Quantifying the Interdependency Strength Across Critical Infrastructure Systems Using a Dynamic Network Flow Redistribution Model

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Critical infrastructure networks are becoming increasingly interdependent which adversely impacts their performance through the cascading effect of initial failures. Failing to account for these complex interactions could lead to an underestimation of the vulnerability of interdependent critical infrastructure (ICI). The goal of this research is to assess how important interdependent links are by evaluating the interdependency strength using a dynamic network flow redistribution model which accounts for the dynamic and uncertain aspects of interdependencies. Specifically, a vulnerability analysis is performed considering two scenarios, one with interdependent links and the other without interdependent links. The initial failure is set to be the same under both scenarios. Cascading failure is modeled through a flow redistribution until the entire system reaches a stable state in which cascading failure no longer occurs. The unmet demand of the networks at the stable state over the initial demand is defined as the vulnerability. The difference between the vulnerability of each network under these two scenarios is used as the metric to quantify interdependency strength. A case study of a real power-water-gas system subject to earthquake risk is conducted to illustrate the proposed method. Uncertainty is incorporated by considering failure probability using Monte Carlo simulation. By varying the location and magnitude of earthquake disruptions, we show that interdependency strength is determined not only by the topology and flow of ICIs but also the characteristics of the disruptions. This compound system-disruption effect on interdependency strength can inform the design, assessment, and restoration of ICIs.

Keywords: Interdependency Strength, Vulnerability Analysis, Flow Redistribution, Cascading Failures, Network-Disruption Effect.

1. Introduction

The economic development of a country and the well-being of its citizens rely heavily on the proper operation of infrastructure networks such as transportation systems and power grids. When extreme events adversely impact these infrastructure networks, commercial activities and daily life of nearby residents are severely hindered (Ouyang, 2016). For example, the 2003 North American Blackout, which lasted up to 4 days, cost the US around $5 billion according to the U.S. Department of Energy (Amin, 2003). The 2008 Wenchuan Earthquake that hit Sichuan Province of China caused massive disruptions in critical infrastructure systems, such as the water supply and transportation systems, leading to a significant lack of resources for the victims and severely hampering rescue activities (Zhang et al., 2018).

Critical infrastructure networks do not operate in silos and are instead highly interconnected through interdependent links, (Rinaldi et al., 2001; Ouyang et al., 2009; Ouyang, 2016). Examples of such interdependent links are present in water-electricity systems where pumping stations require power from 12-kV substations to lift water from the nearby river and power generation plants rely on water from storage tanks for cooling. While these interdependent links help infrastructure systems become more efficient during normal business operations, they may contribute to their vulnerability during a disruption. A disruption within one network may cause cascading failures across multiple networks, rendering substantial economic loss and adverse effects across commu-

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nities and economic sectors. For instance, the 2001 World Trade Center attack impacted various types of interdependent infrastructure systems (Mendonça et al., 2004). The concept of infrastructure interdependency was first raised in (Rinaldi et al., 2001) and several scholars proposed different classifications of interdependency (Rinaldi et al., 2001; Zimmerman, 2001; Zhang and Peeta, 2011). This paper adopts the classification of Rinaldi et al. (2001) and focuses on the physical interdependency, which arises between two networks when one is dependent on the material output of another.

The focus of this research is to assess the importance of the interdependent links, i.e., interdependency strength, and their impact on the networks' vulnerability and ability to recover during disruptions. A graph-based method is employed (Ouyang, 2016) to incorporate topological and geographical information. Infrastructure systems are modeled as graphs where nodes represent facilities and links represent pipelines and grids. The interdependencies are modeled as inter-links connecting nodes from different networks, which characterize system topological feature and flow variation. Failure modes and performance metrics need to be specified to assess system performance. The initial failure can be (i) random, (ii) intentional, or (iii) due to a natural hazards represented by the probability of exceeding a certain damage state threshold (Ouyang, 2016). To include uncertainty in the analysis, natural hazards are chosen to be the initial failure here.

Interdependency strength, which is defined as the effect of the interdependency on system performance, quantifies how much the system performance changes after considering interdependent links across networks in the model (Ouyang et al., 2009). While research advances in network modeling have addressed the performance of interdependent systems, the strength of the interdependent links is yet to be studied. Topological-based models consider interdependency strength as the conditional failure probability of the dependent components and assume without any prior knowledge that the value of the conditional probability is known (Lehmann and Bernasconi, 2010; Zhang et al., 2016; Yodo and Wang, 2016; Hosseini and Barker, 2016). Flow-based models build interdependency relationships directly using flow conservation without quantifying their strengths (Holden et al., 2013; Mooney et al., 2018; Almoghathawi and Barker, 2019; Goldbeck et al., 2019). This paper develops a dynamic flow redistribution model to fully characterize the interdependency strength and evaluate its effect on infrastructure performance.

The remainder of the paper is organized as follows, Section 2 introduces the methodological framework to comprehensively analyze the vulnerability of interdependent infrastructure systems and provides an approach to quantify interdependency strength, Section 3 presents a case study of power-water-gas interdependent systems, and concluding remarks are provided in Section 4.

2. Methodology

In this section, a framework to analyze interdependency strength across ICISs is proposed. Interdependency strength is quantified by measuring the difference between the vulnerability of infrastructure systems under two scenarios, one with interdependent links and the other without interdependent links (Ouyang et al., 2009). System vulnerability under these two scenarios is considered based on performance deterioration through failure simulation and flow redistribution. The framework is presented in the diagram in Fig. 1.

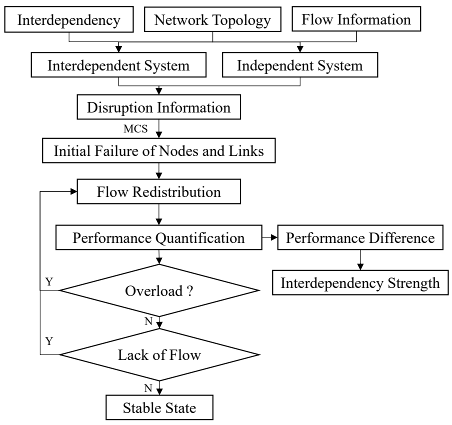

Fig. 1.: Framework for quantifying interdependency strength of infrastructure systems.

First, topology extraction and flow estimation for each infrastructure network are introduced. Then the failure simulation is performed and based on the results, system vulnerability and interdependency strength are calculated.

2.1. *System Structure Extraction*

A network which is composed of nodes and links, is usually modeled as a graph where nodes correspond to vertices and links correspond to edges (Dueñas-Osorio et al., 2004; Dueñas-Osorio, 2005; Dueñas-Osorio et al., 2007). In the case of infrastructure networks, nodes represent stations or facilities such as power plants, storage towers or gas substations, which generate or distribute resources. Links represent pipelines or grids which transport or deliver resources to end-users. Infrastructure systems do not operate individually and rely on resources from different types of networks which makes them interdependent. The approach for modeling infrastructure networks and their interdependencies are introduced in the following subsection.

2.1.1. *Network Topology*

In this paper, an interdependent gas-power-water system is considered. For the gas network, natural gas is extracted from underground at gas pumping stations, transported through gas pipelines to intermediate stations and then delivered to end-users. For the power network, electricity is first generated by burning gas at power plants and then transported through 23-kV, 12-kV substations to communities. For the water network, water is lifted from the nearby river at pumping stations and stored in storage tanks for future use (Yu and Baroud, 2019; Zhang et al., 2016).

Without loss of generality, this paper considers two types of nodes, (i) generation (source) nodes which generate resources or energy, and (ii) load (demand) nodes which provide residents with daily necessities (Johansen and Tien, 2018; Almoghathawi et al., 2019). Water pumping stations, gas extraction stations, and power plants serve as generation nodes while water storage tanks, gas and power substations serve as load nodes. Water and gas pipelines as well as power grids serve as links to transfer resources and energy. In the case of real infrastructure networks, node location and adjacent relationships can be obtained directly from maps or historical data. However, information on capacity of nodes and flows along links is often challenging to obtain due to security reasons or lack of technology to collect such data. Therefore, simulated networks are often used where graph algorithms are employed to generate networks based on topological information of real systems (Mukherjee and Manna, 2006; Xu et al., 2007; Zhang et al., 2016). The simplified model for the system of interdependent infrastructure networks considered in this paper is shown in Fig. 2.

2.2. *Flow Estimation and Redistribution*

Resources and energy move between nodes within and across networks in the form of flow. To quantify the interdependency strength based on the difference of system vulnerability with consideration of cascading failure, the initial flow and its redistribution process are modeled. The initial flow is calculated by solving a linear programming problem and a redistribution process assigns subsequent flows based on the disruption and corresponding failures. When a node fails, the load that it was carrying right before the failure is redistributed to its adjacent nodes equally or proportionally (Lehmann and Bernasconi, 2010; Zhang and Yağan, 2019). Since this paper mainly focuses on quantifying interdependency strength, the two procedures of initial and subsequent flow distribution are not presented in details.

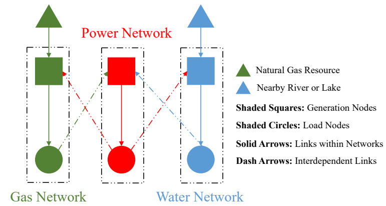

Fig. 2.: An interdependent gas-power-water system.

2.3. *Failure Simulation*

To analyze the performance deterioration, i.e. the vulnerability of the system, the failure scenario needs to be specified first. Prior work on simulation of initial failure is based on (i) random or local attacks (Dueñas-Osorio et al., 2007; Ouyang, 2016), or (ii) Monte Carlo simulation of natural hazards including earthquakes, floods, and thunderstorms (Yu and Baroud, 2019). Due to failure propagation within and across networks, the effect of the initial failure becomes more significant due to cascading effects. When the entire system reaches a stable state where cascading failure no longer occurs, the system vulnerability is calculated using the performance deterioration and further used to quantify the interdependency strength.

2.3.1. *Generating the Initial Failure Scenario*

The initial failure scenario is determined by the disaster affecting the system. Different types of disasters require different modeling techniques. In this paper, we suppose that the system is impacted by an earthquake. Median Peak Ground Acceleration (PGA) is typically used to characterize the seismic intensity, the logarithmic values of which can be calculated based on the earthquake magnitude M_w and the distance from the epicenter to the specific component according to Eq. (1) (Adachi and Ellingwood, 2009). The failure probability, i.e. the conditional probability of exceeding the complete damage state given median values of PGA, is defined by Eq. (2) (Department of Homeland Security, 2013) where λ and ζ are two parameters varying according to the types of facilities, and ϕ is the standard normal cumulative distribution function.

$$\begin{aligned}\log(PGA) = 3.79 + 0.298 \times (M_w - 6) \\ - 0.0536 \times (M_w - 6)^2 \\ - \log(R) - 0.00135 \times R\end{aligned} \tag{1}$$

$$P\,(PGA) = \phi\left[\frac{\ln\,(PGA) - \lambda}{\zeta}\right] \tag{2}$$

If the random number generated by the Monte Carlo simulation is less than the failure probability, the component is assumed to be inoperable. To simplify the analysis, partial functionality and restoration after disruptions are not considered. Once the component is inoperable, its incident links cannot transport resources properly due to blockage or leakage at both ends of the links. The failure of a link between vertex i and vertex j is represented by setting its corresponding entry a_{ij} to 0 in the adjacent matrix A, a square matrix used to represent the structure of graphs. The detailed procedure of the simulation is summarized in Algorithm 1.

Algorithm 1: Simulating the initial failure scenario

Input: Earthquake magnitude, coordinates of the epicenter and network components, the adjacent matrix A, the value of parameters of fragility curves λ, ζ

```
for i = 1 to N do
    Calculate the distance R_i(km) from the component i to the earthquake epicenter
    Calculate the failure probability p_i of the component i based on Eq. (1) and Eq. (2)
    Run MCS: generating a random number u_i ~ U(0,1) for the component i
    if p_i < u_i then
        Component i is not damaged
    else
        Component i is damaged
        Update the corresponding adjacent matrix, A[i,:] = A[:,i] = 0
    end if
end for
```

2.3.2. *Cascading Failure*

Initial failures in nodes and links trigger a redistribution of flow within and across the networks. According to (Lehmann and Bernasconi, 2010; Zhang and Yağan, 2019), the process of flow redistribution is simulated by assigning the load from the failed node to its adjacent nodes equally or proportionally. Here, we assume it is distributed proportionally. After flow redistribution, the amount of resources flowing into certain nodes may increase, which can exceed their original capacity and prompt overload failure, while other nodes may receive less flow, leading to higher levels of unmet demand for their users. Cascading failure occurs in both of these cases. For each additional failure in a node or a link, flow is redistributed and survival nodes are suffer from either overload or lack of resources. The process keeps alternating between flow updating and node failure until failure nodes or links, indicating that the system has reached a new disrupted stable state.

2.3.3. *Vulnerability Quantification*

Vulnerability refers to the impact of the disruption on system performance which corresponds to (i) structural vulnerability and (ii) functional vulnerability. For structural vulnerability, the network topology is the only information considered while for functional vulnerability, both topology and flow information are considered. In this paper, functional vulnerability is used to measure the performance deterioration of the system and it is calculated as the average ratio of the unmet demand of each load node to its initial demand value. The initial demand value of each load node is determined by Eq. (4) given the population of the nearby areas served by that load node and the corresponding resources required per capita. The unmet demand is obtained by subtracting the value of the current flow going into the node from its initial demand. The equation to calculate the vulnerability is given by:

$$\delta_M(t) = \frac{1}{N_l^M} \sum_{i=1}^{N_l^M} \frac{\varphi_i^M(t) - \sum\limits_{j \in E_i^{t,M}} f_{ji}^{t,M}}{\varphi_i^M(t)} \tag{3}$$

$$\varphi_i^M(t) = d_i r_i^M(t) \tag{4}$$

In Eq. (3), N_l^M is the number of load nodes in the initial undamaged network M, $\varphi_i^M(t)$ is the initial demand value of load node i, $E_i^{t,M}$ is the edge set containing all edges incident to load node i at time t, and f_{ji}^t is the flow from node j to node i at time t. The parameters above all refer to the state of the corresponding network M. In Eq. (4), d_i is the population served by load node i and it can be assumed to be constant within a very short period of time when cascading failure happens. $r_i^M(t)$ is the demand for the resource corresponding to network M per capita. It should be noted that $r_i^M(t)$ is a time-dependent variable due to the increase demand for daily supplies after disasters.

2.4. *Interdependency Strength*

Cascading failures propagate through interdependent links, transferring damage from a single network to multiple networks and increasing the entire system's vulnerability. The interdependency strength, calculated according to Eq. (5), is based on the integration of the difference in the system's vulnerability considering the presence of interdependent links over time.

$$\varepsilon_S^\alpha = \sum_{t \in T} \sum_{M_i \in S} \gamma_{M_i} (\delta_{\overline{M_i}}^\alpha(t) - \delta_{M_i}^\alpha(t)) \tag{5}$$

In Eq.(5), ε_S^α characterizes the interdependency strength of system S subject to earthquake α,

N_S represents the number of networks in system S. M_i and $\overline{M_i}$ denote the i_{th} network with and without interdependency in system S respectively. T refers to the period before the system reaches a new stable state. γ_{M_i} quantifies the relative importance of each single network to the whole system, which is a normalized variable following the relationship $\sum_{M_i \in S} \gamma_{M_i} = 1$.

3. Simulation Analysis

This section uses an interdependent gas-power-water system as an example to illustrate the approach outlined in Section 2.

3.1. *System Modeling*

The case study considers the gas-power-water system in Shelby County, Tennessee, with the latitude of 35°N and longitude of 90°W. All three networks are run by the same utility company, Memphis Light, Gas and Water, the largest three-service utility company in the US. The layout of the three networks is depicted in Fig. 3. The water distribution network includes 9 pumping stations, 6 storage tanks and 34 deliver nodes. The power grid includes 9 power plants, 37 23-kV and 12-kV substations and 14 intersection points. The gas distribution network includes 3 extraction stations and 13 regulator stations. Pumping stations, power plants and extraction stations are considered supply nodes where resources are generated or extracted, while all other types of facilities are considered to be demand nodes that directly serve end-users.

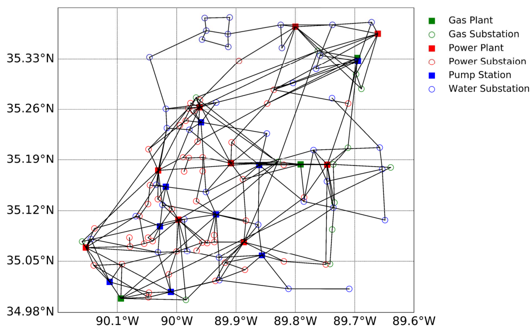

Fig. 3.: The topology of the gas-power-water system in Shelby County, Tennessee.

To generate interdependent links between each pair of networks, each supply node is connected with its three nearest demand nodes in the corresponding dependent network. Since the interdependent infrastructure system of Shelby County is located within a relatively small geographical area, the population is assumed to be evenly distributed with a density of 166 p/mi^2 (Bureau, 2019). The initial flow is estimated by solving a linear programming problem. The system and corresponding flow information is visualized in Fig. 4.

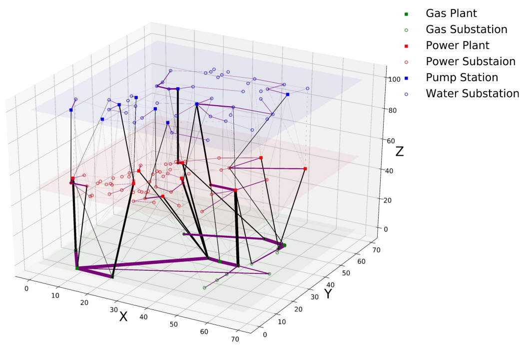

Fig. 4.: The gas-power-water system of Shelby County. The nodes in green, red, and blue represent facilities in gas, power and water networks. Intra-network flow is in purple while inter-network flow is in black. The thickness of each link represents the capacity of flow.

While Shelby County is subjected to a wide range of hazards, such as earthquakes, floods, and storms, the extreme event considered in this case study is assumed to be an earthquake with varying magnitudes and a hypothetical situation of varying geographical locations of the epicenter. The value of the parameters used for calculating the PGA of each component is listed in Table 1.

Table 1.: Values of λ and ζ for different facilities

Parameter	λ	ζ
Gas Pumping Station	$\ln(1.5)$	0.8
Gas Substation	$\ln(1.2)$	0.6
Power Plant	$\ln(1.4)$	0.4
Power Substation	$\ln(1.2)$	0.4
Water Pumping Station	$\ln(1.5)$	0.8
Water Storage Tank	$\ln(1.2)$	0.6

The focus of this paper is the quantification of interdependency strength. Therefore, for the purpose of illustration and simplicity, the demand value per capita $r_i^M(t)$ in Eq. (4) is considered a constant. Additionally, the three networks are considered to be of the same importance to the system, i.e. γ_{M_i} in Eq. (5) is $\frac{1}{3}$ for all $M_i \in S$. For each earthquake with a specified intensity and epicenter, 100 initial failure scenarios are generated with Monte Carlo simulation.

3.2. *Functional Vulnerability*

When the earthquake location is set at 30°N, 90°W and the magnitude varies from 0 to 10, it can be seen that the system performance decreases over time, Fig. 5. Regardless of the earthquake magnitude, having interdependent links decreases the system performance which is expected since interdependent links propagate the initial failure through links and nodes in other networks. These newly affected nodes then become the seeds and initialize the failure propagation in their corresponding networks.

3.3. *Interdependency Strength*

To explore the relationship between interdependency strength and the earthquake magnitude, we calculate the difference between the system performance with and without interdependency under different earthquake magnitudes. As shown in Fig. 6, interdependency strength varies with seismic intensity. It can be observed that the interdependency is strongest when the magnitude of earthquake is within the middle range but weakest when the magnitude is either too high or too low.

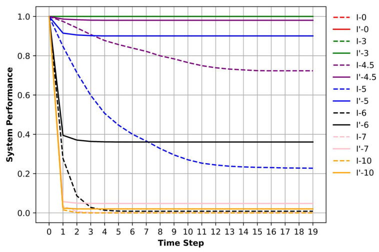

Fig. 5.: The performance deterioration of the system under different seismic intensities.

This result is counter-intuitive because to the idea that a stronger the earthquake will result in a more severe disruption and a stronger contribution of interdependent links to cascading effects and system vulnerability. However, in this case, when the intensity of an earthquake is so extreme that many nodes at both ends of the interdependent links are damaged and the initial failure scenarios will be the same regardless of whether or not there are interdependent links.

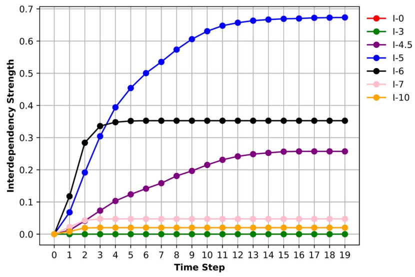

Fig. 6.: The interdependency strength under different seismic intensity.

Thus the flow redistribution and performance deterioration in the interdependency case is not significantly different from the independent one. However, when the earthquake magnitude is within a specific interval such that only one of the two nodes incident to interdependent links is damaged, the nodes at the other end will not be damaged due to lack of propagation medium in a system of independent networks. However, in a system of interdependent networks, the failure may propagate along the interdependent links to the nodes in the other network, which further highlights the role of interdependency strength.

As such, weak interdependency arises when seismic intensity is extremely high or low, which can be validated by Fig. 7. It can be seen that interdependent links impact system performance only when the seismic intensity is between 4 to 8. The maximum interdependency strength is 0.68 when seismic intensity is 5.2.

The relationship between the interdependency strength and the earthquake epicenter is further analyzed. In particular, Fig. 8 and Fig. 9 depict the interdependency strength of the gas-power-water system of Shelby County as a function of hypothetical varying locations of the earthquake epicenter. The color of each point in the heatmaps indicates the interdependency strength when the earthquake occurs at that point.

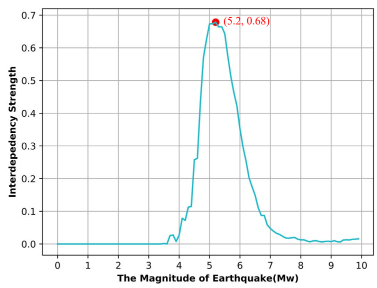

Fig. 7.: The relationship between interdependency strength and seismic intensity.

In both Fig. 8 and Fig. 9, there exists a clear light circular ring where the interdependency strength is much higher than in other areas. When the earthquake epicenter is closer to Shelby County, referring to the dark area inside the circular ring, the seismic intensity at the location of nodes on both ends of interdependency links is high and thus the nodes are more likely to be damaged. Similarly, when the earthquake occurs far away from Shelby County, referring to the dark area outside the circular ring, the earthquake effect is attenuated so much that nodes on both ends remain undamaged. In both of these two situations, the system performance remains the same when interdependency is incorporated, indicating low interdependency strength (the difference of the performance between the two scenarios).

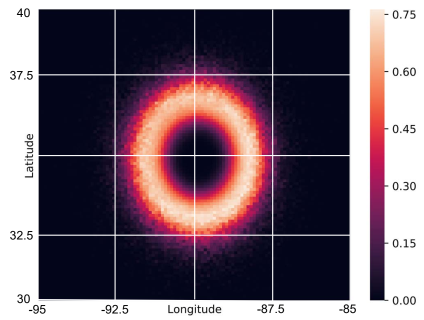

Fig. 8.: The interdependency strength under different locations of earthquake epicenter with magnitude 3. The lighter color represents higher interdependency strength while the darker color indicates a less significant interdependency.

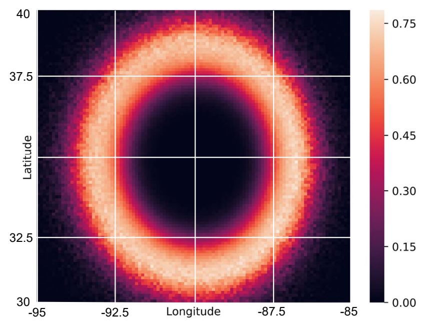

Fig. 9.: The interdependency strength under different locations of earthquake epicenter with a magnitude of 4.

It is only when the epicenter of the earthquake is located within the circular ring that only one of the two nodes has a higher likelihood of being damaged, hence, the interdependency can impact the system functionality. We define this circular ring as the ”Activation Zone” (AZ) and the dark area the ”Silent Zone” (SZ) of the interdependency. It can be also observed that the AZ is smaller in Fig. 8 than in Fig. 9. Since the effect of a stronger earthquake requires longer distance to be attenuated when compared to a weaker earthquake, the original AZ in Fig. 8 where exactly one of two nodes is damaged becomes SZ in Fig. 9 and the new AZ moves further away from the center.

4. Conclusion

This paper presents a probabilistic framework for assessing the interdependency strength of systems considering physical interdependency and cascading failures. The case study reveals that the strength of interdependency is affected by both seismic intensity and epicenter location. Concerning the intensity, there exists a threshold below which interdependency strength increases with the intensity and beyond which interdependency decreases with the intensity. For the epicenter location, interdependency responds only to the earthquake happening in the activation zone of the system. Different systems have different activation zones, even within the same system, the activation zone will change according to seismic intensity. It is only when the earthquake occurs in the activation zone that the interdependency will impact the system performance.

This paper reveals a counter-intuitive but critical phenomenon that the interdependency effect is not exclusively determined by system factors such as network topology and flow. It is also affected by external factors such as the intensity and location of disruptions. The insight can inform prioritization of resource allocation and assist risk managers and decision makers in identifying strategies for the protection of specific interdependency links, i.e. investment should be made in the case of the earthquake occurring in the activation zone.

Future work will expand the proposed framework to investigate the resilience of infrastructure systems with real interdependent links and include additional types of disruptions and interdependencies.

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