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Assessing the impact of systemic heterogeneity on failure propagation across interdependent critical infrastructure systems

Fei Wang [a], Joseph Jonathan Magoua [a], Nan Li [a,b,*], Dongping Fang [a]

[a] Department of Construction Management, Tsinghua University, Beijing, 100084, China
[b] Hang Lung Center for Real Estate, Tsinghua University, Beijing, 100084, China

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ABSTRACT

The systemic heterogeneity between different critical infrastructure systems (CISs) can significantly influence the failure propagation process across the systems. For instance, when power supply systems are affected by an earthquake, physical damages mainly occur at nodes and seldom occur at links, since the cables are flexible enough to withstand the impacts. Water supply systems on the other hand are prone to experience physical damages at both nodes and links. However, despite the increasing volume of literature that examines failure propagation risks across interdependent CISs, only few studies have accounted for various systemic heterogeneity factors (HFs) and their potential impact on cascading failures. The aim of this study is to reveal and quantify the significance of such impact, for which a four-step approach is introduced. A case study was conducted, which examined the impact of three HFs on failure propagation across two interdependent power and water supply systems in the event of a simulated earthquake. Seven improved models were developed and their respective simulation results were compared. The comparison of simulation results from the baseline model and improved models revealed that the impact of the simulated earthquake disaster on CISs would be significantly mis-estimated if the HFs were not considered, and that each HF impacted the failure propagation in a different way. The proposed approach and the findings in the case study are expected to uncover the drawbacks in current CISs failure propagation models, and provide a foundation for the development of more reliable failure propagation modeling approaches in future research.

1. Introduction

Critical infrastructure systems (CISs), such as power and water supply systems, constitute the backbone of our cities and therefore, their reliable performance is crucial to ensure the sustainable development and security of human societies [1]. CISs are not independent of each other but rather show a variety of dependency relationships [2–4]. Physical components from one infrastructure system may depend on components from the other infrastructure systems and vice versa, as a result, failure of a component in one system may cause failure of components in the dependent systems [5]. For example, the power supply system supplies electricity needed to power the pumping station of the water supply system, which in turn supplies the power system with cooling water needed by its power plant. These bi- or multi-directional dependences, also referred to as interdependencies [3,6], may result in a set of complex topological network interactions and hidden feedback loops between the CISs, which subsequently could alter the disaster response behavior of individual CISs [7]. In a system-of-systems that is composed of multiple CISs, local disturbances may propagate in an unusual and unpredictable manner, resulting in ripple effects across the entire CISs, which in the worst cases can lead to global failure [8,9].

Systemic heterogeneity of interdependent CISs refers to the differences between the CISs in terms of their physical network features, transported material properties, operational characteristics and responses to disaster [10–14]. Systemic heterogeneity is the main cause of the difference in failure propagation mechanisms among CISs [10,13]. For instance, compared to the water supply system, the power grid is more susceptible to overload damage of components due to power flow redistribution within the system after some components are damaged by a disaster event [15]; Also, in power supply system, physical damage mainly occurs at the nodes since the links (i.e. cables) are flexible enough to withstand the impacts. On the other hand, in the water supply system, both the nodes and links are prone to physical damages since they are rigid elements [15,16]. Heterogeneity is an important aspect

* Corresponding author. Department of Construction Management, Tsinghua University, Beijing, 100084, China.
E-mail address: nanli@tsinghua.edu.cn (N. Li).

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not to be overlooked when analyzing the mechanisms of self-organization and synchronization schemes in the field of statistical physics [17]. Despite its prevalence and significance, the impact of systemic heterogeneity on failure propagation across CISs and its overall disaster responses have not been adequately recognized and addressed in prior research. Although several studies have pointed out the possible impact of systemic heterogeneity, and emphasized the need to account for this impact in the modeling of CISs failure propagation as well as the estimation of CISs disaster losses [6,7,18,19], the magnitude of this impact and its underlying mechanism have largely remained unknown. This is manifested by the fact that most existing models of interdependent CISs do not incorporate various systemic heterogeneity factors (HFs) such as heterogeneity in susceptibility to overload damage and heterogeneity in locations of the main physical damage, that may have significant implications for failure propagation across the CISs. Instead, the CISs are largely considered homogenous in these models with respect to their disaster response patterns, which would inevitably lead to considerable inaccuracies in the simulated failure propagation processes and outcomes.

It is therefore hypothesized that if not properly considered, systemic heterogeneity would notably amplify or attenuate the overall disaster impact on interdependent CISs reported by simulation models. Such inaccurate estimate of disaster impact would prevent the implementation of appropriate disaster risk reduction measures and subsequently lead to insufficient disaster preparedness or overreaction. The aim of this study is to test the above hypothesis by proposing a four-step approach for assessing the impact of systemic heterogeneity on failure propagation across interdependent CISs, and hence investigate the importance of considering systemic heterogeneity in interdependent CISs models. Based on the proposed approach, semi-empirical fragility models should first be selected for different types of CISs components. A baseline CISs model should then be developed, followed by the development of a series of improved models that incorporate different HFs to the baseline model. Lastly, the above models should be subjected to a simulated disaster, and the results from each improved model should be compared to the results from the baseline model in terms of a set of criteria, to assess the impacts of the HFs on the failure propagation process and outcomes. In a case study conducted to demonstrate the efficacy of the proposed approach, a typical coupling of two CISs (i.e. power supply system and water supply system) was modeled using a widely adopted modeling approach (i.e. artificial flow-based (AFB) network modeling). The impact of systemic heterogeneity was then assessed under a simulated earthquake scenario by comparing the failure propagation results from a series of improved models which incorporated different systemic HFs, to the results from a baseline model which did not consider systemic heterogeneity. Results from this study are expected to raise the awareness of the drawbacks in current CISs failure propagation models, and serve as a foundation for the development of more reliable failure propagation modeling approaches in future research.

The remainder of this paper is organized as follows: Section 2 presents related works and discusses current research gaps; Section 3 describes the methodology of this study; Sections 4 and 5 presents a case study and the results, respectively, followed by Section 6 that discusses the findings as well as their theoretical and practical implications; Section 7 concludes the paper.

2. Related work

2.1. Approaches for modeling CISs

Many approaches for modeling interdependent CISs have been developed in prior research. Earliest studies relied mostly on data from historical events and professional experience to identify the relationships between different CISs [16]. However, the limited amount of historical data and the subjectivity of expert opinion often led to incomplete and inaccurate understanding of the characteristics of interdependency between the CISs.

With the development of network science, many research barriers were lifted and considerable progress was observed in the area of CISs modeling [20,21]. Since CISs can easily be represented as networks, with the nodes and links representing different system components and their connections respectively, researchers began to use complex network models to solve CIS-related problems [22]. For instance, interdependency links were introduced to model and analyze the interdependent relationships between different CISs [7,23]. CIS modeling approaches that use complex network representation can be classified under two main categories namely, topology-based (TB) approaches and flow-based approaches [24]. These two categories mainly differ in terms of whether the approaches only model the topology of the network or both the topology and material flow within the network. A few other network models have also been proposed to represent and analyze CISs by integrating other logical algorithms to describe interactions. Examples include the petri-net model [25] and Bayesian network model [26–28]

CISs can also be described as complex adaptive systems consisting of many unique components or elements that have different individual characteristics and operational mechanisms [29]. The agent-based modeling (ABM) is a widely used bottom-up modeling approach for analyzing complex adaptive systems. An ABM model usually consists of a number of autonomous units called agents, which are linked together by interactions or relationships [30]. An agent can be a component, operator, element or signal of a CIS or even a CIS itself [20,31]. Developing an ABM model follows two important and relatively difficult steps [32]: the first is the identification of agents, i.e. how many and which of the agents should be taken into consideration; the second is the description of agent interactions, i.e. how these agents interact with each other. In prior research, the ABM approach has been adopted mainly to model and analyze the nonphysical relationships between CISs, such as the economic relationship between the CISs [33]. ABM can also be adopted to study the physical relationships between CISs. For example, an ABM model was used to assess the seismic resilience of an interdependent electric power supply system (EPSS), transportation system (TS), and the community, by defining three agents, including an EPSS operator, TS operator and community administrator [31].

The system dynamics (SD) modeling approach, which is a top-down approach for analyzing complex adaptive systems involving interdependencies [34], has also been occasionally applied to CISs analysis. Feedback loops, stock and flow diagrams are the basic components of a SD model [35]. Feedback loops represent the connection and direction of effects between CIS components; Stocks represent quantities or states of the system, the level of which is controlled over time by flow rates between stocks. In order to establish the causal relationships between elements of an SD model, modelers require expert knowledge or sometimes have to rely on assumptions. Furthermore, extensive data is required to calibrate the various parameters and functions of the model. These prerequisites coupled with the fact that SD models lack the ability to capture component-level dynamics makes this approach difficult to adopt for modeling the systemic heterogeneity between CISs [32]. Prior research that adopted SD for modeling CISs mostly focused on the systemic interactions between nonphysical systems and CISs rather than the interdependencies between different CISs.

In addition, CISs play a fundamental role in production, transportation and supply of various products on the economical market. Economic theory based modeling approaches, more particularly the input–output modeling (IOM) [36,37], have therefore been used to model CISs. In the event of an external disturbance such as a disaster, if a certain CIS is not able to perform its intended functions then the provision of products that rely on this CIS would be affected. IOM models are based on various economic theories and are used in prior research to analyze the ripple effect of disasters. There are two main limitations to IOM: Firstly, IOM for infrastructure analysis does not provide spatial representation of the infrastructure systems; Secondly, IOM models cannot account for the interdependencies at the level of individual component of an infrastructure. Therefore, IOM is inadequate for modeling heterogeneity of interdependent CISs [33].

2.2. Simulation of failure propagation across CISs

CISs are constantly exposed to risks of various nature such as natural and man-made disasters. Estimation of potential disaster impacts on the CISs is of significant importance to disaster risk reduction. This requires that failure propagation across interdependent CISs be taken into consideration. Hence, prior research has looked into this issue and proposed different simulation models, most of which are essentially based on existing CISs modeling approaches, to investigate the mechanisms of failure propagation across CISs.

Earlier research modeled interdependent CISs as multilayered network systems, based on which several TB approaches were proposed to simulate failure propagation [7]. According to the TB approach, failure of a node would lead to the failure of all edges connected to the node and vice versa [7]. A typical model based on the TB approach is the percolation model [38], which is widely adopted to analyze the topological failure of multilayered interdependent infrastructure networks. In order to more accurately represent both the topological and functional impact of failure propagation across CISs, the concept of artificial flow index was introduced into network models to describe the functional behavior of CISs. Mainstream artificial flow indices used in literature include betweenness [38] and number of shortest paths [39]. Based on these artificial flow indices, several models that adopted overload damage mechanisms were proposed to simulate the failure propagation across interdependent CISs [40]. These models assume that each component in the network has an optimal load capacity and would fail when the actual load reaching the component exceeds this capacity. Although more recently researchers have attempted to use real flow indices such as water flow rate and current flow rate to describe the operational characteristics of CISs, which led to the development of several real flow based (RFB) models [41], the applicability of these models is largely limited. This is mainly because it is highly difficult to accurately model real flow within the CISs [42]. As a result, AFB models are used in the vast majority of existing studies, such as betweenness-based AFB models for power systems [37] and maximum flow models for water supply systems [43].

Another existing practice for analyzing failure propagation is the use of flow equilibrium models that also consider overload damage mechanisms. However, the critical conditions for component failure which are at the core of the failure propagation mechanisms are usually set subjectively [44]. This largely limits the reliability of the simulation outcomes of these models. In addition, other modeling approaches such as ABM, SD and IOM also provide some references for analysis of failure propagation. However, most related studies that adopted these approaches rather focused on the interactions between different CISs or between CISs and economic system or social systems [45–47]. Little attention has been paid to develop effective failure propagation models using these approaches.

All existing approaches for modeling failure propagation across CISs, as reviewed above, are further assessed and compared based on four criteria, including effectiveness, complexity, maturity and replicability:

- Effectiveness: this criterion measures the ability of a modeling approach to accurately model the failure propagation. This rating criterion is adapted from Ref. [20] and includes three levels as follows: low, moderate and high. The failure propagation of CISs includes two aspects, namely topological failure and functional failure [7,23]. The main characteristics of the topological failure are the number of failure paths [48], the rate of failure nodes [7], and the phase transition in the percolation process [19]. The main characteristics of the functional failure are the flow reduction rate [12], the location of overload damage [49], and the extent of functionality loss [50]. Accordingly, low effectiveness means that only a few characteristics of failure propagation, mainly the topological characteristics, can be modeled. Moderate effectiveness means that most characteristics of topological failure and a few characteristics of functional failure can be modeled. High effectiveness means that the characteristics of both topological failure and functional failure can be modeled;
- Complexity: this criterion mainly measures the computational cost in modeling the failure propagation. This rating criterion is adapted from Ref. [14,20] and includes three levels as follows: low (less than 1 s), medium (several seconds to several minutes) and high (several minutes and above);
- Maturity: this criterion measures the development level of each approach. Adapted from Ref. [14,20], this criterion uses the number of relevant publications in the literature to assess an approach's level of maturity, and includes three levels as follows: low (less than 10 publications), medium (10–30 publications) and high (more than 30 publications);
- Replicability: this criterion measures the difficulty in replicating an approach based on available information in the existing literature. In theory, the methodology of any peer-reviewed academic publication should be replicable. In reality, however, exactly replicating a previously reported CISs failure propagation model could be challenging due to the incompleteness or inaccessibility to input data and unclear model details in the literature [20]. As a result, the usability of some models proposed in the literature is highly limited. These challenges are assessed using the replicability criterion which includes three levels: low (hardly replicable), medium (partially replicable) and high (fully replicable).

Based on the criteria listed above, all aforementioned approaches for modeling failure propagation are assessed. The results are summarized in Table 1.

The best approach should be of low complexity, high maturity, high effectiveness and high replicability. It can be concluded from the comparison in Table 1 that none of the existing approaches meets all of the above criteria, and that the overall ratings of the AFB approach based on these criteria are the closest to the best case.

In summary, considerable progress has been made in unveiling the mechanism of failure propagation across CISs, however, the impact that systemic heterogeneity may have on this mechanism is still a relatively unexplored area. This is manifested by the fact that existing approaches do not fully consider the various systemic heterogeneity factors when modeling failure propagation of interdependent CISs. These usually oversimplified models fail to incorporate the unique failure response patterns of different systems and thus do not reasonably reflect the actual failure propagation across interdependent CISs.

3. Methodology

Motivated by the aforementioned gap in literature, this study aims to assess the impact of systemic heterogeneity on failure propagation across the interdependent CISs. While such impact is almost certain to vary from case to case, for any given case, this impact can always be

Table 1
Assessment of the approaches for modeling failure propagation across CISs.

Approach	Criteria			
	Effectiveness	Maturity	Complexity	Replicability
TB	L	H	L	H
AFB	M	H	M	H
RFB	H	M	H	L
AB	M	M	H	L
SD	M	M	H	L
IOM	M	M	M	L

Note: "L", "M" and "H" stand for low, medium and high, respectively.

measured using a four-step approach as proposed below. Firstly, semi-empirical fragility models should be selected for different types of CISs components. Secondly, a baseline model of the CISs in question should be developed using a representative modeling approach that is typical and replicable. Thirdly, all HFs that are likely to impact the failure propagation should be identified. A series of improved models should then be developed, each incorporating a different HF or a different combination of HFs. Lastly, all models should be subjected to a simulated disaster, and the results from each improved model should be compared to the results from the baseline model in terms of a set of criteria, to assess the impacts of the HFs on the failure propagation process and outcomes. The above approach is further explained in the remainder of this section, and tested in a case study that is reported and discussed in the following sections.

3.1. Fragility models of CISs components

The first step of the proposed approach is to select fragility models for CISs components. The CISs components have distinct fragility characteristics under different types of disasters such as earthquake, flooding and hurricane. Without loss of generalizability, this study focuses on seismic fragility models for predicting the failures of components impacted by earthquakes. Fragility models for other types of disasters can be examined in future research.

3.1.1. Fragility model of nodes

For modeling the seismic fragility of CISs components, the peak ground acceleration (PGA), namely the motion induced by the seismic waves, is the main input parameter used to represent the earthquake disaster in simulation. In the event of an earthquake, substations, switching stations, groundwater wells and pump stations are likely to suffer failures resulting from either the physical damage caused by induced ground motions or the destruction of the structural facilities on which they depend for functioning. To determine the fragility of the infrastructure nodes, this study refers to the HAZUS technical manual [51], which is a widely adopted method in prior research for fragility analysis of CISs components [48,52]. According to the HAZUS technical manual, the damage or limit state k of an infrastructure node, which can be categorized as slight/minor, moderate, extensive or complete, is determined by the impact of a disaster event on this node and the components it depends on. The failure of a network node is defined by the seismic response probability of the node's real damage state d achieving or exceeding a certain damage threshold C_k, where k represents the node's limit state [52]. This conceptualization of nodal fragility allows for network components to exhibit different failure modes. For example, the failure of a pumping station can result from either its internal damage or from the failure of the electric components it depends on for power supply.

The fragility curves per limit state k are lognormally distributed and tabulated using the median m_k and the lognormal standard deviation β. Specifically, the probability of d exceeding a certain damage state threshold C_k can be calculated based on the following equation [52]:

$$P(d > C_k|PGA) = \Phi\left(\frac{\ln(GPA) - \ln(m_k)}{\beta}\right) \tag{1}$$

The values of parameters m_k and β can be selected from the HAZUS technical manual. The selection of the limit state capability C_k, which determines when the component represented by the node loses its complete functionality, depends on the component's attributes, its surroundings, the damage state of other system components it relies on, and its past disaster records [48,53].

3.1.2. Fragility model of pipelines

To determine the fragility of pipeline, this study refers to the method proposed by the ALA (American Lifelines Alliance) [54], which is a widely adopted method in prior research for fragility analysis for pipeline [48,52]. The breakage probability of a water pipe is considered to follow the Poisson distribution. The breakage probability can be calculated as follows under the assumption that at least one breakage occurs along the pipe length:

$$P_f(t) = 1 - \exp\left(-R_f(t)\cdot l(t)\right) \tag{2}$$

where $P_f(t)$ denotes the breakage probability of pipe t, $R_f(t)$ denotes the modified repair rate (failures/km) of pipe t under the assumption that a repair automatically implies a pipe breakage, and $l(t)$denotes the length of pipe t that is calculated based on the nodes' geographic coordinates [55].

Repair rate can be affected by many factors, such as joint type, joint materials, pipe attributes, and so on [54]. Hence, the calculation of repair rate would require access to a substantial amount of detailed data. To simplify this calculation, based on historical earthquake damage records, Isoyama et al. [56] related the repair rate to the PGA by multiplying certain correction coefficients, which only depend on pipe attributes and surrounding soil characteristics, and achieved accurate and reliable results. According to Isoyama et al. [56], the damage rate of pipe t can be empirically calculated as follows:

$$R_f(t) = C_p \times C_d \times Cg \times C_l \times R \tag{3}$$

where, C_pC_d, C_g and C_l represent the correction coefficients corresponding to pipe diameter, pipe material, topography and soil liquefaction condition, respectively, and R represents the standard damage rate. The material composition and diameter of each pipe can be obtained from relevant design documents, while the correction coefficients can be selected from recommended values in Refs. [56]. The standard damage rate R depends on the PGA and material type of the water pipes. The most typical types of material include ductile-iron pipe (DIP) and cast-iron pipe (CIP), for which the values of R can be calculated using Eqs. (4) and (5), respectively [56]:

$$R = 1.32 \times 10^{-6}(PGA - 100)^{1.93} \tag{4}$$

$$R = 2.88 \times 10^{-6}(PGA - 100)^{1.97} \tag{5}$$

3.2. Artificial flow-based network model

The second step of the proposed approach is to model the CISs in question using a representative modeling approach. The selection of the approach is based on the four criteria described in Section 2.2. Specifically, in the best case, the selected approach should be of low complexity, high maturity, high effectiveness and high replicability. While none of the existing approaches meets all these criteria, as shown in Table 1, the ratings of AFB approach in the four criteria are the closest to the best case. The AFB approach shows medium complexity, high maturity, medium effectiveness and high replicability. The AFB approach is thus selected for this study. The modeling of CISs using the AFB approach is described in detail below.

The set S of all interdependent CISs can be expressed in the form $S = \{S_1,\ldots,S_a,\ldots,S_N\}(1 \leq a \leq NN \geq 2)$, where N denotes the total number of systems. A CIS can be represented using a matrix $S_a = (V_a, E_a)$. The column elements V_a represent the system nodes while the row elements E_a represent the system links. The flow relationship R_a^{ik} between nodes i and k in S_a can be expressed as follows:

$$R_a^{ik} = \begin{cases} 1 & \text{if there is flow from node } i \text{ to node } k \\ 0 & \text{if there is no flow from node } i \text{ to node } k \end{cases} \tag{6}$$

When the interdependencies between CISs are taken into consideration, they can be described as unidirectional dependency links between CISs. Interdependency $I^{ij}_{\forall a,b\in S}$ between node i in S_a and node j in S_b can be expressed as follows:

$$I^{ij}_{\forall a,b\in S}=\begin{cases}1 & \text{if node } i\ (i\in V_a) \text{ is dependent on node } j\ (j\in V_b)\\ 0 & \text{if there is no relationship between node } i\ (i\in V_a) \text{ and node } j\ (j\in V_b)\\ -1 & \text{if node } j\ (j\in V_b) \text{ is dependent on node } i\ (i\in V_a)\end{cases} \tag{7}$$

Betweenness is a widely used index to represent the flow within a system [38]. In a CISs network, there may exist more than one shortest path from node i to node k. Let $BV(t)$ denote the betweenness of node t, which is defined as:

$$BV(t)=\sum_{i\neq k,i\neq t,k\neq t,}\frac{g^{t}_{ik}}{g_{ik}} \tag{8}$$

where g_{ik} denotes the number of shortest paths starting from node i and ending at node k, and g^{t}_{ik} denotes the number of shortest paths from node i to node k and passing through node t. The shortest path between two nodes in a network is one in which the total sum of the edges is minimum [57].

$BV(t)$ is used as an approximation of load $LV(t)$ that flows through each node [38]. $BV_0(t)$ is the initial load of node t, which is assumed to be the normal state, with full operational capacity, of a CIS [38,58], and is calculated based on Eq (8). It is also assumed that the capacity of node t, $CV(t)$, is proportional to the initial load $BV_0(t)$[38]:

$$CV(t)=(1+\beta)\cdot BV_0(t) \tag{9}$$

where $\beta>0$ is the tolerance parameter. Tolerance refers to a system's capacity to endure the effects of disaster. Its value depends on a range of factors such as robustness of system, resistance of physical components and so on. While there is no rule of thumb to determine the value of β for any given CIS, prior research adopted different values that generally ranged between 0 and 0.5 [38,58].

Failure propagation in AFB models involves two main steps, namely, overload damage of components and flow redistribution. For any node t in the network, if its actual load $BV(t)$ exceeds its capacity $CV(t)$, the node will experience overload damage. The failed node is automatically removed from the network and the betweenness value of every other node in the redistributed network is recalculated and updated. The above process is repeated iteratively until the actual load at every node in the network does not exceed its capacity. Fig. 1 illustrates the computational process of failure propagation across the interdependent physical networks.

3.3. Improved models

Failure propagation through CISs is affected differently by different HFs. This section first describes how the HFs can be identified, and then explains how to develop improved variants of the above baseline model. Model improvement is done by incorporating different HFs in order to assess their respective impacts on failure propagation. It should be noted that although CISs may be heterogeneous in a variety of aspects, only HFs that can affect the failure propagation are considered in this study [10].

Every CIS can be described based on four main dimensions, including physical network features [7], transported material properties [15], operational mechanisms [5] and disaster response patterns [3]. Accordingly, the systemic heterogeneity factors among different CISs may arise from the following four dimensions:

- Heterogeneity in physical network features (H1): CISs are generally represented as networked systems; however, these networks may have significantly different features [59]. Such features include physical attributes and laws governing interactions within the

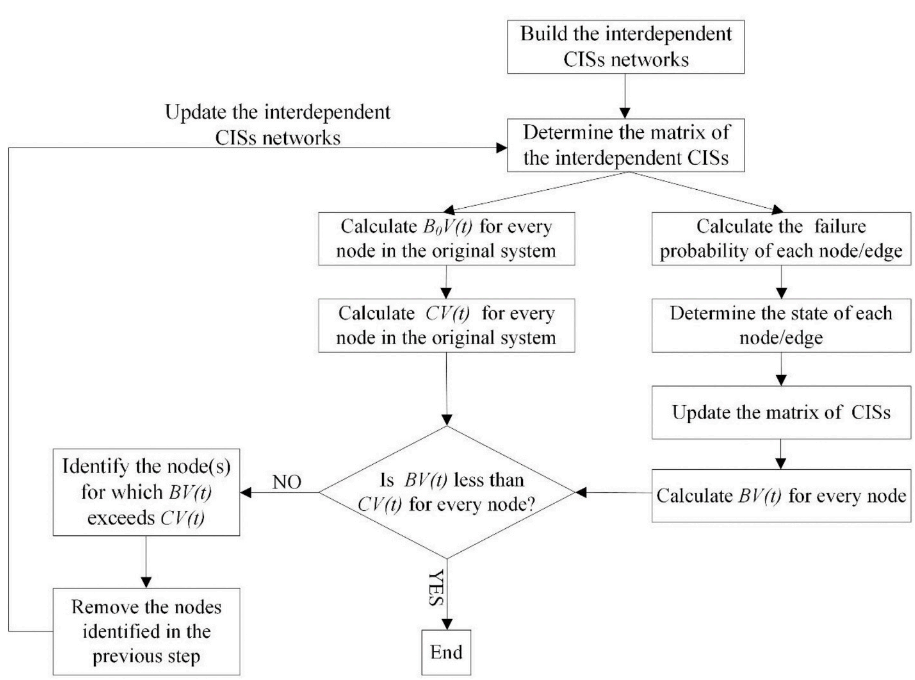


Fig. 1. Flowchart of the computational process of failure propagation in the interdependent CISs network.

network, e.g. average network degree, power-law distribution and exponential distribution;

- Heterogeneity in transported material properties (H2): Every CIS is designed to transport a specific type of material or information [15]. Heterogeneity of transported material properties refers to the difference in the intrinsic properties of these materials, e.g. the flow of water in pipelines is at a completely different speed than the flow of current in powerlines;
- Heterogeneity in operational mechanism (H3): Operational mechanism refers to the process of establishing and arranging clear ways to operate CISs [15]. Heterogeneity of operational mechanism refers to the differences in operational methods, environment, conditions and component glitches. For example, during the operation of a power supply system, power cables and other electric components release a considerable amount of heat due to current flow and resistance of the wires, whereas in water supply systems, water leakages at pipe connections can be observed during operation. Both types of leaks may affect components in their proximity;
- Heterogeneity in disaster response patterns (H4): Every CIS has a unique disaster response pattern. Heterogeneity of disaster response patterns refers to the difference in the response behavior of CISs to disasters. For example, in the event of an earthquake, node components of the power supply system are more prone to experience failure than the links. This is because the links (power cables) are flexible enough to overcome the induced motion from seismic waves without suffering damage; in a water supply system on the other hand, the links (water pipes) are mostly rigid elements and thus both the nodes and the links are susceptible to rupture and other forms of motion related damages.

The above four heterogeneity dimensions are used to guide the identification of the systemic heterogeneity factors following three steps. Firstly, all potential HFs and their possible impact on failure propagation should be identified through the review of academic publications, as well as professional operation manuals, operational standards and historical maintenance records of the CISs being studied. Secondly, face-to-face interviews with professionals in related fields should be conducted to verify whether the above-identified factors and impacts are relevant and consistent with reality. Lastly, the set of identified HFs should be reviewed and adjusted to fit the scope of the present study by discarding factors that have already been well understood in prior research and those that cannot be properly accounted for in an AFB network model. An example of an obvious HF that has been considered in prior research and is thus discarded in this study is the difference in average network degree of each CIS network [18], which is a typical HF classified under heterogeneity in network feature of different CIS (H1).

Based on the failure propagation mechanism of baseline model, a series of improved models can then be developed by factoring in the HFs. The settings of the baseline model should first be determined based on modeling details provided in prior research as well as the actual conditions of the CISs being studied. Improved models should then be developed for each individual HF by making appropriate adjustments to the model settings, such as network representation, initial damage location, node capacity and flow calculations. Other settings should be left unchanged and identical to the baseline model settings. Lastly, since failure propagation may be simultaneously affected by multiple HFs, improved models that consider multiple HFs at a time should also be developed. In these cases, all relevant model settings should be adjusted in a similar manner as when single HFs are considered.

3.4. Impact metrics

According to prior research [38], failure propagation through a system can be characterized from three main aspects, namely, the time the system takes to reach a new steady state after being affected by the disaster, the difference between the final steady state and the original state, and the failure propagation routes as it transitions from the original state to the new steady state. Therefore, the overall impact of HFs on the failure propagation of interdependent CISs can be assessed from three aspects, including, the failure propagation time [2], the failure propagation scale [38], and the failure propagation sequence [60]. Accordingly, three metrics are proposed in this study to assess these impacts, as explained below.

Failure propagation time refers to the time the system takes to reach a steady state after being affected by disaster [2]. While measuring the actual time in CISs models is challenging, a commonly used proxy for the propagation time is the number of iteration steps in the simulation for the system to reach a post-disaster steady state. Taking $\eta_0$and $\eta$to be the failure propagation time in the baseline model and an improved model respectively, the impact of HFs on failure propagation time, denoted as p_1, can be calculated as follows:

$$p_1 = \frac{\eta - \eta_0}{\eta_0} \tag{10}$$

A value $p_1 = 0$ indicates that the HF considered for simulation has no impact on failure propagation time, otherwise, a positive or negative value indicates that the HF either increases or reduces failure propagation time, respectively.

Failure propagation scale, denoted as λ, can be described as the rate of path losses in the CISs [38].

$$\lambda = \frac{\theta - \theta'}{\theta} \tag{11}$$

where θ and $\theta'$are the number of functional paths within the system before and after the disaster occurs respectively. Taking λ_0 and λ to be the failure propagation scale results obtained from the baseline model and an improved model respectively, the impact of HFs on failure propagation scale, denoted asp_2, can be calculated as follows:

$$p_2 = \frac{\lambda - \lambda_0}{1 - \lambda_0} \tag{12}$$

A value $p_2 = 0$ indicates that the HF considered for simulation has no impact on failure propagation scale, otherwise, a positive or negative value indicates that the factor either increases or reduces failure propagation scale, respectively.

In addition, HFs may affect the failure propagation sequence of CISs, which is composed of the failure propagation step at which each node fails (operational nodes maintain the initial failure propagation step value 0) [60]. The failure propagation sequence through each CIS can therefore be denoted as a vector$\theta = (o_1, \cdots, o_m, \cdots, o_n)$, where o_m refers to the averaged failure propagation step at which node m fails. The vector $\theta^0 = (o_1^0, \ldots, o_m^0, \ldots, o_n^0)$ is taken to be the propagation sequence obtained from the baseline model. The comparison results of failure propagation sequence between the baseline and improved models, denoted as a vector$\pi = (\tau_1, \cdots, \tau_m, \cdots, \tau_n)$, can be expressed as follows:

$$\tau_m = \begin{cases} 1 & if\ o_m = o_m^0 \\ 0 & if\ o_m \neq o_m^0 \end{cases} \tag{13}$$

The number of nodes that fail at the same failure propagation step in both the baseline and improved models, denoted asn'', can be calculated as follows:

$$n'' = sum(\pi) \tag{14}$$

Then, the impact of HFs on failure propagation sequence, denoted as p_3, can be calculated as follows:

$$p_3 = \frac{n - n''}{n} \tag{15}$$

A value $p_3 = 0$ indicates that the HF considered for simulation has no impact on the failure propagation sequence, otherwise, a positive value of p_3 indicates that the factor notably impacts the failure propagation sequence.

4. Case study

4.1. Case description

A case study of the interdependent water and power supply systems at Tsinghua University campus was conducted to illustrate the impact of systemic heterogeneity on failure propagation across the CISs. Located in the Haidian district of Beijing, the campus has an area of approximately 4 km^2 and hosts a population over 60,000. The case study focused on the water and power supply system due to the following reasons: Firstly, drinking water and electric power are the most critical resources needed by any city or community in order to sustain its operation. Secondly, the interdependency between water and power supply systems is bidirectional, which makes the coupling of these two systems a representative case for studying failure propagation across interdependent CISs. Lastly, these two systems are widely modeled in prior research, thus studying them could address an issue that is of significant concern in the existing literature.

Table 2
Summary of the facilities and connections in the case systems.

System	Facility (acronym and count)	Link (number)	
		Connectivity within systems	Dependency between systems
Power supply system	• Electric substation - 110kv-10kv (ES,1) • Switching station (SS,12) • End user (EU,29)	• Power cable (51)	• Water pipe (1)
Water supply system	• Groundwater well (GW,13) • Pump station (PS,13) • End user (EU,18)	• Water pipe (83)	• Power cable (13)

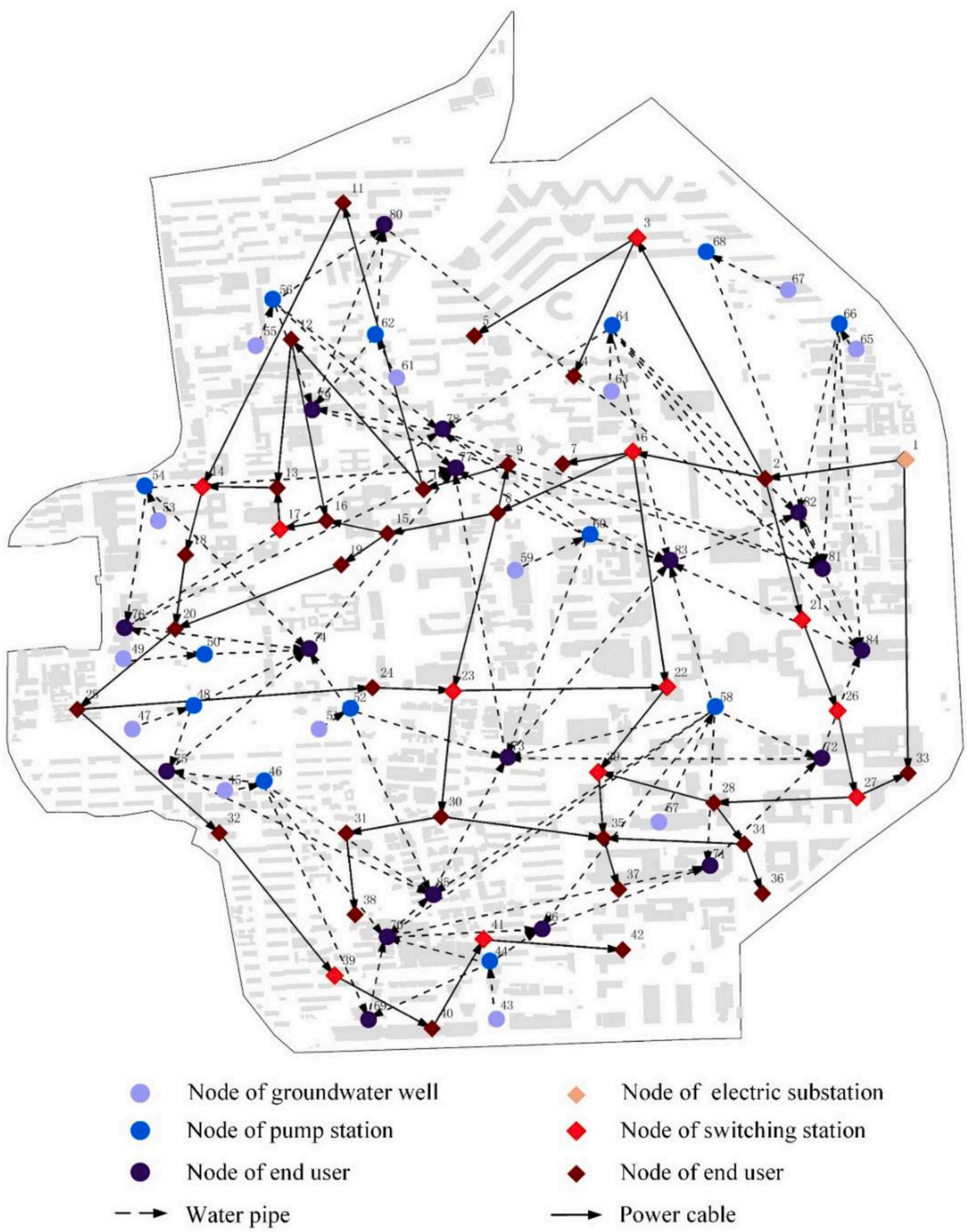


Fig. 2. Layout of the case systems.

The number and location of each CIS's facilities as well as the links between them were obtained from available design documents of both systems. The water source of the campus consists of 13 groundwater wells, suggesting that the water supply system on campus is self-sufficient and completely independent of the external municipal water supply system. On the other hand, the campus has no power plant and relies entirely on the municipal power supply system for electric power supply via a single 110 KV power cable.

Fig. 2 illustrates the layout of both systems superimposed over the campus map. All facilities and major components of the two systems, such as groundwater wells, pump stations and electric substations, were regarded as nodes, whilst power cables and water pipes were regarded as links. A total of 86 nodes and 148 links were identified, as summarized in Table 2. Nodes belonging to the power supply network were labeled nodes 1 through 42, and those belonging to the water supply system were labeled nodes 43 through 86. The power supply for the water pump station and the cooling water supply for the power substation are two types of dependency relationships existing between the systems. Details on the related components were determined from the design documents of each CIS. The layout of the dependency links between the two systems is illustrated in Fig. 3.

4.2. Heterogeneity factors

Following the review of all relevant documents and the face-to-face interviews with professionals and management teams from the logistics management department of the university, a total of 12 HFs were identified. These HFs are listed as follows:

- HF 1: Difference in average node degree of each CIS;
- HF 2: Difference in node degree distribution of each network;
- HF 3: Difference in storability of transported materials;
- HF 4: Difference in flow velocities of transported materials;
- HF 5: Difference in system glitches during operation;
- HF 6: Difference in available backup components;
- HF 7: Difference in system susceptibility to overload damage;
- HF 8: Difference in tolerance to disaster impacts;
- HF 9: Difference in locations of the main physical damage;

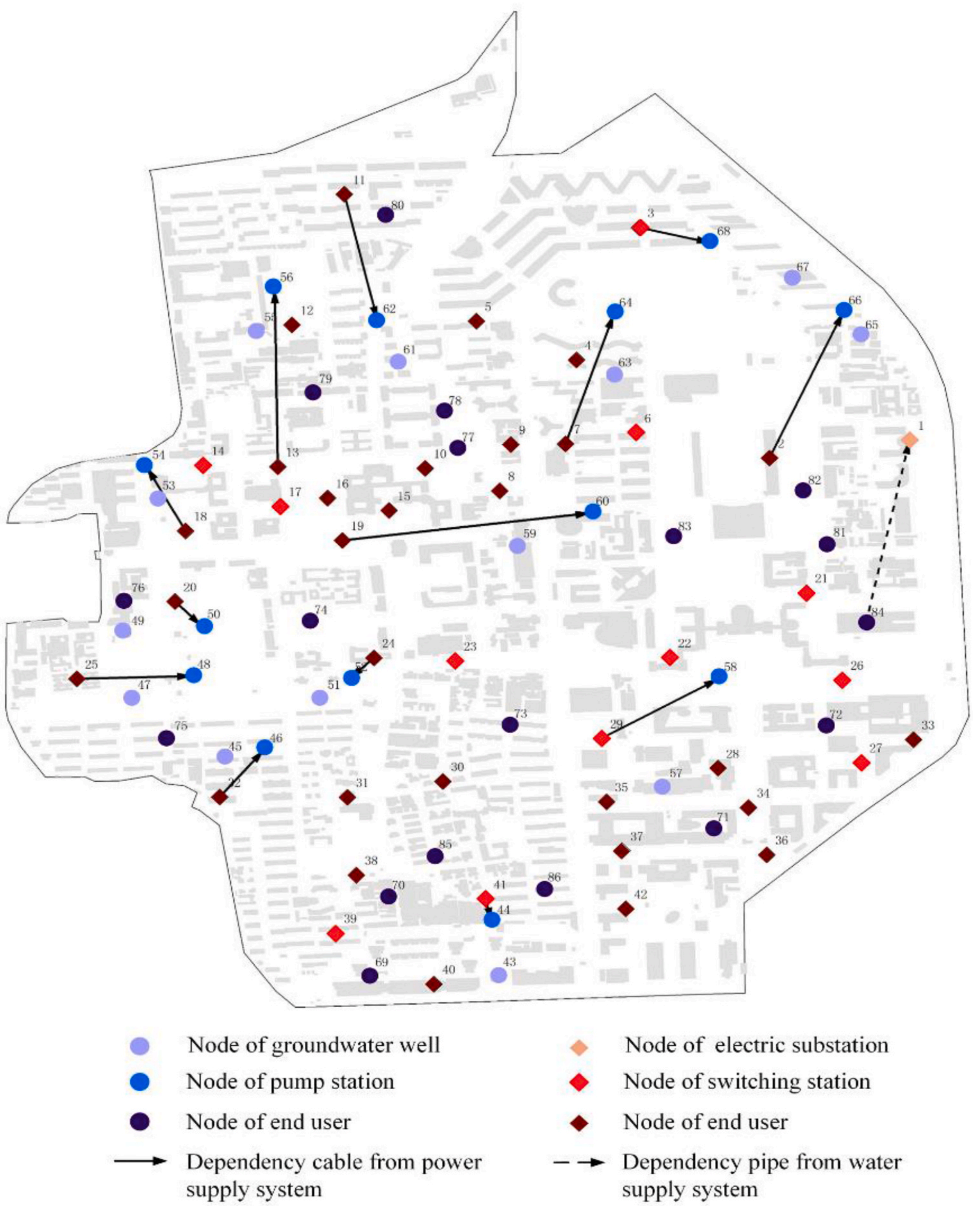


Fig. 3. Dependency links between the water and power supply systems of the case.

Table 3
Summary of the systemic heterogeneity factors.

HD	HF	Description of HF	Possible impact on failure propagation	Whether considered in prior research	Modelability using AFB approach
H1:	HF 1	This HF suggests that different system networks have different average node degree due to differences in layout, sparseness, number of nodes and edges.	A large value of average node degree indicates that a failed node will trigger the failure of many links and perhaps lead to large failure propagation scale.	Yes	H
	HF 2	This HF suggests that the node degree distribution of system networks differs due to differences in network feature. For example, some CIS networks may follow power-law or exponential distributions.	Power-law networks display a surprisingly high degree of tolerance to damages, a property not shared by their exponential counterparts, which will affect failure propagation through interdependent CISs.	Yes	H
H2:	HF 3	This HF suggests that the storability of transported material differs among CISs due to differences in transported material attributes. For example, the water supply system transports water that can be stored for a period of time, whereas the electric power transported through the power supply system cannot be stored on a large scale. Electric power is produced and distributed in response to the end point demand.	A storable transported material can help delay the failure of the related CIS, thus decreasing the overall disaster impact.	No	M
	HF 4	This HF suggests that the flow velocities of transported materials differ among CISs due to various material attributes. For example, Electric current flows at the speed of light whilst water flows at a much slower speed.	Difference in flow velocities of CISs may cause differences in individual failure patterns which in turn may affect the overall disaster propagation paths.	No	L
H3:	HF 5	This HF suggests that different CISs experience different types of glitches during operation due to differences in operation conditions, surroundings and mechanism. For example, water supply system is likely to suffer from leakages, whilst power supply system rather suffers from heat release during operation.	In areas where the water and power networks are in close proximity, the water leaks may affect the power system components. Likewise, the heat released from the electric components may heat up adjacent water pipes and perhaps cause them to swell or burst open.	No	L
	HF 6	This HF suggests that the availability of backup components differs among CISs due to various constraints. For example, some important node pairs in the power supply system are linked by two parallel lines, one acting as a backup link. Whilst there is only one water pipe between any node pairs of the water supply system.	The backup link of the power supply system enhances the robustness of the system and provides effective protection against failure of important nodes.	No	M
H4:	HF 7	This HF suggests that different CISs have different component susceptibility to overload damage. For example, flow redistribution in power supply system under disaster can cause overload damage of components. It is usually not the case in water supply system because proper technical or managerial measures can be taken in a timely manner to avoid the amplification of failure effects.	If the failure propagation conditions are not accurately described, then it is difficult to evaluate the disaster impact on the whole network.	No	H
	HF 8	This HF suggests that system capacity to endure the effects of disaster differs among CISs. This tolerance to disaster of systems vary based on their network features, operation mechanisms, etc.	The failure impact of different CISs is strongly related to their tolerance to disaster, which will affect the failure propagation path.	No	H
	HF 9	This HF suggests that the locations of the main physical damage differ among CISs due to differences in the attributes of physical components and disaster characteristics. For example, in power supply system, physical damage mainly occurs at nodes since the buried cables are flexible enough to withstand the disaster. Water supply system on the other hand is prone to experience physical damages at both nodes and edges.	If the precise damage locations cannot be determined, the initial state of simulation will be inaccurate and hence will generate an incorrect disaster impact result.	No	H
	HF 10	This HF suggests that different CISs have different serviceability conditions due to differences in operational mechanism. For example, the water supply system is not completely dependent on the support from the power supply system and can continue functioning even when power supply is insufficient since water can also rely on gravity to ensure continuous flow. However, the power supply system will lose its functions when the support from the water supply system is less than a certain proportion.	If the serviceability conditions of each CIS are not properly considered, the resultant disaster impact might be an overestimation of actual values.	No	M
	HF 11	This HF suggests that the way and speed at which failed components are cut off from the system differs among CISs due to differences in degrees of automation. For example, failed components in water supply system are cut off manually by detecting and closing the related upper valves, whereas failed components in power supply system are cut off automatically by relay protection equipment.	A manual cutoff is slow but accurate whilst using relay protection equipment is fast but less accurate. This difference has a great impact on the failure propagation scale of interdependent CISs under disaster.	No	L
	HF 12	This HF suggests that flow rate variations under disaster differs among CISs due to differences in operation mechanism. For example, flow rate through the water supply system does not increase under disaster, whilst voltage or current flow may alternate under disaster.	Flow rate variation is an important variable in determining the performance of the system. If the variations are not accurately measured, it will result in inaccurate measurements of disaster impact.	No	L

- HF 10: Difference in serviceability conditions;
- HF 11: Difference in the way and speed at which failed components are cut off from the system;
- HF 12: Difference in flow rate variations when impacted by disaster.

Table 3 summarizes these 12 HFs by presenting their detailed descriptions, possible impact on failure propagation across CISs, whether they have been considered in prior research, and their modelability using the AFB network model. The modelability was analyzed and rated "L" (low), "M" (medium), or "H" (high). Factors that were not rated "H" were excluded from further investigation due to limited modelability. In addition, all HFs belonging to H1 were also excluded since they were relatively well understood in prior research. Therefore, only HF 7, HF 8 and HF 9 were analyzed in the following analysis.

4.3. Development of the improved models

Following the steps described in Section 3.2, a total of seven improved AFB models were developed by incorporating HF 7, HF 8 and HF 9 into the baseline model. These models are summarized in Table 4 and explained in detail below. In addition, according to the seismic ground motion parameters zonation map of China [61], the PGA of Beijing is 0.3g, where g is taken as 10 m/s^2. Hence, the disaster input of all models was set as 0.3g.

In *Model 0* (the baseline model), overload damage may occur in both the power supply system and the water supply system. The tolerance parameters of both systems were set as 0.02 based on the National Standard of Admissible Deviation of Supply Voltage in China [62]. Failure was set to only occur at the nodes. Based on the fragility model presented in Section 3.1.1, the probability of complete loss of functionality of every component can be determined. Accordingly, the state of every component was randomly generated 1,000 times based on their probability of complete loss of functionality. As a result, 1,000 different network inputs of *Model 0* were simulated.

Model 1 was built to simulate failure propagation across the CISs while considering HF 7. HF 7 suggests that overload damage due to flow redistribution would not occur in the water supply system and therefore, components in the water supply system could only be physically damaged by earthquake-induced ground motion. The corresponding model setting that needed to be modified in order to account for HF 7 in this improved model was the tolerance parameter of the water supply system $\beta(w)$. The value of $\beta(w)$ in Eq. (4) was set to a very large value of 10, which was determined after several test simulations. This large value of $\beta(w)$ ensured that the actual artificial flow of one node never exceeded its capacity and thus no overload damage could occur. The tolerance parameter of the power supply system $\beta(p)$ was kept as 0.02. Similar to *Model 0* above, the probability of complete loss of functionality of components had to be considered and thus, 1,000 different network inputs of *Model 1* were simulated.

Models 2a and 2b were built to simulate failure propagation across the CISs while considering HF 8. HF 8 suggests that tolerance to disaster is system-specific and may differ from one system to the other. However, determining the actual tolerance parameter of each system would have been a complicated experiential task lying beyond the scope of this study. Hence, a tolerance value of 0.06 was set for the power supply system in *Model 2a*, and the same tolerance value of 0.06 was set for the water supply system in *Model 2b*. In both models, the tolerance parameter of the other system was kept as 0.02. Similar to *Models 0* and *1* above, the probability of complete loss of functionality of components had to be considered and thus, 1,000 different network inputs of *Model 2* were simulated.

Model 3 was built to simulate failure propagation across the CISs while considering HF 9. HF 9 suggests that water pipes in the water supply system are also likely to be damaged by earthquake-induced ground motion. In order to describe the functional or damaged state of each water pipe under an earthquake event, the input matrix, derived from Eqs. (6) and (7), was randomly generated 1,000 times while considering the breakage probability of each pipe determined in Section 3.1.2. If the state of a pipe t was operational, the related element R_a or$I_{\forall a,b\in S}$ took the value of 1, otherwise, the element took the value of 0. Finally, the state of each pipe had to be consistent with its breakage probability. The main modification that needed to be applied to the baseline model setting in order to account for HF 9 in this improved model was the integration of a random input matrix as model input. As a result, 1,000 different network inputs of *Model 3* were simulated, which simultaneously considered the random generation of the state of system components and pipelines.

Model 4 was built to simulate failure propagation across the CISs while considering both HF 7 and HF 9. This means the model considered that overload damage due to flow redistribution would not occur in the water supply system and that the water pipes were likely to be damaged by the earthquake-induced ground motion. The model settings were modified and the model inputs were generated the same way as in *Models 1* and *3*.

Models 5a and *5b* were built to simulate failure propagation across the CISs while considering both HF 8 and HF 9. These two models considered not only that the tolerance to disaster parameter is system-specific, but also that water pipes were likely to be damaged by the earthquake-induced ground motion. The model settings were modified and the model inputs were generated in the same way as in *Models 2a*, *2b* and *3*.

5. Assessment results and analysis

Based on the component attributes, damage of dependent system, surroundings and past disaster records, the facility nodes (nodes 14, 29, 39 and 41) of the power supply system, which were located in the west or southwest of Tsinghua campus, would completely loss their functionality when the damage state exceeded the "minor damage" threshold. This was because the above-mentioned facilities and dependent building were decades old and highly vulnerable. The other facility nodes (nodes 1, 3, 6, 17, 21, 22, 23, 26 and 27) of the power supply system, which were located in the east of Tsinghua campus, would completely lose their functionality when the damage state exceeded the "moderate damage" threshold. With regard to the water supply system, nodes 43, 44, 61 and 62, which were located in the southwest and northwest of Tsinghua campus, would completely lose their functionality when the damage state exceeded the "minor damage" threshold, due to the structural vulnerability of the associated facilities. Nodes 63, 64, 65and 67, which were located in the east of Tsinghua campus, would completely lose their functionality when the damage state exceeded the "extensive damage" threshold. The remaining nodes (nodes 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59 and 60) of the water supply system would completely lose their functionality when the damage state exceeded the "moderate damage" threshold. The probability of a component exceeding a certain damage threshold was determined based on methods described in Section 3.1.1. The state of every component was randomly generated 1,000 times based on their probability of complete loss of functionality.

All improved models were built and simulated using MATLAB. The impacts of the HFs on failure propagation were then assessed based on the simulation results using the impact metrics explained in Section 3.4. The impact assessment results were calculated as the mean of results from all simulations. The results are described in detail below.

5.1. Failure propagation time and scale

Based on the simulation results, the failure propagation pattern through the coupled systems was recorded for each model, as illustrated in Fig. 4.

As observed in Fig. 4, the models generated different failure propagation patterns under the same earthquake scenario. In the baseline

Table 4
Details of the improved models.

Model #	Difference in system susceptibility to overload damage (HF 7)	Difference in failure tolerance (HF 8)		Difference in locations of the main physical damage (HF 9)
		β(p) = 0.02; β(w) = 0.06	β(p) = 0.06; β(w) = 0.02	
0 (baseline)	–	–	–	–
1	✓	–	–	–
2a	–	✓	–	–
2b	–	–	✓	–
3	–	–	–	✓
4	✓	–	–	✓
5a	–	✓	–	✓
5b	–	–	✓	✓

Note: β(p) is the tolerance parameter of power supply system; β(w) is the tolerance parameter of water supply system. The default tolerance parameter value of both systems is 0.02.

model (Fig. 4 (a)), the coupled CISs reached a steady state after five propagation steps and 99.96% of the paths were damaged. In *Model 1* involving HF 7 (Fig. 4 (b)), four propagation steps were necessary to bring the system to a steady state and the rate of damaged paths decreased to 99.72%, as 2,646 more paths survived under the disaster than in the baseline model. The impact of HF 7 was significant as indicated in Fig. 4 (b). In *Model 2a* (Fig. 4 (c)) where the tolerance parameters of the power and water supply systems were set at 0.02 and 0.06 respectively, 99.93% of the paths were damaged; whereas in *Model 2b* where the tolerance parameters of the power and water supply systems were set at 0.06 and 0.02 respectively, 99.94% of the paths were damaged. The rate of surviving paths and propagation steps observed in *Models 2a* and *2b* were close to those of the baseline model, which indicated that the impact of HF 8 was relatively insignificant. On the other hand, the impact of HF 9 in *Model 3* (Fig. 4 (d)) was significant because it was observed that more paths were damaged in the first iteration step compared to the baseline model. This indicated that more paths were lost when the pipeline damage was taken into consideration. Accordingly, the failure propagation time of *Model 3* increased to 6 (the final rate of surviving paths calculated after the last iteration step was very close to 0), which was greater than that of the baseline model. The result of *Model 4* (Fig. 4 (e)) was notably similar to that of *Model 1,* suggesting that the impact of the combination of HF 7 and HF 9 was significant, and that HF 7 was more influential than HF 9. Lastly, the results of *Models 5a* and *5b* (Fig. 4 (f)) were slightly different from those of the baseline model, showing a similar pattern to when only HF 8 was considered.

In summary, comparing the results from all improved models, it was observed that four to six failure propagation steps were completed before the whole system would reach a new steady state. The fastest failure propagation was observed in *Models 1* and *4*, totaling four steps, and the slowest failure propagation was observed in *Models 3,* totaling six steps. With regard to failure propagation scale, most paths failed at the first failure propagation step and only a few paths remained operational after several failure propagation steps in all models.

5.2. Failure propagation sequence

The failure propagation sequence in each model can be illustrated using the simulation results. All models have different possible propagation sequence since these models were subjected to 1,000 different network inputs. Nevertheless, in order to likewise illustrate a single representative propagation sequence for these models, the failure propagation sequence of each model was chosen to be the sequence with the highest frequency (i.e. that appears the most) over the 1,000 different simulations. The results are summarized and illustrated in Fig. 5.

As observed in Fig. 5, amongst all other failed nodes, eight nodes (nodes 14, 17, 29, 44, 46, 51, 58, 64) commonly failed in all models. The components represented by nodes 14, 17 and 29 were switch stations of the power supply system. The electric substation represented by node 1, which was the most important component in the power supply system, did not fail in any of the models. This indicated that the electric substation serving the campus was highly reliable. Four pump stations (nodes 44, 46, 58 and 64) and one groundwater well (node 51) failed in all models. This indicated that these components were highly vulnerable under earthquake. It could also be observed from Fig. 5 that there is a considerably larger number of circle-shaped failed nodes than diamond-shaped failed nodes, which indicates that the water supply system suffered much more damage than the power supply system. In addition, most damaged nodes were found in the west side of Tsinghua campus, which is an area where most of the century-old buildings and older components of the campus' power and water supply systems are located. This explains their greater vulnerability to external disturbances such as earthquakes.

5.3. Impact assessment results

Based on the simulation results described above, the impact metrics were calculated for each model, and the results are summarized in Table 6.

The results summarized in Table 6 showed that the systemic heterogeneity indeed had a significant impact on failure propagation across CISs, with each heterogeneity factor affecting the propagation in a different way. Based on the results, it could be concluded that the CISs reached a new steady state rather quickly after being impacted by the earthquake. HFs 7 and 9, incorporated in *Models 1* and *4*, had the largest impact on propagation time, whilst the impact of HF 8 was negligible.

With respect to the failure propagation scale, HF 7 had the largest impact as observed from results of *Model 1*. In the baseline model, a total of 530 paths survived. However, when HF 7 was considered, a total 3,177 paths survived. This indicated that the disaster impact was

Table 6
Summary of the impact assessment results for all improved models.

Model	Impact on failure propagation time p_1	Impact on failure propagation scale p_2	Impact on failure propagation sequence p_3
0	–	–	–
1	−0.2304	−4.9606	0.7093
2a	−0.0065	−0.3338	0.6977
2b	−0.0031	−0.1058	0.6977
3	−0.0350	0.1785	0.7209
4	−0.2477	−4.7319	0.7209
5a	−0.0357	0.0462	0.8256
5b	−0.0252	−0.5000	0.7907

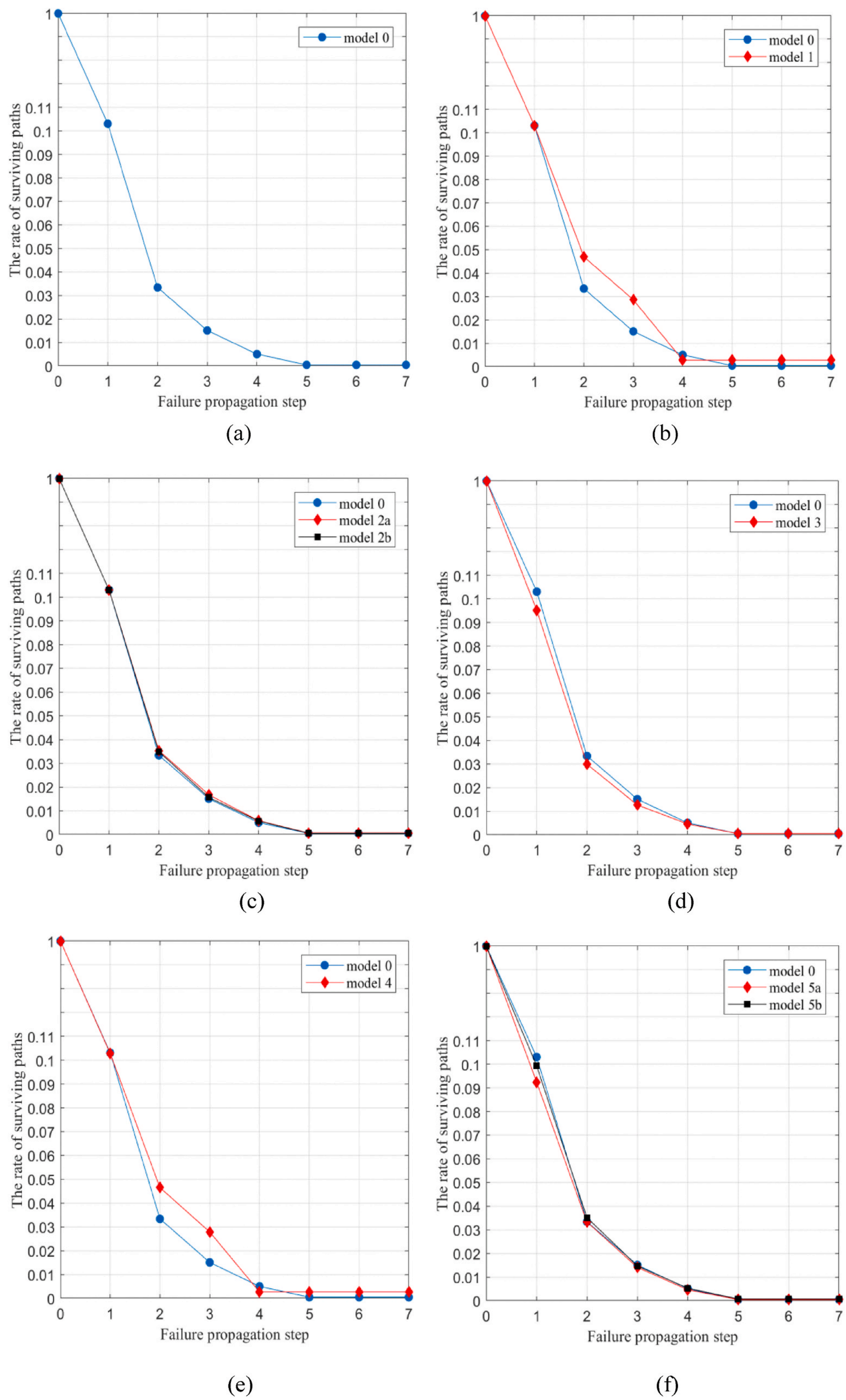


Fig. 4. Failure propagation pattern observed in each improved model in comparison to the baseline model.

overestimated by the baseline model simulation.

With regard to the failure propagation sequence, the largest impact was observed from *Model 5a*, which indicated that the combination of HF 7 and HF 9 had the largest impact on the failure propagation sequence across the CISs. On the other hand, *Models 2a* and 2*b* which considered HF 8 had the least impact on the failure propagation sequence.

5.4. Sensitivity analysis

Global sensitivity analyses of the impact assessment results, to three input parameters were conducted. The sensitivity analyses were performed by varying one parameter of the baseline model while keeping other parameters constant. Three input parameters, including the tolerance values of both systems and the PGA value, were considered in the analyses due to their potentially significant impact on the simulation results. When performing the sensitivity analysis on the tolerance of one system, its value was varied from 0 to 0.5, taking intervals of 0.02, while the tolerance of the other system was kept at a constant value of 0.02. When performing the sensitivity analysis on the PGA, three typical values, including 0.2g, 0.3g and 0.4g, were simulated.

5.4.1. Sensitivity analysis of impact assessment results to the tolerance parameter

With respect to the impact on failure propagation time (p_1), the simulation results showed that it had an overall decreasing trend when either tolerance value increased, as shown in Fig. 6 (a). The value of p_1 decreased faster when β(p) was fixed as 0.02, which suggested that the impact on failure propagation time was relatively more sensitive to the tolerance of the water supply system.

With respect to the impact on failure propagation scale (p_2), as shown in Fig. 6 (b), its value slightly decreased when β(p) was fixed at 0.02 and β(w) exceeded 0.04, slightly bounced back at β(w) = 0.12, and remained steady afterwards. On the other hand, when β(w) was fixed at 0.02, the value of $p_2$notably decreased when β(p) exceeded 0.06, bounced back twice at β(p) = 0.1 and β(p) = 0.26, and remained steady afterwards. The wider range and more complex pattern of variability observed in the values of $p_2$when β(w) was fixed at 0.02 suggested that p_2 was relatively more sensitive to the tolerance parameter of the power supply system. The simulation results are presented in Fig. 6 (b).

As for the impact on failure propagation sequence (p_3), the sensitivity analysis results revealed an even more complex trend compared to those from the other two metrics. The values of p_3 repeatedly increased and decreased in a wavelike pattern when either tolerance value increased. The range of values of p_3 was very concentrated between 0.69 and 0.76, which suggested that p_3 was generally insensitive to the variations in tolerance parameter of both the water and the power supply system. The simulation results are presented in Fig. 6 (c).

In summary, it can be inferred from the above results that p_1 and p_2 were sensitive to variations in system tolerance values, revealing clearer and distinct patterns. This indicated that the impact of HF 8 onp_1 and p_2 was non-negligible, and would become more substantial as the value of system tolerance increased. When the tolerance value was less than 0.02, more nodes suffered overload damage since they were more fragile, which could explain the positive values of p_1 and p_2. As the tolerance value increased, fewer nodes were damaged as compared to the baseline model and thus p_1 and p_2 turned negative. These results are consistent with the hypothesis that the more robust the nodes are, the lesser the damage suffered by the network, which indicates that the models and parameter settings were reasonable.

5.4.2. Sensitivity analysis of impact assessment results to the PGA

Fig. 7 illustrates the results of the sensitivity analysis on the PGA value. The analysis was conducted for three typical PGA values, including 0.2g, 0.3g and 0.4g. From the analysis results of p_1, p_2 and p_3, no particular increasing or decreasing trend was observed in any of the improved models when the PGA value was increased from 0.2g to 0.4g. The value of p_1 was negative in all improved models at PGA value 0.3g, which indicated that under this scenario the improved models all experienced shorter failure propagation time as compared to the baseline model. The largest values of p_1 and p_2 were observed at the PGA value of 0.3g in *Models 1* and *4*, which indicated that HF 7 had the most

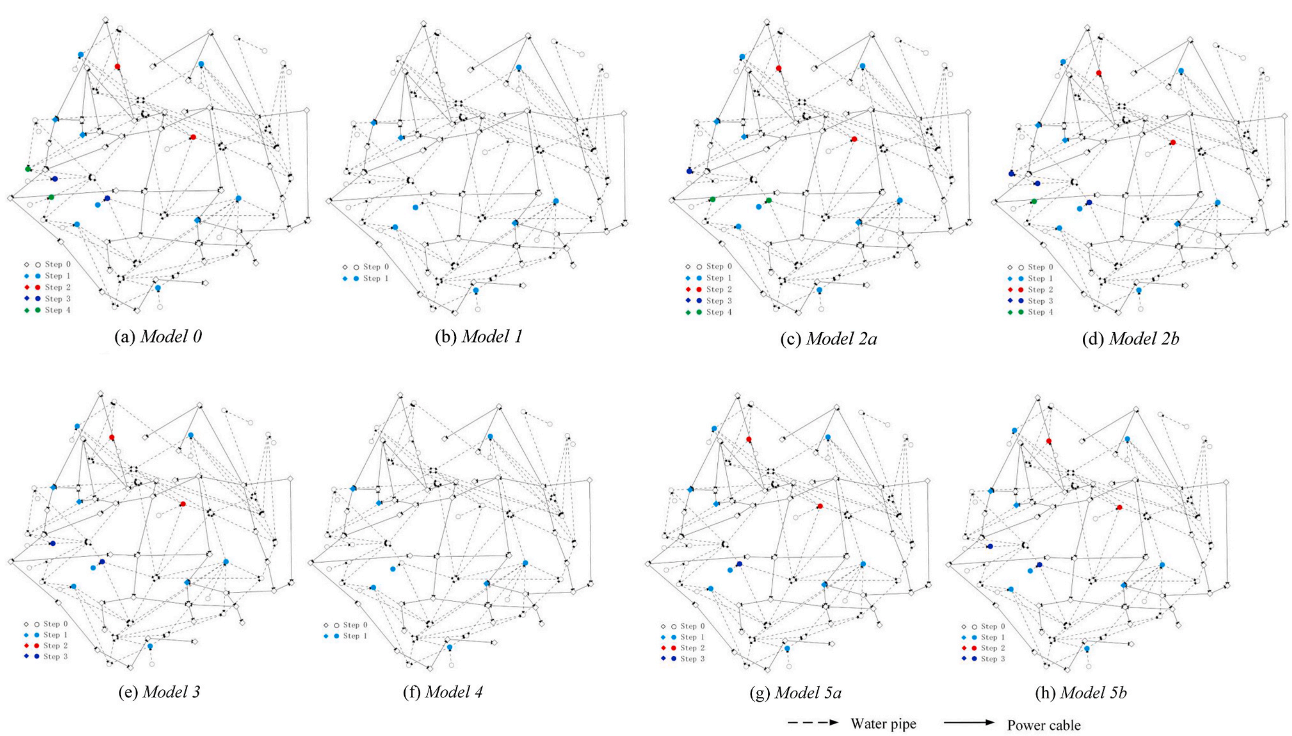
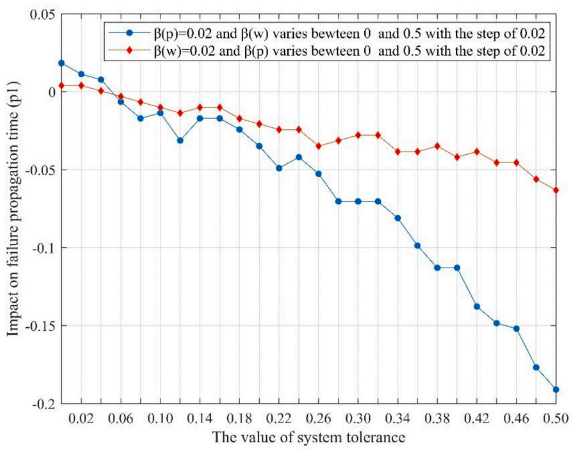
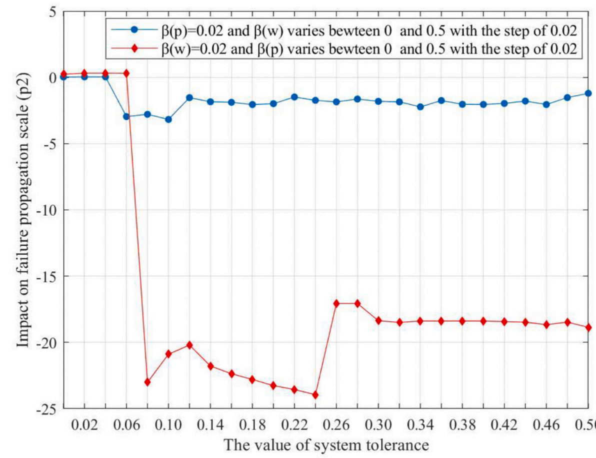


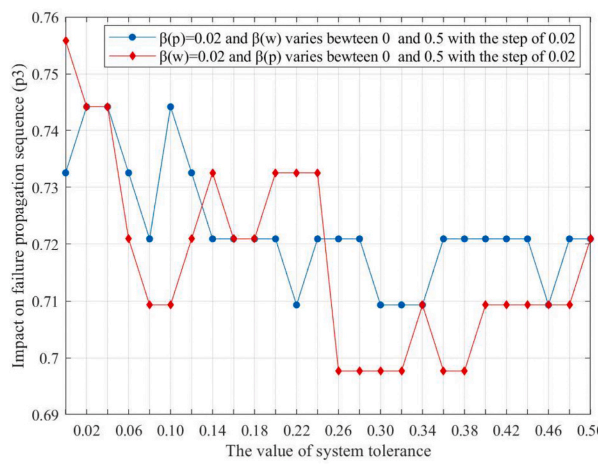
Fig. 5. Failure propagation sequence in each model.



(a) Sensitivity of p_1 to system tolerance values



(b) Sensitivity of p_2 to system tolerance values



(c) Sensitivity of p_3 to system tolerance values

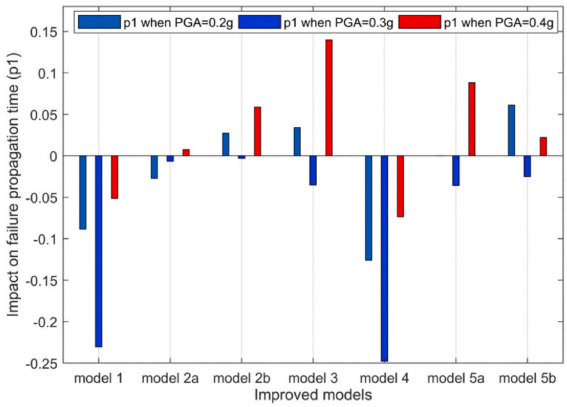
Fig. 6. Sensitivity analysis of the impact assessment results to system tolerance values.

significant impact on failure propagation under these scenarios. All impact values in Fig. 6 (c) were positive and non-negligible for all improved models, which indicated that the failure propagation sequence would be notably impacted if HFs 7, 8 and 9 were not considered. In addition, the range of values of p_2 was much larger than that of p_1 and p_3, which indicated that the sensitivity analysis result to PGA values was more prominent for p_2. On a side note, all paths in all models suffered complete failure at the PGA value of 0.4g, and therefore the impact on failure propagation scale under this PGA value was not computable.

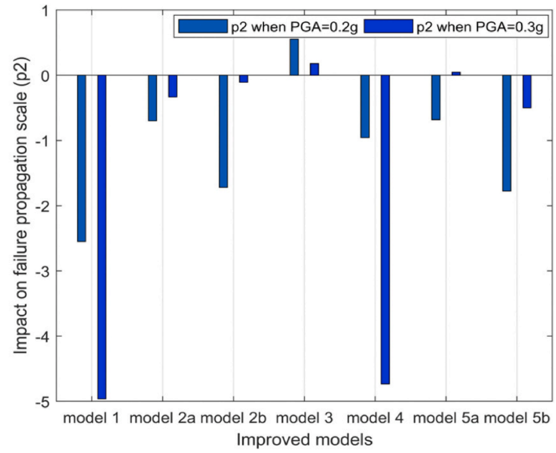
6. Discussions

Based on the simulation outcomes and assessment results reported in the previous section, it can be reasonably inferred that systemic heterogeneity has a significant impact on failure propagation across interdependent CISs. This finding is consistent with the findings reported in Refs. [6,7,18]. For instance, Buldyrev et al. [7] simulated failure propagation through two tightly interdependent CISs, each modeled using power-law degree distribution. In this interdependent network, total fragmentation was found above a finite and small fraction of damaged nodes, and the more heterogeneous the networks the smaller the damages that could be sustained before functional integrity was totally compromised. This finding strongly supports the main finding of this study, which argues that systemic heterogeneity has significant impact on failure propagation across CISs. More importantly, by considering the heterogeneity of network features (H1), Buldyrev et al. [7] were able to achieve high accuracy in disaster impact estimation compared with studies that did not consider any systemic heterogeneity [63,64]. It is expected that when systemic heterogeneity in the other three dimensions (H2, H3 and H4) are also considered, the performance of simulation models of failure propagation will be further improved.

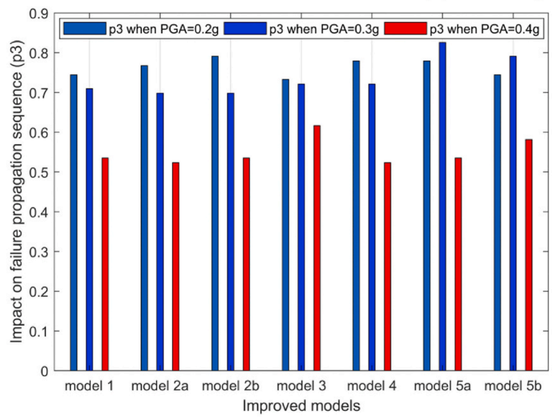
There exist notable differences in the way each heterogeneity factor impacted failure propagation through the systems. When HF 7 was considered, overload damage of components could occur only in the power supply system. As a result, though the initial set of failed nodes in the improved model was identical to that in the baseline model (i.e. nodes 14, 17, 29, 44, 46, 51, 58 and 64), failure propagation was considerably impacted, resulting in a significant decrease in failure propagation scale and time in the improved model. In addition, HFs 7 and 8 were both incorporated in the AFB model by modifying corresponding systems' tolerance parameters, however, the main difference between them was that when considering HF 8, both CISs were still susceptible to overload damage of components. As a result, the impact of HF 8 on failure propagation time, scale and path was reasonably much



(a) Sensitivity of p_1 to PGA value



(b) Sensitivity of p_2 to PGA value



(c) Sensitivity of p_3 to PGA value

Fig. 7. Sensitivity analysis of the impact assessment results to PGA value.

smaller than that of HF 7. HF 9 on the other hand could affect both the initial set of failed nodes and failure propagation mechanism of the improved model since it incorporated the probability that links could suffer damages. This suggested that HF-specific measures may be needed to appropriately model the HFs and address their impacts.

The results from this study indicated that the impact of systemic heterogeneity should not be overlooked, otherwise, disaster assessment results will be inaccurate. These results also raise the awareness of the need for more reasonable and reliable failure propagation modeling approaches, which can accurately take into account the systemic heterogeneity of different CISs. It is also useful to note that the approach introduced in this study could provide theoretical reference on how systemic heterogeneity can be identified and considered during the modeling process. Moreover, the assessment results can help system owners, operators and emergency responders to better understand the systemic heterogeneity of CISs. A better understanding of systemic heterogeneity would lead to more accurate estimations of disaster impact, a better decision support system in the design, construction and maintenance of the CISs, and thus enhance the overall preparedness and response capabilities of the systems towards disasters.

7. Conclusions

Modern CISs are becoming increasingly topologically networked and functionally interdependent to ensure their reliable performance. Different CISs are heterogeneous in various aspects. This study aimed at assessing the impact of systemic heterogeneity on failure propagation across interdependent CISs, by comparing simulation results from a series of improved AFB models to that from a baseline model. The improved models differed from the baseline model in that they considered different HFs within their model settings while the baseline model did not. The results showed that the impact of systemic heterogeneity on failure propagation across interdependent CISs was significant. More specifically, the combination of heterogeneity in system susceptibility to overload damage and heterogeneity in locations of the main physical damage had the largest impact on the failure propagation time; Heterogeneity in system susceptibility to overload damage had the largest impact on the failure propagation scale; The combination of heterogeneity in tolerance to disaster impacts and heterogeneity in locations of the main physical damage had the largest impact on the failure propagation sequence. Furthermore, the impacts of HFs on failure propagation time and failure propagation scale were sensitive to the tolerance parameter of the water supply system and power supply system, respectively, while the impact of HFs on failure propagation sequence was not sensitive to the tolerance parameters of both systems. Finally, the impact of HFs on failure propagation was observable under different PGA values, and larger PGA values did not necessarily result in larger impacts.

In sum, the results revealed that the systemic heterogeneity could amplify or attenuate the overall impact of a disaster event on the interdependent CISs. Therefore, systemic heterogeneity should be appropriately considered when modeling failure propagation across CISs. In-depth knowledge on systemic heterogeneity and how to incorporate the HFs in the modeling process is imperative to ensure the accuracy and reliability of models used in predicting disaster response behavior of CISs. Results from this study not only provided a better understanding of the three studied HFs, but also demonstrated the efficacy of the proposed approach in studying other HFs. Lastly, this study bears two limitations that are noteworthy. Firstly, a few HFs identified in this study could not be properly modeled and assessed due to the intrinsic limitations of the selected CISs modeling approach, despite that this approach already outperforms other approaches found in the literature. As emphasized by this study, more advanced models that can be used to study a wider range of HFs should be developed. In future works, the distributed simulation approach, which has the potential to integrate different fine-grained CIS domain models, could be explored as a promising solution to overcome the limitations of current models. Secondly, the accuracy of the impact magnitude of each HF could not be fully validated, because only limited HFs were considered in each improved model, which means that no real-life benchmark data could be found for an apples-to-apples comparison. This issue, however, could be partially addressed when the aforementioned more advanced modeling approach becomes available, which would account for the impact of HFs more accurately and comprehensively and allow for better verification of the conclusions reached in this study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2020.101818.

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