13th International Conference on Applications of Statistics and Probability in Civil Engineering, ICASP13
Seoul, South Korea, May 26-30, 2019

Modeling the Resilience of Interdependent Infrastructure Systems under Uncertainty

Jin-Zhu Yu
Graduate Research Assistant, Department of Civil Engineering and Environmental Engineering , Vanderbilt University, Nashville, United States

Hiba Baroud
Assistant Professor, Department of Civil Engineering and Environmental Engineering , Vanderbilt University, Nashville, United States

ABSTRACT: The objective of this study is to explore the impact of uncertain interdependencies on the resilience assessment of infrastructure systems. Existing models for analyzing interdependent infrastructures do not account for the underlying uncertainties in the strength and type of interdependent relations. Taking these into account, this paper proposes a probabilistic framework to assess the serviceability of interdependent infrastructures. A preliminary analysis is presented focused on the uncertainty of physical interdependencies. The case study reveals that the strength of a physical interdependency increases as the distance between the interconnected components increases. Accounting for the uncertainty in the interdepndencies results in larger differences in the mean functionality of network components as the physical interdependency strength increases.

1. Introduction

Critical infrastructures, such as water supply systems and power grids, are essential to the society and the economy. When the operations of these infrastructures are impaired by extreme events, commercial activities and the day-to-day life of local residents are severely disrupted. Examples of such events include the 2003 North American blackout and the 2017 disastrous flooding in Houston that rendered multiple infrastructure systems inoperable resulting in cascading effects throughout multiple economic sectors and through the community. A particular challenge in assess the impact of such events on infrastructure lies in understanding the influence of interdependencies on the performance of the infrastructure system before, during, and after a disruption. Driven by the development of social economy and advances in technology, infrastructure systems are becoming increasingly interconnected (Pederson et al., 2006). Although interdependencies between infrastructures can improve the overall efficiency and robustness during normal operations, these interdependencies can make infrastructure systems more vulnerable to disruptive events due to the cascading effect of losses and failures (Buldyrev et al., 2010; Bashan et al., 2013; Ouyang, 2014; Danziger et al., 2016). For example, damage to the power grid can cascade into the water supply system as pumping stations fail due to loss of power, and the lack of water for cooling can then impact the generation of electricity. As such, interdependencies among infrastructures must be taken into account to understand the operational characteristics of infrastructure systems (Rinaldi, 2004), in order to develop more robust and resilient systems, ensure rapid recovery after disruptive events, and reduce economic loss (Zhang et al., 2018).

Interdependency refers to "the bidirectional relationship between two infrastructures through which the state of each infrastructure influences or is correlated to the state of the other" (Rinaldi et al., 2001). Rinaldi et al. (2001) formalize the concept of infrastructure interdependency and propose a classification of different types of interdependencies. Later, other classifications of interdependencies between infrastructure systems have also been proposed (Zimmerman, 2001; Lee II et al., 2007; Dudenhoeffer et al., 2006). This study adopts the classification of Rinaldi et al. (2001) and focuses on the physical and geographic interdependencies between the water and electricity systems. A physical interdependency arises between two networks when a commodity produced or modified by one infrastructure (an output) is required by another infrastructure for it to operate (an input). Geographical interdependency occurs if a local event can impact the sate of components of different infrastructure systems that are located in close proximity (Rinaldi et al., 2001).

The proposed approach for modeling the resilience of interdependent infrastructure systems under uncertainty considers the effect of both hazard and interdependency strength on the performance of power and water systems. The remainder of this paper is organized as follows, Section 2 provides a brief literature review on existing work in infrastructure interdependency modeling, in Section 3 the modeling approach is presented with the case study described in Section 4 and results in Section 5. Concluding remarks are provided in Section 6.

2. Background

To model the interdependencies among critical infrastructure systems, several methods have been developed, including agent-based approaches (Barton et al., 2000), graph-based approaches (Wallace et al., 2001; Dueñas-Osorio, 2005; Xu et al., 2007; Holden et al., 2013; Milanovic and Zhu, 2018), Leontief input-output approaches (Haimes and Jiang, 2001), and Bayesian networks-based approaches (Di Giorgio and Liberati, 2012; Johansen and Tien, 2018), among others. Among these methods, the graph-based approach is more commonly used to model interdependent infrastructures because of the networked nature of these systems (Dueñas-Osorio et al., 2007) and the convenience to extend this approach to model the restoration process (Lee II et al., 2007; Wang et al., 2012). This work adopts the graph-based approach to explore the physical and geographic interdependencies.

Prior work on the interdependency between water and electric power systems considers a probabilistic assessment of the earthquake-induced damage of a municipal water system, taking into account the dependence of the water system functionality on the availability of electrical power and the uncertainty about earthquake intensity and component fragility (Adachi and Ellingwood, 2008). In the study of Dueñas-Osorio et al. (2007), intedependencies among network components are established by spatial proximity. Later, González et al. (2017) extend the work using an optimization model for recovery management by incorporating both the physical and geographic interdependencies between infrastructure systems, specifically the physical interdependency between the power network and the gas and water networks, and the geographical interdependency between the gas and the water networks. Existing work in the literature has not so far accounted for the uncertainties about interdependencies, which may lead to an underestimation of the vulnerability of the interdependent infrastructures. This paper develops an approach that models the uncertainty within the interdependencies to assess the resilience of infrastructure systems under different levels of interdependency strengths. The resilience is evaluated based on the serviceability of the two networks after a disruption.

To evaluate the serviceability of interdependent infrastructure systems, several sources of uncertainties need to be considered. First, components are widely distributed over the service area and experience various levels of damages when subject to the same disruptive event. The lack of data often poses the biggest challenge for deterministic models (Rinaldi, 2004). Without adequate knowledge about component characteristics (and consequently the randomness in the intensities of disruptive events at the location of each component), the fragility of each component is uncertain. Further, due to the dynamic nature of the relations between infrastructure systems, the type and strength of interdependencies are probabilistic. As the topology of infrastructure systems evolves over time during the recovery , the interdependencies are not static as damaged components are restored and new components might be added temporally to enhance the recovery rate. However, dynamic data during the recovery process is expensive to collect. As a result, a probabilistic analysis of the performance of infrastructures in the presence of uncertain interdependencies is essential in order to i) assess the impact of extreme events on interdependencies, and ii) model the influence of interdependencies on the performance of infrastructure systems during the recovery process.

3. MODELING APPROACH

This study focuses on the analysis of the serviceability of water supply and electric power infrastructure with consideration of both hazard-related and interdependency-related failures. Physical interdependency is included and modeled in a probabilistic manner. Monte Carlo simulation is employed to reveal how the probabilistic failures on the component level propagate through the system. The proposed methodology is illustrated through a case study of the water and electric power systems in Shelby County, Tennessee, USA.

The assessment of component functionality ratio and system serviceability is carried out using Monte Carlo simulation illustrated in Fig.1 and following the algorithm described below.

1. Simulate the natural hazard scenario.
2. Compute the intensity of the natural hazard at the location of each network component.
3. Calculate the probability of failure for each component of the network. A vector p is used to represent the failure probabilities for the components. For simplicity, components are assumed to be inoperable once they are damaged, i.e., partial functionality is not considered.
4. Generate a random vector u ($u \sim U(0,1)$) of correlated hazard intensities at each of the sites within the network. If the failure probability of a certain component is greater than the random number drawn from $U(0,1)$, then it is assumed to be inoperable .
5. Generate the network consisting of the functional components only. The generated network is a subgraph of the network before the disruption.
6. Apply the Floyd-Warshall algorithm to detect demand components that are still connected to the supply nodes. This algorithm calculates the shortest path between all pairs of nodes simultaneously. If at least one path exists from a demand node to a source node, then the demand node is considered to be functional. Otherwise, the component is considered inoperable. The serviceability of the system is defined by the ratio of functional demand nodes.
7. Repeat steps 3-5 for a sufficient number of iterations, N, to evaluate the component functionality rate and the average network serviceability. The functionality ratio of the demand nodes can be determined by Eq. 1.

$$X_i = \frac{n_f}{N} \tag{1}$$

In Eq. 1, X_i describes the number of simulations in which demand node i remains functional and is divided by the total number of simulations. The mean serviceability of the system, $\bar{S}$, is calculated using Eq. 2 where S_i is the serviceability at iteration i.

$$\bar{S} = \frac{S_i}{N} \tag{2}$$

The modeling approach provides a comprehensive methodology that addresses multiple sources of uncertainty that affect the performance of infrastructure networks. In this particular paper, the focus is on the calculation of the probability of failure and the corresponding serviceability and functionality ratio. In particular, the work provides a model that accounts for the hazard intensity as well as the interdependency strength in the calculation of the component's probability of failure. In this paper, only physical interdependencies are considered.

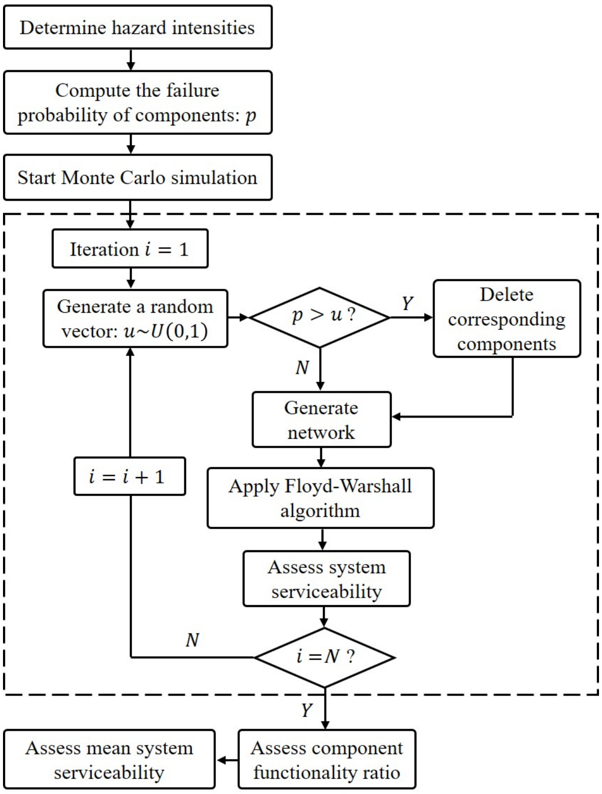

Figure 1: Modeling approach for the infrastructure serviceability assessment under uncertainty

4. Case Study

This section summarizes a real world case study used to illustrate the modeling approach outlined in Section 3.

4.1. Interdependent infrastructure Systems

The case study considers the water and electric power systems in Shelby County, Tennessee where Memphis is located. Both systems are governed by the same utility company, Memphis Light, Gas, and Water, the largest three-service utility company in the US serving close to one million customers. The layout of the two systems is depicted in Fig.2. The water distribution network includes 6 elevated storage tanks, 9 pumping stations, 34 intermediate delivery nodes, and 71 water pipes while the power grid consists of 14 gate stations, 23 23-kV substations, and 23 12-kV substations. Gate stations and pumping stations are considered as the supply facilities while the substations and intermediate delivery nodes are considered as demand facilities (Adachi and Ellingwood, 2008). It should be noted that intermediate delivery nodes are the intersection points of water pipes and they are assumed to be undamaged after earthquakes since there are no large-scale facilities at the site of these nodes. Since the electric power system does not have generators within Shelby County, which requires water for cooling and is thus dependent on the water distribution system, only physical dependency of pumping stations on the closest power stations is considered.

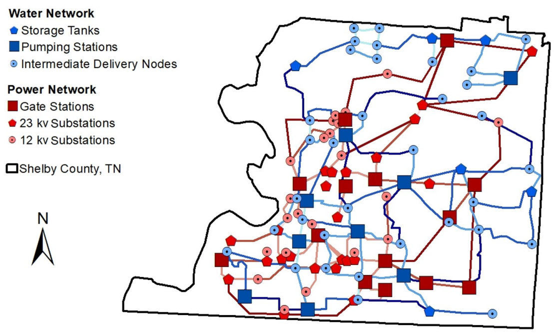

Figure 2: Layout of power and water systems

4.2. Hazard Intensity

While Shelby County is subject to a wide range of hazards including earthquakes, flooding, and thunderstorms, the extreme event for this case study is assumed to be an earthquake of magnitude, M_W, equal to 7.7 which is the maximum probable earthquake for the New Madrid Seismic Zone according to Harmsen et al. (2003). The epicenter of the maximum probable earthquake is located at 35.3N and 90.3W. The distance from the epicenter to the components of two infrastructure systems, R, ranges from 20 km to 65 km. The seismic intensity is typically characterized by the median Peak Ground Acceleration (PGA) or Peak Ground Velocity (PGV), whose logarithmic (base 10) values can be calculated using Eqs. 3 and 4, respectively (Adachi and Ellingwood, 2009). The median PGA values in Shelby County are shown in Fig.3.

$$\log(PGA) = 3.79 + 0.298 \times (M_w - 6) - 0.0536 \times (M_w - 6)^2 - \log(R) - 0.00135 \times R \quad (3)$$

$$\log(PGV) = 2.01 + 0.422 \times (M_w - 6) - 0.0373 \times (M_w - 6)^2 - \log(R) \quad (4)$$

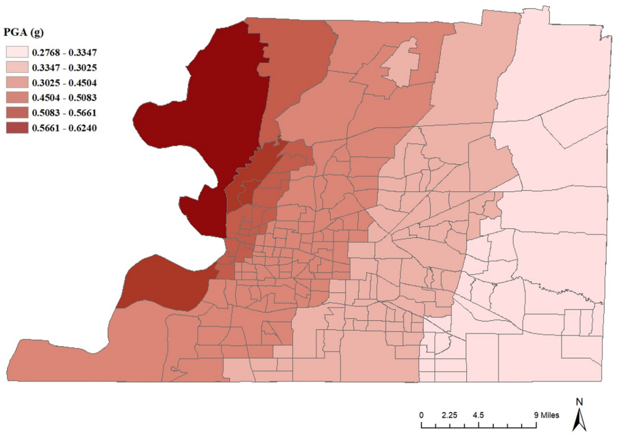

Figure 3: Median PGA in Shelby County (Yu et al.)

4.3. Component Fragility

Given the seismic intensity, the failure probability of infrastructure components can be determined. The failure probability of nodes given seismic intensity is dependent on the type of facility and the damage state. A total of five damage states are defined, including none (ds_1), minor (ds_2), moderate (ds_3), extensive (ds_4), and complete (ds_5) (FEMA, 2013). As an example, the fragility curve for above ground steel tank entering different damage states is shown in Fig.4. In this study, damage state V is adopted. The failure probability, i.e. the conditional probability of exceeding the complete damage state given median values of PGA, is defined by Eq. 5 (FEMA, 2013)

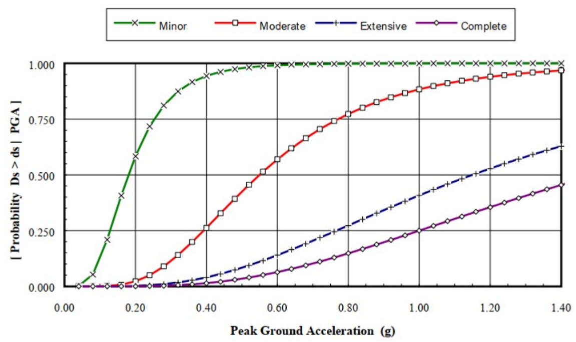

Figure 4: Fragility curve for above ground steel tank (FEMA, 2013)

$$P_n(PGA) = \phi\left[\frac{\ln(PGA) - \lambda}{\zeta}\right] \tag{5}$$

In Eq. 5, $P_n(PGA)$ describes the probability of failure of each node given the corresponding median PGA value; λ is the logarithmic mean value of PGA (measured in the gravitational acceleration g), at which the facility exceeds the threshold of complete damage state; ζ describes the standard deviation of $\ln(PGA)$; ϕ is the standard normal cumulative distribution function. Values of λ and ζ vary with the type of facilities, Table 1. Values of λ and ζ for water distribution facilities are determined according to FEMA (2013). Due to lack of data, values of λ and ζ for electric power stations are determined in such a way that their failure probabilities are in the same order of magnitude to water distribution facilities.

Table 1: Values of λ and ζ for different facilities

Parameter	λ	ζ
Storage tank	ln(1.5)	0.8
Pumping station	ln(1.2)	0.6
Gate station	ln(1.2)	0.4
23-kV Substation	ln(1.3)	0.4
12-kV Substation	ln(1.4)	0.4

The failure probability of a link in the infrastructure network is determined by the average number of failures per 1000 feet of link length, i.e. the repair rate, RR, and the median value of PGV. RR can be calculated by Eq. 6 (American Lifelines Alliance, 2001)

$$RR = K \times a \times PGV \tag{6}$$

This equation is originally derived for water pipes, however, it is assumed to be applicable to power transmission links with different value of a and K. For water pipes, $a = 0.002$ and $K = 0.5$ while for power transmission lines, $a = 0.001$ and $K = 0.5$. The number of failures, N_l, is assumed to follow a Poisson distribution, thus the failure probability of a link, P_l, can be expressed as a function of the repair rate and the link length, L, as shown in Eq. 7.

$$P_l = 1 - P[N_l = 0] = 1 - \exp(-RR \times L) \tag{7}$$

Ideally, as the seismic intensity varies along a link, the corresponding difference in the failure probability should be taken into account. In order to minimize computational effort and without loss of generality, the link is equally divided to m segments. For this case study, $m = 20$. The failure of different segments are considered to be independent. The repair ratio for each segment is then computed using the PGV value at the center of each segment. Then, the failure probability of a link is approximately determined using Eq. 8 where RR_i is the repair ratio of segment i.

$$P_l = 1 - \exp\left(-\sum_{i=1}^{m} RR_i \times \frac{L}{m}\right) \tag{8}$$

4.4. Interdependency Strength

Interdependency strength between system A and system B is measured using the conditional failure probability of system A given the failure of system B, Eq. 9.

$$Ist = P(\text{failure of } A \mid \text{failure of } B) \tag{9}$$

The strength of interdependency, Ist, is tuned by changing the value of a in Eq. 6.

4.5. Component Functionality

To evaluate the mean functionality of components, 5000 Monte Carlo simulation runs are performed. The mean functionality of intermediate delivery nodes is considered since it can be used to determine the system performance, such as how much water can be provided to the end customers in Shelby County.

5. RESULTS AND DISCUSSION

Results of infrastructure resilience assessment are explored in this section. In particular, interdependency strength and functional ratio are evaluated. The impact of distance between components on the physical interdependency strength is shown in Fig. 5. The strength of physical interdependency increases as the distance between the dependent components is larger. This trend holds true for multiple levels of hazard intensity. As the hazard becomes more intense, the physical interdependency becomes stronger as components are further away from each other. However, the rate at which the physical interdependency increases

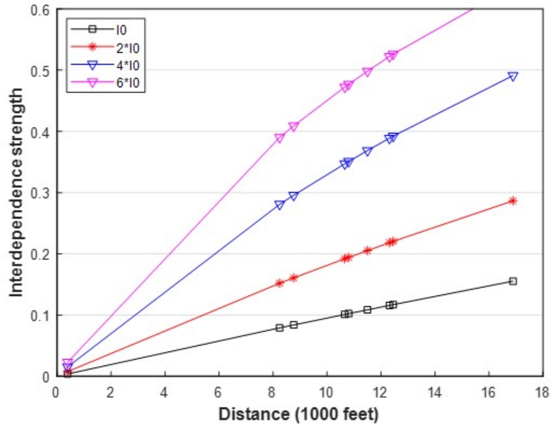

Figure 5: Strength of interdependence vs. distance (I_0 represents the initial hazard intensity)

becomes slower. This particular observation may not hold true for other types of interdependencies, pointing to the need of modeling the uncertainty and dynamic of interdependent connection between infrastructure systems. For example, it is likely that the strength of geographical interdependencies will decrease as a function of the distance between components.

In the next step, the effect of physical interdependency over the functionality ratio of intermediate delivery nodes is explored. Figure. 6 shows the difference in the functionality ratio of the water system's nodes before and after accounting for physical interdependency. This figure indicates that all the intermediate delivery nodes of the water distribution system show a decrease in their mean functionality after incorporating the impact of physical interdependency on the electric power system. For all intermediate delivery nodes, the difference is larger with the increase of physical interdependency strength. Another observation is that the difference caused by physical interdependency ranges widely. Node 38, 41 and 49 have the highest difference in the functionality ratio and can be the most influenced by the physical interdependency. This large difference can be attributed to the limited path to the supply and the relatively large distance of the pumping stations for these nodes to the power stations.

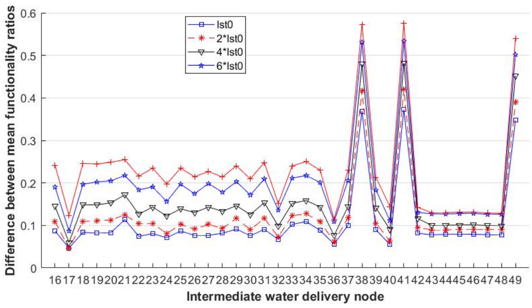

Figure 6: Difference in functionality by node (Ist_0 represents the initial strength of physical interdependency)

6. CONCLUSION

This paper presents a probabilistic framework for assessing the resilience of power and water systems with consideration of the uncertainty associated with the interdependent connections between the two networks. The case study reveals that the strength of physical interdependency increases with the distance between the interconnected components. Given the requisite data, this method can be applied to other independent infrastructure systems.

The outcome of this work can assist risk managers and decision makers in identifying vulnerable components and inform prioritization of resourca allocation before, during, and after a disaster. The ability to account for uncertainty in modeling the resilience of interdependent infrastructure systems improves the performance assessment of these networks and the corresponding impact of potential disruptions.

Future work will consider the extension to model the restoration process and the impact of capacity redundancy in determining the strength of physical interdependency.

Acknowledgement. This work was partially funded by the National Science Foundation (Grant No. 1635717).

7. REFERENCES

Adachi, T. and Ellingwood, B. R. (2008). "Serviceability of earthquake-damaged water systems: Effects of electrical power availability and power backup systems on system vulnerability." *Reliability Engineering & System Safety*, 93(1), 78–88.

Adachi, T. and Ellingwood, B. R. (2009). "Serviceability assessment of a municipal water system under spatially correlated seismic intensities." *Computer-Aided Civil and Infrastructure Engineering*, 24(4), 237–248.

American Lifelines Alliance (2001). "Seismic fragility formulations for water systems part 1 - guideline." *Washington D.C.*

Barton, D. C., Eidson, E. D., Schoenwald, D. A., Stamber, K. L., and Reinert, R. K. (2000). "Aspen-ee: an agent-based model of infrastructure interdependency." *SAND2000-2925. Albuquerque, NM: Sandia National Laboratories*.

Bashan, A., Berezin, Y., Buldyrev, S. V., and Havlin, S. (2013). "The extreme vulnerability of interdependent spatially embedded networks." *Nature Physics*, 9(10), 667.

Buldyrev, S. V., Parshani, R., Paul, G., Stanley, H. E., and Havlin, S. (2010). "Catastrophic cascade of failures in interdependent networks." *Nature*, 464(7291), 1025.

Danziger, M. M., Shekhtman, L. M., Bashan, A., Berezin, Y., and Havlin, S. (2016). "Vulnerability of interdependent networks and networks of networks." *Interconnected Networks*, Springer, 79–99.

Di Giorgio, A. and Liberati, F. (2012). "A bayesian network-based approach to the critical infrastructure interdependencies analysis." *IEEE Systems Journal*, 6(3), 510–519.

Dudenhoeffer, D. D., Permann, M. R., and Manic, M. (2006). "Cims: A framework for infrastructure interdependency modeling and analysis." *Proceedings of the 38th conference on Winter simulation*, Winter Simulation Conference, 478–485.

Dueñas-Osorio, L., Craig, J. I., Goodno, B. J., and Bostrom, A. (2007). "Interdependent response of networked systems." *Journal of Infrastructure Systems*, 13(3), 185–194.

Dueñas-Osorio, L. A. (2005). "Interdependent response of networked systems to natural hazards and intentional disruptions." Ph.D. thesis, Georgia Institute of Technology, Georgia Institute of Technology.

FEMA (2013). *Hazus-MH 2.1 User Manual: Earthquake Model Technical Manual, Washington, DC.*

González, A. D., Chapman, A., Dueñas-Osorio, L., Mesbahi, M., and D'Souza, R. M. (2017). "Efficient infrastructure restoration strategies using the recovery operator." *Computer-Aided Civil and Infrastructure Engineering*, 32(12), 991–1006.

Haimes, Y. Y. and Jiang, P. (2001). "Leontief-based model of risk in complex interconnected infrastructures." *Journal of Infrastructure systems*, 7(1), 1–12.

Harmsen, S., Frankel, A. D., and Petersen, M. (2003). "Deaggregation of us seismic hazard sources: the 2002 update." *Report no.*

Holden, R., Val, D. V., Burkhard, R., and Nodwell, S. (2013). "A network flow model for interdependent infrastructures at the local scale." *Safety Science*, 53, 51–60.

Johansen, C. and Tien, I. (2018). "Probabilistic multiscale modeling of interdependencies between critical infrastructure systems for resilience." *Sustainable and Resilient Infrastructure*, 3(1), 1–15.

Lee II, E. E., Mitchell, J. E., and Wallace, W. A. (2007). "Restoration of services in interdependent infrastructure systems: A network flows approach." *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 37(6), 1303–1317.

Milanovic, J. V. and Zhu, W. (2018). "Modeling of interconnected critical infrastructure systems using complex network theory." *IEEE Transactions on Smart Grid*.

Ouyang, M. (2014). "Review on modeling and simulation of interdependent critical infrastructure systems." *Reliability engineering & System safety*, 121, 43–60.

Pederson, P., Dudenhoeffer, D., Hartley, S., and Permann, M. (2006). "Critical infrastructure interdependency modeling: a survey of us and international research." *Idaho National Laboratory*, 25, 27.

Rinaldi, S. M. (2004). "Modeling and simulating critical infrastructures and their interdependencies." *System sciences, 2004. Proceedings of the 37th annual Hawaii international conference on*, IEEE, 8–pp.

Rinaldi, S. M., Peerenboom, J. P., and Kelly, T. K. (2001). "Identifying, understanding, and analyzing critical infrastructure interdependencies." *IEEE Control Systems*, 21(6), 11–25.

Wallace, W. A., Mendonça, D., Lee, E., Mitchell, J., and Chow, J. (2001). "Managing disruptions to critical interdependent infrastructures in the context of the 2001 world trade center attack." *Impacts of and Human Response to the September 11, 2001 Disasters: What Research Tells Us*.

Wang, S., Hong, L., and Chen, X. (2012). "Vulnerability analysis of interdependent infrastructure systems: A methodological framework." *Physica A: Statistical Mechanics and its applications*, 391(11), 3323–3335.

Xu, N., Nozick, L. K., Turnquist, M. A., and Jones, D. A. (2007). "Optimizing investment for recovery in interdependent infrastructure." *System Sciences, 2007. HICSS 2007. 40th Annual Hawaii International Conference on*, IEEE, 112–112.

Yu, J. Z., Whitman, M. G., Kermanshah, A., and Baroud, H. "A bayesian modeling approach to assess the serviceability of infrastructure systems under natural hazards." *Unpublished manuscript*.

Zhang, X., Mahadevan, S., Sankararaman, S., and Goebel, K. (2018). "Resilience-based network design under uncertainty." *Reliability Engineering & System Safety*, 169, 364–379.

Zimmerman, R. (2001). "Social implications of infrastructure network interactions." *Journal of Urban Technology*, 8(3), 97–119.