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Original
System Dynamics Modeling-Based Approach for Assessing Seismic Resilience of Hospitals: Methodology and a Case in China / Li, Z.; Li, N.; Cimellaro, G. P.; Fang, D.. - In: JOURNAL OF MANAGEMENT IN ENGINEERING. - ISSN 0742-597X. - ELETTRONICO. - 36:5(2020), p. 04020050.

Availability:
This version is available at: 11583/2840599 since: 2020-07-17T15:56:00Z

Publisher:
American Society of Civil Engineers (ASCE)

Published
DOI:10.1061/(ASCE)ME.1943-5479.0000814

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 the badly needed medical care after earthquakes. Meanwhile, hospitals are themselves likely subjects to earthquake impacts and may fail to function, which highlights that there is significant need for enhancing the resilience of hospitals to earthquakes. Nevertheless, there lacks an effective assessment approach of hospital seismic resilience, which makes it challenging for devising and benchmarking appropriate resilience enhancement measures. 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 the 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 the understanding on 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.

Introduction

Earthquakes are one of the most destructive natural disasters. From 1998 to 2017, earthquakes occurred 563 times, which accounted for 7.8% of the numbers 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 the mitigation and recovery of disaster-hit regions, providing continued access to care (Arboleda et al. 2009, Cimellaro et al. 2018). Almost 97% of the injuries occur within the first thirty minutes after earthquakes (Gunn 1995), which requires a rapid and effective medical response. However, hospitals are themselves likely subjects 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 the hospitals, equipment and supplies, loss of staff will undoubtedly result in a loss of hospital functionality, which would substantially exacerbate disaster consequences (Albanese et al. 2008).

During disasters like earthquakes, hospitals are required to be more than structurally safe but to maintain their functions and continue to provide medical care. The resilience of hospitals, which is focused on hospitals' 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 part of "Priorities for action" (UNDRR 2015). There have also been an increasing volume of recent 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 face of disasters, which is crucial for the propositions of targeted and effective resilience enhancement measures. However, the need for an effective approach for 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 for parametric analysis, which is crucial for evaluating possible resilience enhancement measures. Although "functionality-based" resilience assessment approaches, which assess 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 of hospital resilience to earthquakes. Firstly, a new indicator of hospital functionality is proposed, and factors affecting the hospital functionality are identified and discussed in detail. Then, system dynamics (SD) modeling is employed to simulate the changes of hospital functionality after earthquakes, which considers both the loss and the recovery of hospital functionality. The simulation results provide the basis for seismic resilience assessment of the hospitals. 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 could be enhanced against possible seismic impacts in the future.

Literature Review

There are two types of assessment approaches of hospital disaster resilience that are available in the existing literature, including “indicator-based” approaches and “functionality-based” approaches. Indicator-based approaches assess hospital disaster resilience with a series of evaluation indicators. The World Health Organization released the Hospital Safety Index Guide for Evaluators (Second Edition) 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 of the indices is evaluated qualitatively by professionals who check one of three options (low, average and high). Similarly, Zhong et al. (2015) established a conceptual framework of hospital disaster resilience and proposed a set of indicators for resilience assessment, which includes 8 domains, 17 sub-domains, and 43 indicators. Assessment of hospital resilience using “indicator-based” assessment approaches can be relatively comprehensive, because of the flexibility to introduce different evaluation indicators to cover various dimensions. However, these indicators such as the aforementioned ones are usually described qualitatively, which are inherently vague and subject to evaluators’ different interpretations when they are put into practice. Meanwhile, indicator-based approaches are usually used for the resilience assessment of the current status of the hospitals (WHO 2015). It is difficult to apply these approaches to different scenarios, which prohibits the 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 (see Fig. 1). The functionality ($Q(t)$) of a system varies within the range between 0 and 100%. One hundred percentage means the system is fully functional, providing full service, while 0 means 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 approaches, functionality-based assessment approaches provide more details on the behavior of a system over time after being attacked by disruptions. Moreover, such formula-format definition of system resilience makes it much more feasible to be adopted in different application scenarios, especially with simulation tools (Cimellaro and Pique 2016, Khanmohammadi et al. 2018).

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

[Insert Fig. 1 here]

When applying functionality-based assessment approaches to assess hospital disaster resilience based on Eq. (1), it is essential to first define and calculate the hospital functionality. Yavari et al. (2010) divided a hospital into four major systems, namely structural, nonstructural, lifelines, and personnel systems, and defined the 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, including staff, structure, and stuff. However, the above two approaches do not clarify how much each system or each component affects the 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 approaches which contain 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 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). The hospital functionality based on waiting time can be determined based on Eq. (2) (Cimellaro and Pique 2016):

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

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

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

$$Q(t) = \begin{cases} \frac{A}{P(t)} & A \leq P(t) \\ 1 & A > P(t) \end{cases} \quad (3)$$

where $Q(t)$ is hospital functionality; A is the acceptable number of patients waiting to be treated; $P(t)$ is the number of patients waiting to be treated at time t. The parameter A could 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 to analyze the "lifecycle" of the 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, named as "technical systems", which overlooked the specific effect of each type of utilities 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 vulnerability of hospitals. Second, the recovery of the components was considered to only depend on monetary resources, which was too simplistic and ignored technical feasibility, causing potential bias in the calculation of recovery time and hence the overall hospital resilience. Similarly, 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 the damage of the hospital in terms of damages to hospital buildings and losses of medical staff.

Methodology

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

1. 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 literature review and expert interviews.

2. Modeling hospital functionality after earthquakes. Given the complexity of hospitals and their risks of being destroyed by sudden and devastating earthquakes, assessing and predicting the loss and the recovery of hospital functionality after earthquakes via physical experiments could be highly challenging (Lu and Guan 2017). In this paper, SD modeling, a widely used approach for describing processes of 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 hospital functionality ($Q(t)$) after earthquakes. 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.

3. Hospital functionality 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. the inputs of 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, including one part that describes the states of the factors affecting $Q(t)$ right after the occurrence of the earthquake, and a second part that describes the variations of the 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 $Q(t)$. Then, after $Q(t)$ is calculated and t_0 and t_{LC} are set, the hospital resilience to earthquakes can be assessed based on Eq. (1).

Above provides an overview of the methodology to propose the functionality-based assessment approach of hospital resilience to earthquakes in this study. More details of the methodology will be discussed in next sections. In addition, to support the proposition of the functionality-based assessment approach 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, China, 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.

1. The first round (R1) was conducted in December 2017, which 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 hospitals) in Mianzhu, were interviewed. The interviewees were requested to reflect on the scenario of the medical rescue after the earthquake and provide their opinions on the definition of hospital functionality.

2. 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 hospitals) were surveyed. They were requested to evaluate a list of factors the authors extracted from the literature that may affect $Q(t)$.

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

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

[Insert Table 1 here]

Indicator of Hospital Functionality after Earthquakes

Hospitals are aimed to provide complete medical care for the population (Gilder 1957). During emergencies, such as earthquakes, the focus of their service may be changed compared with normal conditions. 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 of hospitals 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 also argued that they tried every means to save lives after the earthquake in spite of tough medical working conditions. Therefore, the capability of treating patients in hospitals is the main functionality of hospitals during earthquakes, which, hence, is used as an indicator of hospital functionality after earthquakes in this study.

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

$$Q(t) = \begin{cases} \dfrac{\sum_{i=1}^{n} \beta_i \cdot N_i^a(t)}{\sum_{i=1}^{n} \beta_i \cdot N_i^r(t)} & N_i^a(t) \le N_i^r(t) \\ 1 & N_i^a(t) > N_i^r(t) \end{cases} \quad (4)$$

where $Q(t)$ denotes hospital functionality; t denotes time in days; $N_i^r(t)$ denotes the number of patients with disease i that the hospital is required to treat on day t; $N_i^a(t)$ denotes the number of patients with disease i that the hospital is able to treat on day t; β_i denotes the weight of disease i based on its urgency; n denotes the number of the types of diseases considered for medical care during earthquakes. $N_i^r(t)$ can be set by the hospital or by local health authorities according to the capability of the hospital and the historical data of patient arrivals during similar disasters; β_i can be set by medical experts.

Factors Identification

A hospital is a complex system, whose functionality is subject to the impact of a variety of factors. In this section, these factors were firstly identified from literature and then discussed in detail. Major databases and search engines including Web of Science, Google Scholar and CNKI were searched and literature including academic papers, theses and working reports was retrieved. Snowballing method, i.e. identifying literature from the references of publications, was also applied. The factors were divided into three categories based on a trio-space framework proposed by Kasai et al. (2015), namely physical, social and cyber factors. Physical factors were those owning an entity, such as medical resources, utilities, and buildings; social factors were those related to human activities, such as professional knowledge of medical staff, emergency plans, and leadership of hospital administrators; cyber factors were those related to information and data such as Hospital Information System (HIS). During the R2 interviews, after a comprehensive introduction of the goal of the interview and the meanings of the factors, the interviewees were required to give advice on adjusting the list of factors and 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 of 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. These factors are further explained below.

[Insert Table 2 here]

Medical Resources (Medical Staff, Supplies, and Equipment)

A hospital is unable to function without medical staff. Human resource management is an essential part of hospital emergency management (WHO 2011, WHO 2015). During emergencies like disasters when there will be a surge of patients, the shortage of medical staff can be a critical issue (Ukai 1996, Ochi et al. 2016). Medical supplies like medicine, disinfectant, bandages, oxygen, and beds are also essential for medical treatment in most cases. During emergencies, continuity of the hospital supply and delivery chain plays a critical role in achieving the 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, Telecommunication, and Transportation)

Power probably is the most important utility, which also supports other utilities such as water and telecommunication (Beatty et al. 2006). A power failure will result in various problems in a hospital, such as unavailability of equipment, loss of lighting, malfunction of information system 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 many critical services in a hospital including surgery preparation, heating, ventilation, and air-conditioning (HAVC), sanitation, dialysis, sterilization and cooling some medical equipment (Milsten 2000, Roberson and Hiltebrand 2010, Welter et al. 2013, Matsumura et al. 2015). Interruptions of 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 water supply disruption. However, the stored water cannot solve the special water needs such as water used in dialysis (Klein et al. 2005), which needs secondary purification by specialized devices.

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

Buildings

Hospital buildings always need to be available for medical activities, where the medical staff can perform the treatment and the patients can be protected. In Mianzhu, the hospital buildings were structurally damaged in the 2008 Sichuan Earthquake and were hence unsafe to enter after the earthquake. The medical staff had to work outdoors, where the hygienic condition could not be guaranteed for treatment. Although they moved to tents and portable dwellings several days later, the medical staff argued that the tents and portable dwellings 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 such a sudden disaster. To improve the working performance of the medical staff during disasters, it is important to provide them with routine training (WHO 2011, Zhong et al. 2015). A comprehensive emergency plan, which pre-specifies how each department of the hospital should response in emergencies, will contribute to the preparedness of hospitals to cope 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 of 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 factor, the HIS has been an indispensable part of modern hospitals. It supports hospital affairs and helps to increase efficiency and reduce errors of 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 could be replaced by labor, however, in that case, the working efficiency of medical staff would be significantly impacted.

Based on the above discussions, some simplifications and hypotheses are made, as explained below, in order to quantify $N_i^a(t)$ in Eq. (4) and ultimately to quantify $Q(t)$:

1. Only treatment in hospital is considered, while pre-hospital care is not.
2. Once a patient receives treatment, he or she will be cured and released from the hospital.
3. Medical staff, medical supplies, and medical equipment for the treatment of each disease are independent on each other, which means the staff, supplies, and equipment are disease-specific and cannot be shared across diseases.
4. 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.
5. Drinking water, which does not need secondary purification, is considered necessary for all treatment.

Purified water from specialized devices, which relies on power, is only needed for some medical equipment such as Dialysis Machines.

6. Telecommunication and transportation affect medical treatment indirectly, e.g. by affecting patient transfer and the supplement rate of medical supplies.

7. Buildings are necessary for all treatment activities.

8. Social factors affect medical treatment indirectly through other impact factors: professional knowledge affects the service capacity (the maximum number of patients who are able to be treated) of medical staff; emergency plans affect the recovery rate of physical factors; leadership of hospital administrators affects the implementation of emergency plans.

9. The cyber factor, i.e. the HIS, is regarded to affect the service capacity of medical staff.

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

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

where $St_{i,o}^a(t)$, $Su_{i,p}^a(t)$ and $E_{i,q}^a(t)$ denote the service capacity of each kind of medical staff, supplies and equipment respectively for disease i on day t; n_{St}, n_{Su}, and n_E denote the number of kinds of medical staff, supplies and equipment respectively; $P_L(t)$ denotes the power supply for lighting (given that lighting power is only necessary for the treatment in the night time, $P_L(t) = 1$ when power is available for lighting and $P_L(t) = 0.7$ when power is not available for lighting); $W_D(t)$ denotes the drinking water supply (binary, 1 when drinking water is available, while 0 when unavailable); and $B(t)$ denotes the availability of hospital buildings, equaling to the percentage of residual capacity of the buildings after earthquakes.

SD Modeling

Once the value variations over time of the factors in Eq. (5) are obtained, $Q(t)$ can be obtained using Eq. (4) and Eq. (5). However, as aforementioned, some of these factors are interacted and their values are correlated in complicated, non-linear relationships. Therefore, the value variations of 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 dynamics and interactions of the factors, 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 which Fig. 2 illustrates the high-level causal loops of the model (i.e. the overall structure of the model), while Figs. 3-9 further illustrate the detailed causal loops of the factors (i.e. parts of the model) included in Fig. 2. 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 happens, patients arrive at hospitals and are first triaged by disease type. Patients with different types of disease are treated separately. Those who have received treatment are cured and released from the hospital. Some patients waiting to be treated are transferred to other healthcare facilities by ambulance and some patients, who die during the waiting, are sent to morgues (Cimellaro et al. 2017). In the SD-HFE, two types of medical supplies are considered, namely medical consumables and beds. Medical consumables, such as medicine, bandages, and oxygen, can be consumed and supplemented, while beds are reusable medical supplies. 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".

[Insert Fig. 2 here]

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's "Knowledge of disaster medicine" (see Fig. 3). "Number of medical staff" may decrease due to the staff's 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" (see 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 also 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”.

[Insert Fig. 3 here]

[Insert Fig. 4 here]

[Insert Fig. 5 here]

[Insert Fig. 6 here]

With regard to utilities, two parts are considered, including the municipal part (Fig. 7), which is beyond the boundaries of hospitals, and the hospital part (Fig. 8), which is within the boundaries of hospitals. The municipal part includes roads, telecommunication, municipal power, and municipal water; the hospital part includes ambulances, satellite telephones, power generators, fuel, and stored water. Each type of municipal part of utilities has a “state” to describe its availability, which then determines its serviceability. The utilities’ states may be worsened and their availability may be lost after the earthquake hit, while the states can also be improved after recovery measures are taken. For municipal water and telecommunication, their availability also relies on the availability of municipal power supply (Fig. 7). As aforementioned, the supply of power and water in the hospital mainly depends on the municipal supply, while the hospital can also prepare power generation instruments 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 also requires water for cooling (Vugrin et al. 2015). The stored water, as another source of “Drinking water supply” in the hospital, can also be consumed and supplemented by hospital. “Medical water supply” relies on both “Drinking water supply” and “Power supply” as power is needed to run the purification equipment.

[Insert Fig. 7 here]

[Insert Fig. 8 here]

Fig. 9 shows the dynamics of the 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 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.

[Insert Fig. 9 here]

The relationships among different factors can be classified in two types: one is one-way relationships, namely one factor is affected by another; the other one is interactions, namely two factors are affected by each other. For one-way relationships, one example is that transportation condition affects the supplement 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), fuel and stored water (Fig. 8), as the recovery processes of the factors are usually pre-specified in emergency plans of hospitals. As for interactions, one example is that two types of utilities, namely power and water, are interacted, where “Municipal power supply”, as one source of “Power supply”, affects “Municipal water supply” and further affects “Drinking water supply” (Fig. 7), while conversely “Drinking water supply” affects “Generator power supply” (Fig. 8), which is another source of “Power supply”. Some factors and the treatment activity are also interacted. For instance, “Service capacity of medical consumables” (Fig. 4) and “Number of available beds” (Fig. 5) contribute to “Treatment rate” of patients (Figs. 4-5), 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, the inputs include the ones describing the states of the factors right after the occurrence of the earthquake, which depend on potential loss or damage of the factors, and the ones describing the variations of the factors over time. Potential methods to determine the inputs are given in this section. FEMA (2012a) proposes 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 the data on building information (story height, area etc.), occupancy, component fragilities, the earthquake scenario and so forth, the PACT is able to perform loss calculations including repair cost, downtime, and casualty estimates (FEMA 2012b). Hence, the casualties of medical staff and the loss of the hospital buildings can be obtained using the PACT. The PACT can also potentially be used to determine the loss of the components located in the hospital building such as medical supplies, medical equipment, hospital part of utilities, and the HIS once their fragility data are obtained. With regard to the recovery of the above factors, the supplement of medical staff, medical supplies, fuel for generators, and drinking water, and recovery of medical equipment can be estimated according to the interviews with the hospital staff. The time needed for retrofitting the hospital building can be obtained using the PACT. In addition, the loss and recovery rates of municipal part of utilities can be estimated using Hazus - MH 2.1, which is 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. For the inputs which require medical knowledge and historical experience, such as patient arrivals, death rates, hospitalization rates, and 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. $N_i^a(t)$ 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 resilience level of the hospital 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 of 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 m/s^2 was used in this case study.

Residual “Number of medical staff” was set by taking into consideration the casualty of the medical staff estimated using the FEMA PACT. It was assumed that all the 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 the fragility data which were necessary for damage analysis in the FEMA PACT, the loss of medical supplies and damage of medical equipment and the HIS was estimated based on the damage state of the hospital building, and it was assumed that there was no damage of hospital part of utilities. Using the method proposed by Xiong et al. (2016), the damage state (none, slight, moderate, extensive or complete) of each floor of the hospitals under the ground motion was obtained. Then, the loss or availability of the above components was estimated according to the damage state of the targeted floor using a lookup table (Table 3) developed by the authors in this study. For loss or availability estimation of medical consumables, beds, operating rooms, and the HIS, the targeted floor in Table 3 referred to the floor where the pharmacies, wards, operating rooms, and HIS were located respectively. The availability of the building equaled to 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 by the “Road state”, “Availability of communication” and “Emergency plan effect”; the recovery rates of hospital part of utilities were assumed or estimated by the interviewees; “Recovery rate of building” was set based on the repair time of the building estimated using the FEMA 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 part of utilities were not available, the damage and recovery rates were set as the actual rates that were observed in the 2008 Sichuan Earthquake and reported in the interviews. This may lead 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, the current municipal part of utilities should be more resilient to earthquakes than they were in 2008. There were four typical kinds of diseases 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 (other diseases) (Liu et al. 2008). The weights of these four types of diseases (β_i in Eq.(4)) were set by the average death rate of each type of disease. Operations were only necessary for all patients with disease B and 10% of the 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. $N_i^r(t)$ of each hospital was set according to the daily service capacity of the current medical resources. Gaussian noise was introduced to reflect the fluctuations of the service capacity of the medical resources. Table S1 summarized the main inputs for the calculation of hospital functionality in the case study, and Table S2 provided 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.

[Insert Table 3 here]

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 occurrence of the earthquake (Day 0), $Q(t)$ dropped to 0.65, which was mainly due to the loss of serviceability of the hospital building. In the meantime, there was municipal power failure caused by the earthquake. Although the hospital was equipped with power generators, the stored diesel fuel was only enough for one-day use. Hence, $Q(t)$ fell to 0.26 at the end of Day 1. $Q(t)$ bounced back when the 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, $Q(t)$ had 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 the 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).

[Insert Fig. 10 here]

In order to further explore the reasons behind the variations of the functionality curves, the performance

($Per(t)$) of the hospital was assessed per each kind of 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 occurred (Day 0), $Per(t)$ for Disease A, B, C, and D fell to 0.68, 0.80, 0.90, and 0.41 respectively. The differences in the 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. Among the performance, $Per(t)$ 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 with the trend of $Q(t)$ in Fig. 10. On Day 4, a decrease of $Per(t)$ for Disease B was observed. It was due 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 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 of $Q(t)$ from Day 4 was not very obvious because $Per(t)$ for Disease A and D kept increasing with the recovery of the building from Day 2 when the municipal power was recovered, which neutralized the effects of the decrease of $Per(t)$ for Disease B and C. As shown in Fig. 11, $Per(t)$ for Disease B got fully recovered on Day 13 rather than on Day 19 when the building was fully recovered. It was due to that the storage of medical resources for Disease B was higher than it was actually needed so that $Per(t)$ for Disease B could be at a relatively high level and be 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 the HIS was recovered and so was the service capacity of medical staff, $Per(t)$ for Disease D bounced by to around 1.00, which contributed to the full recovery of $Q(t)$ on the same day.

[Insert Fig. 11 here]

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 administration staff from the local Heath Bureau. The experts all commented that the results were in line with their expectations and could well reflect the characteristics of the behavior of the hospital after earthquakes.

Discussions

Extreme Condition Test

In order to ensure that the SD-HFE was structurally valid, extreme condition tests were conducted. The inputs of the variables in the model were set to zero or infinite (values large enough, around ten thousand times larger than other variables) individually, which examined 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 were given as examples. One condition (Condition 1) was to assume that the roads around the hospital were totally impassable and “Recovery rate of roads” was zero with other conditions unchanged compared with the case study. Under such condition, the hospital had no access to supplement of medical supplies and could not transfer patients to other locations (patient arrivals were considered unaffected by "Road state"). Another condition (Condition 2) was to assume that "Recovery rate of municipal power" was zero, which indicated that the municipal power would be continuously unavailable due to the damage caused by the earthquake. 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 the medical consumables, $Q(t)$ began to decrease. The first decreases occurred on Day 4 and Day 5 when medical consumables for Disease B was running out; the second decreases occurred on Day 6 and Day 7 when medical consumables for Disease C was running out; the third decreases occurred on Day 20 and Day 21 when medical consumables for Disease D was running out. After then, $Q(t)$ 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 the 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. It was because that the 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 could have access to drinking water that was critical to $Q(t)$. Thus, from the curve in Condition 2, it could be seen that $Q(t)$ was kept at a level of 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.

[Insert Fig. 12 here]

Adaptation of the Hospital

During the 2008 Sichuan Earthquake, the case hospital was severely damaged. The power and water supply was cut off for days and almost all the functional departments were unavailable. The medical staff the authors talked to during the R4 interviews were asked to recall and estimate $Q(t)$ of the case hospital after the occurrence of the 2008 Sichuan 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 then 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 of the disease in the case study. Hence, the estimated $Q(t)$ would be 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 current hospital was reconstructed and put into use, $Q(t)$ recovered to 1.00 (not shown in Fig. 13). Setting t_0 as the day when the earthquake happened and t_{LC} as 60 days, the resilience level of the hospital to the 2008 Sichuan Earthquake was calculated as 0.61 based on Eq. (1).

[Insert Fig. 13 here]

In Fig. 13, both curves had significant decreases in the first few days after the earthquake occurred. It was because that the decreases were mainly caused by the failure of utilities like power and water and the inputs of the damage and recovery rate of municipal utilities in the case study were set to be the same as in the year 2008. Nevertheless, the decrease of $Q(t)$ 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 the year 2008, contributing to fewer casualties of medical staff and less loss or damage of medical supplies and equipment, which in turn contributed to a 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 could perform much better if the same earthquake in 2008 happened again.

According to Eq. (4), $Q(t)$ depends on not only $N_i^a(t)$ but also $N_i^r(t)$. $N_i^r(t)$ reflects the expected serviceability of the hospital which is related to the resources it has. Obviously, a tertiary hospital is usually required to serve more people and handle more types of 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 ten thousand. The current $N_i^r(t)$ is much higher than that in 2008. Therefore, the resilience level of the hospital increases by 49% from 0.61 to 0.91 since the year 2008, 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 of $Q(t)$ mainly due to three issues, namely power failure, deficiency of beds and the loss of serviceability of the hospital building. In this section, the authors tested the effectiveness of three policies that were supposed to address the above issues using the SD-HFE. Herein, the policies are: 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; Policy 3 - the hospital shortens the recovery time of the building from 19 days to 10 days by hiring more workers. The inputs of the model were adjusted according to each policy. The effects of the three policies based on simulation results were illustrated in Fig. 14, where the result of the case study was also shown marked as Policy 0.

[Insert Fig. 14 here]

Fig. 14 showed 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 were also important to enhance the hospital resilience to earthquakes. However, such a "distribution" is disease-specific and the distribution for earthquakes might not work for other types of disasters once the distribution of the diseases caused by the disaster was different. Policy 3's effectiveness indicated that a higher recovery rate of hospital building 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 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 using the SD-HFE was sensitive to the proposed policies and the evolution of $Q(t)$ under the three polices headed for the same trend, which proved the reliability of the SD-HFE (Jiang et al. 2015).

Conclusions

This research proposes a new functionality-based assessment approach of quantifying hospital resilience to earthquakes. A new indicator of hospital functionality is proposed and the SD-HFE is developed to simulate and compute the hospital functionality after earthquakes, which considers both the damages and the recovery processes of the hospital. The validity of the approach is 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 assess hospital earthquake resilience. Moreover, the approach can serve as a tool for the decision makers of the hospitals to identify the weakness in hospital earthquake resilience and compare the effectiveness of different resilience enhancement measures so as to propose targeted solutions.

While the proposed approach provides a promising tool to enable the assessment of hospital resilience to earthquakes, there are several limitations in this study that should be acknowledged. A few assumptions were made for the proposed assessment approach. Some of those assumptions, however, may be strict. For instance, medical resources (medical staff, medical supplies, and medical equipment) for the treatment of each disease are considered independent on 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 the medical resources needed in the treatment for different diseases, which may require more domain knowledge in medicine and pharmacy. Moreover, there could be other potential factors that may affect hospital functionality after earthquakes, in addition to the ones identified in the SD-HFE. These factors could be identified and examined in future research for further improvement of the SD-HFE. For a practical assessment of hospital resilience, it is also suggested to consider the uncertainties of the occurrences, as well as the intensities of earthquakes. In addition, while the feasibility of using the proposed approach to compare the effectiveness of possible resilience enhancement policies has been demonstrated, how to develop or optimize these policies, which should consider their costs, feasibility, and interactions, is worth further investigation in future research.

Acknowledgment

This material is based on work supported by National Key Research and Development Program of China under Grant No. 2018YFC0809900, National Natural Science Foundation of China under Grant No. U1709212 and No. 71974106, Smart City Research Center of Zhejiang Province, Smart City Regional Collaborative Innovation Center of Zhejiang Province, and the European Research Council under the Grant Agreement No. 637842 of the project IDEAL RESCUE-Integrated Design and Control of Sustainable Communities during Emergencies. Any opinions, findings, and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the funding agencies. The authors are also thankful for Prof. Xinzheng Lu and his group from Tsinghua University as well as the experts in Mianzhu, China, for providing valuable advice on the preparation of this work.

Supplemental Data

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

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.

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Table List

Table 1. Qualifications of the interviewees

Items	Categories	Number of interviewees			
		R1	**R2**	**R3**	**R4**
Current titles	Associate chief physician	3	5	4	3
	Attending doctor	1	3	1	3
	Practitioner	0	3	1	2
	Senior nurse	3	2	0	3
	Nurses	0	1	0	0
	Administration staff	0	4	0	0
Years of professional experience	⩾30 years	1	1	1	4
	20-29 years	5	11	4	5
	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

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

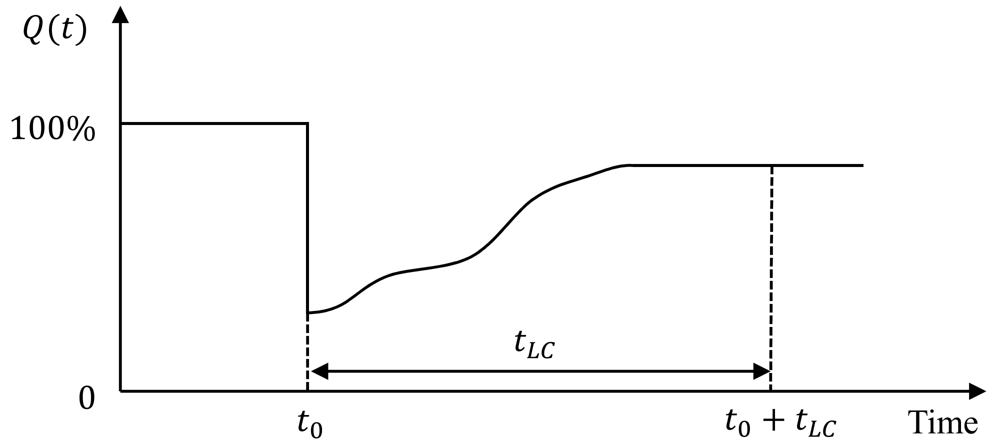
No.	Factors	Categories	Results[a]
F1	Sufficient medical staff	Physical	Strongly agree
F2	Sufficient medical supplies	Physical	Strongly agree
F3	Available medical equipment	Physical	Strongly agree
F4	Available electricity supply	Physical	Strongly agree
F5	Available water supply	Physical	Strongly agree
F6	Available telecommunication	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 Hospital Information System (HIS)	Cyber	Strongly agree

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

Table 3. Lookup table for the inputs for the SD-HFE 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

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



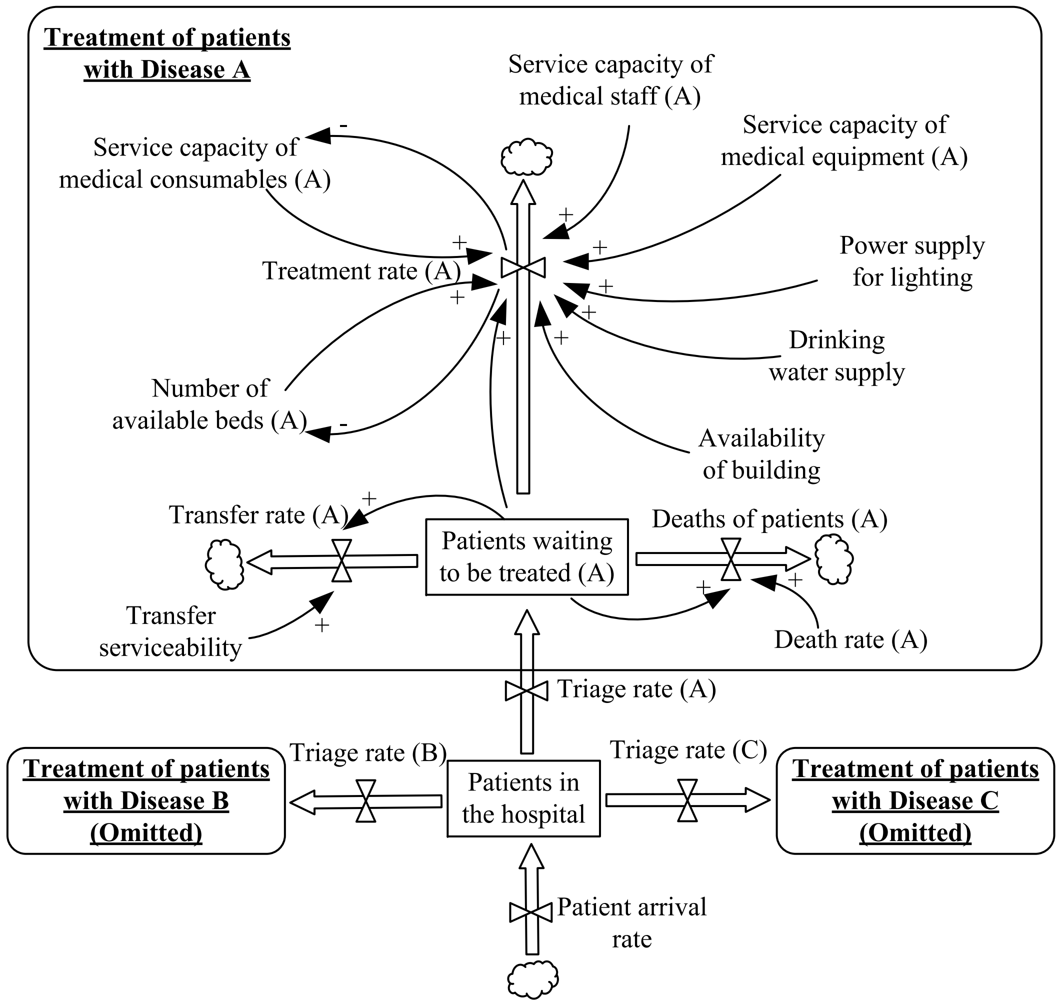

Treatment of patients
with Disease A
Service capacity of
medical staff (A)
Service capacity of
medical equipment (A)
Service capacity of
medical consumables (A)
Treatment rate (A)
Power supply
for lighting
Drinking
water supply
Number of
available beds (A)
Availability
of building
Transfer rate (A)
Patients waiting
to be treated (A)
Deaths of patients (A)
Transfer
serviceability
Death rate (A)
Triage rate (A)
Triage rate (B)
Triage rate (C)
Treatment of patients
with Disease B
(Omitted)
Patients in
the hospital
Treatment of patients
with Disease C
(Omitted)
Patient arrival
rate

Fig. 3. Dynamics of medical staff

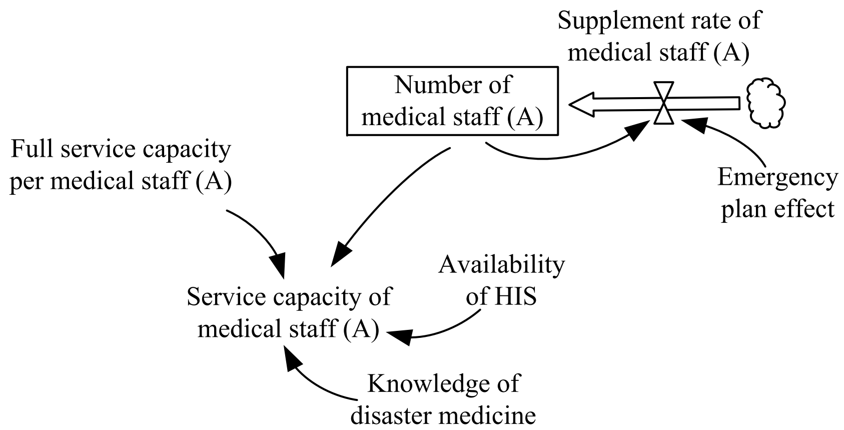


Fig. 4. Dynamics of medical consumables

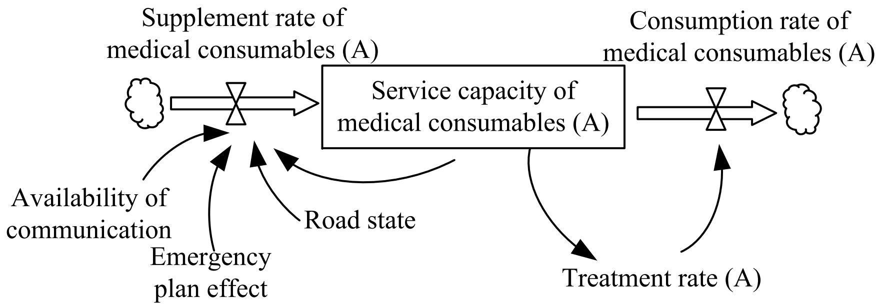


Fig. 5. Dynamics of beds

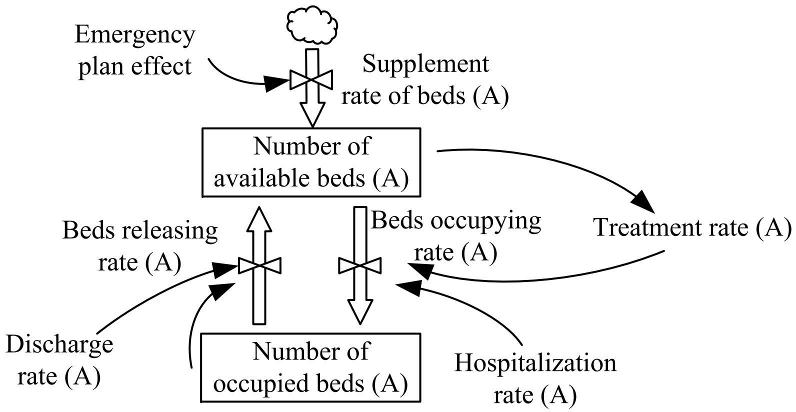


Fig. 6. Dynamics of medical equipment

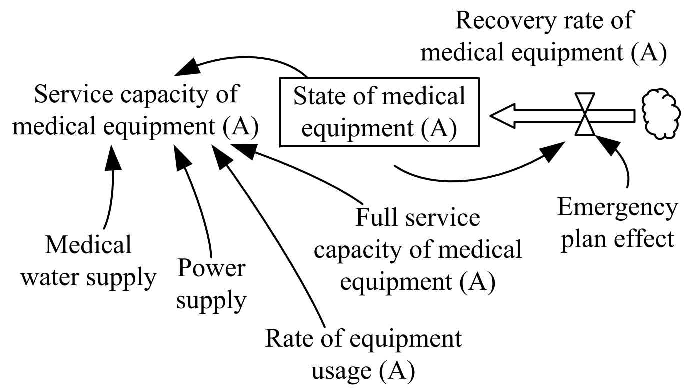


Fig. 7. Dynamics of utilities (municipal part)

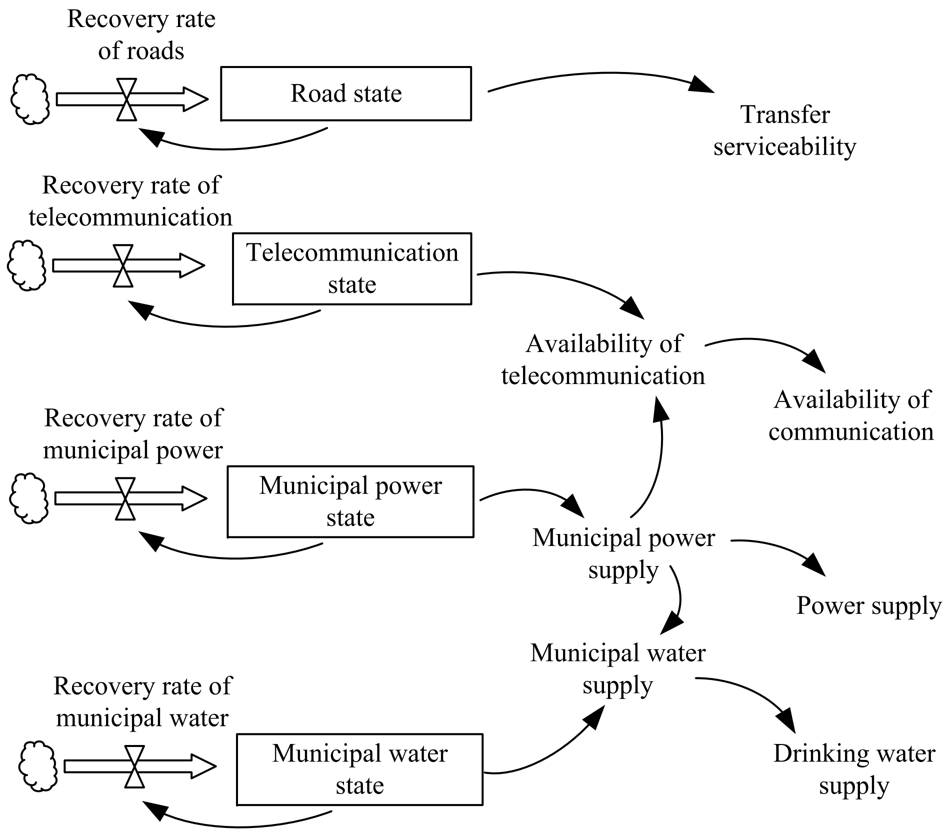


Fig. 8. Dynamics of utilities (hospital part)

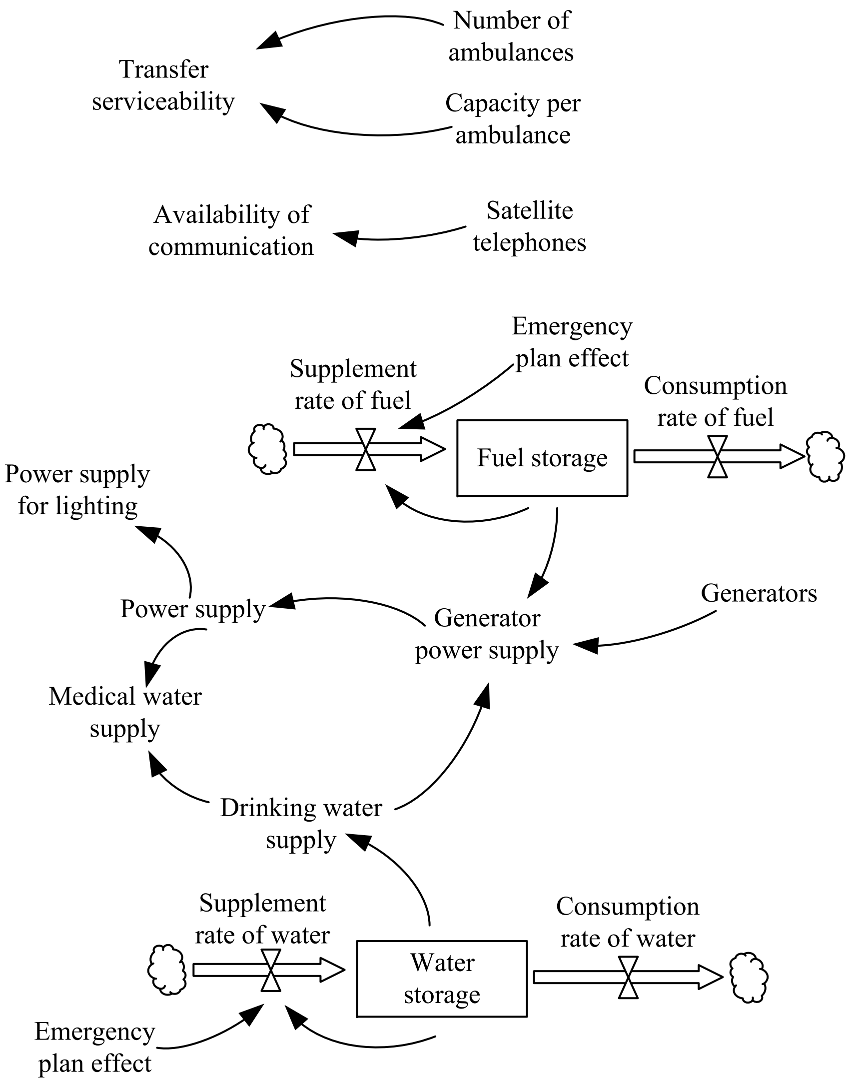


Fig. 9. Dynamics of the hospital buildings, social factors and cyber factors

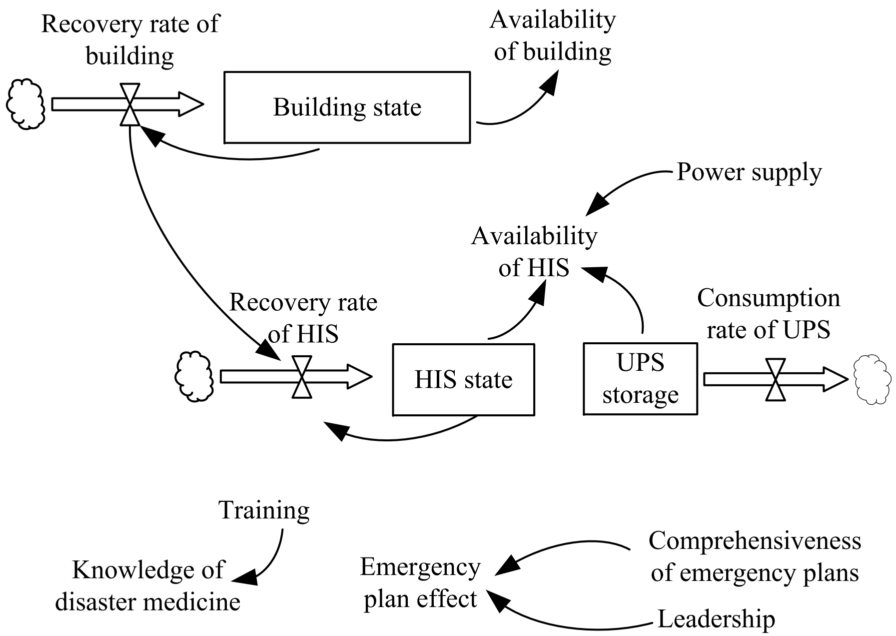


Fig. 10. Functionality curve of the hospital

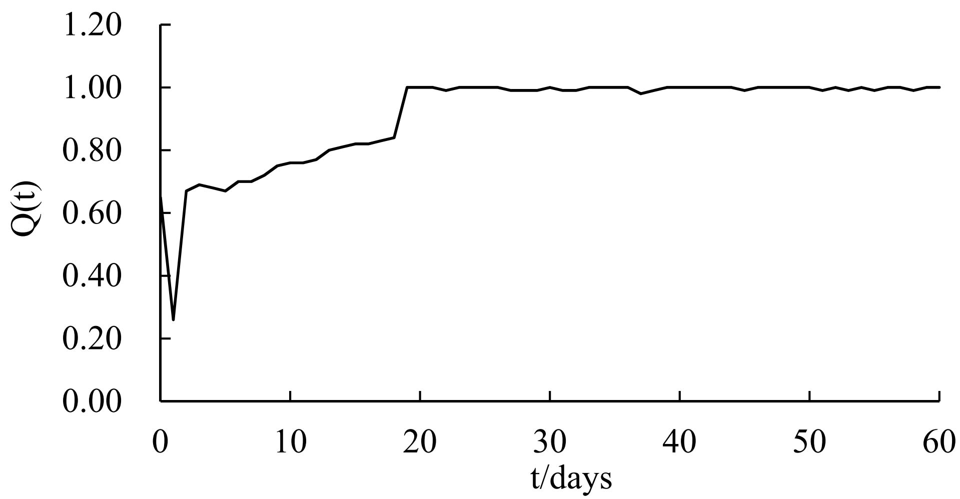


Fig. 11. Performance of treating each kind of disease of the hospital

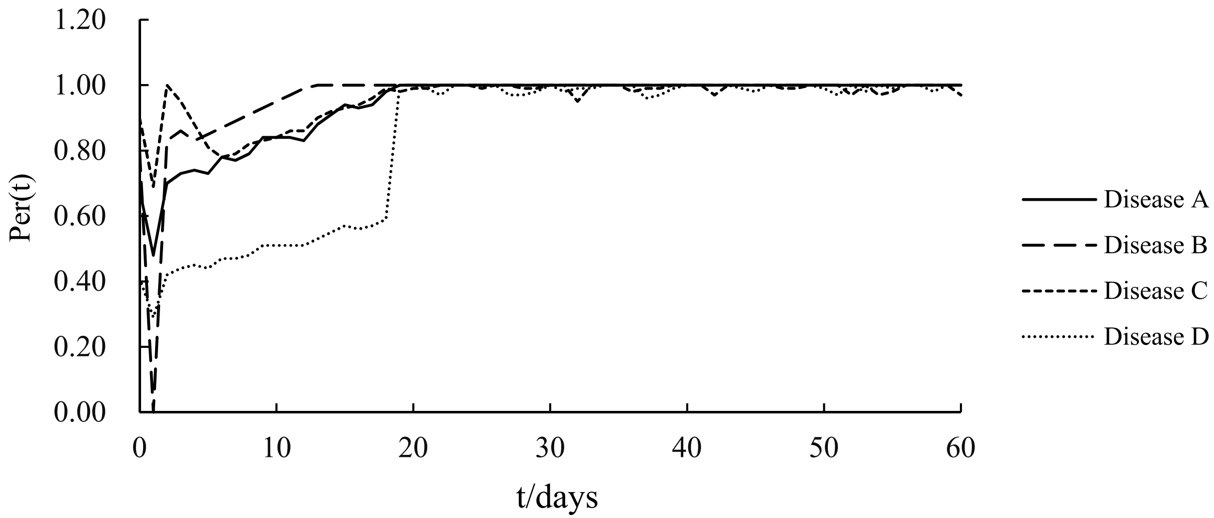


Fig. 12. Results of extreme condition test

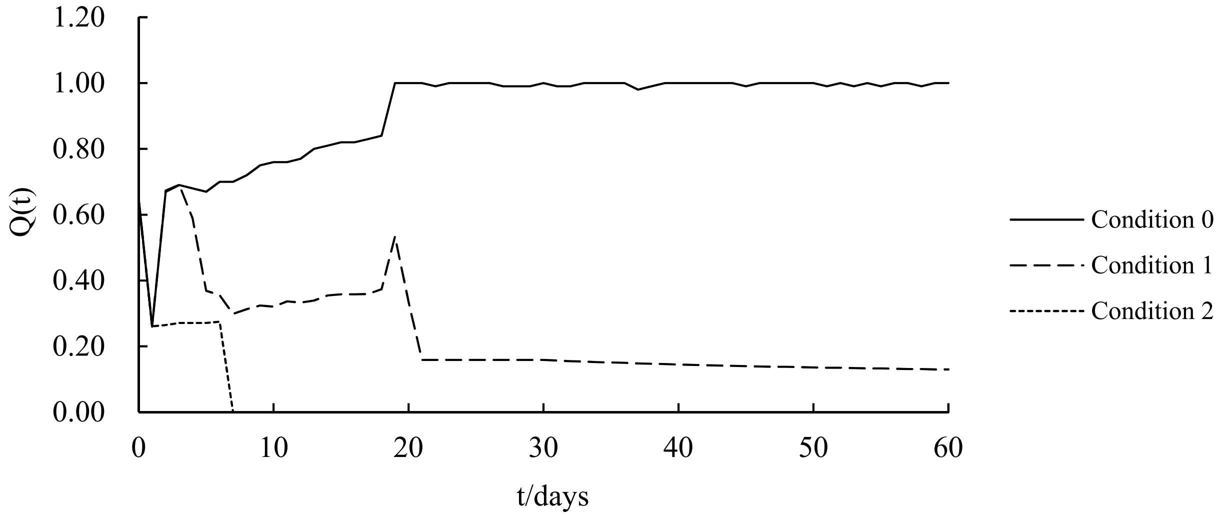


Fig. 13. Adaptation of the hospital

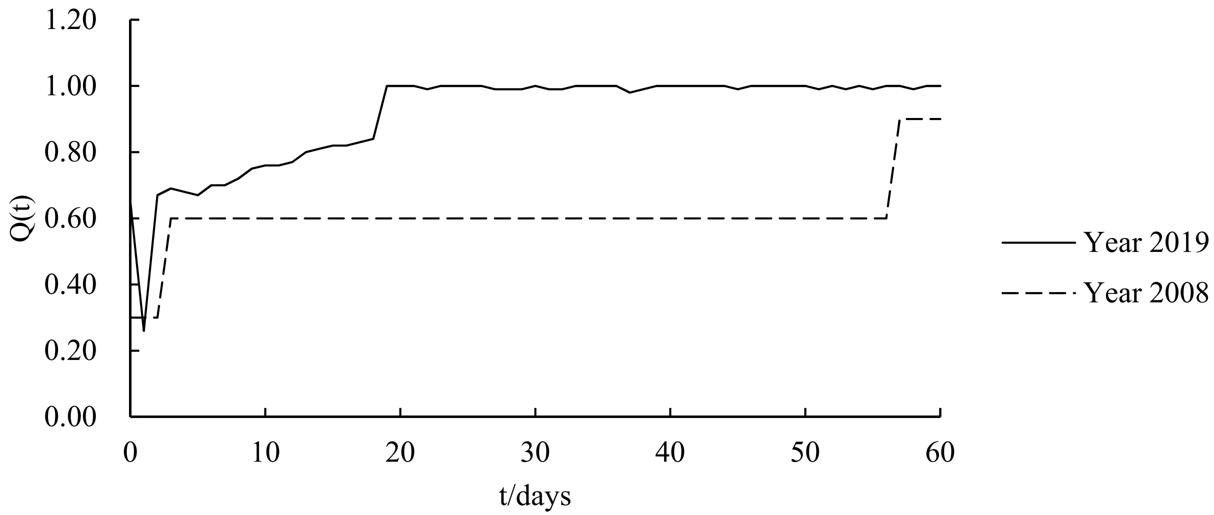


Fig. 14. Results of policy sensitivity test

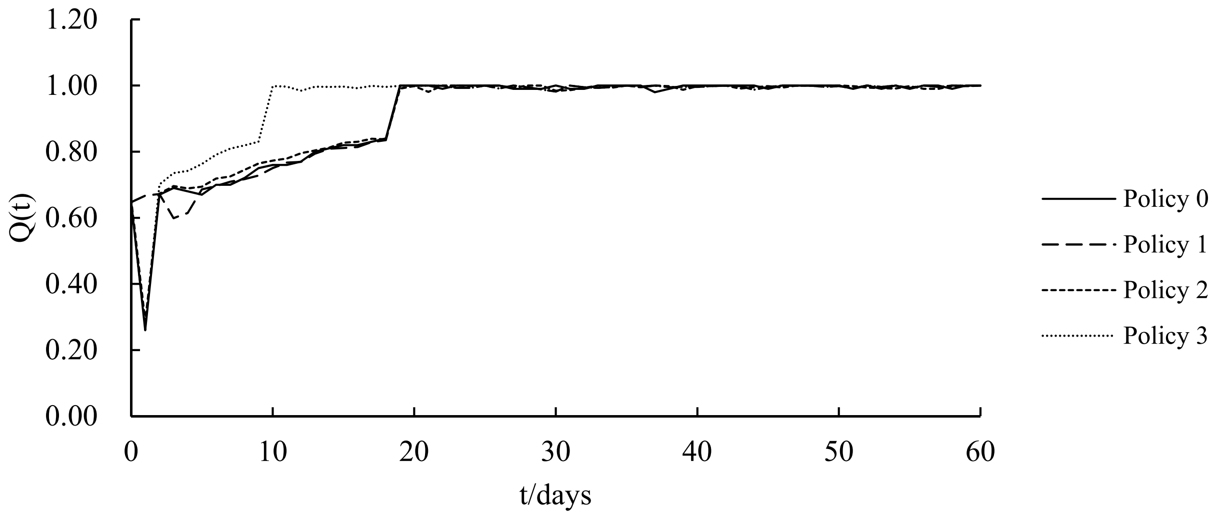


Figure List: