Research Article

Epidemic Spreading in Interdependent Networks

Lurong Jiang ¹, Qiaoyu Xu,¹ Bo Ouyang,² Yicong Lang,³ Yanyun Dai,¹ and Jijun Tong ¹

¹School of Information Science and Technology, Zhejiang Sci-Tech University, Hangzhou 310018, China

²College of Electrical and Information Engineering, Hunan University, Changsha 410015, China

³College of Information Science and Electronic Engineering, Zhejiang University 310027, Hangzhou, China

Correspondence should be addressed to Jijun Tong; jijuntong@zstu.edu.cn

Received 24 January 2018; Accepted 12 June 2018; Published 5 July 2018

Academic Editor: Qingling Zhang

Copyright © 2018 Lurong Jiang et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

We introduce a dynamic process of epidemic spreading into interdependent networks because, in reality, interdependent networks are facing the threat of epidemic spreading, which still lacks research. With our model, we reveal that (i) interdependent networks are more fragile than an isolated single network when facing the threat of an epidemic; (ii) an epidemic is not massively blocked by cascading failure, even if cascading failure spreads much faster; (iii) interdependent networks are more fragile, with a larger value of average degree compared with epidemic spreading. Moreover, we propose an iterative method for estimating the fraction of removed or failed nodes in a system of interdependent networks using percolation theory. This research can improve the comprehension of interdependent networks from the point of view of epidemic spreading.

1. Introduction

With deeper research in network science, people have begun to realize that many interdependent relations exist among networks [1–3]. One of the core features of interdependent networks is that the existence or functioning of nodes in one network highly interacts with and depends on the existence or functioning of nodes in another network and vice versa [4–6]. For example, in a typical system of interdependent networks formed by a communication network and power grid network, communication nodes depend on power stations for electricity supply, and power stations depend on communication nodes for control. Motivated by the exploration for the robustness of interdependent networks, current research on interdependent networks mainly focuses on the robustness of a system under the conditions of removing or deleting a fraction of nodes, which then leads to a chain reaction of node failure [7–11].

In reality, interdependent networks, especially those systems of interdependent networks formed by communication networks and other infrastructure networks, face many other threats, such as failure of overload [12–14] and epidemic spreading [15]. The interdependent relationship among networks is considered as a major issue in diffusion and spreading processes over a multilayer networks system

[16, 17]. In recent years, some researchers have explored the mechanism of epidemic spreading in multilayer networks, especially in interdependent networks according to the features of virus spreading in real multilayer network system [18, 19]. Most of these researches focus on revealing the epidemic threshold in interconnected and interdependent networks [20, 21]. However, until now, there are still only very few studies on these threats of epidemic spreading in interdependent networks. The spreading of an epidemic is one of the threats in interdependent networks. Some reports have shown that systems of interdependent networks coupled with a communication network and power grid network becomes vulnerable to the threat of computer viruses, leaving the power grid networks vulnerable to fail [22, 23]. Interdependent networks can lead to cascading failure after only a few nodes in a communication network become infected and no longer work.

Therefore, it is necessary to explore the dynamic process of epidemic spreading in interdependent networks. Although interdependent networks are threatened by epidemics, to the best of our knowledge, this subject still has largely unexplored issues.

In this study, we introduce the dynamic process of epidemic spreading into interdependent networks and explore the complicated dynamical interplay between epidemic

FIGURE 1: Node status transition in interdependent networks. The statuses S, I, R, and F are abbreviations for susceptible, infected, removed, and failed, respectively.

spreading and cascading failure in interdependent networks using percolation theory. The remainder of this article is organized as follows. In Section 2, we introduce the network model and epidemic spreading model. In Section 3.1, we qualitatively analyze the results of epidemic spreading in interdependent networks. In Section 3.2, we propose an iterative method for estimating the fraction of removed or failed nodes in a system of interdependent networks using percolation theory and validate it via simulations. Section 4 provides concluding remarks.

2. Models

2.1. Network Model. We first present an interdependent network model to describe the coupled patterns system structure. To simplify and clarify the results, we make reference to the model presented in [4] to construct interdependent networks. A system of interdependent networks Π consisting of two networks, A and B , is considered. Without loss of generality, networks A and B , with the same size $N = N^A = N^B$ and the same average degree $\langle k \rangle = \langle k^A \rangle = \langle k^B \rangle$, follow degree distributions of $p^A(k)$ and $p^B(k)$, respectively. These two networks are coupled with random bidirectional interdependent links: (i) the functioning of an arbitrary node a_i in network A depends and only depends on a randomly picked node b_i in network B and vice versa; (ii) if a_i stops functioning, b_i also stops functioning and vice versa. Here, we say that node a_i depends on node b_i and vice versa.

2.2. Dynamical Behavior Model. For example, in a system of interdependent networks Π , network A is a communication network through which the epidemic spreads, while network B is a power grid network. Combining the SIR epidemic spreading model and interdependent networks model, nodes statuses transition relations are revealed, as in Figure 1. In network A , an arbitrary node is only in one of the four statuses: **susceptible**, **infected**, **removed**, and **failed**. Susceptible nodes are those healthy and functioning nodes that can be infected. Infected nodes have the ability to

infect their susceptible neighbors. Removed nodes are those nonfunctioning nodes from infected status, which cannot be infected again. A susceptible node becomes infected with a probability β for each of its links, leading to an infected node, while an infected node becomes removed with probability γ for every time step. The epidemic effective spreading rate is $\lambda = \beta/\gamma$. Without loss of generality, we let $\gamma = 1$. A node in network A fails due to three possible reasons: (i) an infected node loses its dependent node in network B ; (ii) a susceptible node loses its dependent node in network B ; (iii) a susceptible node is not in the mutually connected clusters (MCC). Both removed and failed nodes in network A are nonfunctioning and cannot provide support for nodes in network B . These failed nodes also no longer interact with other nodes in the consequent process either.

In network B , each node is in only one of two statuses: **susceptible** and **failed**. A susceptible node in network B fails if (i) it loses its dependent node in network A or (ii) it is not in the giant component formed by susceptible nodes. The dynamic process of epidemic spreading in interdependent networks is detailed in the following steps:

- (1) First, all nodes in the system of interdependent networks Π are susceptible. Randomly select a few nodes in network A as the initial infected nodes.
- (2) *Substep 2.1.* In network A , for every link connecting an infected node to a susceptible node, the susceptible node becomes infected with probability λ , and, for every infected node, it becomes removed with probability 1.
Substep 2.2. The removal of nodes in network A may cause chain reaction of nodes failure in both networks A and B . Repeat these cascades until all remaining nodes in network A are in the MCC and supported by nodes in network B and vice versa.
- (3) If there still exist infected nodes in network A , go back to (2) to start the next stage of epidemic spreading; otherwise, the process halts.

FIGURE 2: An example of epidemic spreading in a system of interdependent networks Π . Links inside networks A and B are shown as arcs, while interdependent links between networks A and B are shown as horizontal straight lines. Susceptible nodes in networks A and B are marked as $\circ$ and $\square$, respectively. Infected nodes in network A are marked as $\bullet$. Removed and failure nodes are no longer functioning; thus, these nodes and the links to them are not presented in this figure.

Note that we make an important assumption, i.e., that the time scale of the cascading failure is much smaller than that of epidemic propagation. This is because we consider the duration of cascading failures as much longer than that of epidemic spreading. For example, the cascading overload of the power grid network in the United States and Canada in 2003 only lasted for 8 minutes [24], while the spread of a computer virus can usually last for several months [25, 26]. Therefore, in our model, every single substep of epidemic spreading is executed until the chain reaction of node failure stops.

2.3. An Example. To better understand the model, we give a simple example here, as shown in Figure 2. Networks A and B are coupled with each other to form a system of interdependent networks Π . Node a_i in network A depends on node b_i in network B and vice versa. First, all nodes in networks A and B are susceptible and functioning. Then, node a_1 in network A becomes infected as shown in Figure 2(a) and the system Π falls into an unstable dynamic process. In stage 1, node a_3 is infected by node a_1 with probability λ , and then a_1 is removed due to infection. Node a_2 fails because it does not connect to the MCC. In network B , nodes b_1 and b_2 fail because they lose their dependent nodes a_1 and a_2 in network A . Then, all survival nodes (including node a_3) in network A connect to the MCC and are supported by nodes in network B and vice versa. Therefore, stage 1 finishes as illustrated in Figure 2(b). However, there still exists an infected node in network A ; thus, the dynamic process enters into stage 2. Node a_5 becomes infected with probability λ as it connects to node a_3 ; then, node a_3 is removed. Node b_3 fails because it loses its support node a_3 . Then, all survival nodes in network

A connect to MCC and are supported by nodes in network B and vice versa. Therefore, stage 2 finishes, as shown in Figure 2(c). Because there still exists an infected node a_5 in network A , the dynamic process enters the next stage. In stage 3, none of the neighbors of a_5 in network A become infected, and node a_5 is removed after a time step. Node a_4 fails because it does not connect to the MCC in network A . Nodes b_4 and b_5 fail because a_4 and a_5 either fail or are removed in this stage. Now, there is no infected node in network A , and the dynamic process halts; thus stage 3 is the final status after epidemic spreading in interdependent networks.

3. Analysis

3.1. Qualitative Analysis. In this section, we qualitatively analyze the epidemic spreading in interdependent networks using the simulation results. Figures 3 and 4 exhibit the fractions of removed nodes σ_r^A and failed nodes σ_f^A in network A and the fraction of failed nodes σ_f^B in network B with varied epidemic effective spreading rates λ , in coupled ER (Erdős Rényi) and BA (Barabási Albert) networks. Notice that the fraction of failed nodes in network B equals the sum of the fractions of removed and failed nodes in network A , which indicates that $\sigma_f^B = \sigma_r^A + \sigma_f^A$. All the results shown are averaged over 50 realizations. The performances of results are enumerated qualitatively as follows.

- (1) Interdependent networks are more fragile than an isolated single network with the same value of average degree k when compared with epidemic spreading. Both $\sigma_r^A + \sigma_f^A$ and σ_f^B exist as two critical points, which vary by λ . First, there is a small critical value of λ , at

FIGURE 3: Numerical simulations of coupled ER networks with $\langle k \rangle = 6, 8, 10, 12$ and $N = 5000$.

FIGURE 4: Numerical simulations of coupled BA networks with $\langle k \rangle = 6, 8, 10, 12$ and $N = 5000$.

which $\sigma_r^A + \sigma_f^A$ and σ_f^B increase from zero to nonzero. This indicates that the epidemic starts to spread out in network A and begins to lead to a chain reaction of cascading failure in both networks A and B. We believe this critical value of λ is the same as the critical value of the epidemic effective spreading rate in an isolated single network with the same structure as network A. This is because the cascading failure in interdependent networks is caused by the spreading of the epidemic. When λ is extremely small, only very few nodes become infected, and it is too far from the threshold to lead to a chain reaction of cascading failure. Second, by further increasing λ , $\sigma_r^A + \sigma_f^A$ and σ_f^B increase to 1. This critical moment implies that epidemic and cascading failure kill all nodes in system II. The appearance of these two critical points indicates the fragility of interdependent networks compared with epidemic spreading.

- (2) An epidemic is not blocked massively by a cascading failure; even the speed of a cascading failure is much faster than that of epidemic spreading. When λ is sufficiently large, an epidemic can still infect most nodes in network A, although the strength of the cascading failure is much more intense than that of

FIGURE 5: In each time step of epidemic spreading, the fraction of newly removed and failed nodes in network A ($\Delta \phi_r^A$ and $\Delta \phi_f^A$, respectively) and newly failed nodes in network B ($\Delta \phi_f^B$) in a coupled ER network with $\langle k \rangle = 10$ and $\lambda = 0.18$ is shown. All the results shown are averaged over 50 realizations.

epidemic spreading. Figure 5 exhibits the dynamic process of epidemic spreading and cascading failure in the time domain. In each time step of epidemic spreading, only a small fraction of nodes in network A are removed from infected status and cause another

small fraction of nodes to fail in both networks A and B . Therefore, the intensity of cascading failure is not strong enough to block an epidemic, although cascading failure spreads much faster than an epidemic at each time step.

- (3) Interdependent networks are more fragile, with a larger value of $\langle k \rangle$ compared with epidemic spreading. In contrast, interdependent networks with the same network structure as our model are more fragile, with a smaller value of $\langle k \rangle$ compared with cascading failure [4]. This contradictory performance is caused by the different mechanisms of these two dynamic processes. In [4], cascading failure is first caused by the removal of $(1-p)$ fraction of nodes in network A at first. With the increase of $\langle k \rangle$, the probability that a functioning node is not in the MCC decreases, and the robustness of interdependent networks against cascading failure is improved. In our model, with a higher value of $\langle k \rangle$, it is easier for the epidemic in network A to spread out, leading to a more intense cascading failure.

3.2. Quantitative Analysis. In this section, we quantitatively analyze the proportion of removed nodes σ_r^A and failed nodes σ_f^A in network A and the proportion of failed nodes σ_f^B in network B .

3.2.1. Two Types of Percolation Processes. The spreading of an epidemic is a *bond percolation* process [27, 28]. The process of epidemic spreading is equivalent to selecting a link from a network with probability λ , and the outbreak of an epidemic indicates that the set of chosen links forms a connectivity cluster. Cascading failure is equivalent to a *site percolation* [29, 30]. In our model, when an epidemic spreads out, there exist several nodes in network A participating in both bond percolation and site percolation. We assume that these nodes in network A belong to the bond percolation process rather than to the site percolation process, because, in each time step, the spreading of the epidemic causes a further dynamic process of cascading failure and cascading failure is not strong enough to block an epidemic as mentioned in the **Qualitative Analysis**.

We denote s_k^A and b_k^A as the probability that a node of degree k in network A participates in site percolation and bond percolation, respectively. We denote f_k^A and r_k^A as the probability that a node of degree k in network A fails or is removed, respectively, after the dynamic process terminates in steady state. We denote s_k^B and f_k^B as the probability that a node of degree k in network B participates in site percolation or fails in steady state, respectively. According to our assumption regarding those nodes for both participating bond percolation and site percolation, we have

$$f_k^A = (1 - b_k^A) s_k^A, \quad (1)$$

$$r_k^A = b_k^A, \quad (2)$$

$$f_k^B = s_k^B. \quad (3)$$

In a coupled degree-degree uncorrelated interdependent system of networks, the neighbor of an arbitrary node in network A becomes a failed node or removed node with probability ϕ^A or ρ^A , respectively, and the neighbor of an arbitrary node in network B becomes a failed node with probability ϕ^B , which are calculated as follows:

$$\phi^A = \sum_j \frac{j p_j f_j^A}{\langle k^A \rangle} = \sum_j \frac{j p_j (1 - b_j^A) s_j^A}{\langle k^A \rangle}, \quad (4)$$

$$\rho^A = \sum_j \frac{j p_j r_j^A}{\langle k^A \rangle} = \sum_j \frac{j p_j b_j^A}{\langle k^A \rangle}, \quad (5)$$

$$\phi^B = \sum_j \frac{j p_j f_j^B}{\langle k^B \rangle} = \sum_j \frac{j p_j s_j^B}{\langle k^B \rangle}. \quad (6)$$

3.2.2. The Proportion of Removed Nodes in Network A. In network A , a susceptible node will be infected with probability λ for each link connecting to an infected node. Therefore, considering the locally tree-like approximation in percolation, the probability that nodes of degree k in network A participate in bond percolation is

$$b_k^A = 1 - \left(1 - \lambda \sum_j \frac{j p_j b_j^A}{\langle k^A \rangle} \right)^{k-1} = 1 - (1 - \lambda \rho^A)^{k-1}. \quad (7)$$

Substituting (7) into (2), we get the probability that nodes of degree k in network A will become removed nodes is

$$r_k^A = b_k^A = 1 - (1 - \lambda \rho^A)^{k-1}. \quad (8)$$

3.2.3. The Proportion of Failed Nodes in Network A. From a microscopic view, the failure of a coupled pair of nodes a_i and b_i starts from one side to the other side. Thus, we define two parameters describing the direction of reaction between this coupled pair of nodes:

- (i) α : the probability that the failure of node a_i in network A is caused by losing the dependent node b_i in network B directly.
- (ii) β : the probability that the failure of node b_i in network B is caused by losing the dependent node a_i in network A directly.

Then, an arbitrary node a_i of degree k in network A who participates in site percolation can be divided into two situations:

- (i) The probability that the failure of a_i is caused by losing the dependent node b_i directly is defined as

$$s_k^{A1} = \alpha. \quad (9)$$

- (ii) The probability that node a_i fails and the failure is NOT caused by losing the dependent node b_i directly is defined as

$$s_k^{A2} = (1 - \alpha) (\rho^A + \phi^A)^k. \quad (10)$$

Substituting (8), (9), and (10) into (1), we can get the probability that nodes with degree k in network A fail

$$\begin{aligned} f_k^A &= (1 - r_k^A) (s_k^{A1} + s_k^{A2}) \\ &= (1 - r_k^A) (\alpha + (1 - \alpha) (\rho^A + \phi^A)^k). \end{aligned} \quad (11)$$

3.2.4. The Proportion of Failed Nodes in Network B. Similarly, an arbitrary node b_j of degree k in network B that participates in site percolation can be divided into two situations:

- (i) The probability that the failure of b_j is caused by losing the dependent node a_j directly is defined as

$$s_k^{B1} = \beta. \quad (12)$$

- (ii) The probability that node b_j fails and the failure is NOT caused by losing the dependent node a_j directly is defined as

$$s_k^{B2} = (1 - \beta) (\phi^B)^k. \quad (13)$$

Substituting (12) and (13) into (3), we can get the probability that nodes with degree k in network B fail:

$$f_k^B = s_k^B = s_k^{B1} + s_k^{B2} = \beta + (1 - \beta) (\phi^B)^k. \quad (14)$$

3.2.5. The Relationship between Parameters α and β . According to the definition of α , it is equivalent to the probability that a node of network B fails first and then leads to the failure of a random node in network A as shown in the following equation:

$$\alpha = \sum_j p_j s_j^{B2} = \sum_j p_j (1 - \beta) (\phi^B)^j. \quad (15)$$

β is equivalent to the probability that a node of network A is removed or fails first and then leads to the failure of a random node in network B as follows:

$$\begin{aligned} \beta &= \sum_j p_j (b_j^A + (1 - b_j^A) s_j^{A2}) \\ &= \sum_j p_j (r_j^A + (1 - r_j^A) (1 - \alpha) (\rho^A + \phi^A)^j). \end{aligned} \quad (16)$$

3.2.6. The Proportion of All Nodes. Now we achieve the derivation by using (4), (5), (6), (8), (11), and (14). For clarity, we relist them as follows:

$$\phi^A = \sum_j \frac{j p_j f_j^A}{\langle k^A \rangle}, \quad (17)$$

$$\rho^A = \sum_j \frac{j p_j r_j^A}{\langle k^A \rangle}, \quad (18)$$

$$\phi^B = \sum_j \frac{j p_j f_j^B}{\langle k^B \rangle}, \quad (19)$$

$$r_k^A = 1 - (1 - \lambda \rho^A)^{k-1}, \quad (20)$$

$$f_k^A = (1 - r_k^A) (\alpha + (1 - \alpha) (\rho^A + \phi^A)^k), \quad (21)$$

$$f_k^B = \beta + (1 - \beta) (\phi^B)^k. \quad (22)$$

Obviously, these six equations depend on each other. Thus we can get the fraction of removed nodes ρ^A and the fraction of failed nodes ϕ^A of network A and the fraction of failed nodes ρ^B of network B in a steady state from these six equations via the following iteration process:

- (1) Assign a very small initial value to $r_{k_{\min}}^A$, where $k_{\min}$ represents the minimum degree of nodes in network A . Let $r_k^A = 0 (k \leq k_{\min})$, $f_k^A = 0$, and $f_k^B = 0$. Substitute r_k^A , f_k^A , and f_k^B into (17), (18), and (19) and get the initial values of ϕ^A , ρ^A , ϕ^B , α , and β .
- (2) Substitute ϕ^A , ρ^A , ϕ^B , α , and β into (20), (21), and (22) to get the values of r_k^A , f_k^A , and f_k^B . Next, substitute the new values of r_k^A , f_k^A , and f_k^B into (17), (18), and (19) and then update ϕ^A , ρ^A , ϕ^B , α , and β . Repeat this step until convergence.
- (3) Get the fraction of removed and failed nodes in network A by using $\sigma_r^A = \sum_k p_k r_k^A$ and $\sigma_f^A = \sum_k p_k f_k^A$ and the fraction of failed nodes in network B by using $\sigma_f^B = \sum_k p_k f_k^B$.

4. Simulations and Discussion

We test the validity of the analytical predictions/results in coupled ER random networks and coupled BA scale-free networks with varied average degree $\langle k \rangle = 6, 8, 10$. The simulation results are illustrated in Figures 6–11. Each data point is the average of 50 dependent realizations.

It can be seen from Figures 6–11 that, on the whole, our theoretical values are in good, though not perfect, agreement with the simulation results. In Figures 6–11 (a), the epidemic breaks out if λ is larger than a critical value. When λ is large enough for the epidemic to break out, the theoretical value of σ_r^A is a little smaller than the simulation result of σ_r^A . As $\langle k \rangle$ increases, the deviation of σ_r^A between the theoretical value and simulation result becomes smaller. In contrast, the theoretical value of σ_f^A becomes larger than the simulation result of σ_f^A , which is larger than the simulation results of σ_f^A when the epidemic breaks out, and the deviation of σ_f^A decreases as $\langle k \rangle$ increases, as shown in Figures 6–11 (b). The reason for these deviations is that nodes that participate both in the bond percolation (epidemic spreading) and in site percolation (cascading failure) processes are supposed to belong to the former one in the theoretical prediction. Therefore, in network A , the fraction of removed nodes is

FIGURE 6: Coupled ER networks with $\langle k \rangle = 6$. FIGURE 7: Coupled ER networks with $\langle k \rangle = 8$. FIGURE 8: Coupled ER networks with $\langle k \rangle = 10$.

overvalued, while the fraction of failed nodes is undervalued. However, the theoretical values of σ_r^A and σ_f^A can describe the trend of simulation values of σ_r^A and σ_f^A with increasing λ , as shown in Figures 6–11(a),(b). In Figures 6–11 (c), the fraction of nonfunctioning nodes in networks A and B is well estimated.

In order to understand the dynamic behaviors closer to the real network topology structure, we further constructed

an scene that a wireless network coupled with a scale-free network. Assume that epidemic spreads in the wireless network, which causes the entire coupled networks into cascading failure. We select DNG (Delaunay triangulation graph), KNN (k-nearest neighbor), and LAEE (local-area and energy-efficient) topologies for wireless networks [31]. In the experiment, the number of nodes in each network is 4000, and the transmission range is 100 meters. Each value is the average of 50 dependent realizations. As Figure 12(a)

FIGURE 9: Coupled BA networks with $\langle k \rangle = 6$. FIGURE 10: Coupled BA networks with $\langle k \rangle = 8$. FIGURE 11: Coupled BA networks with $\langle k \rangle = 10$.

shows, with the epidemic effective spreading rate λ increases, only some nodes in the wireless network eventually become removed. This shows that the spread of epidemic has been significantly hampered in these coupled structure. The reason for this phenomenon is that when λ is very large, a large number of nodes in the network are removed and failed, and then some of the epidemic transmission paths are cut off, as shown in Figure 12(b). Compared with separate wireless networks, coupled networks of wireless networks and other

networks are more vulnerable to epidemic spreading. This is because there are both epidemic transmission and cascade failure in these coupled networks, as shown in Figure 12(c).

5. Conclusion

Researching interdependent networks has been one of the hotspots of complex network science in recent years. Current studies on interdependent networks mainly focus on the

FIGURE 12: Numerical simulations of coupled wireless network and BA network with $\langle k \rangle = 6$.

robustness of a system with the condition of deleting a fraction of nodes. In reality, interdependent networks face other threats, such as the spread of epidemics, which still lacks research. Therefore, we propose a model that introduces the dynamic process of epidemic spreading into interdependent networks. With our model, we reveal that (i) interdependent networks are more fragile than an isolated single network when facing the threat of an epidemic, (ii) an epidemic is not massively blocked by cascading failure, even if cascading failure spreads much faster, and (iii) interdependent networks are more fragile, with a larger value of $\langle k \rangle$ compared with epidemic spreading. Moreover, we propose an iterative method for estimating the fraction of removed or failed nodes in a system of interdependent networks using percolation theory and validate it via simulations. We believe this research can improve the comprehension of interdependent networks from the point of view of epidemic spreading.

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 there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (61602417), Zhejiang provincial key research and development plan (2015C03023), Public Welfare Project of Zhejiang Province under Grant No. 2014C33102, and “521” Talent Project of ZSTU.

References

- [1] V. Rosato, L. Issacharoff, F. Tiriticco, S. Meloni, S. De Porcellinis, and R. Setola, “Modelling interdependent infrastructures using interacting dynamical models,” *International Journal of Critical Infrastructures*, vol. 4, no. 1-2, pp. 63–79, 2008.
- [2] R. Parshani, C. Rozenblat, D. Ietri, C. Ducruet, and S. Havlin, “Inter-similarity between coupled networks,” *EPL (Europhysics Letters)*, vol. 92, no. 6, 2010.
- [3] R. Parshani, S. V. Buldyrev, and S. Havlin, “Interdependent networks: reducing the coupling strength leads to a change from a first to second order percolation transition,” *Physical Review Letters*, vol. 105, Article ID 048701, 4 pages, 2010.
- [4] S. V. Buldyrev, R. Parshani, G. Paul, H. E. Stanley, and S. Havlin, “Catastrophic cascade of failures in interdependent networks,” *Nature*, vol. 464, no. 7291, pp. 1025–1028, 2010.
- [5] S. Havlin, H. E. Stanley, A. Bashan, J. Gao, and D. Y. Kenett, “Percolation of interdependent network of networks,” *Chaos, Solitons & Fractals*, vol. 72, pp. 4–19, 2015.
- [6] G. Dong, R. Du, L. Tian, and R. Liu, “Robustness of network of networks with interdependent and interconnected links,” *Physica A: Statistical Mechanics and its Applications*, vol. 424, pp. 11–18, 2015.
- [7] S. Watanabe and Y. Kabashima, “Cavity-based robustness analysis of interdependent networks: Influences of intranetwork and internetwork degree-degree correlations,” *Physical Review E*, vol. 89, no. 1, Article ID 012808, 2014.
- [8] X. Yuan, S. Shao, H. E. Stanley, and S. Havlin, “How breadth of degree distribution influences network robustness: Comparing localized and random attacks,” *Physical Review E*, vol. 92, Article ID 032122, 2015.
- [9] D. Hao, Z. Rong, and T. Zhou, “Extortion under uncertainty: zero-determinant strategies in noisy games,” *Physical Review*, vol. 91, no. 5, Article ID 052803, 2015.
- [10] A. Ranjesh, M. Ambrožič, S. Kralj, and T. J. Sluckin, “Computational studies of history dependence in nematic liquid crystals in random environments,” *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics*, vol. 89, no. 2, Article ID 022504, 2014.
- [11] X. Huang, S. Shao, H. Wang, S. V. Buldyrev, H. Eugene Stanley, and S. Havlin, “The robustness of interdependent clustered networks,” *EPL (Europhysics Letters)*, vol. 101, no. 1, p. 18002, 2013.
- [12] Z. Chen, W.-B. Du, X.-B. Cao, and X.-L. Zhou, “Cascading failure of interdependent networks with different coupling

- preference under targeted attack,” *Chaos, Solitons & Fractals*, vol. 80, pp. 7–12, 2015.
- [13] T. I. Tylec and M. Kuś, “Non-signaling boxes and quantum logics,” *Journal of Physics A: Mathematical and Theoretical*, vol. 48, no. 50, Article ID 505303, 17 pages, 2015.
 - [14] L. Tang, K. Jing, J. He, and H. E. Stanley, “Complex interdependent supply chain networks: cascading failure and robustness,” *Physica A: Statistical Mechanics and its Applications*, vol. 443, pp. 58–69, 2016.
 - [15] M. Salehi, P. Siyari, M. Magnani, and D. Montesi, “Multi-dimensional epidemic thresholds in diffusion processes over interdependent networks,” *Chaos, Solitons & Fractals*, vol. 72, pp. 59–67, 2015.
 - [16] R. Pastor-Satorras, C. Castellano, P. Van Mieghem, and A. Vespignani, “Epidemic processes in complex networks,” *Reviews of Modern Physics*, vol. 87, no. 3, pp. 925–979, 2015.
 - [17] M. Salehi, R. Sharma, M. Marzolla, M. Magnani, P. Siyari, and D. Montesi, “Spreading Processes in Multilayer Networks,” *IEEE Transactions on Network Science and Engineering*, vol. 2, no. 2, pp. 65–83, 2015.
 - [18] L.-X. Yang, X. Yang, and Y. Y. Tang, “A bi-virus competing spreading model with generic infection rates,” *IEEE Transactions on Network Science and Engineering*, vol. 5, pp. 2–13, 2018.
 - [19] L.-X. Yang, X. Yang, and Y. Wu, “The impact of patch forwarding on the prevalence of computer virus: A theoretical assessment approach,” *Applied Mathematical Modelling*, vol. 43, pp. 110–125, 2017.
 - [20] A. Saumell-Mendiola, M. A. Serrano, and M. Boguñá, “Epidemic spreading on interconnected networks,” *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics*, vol. 86, no. 2, 2012.
 - [21] H. Wang, Q. Li, G. D’Agostino, S. Havlin, H. E. Stanley, and P. Van Mieghem, “Effect of the interconnected network structure on the epidemic threshold,” *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics*, vol. 88, no. 2, 2013.
 - [22] A. R. Metke and R. L. Ekl, “Security technology for smart grid networks,” *IEEE Transactions on Smart Grid*, vol. 1, no. 1, pp. 99–107, 2010.
 - [23] R. Tan, V. B. Krishna, D. K. Y. Yau, and Z. Kalbarczyk, “Integrity attacks on real-time pricing in electric power grids,” *ACM Transactions on Information and System Security*, vol. 18, no. 2, 2015.
 - [24] B. Liscouski and W. Elliot, “Final report on the august 14, 2003 blackout in the united states and canada,” Causes and Recommendations. A Report to US Department of Energy 40, 2004.
 - [25] X. Han and Q. Tan, “Dynamical behavior of computer virus on Internet,” *Applied Mathematics and Computation*, vol. 217, no. 6, pp. 2520–2526, 2010.
 - [26] C. C. Zou, D. Towsley, and W. Gong, “Email virus propagation modeling and analysis,” Tech. Rep. TR-CSE-03-04, Department of Electrical and Computer Engineering, Massachusetts University, Amherst, Mass, USA, 2003.
 - [27] M. E. Newman, “Spread of epidemic disease on networks,” *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics*, vol. 66, no. 1, 016128, 11 pages, 2002.
 - [28] B. Karrer and M. Newman, “Message passing approach for general epidemic models,” *Physical Review E*, vol. 82, Article ID 016101, 2010.
 - [29] J. P. Gleeson, “Cascades on correlated and modular random networks,” *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics*, vol. 77, no. 4, Article ID 046117, 2008.
 - [30] A. Hackett, S. Melnik, and J. P. Gleeson, “Cascades on a class of clustered random networks,” *Physical Review E*, vol. 83, Article ID 056107, 2011.
 - [31] L. Jiang, X. Jin, Y. Xia, B. Ouyang, D. Wu, and X. Chen, “A scale-free topology construction model for wireless sensor networks,” *International Journal of Distributed Sensor Networks*, vol. 10, no. 8, Article ID 764698, 2014.

Submit your manuscripts at
www.hindawi.com