Hindawi
Discrete Dynamics in Nature and Society
Volume 2022, Article ID 8076551, 11 pages
https://doi.org/10.1155/2022/8076551

Research Article

Research on the Model of Industrial Interconnection Intelligent Manufacturing Supply and Demand Network and Its Robustness

Jianjia He and Tianyuan Zheng

Buisiness School, University of Shanghai for Science and Technology, Shanghai 200093, China

Correspondence should be addressed to Tianyuan Zheng; 117882209@qq.com

Received 18 January 2022; Accepted 24 February 2022; Published 24 March 2022

Academic Editor: Luca Pancioni

The industrial interconnection intelligent manufacturing supply and demand network is the carrier for the cooperation of related enterprises, and research on its evolution helps to optimize the cooperation between enterprises. This paper considers the factors that affect enterprise cooperation, applies consensus, disconnection, reconnection, and change of opinion into one model, and constructs two models of industrial interconnection intelligent manufacturing supply and demand networks. Because the industrial interconnection intelligent manufacturing supply and demand network is affected by certain factors, the network will be subject to fluctuations and the functions of the network will change. The smaller the function change, the higher the robustness of the model. The related topological structure statistics (such as clustering coefficient, average path length, and degree distribution) of the two models are analyzed, and the analysis results indicate that the network structure of the two models has changed. In addition, different attack algorithms are used to verify the robustness of the model. The experimental results show that under the four different attack algorithms, compared with the BA model, the two models proposed in this paper have stronger robustness. Research on the industrial interconnection of intelligent manufacturing supply and demand networks and its robustness optimization has certain guiding significance.

1. Introduction

With the emergence of new technologies such as big data, artificial intelligence, the Internet of Things, cloud computing, and 5G, lower-cost sensors, data storage, and faster data analysis have promoted the development of traditional enterprises toward intelligence, data, and interconnection. The refinement of the industrial division of labor has become the new normal, so a single enterprise to the entire industry is experiencing new opportunities and new impacts brought about by changes. The industry under change has expanded from external boundaries to internal integration. In this context, companies have begun to penetrate each other, frequently cross-border, and integrate the entire supply chain. This requires companies not only to strengthen internal resource integration and process optimization but also to share resources and collaborate with other corporate partners [1–3]. After continuous development, the trend of industrial interconnection that integrates the real economy and the virtual economy of the Internet has gradually formed. Many enterprises have begun to develop across multiple fields and industries. The concept of the industrial Internet has prompted enterprises to use the Internet and other technologies to build open and shared information platforms, thereby breaking through geographical restrictions and industry barriers and forming closer cooperative relations with other companies. This enables companies to form a cluster of information, thus breaking the original chain-like industrial structure and reorganizing production and operation models, and the orientation matches supply and demand, finally forming a complete networked industrial system.

The industrial interconnected intelligent manufacturing network is a network formed by manufacturing enterprises as the core and suppliers with long-term trading relationships. These trading relationships can be formal or informal.

In the industrially interconnected intelligent manufacturing network, enterprises usually circulate and share resources, and use the division of labor and cooperation to achieve the goal of maximizing the benefits of network enterprises [4]. However, due to the dynamic nature of the industrial interconnection intelligent manufacturing supply and demand network and the heterogeneity between different organizations, cross-border cooperation between enterprises is affected by many factors inside and outside the enterprise, and it is easy to form cooperation barriers for enterprises to carry out cross-border cooperation. It affects the efficiency and benefits of the production collaboration, and it is difficult to give full play to the advantages of industrial interconnection. Based on the analysis of industrial interconnection theory and practice, this paper explores the relationship between industrial interconnection structure and practice.

Enterprises continue to cooperate across borders, resulting in a phenomenon of industrial linkage. At present, scholars have not fully studied industrial interconnection and intelligent manufacturing supply and demand network because the multifunctional open supply and demand networks (hereinafter referred to as the supply and demand networks) have structural networking, functional diversity, and sufficient openness. The analysis of the industrial interconnection intelligent manufacturing supply and demand network with the supply and demand network theory will help to study the evolution of the industrial interconnection intelligent manufacturing supply and demand network, help characterize the underlying logic of industrial interconnection and make it easier to realize intelligence manufacturing. The function of the network is realized by the structure and the dynamic process of the structure. However, in some past research on industrial interconnection, the dynamic and openness of industrial interconnection were not considered, for e.g., in BA, WS, and other models, only the connection was considered. The relationship does not incorporate the dynamic process on the network, but in fact, the network structure will continue to evolve, and the dynamically changing network structure will affect the behavior of the dynamic process; conversely, the dynamic process can also affect the evolution of the structure [5]. For example, when the virus spreads among the population, infected individuals can disconnect from uninfected individuals to prevent uninfected individuals from becoming infected. Therefore, the process of virus transmission and the adaptive change of topology behavior of nodes will interact with each other. The topological structure affects the behavior of the virus propagation process, and the change of the topological structure is also affected by the virus propagation process. In the interconnected intelligent manufacturing network, uncontrollable factors cause the defects of the network to be exposed and eventually cause the network to collapse. Therefore, it is necessary to consider the reliability of the network from the perspective of the entire network.

The purpose of the research on the structure of the industrial interconnection intelligent manufacturing supply and demand network is to better understand its internal mechanism [6], and the functions of the industrial interconnection intelligent manufacturing supply and demand network are often reflected by the dynamic model of the network. The network structure determines the various "functions" undertaken by the industrial interconnection intelligent manufacturing supply and demand network. Therefore, structural changes will affect the expression of functions; that is, structural changes affect the dynamic behavior of the network. However, the dynamics of the network will also affect the network structure. When the network topology is attacked, the functions assumed by the network will change. The smaller the function change, the higher the robustness of the network [7, 8]. Xiao et al. [9] studied the formation mechanism of eco-industrial networks by improving the BA [10] model and analyzing relevant statistical characteristics. Wang et al. [11] proposed a robust method for optimizing the eco-industrial symbiosis network system, which improves the robustness of the eco-industrial symbiosis network. It has very important theoretical and practical significance to pay attention to whether the network function and structure can maintain integrity after the network structure is damaged.

Based on the previous research work, this paper has conducted a more in-depth discussion on the industrial interconnection intelligent manufacturing supply and demand network based on the complex network supply and demand network, studied the network growth model and the dynamic model, and proposed a model that combines Deffuant dynamic model [12] and a new BA network growth model. The model considers three factors: (1) Reach a consensus. If the viewpoint values of the network nodes are similar, a consensus can be reached according to the rules in the dynamics model. (2) The broken edge is reconnected. The nodes in the network may disconnect from the nodes with different opinions, and then re-select the nodes to connect. (3) Views change. The nodes in the network may change their views for other reasons besides reaching a consensus. These models are more likely to reflect what we observe in real life.

The rest of the structure of this paper is as follows: in Section 2, the relevant knowledge is introduced; in Section 3, the model proposed in this paper is introduced; and in Section 4, the network robustness evaluation standard and related methods of attack are introduced. Section 5 gives the experimental results and analysis, and finally concludes and discusses in Section 6.

2. Related Method

2.1. BA Model. There is a wide range of complex systems in nature and human society, and various complex networks can be used to describe them. Studies have shown that most nodes in many actual networks, such as metabolic networks, Internet networks, and communication networks, have only a small number of edges, while a small number of nodes have high degrees, and their degree distribution obeys the power-law distribution, that is, a scale-free network. In order to explain the generation mechanism of the scale-free network, Barabasi–Albert proposed the BA scale-free network model.

They believe that the scale-free phenomenon is attributed to the two characteristics of growth and preferential attachment:

(1) Growth: starting from an initial network with M0 nodes, each step adds a new node with M connections, where $M \leq M0$

(2) Preferential attachment: the newly added node is connected to the existing node i with a probability of ω_i

$$\omega_i = \frac{k_i}{\sum_n k_n}, \tag{1}$$

where k_i is the degree of node i.

2.2. Deffuant Model. The Deffuant model is kind of a bounded trust model. It uses the real number d to represent the degree of confidence. Individuals within the degree of confidence can interact with each other, while individuals outside the degree of confidence cannot interact. In a group with N individuals, a network with N nodes is used to describe the group. First, for each node in the network, randomly select a number from [0, 1] as the node to get the opinion O_i. At time t, nodes i and j are randomly selected and their viewpoint values are $O_i(t)$ and $O_j(t)$. If $|O_i - O_j| > d$, then the opinions of these two nodes will not be updated.

$$\begin{cases} O_i(t+1) = O_i(t) \\ O_j(t+1) = O_j(t) \end{cases}, \left|O_i - O_j\right| > d. \tag{2}$$

If $|O_i - O_j| < d$, their opinions $O_i(t+1)$ and $O_j(t+1)$ at time t+1 will be updated according to the following formula:

$$\begin{cases} O_i(t+1) = O_i(t) + \mu\left(O_j(t) - O_i(t)\right) \\ O_j(t+1) = O_j(t) + \mu\left(O_i(t) - O_j(t)\right) \end{cases}, \left|O_i - O_j\right| < d. \tag{3}$$

Among them, $\mu \in [0, 0.5]$ is the convergence parameter, which reflects the magnitude of the change in the opinions of the two nodes in the direction of each other. When $\mu = 0$, there will be no change between the two interacting parties; when $\mu = 0.5$, the two interacting parties will get the average value of the opinions of the both parties. These two situations indicate that the two interacting parties with different characteristics correspond to individuals with tougher strategies when μ is smaller they are not easy to change their views, while when μ is larger, they are easy to compromise their views. In the Deffuant model, the value of μ is usually fixed at 0.5 [13].

3. The Proposed Model

The connection mechanism in the BA model considers the optimal connection, which considers the degree of the node, that is, the greater the degree, the greater the possibility of being connected. In the industrial interconnection intelligent manufacturing supply and demand network, each node is an enterprise or enterprise alliance. When it is connected with other enterprises or enterprise alliances, due to differences in various aspects, opinions are inconsistent, and it may be cut off from holders of different views. Some companies will keep in touch with holders of different views for various reasons. However, the above-mentioned problems are not reflected in the evolution of the BA model. Once the BA model is connected, the edges will not be disconnected. Therefore, the above-mentioned problems should be considered when constructing an industrial interconnected intelligent manufacturing supply and demand network. Besides, in addition to reaching a consensus, changes in the views of companies may change their views due to other reasons such as unexpected key events, changes in their minds, problems with the capital chain, or the introduction of related policies. Through the above analysis, we propose two different evolution models, both of which are improved based on the BA model combined with the Deffuant model. Two different evolution models are described in detail in the following.

3.1. Model A. The model assumes that after the number of members in the industrial interconnection intelligent manufacturing supply and demand network reaches the preset number, the network stops evolving. In this model, the final number of nodes is set to N, the system grows by M, and each time a node is added, the node will have an edge with M nodes, and a viewpoint value between [0, 1] is randomly assigned to the node. In these M-connected edges, if the trust degree between the nodes (belonging to M nodes) is less than d, the connected edge will not be disconnected; otherwise, the disconnected edge will be reconnected. In the growth of the network, the ratio of growth to formation is 1 : 1, that is, adding one node at a time and then interacting once, and the probability of p causes a sudden change in the views of members, which becomes a random value in [0, 1]. The number of nodes in the direct network reaches the set value N.

3.2. Model B. The model assumes that there are a certain number of members N in the industrial interconnection intelligent manufacturing supply and demand network, then randomly assigns a viewpoint value between [0, 1] for these N members, and then sets the number of time steps t. In each step, randomly select a node and its neighbor nodes. If the absolute value difference between their viewpoint values is less than d, then keep the edge connected; otherwise, the edge is broken and reconnected. And there is a probability of p that causes the member to have a sudden change of opinion, which becomes a random value in [0, 1].

In the above model, there will be cases where a consensus is reached, and the update strategy is as in formulas (2) and (3).

4. Robustness Evaluation Criteria

This paper uses different deliberate attack methods to evaluate the robustness and vulnerability of the network. The maximum connected subgraph coefficient and the network efficiency index are used to quantify the impact on network structure and function after a deliberate attack. This result is used to evaluate the robustness and vulnerability of the network.

4.1. Maximum Connected Subgraph Coefficient. There is one or more paths between any two nodes in the network, indicating that the two nodes are connected. If all the nodes in the network are connected, it is a connected network. When the network is destroyed, the network may be decomposed into multiple connected subgraphs, and the one with the largest number of nodes becomes the largest connected subgraph [14]. The formula for calculating connectivity is as follows:

$$G = \frac{N'}{N}. \tag{4}$$

Among them, N represents the initial size of the network and N′ represents the number of enterprise nodes included in the largest connected subgraph of the network after the node fails.

4.2. Network Efficiency. Network efficiency [15] measures the operating efficiency of the network after a node fails, and its calculation formula is as follows:

$$\alpha = \frac{1}{N(N-1)} \sum_{(i,j \in V, i \neq j)} \frac{1}{d_{ij}}. \tag{5}$$

Among them, d_{ij} represents the shortest path length between two nodes. The change in network efficiency can be more intuitively reflected by the rate of decline in network efficiency. The calculation formula is as follows:

$$\mu = 1 - \frac{\alpha}{\alpha_0}. \tag{6}$$

Among them, α_0 represents the initial efficiency of the network and α represents the network efficiency after the node fails.

4.3. Methods of Deliberate Attack. The reason why this paper adopts a deliberate attack method based on local information instead of a method based on global information is that the method based on global information needs to traverse the entire network when obtaining node information, while the method based on local information only needs part of the topology. The time complexity based on local information is much smaller than that based on global information.

4.3.1. Degree Centrality. Degree centrality [16] refers to the number of connected edges of a node, and its calculation formula is as follows:

$$DC(v_i) = \sum_{j=1}^{N} A_{ij}. \tag{7}$$

4.3.2. Semilocal Centrality. The semilocal centrality [17] metric considers the number of neighbors within two hops to measure the centrality of a node:

$$Q(u) = \sum_{w \in \Gamma(u)} N(w), C_L(v) = \sum_{u \in \Gamma(v)} Q(u), \tag{8}$$

where $\Gamma(u)$ is the node's neighbor node and $N(w)$ is the number of one-hop and two-hop neighbors of the node w.

4.3.3. LLS. Ruan et al. [18] combined the degree of the node itself and the degree of dependence of neighbor nodes on the node, and defined the domain similarity of nodes by calculating the overlap degree of neighbor nodes in the topology:

$$\begin{aligned} \operatorname{sim}(b,c) &= \begin{cases} \dfrac{|N(b) \cap N(c)|}{|N(b) \cup N(c)|}, b \text{ and } c \text{ have no edge}, \\ 1, \text{and } c \text{ have edge} \end{cases} \\ LLS(i) &= \sum_{b,c \in N(i)} (1 - sim(b,c)), \end{aligned} \tag{9}$$

where $N(i)$ represents the set of neighbor nodes of node i.

4.3.4. LLSR. Liu et al. [19] considered the information dissemination factors in the network to further improve the LLS algorithm:

$$\begin{aligned} ReLU(x) &= \begin{cases} x & \text{if } x > 0 \\ 0 & \text{otherwize.} \end{cases}, \\ LLSR(i) &= \sum_{j \in N(i)} ReLU(LLS(i) - LLS(j)). \end{aligned} \tag{10}$$

5. Experiment and Analysis

5.1. Analysis of the Statistical Characteristics of the Industrial Interconnection Intelligent Manufacturing Supply and Demand Network. A complex network is a highly complex network. It is a network structure composed of a huge number of nodes and intricate relationships between nodes. It is a graph with sufficiently complex topological structure characteristics. In this paper, clustering coefficient, average path length, and degree distribution are used as basic statistics to describe the characteristics of complex network topology [20].

5.1.1. Analysis of the Clustering Coefficient. The clustering coefficient is used to describe the clustering of complex networks, and the clustering coefficient of a node describes the connectivity density of the neighbors of the node.

$$C_i = \frac{2E_i}{k_i(k_i - 1)}, \tag{11}$$

where E_i is the actual number of edges of the node.

The aggregation coefficient of the entire network is the arithmetic mean of the aggregation coefficients of all the nodes in the network.

$$C = \sum_{i=1}^{N} \frac{C_i}{N}, \tag{12}$$

Table 1: Comparison of network models.

Network	N	M	The threshold	p	The average path length	The average shortest path
BA	200	3	—	—	0.0950	2.8709
Model A	200	3	0.1	0.001	0.0413	3.1194
	200	3	0.2	0.001	0.0491	3.0897
	200	3	0.3	0.001	0.0557	3.0487
	200	3	0.4	0.001	0.0593	3.0154
	200	3	0.5	0.001	0.0660	2.9789
	200	3	0.5	0.01	0.0348	3.1062
	200	3	0.5	0.1	0.0282	3.1543
Model B	200	3	0.1	0.001	0.0302	3.1318
	200	3	0.2	0.001	0.0323	3.1512
	200	3	0.3	0.001	0.0302	3.1401
	200	3	0.4	0.001	0.0285	3.1520
	200	3	0.5	0.001	0.0285	3.1547
	200	3	0.5	0.01	0.0293	3.1453
	200	3	0.5	0.1	0.0296	3.1539

where C represents the agglomeration of nodes in the entire network, that is the agglomeration of the network. The larger the C, the greater the degree of distance connectivity between nodes in the entire network.

It can be seen from Table 1 that the agglomeration coefficient of Model A increases with the increase of the threshold, but they are all smaller than the BA model. In the interconnected intelligent manufacturing network, it should be a decentralized network, which cannot be reflected by the BA network. The current interconnected intelligent manufacturing network and Model A portray a decentralized network to a certain extent, and the average clustering coefficient of its nodes is small. The evolution of Model B was carried out after the evolution of the BA model, and its agglomeration coefficient was lower than that of the BA model, but the agglomeration coefficient of Model B was not much different, indicating that the size of the threshold has a certain effect on the role of Model B in changing the network structure and that the threshold is related to the number of time steps set.

5.1.2. Analysis of the Average Path Length. The average path length of the network is defined as the average value of the distance between any two nodes [21], namely,

$$l = \frac{2\sum_{i>j} d_{ij}}{N(N-1)}. \tag{13}$$

For the industrial interconnection intelligent manufacturing supply and demand network, the average path length indicates that in the industrial network, cross-field cooperation on average requires the role of an enterprise to complete the corresponding cooperation. The smaller the l, the smaller the topological distance between any two nodes in the network and the better the reachability of the entire network.

It can be seen from Table 1 that the average shortest path of Model A is increasing compared to the BA model. The reason is that the central capacity of the hub node is dispersed to a certain extent. Some nodes can be reached without passing through the hub node, which improves the robustness of the network. The average shortest path of Model B is also larger than that of the BA model that changes the topology of the network, thereby improving the robustness of the network and providing relevant references for the optimization of the actual network.

5.1.3. Degree Distribution Analysis. Record the degree distribution diagrams under the double logarithm of one of the BA models, Model A and Model B, as shown in Figures 1 and 2. By comparing Model A and Model B with the BA model, we found that the double logarithmic distribution of Model A and Model B is different from the BA model. From Figure 1, it can be seen that Model A can be fitted with a straight line, but it is different from the BA model. It is slightly different from Figure 2, where Model B is no longer like a straight line, but similar to a Poisson distribution. According to Table 1, the network structure of Model A and Model B has changed.

5.2. Network Robustness Analysis. Node failure is difficult to predict for the entire network. From the point of view of risk sources, node failure includes external and internal factors; from the perspective of attack modes, it is divided into deliberate attacks and random attacks. There are two types of attack methods. One is the failure of a node in the network, which means that the node exits the network and all companies that have business relationships with it will be affected; the other is that the edge of the network fails, which means that the business relationship is disconnected. Edge failure usually only affects part of the network, while node failure often causes the entire network to be paralyzed, and the consequences are more serious. Therefore, this article mainly discusses the research on the reliability of the industrial interconnection intelligent network structure under the condition of node failure.

To measure the robustness of the network, different algorithms are used to deliberately attack the model proposed in this paper to simulate the changes in the maximum connected subgraph coefficient and network efficiency when the network is under attack. If the network still has high connectivity and network efficiency under attacks from

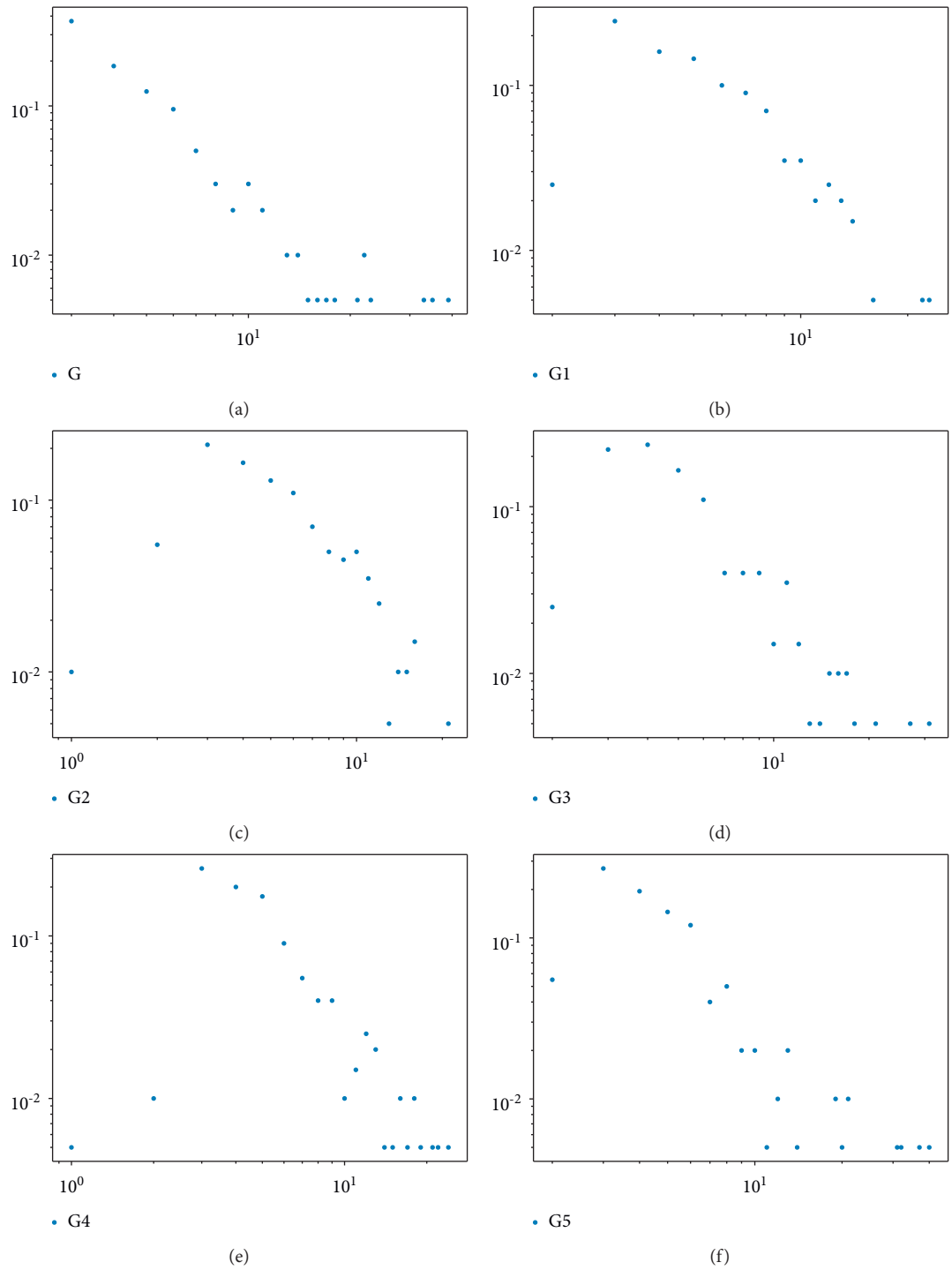

Figure 1: Comparison of the degree distribution between Model A and BA, in which G represents the BA network and G1–G5 represent the comparison of different thresholds of Model A (0.1–0.5).

different algorithms, it means that the network is robust. All the results in this paper are averaged 50 times.

5.2.1. Model A Analysis. Figures 3 and 4 show the changes in the network's maximum connectivity coefficient and network efficiency reduction rate under four different attack angles, which reflect the robustness of the network. In the experiment, different thresholds were set to affect the robustness of the network. First of all, it can be seen that the curve A represented by the BA network decreases faster under the same conditions when the network efficiency and network connectivity are under attack, while the curves represented by model A are more anti-interference than BA network, and as the threshold decreases, the robustness of the network is better. The degree of decline in the curves of

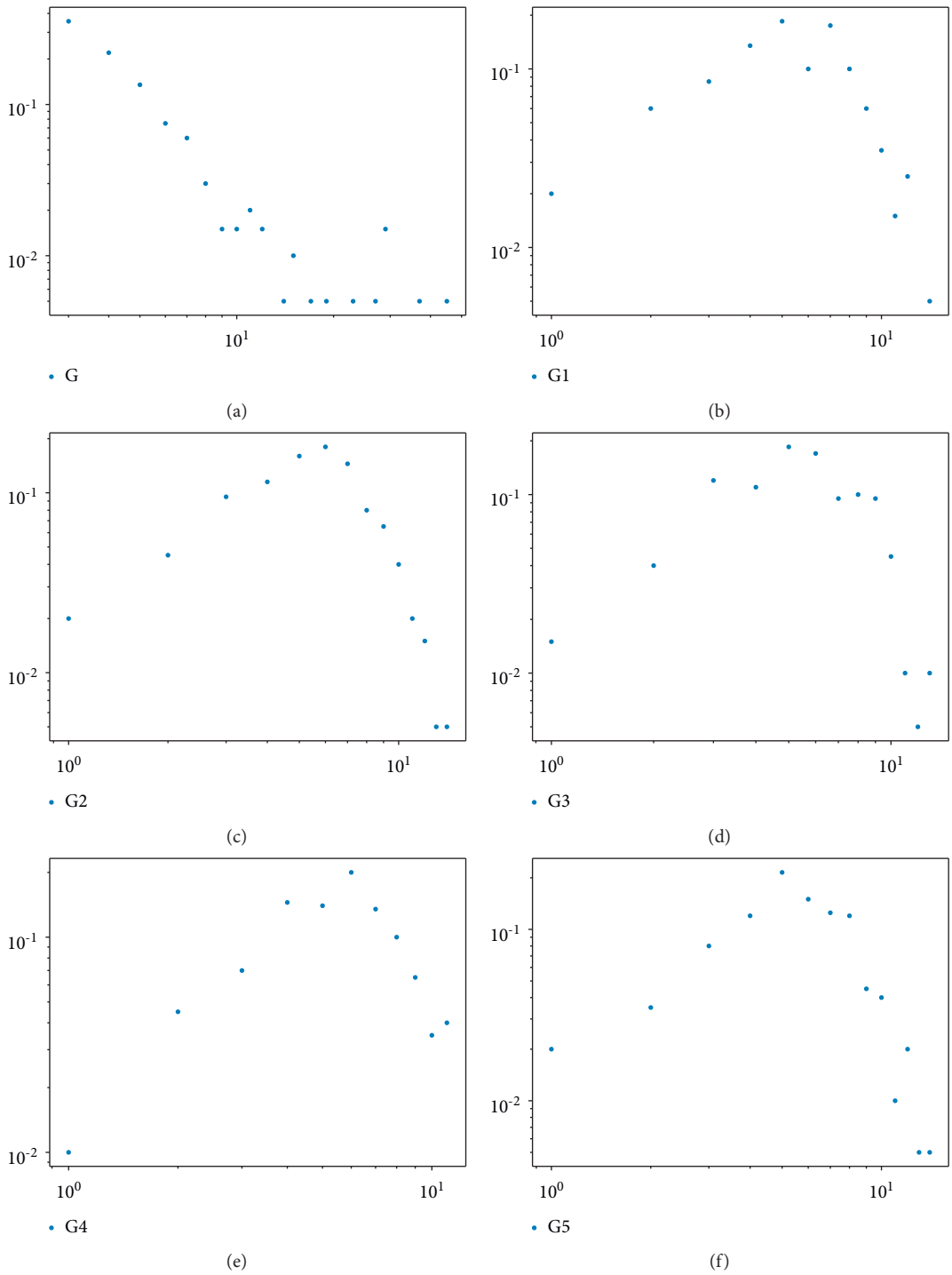

Figure 2: Comparison of degree distribution between Model B and BA, where G represents BA network and G1–G5 represents the comparison of different thresholds of Model B (0.1–0.5).

the BA model and model A is different because the hub node in the BA network is attacked and the number of failure edges caused by it is large, resulting in poor network connectivity and network efficiency. The connection mechanism leads to changes in the network topology, which in turn lead to changes in robustness.

5.2.2. Model B Analysis. Figures 5 and 6 show the changes in the network's maximum connectivity coefficient and network efficiency decline rate under four different attack angles to measure the network's robustness and immunity. Different parameters are set in the experiment to form a comparison. The most intuitive thing in the figure is that the curve A represented

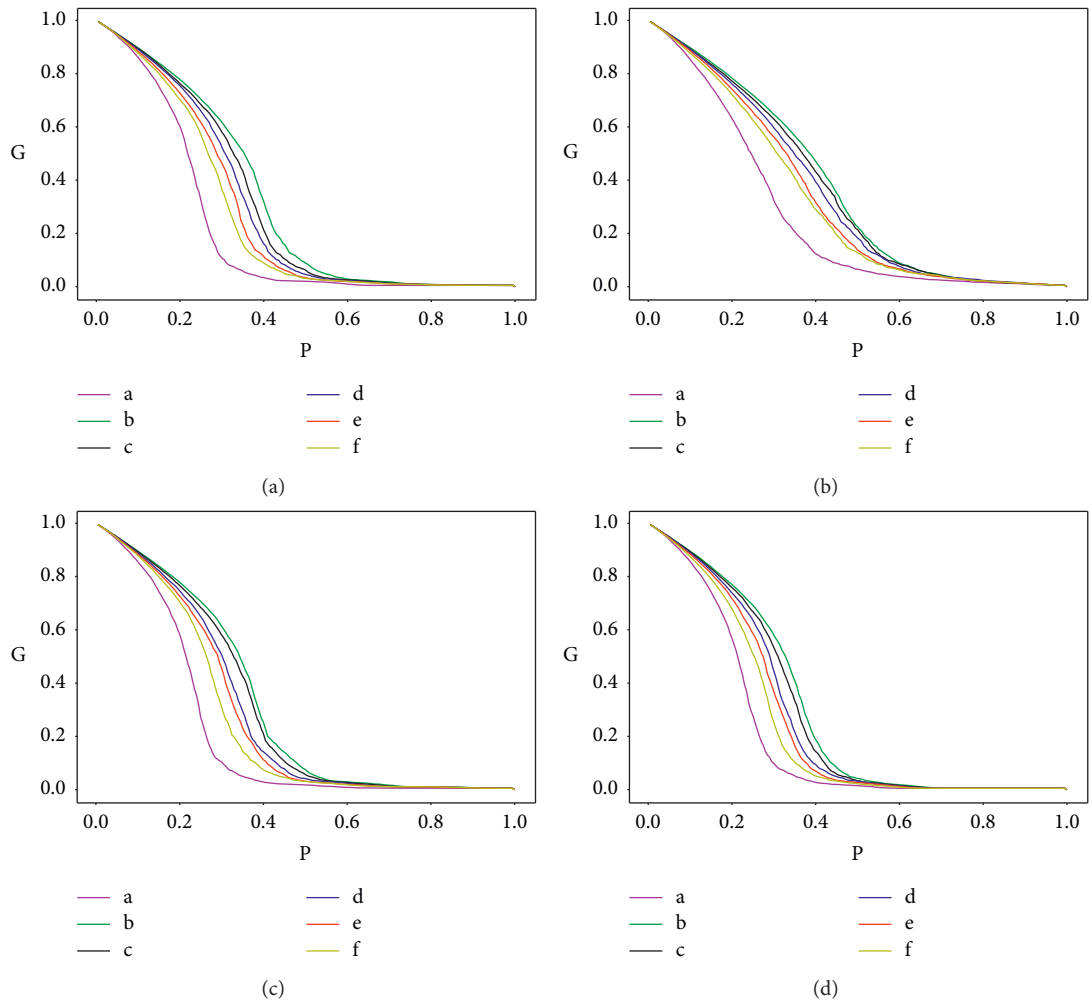

Figure 3: The change of the maximum connectivity coefficient G after model A is attacked by different algorithms, where $N = 200$, $M = 3$, curve A represents the BA network, and curve b–f represents the comparison of different parameters of model A (where threshold = 0.1–0.5, changes = 0.003). (a) deg, (b) SL, (c) LLS, and (d) LLSR.

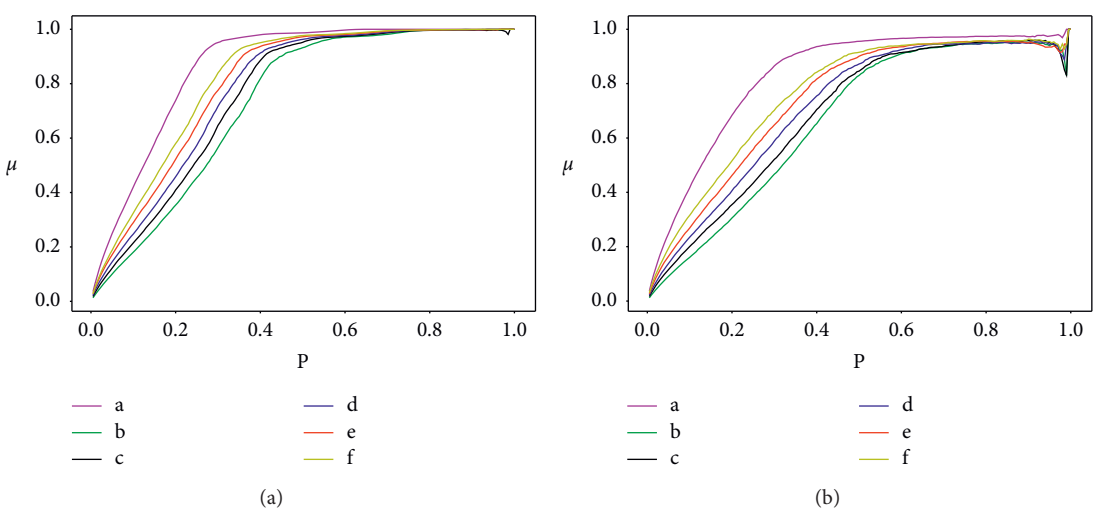

Figure 4: Continued.

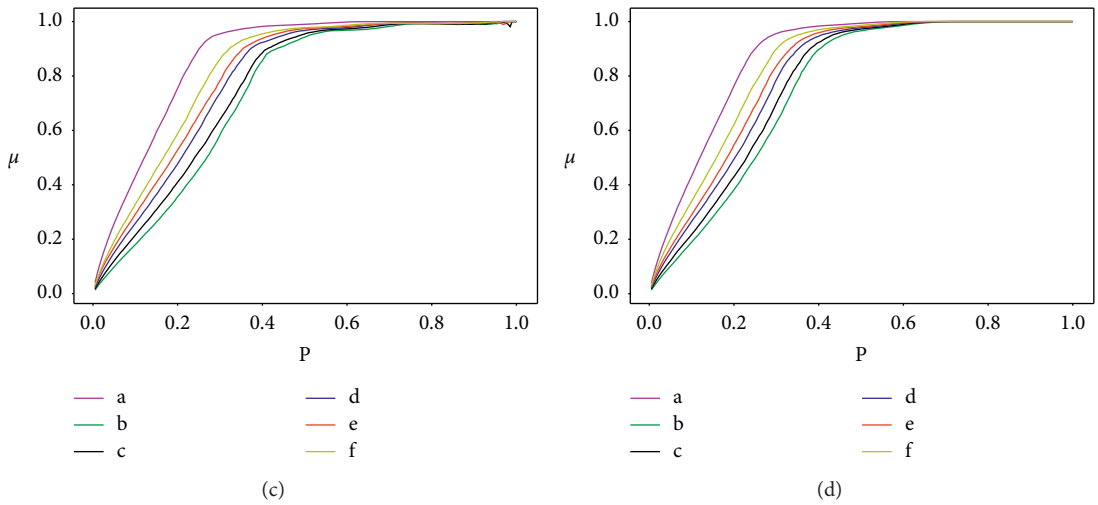

Figure 4: The change in network efficiency reduction rate μ after model A is attacked by different algorithms where $N = 200$, $M = 3$, curve A represents the BA network, and curve b–f represents the comparison of different parameters of model A (threshold = 0.1–0.5, changes = 0.001). (a) deg, (b) SL, (c) LLS, and (d) LLSR.

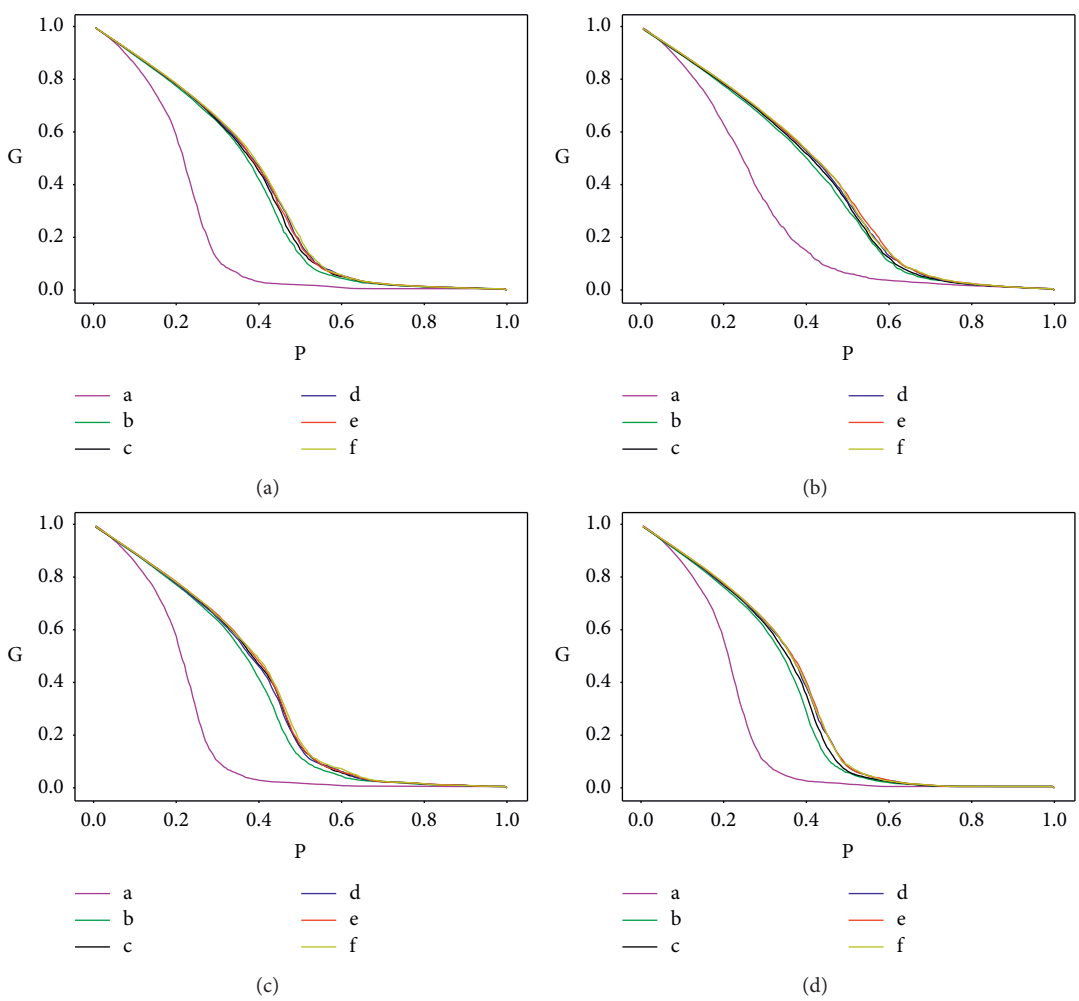

Figure 5: The change of the maximum connectivity coefficient G after model B is attacked by different algorithms, where $N = 200$, $M = 3$, curve a represents the BA network, and curve b-f represents the comparison of different parameters of model B (where threshold = 0.1–0.5, changes = 0.001). (a) deg, (b) SL, (c) LLS, and (d) LLSR.

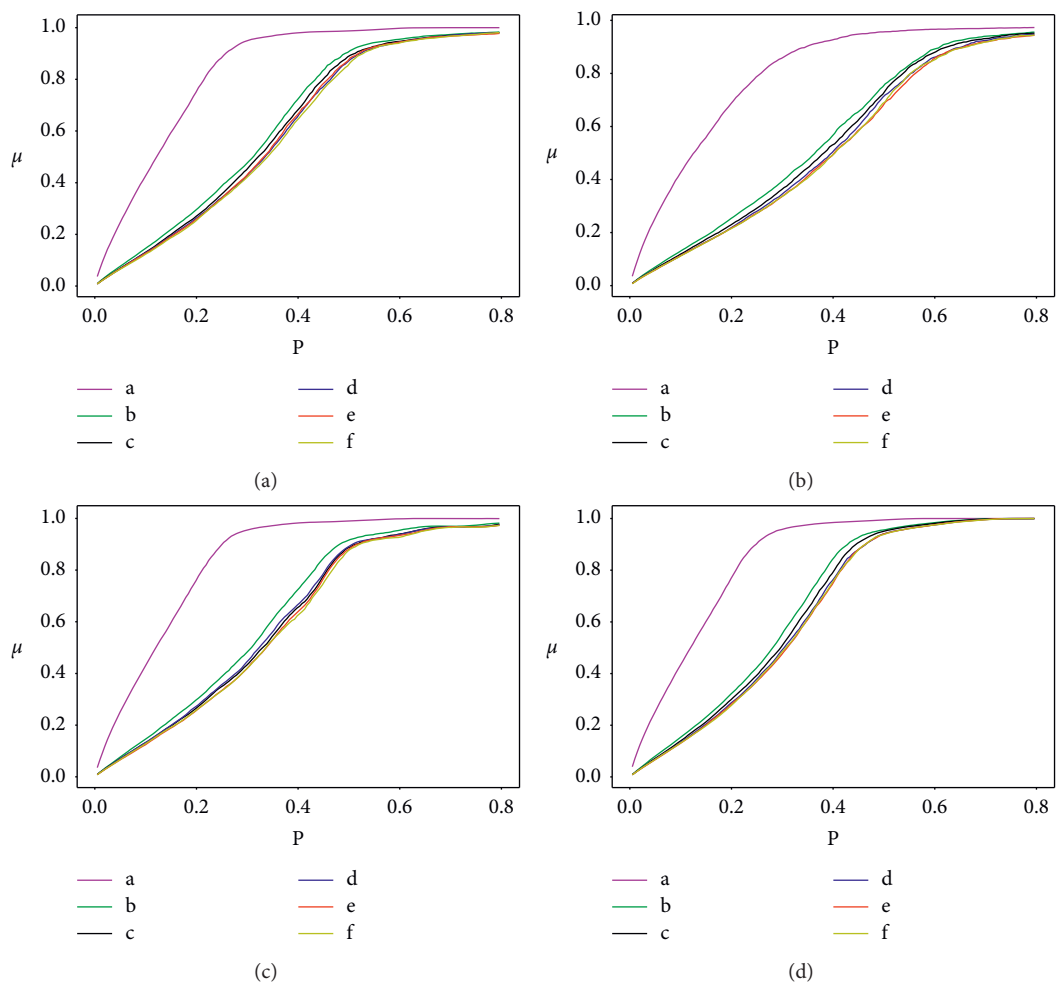

Figure 6: The change of the maximum connectivity coefficient G after model B is attacked by different algorithms, where $N = 200$, $M = 3$, curve a represents the BA network, and curve b-f represents the comparison of different parameters of model B (threshold = 0.1–0.5, changes = 0.001). (a) deg, (b) SL, (c) LLS, and (d) LLSR.

by the BA network has the worst noise immunity. The reason is that a large number of nodes have a small number of edges, and most of the nodes have relatively small degrees, which means that these nodes are in the range of activities in the network relatively small. A small number of nodes have a large number of edges, and a small number of nodes have a large degree, indicating that these nodes have a larger range of action in the network than other nodes. Once these nodes are disturbed or fail, it will cause damage to the network. In model B, as the threshold increases, the robustness of the network has a certain degree of improvement. The increase in the threshold means that the probability of reconnection of the broken edge increases, leading to slight differences in the network topology, resulting in different network robustness.

6. Conclusion

In the industrial interconnected intelligent manufacturing supply and demand network, the interaction between enterprises will affect the complexity of the industrial interconnected intelligent manufacturing supply and demand network. In the current related research, in the research model of the evolution process of the industrial interconnected intelligent manufacturing supply and demand network, there is no taking into account the differences among enterprises, which will lead to the termination of cooperation and the re-selection of partners. In addition, the policy and other factors have not been considered to cause changes in the enterprise. This paper studies the industrial interconnection intelligent manufacturing supply and demand network under complex networks and combines the relevant knowledge of the Deffuant model and the BA model to propose a new industrial interconnection intelligent manufacturing supply and demand network model that integrates consensus, disconnection, reconnection, and change of opinion into the model.

Analyzing the statistical characteristics of the industrial interconnected intelligent manufacturing supply and demand network by calculating the aggregation coefficient, average shortest path length, and degree distribution of the network model can provide practical guidance and reference significance for the optimization of the industrial interconnected intelligent manufacturing supply and demand network. The experimental results under deliberate attacks

show that the two models proposed in this paper have stronger robustness under related attack algorithms. Our research helps to better understand the evolution of the industrial interconnected intelligent manufacturing supply and demand network and provides a research foundation for subsequent research. There are a small number of companies in the industrial interconnected intelligent manufacturing supply and demand network that play an important core hub role. That is, when these companies have problems, these companies have large impact and wide scope. This means that the normal operation of these companies must be ensured in the network. At the same time, with these companies as the focus and center, other companies must also be coordinated, so that the operation of the entire industrial interconnection intelligent manufacturing supply and demand network can be fast, smooth, and efficient, and the robustness of the network can be improved.

The future work is to further study the relationship direction and weight of the supply and demand network of industrial interconnected intelligent manufacturing. Strive to establish a weighted directed network that can better explain the essential characteristics of the supply and demand network of industrial interconnected intelligent manufacturing. In turn, the reliability of the network can be more effectively improved and the network loss caused by node failure can be reduced.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work supported by the National Social Science Fund of China (Grant no. 718711144) and the Science and Technology Development Project of University of Shanghai for Science and Technology (Grant no. 2020KIFZ046).

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