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Key Factors Influencing Network Resilience in Dynamical Networks

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Abstract: There has been much recent research focusing on the resilience of networks, providing theoretical insights into the effective response of real-world systems systems to disasters. However, few studies have analyzed the factors that affect the resilience of networks. And the network operation process varies greatly so that the dynamic behavior of the network is a factor that has to be considered. To bridge these gaps, we analyze the factors affecting dynamic network resilience in terms of network dynamics. There are two main influencing factors: differentiation of failure probability, differentiation of impact. We build a generic resilience model for the network and validate these influencing factors by simulating them in different networks. By summarizing these factors, we point out constructive strategies. These strategies can help dynamic networks enhance network resilience, which is an important criterion for reducing network failures in real-world systems.

Keywords: Network Resilience; Dynamic Network; Spontaneous Recovery.

1. Introduction

There are various networks in our lives, and network science provides many useful tools to help us understand them. From economic sciences, social sciences, communication sciences and power sciences to biological sciences, many real-world systems can be abstracted into complex networks to allow us to explore the functions and characteristics of the systems[1]. Almost all networks are exposed to a wide variety of perturbations that can severely disrupt the system leading to network failures. For example, environmental degradation may lead to species extinction in ecological networks[2], cascading failure attacks on power grids may lead to widespread power outages[3]. So how to improve network resilience and thus avoid network failures is a hot topic. The resilience of the network structure refers to the ability of the network structure to cope with shocks in the face of external disturbances and to recover, maintain or improve the original system characteristics and functions[4]. According to the study of Gao et al., there are three main factors of network failure[5]: network structure, network dynamics and failure mechanism.

On the one hand, real-world networks are dynamic. Networks vary in shape, structure, and size, but the process of "running" the system varies even more. Many real-world networks are not static. On the other hand, the states of nodes of real-world networks propagate to each other. From transport structures to human bodies, the propagation of failures and damage is the basis of many network systems[6]. For example, during transmission or exposure, it is possible for disease to spread from an infected source to other neighboring individuals. Whereas many phenomena are characterized by complex contagion, nodes need to be connected to multiple sources to induce a change in their state[7]. Finally, nodes of real-world networks tend to have spontaneous recovery. Recently, it has been found that some systems exist to recover autonomously. For example, traffic may recover smoothly after congestion[8], the patient may recover spontaneously after a seizure[9].

Based on these general features, Majdandzic et al.[10] make the nodes also spontaneous recoverable so that there are three basic processes in the system: failure, damage conduction and recovery, and find interesting recoverable hysteresis phenomena. Podobnik et al.[11] modify the exogenous failure principle on its basis to make it more suitable for degree heterogeneous networks. However, the above studies all stop at the discovery of recovery phenomena without identifying the factors that influence network resilience.

In this work, we develop a framework for the resilience of dynamic networks and discover several factors that influence network resilience. In our framework, the network rapidly switches states when it reaches a certain critical point in both failure and recovery processes. The dynamic behavior of the network under the same parameter varies while the active state of the network varies, presenting a hysteresis phenomenon. The location of the critical point and the active state of the network can be used to indicate the resilience of the network, which can be used to observe the influence of the factors. We find that the average degree of the network in terms of network dynamics, there are two main influences: the differentiation of failure probability and the differentiation of impact. We perform simulations in different network models to verify the general validity of this factor.

2. Methodology

2.1. Construction of Spontaneous Recovery Model

We build a model to simulate the failure and recovery process of a dynamic network. For a network, each of its nodes has two states: active and failed. During the dynamic change of the network, nodes may be in four different states: internal failure, external failure, internal recovery, and external recovery:

a) Internal failure: an active node in the network may fail at any time, and this probability is the internal failure probability p.

b) External failure: a node has a certain probability of failure when the proportion of active neighbors is below the threshold m_f, and this probability is the external failure probability r.

c) Internal recovery: the failed nodes in the network will recover spontaneously after a period of time, and the defined time interval is the recovery time t.

d) External recovery: The node turns active when its neighbor active ratio is higher than the threshold m_f.

A network with an initial state that changes dynamically over time eventually reaches a state of dynamic equilibrium. This means that the internal state of the network is still changing, but the overall network state is balanced. We use the average proportion of active nodes z in the network to represent the state of the network. Adjusting parameters such as the failure probability and recovery time of the network, the network state will change again to reach a new equilibrium. According to Majdandzic et al.[10], recovery time t and average internal failure probability p jointly determine the average internal failure score p^* of network ($p^* = 1 - e^{-p\tau}$). So we can analyze the relationship between p^* and network state z to provide insights for network resilience improvement.

The nodes in the network may undergo internal failure or external failure, and the total failure probability is the superposition of both. The change in the average internal failure score p^* indicates the recovery or failure of the network as a whole, so we analyze the effect of changing p^* on the network state. Figure1 shows the failure and recovery processes of the network, demonstrating a clear hysteresis phenomenon. When the same network is in two different processes of recovery and failure, the states may also be different under the same parameters. During the slow failure of the network, a sudden first-order phase transition occurs at $p^{'}$. Threshold $p^{'}$ serves as a significant observation point, reflecting the resilience of the network.

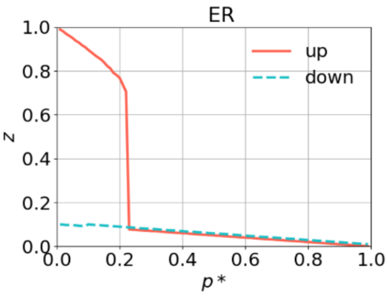

Figure 1. The failure and recovery process of the network in the ER network

2.2. Construction of the Network Model

We first use the classical Erdös-Rény(ER) networks model. When the network size reaches a certain scale, the state of the network is almost independent of the scale size. In order to fit the real-world network and make our system generalizable, we use the number of nodes n is 10000, the number of linked edges is 50000, and the degree $\langle k \rangle$ of each node is about 10.

Scale-free(SF) networks are widely used because they have the scale-free property of real-world networks. We modeled the SF network similarly. SF networks with power-law exponent of 2-3 have power-law distributions that are more realistic. Here we use SF networks with power-law exponent of 2.4. The rest of the properties are the same as those of the ER network.

Finally, we also selected the real network for validation. Large network in the Delaware Valley region of the Philadelphia network (13,389 nodes, 40,003 links), courtesy of Dr. W. Thomas Walker, Manager, Office of Corridor/ System Planning, Delaware Valley Regional Planning Commission, Philadelphia, Pennsylvania.

3. Experiments

Figure 1 shows the sudden first-order phase transition at $p^{'}$ during the slow failure of the dynamical network. Threshold $p^{'}$ serves as a significant observation point reflecting the resilience of the network. The degree of a node is an important parameter to measure the importance of the node. We consider that the difference in the distribution of node degrees affects the network resilience. Therefore, we change the weights of the parameters in the resilience model according to the degree of the nodes. Here, we consider the nodes with large degree as key nodes. It is worth mentioning that our experiments are based on the premise that the total network resources are guaranteed to be constant, i.e., the parameters of the remaining nodes may decrease when the parameters of some nodes are raised accordingly. This approach also fits our realistic system, where resources are not infinite and reasonable resource allocation is the key to study. We validated the two influencing factors we find in three different networks.

3.1. Differentiation of Failure Probability

Different degrees of nodes have different internal failure probabilities, resulting in the variability of internal failure probabilities of nodes. So the differentiation of failure probability affects the resilience of the network. In real systems, key nodes are more robust. The key nodes tend to have stronger protection and fault tolerance strategies. So we initially assign a weight to all nodes, the higher the degree, the smaller the weight, and the total weight of all nodes in the network is constant. Here, the greater the degree of the node, the smaller its probability of internal failure p^*. Accordingly, if the degree of a node is less than the average degree of the network $\langle k \rangle$, the probability of internal failure of the node can increase accordingly. According to this strategy, we simulate different network models separately [see Figure 2].

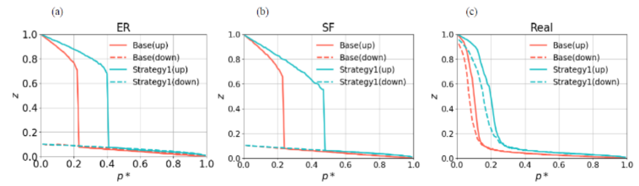

Figure 2. Comparison of the dynamic change process between the base networks and the networks in which the internal failure of key nodes is weakened. Where (a) is the ER network, (b) is the SF network, and (c) is the real network. The 'Base' curve is the dynamics of the baseline network and the 'Strategy1' curve is the dynamics of the network in which the internal failure of key nodes is weakened.

3.2. Differentiation of Impact

Different degrees of nodes have different impacts on neighboring nodes, i.e., differential probability of failure, which affects the resilience of the network. We assign a weight to all nodes, and the higher the degree the greater the weight. The weight represents the influence factor of the node, i.e., the node with the higher degree has more influence on other nodes. This fits well with our realistic system, where often the key nodes cause more impact. For example, in a traffic network, a congestion at a critical intersection has a greater impact on other roads. In our model, the comparison of the weighted average of nodes' active neighbor nodes with the threshold value indicates whether the node is likely to experience external failure. We simulate the simulation on different network models [see Figure 3].

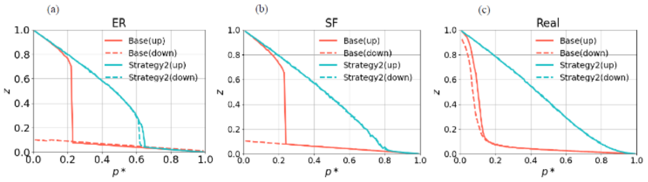

Figure 3. Comparison of the dynamic change process between the base networks and the networks in which the external failure caused by key nodes is enhanced. Where (a) is the ER network, (b) is the SF network, and (c) is the real network. The 'Base' curve is the dynamics of the baseline network and the 'Strategy2' curve is the dynamics of the network in which the external failure caused by key nodes is enhanced.

4. Results and Discussion

4.1. Results of the Effect of Differentiation of Dynamic Parameters between Nodes

Our experiments demonstrate the impact of our proposed three factors on network resilience. Figure 2 shows the comparison of the dynamic change process between the base networks and the networks in which the internal failure of key nodes is weakened, demonstrating that the weakening of internal failures of key nodes can help the network improve its resilience. The Figure 2(a) indicates that the ER network in which the internal failure of key nodes is weakened has a lager critical value of network state transition during failure than the baseline ER network, and the overall state of the network is more active. The Figure 2(b) demonstrates the generality of the effect in the SF network. The Figure 2(c) shows a comparison of the two networks in a real network. In the real system, it is difficult for us to change the internal failure probability of the nodes. However, discovering such influences can help us to use key node protection schemes. For example, in economic networks, large financial companies tend to use more schemes to keep themselves up and running, which improves the resilience for financial networks.

Figure3 shows the comparison of the dynamic change process between the base networks and the networks in which the external failure caused by key nodes is enhanced, demonstrating that enhancing the external failure caused by key nodes can help the network improve its resilience. The Figure 3(a) indicates that the ER network in which the external failure caused by key nodes is enhanced has a lager critical value of network state transition during failure than the baseline ER network, and the overall state of the network is more active. The Figure 3(b) shows that in the SF network, the failure threshold of the network disappears after changing the node influence, but the network is more active overall. The Figure 3(c) shows a comparison of the two networks in a real network. The difference in the influence of nodes in the network clearly influencing the network resilience. In response we propose a strategy to help the network improve its resilience. We should increase the influence of the key node so that the key node has a deeper influence on the rest of the nodes. Also when a new node is created or rebuilt, this node should be more dependent on the key node.

5. Conclusion

Resilience is a very important feature of the network. How to improve the resilience of a network has been a hot topic. Here, we find two factors that specifically affect the resilience of a network. We built three types of network models to verify their popularity.

The ER networks are commonly used in the field of complex networks, the SF networks fit real networks in probabilistic power-law distribution, and the Philadelphia road network is a real network. Then we develop a dynamic framework of the network considering the node failure, failure propagation and spontaneous recovery phenomena of the real network. By analyzing the dynamic behavior of the network, we find the factors affecting the network resilience in terms of network dynamics. There are the difference of failure probability and the difference of impact. We validate the impact of these two factors on network resilience on different network models and propose three strategies to improve network resilience: protecting key nodes, increasing the impact of key nodes, which has important practical implications.

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