Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
 Volume 26, Issues 1, pp. 136–150, DOI 10.12694/scpe.v26i1.3537

RECOVERY MODELING AND ROBUSTNESS STUDY AFTER CASCADING FAILURES IN LOGISTICS-BASED NETWORKS

XIAODONG QIAN* AND SICHEN WANG†

Abstract. In order to ensure the normal operation of the logistics network and improve the robustness of the network in case of cascading failure faults, this study introduces the concept of node recovery threshold based on the existing failure model to optimize the recovery time lag. Further, a criticality-first recovery model is proposed, which defines the capacity of a recovery node as a function related to its original capacity and opens the recovery node selectively to critical neighboring nodes to reduce the risk of secondary failure. Finally, a postal logistics network in Northwest China is used as a case study to investigate the recovery robustness of this network when it encounters cascading failures. The effects of various parameter variations on the network robustness are examined through experimental simulations. The experimental results show that timely recovery measures can significantly reduce the number of failed nodes when cascade failure occurs in the logistics network; setting a higher recovery threshold can reduce the impact of cascade failure on the network, effectively reduce the scale of network failure, and thus significantly improve the robustness of the logistics network; at the same time, increasing the capacity parameter can effectively delay the time of cascade failure in the network, and can slightly improve the robustness of the network.

Key words: complex networks, logistics networks, robustness, cascading failures, recovery modeling

1. Introductory.

With the tremendous growth of science and technology, and economic development, the logistics industry in its context also began to flourish, and logistics facilities continued to improve, the growing development of transportation, greatly improved the operating conditions of logistics, making the traditional logistics industry the transformation of the network, and a highly efficient and reliable logistics network is a prerequisite for the healthy development of the logistics industry and the foundation. However, in recent years, all kinds of emergencies have occurred frequently, such as the general strike of German freight train drivers in 2015, the outbreak of the new crown epidemic in 2020, the congestion of the Suez Canal caused by the stranding of the cargo ship "Chang Ci" in 2021, and the extremely heavy rain in Henan in 2022, which had a serious impact on the normal operation of the logistics network and disrupted the normal production of social life. These events have seriously affected The logistics network operates normally, disturbed the normal order of production and life of the society, and threatened the peace and stability of the countries in the world. In real life, The efficient and dependable movement of goods is dependent on the proper operation of the logistics network, and all types of emergencies are unavoidable; thus, effective and reliable preventive measures are critical to the overall safety of the logistics network.

Numerous scholars have found that there is no one hundred percent reliable real network, and the failure of the network is unavoidable, and the same is true for the logistics network, through the study of the structural characteristics, dynamic characteristics reliability, and other characteristics of many real networks. At present, some scholars optimize the network by changing the topology of the network to improve the robustness of the network, and this scheme can effectively improve the robustness of the network, but in practice, it may not be easy to change the original topology of the network due to the limitations of various aspects, and we can't improve the robustness of the network promptly by adjusting and improving the topology of the network. Therefore, the recovery characteristics of the network have aroused the research interest of the majority of scholars. In real logistics networks, the network generally has a certain ability to resist risk and recovery, and when the logistics network fails, the failed nodes will be restored to normal nodes through some recovery strategies. It can assist us in increasing the robustness of the logistics network through recovery mechanisms

*School of Economics and Management, Lanzhou Jiaotong University, Lanzhou 730070, China; School of Automation and Electrical Engineering, Lanzhou Jiaotong University, Lanzhou 730070, China (qianxd@mail.lzjtu.cn).
†School of Automation and Electrical Engineering, Lanzhou Jiaotong University, Lanzhou 730070, China.

without affecting the network topology. avoiding policy, technical and economic constraints, and reducing costs. Therefore, it has become an important research topic to formulate recovery strategies to improve the robustness of logistics networks when unexpected events occur.

2. Research Basis. In recent years, research based on complex network theory [1, 2, 3, 4, 5, 6] has attracted widespread attention in many fields, and currently, research on complex networks focuses on complex network modeling, network robustness, network recovery, and network optimization.

In terms of constructing a logistics network, Qin et al [7] built a network using epidemiological modeling and network coupling, and argued that the peak infection rate is an indicator of the infectious disease in a certain location, regardless of network topology. Yang et al [8] constructed an evolutionary model of supply chain network enterprise cooperation based on a bipartite power law distribution in a complex network environment and proved that the degree of adaptation is the dominant factor in the generation of bipartite power law distribution. Chen et al [9] investigated the resilience of the logistics network to node failure under the background of the logistics industry disruption, simulated and proposed algorithms for two cascading failure scenarios, proving the improvement of resilience by different adjustment strategies. Wang et al [10] constructed a multi-stage three-level logistics network model for the dynamic logistics network optimization problem and proposed a dynamic adaptive multi-objective differential evolutionary algorithm to solve the model, proving that the algorithm can compute the optimal feasible supply solutions for each stage of the logistics network. Zhang et al [11] proposed a multi-modal express logistics network optimization decision-making model from the perspective of low carbon economy and proposed a corresponding optimization solution algorithm by analyzing the topology of the logistics network and comparing and analyzing the advantages and disadvantages of different transportation modes.

In terms of network robustness, Qian et al [12] proposed a diffusion model for risk factors in logistics networks based on the contagion model in complex networks, using node topological weights and supply and demand fluctuations to improve the mechanism of diffusion. Wang et al [13] introduced dynamic factors on the basis of the original initial residual capacity load redistribution strategy, and by adjusting the network cost e and capacity parameter gamma, the logistics cost is effectively reduced and the controllable robustness against cascading failures is enhanced. Zhen et al [14] built a cascade failure model based on Dynamic Control of Node Redundancy Capacity (DRC) by introducing a network phase change critical factor μ based on the literature [13].The probability of cascade failure triggered by a node failure is measured by defining a phase change critical factor μ in the network,and the correlation μ between the network robustness and μ is analyzed. German R M et al [15] proposed a new method to measure the robustness of inverse logistics networks, using an integer mixed linear programming model to design the network and analyze its robustness, and proved the effectiveness of the method. Yang et al [16] combine the bus network and subway network as a multi-subnet composite complex network of urban public transportation to establish the passenger flow transfer rules under node and edge failure. Yu et al [17] proposed a cascading failure model of dependent networks considering dependent edge loads based on literature [16], and studied the robustness of dependent networks by analyzing different load redistribution strategies, different network coupling methods and network attacks.

In terms of network recovery, Zhang & Du [18] developed a geographical The data network model that combines complex networks and hypergraphs. When the network is subjected to an unavoidable attack, a central node recovery technique based on global and community data is presented to restore network performance with the fewest amount of components.Yang et al [19] proposed two supply chain recovery strategies, the suppliers' pre-set emergency inventory strategy and the manufacturer's product change strategy, and demonstrated that the proposed disruption recovery strategy can not only effectively assist suppliers in stopping losses, but also meet market demand. Wu et al [20] proposed a new sequential recovery model, introduced a sequential recovery graph to determine the key nodes and their recovery order, and verified that the network can obtain better performance during the recovery process. Ju et al [21] made improvements on the basis of literature [20] and proposed a system optimal recovery strategy based on the network elastic structure evaluation method. Tang et al [22] proposed a probabilistic recovery model and a stage recovery model and investigated the recovery robustness for four types of networks, ER, WS, NC and BA, and verified that both probabilistic recovery strategy and stage recovery strategy can have an impact on the robustness of the four types of networks. Huang et al [23] constructed an urban subway network recovery model using the average network efficiency as the toughness index and the maximum network resilience as the objective function and proved that the optimal recovery strategy of the urban subway network solved by the genetic algorithm has a higher solving efficiency under the failures of different sizes of stations. Fan et al [24] aimed to develop a realistic cascading failure model for an automotive manufacturing supply chain network to explore its cascading failure characteristics. Based on this model, a two-stage recovery strategy was proposed to enhance the network's cascading failure recovery capability. Yoshihisa et al [25] designed a recovered, efficient reverse logistics network using a cost minimization model with recovery constraints using a Japanese reverse logistics network as an example.

Existing studies have investigated the recovery behavior after the end of network cascade failure and proposed many classical models such as random recovery model, probabilistic recovery model, and local recovery model. The recovery order of the random recovery model is completely random and does not consider the strategic position of nodes or the structural characteristics of the network, which may lead to untimely recovery of key nodes and prolong the overall recovery time of the network, and is suitable for networks with high node homogeneity. The probabilistic recovery model recovers nodes based on preset probability distributions, which can be set based on the importance of nodes, failure probabilities, or other criteria, and is suitable for network environments that require balancing multiple decision factors. Local recovery models perform systematic recovery only in local areas of the network, which may be partitioned based on geographic location or network partitioning, and help to quickly resolve local failures, but may neglect network-wide coherence and efficiency, and are suitable for distributed networks or large geographically dispersed networks, which can quickly deal with local problems without affecting the overall network.

In summary, the existing models do not satisfy the characteristics of logistics network dynamics and complexity. Therefore, in this paper, we construct a node-importance-priority recovery model in which the failure process and the recovery process occur within adjacent time steps, optimize the recovery time lag, redefine the load and capacity of the recovered nodes, and adopt appropriate strategies to reduce the risk of secondary node failures. Compared with the classical model, using the node importance priority recovery model, the recovery order can be arranged according to the importance of the nodes in the network, prioritizing the recovery of those nodes that have the greatest impact on the network function, which can not only recover the core nodes of the network faster, but also significantly improve the overall stability and robustness of the network, which is very in line with the characteristics of the logistics network dynamics and complexity. Finally, an empirical study of the logistics network in Northwest China is carried out in the hope that the study can help repair the damaged network with a more flexible strategy, thus improving the robustness of the logistics network.

3. Research Methodology.

3.1. Analysis of Network Recovery Models under Cascade Failure. In 2002, Motter and Lai et al [26] first introduced the cascading failure mechanism into complex networks and proposed the classical ML capacity-load linear model, which defines the initial load L_i^0 of a node i as a function related to its degree value K_i, namely

$$\begin{cases} L_i^0 = K_i^\theta \\ C_i = (1+\alpha)L_i^0 \end{cases} \tag{3.1}$$

In 2008, literature [27] found that the load and capacity of a real network should have a nonlinear relationship. Therefore, in this paper, we refer to the literature [28],which defines the relationship between the load L_i^0 and capacity C_i of a node as shown in Equation (3.2), and the load is redistributed as shown in Equation (3.3).

$$\begin{cases} L_i^0 = I_i \\ C_i = (1+\beta)\cdot(L_i^0)^\alpha \end{cases} \tag{3.2}$$

where I_i is the importance degree of the node, which is defined as the initial load of the node, the importance degree of the node is obtained by calculating the weight of each index by hierarchical analysis method using the four characteristics of the node, namely, degree value, median, proximity centrality, and eigenvector centrality as the indexes. α and β are the capacity parameters.

$$\begin{cases} \Delta L_{i\to j} = L_i^1 \times \frac{L_j^0}{\Sigma_{m\in\Gamma_i} L_m^0} \\ L_j^1 = \Delta L_{i\to j} + L_j^0 \end{cases} \tag{3.3}$$

Existing studies [29, 30, 31] have shown that the occurrence of cascading failure phenomenon is often accompanied by network recovery, which can improve the robustness of the network without adding redundant nodes and paths to the network. In recent years, scholars have proposed a series of recovery models, which can be applied to different situations and different networks to minimize the loss caused by network failure and improve the robustness of the network as much as possible without changing the network topology.

Currently, the target recovery model based on cascade failure has the following problems: a) The problem of recovery time lag. In reality, complete network failure is only a worst possibility, after the cascade failure phenomenon, the network will keep normal operation of the network through some recovery means, some existing studies start the recovery of nodes only after the complete failure of the network, and do not consider the impact of the introduction of the recovery model on the network's resiliency when cascade failure issues arise. b) Problems of irrational selection of the recovery nodes. Some models recover the network by the failure order or degree value order of the nodes, such models are too one-sided, which may lead to repairing some non-critical nodes and affect the overall recovery of the network, and do not consider the load capacity situation of the recovered nodes as well as the possibility of the recovered nodes having the risk of secondary failures.

3.2. Improvement of Recovery Modeling under Cascade Failure.

3.2.1. Improvement of Node Recovery Time Lag. The original failure model, shown in (3.4), directly defines a node as a failed node when its load exceeds its capacity, and recovery of the failed node begins only after the entire cascade of failed failures is over. The network has been severely affected at this point.

$$\begin{cases} L_j^1 = \Delta L_{i\to j} + L_j^0 < C_j \\ L_j^1 = \Delta L_{i\to j} + L_j^0 > C_j \end{cases} \tag{3.4}$$

Based on the above analysis, when the network cascade failure fault occurs, the faulty nodes need to be recovered in a shorter time, and the recovery of the network nodes should not be started only after the network cascade failure fault is over so that the robustness of the network can be reasonably enhanced. Therefore, based on the original failure model, the concept of node recovery threshold is introduced, When the load on a network's node reaches its capability. but does not exceed the recovery threshold, the node at this point is defined as overloaded rather than directly determined as a node failure, and the network node starts to recover in the process, in which the time required for the faulty node to start recovering needs to be taken into account, and the parameter T is used to characterize the time step required for the node to begin to recovery by using parameter T to characterize the time step required for the node to start recovery, i.e., it takes T time steps for the node to start recovery after the node fails. When a network node fails to recover in time due to various reasons, the node load exceeds the threshold value, and only then the node is determined to be completely failed and removed from the network. The improved failure model shown in (3.5), $(1+\lambda)C_j$ is the recovery threshold of the node and λ is an adjustable parameter.

$$\begin{cases} \Delta L_{i\to j} + L_j^0 \le C_j & \text{①} \\ C_j < \Delta L_{i\to j} + L_j^0 \le (1+\lambda)C_j & \text{②} \\ (1+\lambda)C_j < \Delta L_{i\to j} + L_j^0 & \text{③} \end{cases} \tag{3.5}$$

In this case, Equation ① indicates that the load distributed by node i to its neighbor node j does not exceed its maximum capacity, and the network is in a normal working state. Equation ② indicates that the load of the node at this moment exceeds its maximum capacity but does not exceed the recovery threshold, the node at this time is defined as an overloaded node, and the load of the overloaded node j will be assigned to its neighboring nodes according to the rules, and the overloaded node recovers in the process. Equation ③ indicates that when the overloaded node fails to recover in time, the load of the node j eventually exceeds the node recovery threshold, and then the node j fails completely.

3.2.2. Network Recovery Model Optimization. In summary, this paper proposes an importance-priority recovery model suitable for real logistics networks, which is in line with the characteristics of unequal importance of nodes in the logistics network, and the recovery of important nodes can help the logistics network to share the pressure of larger goods and ensure the circulation of goods.

The original recovery model is to recover the network through the node's failure sequence or degree value sequence, there are many problems in the selection of the recovery nodes, the most important nodes should be comprehensively selected for recovery, the model uses the node's importance sequence as the basis for recovery, defines the capacity of the recovered node as a function related to the original capacity, and selectively opens up the recovered node to the important nodes around it to reduce the node's secondary failure risk. In this study, when cascading failure occurs, overloaded nodes in the network that exceed the maximum capacity of a node but do not exceed the recovery threshold are defined as recoverable nodes, and these nodes are repaired by the importance-first recovery model. The recovery process of overloaded nodes is defined as follows.

Step 1: Implement a merit recovery strategy according to the importance of the nodes, repair the overloaded nodes in descending order of importance, and the repaired nodes are restored as normal nodes again.

Step 2: Redefine the load of the recovered node, since the node assigns its load to the neighboring nodes when it is overloaded, the load $L_i(R)$ of the recovered node is defined to be zero, That is.

$$L_i(R) = 0 \tag{3.6}$$

Step 3: Redefine the capacity of the restored node, in reality, the restored system components may be more reliable than before the failure [32, 33]. Therefore, define the capacity $C_i(R)$ of the restored node as shown in Equation (3.7). Where, β_1 is the capacity parameter of the restored node, $0 < \beta_1 < 1$, the larger β_1 is, the larger the capacity of the restored node is, and the more difficult it is for the node to fail twice.

$$C_i(R) = (1 + \beta_1) \cdot C_i \tag{3.7}$$

To strengthen the network, the recovered nodes need to re-work as quickly as possible to start sharing the load pressure of the rest of the nodes, and because of the load of the recovered nodes at this moment $L_i(R) = 0$, the original strategy of distributing the load proportionally according to the initial load is not applicable to the load distribution at this time, so this paper also proposes a load redistribution model for the recovered nodes, namely

$$\Delta L_{i \to j} = L_i^1 \times \frac{C_j(R)}{\Sigma_{m \in \Gamma_i} C_m + \Sigma_{n \in \Lambda_i} C_n(R)} \tag{3.8}$$

where when a node i in the network redistributes its own load to a recovered node j, then the product of the node's load and the ratio of the capacity of the neighboring node j to the capacity of all neighboring nodes is assigned as an additional load to the recovered node j. Γ_i denotes the set of normal neighboring nodes of the node i, and Λ_i denotes the set of recovered nodes among the neighboring nodes of the node i.

In real life, when a faulty node is repaired, the most common practice to avoid secondary failures is to block the load inflow from the surrounding faulty nodes until most of the faulty nodes have been restored before the network is active again. However, this does not take into account the network timeliness and network robustness. If all the restored nodes are opened to the surrounding overloaded nodes, the possibility of secondary failure of the restored nodes will be greatly increased. Therefore, this paper defines that the restored nodes selectively open to the surrounding overloaded nodes, and only select some restored nodes with larger importance for load redistribution, because restored nodes with larger importance have larger load carrying capacity, which can reasonably accommodate the load of the nodes, and also effectively reduce the probability of the restored nodes' secondary failures.

3.3. Model Analysis. The design simulation algorithm is as follows:

Step 1: Construct a logistics network for the Northwest region.

Step 2: Initialize network parameters α,β, and λ, and determine node load L_i^0 and capacity C_i.

Step 3: Perform an initial node attack and define the attacked node as an overloaded node.

Step 4: Redistribute the load of the overloaded node to its neighboring nodes in accordance with the initial load redistribution strategy, and determine whether the load of its neighboring nodes exceeds its own capacity; if the load of the node does not exceed its own capacity, go to Step 5; if the load of the node exceeds its own capacity, go to Step 6.

Step 5: The node continues to work normally, go to step 10.

Step 6: The node is also defined as an overloaded node and the node load distribution process continues by repeating step 4 and determining whether the load of the node exceeds the recovery threshold by the optimized failure model in chapter 3.2.1, if the load of the node does not exceed the recovery threshold, then go to step 7, if the load of the node exceeds the recovery threshold, then go to step 8.

Step 7: The node starts to recover according to the recovery model in chapter 3.2.2, go to step 9.

Step 8: Then the node is determined to be completely failed, go to step 10.

Step 9: Determine the load $L_i(R)$ and capacity $C_i(R)$ of the recovered node, reopen the recovered node to the network, and determine whether the recovered node will fail again due to re-working, if the recovered node fails, go to step 4.

Step 10: Update the network.

Step 11: The cascade failure process ends, and the maximum connected subgraph size of the network and the ratio of the number of network nodes failed to the total nodes are calculated.

The flowchart is shown in Fig. 3.1:

4. Simulation Verification and Empirical Analysis. The experiments use the network maximum connectivity subgraph size G and the ratio P of the number of network nodes failed to the total nodes as the evaluation metrics to measure the robustness of the network. The network maximum connectivity subgraph size G can be used to measure the overall connectivity of the network, when the network is attacked it will be divided into a number of sub-networks that are not connected to each other, and the sub-network that contains the largest number of nodes is called the maximum connectivity subgraph. The proportion of network failed nodes P indicates the degree of failure of network nodes, and the proportion of failed nodes to all nodes is used to indicate the spread of risk. To some extent, the network maximum connected subgraph size and network failure node proportion can reflect the change of network robustness, The formula is shown below.

$$\begin{cases} G = \frac{N^{'}}{N} \\ P = \frac{N^{''}}{N} \end{cases} \tag{4.1}$$

where $N^{'}$ denotes the number of nodes in the maximum connectivity subgraph of the network after the occurrence of cascade failure, $N^{''}$ denotes the number of failed nodes in the network after the occurrence of cascade failure, and N denotes the total number of nodes in the network.

When the network is affected by node failure, the connectivity within the network will change. The larger P is, the smaller G is, indicating that there are fewer nodes connected in the logistics network and the network is less robust. The smaller P is, the larger G is, indicating that the network still maintains a larger connectivity, and the network is more robust.

4.1. Simulation Verification.

4.1.1. Robustness of the Network with Different Recovery Times. To study the impact of different start recovery times on the network, the change in network robustness is examined by adjusting the start recovery time parameter T. Without considering the secondary failure of network nodes, the real supply chain network of an enterprise is taken as an example, and the above model is simulated and analyzed by pycharm, with the capacity parameters α and β taken as 1.5 and 0.5, respectively, and the adjustable parameter λ taken as 0.3, The findings from the simulation are presented in Fig. 4.1 and Fig. 4.2.

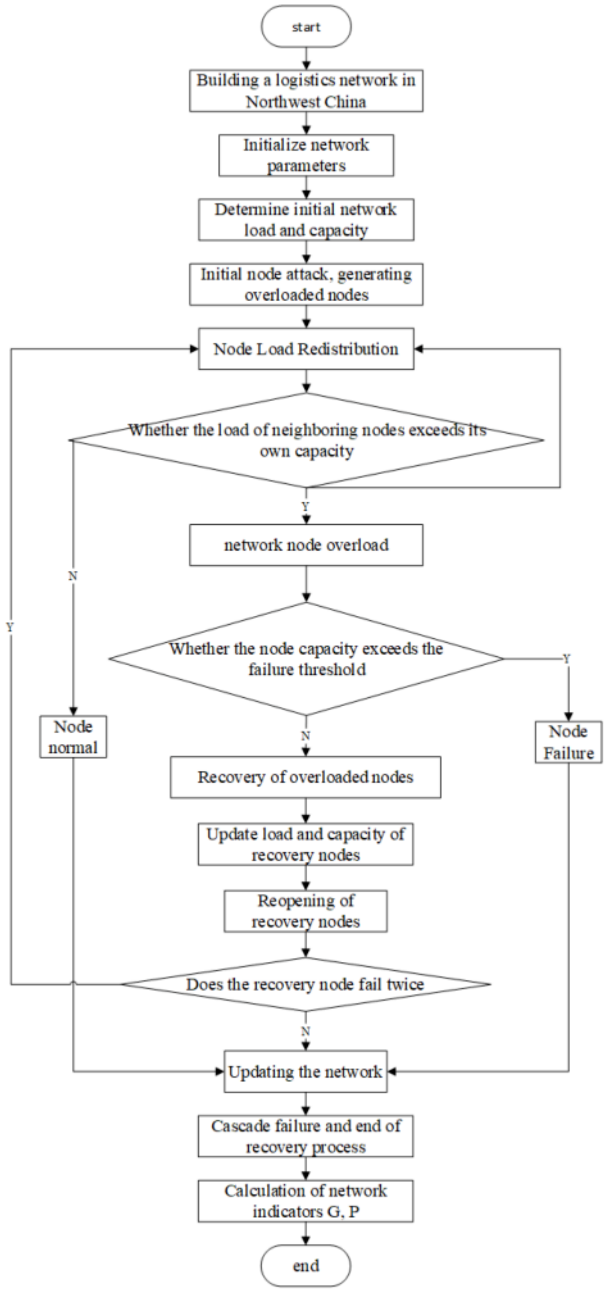

Fig. 3.1: Recovery flowchart under network cascade failure.

From Fig. 4.1 and Fig. 4.2, it can be seen that different parameters T have different impacts on the network, when T= 1, The network has the lowest proportion of failing nodes and the strongest robustness. with the increasing of T, proportion of failed nodes in the network gradually rises, and it can be known from T= 12 that when the start of the recovery time is too long, the overload nodes cannot be recovered in time, and eventually also transform into failed nodes, which causes serious harm to the operation of the network. serious harm to the operation of the network. Therefore, when the network is recovered, a smaller start recovery time should be chosen, the shorter the start recovery time is, the fewer the failed nodes will be when the network is finally

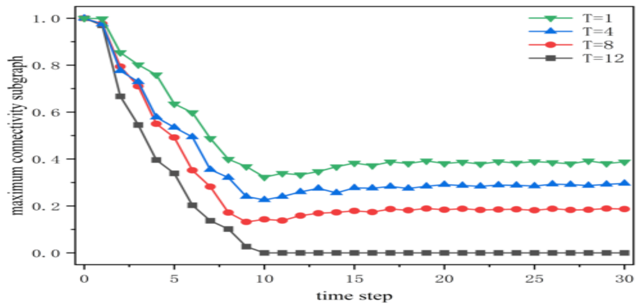

Fig. 4.1: Trend of the maximum connectivity subgraph of the network under different recovery times.

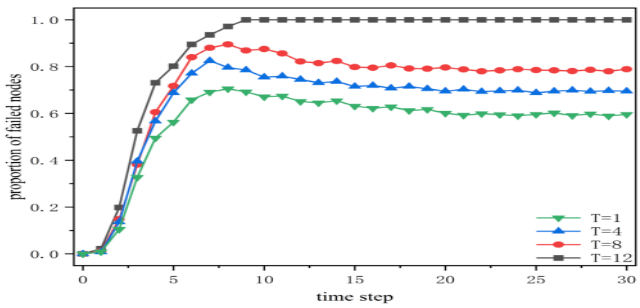

Fig. 4.2: Trend of network failed nodes under different recovery times.

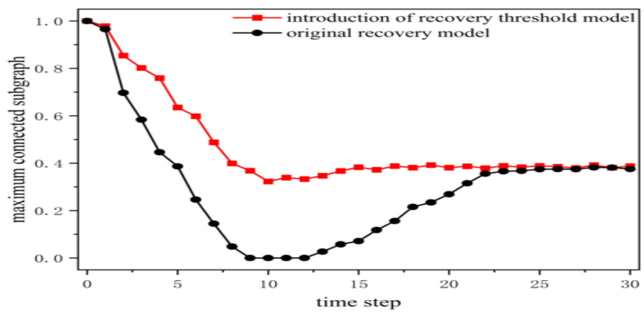

Fig. 4.3: Trend of the maximum connectivity subgraph of the network after the introduction of a recovery threshold

stabilized, and the higher the recovery ability of the network will be, and the stronger the robustness will be.

4.1.2. Introducing Robustness of Recovery Threshold Networks. On the basis of the above model, compare and analyze the change trends before and after the improvement of the recovery model under cascading fault conditions, and verify the impact of introducing node recovery threshold on the robustness of the network, the recovery time parameter is selected as $T=1$, and the rest of the parameters are kept unchanged, and the simulation results of the original recovery model and the model with the introduction of node recovery threshold are shown in Fig. 4.3 and Fig. 4.4.

As can be seen from Fig. 4.3 and Fig. 4.4, in the original recovery model, the recovery of the failed nodes starts only after all the network nodes have failed, at which time the network has already lost the ability to

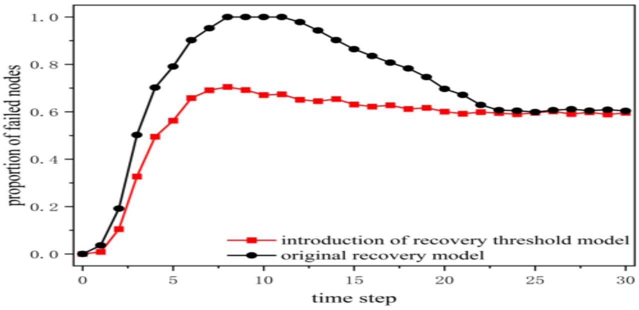

Fig. 4.4: Trend in the proportion of failed nodes in the network after the introduction of recovery thresholds

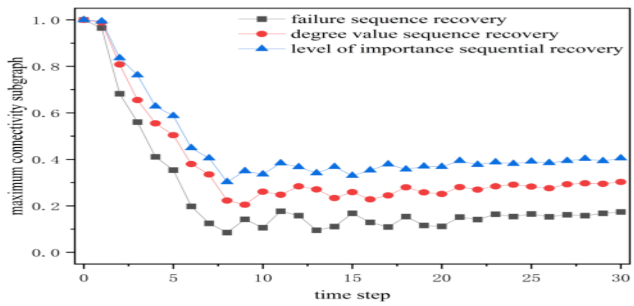

Fig. 4.5: Trend of maximum connectivity subgraph of the network under different recovery models.

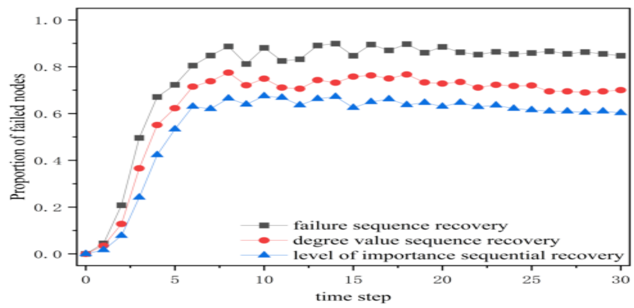

Fig. 4.6: Trend of the proportion of failed network nodes under different recovery models.

work normally, and perhaps has already caused serious impacts on human production and life. When the recovery threshold is introduced, it is equivalent to increasing the maximum capacity of the nodes, so that the nodes that should have failed are transformed into overloaded nodes instead of directly failing, and then these overloaded nodes are repaired in a timely manner. Therefore, the introduction of the recovery threshold can minimize the complete failure of the network, which can appropriately enhance the robustness of the network and avoid unnecessary losses.

4.1.3. Robustness of the Network under Different Recovery Strategies. On the basis of the above simulation experiments, considering the possibility of secondary failure of nodes, different recovery methods are compared and analyzed to verify the validity and feasibility of the model, the capacity parameter and recovery threshold parameter are kept unchanged, and the recovery time parameter is selected as T= 1, and the simulation results of different recovery methods are shown in Fig. 4.5 and Fig. 4.6.

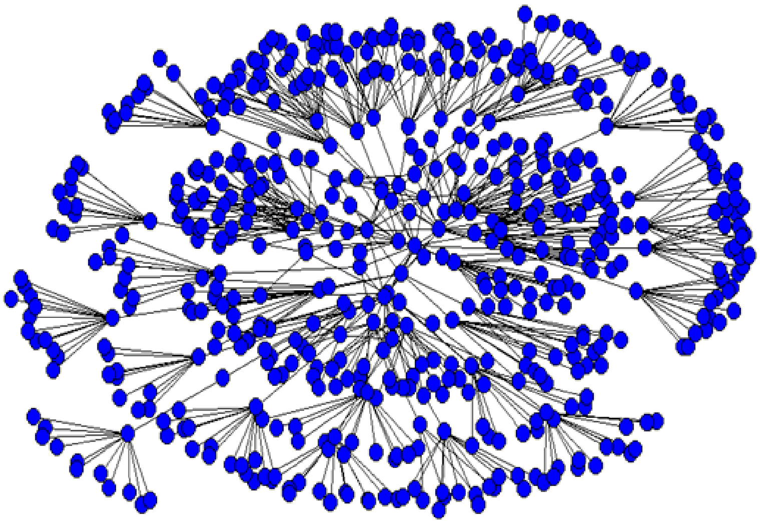

Fig. 4.7: Northwest Logistics Network.

As can be seen from Fig. 4.5 and Fig. 4.6, when the network starts to recover, the maximum connectivity subgraph curve of the network nodes and the failure ratio curve of the nodes will oscillate, fluctuating back and forth around a certain value due to the existence of the secondary failure of the nodes, and will eventually stabilize. When various conditions are the same, the effect of recovery in the order of node importance is the most obvious, and the effect of recovery in the order of network node failure is the worst, and The simulation findings show that an appropriate recovery model can improve the network's robustness.

4.2. Empirical Research.

4.2.1. Logistics Network Construction in Northwest China. This paper focuses on the logistics network in Northwest China, modeling it, cascading it to failure, and studying its robustness after recovery. Therefore, the activities of China Post Logistics in Northwest China are taken as an example to construct the postal logistics network in Northwest China. Based on the postal logistics activities of 25 municipal units, including the first-class postal district central bureau, second-class postal district central bureau, and third-class postal district central bureau established by China Post in Northwest China, the improved gravitational model establishes the logistics network between these 25 cities and then climbs a total of 25 logistics centers, 51 distribution centers and 495 business outlets within the cities to establish a total of 596 intra-city logistics activity networks. activity network, to build a total of 596 nodes of the logistics network in the northwest region, as shown in Fig. 4.7. The logistics data in this paper comes from the Postal Industry Development Statistics Bulletin of each city in 2021, and the data of logistics distribution centers and business sites are crawled from the Baidu map and the official website of China Post.

4.2.2. Characteristics of the Northwest Territories Logistics Network. On the basis of the logistics network model of Northwest China, the basic characteristic indexes of the logistics network of Northwest China are calculated by Ucinet software, and the results are shown in Table. 4.1.

The degree value, median, proximity centrality, and eigenvector centrality of the logistics network in Northwest China are calculated by Ucinet, and the sequence of the importance of the logistics network in Northwest China is obtained by hierarchical analysis based on these four indexes, and the partial ordering of these five indexes is shown in Table. 4.2.

4.2.3. Network Robustness Analysis under Recovery Policy.

(1) Effect of different recovery thresholds on network robustness. In order to study the effect of different recovery thresholds on the recoverability of the logistics network, the adjustable parameters of 0.2, 0.4, 0.6,

Table 4.1: Indicators of basic characteristics of the Northwest Territories logistics network.

Network Characteristics	calculated value
Number of nodes	596
number of connecting edges	635
average degree	2.13
network density	0.004
Average shortest path	7.03
clustering factor	0.087
Network global efficiency	0.99

Table 4.2: Comparison of various indicators of urban nodes of the logistics network in the Northwest Region.

Rankings	nodal	degree	nodal	betweenness	nodal	Proximity	nodal	eigenvector	nodal	significance
1	102	15	231	39.67	1	25.34	296	40.7	1	0.899
2	525	15	1	33.82	296	25.3	1	37.1	231	0.88
3	582	15	296	25.53	231	24.85	117	34.4	296	0.856
4	54	14	117	23.5	117	24.78	231	29.4	117	0.759
5	119	14	2	20.48	180	23.55	343	29.2	343	0.556
6	282	14	232	15.08	343	22.7	475	26	475	0.513
7	296	14	118	15.07	475	22.56	68	23.1	180	0.5
8	345	14	180	12.5	68	22.38	180	21.8	68	0.48
9	373	14	181	11.97	166	22.33	100	20.6	2	0.416
10	509	14	297	10.39	280	22.24	166	16.4	100	0.415
11	1	13	343	10.08	100	22.03	280	16.3	166	0.412
12	231	13	68	9.89	219	21.85	219	15.9	280	0.391
13	421	13	69	9.76	371	21.41	330	13.8	219	0.349
14	436	13	475	9.41	397	21.38	371	12.4	118	0.348
15	489	13	166	9.03	2	21.16	397	12.4	232	0.347
16	3	12	345	8.47	462	20.77	462	10.6	371	0.345
17	42	12	476	8.15	330	20.67	523	8.1	397	0.332
18	168	12	554	8.15	297	20.65	419	7.9	330	0.320
19	298	12	371	8.06	232	20.56	554	7.6	297	0.301
20	359	12	372	7.83	419	20.54	449	7.4	554	0.298

and 0.8 are selected for simulation verification, the capacity parameter is set as α= 1.5, β= 0.5, β_1= 0.2, and the start recovery time parameter T is taken as 1, and the simulation results are taken as the average value of 30 times. Fig. 4.8 depicts the influence of different recovery thresholds on the logistics network's maximum connectivity subgraph in Northwest China, while Fig. 4.9 depicts the impact of different healing thresholds on the proportion of failed nodes to total nodes in Northwest China.

As can be seen from Fig. 4.8, when the adjustable parameter λ= 0.2 of the recovery threshold, the size of the maximum connected subgraph of the network fluctuates around 7%, and when λ is 0.4, 0.6, and 0.8, the size of the maximum connected subgraph of the network fluctuates around 13%, 21%, and 31% and finally tends to be stabilized, which indicates that the bigger the recovery threshold, the more normal nodes there are in the maximum connected subgraph of the network. From Fig.4.9, it can be seen that when the adjustable parameter λ= 0.2 of the recovery threshold, the proportion of network failure nodes is as high as 92%, and as the parameter λ keeps increasing, the proportion of network failure nodes decreases to about 63% when λ increases to 0.8. Therefore, in the event of cascading failure faults, the higher the recovery threshold, the smaller the impact of cascading failure on the network, and the stronger the network robustness, so increasing the recovery threshold has a positive impact on improving the robustness of the logistics network in Northwest

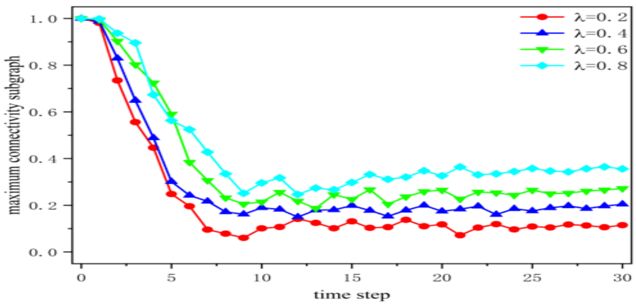

Fig. 4.8: Maximum connectivity subgraph of logistics network.

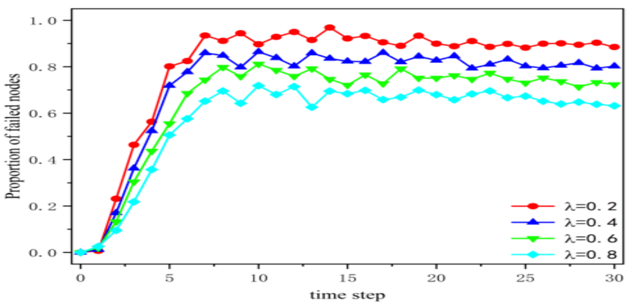

Fig. 4.9: Proportion of failed nodes in the logistics network under different recovery thresholds

China.

(2) Effect of different capacity parameters on network robustness. In order to study the influence of different capacity parameters on the recoverability of the logistics network, the adjustable parameter of recovery threshold λ is selected as 0.5, the parameter of start recovery time T is taken as 1, the capacity parameter α is taken as 1.5, β_1 is taken as 0.2, and β is taken as 0.3, 0.6, and 0.9 respectively, and simulation experiments are carried out, and the average value of 30 such results is taken. Fig. 4.10 depicts the influence of different capacity values on the logistics network's maximum connectivity subgraph in Northwest China, while Fig. 4.11 depicts the effect of various capacity parameters on the proportion of failed nodes compared to all nodes in Northwest China.

As shown in Fig. 4.10 and Fig. 4.11, when the value of λ is fixed, the different capacity parameters mainly affect the initial phase of the network, and there is less difference between the final recovery effects of the network as time passes. In both figures, $\beta = 0.3$, the network starts to fail massively at time step 1, when $\beta = 0.6$, The network's maximum connectivity subgraph begins to break severely at time step 3. and the node failure ratio of the network starts to fail massively at time step 4, whereas when $\beta = 0.9$, the network starts to fail massively at time step 5, indicating that a larger capacity parameter not only improves the robustness of the network on a small scale, but also delays the network cascade failure faults and provides some protection to the network.

(3) Recommendations for Enhancing the Robustness of Logistics Networks. Through the research and simulation of the above cascade failure and recovery strategy of the logistics network in Northwest China, It is clear that the logistical network is sturdy. in Northwest China changes with the change of the recovery threshold and capacity parameter, and the reasonable improvement of the recovery threshold and capacity parameter has a positive effect on the enhancement of the robustness of the logistics network in Northwest China. Therefore, in order to guarantee the high efficiency and stability of the logistics network in Northwest China, the following suggestions are made to suppress cascading failure faults.

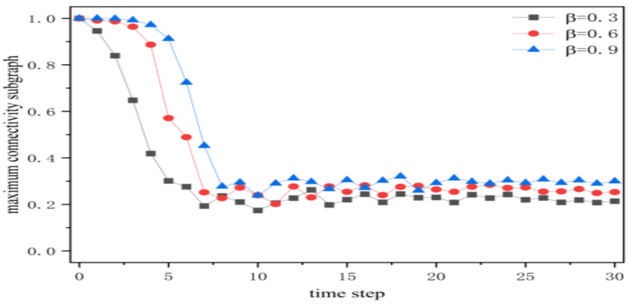

Fig. 4.10: Maximum connectivity subgraph of logistics network in Northwest China under different capacity parameters

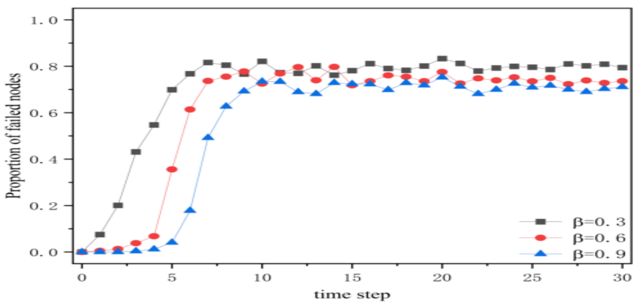

Fig. 4.11: Proportion of failed nodes in the logistics network in Northwest China under different capacity parameters

In terms of curbing cascading failures, firstly, the disaster-resistant capacity of the logistics infrastructure should be strengthened, and key nodes and facilities should be reinforced and remodeled to improve their resistance to natural disasters. Second, decentralization and redundancy strategies should be implemented to reduce the impact of a single node or path failure on the entire network by establishing backup facilities, multiple routes and other strategies. In addition, regular emergency response drills are conducted to improve practitioners' emergency response capabilities and teamwork.

In terms of recovering nodes, develop a prioritized recovery plan, set recovery priorities based on the importance of nodes, and prioritize the recovery of nodes that have the greatest impact on the entire network. At the same time, establish emergency resource reserves, including manpower, materials and technical support, so that they can be quickly put into recovery work in the event of a failure. Finally, a real-time monitoring and early warning system is established to continuously monitor the operational status of the logistics network, so that failure points can be discovered and localized in a timely manner so that recovery measures can be taken quickly.

5. Conclusions. Logistics networks need to resume normal work as fast as possible when encountering unexpected events. Therefore, it is of practical significance to take the logistics network in Northwest China as an example to conduct an empirical study to analyze its cascade failure fault and recovery behavior. In this paper, based on the original failure model, the concept of node recovery threshold is introduced to optimize the recovery time lag. Based on the original recovery model, a criticality-first recovery model is proposed, which defines the capacity of the recovered node as a function related to the original capacity, and selectively opens the recovered node to the surrounding critical nodes to reduce the risk of secondary node failure. The relationship between capacity parameters and recovery thresholds and the robustness of the logistics network in Northwest China is verified through simulation experiments, and suggestions are made to enhance the robustness of the logistics network in Northwest China. Of course, there are some limitations in this paper. In reality, the validity of the model depends on real-time accurate data, but it is often difficult to obtain such data. Monitoring the network load in real time and adjusting the recovery strategy accordingly requires an accurate control system. Limited resources may make it difficult for computational and technical requirements to be met, leading to more difficult implementations. To solve the above problems, we can improve the technology of data acquisition to enhance the real-time and accuracy of data, or we can cooperate with other companies to share data resources to increase the availability of data and reduce the cost of acquiring it, and develop modular control systems that allow for flexible adjustments and upgrades to adapt to different environments and demands, and in terms of cost, maximize the use of the limited resources. The technologies and limitations faced in reality can be overcome to a certain extent by the above mentioned ways, in order to ensure that the entire logistics network in the Northwest Territories can function properly and guarantee the smooth flow of goods in case of risks.

Funding. Natural Science Foundation of Gansu Province (Project No. 23JRRA898)

REFERENCES

[1] Zhang W D, Yin Y, Gu W J et al., *Association network modeling of multidimensional smart shop floor data in complex spatio-temporal domain*, Control and Decision Making, 2024, 1-9.

[2] Lai Q, Ma X, Zhang HH, et al., *Robustness analysis of aviation network structure*, Journal of Huazhong University of Science and Technology (Natural Science Edition), 2023, 1-6.

[3] Li R, Chen X, *Reverse Logistics Network Design under Disruption Risk for Third-Party Logistics Providers*, Sustainability, 2022, 14(22):14-31.

[4] Yu J, Xiao B, Cui Y Z, *Recovery method of group-dependent combat network under overload situation*, Journal of Harbin Institute of Technology, 2024, 1-11.

[5] Cheng G , Hongyi P , Mengchao W , et al., *Identifying priority areas for ecological conservation and restoration based on circuit theory and dynamic weighted complex network: A case study of the Sichuan Basin*, Ecological Indicators, 2023, 155:45-57.

[6] Yang Q, Zhang Y N, Zhou Y Q et al., *A review of complex network theory and its application in public transportation resilience*, China Highway Journal, 2022, 35(04):215-229.

[7] Qin L ,Hongkai C ,Yuhan L , et al., *Network spreading among areas: A dynamical complex network modeling approach*, Chaos (Woodbury, N.Y.), 2022, 32(10):103102-103102.

[8] Yang B, Qian X D, *Research on the evolution of supply chain enterprise cooperation based on complex network model*, Complex Systems and Complexity Science, 2018, 15(03):1-10.

[9] Chen D Q, Sun D Z, Yin Y Q, Dhamotharan L, Kumar A, Guo Y H, *The resilience of logistics network against node failures*, International Journal of Production Economics, 2022, 244-255.

[10] Wang Y D, Shi Q, Song S, Hu Q W, *Multi-objective optimization model and solution algorithm for dynamic logistics network*, Computer Integrated Manufacturing Systems, 2020, 26(04):1142-1150.

[11] Zhang D Z, He R Z, Zhu W, Zhang Z, *Research on optimization of multi-mode express logistics service network based on low carbon economy perspective*, Journal of Railway Science and Engineering, 2018, 15(06):1601-1608.

[12] Qian X D, Xuan Z, *Research on the diffusion of risk factors in logistics networks under the background of complex networks*, Computer Engineering and Application, 2022, 58(13):303-314.

[13] Wang S H, Yang Y, Sun L Y, Li X N, Li Y X, Guo K H, *Controllability Robustness Against Cascading Failure for Complex Logistic Network Based on Dynamic Cascading Failure Model*, IEEE Access, 2020, 8, 34-47.

[14] Zhang Z, Liu D Y, Zhang J et al., *Robustness study of complex networks based on dynamic control of node redundancy capacity*, Journal of Electronics and Information, 2021, 43(05):1349-1356.

[15] German R M, Daniel M, John E W, *A new method for the measurement of robustness in reverse logistics supply chains based on entropy and nodal importance*, Computers & Industrial Engineering, 2023, 183, 121-135.

[16] Haihua Y, Shi A, *Robustness evaluation for multi-subnet composited complex network of urban public transport*, Alexandria Engineering Journal, 2021, 60(2):64-78.

[17] Yu R B, Jiang Y, Yan Y W et al., *Robustness study of dependent networks considering dependent edge loading*, Journal of University of Electronic Science and Technology, 2022, 51(05):774-785.

[18] Zhang L, Du Y, *Resilience of space information network based on combination of complex networks and hypergraphs*, Computer Communications,2022,195,124-136.

[19] Yang Y, Peng C, Yang Y J et al., *Research on supply chain recovery strategy under disruption risk*, Journal of System Simulation, 2021, 33(12):2771-2781.

[20] Wu J ,Chen Z ,Zhang Y , et al., *Sequential Recovery of Complex Networks Suffering From Cascading Failure Blackouts*, IEEE Transactions on Network Science and Engineering, 2020, PP(99).

[21] Ju Y N, Li Z P, Chen Y F, et al., *Study on node importance and fault recovery of regional rail transit systems*, Chinese Journal of Safety Science, 2021, 31(02):112-119.

[22] Tang L, Jiao P, Li J K, et al., *Research on cascading failure mechanism and robustness of complex networks with recovery strategies*, Control and Decision Making, 2018, 33(10):1841-1850.

[23] Huang Y, Liu M R, Wei J G, et al., *Study on the recovery strategy of urban subway network based on resilience curve*, Disaster Science, 2021, 36(01):32-36.
[24] Xiuwen F, Xiaojie X, Wenfeng L, *Cascading failure resilience analysis and recovery of automotive manufacturing supply chain networks considering enterprise roles*, Physica A: Statistical Mechanics and its Applications, 2024, 634129478-634129489.
[25] Yoshihisa S, Shinsuke M, *Designing a resilient international reverse logistics network for material cycles: A Japanese Case study*, Resources, Conservation Recycling, 2021, 170:25-36.
[26] Motter A E, Lai Y C, *Cascade-based attacks on complex networks*, Physical Review E, 2002, 66(6):76-89.
[27] Dong-Hee Kim, Adilson E Motter, *Resource allocation pattern in infrastructure networks*, Journal of Physics A: Mathematical and Theoretical, 2008, 41(22):97-109.
[28] Wang S C, Qian X D, *Optimization of cascading failure model and network robustness analysis based on complex networks-an example of postal logistics network in Northwest China*, Control Engineering, 2024, 1-11.
[29] Di Muro M A, La Rocca C E, Stanley H E, et al., *Corrigendum: Recovery of Interdependent Networks*, Scientific reports, 2017, 7(1-4):46586.
[30] Böttcher, Lucas, et al., *Failure and recovery in dynamical networks*, Scientific reports, 2017, 7(1-4):41729.
[31] Hu B, Li F, *Repair strategies of scale-free networks under multifold attack strategies*, Systems Engineering and Electronics, 2010, 32(1):86-89.
[32] Jiarong X, Youyou Y, Zhengping F, et al., *Eradicating abrupt collapse on single network with dependency groups*, Chaos (Woodbury, N.Y.), 2019, 29(8):083111.
[33] Xin Y, Yanqing H, Eugene H S, et al., *Eradicating catastrophic collapse in interdependent networks via reinforced nodes*, Proceedings of the National Academy of Sciences of the United States of America, 2017, 114(13):3311-3315.

Edited by: Jingsha He
Special issue on: Efficient Scalable Computing based on IoT and Cloud Computing
Received: Mar 18, 2024
Accepted: May 20, 2024