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Development of a mitigation strategy against the cascading propagation of risk in R&D network

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A R T I C L E I N F O

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Considering severe consequences caused by cascading propagation of risk to R&D network, it is essential to develop a mitigation strategy against it for keeping network safety. Firstly, we propose the generation algorithm of R&D network based on two rules of preferential attachment. Then we develop a mitigation strategy on restoring failed firms against cascading propagation of risk, where three types of restoration methods (i.e. random restoration, high-degree restoration and high-capacity restoration) and restoration mechanism are described. Finally, we explore the effects of mitigation strategy under different values some critical parameters through numerical simulation. The simulation results show that all three restoration methods can generally enhance the robustness of R&D network, which is increasingly improved with the increasing homogeneity of firms' capacities distribution. High-capacity restoration is the most efficient one on mitigating cascading propagation of risk for any degree of capacity distribution, any proportion of restored firms and any kind of attack. But the gap between high-capacity restoration and any other restoration in the efficiency of mitigating cascading propagation of risk is increasingly less with the increasing proportion of restored firms. For any given restoration method, random attack has the least impact on the robustness of R&D network, whereas the other attacks have almost the similar impacts. This research work will provide a useful theoretical basis on building the optimal risk-mitigation strategy to keep the safety of R&D network in the real world.

1. Introduction

Facing the dynamic market, complex technology and limited resources, R&D collaborations among firms have become increasingly common in modern commercial activities, especially in those industries characterized by rapid technological innovation, e.g. information technology, electronic, pharmaceutical industries (Hagedoorn, 2002; Powell et al., 2005). As a new organizational pattern, R&D network allows firms to efficiently acquire the knowledge, skills and other physical resources needed for them to innovate (Todtling, 1999; Ahuja, 2000; König et al., 2012). Nevertheless, there still exist some interrelated potential risks in R&D network, such as market risk, collaboration risk, and ethical risk (Han, 2006). And when a risk occurs on some firms, it could trigger other potential risks on other firms (Fang et al., 2012). This phenomenon is called the cascading propagation of risk (Zhang and Yang, 2013), which might cause many member firms to malfunction just like cascading failures, and finally lead the entire R&D network to collapse if not controlled or prevented proactively. Therefore, it becomes essential to develop a mitigation strategy against the cascading propagation of risk for keeping the safety of R&D network.

In fact, cascading failures have become a common phenomenon in many of real-world networks, e.g. the large power grid blackout in North East USA and Canada on 14th August 2003 (US-C PSOTF, 2004), congestion of Internet (Goh et al., 2002), transport networks jam (Ferber et al., 2009; Wu et al., 2007), large-scale bankruptcy of social and economical systems (Wang et al., 2010c). Many researchers studied the dynamic characteristics of cascading failures, and proposed many useful models in diverse networks, such as ML model (Motter and Lai, 2002), CASCADE probabilistic model (Dobson et al., 2005), Binary Influence model (Watts, 2005), Sandpile model (Igbid, 2010), OPA model (Carreras et al., 2004), Coupled Map Lattice model (Wang and Xu, 2004) and Dynamic Flow model (Simonsen et al., 2008). Considering the potential severe consequences caused by cascading failures to the entire networks, some researchers started to study on mitigation or control strategies against cascading failures. So far, these proposed mitigation or control strategies can be mainly divided into two categories: network

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interdiction and line switching (Li et al., 2013). Network interdiction is a common approach to enhancing complex networks by designing components and/or allocating redundancies proactively before the occurrence of cascading failures (Zio et al., 2012). More specifically, this approach is to identify a set of elements to be interdicted whose failure may yield the largest disruption to the whole network from the viewpoint of static topological analysis. Several models have also been proposed to identify optimal strategies for network interdiction, e.g. genetic algorithm (Dai and Poh, 2002; Arroyo and Fernández, 2009), greedy algorithm (Bier et al., 2007) and nonlinear programming (Salmeron et al., 2004), evolutionary algorithm (Rocco and Ramirez-Marquez, 2009). However, these methods in network interdiction fail to describe the dynamic characteristics of an attack or failure, i.e. to account for the cascading propagation of an initial failure in the network (Zio et al., 2012). The second common approach is line switching, which is implemented immediately after the initial cascading failures. More specifically, line switching is to hinder the propagation of failures by cutting off the optimal set of links within the network. It has already been adopted intensively in the energy field for solving the problem of line overloads (Shao and Vittal, 2005; Granelli et al., 2006). For instance, Shao and Vittal (2005) proposed a corrective switching algorithm to relieve the optimization problem of wire overloads and voltage violations; Granelli et al. (2006) developed the deterministic branch-and-bound algorithm and genetic algorithm to resolve the large-scale mixed-integer programming problem of alleviating line overloads; Zio et al. (2012) suggested three different protection strategies against cascading failures based on the binary differential evolution (MBDE) algorithm (Wang et al., 2010a), i.e. global protection, local protection and hybrid protection; Li et al. (2013) further proposed a developed non-dominated sorting binary differential evolution (NSBDE) algorithm in order to alleviate component overloads that arise from cascading failures in the networks.

Based on the literature review about network interdiction and line switching, we find that the two approaches can lead to changes of network structure through adding redundancies or removing components, which can further induce an undesired severe structural damage to the network and split it into several isolated clusters (Motter, 2004; Eusgeld et al., 2009). Besides, adding, replacing or removing those identified components by adopting those optimization algorithms is inefficient, expensive and complex given the limited mitigation resources when the networks become large-scale (Zio et al., 2012). For these reasons, the two approaches may not be applicable to mitigating the cascading propagation of risk in R&D network. In this paper, we will focus on the mitigation strategy by restoring some failed firms without changing the topological structure of R&D network.

So far, there have been few works on how to mitigate the cascading failures by restoring the failed nodes (Mao, 2010). Yang et al. (2009) proposed an optimal weighting strategy of redistributing the overloads of those failed nodes to mitigate the traffic congestion in the Internet and power grids. Considering that neighboring nodes of those overloaded nodes may provide some protection resources for maintaining their normal functions, Wang introduced a local protection strategy against cascading propagation of failures in BA scale-free network (Wang, 2013a). Then Wang (2013b) proposed four kinds of protection methods (i.e. MHL, MLL, MHHC and MHC) based on the dynamic characteristics of the cascading failures in the scale-free networks. Chen et al. (2013) proposed the load-capacity optimal relationship (LCOR) model based on the relationship between capacity and load of weighted networks. These research works can provide some useful viewpoints and references for mitigating the cascading propagation of risk in R&D network. Therefore, we will develop a mitigation strategy against cascading propagation of risk by restoring those failed firms in R&D network, and then analyze its effects under different values of some critical parameters through numerical simulation. Our research work will provide a new useful theoretical basis on keeping the safety of R&D network in the real world.

2. Generation of R&D network

In order to propose the mitigation model against cascading propagation of risk in R&D network, the first step is to generate R&D networks, i.e. what is described as node and what is described as edge. First of all, we hypothesize that R&D network is modeled as a complex network with nodes (i.e. firms) and edges (i.e. relationships among firms). Then we let the undirected and unweighted graph $G(V, E)$ to denote R&D network, where $V = \{1, 2, \ldots, N\}$ is the set of nodes, $E = \{e_{ij} | i, j \in V\} \subseteq V \times V$ is the set of edges. Let $d_i (1 \leqslant i \leqslant N)$ be the degree of node i, which is the number of nodes connecting directly to node i. Define the average degree of network with $\langle k \rangle$, which is the average value of all nodes' degrees in network.

As we all know, there is a strong correlation between the topological structure of a complex network and its function. Therefore, the first step should be to explore properly the topology of R&D network, which has been extensively studied by Protogerou et al. (2007), Roediger-Schluga and Barber (2008), Hanaki et al. (2010), Cloodt et al. (2010), Wang et al. (2010b), Zhang et al. (2012). So far, there has been a general consensus that R&D network is typically characterized by the scale-free network that displays the presence of a few hubs connecting directly many firms. The main reason is that firms always collaborate with their partners consciously during the growth of R&D network (Wang et al., 2010b). And this preferential attachment will lead to an interesting phenomenon that those firms that have more partners are more likely to become the objects with which other firms expect to collaborate. Consequently, only a minority of firms become the hubs that obtain a great number of links in R&D network, whereas the remaining firms become the non-hub nodes that have a few links. In addition to this preferential attachment, there also exists another phenomenon in R&D network that most of firms will usually select their partners that are geographically close to them given the limited resources (Autant-Bernard et al., 2007; Zhang et al., 2012). Therefore, it is reasonable to assume that R&D network is also generated based on the spatial proximity of firms. Based on the two attachment rules, we finally give the generation algorithm of R&D network, which is shown as follows:

(1) Initially, it is hypothesized that R&D network starts with m_0 fully connected but randomly distributed firms. So we can assume that their coordinates are m_0 pairs of independent random values within the interval [0,1], i.e.$<x_1, y_1>$, $<x_2, y_2>$, …, $<x_{m0}, y_{m0}>$.

(2) At each time step, it is assumed that a new firm i with a randomly distributed coordinate $<x_i, y_i>$ ($i = m_0 + 1, m_0 + 2, \ldots, N$) is connected to m existing firms in R&D network based on the two attachment rules. Therefore, the probability Π_{ij} that a new firm i connects to an existing firm j is given as follows (Xu et al., 2007):

$$\Pi_{ij} \sim d_j^{\lambda} / D_{ij}^{\mu} \tag{1}$$

where d_j is the degree of firm j; D_{ij} is the Euclidean Distance between firm i and j, i.e. $D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$; $\lambda (\lambda \geqslant 0)$ and μ $(\mu \geqslant 0)$ are the parameters that govern the respective degrees of two attachment rules. Obviously, a higher value of λ will favor connecting to firms with higher degrees, whereas increasing value of μ will discourage longer