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ORIGINAL PAPER

Assessment of the impact of interdependencies on the resilience of networked critical infrastructure systems

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Abstract Critical infrastructure systems (CISs) have a fundamental role in delivering commodities that are essential to various functions in urban systems. The resilience of CISs concerns the robustness of system performance against extreme events, the ineffectiveness of disturbance propagation, and the efficiency of post-disaster system performance restoration. The resilience of CISs is significantly impacted by the interconnectivity among CISs and the interactions among different systems. Although this impact has been recognized by numerous studies, it has rarely been comparatively assessed using different metrics that reflect the different perspectives of various stakeholders. Moreover, the existing literature on the impact of interdependencies in the context of CIS disaster risk reduction has primarily focused on the resistance stage rather than the entire life cycle of disaster events. To address these gaps, this study assesses this impact at different stages of the life cycle of disturbance events, analyzes the effect of interdependencies on determining the total resilience of CISs, and discusses the implications of the results in the context of resilience enhancement of CISs in practice. To achieve this objective, this study models interconnected CISs using four different network-based approaches, simulates the disturbance propagation process and system restoration process of CISs in three different scenarios, and measures the resilience of disturbed CISs with three different resilience metrics. A case study of three CISs in a middle-sized city in Eastern China was conducted. The CISs included an electric power system, a telecommunication system, and a water supply system. The results revealed that the vulnerability of CISs to extreme events would be significantly underestimated if interdependencies of the CISs were not considered, which would cause a misleading estimation of the total resilience of the CISs. The findings also suggested the importance of considering the interdependencies of CISs in the sequencing of restoration tasks to optimize the efficiency of post-disaster restoration tasks.

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1 Introduction

Cities worldwide have experienced significant damages and losses due to a variety of disasters in recent years. According to a recent United Nations International Strategy for Disaster Reduction (UNISDR) report (2015), natural hazards, such as earthquakes, hurricanes, floods, and snowstorms, are causing economic losses of up to US$300 billion each year. An increasing amount of evidence has indicated that the exposure of urban assets worldwide has increased faster than vulnerability has decreased, which has generated new risks for urban assets and consequently a steady increase in hazard-related losses (United Nations 2015). Critical infrastructure systems (CISs), such as electric power systems and water supply systems, are critical assets of cities because they have a fundamental role in delivering commodities that are essential to various functionalities of urban systems. The protection of CISs has a substantial impact on cities' capabilities of addressing disasters and their post-hazard recovery. For instance, the city of New Orleans was affected by Hurricane Katrina in 2005, where levees were overrated and unexpectedly failed in some critical areas (Colten et al. 2008). In addition, the majority of buildings, highways, and infrastructure facilities, which were located below sea level, were drowned by floodwaters (Pistrika and Jonkman 2010). The breakdown of these CISs caused a significant inefficiency of post-hazard restoration efforts. As a result, nearly half of the population permanently left the city, and some communities have not been restored (Yaukey 2012).

According to the President's Commission on Critical Infrastructure Protection (PCCIP) (1997), a CIS is defined as a network of urban manmade systems that synergistically work to produce and deliver essential commodities that are fundamental to urban functions. Various components of CISs are highly interconnected and interdependent (Rinaldi et al. 2001). The interdependency can be defined as an interactive relationship between two CISs by which the state of one CIS influences the state of the other CIS (Rinaldi et al. 2001). For instance, water-supply-pumping stations need electric power from electric power systems, whereas electric distribution needs information from telecommunication systems. Although the ever-increasing interdependencies among various CISs have improved the efficiency of urban functionalities, they have also created significant complexities in the manner in which these systems respond to various disturbances (Ouyang 2014; Satumtira and Dueñas-Osorio 2010; Choi et al. 2017). The interdependencies may aggravate the disturbance propagation among CISs and cause significant performance losses due to disturbance events. The interdependencies also have a significant role in post-disturbance restoration, in which the efficiency of restoration efforts of a CIS can be substantially impacted by the efficiency of the restoration efforts of other CISs (Sharkey et al. 2016). The sequence of restoration tasks can be rescheduled and optimized by considering these interdependencies among CISs, which helps to improve the effectiveness of restoration tasks. This study considers the impact of interdependencies on disturbance propagation and the restoration of networked CISs.

The concept of resilience provides a new perspective for examining the ability of CISs to maintain their performance during extreme events (Ouyang and Duenas-Osorio 2012). The resilience concept has been introduced to measure not only a system's ability to absorb disturbances at the resistance stage but also its ability to rapidly recover from disturbances at the restoration stage (Adjetey-Bahun et al. 2016). The resilience of CISs generally concerns the robustness of system functionality against extreme events, the ineffectiveness of disturbance propagation, and the efficiency of restoration efforts, which are significantly determined by the interconnectivity among CISs and their interactions. The resilience of CISs is substantially impacted by their interdependencies. Although this impact has been recognized by numerous studies (Cartalis 2014; Jabareen 2013; McDaniels et al. 2008; Abramson and Redlener 2012; Colten et al. 2008; Ouyang 2014; Rinaldi et al. 2001; Chopra and Khanna 2015; Cimellaro et al. 2014a), it has rarely been quantitatively assessed. Several resilience metrics have been proposed in the literature, yet these metrics reflect different perspectives of various stakeholders and may not yield congruent results when applied to the assessment of CISs resilience. A holistic and comparative assessment of the resilience of CISs using different metrics is necessary to enable stakeholders to appreciate each other's concern and make collective and coordinated decisions. Moreover, existing literature on the impact of interdependencies in the context of CIS disaster risk reduction has primarily focused on the resistance stage while to a large extent disregarding the restoration stage, in which the interdependencies also play a significant role (Sharkey et al. 2016). What remains ambiguous and warrants further investigation is whether the impact of interdependencies varies over different stages of the life cycle of disturbance events and, if so, whether different strategies are required to incorporate this impact in the decision-making of CISs resilience enhancement.

To address these gaps, this study aims to assess the magnitude of the impact of interdependencies on the level of resilience of CISs against disturbances, examine the characteristics of this impact at different stages of the life cycle of disturbance events, and reveal the implications of this impact for the resilience enhancement of CISs in practice. To achieve this objective, this study models interconnected CISs using four different network-based approaches, simulates the disturbance propagation process and system restoration process in three different scenarios, and measures the resilience of disturbed CISs with three different resilience metrics. The methodology and results are detailed in the remainder of the paper.

2 Literature review

2.1 Quantitative assessment of resilience of networked CISs

The quantitative assessment of resilience has fundamental importance in the understanding of the microcosmic mechanism of resilience and the investigation of its impact factors. Prior studies have proposed different frameworks or methods to quantify or assess resilience. An extensively adopted framework was proposed by Bruneau et al. (2003). Their framework defines the resilience of communities or any type of physical and organizational system as the ability to resist the impact of disasters and sustain system performance over time. Resilience is calculated by integrating a functionality curve during the disasters. Chang and Shinozuka (2004) quantified resilience as the probability that a system would satisfy both robustness (minimum performance loss) and rapidity (maximum recovery time) standards during a specific event. Cimellaro et al. (2010a) contended that resilience should be assessed based on analytical functions regarding system robustness and rapidity. Zobel (2011) proposed a method of multi-dimensional resilience measurement that considers the balance between initial functionality losses and recovery speeds. Henry and

Ramirez-Marquez (2012) proposed a measurement method in which resilience is defined as the time-dependent ratio of recovery over maximum loss.

To implement these resilience quantification approaches, the system functionality or performance should be defined and quantified. Different types of CIS performance metrics have been proposed in the literature for this purpose. Since CISs are extensively networked, certain topological properties are required to measure the CIS performance. Examples of typical topology-based system performance metrics include the number of nodes, average degree of nodes, and average critical path length (Duenas-Osorio et al. 2007a, b). The network connectivity of CISs measured by these metrics is regarded as the level of accessibility to commodities delivered by CISs. An alternative type of metric that measures the properties of the delivered commodities by CISs was introduced. Examples include the amount of electricity provided by power grids (Omer et al. 2009; Ouyang and Duenas-Osorio 2012), the quality and quantity of water provided by water distribution networks (Christodoulou et al. 2018), the available traffic flow on roads (Ip and Wang 2011), and the number of patients served by healthcare systems (Bruneau and Reinhorn 2007; Cimellaro et al. 2010b). These metrics may also be calculated as the ratio of the current amount of delivered commodities to the amount of delivered commodities in normal conditions (Reed et al. 2009). To consider the impact of system performance loss on social and organizational systems, economic and social metrics, such as asset losses (Cimellaro et al. 2010a), loss of gross regional product (GRP) (Chang and Shinozuka 2004; Ouyang and Duenas-Osorio 2014), and the number of interrupted customers (Ji et al. 2017), were introduced.

To implement these approaches for resilience quantitative assessment, the time-variant performance of CISs at different stages of an event life cycle, including the post-disaster restoration, should be described. These descriptions can be prepared based on a historical analysis of disaster events using materials such as news reports (Olshansky et al. 2008; McGee et al. 2016), official data statistics (Papathoma-Koehle et al. 2012; Cimellaro et al. 2014b), and field surveys (Kwasinski et al. 2009; Suppasri et al. 2013). Based on these case-based methods, different stages can be identified and defined to describe the time-variant post-disaster CIS performance. For example, Henry and Ramirez-Marquez (2012) proposed a framework to describe various stages (including disruption, disrupted state, and recovery) of CIS performance response to extreme events. Similarly, Ouyang et al. (2012) proposed a three-stage (including resistance, absorption, and restoration) resilience analysis framework. Different approaches were also proposed to quantitatively assess these stages based on simulation techniques. Given a specific extreme event, the CIS performance at the resistance stage can be simulated with agent-based models (Dudenhoeffer et al. 2006; Casalicchio et al. 2010) or network-based models (Duenas-Osorio et al. 2007b; Lee et al. 2007; Holden et al. 2013). The CIS performance is assumed to be constant at the absorption or disrupted stage (Henry and Emmanuel Ramirez-Marquez 2012; Ouyang et al. 2012; Panteli et al. 2017). The time-variant performance of CISs is significantly dependent on external factors, such as the availability of restoration resources and the scheduling of restoration tasks. In prior studies, CIS performance at the restoration stage was described with different types of curves, including linear, exponential, or trigonometric curves. (Cimellaro et al. 2010b). The linear curve is suitable for situations in which information about preparedness and resources is not available (Cimellaro et al. 2010b). The exponential curve is suitable for situations in which the initial response is fast due to a high level of resources and preparedness (Kafali and Grigoriu 2005). The trigonometric curve is suitable for situations in which the response is initially slow due to a lack of preparedness and resources (Chang and Shinozuka 2004).

The existing literature on the quantitative assessment of resilience can be improved in two ways. First, the majority of previous studies adopted only one type of CIS performance metric. However, in reality, different stakeholders are usually concerned with the performance of CISs from different perspectives (Bruneau et al. 2003). For instance, system operators may be more concerned with the technical functionality of a system, whereas city managers may be more concerned with the social impact. These different perspectives and concerns can only be reflected with different system performance metrics, which may not always provide congruent results. Second, the restoration curves of the CISs are coarse-grained, based on simplified system-level assumptions and do not fully capture the impact of the interdependencies among infrastructure systems. To address the first gap, this paper introduces three system performance metrics, which reflect the topological, functional and social perspectives, to assess the resilience of CISs. The results quantitatively reveal the discrepancies among different system performance metrics, behind which are the discrepancies among the concerns of various stakeholders. As a result, the findings may enable stakeholders to appreciate each other's concerns and make collective and coordinated decisions. To address the second gap, this paper describes the time-variant CIS performance at the restoration stage based on a component-level assessment. The time-variant state of each component is determined based on its previous state and the progress of restoration tasks, and the states of all components are integrated to assess the CIS performance at the system level. This bottom-up approach not only provides a fine-grained system performance assessment but also allows consideration of the interdependencies among components from different infrastructure systems.

2.2 Effects of interdependencies in the context of disaster risk reduction

Due to the increasing significance of interdependencies in disaster risk reduction, various empirical approaches have been developed in the literature to identify the CIS interdependencies and analyze their impact. Analyzing historical data is one approach. According to Ouyang (2014), disturbance propagations that repeatedly occur between the components of two CISs in different disaster events suggest the close interdependency between these CISs. Thus, historical data of natural disasters, such as earthquakes and hurricanes, can be collected and analyzed to identify and quantify potentially important interdependency patterns at both the system level (Mendonca and Wallace 2006; Luiijf et al. 2009; McDaniels et al. 2007) and the component level (Chou and Tseng 2010). To facilitate this purpose, several open databases have been made publicly available. For instance, Luiijf et al. (2009) introduced a database that includes 1749 CISs failure incidents in 29 Europe nations; Mendonca and Wallace (2006) built a database that includes 3 months of incident reports about the World Trade Center attack. In addition, different modeling approaches have been developed to simulate the performance of CISs during extreme events. These approaches include agent-based modeling (Dudenhoeffer et al. 2006; Casalicchio et al. 2010), input–output modeling (Haimes and Jiang 2001; Haimes et al. 2005) and network-based modeling (Duenas-Osorio et al. 2007a, b; Lee et al. 2007; Holden et al. 2013). Using these models, the performance of CISs in responding to extreme events can be simulated by either considering interdependencies or not considering interdependencies, and the two sets of results can be compared to identify the time-variant impact of interdependencies on CIS performance (Laprie et al. 2007; Zhang and Peeta 2011; Nan et al. 2013; Portante et al. 2017).

Based on the understanding of the impact of interdependencies on the disaster risk reduction in CISs, numerous recent studies have focused on post-disaster capacity planning by considering interdependencies. Reliability and risk assessment techniques, including failure modes and effects analysis (Uday and Marais 2015), fault and event trees (Fleming et al. 2013), and Bayesian belief networks (Aven 2013), were employed to identify the weaknesses of CISs and suggest pointed enhancement measures. The criticality of different systems and their components were measured using theory-based metrics, such as node degree and network betweenness (Zio and Golea 2010; Winkler et al. 2011), or by considering their connections with associated industries and communities (Oh et al. 2013). The results were applied to guide the design of possible measures to protect the most important systems and components (Pregnolato et al. 2016). Using high-fidelity simulation techniques, CIS performance in responding to extreme events can be simulated. With the objective of minimizing potential system performance losses, a trial-and-error process was conducted to optimize CIS design schemes by varying the characteristics of infrastructure components in simulations (Morcous and Lounis 2005; Ash and Newth 2007; Santella et al. 2009; Martinez-Mares and Fuerte-Esquivel 2013; Wang et al. 2017; Ouyang 2017).

Prior studies have achieved considerable progress in understanding the effects of infrastructure interdependencies in the context of disaster risk reduction and developing appropriate capacity planning measures. Note that these studies have predominantly focused on the resistance stage and to a large extent disregarded the restoration stage, in which the interdependencies also play a significant role (Sharkey et al. 2016). In reality, restoration efforts are usually separately planned and performed in different CISs and lack necessary communication and coordination across CISs, consequently preventing the optimal scheduling of restoration tasks and mobilization of resources. Cavdaroglu et al. (2013) presented a model for optimizing restoration tasks in a single CIS by considering its interdependencies with other CISs. They reported that the restoration process was significantly improved when these interdependencies were considered. This paper simulates the concurrent restoration of different CISs, with holistic consideration of their interdependencies in the sequencing of all restoration tasks. This study enables a comprehensive assessment of the effects of infrastructure interdependencies throughout an entire disturbance event cycle.

3 Representative models and metrics

This section presents the details of four existing network models, including their characteristics, variables and configurations, application scenarios and implementation processes, and the details of three existing resilience metrics, which are adopted in this study for assessing the impact of interdependencies of CISs on their level of resilience.

3.1 Network-based models

3.1.1 Related work

As an emerging approach for CISs modeling, network-based modeling is increasingly adopted in recent studies. CISs can be modeled as networks, in which nodes represent built facilities, and links represent relational connections among the nodes. Different network-based models can be generally grouped into topology-based models and flow-based models, according to a holistic review by Ouyang (2014). These two approaches primarily differ in terms of the definition and calculation of the state of CIS components. The topology-based approaches model each component (node or link) of CISs with discrete states, which are usually binary, including the failed state and the normal state. Numerous studies have been performed with topology-based methods to simulate the failures of nodes and networks (Poljanek et al. 2012; Ouyang and Duenas-Osorio 2011; Duenas-Osorio et al. 2007b; Johansson and Hassel 2010). The flow-based approaches model each component of CISs with continuous states, which are usually calculated as the percentage of the current flow of commodities that pass through a component to the normal level of flow. Numerous studies have applied the flow-based models to examine the interdependencies among different CISs and simulate their responses to different extreme events (Ouyang 2014; Ouyang and Duenas-Osorio 2011; Svendsen and Wolthusen 2007a, b).

3.1.2 Selected modeling approaches

In this study, four network models were selected from the literature and implemented to investigate the impact of the interdependencies among CISs on their disaster resilience. These models include the models proposed by Johansson and Hassel (2010) (referred to as *Model 1*), Duenas-Osorio et al. (2007a) (referred to as *Model 2*), Lee et al. (2007) (referred to as *Model 3*), and Trucco et al. (2012) (referred to as *Model 4*). The representativeness of these models and their detailed configurations, as well as their implementation in this study, are described in this subsection.

Model 1 is a deterministic topology-based network model with limited consideration of the functional properties of CISs. This model was proposed by Johansson and Hassel (2010) to capture the geographic and functional interdependencies among railway, traction power, telecommunication, auxiliary power and electrical in-feed systems in a fictional railway network. This model consists of a topological submodel and a functional submodel. The topological submodel describes the connection relationships among infrastructure facilities, including nodes and directed links, in which each node has a binary state of normal or failed. The functional submodel describes certain functions (e.g., amount of delivered flow) of each node. If the state of a node is normal, the node is fully functional; otherwise, it loses all functionality. In the topological submodel, when a node fails, this failure causes the failure of all nodes that are directly connected to it by links; this propagation of failures will continue throughout an entire network. Then, the functional submodel is applied to recalculate the function of each node and the total function of the network. This model is extensively applied in the vulnerability and resilience analysis of various CISs, such as water distribution systems (Diao et al. 2016) and railway networks (Zhang et al. 2016).

Model 2 is a probabilistic topology-based network model that was proposed by Duenas-Osorio et al. (2007b) to simulate the interdependencies between electric power systems and water supply systems. This model is similar to *Model 1,* with the exception of how it models the disturbance propagation across CISs via their interdependencies. The researchers proposed that the failure of a node in one CIS is conditional, at a certain probability, to the failure of nodes in another CIS on which it relies to function. They also proposed that this probability can be determined based on experience or historical data. For instance, in reality, a failed node in an electric power supply system may cause the failure of interconnected nodes in a water supply system at a certain probability, and vice versa. Based on empirical data, closer proximity of the interconnected nodes can produce a larger probability of cascading failure. The conditional probability of cross-CIS cascading failure can be determined based on the spatial proximity of the connected nodes. This model has been extensively adopted in prior research for vulnerability analysis of CISs (Ouyang et al.

2009; Duenas-Osorio and Rojo 2011), cascading failure simulation (Duenas-Osorio and Vemuru 2009; Hernandez-Fajardo and Duenas-Osorio 2013) and disaster risk assessment (Poljanek et al. 2012).

Model 3 is a flow-based network model that was proposed by Lee et al. (2007) to simulate the interdependencies among electric power systems, telecommunications systems, and subway systems. In this model, each node or link has two parameters (i.e., flow and capacity). Flow refers to the actual rate at which commodities pass through a given node or link, and capacity refers to the maximum flow allowed by a given node or link. The node state is a continuous variable between zero and one, which represents the ratio of current flow to normal flow. The disturbance propagation is modeled in such a manner that, for a node in one CIS that relies on commodities from nodes in other CISs to function, the decrease in these commodities may proportionally reduce the capacity of this node. For instance, a water-pumping station relies on electric power to work. If the amount of electric power that is provided is decreased to a critical level on which it becomes the bottleneck for the water-pumping station to function, then the capacity of the water-pumping station would be assumed to proportionally decrease, regardless of whether the serviceability of other infrastructures on which the water-pumping station relies to function also decreases. In addition, this model assumes that the flow of a node or link cannot exceed its capacity and that the total flow supply in a CIS equals the total flow demand. The model also considers flow redistribution, which is aimed at satisfying as much flow demand as possible in a CIS immediately after a disturbance by changing and rebalancing the flow of all nodes and links within their respective capacities. *Model 3* has been adopted in original or revised forms in numerous studies and applied to, e.g., resilience assessment of railway systems (Adjetey-Bahun et al. 2016), and a vulnerability analysis of interdependent infrastructures (Holden et al. 2013).

Model 4 is another flow-based network model that was proposed by Trucco et al. (2012) to simulate the interdependencies among transportation systems, electric power systems, and gas systems. In reality, the demands of different end users for CIS commodities are not always indifferently satisfied. For instance, when commodities are limited, the demand of critical components in interconnected CISs may be prioritized. *Model 4* reflects this situation. It is similar to *Model 3,* with the exception of how it models disturbance propagation. *Model 4* assumes that when the commodities delivered by components in a CIS decrease, the supply of these commodities to certain critical and prioritized components in other CISs remains at a certain level, while the supply to other components proportionally decreases. Numerous studies have adopted or extended this model in the simulation and risk assessment of interdependent CISs (Lu et al. 2015; Rehak et al. 2016).

3.2 Resilience metrics

The assessment of resilience has fundamental importance to the understanding of the microcosmic mechanism of resilience and investigation of its impact factors. Existing studies of resilience metrics have been reviewed in Sect. 2. In this study, three metrics were employed: metrics proposed by Duenas-Osorio et al. (2007b) (referred to as *Metric 1*), Omer et al. (2009) (referred to as *Metric 2*) and Reed et al. (2009) (referred to as *Metric 3*). These three metrics focus on the structure, functionality, and social impact of CISs. Their representativeness, computation, and implementation in this study are described in this subsection.

The three resilience metrics adopted in this study are calculated as the integral of the ratio of the actual level of system performance to the normal or desired level of performance over the entire disturbance event cycle, including the destruction stage and the restoration stage. They can be calculated as follows:

$$R = \frac{\int_{t_0}^{t_1} Q(t)\mathrm{d}t}{Q_0(t_1 - t_0)} \tag{1}$$

where R denotes the level of resilience, Q_0 denotes the normal or desired level of system performance, $Q(t)$ denotes the actual level of system performance, and t_0 and t_1 denote the time of disturbance occurrence and system full recovery, respectively. The system performance is assumed to fully recover to the normal or desired level after a certain amount of time, where t_1 is definite. The units of Q_0 and $Q(t)$ are determined by the definition of system performance, which differs among different metrics. The three metrics primarily differ with regard to how they define system performance.

Metric 1 defines system performance as the average of the shortest path lengths between any two nodes. This definition reflects the structure connectivity of the CISs network (Duenas-Osorio et al. 2007b). The average of all shortest path lengths can be calculated based on Eq. (2):

$$\mathrm{CPL} = \frac{n(n-1)}{\sum_{i \neq j \in V} \frac{1}{d_{ij}}} \tag{2}$$

where CPL denotes the average of all shortest path lengths, d_{ij} denotes the shortest path length (measured by the number of links traversed) from node i to node j, V denotes the set of all nodes, and n denotes the number of nodes in V. When a node fails, all links from this node and toward this node become invalid. This metric reflects the accessibility of users to commodities delivered by the CISs. *Metric 1* has been extensively adopted in prior studies for CIS network resilience assessment (Ouyang et al. 2009; Holden et al. 2013).

Metric 2 defines system performance as the actual flow in a system at a given point of time in the disturbance event cycle. This definition emphasizes the functionality of CISs (Omer et al. 2009). The actual flow can be calculated as the sum of the actual flow delivered by all nodes to end users, as expressed in Eq. (3):

$$F = \sum_{i}^{N} s_i f_i \tag{3}$$

where F denotes the current flow, s_i denotes the state of node i, f_i denotes the flow that each node normally delivers to end users, and N denotes the number of nodes in the network. *Metric 2* has been employed in numerous studies (Ouyang and Duenas-Osorio 2012; Ouyang et al. 2012).

Metric 3 defines system performance as the satisfied end user demand. The actual satisfied end user demand is usually measured by the number of consumers served by a CIS and can be calculated as follows:

$$P = \sum_{i}^{N} s_i p_i \tag{4}$$

where P denotes the number of consumers served by a CIS serves, s_i denotes the state of node i, p_i denotes the number of consumers typically served by each node, and N denotes the number of nodes in the CIS. *Metric 3* is an extensively adopted resilience metric in various studies (Bruneau and Reinhorn 2007; Ouyang and Duenas-Osorio 2014). This metric reflects the social impact of the system to some extent (Reed et al. 2009).

4 Model implementation and resilience assessment

4.1 Case city

A case study was conducted in a middle-sized Chinese city for this study. Located at an intersection of several major economic regions in Eastern China, the case city has an area of approximately 1000 km^2 and a population of approximately 300,000. Three CISs in the case city—the electric power supply system, water supply system, and telecommunication system—were examined. The number and location of the CIS facilities and their connections were determined based on the CIS design and operation data obtained from local authorities and field visits. Built facilities, such as water plants and electric substations, were regarded as nodes, whereas transmission lines and pipelines were regarded as links, as shown in Fig. 1. A total of 45 nodes and 90 links were identified, as summarized in Table 1. The data of system flows were collected based on system monitoring data and historical records provided by local authorities. Due to the incompletion of actual data, a few interdependencies that were not documented in available design schemes were set in

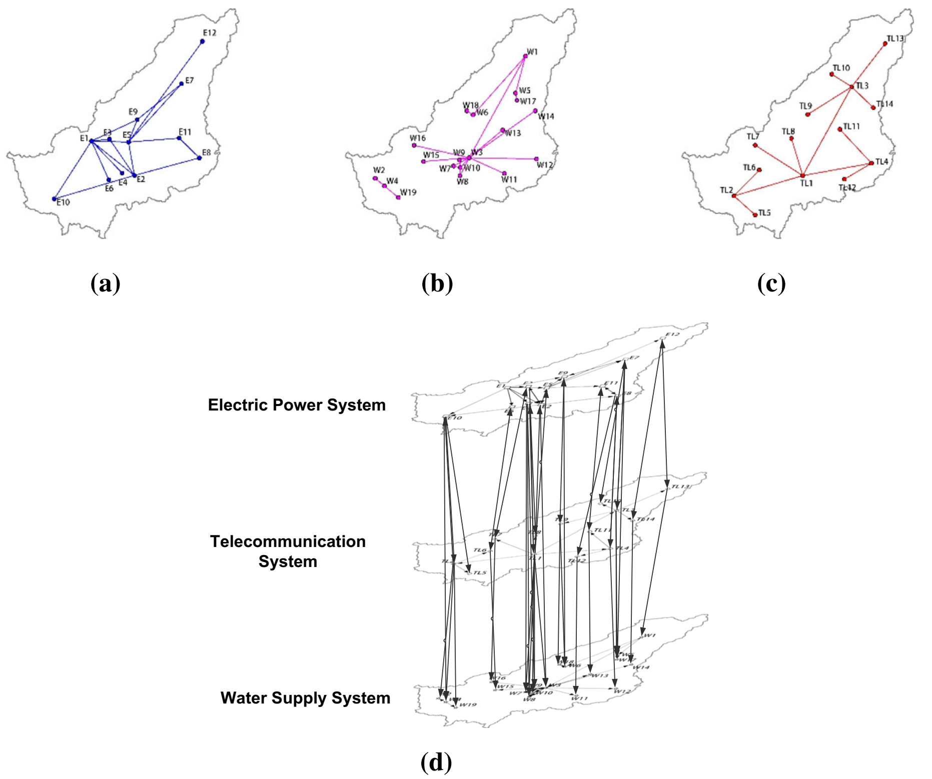

Fig. 1 CISs in the case city: **a** electric power supply system; **b** water supply system; **c** telecommunication system; **d** interdependencies among three CISs

Table 1 CIS facilities and connections in the case city

Systems	Facilities	Connections
Electric power system	Substations (12)	Power cables (38)
Water supply system	Reservoirs (2), plants (4), pumps (3), control valves (10)	Water pipelines (20)
Telecommunication system	Data centers (14)	Fibers (32)

this case study based on common sense. For instance, the facilities in water supply and telecommunication systems require power supply from nearby electrical substations to operate, and the facilities in the water supply and electric power supply systems rely on nearby data centers for remote sensing and control.

4.2 Hazard simulation

A possible disaster scenario was simulated in the case city to expose the CISs to a regional disturbance event, in which multiple nodes and links would undergo destruction and restoration. A typhoon was the most likely type of disturbance in the case city according to the city's historical hazard records. The HAZUS-MH Hurricane Model (Vickery et al. 2006a, b) was utilized to simulate a typhoon disaster. Each CIS component in the case city had a fragility curve against a typhoon. When given the strength of the typhoon, the failure probability of a CIS component could be calculated as the cumulative probability below the strength in the fragility curve. Different parameters of CIS components were used to determine the fragility curve of the CIS components in the case city. These parameters primarily included altitude and land use, which were established based on hypsometric maps and urban planning data; structural strength, which was determined based on the type of components and their construction standards; and surface roughness, which was assumed to be uniform for all components for simplicity purpose. When the strength of the typhoon was determined, the failure probability of every CIS component was calculated based on its fragility curve.

A grade-12 typhoon (33 m/s wind speed) was simulated in the case city. CIS components whose probability of failure exceeded 50% in the simulations were regarded as physically damaged and functionally failed. These failures were applied as the initial impact of the typhoon event that would subsequently propagate throughout the entire networked CISs. The distribution of the initially failed nodes in the simulation is depicted in Fig. 2.

4.3 Disturbance propagation simulation

Models 1–4 were implemented in the case study to model the three CISs and their interdependencies. The initial and propagated impacts of typhoon disturbance on these CISs were simulated. The disturbance propagation process simulated at the resistance stage was decomposed into sequential steps. In each step, the disturbance propagated from the current failed nodes in the network to the nodes that were directly connected to them. The state of every node was updated after each step, and the disturbance propagation process ended when the state of all nodes became stable. The time series data of the node states over the entire resistance stage was analyzed to reveal the disturbance propagation paths

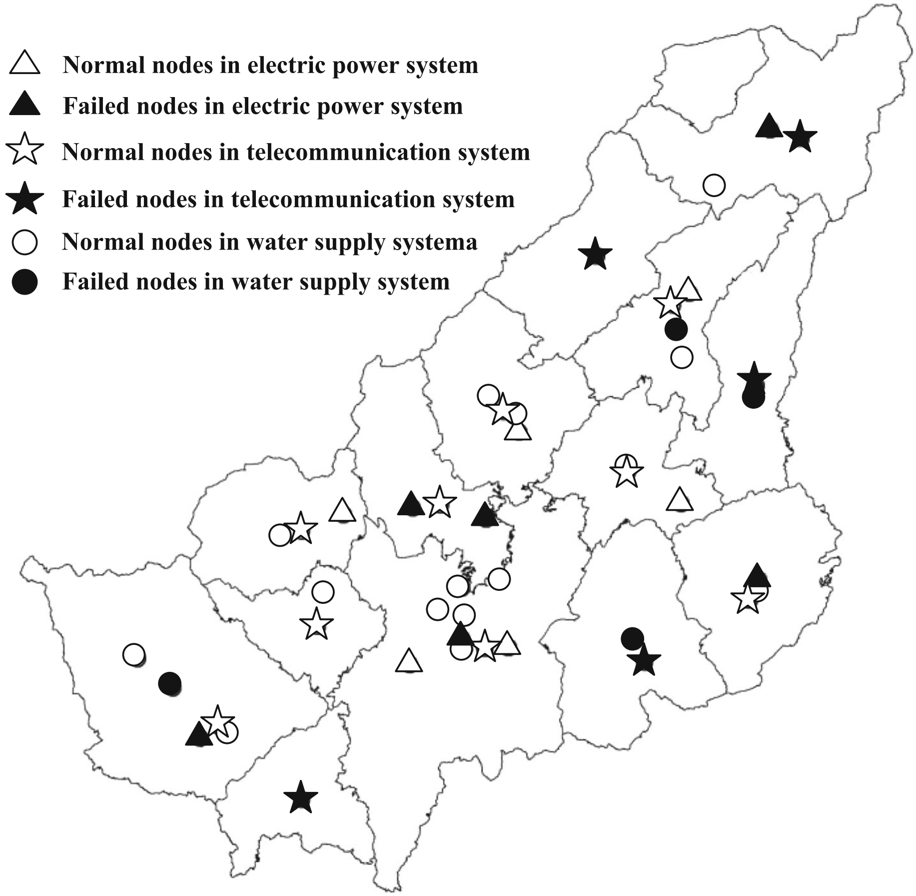

Fig. 2 Initial damages by typhoon in the case city

and patterns. Two sets of simulations were conducted. The first simulation considered CISs interdependencies, and the second set did not consider CIS interdependencies. If interdependencies were not considered at the resistance stage, each CIS was regarded as independent, and disturbance propagation was restrained within individual CISs without crossing different CISs.

The simulation of disturbance propagation is further explained as follows:

In *Model 1*, following Johansson and Hassel's work (2010), a disturbance propagated from one node to another node when a link between the two nodes existed.

In *Model 2*, following Duenas-Osorio et al.'s work (2007b), a disturbance propagated between two connecting nodes at a conditional probability, which was determined based on the spatial proximity of the nodes. Specifically, the conditional probability was proportional to the reciprocal of the geographical distance between two connecting nodes (Duenas-Osorio et al. 2007b). In addition, the conditional probability between the closest connecting nodes in the network was set to 0.7 (Duenas-Osorio and Vemuru 2009), and other conditional probabilities were normalized accordingly. One exception was the cascading failure caused by cyber interdependency, which primarily affected the flow redistribution capability of the CISs. A constant value of 0.2 was employed as the probability of the disturbance propagation through the cyber interdependencies (Dudenhoeffer et al. (2006).

In *Model 3*, the normal flow of CIS facilities was determined based on historical flow records following Lee et al.'s work (2007), and the normal capacity was set to 1.2 times the normal flow according to Ouyang and Duenas-Osorio (2012). In addition, this model assumed that nodes in the electric power supply or water supply systems would not be able to conduct flow redistribution due to a loss of remote sensing and control functions if telecommunication nodes on which they relied failed.

In *Model 4*, following Trucco et al.'s work (2012), the disturbance propagation was established based on a literature review and actual practice surveyed in the case city. Specifically, the model assumed that when the flow of commodities delivered by a node decreased below 50% of its normal level, the supply of these commodities from this node to predetermined critical nodes would stop decreasing, whereas the supply to other nodes would continue to proportionally decrease.

4.4 Restoration simulation

In the simulation of the restoration stage, some assumptions were made according to the literature on restoration simulation (Shoji and Toyota 2009; Matisziw et al. 2010; Nurre et al. 2012). Restoration efforts were assumed to be coordinated and separately undertaken within each CIS, which is common in practice. The resources required to restore CIS facilities were assumed to be limited, and therefore, in each CIS, a maximum of one node could be under restoration at any given point of time. The scheduling of restoration tasks was based on the priority of nodes that required repair and did not consider any logical relationships for simplification. The priority of a node was based on the population that would be affected by the failure of this node (Guha et al. 1999; Xu et al. 2007). When interdependencies in restoration were not considered in the simulation, this population included only consumers of commodities that pass through the failed node; when interdependencies were considered, this population also included consumers impacted in other CISs. Note that only physically damaged nodes required restoration. Nodes that were physically intact but functionally failed due to propagated disturbance impact did not require restoration. These nodes would restore as soon as all nodes on which they relied to function were restored.

Repairing a failed node required a certain amount of time. The simulation assumed that the level of functionality of the node being repaired would gradually increase over time until it was fully restored. A performance curve was introduced to describe this process. This curve could be linear, exponential, or trigonometric according to the literature review in Sect. 2. Considering the fact that emergency plans and restoration resources are generally available for CISs in cities, an exponential curve was established in this study. Specifically, the following performance curve was employed in this study (Reed et al. 2009):

$$Q(t) = Q_0 - Q_0 e^{-bt} \tag{5}$$

where Q_0 denotes the normal level of system performance, $Q(t)$ denotes the actual level of system performance at time t, t denotes the time required after restoration starts, and b denotes a parameter that adjusts the total restoration time. Each failed node was assumed to require the same amount of time to be restored to its normal state. In addition, to simulate the node restoration as discrete events, the restoration process of a node was divided into five phases, with each phase requiring time T. In *Models 1* and *2,* in which the node state was binary, a failed node would recover to its normal performance level after 5T. In *Model 3* and *Model 4*, the performance level of a failed node was updated after each phase based on Eq. (5).

4.5 Resilience assessment

Metrics 1–3 were employed to measure the resilience of CISs in the case study. The state of each node in the CISs was continuously updated throughout the life cycle of the disturbance event. Specifically, to compute *Metric 1*, the average of all shortest path lengths was calculated based on the network topologies. To compute *Metric 2*, the amount of commodities of each leaf node delivered to the end users was calculated by subtracting the node's out-flow from its in-flow. To compute *Metric 3*, the number of consumers served by each node was estimated based on the population of the administrative district in which the node was located. The population statistics were obtained from the latest census data of the case city. In addition, for *Metric 2* and *Metric 3,* the level of resilience was assessed within each CIS, and the results were mathematically averaged to calculate the total resilience of the entire networked system for simplicity. Because the node state in *Models 3* and *4* was a continuous variable and *Metric 1* was only applicable to the discrete node state, *Metric 1* was not applied to assess the resilience of the CISs represented using *Model 3* and *Model 4*.

5 Simulation results

Simulations were performed in three different scenarios in this study. The results of the simulations were compared to assess the impact of the interdependencies on the level of resilience of the networked CISs at different stages of the life cycle of the simulated extreme event. The three simulation scenarios are described as follows: (1) disregard the interdependencies at both the resistance stage and the restoration stage (*simulation scenario* 1), (2) consider the interdependencies at only the resistance stage (*simulation scenario 2*), and (3) consider the interdependencies at both the resistance stage and the restoration stage (*simulation scenario* 3). For each simulation scenario, extensive simulations were run using 10 different simulation settings. Each simulation setting refers to a combination of one of the four CISs models and one of the three resilience metrics. These simulation settings are summarized and labeled in Table 2.

Strictly following the model implementation and resilience assessment procedures explained in Sect. 4, the responses of the CISs to a typhoon disaster in the case study were simulated using MATLAB. Given the probabilistic nature of *Model 2*, its simulation was

Table 2 Simulation settings with different models simulation and metrics assessment

	Model 1	Model 2	Model 3	Model 4
Metric 1	a	d	–	–
Metric 2	b	e	g	i
Metric 3	c	f	h	j

run 10,000 times, and the results were averaged. The simulation results for the other three models were deterministic; thus, these simulations were run once. As previously mentioned, the resistance stage, which can instantaneously occur in reality, was decomposed into a number of sequential steps for an analytical purpose, and the restoration stage was decomposed into phases that each required time T. The simulation results are depicted in Figs. 3 and 4.

As shown in Fig. 3, the decline in system performance was significantly higher, regardless of the simulation settings, when the interdependencies and the resulting cascading failures were considered. In scenario 1, the performance losses, which were based on *Metric 1, Metric 2, and Metric 3* and averaged over different models, were 68, 43, and

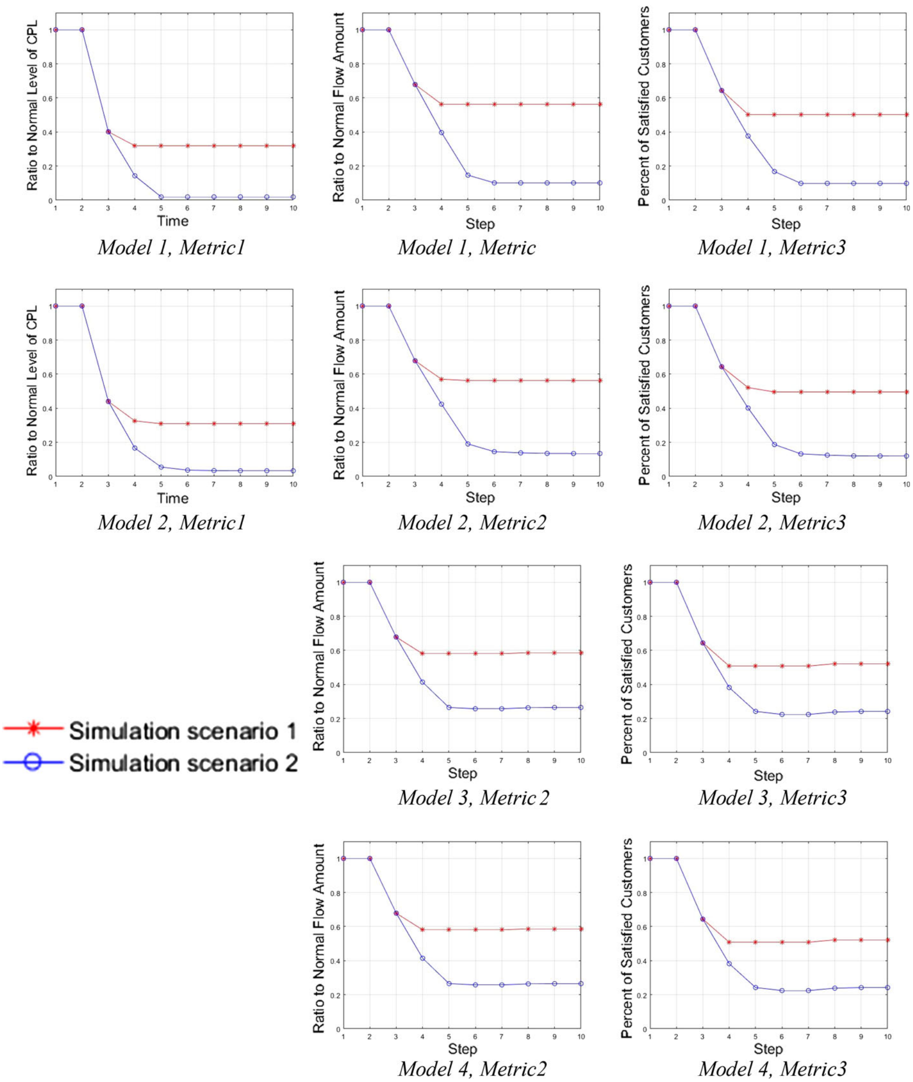

Fig. 3 Simulation results of disturbance propagation in CISs for different simulation scenarios and settings

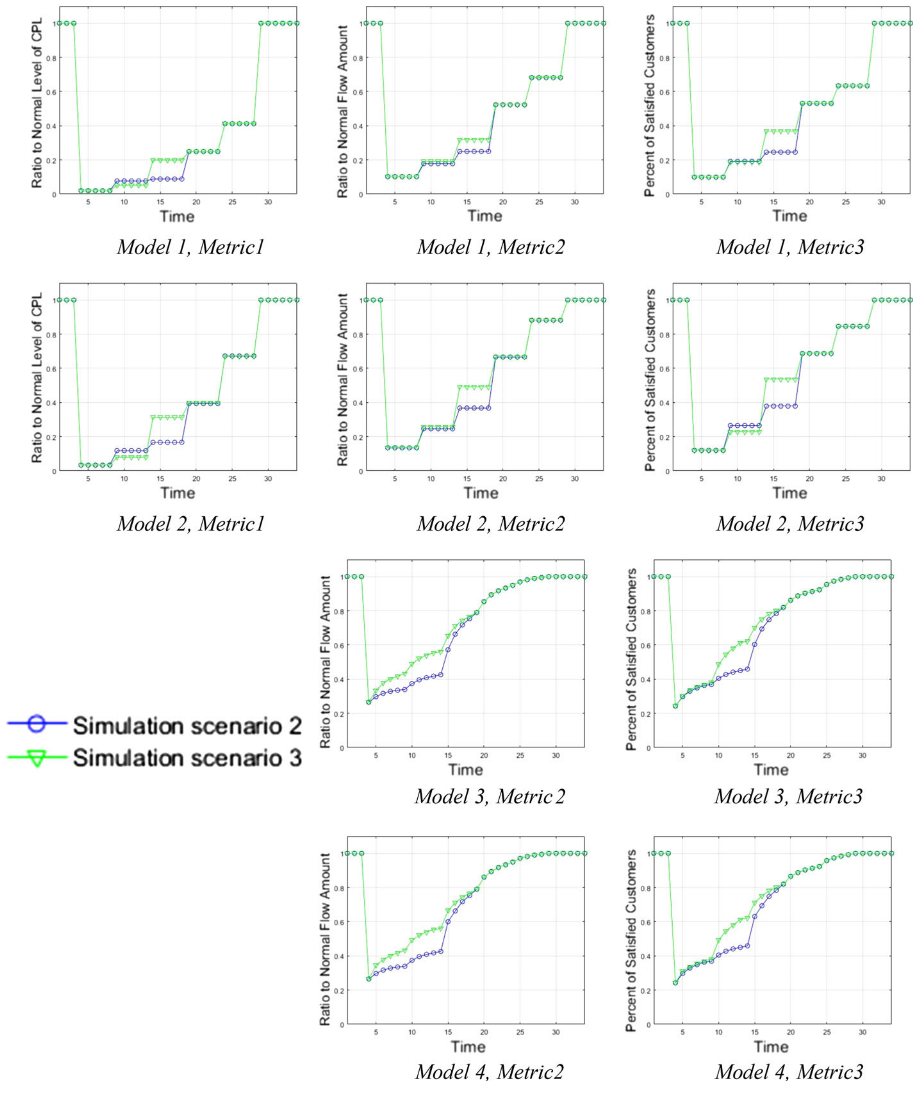

Fig. 4 Simulation results of the response of CISs to a typhoon event for different simulation scenarios and simulation settings

49%, respectively, whereas the performance losses in scenario 2 were 97, 81, and 82%, respectively. This result suggested that the actual maximum performance losses could be up to twice of what people would expect if they ignored the interdependencies across CISs, which would cause underestimation of disaster impacts and insufficient preparedness. The simulation results indicated that a total of 20 nodes failed in *Models 1* and *2* in scenario 1, whereas this number increased to 41 in *Model 1* and 37 in *Model 2* in scenario 2. Similarly, in scenario 1, a total of 18 nodes completely failed and two nodes partially lost their functionality in *Models 3* and *4*, whereas a total of 30 nodes completely failed and five nodes partially lost their functionality in both models in scenario 2. The additional node failures were primarily caused by power outages that caused malfunctions of facilities in other CISs and the unavailability of telecommunication services that caused a loss of remote sensing and control and invalidation of the flow redistribution.

Table 3 summarizes the resilience assessment results for scenarios 1 and 2. As shown in the table, the resilience level was 0.36, 0.31 and 0.30 lower when the interdependencies were considered in the resistance stage, based on *Metric 1, Metric 2*, and *Metric 3*, respectively. This finding indicated that the resilience of interconnected CISs could be substantially overestimated when interdependencies across CISs were disregarded, considering the entire life cycle of disaster events. Note that the resilience assessment was generally consistent across different models, with small standard deviations of 0.008, 0.030, 0.034 in scenario 1 and 0.076, 0.142, 0.151 in scenario 2, based on the three metrics. Comparing the results across metrics, the resilience level assessed with *Metric 1* was lower than the resilience level assessed with *Metrics 2* and *3*, which suggested that CIS network topologies can be more vulnerable to disaster impacts than CIS network functionalities. In addition, in scenario 2, the system performance increased by 0.7 and 1.8% based on *Metrics 2* and *3*, respectively, due to the flow redistribution.

A comparison of the simulation results between scenario 2 and scenario 3 is depicted in Fig. 4. The optimized restoration sequencing in scenario 3 always produced a faster restoration of system performance, regardless of the simulation settings. The time required for the system performance to recover to 50, 70, and 90% of its normal level was reduced by 3.17T, 2.34T, and 0.11T, respectively, when the interdependencies were considered in the scheduling of restoration tasks, based on *Metric 1, Metric 2, and Metric 3*, respectively. This difference was particularly distinct before the system performance recovered to 70%, which suggests that improving restoration tasks sequencing has significant importance in the efficiency of the initial performance, which is also the most important stage in post-disaster restoration.

The resilience level was improved by 0.04, 0.03, and 0.03 by considering the interdependencies in the optimization of the restoration tasks sequencing, as measured by *Metric 1, Metric 2,* and *Metric 3*, respectively. The results are summarized in Table 4. Due to the simple structures of the CISs in the case study, the restoration tasks sequencing in scenarios 2 and 3 was similar, with the exception on one node in the electric power system, which was prioritized in scenario 3 due to its interconnections with nodes in the water supply and telecommunication systems. In reality, CIS structures can be substantially complicated and interlinked, which will likely create larger differences between local optimal restoration

Table 3 Resilience assessment that compares simulation scenarios 1 and 2

	Model 1	Model 2	Model 3	Model 4
Metric 1				
Scenario 1	0.587	0.598		
Scenario 2	0.169	0.277		
Metric 2				
Scenario 1	0.770	0.767	0.820	0.820
Scenario 2	0.347	0.459	0.635	0.637
Metric 3				
Scenario 1	0.767	0.764	0.824	0.824
Scenario 2	0.340	0.459	0.647	0.648

Table 4 Resilience assessment that compares simulation scenarios 2 and 3

	Model 1	Model 2	Model 3	Model 4
Metric 1				
Scenario 2	0.169	0.277		
Scenario 3	0.186	0.348		
Metric 2				
Scenario 2	0.347	0.459	0.635	0.637
Scenario 3	0.363	0.489	0.682	0.683
Metric 3				
Scenario 2	0.340	0.459	0.647	0.648
Scenario 3	0.363	0.484	0.683	0.684

tasks sequencing and global optimal restoration tasks sequencing and consequent differences in restoration efficiency.

6 Discussion

This study aimed to assess the impact of interdependencies on the resilience of networked CISs. The resistance and restoration stages of CISs in response to certain hazard events were simulated with four existing modeling approaches of interconnected CISs. Three existing resilience metrics were employed to assess the level of resilience of CISs modeled with these approaches. The simulations were based on different combinations of CISs modeling approaches and resilience metrics to assure that the assessment of the impact of CISs interdependencies would be independent of the selection of modeling approaches or resilience metrics.

The simulation results indicated that the performance losses were significantly higher and the level of resilience was significantly lower when the interdependencies were considered in the resistance stage. This finding was consistent with the findings reported in various studies (Duenas-Osorio et al. 2007b; Johansson and Hassel 2010; Arboleda et al. 2006). Quantitative assessments revealed that indirect disaster impacts caused by CISs interdependencies were as severe as direct disaster impacts, which reveals the significance of cross-CIS disturbance propagation. The results suggested that the disaster risk reduction (DRR) of CISs should adopt a system-of-systems (SoS) approach (Kasai et al. 2015) to identify vulnerable components that have the most significant global impact and take appropriate measures. By tracing the disturbance propagation over time in the simulation, the outage of electric power was determined to have an important role in escalating the magnitude of indirect disaster impacts, which was consistent with prior studies (Duenas-Osorio et al. 2007b; Lee et al. 2007; Trucco et al. 2012). In this study, node failures in the electric power system were responsible for approximately 70% of all node failures. This finding highlighted the criticality of sufficient redundancy for interconnectivity between electric power systems and systems that require electric power supply to function. The node failures in the communication system caused an additional 30% of failed nodes. This finding suggested that remote control in electric power and water supply systems should be strengthened and protected. The results also indicated that the flow redistribution and the practice of prioritizing the demand of certain critical components caused a slight increase in CIS resilience. The effect of these two measures would be more significant and distinct and cause further mitigation of disaster impacts when the structures of CISs become more complicated.

In current practice, restoration sequencing is usually determined ad hoc and is substantially dependent on the order by which failures are reported (Ouyang et al. 2012). Optimizing the restoration sequencing can significantly increase the efficiency of restoration tasks with the same resource limit (Xu et al. 2007; Ouyang et al. 2012). To assess the impact of interdependencies, the restoration sequencing was optimized in scenarios 2 and 3, which differed in whether interdependencies were considered. The simulation results indicated that the level of resilience was noticeably higher when restoration sequencing was optimized with interdependencies considered, especially during the immediate aftermath of disasters when fast restoration of critical infrastructure components is critical. These results suggested that global planning and management that coordinate different CISs, rather than decentralized management that focuses on the component level, should be adopted. An SoS approach, which would enable the development of a globally satisfactory and sustainable solution, rather than a locally optimal solution, is preferred in restoration task sequencing problem.

The simulation results were generally consistent across different simulation settings with four observations: (1) the simulation results, including performance losses, node failure, resilience assessment, were generally consistent with slight deviations across simulation settings, (2) the topology-based models were more sensitive to interdependencies than the flow-based models; (3) the difference in the simulation results across models was slightly enlarged when the interdependencies were considered; and (4) although the resilience assessments were metric-dependent, the magnitude of the differences in resilience, either between scenario 1 and scenario 2 or between scenario 2 and scenario 3, was generally consistent across metrics. These results suggested that the models and metrics that were selected in this study were reasonable and that the conclusions of this study regarding the impact of interdependencies on interconnected CISs were generally independent of the CISs modeling approaches and resilience metrics.

7 Conclusions

This study simulated the resistance and restoration stages of interconnected CISs in response to a regional disturbance. The CISs were modeled using four network-based approaches, and their resilience levels were assessed using three different metrics. By comparing the simulation results for three different scenarios, the impact of interdependencies on the resilience of CISs was identified and quantitatively assessed. The simulation results indicated that regardless of the network-based CIS models and CIS resilience metrics, the interdependencies between different CISs had a significant impact on the responses of the networked CISs to simulated extreme events during the resistance and restoration stages and on their total level of resilience. Specifically, the results revealed that the vulnerability of CISs to extreme events would be significantly underestimated if the interdependencies of the CISs were not considered, which would cause a misleading estimation of the total level of resilience of the CISs. The findings also suggested that the interdependencies of CISs must be considered in the restoration task sequencing to optimize the efficiency of post-event restoration tasks. It was speculated that the impact of interdependencies would be more distinct when the structure of CISs increased and became complex. Note that the methodology described in this paper is applicable to CISs with the network type of topology and measurable flows. Extending this methodology to other types of critical infrastructures requires additional research. The study could also be extended in future research by modeling other types of CISs interdependencies and simulating other types of extreme events.

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