Hindawi
Complexity
Volume 2019, Article ID 7912857, 10 pages
https://doi.org/10.1155/2019/7912857

Research Article

The Effective Healing Strategy against Localized Attacks on Interdependent Spatially Embedded Networks

Kai Gong,[1] **Jia-Jian Wu**,[1] **Ying Liu**,[2] **Qing Li**,[1] **Run-Ran Liu**,[3] **and Ming Tang**[4,5]

[1] *School of Economic Information Engineering, Southwestern University of Finance and Economics, Chengdu, Sichuan, China*
[2] *School of Computer Science, Southwest Petroleum University, Chengdu, Sichuan, China*
[3] *Alibaba Research Center for Complexity Sciences, Hangzhou Normal University, Hangzhou, Zhejiang, China*
[4] *School of Information Science and Technology, East China Normal University, Shanghai, China*
[5] *Shanghai Key Laboratory of Multidimensional Information Processing, East China Normal University, Shanghai, China*

Correspondence should be addressed to Run-Ran Liu; runranliu@163.com and Ming Tang; tangminghan007@gmail.com

Received 7 February 2019; Revised 19 April 2019; Accepted 30 April 2019; Published 15 May 2019

Academic Editor: Rosa M. Lopez Gutierrez

Many real-world infrastructure networks, such as power grids and communication networks, always depend on each other by their functional components that share geographic proximity. A lot of works were devoted to revealing the vulnerability of interdependent spatially embedded networks (ISENs) when facing node failures and showed that the ISENs are susceptible to geographically localized attacks caused by natural disasters or terrorist attacks. How to take emergency methods to prevent large scale of cascading failures on interdependent infrastructures is a longstanding problem. Here, we propose an effective strategy for the healing of local structures using the connection profile of a failed node, called the healing strategy by prioritizing minimum degrees (HPMD), in which a new link between two active low-degree neighbors of a failed node is established during the cascading process. Afterwards, comparisons are made between HPMD and three healing strategies based on three metrics: random choice, degree centrality, and local centrality, respectively. Simulations are performed on the ISENs composed of two diluted square lattices with the same size under localized attacks. Results show that HPMD can significantly improve the robustness of the system by enhancing the connectivity of low-degree nodes, which prevent the diffusion of failures from low-degree nodes to moderate-degree nodes. In particular, HPMD can outperform other three strategies in the size of the giant component of networks, critical attack radius, and the number of iterative cascade steps for a given quota of newly added links, which means HPMD is more effective, more timely, and less costly. The high performance of HPMD indicates low-degree nodes should be placed on the top priority for effective healing to resist the cascading of failures in the ISENs, which is totally different from the traditional methods that usually take high-degree nodes as critical nodes in a single network. Furthermore, HPMD considers the distance between a pair of nodes to control the variation in the network structures, which is more applicable to spatial networks than previous methods.

1. Introduction

It is clear that almost all real-world infrastructure networks interact with each other [1]. This has led to a new field of study in network science that is called interdependent networks [2]. The interactions across networks keep systems functional by providing critical sources to each other. However, these dependency connections enhance the vulnerability of interdependent networks against random failures or malicious attacks by providing the risk of failure diffusion across networks [3], and even a small fraction of nodes can cause the breakdown of the whole network [4]. The robustness of interdependent networks has been studied in many aspects [5–8], such as the effects of attack strategies, topology properties, or coping methods across networks. Some infrastructural networks (like power grids and water networks) are subject to long-range dynamics [9], and the cascading processes are thus nonlocal in these networks [10–12]. In fact, many modern infrastructure networks are embedded in geographic space and the dependency connections among the functional components in different infrastructures are restricted by their spatial distance [13]. Therefore, it is reasonable to consider the space restrictions as an important property for the investigation of the interdependence of complex networks. Two-dimensional lattices can be used as a typical metaphor to model networks with spatial properties [14], and thus some interdependent systems embedded in the ground space can be represented by two coupled square lattices with nodes in one lattice depending on the ones in the other within a certain range [15–17], called *interdependent spatially embedded networks* (ISENs). It is worth noting that, facing random failures, the ISENs are more vulnerable than nonembedded interdependent networks [18].

Recent researches revealed that failures in systems are not often random [19]. *Localized attack* is a geographical attack induced by natural disasters (e.g., earthquakes) or malicious attacks (e.g., weapons of mass destruction); i.e., the connected cluster in a certain geographical radius breaks down [20, 21]. The main difference between localized attack and random failure is that the former is always limited to local area, while the latter is distributed throughout the whole network without any space restriction. Such localized attacks on some networks are significantly more destructive than random failures [22–25], since the failures of several nodes can trigger an avalanche. Therefore, it is interesting and of practical application to study how to enhance the resilience of ISENs against localized attacks. In the past years [26], several strategies have been proposed to restrain the cascading of failures on interdependent networks (like autonomous mechanism [27, 28] and protecting high-degree nodes [29, 30]). Moreover, there are self-healing procedures that are limited to a given set of redundant resources, and these procedures can highly improve the resilience of infrastructural networks [31–34]. Among them, the spontaneous recovery strategies of single network [35] and interdependent networks [36] have recently attracted more attention. Muro *et al.* [36] showed that the recovery strategy, which selects a pair of nodes that belong to the mutual boundary of the giant component during the cascading of failures and reconnecting them to the giant component and reactivating them, can greatly enhance the resilience of interdependent networks. However, the recovery strategy on ISENs may be effective to resist the spreading of random failures, but not for localized attacks [37]. This is because the localized attacks always simultaneously destroy a set of connected nodes and their edges. In order to avoid catastrophic events, it is necessary to improve the ratio of restored nodes on ISENs. On the other hand, when the localized attacks occur, considerable effort is made to reorganize the remaining networks by *healing* strategy [38], i.e., establishing new links among active nodes.

A lot of link-addition strategies for the network healing have been proposed in both single network [39] and interdependent networks [40–43]. For instance, Stippinger *et al.* [38] developed a simple healing strategy as a remedy of the collapse instability, where a new connectivity link is generated with a probability, called random healing, to bridge two random active neighbors of a failed node in the cascading process. However, the random healing may not work well for localized attacks or other types of attacks. Firstly, the random healing proved the effect of adding new links under random failures but in realistic failures may be resulting from localized attacks. Secondly, it is more reasonable to consider different healing strategies to response different types of failures caused by various attacks [44–47]. In this paper, we propose an effective strategy for the healing of local structures by using the connection profile of a failed node, called the *healing strategy by prioritizing minimum degrees* (henceforth labeled as HPMD), which establishes a new link between two active low-degree neighbors of a failed node during the cascading process. It is clearly different from the previous approaches that usually take the high-degree nodes as critical nodes. Meanwhile, HPMD also considers the distance between a pair of nodes to avoid changing the network structures too much. Applying HPMD to synthetic networks, we find that our strategy is more effective than other healing strategies, including random choice (HRC), degree centrality (HDC), and local centrality (HLC). Specifically, our strategy has a higher size of the final giant component, higher critical attack radius, and lower peak of the number of iterative cascade steps for a given quota of newly added links.

This paper is organized as follows: Section 2 describes the model of ISENs and the localized attack. Section 3 introduces the procedures of healing and the HPMD strategy. Section 4 shows the simulation results and corresponding analyses. Section 5 makes a summary and expectation for this work.

2. Network Model and Localized Attack

In this section, we introduce the interdependent spatially embedded networks and the localized attack.

2.1. Interdependent Spatially Embedded Networks. According to Ref. [15], the ISENs have two distinctive characteristics: (a) each node is only connected to the nodes in its spatial vicinity in a network; (b) the dependence links between networks are not random but have a certain dependency distance r, which represents the maximum distance from a node in one network to its counterpart node in another network. Here, for the sake of simplicity and without loss of generality, we generate two $N = L * L$ diluted square lattices (as the real power grids have a mean degree of $2.5 \leq \langle k \rangle \leq 3$ [48]) A and B with periodic condition, to represent the real complex system embedded in geographic space. In the ISENs, a node has two kinds of links: connectivity links and dependency links. Each node in network A is connected with its nearest neighbors in the same network by connectivity links and depends on a node in network B via a dependency link which is chosen at random from all the nodes within a radius r. That is, a node a_i located at (x_i, y_i) in network A is only coupled with a node b_j located at (x_j, y_j) in network B with the condition:

$$\begin{aligned} &\left|x_i - x_j\right| \leq r \\ \text{and } &\left|y_i - y_j\right| \leq r. \end{aligned} \tag{1}$$

This work used the same assignment of parameters as in Ref. [16], namely, $r = 15$, $L = 100$, and the value of $\langle k \rangle$ is approximately equal to 3. A schematic diagram of the ISENs can be found in Figure 1.

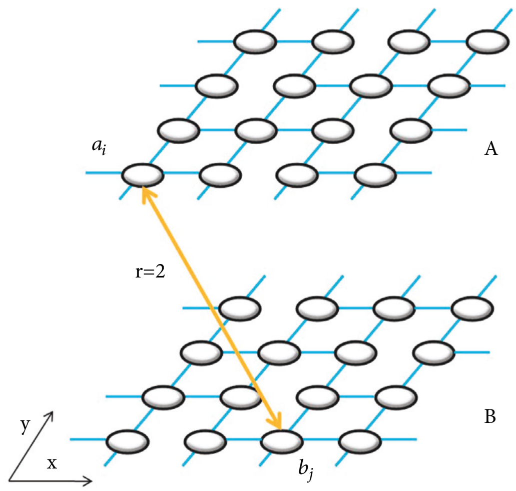


Figure 1: *A schematic diagram of the ISENs.* The ISENs are constructed by coupling two diluted square lattices A and B with the same size, where each node has two kinds of links: connectivity link (blue) and dependency link (yellow). Each node is connected with its neighbors via connectivity links, and each node a_i located at (x_i, y_i) in network A is coupled with one and only one node b_j located at (x_j, y_j) in network B via a dependency link, with the constraint $|x_i - x_j| \le r$ and $|y_i - y_j| \le r$. The dependency link means that for an interdependent node pair; if one node fails, the other fails too.

2.2. Localized Attacks. Localized attacks that are often caused by natural disasters or malicious attacks can result in geographically localized damage. A group of failed nodes concentrate in a geographical domain, triggering failure of adjacent nodes. According to Ref. [16], localized damage forms an initial circular hole with a root as center and the r_h as attack radius, and the failures propagate from the random location to the entire network. Following this way, we firstly initiate the localized attack process by randomly choosing a node in network A as a root. Next, we remove all nodes within a radius r_h from the root in the network, as the initial hole. The dependent partners of the removed nodes in network B fail and trigger more failures in network A due to the dependencies between networks. This cascading process will not terminate until no more nodes fail. After the attack, only nodes in the giant component (GC) of network are still functioning [49].

3. Healing Procedure and HPMD Strategy

3.1. Healing Procedure. The healing strategy adds new links among active nodes, which is immediately implemented at the first stage of the cascading failures, to avoid or resist the collapse of the interdependent networks [38]. The healing process mimics the repair or recovery of complex system in the real world: (i) failures propagate rapidly in networks, and damaged devices cannot be timely replaced by new ones; (ii) in many real infrastructure networks it is reasonable to reinforce adjacent active nodes of a failed node. After the failures occurring in network A, the healing strategy intervenes in that time step. Then the failures spread from network A to B, and the coupled nodes of the failed nodes are removed from the network B through the dependent links. Due to the dependence of embedded spatial systems, further failures might propagate back and forth within the system and are also intervened by healing strategy. Note that the traditional *random* healing strategy [38], which establishes a new link among two random active neighbors of a failed node, may greatly change the topology. Here, we denote $n = 0, 1, \ldots$ as the time steps of the cascading processes, and the procedures in the n-th step are given by the following:

(1) Cascading in network A, at n-th step:

Nodes in network A become failed if they lose dependent partners in network B at (n-1)-th step, or if they do not belong to the *GC* of network A via connectivity links.

(2) Healing in network A, at n-th step:

Select a pair of active neighbors of a failed node and build a link between them. Self-loop and multiple links are not allowed. This procedure will be repeated unless the maximum number of newly added links reaches.

(3) Cascading in network B, at n-th step:

Nodes in network B fail if they lose their counterpart nodes due to the cascade of failures, or if they do not belong to the *GC* of network B via connectivity links.

(4) Healing in network B, at n-th step:

It is the same as (2).

This procedure is repeated until a steady state reaches, and then we are left with the giant component. Note that a steady state reaches only when the network is still functioning and no more nodes fail, or fully collapsed.

3.2. HPMD Strategy. In a recent study [16], it is found that the localization of dependency links amplifies the destructive effect of localized attacks and leads to a cascading collapse of the whole network. The interdependent nodes will fail due to the loss of dependency partners. The next damage is highly concentrated around the initial hole via connectivity links, making a failure propagates back and forth. It is quite obvious that the most straightforward healing strategy is random choice (RC), where two random active neighbors of a failed node will be connected by a new link. However, there is no guarantee that this RC leads to the most effective healing. Furthermore, the RC strategy can change the network structures because it does not consider the distance between remote nodes of a new link. The low-degree nodes that bordered the initial hole are more easy to disconnect from the giant component and go to fail in the cascading failures, and failed nodes can disenable the corresponding dependent partners in the other network, which keep failures propagating [50]. On the contrary, the higher the degree of a node is, the lower the probability of failure is in next time step. Therefore, our strategy, namely, the healing strategy by prioritizing minimum degrees (HPMD), is reasonable to establish a new link between two active low-degree neighbors

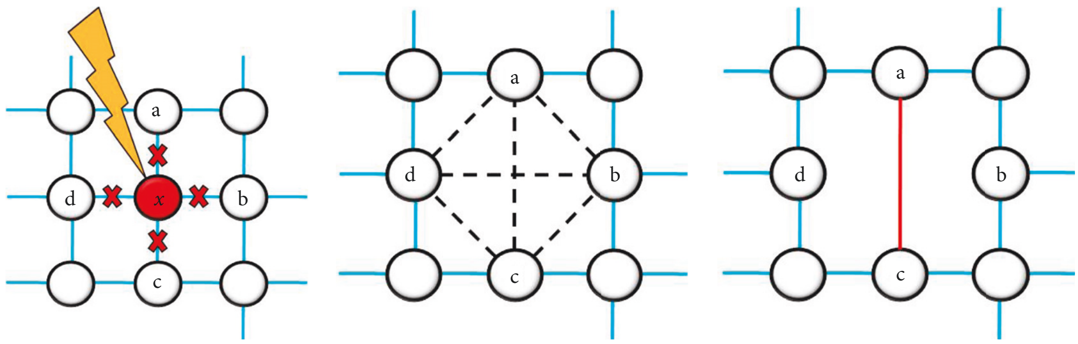


Figure 2: *A schematic illustration of HPMD strategy*: (a) a failed node x which is represented by red solid circle at the end of the arrow is removed and affects its functioning neighbors ($v_a^x, v_b^x, v_c^x, v_d^x$) via connectivity links (blue). (b) In random healing, two active neighbors of the failed node x are randomly chosen to establish a new link. (c) According to the HPMD strategy, by counting the number of connectivity links of active nodes v_a^x and v_c^x with $k_c(v_a^x) = k_c(v_c^x) = 2$ of the failed node x, and their distance that is equal to 2 in the original network, after calculating the healing priority index $H(v_a^x, v_c^x) = 4$, then a new connectivity link (red) is preferentially established between two remaining neighbors v_a^x and v_c^x to heal the network.

of a failed node. HPMD enhances the connectivity of low-degree neighbors and reduces the risk of dependency failures in each time step and is quite different from the previous approaches that usually take the high-degree nodes as critical nodes. Our healing strategy can limit the distance between two neighbors of a failed node to make sure connectivity links remain local. The procedures of HPMD at healing stage are described as follows (see Figure 2).

(1) In healing stage, F is the set of all failed nodes in the network.

(2) Let L be the union of all pairs (v_i^x, v_j^x) of active neighbors of a failed node x in F; self-loop and multiple links are not allowed. Then, we calculate the healing priority for each pair (v_i^x, v_j^x). The healing priority index H of pair (v_i^x, v_j^x) is defined as follows:

$$H\left(v_i^x, v_j^x\right) \underset{e_{i,j} \in local}{=} k_c\left(v_i^x\right) + k_c\left(v_j^x\right) \quad (2)$$

where $e_{i,j} \in local$ denotes the length of the shortest path between nodes v_i^x and v_j^x that are no more than 2 in original network. $k_c(v)$ denotes the current number of the remaining connectivity links of node v. In real world, the local information of a power station or an Internet node is easy to capture, but the global structural information is unavailable [51, 52]. If it is far from chosen range of functioning neighbors to failed nodes, the search region is wider, search time is longer, and computation complexity is higher. Furthermore, installing a new electrical cable between two remote stations in spatial system is impractical and expensive. Therefore, reconnecting two nodes in spatial neighborhood is a fast and costless way for healing the local structures of a spatial network.

(3) We sort all pairs in the L by healing priority index H in ascending order. If some pairs have the same H, randomly sort them.

(4) Next, we build a queue $Q = \{H_1, H_2, H_3, \ldots\}$, where H_i represents the ith healing priority index H. Select a node pair v_i^x and v_j^x from the queue in turn, and connect node v_i^x to node v_j^x by a new connectivity link.

(5) Repeat (4) until the maximum number of new links is reached, which is calculated as the total number of pairs in L multiplied by the healing rate ω.

Many criteria in complex networks have been presented for evaluating the importance of nodes [36]. To demonstrate the effect of HPMD, we use three well-known criteria to rank the priority of active neighbor pairs in the healing process: *random choice* (HRC), *degree centrality* (HDC), and *local centrality* (HLC).

(1) In HRC strategy, a pair of nodes in the union L are picked randomly.

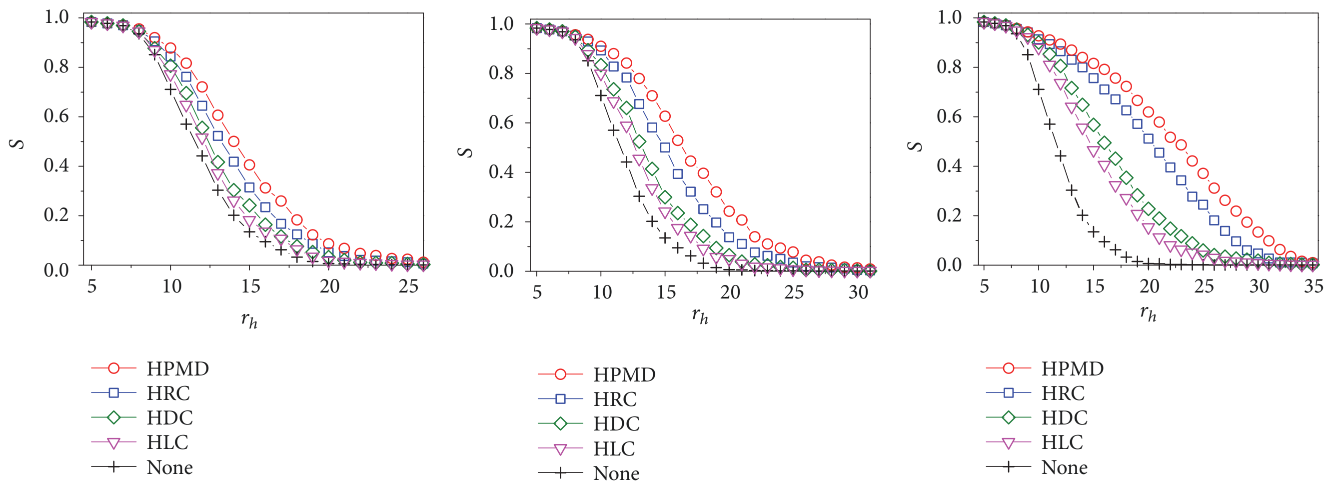
(2) In HDC strategy, we sort all pairs in L by healing priority index H in descending order, but not in ascending order. In other words, the new link is added between the pair of nodes with maximum degrees [53].

(3) In HLC strategy, the healing priority index H is calculated by computing local centrality of v_i^x and v_j^x, where the local centrality is defined as the total number of the nearest and the next nearest neighbors of node v as in Ref. [52, 54], and then all pairs in L by H are sorted in descending order.

4. Results

To compare the performance of our proposed strategy in healing process, we present experimental results of different strategies, including HRC, HDC, HLC, and HPMD strategies on ISENs when facing localized attacks. All experimental results are obtained by average over 10^4 independent runs for each healing rate ω and attack radius r_h.

For different healing rates ω, the robustness of ISENs under localized attacks with different healing strategies is shown in Figure 3. Here, we define r_h as attack radius of initial hole from network A and S as the size of the giant component at the end of the cascading failures [15, 38].



(a) $\omega = 3\%$ (b) $\omega = 5\%$ (c) $\omega = 10\%$

FIGURE 3: *The effectiveness of healing strategy on the giant component.* The size of the giant component S as a function of attack radius r_h under different healing strategies, for different $\omega = 3\%$ (a), $\omega = 5\%$ (b), and $\omega = 10\%$ (c), respectively.

The higher S indicates the better performance of healing strategy. In Figure 3, the black cross-shaped curve labeled as None represents the result without healing. It is obvious that the maintenance of network connectivity by using healing strategy is much better than that without healing under localized attacks, and the resilience of ISENs is improved. Furthermore, we compare HPMD with the other strategies for $\omega = 3\%$ (a), $\omega = 5\%$ (b), and $\omega = 10\%$ (c). It can be seen that from the perspective of S that the order of performance is HPMD > HRC > HDC > HLC in most cases of r_h, at different healing rates ω. The advantage of HPMD becomes more apparent as r_h increases. Results indicate that HPMD is, in general, more effective against localized attacks since it resists the collapse of the ISENs.

The critical attack radius r_c^h is the minimum radius of localized attacks needed to break the entire network [16]. It will trigger a cascade failure which destroys the entire network as long as $r_h > r_c^h$. A larger r_c^h means a better effect of healing strategy. We calculate the point of maximum fluctuation of σ of giant component S which is usually expected to be large for both first-order and second-order transitions [55–57], to estimate the r_c^h [see Figure 4(b)]. In Figure 4(a), the r_c^h of HPMD is always higher. The HPMD is significantly more effective and works better than three others in the same condition. In comparison, the HDC and HLC have similar results and perform the worst. Figure 4 indicates that HPMD works better than the other three strategies within a small certain healing rate ω and is more effective to resist localized attacks on the ISENs.

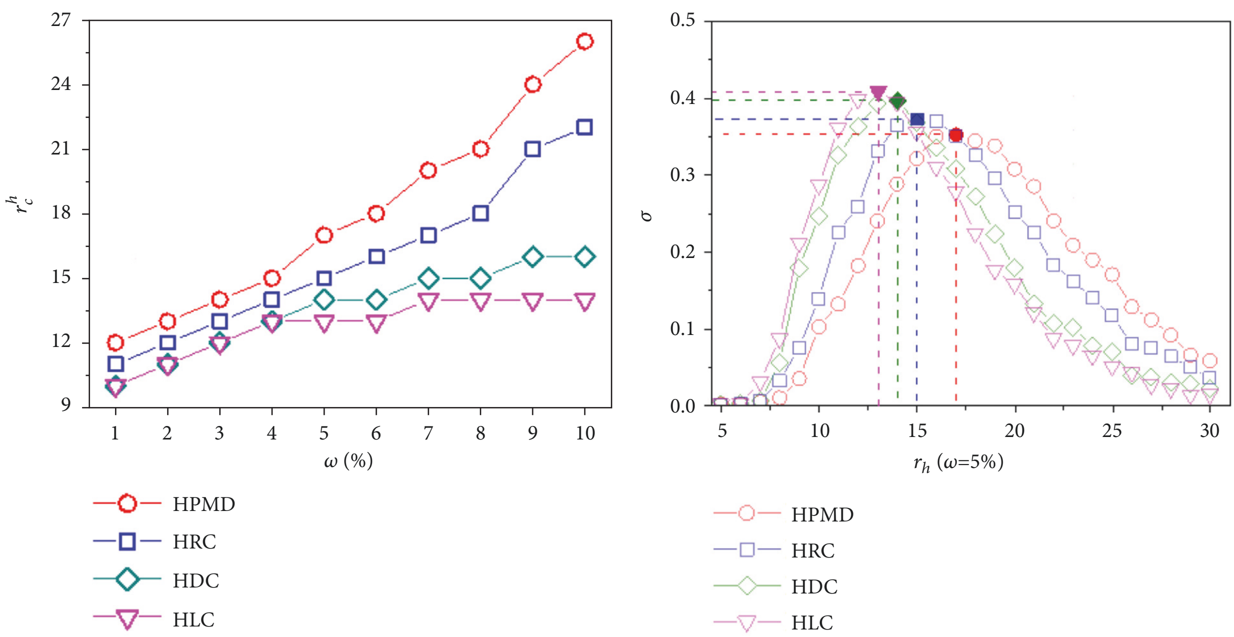
The NOI is the number of iterative cascade steps required for the ISENs to reach the steady state, which indicates the time scale of the process, as shown in Figure 5. It is known that in a conventional cascade failure the NOI displays a sharp peak at the critical threshold [36], which means the network requires a long period of time to reach the steady state. Therefore, an effective healing strategy is expected to have a low peak of NOI. Figure 5 shows that the peak of NOI is lower for that of HPMD, as compared with HRC, HDC, and HLC strategies. From these subfigures, we find the following: (i) the NOI increases with r_h, when $r_h < r_c^h$; (ii) the NOI with the HPMD displays a lower peak and few steps. The first result means that larger attack radius r_h requires higher NOI. The second indicates that the required time steps for controlling the failures by the HPMD are lease at the same attack radius, and r_c^h for HPMD is greater than all other strategies.

Let E_h be the total number of established new connectivity links during the healing process until the steady state reaches, which means that an efficient healing strategy is one that fewer new links are required when the cascade terminates. Figure 6 reports E_h as a function of attack radius r_h at different ω. It is shown that HPMD still has the best performance as E_h increases slowly, and HDC and HLC strategies will have a higher cost under the same conditions. The results further confirm that HPMD needs fewer new links to enhance the resilience in a reasonable cost. Clearly, our strategy is the first choice to determine which pairs of active neighbors of a failed node should be connected by a new link.

One drawback of random healing is that it does not consider the topology distance between nodes and may change the structure considerably by bridging long-range edges as the time goes on [38]. Here, the long-range edges refer to the links between two nodes whose topology distance $d > 2$ in the original network. Table 1 shows the proportion of long-range edges in the current network until steady state reaches at a certain ω. Let E_d be the number of long-range edges with original topology distance d in remaining networks at steady state, and let E_r be the total number of edges in remaining networks at steady state. Furthermore, we calculate the proportion of edges, $P(d) = E_d/E_r$, with a

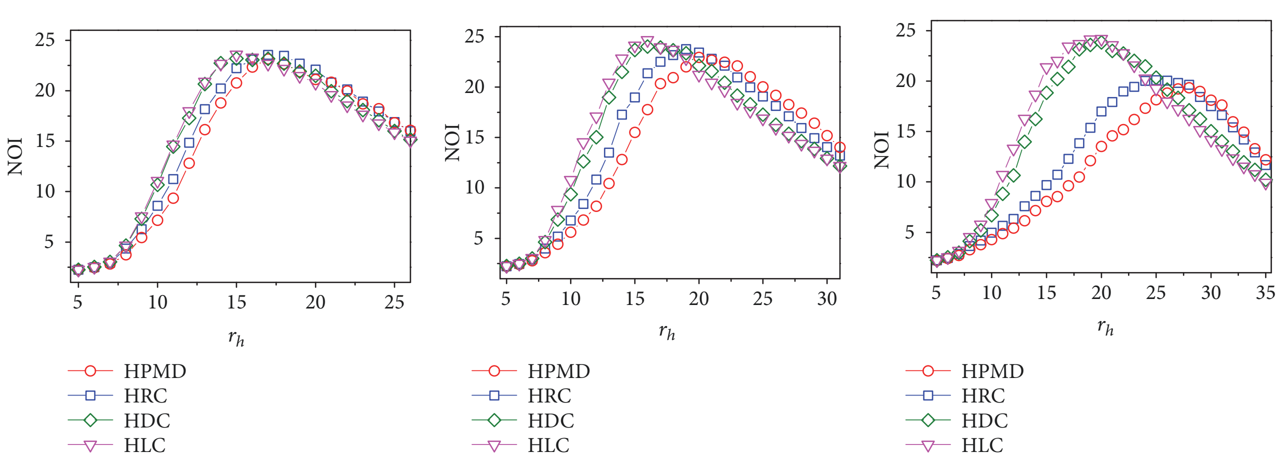
Table 1: Comparisons of the proportion of long-range edges between pairs under different healing strategies, when healing rate $\omega = 10\%$.

	$\overline{P}(d=1)$	$\overline{P}(d=2)$	$\overline{P}(d=3)$	$\overline{P}(d=4)$
HPMD	99.56%	0.44%	0%	0%
HRC	99.46%	0.51%	0.02%	0.01%
HDC	99.11%	0.83%	0.05%	0.01%
HLC	99.05%	0.80%	0.10%	0.05%



(a) (b)

Figure 4: *The effectiveness of healing strategy on the critical attack radius*. (a) The critical attack radius r_c^h as a function of healing rate ω under different healing strategies. (b) To estimate the r_c^h, we calculate the point of r_h of maximum σ of the size of the giant component by different healing strategies. For example, when $\omega = 5\%$, the r_c^h of HPMD is 17 for the reason that the fluctuation of giant component at that point ($r_h = 17$) is maximum ($\sigma = 0.35$).



(a) $\omega = 3\%$ (b) $\omega = 5\%$ (c) $\omega = 10\%$

Figure 5: *The effectiveness of HPMD on the number of iterative cascade steps*. The number of iterative cascade steps (NOI) required for the ISENs to reach the steady state as a function of attack radius r_h for different healing strategies, at different $\omega = 3\%$ (a), $\omega = 5\%$ (b), and $\omega = 10\%$ (c), respectively.

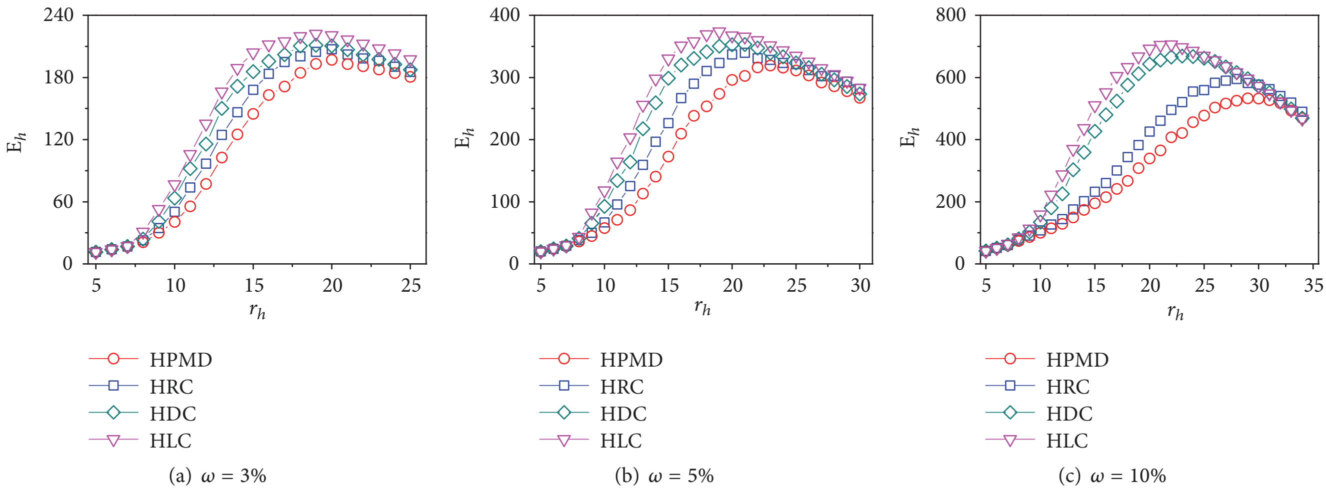


FIGURE 6: *The effectiveness of healing strategy on the number of established new links*. The total number of established new connectivity links during the healing process E_h as a function of attack radius r_h for different healing strategies, at different $\omega = 3\%$ (a), $\omega = 5\%$ (b), and $\omega = 10\%$ (c), respectively.

given original topology distance d. The average of $\overline{P}(d)$ over different attack sizes r_h is defined as

$$\overline{P}(d) = \overline{\sum_{r_h} P(d)} \tag{3}$$

where $r_h \in [4, 35]$ and $\Delta r_h = 1$, when $\omega = 10\%$. In Table 1, when $\overline{P}(d = 2)$, the order is HPMD < HRC < HDC < HLC, and the proportion of edges between remote nodes $\overline{P}(d = 3)$ and $\overline{P}(d = 4)$ are zero by the HPMD. It is because HPMD aims at adding the link only between two adjacent active neighbors of a failed node, and the changing of network structure is minor. As a result, the giant component at the end of the cascading process is still lattice structure by HPMD. In general, our proposed strategy can avoid changing the network structure a lot, which is more applicable to real spatial networks.

To study the influence of spatial constraints on healing effectiveness, we have performed experiments on the critical attack radius r_c^h as a function of the distance of dependency links r on the ISENs, as shown in Figure 7. The r_c^h of HPMD is higher than which of the other three strategies, when the distance of dependency links r is variable. Furthermore, we can see the nonmonotonic curves of the r_c^h that decrease firstly and then increase, because (i) for a small spatial distance (e.g., $r \leq 10$), where nodes can only couple with their adjacent nodes, the cascading failure is mostly restricted in a local area and a larger attack radius is required to initiate an avalanche; (ii) for an intermediate spatial distance, the failure could not only propagate away, but also lead to large scale of failed nodes. But even so, HPMD still has better performance compared with the other strategies; (iii) for a long spatial distance (e.g., $r = 100$) a given node's dependency link can be located farther away, and failures can also propagate away, but the density of failed nodes is too sparse to trigger a cascading process.

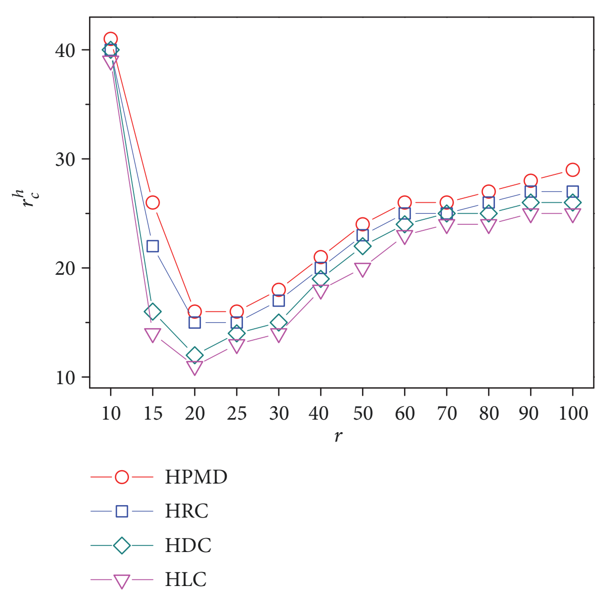


FIGURE 7: *The influence of the spatial constraints on healing effectiveness*. The critical attack radius r_c^h as a function of the distance of dependency links r under different healing strategies, at $\omega = 10\%$.

The reasons why HPMD can reinforce the resilience of the ISENs effectively are as follows. Firstly, the low-degree nodes are more easily apart from the giant component, and their coupled nodes would be failed easily. Figure 8 shows that the failure probability of nodes with different degrees P_f varies with time steps n, without any healing. Except for the initial stage, the $P_f(k = 1)$ is always higher than $P_f(k = 2)$, $P_f(k = 3)$, and $P_f(k = 4)$, when $r_h = 12$ (the point of maximum fluctuation without healing). More fundamentally, the low-degree nodes may be connected to other nodes with high degrees through one interdependency link, therefore magnifying the impact of low-degree nodes. Such interdependency characteristics make the local low-degree nodes

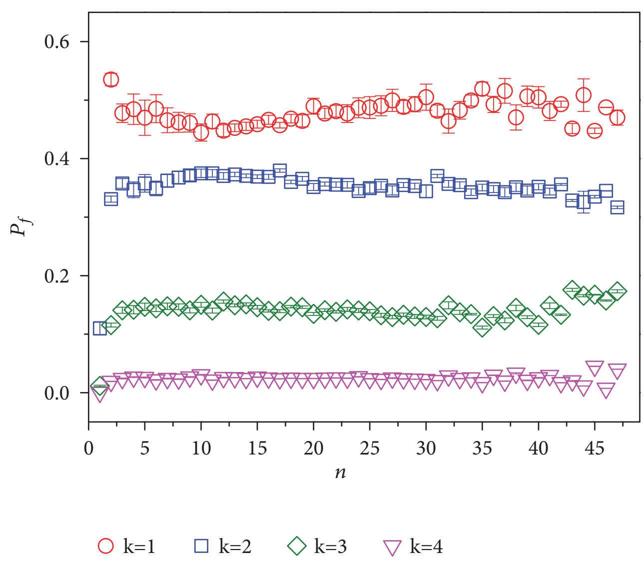


FIGURE 8: *The failure probability of nodes at different degrees varies with time steps.* The failure probability of node P_f with different degrees k in network A, as a function of time n-th step during the cascading process when $r_h = 12$.

result in a cascade of failures with catastrophic consequences. It is completely different from a single network, where the failures of low-degree nodes do not have a great impact on the network due to their low connectivity. HPMD aims at adding new link between two active low-degree neighbors of a failed node in healing process, in the sense that HPMD can keep the functionality of ISENs adaptively.

5. Conclusions

In this paper, we aimed at improving the performance of healing strategy against localized attacks on interdependent spatially embedded networks and found that two active low-degree neighbors of a failed node should be the first choice to heal by establishing a new link between them. An effective healing strategy based on local structures by using the connection profile of a failed node, called HPMD, was proposed. We launch a series of simulations to compare HPMD with the other three healing strategies based on three metrics: random choice, degree centrality, and local centrality on the ISENs. Results show that HPMD remarkably outperforms the others in the size of the giant component of networks, critical attack radius, and the number of iterative cascade steps for a given quota of newly added links. The comparisons also demonstrate that HPMD is more effective, more timely, and less costly for the healing of the ISENs. In addition, HPMD considers the distance between two nodes at the ends of a new added link to restrain a great variation in the network structures. In general, HPMD can significantly improve the robustness of the system by enhancing the connectivity of low-degree nodes, which prevent the diffusion of failures from low-degree nodes to moderate-degree nodes. The high performance of HPMD indicates that low-degree nodes should be placed on the top priority for effective healing to resist localized attacks in the ISENs, which is totally different from the traditional methods that usually take high-degree nodes as critical nodes in a single network. In the meantime, HPMD is operational in reality, because a node typically has the local information of its neighborhood.

In this work, we considered the robustness of spatially embedded coupled systems and designed a new healing strategy. Except the model networks with diluted square lattices, our next study will involve evaluating effect of HPMD in real spatially embedded networks that would more closely resemble the natural world. Overall, our strategy is helpful in the development of intervention strategies against crisis and provides guidance on how to build robust ISENs against potential localized attacks.

Data Availability

The synthetic data used to support the findings of this study are included within the article. In particular, the performance of HPMD is evaluated on synthetic networks generated by the model of ISENs in Section 2.1. The synthetic networks have the same assignment of parameters as in Ref. [16]; namely, $r = 15$, $L = 100$, and $\langle k \rangle \approx 3$.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grants No. 61802321, No. 61773148, and No. 11575041) and the Natural Science Foundation of Shanghai (Grant No. 18ZR1412200). Kai Gong acknowledges the support from the Key Laboratory of Financial Intelligence and Financial Engineering of Sichuan Province and wishes to thank Yu Huang and Shi-Jie Zhang for their linguistic assistance.

References

[1] J. Gao, S. V. Buldyrev, H. E. Stanley, and S. Havlin, "Networks formed from interdependent networks," *Nature Physics*, vol. 8, no. 1, pp. 40–48, 2012.

[2] 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.

[3] S. M. Rinaldi, J. P. Peerenboom, and T. K. Kelly, "Identifying, understanding, and analyzing critical infrastructure interdependencies," *IEEE Control Systems Magazine*, vol. 21, no. 6, pp. 11–25, 2001.

[4] A. Vespignani, "Complex networks: the fragility of interdependency," *Nature*, vol. 464, no. 7291, pp. 984-985, 2010.

[5] J. Gao, S. V. Buldyrev, S. Havlin, and H. E. Stanley, "Robustness of a network of networks," *Physical Review Letters*, vol. 107, no. 19, Article ID 195701, 2011.

[6] R. G. Morris and M. Barthelemy, "Interdependent networks: the fragility of control," *Scientific Reports*, vol. 3, no. 1, article 2764, 2013.

[7] X. Liu, H. Peng, and J. Gao, "Vulnerability and controllability of networks of networks," *Chaos, Solitons & Fractals*, vol. 80, pp. 125–138, 2015.

[8] M. Korkali, J. G. Veneman, B. F. Tivnan, J. P. Bagrow, and P. D. H. Hines, "Reducing cascading failure risk by increasing infrastructure network interdependence," *Scientific Reports*, vol. 7, Article ID 44499, 2017.

[9] A. Scala, V. Zlatić, G. Caldarelli, and G. D'Agostino, "Mitigating cascades in sandpile models: an immunization strategy for systemic risk?" *The European Physical Journal Special Topics*, vol. 225, no. 10, pp. 2017–2023, 2016.

[10] S. Pahwa, C. Scoglio, and A. Scala, "Abruptness of cascade failures in power grids," *Scientific Reports*, vol. 4, article 3694, 2014.

[11] A. Scala and P. G. De Sanctis Lucentini, "The equal load-sharing model of cascade failures in power grids," *Physica A: Statistical Mechanics and its Applications*, vol. 462, pp. 737–742, 2016.

[12] A. Scala, P. G. De Sanctis Lucentini, G. Caldarelli, and G. D'Agostino, "Cascades in interdependent flow networks," *Physica D: Nonlinear Phenomena*, vol. 323/324, pp. 35–39, 2016.

[13] L. Daqing, K. Kosmidis, A. Bunde, and S. Havlin, "Dimension of spatially embedded networks," *Nature Physics*, vol. 7, no. 6, pp. 481–484, 2011.

[14] M. Barthélemy, "Spatial networks," *Physics Reports*, vol. 499, no. 1–3, pp. 1–101, 2011.

[15] W. Li, A. Bashan, S. V. Buldyrev, H. E. Stanley, and S. Havlin, "Cascading failures in interdependent lattice networks: the critical role of the length of dependency links," *Physical Review Letters*, vol. 108, no. 22, Article ID 228702, 2012.

[16] Y. Berezin, A. Bashan, M. M. Danziger, D. Li, and S. Havlin, "Localized attacks on spatially embedded networks with dependencies," *Scientific Reports*, vol. 5, no. 1, Article ID 8934, 2015.

[17] Z. Limiao, L. Daqing, Q. Pengju et al., "Reliability analysis of interdependent lattices," *Physica A: Statistical Mechanics and its Applications*, vol. 452, pp. 120–125, 2016.

[18] A. Bashan, Y. Berezin, S. V. Buldyrev, and S. Havlin, "The extreme vulnerability of interdependent spatially embedded networks," *Nature Physics*, vol. 9, no. 10, pp. 667–672, 2013.

[19] D. Vaknin, M. M. Danziger, and S. Havlin, "Spreading of localized attacks in spatial multiplex networks," *New Journal of Physics*, vol. 19, no. 7, Article ID 073037, 2017.

[20] P. K. Agarwal, A. Efrat, S. Ganjugunte, D. Hay, S. Sankararaman, and G. Zussman, "The resilience of WDM networks to probabilistic geographical failures," *IEEE Info*, vol. 21, pp. 1521–1529, 2011.

[21] S. Neumayer, G. Zussman, R. Cohen, and E. Modiano, "Assessing the vulnerability of the fiber infrastructure to disasters," *IEEE/ACM Transactions on Networking*, vol. 19, no. 6, pp. 1610–1623, 2011.

[22] S. Shao, X. Huang, H. E. Stanley, and S. Havlin, "Percolation of localized attack on complex networks," *New Journal of Physics*, vol. 17, Article ID 023049, 2015.

[23] 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: Statistical, Nonlinear, and Soft Matter Physics*, vol. 92, no. 3, Article ID 032122, 2015.

[24] X. Yuan, Y. Dai, H. E. Stanley, and S. Havlin, "K-core percolation on complex networks: Comparing random, localized, and targeted attacks," *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics*, vol. 93, no. 6, Article ID 062302, 2016.

[25] M. Ouyang, "Critical location identification and vulnerability analysis of interdependent infrastructure systems under spatially localized attacks," *Reliability Engineering & System Safety*, vol. 154, pp. 106–116, 2016.

[26] L. M. Shekhtman, M. M. Danziger, and S. Havlin, "Recent advances on failure and recovery in networks of networks," *Chaos, Solitons & Fractals*, vol. 90, pp. 28–36, 2015.

[27] C. M. Schneider, N. Yazdani, N. A. M. Araújo, S. Havlin, and H. J. Herrmann, "Towards designing robust coupled networks," *Scientific Reports*, vol. 3, pp. 1969–1972, 2013.

[28] L. D. Valdez, P. A. Macri, and L. A. Braunstein, "A triple point induced by targeted autonomization on interdependent scale-free networks," *Journal of Physics A: Mathematical and Theoretical*, vol. 47, no. 5, pp. 141–151, 2014.

[29] M. Gong, L. Ma, Q. Cai, and L. Jiao, "Enhancing robustness of coupled networks under targeted recoveries," *Scientific Reports*, vol. 5, no. 1, article 8439, 2015.

[30] R. Du, G. Dong, L. Tian, and R. Liu, "Targeted attack on networks coupled by connectivity and dependency links," *Physica A: Statistical Mechanics and its Applications*, vol. 450, pp. 687–699, 2016.

[31] W. Quattrociocchi, G. Caldarelli, and A. Scala, "Self-healing networks: redundancy and structure," *PLoS ONE*, vol. 9, no. 2, Article ID e87986, 2014.

[32] A. Scala, W. Quattrociocchi, G. A. Pagani, and M. Aiello, "Self-healing protocols for infrastructural networks," in *Proceedings of the Internationl Conference on Critical Information Infrastructures Security*, pp. 308–313, 2014.

[33] F. Morone, L. Ma, H. Makse, and A. Scala, "Enhancing network resilience via self-healing," in *Proceedings of the 2016 IEEE Workshop on Environmental, Energy, and Structural Monitoring Systems (EESMS)*, pp. 1–5, Bari, Italy, June 2016.

[34] A. Scala, F. Morone, and H. Makse, "Self-healing networks: a theoretical approach to smart grids resilience," in *Safety and Reliability-Safe Societies in a Changing World*, S. Haugen, A. Barros, C. V. Gulijk, T. Kongsvik, and J. E. Vinnem, Eds., pp. 759–763, CRC Press, Trondheim, Norway, 2018.

[35] A. Majdanzic, B. Podobnik, S. V. Buldyrev, Y. Kenett, S. Havlin, and H. E. Stanley, "Spontaneous recovery in dynamical networks," *Nature Physics*, vol. 10, pp. 34–38, 2014.

[36] M. A. Di Muro, C. E. La Rocca, H. E. Stanley, S. Havlin, and L. A. Braunstein, "Recovery of interdependent networks," *Scientific Reports*, vol. 6, no. 1, Article ID 22834, 2016.

[37] S. Hong, J. Zhu, L. A. Braunstein, T. Zhao, and Q. You, "Cascading failure and recovery of spatially interdependent networks," *Journal of Statistical Mechanics: Theory and Experiment*, no. 10, 103208, 9 pages, 2017.

[38] M. Stippinger and J. Kertész, "Enhancing resilience of interdependent networks by healing," *Physica A: Statistical Mechanics and its Applications*, vol. 416, pp. 481–487, 2014.

[39] F. Hu, C. H. Yeung, S. Yang, W. Wang, and A. Zeng, "Recovery of infrastructure networks after localised attacks," *Scientific Reports*, vol. 6, no. 1, Article ID 24522, 2016.

[40] X. Wang, J. Cao, R. Li, and T. Zhao, "A preferential attachment strategy for connectivity link addition strategy in improving the robustness of interdependent networks," *Physica A: Statistical Mechanics and its Applications*, vol. 483, pp. 412–422, 2017.

[41] 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.

[42] X. Ji, B. Wang, D. Liu et al., "Improving interdependent networks robustness by adding connectivity links," *Physica A: Statistical Mechanics and its Applications*, vol. 444, pp. 9–19, 2016.

[43] P. Cui, P. Zhu, K. Wang, P. Xun, and Z. Xia, "Enhancing robustness of interdependent network by adding connectivity and dependence links," *Physica A: Statistical Mechanics and its Applications*, vol. 497, pp. 185–197, 2018.

[44] C. M. Schneider, A. A. Moreira, J. S. Andrade, S. Havlin, and H. J. Herrmann, "Mitigation of malicious attacks on networks," *Proceedings of the National Acadamy of Sciences of the United States of America*, vol. 108, no. 10, pp. 3838–3841, 2011.

[45] X. Huang, J. Gao, V. S. Buldyrev, S. Havlin, and E. H. Stanley, "Robustness of interdependent networks under targeted attack," *Physical Review E*, vol. 83, Article ID 065101, 2011.

[46] S. Sun, Y. Wu, Y. Ma, L. Wang, Z. Gao, and C. Xia, "Impact of degree heterogeneity on attack vulnerability of interdependent networks," *Scientific Reports*, vol. 6, no. 1, Article ID 32983, 2016.

[47] X. Wang, J. Cao, and X. Qin, "Study of robustness in functionally identical coupled networks against cascading failures," *PLoS ONE*, vol. 11, no. 8, Article ID e0160545, 2016.

[48] D. Deka and S. Vishwanath, "Generative growth model for power grids," in *Proceedings of the 2013 International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)*, pp. 591–598, Kyoto, Japan, December 2013.

[49] F. Radicchi, "Percolation in real interdependent networks," *Nature Physics*, vol. 11, no. 7, pp. 597–602, 2015.

[50] X. Wang, W. Zhou, R. Li, J. Cao, and X. Lin, "Improving robustness of interdependent networks by a new coupling strategy," *Physica A: Statistical Mechanics and its Applications*, vol. 492, pp. 1075–1080, 2018.

[51] Y. Liu, M. Tang, Y. Do, and P. M. Hui, "Accurate ranking of influential spreaders in networks based on dynamically asymmetric link weights," *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics*, vol. 96, no. 2, Article ID 022323, 2017.

[52] Y. Liu, M. Tang, T. Zhou, and Y. Do, "Identify influential spreaders in complex networks, the role of neighborhood," *Physica A: Statistical Mechanics and its Applications*, vol. 452, pp. 289–298, 2016.

[53] L. C. Freeman, "Centrality in social networks conceptual clarification," *Social Networks*, vol. 1, no. 3, pp. 215–239, 1978.

[54] D. Chen, L. Lü, M. Shang, Y. Zhang, and T. Zhou, "Identifying influential nodes in complex networks," *Physica A: Statistical Mechanics and its Applications*, vol. 391, no. 4, pp. 1777–1787, 2012.

[55] K. Gong, M. Tang, H. Yang, and M. Shang, "Variability of contact process in complex networks," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 21, no. 4, Article ID 043130, 2011.

[56] D. Zhou, H. E. Stanley, G. D'Agostino, and A. Scala, "Assortativity decreases the robustness of interdependent networks," *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics*, vol. 86, no. 6, Article ID 063103, 2012.

[57] P. Shu, W. Wang, M. Tang, and Y. Do, "Numerical identification of epidemic thresholds for susceptible-infected-recovered model on finite-size networks," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 25, no. 6, Article ID 063104, 2015.