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Model for estimating the impact of interdependencies on system recovery

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ABSTRACT

Infrastructure interdependencies have been widely recognized, especially in the post-disaster restoration process. It is essential to develop models to simulate interdependencies and quantify their impact on the functionality recovery of infrastructures. This study presents a generalized simulator to investigate the impact of different types of interdependency on the functionality recovery. The proposed simulator considers that there are multiple possible modes to execute a restoration task by framing the restoration process of interconnected systems as a multi-mode resource-constrained project scheduling problem (MRCPSP). In addition, it considers three sets of uncertainties: restoration duration and resource demand to execute a task, as well as inter-system functionality dependency. By solving the MRCPSP with the objective of minimal restoration completion time, the optimal restoration schedules for different systems are calculated to predict functionality recovery. This simulator implements three types of interdependencies at both the component level and the system level, which are resource-sharing interdependency, restoration precedence dependency, and functionality dependency. Through a simple example, it is demonstrated how the proposed approach can quantitatively evaluate the impact on the system recovery

due to different types of interdependency. Research findings from this study can help to identify the interdependencies with the strongest impact and then develop preventive mitigation actions and effective plans of emergency response and disaster recovery for interconnected systems.

INTRODUCTION

Infrastructure systems such as power, water, transportation, telecommunication, and emergency services are so vital that any damage or functionality loss would have debilitating impacts to the security, economy, and well-being of our society (The White House 2013). Infrastructure systems are interconnected in complex ways, relying on each other to produce and distribute essential goods and services (Sun et al. 2018). In fact, infrastructure interdependencies may present different impacts on the performance of a system at different service conditions. In normal operations, interdependencies may be difficult to notice (Ouyang 2014). However, after an extreme event, they would become obvious, which may cause significant adverse impacts and hinder the restoration because of complicated interconnections. Historical disasters, such as the 1998 ice storm in Canada, Tōhoku earthquake and tsunami in 2011, and hurricanes Katrina, Harvey, and Irma, have demonstrated recovery delays due to infrastructure interdependencies (Bigger et al. 2009; Chang 2009; Pescaroli and Alexander 2015; Tang 2017). For instance, observations after the 2011 Tōhoku earthquake showed that severe road damage delayed the transport of repair crews and equipment to restore the electric power system. After hurricanes Irma and Maria, the shortage of fossil fuel in Puerto Rico led to a slow recovery of the electricity service, which consequently disrupted service recoveries of other critical infrastructures (Eakin et al. 2018). As a result, it is essential to study the interdependencies between infrastructure systems to improve the design of future infrastructures and eliminate functionality disruptions in future events.

Infrastructures have become increasingly interdependent with important implications for infrastructure security and resilience. The growing interdependencies make systems vulnerable to cascading failures during extreme events (Korkali et al. 2017). For instance, the 2003 Northeast Blackout disabled traffic control and water treatment for 31 hours, and significantly impacted many other infrastructure operations, with the economic loss exceeding $4 billion in the US alone (U.S.-

Canada Power System Outage Task Force 2004; Lin et al. 2011). There are many interdependecy models developed, such as empirical judgments (The Lifelines Council 2014), system dynamics (Santella et al. 2009), correlation analyses (Dueñas-Osorio and Kwasinski 2012; Cimellaro et al. 2014), discrete event simulations (Volkanovski et al. 2009; Kelly 2015; Tahmasebi 2016), economic-theory-based analyses (He and Cha 2018), interdependency matrices (Guidotti et al. 2016), and formulations from operations research (González et al. 2016; Smith et al. 2017; Sun et al. 2019a). All these approaches help us better evaluate different types of interdependencies and quantitatively measure cascading failures due to interdependencies. Among them, formulations from operations research are one of the most popular methods to investigate the restoration process of interdependent systems.

Depending on whether restoration uncertainties are addressed, restoration models for interdependent systems can be classified into deterministic and probabilistic. Deterministic models compute the restoration evolution in terms of the sequence and starting/finishing time of all restoration activities, without addressing uncertainties. In practice, the restoration process is complex, involving many uncertainties in restoration duration, resource availability, and so on. Restoration models not addressing the large uncertainties may yield inaccurate results (Barker and Haimes 2009; Karamlou and Bocchini 2017). Due to this reason, many other studies have developed probabilistic models to estimate restoration uncertainties in the aspects of restoration duration (Xu et al. 2010; Tabucchi et al. 2010; Karamlou and Bocchini 2017; Karamlou et al. 2017), and transition state (Zhang 1992), among others. Multiple techniques have been implemented to address uncertainties in the restoration of interdependent systems, such as Markov process (Zhang 1992), Bayesian network (Johansen and Tien 2018), and Monte Carlo simulation (Karamlou and Bocchini 2017). However, these studies do not explicitly quantify the impact of different types of interdependencies on the functionality recovery with a mechanistic explanation.

This study presents a simulator of the restoration of interconnected systems. The restoration decision-making is modeled as the solution of multi-mode resource-constrained project scheduling problem (MRCPSP); the functionality recovery is modeled with mechanistic functions, which account for dependencies. Therefore, herein the term "simulator" indicates an artificial model to capture the restoration decision process and the recovery of interdependent systems. This simulator captures three types of interdependency: resource-sharing interdependency, restoration precedence dependency, and functionality dependency. Moreover, this simulator takes into account three sets of restoration uncertainties: restorarion duration, resource demand, and functionality dependency. Possible restoration methods for finishing a task are considered as different modes. By comparing the computational results under different levels of interdependencies, we can quantitatively evaluate the impact of interdependencies on the functionality recovery. The proposed simulator exhibits the following features. (1) It implements different types of interdependency involved in the restoration process in a mechanistic manner. (2) As a full probabilistic model, it considers three sets of restoration uncertainties and quantifies the impact of different types of interdependency on the system recovery in a probabilistic fashion. (3) It can assist in identifying the effectiveness of multiple recovery plans and strategies to mitigate interdependencies with adverse impact in the restoration.

The remainder of this study is organized as follows. The next section precisely classifies interdependency types in the restoration process, followed by a brief summary of existing interdependency models. The following section describes the proposed simulator in four steps, and it explains how to implement different types of interdependency and how to consider restoration uncertainties. After that, a simple example is presented to demonstrate the applicability of the proposed model in quantifying the impact of different types of interdependency on the functionality recovery. Major findings are presented at the end.

BACKGROUND

Dependencies and Interdependencies in the Restoration Process

In general, the term "dependencies" represents unidirectional relationships, whereas "interdependences" indicates bidirectional interactions (Rinaldi et al. 2001). For instance, the fact that a water pump requires electricity from a nearby distribution substation to be properly functional represents a functional dependency (one-way). Conversely, the fact that a utility company has a limited number of crews and trucks to send to the different sites for repairing power outages represents resource-sharing interdependency among each pair of damaged power line segments (two-way). However, in some studies, the two terms are used interchangeably. Based on the nature of dependency, many researchers have developed different classifications. For instance, Zimmerman (2001) has a coarser classification as functional and spatial dependencies, where spatial dependencies refer to the spatial proximity between systems, and functional dependencies apply when the proper function of one system requires the functionality support of another system. Rinaldi et al. (2001) identified four types of dependencies: physical, cyber, geographic, and logical. Physical dependencies are cases when the functionality of one system depends on the output from another system. For instance, traffic lights rely on the electric power system for the electricity support. Cyber dependencies indicate that the functionality of one system requires information transferred from the other system(s) via the cyber infrastructure. For example, subway trains require telecommunication systems for communicating operational decisions. In most cases, physical dependencies and cyber dependencies at the component level are one-way relations, such as the physical dependency of a traffic light on a nearby electric line for electricity, but in some cases they can be two-way interdependencies. Geographic dependencies represent the co-location issue between systems, such as utility tunnels that carry multiple utility lines and pipes. The other dependencies fall into logical dependencies. An example is that highways get congested because people choose driving over flying due to a low gas price. Dudenhoeffer et al. (2006) provided a classification similar to Rinaldi et al.'s, by calling the categories: physical, informational, geospatial, and policy. In contrast, Zhang and Peeta (2011) put more emphasis on economic relations. Their dependency classification is physical, functional, budgetary, and market. The aforementioned classifications of dependencies are mainly at the system level, and they seldom explicitly address the component-level dependencies. In fact, dependencies and interdependencies between infrastructure systems usually originate from their components. For example, the power system and the communication system have mutual functionality dependencies at the component level, such as the dependency of a telecommunication central office on a nearby power substation, and the dependency of a power plant in daily operations on the supervisory control and data acquisition (SCADA), a component in the communication system. Studying both component-level and system-level interdependencies can help us understand how they will impact the functionality recovery.

By using the MRCPSP formulation and its solution to simulate the restoration decisions, this study implements three types of interdependencies: resource-sharing interdependencies, restoration precedence dependencies, and functionality dependencies. Resource-sharing interdependencies represent *[system]-[component in the system]* and *[system]-[other system]* interdependencies, which are implemented through resource constraints. For instance, restorations of all damaged power lines are conducted by a limited number of crews from the same utility company; restoration projects for the water system and the wastewater system in the same administrative region compete for the limited restoration budget from the same federal/state government after a disaster. Restoration precedence dependencies are implemented as precedence relations. They represent both *[component]-[other component in same system]* dependencies as intra-system precedence and *[component]-[component in other system]* dependencies as inter-system precedence. For example, in a damaged transportation system, restorations of damaged roadway segments on the other side of a river cannot be performed until a damaged bridge is repaired to transport crews and equipment trucks across the river; new utility pipelines cannot be properly installed underneath bridge decks until the this damaged bridge is repaired. Functionality dependencies are modeled by mechanistic restoration functions, which can represent *[system]-[component in the system]* and *[system]-[component in other system]* dependencies. For example, the functionality of a water distribution network is related to the functionality of all water pipes and pumps; the functionality of this water distribution system also depends on the functionality of some electric substations and power lines in the power system to support the distribution of water. There is another set of dependencies and interdependencies that directly affect functionality under the normal operation conditions (Sun et al. 2019b). For example, during the normal operation, a subway system requires the electric system for the traction power and the telecommunication system for the system control. This last set of dependencies and interdependencies is not related to the restoration process and is beyond the scope of this study.

Mechanistic Models for Interdependencies

Previous studies have developed various models to capture interdependencies. We classify them into the following categories: empirical models, correlation analyses, input-output models, discrete event simulations, agent-based models, and network models. Among them, empirical models refer to empirical interdependency relations derived and calibrated from disaster events (McDaniels et al. 2007; Luiijf et al. 2010; The Lifelines Council 2014), and correlation analyses represent interdependencies based on correlation coefficients from the time-series analysis of historical recovery data (Dueñas-Osorio and Kwasinski 2012; Cimellaro et al. 2014; Krishnamurthy et al. 2016). These two categories cannot provide mechanistic understanding of interdependencies, but the other categories can do so. Discrete event simulations use fault tree analysis to determine the chain of events that causes a disruption (Volkanovski et al. 2009; Forss 2011), use event tree analysis to determine the associated probability of possible negative outcomes (Apostolakis and Lemon 2005; Li et al. 2008; Tahmasebi 2016), and sometimes use the Markov Chain to simulate the vulnerability of interdependent infrastructures (Sultana and Chen 2009; Shafiee 2016). Agent-based models consider critical components and human operators as agents, by simulating the actions and interactions between agents based on a set of rules (Basu et al. 1996; Barton et al. 2000; North 2001a; North 2001b; Permann 2007). Input-output models are suitable to evaluate economic losses at the system level from cascading failures (Leontief 1951; Kelly 2015), due to interdependencies at the system level rather than at the component level. Network models can capture topology features and flow capacities of infrastructure network systems, by considering critical components as nodes and inter-system functional interactions and geographical proximity as link connections between nodes from different networks (Dueñas-Osorio et al. 2007; Johansson and Hassel 2010; Wang et al. 2012).

Because network models can identify critical components and capture interdependencies from the bottom up, they have been extensively used to analyze infrastructure systems with network features, such as transportation, power, water, gas, and communication systems. When addressing interdependencies in the restoration phase, some network models consider the decision-making process as the result of an optimization problem under a limited amount of resources (González et al. 2016). For instance, Lee et al. (2007) used the interdependent layer network modeling approach by framing the restoration process as an optimization problem to capture five interdependencies: input dependence, mutual interdependence, shared dependence, exclusive or dependence, and colocated interdependence. González et al. (2016) considered the restoration of interdependent network systems as an optimization problem with the objective of minimum restoration cost and used mixed integer programming (MIP) to solve a problem, capturing four types of interdependencies: physical, geospatial, cyber, and logical. However, these two studies do not explicitly capture the restoration precedence dependency, and they do not evaluate how different types of interdependency influence the system recovery. In addition, they do not address restoration uncertainties. For instance, which possible mode will be used to execute a restoration task? How long will a task take and how many resources will it require? How likely will a component be using an alternative resource to relieve the original functionality dependency in restoration? For example, a water pump using the electricity from the external power grid in normal service conditions may use the electricity from a mobile generator in emergency conditions.

PROPOSED METHODOLOGY

Based on an optimization formulation, this study focuses on presenting a generalized simulator to implement different types of interdependency in the restoration process in a rigorous way and uses it to assess the impact of interdependency on functionality recovery. This work enhances the technical proposal by Karamlou and Bocchini (2017) and Karamlou et al. (2017), which consider uncertainties in the restoration duration at the component level. While resource-constrained project scheduling problem (RCPSP) has been widely employed to efficiently model the restoration, MRCPSP is more realistic in simulating the practical project management decisions, by allowing allocations of varying resource levels to execute a restoration activity in different ways. Every restoration mode corresponds to a different task duration and different resource requirements. In different modes, the task duration varies with the resource level. Usually, allocating a higher resource level (or implementing an advanced technique) helps to accelerate the restoration. For instance, removing debris on roadways may be finished by four crews by hands in two days, or by heavy machinery within one day. In this respect, a major improvement of this model is that every restoration activity is allowed to be executed in one out of multiple possible modes.

A unique feature of this simulator is that it accounts for three types of interdependency in the restoration process: resource-sharing interdependencies, restoration dependencies, and functionality dependencies, as shown in Table 1. Resource-sharing interdependencies represent interactions due to a common limited pool of restoration resources. With limited resources, some restoration tasks have to be delayed in the schedule. In this study, restoration precedence dependencies only refer to the unidirectional interactions due to construction precedence requirements within a system and across systems. Functionality dependencies refer to the cases when the operational state of an object (i.e., a component, or a system) relies on the functionality of another object, potentially from another system (Guidotti et al. 2016; Rueda and Calle 2017). An example of functionality dependencies could be that even after the repairs of all damaged components, a water distribution system may not be functional, simply because the corresponding power substation has not been restored to provide electricity for the control system and the water pump.

Another unique feature of this simulator is that it considers three sets of restoration uncertainties. The duration and the resource demand for executing a task may be uncertain because of unexpected weather conditions, different degrees of professional efficiency, etc. The functionality dependency of a component in a system on the functionality of another component might also change in emergency circumstances due to the presence of unexpected external resources to eliminate the original functionality dependency (e.g., hospitals using the electricity from mobile generators in case of a power outage). These three sets of uncertainties are implemented by treating the restoration duration and the resource demand as random variables, as well as describing the presence of alternative resources to relieve the functionality dependency as a random event with a certain probability of occurrence. The probability of the random event can be determined from published literature, historical data analyses, and discussion with construction managers and experienced engineers.

Figure 1 presents four computational steps of the proposed simulator, discussed in the following subsections. The mathematical formulation of the MRCPSP in Step 3 is relatively simple, facilitating readers to understand and implement different types of interdependencies and estimate the impact of interdependencies. The solution of this optimization formulation is intended to mimic the actual restoration decision of utility companies and emergency managers, rather than necessarily using the optimization technique to find the best restoration schedule.

Step 1: Identify interdependent systems

The first step is to define the interconnected systems of interest. In each system, major components are defined as components that require considerable repair efforts if damaged. These components can be identified from historical observations and the analysis of survey data and simulation data. For instance, the transportation infrastructure can be considered as a network system consisting of road segments and bridges, which are critical and vulnerable components (Karamlou and Bocchini 2015). The water distribution system can be considered as a system consisting of water pumps and distribution pipes (da Conceição Cunha and Sousa 1999). The gas supply system consists of distribution pipes, cylinders and outlet valves (Cimellaro et al. 2015; Helseth and Holen 2006). The electric transmission system consists of electric substations, transmission towers, and conductors (McDonald 2012; Fujisaki et al. 2014; Kongar et al. 2017).

Step 2: Identify restoration tasks

The next step is to determine damaged components and the corresponding restoration tasks in the interconnected systems. Depending on the damage state of a component, the corresponding restoration tasks are identified. A restoration task may be executed in one out of several different modes. For every restoration task and each mode, the resource demand and the time required to execute a task can be determined based on the experience from the construction industry and common practices (Karamlou and Bocchini 2017; Mackie et al. 2008). As a result of weather conditions, equipment efficiency, and crew proficiency, as well as availability of alternative functionality support, there are many restoration uncertainties when developing a restoration plan. To account for restoration uncertainties, a probabilistic duration distribution and a probabilistic resource demand distribution can be determined for every restoration task and mode. In addition, the probability of the presence of alternative resources to relieve the functionality dependency can be estimated for related components. Random samples of duration, resource demand, and functionality dependency can be generated from the corresponding probabilistic distributions using Latin hypercube sampling (McKay et al. 2000). A sample of task duration represents a possible scenario of the task duration at a certain mode. A sample of resource demand represents a possible required amount of resources to execute a task at a certain mode. A sample of functionality dependency represents a possible scenario of a component using alternative functionality support or not during the restoration; for instance, a telecommunication tower uses the electricity from a mobile generator in emergency restorations, instead of using the electricity from the power grid in normal service conditions. The output at this step is the list of all restoration tasks, i.e., the task duration sample and the resource demand sample for every task at each mode, and the functionality dependency sample representing that a damaged component depends on the functionality of other components or not.

Step 3: Develop the restoration plan from the MRCPSP model

After inputting the list of restoration tasks and associated information, the third step is to generate restoration schedules from the MRCPSP solution. A mixed integer linear programming (MILP) formulation is adopted to solve the MRCPSP. In this formulation, the restoration requires a set J of restoration tasks. Tasks 2 to $n-1$ represent actual restoration tasks. Task 1 and task n are dummy tasks, representing the start and the end of all restoration tasks. The precedence relationships between tasks are represented in the form of a finish-to-start project network. Each task $j \in J$ can be processed in one of several different modes $s \in \{1, 2, ..., p_j\}$. The set of renewable resource types denoted by R represents cases in which the resource is temporarily occupied by a certain task, but can be used for other tasks upon the completion of the current task, as is the case for crews and equipment. The set of non-renewable resource types denoted by N refers to resources that are consumed during a task and are permanently lost once a task is complete, such as building materials and financial budget. For every task j, there is a duration $d_{j,s}$ and a demand of $u_{j,s,r}$ for the type $r(\forall r \in R, N)$ resource when executing at mode s. For the dummy start and end tasks, there is only a single mode $s = 1$. The duration is $d_{1,1} = 0$, and $d_{n,1} = 0$; the resource demands are $u_{1,1,r} = 0$ and $u_{n,1,r} = 0, \forall r$. The resource availability of type r is represented by a_r and $a_r(t)$, where a_r is constant and $a_r(t)$ can be either constant values or nonuniform values over time $\forall t = 1, ..., T^h$. The formulation of the MRCPSP is presented as follows, based on (Klein 2000; Cheng et al. 2015).

Find

$$x_{j,s,t} \in \{0,1\},\ \forall j \in J,\ \forall s \in \{1,2,...,p_j\},\ \forall t \in [EFT_j, LFT_j] \tag{1}$$

so that the completion time (CT) of all restoration tasks is minimal.

$$\text{minimize}\left(CT = \sum_{t=EFT_n}^{LFT_n} t \cdot x_{n,1,t}\right) \tag{2}$$

subjected to

$$\sum_{t=EFT_j}^{LFT_j} \sum_{s=1}^{p_j} x_{j,s,t} = 1,\ \forall j \in J \tag{3}$$

$$\sum_{t=EFT_i}^{LFT_i} \sum_{s=1}^{p_i} t \cdot x_{i,s,t} \leqslant \sum_{t=EFT_j}^{LFT_j} \sum_{s=1}^{p_j} \left(t - d_{j,s}\right) \cdot x_{j,s,t},\ \forall i \in \text{Pre}_j,\ \forall j \in J \tag{4}$$

$$\sum_{j \in E(t)} \sum_{s=1}^{p_j} u_{j,s,r} \cdot \sum_{q=\max(EFT_j,t)}^{\min(LFT_j, t+d_{j,s}-1)} x_{j,s,q} \leqslant a_r(t),\ \forall t \in H,\ \forall r \in R \tag{5}$$

$$\sum_{j=1}^{n} \sum_{s=1}^{p_j} u_{j,s,r} \cdot \sum_{q=EFT_j}^{LFT_j} x_{j,s,q} \leqslant a_r,\ \forall r \in N \tag{6}$$

where $x_{j,s,t}$ represents the decision variable to determine whether task j finishes with mode s at time step t; J is the set of restoration tasks $\{1, 2, ..., n\}$; n is the total number of tasks; Pre_j represents the set of tasks which precede task j. T^h is an upper bound for the total restoration duration, which can be determined from pre-processing; a simple way to assign a reasonable T^h is to assign a value no less than the summation of the longest duration of all tasks among their possible modes, i.e.,

$T^h \geq \sum_j(\max\{d_{j,s}|\forall s\})$. $H = \{1, 2, ..., T^h\}$ is the set of discrete time steps considered during the assignment of task j. $E(t) = \{j|j \in J, EST_j \leq t \leq LFT_j\}$, is the collection of restoration tasks that may be processed at t; EST_j is the earliest starting time of task j; EFT_j and LFT_j are the earliest finishing time and the latest finishing time of task j, respectively.

The solution of this MRCPSP formulation assigns a time and a mode to every restoration activity to achieve the minimal finishing time, by satisfying all precedence and resource constraints. Eq. 1 gives the binary decision variables. $x_{j,s,t} = 1$ only if the task j finishes with mode s at the time step t, and $x_{j,s,t} = 0$ otherwise. Eq. 2 presents the optimization objective of minimal finishing time, with the left-hand side of this equation as the finishing time of the dummy end task n (i.e., $j = n$). Eq. 3 enforces that every task can only be executed once in one of the alternative modes. Eq. 4 ensures that all precedent tasks in Pre_j finish before scheduling task j, and this equation implements restoration precedence dependencies as precedence requirements. Eqs. 5 - 6 ensure the schedule of restoration activities satisfies resource constraints at all time steps for renewable resources and non-renewable resources, respectively. These two equations implement resource-sharing interdependencies. In Eq. 5, the lower bound of the third summation is the maximum value of two time indices at every time step: EFT_j and time t; the upper bound is the minimum value of two other time indices at every time step: LFT_j and $t + d_{j,s} - 1$.

The aforementioned EST_j, EFT_j and LFT_j in Eqs. 1 - 6 can be determined from the critical path analysis through forward pass and backward pass as follows. By setting the $EST_1 = EFT_1 = 0$ for the dummy start task, the forward pass computes EST_j as the summation of the shortest duration for all tasks that need to be executed prior to task j due to precedence constraints. EFT_j can be computed as the summation of EST_j and the minimal duration $d_{j,s}$, for $s = 1, ..., p_j$.

$$EST_j = \max\left(EFT_i | i \in \text{Pre}_j\right),\ j = 2, ..., n \tag{7}$$

$$EFT_j = EST_j + \min d_{j,s},\ s = 1, ..., p_j,\ j = 2, ..., n \tag{8}$$

Considering LST_j as the latest starting time for task j, by setting $LFT_n = LST_n = T^h$ for the dummy end task, the backward pass computes the latest finishing time of every task as follows.

$$LFT_j = \min\left(LFT_k | k \in F_j\right),\ j = n-1, ..., 1 \tag{9}$$

$$LST_j = LFT_j - \min d_{j,s},\ s = 1, ..., p_j \tag{10}$$

where F_j represents the set of restoration tasks that follow task j.

If there is only one mode to execute every task, the above equations will have $p_j = 1$, and MRCPSP becomes the resource-constrained project scheduling problem (RCPSP). That is to say that RCPSP is a special type of MRCPSP. Compared with RCPSP, MRCPSP has the advantage of being able to consider one of multiple possible modes for every restoration task, which is very likely to be the case in practice (Fang and Sansavini 2019). MRCPSP is an NP-hard optimization problem in the strong sense (Kolisch 1995). There have been various computational formulations developed to efficiently solve large scheduling projects using MRCPSP (Mori and Tseng 1997; Alcaraz et al. 2003; Peteghem and Vanhoucke 2010; Kyriakidis et al. 2012). In this study, the MRCPSP problem in the MILP format is solved using Gurobi 6.5.2, a commercial software package (Gurobi 2017).

Under the resource constraints, each task will be assigned with exactly one mode and one finishing time. The optimization solution provides a sample optimal schedule as a restoration plan that gives the finishing time of every restoration task and its execution mode. Based on the restoration schedule and the functionality dependency sample representing the existence of alternative inter-system functionality support or not, a sample of the restoration function can be computed, as described in Step 4.

In practice, decision-makers may not know the exact duration of a restoration task when developing the schedule plan and may adjust the plan in the restoration process. This study assumes that distributions (represented by mode, minimum, and maximum) of duration and resource demand to execute any task at any possible mode are known at the restoration planning (Step 3), which may seem to induce unrealistic schedules. However, Karamlou and Bocchini (2017) found that statistically, the dependency case using the original schedule developed upfront with task duration modes yields very similar results of the functionality recovery probability as those from another case always using the actual task duration samples. That is to say, using the restoration schedules developed upfront with task duration modes would yield reasonable estimates of the functionality recovery from a probabilistic perspective.

Step 4: Predict system functionality recovery

A restoration function represents the system functionality at different time steps during the restoration. Based on a sample of the restoration schedule, a sample of the restoration function for every system can be calculated. The restoration function of a system is related to the functionality of all components in this system.

For a damaged component j in the is-th system, such as a damaged transmission tower (j) in the power system (is), whose functionality is not influenced by the functionality of any other component from another system, the functionality is computed as follows.

$$q_{is,j}(t) = \begin{cases} 100\%, & \text{if } t \geq FT_j \\ 0, & \text{if } 0 \leq t < FT_j \end{cases} \tag{11}$$

where $q_{is,j}(t)$ is the functionality of component j in the is-th system at time t; FT_j is the finishing time of its restoration and is computed as $FT_j = \sum_s \sum_t x_{j,s,t} \cdot t$. This equation presents a binary functionality state, which is a very common case. In different cases, other discrete and continuous functionality states can be used as substitutes.

For a component k in the is-th system, whose functionality depends on the status of other components from a different system, the functionality is defined as follows.

$$q_{is,k}(t) = \begin{cases} 100\%, & \text{if } t \geq FT_k \text{ and } q_{rs,fd_k}(t) = 100\%,\ \forall rs, fd_k \in DP_{is,k} \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

where is is an index running over the considered system, rs is an index of another system, $is \neq rs$; $q_{is,k}(t)$ is the functionality of component k in the is-th system at t; FT_k is the time when the restoration of the damaged component k finishes; fd_k is the label of the component in the rs-th system that is required to support the functionality of component k in the is-th system; $q_{rs,fd_k}(t)$ is the functionality of component fd_k in the rs-th system at t; $DP_{is,k}$ is a set of all dependencies to support the full functionality of component k in the is-th system. For instance, a water pump (k) from the water distribution system (is) will be functionally dependent on a nearby substation (fd_k) in the electric power system (rs).

Similar to the functionality metric defined in Karamlou et al. (2016), the system functionality recovery, i.e., restoration function, is defined as follows.

$$Q_{is}(t) = \frac{\sum_j w_{is,j} \cdot q_{is,j}(t)}{\sum_j w_{is,j}} \tag{13}$$

where $Q_{is}(t)$ is the functionality of the is-th system at time t; $w_{is,j}$ is a component functionality weight, which represents the contribution of restoring component j to the functionality of the is-th system. $w_{is,j}$ may depend on multiple factors, such as the system architecture. It can be determined based on system characteristics and the analysis of historical data and engineering judgments.

Based on the original definition from Reed et al. (2009), the resilience index is used as a scalar value with the analyst defining a time horizon of interest t_h, computed from the functionality recovery curve, shown in Figure 2.

$$RI_{is} = \frac{\int_{t_0}^{t_h} Q_{is}(\bar{t})\mathrm{d}\bar{t}}{t_h - t_0} \tag{14}$$

If the time horizon t_h is made to vary, the resilience index then becomes a function of time:

$$RI_{is}(t) = \frac{\int_{t_0}^{t} Q_{is}(\bar{t})\mathrm{d}\bar{t}}{t - t_0} \tag{15}$$

where RI_{is} is the resilience index of the is-th system at $t = t_h$; $RI_{is}(t)$ is the resilience index with the time horizon t; t_0 is the time when the extreme event occurs; $Q_{is}(\bar{t})$ represents the functionality of the is-th system at time $\bar{t}$.

Assumptions

The proposed simulator uses assumptions related to uncertainty quantification and system functionality computation, as shown in Table 2. On the one hand, this model considers uncertainties in restoration duration, resource requirement, and functionality dependency. The probabilistic distributions of duration and resource demand to execute every task at each mode are assumed to be known, being used as input for the MRCPSP at Step 3. The uncertainty in functionality dependency is implemented by considering the presence of additional resources to relieve the functionality dependency as a random event. Distributions of these random variables could be collected from literature and analyses of historical data and expert surveys. On the other hand, this model uses the functionality weight $w_{is,j}$ in Eq. 13 to compute the system functionality, assuming that the weight is independent of time and restoration sequence. In the past, the authors have used also more sophisticated objective functions that account for the evolving network flows, to capture the fact that the importance of each component changes over time, and depends on the restoration sequence (Bocchini and Frangopol 2012a; Bocchini and Frangopol 2012b; Karamlou and Bocchini 2016). However, in this study we preferred to use metrics that represent the objectives actually considered by disaster managers, and we concluded that static weights serve this purpose well. In the common practice, static weights are used as a surrogate to capture the contribution of each component to system functionality, while avoiding expensive system-level analyses. The value of $w_{is,j}$ may be determined from published historical data and through consulting experienced engineers. For complex network systems, it becomes challenging to compute the functionality weight $w_{is,j}$ due to dynamic effects and complex topological dependencies. In this case, the system functionality can be computed via the system-wide flow analysis throughout the restoration process, such as traffic allocation and distribution (Bocchini and Frangopol 2011), and electric power distribution (Ma et al. 2019).

APPLICATION EXAMPLE

The proposed simulator is general, applicable to restoration projects within one system and restoration projects of different systems. While many utility companies develop individual restoration plans to perform restoration activities separately, research studies have clearly showed that coordinated restoration activities help to improve the restoration efficacy of interdependent systems (Martí et al. 2008; Sharkey et al. 2016). In this respect, this application example presents coordinated restorations for two interdependent systems. The objective is to restore both systems as fast as possible. Being simple, this example allows the direct interpretation of simulation results about the impact of different types of interdependencies.

Problem statement

Figure 3 shows a wind map with the two-minute sustained wind speed in the unit of m/s, determined from the scenario of Hurricane Sandy (National Weather Service 2012; Person 2018). Figure 4 presents two interdependent systems of power and communication. The power system consists of a power plant and two sub-systems, with a total of five electric substations and ten power lines, as shown in Figure 4(a). The communication system consists of three central offices, six communication towers, and nine communication lines, shown in Figure 4(b). Table 3 shows the total number of customers served by the two systems at the component level, and the system functionality is computed as the percentage of customers with service. Table 4 presents functionality dependencies of communication components on substations in the power system. For instance, the communication component 1 (a central office) requires the functionality support from the power component 2 (a substation).

Under the hazard scenario, there is one substation, one transmission tower, two power lines, and two communication towers damaged, requiring restoration efforts. Tables 5 and 6 present two lists of restoration tasks for restoring damaged components in the power system and the communication systems, respectively. Power task data of duration and resource demand are determined based on Çağnan (2005) and California ISO (2012), as well as personal communications with a local electrical engineer expert in dispatch and operation of crews that repair power lines (Lacouve 2017); communication task data of duration and resource demand are assumed by the authors, considering

Nasdaq (2017). There are two possible modes to execute a restoration task: fast and slow. The fast restoration mode requires more resources to execute a task and the task can finish in less time, vice versa, the slow restoration mode uses fewer resources to execute the same task and the task takes longer to complete. Figure 5 presents all restoration tasks for both systems in the form of the start-to-finish relationships.

As mentioned earlier, there are many restoration uncertainties in the recovery planning stage. Tables 5 and 6 also present two sets of restoration uncertainties: duration and resource demand. The restoration duration of a task follows either the triangular distribution or the uniform distribution. The minimal value, the maximum value, and the mode value in the duration distribution indicate cases of the minimum, maximum and most likely duration, which are commonly known in the construction industry (Karamlou and Bocchini 2017). The resource demand follows either a triangular distribution or an uniform distribution; the minimal value and the maximum value represent the minimal amount and the maximum amount of resources required to finish a task, which can be determined from discussion with construction managers.This example assumes that there is a 50% of chance that alternative resources are present to relieve the original functionality dependency. For more practical applications, the probability of the functionality dependency being relieved should be determined and calibrated from the analysis of historical data and expert surveys.

Dependency cases

Table 7 presents twelve dependency cases in order to evaluate the impact of different types of interdependency on the system recovery. These cases represent different levels of resource-sharing interdependencies, inter-system restoration dependencies, and inter-system functionality dependencies. For the power system, restoration tasks in sub-system 1 and sub-system 2 share power resources together; restoration tasks in the communication system share communication resources. The restorations of power and communication systems are planned together to represent coordinated restorations for interdependent systems.

Resource-sharing interdependencies are represented by three levels of resource availability: *Wres*, *Sres*, and *Sresv*. *Wres* represents weak resource-sharing interdependencies, corresponding to abundant resources; *Sres* represents strong resource-sharing interdependencies, corresponding to limited resources available. Regardless of the resource levels, all cases of *Wres* and *Sres* adopt uniform resource availability over time. Conversely, *Sresv* adopts non-uniform resource availability with strong resource-sharing interdependencies, shown in Table 7.

There are two levels of inter-system restoration dependencies. *Spre* means strong precedence dependency, that is the inter-system restoration precedence dependencies are all in place, whereas *Wpre* is weak precedence dependency, meaning there is no inter-system restoration precedence dependency due to advanced construction technologies. In particular, this study considers inter-system precedence dependencies of communication restoration tasks on certain power restoration tasks, as explained in the footnote of Table 7.

There are two levels of inter-system functionality dependencies as well. *Sfun* indicates strong inter-system functionality dependency, meaning that there are functionality dependencies of communication components on power components, as shown in Table 4. Conversely, *Wfun* represents weak inter-system functionality dependency, and there is no inter-system functionality dependency. For example, a communication tower in normal service usually uses the electricity from external grids distributed by a nearby substation; if this substation is still in restoration, this communication tower after the restoration may be temporally functional with the electricity provided by mobile generators.

One thousand samples were generated using Latin hypercube sampling to consider restoration uncertainties. For real applications, convergence research should be performed to determine an appropriate number of samples. These samples were input into the optimization solver to calculate optimal restoration schedules. From every sample of the optimal restoration schedule, a restoration function was calculated for every system, considering both the contribution of restoring a damaged component to the functionality recovery at the system level (shown as q_{ij} in Table 5 and Table 6) and how likely a component may be relieved from the functionality dependency on another component from a different system. The system functionality is computed using Equation 11 ∼ Equation 13. The weight $w_{is,j}$ is set as the number of customers served by every substation in the power system, and the number of customers served by every communication tower in the communication system, presented in Table 3.

Results on restoration time

For every functionality recovery sample, the restoration starting time of a system is computed as the starting time of its first restoration task. Similarly, the restoration finishing time of a system is computed as the time when all restoration tasks are completed for that system. After that, mean values and standard deviations of the starting time and the finishing time of every system are determined over 1000 samples for each simulation instance. Figure 6 depicts mean values and standard deviations of the starting time and the finishing time for the two systems in Cases 1 ∼ 8. As expected, both systems take less time to complete the restoration when the restoration resources are sufficient in Cases 1 and 2 (*Wres*) than that at the low resource availability in Cases 3 and 4 (*Sres*). Similarly, as the dependency level increases from Case 1 (*Wpre*) to Case 2 (*Spre*), restorations take longer to complete. That is to say, relieving interdependencies from strong levels (*Sres, Spre*) to weak levels (*Wres, Wpre*) by providing sufficient resources and using advanced techniques, more restoration tasks can be executed in parallel as early as possible, speeding up the recovery process. In this particular example, the restoration time is sensitive to inter-system precedence dependencies for the communication system, but not for the power system. The reason is that at *Spre*, there are one-way precedence dependencies of communication restoration tasks (T_{c5} & T_{c10}) on the power restoration task (T_{p5}), as shown in Figure 5, constraining the execution of communication restoration tasks after the completion of the power restoration task, whereas there are no precedence relationships in the opposite direction.

In this model, inter-system functionality dependencies do not affect the restoration duration at all, they only affect the functionality recovery. The starting time and finishing time at Case 5 ∼ 8 are the same as the starting time and finishing time at Case 1 ∼ 4 for both systems. That is because the proposed simulator considers the inter-system functionality dependency through the rigorous computation of restoration functions at Step 4, rather than directly implementing the functionality dependency in developing restoration plans at Step 3. As a result, the inter-system functionality dependency influences how a system recovers its functionality, rather than when to restore damaged components. In this example, functionality dependencies have an obvious impact on system resilience of the communication system, as the communication system shows greater functionality values during restoration at *Wfun* than *Sfun*. The following subsections will discuss the impact of interdependencies on functionality recovery and system resilience.

Results on probabilistic restoration function

A probabilistic restoration function shows the likelihood of a system reaching a certain level over time. Figure 7 presents probabilistic restoration functions of the communication system for reaching the full functionality (Q_c = 100%). In Figure 7(a), because of strong resource-sharing interdependencies at *Sres* in Case 3, the communication system is likely to be fully recovered much later than that at *Wres* in Case 1. On the other hand, the communication system shows smaller probability values in the range of $t = 15 \sim 21$ due to the existence of inter-system restoration precedence at *Spre* compared to *Wpre*. Similarly, the communication system shows smaller probability values in the range of $t = 15 \sim 21$ due to the existence of the functionality dependency at *Sfun* in Case 5, meaning that it is less likely to fully recover in that time range, compared to *Wfun* in Case 1.

Results on system resilience

The resilience index of every functionality recovery sample can be computed using Eq. 14 by setting the time horizon $t_r = 40$. Figure 8 shows violin plots of the resilience index at different dependency cases for the two systems. Every violin plot shows the probability density of the resilience index over all samples in a case, with the mean value shown as a white circle. As the inter-system functionality dependency is unidirectional from power to communication in this example, the power functionality is not impacted by the enforcement of functionality dependency at *Sfun*. Therefore, the power functionality sample in Case 1 is very similar to functionality samples in Case 5, and so forth. For this reason, power resilience distributions of Cases 5 $\sim$ 8 are similar to distributions of Cases 1 $\sim$ 4. The resilience of the power system shows similar narrow distributions at *Wres* (Cases 1 and 2), and wide distributions at *Sres* (Cases 3 and 4). The inter-system precedence dependency seems to slightly improve the resilience for the power system. That is because, unlike *Wpre*, some communication tasks (T_{c5} and T_{c10}) will not be timely executed due to the inter-system precedence constraints at *Spre*, and the corresponding available resources are used to execute power tasks. This leads to slightly greater functionality values in the recovery process for the power system at *Spre* than *Wpre*, i.e., better resilience for the power system at *Spre* than *Wpre*. Conversely, the resilience of the communication system is more sensitive to all types of interdependency. A positive impact on system resilience due to loose resource-sharing interdependency at *Wres* is also found for the communication system. The fact that the resilience of the communication system is sensitive to the other types of interdependency is mainly due to two reasons. First, some communication restoration activities cannot be executed because of precedence dependencies at *Spre*. For example, replaced telecommunication devices cannot be re-energized (i.e., T_{c5} and T_{c10}) timely, because the nearby substation has not restored yet at *Spre*. Second, even if all restoration activities are completed, the functionality of the dependent system may not be fully recovered at *Sfun*, because some components in the affecting system are not functional yet. For example, the communication tower is not fully functional the moment after its restorations, if the corresponding electric substation is not restored for providing the electricity at *Sfun*.

As defined in Eq. 15, by making t vary, $RI(t)$ becomes a function of time. To evaluate the impact of interdependencies of different types on resilience over time, the relative variation of resilience index from the ic case to the jc case is defined as follows.

$$\rho(ic, jc, t) = \frac{RI_{ic}(t) - RI_{jc}(t)}{RI_{jc}(t)} \tag{16}$$

where $\rho(ic, jc, t)$ is the relative variation of $RI(t)$ from the ic case to the jc case; $RI_{ic}(t)$ and $RI_{jc}(t)$ are the resilience at time t of a functionality recovery sample in the ic case and the resilience of a functionality recovery sample in the jc case, respectively; ic and jc are two labels of dependency cases, described as Case IDs in Table 7. A positive value of $\rho(ic, jc, t)$ represents better resilience in the ic dependency case than that in the jc dependency case at time t.

Figure 9 and Figure 10 depict the relative variations of resilience index for the two systems as the 95% of confidence interval and the mode value at different time step, in order to quantify the impact of different types of interdependency on resilience over time. In each plot, the vertical axis represents $\rho(ic, jc, t)$, the variation of mean resilience index $RI_{\text{mean}}(t)$ at different levels of interdependency. The horizontal axis is set from $t = 0$, when the event occurs, until a time window of $t_h = 70$, in order to demonstrate how $\rho(ic, jc, t)$ varies at different time steps. As t goes beyond the finishing time to restore a system, $RI_{\text{mean}}(t)$ takes into account the full functionality after restoration, so the impact on RI due to the functionality recovery related to dependency and interdependency is diluted. This explains why all $\rho(ic, jc, t)$ values gradually approach 0.

For the resource-sharing interdependency, $\rho(ic, jc, t)$ is calculated by comparing $RI_{Wres}(t)$ with the sufficient resources in Case 1 to $RI_{Sres}(t)$ with the limited resources in Case 3. As expected, both systems show positive values of $\rho(ic, jc, t)$, meaning that sufficient resources lead to enhanced resilience. This is because more tasks can be executed in fast mode in parallel as early as possible. In this example, greater positive values indicate that the power system seems to benefit more in the resilience enhancement from sufficient resources than the communication system. This is probably because the power system requires more resources to complete all restoration tasks.

For the restoration precedence dependency, $\rho(ic, jc, t)$ is calculated by comparing $RI_{Wpre}(t)$ without inter-system precedence in Case 1 to $RI_{Spre}(t)$ with inter-system precedence in Case 2. In this example, the communication system has a precedent task from the power system during the restoration at $Spre$. As a result, when resources are sufficient, the zeros mode values of $\rho(ic, jc, t)$ in Figure 9(b) indicate that the power system is not impacted by the inter-system restoration precedence dependency. Conversely, small positive values of $\rho(ic, jc, t)$ in Figure 10(b) mean that less inter-system restoration precedence is likely to slightly improve the resilience for the communication system.

For the functionality dependency, $\rho(ic, jc, t)$ is calculated by comparing $RI_{Wfun}(t)$ without inter-system functionality dependency in Case 1 to $RI_{Sfun}(t)$ with inter-system functionality dependency in Case 5. As explained earlier, this example does not model how the functionality of the power system depends on the other system, index $\rho(ic, jc, t)$ for the functionality dependency is computed only for the communication system. A positive value of $\rho(ic, jc, t)$ indicates that less inter-system functionality dependency improves the resilience of the communication system. For the communication system in this example, inter-system functionality dependency has the most significant impact on resilience among all three types of interdependencies, as indicated by the greatest mode values of $\rho(ic, jc, t)$ among all three types of interdependency. Therefore, using alternative resources to relax the functionality dependency of the communication system is more likely to effectively improve the resilience of the communication system, compared with mitigating the other two types of interdependency.

Results on task execution mode

This study presents a simulator based on an optimization algorithm with multiple modes of finishing each restoration task. In this example, the simulator determines the optimal schedule by choosing from two different modes: slow and fast. The two modes differ in the resource demand and the restoration duration; as a result, the resource availability constraint influences the task execution mode. To investigate how the resource-sharing interdependency affects the mode selection, the fast mode ratio is computed for each sample as the ratio between the number of tasks executing in the fast mode and the total number of tasks to restore a damaged system. As a reminder, 1000 random samples of task duration and resource demand are analyzed for each case. Figure 11 depicts the relative frequency histogram of the fast mode ratio for Cases 1 ∼ 8. A general trend is that more tasks are performed in the fast mode for both systems when resources are abundant (*Wres*), i.e., weak resource-sharing interdependencies. Conversely, more tasks are executed in the slow mode when resource-sharing interdependencies are tight (*Sres*). For instance, the power system has similar fast mode ratios approaching to 1 in Cases 1 and 2 when resources are sufficient and similar fast mode ratios around 0.6 in Cases 3 and 4 when resources are insufficient. Conversely, the inter-system precedence dependency does not show an obvious impact on the fast mode ratio. As the task mode is determined at Step 3 and the system functionality is computed at Step 4, the inter-system functionality dependency does not affect the task execution mode. Therefore, the fast mode ratio distributions in Cases 1 ∼ 4 are the same as the fast mode ratio distributions in Cases 5

~ 8 in this example.

In practice, decision makers of disaster response agencies want to make the best of the available resources to reach management goals, such as recovering utility services as fast as possible. The recovery speed is directly related to the task mode adopted. As discussed previously, resource-sharing interdependency shows a great impact on the task mode. For this reason, a more detailed analysis has been performed to study the use of the fast mode for each task. In Case 1 (*Wres*), with abundant resources, all tasks associated with the power system ($T_{p1} \sim T_{p14}$) are performed in fast mode, and for the communication system, only tasks T_{c4} and T_{c9} sometimes are performed in the slow mode (less than 20% of the time). Instead, when resources are tighter, there is much more variability in the mode choice. For instance, Figure 12 shows with what frequency slow and fast modes are chosen for every task over all samples. At Case 3 (*Sres-Wpre-Wfun*), $T_{p2} \sim T_{p4}$ and T_{p9} use the slow mode more often (over 50%) for the power system; all communication tasks select the slow mode most often. This also explains why the restoration process takes longer time on average in Figure 6 when resources are tight.

Results on non-uniform resource availability

Cases $1 \sim 8$ implement uniform resource availability in this example. In the post-disaster scenario, resources are often limited in the amount at the initial restoration stage and then become sufficient afterwards. Cases $9 \sim 12$ represent such scenarios of non-uniform resource availability, following a similar variation trend of manpower for the Pennsylvania electricity service after Hurricane Sandy (Bureau of Technical Utility Services 2013). Figure 13 presents three levels of the renewable resource availability in all dependency cases and the computational results of Cases $9 \sim 12$ for the communication system. Figure 13(a) shows the availability of renewable resource over time for the communication system at *Wres*, *Sres*, and *Sresv*. The power system has a similar variation trend of renewable resource constraint. The non-renewable resource constraints for both systems in Cases $9 \sim 12$ are set as the same values as the non-renewable resource constraints in Cases 3 and 4. Renewable resources are increases in the time interval $t \in [10, 20]$ for both systems in *Sresv* Cases. As a result, both systems are likely to adopt more tasks in fast modes than that in

Sres (Cases 3 and 4 in Figure 11(b)) and less than those in *Wres* (Cases 1 and 2 in Figure 13(b)). Therefore, damaged systems are fully restored faster in *Sresv* Cases than *Sres* Cases and slower than *Wres* Cases. For the same reason mentioned above, Cases 11 and 12 show the same restoration time as Cases 9 and 10, respectively. As expected, due to inter-system functionality dependency, Cases 11 and 12 show smaller values of resilience than Cases 9 and 10. In this example, providing more resources in a short time in these *Sresv* cases can speed up the restoration process and improve system resilience, compared with *Sres* cases. *Sresv* cases are not as efficient as the *Wres* cases in speeding up the restoration. For instance, Cases 1, 3, and 9 have the same dependency levels of precedency and functionality, with different resource-sharing interdependencies. For the communication system, the mean restoration finishing time is 23.66 hours in Case 9, 16.29 hours in Case 1, and 27.29 hours in Case 3, as shown in Figure 6 and Figure 13(c), respectively. Even though shortly boosting resources does not significantly speed up the recovery in this example, this study presents a simulator for analyzing the most cost-effective resource level in a critical period to make the most of limited restoration resources.

DISCUSSION

The major contribution of this study is to present a simulator that can explicitly capture the effect of different types of interdependency related to restoration and functionality in a mechanistic manner. This simulator is a model of the restoration decision and the recovery process of interdependent systems in the post-disaster scenario, based on an optimization formulation. It is general and applicable to different interdependent systems, but it has the following limitations.

First, a sample restoration schedule obtained from the MRCPSP solution is optimal in terms of the selected objective function. The proposed formulation of MRCPSP chooses the minimal completion time as the objective function, because it appears to be the most common criterion in our conversations with many disaster responders, and the goal of the methodology is to simulate human decision making in restoration planning. Restoration schedules determined exclusively with this objective function may not be real, but they are reasonably realistic. In case the analysts want to simulate decision making with another objective or multiple objectives, different formulations of MRCPSP can be used to generate restoration schedules (Phruksaphanrat 2014), still preserving the proposed models of interdependencies and the approach to assess their impact. Due to dynamic features of actual disaster recovery, the computed schedules may be different from the schedules developed by considering various management concerns in real time (Orabi et al. 2009; Orabi et al. 2010; Plotnick and O'Brien 2009), resulting in different functionality recoveries. Future research could be conducted on implementing other objective functions and using different optimization techniques, such as generalized resource-constrained project scheduling (Klein 2000), multi-objective optimization (Bocchini and Frangopol 2012a; Bocchini and Frangopol 2012b; Almoghathawi et al. 2019), and stochastic optimization (Klerides and Hadjiconstantinou 2010), to represent real targets and dynamic features of actual restorations.

Second, this study uses the exact procedure of MRCPSP in the mixed-integer linear programming (MILP) format. As MRCPSP is an NP-hard problem, and the computational complexity exponentially increases with the number of decision variables and the number of constraints (Sabzehparvar and Seyed-Hosseini 2008). Exact methods may not be able to solve a MRCPSP problem in a timely manner with more than 20 tasks and three modes when resource constraints are extremely tight (Sprecher and Drexl 1998). Developing more computationally efficient algorithms would be helpful to rapidly solve the restoration planning problem for large interdependent systems, which may involve more restoration tasks and more complex interactions. For example, heuristic and meta-heuristic procedures can also be used to solve these problems within an acceptable time frame (Liao et al. 2011), even though they may not guarantee finding the optimal solution. Due to the complexity of restoration decision making in practice, the solution of MRCPSP, determined from either the exact procedure, the heuristic procedure, or the meta-heuristic procedure, can serve as a good representation of human decisions in the actual restoration planning.

Third, the proposed simulator captures all three types of interdependencies from the bottom up. As a result, this simulator requires as input information on restoration tasks and task precedence relations for simulating the restoration plan, as well as component functionality weights for computing the system functionality. Collecting such information for large complex systems is still a challenge, especially if there are different organizational units involved. Projects like PRAISys have faced this challenge when analyzing interdependent systems of communities in the United States (The PRAISys Team 2019). When this detailed information cannot be collected, large interdependent systems can be considered as systems consisting of interdependent meta-components. Interactions at the meta-component level can be identified through conversations with emergency managers and stakeholders, and expert tabletop exercises, or estimated from educated guesses. Based on this input, the proposed model can be used for capturing all interdependencies to make estimations of interdependency impacts. With the advancement of sensing technology, such as the Internet of Things (IoT), interactions at the component level are increasingly likely to be known for many sectors. More accurate information is expected to be available for using the proposed model in the near future to capture interdependencies in a rigorous way.

Last but not least, it is worth noting that the same type of interdependency may not show the same impact on the recovery of different systems. A major reason is that different systems may have different architectures and variations of network topology and flow-related features, leading to differences in restoration tasks and inter-system precedence relations. Therefore, results on the impact of the various types of interdependency generated from computational results in this example are not directly applicable to other systems. However, the proposed simulator can be applied to assess the impact of various interdependencies in those cases by setting up new input data for other systems.

CONCLUDING REMARKS

This study proposes a simulator to capture different types of interdependencies. The decision-making model is implemented by solving an optimization problem in the form of multi-mode resource-constrained project scheduling problem (MRCPSP). The optimal solution from the MRCPSP model is an estimation of human decisions in restoration planning. The proposed decision model considers that every task may be performed in one out of multiple different possible modes, which is more flexible and practical than single-mode models. Uncertainties in the restoration duration and the resource demand, as well as the functionality dependency are considered. Three types of interdependencies can be easily implemented at both the component level and the system level, in terms of resource-sharing interdependency, restoration precedence dependency and functionality dependency.

To demonstrate the applicability of the proposed simulator, a simple example is presented. Results from the example show that providing sufficient resources to alleviate resource-sharing interdependencies can help to speed up the restoration process and enhance the resilience of interdependent systems. In this example, relaxing inter-system restoration dependencies can improve the system resilience for the communication system, not as significantly as relaxing the resource-sharing interdependencies. Using the alternative inter-system functionality support can also improve the resilience of the communication system that depends on the functionality of the other system. Some findings from the application example are intuitive to understand, such as the fast recovery and large resilience by relaxing resource-sharing interdependencies (i.e., provided with sufficient resources), confirming that this simulator yields reasonable results. In a few cases, some findings about the impact of dependencies may initially seem counterintuitive, but they can be explained, which shows that this model can capture and unveil non-obvious features in the interdependent recovery process.

Finally, it should be noted that findings on the impact of a certain type of interdependencies on system recovery may not be the same on other systems. However, the same computational procedure using the proposed simulator can be applied to other systems to assess the impact of interdependencies. These results can help to identify dependencies and interdependencies that have the greatest impact. In this way, optimal restoration strategies that may not be directly determined from intuition can be identified by alleviating dependencies and interdependencies with the greatest adverse impact. By collecting real data of interconnected systems in local communities, this simulator is expected to provide more accurate recovery predictions and suggest optimal restoration strategies. For instance, efficient countermeasures can be developed to make the most of tight resources in a short period for improving restoration efficiency and enhancing disaster resilience.

DATA AVAILABILITY STATEMENT

All data used in the study are available from the authors by request (including constraints of resource and precedence, task samples, and functionality dependency samples). The code of MRCPSP is available in MATLAB on GitHub (DOI: 10.5281/zenodo.2669680).

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TABLE 1. Implementation of interdependencies in the restoration process

No.	Interdependency type	Implementation method
1	Resource-sharing interdependencies	Constraints of both renewable and nonrenewable resources
2	Restoration precedence dependencies	Precedence constraints among tasks
3	Functionality dependencies	Mechanistic functionality functions

TABLE 2. Discussion of underlying assumptions

Classification	Assumption description	Discussion
Uncertainty quantification	(1) The task duration distribution at different modes is assumed to be known as the input of the proposed model. (2) The distribution of resource demand to execute a task at each mode is known as the input of the proposed model. (3) Uncertainties in the functionality dependency are implemented by describing the presence of additional resources to relieve functionality dependency as a random event.	These distributions can be determined from published literature and through consulting with construction managers and experienced engineers.
System functionality computation	This study computes the system functionality using Equation 13, assuming that $w_{is,j}$ is independent of the restoration sequence.	For complex networks, this assumption of constant functionality weight may not be valid, and system-wide flow analysis can be performed to compute the system functionality.

TABLE 3. Number of customers served by different systems

Power component	No. of customers	Communication component	No. of customers
2	4000	4	2000
3	5000	5	3000
4	2000	6	2000
5	2000	7	3000
6	1000	8	1500
		9	2500
Total	14000	Total	14000

TABLE 4. Inter-system functionality dependencies at component-level

Dependent component (Communication)	Required component (Power)
1	2
2	3
3	6
4	1
5	2
6	5
7	3
8	3
9	4

TABLE 5. Restoration tasks in the power system

						Fast restoration mode											Slow restoration mode										
										Power resources[5]											Power resources						
						Duration (hour)[4]				Renewable				Nonrenewable ($k)			Duration (hour)				Renewable				Nonrenewable ($k)		
S/S[1]	Cmpt i	Tsk j	Description	q_{ij}^2	Pre_j^3	type	min	max	mod	type	min	max	mod	type	min	max	type	min	max	mod	type	min	max	mod	type	min	max
1	3	T_{p1}	Assess local damage	0	NA	Tri.	8	12	10	Uni.	1	2	NA	Uni.	100	200	Tri.	16	24	20	Uni.	0.5	1	NA	Uni.	50	100
	3	T_{p2}	Repair circuit breaker	0	T_{p1}	Tri.	1	3	2	Tri.	1	3	2	Uni.	2000	4000	Tri.	2	6	4	Tri.	0.5	1.5	1	Uni.	1000	2000
	3	T_{p3}	Repair disconnected switch	0	T_{p1}	Tri.	1	3	2	Tri.	1	3	2	Uni.	1000	3000	Tri.	2	6	4	Tri.	0.5	1.5	1	Uni.	500	1500
	3	T_{p4}	Repair transformer bushing	0	T_{p1}	Tri.	1	3	2	Tri.	1	3	2	Uni.	7000	12000	Tri.	2	6	4	Tri.	0.5	1.5	1	Uni.	3500	6000
	3	T_{p5}	Re-energize	0	T_{p2}, T_{p3}, T_{p4}	Tri.	0.5	1.5	1	Uni.	1	2	NA	Uni.	10	20	Tri.	1	3	2	Uni.	0.5	1	NA	Uni.	10	20
	$pl10$	T_{p12}	Assess local damage	0	NA	Tri.	4	8	6	Uni.	1	2	NA	Uni.	100	200	Tri.	8	16	12	Uni.	0.5	1	Uni.	50	100	
	$pl10$	T_{p13}	Replace damaged conductor	0	T_{p9}	Tri.	4	10	8	Tri.	1	3	2	Uni.	2000	4000	Tri.	8	20	16	Tri.	2	6	4	Uni.	1000	2000
	$pl10$	T_{p14}	Re-energize	0	T_{p10}	Tri.	0.5	1.5	1	Uni.	1	2	NA	Uni.	10	20	Tri.	1	3	2	Uni.	0.5	1	NA	Uni.	5	10
2	9	T_{p6}	Assess local damage	0	NA	Tri.	8	12	10	Uni.	1	2	NA	Uni.	100	200	Tri.	16	24	20	Uni.	0.5	1	NA	Uni.	50	100
	9	T_{p7}	Replace buckled member	0	T_{p6}	Tri.	4	10	8	Tri.	1	3	2	Uni.	50	100	Tri.	8	20	16	Tri.	0.5	1.5	1	Uni.	25	50
	9	T_{p8}	Re-energize	0	T_{p7}	Tri.	0.5	1.5	1	Uni.	1	2	NA	Uni.	10	20	Tri.	1	3	2	Uni.	0.5	1	NA	Uni.	5	10
	$pl6$	T_{p9}	Assess local damage	0	NA	Tri.	4	8	6	Uni.	1	2	NA	Uni.	1000	2000	Tri.	8	16	12	Uni.	0.5	1	NA	Uni.	500	1000
	$pl6$	T_{p10}	Replace damaged conductor	0	T_{p9}	Tri.	4	10	8	Tri.	1	3	2	Uni.	2000	4000	Tri.	8	20	16	Tri.	2	6	4	Uni.	1000	2000
	$pl6$	T_{p11}	Re-energize	0	T_{p10}	Tri.	0.5	1.5	1	Uni.	1	2	NA	Uni.	10	20	Tri.	1	3	2	Uni.	0.5	1	NA	Uni.	5	10

Note:

1. S/S means subsystem.
2. q_{ij} represents the functionality of the component i when executing the task j.
3. Pre_j represents the precedence task of the task j. NA in the column of Pre_j means that there is no precedent task for the task j.
4. The distribution of task duration is assumed to follow the triangular distribution (Tri.), which is defined by distribution parameters of the minimal value (min), the maximal value (max), and the mode value (mod).
5. The resource requirement of every task is assumed to follow the uniform distribution (Uni.) or the triangular distribution, with the minimal value, the maximal value, and the mode value. NA in the column of mod means "not available", i.e., there is no mode value in the uniform distribution of the resource demand.

TABLE 6. Restoration tasks in the communication system

					Fast restoration mode											Slow restoration mode										
									Communication resources											Communication resources						
					Duration (hour)				Renewable				Nonrenewable ($k)			Duration (hour)				Renewable				Nonrenewable ($k)		
Cmpt i	Tsk j	Description	q_{ij}	Pre $_j$	type	min	max	mod	type	min	max	mod	type	min	max	type	min	max	mod	type	min	max	mod	type	min	max
8	T_{c1}	Assess local damage	0	NA	Tri.	2	5	3	Uni.	1	2	NA	Uni.	50	80	Tri.	4	10	6	Uni.	0.5	1	NA	Uni.	25	40
8	T_{c2}	Reinstall monopole	0	T_{c1}	Tri.	1	3	2	Uni.	2	3	NA	Uni.	225	350	Tri.	2	6	4	Uni.	1	1.5	NA	Uni.	113	175
8	T_{c3}	Realign microwave device	0	T_{c2}	Tri.	2	6	4	Uni.	2	3	NA	Uni.	100	300	Tri.	4	12	8	Uni.	1	1.5	NA	Uni.	50	150
8	T_{c4}	Replace aviation light	0.5	T_{c2}	Tri.	1	4	3	Uni.	2	3	NA	Uni.	10	20	Tri.	2	8	6	Uni.	1	1.5	NA	Uni.	5	10
8	T_{c5}	Re-energize	0	T_{c3}	Tri.	0.5	1.5	1	Uni.	2	2	NA	Uni.	10	20	Tri.	1	3	2	Uni.	1	1	NA	Uni.	5	10
9	T_{c6}	Assess local damage	0	NA	Tri.	2	5	3	Uni.	1	2	NA	Uni.	50	80	Tri.	4	10	6	Uni.	0.5	1	NA	Uni.	25	40
9	T_{c7}	Reinstall monopole	0	T_{c1}	Tri.	1	3	2	Uni.	2	3	NA	Uni.	225	350	Tri.	2	6	4	Uni.	1	1.5	NA	Uni.	126	175
9	T_{c8}	Realign microwave device	0	T_{c2}	Tri.	2	6	4	Uni.	2	3	NA	Uni.	100	300	Tri.	4	12	8	Uni.	1	1.5	NA	Uni.	50	150
9	T_{c9}	Replace aviation light	0.5	T_{c2}	Tri.	1	4	3	Uni.	2	3	NA	Uni.	10	20	Tri.	2	8	6	Uni.	1	1.5	NA	Uni.	5	10
9	T_{c10}	Re-energize	0	T_{c8}	Tri.	0.5	1.5	1	Uni.	2	2	NA	Uni.	10	20	Tri.	1	3	2	Uni.	1	1	NA	Uni.	5	10

TABLE 7. Dependency cases

Case ID	Case label	Resource-sharing interdep.[1]	Precedence dependency[2]	Functionality dependency[3]
Case 1	*Wres-Wpre-Wfun*	Weak	Weak	Weak
Case 2	*Wres-Spre-Wfun*	Weak	Strong	Weak
Case 3	*Sres-Wpre-Wfun*	Strong	Weak	Weak
Case 4	*Sres-Spre-Wfun*	Strong	Strong	Weak
Case 5	*Wres-Wpre-Sfun*	Weak	Weak	Strong
Case 6	*Wres-Spre-Sfun*	Weak	Strong	Strong
Case 7	*Sres-Wpre-Sfun*	Strong	Weak	Strong
Case 8	*Sres-Spre-Sfun*	Strong	Strong	Strong
Case 9	*Sresv-Wpre-Wfun*	Strong, varying	Weak	Weak
Case 10	*Sresv-Spre-Wfun*	Strong, varying	Strong	Weak
Case 11	*Sresv-Wpre-Sfun*	Strong, varying	Weak	Strong
Case 12	*Sresv-Spre-Sfun*	Strong, varying	Strong	Strong

Note:
1. "Resource-sharing interdependency" represents the availability level of resource constraint. "Weak (*Wres*)" represents abundant resources available in restoration, and "strong (*Sres*)" represents insufficient resources in restoration. In the computation, the "weak" level has $a_r(t) = [8, 6]$ for the renewable resource throughout the restoration process, meaning constant 8 units of power renewable resource and 6 units of communication renewable resource constantly available. In this example, the unit cost of nonrenewable resource is set as $3,625,000 for the power system and $250,000 for the communication system, respectively. The cost data are selected by the authors based on the public information from utility companies, such as Western Electricity Coordination Council (2014), Southern California Edison (2018), and American Tower Corporation (2019). Therefore, for non-renewable resources, the constraint is $29,000,000 for the power system, and $1,500,000 for the communication system. The "strong" level has $a_r(t) = [4, 3]$ for renewable resources. For non-renewable resources, the constraint is $14,500,000 for the power system, and $750,000 for the communication system. *Sresv* (Cases 9 ∼ 10) uses the non-uniform insufficient availability of renewable resources over time. In *Sresv*, the nonrenewable resources are set as the same constraints of non-renewable resources in *Sres* cases; the renewable resource availability $a_r(t)$ is set up as follows.

$$a_r(t) = \begin{cases} [4, 3], & \text{if } t = 1 \sim 9. \\ [7, 5], & \text{if } t = 10 \sim 20. \\ [4, 3], & \text{if } t = 21 \sim t_h. \end{cases} \tag{17}$$

2. "Precedence dependency" represents restoration precedence relations between tasks for restoring damaged components from different systems. In the computation, the "strong (*Spre*)" level represents that there are precedence relations between tasks in the communication system and tasks in the power system. Specifically, T_{c5} and T_{c10} are executed after T_{p5} to re-energize. Conversely, the "weak (*Wpre*)" level represents the aforementioned inter-system precedence relations are relieved due to advanced or alternative technologies, such as mobile generators.
3. "Functionality dependency" represents whether there is any dependency of a component in a system on the functionality of another component from another system. the "strong (*Sfun*)" level represents that the component functionality dependency across systems is present, and the "weak (*Wfun*)" level represents that the component functionality dependency across systems is not present.

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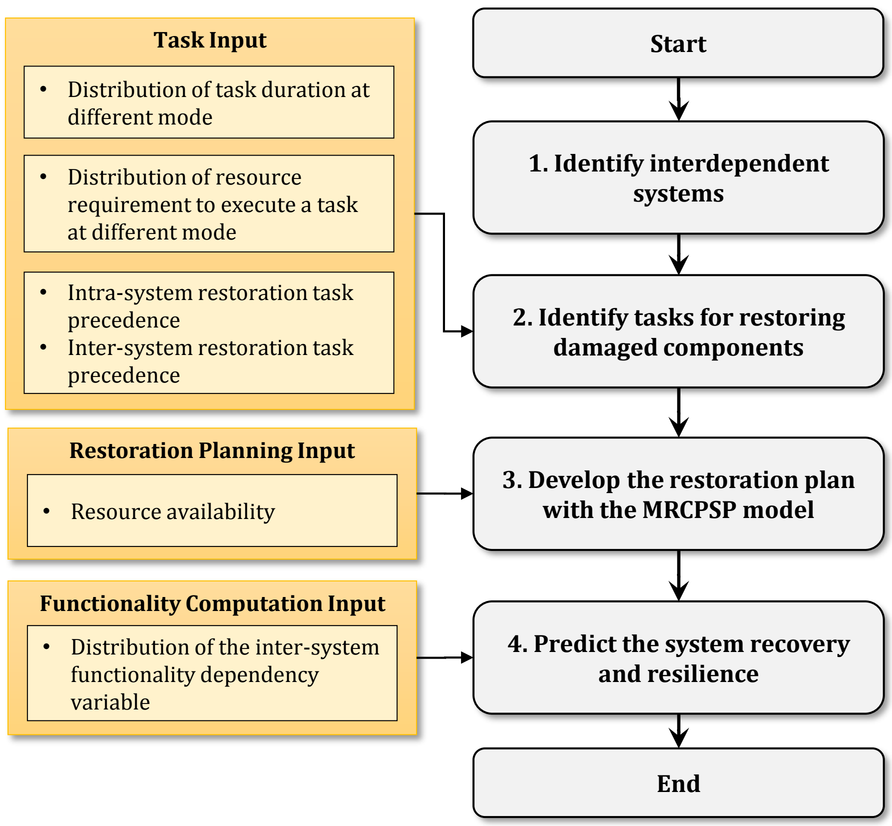


Fig. 1. Flowchart of the proposed MRCPSP model.

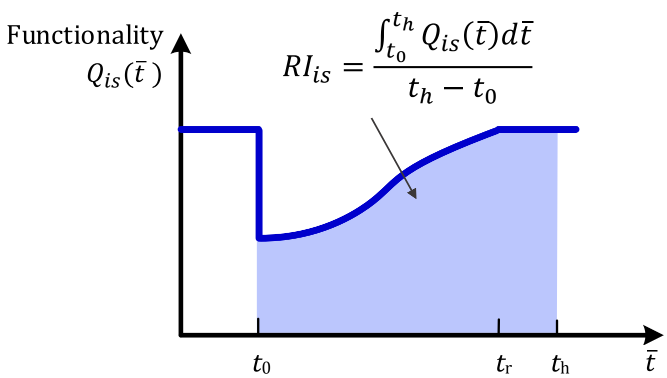


Fig. 2. Illustration of resilience index.

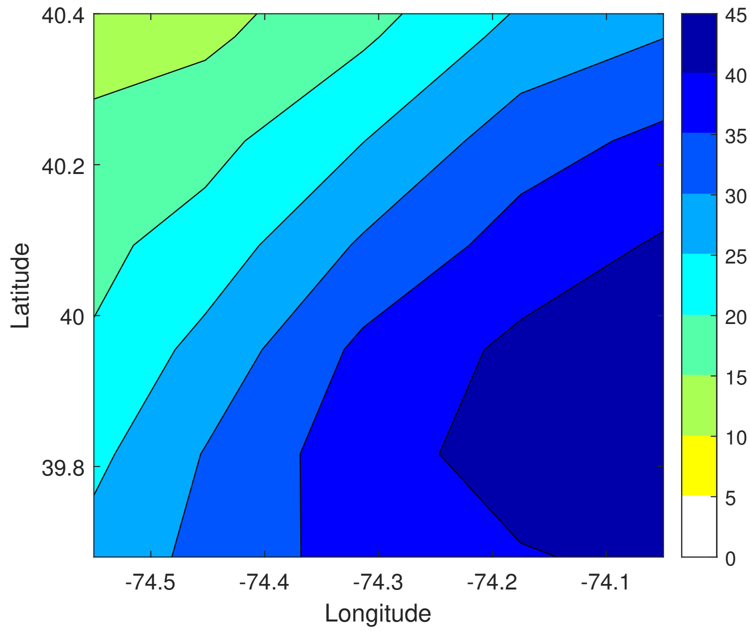
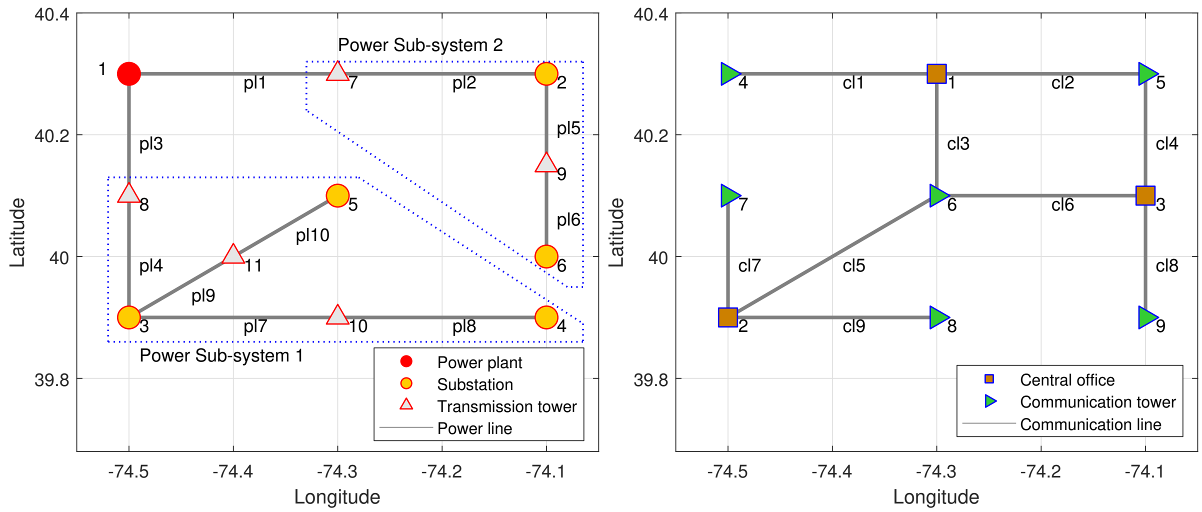


Fig. 3. Wind map (m/s)



(a) Power **(b)** Communication

Fig. 4. Interdependent systems: (a) power; and (b) communication.

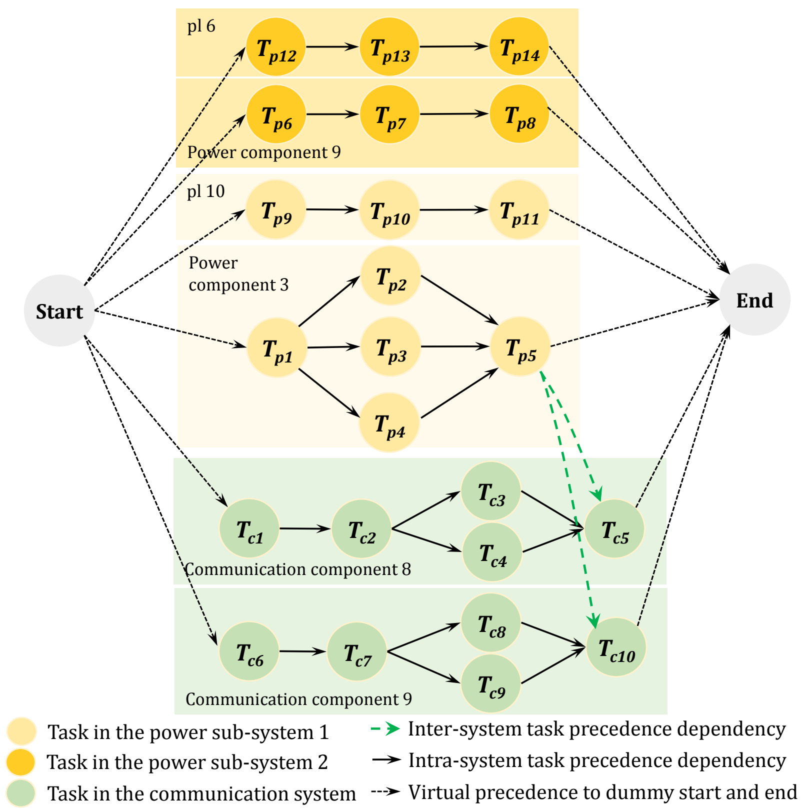


Fig. 5. Restoration tasks with the finish-to-start relationships

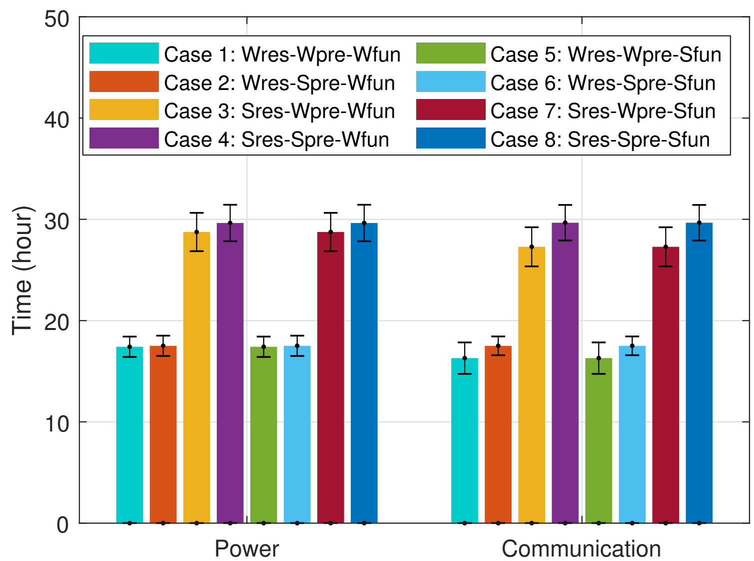
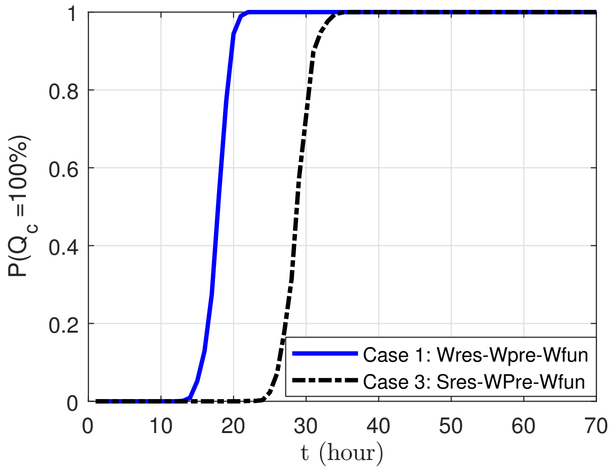
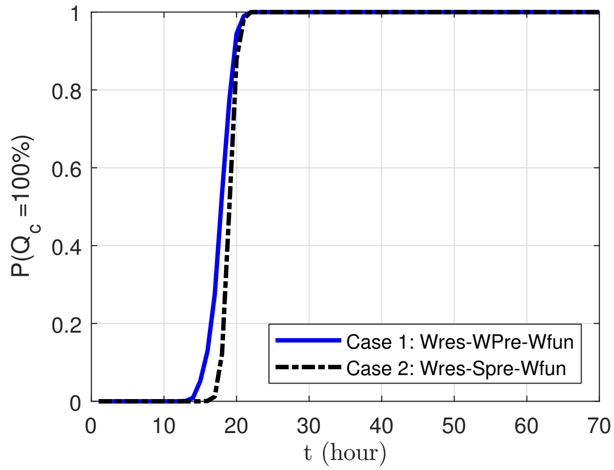


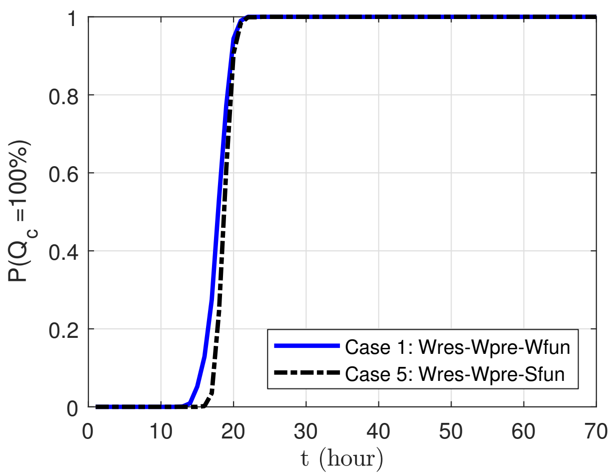
Fig. 6. Starting time and finishing time in Cases 1 ~ 8.



(a) Resource-sharing interdependency: weak vs strong

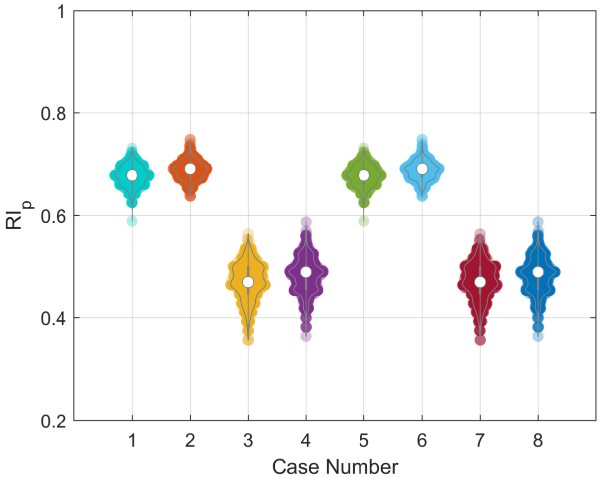


(b) Inter-system restoration precedence: weak vs strong

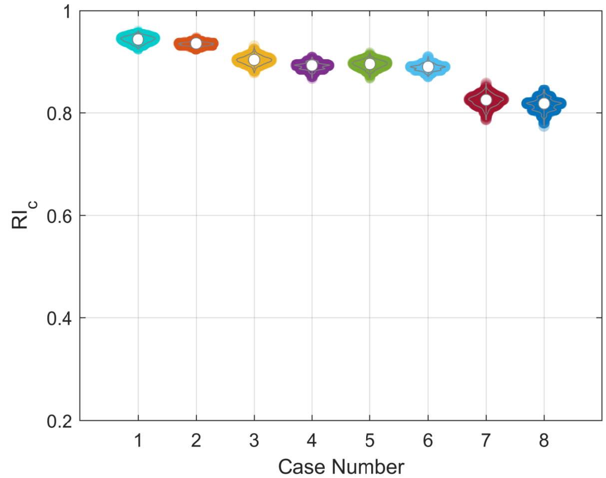


(c) Inter-system functionality dependency: weak vs strong

Fig. 7. Probabilistic restoration functions of the communication system: (a) resource-sharing interdependency; (b) inter-system restoration precedence; and (c) inter-system functionality precedence.



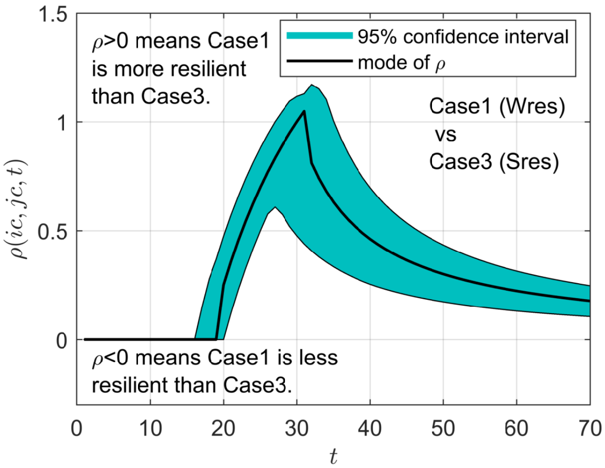
(a) Power



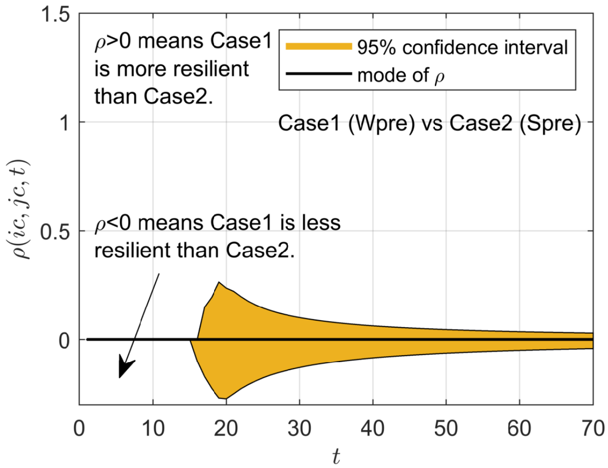
(b) Communication

Fig. 8. Resilience index distributions of the two systems in Cases 1 ~ 8: (a) power; and (b) communication.

Note: Case 1 - *Wres-Wpre-Wfun*, Case 2 - *Wres-Spre-Wfun*, Case 3 - *Sres-Wpre-Wfun*, Case 4 - *Sres-Spre-Wfun*, Case 5 - *Wres-Wpre-Sfun*, Case 6 - *Wres-Spre-Sfun*, Case 7 - *Sres-Wpre-Sfun*, Case 8 - *Sres-Spre-Sfun*.

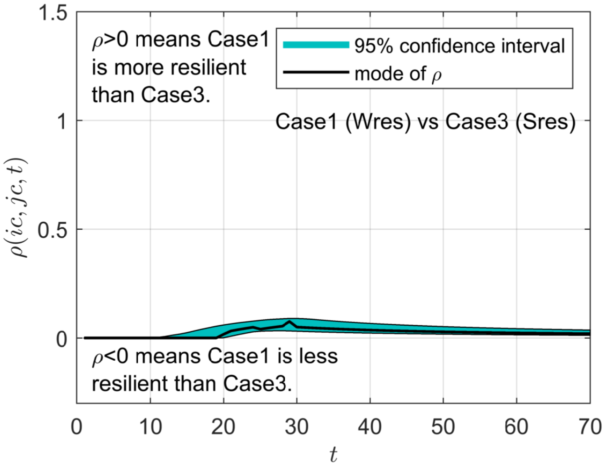


(a) Resource-sharing interdependency

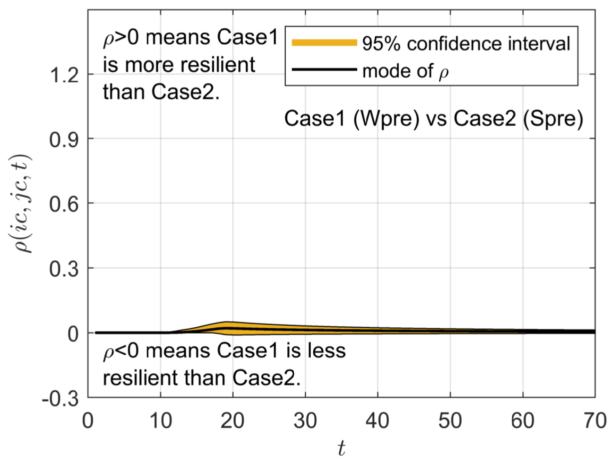


(b) Inter-system restoration precedence

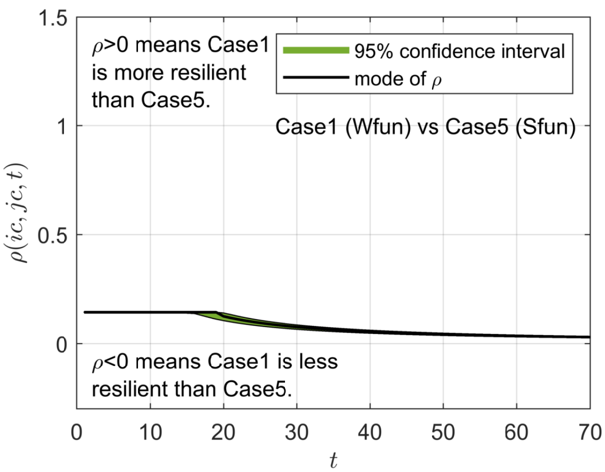
Fig. 9. Impact of interdependency on resilience over time for the power system: (a) resource-sharing interdependency; and (b) inter-system restoration precedence.



(a) Resource-sharing interdependency

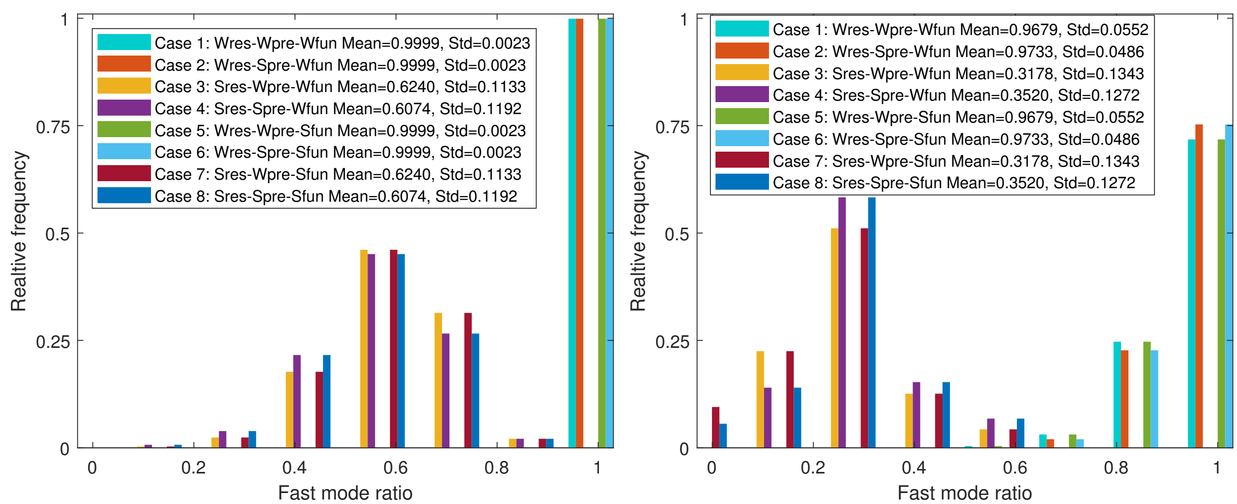


(b) Inter-system restoration precedence



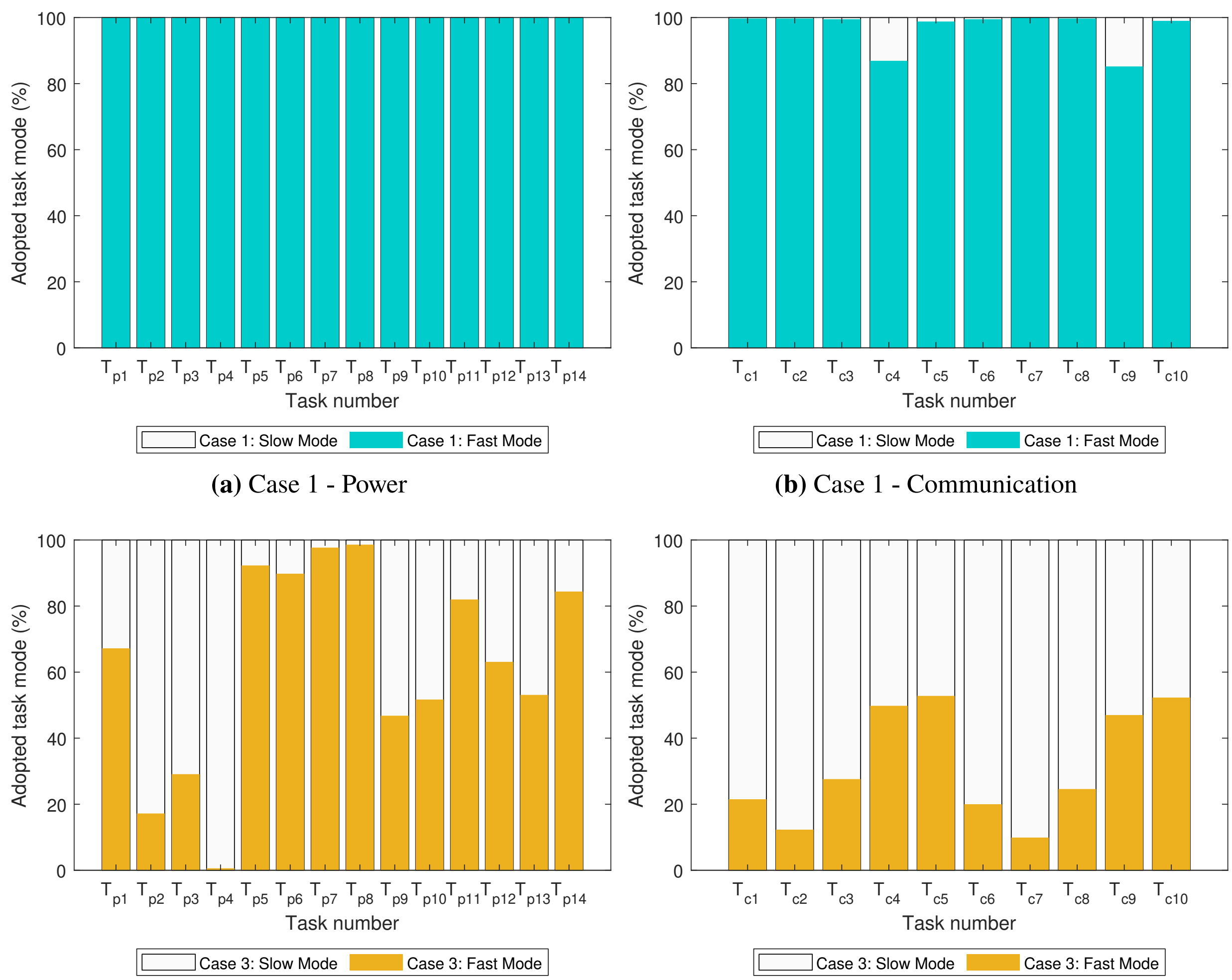
(c) Inter-system functionality dependency

Fig. 10. Impact of interdependency on resilience over time for the communication system: (a) resource-sharing interdependency; (b) inter-system restoration precedence; and (c) inter-system functionality precedence.



(a) Power **(b)** Communication

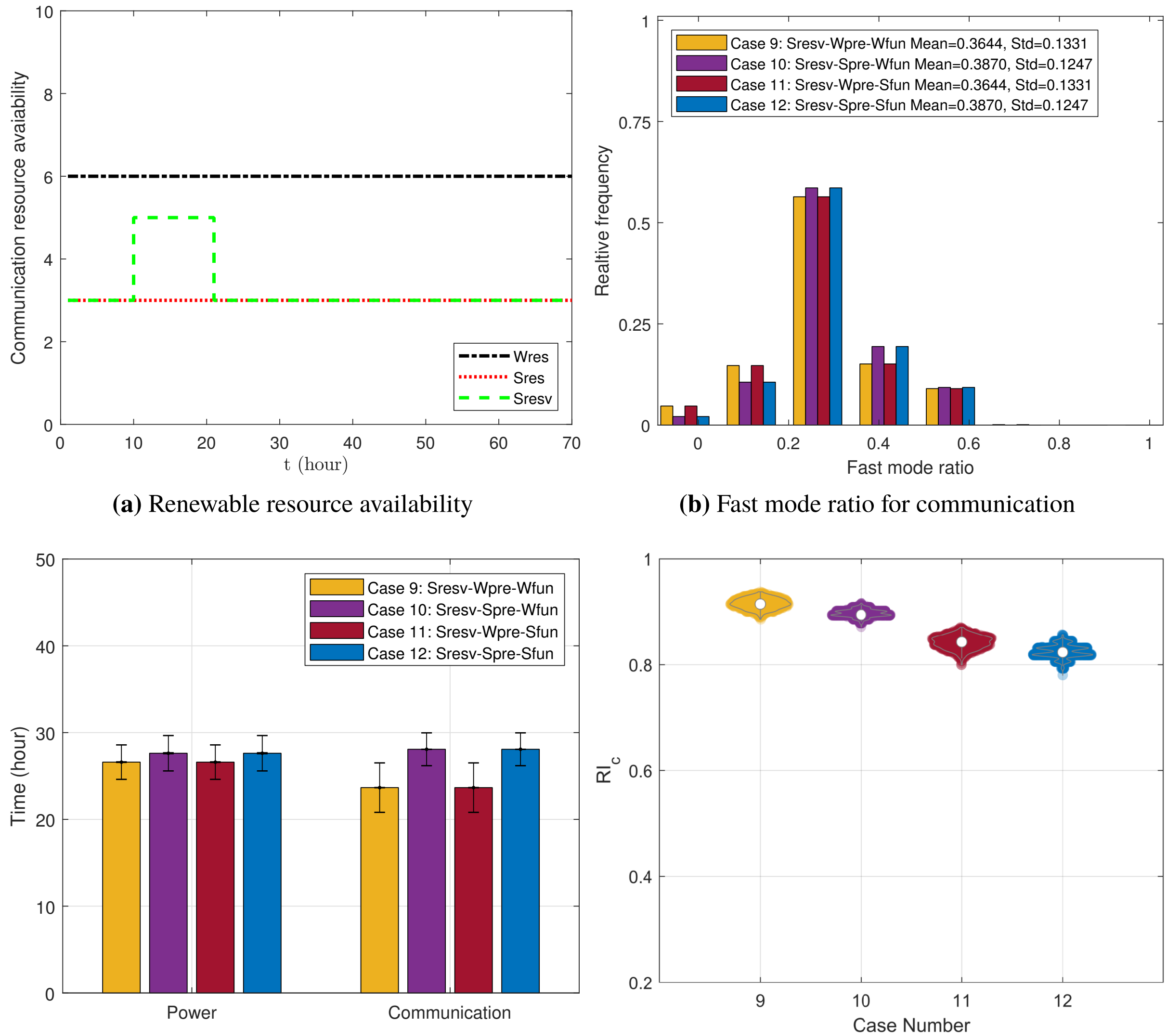
Fig. 11. Fast mode ratio: (a) power; and (b) communication.



(a) Case 1 - Power **(b)** Case 1 - Communication

(c) Case 3 - Power **(d)** Case 3 - Communication

Fig. 12. Frequency of the execution mode adopted for every task over all samples: (a) Case 1 - power; (b) Case 1 - communication; (c) Case 3 - power; and (d) Case 3 - communication.



(a) Renewable resource availability

(b) Fast mode ratio for communication

(c) Finishing time

(d) Resilience index (t_h=40)

Fig. 13. Computational results of the communication system under non-uniform resource availability: (a) renewable resource availability; (b) fast mode ratio for communication; (c) finishing time; and (d) resilience index.