating SCN disruption and resilience, primarily at the node level [39]. As a result, this paper simulates the removal of edges and nodes. The difference between node and edge levels is explained in this experiment, which adds to the existing body of research.

The remaining sections of this paper are organized as follows. After covering the theoretical foundation and related papers on SCNs in Section 2, we propose the supply chain evolving model in Section 3, including its assumption, algorithm, and theoretical analysis. Section 4 discusses our simulation results, and in Section 5, we present the conclusions.

2. Literature review

We conduct a literature review in three parts. We first introduce the ER model, the WS model, and the BA model, which are three representative network evolving models because many real-world networks can be abstracted into these three models, then review related SCN models, and last highlight the knowledge gap.

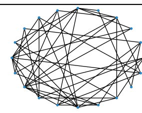
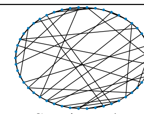
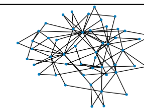
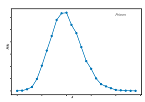
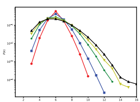
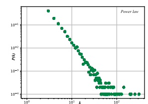
2.1. Three network evolving models

In the last two decades, network science has helped to uncover complex network topologies for describing and understanding many real-world systems [7,40]. In complex network theory, there are three most characteristically distinct network evolving models based on their evolving rules: The ER model [41], the WS model [42], and the BA model [43]. (1) The ER models produce random networks with *Poisson degree distribution* which are frequently employed for benchmarking to confirm that the questioned topology possesses specific characteristics [3,23]. In the ER model, edges of new nodes are added randomly, which is called random attachment (RA). The generation model, $G(n,p)$ model, assumes that connections between n nodes are chosen according to the probability p. (2) The WS models generate semi-random and semi-structured networks with *similar Poisson degree distribution*. Refs. [44,45] argue the SCNs have the features of WS topologies. In the WS model, regular networks are randomly re-connected. The generation model, $G(n,k,p)$ generates a WS network with n nodes, each node having k neighbors, and re-connecting edges randomized with probability p. (3) The BA models form random scale-free networks with *power-law distribution* which are the results of the growth mechanism and preferential attachment (PA) mechanism. In many real-world networks, the degree distribution follows a power-law distribution [46], in which most nodes have relatively few edges, while some nodes have many edges. Refs. [6,10,11,35] suggest the SCNs have the features of BA topologies. The generation model, $G(n,m)$ generates a BA network with n nodes and m edges added each time. The main differences among these models are summarized in Table 1.

2.2. Related supply chain network models

In this paper, we use the definition of SCNs by Ref. [47] p.265, "SCNs are defined as networks of *exchange relationships* between suppliers, customers, and their partner firms that are necessary for manufacturing and providing goods and services to the market". Based on the definition, we view an SCN as an undirected graph. Extending the complex network topological structure to the supply chain context, the relevant research can be roughly divided into three categories.

Table 1
Summary of three network evolving models.

Network evolving models	**ER model**	**WS model**	**BA model**
Exemplary visualization			
Network characteristics	• Completely random structure • Generally used as a baseline model	• Semi-random, semi-structured • Short average path length, large cluster coefficient	• Hub-and-spoke structure • Few nodes with many connections, many nodes with few connections
Degree distribution	**Poisson distribution**	**Similar Poisson distribution**	**Power-law distribution**
			
Responses to disruptions	• Similar robustness to random/targeted attacks	• Robust as most edges are redundant	• Robust to random attacks and highly vulnerable to targeted attacks

(1) *Modeling and topology analysis of supply chain networks* [3,5,21,47–49]. The context of which is mostly focusing on the topological structure of SCNs. For example, Ref. [47] empirically construct 21 extended (five-layer) supply chain networks representing different industries, analyze their topology, and find community, scale-free, and hierarchical structures in complex supply chain networks. According to the intrinsic properties of ecological industrial systems, the green logistics network is constructed and designed by modifying the BA model and its topology is analyzed [21], whereas a lack of robustness analysis. Ref. [49] examine the topological structure and COVID-19-related risk propagation in Thin-film-transistor liquid-crystal displays (TFT-LCD) supply networks from a dynamic perspective.

(2) *Network topology and robustness interact in mitigating disruptions* [4,10,22,23,34–37,50–56]. This aspect pays attention on analyzing the robustness of SCNs from the perspective of network structure, revealing the fragility, collapse conditions, and evolution of the SCN. This kind of study measures the robustness of the SCN by arguing that in the case of continuous elimination of components (i.e., node/edge removals), the more functionality the system maintains, the more robust the network. For example, Ref. [35] extend the linear supply chain proposed by Ref. [57] to a complex supply network, studying the relationship between the network topology and its robustness to supply disruptions in the face of random failures and targeted attacks, one of the key indicators being the largest connected components (LCC). Ref. [54] use empirical datasets to study the robustness of manufacturing networks, as well as the LCC.

(3) *Robustness measurement, design, and optimization* [22,23,29,36,52,58–62]. In terms of robustness measurement, Ref. [58] evaluate the structure and risk exposure of the SCN by multiplying a single node value and the adjacency matrix as a measure of structural robustness. Ref. [61] consider the robustness evaluation mechanism of the supply chain structure for disruption propagation, and measure the robustness of the SCN. As for design and optimization, Ref. [36] propose a Decision Support System based on the rewiring strategy of Ref. [34] to design and optimize the network performance by analyzing the robustness of the SCN to disruptions through appropriate topology analysis and network optimization. Ref. [52] design robust SCNs from the perspective of complex network topologies, i.e., network generation algorithms. In addition, network characteristics, including network topology, can be used to better understand supply chain network robustness than network types [29], which provides a useful perspective for designing and optimizing robust SCNs.

2.3. Knowledge gap

The related literature on the overlapping of SCNs, disruptions, and robustness is presented in Table 2. The most commonly used investigation method is simulation. Existing models either focus on the structure of the SCN and ignore the structural robustness (e.g., Refs. [21,63]), or neglect the real-world features of SCNs (e.g., Refs. [29,35]). Here we address the research gaps.

First, for the evolving models for SCNs, the attachment rules capture real-world SCNs either only taking into account the location or heterogeneity of SCN members. Therefore we address this research gap by incorporating the features of regional economy and firms' attractiveness, which considers both the locality preference and the heterogeneity of SCN nodes in the model. Specifically, the BA model, the DLA model, and the GMD model describe the evolving process of SCN by the preference for only degree, or degree and locality, neglecting the fitness of the new node. To overcome such deficiencies, we consider these factors at the same time in the SCNE model.

Second, regardless of the robustness measuring and in the presence of disruptions, most of the studies focus only on the removal of the node level, and very little literature focuses on the removal of the edge level. So we try to enrich the research by considering removal at both the node and edge levels.

Third, yet we know remarkably little about how the dynamic nature of SCNs is interrelated with network structures, especially network topologies under both random and targeted disruptions. To fill this research gap, we pay equal attention to network topological structures and their robustness under disruptions. In this paper, we show its equality in the simulation part, focusing on the analysis of the network structure characteristics on the one hand, and testing its robustness on the other hand.

3. Model

This section presents the SCNE model, consisting of model assumptions in Section 3.1, model algorithm in Section 3.2, and theoretical analysis of the SCNE model in Section 3.3.

3.1. Model assumptions

SCN is a dynamic and complex system [6,11,64], consisting of different types of firms (i.e., suppliers, manufacturers, distributors, and retailers), complicated flows, connections, and relationships (i.e., material, information, contract, and financial flows). The topological structure of the SCN is changing through the evolving time because new

Table 2
Related papers on the SCN, disruptions, and robustness.

References[a]	Supply chain network		Robustness measuring		Approach
	Graph	Evolving rules[b]	Disruptions[c]	Robustness[d]	
Ref. [4]	Undirected	PA & RA	NR	1,2,3	Simulation
Ref. [34]	Undirected	RLR	NR	4,5,6,7	Simulation
Ref. [22]	Undirected	MPA	NR	4,5,7,8	Simulation
Ref. [35]	Undirected	PA, RA	NR	1,3,10,11	Simulation
Ref. [21]	Directed	MPA	–	–	Simulation & Case study
Ref. [52]	Directed	PA	NR	4,5,11,12	Simulation
Ref. [10]	Directed	–	NR & AR	13	Simulation
Ref. [54]	Undirected	–	NR & CF	1,10,14,15,16	Simulation & Empirical
Ref. [63]	Undirected	MPA	–	–	Simulation
Ref. [36]	Directed	PA & RA	NR	5,17	Simulation & Case study
Ref. [27]	Directed	PTR & PPR & PRR	NR	5,18	Simulation
Ref. [23]	Undirected	PA & RA	NR	19,20,21	Simulation
Ref. [29]	Undirected	PA & RA	RP	22,23,24	Simulation & Case study
Ref. [37]	Undirected	PA & RA	HCF	25	Simulation
This paper	Undirected	MPA	NR & ER	1,2	Simulation

[a]The literature is mostly based on complex network theory.
[b]RLR: Randomized local rewiring; PTR: Preferred trust rule; PPR: Preferred price rule; PRR: Preferred random rule.
[c]NR: Node removal; AR: Arc removal; ER: Edge removal; CF: Cascades of failures; RP: Risk propagation; HCF: Hybrid cascading failure.
[d]Note that similar to the work of [27,34], we also do not distinguish the terms resilience and robustness. 1: Size of the LCC; 2: Average path length(APL) of the LCC; 3: Max. distance of the LCC; 4: Supply availability rate; 5: Size of the largest functional sub-network (LFS); 6: Inverse of avg min. supply-path length(SL); 7: Adjusted avg inverse SL; 8: Avg SL in the LFS; 9: Max. SL in the LFS; 10: APL; 11: Clustering coefficient; 12: Average SL of the LFS; 13: Supply network resilience; 14: Assembly completeness; 15: Cascading failures of companies; 16: Cascading failures of products; 17: Avg SL; 18: Number of sub SCN; 19: Size of the LCC that includes at least one node of each subset(LACC); 20: Weighted APL of the LACC; 21: Max. vertical path length of the LACC; 22: Size of the LCC at initial impact(LCC_II); 23: Size of the LCC at full impact(LCC_FI); 24: Number of healthy nodes at full impact(NH_FI); 25: Interdependent supply network robustness.

firms will continuously enter the network to keep the operational function of the SCN. In our model, nodes represent firms in supply chain networks, and edges between nodes represent exchange relationships (e.g., business collaboration). We develop the BA model for the supply chain network, which is called the supply chain network evolving model, i.e., the SCNE model, by focusing on the phenomenon of regional economy [63], and the factor of firms' attractiveness [21].

(1) *Regional economy.*
Firms in the SCN will speed up their business collaboration more easily in the regional economy. The reasons behind this phenomenon are as follows: (a) From a political, economic, and cultural point of view[1], there are no trade restrictions locally. Political or defense factors are nonexistent. Language and cultural barriers do not exist. Within the region, there is greater mobility of labor and capital [65–67]. (b) From the operational level, to cut down on transportation costs as well as to boost the synergy effect and share efficiency across partnerships [63]. (c) Organizations for regional economic cooperation exist, including the EU, APEC, FTAA, AFTA, and others.
In our model, we consider the *locality preference* i.e., the new node prefers nodes in its neighborhood over distant nodes [22,23,63] to capture the features of the SCN with the regional economy when firms are establishing cooperative relations. This characteristic is reflected in Eq. (1).

(2) *Firms' attractiveness.*
Firms in the SCN have heterogeneous attractiveness. There are focal firms and other ordinary firms in the SCN. In terms of business volume, market share, and technological competition, focal firms have more advantages. Firms also vary in the aspects of social status, business reputation, and corporate strength. New firms prefer to cooperate with firms with higher attractiveness to acquire more abundant operational resources and reduce risks. This phenomenon is regarded as "rich gets richer" [43]. The BA model captures this phenomenon via new nodes' established edges with high-degree nodes, only utilizing *degree* to measure the nodes' attractiveness in the network. However, this setting does not correspond to reality. For example, when a new firm has innovative high-tech technologies in the supply chain network, many firms are still willing to establish cooperative relations with it. To overcome such shortcomings, our model introduces *fitness* η_i to measure the heterogeneous attractiveness of firms in the SCN, making it possible for new firms to get more opportunities to be connected. In our model, the nodes have different fitness to compete for links [21,68], and the greater the node's fitness is, the greater the probability of attracting new nodes to connect to it will be. This characteristic is reflected in Eq. (2).

(3) *An exemplary SCN.*
Apple's SCN is a representative example of the supply chain network. Fig. 1(a) shows some major suppliers and retailers of Apple. Fig. 1(b) shows Apple's position within the supply chain network. It is evident that Apple's SCN is large-scale, compared with previous studies (e.g., Ref. [21], 82 firms; Ref. [5], 70 firms; Ref. [35], 18 firms; Ref. [69], 106 firms; Ref. [36], 184 firms; and Ref. [29], 250 firms). There are thousands of firms and each firm has multiple supply chain relationships with others. Also, the mobile phone manufacturing process involves numerous node firms, and firms with different attractiveness from different regions of the world have cross-regional business collaboration. Therefore, when developing a supply chain network evolving model, it is vital to consider the regional economy and firms' attractiveness.

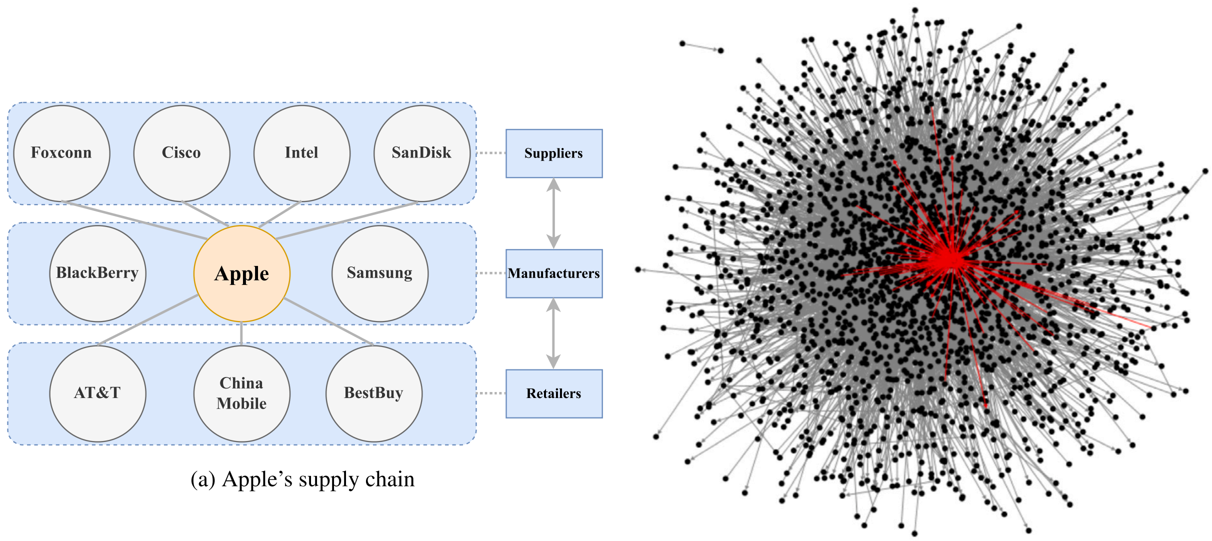
To conclude, we have the following assumptions.

- *Assumption 1*: The supply chain network is an undirected graph $G = (V, E)$.
- *Assumption 2*: To capture the features of the SCN, i.e., regional economy and attractiveness, consider the locality preference and the fitness of the SCN nodes.

3.2. Model algorithm

By amending the BA model, a novel evolving model for an SCN is proposed by using a modified preferential attachment. For ease of reference, we summarize the notations and definitions in Table 3. The SCN evolving process is described as follows:

[1] https://www.economicsnetwork.ac.uk/true_showcase/regional_economies



(a) Apple's supply chain

(b) Apples position within the SCN

Fig. 1. Apple's supply chain network.
Source: Bloomberg Finance LP, FactSet Deutsche Bank Quantitative Strategy [70].

Table 3
The notations and definitions in the SCNE model.

Notation	Definition
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 with a node adding in the SCN at each time step;
N	The total number of the nodes in the SCN;
G	Undirected network graph with V nodes and E edges, $G = (V, E)$;
t/T	Time step;
(x_i, y_i)	The coordinate of node i in the SCN;
d_{ij}	The distance between node i and node j, $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$;
R	The coverage radius of each node;
L	The choosing radius of each node;
W_i	The local-region(choosing region) of node i, $W_i = \{j \mid d_{ij} \leq min(L, R) \wedge j \in G\}$;
η_i	The fitness of node i, $\eta_i \in (0, 1)$ follows some distribution;
α	The tunable parameter that can adjust the relationship between fitness and locality preference;
p_{region}	The probability of the new node i comes into a local-region;
$\prod_{i,j}$	The probability of connection between new node i and old node j.

- **Initial state-Step 1:** $t = 0$, the network begins to evolve. The number of nodes and edges at the start is denoted as m_0 and e_0, respectively. Each node i is randomly given a coordinate (x_i, y_i). These nodes connect with surrounding nodes based on their distance d_{ij} from each other and their own coverage R.
- **Growth-Step 2:** at each time step t, add a new node with m ($m < m_0$) edges into the network. The new node will enter a certain area based on the locality preference, i.e., the node will choose a corresponding location within a certain range to appear in the network according to a specific network characteristic. Commonly defined network characteristics are node degree, betweenness, closeness, eigenvector, or other physical properties [5,10,29,54,71]. In this paper, the node degree is considered as the basis for nodes to join the network. Eq. (1) defines the probability that the new node comes into a local-region:

$$p_{region} = \frac{\sum_{i \in W_i} k_i}{\sum_{j \in G} k_j} \tag{1}$$

where k denotes the degree of the node, $\sum_{i \in W_i} k_i$ indicates the sum of the degree of all nodes in the selected local-region W_i, $\sum_{j \in G} k_j$ represents the sum of the degree of all nodes in the SCN G. Call the local-region's radius as *choosing radius*, denoted L. It can be seen from Eq. (1) that the location of the new node is determined by the sum of the degrees of the nodes in the choosing region, which refers to the extent of the activity level of the SCN members in the region. High activity levels can be understood that there are numerous nodes closely coupled in the region, reflecting the aggregation features of the SCN structure and maintaining high practical implications.
- **Preferential attachment-Step 3:** when a new node enters the network, it selects certain nodes in its local-region to link with. The probability that a new node is connected to an already existing node in the network is defined in Eq. (2):

$$\prod_{i,j} = \frac{f(\eta_i, d_i) k_i}{\sum_{j \in W_j} f(\eta_j, d_j) k_j} \tag{2}$$

where $f(\eta_i, d_i) = \eta_i^{\alpha}(1 - \frac{d_i}{\sum d_i})^{1-\alpha}$, and η is chosen from the distribution $\rho(\eta)$, i.e., η_i follows some distribution (e.g., uniform, exponential, power-law, and etc.). Eq. (2) means that the greater the fitness(i.e., wealth, reputation, and competitiveness) of the node is, the closer the distance between the two nodes is, and the greater the probability that the new node is connected to it

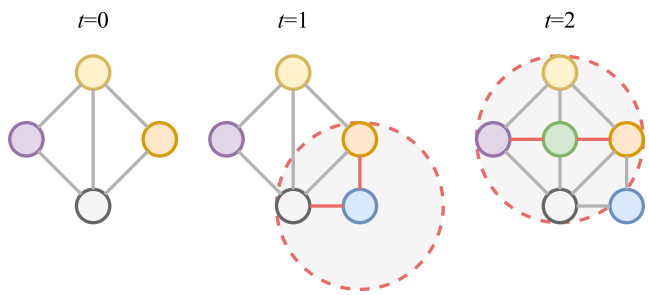


Fig. 2. An example of the SCNE model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

will be. α is a tunable parameter that can adjust the relationship between fitness and locality preference.

- **Iteration:** repeat Steps 2 and 3 until the SCN reaches the desired size N.

After T time steps, an SCN with $N = m_0+T$ nodes with e_0+mT edges is generated. Fig. 2 illustrates a simple example of the SCNE model. In this example, each new node will establish two edges, i.e., $m = 2$. Initially $t = 0$, the network starts with $m_0 = 4$ connected nodes (different colors) with $e_0 = 5$ edges (gray). When $t = 1$, a new node (blue) comes into the local-region(dotted shadow part) with the probability of p_{region}, within the coverage radiant and choosing radiant, i.e., R and L, the $m = 2$ edges of the new node will prefer the node with high degree, great fitness, and close nodes, say, nodes connected by red lines. Similarly, when $t = 2$, a new node (green) connects to existing nodes by following the same rule. The white node (the greatest degree) does not compete with the orange and purple nodes because its fitness is not as high as theirs. As more nodes are added, an SCN will emerge from this attachment process.

3.3. Theoretical analysis

According to the mean-field approach [72], for any node i in the SCN, based on the assumption that k_i is distributing continuously, the degree in unit time step t of node i will match to:

$$\frac{\partial k_i}{\partial t} = m\prod_{i,j} = m\frac{f(\eta_i, d_i)k_i}{\sum_{j\in W_j} f(\eta_j, d_j)k_j}. \tag{3}$$

First, assume the total number of nodes in the network (i.e., N) is large enough, thereby there are enough nodes connected to the new-adding nodes. Then we can approximate as $\frac{d_j}{\sum_{j=1}^{n} d_j} = 0$. Second, assume that there is an average attractiveness (i.e., fitness) of nodes in local-region, namely, $\eta_{avg} = \langle\eta\rangle$. Third, in large complex networks, the average degree of nodes in choosing region is calculated as $\langle k\rangle = \frac{2(e_0+mt)}{m_o+t} = 2m$. Therefore, $\sum_{j\in W_j} f(\eta_j, d_j)k_j = \sum_{j\in W_j} \eta_j^{\alpha}(1 - \frac{d_j}{\sum_{j=1}^{n} d_j})^{1-\alpha}k_j = \sum_{j\in W_j} \eta_j^{\alpha}k_j = n\cdot\eta_{avg}^{\alpha}\langle k\rangle = n\cdot\eta_{avg}^{\alpha}\frac{2(e_0+mt)}{m_o+t} = 2mn\cdot\eta_{avg}^{\alpha}$, where n is the number of nodes within the coverage of the new node.

Then, simplifying the formula (3), we have

$$\frac{\partial k_i}{\partial t} = \frac{g(f)k_i}{2}, \tag{4}$$

where $g(f) = \frac{f(\eta_i, d_i)}{n\eta_{avg}^{\alpha}}$.

Adjusting formula (4), we have

$$\frac{\partial k_i}{k_i} = \frac{g(f)}{2}\mathrm{d}t. \tag{5}$$

Solving differential equations, we have

$$k_i(t) = e^{\frac{g(f)}{2}t+C}. \tag{6}$$

According to the initial condition $k_i(t_i) = m$, we solve $C = ln(m) - \frac{g(f)}{2}t_i$. Put C into formula (6), then

$$k_i(t) = me^{\frac{g(f)}{2}(t-t_i)}. \tag{7}$$

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

$$p(k_i(t) < k) = p(t_i > t - ln(\frac{k}{m})\frac{2}{g(f)}). \tag{8}$$

Implanting new nodes at constant intervals:

$$p(t_i) = \frac{1}{m_0 + t}, \tag{9}$$

then we have:

$$p(k_i(t) < k) = 1 - p(t_i \le t - ln(\frac{k}{m})\frac{2}{g(f)}) = 1 - \frac{1}{m_0+t}(t - ln(\frac{k}{m})\frac{2}{g(f)}). \tag{10}$$

The probability of node degree distributions should be match

$$\begin{aligned} p(k) &= \frac{\partial p(k_i(t) < k)}{\partial k} \\ &= \frac{2}{g(f)(m_0+t)}k^{-1}. \end{aligned} \tag{11}$$

k is the continuous random variable for the degree of the node in the SCN. Thus, we obtain:

$$P(k) \propto \theta k^{-1} \tag{12}$$

where $\theta = \int_\eta \int_d \varepsilon\delta p(k)\mathrm{d}\eta\mathrm{d}d$. ε and δ are the distributions of η and d, respectively.

Therefore, the degree distribution of the SCN is simultaneously determined by the distributions of η and d. And by adjusting these parameters, we can obtain different network structures.

Property 1. *The SCNE model can produce a supply chain network with the scale-free feature, and the heterogeneity of the network is lower than the BA network.*

Proof. According to the generation process of the SCNE model, we can obtain the degree distribution $P(k) \sim k^{-1}$ of the SCN, which has a power-law form with degree exponent $\gamma = 1$, lower than the BA network degree exponent $\gamma = 3$.

According to Ref. [43], this result indicates our model can produce scale-free SCNs. To summarize, our model not only considers the locality preference of the new node but also balances the relationships and fitness of nodes in the SCN. By varying settings of the parameters, supply chain networks with different topologies are generated.

4. Simulation

In this section, we take simulation experiments, and the reasons are as follows. (1) The operational data of supply chain firms are generally confidential and not publicly available, making it difficult to obtain [44,73]. (2) To investigate the proposed RQs and verify the theoretical analysis. (3) It is impossible to build a real-world SCN and destroy it. Consequently, we undertake computer simulations in the following fashion: (1) *Experiment I: Network structure of supply chain networks.* Firstly, given the parameters according to the real-world situation, an SCN is generated based on the proposed SCNE model. We analyze the network topological structure by adjusting the choosing radius L, the coverage radius R, and the distribution of the fitness η_i. (2) *Experiment II: The robustness of supply chain networks.* Then, we simulate disruptions for four different network models(i.e., the SCNE model, the ER model, the WS model, and the BA model) under four different disruption scenarios, i.e., node and edge removals × targeted attack and random failure (the reasons are analyzed further in Section 4.2.1), and calculate the robustness metrics in each case.

Lastly, we analyze, compare, and derive several important managerial implications based on the results obtained from the simulation.

The baseline parameters of our experimental setup are provided below. Note that $N = 250$ is a common network size [29], Ref. [23] set $N = 600$, and Refs. [4,52] set $N = 1000$, the scale of the SCN is relatively large. So we suppose there is a supply chain network composed of $N = 1000$ firms. According to Refs. [23,43], we set the number of firms in the initial network $m_0 = 7$ because this value is small, and does not affect the final network structure. As described by previous researchers [22,43,52], assume new-adding firms' edges $m = 5$. The coverage radius and choosing radius determine the locality preference at the same time. Usually, they are different, but not much. Hence, we set coverage radius $R = 70$, choosing radius $L = 50$. Additionally, let locality preference and fitness have the same effect on the SCNE model, we set the adjusting parameter $\alpha = 0.5$. Ref. [74] found that firms' wealth and competitiveness follow Pareto distributions in competitive industries, which means firms' attractiveness is very different, so we let fitness η_i satisfy the power-law distribution.

4.1. Experiment I: Network structure of supply chain networks

In this part, we explore network topology and network degree distribution of the SCNE model, respectively. First, the proposed SCNE model is used to generate an SCN topology from the given parameters. Then, by adjusting the parameters(i.e., the rest of the parameters remain unchanged and change the choosing radius L, the coverage radius R, and the distribution of the fitness η_i respectively), we address the degree distribution of the network.

4.1.1. Network topology

Fig. 3 shows the topology of the supply chain network, which is a large-scale network. It shows how firms in the SCN are connected. An edge shows the business cooperation between two nodes. Where the degree centrality (DC) measures how many direct neighbors the node has. DC is defined as $\frac{\sum_{i\neq j} e_{ij}}{n-1} = 0$, where e_{ij} is binary, and $e_{ij} = 1$ if there is an edge between node v_i and node v_j; otherwise $e_{ij} = 0$. Actually, in a supply chain network, a node with a high DC reflects the fact that the firm often plays a key role in operational activities such as material transportation, information exchange, and capital flow, which also indicates that a disruption of the firm can have a considerable impact on network performance. In contrast, a disruption of a node with low DC has a limited impact on the network. Fig. 3 also shows that the resulting supply chain network has strong heterogeneity, that is, the number of important hub firms ($DC > 0.15$) is relatively small, while the number of ordinary firms with low DC is large, which has obvious scale-free characteristics, which verifies the theoretical analysis above in Section 3.3.

4.1.2. Network degree distribution

The degree distribution of the SCN is closely related to its topology and is often used to analyze network structure [75]. Degree distributions, which are charts that show the frequency of DC throughout the network, are used to illustrate variations. A homogeneous distribution indicates that the majority of firms have a similar amount of connections, which has a similar effect on overall connectivity. Certain firms (i.e., hub firms) would have a stronger influence on connection than others if the distribution is heterogeneous.

(1) *Locality preference.*
In our simulation, we determine the parameters, i.e., choosing radius L and coverage radius R to observe the influence of locality preference on degree distribution.
Fig. 4(a)–(e) shows the changes of position forms under different settings of the SCN. Fig. 4(a) plots the position form of firms without locality preference (randomly) for SCN, while Fig. 4(b)–(e) plots position forms of firms considering locality preference with different choosing radius L. We find that when the choosing radius L gradually decreases, the more likely firms are to enter the SCN to cluster in regions with a high density of firms. In this case, the regional economy feature of the SCN becomes apparent. Taking the mobile phone manufacturers SCN in China as an example, firms have locality preferences based on the regional economy and are mostly distributed in Guangdong, Jiangsu, and Taiwan [76]. The practical advantages of this phenomenon are, for one thing, firms in the SCN will reduce transportation costs, and for another, strengthen synergies and improve efficiency.
Fig. 5(a) and (b) illustrate comparisons of the degree distribution under different choosing radius L and coverage radius R. Fig. 5(a) verifies the findings of Fig. 4 again. Obviously, as L gradually increases, the distribution of firms in the SCN tends to be scattered, so the proportion of firms with a larger degree is lower than that when the choosing radius is small. This variation tendency is consistent with the decrease of coverage radius R. In other words, as R increases, firms with a high degree in the SCN will be more likely to be connected by a new firm, so the heterogeneity of node degree in the SCN is increased.

(2) *Fitness.*
In order to investigate the heterogeneity of nodes' fitness, that is, to characterize the different attractiveness of firms in the SCN, we consider η_i to obey three distributions (i.e., uniform, exponential, and power-law distribution) [21]. This setting can reflect the change in the heterogeneity of nodes' attractiveness from low to high.
Fig. 6(a)–(c) shows the fitness distribution of firms in the SCN. The horizontal axes denote the fitness value of firms and the vertical axes are the number of the corresponding firms. The uniform distribution reflects that firms' attractiveness is mostly the same while the power-law distribution indicates that firms' attractiveness is very different. And the difference in firms' attractiveness of exponential distribution is between them.
Fig. 6(d) shows the comparison of the degree distribution under different fitness distributions. We find that the higher the heterogeneity of nodes' fitness, the higher the heterogeneity of network degree distribution. The explanation is that a limited number of firms with great attractiveness have a higher probability of cooperating with the new firms in the SCN. A positive feedback loop is created consequently: As node degree increases, hub nodes are more likely to form.

To conclude, the SCNE model holds the following properties.

Property 2. *The degree distribution of the SCN produced by the SCNE model will be more homogeneous with increasing choosing radius or decreasing coverage radius of SCN firms, holding other parameters constant.*

Property 3. *The degree distribution of the SCN produced by the SCNE model will be more heterogeneous with more various attractiveness of SCN firms, holding other parameters constant.*

4.2. Experiment II: The robustness of supply chain networks

In this part, we define disruptions, measure robustness, and compare the robustness of the SCNE model with the ER model, the WS model, and the BA model. Note that BA and WS models are always viewed as the typical models for supply chain networks [47]. To ensure a fair comparison, assume that the number of nodes (firms) of the four models is $N = 1000$. Fig. 7 shows the degree distribution for four different network models. The degree distribution of ER model is shown as the Poisson distribution, BA model follows a power-law distribution. WS model follows similarly to the Poisson distribution. The SCNE model behaves like power-law distribution, but the heterogeneity is lower than that of the BA model. Next, we define disruptions for the SCN, as well as robustness measuring from the perspective of topology. And finally, the simulation results are obtained.

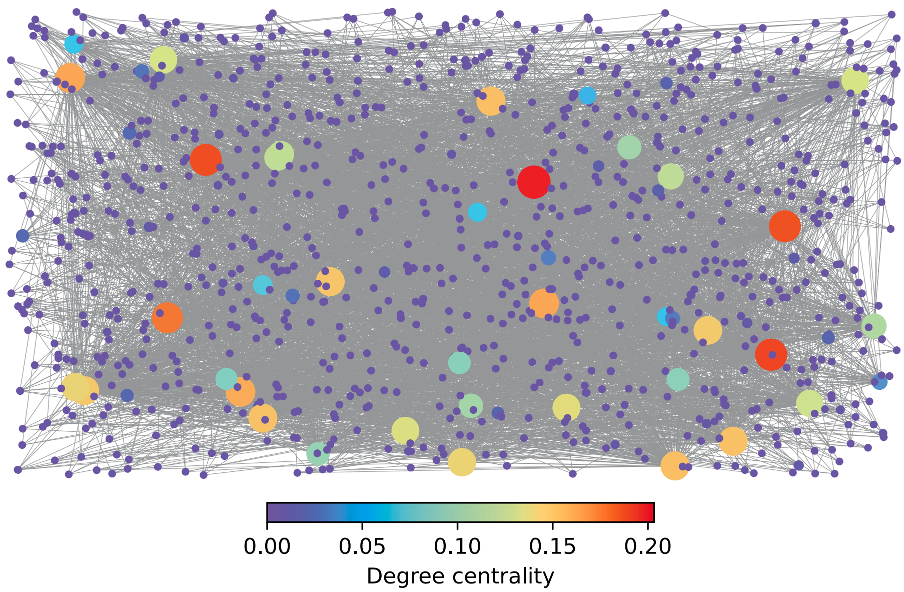
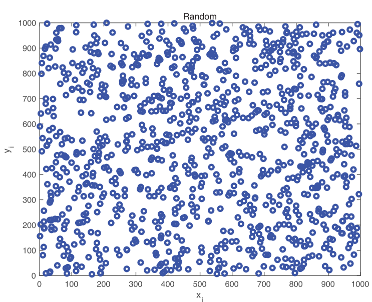
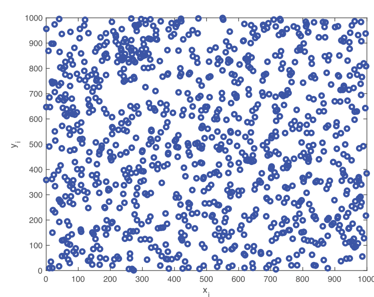


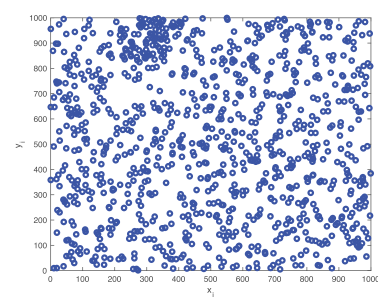
Fig. 3. Supply chain network topology.



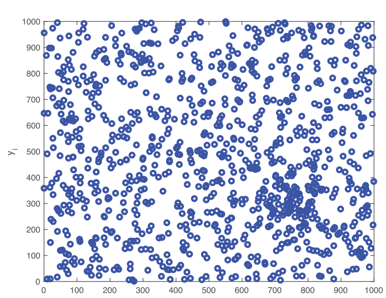
(a) Random, without locality preference



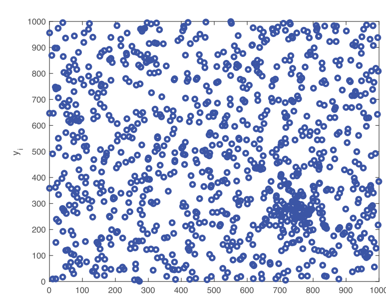
(b) Locality preference with $L = 80$



(c) Locality preference with $L = 70$



(d) Locality preference with $L = 60$



(e) Locality preference with $L = 50$

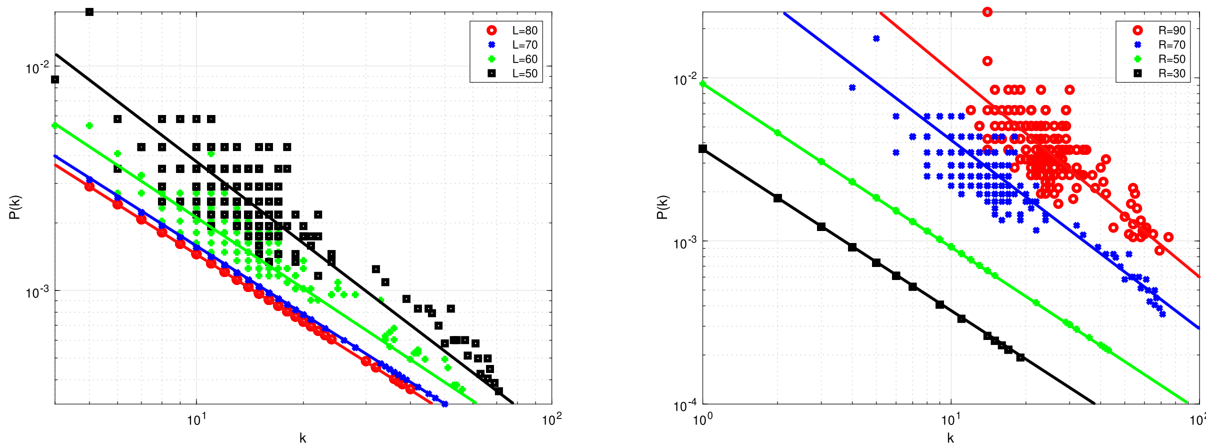
Fig. 4. Position forms under different settings of the SCN.

4.2.1. Defining disruptions: Random failure and targeted attack

Traditionally, there are two types of disruption risks: random and targeted disruptions [23]. *Random disruptions*, in which every node/edge has an equal probability of being removed, represent many events that have a low likelihood of occurrence but have a prominent impact on an SCN, such as natural disasters(floods, earthquakes, hurricanes), disease & epidemics, plant fire, and economic crises[2]. *Targeted disruptions* refer to emergencies like political systems (war, terrorism, labor disputes, regulations, terrorist attacks) and economic sanctions, in which the vital nodes/edges are more likely to be removed[3]. There are many metrics to measure the node's/edge's importance. For node's importance, such as degree centrality, betweenness, closeness, and eigenvector centrality [40]. Referring to the vast majority of the literature in Table 2, we opt for *DC* of nodes and the betweenness of edges to measure the importance. Here, the betweenness of edges is defined as the ratio of the number of paths passing through the edge among all the shortest paths in the SCN to the total number of shortest paths.

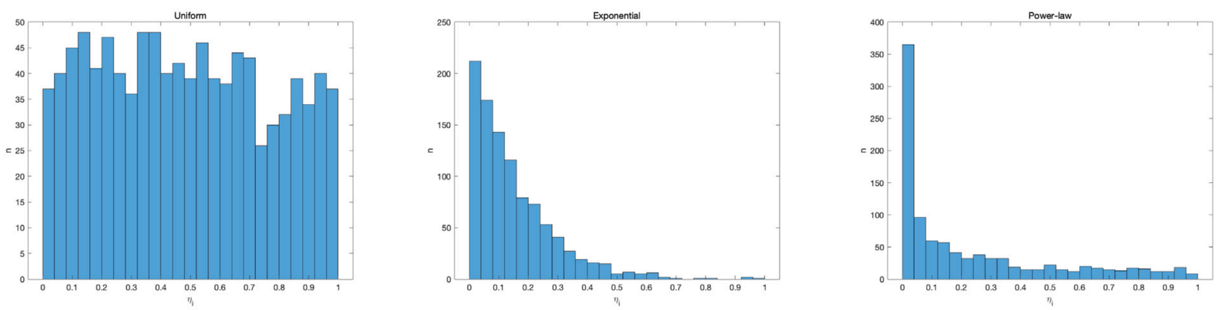
[2] See the examples in Section 1, fire at a Philips chip factory and COVID-19 cases.

[3] See the examples in Section 1, 911 attacks and Russia-Ukraine conflict.

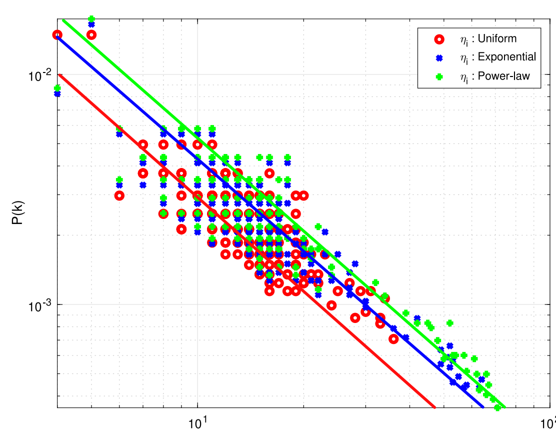


(a) Different choosing radius L (b) Different coverage radius R

Fig. 5. Degree distribution comparison.



(a) Uniform distribution   (b) Exponential distribution   (c) Power-law distribution



(d) Degree distribution comparison

Fig. 6. Degree distribution comparison under different fitness distribution.

Fig. 8 presents an example of the robustness of an SCN subjected to (a) repeated, targeted node removal [53] and (b) repeated, random edge removal. For operation (a), the red node and its incident edges are removed at each attack. At the time t_1, a single node is disrupted intentionally (i.e., removed by calculated node DC) from the SCN, and the axis shows the change of the robustness of the SCN with each time epoch.

4.2.2. Robustness measuring

In the context of supply chain networks, topological metrics can be good indicators of network performance [5]. When the network's nodes and edges are disrupted, the network's structure and efficiency change, *the size of the largest connected component* (LCC) and *network efficiency* can be used to indicate the network's robustness in the presence of disruptions. Here we define two metrics: the relative size of the largest connected component R and the relative network efficiency E.

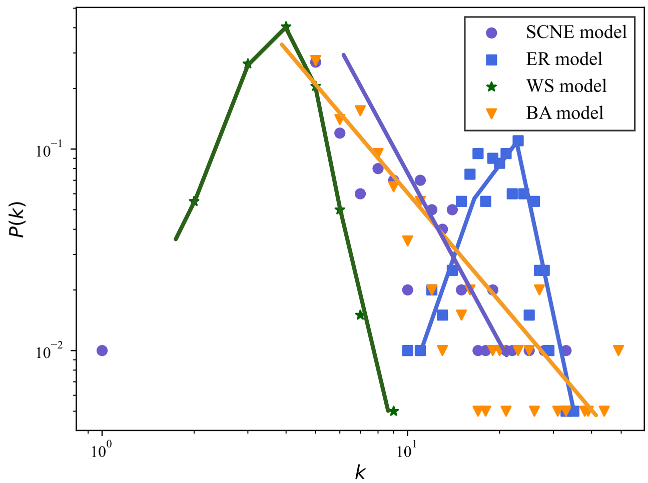


Fig. 7. Degree distribution for four different SCN models.

The relative size of the largest connected component R. According to percolation theory [77] and Table 2, the robustness of an SCN can be measured by finding out the size of the LCC. So we define R as the relative size of the LCC

$$R = \frac{S(t)}{S(0)} \tag{13}$$

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

The relative network efficiency E. Network efficiency was firstly proposed by Ref. [72] to characterize the properties of small-world networks, which presents an approach to identify the spread of a network by calculating the average of the reciprocal of shortest path lengths between each node pair in the SCN, defined as

$$Efficiency = \frac{1}{N(N-1)/2} \sum_{i \neq j} \frac{1}{d'_{ij}} \tag{14}$$

where d'_{ij} is the shortest path length between node i and j, and N is the number of nodes in the SCN. The shorter the APL, the more efficient the exchange/cooperation will be. Network efficiency is the degree to which the network can operate normally and function within a certain period of time, and it can describe the efficiency of the network to transmit trade/information. Accordingly, we define E as the relative network efficiency

$$E = \frac{Efficiency(t)}{Efficiency(0)} \tag{15}$$

where $Efficiency(t)$ is the network efficiency of the SCN after the repeated disruption, and $Efficiency(0)$ refers to the network efficiency initially.

4.2.3. Results for the comparison of the robustness

In order to reduce statistical fluctuations and overcome the interference of random factors, we perform *30* independent simulations for each case and record the average as the final result.

(1) *Results for random disruptions.* Figs. 9 and 10 show the four SCN models' responses to random disruptions from both node and edge levels. The horizontal axes denote the node and edge removal percentage respectively and the vertical axes are the robustness metrics. The ER model performs best against disruptions. But the real supply chain network structure is not random(Ref. [46], p. 96), so the ER model is generally used as a benchmark model for comparative analysis. Surprisingly, for the relative network efficiency E, we find that the SCNE model always performs better than the BA model and the WS model. For the relative size of the LCC, R, when the nodes are removed before approximately 30% (or the edges are removed before approximately 45%), the SCNE model is only slightly poorer than the BA model and the WS model. In other words, the four models' responses to disruptions are very close. After that percentage, the SCNE model performs better than the BA model and the WS model observably. That means the SCNE model has a better performance than the BA model and the WS model on the whole, which implies the SCNE model is basically robust under random disruptions. Additionally, the decrease in network efficiency of the SCNE model is also small, which proves the robustness of the SCNE model against random disruptions again.

(2) *Results for targeted disruptions.* Figs. 11 and 12 demonstrate the four SCN models' responses to targeted disruptions from both node and edge levels. The horizontal axes show the node and edge removal percentage respectively and the vertical axes are the robustness metrics. Similarly, the ER model performs best. And for the relative network efficiency E, the SCNE model performs better than the BA model and the WS model. In terms of the relative size of the LCC, R, their performance in front of the percentage(30% for nodes removal and 70% for edges removal) is not much different, but beyond which, the SCNE model is always better than the BA model and the WS model. It is notable that SCNs deteriorate rapidly over some value of the percentage, which is around 20% for the BA model, 25% for the WS model, 35% for the SCNE model, and 70% for the ER model from the node level. From the edge level, it is 40%, 75%, 80%, and nearly 95% for the WS model, the BA model, the SCNE model, and the ER model, respectively. The results are consistent with the previous observation [22,23,51], showing the fragility of the SCNs. Nonetheless, we can also draw the conclusion that the SCNE model performs better than the BA model and the WS model under targeted disruptions overall.

(3) *Targeted disruptions vs. random disruptions.* Arguably, random disruptions are more frequent than targeted disruptions, but the latter is more harmful. Comparing Figs. 9 and 11, it is shown that from the node level, the SCNE model features robustness, behaving similarly to the ER model against random disruptions. Although the SCNE model shows vulnerability under targeted disruptions and behaves in line with the BA model and the WS model, it is stronger than these two models. In fact, according to the *Molloy-Reed Criteria* [78], $p_c = 1/(\kappa - 1)$, where p_c refers to the percentage of nodes removal and κ measures the heterogeneity of networks, describes the strength of SCN heterogeneity playing an extremely important role in the coexistence of robustness and fragility of SCNs. The SCNE model has more tolerance against disruptions than the BA model and the WS model because the heterogeneity of the SCNE model is lower.

(4) *Node level vs. edge level.* Clearly, we find that the network efficiency of the SCN models changes slowly from the edge level compared with the node level. The reason behind this is, the removal of edges affects the performance of information/trade exchange is smaller than node removals in SCNs. Intuitively, nodes removed randomly are supposed to be equated to edges removed randomly. However, they are not. Note that the WS model performs worse than the BA model under edge removals while it does oppositely under the removal of nodes. It is because when a node is removed, the edges of the node are passively changed, but after an edge is removed, the node may still exist. This is in line with reality. In practice, if the exchange relationships of some firms in the SCN end, it will not lead to the destruction of the firm. On the other hand, it is also related to the evolving rules. The WS model is based on the rules of reconnecting edges, while the BA model is based on growth and preferential mechanisms, which results in the change of edges

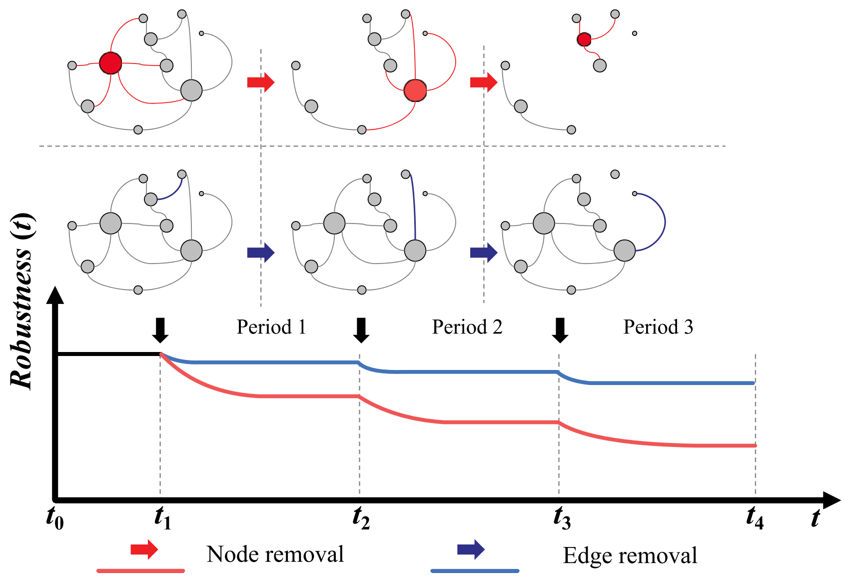


Fig. 8. Repeated disruption scenario. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

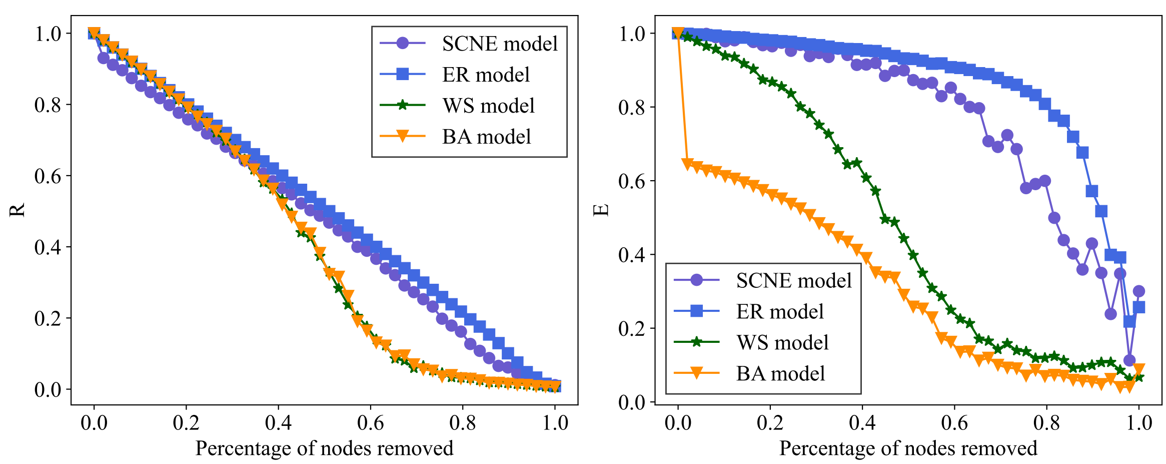


Fig. 9. Responses of the supply chain network models under random disruptions (node level).

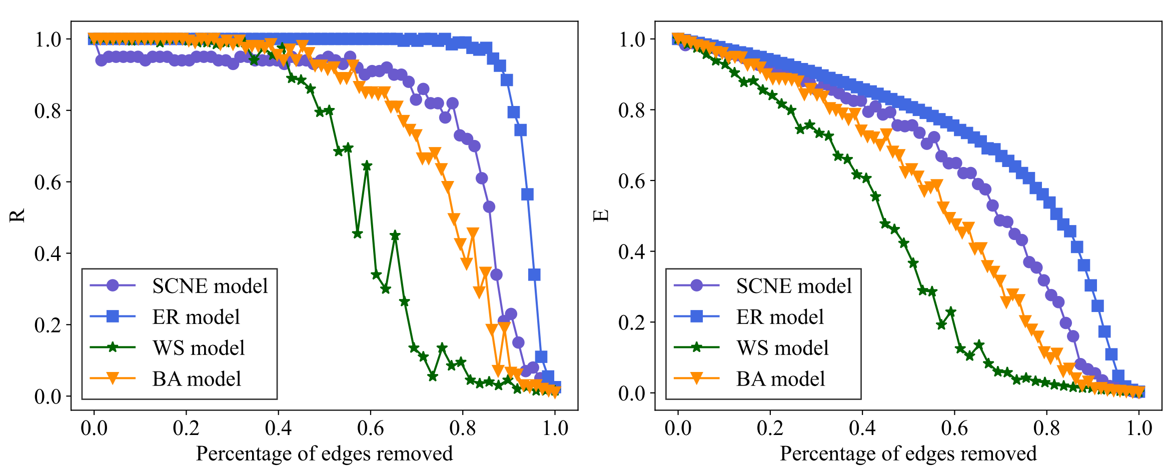


Fig. 10. Responses of the supply chain network models under random disruptions (edge level).

significantly impacting the WS model. Furthermore, we also find that the relative size of the LCC, R, is barely changed at first and then (at some value) decreases dramatically. That is the same reasons addressed above, in other words, only removing a higher number of edges can result in a noticeable change in the topology of SCNs from the edge level.

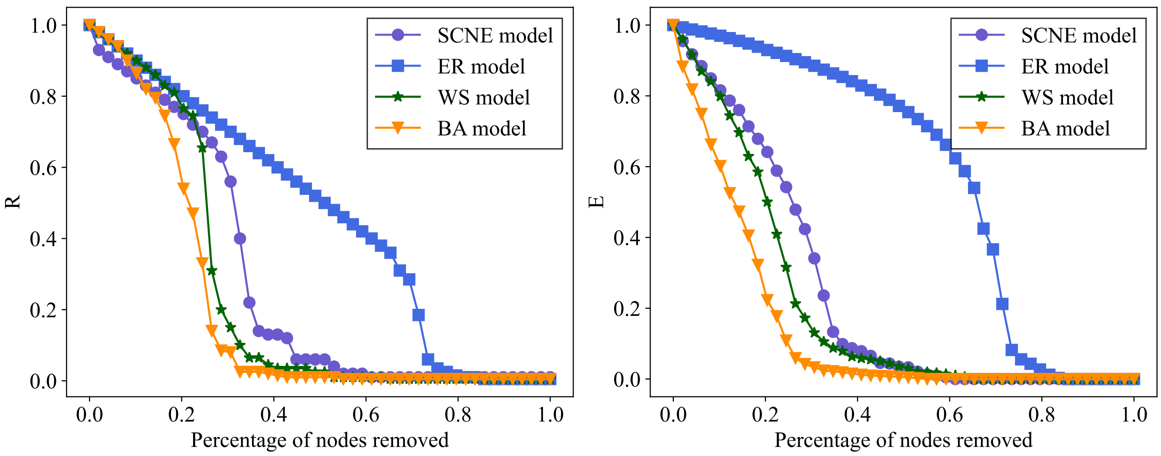


Fig. 11. Responses of the supply chain network models under targeted disruptions (node level).

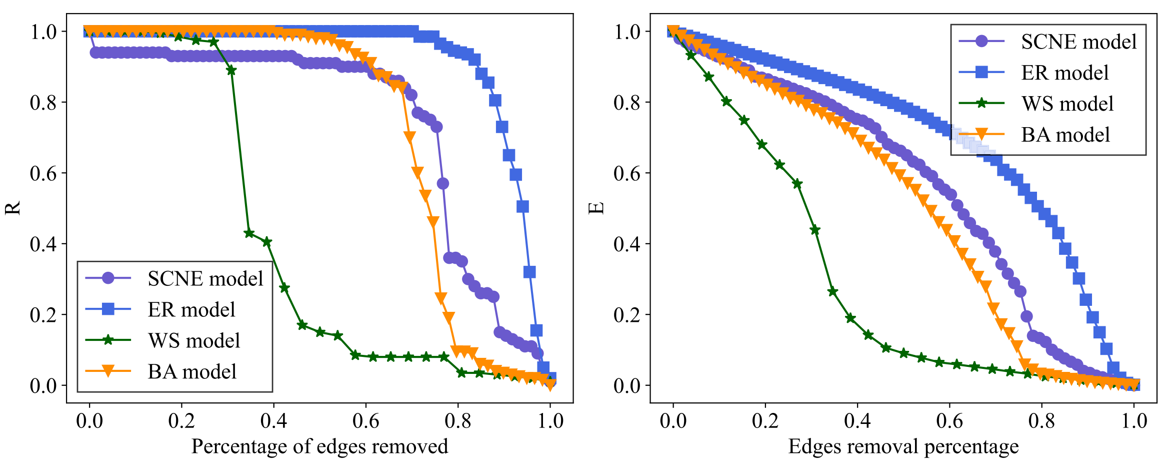


Fig. 12. Responses of the supply chain network models under targeted disruptions (edge level).

The main findings from the simulation of robustness measuring can be summarized as the following properties.

Property 4. *The robustness measuring of the proposed SCN evolving model performs better than the BA model and the WS model on the whole in the presence of disruptions.*

Property 5. *From the node level, the proposed SCN evolving model holds the coexistence of robustness and fragility: It maintains resilience, behaving similarly to the ER model against random disruptions while it shows vulnerability under targeted disruptions, responding in line with the BA model and the WS model.*

Property 6. *From the edge level, the network efficiency of the proposed SCN evolving model changes slowly, and the topological structure of the proposed SCN evolving model slightly changes initially but decreases rapidly at some value, as well as the BA model, the WS model, and the ER model.*

5. Conclusions

Supply chain networks evolve over time based on their dynamic formation process. To address the *RQ1: How can we model a large-scale supply chain network based on its dynamic processes*, we proposed a novel evolving model of supply chain network, since complex networks are proven to be an effective abstraction tool to describe the topological structure and macro aspects of SCNs. Instead of focusing on the interactions between specific SCN members, this simplification depicts what occurs at the network level. We develop the revised BA model to illustrate the regional economy and firms' attractiveness by considering the degree, the locality preference, and the heterogeneity of SCN members simultaneously. To answer the *RQ2a: What happens when supply chain network nodes/edges fail*, we adopt computer simulations to create four different disruption scenarios. For the purpose of quantifying robustness and dynamic response to disruptions, we compare the proposed model with the ER model, the BA model, and the WS model. Specifically, the ER model is set to be the benchmark, and the BA model and the WS model map onto prototypes of real-world supply chain networks. Several properties of the proposed model have been drawn, which lays a solid foundation for supply chain management development. (a) The SCN generated by the SCNE model holds the characteristics of scale-free, and the heterogeneity of the network is lower than the BA model. The degree distribution will be more homogeneous if the choosing radius increases, or the coverage radius and the heterogeneity of fitness decrease. (b) No matter whether under random or targeted disruptions, the responses of SCNE model are better than the BA model and the WS model. From the node level, the SCNE model coexists the robustness and fragility. And from the edge level, the changing trend of the network efficiency and the topological structure differs. The former is slow and the latter has a jumping point.

5.1. Theoretical contributions

Theoretically, this study makes the following contributions. First, we present a novel evolving model of SCNs, combining the interdisciplinary knowledge of complex network theory and the content of supply chain management. This work contributes to the growing literature on quantitative studies of supply chain networks modeling [7, 38].

Second, this study offers a comprehensive understanding of the formation, evolution, and collapse of the SCNs by focusing on the macroscopic perspective of network behavior. Meanwhile, we additionally consider the behavior of SCN members. For the generation of the SCN, we study how the preference and differences of SCN members influence the topological structure of SCNs. Accordingly, we explore how these factors affect the degree distribution evolution. Furthermore, we crash the SCN by removing nodes and edges via simulation, which helps understand the robustness of the SCN.

Third, this study enriches the emerging research on supply chain network robustness, which has not fully incorporated the role of network structure [10]. We address this by studying how the dynamic nature of SCNs interrelates with network structures, especially network topologies under disruptions.

Finally, researchers have started looking into supply chain network disruption and resilience, primarily at the node level [39]. Therefore, we perform both node and edge removals simulations. This experiment supplements the current literature by explicating the difference between node and edge levels.

5.2. Managerial implications

Our findings address the *RQ2b: how can we mitigate the effects of those failures*. Properties 1–3 show the findings of degree distribution corresponding to structural topology, and Properties 4–6 state the relatively high robustness of the SCNE model under disruptions. Therefore, to mitigate the effects of those failures efficiently, managers need to build a robust SCN, that is, to follow the process of the SCNE model, featuring by regional economy and firms' attractiveness. From a practical perspective, managers can, in a timely and appropriate manner, strengthen the stability and closeness of business cooperation between firms by establishing firm alliances in the local-region, to ensure forming the topology of the SCNE model.

Also, this study sheds light on how to manage supply chain networks. There are some practice implications for managers in the following logic based on the observations. The diversification of degree distribution of the SCNE model is affected by the choosing radius, the coverage radius, and the fitness distribution. The greater the choosing radius is, the smaller the coverage radius is, and the more homogeneous fitness distribution is, the lower the degree distribution of the SCNE model will be. And the SCNE model with a lower heterogeneity leads to a more robust topological structure against disruption risks. Lastly, from the perspective of the focal firm of a supply chain network (e.g., smartphone supply chain networks [76]), we can propose optimization strategies for the robustness of SCN from firm-level and network-level, respectively. (a) *Firm-level.* Note that SCNs with scale-free properties are weak against targeted disruptions, thus the focal firm plays a pivotal role in managing such disruptions. Therefore, the capital and resources of focal firms need to be controlled more carefully and systematically to resist targeted risks. For other ordinary firms, take full advantage of their flexibility to improve responsiveness in limited business relationships and avoid relatively large structural risks [79,80]. (b) *Network-level.* It is pointed out that the robust topological structures of SCNs are necessary to *maintain* features of the regional economy, but the characteristics should not be *too obvious*. The apparent regional economy features lead to the phenomenon of "rich gets richer" in the local-region, which is extremely vulnerable against targeted disruptions. Taking advantage of the reduced logistics costs, and increased efficiency of information transmission brought about by the regional economy, regional organizations (e.g., EU, APEC) or governments should work together to promote multi-regional coordinated regional industrial development strategies. At the same time, they should avoid the over-intensive distribution of similar exchange relationships to reduce the SCN characteristics of the regional economy.

5.3. Limitation and future research

There are a few limitations in this study that provide directions for future research. First, this work provides a single-layer supply chain network model, which ignores the *hierarchical* [47,81] topological structure of the SCN. In fact, the supply chain network is complex, composed of thousands of firms, with multi-agent, multi-layer characteristics [7]. Multi-layer considerations could bring a more in-depth analysis of how this topology influences the robustness of the SCN. Second, along with random and targeted disruptions, local disruptions are an important way to study network robustness [82,83]. Future extensions could incorporate different types of disruption scenarios at the same time, e.g., local and global, random and targeted, or the mixed scenario [23], because in reality there are numerous disruption risks coupled together [84]. Third, we only analyze the robustness of the proposed model, lacking a quantitative method to improve the robustness. In future work, we aim to design an optimization approach to build high robustness of SCNs without changing costs, to address this shortcoming.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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