To cite: Wenjuan Sun, Paolo Bocchini, Brian D. Davison. Policy-based disaster recovery planning model for interdependent infrastructure systems under uncertainty. Structure and Infrastructure Engineering, DOI: 10.1080/15732479.2020.1843504

Policy-based disaster recovery planning model for interdependent infrastructure systems under uncertainty

Wenjuan Sun[a] and Paolo Bocchini[a] and Brian D. Davison[b]

[a]Civil and Environmental Engineering Department, Lehigh University, Bethlehem PA, USA
[b]Computer Science and Engineering Department, Lehigh University, Bethlehem PA, USA

ARTICLE HISTORY
Compiled November 16, 2020

ABSTRACT
Due to continuous population expansion and the threat of climate change, the past century has witnessed increasing occurrences of natural hazards, leading to significant global losses and requiring substantial restoration efforts. This issue challenges decision makers to act in a timely and effective manner to protect infrastructure systems from future natural hazards. This study presents a policy-based decision model for restoration planning, as part of the PRAISys platform, to support informed disaster mitigation of interdependent infrastructure systems under uncertainty. Following the concept of disaster recovery priority used in practice, this model determines the priority rank of each recovery task from pre-defined policies and simulates the restoration accordingly. This model captures different types of interdependencies with rigorous models at the component and system levels and predicts possible system recoveries under a given damage scenario in a probabilistic manner. This model can quantitatively evaluate the effectiveness of decision strategies on system recovery and resilience under different disaster recovery policies. As a demonstration example, this study applies the proposed model to the post-earthquake recovery simulation of three interdependent infrastructure systems (i.e., power, communication, and transportation) in the Lehigh Valley, Pennsylvania, USA. A total of sixteen cases were considered to represent different restoration strategies. For every case, the uncertainties in the recovery steps are captured by probabilistic simulation, and system resilience is calculated for every recovery sample. Simulation results from different strategies are compared to evaluate the effectiveness of non-intuitive strategies on system recovery and resilience. The proposed model uses a simple and straightforward concept to mimic practical disaster recovery plans. It is easy to understand and implement for modelers, and it is also useful to compare outcomes from different recovery criteria and decision strategies for practitioners.

KEYWORDS
Infrastructure management; decision model; management strategies; interdependency model; uncertainty; natural disasters; resilience

1. Introduction

Critical infrastructure plays an important role in supporting public welfare and the national economy. In recent decades, natural hazards have caused catastrophic damage to critical infrastructures with devastating socioeconomic losses (Bocchini & Frangopol, 2012a; Mitsova, Escaleras, Sapat, Esnard, & Lamadrid, 2019; Sun, Bocchini, & Davi-

CONTACT P. Bocchini. Email: paolo.bocchini@lehigh.edu

son, 2020c). Such adverse impacts from natural hazards pose a pressing challenge for decision makers in developing efficient management strategies to rapidly bring back functionality of critical infrastructure.

While natural disasters are inevitable, implementing a holistic pre-disaster recovery planning approach can facilitate disaster recovery, strengthen resilience, and save money in the long run (FEMA, 2017; Rose et al., 2007; Shreve & Kelman, 2014). Disaster recovery planning can consider needs and resources of all community members and engage the whole community to provide effective leadership in disaster management (FEMA, 2017). These disaster recovery plans are frequently updated to identify priorities, based on the most recent community needs for public safety and health, business continuation, and economic recovery. Recovery priorities represent the importance of all critical services and components. By following predefined recovery plans, i.e., the sequence of recovery priority from high to low, restoration activities are expected to be executed in an effective manner in the wake of a disaster (Olson, Olson, & Gawronski, 1998; Wu & Lindell, 2004).

Decision-making in the disaster recovery is extremely challenging. In emergency conditions, the limited and changeable availability and accessibility of resources lead to a large discrepancy between a plan and reality (Sahebjamnia, Torabi, & Mansouri, 2015; Sun, Bocchini, & Davison, 2020a). Moreover, critical infrastructure systems are dependent on each other with complex relations. Some of these dependencies are introduced to achieve the objectives of efficiency and reliability in ordinary service conditions. The same interdependencies may introduce additional vulnerabilities and cause cascading failures to dependent systems in emergency situations (Ouyang, 2014). Understanding the impact of interdependencies on infrastructure recovery can help identify restoration priorities and develop management strategies (Mitsova, Sapat, Esnard, & Lamadrid, 2020; Sun, Bocchini, & Davison, 2020b). It is essential to capture infrastructure interdependencies when conducting resilience assessment with computational models. Additionally, there are large uncertainties involved in computational models for evaluating disaster resilience. These uncertainties need to be carefully quantified to perform a reasonable computational analysis.

To develop efficient disaster recovery plans, great attention has been paid on developing frameworks and tools for resilience assessment. Example frameworks and tools include the Community Resilience Planning Guide (NIST, 2015), Pre-Disaster Recovery Planning Guide for Local Governments (FEMA, 2017), ResilUS (Miles & Chang, 2011), IN-CORE (NIST CoE, 2019), and PRAISys (Bocchini et al., 2019), to name a few. A critical component of these frameworks and tools is a model that can represent human decisions in restoration planning, which is essentially a sequence of restoration activities. The criteria that drive restoration sequencing can be learned from expert surveys, interviews, and tabletop exercises in a qualitative form (Alshehri, Rezgui, & Li, 2015; Johnsen & Veen, 2013; Tonn, Czajkowski, Kunreuther, & Angotti, 2020). Alternatively, the restoration sequence can be simulated with quantitative computational models. For example, the decision on restoration sequencing can be simulated as the solution of an optimization model (Bocchini & Frangopol, 2012a; Chang, 2003; Fang, Fang, Zio, & Xie, 2019; González, Dueñas-Osorio, Sáchez-Silva, & Medaglia, 2015; Karamlou & Bocchini, 2016; Miles, 2018; Zhang, Wang, & Nicholson, 2017). However, the modeling and solution of optimization problems require the implementation of complicated mathematical formulations and become computationally expensive for large and complex applications, which may render this approach inappropriate for some practitioners.

As part of the PRAISys project, this study presents a straightforward approach where restoration sequencing is performed simply by following recovery priorities, as determined by a predefined set of policies. This model has three advantages. First, it captures the priority concept common in practical disaster recovery planning. Second, this model captures infrastructure interdependencies with rigorous models and addresses restoration-related uncertainties with probabilistic analyses. Third, this model is computationally more efficient than optimization-based decision-making simulation models. This model is particularly useful for practitioners, who can easily adopt it to evaluate the effectiveness of different decision strategies; it is also useful to modelers, who can determine the implications of different modeling assumptions for capturing practical disaster recovery policies.

In the following, the PRAISys platform, which serves as the framework in which the proposed model operates, is briefly introduced. Then the proposed model is described in detail. Afterwards, the proposed model is applied to the post-earthquake recovery simulation of a real community in the Lehigh Valley, Pennsylvania, USA, which consists of three interdependent infrastructure systems, in order to evaluate the impact of different restoration strategies on system recovery. Simulation results from different decision strategies are compared to provide insights on how different decisions may lead to variations in practical outcomes.

2. Overview of PRAISys

PRAISys, standing for "*P*robabilistic *R*esilience *A*ssessment for *I*nterdependent *Sys*tems", is a comprehensive platform for supporting pre-event decision-making in disaster mitigation under uncertainty. For a given hazard scenario, it can assess damage and predict functionality recovery of critical infrastructure systems, in consideration of large uncertainties and complex interdependencies. As shown in Figure 1, the PRAISys platform consists of five major steps. In *Step 1*, PRAISys reads input data on the given hazard scenario and infrastructure system(s) of interest, as well as the analyst's choices for setting up different decision options. In *Step 2*, PRAISys uses fragility curves to perform initial damage assessment for every structural component under the given hazard scenario and conducts cascading failure analyses. After that, PRAISys develops the restoration plan for the given damage scenario (*Step 3*). Following the restoration plan from *Step 3*, PRAISys simulates the recovery process of infrastructure system(s) (*Step 4*). Based on recovery curves, PRAISys assesses the infrastructure system resilience in a probabilistic manner (*Step 5*). PRAISys considers large uncertainties and complex interdependencies in different ways, as explained in the following.

2.1. Uncertainty

PRAISys considers uncertainties related to damage assessment (*Step 2*) and restoration simulation (*Step 4*). Damage-related uncertainties are implemented via fragility analyses. Under a given hazard scenario, PRAISys uses fragility curves to determine the probabilities of every structure component falling into different damage states. In PRAISys, fragility curves are either developed in-house (Karamlou & Bocchini, 2015, 2017b; Ma, Bocchini, & Christou, 2020; Ma, Christou, & Bocchini, 2019) or collected from the literature (Cai, Xie, Xue, Hu, & Kareem, 2019; FEMA, 2019; Fu, Li, & Li, 2016; Giaccu & Caracoglia, 2018; Hwang & Huo, 1998; Sadeghi, Mohajeri, & Khalaghi, 2010; Straub & Der Kiureghian, 2008). Among them, most fragility curves currently

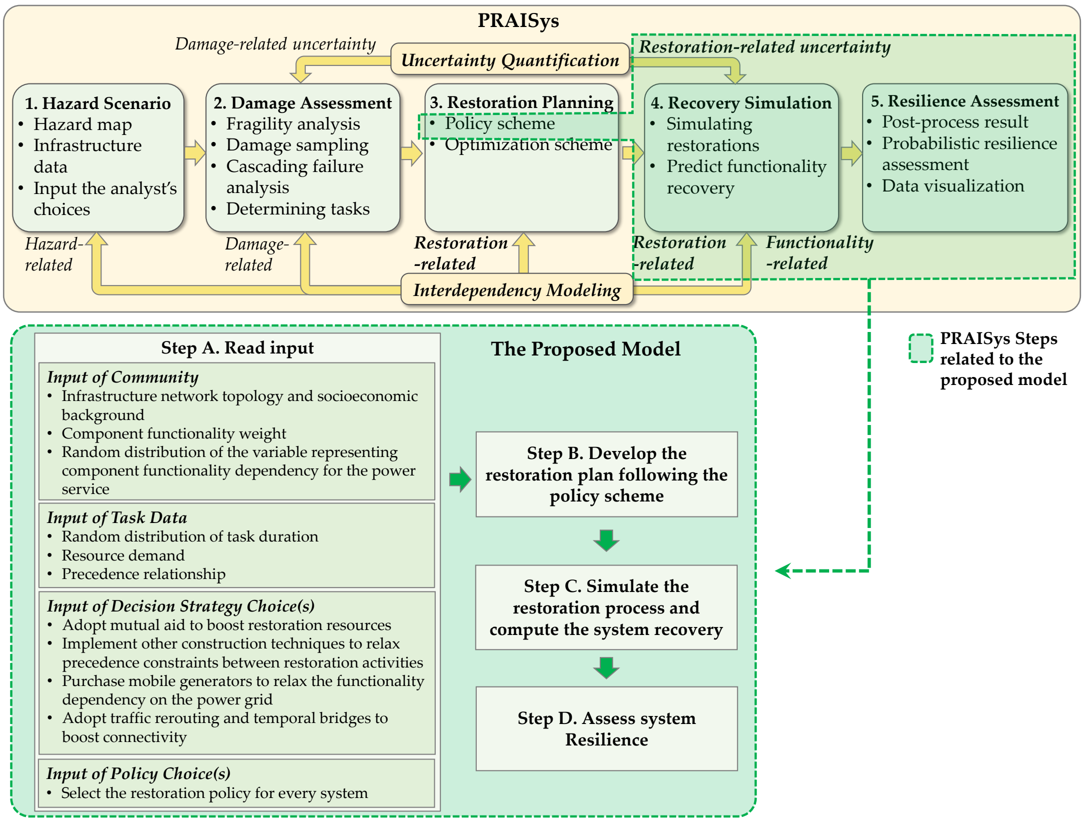


Figure 1. The PRAISys platform and the proposed model.

implemented in PRAISys are based on single hazard fragility analysis, meaning that they are functions of either a single intensity measure or multiple intensity measures describing the same type of hazard. However, critical infrastructure may be exposed to multiple types of hazard in reality, such as an earthquake followed by a tsunami. In this case, fragility curves developed from multi-hazard fragility analysis can be used to address the problem (Gehl & D'Ayala, 2016; Gidaris et al., 2017; Martin, Alipour, & Sarkar, 2019). In the current implementation, PRAISys only considers the age of a structure if it affects the structure design, and it does not consider the aging effect in maintenance cycles. Time-dependent fragility curves can be implemented to consider the aging effect (Ghosh & Padgett, 2010; Guo, Yuan, Lan, Guan, & Li, 2015; Ramanathana, Padgett, & DesRoches, 2015; Shafieezadeh, Onyewuchi, Begovic, & DesRoches, 2013).

Restoration-related uncertainties are considered in two aspects. First, there are often large uncertainties in restoration duration due to reasons of weather, the level of proficiency, and equipment readiness. Second, a component that relies on the functionality of another component from a different system in normal service conditions may use other sources in emergency conditions. For instance, a telecommunication device may use the electricity from generators in case of a power outage, temporarily relaxing the functionality dependency on the external power grid. PRAISys can consider these restoration-related uncertainties via probabilistic analyses, which will be illustrated in more detail in Section 3.5.

2.2. Interdependency

PRAISys can capture a total of eleven types of interdependencies and relationships with rigorous models, related to hazard, damage, restoration, and functionality. For a hazard scenario, such as a hurricane, the intensity measure at a location is usually related to the intensity measure at adjacent locations. Moreover, an event can be associated with multiple hazard intensity measures, e.g., a hurricane event usually brings along high winds, heavy rainfall, and storm surge. These correlations represent *spatial correlations* of an intensity measure and *correlations between multiple intensity measures*. These two types of hazard-related interdependencies are implemented as correlated hazard maps.

Damage-related interdependencies are involved in correlated failures of subcomponents and cascading failure analyses. The *correlated damage of sub-components* captures the fact that multiple structural elements of the same structure tend to reach similar damage states for a specific event. For instance, among all the earthquakes with the same peak ground acceleration, those who end up damaging heavily a certain bridge column, are likely to damage heavily also the other columns of the same bridge. This type of correlated failures can be implemented via a correlation matrix of subcomponent damage. *Mechanical cascading failures* represent the fact that a damaged component may cause additional damage to adjacent components, such as a falling transmission tower tearing down power conductors. This type of cascading failure is implemented via a cascading failure function. *Flow-related cascading failures* represent cascading failures due to the system-wide flow redistribution. For instance, for power transmission systems, this feature can be captured with the system-wide power flow analysis, but it is not implemented in the current version of the PRAISys platform yet (even though the team has included network flow analysis in some independent modules of PRAISys (Ma et al., 2019; Sedzro, Lamadrid, & Zuluaga, 2018; Sedzro, Shi, Lamadrid, & Zuluaga, 2018)).

Restoration-related interdependencies include *resource-sharing interdependency*, *restoration precedence dependency*, *the restoration delay effect due to functionality disruption of other infrastructure systems*, and *functionality dependency for executing certain tasks*. As this study focuses on presenting a decision model that considers interdependencies involved in the restoration process, further elucidations on how to implement different types of restoration-related interdependencies are presented in Section 3.5.

Functionality-related interdependency can be implemented through restoration functions, addressing two aspects. First, the *compositional functionality dependency* represents the fact that the functionality of a system depends on its components' functionality, which can be implemented using system-level analysis functions. Second, the *inter-system functionality dependency* represents the functionality dependency across systems. For example, a water pump in the water distribution system uses the electricity from a nearby electric substation; therefore, the functionality of the water distribution system depends on the functionality of the electric power system. This type of dependency can be represented by a conditional restoration function of the component that depends on the functionality of another component.

2.3. Restoration planning

At *Step 3*, for every damage scenario PRAISys simulates the decisions on restoration planning following one out of two alternative schemes: optimization-based (Scheme 3B) and policy-based (Scheme 3A). Optimization-based modules frame the restoration process into a mathematical problem that can be described by sophisticated formulations in operations research. PRAISys uses the solution returned by the optimization-based modules as a way to mimic human decisions on restoration planning, rather than aiming at finding the optimal restoration plan (Sun et al., 2020b).

PRAISys has implemented multiple optimization modules, allowing the analysts to choose from them based on their needs. In PRAISys, every optimization module uses an optimization algorithm with a single objective function. These objective functions are different and all related to restoration time. Completing the restoration as soon as possible is a commonly used goal in disaster recovery planning based on our conversations with many emergency managers (Sun et al., 2020b). Practical recovery plans may have different goals (such as minimal repair cost) and conflicting goals (such as minimal life-cycle cost and maximum resilience). The first problem can be addressed by using optimization formulations with a different objective function; the second problem can be addressed by multiple objective optimization methods, such as multi-objective genetic algorithms (Bocchini & Frangopol, 2012b; Karamlou & Bocchini, 2016) and the weighted sum method (Bueno, Haeser, & Martínez, 2016; Zhang et al., 2017).

However, using optimization modules may be challenging for practical applications due to the following two reasons. First, PRAISys relies on third-party software for the formulation and solution of the optimization problem, and such software may not be available to all analysts. Second, optimization models become computationally expensive when there are a large number of restoration tasks with complex precedence constraints, requiring high performance computing facilities, and this level of complexity is very often met in practical applications.

In practice, community and organizational disaster recovery plans usually contain information on recovery priorities. As a recovery priority represents the importance and criticality level of services and components, a restoration sequence can be determined imposing the restoration of the damaged component with a higher priority earlier (under the given constraints). Therefore, these policy-based models can estimate human decisions on restoration planning by simply following the priority rank based on pre-defined policies. As a result, policy-based models are computationally simple and easy to understand and implement. Section 3 describes how the proposed model implements the concept of recovery priority for restoration planning and simulates the recovery of interdependent systems under uncertainty.

3. The proposed model

The proposed model follows the policy scheme, as shown in Figure 1, consisting of four steps.

3.1. Read input (Step A)

The proposed model starts with the initial step of reading input data (*Step A*). Required input data fall into four categories: community data, task data, decision strategy choices, and restoration policy choices.

Community data include both infrastructure data and socioeconomic data. Infrastructure data refer to major component data and network topological features. Major components are those that require considerable repair efforts if damaged (Sun et al., 2020b), such as power plants, electric substations, transmission towers, and power conductors in the power system (Ma et al., 2020, 2019; Ouyang & Dueñas-Osorio, 2014), and road segments and bridges in the transportation system (Karamlou & Bocchini, 2015). Major component data include the location, structural type, and other characteristics (such as material, served voltage, and average traffic) for every major component. Socioeconomic data refer to the population and the number of households served by major components to provide their service. Socioeconomic data for every infrastructure system are collected based on spatial coverage analyses of individual components using ArcGIS (Esri, 2019). As mentioned in Section 2.1, there might be some additional resources that can boost the functionality of disrupted infrastructure systems and relax some functionality dependencies. The presence of additional resources to relax functionality dependency can be described as a random event, whose distribution can be estimated from historical data and interviews with emergency managers.

Task data include their duration, resources required, and precedence constraints. Under a given damage scenario, the necessary restoration tasks to fix all damaged components can be determined based on engineering experience and common practice (Karamlou & Bocchini, 2017a). As mentioned in Section 2.1, there are uncertainties on the task durations. Experienced engineers and construction managers can usually estimate general ranges of task duration, such as the maximum value, the minimum value, and the most likely value. Therefore, this study uses triangular distributions and uniform distributions as an estimate of actual distributions of task duration. Distribution parameters can be determined from public literature (Çağnan, 2005; Karamlou & Bocchini, 2017a; Nielson, 2003) and interviews with experienced engineers and construction managers (Karamlou & Bocchini, 2017a; Sun et al., 2020b).

The proposed model can implement the following four decision strategy options:

(i) building mutual aid agreements for receiving resources in disaster restoration, (ii) adopting advanced construction techniques to relax precedence constraints between restoration tasks, (iii) purchasing mobile generators to relax the functionality dependency on the power service, and (iv) implementing temporary re-routing and temporary bridges to boost roadway connectivity. The proposed model implements the four decision strategy options as different settings of interdependency, which will be further explained in Section 4.4.

The fourth category of input data is the restoration policy choice(s). A restoration policy defines the criteria for determining recovery priorities in a system, resulting in a pre-defined disaster recovery plan. The proposed model implements different disaster recovery policies for every infrastructure system, with further descriptions presented in Section 3.2.

3.2. Develop the restoration plan (Step B)

The second step is to determine a priority rank based on the selected restoration policy and develop the restoration plan accordingly. The most common criteria of disaster recovery prioritization adopted in practice for three different infrastructure systems are described in the following.

For the power system, a typical restoration prioritization follows this order: (i) generation, (ii) transmission, and (iii) distribution (APPA, 2018). Within the distribution network, the restoration sequence usually starts with (i) dangerous situations that may endanger public safety without repairs; then addresses (ii) critical customers and critical infrastructure (such as hospitals, nursing homes, emergency shelters, schools, police and fire stations); (iii) commercial areas, including gas and groceries; and (iv) repairs that energize the largest number of customers (APPA, 2018). Depending on the company, the restoration prioritization slightly varies. For instance, the Florida Power & Light (FPL) considers repairing power plants, damaged transmission lines and substations as the top priority in disaster restoration and restoring power to critical facilities as the second priority (FPL, 2019). Conversely, PPL Electric Utilities considers restoring service to critical facilities as the top priority, with repairing major power lines and substations that serve large numbers of customers as the second priority (PPL Electric Utilities, 2019).

For the communication system, most telecommunication companies have applied for the telecommunication service priority (TSP) program supported by the U.S. Department of Homeland Security to receive priority treatment for vital voice and data circuits before any non-TSP service (CISA, 2019). Main trunk circuits and 911 centers have higher priority for disaster emergency response. Other than that, most communication companies address restorations of major components that serve the most customers as high priority in disaster recovery.

For the transportation system, top priorities are assigned to roadways and transits that connect critical facilities, including emergency broadcast facilities, fire and police stations, airports, hospitals, and emergency shelters, etc., to ensure the essential transportation in emergency conditions (Matherly et al., 2013). Additionally, there are many priority criteria available in current practice that can consider important factors, such as population, traffic, and road type (Lambert et al., 2002).

The proposed model implements multiple restoration policies that follow different priority criteria for every infrastructure system. Implemented criteria include the voltage, the population, and the number of households served by a component in the power system, the population, and the number of households served by a component in the communication system, and the traffic served by the component and structural length of a component in the transportation system.

3.3. Simulate system recovery (Step C)

Following the restoration plan from *Step B*, the third step is to simulate the actual restoration over time (*Step C*). Restoration-related uncertainties are considered in the simulation. Once a restoration task completes, the functionality of every major component is updated, along with the progress in the overall system functionality.

The functionality of a component j, not influenced by the functionality of another system, is defined by Equation (1). This equation represents a ternary functionality state.

$$q_j(t) = \begin{cases} 100\%, & \text{if } t \geq CT_j \\ \bar{q}_j, & \text{if } ST_j \leq t < CT_j \\ q_j^0, & \text{if } 0 \leq t < ST_j \end{cases} \tag{1}$$

where $q_j(t)$ is the functionality of component j at time t; ST_j and CT_j are the time when starting the restoration task and the time when completing the last restoration task for repairing this damaged component, respectively; q_j^0 is the residual functionality of the damaged component prior to any restoration; $\bar{q}_j$ is the temporary functionality when executing the restoration task(s), $0 \leq \bar{q}_j \leq 100\%$. For instance, a four-lane roadway segment that is flooded on the left lane may still be temporarily functional by using other non-flooded lanes ($q_j^0 = 75\%$). After completing the restoration, this road segment would be fully recovered ($q_j = 100\%$). When closing the left two lanes to perform restoration tasks, people may still be able to use the two lanes on the right ($\bar{q}_j = 50\%$); if all four lanes are closed for carrying out restoration tasks, this road segment would not function at all ($\bar{q}_j = 0$).

In some cases, the functionality of the component j depends on the functionality of another component k. For instance, a communication tower uses the electricity from a nearby substation; a road segment with a bridge crossing a river is fully functional only if both roadway pavements and the bridge are fully functional. The functionality of this type of component j can be defined as follows:

$$q_j(t) = \begin{cases} 100\%, & \text{if } t \geq CT_j \text{ and } q_k(t) = 100\%,\ \forall k \in FD_j \\ \bar{q}_j, & \text{if } ST_j \leq t < CT_j \text{ and } q_k(t) = 100\%,\ \forall k \in FD_j \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where $q_k(t)$ is the functionality of component k from a different system at time t; FD_j is a set of components whose functionality is required to support the functionally of the component j.

The functionality of an infrastructure system can be defined by different metrics, such as network connectivity (Bocchini & Frangopol, 2013), network flow (Bocchini & Frangopol, 2012b; Ma et al., 2019), and the percentage of customers with service (Mitsova, Escaleras, Sapat, Esnard, & Lamadrid, 2018; Ouyang & Dueñas-Osorio, 2014). This study uses the following metric based on a weighted network (Karamlou

& Bocchini, 2016).

$$Q(t) = \frac{\sum_{j=1}^{n} w_j \cdot q_j(t)}{\sum_{j=1}^{n} w_j} \tag{3}$$

where $Q(t)$ is the functionality of an infrastructure system at time t; w_j is a component functionality weight, representing how much the functionality of component j contributes to the functionality of the entire system. This equation presents w_j as constant values for the sake of simplicity. The values of w_j can be determined as the number of customers served by every individual component or estimated from other characteristics of the infrastructure system. For instance, for a road segment, w_j depends on its length and traffic capacity. In reality, w_j may evolve over time and depend on many factors, such as system architecture, requiring more sophisticated analyses.

3.4. Resilience assessment (Step D)

For every recovery sample $Q(t)$ from *Step C*, restoration time (RT) and resilience index (RI) (Reed, Kapur, & Christie, 2009) are computed, as shown in Figure 2, to assess the system resilience (*Step D*).

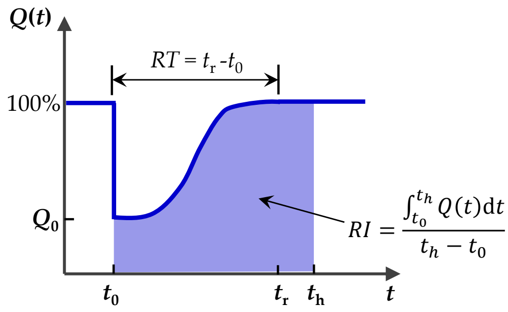


Figure 2. Resilience metrics determined from a functionality recovery sample.

$$RT = t_r - t_0 \tag{4}$$

$$RI = \frac{\int_{t_0}^{t_h} Q(t)\mathrm{d}t}{t_h - t_0} \tag{5}$$

where t_0 is the time when the event strikes; t_r is the time when the system functionality recovers to 100%; t_h is the time horizon of interest; $Q(t)$ is a restoration function, representing the functionality evolution over time.

Table 1. Interdependency implementations.

Interdependency type	Implementation method	Implementation level
Resource-sharing interdependency	Resource constraint	System-level
Precedence dependency	Task precedence constraint	Component task-level
Functionality dependency on the power service	Conditional restoration function	Component-level
Restoration delay due to transportation service disruption	Prolonged task duration	System-level

Table 2. Uncertainty-related assumptions.

Assumption	Implementation
The task duration is assumed to follow a probabilistic distribution.	Task duration distributions are implemented as either triangular distributions or uniform distributions.
The presence of unexpected external resources, such as mobile generators, to relax functionality dependency is assumed as a random event.	The event is implemented as random, with a given probability of occurrence.

3.5. Implementation of interdependency

This study differentiates interdependency from dependency, considering that dependency is a *one-way* relationship and interdependency is a *two-way* relationship. For instance, a water pump depends on a substation for the electricity, but not vice versa. A construction company that needs to restore two adjacent damaged bridges may not be able to perform restorations on the two bridges in parallel due to limited crew members and limited amount of equipment available, indicating the mutual relation of interdependency when executing restoration activities due to resource constraints.

The proposed model implements four types of restoration-related interdependency, as shown in Table 1. Resource-sharing interdependency represents the fact that executing tasks occupy a certain amount of restoration resources that should be within resource limits. Resource-sharing interdependencies are implemented as resource constraints. Precedence dependency, representing some tasks executing in a certain sequence due to construction requirements, is implemented via precedence constraints among tasks. The third type is functionality dependency on the power service from a component in another system, such as a communication device using electricity from the power grid. This type of functionality dependency is implemented as a restoration function; the simulation code explicitly checks if power is available at the location of each component that requires it, and sets the functionality accordingly. The restoration delay effect represents that restorations take longer time due to delays in transporting repair crews and resources, when the transportation network is disrupted. The delay effect is implemented as a prolonged task duration by multiplying the original duration by a scaling factor, when the transportation functionality is below a threshold.

3.6. Assumption

The proposed model requires assumptions on the static functionality weight and uncertainty implementation. This model computes the system functionality with Equation (3), by assuming that the weight w_j is a static value, independent of time and restoration sequence. This may not be the case in a dynamically changing environment after a disaster. To address this issue, sophisticated system-level analyses can be adopted to capture the evolving features of service demand and network capacity that depend on time and restoration sequence (Bocchini & Frangopol, 2012a, 2012b; Karamlou & Bocchini, 2016). However, this study aims at presenting a simple decision model that requires minimal computational cost to facilitate practical applications. Using static weights to compute system functionality can capture actual objectives commonly used by practitioners, serving this purpose well. For practical use, the value of w_j can be calibrated based on interviews with decision makers in emergency management.

The proposed model captures two types of restoration-related uncertainties: task duration and functionality dependency. The proposed model uses two assumptions in the implementation of uncertainty, as shown in Table 2. This model assumes that the task duration follows either a triangular distribution or a uniform distribution. As previously mentioned, this assumption captures typical patterns of collected task duration data through expert surveys/interviews, in which estimated maximum, minimum, and most likely duration are often collected. Such an assumption about task duration has been adopted in multiple studies on disaster recovery simulations (Çağnan, 2005; Karamlou & Bocchini, 2017a; Tabucchi, Davidson, & Brink, 2010). This model also assumes that the presence of alternative resources (such as mobile generators) in emergency restorations to relax the functionality dependency on the external power grid is modeled as a random event, with a given probability of occurrence. For practical applications with more accurate analyses, historical data of disaster restoration should be collected to verify the two assumptions and calibrate the probabilistic parameters.

4. Application

The proposed model is applied to the disaster recovery simulation of three interdependent systems in the Lehigh Valley. The problem statement, input data, restoration policy, and decision strategies are described in the following.

4.1. The Lehigh Valley testbed

The Lehigh Valley is a metropolitan region in eastern Pennsylvania, United States. It consists of Lehigh and Northampton counties, spanning 725 square miles. This region has a total population of 647,232 as of April 2010 (United States Census Bureau, 2010), with the median annual household income of around $62,900 in 2019 (Tuerk, 2019). This study focuses on three interdependent infrastructure systems in the Lehigh Valley: power, communication, and transportation.

Even though Pennsylvania is at low risk of earthquake, historical records show that seismic activities in the commonwealth are not uncommon. For example, there have been the 1984 Martic Earthquake ($MbLg = 4.1$) in southeastern Pennsylvania, and the 1998 Pymatuning Earthquake ($MbLg = 5.2$) in western Pennsylvania (Maceira, Ammon, & Herrmann, 2000). In particular, the 1994 Cacoosing Valley earthquake took place near the city of Reading, about 30 miles away from the Lehigh Valley, and caused $2 million damage at the time (Ammon, Hermann, Langston, & Benz, 1998; Seeber, Armbruster, Kim, Barstow, & Scharnberger, 1998). Considering that many infrastructure components in the region were built with pre-seismic code designs, critical infrastructure in the Lehigh Valley are vulnerable to earthquakes. Therefore, it is worth investigating how interdependent infrastructure systems in the region may recover under different restoration strategies in the case of an earthquake.

In seismic engineering, the most popular scenario event is the so called "maximum considered earthquake" (MCE), which is an earthquake with a return period of 2,475 years. Considering this, this study investigates an earthquake scenario of magnitude

5 with the return period of 2500 years in the Lehigh Valley. The epicenter is chosen at the center of the Lehigh Valley and ground motion prediction equations are used to assess the ground shaking intensity at the various locations. The resulting intensity measure maps are provided in Figure 3, in terms of spectral acceleration (0.3 second), peak ground acceleration, and peak ground velocity. Under this scenario event, the probability of every individual component falling into different damage states can be determined using fragility analysis. Based on the probabilities, possible damage scenarios can be sampled. Out of many possible damage scenarios, one example for the three infrastructure systems is presented in Figure 4.

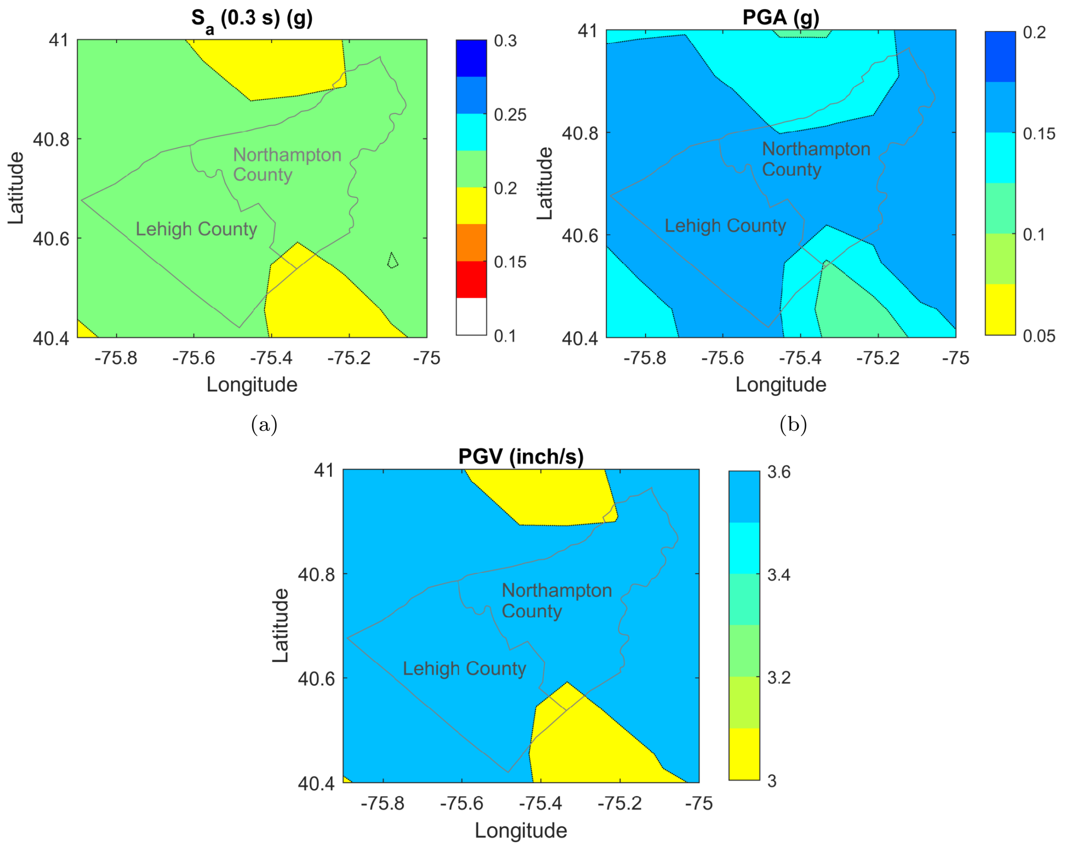
Figure 4a presents the power system that consists of power plants, electric substations (Sub), transmission towers (TT), and power lines (PL). The location and features (such as capacity and voltage) of power plants and electric substations are collected from public databases (EEI, 2016; HIFLD, 2017); the topology layout and the voltage of power lines connecting power plants and substations are collected from published reports (PA PUC, 2015; PJM, 2016, 2017) and Google Earth; transmission towers are distributed along power lines. In this testbed, there are a total of 3 power plants, 67 electric substations, and 79 power lines. Among them, 16 substations and 7 transmission towers are damaged in this sample scenario.

Figure 4b shows the communication system, consisting of central offices (CO), communication towers (CT), and communication lines. Central office data are collected from online databases (Sandman, 2016; TelcoData, 2016); the location, structural type, and height of telecommunication towers are collected from online databases (CellReception, 2016; HIFLD, 2017). Due to reasons of national security and commercial competitiveness, we do not know actual locations of cables and optical fibers that connect central offices and communication towers in the region. To build the network connectivity, we have made two assumptions. First, every central office is connected to 3 adjacent central offices. Second, every communication tower is connected to 2 adjacent central offices. These two assumptions lead to a total of 273 communication lines for connecting 34 central offices and 114 communication towers. In this sample damage scenario, there are 9 central offices and 19 communication towers damaged.

Figure 4c shows the transportation system that represents major roadways in the region, including interstate highways 78 and 476, and major routes US 22, PA 33, PA 378, PA 191, and PA 309. As shown in Figure 4c, the transportation system consists of 192 road segments (Rd), 245 bridges (Br), and 403 traffic lights (TL). For transportation infrastructure, bridge data are collected from NBI (2017); road data are collected from PennDOT (2017a, 2017b); traffic light data are also collected from PennDOT (2017c). In this sample damage scenario, 10 bridges, 23 road segments, and 20 traffic lights are damaged.

This example considers the following functionality dependencies between components. First, compositional functionality dependencies are set as follows. In the power system, a substation is not functional when power lines are not connected from the substation to at least a functional power plant; a power line is not functional when any connected substation is not functional. In the communication system, a communication tower is not functional when communication lines are not connected from the communication tower to at least one functional central office. In the transportation system, a road segment is not functional if the bridge that carries this road segment is not functional; a road segment is considered as partially functional ($\bar{q}_{Rd} = 50\%$) when the traffic light that controls the traffic on this road segment is not functional.

Second, functionality dependencies of components across systems are set as follows. Without actual information of which substations provide the electricity to individual



(a) (b) (c)

Figure 3. A hypothetical earthquake scenario: (a) spectral acceleration (0.3 s), (b) peak ground acceleration, and (c) peak ground velocity.

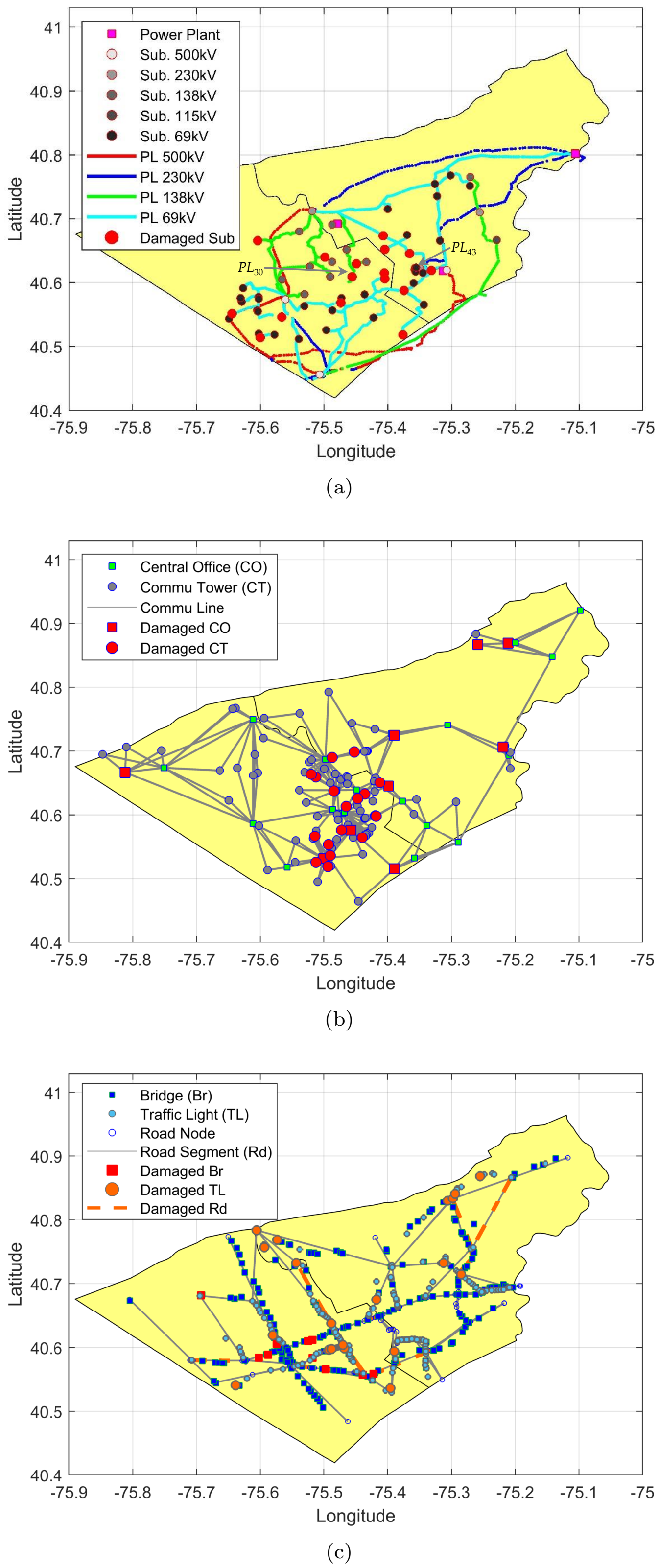


Figure 4. The Lehigh Valley testbed: (a) power, (b) communication, and (c) transportation.

components that consume the electricity in the testbed, this study assumes that every communication component and every traffic light use the electricity from the nearest substation by distance. Specifically, Table 3 presents examples of how central offices, communication towers, and traffic lights functionally depend on the electricity from nearby substations under normal service conditions. For instance, the communication tower CT_4 uses the electricity of the nearby substation Sub_{39}, and the traffic light TL_{45} requires support from the power component Sub_{31}. As mentioned in Section 3.5, the proposed model assumes that the presence of generators to relax the functionality dependency on the power service is a random event. This example assumes that there is a 50% chance that the traffic lights, central offices, and communication towers have backup emergency generators on-site.

Table 3. Damaged components with inter-system functionality dependency on the power service.

Communication Damaged cmpt	Power Required cmpt	Transportation Damaged cmpt	Power Required cmpt
CO_7	Sub_{45}	TL_{45}	Sub_{31}
CO_9	Sub_{53}	TL_{78}	Sub_{31}
CO_{12}	Sub_8	TL_{89}	Sub_{13}
CO_{13}	Sub_{41}	TL_{97}	Sub_{11}
CO_{14}	Sub_{39}	TL_{107}	Sub_{15}
CO_{17}	Sub_6	TL_{183}	Sub_5
CO_{21}	Sub_{33}	TL_{199}	Sub_{11}
CO_{22}	Sub_{35}	TL_{208}	Sub_{64}
CO_{29}	Sub_8	TL_{267}	Sub_{41}
CT_4	Sub_{39}	TL_{270}	Sub_9
CT_{12}	Sub_{15}	TL_{278}	Sub_6
CT_{13}	Sub_{15}	TL_{280}	Sub_8
CT_{16}	Sub_{42}	TL_{289}	Sub_{29}
CT_{20}	Sub_{17}	TL_{301}	Sub_{13}
CT_{24}	Sub_{46}	TL_{343}	Sub_{32}
CT_{27}	Sub_{42}	TL_{348}	Sub_{27}
CT_{28}	Sub_{12}	TL_{358}	Sub_5
CT_{30}	Sub_{39}	TL_{359}	Sub_5
CT_{31}	Sub_{11}	TL_{373}	Sub_{31}
CT_{34}	Sub_{47}	TL_{387}	Sub_5
CT_{37}	Sub_{39}		
CT_{39}	Sub_{33}		
CT_{48}	Sub_{18}		
CT_{49}	Sub_{18}		
CT_{50}	Sub_{14}		
CT_{51}	Sub_{19}		
CT_{52}	Sub_{45}		
CT_{69}	Sub_{48}		

4.2. Damaged components and restoration tasks

To repair damaged components in the three systems, restoration tasks are determined according to the damage state. Tables 4 $\sim$ 10 list the properties of damaged components in the three systems, along with IDs of required restoration tasks for fixing every damaged component. Tables 11 $\sim$ 13 present the data on the restoration tasks in the three systems, including task description, duration distribution, and resource demand, etc. Specifically, task data for the power system are derived from published literature (ATC, 2016; Çağnan, 2005; FEMA, 2019; Schweiner, Twomey, & Lindsey, 2003; Vadivel, 2017; Xu et al., 2007) and interviews with a local electric engineer (Lacouve, 2017). Task data for the communication system are designed by referring to published literature (FEMA, 2019; Sun et al., 2020b). Task data for the transportation system are designed based on other reports and papers (FEMA, 2019; Irfan, Khurshid, Anastasopoulos, Labi, & Moavenzadeh, 2011; Karamlou & Bocchini, 2016, 2017b).

Table 4. Damaged substation components and required tasks.

Cmpt ID	Latitude	Longitude	Max. voltage (kV)	Population[a]	Damage state	Restoration task[b]
Sub_4	40.5514	-75.6442	500	4,714	Slight damage	$T_{p1} \rightarrow T_{p2}$
Sub_{11}	40.6093	-75.4560	138	59,875	Slight damage	$T_{p1} \rightarrow T_{p2}$
Sub_{14}	40.6293	-75.4493	138	28,238	Slight damage	$T_{p1} \rightarrow T_{p2}$
Sub_{17}	40.6400	-75.4988	138	17,820	Slight damage	$T_{p1} \rightarrow T_{p2}$
Sub_{21}	40.6657	-75.6040	138	5,480	Slight damage	$T_{p1} \rightarrow T_{p2}$
Sub_{24}	40.6149	-75.4056	69	35,079	Slight damage	$T_{p1} \rightarrow T_{p4}$
Sub_{25}	40.6188	-75.3317	69	11,724	Slight damage	$T_{p1} \rightarrow T_{p2}$
Sub_{26}	40.6456	-75.3659	69	30,789	Slight damage	$T_{p1} \rightarrow T_{p4}$
Sub_{29}	40.5876	-75.3746	69	17,714	Slight damage	$T_{p1} \rightarrow T_{p4}$
Sub_{32}	40.6733	-75.4075	69	10,521	Slight damage	$T_{p1} \rightarrow T_{p2}$
Sub_{33}	40.6521	-75.4049	69	16,143	Slight damage	$T_{p1} \rightarrow T_{p2}$
Sub_{41}	40.5182	-75.3766	69	6,098	Slight damage	$T_{p1} \rightarrow T_{p2}$
Sub_{42}	40.6061	-75.4049	69	28,099	Slight damage	$T_{p1} \rightarrow T_{p2}$
Sub_{43}	40.5461	-75.5662	69	17,964	Moderate damage	$T_{p1} \rightarrow T_{p3}$
Sub_{44}	40.5684	-75.4736	69	21,496	Slight damage	$T_{p1} \rightarrow T_{p2}$
Sub_{59}	40.5139	-75.6002	69	7,644	Moderate damage	$T_{p1} \rightarrow T_{p3}$

[a] Population means the population served by the substation component for the power service.
[b] In the column of restoration task, every cell lists tasks required to fix the damaged component in the power system. The detailed description of every task is presented in Table 11. The arrow between task IDs represents a precedence relation. For instance, $T_{p1} \rightarrow T_{p2}$ means that T_{p2} cannot proceed until T_{p1} completes.

4.3. Recovery policy

The proposed model considers that recovery priorities are defined pre-event by expert groups in disaster recovery policies and then followed rigorously in the restoration simulation. Table 14 shows the restoration policy with a general rank of recovery priority of every infrastructure system by component type. In addition, for damaged components of the same type, the rule is to restore components with greater capacity earlier. For damaged components of the same type with the same capacity, damaged components are restored randomly.

In the power system, restoration sequencing by component type is as follows: power plant, electric substation, power line, and transmission towers. In this example, no power plant is damaged. Damaged substations with the highest maximum voltage are restored first. Among damaged electric substations with the same maximum voltage, the damaged substation that serves the most people are restored earlier. When repairing damaged transmission towers, towers that carry the power line at a high voltage are restored earlier than those carrying a low voltage power line, and towers that carry the power lines of the same voltage are restored in a random sequence.

Table 5. Damaged components of transmission tower and required tasks.

Cmpt ID	Latitude	Longitude	Carried PL	Carried PL voltage (kV)	Damage state	Restoration task
TT_A	40.6093	-75.4605	PL_{30}	138	Slight damage	$T_{p5} \rightarrow T_{p7}$
TT_B	40.6093	-75.4606	PL_{30}	138	Slight damage	$T_{p5} \rightarrow T_{p7}$
TT_C	40.6094	-75.4606	PL_{30}	138	Slight damage	$T_{p5} \rightarrow T_{p7}$
TT_D	40.6226	-75.3495	PL_{43}	69	Moderate damage	$T_{p5} \rightarrow T_{p6} \rightarrow T_{p7}$
TT_E	40.6227	-75.3495	PL_{43}	69	Slight damage	$T_{p5} \rightarrow T_{p7}$
TT_F	40.6226	-75.3496	PL_{43}	69	Slight damage	$T_{p5} \rightarrow T_{p7}$
TT_G	40.6226	-75.3501	PL_{43}	69	Slight damage	$T_{p5} \rightarrow T_{p7}$

Table 6. Damaged components of central office and required tasks.

Cmpt ID	Latitude	Longitude	Population[a]	Damage state	Restoration task[b]
CO_7	40.5759	-75.4579	22,342	Slight damage	T_{c1}
CO_9	40.7245	-75.3893	5,567	Slight damage	T_{c1}
CO_{12}	40.8696	-75.2112	26,986	Slight damage	T_{c1}
CO_{13}	40.5156	-75.3892	39,680	Moderate damage	T_{c2}
CO_{14}	40.5316	-75.5004	126,603	Slight damage	T_{c1}
CO_{17}	40.7063	-75.2193	114,920	Slight damage	T_{c1}
CO_{21}	40.6451	-75.3988	204,362	Slight damage	T_{c1}
CO_{22}	40.6670	-75.8124	6,478	Slight damage	T_{c1}
CO_{29}	40.8673	-75.2585	28,950	Slight damage	T_{c1}

[a] Population means the population served by the component for the communication service.
[b] In the column of restoration task, every cell lists the tasks required to fix the damaged component in the communication system. The description of every task is presented in Table 12. The arrow between task IDs represents a precedence relation.

Table 7. Damaged components of communication tower and required tasks.

Cmpt ID	Latitude	Longitude	Population	Damage state	Restoration task[a]
CT_4	40.5189	-75.4936	6,080	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{12}	40.6369	-75.4839	110,196	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{13}	40.6372	-75.4844	109,611	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{16}	40.5986	-75.4197	96,775	Moderate damage	$T_{c3} \rightarrow T_{c4}$
CT_{20}	40.6594	-75.5125	47,590	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{24}	40.5644	-75.4400	45,405	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{27}	40.5982	-75.4186	94,920	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{28}	40.6327	-75.4363	93,604	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{30}	40.5256	-75.5124	34,207	Moderate damage	$T_{c3} \rightarrow T_{c4}$
CT_{31}	40.6133	-75.4653	137,031	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{34}	40.5532	-75.4982	52,162	Moderate damage	$T_{c3} \rightarrow T_{c4}$
CT_{37}	40.5362	-75.4902	31,043	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{39}	40.6506	-75.4125	61,438	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{48}	40.6989	-75.4526	21,826	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{49}	40.6902	-75.4873	34,207	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{50}	40.6254	-75.4474	118,992	Extensive damage	$T_{c5} \rightarrow T_{c4}$
CT_{51}	40.6637	-75.5200	5,212	Moderate damage	$T_{c3} \rightarrow T_{c4}$
CT_{52}	40.5762	-75.4726	115,913	Slight damage	$T_{c3} \rightarrow T_{c4}$
CT_{69}	40.5665	-75.5142	76,895	Slight damage	$T_{c3} \rightarrow T_{c4}$

[a] The description of every task is presented in Table 12 for the communication system. The arrow between task IDs represents a precedence relation. For instance, $T_{c3} \rightarrow T_{c4}$ means that T_{c3} should complete before the start of T_{c4}.

Table 8. Damaged bridge components and required tasks.

Cmpt ID	Latitude	Longitude	AADT[a]	Carried Rd[b]	Crossed Rd[c]	Damage state	Restoration task[d]
Br_8	40.6101	-75.5248	78,148	Rd_4, Rd_{32}	NA	Slight damage	$T_{t1} \rightarrow T_{t2}, T_{t4}, T_{t5}$
Br_9	40.6118	-75.5180	78,148	Rd_4, Rd_{32}	NA	Slight damage	$T_{t1} \rightarrow T_{t2}, T_{t4}, T_{t5}$
Br_{21}	40.5842	-75.6023	85,766	$Rd_{58}, Rd_{75}, Rd_{191}$	NA	Slight damage	$T_{t1} \rightarrow T_{t2}, T_{t4}, T_{t5}$
Br_{23}	40.5889	-75.5878	34,929	Rd_{58}, Rd_{75}	NA	Slight damage	$T_{t1} \rightarrow T_{t2}, T_{t4}, T_{t5}$
Br_{34}	40.5657	-75.4974	85,195	Rd_{60}, Rd_{72}	NA	Slight damage	$T_{t1} \rightarrow T_{t2}, T_{t4}, T_{t5}$
Br_{40}	40.5570	-75.4394	64,948	Rd_{62}, Rd_{70}	NA	Slight damage	$T_{t1} \rightarrow T_{t2}, T_{t4}, T_{t5}$
Br_{41}	40.5586	-75.4227	64,948	Rd_{63}, Rd_{68}	NA	Moderate damage	$T_{t1} \rightarrow T_{t3}, T_{t6}$
Br_{53}	40.5839	-75.5178	11,739	Rd_{105}, Rd_{108}	NA	Slight damage	$T_{t1} \rightarrow T_{t2}, T_{t4}, T_{t5}$
Br_{67}	40.6820	-75.6932	7,064	Rd_{126}, Rd_{144}	NA	Slight damage	$T_{t1} \rightarrow T_{t2}, T_{t4}, T_{t5}$
Br_{93}	40.6059	-75.5745	3,247	NA	Rd_{159}, Rd_{165}	Moderate damage	$T_{t1} \rightarrow T_{t2}, T_{t4}, T_{t5}$

[a] AADT means annual average daily traffic.
[b] Every cell in the column of carried Rd presents the ID(s) of road segment that is carried by the bridge listed in the first column, and this bridge is part of the carried road segment(s). For instance, the bridge Br_8 carries two road segments of Rd_4 and Rd_{32}. NA means not applicable, i.e., this bridge does not carry any road segment.
[c] Every cell in the column of crossed Rd presents the road segment(s) that is crossed by the bridge from the top, and this bridge is not part of the crossed road segment(s). For example, the bridge Br_{93} crosses road segments of Rd_{159} and Rd_{165} from the above. NA means not applicable, i.e., this bridge does not cross any road segment.
[d] In the column of restoration task, every cell lists the tasks required to fix the damaged bridge component in the transportation system. The description of every task is presented in Table 13. The arrow between task IDs represents a precedence relation. For instance, $T_{t1} \rightarrow T_{t2}, T_{t4}, T_{t5}$ means that T_{t1} needs to be completed prior to the start of T_{t2}, T_{t4}, and T_{t5}, and there is no precedence requirement between tasks T_{t2}, T_{t4}, and T_{t5}.

Table 9. Damaged components of road segment and required tasks.

Cmpt ID	Start node[a]		End node[b]		AADT	Damage state	Restoration task[c]
	Latitude	Longitude	Latitude	Longitude			
Rd_1	40.5929	-75.5819	40.5985	-75.5632	42,000	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_8	40.5985	-75.5632	40.6005	-75.5582	42,000	Moderate damage	$T_{t7} \rightarrow T_{t8}$
Rd_{20}	40.6951	-75.2292	40.6892	-75.2500	21,500	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{27}	40.6481	-75.4170	40.6450	-75.4266	41,500	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{37}	40.7804	-75.2843	40.7571	-75.2706	11,500	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{38}	40.7571	-75.2706	40.7409	-75.2666	11,500	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{39}	40.7409	-75.2666	40.7168	-75.2890	11,500	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{42}	40.6877	-75.2891	40.6821	-75.2889	34,000	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{46}	40.6400	-75.2747	40.6400	-75.2748	24,500	Moderate damage	$T_{t7} \rightarrow T_{t8}$
Rd_{55}	40.7534	-75.2664	40.8351	-75.2997	11,500	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{56}	40.5803	-75.7105	40.5792	-75.6280	23,000	Moderate damage	$T_{t7} \rightarrow T_{t8}$
Rd_{68}	40.5957	-75.3323	40.5550	-75.4292	31,500	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{69}	40.5550	-75.4292	40.5563	-75.4373	46,000	Moderate damage	$T_{t7} \rightarrow T_{t8}$
Rd_{72}	40.5641	-75.4809	40.5675	-75.5150	42,000	Moderate damage	$T_{t7} \rightarrow T_{t8}$
Rd_{73}	40.5675	-75.5150	40.5706	-75.5359	42,000	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{85}	40.6276	-75.4838	40.6258	-75.4829	18,000	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{86}	40.6258	-75.4829	40.5575	-75.4364	9,000	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{87}	40.5571	-75.4352	40.6231	-75.4815	8,000	Moderate damage	$T_{t7} \rightarrow T_{t8}$
Rd_{92}	40.6460	-75.4939	40.7329	-75.5433	10,000	Moderate damage	$T_{t7} \rightarrow T_{t8}$
Rd_{98}	40.8669	-75.2061	40.7560	-75.2673	4,600	Slight damage	$T_{t7} \rightarrow T_{t8}$
Rd_{99}	40.7560	-75.2673	40.7548	-75.2696	8,500	Moderate damage	$T_{t7} \rightarrow T_{t8}$

[a] The road segment component is one-way traffic road segment. Start node refers to the starting node of the road segment.
[b] End node refers to the ending node of the road segment.
[c] In the column of restoration task, every cell lists the tasks required to fix the damaged road segment in the transportation system. The description of every task is presented in Table 13.

Table 10. Damaged components of traffic light and required tasks.

Cmpt ID	Latitude	Longitude	Related Rd[a]	Damage state	Restoration task[b]
TL_{45}	40.8341	-75.2981	Rd_{173}	Moderate damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{78}	40.8303	-75.3064	Rd_{174}	Slight damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{89}	40.5966	-75.4922	Rd_{105}	Moderate damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{97}	40.5987	-75.4683	Rd_{87}	Complete damage	$T_{t9} \rightarrow T_{t11}, T_{t12}$
TL_{107}	40.6376	-75.4885	Rd_{83}	Moderate damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{183}	40.7572	-75.5937	Rd_{82}	Slight damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{199}	40.6042	-75.4704	Rd_{88}	Extensive damage	$T_{t9} \rightarrow T_{t11}, T_{t12}$
TL_{208}	40.5407	-75.6384	Rd_{102}	Moderate damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{267}	40.5362	-75.3957	Rd_{149}	Complete damage	$T_{t9} \rightarrow T_{t11}, T_{t12}$
TL_{270}	40.6193	-75.5806	Rd_{127}	Moderate damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{278}	40.7148	-75.2853	Rd_{119}	Slight damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{280}	40.8686	-75.2550	Rd_{168}	Complete damage	$T_{t9} \rightarrow T_{t11}, T_{t12}$
TL_{289}	40.5943	-75.3896	Rd_{149}	Slight damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{301}	40.5977	-75.4880	Rd_{108}	Slight damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{343}	40.6754	-75.4182	Rd_{189}	Slight damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{348}	40.7326	-75.3128	Rd_{122}	Slight damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{358}	40.7839	-75.6056	Rd_{125}	Moderate damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{359}	40.7690	-75.5737	Rd_{125}	Slight damage	$T_{t9} \rightarrow T_{t10}, T_{t12}$
TL_{373}	40.8414	-75.2947	Rd_{168}	Complete damage	$T_{t9} \rightarrow T_{t11}, T_{t12}$
TL_{387}	40.7324	-75.5440	Rd_{82}	Extensive damage	$T_{t9} \rightarrow T_{t11}, T_{t12}$

[a] Related Rd refers to the road segment on which the traffic light controls the traffic. [b] In the column of restoration task, every cell lists the tasks required to fix the damaged traffic light in the transportation system. The description of every task is presented in Table 13.

Table 11. Task library for repairing damaged components in the power system.

Cmpt type	Task	Task description	$\bar{q}(\%)^a$	Duration distribution (hour)				Power resources	
				Type[b]	min	max	mode	Crew	Truck
Substation	T_{p1}	Assess local damage	0	Tri.	10	13	11.5	2	1
	T_{p2}	Repair 5% of disconnected switches	50	Tri.	5	15	10	2	0
	T_{p3}	Repair 5∼40% of circuit breakers	0	Tri.	5	15	10	2	0
	T_{p4}	Repair transformer bushing	50	Tri.	5	15	10	2	0
Trans. tower	T_{p5}	Damage assessment	0	Tri.	24	72	48	1	0
	T_{p6}	Purchase new materials	0	Tri.	10	30	20	2	1
	T_{p7}	Replace members and bolts	0	Tri.	10	40	20	4	1

[a] $\bar{q}$ represents the temporary functionality of a damaged component while executing the task.
[b] In the column of duration distribution type, Tri. represents a triangular distribution.

Table 12. Task library for repairing damaged components in the communication system.

Cmpt type	Task	Task description	$\bar{q}(\%)$	Duration distribution (hour)				Comm. resources	
				Type	min	max	mode	Crew	Truck
Central office	T_{c1}	Repair small cracks on the wall	50	Tri.	12	14	16	2	1
	T_{c2}	Repair moderate cracks	50	Tri.	20	40	32	2	1
Communication tower	T_{c3}	Realign distorted antennas	0	Tri.	6	8	12	4	2
	T_{c4}	Re-energize devices on the tower	0	Tri.	1	3	2	2	2
	T_{c5}	Reinstall the tower and antennas	0	Tri.	24	48	30	16	4

Table 13. Task library for repairing damaged components in the transportation system.

Cmpt type	Task	Task description	$\bar{q}(\%)$	Duration distribution (day)				Transportation resources			
				Type	min	max	mode	Crew	Truck	Crane	Machine
Bridge	T_{t1}	Damage assessment	0	Tri.	10	20	15	1	0	0	0
	T_{t2}	Repair small abutment cracks	50	Tri.	3	9	6	2	0	0	0
	T_{t3}	Repair slightly moved abutment	50	Tri.	5	10	8	5	0	1	1
	T_{t4}	Repair minor deck cracks	50	Tri.	1	3	2	3	0	0	1
	T_{t5}	Repair minor column cracks	50	Tri.	3	9	6	2	0	0	1
	T_{t6}	Repair moderate column cracks	50	Uni.	3	6	NA	5	0	1	2
Road segment	T_{t7}	Damage assessment	50	Tri.	10	20	15	1	1	0	0
	T_{t8}	Pavement milling and resurfacing	50	Tri.	7	10	8	3	1	1	1
Traffic light	T_{t9}	Damage assessment	0	Tri.	0.42	0.83	0.5	1	0	0	0
	T_{t10}	Repair minor damage	50	Tri.	0.04	0.12	0.08	1	0	0	0
	T_{t11}	Replace the traffic pole	0	Tri.	0.17	0.83	0.5	2	0	0	0
	T_{t12}	Re-energize the traffic light	0	Tri.	0.02	0.06	0.04	1	0	0	0

[a] In the column of duration distribution type, Tri. represents a triangular distribution, and Uni. represents a uniform distribution.

Table 14. Recovery priority by component type in every infrastructure system.

Priority rank[a]	Power system	Communication system	Transportation system
1	Power plant	Central office	Bridge
2	Substation	Communication line	Road segment
3	Power line	Communication tower	Traffic light
4	Transmission tower		

[a] In the priority rank, "1" represents the highest recovery priority, and "4" represents the lowest recovery priority.

In the communication system, the restoration prioritization is from central offices to communication lines, and to communication towers. Damaged central offices that serve the largest population are restored first. Restoring damaged communication towers follows the same criterion of recovering the service to the most population.

In the transportation system, damaged bridges are restored ahead of damaged road segments, and restoring damaged traffic lights has the lowest priority. Among all damaged bridges, bridges serving larger traffic (by annual average daily traffic, AADT) are restored earlier than those serving less traffic, bridges that serve the same amount of traffic are restored in a random sequence. Road segments follow the same criterion for carrying out restoration activities. Traffic lights on the busiest road segment, i.e., with the most traffic, are restored first, and traffic lights on road segments with the same traffic are restored randomly in sequence.

4.4. Computational cases

Table 15 presents sixteen cases, representing different restoration decision strategies. These decision strategies are implemented as either strong-level or weak-level of different types of interdependency. Among all cases, Case 1 represents the decision of taking the most actions for speeding up the restoration by relaxing all interdependencies; Case 16 represents the decision of taking the fewest actions to relax interdependencies during restorations.

In disaster recovery, while most efforts are made to utilize local resources as much as possible, mutual aid and contracting are often adopted to timely restore the functionality of critical infrastructure. The mutual assistance program is a voluntary partnership of domestic utility companies and agencies for service restoration and contingency planning. In case of a major power outage, the impacted utility companies can expect more repair crews and contractors, as well as specialized equipment available from fellow companies (National Academies of Sciences, Engineering, and Medicine, 2017). Mutual aid agreements are also developed for disaster recovery from state to state in the transportation sector (USDOT, 2019) and from company to company in the communication sector (FCC, 2019). The decision strategy of mutual aid agreements is implemented via resource constraints. Labels *Sres* and *Wres* indicate the strong and weak levels of resource-sharing interdependency, representing the decision strategy with mutual aid agreements for all three systems and the decision strategy without mutual aid agreements, respectively. In the computation, the weak level (*Wres*) sets the constant resource constraints as $a_{r,p} = [20, 20]$ for the power system, $a_{r,c} = [60, 60]$ for the communication system, and $a_{r,t} = [56, 56, 40, 40]$ for the transportation system. The a_r values mean that there are 20 electrician crews and 20 electrical trucks constantly available for restoring damaged components in the power system, 60 telecom crews and 60 bucket trucks for repairing damaged components in the communication system, 56 transportation crews, 56 transport trucks, 40 cranes and 40 concrete machines available for performing restoration tasks in the transportation system. The strong level (*Sres*) of resource-sharing leads to fewer resources available: $a_{r,p}$ = [10, 10], $a_{r,c}$ = [30, 30], and $a_{r,t}$ = [28, 28, 20, 20].

The decision of adopting alternative restoration techniques is implemented via the inter-system precedence dependency as precedence constraints between restoration tasks of damaged substations and tasks for re-energizing other related components. In this example, this inter-system restoration precedence dependency is present because there is a functionality requirement on electrical service from a nearby substation for executing certain re-energizing tasks (i.e., T_{c4} in Table 12 and T_{t12} in Table 13). *Wpre* represents the decision strategy of adopting alternative techniques by relaxing precedence relations through re-energizing with the electricity from generators in case of a power outage. *Spre* represents the opposite decision strategy of not using alternative techniques to relax precedence dependency. Therefore, repair crews cannot re-energize communication towers and traffic lights until the nearby substations are restored to provide the electricity. This inter-system precedence dependency due to a functionality requirement for executing certain tasks (T_{c4} and T_{t12}) is different from the inter-system functionality dependency described in the following.

Past experience demonstrates that using generators can provide temporary electricity in the post-disaster emergency scenario, boosting resilience of different infrastructure systems (FEMA, 2014). The decision strategy of adopting backup power, such as via portable generators, to relieve the functionality dependency on the power grid is implemented through the restoration function. *Wfunp* is the weak level of functionality dependency on the power system, representing the strategy of purchasing portable generators for every traffic light and every communication component. This means that every traffic light and every communication component are functional once completing their restoration, regardless of the functionality of the nearby substation. *Sfunp* indicates the opposite strategy of not purchasing portable generators. As mentioned in Section 4.1, there is still a 50% chance of a backup generator being present on-site for every communication tower and every traffic light. When backup generators are absent, traffic lights and communication components are not functional until the nearby damaged substations are restored to provide the electricity.

The decision strategy of resorting to temporary bridges and traffic rerouting is implemented through task duration. *Wfunt* is the weak level of functionality dependency on the transportation system, representing the strategy of using temporary bridges and traffic rerouting to boost traffic flow when the transportation functionality is severely disrupted. Therefore, there is no delay to restoration activities, and task duration remains as the original value. *Sfunt* is the strong level of functionality dependency on the transportation system, indicating the opposite strategy of not using temporary bridges and traffic rerouting. Therefore, when severely disrupted, the transportation system would delay traffic flows and slow down restoration activities. To represent the delay effect at *Sfunt*, this study implements it as longer task durations by multiplying the original durations of all tasks that are currently in the execution by a scaling factor of 1.5, when the transportation functionality $Q_t(t)$ is less than a threshold of 90%. Values of the delay factor and the functionality threshold are chosen in consideration of the traffic speed-flow relations (Hall, 1991).

Table 15. Computational cases.

No.	Case Label	Decision Strategy Description	Res[a]	Pre[b]	Funp[c]	Funt[d]
1	*Wres-Wpre-Wfunp-Wfunt*	•Mutual Aid •Alternative Technique •Portable Generator •Traffic Rerouting & Temporary Bridge	Weak	Weak	Weak	Weak
2	*Sres-Wpre-Wfunp-Wfunt*	•No Mutual Aid •Alternative Technique •Portable Generator •Traffic Rerouting & Temporary Bridge	Strong	Weak	Weak	Weak
3	*Wres-Spre-Wfunp-Wfunt*	•Mutual Aid •No Alternative Technique •Portable Generator •Traffic Rerouting & Temporary Bridge	Weak	Strong	Weak	Weak
4	*Sres-Spre-Wfunp-Wfunt*	•No Mutual Aid •No Alternative Technique •Portable Generator •Traffic Rerouting & Temporary Bridge	Strong	Strong	Weak	Weak
5	*Wres-Wpre-Sfunp-Wfunt*	•Mutual Aid •Alternative Technique •No Portable Generator •Traffic Rerouting & Temporary Bridge	Weak	Weak	Strong	Weak
6	*Sres-Wpre-Sfunp-Wfunt*	•No Mutual Aid •Alternative Technique •No Portable Generator •Traffic Rerouting & Temporary Bridge	Strong	Weak	Strong	Weak
7	*Wres-Spre-Sfunp-Wfunt*	•Mutual Aid •No Alternative Technique •No Portable Generator •Traffic Rerouting & Temporary Bridge	Weak	Strong	Strong	Weak
8	*Sres-Spre-Sfunp-Wfunt*	•No Mutual Aid •No Alternative Technique •No Portable Generator •Traffic Rerouting & Temporary Bridge	Strong	Strong	Strong	Weak
9	*Wres-Wpre-Wfunp-Sfunt*	•Mutual Aid •Alternative Technique •Portable Generator •No Traffic Rerouting or Temporary Bridge	Weak	Weak	Weak	Strong
10	*Sres-Wpre-Wfunp-Sfunt*	•No Mutual Aid •Alternative Technique •Portable Generator •No Traffic Rerouting or Temporary Bridge	Strong	Weak	Weak	Strong
11	*Wres-Spre-Wfunp-Sfunt*	•Mutual Aid •No Alternative Technique •Portable Generator •No Traffic Rerouting or Temporary Bridge	Weak	Strong	Weak	Strong
12	*Sres-Spre-Wfunp-Sfunt*	•No Mutual Aid •No Alternative Technique •Portable Generator •No Traffic Rerouting or Temporary Bridge	Strong	Strong	Weak	Strong
13	*Wres-Wpre-Sfunp-Sfunt*	•Mutual Aid •Alternative Technique •No Portable Generator •No Traffic Rerouting or Temporary Bridge	Weak	Weak	Strong	Strong
14	*Sres-Wpre-Sfunp-Sfunt*	•No Mutual Aid •Alternative Technique •No Portable Generator •No Traffic Rerouting or Temporary Bridge	Strong	Weak	Strong	Strong
15	*Wres-Spre-Sfunp-Sfunt*	•Mutual Aid •No Alternative Technique •No Portable Generator •No Traffic Rerouting or Temporary Bridge	Weak	Strong	Strong	Strong
16	*Sres-Spre-Sfunp-Sfunt*	•No Mutual Aid •No Alternative Technique •No Portable Generator •No Traffic Rerouting or Temporary Bridge	Strong	Strong	Strong	Strong

[a] "Res" represents the resource-sharing interdependency, implemented as resource constraints. "Weak (*Wres*)" represents more resources in restoration, and "Strong (*Sres*)" represents less sufficient resources in restoration.
[b] "Pre" represents the inter-system precedence dependency, implemented as precedence constraints between tasks from different systems. "Weak (*Wpre*)" represents no precedence constraint of the re-energizing tasks due to repairing damaged nearby electric substations; "Strong (*Spre*)" enforces these inter-system precedence constraints from tasks to restore the damaged substation before executing re-energizing tasks before executing tasks for repairing damaged communication towers.
[c] "Funp" represents the functionality dependency on the electric power. "Weak (*Wfunp*)" is the weak level of functionality dependency on the electric power, representing the strategy of using portable generators; "Strong (*Sfunp*)" is the strong level of functionality dependency on the electric power, representing the strategy of not using portable generators.
[d] "Funt" represents the delay effect due to the transportation functionality disruption. "Weak (*Wfunt*)" means no delay effect by using rerouting and temporary bridges to boost the connectivity; "Strong (*Sfunt*)" means the transport delay effect is in effect; therefore, restorations are delayed.

4.5. Computational setting

Considering restoration uncertainties, two thousand samples were generated using Latin hypercube sampling. To assess the confidence interval of the results, a convergence analysis should be performed, but it was not deemed necessary in this illustrative example. Given the entire list of all restoration tasks, the restoration process is simulated to compute the component-level functionality at every time step in the three systems, following Equations (1) and (2). When computing the component functionality, functionality dependencies on the power service are considered in Cases *Sfunp*, as shown in Table 3 in Section 4.1.

Based on the component functionality at every time step, the functionality of every system is computed with Equation (3). For the power system, the system functionality is defined as the percentage of population with the electricity from nearby substations, and the component functionality weight w_j is the population that is served by substation j. For the communication system, the functionality is defined as the percentage of population with service from functional communication towers, and the component functionality weight w_j is the population that is served by communication tower j. For the transportation system, the functionality is defined as the percentage of traffic capacity restored in the transportation network, computed based on the AADT. Hence, the traffic (i.e., AADT) served by road segment j is the component functionality weight w_j for the transportation system.

5. Results

5.1. System functionality recovery

Based on all samples of system functionality for every analysis case, the mode value of system functionality is computed at every time step as $Q_{mode}(t)$, representing the evolution of the functionality value that appears most often over time. Figure 5 depicts $Q_{mode}(t)$ for the three systems at five dependency cases: Case 1 (*Wres*), Case 2 (*Sres*), Case 3 (*Spre*), Case 5 (*Sfunp*), and Case 9 (*Sfunt*). Both power and communication systems can recover after 3 days of restoration, whereas the transportation system takes about one to two months. Local variations of $Q_{mode}(t)$ values, particularly for the transportation system, are because the temporary functionality $\bar{q}$ of a component may vary when executing different restoration tasks, as shown in Tables 11∼13. $Q_{mode}(t)$ plots show two general trends. First, all three systems reach the full recovery in the shortest time in Case 1 (*Wres-Wpre-Wfunp-Wfunt*), when four types of interdependency are all relaxed. This confirms that adopting strategies to relax interdependencies can accelerate restorations for all three systems. Second, all three systems show extremely slow recoveries when restoration resources are tight in Case 2 (*Sres*) and when the restoration delay effect is in place in Case 9 (*Sfunt*). This indicates that the shortage of resources and the delay effect due to transportation disruption are two leading factors of restoration delays in this example.

The impact of different types of interdependency on functionality recovery varies from system to system. For the power system, $Q_{p,mode}(t)$ shows similar values in Cases 3 and 5 throughout the recovery process (Figure 5a). This means that the power system is not sensitive to the enforcement of inter-system precedence dependency (*Spre*) and functionality dependency on the power service (*Sfunp*). Conversely, large discrepancies of $Q_{p,mode}(t)$ values between Cases 1 (*Wpre*) and 3 (*Spre*) indicate that the communication system is very sensitive to inter-system precedence dependency (Figure 5b).

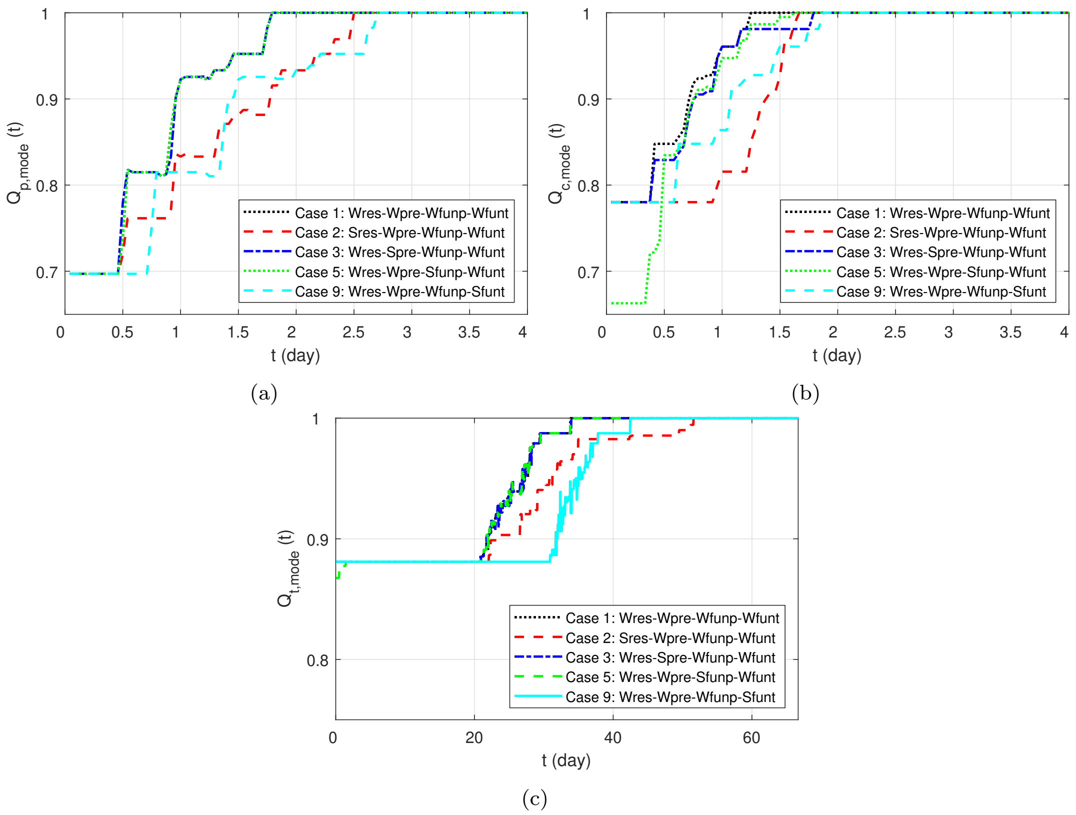


Figure 5. Mode value of the system functionality at every time step $Q_{mode}(t)$: (a) power, (b) communication, and (c) transportation.

That is because the one-way precedence dependency at *Spre* requires that tasks of re-energizing communication devices can only be executed after the full restoration of the nearby damaged substation. There is no precedence dependency in the opposite direction between communication tasks and power tasks. Therefore, the precedence dependency only impacts the recovery of the communication system, rather than the recovery of the power system. In addition, the communication system is very sensitive to functionality dependency on the power system. In particular, the communication system starts with an initial functionality mode value of 66.2% ($t = 0$) in Case 5 (*Sfunp*), smaller than the other four cases (Cases 1, 2, 3, and 9). Such distinct impacts on power and communication from the same functionality dependency are explained as follows. The one-way functionality dependency of communication components on substations for electricity at *Sfunp* results in the fact that some communication components are not functional, even if not damaged in the disaster, as long as the nearby substation is not restored to be functional. For the same functionality dependency of traffic lights on substations, the transportation system shows a smaller initial functionality value at the beginning for Case 5 (*Sfunp*), as shown in Figure 5c.

5.2. Recovery time

Following Equation (4), the recovery time of an infrastructure system is determined for every recovery sample as the time to reach full functionality, also shown in Figure 2. It is worth mentioning that the recovery time is not necessarily the same as the time when the last restoration task is complete, as the system functionality may not be fully recovered due to functionality dependency on a component from another system that may not be functional.

Figure 6 presents the mean value and standard deviation of recovery time for three systems across sixteen dependency cases in bar plots. There are two general trends. The first general trend is that all three systems have faster recoveries when all types of interdependencies are relaxed (Case 1). When relaxing resource-sharing interdependencies by providing more resources with mutual aid (*Wres*), more restoration tasks are expected to be executed in parallel, leading to accelerated recovery. On average, the power system fully recovers after 1.88 days in Case 1 (*Wres*) and 2.60 days in Cases 2 (*Sres*), as shown in Figure 6a. The average recovery time increases from 2.83 days in Case 9 (*Wres*) to 3.89 days in Case 10 (*Sres*). When mutual aid is present (*Wres*), similar recovery accelerations from *Sres* to *Wres* are also found for the other two systems. The second general trend is that all three systems take longer time to recover when the transport delay effect is in place at *Sfunt* (such as Case 9) than cases of *Wfunt* (such as Case 1). That is because the proposed model considers the delay effect on restoration activities for all three systems when the transportation system's functionality is below the threshold value of 90%, as mentioned in Section 4.4. This delay effect leads to longer restorations of all three systems and consequently an increase of the overall recovery time.

The inter-system precedence dependency and the functionality dependency on the power system show quite different impacts on the recovery of three systems. As explained earlier in Section 5.1, these two types of dependency are one-way dependency relations from power to communication. For this reason, the power system recovery time is sensitive to neither inter-system precedence dependency (*Spre*) nor functionality dependency on the power system (*Sfunp*), whereas the communication system recovery time is sensitive to both types of dependency (*Spre* and *Sfunp*). This means that relaxing either the inter-system precedence (*Wpre*) or the inter-system functionality dependency on the power system (*Wfunp*) can significantly speed up the recovery of the communication system. Conversely, the transportation system shows a different trend. The slight increase of mean recovery time from 34.37 days in Case 1 (*Wpre*) to 34.39 days in Case 3 (*Spre*) indicates that the transportation system is not very sensitive to the inter-system precedence dependency, despite the fact that there are one-way precedence dependencies between the task for re-energizing a traffic light (T_{t12}) and tasks for repairing the nearby substation ($T_{p1} \sim T_{p4}$). In addition, the recovery time of the transportation system is not sensitive to the functionality dependency on the power service, even though traffic lights are functionally dependent on the electric power. That is mainly because repairing damaged bridges and damaged roads takes a long time, usually on the magnitude of days or even weeks. Tasks for repairing the damaged traffic light have the lowest priority in the transportation system, as shown in Table 14. By the time damaged traffic lights are restored, nearby substations, if damaged, are most likely to be restored as well, to provide the electricity for both re-energizing traffic lights during the restoration and powering traffic lights afterwards.

5.3. System resilience

For every functionality recovery sample, the resilience index is computed using Equation (5), by setting the time horizon $t_h = 3$ days for power and communication systems and $t_h = 60$ days for the transportation system. Figure 7 presents the resilience index

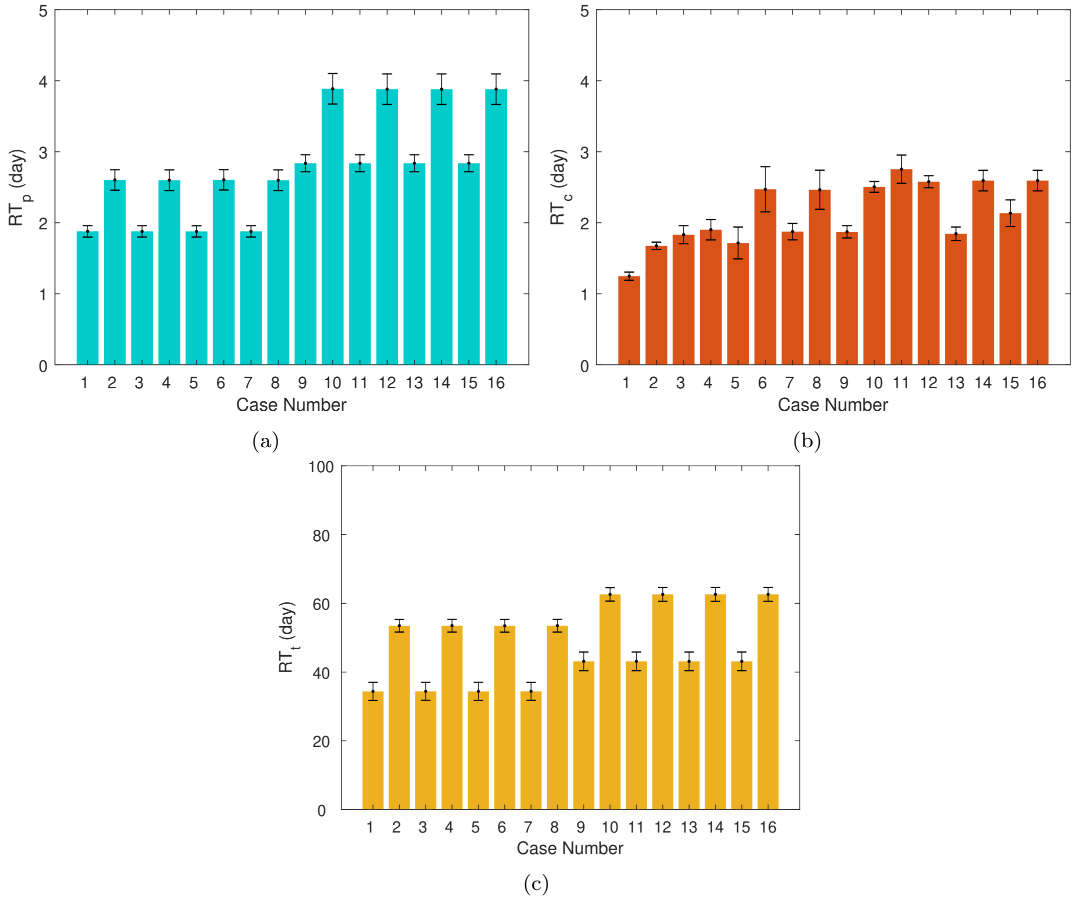


Figure 6. Mean values and standard deviations of recovery time (RT) of three systems: (a) power, (b) communication, and (c) transportation.

over all samples in violin plots for three systems. Every violin plot represents the probability distribution of resilience index for every computational case, and the median value of the resilience index is shown as a black dashed line in the violin plot. For all three systems, a general trend is that the system resilience is enhanced when interdependencies are relaxed from strong-level (*Sres, Spre, Sfunp, Sfunt*) to weak-level (*Wres, Wpre, Wfunp, Wfunt*).

The resource-sharing interdependency (*Sres*) shows a significant impact on the system resilience. All three systems show greater resilience values when more resources are available to carry out more restoration tasks in parallel at *Wres*. This confirms that establishing mutual aid can significantly improve the disaster resilience of all three infrastructure systems.

The inter-system precedence dependency shows a strong impact on the resilience of the communication and transportation systems, with no obvious impact to the resilience of the power system. This is because the precedence dependency at *Spre* is a one-way relation from power tasks to communication and transportation tasks (T_{c4} and T_{t12}). This means using alternative techniques to relax precedence dependencies can also improve the resilience for communication and transportation systems.

The functionality dependency on the power service (*Sfunp*) negatively impacts the resilience of communication and transportation systems. That is because damaged communication towers and damaged traffic lights may not be functional until the nearby damaged substations are restored to provide electricity at *Sfunp*. This leads to longer recovery time and smaller functionality values, and consequently smaller values of resilience index. As the functionality dependency on the power service is unidirectional from power to communication and transportation, the enforcement of inter-system functionality dependency does not influence functionality values of the power system. The resilience index of the power system shows the same distributions for the *Wfunp* cases and the corresponding *Sfunp* cases in Figure 7a, such as Cases 1 and 5, and Cases 2 and 6.

The delay effect due to transportation functionality disruption (*Sfunt*) shows a significantly negative impact on the system resilience as well. In the first phase of the restoration, the functionality of the transportation system $Q_t(t)$ is less than 90%, and the restoration delay effect is in place for *Sfunt* (Cases 9∼16). Consequently, the restoration of all systems is delayed until the functionality of the transportation system is above the threshold value, $Q_t(t) \geq 90\%$. Therefore, boosting network connectivity by adopting temporary bridges and traffic rerouting (*Wfunt*) can facilitate crews to reach damage sites for timely restoration, boosting the resilience.

5.4. Combined resilience of interdependent systems

In practice, emergency management in local government may be interested in the disaster resilience of interdependent infrastructure systems as a whole. This study assesses also the resilience of the three interdependent systems. Previously, the community resilience has been quantified via a metric that is determined from cross correlation coefficients of post-disaster functionality recovery curves for interdependent infrastructure systems (Cimellaro, Solari, & Bruneau, 2014). However, the aforementioned metric is the result of complex computations involving correlation coefficients, and its final interpretation may not be straightforward.

Instead, this study computes the combined resilience, by computing the mean functionality of the three systems first and determining the overall resilience with Equa-

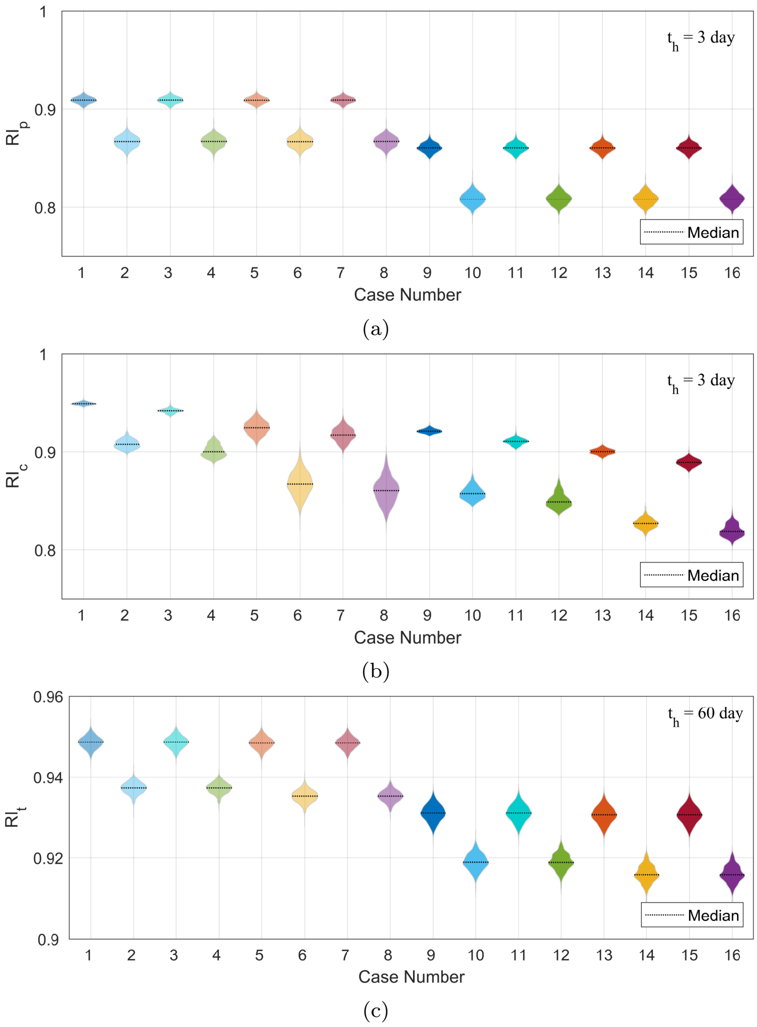


Figure 7. Distributions of resilience index: (a) power, (b) communication, and (c) transportation.

tion (5). To start with, a sample of "combined functionality recovery" is defined as the mean value of the functionality values of three infrastructure systems in every sample at every time step. For every sample of combined functionality, the combined resilience is computed using Equation (5) at $t_h = 3$ days and $t_h = 60$ days, respectively. Alternatively, the analyst may just take the average value of the system resilience of all three systems as the combined resilience for every sample. These two ways of computing the combined resilience will yield the same result because both integral and average are linear operators. Table 16 presents the mean value of combined resilience. The rank of resilience mean value can indicate the degree of impact on combined resilience enhancement due to the presence of different types of interdependency (i.e., the effectiveness of different strategies).

After 3 days of restoration, power and communication systems are fully restored, while the transportation restoration is still in process. The rank of $RI_{t_h=3}$ mean value from the smallest to the greatest is Case 2 (*Sres*), Case 9 (*Sfunt*), Case 5 (*Sfunp*), Case 3 (*Spre*), and Case 1 (*Wres-Wpre-Wfunp-Wfunt*). $RI_{t_h=3}$ has the greatest mean value when all types of interdependencies are relaxed at Case 1 (*Wres-Wpre-Wfunp-Wfunt*), which is as expected. The smallest mean value at Case 2 (*Sres*) indicates that resource-sharing interdependency poses the most adverse impact on the combined resilience. Therefore, providing more restoration resources can significantly improve combined resilience in short-term recovery. The second smallest mean value at Case 9 (*Sfunt*) indicates that the transport delay effect also has a great adverse impact on restoration, representing that boosting transportation capacity (such as adopting traffic rerouting and temporary bridges) can also largely contribute to combined resilience enhancement.

At $t_h = 60$ days, all three systems are fully restored. $RI_{t_h=60}$ mean value shows a very similar rank as $RI_{t_h=3}$, except that Case 2 (*Sres*) and Case 9 (*Sfunt*) switch the order. This indicates a similar impact of different management strategy on improving combined resilience, and the transport delay effect shows the most adverse impact in long-term recovery in this example.

Table 16. Mean value of combined resilience.

Case Label	$RI_{t_h=3}$	$RI_{t_h=60}$
Case 1: *Wres-Wpre-Wfunp-Wfunt*	**0.9129**	**0.9805**
Case 2: *Sres-Wpre-Wfunp-Wfunt*	***0.8852***	0.9753
Case 3: *Wres-Spre-Wfunp-Wfunt*	0.9105	0.9804
Case 5: *Wres-Wpre-Sfunp-Wfunt*	0.9036	0.9800
Case 9: *Wres-Wpre-Wfunp-Sfunt*	0.8877	***0.9734***

Note: The greatest value is highlighted in **bold**, and the smallest value is highlighted in ***italic bold***.

5.5. Probabilistic restoration function

Based on all functionality recovery samples for a case, a probabilistic restoration function can be computed as the probability of an infrastructure system reaching a certain functionality level, such as full functionality, at different time steps. Figure 8 presents the probabilistic restoration function of the communication system for reaching the full functionality, $Q_c(t) = 100\%$.

As shown in Figure 8a, the communication system is likely to be fully recovered faster with mutual aid in Case 1 (*Wres*) than that without mutual aid in Case 2

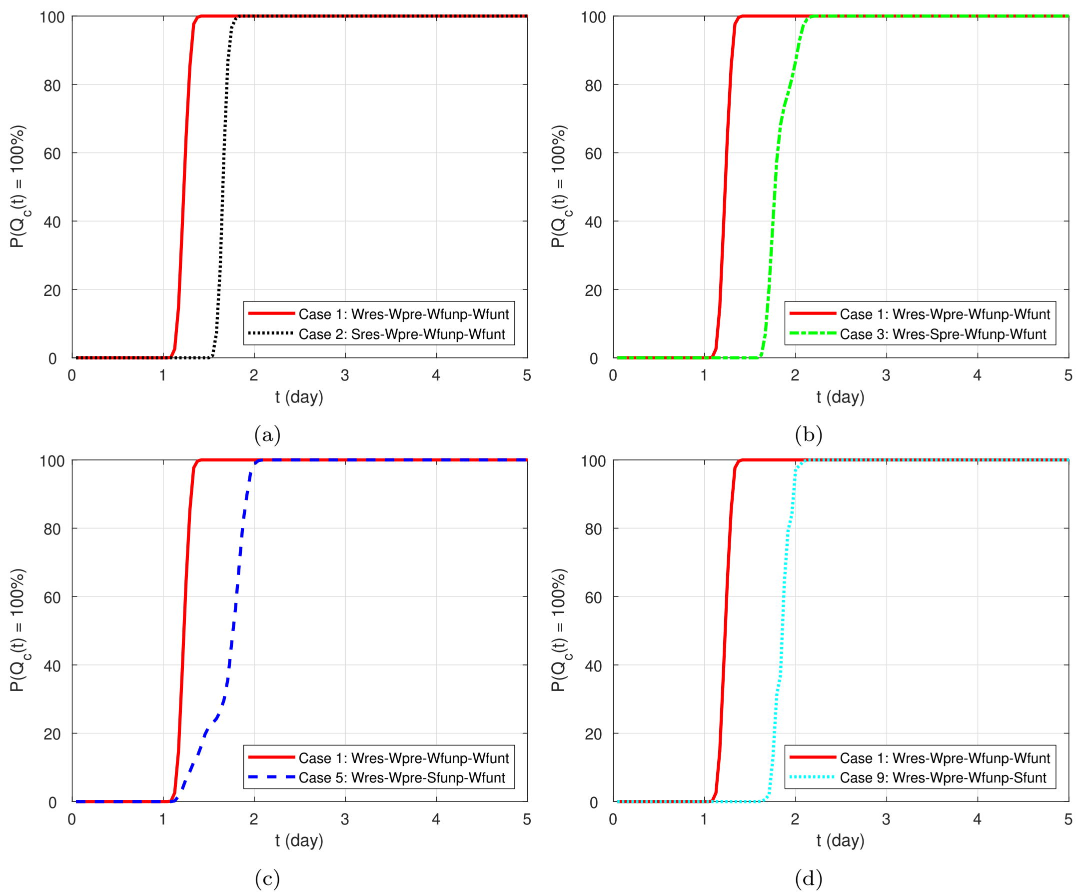


Figure 8. Probabilistic restoration function for the communication system: (a) impact of resource-sharing interdependency, (b) impact of precedence dependency, (c) impact of functionality dependency on power, and (d) impact of transportation delay effect.

(*Sres*). As expected, relaxing resource-sharing interdependency by providing sufficient resources can significantly accelerate the disaster recovery. The smaller probability values at *Spre* in Case 3 than those at *Wpre* in Case 1 in the range of $t = 1 \sim 2$ days indicate that the presence of inter-system restoration precedence at *Spre* delays the recovery of the communication system. Similarly, the communication system shows smaller probability values due to the existence of the functionality dependency on the power service at *Sfunp* in Case 5, meaning that it is less likely to fully recover in that time range, compared to *Wfunp* in Case 1. Finally, because of the transportation functionality disruption causing a restoration delay effect at *Sfunt*, the communication system shows smaller probability of being fully recovered at *Sfunt* in Case 9 than those at *Wfunt* in Case 1.

Overall, the communication system will have a greater probability of a fast recovery when interdependencies are all relaxed, by providing more resources (*Wres*), implementing advanced techniques (*Wpre*), using mobile generators (*Wfunp*), and adopting temporary bridges (*Wfunt*). In this particular example, Case 9 (*Sfunt*) shows the smallest probability values among all five cases. This means that the delay effect shows the most adverse impact on the communication system recovery in this example.

6. Discussion

The major contribution of this study is a simple decision model to represent the concept of recovery priority following restoration policies. This model simulates the recovery of every system according to restoration sequencing, by considering restoration-related uncertainties and complex interdependencies. This model is general, applicable to different infrastructure systems. An earlier study showed that compared with the optimization-based decision model (Scheme 3B), the policy-based decision model (Scheme 3A) yields similar results of recovery time and slightly smaller resilience of infrastructure systems (Sun, Bocchini, & Davison, 2019). The greatest advantage of the proposed policy-based model is that it is simple and straightforward, requiring no sophisticated mathematical formulations, and can reflect political or ethical priorities that are not typically considered in an optimization setting. Therefore, it has minimal computational costs. This model can easily implement the priority policies that are widely used in practical disaster recovery plans. With infrastructure data and socioeconomic data for the community of interest, it is easy to use the proposed model to compare the effectiveness of different decision strategies.

Nevertheless, this model has the following two limitations. First, despite the advantage of being simple and straightforward, the recovery priority policy presented in the proposed model may not be able to capture the actual plan of restoration activities. Under a given damage scenario, following the recovery sequence determined from a predefined priority policy to conduct disaster restoration activities is expected to provide reasonably good service and ease the stress of developing plans on the fly during the disaster. However, actual disaster restorations often differ from what was expected. After a disaster, the restoration process is dynamic, and the restoration plan may often need to be adjusted to satisfy urgent needs. For instance, while most restoration priorities are to restore the infrastructure service to critical facilities, such as hospitals and fire stations, and to the largest number of customers in the shortest period of time, practical restorations need to take other factors into considerations, such as network topologies and resource locations (National Academies of Sciences, Engineering, and Medicine, 2017). For example, restoration crews on-site are often sent to repair the damaged device that is the closest in distance because of travel convenience, or to restore the damaged component that serves a region experiencing the longest outage for humanitarian reasons. Performing restorations by considering these factors may lead to a delay in restoring the service to other originally highly prioritized customers. To capture the complex and dynamic environment of actual disaster restorations, future improvements should focus on implementing more comprehensive policy rules.

Second, the proposed model in this study may overlook other restoration-related uncertainties. The presented model only considers restoration-related uncertainties in two aspects (i.e., task duration and the presence of unexpected resource to relax functionality dependency). However, there are other sources of uncertainty related to the restoration process. For instance, depending on workers' proficiency and equipment efficiency, the amount of resources required for executing the same restoration activity may vary; the available amount of resource often varies significantly in the early stage of the disaster restoration phase. To account for other restoration-related uncertainties, future improvements should focus on implementing additional probabilistic models in the restoration simulation.

The proposed model can capture four types of restoration-related interdependency in a rigorous manner: resource-sharing interdependency, precedence dependency, functionality dependency, and restoration delay due to transportation service disruption.

It requires the analyst to know detailed input information about infrastructure systems and their interdependencies, which may be a challenging task when collecting detailed data for large communities due to reasons of national security and commercial competitiveness. This would be even more challenging when infrastructure systems are so complex that collecting detailed component information may be overwhelming and almost impossible. In this case, infrastructure data can be collected at a coarser level, such as meta-component-level, to built systems with aggregated interdependency interactions. Lastly, infrastructure interdependencies dynamically change over time and space. To capture their dynamic features, the implementation of different types of interdependency presented in Table 1, such as resource constraints for representing a resource-sharing interdependency, can become a function of time and/or space (Sun et al., 2020b). In this way, the proposed model is still applicable to evaluate the impact of different types of interdependency on system recovery and resilience, and ultimately support decision-making in disaster recovery planning.

Obviously, the hazard intensity shows a great impact on physical damage and social damage (Lindell, 2013). Variations of damage may lead to changes of restoration activities, resulting in different functionality recovery and system resilience, even if the same recovery policy is adopted. This study only presents an application example with recovery simulation results under a specific hazard scenario with a return period of 2500 years, which is close to the maximum credible earthquake (MCE) with a return period of 2475 years. When applying the proposed model to the recovery simulation of the same three infrastructure systems under a different damage scenario after a less severe earthquake with magnitude 5 and associated return period of 500 years, by keeping constraints of resource availability and precedence, as well as functionality dependency the same, some interdependencies show a different impact on system recovery. In this new application, relaxing the functionality dependency on power ($Wfunp$) can still boost system functionality and enhance system resilience. However, relaxing the resource-sharing interdependency ($Wres$) and the inter-system precedence dependency ($Wpre$) does not reduce the restoration time, as the small number of restoration tasks can be conducted in parallel. The functionality dependency on transportation ($Sfunt$) shows no impact on system recovery because the initial functionality loss does not reach the threshold for triggering the transport delaying effect (i.e., $Q_t > 90\%$ in the new damage scenario). While the impact of the same type of interdependency on system recovery may vary, the proposed model serves as a simple and general tool that can quantify the impact of management strategies on system recovery under any damage scenario due to different types of hazard at different intensity levels.

7. Conclusions

This study proposes a simple model to simulate pre-event the restoration of interdependent systems based on the concept of recovery priority. This model determines the restoration sequence following the priority rank and simulates the disaster recovery of interdependent systems. Restoration-related uncertainties are considered at component-level through the probabilistic analysis. With rigorous models for capturing different types of interdependency, decision strategies are directly implemented as different levels of interdependency in this model. The proposed model is conceptually simple, straightforward, and computationally efficient. By comparing recovery results from different dependency cases, one can quantify the impact of investments in very different restoration strategies, and this in turn will allow decision makers to take optimal decisions on pre-event mitigation options (e.g., joining mutual aid consortia, purchasing mobile generators, etc.).

The impact of interdependencies on the system/community recovery should be assessed case by case, because the same type of interdependency may show a different impact for different systems, in a different community, at a different time frame, or under a different hazard scenario. For instance, for the Lehigh Valley community, resource-sharing interdependency shows the most adverse impact on combined resilience in short-term recovery and the second most adverse impact in long-term recovery, under the damage scenario in Section 4. However, the same interdependency has no obvious impact on community resilience under a less severe damage scenario, as described in Section 6. Therefore, analysts are recommended to adopt the proposed model to perform tailored computations for the community and the scenario of their interest.

The proposed model is based on the policy scheme, which is part of the framework of the PRAISys platform. PRAISys can simulate possible infrastructure damage under a given hazard scenario and predict the recovery of interdependent systems in a probabilistic manner. The current PRAISys platform can be further improved and expanded including implementing more practical and comprehensive restoration policies.

Acknowledgements

This work is part of the Probabilistic Resilience Assessment of Interdependent Systems (PRAISys) project (www.praisys.org). Support from the National Science Foundation (NSF) through grant CMMI-1541177 is gratefully acknowledged. The views expressed in the paper are solely those of the authors and do not represent the official position of the funding agency. The authors would like to acknowledge contributions from Chase Gallik and Faith Comlo at Lehigh University, and Tyler Radenbaugh at Florida Atlantic University for their kind help with infrastructure data and socioeconomic data in the Lehigh Valley testbed. The authors would also like to acknowledge insightful discussion about the recovery priority from Dr. Diana Mitsova and Dr. Alka Sapat at Florida Atlantic University, and Dr. Ann-Margaret Esnard at Georgia State University.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Wenjuan Sun http://orcid.org/0000-0003-0546-2389
Paolo Bocchini http://orcid.org/0000-0002-5685-2283
Brian D. Davison http://orcid.org/0000-0002-9326-3648

References

Alshehri, S. A., Rezgui, Y., & Li, H. (2015). Disaster community resilience assessment method: a consensus-based Delphi and AHP approach. *Natural Hazards*, *78*, 395–416.

Ammon, C. J., Hermann, R. B., Langston, C. A., & Benz, H. (1998). Faulting parameters of the January 16, 1994 Wyomissing Hills, Pennsylvania earthquakes. *Seismological Research Letters*, *69*(3), 261–269.

APPA. (2018, June). *Restoration best practices guidebook* (Tech. Rep. No. DE-OE0000757). American Public Power Association. Retrieved from https://www.publicpower.org/system/files/documents/Restoration_Best_Practices_Guidebook_2018.pdf

ATC. (2016, April). *Critical assessment of lifeline system performance: Understanding societal needs in disaster recovery* (Tech. Rep. No. NIST GCR 16-917-39). Gaithersburg, MD: Applied Technology Council. (https://dx.doi.org/10.6028/NIST.GCR.16-917-39.pdf)

Bocchini, P., Davison, B. D., Esnard, A.-M., Lamadrid, A. J., Mitasova, D., Sapat, A., ... Sun, W. (2019). *Probabilistic resilience assessment of interdependent systems (PRAISys).* Retrieved from http://www.praisys.org (Online; accessed December 2019)

Bocchini, P., & Frangopol, D. M. (2012a). Optimal resilience- and cost-based postdisaster intervention prioritization for bridges along a highway segment. *Journal of Bridge Engineering*, *17*, 117-129.

Bocchini, P., & Frangopol, D. M. (2012b). Restoration of bridge networks after an earthquake: multicriteria intervention optimization. *Earthquake Spectra*, *28*, 426-455.

Bocchini, P., & Frangopol, D. M. (2013). Connectivity-based optimal scheduling for maintenance of bridge networks. *Journal of Engineering Mechanics*, *139*, 760-769.

Bueno, L. F., Haeser, G., & Martínez, J. M. (2016). An inexact restoration approach to optimization problems with multiobjective constraints under weighted-sum scalarization. *Optimization Letters*, *10*, 1315–1325.

Çağnan, Z. (2005). *Post-earthquake lifeline service restoration modeling* (Doctoral dissertation). Cornell University, Ithaca, NY.

Cai, Y., Xie, Q., Xue, S., Hu, L., & Kareem, A. (2019). Fragility modelling framework for transmission line towers under winds. *Engineering Structures*, *191*, 686-697.

CellReception. (2016). *Cellreception.* Retrieved from https://www.cellreception.com/ (Online; accessed September 2016)

Chang, S. E. (2003). Transportation planning for disasters: an accessibility approach. *Environment and Planning A: Economy and Space*, *35*(6), 1051-1072.

Cimellaro, G. P., Solari, D., & Bruneau, M. (2014). Physical infrastructure interdependency and regional resilience index after the 2011 Tohoku Earthquake in Japan. *Earthquake Engineering & Structural Dynamics*, *43*(12), 1763-1784.

CISA. (2019). *Telecommunication service priority (TSP).* Retrieved from https://www.cisa.gov/telecommunications-service-priority-tsp (accessed May 2019)

EEI. (2016). *Transmission projects at a glance.* Retrieved from http://www.eei.org/issuesandpolicy/transmission/Documents/Trans_Project_lowres_bookmarked.pdf (page 105-108; accessed May 2017)

Esri. (2019). *ArcGIS.* Retrieved from https://desktop.arcgis.com/en/

Fang, Y.-P., Fang, C., Zio, E., & Xie, M. (2019). Resilient critical infrastructure planning under disruptions considering recovery scheduling. *IEEE Transactions on Engineering Management*. (DOI: 10.1109/TEM.2019.2902916)

FCC. (2019). *Wireless resiliency cooperative framework.* Retrieved from https://www.fcc.gov/wireless-resiliency-cooperative-framework (accessed May 2019)

FEMA. (2014, September). *Emergency power systems for critical facilities: a best practices approach to improve reliability* (Tech. Rep. No. FEMA P-1019). Federal Emergency Management Agency. Retrieved from https://www.fema.gov/media-library-data/1424214818421-60725708b37ee7c1dd72a8fc84a8e498/FEMAP-1019_Final_02-06-2015.pdf

FEMA. (2017). *Pre-disaster recovery planning guide for local governments* (Tech. Rep. No. FEMA Publication FD 008-03). Federal Emergency Management Agency.

FEMA. (2019). *HAZUS.* Retrieved from https://www.fema.gov/hazus (Online; accessed December 2019)

FPL. (2019). *How we restore power.* Retrieved from https://www.fpl.com/storm/

restoration/restoration-priorities.html (accessed March 2019)
Fu, X., Li, H.-N., & Li, G. (2016). Fragility analysis and estimation of collapse status for transmission tower subjected to wind and rain loads. *Structural Safety*, *58*, 1-10.
Gehl, P., & D'Ayala, D. (2016). Development of Bayesian networks for the multi-hazard fragility assessment of bridge systems. *Structural Safety*, *60*, 37-46.
Ghosh, J., & Padgett, J. (2010). Aging considerations in the development of time-dependent seismic fragility curves. *Journal of Structure Engineering*, *136*, 1497–1511.
Giaccu, G., & Caracoglia, L. (2018). Wind-load fragility analysis of monopole towers by Layered Stochastic-Approximation-Monte-Carlo method. *Engineering Structures*, *174*, 462-477.
Gidaris, I., Padgett, J. E., Barbosa, A. R., Chen, S., Cox, D., Webb, B., & Cerato, A. (2017). Multiple-hazard fragility and restoration models of highway bridges for regional risk and resilience assessment in the United States: State-of-the-art review. *Journal of Structural Engineering*, *143*, 04016188.
González, A. D., Dueñas-Osorio, L., Sáchez-Silva, M., & Medaglia, A. L. (2015). The interdependent network design problem for optimal infrastructure system restoration. *Computer-Aided Civil and Infrastructure Engineering*, *31*(5), 334-350.
Guo, A., Yuan, W., Lan, C., Guan, X., & Li, H. (2015). Time-dependent seismic demand and fragility of deteriorating bridges for their residual service life. *Bulletin of Earthquake Engineering*, *13*, 2389-–2409.
Hall, F. (1991). Chapter 2: Traffic flow characteristics. In *Traffic stream characteristics* (pp. 2-1–36).
HIFLD. (2017). *Homeland infrastructure foundation-level data (HIFLD).* Retrieved from https://hifld-geoplatform.opendata.arcgis.com/ (Online; accessed January 2017)
Hwang, H., & Huo, J.-R. (1998). Seismic fragility analysis of electric substation equipment and structures. *Probabilistic Engineering Mechanics*, *13*, 107-116.
Irfan, M., Khurshid, M. B., Anastasopoulos, P., Labi, S., & Moavenzadeh, F. (2011). Planning-stage estimation of highway project duration on the basis of anticipated project cost, project type, and contract type. *International Journal of Project Management*, *29*(1), 78-92.
Johnsen, S. O., & Veen, M. (2013). Risk assessment and resilience of critical communication infrastructure in railways. *Cognition, Technology & Work*, *15*, 95–107.
Karamlou, A., & Bocchini, P. (2015). Computation of bridge seismic fragility by large-scale simulation for probabilistic resilience analysis. *Earthquake Engineering & Structural Dynamics*, *44*(12), 1959–1978.
Karamlou, A., & Bocchini, P. (2016). Sequencing algorithm with multiple-input genetic operators: application to disaster resilience. *Engineering Structures*, *117*, 591–602.
Karamlou, A., & Bocchini, P. (2017a). From component damage to system-level probabilistic restoration functions for a damaged bridge. *Journal of Infrastructure Systems*, *23*(3), 04016042.
Karamlou, A., & Bocchini, P. (2017b). Functionality-fragility surfaces. *Earthquake Engineering & Structural Dynamics*, *46*(10), 1687–1709.
Lacouve, N. (2017). *Restoration tasks in the power system.* (Personal communication)
Lambert, J. H., Haimes, Y. Y., Louis, G. E., Moutoux, R. D., Finseth, R. M., Koo, L. H., ... Peterson, K. D. (2002, December). *Hurricane preparedness and recovery by a transportation agency* (Tech. Rep. No. VTRC 02-CR2). Charlottesville, Virginia: .
Lindell, M. K. (2013). Recovery and reconstruction after disaster. In P. T. Bobrowsky (Ed.), *Encyclopedia of natural hazards.* Springer, Dordrecht. (DOI: 10.1007/978-1-4020-4399-4)
Ma, L., Bocchini, P., & Christou, V. (2020). Fragility models of electrical conductors in power transmission networks subjected to hurricanes. *Structural Safety*, *82*, 101890.
Ma, L., Christou, V., & Bocchini, P. (2019, May 26-30). Probabilistic simulation of power transmission systems affected by hurricane events based on fragility and AC power flow analyses. In *Proceedings of the 13th international conference on applications of statistics and probability in civil engineering (ICASP13).* Seoul National University. (Paper 73)
Maceira, M., Ammon, C. J., & Herrmann, R. B. (2000). Faulting parameters of the September

25, 1998 Pymatuning, Pennsylvania earthquake. *Seismological Research Letters*, *71*(6), 742–752.

Martin, J., Alipour, A., & Sarkar, P. (2019). Fragility surfaces for multi-hazard analysis of suspension bridges under earthquakes and microbursts. *Engineering Structures*, *197*, 109169.

Matherly, D., Langdo, N., Kuriger, A., Sahu, I., Wolshon, B., Renne, J., . . . Dixit, V. (2013, December). *A guide to regional transportation planning for disasters, emergencies, and significant events* (Tech. Rep. No. NCHRP 20-59(42)). Washington, D.C.: National Cooperative Highway Research Program. Retrieved from http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_rpt_777supplemental.pdf

Miles, S. B. (2018). Participatory disaster recovery simulation modeling for community resilience planning. *International Journal of Disaster Risk Science*, *9*, 519-529.

Miles, S. B., & Chang, S. E. (2011). ResilUS: a community based disaster resilience model. *Journal of Cartography and Geographic Information Science*, *38*(1), 36–51.

Mitsova, D., Escaleras, M., Sapat, A., Esnard, A.-M., & Lamadrid, A. J. (2018). Socioeconomic vulnerability and electric power restoration timelines in Florida: the case of Hurricane Irma. *Natural Hazards*, *94*, 689–709.

Mitsova, D., Escaleras, M., Sapat, A., Esnard, A.-M., & Lamadrid, A. J. (2019). The effects of infrastructure service disruptions and socio-economic vulnerability on hurricane recovery. *Sustainability*, *11*, 516. (DOI: 10.3390/su11020516)

Mitsova, D., Sapat, A., Esnard, A.-M., & Lamadrid, A. J. (2020). Evaluating the impact of infrastructure interdependencies on the emergency services sector and critical support functions using an expert opinion survey. *Journal of Infrastructure Systems*, *26*(2), 04020015. (DOI: 10.1061/(ASCE)IS.1943-555X.0000548)

National Academies of Sciences, Engineering, and Medicine. (2017). Chapter 6: Restoring grid function after a major disruption. In *Enhancing the resilience of the nation's electricity system* (pp. 110–133). The National Academies Press. Retrieved from https://doi.org/10.17226/24836

NBI. (2017). *Bridges and structures.* Retrieved from https://www.fhwa.dot.gov/bridge/nbi/ascii.cfm (Online; accessed January 2017)

Nielson, B. (2003). *Bridge seismic fragility-functionality relationships: a requirement for loss estimation in mid-America* (Doctoral dissertation). Georgia Institute of Technology, Atalanta, GA.

NIST. (2015). *Community resilience planning guide.* Retrieved from https://www.nist.gov/topics/community-resilience/planning-guide (Online; accessed January 2017)

NIST CoE. (2019). *IN-CORE.* Retrieved from http://resilience.colostate.edu/in_core.shtml (Center of Excellence for Risk-Based Community Resilience Planning; accessed December 2019)

Olson, R., Olson, R. A., & Gawronski, V. T. (1998). Night and day: mitigation policy making in Oakland California, before and after the Loma Prieta Earthquake. *International Journal of Mass Emergencies and Disasters*, *16*, 145–179.

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

Ouyang, M., & Dueñas-Osorio, L. (2014). Multi-dimensional hurricane resilience assessment of electric power systems. *Structural Safety*, *48*, 15–24.

PA PUC. (2015). *Electric power outlook 2015-2020.* Retrieved from http://www.puc.state.pa.us/General/publications_reports/pdf/EPO_2016.pdf (page 12, 26, 57-63; accessed May 2017)

PennDOT. (2017a). *PennDOT One Map.* Retrieved from https://gis.penndot.gov/onemap/?map-id=20435 (Online; accessed January 2017)

PennDOT. (2017b). *PennDOT Open Data.* Retrieved from https://data-pennshare.opendata.arcgis.com/ (Online; accessed January 2017)

PennDOT. (2017c). *Traffic Signal Location Maps.* Retrieved from http://www.dot.state.pa.us/Portal%20Information/Traffic%20Signal%20Portal/MAPS.html (Online; accessed

January 2017)

PJM. (2016). *Transmission expansion advisory committee reliability analysis updates.* Retrieved from http://www.pjm.com/committees-and-groups/committees/teac.aspx (page 41-42; accessed May 2017)

PJM. (2017). *Regional transmission expansion plan.* Retrieved from ttp://www.pjm.com/~/media/library/reports-notices/2016-rtep/2016-rtep-book-3.ashx (page 121-127; accessed May 2017)

PPL Electric Utilities. (2019). *Priorities for restoring power.* Retrieved from https://www.pplelectric.com/outages/priorities-for-restoring-power.aspx (accessed March 2019)

Ramanathana, K., Padgett, J., & DesRoches, R. (2015). Temporal evolution of seismic fragility curves for concrete box-girder bridges in California. *Engineering Structure*, *97*, 29–46.

Reed, D., Kapur, K., & Christie, R. (2009). Methodology for assessing the resilience of networked infrastructure. *IEEE Systems Journal*, *3*(2), 174-180.

Rose, A., Porter, K., Dash, N., Bouabid, J., Huyck, C., Whitehead, J., ... West, C. T. (2007). Benefit-cost analysis of FEMA hazard mitigation grants. *Natural Hazards Review*, *8*, 97-111.

Sadeghi, M., Mohajeri, F., & Khalaghi, E. (2010). Case study: Developing structural and communication fragility curves for 24 m monopole tower. In *Joint conference proceedings of the 7th international conference on urban earthquake engineering (7CUEE) & the 5th international conference on earthquake engineering (5ICEE).* Retrieved from https://www.researchgate.net/publication/277312345_Seismic_Performance_and_Communication_Failure_of_Cellphone_Towers_in_Iran's_Recent_Earthquakes_Case_Study_Developing_Structural_and_Communicational_Fragility_Curves_for_Monopole_Tower

Sahebjamnia, N., Torabi, S. A., & Mansouri, S. A. (2015). Integrated business continuity and disaster recovery planning: Towards organizational resilience. *European Journal of Operational Research*, *242*(1), 261-273.

Sandman. (2016). *Sandman.com.* Retrieved from http://www.sandman.com/colookup (Online; accessed September 2016)

Schweiner, R., Twomey, K., & Lindsey, K. (2003). Transmission line emergency restoration philosophy at Los Angeles Department of Water and Power. In *Proceedings of IEEE 10th international conference on transmission and distribution construction, operation and live-line maintenance.* (DOI: 10.1109/TDCLLM.2003.1196462)

Sedzro, K. S., Lamadrid, A. J., & Zuluaga, L. (2018). Allocation of resources using a microgrid formation approach for resilient electric grids. *IEEE Transactions on Power Systems*, *33*(3), 2633 – 2643. (DOI: 10.1109/TPWRS.2017.2746622)

Sedzro, K. S., Shi, X., Lamadrid, A. J., & Zuluaga, L. (2018). A heuristic approach to the post-disturbance and stochastic pre-disturbance microgrid formation problem. *IEEE Transactions on Smart Grid*, *10*(5), 5574–5586. (DOI: 10.1109/TSG.2018.2887088)

Seeber, L., Armbruster, J. G., Kim, W., Barstow, N., & Scharnberger, C. (1998). The 1994 Cacoosing Valley earthquakes near Reading, Pennsylvania: a shallow rupture triggered by quarry unloading. *Journal of Geophysical Research*, *103*(B10), 24505–24521.

Shafieezadeh, A., Onyewuchi, U. P., Begovic, M. M., & DesRoches, R. (2013). Age-dependent fragility models of utility wood poles in power distribution networks against extreme wind hazards. *IEEE Transactions on Power Delivery*, *129*, 131–139.

Shreve, C. M., & Kelman, I. (2014). Does mitigation save? reviewing cost-benefit analyses of disaster risk reduction. *International Journal of Disaster Risk Reduction*, *10*, 213-235.

Straub, D., & Der Kiureghian, A. (2008). Improved seismic fragility modeling from empirical data. *Structural Safety*, *30*, 320-336.

Sun, W., Bocchini, P., & Davison, B. D. (2019). Comparing decision models for disaster restoration of interdependent infrastructures under uncertainty. In *Proceedings of the 13th international conference on applications of statistics and probability in civil engineering (ICASP13).* Retrieved from https://doi.org/10.22725/ICASP13.238 (No. 238)

Sun, W., Bocchini, P., & Davison, B. D. (2020a). Applications of artificial intelligence for disaster management. *Natural Hazards*. (DOI: 10.1007/s11069-020-04124-3)

Sun, W., Bocchini, P., & Davison, B. D. (2020b). Model for estimating the impact of interdependencies on system recovery. *Journal of Infrastructure Systems*, *26*(3), 04020031. (DOI: 10.1061/(ASCE)IS.1943-555X.0000569)

Sun, W., Bocchini, P., & Davison, B. D. (2020c). Resilience metrics and measurement methods for transportation infrastructure: the state of the art. *Sustainable and Resilient Infrastructure*, *5*(3), 168-199. (DOI: 10.1080/23789689.2018.1448663)

Tabucchi, T., Davidson, R., & Brink, S. (2010). Simulation of post-earthquake water supply system restoration. *Civil Engineering and Environmental Systems*, *27*, 263-279.

TelcoData. (2016). *Telecommunication database.* Retrieved from `https://www.telcodata.us/` (Online; accessed January 2017)

Tonn, G., Czajkowski, J., Kunreuther, H., & Angotti, K. (2020). Measuring transportation infrastructure resilience: Case study with Amtrak. *Journal of Infrastructure Systems*, *26*, 05020001.

Tuerk, M. (2019). *Lehigh Valley's economic renaissance continues at remarkable pace.* Retrieved from `https://lehighvalley.org/lehigh-valleys-economic-renaissance-continues-at-remarkable-pace/` (Online; accessed December 2019)

United States Census Bureau. (2010). *QuickFacts.* Retrieved from `https://www.census.gov/` (Online; accessed December 2019)

USDOT. (2019). *Overview: Incident management overview disaster recovery.* Retrieved from `https://www.transportation.gov/disaster-recovery/incident-management-overview` (accessed March 2019)

Vadivel, K. K. (2017). Emergency restoration of high voltage transmission lines. *The Open Civil Engineering Journal*, *11*(s2), 778-785.

Wu, J. Y., & Lindell, M. K. (2004). Housing reconstruction after two major earthquakes: the 1994 Northridge Earthquake in the United States and the 1999 Chi-Chi Earthquake in Taiwan. *Disasters*, *28*, 63-81.

Xu, N., Guikema, S. D., Davidson, R. A., Nozick, L. K., Çağnan, Z., & Vaziri, K. (2007). Optimizing scheduling of post-earthquake electric power restoration tasks. *Earthquake Engineering & Structural Dynamics*, *36*(2), 265–284.

Zhang, W., Wang, N., & Nicholson, C. (2017). Resilience-based post-disaster recovery strategies for road-bridge networks. *Structure and Infrastructure Engineering*, *13*(11), 1404-1413.