Robustness Analysis of Social Network based on a Dynamic Model

Haitao Wu[1, 2, 3], Shi Ying[1, 2], Xiangyang Jia[1, 2], Liqiang Zhang[1, 2], Xu Chen[1, 2]
[1]State Key Laboratory of Software Engineering
[2]Computer School
[1, 2] Wuhan University
Wuhan, 430072, China
[3]Software School
Huanghuai University
Zhumadian, 463000, China
yingshi@whu.edu.cn

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ABSTRACT: *Due to the high vulnerability of today's social systems against disruptions, it has become critical to measure and manage the robustness of social networks. In this study the relationship between social network's topology and its robustness in the presence of cascading failures is examined. In the attempt to help practice in increasing the robustness of social systems, the concept of the robustness of social systems is discussed and defined first. And then we propose a new dynamic model of social systems to investigate the robustness of social systems. We theorize that network characteristics such as average path length, node degree, and size of the largest connected component in social networks and so on. Based on the model, a good evaluation method is proposed to investigate the robustness of social networks against the cascading failures of component nodes. Finally, the damage degree of social networks considering cascading failures is investigated through our model. The simulation results confirm that there is a positive relationship between the robustness of social systems and social system performance, while a negative relationship between the topology structure and the robustness of social systems. By the dynamic model, we not only identify the potential key nodes, but also obtain the parameter value which can make the social network reach strongest robustness level. Our work develops a new methodology to the real world application. This research is helpful to increase the robustness of such complex systems and tackle the optimization problem of them.*

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1. Introduction

More and more systems in the nature have been described as complex networks to be analyze their internal characteristics, such as physical systems, traffic systems, and power systems and so on [1] [2] [3] [4]. The people have been more and more aware of the importance of safety and robustness of networks in recent years [5] [6] [7] [8] [9]. Especially, there exist various components and very complex inter-relations in today's social networks. And their relations are based on material, energy and information flows [10] [11]. The bad effects of social system risks are more and more concerned by agents. It has been shown that firms that were affected by social system risks suffered from poorer performance of social systems. In addition, social system risks can be harmful to the society's financial performance and lead to lower sales. Therefore, the scholars are interested in risk mitigation practices that analyze and increase the vulnerability of social networks, identify the key components to protect them, as well as enhance their robustness.

Recently, the robustness has been widely studied on different static networks. Especially, many researchers have investigated the structural properties of random networks and scale-free networks [12] [13]. Nonetheless, there is not a clear definition on the robustness of social networks until to now. The concept of robustness has been dealt in depth by adopting the network theory. In the network theory, some common network metrics such as giant connected component, average shortest path length and global efficiency are used to evaluate the robustness of a network based on investigating the effect results of nodes' failures. In the work, failures of nodes are commonly composed of random failure and targeted failure. However, that work does not consider the dynamic processes which could reflect the evolution of real networks. For social networks, a methodology is introduced to iteratively obtain small social networks by using the methods which are based on analyzing the cooperation in the system using the relations between its nodes. Furthermore, some scholars obtained the classification of social networks by calculating different parameters in social network, such as average node degree, average path, clustering coefficient and so on [15] [16]. Based on this, the cyclic entropy was introduced and applied to investigate the dynamic change of social network during chatting [17]. However, the recent vulnerability study on social systems is mainly focused on the research of communication and information exchange between components because it is difficult to find a suitable methodology to deal with a highly unpredictable social environment.

In addition, complex system theories have been recently employed to research cascading failure phenomenon. For social networks, the failure of a component or a relation of supply and demand will induces the overload of other components or relations. And then the load at neighboring nodes will change. Once the flow of the neighboring components increases and exceeds their corresponding capacity, the nodes will further malfunction. As a result, it may lead to the failures of other components due to a new redistribution of loads finally, which is called cascading failures. With the development of global economy, social systems are becoming more interdependent to the components. It is because that there exists the close relation within social networks. Moreover, the cascading failure phenomenon often spread like a plague, resulting in the serious damage within social systems. However, the research on cascading failures mainly focuses on traffic system and power system analysis [18] [19] [20].

Considering the existing problems in social systems, our work focuses on the complex social network, concentrating not only on the materials and information flow analysis, but also on the internal network structure development and redesign of social systems under cascading failures. We analyze the vulnerability characteristics in social systems and propose the influence factors of social network robustness first. Then an example is introduced to illustrate our networked approach for social networks. Furthermore, different from the previous studies, we build a cascading model according to the cascading phenomenon of social systems and propose an evaluation method for the robustness of social networks. The simulation results show the validity and practicality of our proposed model on social networks. This research provides an effective and practical method to enhance the robustness in cascading failures control and defense in social networks.

2. Robustness of social system

The robustness research of the social networks is a relatively new but little research field. Therefore, more and more scholars have paid attention to this field in recent years. The robustness of social networks refers to the performance under the influence of losing some or all of the capacity facing the disturbance and shock. A certain robustness of one social network to emergencies can be seen as the integration of failure likelihood and the potential impact of failures. We can assess the robustness of social networks from the following three perspectives.

2.1 The place of failures

The social networks are very complex. The emergencies of each member may occur. However, the robustness at different members in the different social networks is different. For instance, some social networks are very fragile to the failure of some vendors, while some may be very fragile to the failure of distribution centers. And the overall robustness of social networks often depends on the robustness degree of the network's most robust member. Therefore, we should identify the main factors for the robustness of social networks by examining the nodes and links of social networks.

2.2 The probability of failures

The events of different geographical regions will occur which will affect the operations of social networks almost daily. The failure probability of social networks with high robustness is lower than social networks with low robustness under the impact of failure occurrence.

2.3 The influence caused by failures

The influence degree of the failures to social network is the most important factor to assess the robustness of social networks. The robustness of social networks is different each other. There is no a unified tool and method to measure the robustness of social networks until now. We argue that the four-quadrant model composed of failure probability and impact degree can be used to evaluate the robustness, as is shown in Figure 1.

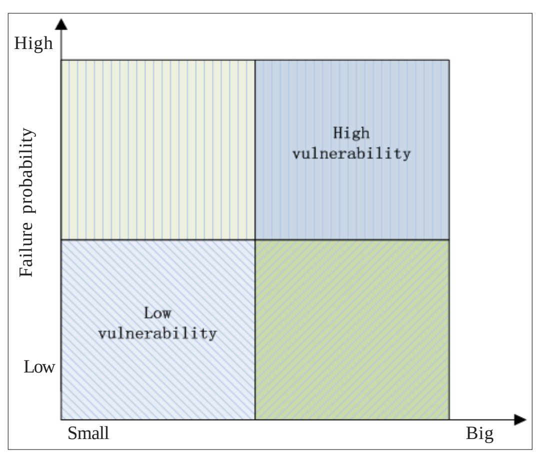

Figure 1. Vulnerability evaluation representation

From Figure 1, the vulnerability of a social network is higher when the system has a high probability of failure events and a large failure affect. Additionally, the globalization distribution of social networks allows that the impact of an incident induced by a single failure in one area can spread to the global social network. Diffusion of geographical scope brings to many difficulties of coordination. It is difficult to make a quick response after the failure of an event. Furthermore, the failure of a single node or connection in social networks will spread on the network, causing severe supply disruptions. This phenomenon is similar to the effect of the bullwhip phenomenon. Figure 2 shows the influence factors of social network vulnerability.

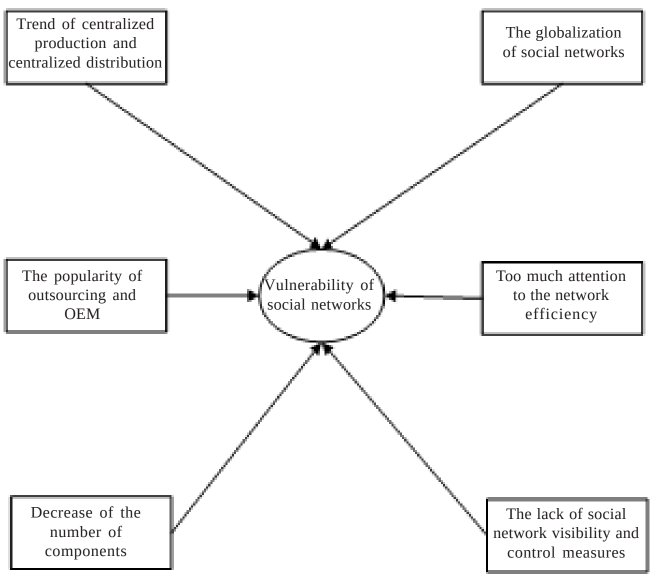

Figure 2. Influence factors of social network vulnerability

Through the analysis in Figure 1 and Figure 2, there are various ways to increase the robustness of social networks. Especially, we conclude that the robustness should be rooted in the structure of social networks. Therefore, we will use complex network theory to construct the topology graph of social systems in the following.

3. Construction of social network

We assume that a graph (a social network) $G = (A, L)$ is defined by a non-empty set which is composed of the node set $A = \{v_1, v_2, ..., v_N\}$ and the edge set $L = \{l_1, l_2, ..., l_M\}$. Next we will descript a social network as an adjacency matrix $A_{ij} = \{a_{ij}\}$, which is a $N \times N$ square matrix. In a square matrix, $a_{ij} = 1$ if there is an information communication between the component v_i and the component v_i to which the interception of row and column refers, while $a_{ij} = 0$ if there is no relation between the two components within the social network. When the matrix is asymmetric, i.e., $b_{ij} \neq b_{ji}$, the adjacency matrix represents a directed network. If not, i.e., $b_{ij} = b_{ji}$, the adjacency matrix is representing an undirected network.

We consider that it is difficult to obtain the exchange data of information and energy between components and unify the measurement standard. Therefore, we here will extract a social system to an undirected and network.

In this paper, the social system of an industry park is introduced as an example to illustrate our method and our model. First, by investigating the social system of the industrial park and collecting data, we make ensure the components of the social system which are composed of workers, retailers, water, resource, coal, electricity, chemical fiber, and so on. Then, some other nodes that exchange matter with the nodes outside the industry park are added as the supplyment nodes. When there is the exchange of matter or information between the two nodes existing in the social system based on the industry park, an edge between them is determined. In this way, we obtain the network adjacency matrix of the social system, which is expressed as following.

$$
\begin{pmatrix}
0&0&0&1&1&1&0&0&0&0&0&0&0&0&0&0\\
1&0&0&1&1&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&1&1&1&0&0&0&0&0&0&0&0&0&0\\
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0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&1\\
0&0&0&0&0&0&0&0&0&0&0&0&1&1&1&0
\end{pmatrix}
$$

We assume that the case has the specific features as following. First, it is an undirected social network without reverse logistic. Second, the information or material transformed from upstream to downstream in turn which is forbidden to skip any position of social network. Finally, the shortest path length is 1 in any pair of adjacent nodes.

Further, we obtain the network representation of this social system according to the adjacency matrix, as shown in Figure 4. The shortest path program based on Dijkstra algorithm is coded in Matlab 2010. Meanwhile, social network analysis software UCINET 6.0 is used to calculate the loads of all nodes.

4. The Dynamic Model

4.1 Vulnerability evaluation of social networks

The safety and vulnerability of social systems have been an important issue. The main purpose of our model is to explore the cascading phenomenon of social networks. Now, we consider the cascading phenomenon by removing a node initially. The failure could not cause the serious results when the load of the failure node is small. Thus,

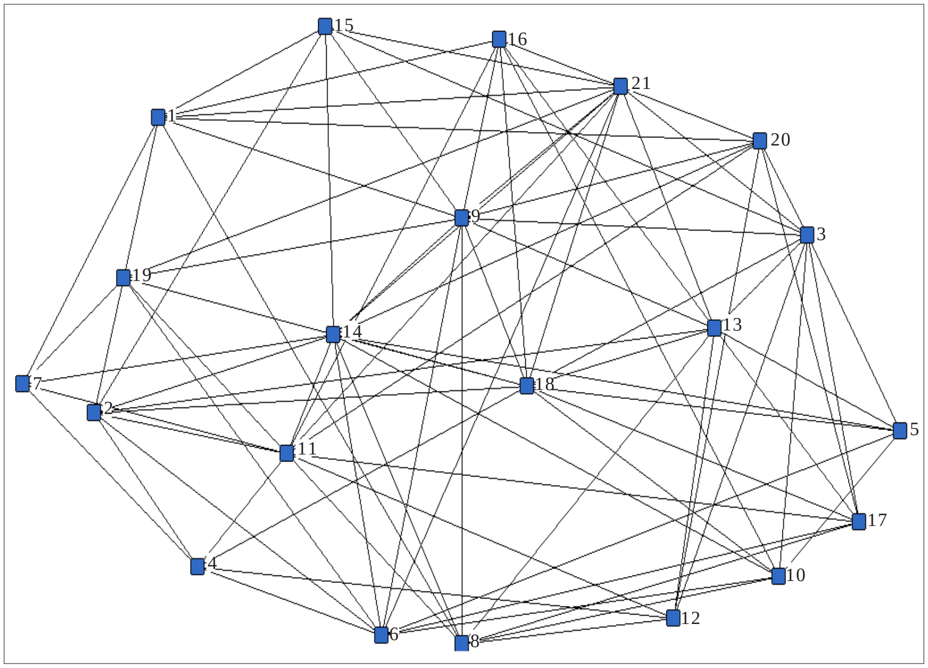

Figure 3. The network graph of the social system based on a park

the network could recover through the load redistribution. However, when the load of the removed node is large, the local failure will cause cascading failures across the whole system, even lead to serious results, and eventually result in the collapsing of the entire network.

For an undirected network G with N nodes and L edges, a $N \times N$ matrix is defined as the transmission efficiency matrix $\{e_{ij}\}$, which is used to describe the connectivity property of each edge. And e_{ij} refers to the transmission efficiency of edge l_{ij}. If the edge l_{ij} connects nodes v_i and v_j, the value of e_{ij} is positive, and $e_{ij} \in (0, 1]$. If there exists no connection between nodes v_i and v_j, then $e_{ij} = 0$. That is, when the value of e_{ij} is larger, this means that a certain amount of information through the transmission-side requires for the shorter time. We use the transmission efficiency e_{ij} to define the length of the edge l_{ij}, which is expressed as

$$|l_{ij}| = \begin{cases} \frac{1}{e_{ij}}, & if\, e_{ij} \neq 0 \\ \infty, & if\, e_{ij} = 0 \end{cases} \tag{1}$$

Between any two nodes in the network, there may be several roads. We denote the shortest path between two nodes by d_{ij}. Then, the connectivity coefficient of between nodes v_i and v_j is defined as following.

$$\eta_{ij} = \frac{1}{d_{ij}} \tag{2}$$

Obviously, when there exists no connection between nodes v_i and v_j, $d_{ij} = \infty$, i.e., $\eta_{ij} = 0$. Furthermore, in order to measure the vulnerability level of the whole supply chain networks against cascading failures, the expression of the connection coefficient is given by:

$$F = \frac{\sum_{i \neq j \in G} \eta_{ij}}{N(N-1)} = \frac{\sum_{i \neq j \in G} \frac{1}{d_{ij}}}{N(N-1)} \tag{3}$$

Thus, we give the following definition:

$$E = 1 - \frac{\sum_{i \neq j \in G} \eta_{ij}}{N(N-1)} = 1 - \frac{\sum_{i \neq j \in G} \frac{1}{d_{ij}}}{N(N-1)} \tag{4}$$

Therefore, the value of E determines the vulnerability of social systems under considering since we give the definition based on the network efficiency, which can characterize the damage degree of social networks and also reflect the robustness of them.

4.2 The dynamic model of social systems under cascading failures

It is known that the network topology is a main factor which impact on the load distribution of the social networks. In our cascading failure model, we regard the load of each node is determined by its corresponding degree. That is, the higher the degree of a node, the higher the load on the node is. Considering that the transmission flow of every node on a social network usually has a certain correlation with its degree, the detailed expression is given by:

$$L_i = \mu k_i^{\theta} \tag{5}$$

where μ and θ are the tunable parameters. The two parameters control the strength of the initial load of the corresponding node.

Because of the limitation of the capacity of each node, the load of the failure node v_i will be redistributed to its some neighboring nodes. It is assumed that v_j is one of its neighboring nodes. Denote that r_j is the preferential probability that the load of the node v_i will redistributed to the node v_j. The preferential probability r_j is defined as following.

$$r_j = \frac{\mu k_j^{\theta}}{\sum_{n \in Q_i} \mu k_n^{\theta}} = \frac{k_j^{\theta}}{\sum_{n \in Q_i} k_n^{\theta}} \quad (6)$$

The received load of node v_j is denoted by ΔL_{ij}. According to Equation (6), we assume the received additional load ΔL_{ij} by the node v_j is proportional to the corresponding initial load, i.e.,

$$\Delta L_{ij} = L_i \frac{k_j^{\theta}}{\sum_{n \in Q_i} k_n^{\theta}} \quad (7)$$

The capacity of each node is limited. The capacity of a node refers to the maximum load that the node can tolerate. The capacity of a node is limited by its construction cost of the social system. It is assumed that the capacity C_i of node v_i is proportional to its initial load $L_i(0)$, i.e.,

$$\begin{aligned} C_i &= (1+\alpha) L_i(0) \\ &= (1+\alpha)\, \mu\, k_i^{\theta} \end{aligned} \quad (8)$$

where the parameter α is the tolerance parameter. The value of α reflects the resistance capacity of a node to the natural disasters. In the following, we get $L_i(0)$ through Equation (5) and the capacity of node v_i through Equation (8) in the simulations.

It is well known that the limitation of the capacity, when a node malfunctions, the load of the node will be redistributed to the corresponding neighbor nodes. However, the capacity of each member in supply chain networks is very limited. The additional load could lead to the further failures of other nodes. Thus, this phenomenon may result in the breakdowns of other nodes. Following the cascading rule, we adopt the following the removal probability expression.

$$p_j = \begin{cases} 0 & L_j + \Delta L_{ij} < C_j, \\ 1 & L_j + \Delta L_{ij} \geq C_j, \end{cases} \quad (9)$$

where p_j refers to the removal probability of node v_j. That is, if $L_j + \Delta L_{ij} \geq C_j$, then node v_j will be removed.

5. Numerial results

In this work, we adopt the dijkstra algorithm to calculate the shortest path and the social network analysis software UCINET 6.0 to obtain the network graph of the park. The cascading process and evaluation results under our dynamic model are shown in Table 1.

The importance degree of all nodes is evaluated according to the connection coefficient before and after cascading failures which is expressed in Equation (3). In the social system, various nodes have different positions and influences. By the simulations, we find that node 17 is the most import and potential node. The failure of a single node 17 could lead to the collapse of the entire social network due to the cascading failures from Table 1. In addition, node 6 and node 13 rank 2th, 3th respectively because the values of the importance degree for the two nodes are 0.9613 and 0.9597 respectively. Their failures cause the failures of so many nodes. Therefore, they are also key component nodes. These components should be provided with more protection in the construction of the social system. On the other hand, the failures of nodes 11, 12, 14, 15, 16, 18, 19, and 20 cannot lead to cascading failures. Therefore, their importance is relatively weak.

Furthermore, we also see that the proposed assessment methodology considering cascade failure is more reasonable for identifying those key nodes in social network. Table 2 lists the node degrees and node loads of the top five places in the social network of the park. Comparing Table 1 with Table 2, it is seen that the highest degree or load node is not necessarily one of the most important nodes. Those nodes with low degree or low load may also occupy an important status. As is shown in Table 2, the load and the degree of node 17 are not highest although it is the most important node according to the Table 1. After node 17 failures, this failure triggers a cascade of overload failures on other neighboring nodes because their capacity could not tackle these additional loads. As a result, the whole network collapses and there is a large drop in the performance level of the social network from Table 1. Therefore, we find that node 17 is actually a potential key node. That is, the high or low of the node importance degree does not absolutely depend on the node degree or the node load, especially for social networks due to the complexity of social systems.

5.1 Numerical simulation and result analysis on the damage degree of infrastructure network

We use the connection coefficient to investigate the robustness degree of networks. In this work, two removals are adopted, that is, removing the highest importance degree node and removing the lowest importance degree node. By simulations, we obtain the relation between E and the tolerance parameter α by removing the highest importance degree node and the lowest importance node at the cases of different parameter θ. As shown in Figures 4, 5 and 6, the removal of the node with the highest importance degree triggers more serious damage degree than the removal of the node with lowest importance degree when the value of the tolerance parameter α is satisfied with $0.3 < \alpha < 0.9$. In the actual situation for social systems, the tolerate parameter α is usually less than 0.3 due to the cost constraints on the construction. Therefore, we can say that the damage degree triggered by removing the node with the highest importance degree is more serious than the result by removing the node with the lowest importance degree.

Additionally, since the removal of the highest importance

Node	Cascading process	Importance degree	Weight
1	None	0.5978	12
2	$1 \rightarrow 16 \rightarrow$ 21, 5, 7, 8, 9, 14, 15, 17, $2 \rightarrow 3$, 6, 13, 12, $10 \rightarrow 20$	0.9578	5
3	None	0.2580	20
4	None	0.4717	14
5	None	0.4372	16
6	$6 \rightarrow 2 \rightarrow 3$, 7, 14, 15, 16, $18 \rightarrow 1$, 5, 9, 17, $20 \rightarrow 8 \rightarrow 13 \rightarrow 4$, 10, 12, 19, 21	0.9613	2
7	None	0.6993	8
8	$9 \rightarrow 10$, $18 \rightarrow 2$, 5, 8, 14, 15, 12, $21 \rightarrow 3$, 4, 6, 13, 16, 19, $20 \rightarrow 7$	0.9516	7
9	None	0.6257	11
10	$10 \rightarrow 1 \rightarrow 9 \rightarrow 2$, 4, 5, 8, 11, 16, 17, 20, $21 \rightarrow 6$, 7, 14, 15, $18 \rightarrow 3$, 13	0.9580	4
11	None	0.1969	21
12	None	0.3769	17
13	$3 \rightarrow 14 \rightarrow 5$, 6, 10, 16, $18 \rightarrow 1$, 2, 4, 7, 8, 9, 11, 15, 17, 12, $21 \rightarrow 3$, 20	0.9597	3
14	None	0.5391	13
15	None	0.3156	18
16	None	0.6687	9
17	$17 \rightarrow 2 \rightarrow 1$, 7, 12, 14, 15, 18, 19, $20 \rightarrow 3$, 5, 6, 10, 11, 13, $16 \rightarrow 4$, 21, $8 \rightarrow 9$	0.9625	1
18	None	0.2589	19
19	None	0.4628	15
20	None	0.6382	10
21	$21 \rightarrow 7 \rightarrow 16$, 8, 10, 12, 14, 17, 18, 19, $20 \rightarrow 3$, 5, 6, 9, $13 \rightarrow 2$, 15, 11	0.9570	6

Table 1. Evaluation results of node importance under considering cascading failures

Node	Degree	Load
17	5	10.389
6	4	17.653
13	8	15.813
10	6	6.510
2	6	6.771

Table 2. Node degree and node load of the top 5 places according to importance ranking

degree node has a bigger impact on the social network than the removal of the lowest importance degree node from the above results, we further investigate the relation between E and the tunable parameter θ by removing node with the highest importance under our method, which is shown in Figure 7 and Figure 8. From Figures 7 and 8, we find that the tunable parameter θ has a significant influence on the robustness performance of the social network. The social network is more resilient when the value of θ is 0.5 under four different values of the parameter α. It is known that the tunable parameter is limited by the cost of social systems. Therefore, the simulation results are very helpful to the construction of social systems at the case of reducing the cost.

We know that few researchers discuss the status of different components within social networks in the presence of cascading failures. By this dynamic model, we not only find these potential critical components, but also obtain the parameter value that can make the social network reach the strongest robustness level. Therefore, our model is reasonable and useful to improve the robustness of social systems in control and defense of the cascading failures. In addition, this proposed dynamic model has the great generality for characterizing cascading-failure-induced disasters in nature and can provide valuable reference to many real-life complex systems.

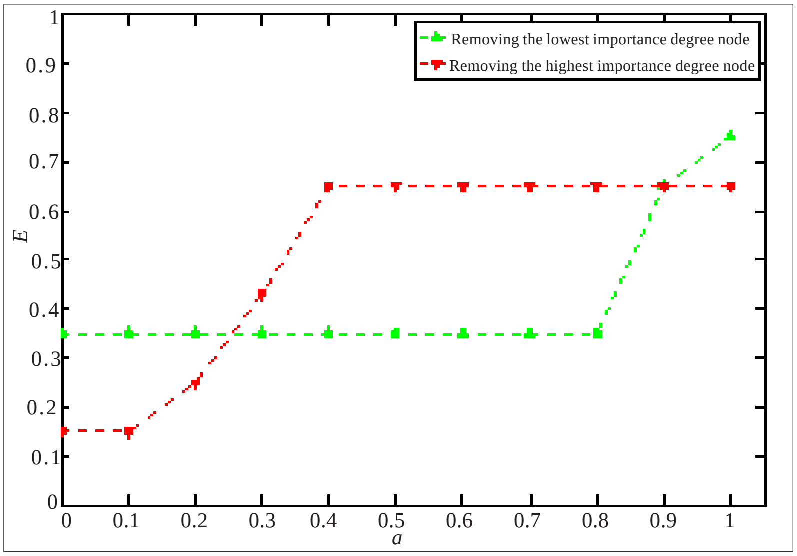

Figure 4. The relation between E and the tolerance parameter α by removing the highest importance degree node and the lowest importance node at the case of $\theta = 0.1$

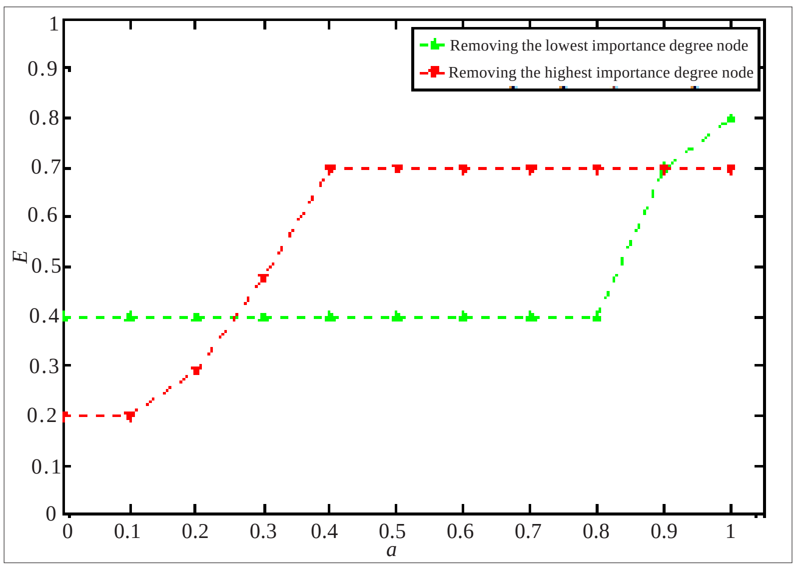

Figure 5. The relation between E and the tolerance parameter α by removing the highest importance degree node and the lowest importance node at the case of $\theta = 0.3$

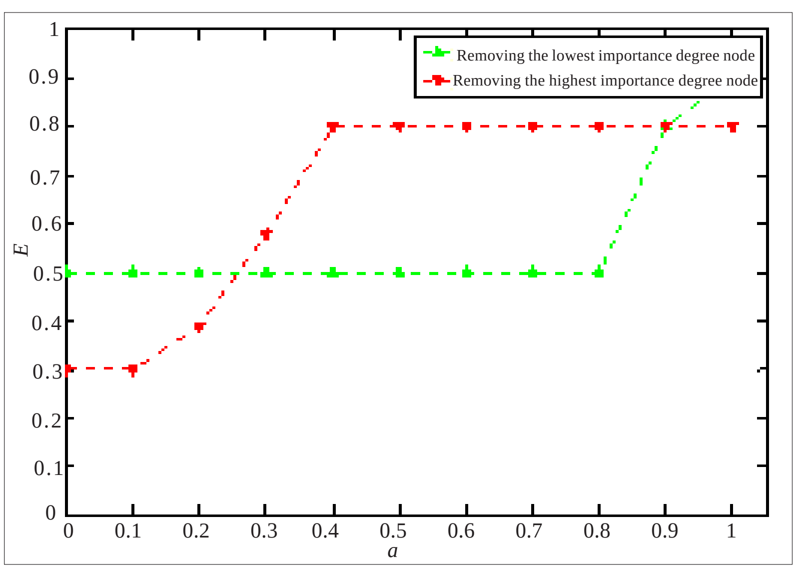

Figure 6. The relation between E and the tolerance parameter α by removing the highest importance degree node and the lowest importance node at the case of $\theta = 0.6$

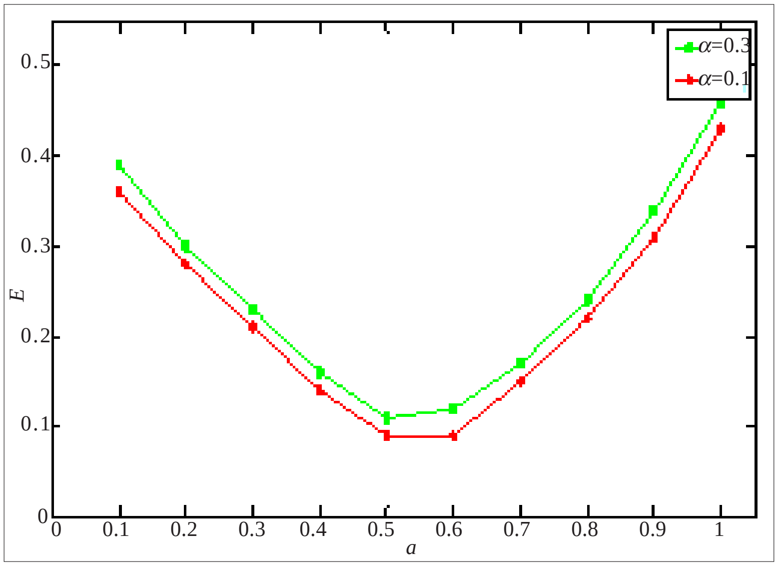

Figure 7. The relation between *E* and the tunable parameter θ by removing the highest node importance under our method

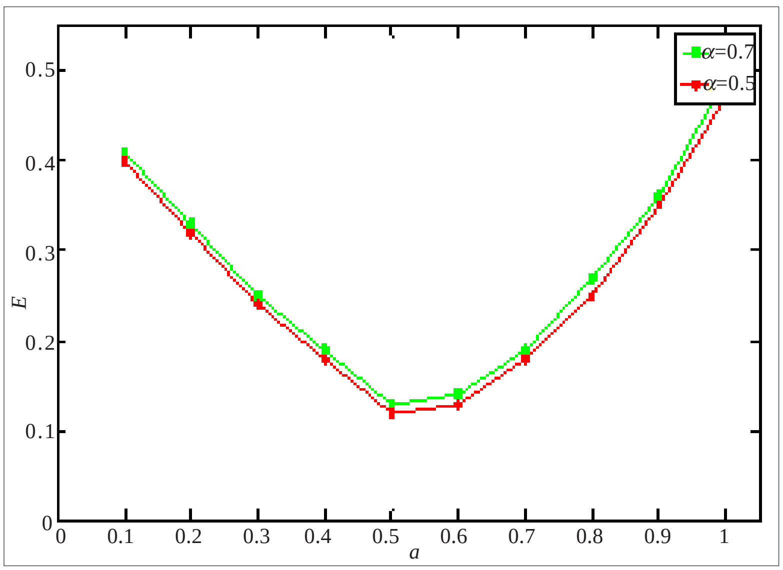

Figure 8. The relation between *E* and the tunable parameter *q* by removing the highest node importance under our method

6. Conclusion

The issues on the vulnerability and robustness of complex systems have been studied for a long time, such as power systems, production systems, social systems, etc. The networked idea has been applied to solve many real problems in recent years. It is due to the increasing number of global connections and the rise of the attacks on various types of complex systems. It has become more and more obvious that relations and interdependencies between components. We have to solve these incidents from a global perspective.

The robustness research of the social networks is a relatively new but little research field. The robustness of social networks is regarded as the performance under the influence of losing some or all of the capacity in the presence of the disturbance and disruption. In this work, we emphasize a new idea that network analysis is a promising method to the research on social systems which are regarded as the complex and dynamic networks. Thus, the social systems could be investigated based on a systemic point of view. This is a simple and fast method going to the internal structure and also providing an idea of the complexity degree of a social network. Especially for the modern society, more frequent cascading phenomena occur due to the close relations between the components. Social systems become vulnerable increasingly. The malfunction even from a simple component could lead to the extremely serious results. The networked systems are more complex and the large-scale cascading failures are therefore more common. Increased interdependencies and the decreased security make the evaluation on the robustness of such complex systems less operational.

In this paper, the robustness of social networks in the presence of cascading failures is explored by using complex network based on internal relations. The vulnerability characteristics in social systems are analyzed and the influence factors of social network robustness are proposed first. According the features of the robustness of social systems, a dynamic model of social networks is built. Then, we propose a dynamic evaluation method to analyze cascading failure characteristics in the social network. Based on this, those potential key nodes which may lead to serious consequences in the whole network are identified. In addition, we propose an evaluation method for the robustness of social networks. Finally, the model simulation analysis is presented by using the dynamic model and our evaluation approach. As a result, we not only find these potential critical components, but also obtain the parameter value that can make the social network reach the strongest robustness level. The simulation results show the validity and practicality of the proposed model on social networks. This research provides an effective and practical method to enhance the robustness in cascading failures control and defense in social networks.

Additionally, the proposed method also could be widely used in traffic, supply chain, power network to find out those critical components. If the key intersections are protected in advance, the robustness of such networks will be enhanced. The future work should further consider emergency strategy after the failures of the important components. We expect that the presented model may help us to promote the construction of social systems and better understand cascading failure phenomena in the real society.

7. Acknowledgment

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