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Research on recovery strategies of supply chain network under disruption propagation using memetic algorithm

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ABSTRACT

In the context of the economic globalization, there is an increased disruption risk in the supply chain network due to the outsourcing, complexity and uncertainty. At the same time, the disruption may propagate across the entire supply chain network because of the interdependence. With the resource constraints, appropriate recovery strategies which can minimize the impact of disruption propagation and effectively improve the supply chain network resilience have attracted a great deal of attention. In this paper, we first construct the disruption propagation model considering the recovery strategy based on the characteristics of the competitiveness, time delay and underload cascading failure in the supply chain network. This model uses the memetic algorithm to determine the set of recovery nodes among all disruption nodes, which can minimize the impact of disruption propagation. And then, the simulation analysis is conducted on the synthetic network and the real-world supply chain network. We compare the proposed recovery strategy with other strategies (according to the genetic algorithm, according to the descending order of the load of failure node, according to the ascending order of the load of failure node, according to the descending order of the node degree, according to the ascending order of the node degree) and provide decision-making reference against supply chain disruptions.

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1. Introduction

In recent years, public health events, global transportation network congestion and large-scale natural disasters have led to frequent disruptions in the supply chain network. Moreover, with the deepening of division of labour and cooperation, supply chains are becoming more global and intertwined. The disruption events may spread in the supply chain network and even cause ripple effects [1, 2]. In 2020, coronavirus-driven supply chain disruptions affected 94 % of the Fortune 1000 companies [3]. On March 23 2021, the Suez Canal was blocked by vast container ship – the Ever Given, which affected over 400 vessels and held up about USD15 billion to USD17 billion [4]. Many researchers have studied to construct agile [5, 6], sustainable [7], and resilient [3] supply chains to withstand disruption risks.

Many industries have increasingly begun to implement supply chain management, including manufacturing, service and so on [8]. Disruption events may cascade through the supply chain resulting in disruption propagation [9] and have a powerful impact on most economic sectors [10]. Other terms related to supply chain disruption propagation in literature include cascading failure [11], ripple effect [2], risk diffusion [12] and so on. Constructing disruption propagation model can dynamically analyse the propagation process in the supply chain network and find the critical firms more accurately in the disruption events. Some studies use the method of complex network [13] to analyse the disruption propagation of supply chain network based on the cascading failure model [9, 14], which commonly used in power, transportation and infrastructure disruption. However, the disruption propagation process in the supply chain network is different from that in infrastructure network because of the characteristics of competition [13, 15], time delay [16], underload failure [17] and adaptivity [13]. Wang and Zhang [17] innovatively used underload failure instead of overload failure to analyse the propagation process of supply network disruption, and constructed synthetic network to conduct a numerical simulation. Zhao *et al.* [13] created a real-world network and competition supply chain network provided by Mergent, and simulated how disruptions propagate in the supply chain network through cascading failures.

What's more, scope of the disruption and its performance impact rely on the speed and scale of recovery strategies [18]. Some studies search for the recovery firms according to characteristics of complex networks, such as the betweenness centrality [9] and degree centrality of nodes [16]. Wang and Xiao [19] developed a resilience method to cascading failures in cluster supply chain network using social resilience of ant colony. They compared the generated random number with the recovery probability to determine whether the node restores timely. Fu *et al.* [9] divided the recovery process into 3 kinds of situations and compared the effect of dynamic recovery strategies which were in descending and ascending orders of node degrees and betweenness centrality. Jing and Tang [16] designed the recovery probability is related to the nodes' degree. However, the above recovery strategies are qualitative methods, and there are few studies using optimization methods to quantitatively recover the critical firms in the supply chain network.

In this paper, we construct a disruption propagation model based on the characteristics of the competitiveness, time delay and underload cascading failure in the supply chain network. Then, considering the restrictions from recovery resources, we use memetic algorithm to quantitatively search for the critical enterprises to determine the recovery strategies, so as to more effectively reduce the impact of supply chain disruptions. The remaining sections of this paper is organized as follows. In Section 2, we construct a supply chain network disruption propagation model considering the recovery strategies. The numerical simulation is conducted on the synthetic network and the real-world supply chain in Section 3. The paper delivers a brief conclusion in Section 4.

2. Simulation model

This section constructs a supply chain network disruption propagation model considering the recovery strategies and the whole process is shown in Fig. 1. This study analyses the above process from three parts: main metrics of supply chain network, recovery strategies, and disruption propagation process. The specific process can be described as follows.

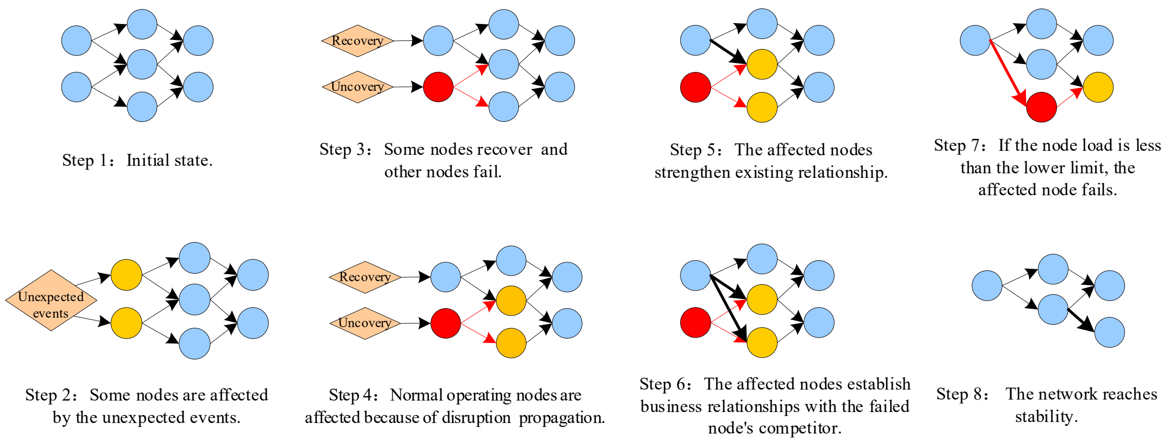

Fig. 1 Process of disruption propagation considering the recovery strategies (red nodes denote failed nodes, yellow nodes denote affected nodes, and blue nodes denote normal operating nodes)

2.1 Main metrics of supply chain network

This section mainly determines the initial node load, capacity and resilience measurement of the supply chain network. The node load represents the operation scale of supply chain members. At present, the initial load of a node is generally estimated by the node degree [20], the total number of shortest paths [21, 22], eigenvector centrality [15] and node degree multiplied by the neighbour node degree[17]. Actually, the business scale of a firm is not only related to the number of neighbour firms, but also to the importance of neighbour firms. Eigenvector centrality of the node load is not only related to the number of neighbour nodes, but also to the importance of neighbour nodes. Therefore, we use eigenvector centrality to measure the initial load of the node i, that is $L_i^0 = c\sum_{j=1}^{n} a_{ij}L_j^0$, where c is the proportional constant, and a_{ij} is the value of row i and column j in the adjacency matrix A. If node i is connected to node j in the graph, 1; otherwise, 0.
There are upper and lower limits to a firm's capacity, which are determined by firm's competitiveness. According to the reference [17], the upper limit of node i load capacity $C_{i(max)}$ is defined as $C_{i(max)} = \alpha L_i^0$ and α is the upper limit parameter. The lower limit of node i load capacity $C_{i(min)}$ is defined as $C_{i(min)} = \beta L_i^0$, and β is a lower limit parameter.

Supply chain network resilience (RN) is a network attribute, which refers to its ability to resist disruption [23]. There are currently a variety of measurement metrics for the resilience, including the size of the network(total number of nodes [24], size of the largest functional sub-network [25], density [24, 26]), network availability(supply availability rate [27] , the proportion of suppliers [24]), network diameter (average shortest-path length [28], average supply-path length [27]) and centrality [24, 29](betweenness centrality, freeman centralization and eigenvector centrality).

In real-world supply chain networks, the normal operation of downstream members may depend on the operation of suppliers. Therefore, this section chooses the size of the largest functional sub-network (LFSN) as a metric, which differs from the largest connected component (LCC) in that there must be at least one supply node in LFSN according to the reference [27]. That is, $RN = N^t$, where N^t is the total number of nodes in LFSN at time t.

2.2 Recovery strategies

The external environment and core enterprises often take strategies to help the affected enterprises against unexpected events. However, the resources of the external environment are limited, which can only help some enterprises to recover initial normal operation and some enterprises are unrecovered. The unrecovered enterprises will still affect the upstream and downstream enterprises in the supply chain until the network reaches a stable state. Recovery resource C_R refers to the sum of available recovery resources. Therefore, constraint $\sum_{i=1}^{N} L_i^0 \le C_R$ need to be satisfied, where N is the number of restored nodes. As shown in Fig. 2, different recovery strategies lead to the different network resilience when it reaches stability.

In order to maximize the resilience of the supply chain network, this section analyses the disruption propagation and takes RN after the network reaches stability as the objective. We obtain the optimal recovery strategy through the memetic algorithm under the capacity constraint of nodes and the recovery resource constraint. Compared with other algorithms, memetic algorithm [30, 31] can not only retain the advantages of genetic algorithm, but also improve the efficiency of local search. The specific process is as follows.

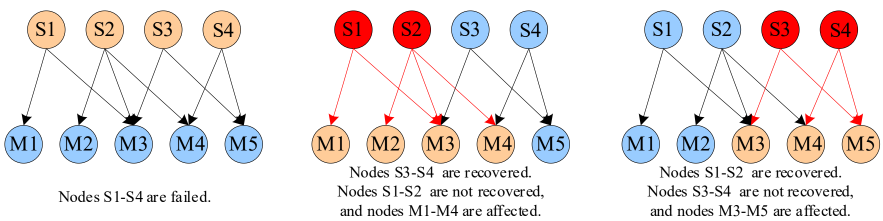

Fig. 2 Supply chain network resilience under different recovery strategies

Encoding and calculating fitness function

In this section, binary encoding is selected to decide whether the failed node is restored. The gene i is set to 1 if node i is restored; otherwise, 0. The number of nodes in the supply chain network corresponds one-to-one to the number of genes in the chromosome. That is, if the supply chain network has 100 nodes, the chromosome contains 100 genes.

A chromosome with a larger objective function value is better. In this section, the objective value is used as fitness, which means that better chromosomes are more likely to be selected into the next generation. The fitness value of each chromosome corresponds to the resilience of the supply chain network. After decoding the chromosome, the fitness value of the chromosome is calculated. A higher fitness indicates that the corresponding supply chain network resilience of the chromosome is greater. And lower fitness indicates that the corresponding supply chain network resilience of the chromosome is smaller.

Crossover and mutation

In the crossover process, we determine the crossover probability P_c and use a single-point crossover with a random cut-point. If all constraints are met, the new chromosome is retained, and the new chromosome is discarded if all constraints are not met. The crossover method is shown in Fig. 3. In order to improve the search process, we determine the mutation probability P_m and use a random selection of chromosomes with the single mutation in the mutation process. After obtaining the new generated chromosomes, the offspring and the parents select the best chromosomes as the new parents.

				k										k			
A0	0	1	0	1	1	0	1	$\Rightarrow$	**A1**	0	1	0	0	1	1	0
B0	1	0	0	0	1	1	0		**B1**	1	0	0	1	1	0	1

Fig. 3 The crossover process of the memetic algorithm

Local search process

The local search process is an important operation of memetic algorithms. This paper designs an algorithm to generate the local optimal value. Firstly, the sets of the chromosomes are randomly selected. Secondly, other gene fragments on the chromosome are selected and exchanged with the former. The new chromosome is retained if the fitness is improved. Otherwise, it is discarded. The optimal value is selected after a certain number of iterations.

2.3 Disruption propagation process

In the supply chain network, if the function that node i supplying products to node j can be replaced by node k, it indicates that there is a competitive relationship between nodes i and k [13, 15]. Considering that the alternative node k can still supply products to the downstream node j after the disruption of node j, the competitive relationship can weaken the cascading failure caused by the supply chain disruption.

Node i will not fail immediately after attacked by unexpected events, and the recovery resource may help some nodes to the operating state. That is, time delay may occur with node failure in the supply chain network [16]. Underload failure [17] is different from overload failure in infrastructure cascading failure. Overload failure refers to node failure when the node load exceeds a certain value, which is applicable to transportation network, infrastructure network, power grid and so on. However, the increase of node load in the supply chain network will not lead to node failure, but the node load below a certain value may lead to node failure.

Considering the characteristics of competitive, time delay and underload failure in the supply chain network, we construct a supply chain network disruption propagation model based on the cascading failure model. The specific process is as follows:

(1) *Recovery some nodes.* This paper takes strategies (see Section 2.2) to recovery some nodes against the disruptions. The other affected nodes will be failed and trigger the disruption propagation.

(2) *Cascading failure.* After a node fails, the effect of neighbour nodes is related to the closeness of it. If node i fails at time t, its upstream and downstream neighbor nodes will be affected and the load of neighbor node j reduces to $L_j^{t+1} = L_j^t - \Delta L_{ij}^{t+1}$, where $\Delta L_{ij}^{t+1} = \min(\delta_{ij} L_i^t, L_j^t)$. δ_{ij} is the strength of relationship between the nodes i and j, where $\delta_{ij} = \frac{W_{ij}}{\sum_{j \in \Gamma_{i(out)}} W_{ij}}$, $\Gamma_{i(out)}$ refers to the set of downstream neighbour nodes of node i, $W_{ij} = (L_i^0 L_j^0)^\tau$ and τ is a constant. The effect on the upstream nodes is the same as that on the downstream nodes.

(3) *Adjusting business relationships.* After the cascading effect occurs, there are two strategies for the upstream and downstream neighbour nodes to adjust business relationships. One is to strengthen the existing business relationships [15, 17, 19], and the other is to establish new business relationships with the competing nodes of the failed nodes with a certain probability [13, 17]. For example, if a node i fails which supplying node j, the node j hopes to establish new connections with node k which competing with node i. Considering its own load, node k will establish a new relationship with node j with a certain probability P_t. Then the load of node j changes to $L_j^{t+2} = L_j^{t+1} + \sum_{k \in \Gamma_{j(in)}} \Delta L_{kj}^{t+2} + \sum_{k \in \Gamma_i} M_j \Delta L_{kj}^{t+2}$, where ΔL_{kj}^{t+2} denotes the increase of load after node j strengthens the existing business relationships with node k or establishes a new relationship with node k, $\Gamma_{j(in)}$ refers to the set of upstream neighbour nodes of node j, Γ_i refers to the set of the competing nodes of node i, and $M_j \in \{0,1\}$. A random number R in range (0, 1) is generated to compare with P_t. If $R > P_t$, $M_j = 1$ that is establishing a new relationship. Otherwise, $M_j = 0$. When the downstream node i of node j fail, the load of node j changes to $L_j^{t+2} = L_j^{t+1} + \sum_{k \in \Gamma_{j(out)}} \Delta L_{jk}^{t+2} + \sum_{k \in \Gamma_i} M_j \Delta L_{jk}^{t+2}$, $\Gamma_{j(out)}$ refers to the set of downstream neighbor nodes of node j, and the other process is the same as the upstream node failure of node j.

If the load of node j at time $t + 2$ is less than the lower limit of node load capacity, that is, $L_j^{t+2} < C_{j(min)}$, node j also fails and affects its neighbor nodes. We loop Stages 2–3 until no node failures occur.

3. Example application

3.1 Supply chain network and competition networks

This paper constructs two directed supply chain networks for simulation analysis including a real-world supply chain network with 37 nodes according to literature [32] and a scale-free network with 1000 nodes. The first network includes 11 suppliers, 3 factories, 5 warehouses and 18 markets and the second network includes 375 suppliers, 18 manufacturers, 16 wholesalers and 591 retailers as shown in Fig. 4. The competition network is constructed for the above two networks, in which the competition network is undirected.

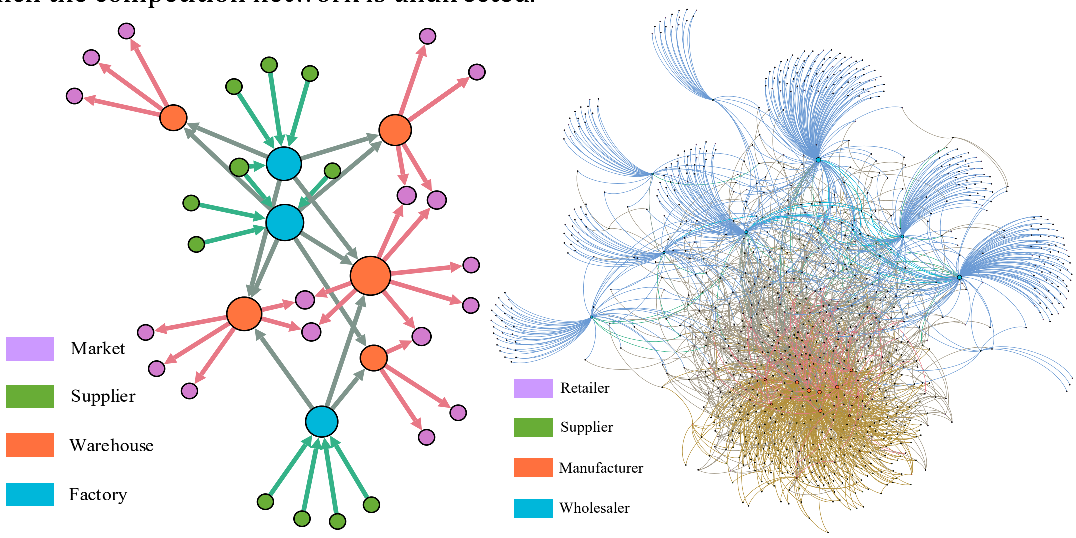

Fig. 4 Visualization of the network

$G_r(V,E)$ denotes the real-world supply chain network and $G_s(V,E)$ denotes the synthetic supply chain network. Competition network of the real-world supply chain network is denoted by $G_{r'}(V,E)$ and competition network of the synthetic supply chain network is denoted by $G_{s'}(V,E)$. $v_i \in V$ denotes the node i in the network and $e_{ij} \in (G_r \cup G_s)$ represents the directed edge from v_i to v_j, indicating that v_i is a supplier of v_j. $e'_{ij} \in (G_{r'} \cup G_{s'})$ represents the undirected edge between v_i and v_j, indicating that v_i and v_j are competitive.

3.2 Performances of memetic algorithm

In this section, the initial population size is set to 30. We simulate the supply chain network resilience under different recovery resources and disruption scenarios. According to Fig. 5(a-c), when the recovery resource is set to 50, the supply chain network resilience becomes smaller as the number of nodes removal increases. According to Fig. 5(d-f), when the number of nodes removal is set to 50, the supply chain network resilience becomes larger as the recovery resource increases. The above six simulations all show that with the increase of iterations, the results tend to be stable which verifies the effectiveness of the memetic algorithm.

As shown in Fig. 5, in most cases, the convergence results obtained by memetic algorithm are similar to those obtained by genetic algorithm, but the convergence speed and initial value of memetic algorithm are better than those of memetic algorithm. This indicates that the memetic algorithm converges faster and can achieve the optimal result through fewer iterations.

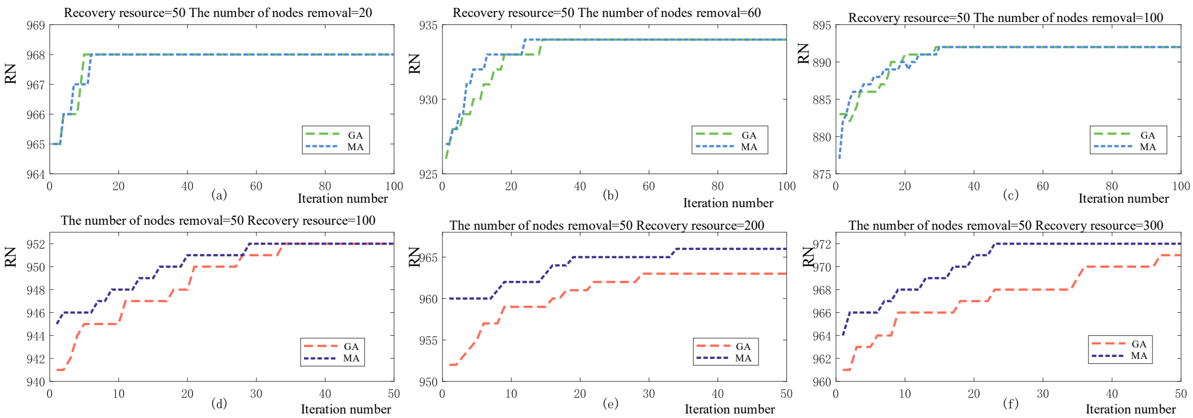

Fig. 5 The relationship between RN and iteration number

3.3 The relationship between network resilience and recovery resources

Fig. 6(a-c) shows the change of the synthetic supply chain network resilience with the increase of the recovery resources against different nodes removal. Fig. 6(d-f) shows the change of the real-world supply chain network resilience with the increase of the recovery resources against different nodes removal. It can be seen that although the change rules of the supply chain network resilience with different structures are not exactly the same, they all conform to the trend that the network resilience increases slowly with the increase of recovery resources. When $C_R = 0$, $RN = 926$, when $C_R = 50$, $RN = 943$, and $\Delta RN = 17$.When $C_R = 100$, $RN = 952$ and $\Delta RN = 9$. These results suggest that the relationship between network resilience and recovery resources also presents the characteristics of diminishing marginal utility. When the recovery resources are gradually increased, the increase of network resilience becomes slower. If the supply chain network is fully restored, it needs large amount of recovery resources.

As shown in Fig. 6(a-c), $RN = 926$ when the number of nodes removal is 50 and $C_R = 0$. $RN = 685$ when the number of nodes removal is 100 and $C_R = 0$. $RN = 13$ when the number of nodes removal is 150 and $C_R = 0$. The results indicate that if we don't take any recovery resources, the supply chain network resilience drops dramatically with the increase of the number of nodes removal. Therefore, the importance of recovery strategies under large-scale unexpected events is much higher than that under small-scale unexpected events. When a large-scale unexpected event occurs, effective recovery strategies can reduce the possibility of supply chain network crash.

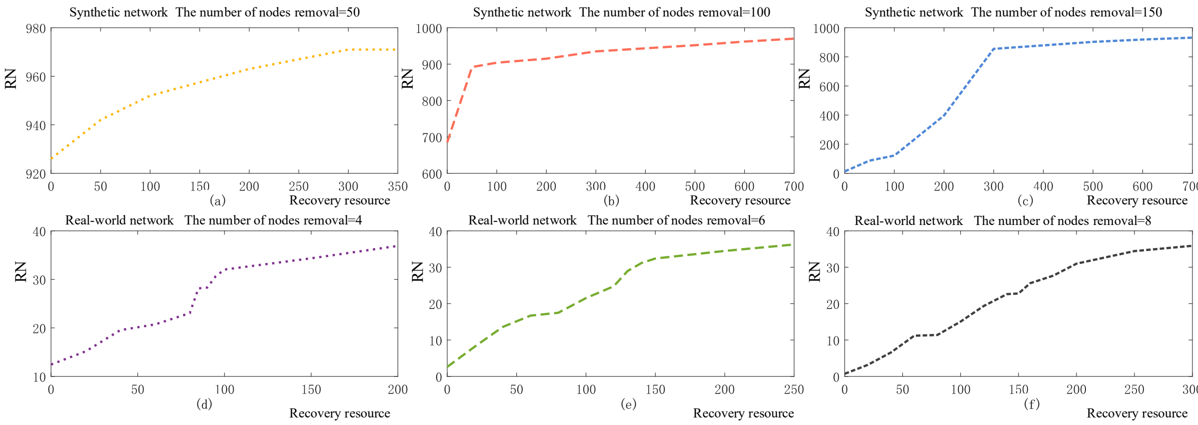

Fig. 6 The relationship between network resilience and recovery resources

4. Comparison of different recovery strategies

We compare the different recovery strategies, including strategies by memetic algorithm (strategy 1), according to the ascending order of the load of failure node (strategy 2), according to the descending order of the load of failure node (strategy 3), according to the ascending order of the node degree (strategy 4), according to the descending order of the node degree (strategy 5). As shown in Fig. 7, the recovery strategy obtained by using the memetic algorithm is always superior to other strategies, and the advantage tends to be obvious with the increase of the number of nodes removal.

According to the simulation results, the recovery strategy obtained through the memetic algorithm is closer to that according to the ascending order when the number of nodes removal is small. For example, when the number of nodes removal is 20, $RN = 968$ obtained by strategy 1; $RN = 968$ obtained by strategy 2; $RN = 956$ obtained by strategy 3; $RN = 964$ obtained by strategy 4; $RN = 956$ obtained by strategy 5. The results indicate that priority will be given to recover small-scale enterprises when the number of attacked enterprises is small.

However, the recovery strategies according to the ascending order no longer have an advantage when the number of nodes removal becomes larger. For example, as shown in Fig. 7(b), when the number of nodes removal is 120, $RN = 895$ obtained by strategy 1; $RN = 384$ obtained by strategy 2; $RN = 531$ obtained by strategy 3; $RN = 92$ obtained by strategy 4; $RN = 188$ obtained by strategy 5. The results indicate that the recovery strategy obtained by memetic algorithm has greater advantage, and the recovery strategies based on the node degree have the worst resilience.

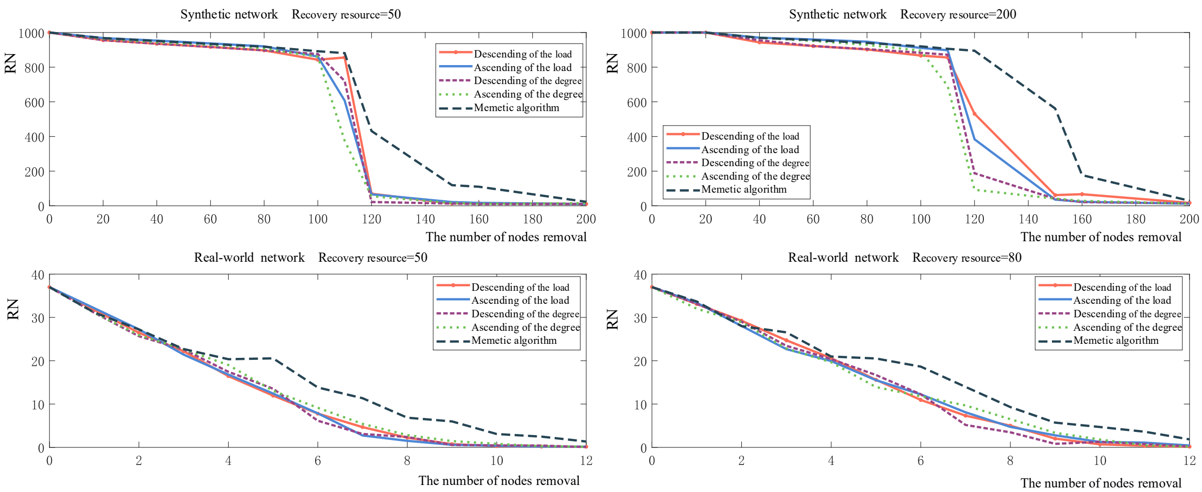

Fig. 7 Comparison of different recovery strategies

As shown in Fig. 7, when the number of nodes removal is 120 and the recovery resource is 200, The order of RN under different recovery strategies is that the memetic algorithm is better than the algorithm according to the order of the load of failure node, and the algorithm according to the order of the load of failure node is better than that of the degree of failure node. The restored nodes of different recovery strategies as shown in Table 1. The recovery strategy obtained by memetic algorithm can recover all kinds of enterprises in the supply chain network. The above results suggest that when a large number of nodes are removed, the strategies of recovery small-scale enterprises first and large-scale enterprises first are not optimal. The optimal strategy is to comprehensively analyse the characteristics of the business scale and supply-demand relationships of the disrupted enterprises, and to recover all kinds of enterprises in the supply chain network in a balanced way.

Table 1 Comparison of different recovery strategies

C_R	The number of nodes removal	Recovery strategies	The characteristic of restored nodes					
			Number	S:M:W:R	S (%)	M (%)	W (%)	R (%)
200	120	Memetic algorithm	44	16:0:1:27	31.4	0	50	42.9
		Genetic algorithm	46	15:2:2:27	29.4	50	100	42.9
		The ascending order of the load	62	14:2:1:45	27	50	50	71.4
		The descending order of the load	6	5:0:0:1	9.8	0	0	1.5
		Ascending order of the node degree	40	8:0:0:32	15.7	0	0	50.8
		Descending order of the node degree	9	5:2:2:0	9.8	50	100	0

Note: S:M:W:R refers to the ratio of the number of restored nodes of suppliers, manufacturers, wholesalers and retailers; S refers to the proportion of restored supplier nodes to disrupted supplier nodes; M refers to the proportion of restored manufacturer nodes to disrupted manufacturer node; W refers to the proportion of restored wholesaler nodes to disrupted wholesaler node; R refers to the proportion of restored retailer nodes to disrupted retailer node.

5. Conclusion

We innovatively construct the disruption propagation model considering the recovery strategy based on the characteristics of the competitiveness, time delay and underload cascading failure in the supply chain network. This model uses the memetic algorithm to determine the set of recovery nodes among all disruption nodes, which can minimize the impact of disruption propagation. The conclusions are as follows:

- The relationship between network resilience and recovery resources presents the characteristics of diminishing marginal utility. When the recovery resources are gradually increased, the increase of network resilience becomes slower. If the supply chain network is fully restored, it needs large amount of recovery resources.
- The recovery strategy obtained by memetic algorithm has greater advantage compared with other recovery strategies. What's more, the advantage tends to be obvious with the increase of the number of attacked enterprises.
- The priority will be given to recover small-scale enterprises when the number of attacked enterprises is small with a certain amount of recovery resources. However, this strategy no longer has an advantage when the number of attacked enterprises becomes larger. The strategy of recovery suppliers first is better than that of recovery retailers, but the optimal strategy is to comprehensively analyse the characteristics of the business scale and supply-demand relationships of the disrupted enterprises, and to recover all kinds of enterprises in the supply chain network in a balanced way.

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