System Dynamics Modeling-Based Approach for Assessing Seismic Resilience of Hospitals: Methodology and a Case in China

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Abstract: Hospitals play a crucial role in providing badly needed medical care after earthquakes. Meanwhile, hospitals are likely to find themselves subject to earthquake impacts and may fail to function, which highlights that there is significant need for enhancing their resilience to earthquakes. Nevertheless, effective assessment of hospital seismic resilience is lacking, which makes devising and benchmarking appropriate resilience enhancement measures challenging. This study proposes a new functionality-based assessment approach of hospital resilience to earthquakes. A new indicator of hospital functionality is proposed, and a system dynamics model of hospital functionality after earthquakes (SD-HFE) is developed to simulate hospital functionality. The resilience assessment can then be conducted based on the functionality curve, which considers both the loss and the recovery of hospital functionality. Based on a case study in China, the efficacy of the proposed approach is tested. The proposed approach advances understanding of how hospital functionality evolves after an earthquake, and allows quantitative assessment of hospital seismic resilience. The outcomes of this study will contribute to the development of informed policies and effective engineering measures to enhance the seismic resilience of hospitals. **DOI: 10.1061/(ASCE)ME.1943-5479.0000814.**

Introduction

Earthquakes are one of the most destructive natural disasters. From 1998 to 2017, earthquakes occurred 563 times, which accounted for 7.8% of all types of natural disasters but were responsible for 56% of all fatalities caused by natural disasters all around the world (Wallemacq and House 2018). Hospitals play a crucial role in mitigation and the recovery of disaster-hit regions, providing continued access to care (Arboleda et al. 2009, Cimellaro et al. 2018). Almost 97% of injuries occur within the first 30 minutes after earthquakes (Gunn 1995), which requires a rapid and effective medical response. However, hospitals are themselves likely subject to earthquake impacts (Li et al. 2019). For instance, the 1995 Great Hanshin earthquake resulted in 110 structurally damaged and 4 completely destroyed hospitals, out of the 180 hospitals in the disaster-hit area (Ukai 1996). Damage to hospitals and equipment and supplies, as well as loss of staff, will undoubtedly result in a loss of hospital functionality, which will substantially exacerbate disaster consequences (Albanese et al. 2008).

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During disasters like earthquakes, hospitals are required to be more than structurally safe; they must maintain their functions and continue to provide medical care. The resilience of hospitals, which is focused on their capability to resist, absorb, and recover from disasters while maintaining necessary functionality, has attracted increasing attention (Zhong et al. 2014, Cimellaro et al. 2018). In 2005, "building hospitals with enough resilience level" was set as one practice to reduce the underlying risk factors in the Hyogo Framework for Action 2005–2015 (UNDRR 2007). Then the Sendai Framework for Disaster Risk Reduction 2015–2030, which was endorsed following the 2015 Third UN World Conference on Disaster Risk Reduction (WCDRR), also highlighted the enhancement of hospital resilience to disasters as an important priority for action (UNDRR 2015). There have also been increasing studies in academia that focus on various challenges related to the disaster resilience of hospitals (Cimellaro et al. 2010b, Achour et al. 2014, Zhong et al. 2015, Hassan and Mahmoud 2019), among which the assessment of hospital disaster resilience is the most urgent. Quantifying hospital resilience to disasters is essential and fundamental to benchmarking hospitals' capability to cope with disasters and to identifying hospitals' vulnerability in the face of disasters, which is crucial for targeted and effective resilience enhancement measures. However, the need for an effective approach to quantifying hospital resilience to earthquakes has largely remained a gap in the literature. Current "indicator-based" resilience assessment approaches, which assess hospital disaster resilience with sets of evaluation indicators (WHO 2015), are difficult to use in parametric analysis, which is crucial for evaluating potential resilience enhancement measures. Although "functionality-based" resilience assessment, which assesses hospital disaster resilience based on the functionality curve (Cimellaro et al. 2010a), can overcome this limitation, efforts are still needed in the development of an indicator of hospital functionality and an approach to analyze both the loss of hospital functionality after earthquakes and its recovery over time.

This study contributes to the existing body of knowledge by proposing a new functionality-based assessment approach to hospital resilience to earthquakes. First, a new indicator of hospital functionality is proposed, and factors affecting hospital functionality are identified and discussed in detail. Then system dynamics (SD) modeling is employed that considers both loss and recovery of hospital functionality. The simulation results provide the basis for hospital seismic resilience assessment. Based on a case study in China, the efficacy of the proposed assessment approach is tested. The proposed approach can provide a tool to better understand how hospital functionality evolves after an earthquake and to quantitatively assess the overall seismic resilience of a hospital. The outcomes of this study are expected to contribute to the resilience management of hospitals by supporting the development of informed policies and effective engineering measures with the proposed resilience assessment approach, so that the resilience of hospitals in seismic-prone regions can be enhanced against possible seismic impacts in the future.

Literature Review

There are two types of assessment approaches to hospital disaster resilience that are available in the existing literature: indicator-based and functionality-based. Indicator-based approaches assess hospital disaster resilience with a series of evaluation indicators. The World Health Organization released the second edition of *Hospital Safety Index Guide for Evaluators* in 2015, which provides a comprehensive checklist of indices for hospital safety and resilience assessment (WHO 2015). The checklist includes four modules covering hazard identification, structural safety, nonstructural safety, and emergency and disaster management. Each is evaluated qualitatively by professionals who check one of three options (low, average, and high). Zhong et al. (2015) established a conceptual framework of hospital disaster resilience and proposed a set of indicators for resilience assessment that includes 8 domains, 17 subdomains, and 43 indicators. Assessment of hospital resilience using "indicator-based" assessment can be relatively comprehensive because of the flexibility to introduce different evaluation indicators to cover various dimensions. However, these indicators are usually described qualitatively and so are inherently vague and subject to evaluators' different interpretations when they are put into practice. Meanwhile, indicator-based approaches are usually used for resilience assessment of the current status of the hospitals (WHO 2015). The difficulty in applying these approaches to different scenarios prohibits comparison of the effectiveness of different resilience enhancement measures.

Functionality-based assessment approaches assess the resilience (R) of a system of any type using a functionality curve (Fig. 1). The functionality [$Q(t)$] of a system varies between 0% and 100%, with 100% meaning that the system is fully functional, providing full service, and 0% meaning that the system malfunctions with zero service availability. Mathematically, R can be calculated by integrating $Q(t)$ from the occurrence of the event (t_0) over a control time for the period of interest (t_{LC}), as shown in Eq. (1) (Cimellaro et al. 2010a, Cimellaro et al. 2016). In comparison with indicator-based assessment, functionality-based assessment provides more details on the behavior of a system over time after being attacked by disruptions. Moreover, such a formula-format definition of system resilience makes it much more feasible to adopt these approaches in different application scenarios, especially with simulation tools (Cimellaro and Pique 2016, Khanmohammadi et al. 2018)

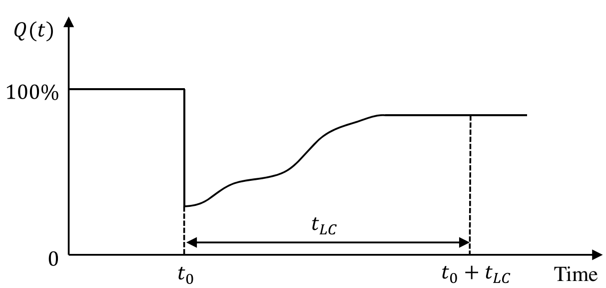

Fig. 1. Disaster resilience. (Adapted from Cimellaro et al. 2010a.)

$$R = \int_{t_0}^{t_0+t_{LC}} \frac{Q(t)}{t_{LC}} dt \tag{1}$$

When applying functionality-based assessment approaches to assess hospital disaster resilience based on Eq. (1), it is essential to first define and calculate hospital functionality. Yavari et al. (2010) divided a hospital into four major systems: structural, nonstructural, lifelines, and personnel systems. They defined overall hospital functionality using a functionality tree, which covered all possible combinations of the performance levels of the four systems. Similarly, Jacques et al. (2014) used a fault tree (Lee et al. 2009) structure to define and calculate hospital functionality, which was composed of three main components: staff, structure, and stuff. However, the approaches of Yavari et al. and Jacques et al. do not clarify how much each system or each component affects overall hospital functionality, which prevents the development of component-specific resilience enhancement measures and assessment of optimal quantities of resources prepared for disasters.

Rather than defining hospital functionality directly, some researchers proposed indicators to reflect the overall level of hospital functionality. Different from indicator-based assessment that uses sets of indicators, a single indicator is usually used for this purpose. For instance, waiting time, which is defined as the time between the receipt of a care request by the hospital and the provision of care to the patient, is widely used to construct the indicator of hospital functionality (Cimellaro et al. 2011, Cimellaro and Pique 2016, Cimellaro et al. 2017). Hospital functionality based on waiting time can be determined based on Eq. (2) (Cimellaro and Pique 2016)

$$Q(t) = \frac{WT(n, \alpha)}{\max(WT(n = n_{\text{tot}} - 1, \alpha))} \tag{2}$$

where $Q(t)$ = hospital functionality; WT = waiting time; n = number of emergency rooms; n_{tot} = total number of emergency rooms in the emergency department; α = amplification factor of the patient arrival rate ; and t = time. The waiting time can be calculated using discrete event simulation (DES) models to simulate patient flows and treatment processes (Cimellaro et al. 2011, Cimellaro and Pique 2016, Cimellaro et al. 2017). DES models shed new light on hospital disaster resilience by viewing the hospital as an integrated system rather than a simple aggregation of independent components. However, DES models from prior studies bear two major limitations. First, they were built based on the assumption that a hospital can remain operational as usual in the aftermath of disasters. In reality, the organizational system and operation can change significantly during disasters, which consequently lead to changes in waiting time compared with normal conditions. Hence, such an assumption inevitably introduces bias into resilience assessment results. Second, the hospital recovery process, which is one of the key determinants of resilience (Cimellaro et al. 2010a), was not considered in studies using DES models.

Khanmohammadi et al. (2018) built an SD model to calculate hospital functionality which characterized the dynamics of hospital operation during an earthquake. In comparison with the aforementioned DES models, the SD model considers both damage and recovery processes. An indicator of hospital functionality for resilience assessment was proposed in this study. The indicator is determined by the number of patients waiting to be treated, as shown in Eq. (3) (Khanmohammadi et al. 2018)

$$Q(t) = \begin{cases} \dfrac{A}{P(t)} & P(t) \geq A \\ 1 & 0 \leq P(t) < A \end{cases} \tag{3}$$

where $Q(t)$ = hospital functionality; A = acceptable number of patients waiting to be treated; and $P(t)$ = number of patients waiting to be treated at time t. The parameter A can be determined by hospital administrators based on a set of performance criteria.

The proposed approach of assessing hospital disaster resilience based on SD modeling provided an inspiring perspective from which to analyze the lifecycle of hospital functionality during disasters. However, there were still some limitations in this research. First, utilities such as electricity, water, and gas were simply aggregated as one type of component in the SD model and named technical systems, which overlooked the specific effect of each type of utility on hospital functionality. These utilities, in reality, play critical roles in supporting hospital functionality (Achour et al. 2014, Vugrin et al. 2015). In-depth analysis of the relationships between these utilities and hospital functionality will contribute to more comprehensive identification of hospital vulnerability. Second, the recovery of the components was considered to depend only on monetary resources, which was too simplistic and ignored technical feasibility, causing potential bias in the calculation of recovery time and hence overall hospital resilience. Choi et al. (2019) built an SD model to simulate the operations of an emergency room and used the serviceability of the emergency room, defined by the authors, to reflect its functionality. A major limitation of this model, however, is that it did not consider damage in terms of damages to hospital buildings and losses of medical staff.

Methodology

Based on the literature review, an appropriate indicator of hospital functionality after earthquakes and an approach to analyzing both loss and recovery of functionality after earthquakes are still lacking. This paper proposes a functionality-based assessment approach to hospital resilience to earthquakes that involves the following three steps:

- Quantification of hospital functionality after earthquakes [i.e., $Q(t)$ in Eq. (1)]. A quantifiable definition of $Q(t)$ is needed which should be able to reflect the desired outcome (Walden et al. 2015) that the hospital aims to achieve after earthquakes. In this paper, a new indicator of hospital functionality after earthquakes is proposed based on the literature review and expert interviews.
- Modeling of hospital functionality after earthquakes. Given the complexity of hospitals and their risks of being destroyed by sudden and devastating earthquakes, assessing and predicting loss and the recovery via physical experiments can be highly challenging (Lu and Guan 2017). In this paper, SD modeling, a widely used approach to describing accumulation and feedback of a complex system using differential equations (Chang et al. 2017, Wang and Yuan 2017, Leon et al. 2018) is adopted to model functionality [$Q(t)$]. Key factors that affect $Q(t)$ and their interactions are identified. These factors and their interactions form the basis of the variables and equations in the SD model.
- Simulation and assessment of hospital resilience to earthquakes. Based on the SD model of hospital functionality, once the initial values of the variables (i.e., inputs to the SD model) are set, $Q(t)$ (i.e., the output of the SD model) can be obtained from model simulations. The inputs include two parts: one describes the states of the factors affecting $Q(t)$ right after the earthquake; the other describes the variations in factors affecting $Q(t)$ over a certain time span. The former can be used to determine the loss of $Q(t)$, and the latter can be used to determine the recovery of $Q(t)$. After $Q(t)$ is calculated and t_0 and t_{LC} are set, resilience to earthquakes can be assessed based on Eq. (1).

The list just given provides an overview of the methodology underlying the functionality-based assessment of hospital resilience to earthquakes in this study. Details will be discussed in the following sections. In addition, to support functionality-based assessment of hospital resilience to earthquakes, a comprehensive review of prior studies was conducted. Moreover, expert interviews were carried out in Mianzhu, an inland Chinese city, in order to strengthen the validity of the proposed approach and gather information and data for an empirical case study. Mianzhu, located in Sichuan Province, was one of the worst hit cities in the 2008 Sichuan Earthquake (also known as the Wenchuan Earthquake) that occurred on May 12, 2008, with a magnitude of 8.0 (Lu et al. 2012). Most hospitals in Mianzhu were destroyed in the earthquake and then reconstructed. The authors conducted a total of four rounds of interviews between 2017 and 2019. The qualifications of the interviewees are summarized in Table 1.

The first round of interviews (R1), conducted in December 2017, aimed at constructing an indicator of $Q(t)$. Four senior doctors and three senior nurses, who participated in the medical rescue in the 2008 Sichuan Earthquake, from four hospitals (one tertiary, two secondary, and one primary) in Mianzhu were interviewed. The interviewees were asked to reflect on the scenario of the medical rescue after the earthquake and provide their opinions on the definition of hospital functionality.

The second round (R2) was conducted in March 2018. Eighteen respondents, including officials from the local Health Bureau and the medical staff from five local hospitals (one tertiary, three secondary, and one primary), were surveyed. They were asked

Table 1. Interviewee qualification

Item	Category	No. of interviewees			
		R1	R2	R3	R4
Current title	Associate chief physician	3	5	4	3
	Attending doctor	1	3	1	3
	Practitioner	0	3	1	2
	Senior nurse	3	2	0	3
	Nurse	0	1	0	0
	Administrative staff	0	4	0	0
Years of professional experience	≥30 years	1	1	1	4
	20–29 years	5	11	4	3
	10–19 years	1	3	1	4
	≤9 years	0	3	0	0
Education	Bachelor or above	5	11	4	7
	Other	2	7	2	4
Worked during earthquakes?	Yes	7	15	6	11
	No	0	3	0	0
Total		7	18	6	11

to evaluate a list of factors the authors had extracted from the literature that may affect $Q(t)$.

The third round (R3) was conducted in August 2018. Six medical staff from four hospitals (the same as in R1) were interviewed and asked to give opinions on the indicator of hospital functionality and the preliminary SD model of hospital functionality proposed by the authors.

The fourth round (R4) was conducted in May 2019. Eleven medical staff from four hospitals (the same as in R1) were interviewed. They were asked to provide opinions on the modified indicator of hospital functionality and SD model after the R3 interviews. In the meantime, one of the hospitals was chosen for the case study. The medical staff in this hospital were asked to provide additional information necessary to construct and run the SD model.

Indicator of Hospital Functionality after Earthquakes

Hospitals aim to provide complete medical care for the population (Gilder 1957). However, during emergencies, such as earthquakes, the focus of their service may change. Although it may not be possible to find a single indicator that can perfectly represent the full functionality of hospitals, it is feasible to find one that reflects the main functionality during earthquakes. During emergencies, minimizing mortality and morbidity has been seen as a primary objective of hospital services (West 2001, Hendrickx et al. 2016). Hospitals are expected to accept and treat as many patients as possible so as to meet the increasing care needs in disasters (Yi et al. 2010). During the R1 interviews, the medical staff stated that they tried every means to save lives after the earthquake in spite of tough medical working conditions. Therefore, the capability of treating patients is the main functionality of hospitals during earthquakes and so was used as an indicator of hospital functionality after earthquakes in this study.

Per Eq. (1), system functionality should have a value range from 0 to 1. The indicator of hospital functionality—the capability of treating patients—is mathematically defined as the ratio of the number of patients a hospital is able to treat to the number of patients the hospital is required to treat over a period, as shown in Eq. (4):

$$Q(t) = \frac{\sum_{i=1}^{n} \beta_i \cdot N_i^a(t)}{\sum_{i=1}^{n} \beta_i \cdot N_i^r(t)} \tag{4}$$

where $Q(t)$ = hospital functionality; t = time in days; $N_i^r(t)$ = number of patients with disease i that the hospital is required to treat on day t; $N_i^a(t)$ = number of patients with disease i that the hospital is able to treat on day t [when $N_i^a(t) > N_i^r(t)$, set $N_i^a(t) = N_i^r(t)$]; β_i = weight of disease i based on its urgency; and n = number of disease types considered for medical care during earthquakes. The variable $N_i^r(t)$ can be set by the hospital or by local health authorities according to the hospital's capability and historical data on patient arrivals during similar disasters; β_i can be set by medical experts.

Factor Identification

A hospital is a complex system whose functionality is subject to the impact of a variety of factors. In this section, these factors are first identified from the literature and then discussed in detail. The major databases and search engines, Web of Science, Google Scholar, and China National Knowledge Infrastructure (CNKI), were searched, and academic papers, theses, and working reports were retrieved. The snowballing method—identifying literature from publications' reference lists—was also applied. The factors were divided into three categories based on a trio-space framework composed of physical, social, and cyber factors proposed by Kasai et al. (2015). Physical factors were medical resources, utilities, and buildings; social factors were professional knowledge of medical staff, emergency plans, and leadership of hospital administrators; cyber factors were information and data such as from a hospital information system (HIS).

Table 2. Factors identified to be influential to hospital functionality after earthquakes

No.	Factor	Category	Results[a]
F1	Sufficient medical staff	Physical	Strongly agree
F2	Sufficient medical supplies	Physical	Strongly agree
F3	Available medical equipment	Physical	Strongly agree
F4	Available electricity supply	Physical	Strongly agree
F5	Available water supply	Physical	Strongly agree
F6	Available telecommunications	Physical	Strongly agree
F7	Available transportation for patient transfer	Physical	Strongly agree
F8	Safe buildings	Physical	Strongly agree
F9	Sufficient professional knowledge	Social	Strongly agree
F10	Comprehensive emergency plans	Social	Strongly agree
F11	Good leadership of hospital administrators	Social	Strongly agree
F12	Functional HIS	Cyber	Strongly agree

[a]"Strongly agree": average factor score falls within [4.21, 5.00] (Hansapinyo 2018).

During the R2 interviews, after a comprehensive introduction of the interview goals and the meanings of the factors, the interviewees were asked to give advice on adjusting the list of factors and state their opinions on how much these factors affected hospital functionality. A questionnaire survey followed the interviews to quantify the effects of the factors on hospital functionality, using a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The average score for each factor was calculated and evaluated based on the rating scale proposed by Hansapinyo (2018). The validity of the results was enhanced by the rich field experience of the interviewees and a combination of interviews and questionnaire surveys (Khalili et al. 2015). Table 2 summarizes the finalized list of factors, which are further explained in the following sections.

Medical Resources (Medical Staff, Supplies, and Equipment)

A hospital is unable to function without medical staff. Human resources management is an essential part of hospital emergency management (WHO 2011, WHO 2015). During emergencies like disasters, when there is a surge of patients, the shortage of medical staff can be a critical issue (Ukai 1996, Ochi et al. 2016). Supplies such as medicine, disinfectant, bandages, oxygen, and beds are also essential for medical treatment in most cases. During emergencies, hospital supply and delivery chain continuity plays a critical role in achieving quality of service and saving lives (WHO 2011, Sabegh et al. 2017). Medical equipment such as X-rays and magnetic resonance imaging (MRI) is necessary for diagnosis or treatment. Operating rooms are also regarded as a type of medical equipment in this study since they need to be well equipped in order to function. In addition, the functioning of medical equipment almost always relies on utilities such as power and water.

Utilities (Power, Water, Telecommunications, and Transportation)

Power is probably the most important utility because it supports other utilities such as water and telecommunications

(Beatty et al. 2006). A power failure will result in unavailability of equipment, loss of lighting, malfunctioning of information systems, and so forth (Milsten 2000, Beatty et al. 2006, Prudenzi et al. 2017). To prepare for unexpected power outages, hospitals can be equipped with generators so as to guarantee uninterrupted power supply. Water also plays an important role in hospitals, as it supports critical services including surgery preparation; heating, ventilation, and air conditioning (HAVC); sanitation; dialysis; sterilization; and medical equipment cooling (Milsten 2000, Roberson and Hiltebrand 2010, Welter et al. 2013, Matsumura et al. 2015). Interruptions of the water supply will significantly disrupt healthcare activities (UK Department of Health 2014). Without water, hospitals would not be able to function since hygiene and sterilization cannot be guaranteed. Many hospitals store water in tanks or reserve bottled water in case of supply disruption. However, stored water cannot solve special water needs such as for dialysis (Klein et al. 2005), which needs secondary purification by specialized devices.

Telecommunications and transportation are not direct necessities in medical treatment but may affect the efficiency of healthcare service delivery. Information exchange is important in disaster rescue (Garshnek and Burkle 1999, Chen et al. 2018). Supplementing of medical supplies may be delayed if the telecommunications are cut off, as happened in Mianzhu in the 2008 Sichuan earthquake. Although the functioning of telecommunications systems is beyond the boundaries of hospitals, hospitals can rely on satellite phones for communication in case of disruptions (Garshnek and Burkle 1999). Transportation also matters for the delivery of medical services. Damages to roads and bridges in earthquakes badly affect the efficiency of patient transfer as well as emergency logistics (Ukai 1997, Caunhye et al. 2012). While road conditions are also out of their control, hospitals are supposed to have vehicles (e.g., ambulances) to ensure successful patient transfer.

Buildings

Hospital buildings always need to be available so the medical staff can perform treatment and patients can be protected. In Mianzhu, hospital buildings were structurally damaged in the 2008 Sichuan Earthquake and were hence unsafe to enter. The medical staff had to work outdoors, where hygienic conditions could not be guaranteed. Although they moved to tents and portable dwellings several days later, the medical staff argued that these were all provided by the government as the hospitals themselves were not able to prepare enough tents or portable dwellings in advance.

Social and Cyber Factors

Professional knowledge of disaster medical rescue is one of the basic requirements of disaster medical responders (King et al. 2019). The interviewees argued that a lack of knowledge in disaster medicine resulted in the inefficient performance of the medical staff in the face of the 2008 Sichuan Earthquake. To improve the performance of medical staff during disasters, it is important to provide them with routine training (WHO 2011, Zhong et al. 2015). A comprehensive emergency plan that prespecifies how each department of the hospital should respond in emergencies contributes to the preparedness of hospitals in coping with disasters (WHO 2015). However, the interviewees argued that effective implementation of emergency plans was more important—"Without implementation, emergency plans are just pieces of paper." Good leadership by hospital administrators is key to ensuring the efficient operation of hospitals during emergencies (Richardson et al. 2013, WHO 2015). According to the interviewees, there was chaos in the operation of Mianzhu hospitals in the immediate aftermath of the 2008 Sichuan Earthquake due to an apparent lack of leadership.

As for cyber factors, the HIS has been an indispensable part of modern hospitals. It supports hospital affairs and helps to increase efficiency and reduce errors in medical service (Handayani et al. 2017, Handayani et al. 2018). The HIS is also subject to damages during earthquakes. According to the R2 interviewees, the HIS is not a must for treating patients since it can be replaced by labor; however, in that case the working efficiency of medical staff is significantly impacted.

Based on the discussions just presented, some simplifications and hypotheses are offered in order to quantify $N_i^a(t)$ in Eq. (4) and ultimately to quantify $Q(t)$.

- Only treatment in the hospital is considered; prehospital care is not.
- Once a patient receives treatment, he or she is considered cured and released.
- Medical staff, medical supplies, and medical equipment for the treatment of each disease are independent of each other, which means that staff, supplies, and equipment are disease-specific and cannot be shared across diseases.
- Power is considered to affect medical treatment in two ways, namely supporting lighting, which is considered necessary for treatment at night and supporting medical equipment such as X-rays, MRI, and operating rooms.
- Drinking water, which does not need secondary purification, is considered necessary for all treatment. Purified water from specialized devices, which rely on power, is only needed for some medical equipment such as dialysis machines.
- Telecommunications and transportation affect medical treatment indirectly—for example, by affecting patient transfer and the rate of supplementing medical supplies.
- Buildings are necessary for all treatment activities.
- Social factors affect medical treatment indirectly through other impact factors: professional knowledge affects medical staff service capacity (the maximum number of patients that can be treated); emergency plans affect the recovery rate of physical factors; leadership of hospital administrators affects the implementation of emergency plans.
- The cyber factor (i.e., the HIS) affects the service capacity of medical staff.

Hence, $N_i^a(t)$ can be calculated using Eq. (5) as follows:

$$\begin{aligned} N_i^a(t) &= \min\{[St_i^a(t)]_{\min}, [Su_i^a(t)]_{\min}, [E_i^a(t)]_{\min}\} \cdot P_L(t) \cdot W_D(t) \cdot B(t) \\ [St_i^a(t)]_{\min} &= \min[St_{i,1}^a(t), \ldots, St_{i,o}^a(t), \ldots, St_{i,n_{St}}^a(t)], \quad o \in (1, n_{St}) \\ [Su_i^a(t)]_{\min} &= \min[Su_{i,1}^a(t), \ldots, Su_{i,p}^a(t), \ldots, Su_{i,n_{Su}}^a(t)], \quad p \in (1, n_{Su}) \\ [E_i^a(t)]_{\min} &= \min[E_{i,1}^a(t), \ldots, E_{i,q}^a(t), \ldots, E_{i,n_E}^a(t)], \quad q \in (1, n_E) \end{aligned} \tag{5}$$

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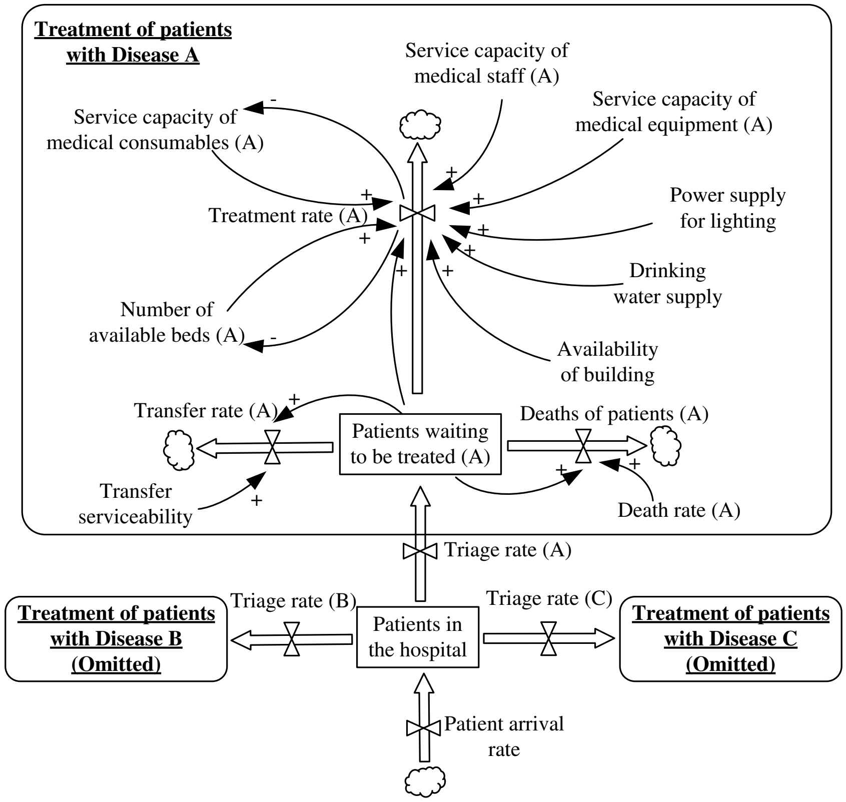

Fig. 2. Overall structure of the SD-HFE.

where $St^a_{i,o}(t)$, $Su^a_{i,p}(t)$, and $E^a_{i,q}(t)$ = service capacity of each type of medical staff, supplies, and equipment, respectively, for disease i on day t; n_{St}, n_{Su}, and n_E = number of types of medical staff, supplies, and equipment, respectively; $P_L(t)$ = power supply for lighting [given that lighting power is only necessary for treatment at night, so $P_L(t) = 1$ when power is available for lighting and $P_L(t) = 0.7$ when power is not available]; $W_D(t)$ = drinking water supply (binary: 1 when drinking water is available; 0 when unavailable); and $B(t)$ = availability of hospital buildings, equal to the percentage of residual capacity of the buildings after earthquakes.

SD Modeling. Once the value variations in the factors in Eq. (5) over time are obtained, $Q(t)$ can be obtained using Eqs. (4) and (5). However, as aforementioned, some of these factors interact and their values are correlated in complicated, nonlinear relationships. Therefore, the value variations in the factors are essentially a type of emergent property that cannot be predicted only by examining individual factors. The relationships of the factors play a fundamental role in determining the factors' values and therefore must also be considered. In order to model these factor dynamics and interactions, from which important inputs for calculating $Q(t)$ can be obtained, an SD model of hospital functionality after earthquakes (SD-HFE) is proposed in this study. In the process of model development, the SD-HFE was revised and finalized by experts through two rounds of interviews (R3 and R4).

The structure of the SD-HFE is split into multiple parts shown in different figures for readability; among these Fig. 2 shows the high-level causal loops of the model (i.e., the overall structure of the model), while Figs. 3–9 show details of those causal loops (i.e., parts of the model). Variables in all figures follow the same naming convention, and the variables that appear in multiple figures are the proxies through which different parts of the model interact. Disease A is used as an example in these figures for brevity. The overall structure of the SD-HFE is developed based on the following logic: after an earthquake, patients arrive at hospitals and are first triaged by disease type. Patients with different types of disease are treated separately. Those who have received

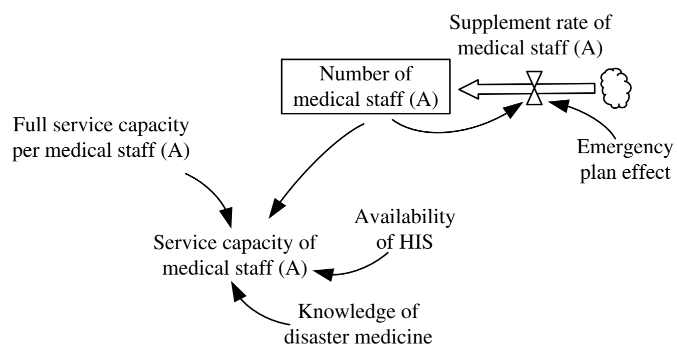

Fig. 3. Dynamics of medical staff.

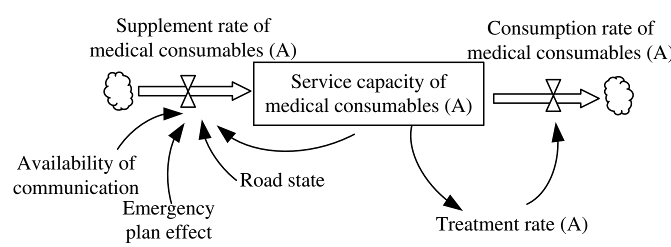

Fig. 4. Dynamics of medical consumables.

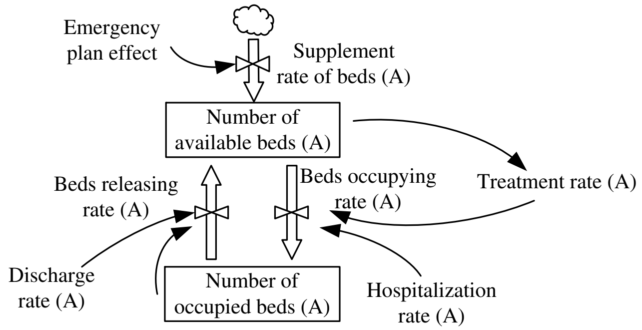

Fig. 5. Dynamics of beds.

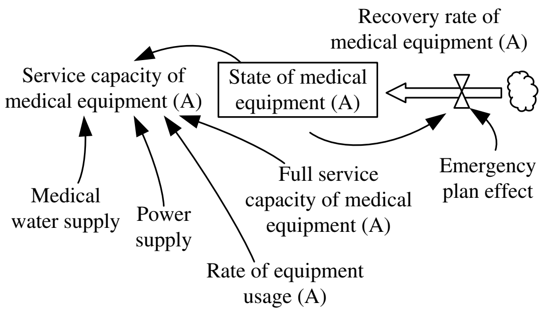

Fig. 6. Dynamics of medical equipment.

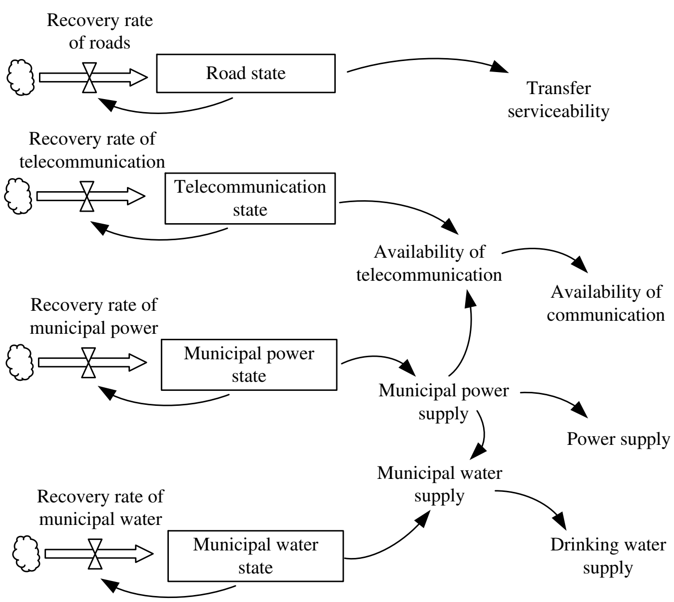

Fig. 7. Dynamics of utilities (municipal).

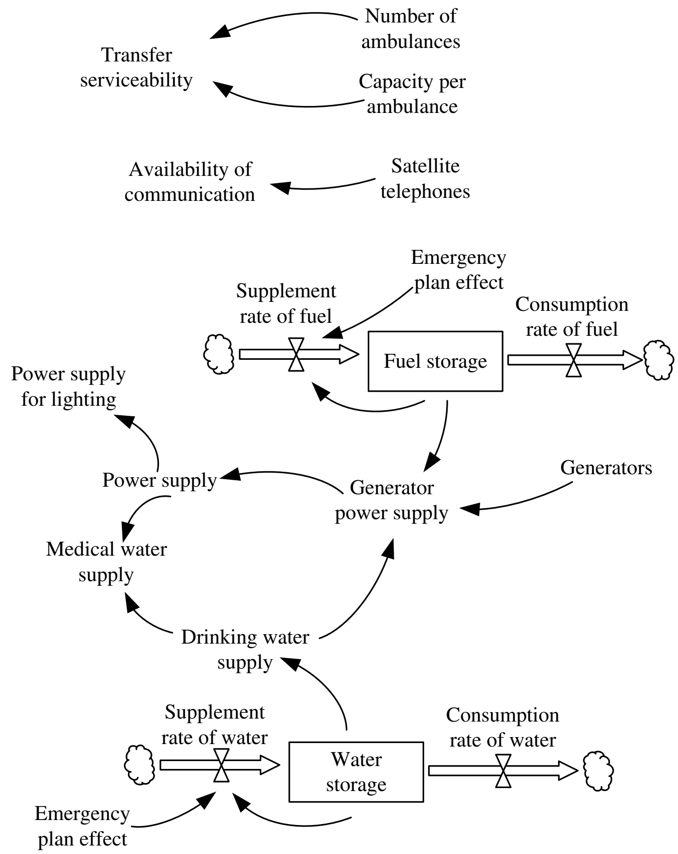

Fig. 8. Dynamics of utilities (hospital).

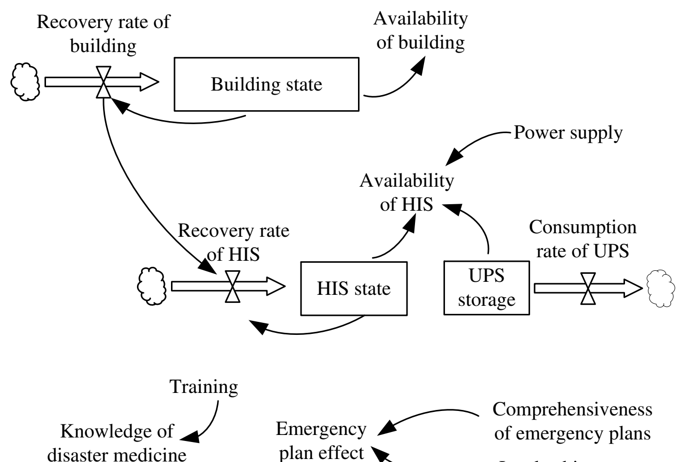

Fig. 9. Dynamics of hospital buildings, social factors, and cyber factors.

treatment are cured and released from the hospital. Some patients waiting to be treated are transferred to other healthcare facilities by ambulance and some, who die during the waiting, are sent to morgues (Cimellaro et al. 2017). In the SD-HFE, two types of medical supplies are considered: medical consumables and beds. Consumables, such as medicine, bandages, and oxygen, can be consumed and supplemented, while beds are reusable. According to Eq. (5), treatment of patients relies on "Service capacity of medical staff," "Service capacity of medical consumables," "Number of available beds," "Service capacity of medical equipment," "Power supply for lighting," "Drinking water supply," and "Availability of building."

Figs. 3–6 illustrate the dynamics of different medical resources, including medical staff, medical consumables, beds, and medical equipment, respectively. Specifically, "Service capacity of medical staff" depends on both "Number of medical staff" and "Full service capacity per medical staff." "Service capacity of medical staff" is also affected by "Availability of HIS" and staff "Knowledge of disaster medicine" (Fig. 3). "Number of medical staff" may decrease due to staff deaths and injuries caused by the earthquake. Medical consumables are consumed while patients are being treated. They can be supplemented, and the supplement rate is affected by "Road state," "Availability of communication," and "Emergency plan effect" (Fig. 4). In Fig. 5, the dynamics of beds mainly depend on "Hospitalization rate" and "Discharge rate" of the patients who receive treatment. Beds can also be supplemented if they are not adequate. In addition, medical equipment (Fig. 6) may suffer damage during earthquakes and lose availability. "Service capacity of medical equipment" is affected by "Medical water supply" and "Power supply," which support the operation of medical equipment, and also affected by "Rate of equipment usage" and "Full service capacity of medical equipment."

With regard to utilities, two parts are considered: municipal (Fig. 7), which is beyond the boundaries of hospitals, and hospital (Fig. 8), which is within the boundaries of hospitals. The municipal part includes roads, telecommunications, municipal power, and municipal water; the hospital part includes ambulances, satellite telephones, power generators, fuel, and stored water. Each municipal utility has a "state" to describe its availability, which then determines its serviceability. Utility states may be worsened and their availability may be lost because of the earthquake, but they may also be improved after recovery measures are taken. For municipal water and telecommunications, their availability also relies on the availability of municipal power supply (Fig. 7). As aforementioned, power and water in the hospital mainly depend on municipal supply, while the hospital can also prepare power generation equipment and store water in case of accidents (Fig. 8). "Generator power supply" relies on both "Generators" and "Fuel storage," which can be consumed and supplemented. In addition, electric power generation requires water for cooling (Vugrin et al. 2015). Stored water, as another source of "Drinking water supply" in the hospital, can also be consumed and supplemented by the hospital. "Medical water supply" relies on both "Drinking water supply" and "Power supply" as power is needed to run the purification equipment.

Fig. 9 shows the dynamics of hospital buildings, social factors, and cyber factors. The state of buildings determines their availability, which can be recovered by repair or reconstruction. "Availability of HIS" depends on "Power supply." The HIS is also equipped with an uninterrupted power supply (UPS). "Recovery rate of HIS" is considered to depend on "Recovery rate of building" where it is installed. For social factors, medical staff's "Knowledge of disaster medicine" can be improved by "Training," and "Emergency plan effect," which can affect the recovery rate of some physical factors as aforementioned, is related to "Comprehensiveness of emergency plans" and "Leadership" of hospital administrators.

The relationships among different factors can be classified as two types: one-way, in which one factor is affected by another; and interactive, in which two factors are affected by each other. For one-way relationships, one example is that transportation condition affects the supplementing of medical consumables, which is modeled by the relationship between "Road state" (Fig. 7) and "Supplement rate of medical consumables" (Fig. 4); another example is that "Emergency plan effect" (Fig. 9) affects the recovery rates of some physical factors such as medical staff (Fig. 3), medical consumables (Fig. 4), medical beds (Fig. 5), medical equipment (Fig. 6), and fuel and stored water (Fig. 8), as the recovery processes of the factors are usually prespecified in hospital emergency plans. As for interactions, one example is that two types of utilities, power and water, interact, where "Municipal power supply," as one source of "Power supply," affects "Municipal water supply" and further affects "Drinking water supply" (Fig. 7); conversely, "Drinking water supply" affects "Generator power supply" (Fig. 8), which is another source of "Power supply." Some factors and treatment activity also interact. For instance, "Service capacity of medical consumables" (Fig. 4) and "Number of available beds" (Fig. 5) contribute to "Treatment rate" of patients (Figs. 4 and 5), which in turn determines "Consumption rate of medical consumables" (Fig. 4) and "Beds occupying rate" (Fig. 5).

Simulation of the SD-HFE and Assessment of Hospital Resilience to Earthquakes. Inputs are needed to run the SD-HFE. As aforementioned, they include those describing the states of factors right after the earthquake, which depend on potential loss or damage to the factors, and those describing the variations in factors over time. Potential methods to determine the inputs are given in this section. FEMA (2012a) has published the FEMA-P58 methodology for seismic performance assessment of buildings as well as an electronic calculation tool called PACT for implementing the methodology. By inputting data on building information (story height, area, etc.), occupancy, component fragilities, earthquake scenario, and so forth, PACT is able to perform loss calculations including repair cost, downtime, and casualty estimates (FEMA 2012b). Hence, medical staff casualties and hospital building losses can be obtained using PACT. PACT can also potentially be used to determine the loss of components in the hospital building such as medical supplies, medical equipment, hospital utilities, and the HIS once their fragility data are obtained. With regard to the recovery of these factors, the supplementing of medical staff, medical supplies, fuel for generators, and drinking water, as well as the recovery of medical equipment, can be estimated according to interviews with the hospital staff. The time needed for retrofitting the hospital building can be obtained using PACT. In addition, loss and recovery rates of municipal utilities can be estimated using Hazus–MH 2.1, which was also developed by FEMA (2018), if required data are made available. For social factors, the variables in the model can be set according to experts' opinions collected in interviews. The profile data of the hospital, such as the initial number of medical staff, initial service capacity of medical supplies, and so on, can be obtained through surveys. Inputs that require medical knowledge and historical experience, such as patient arrivals, death rates, hospitalization rates, discharge rates, and so on, can be estimated by experts.

When the simulation is performed using the SD-HFE, the variables in the model vary over time. The variable $N_i^a(t)$ can be obtained based on Eq. (5) and then $Q(t)$ can be calculated based on Eq. (4). Setting t_0 as the time when the earthquake occurs and t_{LC} as a time window of interest, the hospital's resilience to earthquakes can be obtained based on Eq. (1).

Case Study

A case study was carried out using the proposed approach to quantify the resilience of a tertiary hospital in Mianzhu. The hospital, located in the city center, had 686 beds with annual patient arrivals of around 0.70 million. The hospital building, reconstructed after the 2008 Sichuan Earthquake, had 12 floors. The pharmacy was located on the first floor and the operating rooms were located on the fourth floor. The simulation scenario assumed that the reconstructed hospital suffered an earthquake similar to the 2008 Sichuan Earthquake at the present time. All data that were needed as inputs to the SD-HFE were obtained in the R4 interviews. The ground motion data of the 2008 Sichuan Earthquake with a peak ground acceleration of $6.33\ \mathrm{m/s^2}$ were used in this case study.

Table 3. Lookup table for SD-HFE inputs in the case study

Model input	Damage state of the targeted floor (%)				
	None	Slight	Moderate	Extensive	Complete
Loss of medical consumables	0	5	10	50	90
Loss of beds	0	0	20	60	100
Availability of operating rooms	100	100	0	0	0
HIS state	100	0	0	0	0
Availability of floor	100	80	0	0	0

Residual "Number of medical staff" was set by taking into consideration medical staff casualties estimated using PACT. It was assumed that all medical staff were working in the hospital when the earthquake occurred and hence there was no supplement of medical staff. Due to a lack of fragility data necessary for damage analysis in PACT, the loss of medical supplies and damage to medical equipment and the HIS were estimated based on the damage state of the hospital building, and it was assumed that there was no damage to hospital utilities. Using the method proposed by Xiong et al. (2016), the damage state (none, slight, moderate, extensive, or complete) of each floor of the hospital under the ground motion was obtained. Then the loss or availability of the these components was estimated according to the damage state of the targeted floor using a lookup table (Table 3) developed by the authors. For loss or availability estimation of medical consumables, beds, operating rooms, and the HIS, the targeted floor in Table 3 was the floor where the pharmacies, wards, operating rooms, and HIS were located. The availability of the building equaled the ratio of residual availability of floors. "Supplementary rate of medical consumables" was estimated based on data collected in the R4 interviews, which were adjusted according to "Road state," "Availability of communication," and "Emergency plan effect"; the recovery rates of hospital utilities were assumed or estimated by the interviewees; "Recovery rate of building" was set based on the building repair time estimated using PACT, and the repair process was assumed to be linear; the operating rooms and the HIS were considered fully recovered when the hospital building was fully recovered.

Since data required by Hazus–MH 2.1 for analyzing the damage and recovery of municipal utilities were not available, the damage and recovery rates were set as the actual rates observed in the 2008 Sichuan Earthquake and reported in the interviews. This may have led to somewhat conservative assessment results because after the 2008 Sichuan Earthquake there was a huge investment on the overall capability of the Mianzhu to cope with earthquake. Therefore, current municipal utilities should be more resilient to earthquakes than they were in 2008. Four disease types considered in the case study: Disease A (minor trauma like abrasion), Disease B (severe trauma like fractures and brain injuries), Disease C (upper respiratory infection and enteritis), and Disease D (others) (Liu et al. 2008). Their weights [β_i in Eq. (4)] were set by the average death rate for each type. Operations were necessary only for all patients with Disease B and 10% of patients with Disease D, according to the interviews. Patient arrivals with different diseases after the earthquake were set after scaling the data from the 2008 Sichuan Earthquake according to annual patient arrivals. For each hospital, $N_i^r(t)$ was set according to the daily service capacity of the current medical resources. Gaussian noise was introduced to reflect the fluctuations in service capacity of the medical resources. Table S1 summarizes the main inputs for the calculation of hospital functionality in the case study, and Table S2 provides the system dynamics equations used in the case study. The SD-HFE was run in Anylogic 8.4.0 PLE. The results are reported in the next section.

Results

Fig. 10 illustrates the functionality curve of the case hospital in Mianzhu. The curve reflects a pattern of "first decreasing and then recovering." Immediately after the earthquake (Day 0), $Q(t)$ dropped to 0.65, mainly because of the loss of hospital building serviceability. In the meantime, a municipal power failure was caused by the earthquake. Although the hospital was equipped with power generators, the stored diesel fuel was only enough for one day. Hence, $Q(t)$ fell to 0.26 at the end of Day 1 but bounced back when municipal power was restored on Day 2. Then $Q(t)$ began to increase gradually as measures were being taken to repair the hospital building. Since Day 19 when the hospital building was fully recovered, $Q(t)$ generally remained stable at 1.00 with slight fluctuations caused by the Gaussian noise introduced to the SD-HFE. Setting t_0 as the day when the earthquake happened and t_{LC} as 60 days when the distribution of diseases after the earthquake tended to be stable (Liu et al. 2008), the resilience level of the hospital using the SD-HFE was calculated as 0.91 based on Eq. (1).

In order to further explore the reasons behind variations in the functionality curves, the performance [$Per(t)$] of the hospital was assessed per each disease; in other words, $N_i^a(t)/N_i^r(t)$ was calculated for each value of variable i. The results are depicted in Fig. 11. As can be seen in the figure, after the earthquake (Day 0), $Per(t)$ for Diseases A, B, C, and D fell to 0.68, 0.80, 0.90, and 0.41, respectively. The differences in performance were due to the different initial service capacity of the medical resources. On Day 1, when there was no lighting due to power outage after the generators ran out of fuel, the performance of the hospital for all diseases significantly dropped. Thus, $Per(t)$ for Disease B fell to 0 and $Per(t)$ for Disease D fell to 0.29, as the operating rooms were not available due to the power failure. On Day 2, $Per(t)$ for all diseases bounced back when the municipal power was restored, which was consistent

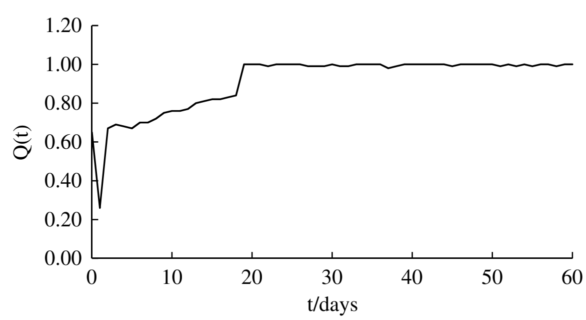

Fig. 10. Hospital functionality curve.

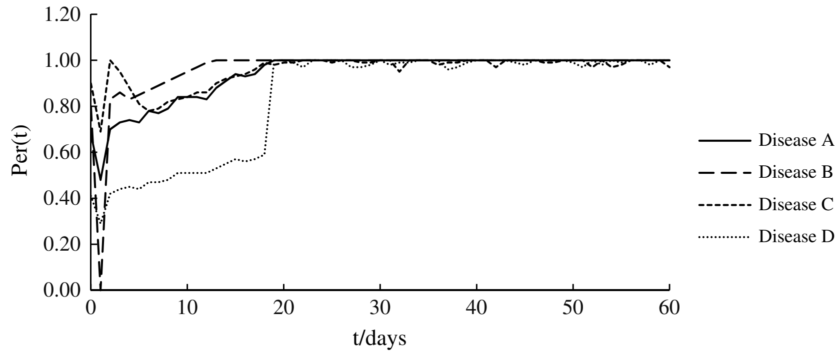

Fig. 11. Treatment performance for Diseases A, B, C, and D.

with the trend of $Q(t)$ in Fig. 10. On Day 4, a decrease of $Per(t)$ for Disease B was observed and attributed to the deficiency of medical consumables, which only lasted for one day as more medical consumables were supplemented. From Day 4, there was a significant drop in $Per(t)$ for Disease C, when the hospital received an increasing number of patients and ran out of beds. However, as the occupied beds were gradually released and the building was being restored, $Per(t)$ for Disease C went back up over time. Nevertheless, the decrease in $Q(t)$ from Day 4 was not very obvious because $Per(t)$ for Diseases A and D kept increasing with the recovery of the building from Day 2, when municipal power was recovered, which neutralized the effects of the decrease in $Per(t)$ for Diseases B and C. As shown in Fig. 11, $Per(t)$ for Disease B was fully recovered on Day 13 rather than on Day 19, when the building was fully recovered, because the storage of medical resources for Disease B was higher than actually needed and so $Per(t)$ for Disease B could be relatively high and recovered earlier in spite of the impact of the damaged building. In addition, $Per(t)$ for Disease D was generally the lowest among all four curves because it was mainly restricted by the service capacity of medical staff, which fell 50% due to the unavailability of the HIS. However, on Day 19, when both the HIS and the service capacity of medical staff were recovered, $Per(t)$ for Disease D bounced back to around 1.00, which contributed to the full recovery of $Q(t)$ on the same day.

The results of the case study were provided for three experts in Mianzhu who had participated in the aforementioned interviews, including one associate chief physician and one senior nurse from the case hospital and one administrator from the local Heath Bureau. The experts all commented that the results were in line with their expectations and well reflected the behavior of the hospital after earthquakes.

Discussion

Extreme Condition Test

In order to ensure that the SD-HFE was structurally valid, extreme condition tests were conducted. The variable inputs to the model were individually set to zero or infinite (around 10,000 times larger than other variable inputs) to examine the behavior of the model under various extreme conditions. The results of the extreme conditions tests showed that the SD-HFE behaved as expected. In this section, two tests are given as examples. Condition 1 assumed that the roads around the hospital were totally impassable and that "Recovery rate of roads" was zero; other conditions were unchanged compared with the case study. Under such conditions, the hospital had no access to supplemental medical supplies and could not transfer patients to other locations (patient arrivals were considered unaffected by "Road state"). Condition 2 assumed that "Recovery rate of municipal power" was zero, which indicated that municipal power would be continuously unavailable due to earthquake damage. The results of the case study served as a reference (marked as Condition 0). Fig. 12 illustrates the results of the two tests. Under Condition 1, for the first two days $Q(t)$ was not impacted compared to Condition 0 due to the initial storage of medical consumables. However, when the hospital was running out of medical consumables, $Q(t)$ began to decrease. The first decreases occurred on Days 4 and 5 when medical consumables for Disease B were running out; the second decreases occurred on Days 6 and 7, when medical consumables for Disease C were running out; the third decreases occurred on Days 20 and 21, when medical consumables for Disease D were running out. After that, $Q(t)$ kept decreasing as medical consumables for Disease A were consumed. Under Condition 2, unlike Condition 0, $Q(t)$ did not bounce back on Day 2 because

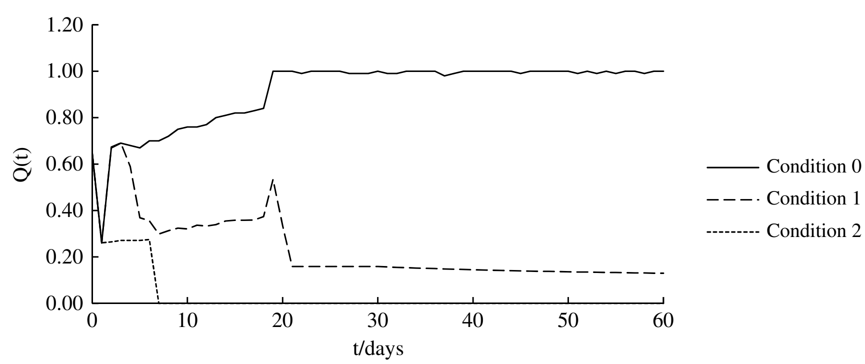

Fig. 12. Results of extreme condition test.

municipal power was not recovered. As power affected $Q(t)$ through access to lighting and medical equipment, the hospital was able to maintain a low level of functionality because treatment activities which did not rely on medical equipment and happened in the daytime were not affected. However, municipal power supply was also essential to municipal water supply, which in turn determined whether the hospital would have access to drinking water that was critical to $Q(t)$. Thus, from the curve in Condition 2, it can be seen that $Q(t)$ was kept at around 0.25 due to the storage of drinking water until Day 7, when the stored drinking water ran out and $Q(t)$ fell to zero. This curve of $Q(t)$ also reflected the interactions among utilities.

Adaptation of the Hospital

During the 2008 Sichuan Earthquake, the case hospital was severely damaged. Power and water were cut off for days and almost all functional departments were unavailable. The medical staff the authors talked to during the R4 interviews were asked to recall and estimate $Q(t)$ for the case hospital after the earthquake. In order to facilitate their understanding of $Q(t)$, it was simplified as "the percentage of patients the hospital was able to treat." It should be noted that such a simplification ignored the weights of diseases [i.e., β_i in Eq. (4)]. According to the interviewees, the patients they were not able to treat were usually those with life-threatening diseases. The weights of these diseases were supposed to be high because β_i was set based on the death rate associated with the diseases in the case study. Hence, $Q(t)$ was overestimated. The interviewees indicated that $Q(t)$ showed three obvious stages, including treatment on site, treatment in tents, and treatment in portable dwellings, where $Q(t)$ was about 0.40, 0.60, and 0.90, respectively, as shown in Fig. 13. Around two years later, when the hospital was reconstructed and put into use, $Q(t)$ recovered to 1.00 (not shown in Fig. 13). Setting t_0 as the day of the earthquake and t_{LC} as 60 days, the hospital's level of resilience to the 2008 Sichuan Earthquake was calculated as 0.61 based on Eq. (1).

In Fig. 13, both curves had significant decreases in the first few days after the earthquake, which were mainly caused by the failure of utilities like power and water and municipal utility damage, and recovery rate inputs were set to be the same as in the year 2008. Nevertheless, the decrease in $Q(t)$ in the case study had a one-day lag due to the implementation of power generators in the hospital. Moreover, the current hospital building suffered much less damage in the case study than in 2008, contributing to fewer medical staff casualties and less loss of or damage to medical supplies and equipment. This in turn contributed to less loss of $Q(t)$ and a higher resilience level. Such results echoed the feedback collected during the R4 interviews. The medical staff in the hospital suggested that they had been much more prepared to cope with earthquakes than before—with a more robust building and more stored supplies. They were quite sure that the hospital would perform much better were an earthquake like that in 2008 to occur.

According to Eq. (4), $Q(t)$ depends not only on $N_i^a(t)$ but also on $N_i^r(t)$, the latter of which reflects the expected serviceability of the hospital. This is related to the hospital's resources. Obviously, a tertiary hospital is required to serve more people and handle more diseases than a primary hospital. From the year 2008 to the present time, the case hospital has become a tertiary hospital with an annual patient arrival of around 0.70 million from a secondary hospital with an annual patient arrival of around 10,000. The current $N_i^r(t)$ is much higher than that in 2008. Therefore, the resilience level of the hospital has increased by 49%, from 0.61 to 0.91, since then, while the number of patients the hospital is able to treat has increased by an even much larger percentage.

Policy Sensitivity Test

In the case study, the decreases in $Q(t)$ were mainly due to three issues: power failure, deficiency of beds, and loss of serviceability of the hospital building. The authors tested the effectiveness of three policies that were supposed to address these issues using the SD-HFE: Policy 1—the hospital reserves twice as much fuel as it does now; Policy 2—the hospital shifts 40 beds from the departments for Disease C to the departments for Disease D after the earthquake; and Policy 3—the hospital shortens the recovery time of the building from 19 to 10 days by hiring more workers. The inputs to the model were adjusted according to each policy. The effects of the three policies based on simulation results are illustrated in Fig. 14, where the result of the case study are also shown as Policy 0.

Fig. 14 shows the effectiveness of the policies, which overall improved $Q(t)$. Policy 1's effectiveness indicated that a higher storage of fuel did work to avoid the abrupt loss of $Q(t)$ caused by municipal power failure. However, a new drop in $Q(t)$ occurred on Day 3. By backtracking the variables in the SD-HFE, it was found that medical consumables for Disease B happened to be deficient on Day 3 because they were consumed faster when the power was uninterrupted from the beginning. Such deficiency caused the drop. Hence, Policy 1 should be accompanied by another policy of enhancing the storage of medical consumables for Disease B so as to better improve $Q(t)$. Policy 2's effectiveness indicated that proper distribution of medical supplies in different departments of the hospital was also important to enhance resilience to earthquakes. However, such a distribution is disease-specific and the

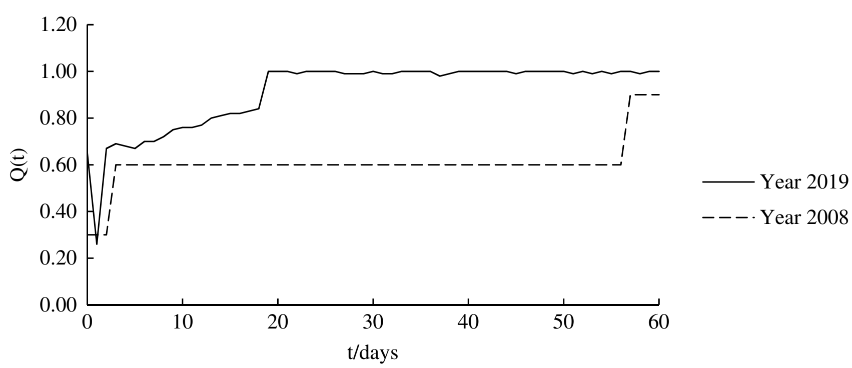

Fig. 13. Adaptation of the hospital.

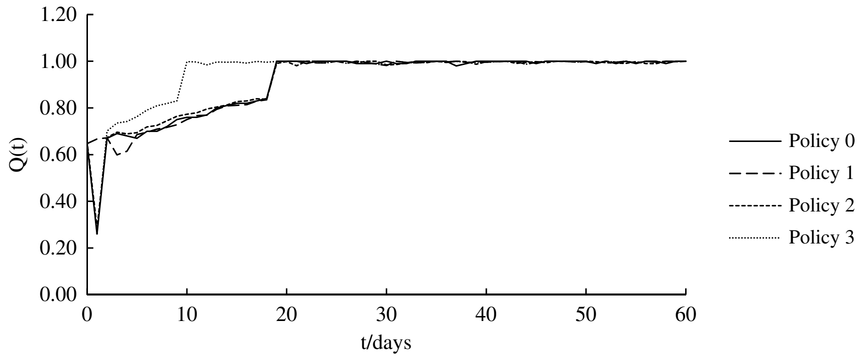

Fig. 14. Results of policy sensitivity test.

distribution for earthquakes might not work for other disasters if the distribution of diseases caused by the disaster were different. Policy 3's effectiveness indicated that a higher hospital building recovery rate would contribute to a higher recovery rate of $Q(t)$, which was as expected. Nevertheless, it should be noted that the purpose of the policy test was to demonstrate the feasibility of using the SD-HFE to assess the effectiveness of possible resilience enhancement policies rather than to develop feasible or optimal resilience enhancement policies. Hence, some factors, such as structural repair and reconstruction activities that may potentially cause interruptions to medical operations, were not considered in the policy test. Overall, $Q(t)$ calculated that the SD-HFE was sensitive to the proposed policies, and that the evolution of $Q(t)$ under the three polices was headed for the same trend, which proved the reliability of the SD-HFE (Jiang et al. 2015).

Conclusions

This research proposed a new functionality-based assessment approach to quantifying hospital resilience to earthquakes. A new indicator of hospital functionality was proposed and the SD-HFE was developed to simulate and compute hospital functionality after earthquakes, considering both the hospital's damages and its recovery processes. The validity of the approach was tested using a case study of a hospital in China. The proposed approach can contribute to analyzing the evolution of hospital functionality after an earthquake and assessing hospital earthquake resilience. Moreover, the approach can serve as a tool for decision makers in identifying weaknesses in hospital earthquake resilience and comparing the effectiveness of different resilience enhancement measures so as to propose targeted solutions.

While the proposed approach is a promising tool, it has limitations that should be acknowledged. A few assumptions were made for the approach. Some of them may be strict. For instance, medical resources (staff, supplies, and equipment) for the treatment of each disease are considered independent of each other. In fact, different diseases may require common medical resources and hospitals themselves may arrange their medical resources flexibly so as to maximize their functionalities in emergencies. Future research should look into the correlation of medical resources needed in the treatment of different diseases, which may require more domain knowledge in medicine and pharmacy. Moreover, there can be other potential factors that may affect hospital functionality after earthquakes in addition to those identified in the SD-HFE. These factors can be identified and examined in future research for further improvement of the SD-HFE. For a practical assessment of hospital resilience, consideration of the uncertainties in earthquake occurrence as well as intensity is suggested. In addition, while the feasibility of the proposed approach in comparing the effectiveness of resilience enhancement policies has been demonstrated, how to develop or optimize these policies, which should consider costs, feasibility, and interactions, is worth investigation in future research.

Data Availability Statement

Some or all data, models, or code generated or used during the study are available from the corresponding author by request. The data, models, or code are the raw data used to generate Figs. 10–14.

Acknowledgments

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Supplemental Materials

Tables S1 and S2 are available online in the ASCE Library (www.ascelibrary.org).

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