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A network-of-networks percolation analysis of cascading failures in spatially co-located road-sewer infrastructure networks

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ABSTRACT

This paper presents a network-of-networks analysis framework of interdependent critical infrastructure systems, with a focus on the co-located road-sewer network. The constructed interdependency considers two types of node dynamics: co-located and multiple-to-one dependency, with different robustness metrics based on their function logic. The objectives of this paper are twofold: (1) to characterize the impact of the interdependency on networks' robustness performance, and (2) to unveil the critical percolation transition threshold of the interdependent road-sewer network. The results show that (1) road and sewer networks are mutually interdependent and are vulnerable to the cascading failures initiated by sewer system disruption; (2) the network robustness decreases as the number of initial failure sources increases in the localized failure scenarios, but the rate declines as the number of failures increase; and (3) the sewer network contains two types of links: zero exposure and severe exposure to liquefaction, and therefore, it leads to a two-phase percolation transition subject to the probabilistic liquefaction-induced failures. This indicates that tiered vulnerability of the liquefaction-prone links will result in multiple percolation transitions. The proposed framework provides a holistic approach to analyze the network robustness under different failure scenarios and can be extended to a larger interdependent system.

1. Introduction

1.1. Background

As human societies continue to develop and expand, modern infrastructure systems become increasingly complex and interdependent [1]. The modern society relies on a bewildering collection of complex and interwoven critical infrastructure systems. As technology advances, infrastructure networks are no longer isolated but rather a connected system consisting of various components interacting with each other in ways which are often not visible. As a result, the functionality of one infrastructure network not only depends on its own components but also is affected by the other networks coupled with it. Failure in one network is likely to result in failures in its dependent/interdependent networks, and vice-versa. This recursive process will eventually lead to cascading failures throughout the connected

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system [2]. The September 28, 2003 blackout in Italy demonstrated the criticality of interdependencies among multiple networks [2]. The power outage resulted in a widespread failure in railway networks, healthcare systems, financial services, and communication networks. The failure in the communication network, in turn, propagated back to the power grid management system, which led to further cascading failures in power network. Also, during the Northeast blackout of 2003, New York City's 11,600 traffic signals went inoperable due to the loss of power, resulting in mass gridlock [3]. In addition, the explosion in Cyprus in July 2011 caused major failures in power networks, which in turn led to a shutdown of water supply [4]. These catastrophes all show how interdependence can magnify the damage in the interconnected infrastructure system [5,6]. Therefore, it is essential to understand how network robustness is affected by the interdependencies to build a resilient infrastructure system [7–9].

A cascading failure occurs when the failure of a single component causes its connected components to fail [1,2,10–14]. An infrastructure network is often modeled as a graph in which nodes are the facilities and links are the connection or interaction between them, infrastructure disruption can then be characterized as link/node removal. This failure propagation closely tied to the idea of percolation modeling [15,16]. Percolation theory is capable to capture the system dynamics during the network failure, and generate a systematic evaluation of the network performance. Furthermore, it only requires network topology information, which is a great advantage when the empirical data are limited. Therefore, this paper developed a percolation-based modeling framework to analyze the network robustness. Using percolation theory, network robustness can be investigated through the occupied fraction of the largest connected component $P_\infty(p)$ which is considered as a proxy for the functionality of the network [17]. It can also be characterized by the integrated size of the largest connected component throughout the entire percolation process [18]. Buldyrev et al. [2] found that the interdependent networks were significantly more vulnerable than the non-interacting networks. Bashan et al. [19] conducted experiments on lattice networks and found that a small portion of interdependent nodes will result in an abrupt collapse of the system. These existing analytical modeling of percolation phenomena normally requires that the network is "locally tree-like" [20]. This assumption is valid for random networks with arbitrary degree distribution. However, spatially embedded infrastructure networks, such as road networks, drinking water, and wastewater pipelines, are far from the tree-like topology. Therefore, the analytical results of percolation process are nearly impossible to obtain [17,21]. This is partially why most of the existing research on spatially embedded networks are investigated through numerical simulation methods [21].

Different from the interdependencies established through wired/wireless connections, such as power and communication networks, co-located interdependencies are fairly common in a transportation network. For example, water and wastewater infrastructure are often buried underneath roads (i.e., below grade), underground leaks and water pipe failures can damage road foundations, cause surface road closures, and may form sinkholes. This will impede the traffic and cut off the access to the impacted site. Moreover, timely and efficient access to disastrous sites is critically important to prevent a localized failure to spread into a catastrophe. Earthquake is one of the worst natural disasters to break the water/wastewater pipeline systems due to strong ground shaking and soil liquefaction. In the collection and conveyance system, pipelines can be easily damaged by ground shaking, but they are more vulnerable to soil liquefaction and associated lateral spreading during seismic events since it can quickly cause the road to buckle as its foundation ceases to be solid [22]. In the 1994 Northridge earthquake, the Los Angeles Department of Water and Power had approximately 1000 pipeline breaks. The Kobe earthquake caused approximately 1200 pipeline failures [22]. Water/wastewater network failure can discharge raw sewage onto city streets and into receiving waters, resulting in road closures, public health issues, and environmental contamination. The Pacific Northwest is susceptible to a M9.0 Cascadia Subduction Zone (CSZ) earthquake [23]. The most recent mega-earthquake in the northwest was in January, 1700 [24], and there is 37%–42% chance of recurrence within the next 50 years [25]. Therefore, investigating the transportation network robustness under seismic impacts of water/wastewater system disruption is urgently needed to prepare the society to enhance the resilience of the urban lifeline infrastructure system.

However, the existing interdependency studies centered on either using theoretical networks such as Erdős–Rényi, Scale-Free networks, or networks that follow power-law distribution [2,6,26–32]. Simple spatial networks such as a lattice network [33] is also investigated. Complex spatial networks such as communication tower networks [34], power grids [35], and cyber/physical networks such as loan network [36], supply chain network [37] are studied through approximated theoretical distributions. Yet, rare studies have been focusing on the co-located interdependency between road network and other critical infrastructure systems. Gao et al. [9] and Dong et al. [38] pointed out that degree correlations and clustering in a spatial network can potentially influence the robustness behavior of the coupled networks. The dynamics of links' or nodes' presence/removal in a network are also critical in interdependent network robustness characterization, which is rather common in the case of an infrastructure network's exposure to natural hazards. Therefore, in this paper, we proposed a network-of-networks percolation simulation framework to characterize the interdependency between spatially co-located sewer and road network facing random, localized, and probabilistic failures.

1.2. Objectives and contribution

The increasing complexity and interdependency among networks require a holistic framework to systematically evaluate critical infrastructure systems. Our objectives are to (1) develop a network-of-networks simulation framework to characterize the propagation of cascading failures among co-located interdependent networks, and assess the network

Table 1
Selected interdependency types in existing literature.

Studies	Interdependency types
Rinaldi et al. [7]	Physical; Cyber; Geographic; Logical
Wallace [40]	Input; Shared; Exclusive or (XOR); Mutual; Co-located
Bühne et al. [41]	Requires dependency; Exclusive dependency; Hints dependency; Hinders dependency
Zimmerman [42]	Functional; Spatial
Dudenhoeffer et al. [39]	Physical; Geographic; Policy; Informational
Pederson et al. [43]	Policy/Procedural; Societal
Zhang and Peeta [44]	Functional; Physical; Budgetary; Market and Economic

robustness; and (2) identify the critical percolation transition threshold of the network robustness, which will then be used to inform decision-making to strategically allocate and prioritize retrofitting resources to enhance network resilience. The integrated analysis framework enables a comprehensive assessment of interdependent infrastructure network robustness by incorporating the empirical disaster-induced probabilistic failures into a percolation modeling process. It also reveals the network robustness behavior under different network failure strategies, and identifies the critical percolation transition thresholds for future network resilience enhancement planning.

1.3. Paper organization

The remainder of this paper is organized as follows. Section 2 presents a literature review of the related research. In Section 3, the methodology used in this research and the proposed framework are described in details. Section 4 presents the geo-spatial co-location property of the road and sewer network, and Section 5 shows the designed interdependency relationship between road and sewer network. Section 6 presents network robustness under the cascading failure initiated by three different types of sewer pipeline failures. Finally, Section 7 concludes the paper with the major findings and future research directions.

2. Literature review

Infrastructure interdependency refers to two or more infrastructure systems where influences of an element in one infrastructure will impart upon another infrastructure [7,39]. Based on different criteria, interdependency can be classified into different types. A summary of different interdependency categorizations are presented in Table 1.

There is a rich body of literature on infrastructure network interdependency analysis. The existing modeling and simulation approach in analyzing interdependent networks can be generally categorized into six genres as summarized in Fig. 1. The empirical approach analyzes infrastructure interdependencies based on historical data and expert experience. However, the infrastructure interdependency failures are underreported, and the previous failure records may not be able to predict the network performance facing new disasters. Agent-based modeling allows us to model the action and interaction of agents, and assess their effects on the system as a whole. However, the assumptions made by modeler will heavily affect the results of the simulation and the simulation parameters are hard to calibrate. Similarly, system dynamics-based models are hard to calibrate and validate due to the lack of data and the fact that component-level behaviors cannot be captured.

Intuitively, an infrastructure network can be abstracted as a graph, where nodes represent different critical infrastructure system components and links denote the interactions among them. The system performance measurement can start by modeling the failures caused by the hazard at the component level, and then examine the cascading failures within and across different networks at the system level. Infrastructure networks are spatially embedded [19] and their component failure probabilities are different. When the node heterogeneity is considered in the interdependent network modeling, simulation-based methods are normally utilized to examine the performance of interdependent networks under different failures scenarios. Defining the possible link formation as probability ω, Stippinger and Kertész [74] found that there is a critical healing probability, below which failure cascades and the average degree of functional nodes declines monotonically, and vice versa. These findings help us to understand how much efforts are needed to prevent cascading failure. Similarly, to prevent/mitigate the complete destruction of an interdependent system that undergoes cascading failures, La Rocca et al. [75] proposed that after removing $1-p$ fraction of nodes, the isolated components are reconnected to the functional giant component with a probability γ. The strategy is proved effective as γ increases, since the resilience of the system to cascading failure also increases.

Inspired by Italy electricity blackout in 2003, Buldyrev et al. [2] developed a cascading failure model for understanding the robustness of interdependent networks subject to cascading failures. The framework comprises three entities: network A, network B, and interdependency between the networks which is represented as $A_i \leftrightarrow B_i$. The interdependency link captures the effect that failure of a node in network A has on the corresponding node in network B, and vice versa. Failures are initiated by randomly removing p fraction of nodes from A. Upon the introduction of the failure in network A, the nodes in network B that are connected via $A_i \leftrightarrow B_i$ to the failed nodes are also removed. This cascading failure will propagate back and forth between two networks until a steady state is achieved when no further removal of edges/nodes

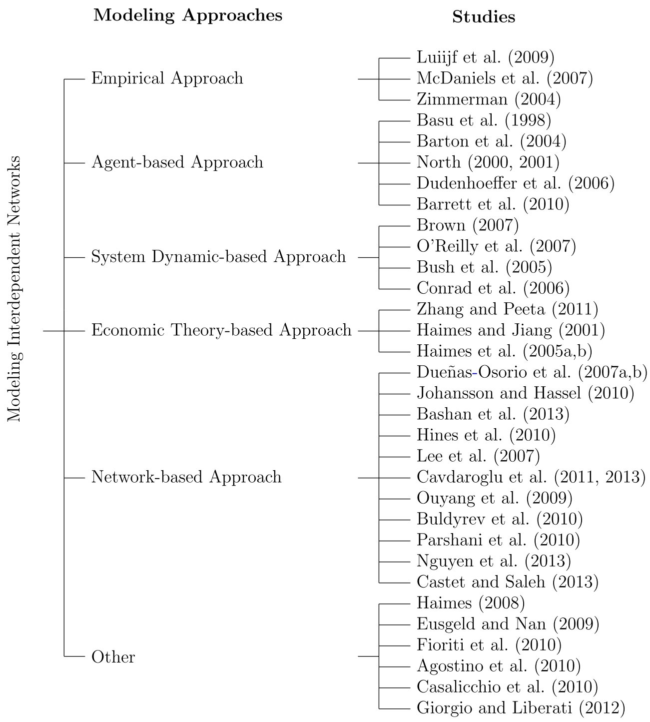


Fig. 1. Modeling approaches summary of interdependent network [2,6,19,35,39,42,44–73].

in the networks are possible. Eventually, the two interdependent networks consist of mutually connected clusters, which satisfies (1) network A and B are connected; (2) each of these nodes that belongs to A has $A_i \leftrightarrow B_i$ edge with B, and vice versa. The experiment suggests that the above cascading process leads to a percolation phase transition for the two interdependent networks at a critical threshold, $p = p_c$. The giant mutually connected cluster is defined as the cluster having the maximum number of nodes. Only giant mutually connected clusters are potentially functional. Below p_c there is no giant mutually connected component, whereas above p_c a giant mutually connected cluster exists. In the model developed by Buldyrev et al. [2], each node in network A depends on one and only one node in network B. However, this assumption may not stand. A single node in network A may depend on more than one node in network B, and vice versa. Also, the resource in one node is limited. For example, one power station cannot support the entire communication network. In order to overcome this shortcoming, Shao et al. [76] extended the work in [2] and provided a theoretical framework for characterizing the interdependent networks' robustness with multiple support-dependence relations. Furthermore, in reality, not all nodes of network A depend on network B and vice versa. Therefore, Parshani et al. [6] introduced a general model that is more realistic to real networks and conducted experiments on Erdős–Rényi and Scale-free network.

Nguyen et al. [35] proposed a model to identify critical nodes whose removal maximally destroy the system's functionality in the interdependent power and communication networks. The results suggest that when interdependent systems are loosely connected they are more vulnerable to failure. Also, the sparse interdependent networks and large networks are more vulnerable to cascading failure. Parandehgheibi and Modiano [34] also considered the interdependent power and communication networks in 2003 Italy blackout scenario. A power node remains functional if it connects to both router and generator; while a communication node remains functional if it connects to both the control center and substation. In this paper, they studied the minimum number of node failures needed to cause the total blackout. The results showed that the northwest part of Italy is acutely vulnerable. Network-based models can capture the dynamics of the interaction among interdependent infrastructures and realistically describe the cascading failure process. It also could help identify the critical infrastructure component, and provide emergency protection suggestions. Therefore, in this paper, we used a network-based approach to develop a network-of-networks modeling framework for modeling the co-location interdependencies among infrastructures. The proposed framework not only captures the cascading failure propagation dynamics but also incorporates the probabilistic failure into the model to investigate the system performance under realistic post-hazard network disruption scenarios.

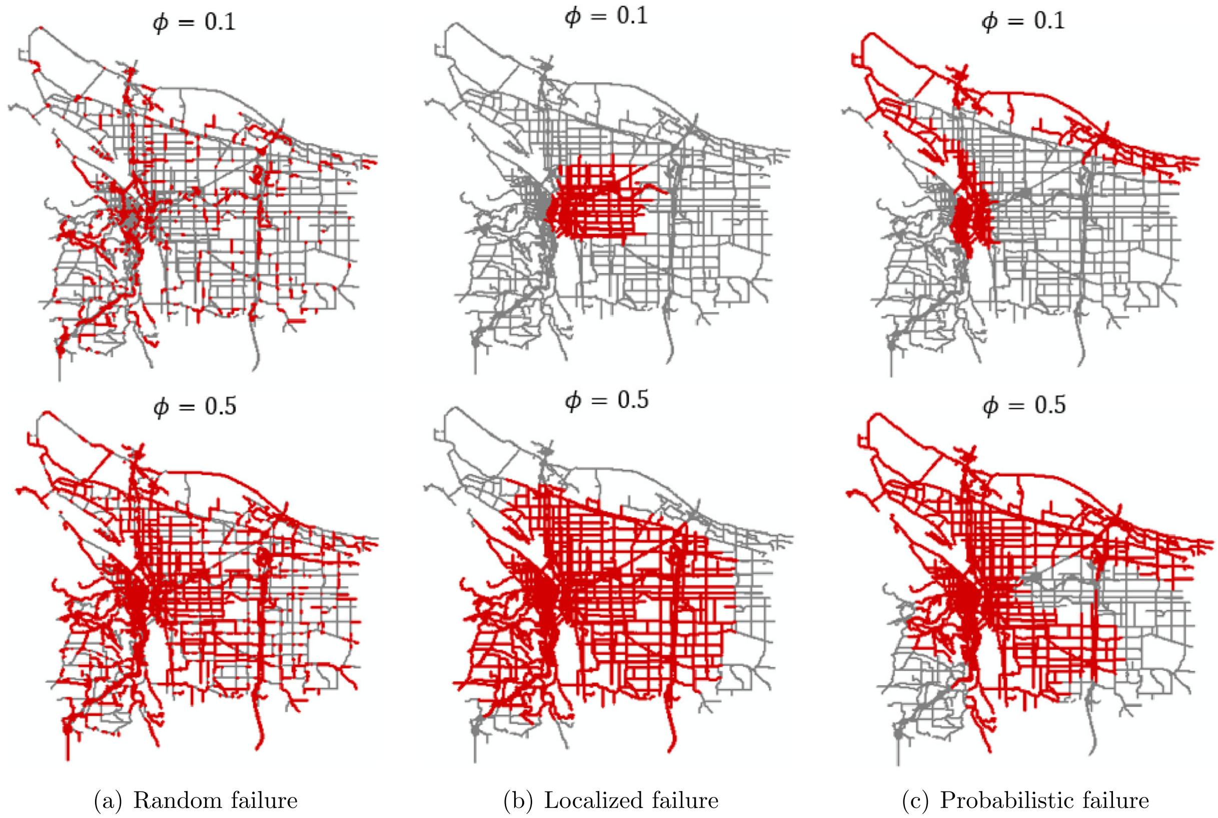


Fig. 2. Network percolation under different failure patterns. (a) random failure is initiated by randomly selecting ϕ fraction of the nodes; (b) localized failure starts by first randomly identifying one failure source, and then spreading to adjacent ϕ fraction of the nodes; (c) probabilistic failure represents the case that links have different probability to be removed from the network, for example, the roads close to water are prone to liquefaction. In a failure scenario, links with higher probability are more likely to be removed.

3. Methodology

3.1. Percolation

The percolation process is characterized by the probability of ϕ that a node is functioning in the network. As ϕ decreases, the system will reach a point, ϕ_c, that the largest connected cluster (also known as the giant component) of the network diminishes to zero. Above ϕ_c the network will be tightly connected. The formation and dissolution of the giant component are called a percolation process [77]. However, the infrastructure network disruption in real life varies. For example, when the entire network faces destruction in a disaster, the disruption can be considered as uniformly distributed and can be approximated with random failures. In a daily operation scenario, the network disruption can be initiated from a couple of nodes/links' failures, this resembles a localized failure pattern. In a natural disaster when different infrastructure components have distinctive exposures to varying levels of damages, this can be reasonably formulated as probabilistic failures. As the dynamics of link/node removal will exhibit prominent percolation behaviors, understanding infrastructure network robustness performance and how it can be enhanced in different network failure scenarios holds great promise for better infrastructure assessment and retrofitting with challenges of limited resource. It also promises to unlock knowledge of how the lifeline infrastructure networks are co-located to enable the society to function in a social world. Fig. 2 illustrates the network percolation under different network disruption patterns.

The transition point ϕ_c is called the critical percolation threshold. Critical percolation transition threshold ϕ_c is often adopted to represent the robustness of the network [78,79]. However, it neglects the cases before the network is completely destroyed [8]. To present a more comprehensive assessment, Schneider et al. [18] introduced the robustness measure R.

$$R = \frac{1}{N}\sum_{Q=1}^{N} s(Q) \tag{1}$$

where N is the total number of the nodes in the network, and $s(Q)$ is the fraction of nodes in the largest connected component after removing $Q = N(1-\phi)$ nodes. $1/N$ normalizes the result so that the results can be compared across different networks sizes. R ranges from $1/N$ (star graph) and 0.5 (fully connected network).

Giant component is commonly used to define the network robustness based on the assumption that after a major disruption, the largest connected cluster will maintain the functionality [77]. This is true when connectivity is the primary goal of the network. For example, when a road network is disrupted, the largest connected cluster will maintain most of the mobility, as it will be significant in transporting goods and evacuation. However, this assumption can be impaired when the nodes need resources to support functionality. In this case, connectivity to the critical facility would be rather important [80]. For instance, the critical facility on sewer network contains the necessary resources or they are vital in controlling the flow of the sewer network, failure of which would result in malfunctioning of its connected nodes. Therefore, we propose the idea of using "robust component"to characterize the network robustness in this setting. Intuitively, the robust component is the union of the nodes that connect to at least one critical facility. In a graph G, two vertices u and v are considered connected if there is path from u to v, which is denoted as $\rho(u, v) = 1$. Given a network of size N, containing M critical facilities, the connected component to the critical facility k can be represented as $C_k = \{v_i \mid \rho(k, v_i) = 1, \forall i = 0, 1, \ldots, N\}$. Following this, the robust component of a network with occupation probability ϕ can be defined as

$$\Re_\phi = \bigcup_{k=0,1,\ldots,M} C_k \tag{2}$$

3.2. Network-of-networks interdependency simulation framework

Modern critical infrastructure systems are no longer isolated but interdependent on each other. Consider two independent networks A and B with p% of network A' nodes depends on the nodes in the network B, and accordingly, q% of network B' nodes depends on the nodes in network A. The cascading failures are initiated by removing a fraction $1-\phi$ of network A nodes and all its connected links. Further, due to the interdependency, its dependent nodes in network B are also removed together along with its connected edges. This failure will result in the fragmentation of the network, and we assume the nodes that belong to the giant component (or robust component) are still functional. Since each network has its unique topology, the nodes that failed at each step are different, which will lead to the further propagation of the failure back and forth between the system through the interdependencies. This cascading process continues until the system reaches a steady state [6].

Parshani et al. [6] formulated cascading failure through a moment generating function approach. Nonetheless, the model is implemented on the ER network and a scale-free network. Due to the associativity in spatially-embedded networks, the generating function methods are often inadequate in accurately characterizing the percolation process. Moreover, most of the existing analytical frameworks of percolation require a "locally tree-like network" [20], which is invalid for spatially-embedded networks [17]. Therefore, a simulation-based analysis is encouraged [21]. In this paper, we propose a network-of-networks simulation framework, summarized in Fig. 3. The proposed framework will enable us to capture the interdependency among multiple infrastructure networks. Given the scope of the study, we first construct the connected networks based on the individual network structure and the interdependencies among networks. We then devise the failure sequence based on the investigated scenario (e.g., random failure, localized failure, or probabilistic failure etc.). With both network and failure sequence, we then impose the failure to the coupled networks at different levels of ϕ. The failure cascades through the system based on the defined interdependency mechanism, and finally, we can examine the network performance through the proposed metrics.

4. Road-sewer network co-location

Road network is the backbone of any city and connects different infrastructure to transport the goods and services. Other infrastructure networks are geospatially closely located on the road network so that their facilities are easier to access, e.g., electricity grid, sewer pipelines etc. This geospatial proximity is defined as co-location in this paper. Studying co-located urban infrastructure networks that distribute critical services over large area is critical for understanding the urban dynamics [81]. For example, the sewer pipeline leaks/breaks can lead to wide spreading of the sewer on street causing public health concerns. It can also result in a sinkhole that cuts off the street. We abstract the infrastructure as a graph, and use complex network theory to analyze the similarities in topologies of above- and under-ground infrastructure networks. Klinkhamer et al. [82] found the strong correlations in topological metrics between surface and subsurface infrastructure networks, where a power-law node-degree distribution was discovered. It is worth mentioning that several studies used a dual approach to study the infrastructure network [81–84]. However, the network conversion of the dual approach will lead to the over-simplification of the network topologies. Therefore, in this paper, we used the prime approach to investigate the co-located sewer and road network.

Fig. 4 presents the Portland Metro sewer and road network. The road network is obtained from public resources such as OpenStreetMap. The sewer network is provided by the Portland Bureau of Environmental Services. There are totally 50,030 links and 50,472 nodes in the sewer network (pipe as the link and the junction as the node), and 39,418 links and 28,382 nodes in the road network (road segment as the link, and intersection and junctions as the node). Fig. 5 shows the

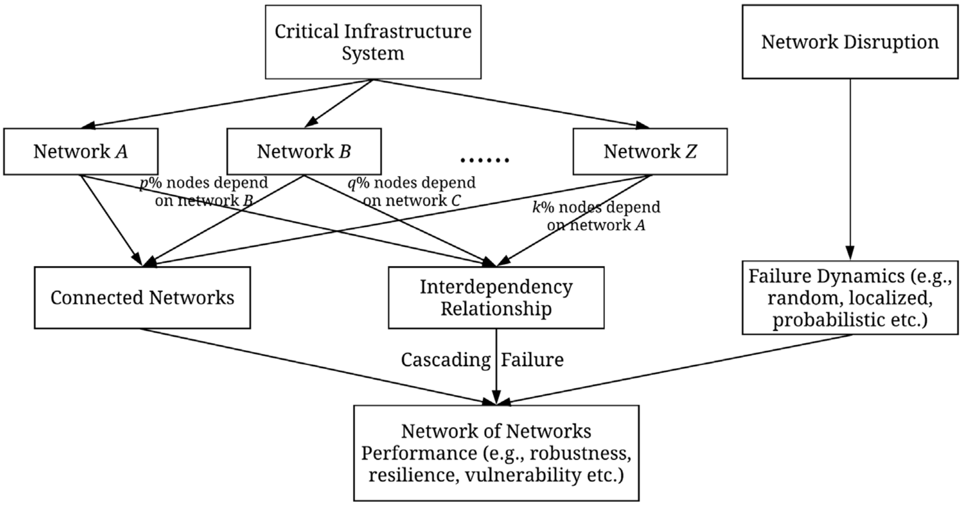


Fig. 3. Network of networks simulation framework.

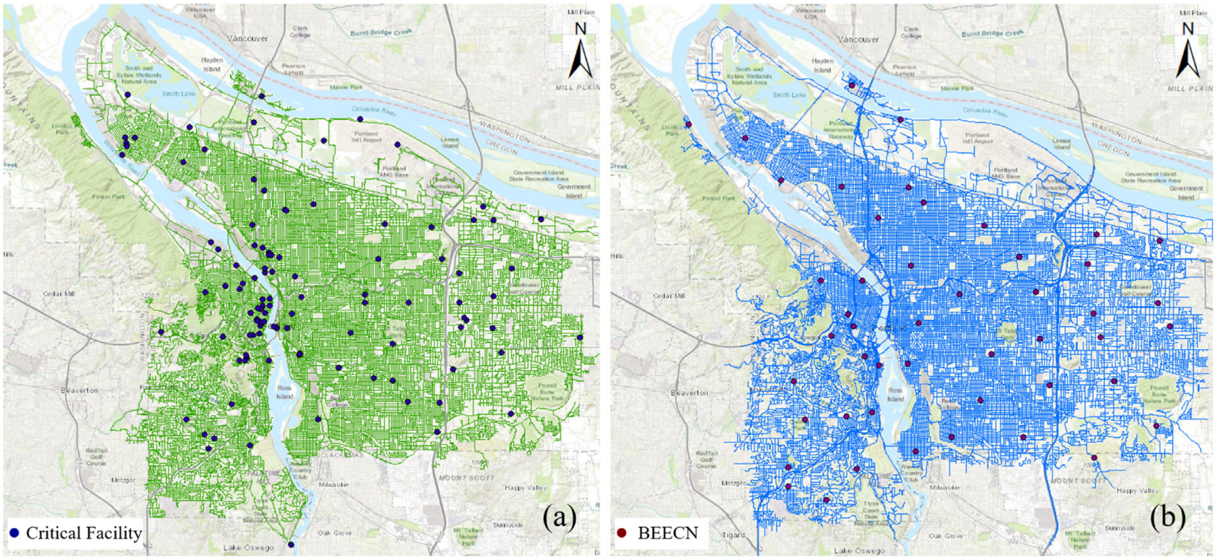


Fig. 4. Portland Metro sewer and road network; (a) green links represent the sewer network, and the blue points mark the critical facilities identified by Portland Bureau of Emergency Management, that has Tier I importance in a post-disaster situation; (b) blue links represent the road network which includes freeway, highway, major arterial, and local street, and purple points denote the Basic Earthquake Emergency Communication Nodes (BEECN) where citizens can respond to, report damage, and receive safety information following a major earthquake [85].

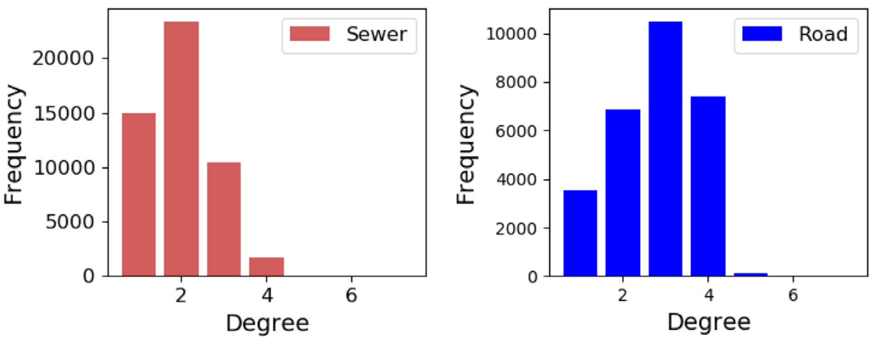


Fig. 5. Portland Metro sewer and road network node degree distribution.

degree distribution of both networks. Sewer network has more chain-like structure since most of the node has a degree of 2. However, the road network shows a peak at a degree of 3. This is because there are a large number of residential roads that are connected to the local street, which creates the ''T'' shape network structure.

To analyze the geospatial co-location of the road-sewer networks, the spatial orientation of the road and sewer network are investigated respectively. Starting with a road centerline, we iterate through the road network nodes and examine if any sewer line appears within a proposed buffer distance. Buffer distance of 1 m, 5 m, 10 m, 15m are used. In the U.S., the design standard for lane width is 3.6 m [86], which means that maximum buffer distance is equivalent to the width of a two-lane road with right-of-way surrounding the road. The results show that 9.86% of the road have a sewer pipe beneath within 1 m buffer, 41.36% of the road have a sewer pipe within 5 m buffer, and 56.5% of the road have a sewer pipe within 10 m buffer. As the buffer increases to 15 m, 65% of the road are expected to have a sewer pipe beneath at least some portion of its length. This shows a strong co-location between road and sewer network.

5. Coupled road-sewer network interdependency design

In a disaster scenario, the roads and other lifeline infrastructures inside the spreading zone are subjected to the severe impact of spreading and ground failures [87]. GIS analysis of Christchurch potable water system performance showed a clear correlation between the damage to network and occurrence/severity of liquefaction [88]. During the 2010–2011 Christchurch earthquakes, 80% of the main water breaks (repairs) occurred in liquefaction impacted area, and approximately 60% of the failures were located within the area of moderate-severe liquefaction, where lateral spreading is the key contributing factor. The wastewater system is even more seriously damaged because its pipes are laid deeper (2.0–3.5 m), and therefore, more susceptible and vulnerable to damage and also more difficult to access for repair [87]. The state of Oregon is extremely vulnerable to the potential CSZ megathrust earthquake. Therefore, in this paper, we investigate the interdependent road-sewer network robustness in Cascadia Subduction Zone earthquake-induced failure.

Fig. 4 showed the co-location between sewer and road network. Sewer and road network are not only geo-spatially co-located, but also functionally interdependent. For example, leaking sewer pipes can cause soil subsidence, which will undermine the overlying road and eventually lead to disruptions ranging from small potholes to complete collapse of a road segment. Also, high traffic on major roadways will increase the deterioration rate of subsurface pipes [81]. Moreover, in addition to the network, there are 115 identified critical facilities in the investigated sewer network. These critical facilities are essential in a post-disaster recovery process. Therefore, ensuring the functionality of the critical facilities and the connection to them is essential to build a robust sewer system. A BEECN is a place in the city of Portland that is designed to provide people with emergency assistance and to address sever infrastructure damages if phone service is down after a major earthquake. Since the BEECNs are sparse, each site will control a part of the region. That is to say, multiple sites are dependent on one BEECN. Without access to these sites, the public will not be able to report the infrastructure damages and the responders cannot act in time, which leads to further spreading of the failure. Fig. 6 illustrates the interdependency between sewer and road network. It is noteworthy that sewer network has high resolution, that is to say, there might be multiple sewer lines underneath one road link, and failure of any of them would lead to the co-located road link closure. Co-located road-sewer interdependency means the sewer line will affect its nearest road link, and this will potentially result in a multiple-to-one relationship from the sewer to road network. The cause of water/wastewater pipe failure can be material degradation due to exposure to aggressive environments or physical defects acting as initiation points from slow crack growth [89]. In this research, we mainly focus on the sewer line failure results from ground shaking in an earthquake. In a disastrous event such as the earthquake, the ground motion will lead to the damage of sewer network, and these damages will cascade to its co-located road segments through spreading of sewer or sinkhole on the road that cuts off the mobility on the road. At the same time, such road network failure will impede the access to BEECN, and thus, the disrupted sewer pipe will not be fixed in a timely fashion. This will result in further failure of the sewer network. These failures will propagate back and forth, and cease until no further failure cascades between the two networks.

6. Interdependent road-sewer infrastructure network robustness

Depending on the nature of the failure, the network will exhibit different post-disruption behaviors such as connectivity and accessibility change. Random and localized failures are commonly investigated in the existing literature. Random failure assumes the link failure probability is uniformly distributed. This replicates the disastrous failure in natural hazards scenario such as a mega earthquake. Although most of the daily network disruption is not randomly generated, investigating random failure can provide a holistic assessment of the network robustness performance. Especially in the case that the focal point of incoming natural disaster and its magnitude level are unknown. Localized failure is rather common in real life, e.g., chemical spill, terrorist attack, pipe leaking/explosion. It replicates the infrastructure operation failure scenario that disruption is initialized at one or more sources, and then it spreads across the network. For instance, an exploded pipeline, chemical spill, disease dispersion, etc. Moreover, the probability of a link being damaged in a disastrous event varies based on its intrinsic vulnerability, such as the infrastructure fragility condition and a region's geographic exposure to natural hazards. Therefore, considering this conditional failure probability will provide us an accurate evaluation of network robustness towards the destruction. Also, it is worth emphasizing that the failure scale 1-ϕ is measured in proportion to the sewer network.

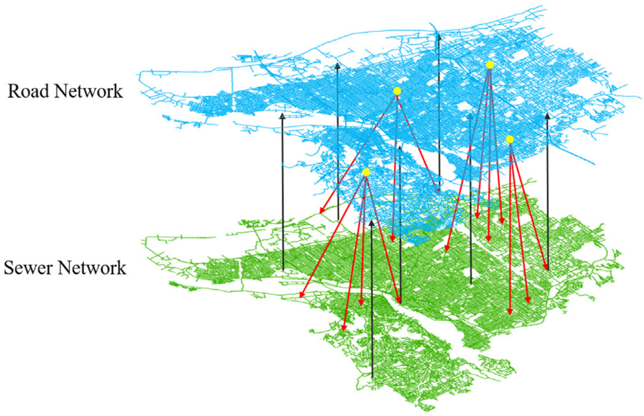


Fig. 6. Illustration of interdependency between sewer and road network.

6.1. Scenario I: Interdependent network robustness under random sewer pipeline failure

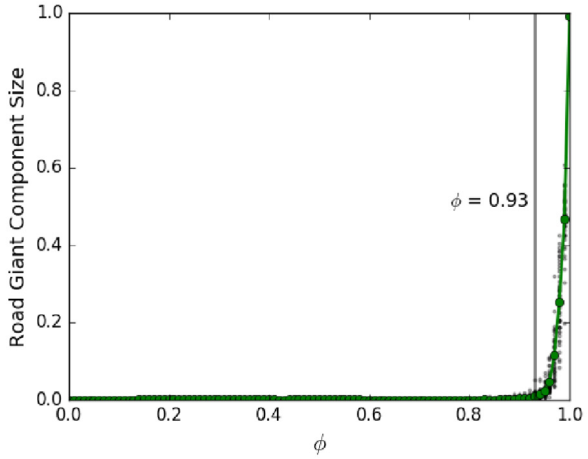
Based on the cascading failure scheme presented in Fig. 6, a network-of-networks assessment is conducted based on the devised random failure of the sewer network. Three different network performance metrics are utilized here: giant component size (GCS) in the road network, robust component size (RCS) in the sewer network, and mutually connected giant component size (MCGCS) in the interconnected networks. Giant component size of the road network is a good indicator of the network connectivity since transporting goods is the main goal of the road network, while sewer lines need to connect to the critical facilities to obtain the necessary resources for normal functioning or post-disaster recovery. The mutually connected giant component provides a venue for critical facilities to exchange the resources through the connected road network.

Fig. 7 presents network performance with random sewer pipeline failure. Here, ϕ represents the percentage of nodes that are functioning in the network. The ϕ varies at a rate of 0.01. In order to obtain a comprehensive assessment, a Monte-Carlo simulation scheme is adopted. Under each ϕ, 50 simulations are conducted and the mean performance is calculated. Fig. 7(a) shows the percolation process of road network GCS under the failure resulted from sewer line disruption. The critical percolation transition occurred at $\phi = 0.93$. That is to say, with 7% of random sewer line failure, the failure will propagate to road network based on the proposed scheme, and eventually lead to the isolation of the road network as the road GCS diminishes to zero. In addition, the robustness index will be $R^{\text{random}}_{\text{road gcs}} = 0.011$. This shows the extreme vulnerability of road network resulted from the co-located interdependency from sewer network.

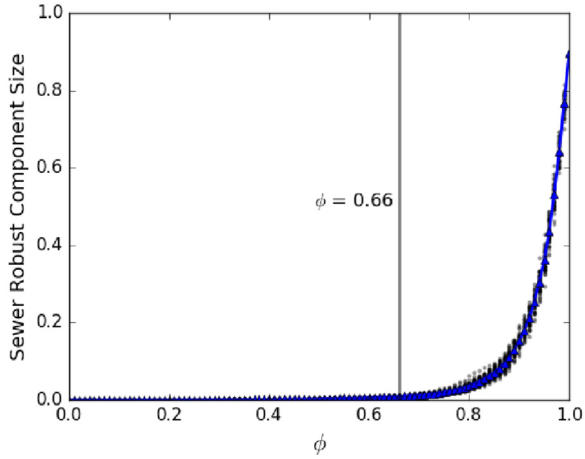
In terms of the sewer network, the connectivity of the whole network does not guarantee the functionality. The accessibility to the critical facilities is the key to maintaining a robust sewer network. Therefore, we utilized the robust component to represent the robustness of the sewer network. As we can observe, with 34% of the nodes disrupted in the sewer network, none of the nodes are connected to critical facilities. That is to say, the sewer network will fail with 37% of the nodes' services down. This leads to $R^{\text{random}}_{\text{sewer rcs}} = 0.055$. It is noteworthy that the maximum value of RCS (0.90) does not reach 1. That is because some sewer lines are connected to the critical facility via the stormwater line. As we are exclusively investigating the sewer network, some of the sewer nodes' access to the critical facility are thus cut off. It is also worth noticing that at the same level of sewer line disruption, sewer network is more robust than the road network, which results from the difference in GCS and RCS measurements.

From a network-of-networks perspective, it is also important to understand the behavior of the interconnected components. In this scenario, the giant component in the interconnected road-sewer network means that different critical facilities and their connected sites can share the resources through the road network. Fig. 7(c) shows the giant component that is connected between the road network and sewer network after the cascading failure as ϕ failures are initiated in the sewer network. We can see that as size of the failure in sewer network increases, the GCS of the mutually connected network is decreasing, and diminished to 0 at $\phi = 0.84$ with $R^{\text{random}}_{\text{mutual gcs}} = 0.023$. This suggests that the interdependent road-sewer system is very vulnerable to cascading failure. With small disruptions, the interconnected system will be isolated and soon the resource will be drained out.

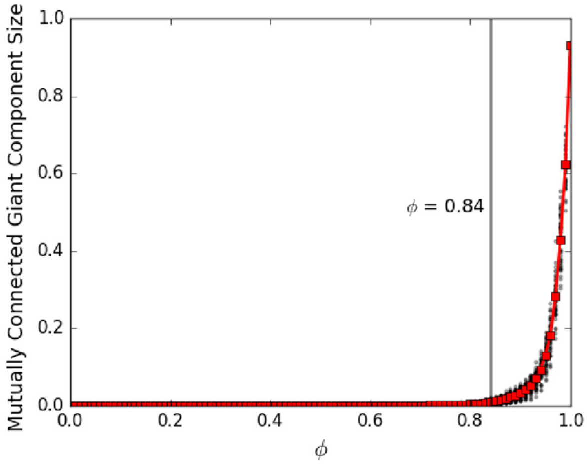
It is worth mentioning that the obtained percolation transition (second-order) is in contrary to some of the existing literature [9,12,90] which show a first-order transition. That is because, in this study, we conducted a Monte-Carlo simulation to obtain the general robustness performance of the coupled network. Therefore, some of the first-order transitions were smoothed by averaging the multiple processes. In addition, the different orders of transition are discovered on theoretical networks such as ER network and scale-free network. This study investigates two spatial networks that contain degree correlation, which will result in different percolation behaviors. Furthermore, there exists multiple-to-one dependency relationships in the designed road-sewer interdependency. For example, there are multiple sewer lines underneath one road segment, any failures of which will lead to whole road segment disruption. This also contributes to the second-order percolation transition in our robustness measurement.



(a) Road GCS robustness under random failure



(b) Sewer RCS robustness under random failure



(c) mutually connected GCS robustness under random failure

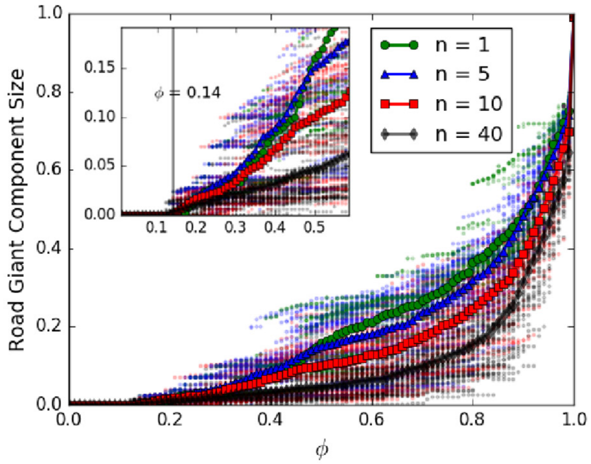
Fig. 7. Network performances under random sewer line disruption induced cascading failure.

6.2. Scenario II: Interdependent network robustness under multi-source localized sewer pipeline failures

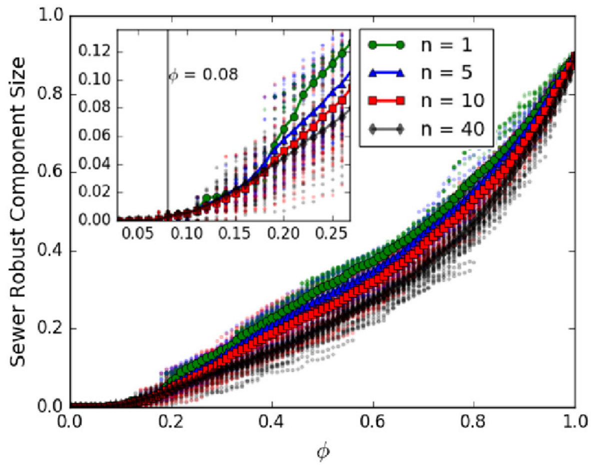
Localized failure replicates the scenario that the failure emerges and spreads to its adjacent nodes. The number of the initial source of failure n obviously will impact the network behavior. Fig. 8 shows network robustness with different numbers of failure sources in the sewer network. As presented in Fig. 8(a), the critical percolation transition threshold ϕ_c occurs around 0.14. Although the critical percolation transition threshold does not vary significantly, the calculated robustness drops as the number of failure sources n drops. As n goes from 1 to 40, $R_{\text{road gcs}}$ goes from 0.196 to 0.102. It is also noteworthy that the decline rate of road GCS robustness decreases as n gets larger.

Fig. 8(b) shows the sewer RCS robustness. We found the network components completely lose their access to the critical facilities when $\phi = 0.08$. Here we calculate the robustness index: $R_{\text{road gcs}}^{\text{local 1 source}} = 0.365$, $R_{\text{road gcs}}^{\text{local 5 source}} = 0.347$, $R_{\text{road gcs}}^{\text{local 10 source}} = 0.327$, $R_{\text{road gcs}}^{\text{local 40 source}} = 0.291$. Similarly we conclude that as the number of failure source increases, the robustness of sewer network decreases. Also, the sewer RCS robustness is higher than road GCS robustness for a similar reason as mentioned for the case with random failures.

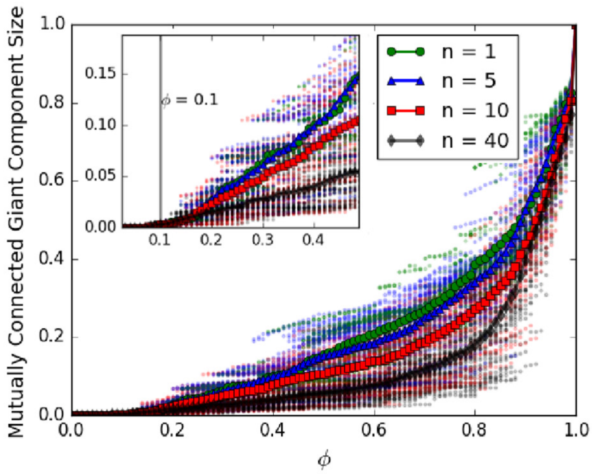
From the mutually connected component in Fig. 8(c), we obtain $R_{\text{mutual gcs}}^{\text{local 1 source}} = 0.209$, $R_{\text{mutual gcs}}^{\text{local 5 source}} = 0.200$, $R_{\text{mutual gcs}}^{\text{local 10 source}} = 0.164$, $R_{\text{mutual gcs}}^{\text{local 40 source}} = 0.125$. Compared to road GCS and sewer RCS, the mutually connected GCS lies in the middle region. Moreover, when $\phi = 0.8$ and $n = 1$, $\text{road}_{\text{gcs}} = 0.37$, $\text{sewer}_{\text{rcs}} = 0.59$, $\text{mutual}_{\text{gcs}} = 0.39$. This implies that, although 59% of the sewer network are connected to the critical facilities via pipeline, they are not necessarily



(a) Road GCS robustness under localized failure with different number of failure sources



(b) Sewer RCS robustness under localized failure with different number of failure sources



(c) mutually connected GCS robustness under localized failure with different number of failure sources

Fig. 8. Network robustness under multi-source localized sewer line disruption-induced cascading failure.

connected by the road. In a case that requires resource transporting and sharing between components, only a small part of the interdependent system can be operational.

6.3. Scenario III: Interdependent network robustness subject to failure from earthquake-induced liquefaction

The potential CSZ mega-earthquake in Pacific Northwest is expected to induce various hazards such as landslides, soil liquefaction, and bridge damages. These earthquake-induced failures will cause both direct and indirect socio-economic losses. Therefore, investigating the network robustness to earthquake-induced disruptions are essential to building a resilient lifeline infrastructure system. Fig. 9 shows the geographic exposure of Portland sewer network to liquefaction in a M9.0 earthquake scenario [91]. As can be seen, the liquefaction is likely to occur in the regions that are closer to the water. Different colors mark the probability that a link will be subject to liquefaction damage after an M9.0 earthquake. Totally, there are 7534 sewer lines (14.9%), 7890 (15.6%) nodes that are located in the liquefaction zone. Larger the probability that the liquefaction impacts the link, more likely it will be destructed during the cascading failure. To create the failure sequence, we first constructed the cumulative probability based on the probability of the link that is prone to liquefaction, and then randomly select the link from the set. The link with the larger probability will be more likely to be selected and included in the failure sequence. The network robustness percolation processes are presented in Fig. 10.

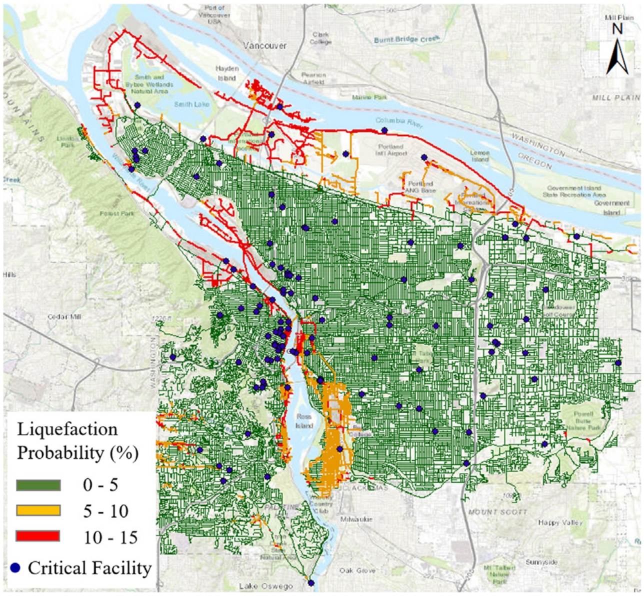
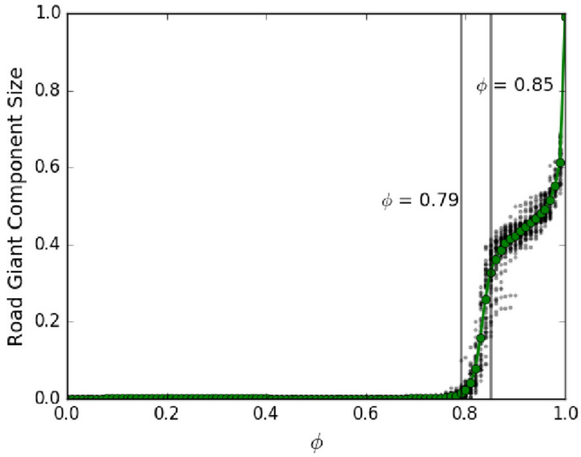


Fig. 9. Geographic exposure of Portland Metro sewer network to liquefaction in an M9.0 earthquake scenario.

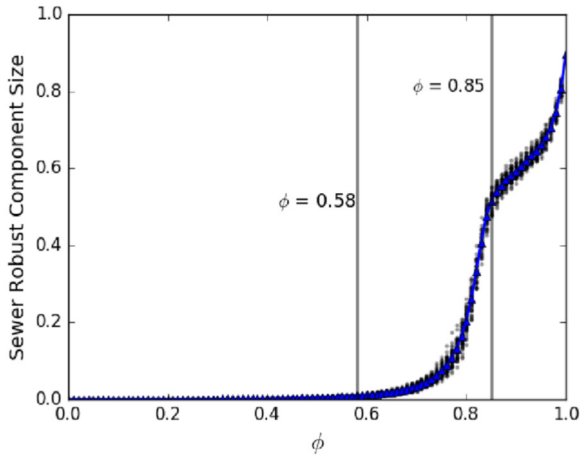
Looking at the three subfigures in Fig. 10, it is worth noting that there is a two-phase percolation transition, and they all share the same first critical percolation threshold at $\phi = 0.85$. This corresponds to the proportion of nodes that are exposed to liquefaction failures (i.e., 15%). This phenomenon can be explained through the network disruption scheme. Due to the different geographic exposure to soil liquefaction hazards, those which are highly prone to soil liquefaction will be more likely to be removed first. Therefore, the first 15% of the network disruptions are likely from the vulnerable section of the network. After the $\phi = 15\%$, the network shares the same probability to liquefaction failure, which is similar to the random failure scenario. Comparing to Fig. 7, similarly we find that road network is extremely vulnerable to the sewer network disruption. The two-step network disruption process eventually caused the two-phase percolation transition of network robustness in the probabilistic failure scenario. That is to say, this two-way division (i.e., zero and non-zero liquefaction probability) of the links will lead to a two-phase transition.

Focusing on the first-phase percolation transition. We show that road network is very vulnerable to the liquefaction-induced failure. The large variance in giant component size (suggested by the scattered black dots) indicates that different failure scenarios can result in different robustness behaviors, and we can devise targeted protection plans to push the upper bound of the percolation process and increase the robustness of the coupled system. Although the first percolation thresholds are the same, the robustness shows significant variation: $\mathrm{gcs}_{\phi_c}^{\mathrm{road}} = 0.43$, $\mathrm{rcs}_{\phi_c}^{\mathrm{sewer}} = 0.57$, $\mathrm{gcs}_{\phi_c}^{\mathrm{mutual}} = 0.43$. Fig. 10(a) shows the road GCS robustness under liquefaction-induced sewer system failure. The critical percolation transition happens at $\phi = 0.79$. It means that with 21% of the nodes removed in the sewer network, the giant component in road network will be completely isolated. The calculated robustness index is $R_{\mathrm{gcs}}^{\mathrm{road}} = 0.075$. Similarly, with 42% of the nodes removed in the sewer network, the whole network will lose its access to the critical facilities due to both failures of critical facilities as well as broken connection between nodes and critical facilities. Its corresponding robustness index is $R_{\mathrm{rcs}}^{\mathrm{sewer}} = 0.137$. At the same time, the critical percolation transition threshold for mutually connected GCS robustness is at $\phi = 0.77$ with robustness index $R_{\mathrm{gcs}}^{\mathrm{mutual}} = 0.085$.

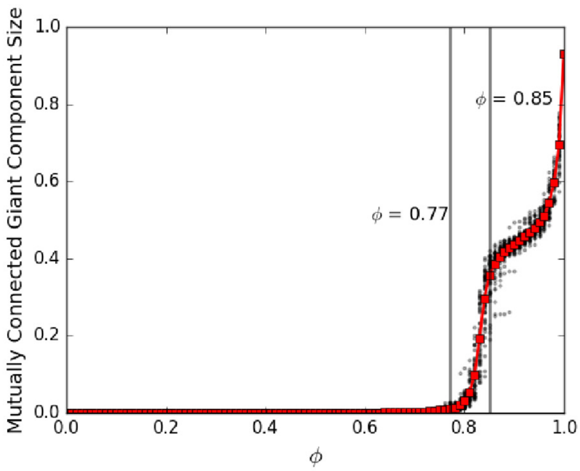
Comparing the network robustness under three different failure patterns, we conclude that (1) infrastructure interdependency greatly increases the networks' vulnerability (e.g., road, sewer, and mutually connected component) to random failures, where 7% of the sewer network failure will propagate through the system and result in complete deterioration of the functional network; (2) localized failure poses less severe threat on networks. However, as the number of initial failure sources n increase, the network becomes more vulnerable, and the robustness decline rate decreases as n gets larger; and (3) co-located road-sewer networks show a two-phase percolation transitions under liquefaction-induced sewer system failures. This results from the distinction between zero and non-zero liquefaction-probable links. The multiple-phase transition in percolation process allows us to deeply understand the robustness performance in face of realistic probabilistic network disruptions and help us devise effective mitigation strategies to protect the critical components of an infrastructure network and improve the robustness of the interdependent lifeline infrastructure system.



(a) Post-earthquake road GCS robustness under liquefaction-induced co-located sewer line failure



(b) Post-earthquake sewer RCS robustness under liquefaction-induced sewer line failure



(c) Post-earthquake mutually connected GCS robustness under liquefaction-induced sewer line failure

Fig. 10. Network robustness under liquefaction-induced sewer line failure: a M9.0 earthquake scenario.

7. Conclusion and future directions

In this paper, we proposed a network-of-networks analysis framework to investigate the network robustness under different failure strategies. Specifically, this study is dedicated to investigating the co-located interdependency between the road network and lifeline system such as sewer network. We constructed a mixed interdependency pattern to represent a post-disaster scenario: co-location of the sewer network to a road network, and one-to-multiple from the road to the sewer network. To fully understand the network robustness behavior, three different scenarios are created: random failure, localized failure, and probabilistic post-earthquake liquefaction failure. Based on the proposed network analysis framework and constructed interdependency relationship, the results show that (1) road infrastructure showed high vulnerability to the failure imposed by the co-located sewer system failure; (2) as the number of the initial localized failure sources n increases, the network robustness decreases and the rate declines when n is high; and (3) two-phase percolation transition occurred in liquefaction-induced sewer system failure scenario due to the proportion distinction of network components that are exposed to natural hazards (i.e., zero and non-zero probability towards failure).

Thus far, percolation studies of spatially interdependent physical networks are very limited. We expect our framework to provide insights on coupled infrastructure interdependency analysis. The proposed model enables a comprehensive analysis of topological and functional robustness of interdependent networks. Other than the probability of disruption varies across the network, the physical condition of the infrastructures also changes. For example, the aging infrastructure will lead to different resilience behavioral challenges facing natural or man-made disasters [92,93]. To accurately measure the infrastructure network robustness, the infrastructure fragility will be included as we further improve the model. In addition, current probabilistic failure only considers one type of hazards while the real-world hazards may occur in combination as multihazard scenarios (i.e., major and secondary). Therefore, more sophisticated probabilistic failure modeling and scenario evaluation tools should be devised to examine the infrastructure network's robustness performance [94]. It is worth noting that existing network disruption is devised based on the static hazards map or historical data. This provides a first-step evaluation of the infrastructure network vulnerabilities, however, significant improvements are required for real-time hazards impact assessment. Disaster information mining through social media allows a fast detection of the infrastructure failures [95–97]. As our cities are becoming smarter and citizens are more engaged in the disaster relief activities, we aim to incorporate the social component (i.e., duration of service losses and their impact on quality of life) into the interdependent infrastructure network studies. More importantly, the rapid recovery of the disrupted network is of critical importance to enhance the overall infrastructure network resilience. Social resilience and risk communication have all proven to significantly impact the post-disaster recovery efficiency [98–101]. Therefore, in the future, the role of the social component (e.g., human behavior and organization influence) and the interdependencies between communication and infrastructure networks will also be examined to advance the overall lifeline infrastructure system resilience. In doing so, this research is expected to provide evidence-driven decision-making support to local/state government and lifeline service providers in hazard mitigation and preparation, infrastructure resilience design standards, retrofitting resources and allocations, and pre-stationing resources for a speedy post-disaster recovery.

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