Seismic Risk Assessment of an Emergency Department of a Chilean Hospital Using a Patient-Oriented Performance Model

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After an earthquake, hospital emergency departments need to provide continuous health care services to respond to the eventual sudden increase in injured people. The service performance of an emergency department is influenced by internal factors, such as physical damage and staff availability, and external factors, such as an increased patient arrival rate and disruptions in its supply chain. This research presents a quantification methodology for the performance of the emergency department. The novelty of the proposed approach lies in the explicit integration of the inelastic structural and nonstructural response of the building and damage with its loss of functionality, downtime, and emergency patient treatment rate. A discrete event simulation model is used to model the flow of patients within the different units of the emergency department. The seismic risk is expressed as return periods of exceeding different levels of patient waiting times. Results show that 1,000 and 30,000 accumulated waiting hours correspond to return periods of 100 and 1,000 years, respectively. It is concluded that this model may contribute to improving the risk management of critical emergency department infrastructure. [DOI: 10.1193/103017EQS224M]

INTRODUCTION

As one of the most seismically active countries in the world, Chile continuously needs to prepare for and deal with the disruption caused by earthquakes. In a postdisaster environment, it is apparent that the role of hospitals is critical in maintaining a continuity of health care services to the population while effectively coping with its potential loss of functionality. These losses may occur from physical damage to the facility (e.g., structural, nonstructural, and contents), the loss of critical hospital lifelines (e.g., water and electricity), discontinuities in different supply chains, or the reduction of critical personnel. Although Chile has a modern seismic code that limits the structural damage of buildings during strong earthquakes, nonstructural damage in several buildings, but more so in hospitals, may cause an extensive and significant loss of functionality, as evidenced by recent cases (Kirsch et al. 2010, Vásquez et al. 2017, Favier et al. 2017). To anticipate such losses and improve resilience, evaluation of

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the seismic risk of critical infrastructure in particular hospitals is key to assist different stakeholders in decision making. Lately, decreasing earthquake-induced losses in hospitals has been the prime concern of international disaster risk reduction institutions promoting resilience (e.g., United Nations Office for Disaster Risk Reduction 2005).

The seismic performance of an emergency department (ED) is commonly assessed by time interval quantification (Sørup et al. 2013) and expressed in terms of the length of stay or waiting time of patients (Welch et al. 2011). Most current research has focused on quantifying the resilience of these facilities (Cimellaro and Piqué 2015, Cimellaro et al. 2017), usually in the case of a given earthquake scenario. However, for decision-making purposes, a risk framework is appropriate, as it considers the uncertainty of all plausible earthquake scenarios. Indeed, there is a consensus that decision theory through risk quantification offers a very rational tool to consider the undesired consequences of uncertain events (Jordaan 2005). As an example, in the seismic field, the performance-based earthquake engineering risk framework developed by the Pacific Earthquake Engineering Research Center explicitly defines the use of decision variables that measure the seismic performance of a given facility (Porter 2003). Some studies have used this probabilistic framework to assess the loss of functionality in hospitals (e.g., Lupoi et al. 2006, Barrera et al. 2017).

Furthermore, various numerical methodologies have been used to predict earthquake-induced functionality and performance losses in hospitals, such as fault-tree analysis (Lupoi et al. 2008, Jacques et al. 2014, Lupoi et al. 2012, Miniati et al. 2014) and discrete event simulation (DES; Gul and Guneri 2015). However, fault-tree analyses are just used to describe the functionality relationships between vulnerable components and hence cannot be used alone to model the seismic response of a hospital over time. On the other hand, DES has typically been used to calibrate metamodels, which simplify the numerous inputs of hospital DES models to a reduced number of variables, such as the number of beds, operating rooms (ORs), and/or the operations per OR within a year (Cimellaro et al. 2009, Yi et al. 2010). These metamodels have included rough penalty factors to account for the effect of physical damage in the hospital model. Recently, in Chile, the direct use of DES models, avoiding metamodels, has shown promising results to predict the performance of an ED for a scenario analysis (Poulos et al. 2015).

Assessing the seismic performance of hospitals by DES models requires key inputs, such as (1) the probability that a hospital room loses functionality after being damaged, (2) distribution of downtime for a damaged room, and (3) postevent arrival rates of patients and their injury severity level. Quantitative studies relative to these inputs in the literature are scarce, as described next.

Estimating functionality losses in the ED requires linking the structural and nonstructural damage to the functional state of the ED critical rooms, e.g., examination rooms and ORs. The functional downtime of damaged hospital rooms is usually estimated after assessing the nonstructural damage that comes from using fragility curves together with structural responses. So far, very few studies have considered this functional dependency in a probabilistic framework (Kuo et al. 2008). In most investigations, this dependency is studied deterministically using binary states; i.e., if the hospital building collapses or a nonstructural element of the room collapses, then the functionality of the room is set to "out of use" (Barrera et al. 2017). Deterministic binary dependency assumptions can be reasonably set for ORs; however, past event surveys showed that this assumption is too restrictive for assessing the true functionality of other rooms used by physicians for examination purposes. For instance, the cracking of partition walls in all the ORs of the hospital in the city of Iquique, North Chile, caused the systematic closure of these rooms for several days to ensure sterile conditions after the earthquake (Vásquez et al. 2017). However, examination stations with a low nonstructural damage may, with a significant probability, remain functional by a reordering effort or fast relocations. In the study by Yavari et al. (2010), they used data from historic events in California and expert elicitation data to establish hospital functionality classes (i.e., fully functional, functional, affected functionality, or not functional) depending on combinations of structural, nonstructural, and lifeline system states.

Downtime is usually defined as the period of time between the occurrence of a disruptive event and completion of the building repair effort (Comerio 2006, Mitrani-Reiser 2007). In this study, downtime is restricted to the dimension of functionality, which is to say the period of time between the occurrence of the earthquake and completion of the recovery effort to guarantee functionality. In Chile, recent studies have documented the interruption time windows in the health care services of some public hospital departments after strong earthquakes. This was done, for instance, after the 2010 M_w 8.8 Maule earthquake (Kirsch et al. 2010), 2014 M_w 8.2 Pisagua earthquake (Vásquez et al. 2017), and 2015 M_w 8.3 Illapel earthquake (Favier et al. 2017). Data shows that after the 2014 Pisagua earthquake, it took 3 hr. to recover the functionality of the Intensive Care Unit and 48 hr. to recover the capacity for surgery in the ED of the regional hospital of Iquique (Vásquez et al. 2017).

Patient arrival rates to hospitals and their injury level in post-earthquake conditions can be estimated using empirical or numerical approaches. Empirical methods rely on scaling the arrival rates of a hospital during a well-documented event to another hospital based on relating the earthquake intensity and hospital size (Malavisi et al. 2015). Moreover, patient arrivals can also be estimated using the number of predicted injuries from building damage, which can be achieved by using a casualty model, such as Hazus [Federal Emergency Management Agency (FEMA) 2012a], SYNER-G (Pitilakis et al. 2014), and PAGER (Jaiswal et al. 2011). A Hazus casualty model has already been adapted for the city of Iquique (Aguirre et al. 2017, 2018).

In this article, the methodology proposed is applied to a hospital of the coastal city of Iquique, named after Dr. Ernesto Torres Galdames. This facility is the only high-complexity hospital in the Tarapacá region, north of Chile, and serves about 239,000 people a year (Vásquez et al. 2017). It is located above the tsunami inundation safety-line established at 30 m above sea level by the Chilean authority and is out of the tsunami evacuation zone. The ED of this hospital received an average of 106.574 patients annually between years 2010 and 2016 [Departamento de Estadísticas e Información de Salud (DEIS) 2017], excluding 2014. After the Pisagua earthquake (2014) in North Chile, nonstructural components were the main factor of service disruptions within the hospital (Vásquez et al. 2017), while only slight structural damage was observed in the facility. The medical and administrative absence of staff was observed the day following the earthquake; however, this had no effect on the functionality of the facility because of an internal reorganization. Electricity, water, and communication services were maintained after the earthquake. Similar observations were made after the Maule earthquake (2010) and Illapel earthquake (2015) in other Chilean hospitals (Kirsch et al. 2010, Favier et al. 2017). Based on these empirical observations, this model will not consider interruptions in the utility lifelines, supply chain, or staff attendance.

This article extends previous work (Poulos et al. 2015) and casts it into a risk framework to assess the loss of performance of the ED of Iquique's regional hospital caused by all plausible earthquake scenarios that may affect the city. The paper is divided into several sections. The next section presents a brief overview of the methodology for seismic risk performance quantification; a risk assessment methodology based on the previous work of Poulos et al. (2017) is used to assess the integrated response of the system to different earthquake intensity levels. Then, the *Seismic Hazard Analysis* section presents the framework to obtain the mean annual rate of seismic events and a selection of particular seismic ground motions. The *Physical Response Assessment* section describes the structural model of the ED building, structural model outputs, and their implications on the level of nonstructural damage by using fragility curves. Next, the *Functionality Loss Assessment* section relates the physical damage with the loss of functionality and downtime of the ED examination and ORs. In the *Performance Assessment* section, the loss of functionality and increased demand for health care attention produced by the earthquake are considered inputs for the DES model of the ED. Results on the performance of the ED, evaluated using the waiting time of patients as a performance index, are presented in the *Results and Analysis* section and finally discussed in the last section.

PERFORMANCE QUANTIFICATION IN A RISK FRAMEWORK

ED performance is expressed herein in terms of the waiting time of patients, which is of interest to hospital stakeholders and public health authorities. The procedure used to compute the waiting times after a specific earthquake is summarized in Figure 1. This flowchart has four main blocks: the seismic hazard assessment, performance quantification, physical response, and functionality loss. The algorithm starts with the definition of a seismic intensity measure (IM) and a set of N discrete values of the chosen IM. For each earthquake intensity, the arrival of patients at the ED because of earthquake-related injuries is estimated, and M earthquake ground motion histories are generated for each seismic intensity to compute the inelastic response of the hospital building. The response of the building, in terms of the interstory drift ratios and floor acceleration, enables assessment of the damage state of nonstructural components by the use of specific fragility curves. The downtime of examination and ORs in the ED are then estimated using the damage level of nonstructural components. Finally, the attention process of the ED is simulated by a DES hospital model, which is run K times to compute the waiting times of patients.

As explained above, the evaluation of the performance value is then repeated for ground motions of different intensities in order to construct the vulnerability of the system. The effect that earthquakes of different intensities have on the system must then be multiplied by their rate of occurrence in order to compute seismic risk, i.e.:

$$\lambda_{PV}(pv) = \int_{im_{min}}^{im_{max}} P(PV > pv \,|\, IM = im)\, |d\lambda_{IM}(im_i)|, \tag{1}$$

where IM is the earthquake IM (e.g., spectral acceleration at the fundamental period of the structure); PV is the performance variable (i.e., waiting time); $P(PV > pv \,|\, IM = im)$ is the exceedance probability of random variable, $PV > pv$, given the occurrence of an earthquake

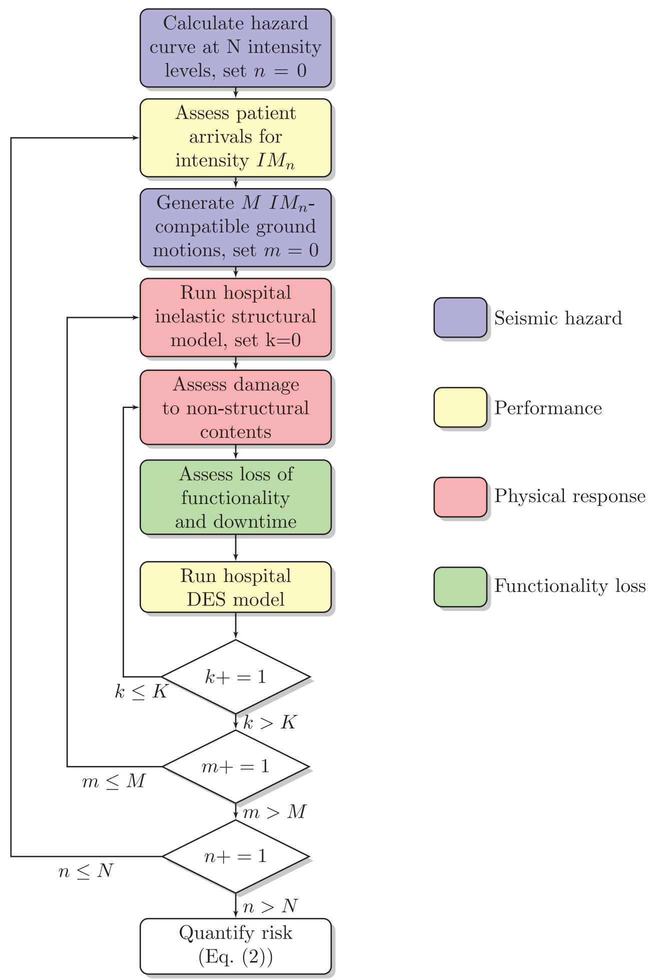


Figure 1. Overview of the seismic risk performance quantification methodology; in this study, the variable have values of $N = 10$, $M = 30$, and $K = 500$.

with $IM = im$, which defines the vulnerability of the system and will be computed using numerical simulations; $[im_{min}, im_{max}]$ is the range of intensities considered in the analysis; and $\lambda_X(x)$ is the mean annual rate of events of an arbitrary variable X exceeding the value x and is the inverse of the return period $T = \frac{1}{\lambda}$. The calculation of the two important terms of Equation 1, mean annual rate of earthquake intensities $\lambda_{IM}(im)$ and system vulnerability $P(PV > pv \,|\, IM = im)$, will be explained in the *Seismic Hazard Analysis* and *Performance Assessment* sections, respectively. The integral of Equation 1 is numerically approximated over the N values of im discretely chosen in the range $[im_{min}, im_{max}]$ and yields:

$$\lambda_{PV}(pv) \approx \sum_{i=1}^{N} P(PV > pv \,|\, IM = im_i) \, |\Delta\lambda_{IM}(im_i)|, \tag{2}$$

where $P(PV > pv \mid IM = im_i)$ is calculated from the $M \times K$ outputs of Monte Carlo simulations of performance, physical response, and functionality loss models (Figure 1).

SEISMIC HAZARD ANALYSIS

The seismic hazard at the location of the hospital was computed using probabilistic seismic hazard analysis (PSHA; Cornell 1968), which adds the contributions of earthquakes of all possible magnitudes originating from all seismic sources in the region. The characteristic output of PSHA is the mean annual rate of events that exceed different levels of a local IM $\lambda_{IM}(im)$, which is normally known as the seismic-hazard curve. The IM used in this study is the spectral acceleration at the fundamental period of the structure, $S_a(T_f)$. PSHA requires an earthquake recurrence model, which was obtained from a previous work (Alvarez 2001), and a ground motion prediction equation (GMPE) that links the global parameters of the earthquake (e.g., magnitude and source-to-site distance) with the local IM. The GMPE used in this study is appropriate for subduction zone earthquakes and has been calibrated by using worldwide data (Abrahamson et al. 2016).

The value of the IM by itself is not enough to perform inelastic dynamic analyses on the structural model of the hospital, and therefore a set of ground motion records needs to be considered. The candidate ground motions are real Chilean accelerograms, scaled to the target intensity. A total of 30 ground motion pairs (two horizontal components) were selected for $N = 10$ discrete intensity levels between $S_a(T_f) = 0.05\,g$ and $S_a(T_f) = 1\,g$. The minimum intensity was selected to not affect the system and the maximum intensity with a mean annual frequency of exceedance of 0.0002, as suggested by *FEMA P-58-1* (FEMA 2012b). At each intensity level, the records were selected by matching a response spectrum mean and standard deviation at periods ranging from $0.2T_f$ to $2T_f$ (Jayaram et al. 2011). Shown in Figure 2 is the conditional mean spectrum (Baker 2011) and its 2.5 and 97.5 percentile lines. As an example, the response spectra of the suite of records selected to match a selected intensity of 0.79 g are also presented in Figure 2.

PHYSICAL RESPONSE ASSESSMENT

First, a three-dimensional inelastic structural model was built for the structure in OpenSees (McKenna et al. 2000). The model consists of a two-story regular reinforced concrete frame building with 6.6-m spans in both directions, as shown in Figure 3a. Both stories are 3.65 m high and modeled with an in-plane rigid diaphragm on each floor to increase the computation efficiency. A frame element with localized hinges was used for modeling beams and columns (Scott and Fenves 2006), which concentrates nonlinearities at both ends over a plastic hinge length taken as $0.08L + 0.022f_y d_h$ (Paulay and Priestley 1992), where L is the element length, f_y is the yield strength of the reinforcing steel, and d_h is the bar diameter. Concrete and reinforcing steel were modeled using the materials Concrete02 and Steel02, respectively, which are already implemented in OpenSees (McKenna et al. 2000). Their stress-strain constitutive relationship curves with all their defining parameters are shown in Figure 3b. In the case of steel, $f_y = 412$ MPa, $E_s = 205{,}940$ MPa, and $b = 0.01$, and in the case of concrete, $f_{c'} = 19.6$ MPa, $E_c = 20{,}940$ MPa, $\varepsilon_0 = -0.00187$, $\varepsilon_u = -0.01$, $\sigma_u = 3.92$ MPa, $\lambda = 0.1$, $f_t = 2.74$ MPa, and $E_t = 1{,}372$ MPa. Only the translational mass was included in the system, which comes from the self-weight of elements, other dead loads from partition walls, stucco, ceilings, etc., and 25% of the specified live load of $300\,\mathrm{kg} \cdot \mathrm{m}^{-2}$

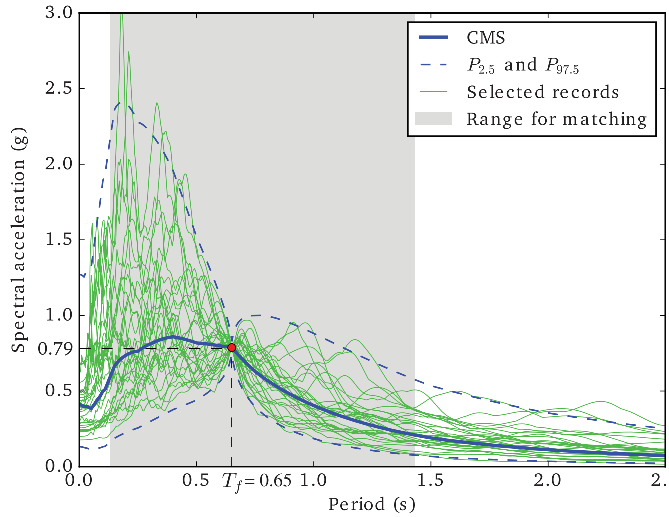


Figure 2. Conditional mean spectrum (CMS) and associated 2.5 and 97.5 percentiles for an intensity of 0.79 g, and response spectra of 30 selected records that were matched at the period range represented by the shaded area.

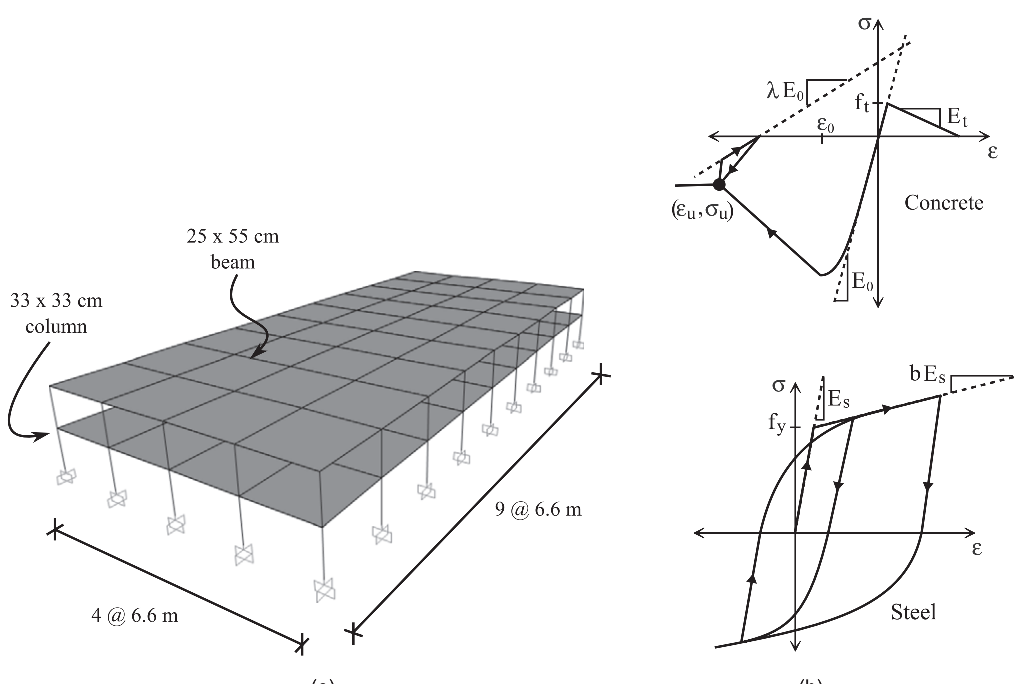


Figure 3. Two-story inelastic structural model of the hospital: (a) isometric view of the model showing a uniform grid of columns and beams; and (b) stress-strain constitutive curves of concrete and steel used for fibers in beams and column hinges.

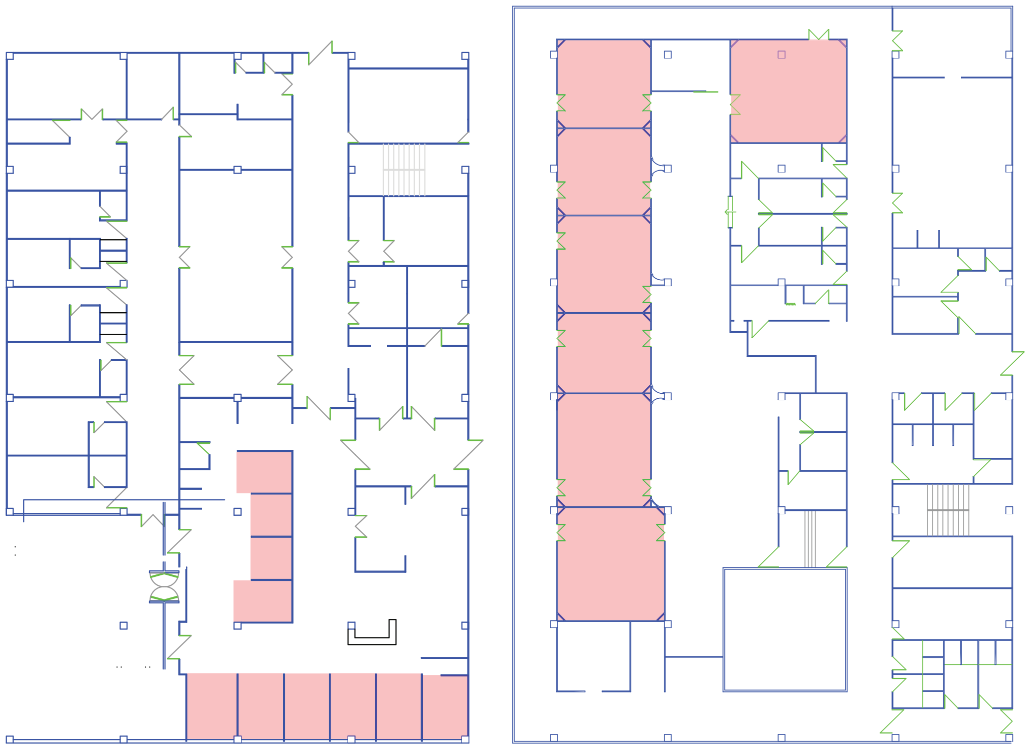
on floors and 77 $\text{kg} \cdot \text{m}^{-2}$ on the roof (Instituto Nacional de Normalización 1986). Inherent damping was included using a Rayleigh damping matrix, $C_r = \alpha_1 M_r + \alpha_2 K_r$, where C_r, M_r, and K_r are the structure's damping, mass, and stiffness matrices, respectively. Parameters α_1 and α_2 were calculated such that ξ was 3% for $1.5T_f$ and $0.2T_f$, following National Earthquake Hazards Reduction Program recommendations (Deierlein et al. 2010), where $T_f = 0.65$ s is the fundamental elastic period of the building model.

Floor accelerations and interstory drifts from the dynamic structural simulations are used as inputs to assess nonstructural damage. The considered nonstructural components prone to damage are partition walls and doors (drift sensitive) and suspended ceilings (acceleration sensitive). The moderate damage state is estimated using the fragility curves available in the literature, such as those in Retamales et al. (2013), Lupoi et al. (2014), and Badillo-Almaraz et al. (2006) for partition walls, doors, and suspended ceilings, respectively.

FUNCTIONALITY LOSS ASSESSMENT

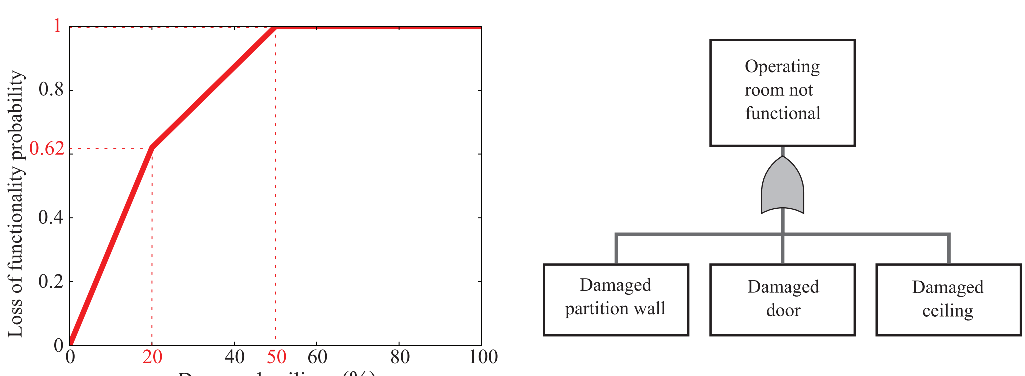
As a simplification of the ED system, it is considered that only examination stations and ORs can lose their functionality as a result of the damage of nonstructural components. The ED of the hospital has 13 examination stations on the first floor and 2 ORs on the second floor (over a total of 7 in the complete hospital), as shown schematically in Figure 4. An examination station is the place where a patient is first checked by a physician in the ED; one examination room may be composed of more than one examination station. Indeed, the hospital of Iquique has 10 examination rooms, which are composed of 13 examination stations in total. An examination station has a probability of losing functionality, which is directly related to the percentage of fallen ceilings in the room. As adapted from Kuo et al. (2008), this functional relation is built using a piecewise affine function of three segments defined by four couples of percentages of fallen ceilings versus the loss of functionality probability, i.e., (0%,0), (20%,0.62), (50%,1), and (100%,1), as depicted in Figure 5a. In the case of an OR, it is assumed from the observed post-earthquake conditions (Vásquez et al. 2017, Favier et al. 2017) that it becomes out of service if there are any nonstructural elements inside the room, such as partition walls, doors, or ceilings, that reach a moderate damage state, as shown by the fault-tree analysis depicted in Figure 5b.

In spite of its frequent seismic events, the downtime of health care services has not been quantitatively studied for Chilean hospitals; indeed, there is little information in the existing literature in general. In the United States, the Hazus technical manual (FEMA 2012a) provides both building repair times and functional downtimes for buildings within several occupancy classes, including hospitals, medical offices, and clinics. Based on this document, the functional downtime of an OR with slight damage is assumed to follow a lognormal distribution $\text{LN}(\mu, \sigma^2)$, where $\mu = \log(2)$ and $\sigma^2 = 1$ (in days), as shown in Table 1. The damage of an OR is defined as "slight" when less or equal to 25% of the nonstructural components of the room are damaged. Table 1 summarizes the references and statistical distributions that were used for each functional downtime assessment of the ED rooms. For damage larger than "slight," support from military field hospitals was considered when calculating functional downtimes. Documented past events in Chile (in 2010, Pan American Health Organization/World Health Organization 2010; in 2014, Vásquez et al. 2017; in 2015, Favier et al. 2017) showed that it took between 3 and 23 days to establish field hospitals after the earthquake (3–7 days, 23 days, and 16 days in the earthquakes of 2010, 2014, and 2015, respectively). Fitting the data via maximum likelihood estimation, the functional downtime



(a) (b)

Figure 4. Two-story reinforced concrete frame building corresponding to the ED: (a) first floor with ten examination rooms, which contain a total of 13 examination stations; and (b) second floor with seven ORs, where the two least damaged are assigned to the ED.



(a) (b)

Figure 5. Loss of functionality assessment of (a) examination stations using a probability curve adapted from Kuo et al. (2008), i.e., a station has a probability of being out of service depending on the percentage of damaged ceilings; and (b) ORs using fault-tree analysis, i.e., an OR is out of service if any partition wall, door, or ceiling reaches a moderate damage state.

Table 1. Statistical distributions of functional downtime and sources for each ED room, depending on the damage state

ED room	Distribution	Source
OR with slight damage state	LN(log(2),1) (in days)	Hazus technical manual (FEMA 2012a)
OR with damage state equal to or greater than moderate	LN(1.7,0.6) (in days)	Data collection fitting (Pan American Health Organization/World Health Organization 2010, Vásquez et al. 2017, Favier et al. 2017)
Examination room with slight damage or above	LN(log(0.5),1) (in days)	Qualitative data collection from hospital survey (Vásquez et al. 2017)

of an OR with a damage state strictly greater than "slight" was found to follow a lognormal distribution $LN(\mu, \sigma^2)$ with $\mu = 1.7$ and $\sigma^2 = 0.6$ (in days). The downtime is calculated for each of the seven ORs in the hospital. The two rooms with the lowest downtime were assigned to the ED, as was the case in reality.

Furthermore, for the case of examination stations, it was assumed that they recover functionality according to a lognormal distribution $LN(\mu, \sigma^2)$, where $\mu = \log(0.5)$ and $\sigma^2 = 1$ (in days), based on information collected during several visits to the hospital in Iquique (Vásquez et al. 2017). Independent of the damage level, the functional downtime of an examination station remains the same, as it is assumed that the relocation of an examination station may be achieved quickly, no matter the damage level of the room. Note that this assumption cannot be made for an OR, because it requires special and complex equipment and very strict prophylactic conditions.

PERFORMANCE ASSESSMENT

ARRIVAL OF PATIENTS

The arrival of patients after an earthquake is composed of two types of patients coming to the ED: (1) some seeking health care needs independent from the earthquake, i.e., normal condition patients; and (2) patients seeking health care needs because of the direct and indirect effects of the earthquake. At time t, assuming the occurrence of an $IM = im$ intensity earthquake, the total arrival rate of patients, $\alpha^{total}(im, t)$, is the sum (see Equation 3) of the normal condition patient arrival rate, $\alpha^{normal}(t)$, and the rate of patients strictly because of the $IM = im$ intensity earthquake, $\alpha^{earthquake}(im, t)$, i.e.:

$$\alpha^{total}(im, t) = \alpha^{normal}(t) + \alpha^{earthquake}(im, t). \tag{3}$$

In normal conditions, the arrival rate of patients in the ED varies depending on the day of the week; this daily variation of the arrival rate is commonly observed and taken into account in ED models (Hoot et al. 2008, Kadri et al. 2014). The comparison of the hourly mean arrival rates for each day of the week in the hospital of Iquique in normal condition showed that the mean on Mondays is higher than that of other days (specifically at 1:00, from 7:00 to 21:00,

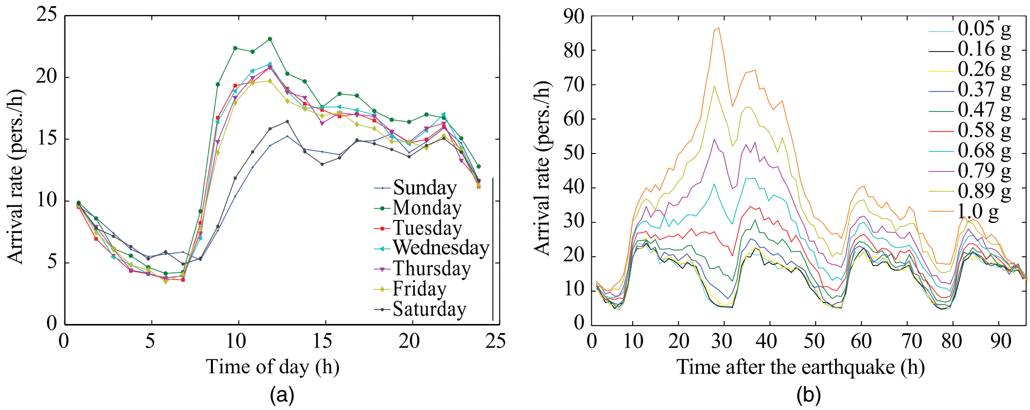


Figure 6. (a) Hourly mean arrival rate depending on the day of the week with data from the ED of Iquique's hospital in normal conditions, i.e., excluding the arrival of earthquake-induced patients (period from 1 January 2013 to 31 March 2014 and from 1 October 2014 to 20 May 2015, which excludes the Pisagua earthquake); and (b) arrival rate in the first 96 hr. after an earthquake of intensity IM occurs on a Monday (mean over 30 simulations for each IM).

and from 22:00 to midnight), making Monday the critical day of the week for the ED (see Figure 6a). In the model, the arrival of patients is sampled from a nonhomogeneous Poisson process with variable rate parameter $\lambda(t)$ obtained from the hourly average arrival rate in the ED in normal conditions (see Figure 6a). The simulations start 15 days before the earthquake strikes.

The estimation of the earthquake-induced arrival rate of patients was divided into the following two major steps for each of the 10 intensities considered: (1) estimation of the total number of injured people; and (2) estimation of the time distribution of the arrival rate of injured people to the ED of the hospital. The first step was carried out for the city of Iquique using Hazus (FEMA 2012a), which allows the estimation of casualties directly caused by structural or nonstructural damage to buildings after an earthquake. The application of Hazus relies on the construction of a comprehensive model of physical and social exposure in Iquique, which was developed by Aguirre et al. (2017, 2018) as part of an earthquake damage assessement analysis for deterministic seismic scenarios. In this exposure model, the total building stock of Iquique was estimated at 33,386 buildings, which are distributed over 1,652 blocks and classified into 12 building types defined in the Hazus framework, with a predominance of masonry and wood constructions. The number of buildings and fraction of building types in each block were determined from data provided by Chilean government entities (for further details, see Aguirre et al. 2018). The city's demographic distribution was also characterized at block level based on Census data, yielding a total resident population of 180,040.

The IM used herein for risk analysis, i.e., the spectral acceleration at the fundamental period $S_a(T_f)$, takes N different values $IM = im$. To generate the input hazard maps for Hazus corresponding to each intensity im, the conditional mean spectrum described in *Seismic Hazard Analysis* section was used to calculate the spectral accelerations at 0 s (equivalent to the peak ground acceleration), 0.3 s, and 1.0 s. These values were used to create acceleration maps for rock sites and then amplified to include the local soil effects following the methodology in Aguirre et al. (2017, 2018).

In order to calculate the physical damage, the fragility and capacity curves of Hazus were used. To quantify the number of injured people in a city, Hazus bases its estimation on the structural damage of the buildings within the city. From the inventory of Iquique, the number of people occupying each building type (e.g., reinforced masonry, concrete frame, and concrete wall) was known at the block level. Therefore, Hazus computes structural damage and provides the probability for each building type to be in one of the damage states $ds_{l\,\{l=1,2,3,4,5\}}$, which are none, slight, moderate, extensive, and complete, given the intensity im and building type bt_k, that is the probability $P(DS = ds_l \,|\, IM = im, BT = bt_k)$ (FEMA 2012a). For each damage state, it also estimates the number of casualties for each injury severity level (ISL) ranging from ISL = 1 to ISL = 4, where level ISL = 1 is defined by injuries requiring basic medical aid (e.g., sprains, cuts, or minor burns); level ISL = 2 is defined by injuries requiring a greater degree of medical care and the use of medical technology (e.g., X-rays, surgery); level ISL = 3 is defined by injuries that expose the patient to an immediate life-threatening condition; and level ISL = 4 corresponds to dead people or the mortally injured who require a critical intervention (FEMA 2012a). Patients with severity level ISL = 4 that arrive to the ED were assumed to still be alive and in need of critical intervention. Therefore, the number of injured people in block j, where $N_{tot}(j)$ people live, calculated for each injury severity level $ISL_{i\,\{i=1,2,3,4\}}$ and intensity im, is:

$$N_{inj}(im, ISL_i, j) = N_{tot}(j) P(ISL = ISL_i \,|\, IM = im, J = j), \tag{4}$$

where the conditioned probability $P(ISL = ISL_i \,|\, IM = im, J = j)$ is quantified as:

$$\begin{aligned} P(ISL = ISL_i \,|\, IM = im, J = j) = \sum_{k=1}^{12} \sum_{l=1}^{5} & P(ISL = ISL_i \,|\, DS = ds_l, BT = bt_k) \\ & \times P(DS = ds_l \,|\, IM = im, BT = bt_k) \\ & \times P(BT = bt_k \,|\, J = j), \end{aligned} \tag{5}$$

where $P(BT = bt_k \,|\, J = j)$ is the probability of being in a particular building type bt_k in block j; $P(ISL = ISL_i \,|\, DS = ds_l, BT = bt_k)$ is an injury severity level probability conditioned on the damage state ds_l of building type bt_k, which is provided by Hazus (i.e., based on statistics; FEMA 2012a); and $P(DS = ds_l \,|\, IM = im, BT = bt_k)$ is as defined above.

Thus the overall number of injured people that go to the hospital for a given intensity, $N_{inj}(im)$, is calculated by:

$$N_{inj}(im) = 0.4 \times \sum_{i=1}^{4} \sum_{j=1}^{N_{blocks}} N_{inj}(im, ISL_i, j), \tag{6}$$

where the factor 0.4 represents the ratio of total injured people that go to the hospital ED, while the remaining 60% go to other primary health care centers distributed throughout the city; these percentages are the annual values in normal conditions (DEIS 2017) and were assumed valid for post-earthquake conditions. Another possibility is to model this quantity as a random variable, but it was herein preferred not to do so given the limited prior knowledge to propose this distribution.

The distribution of ISL_i is further used as the distribution of patient injury categorization in the DES model of the *DES Model of Patients* subsection. For the distribution of the residential population, the Census information was used, and for simplicity, only indoor casualties were considered. Table 2 shows the estimated number of victims by Hazus in the city of Iquique for an earthquake of intensity $IM = im$.

The second step after estimating the total number of injured people is to assess their distribution in time after the earthquake, as they arrive to the ED. In this case, the data set used comes from the well-documented U.S. Northridge Hospital in Northridge, Los Angeles, California, during the M_w 6.7 1994 Northridge earthquake (Yi 2005). In this hospital, the first 96 hr. of patient arrivals were recorded. Moreover, the reader can refer to the Northridge Hospital website. There are a couple of relevant points: (1) it was observed that during this so-called moderate earthquake, the Northridge Hospital logged more than 100 injured local residents into the ED during the first 2 hr. after the earthquake (Northridge Hospital 2018a); and (2) the Northridge Hospital currently has 409 beds (Northridge Hospital 2018b).

To derive the arrival rate curve during the first 96 hr. for each earthquake intensity level, the methodology scales the recorded Northridge arrival rate of patients (up or down). Let $\alpha_N^{earthquake}(t)$ be the arrival rate of patients to the Northridge hospital above its normal conditions. Then the arrival rate of patients to the Iquique hospital because of an earthquake of intensity im is $\alpha^{earthquake}(im,t) = \beta(im) \times \alpha_N^{earthquake}(t)$, where $\beta(im) = N_{inj}(im) / \int_{t=0}^{t=96} \alpha_N^{earthquake}(t)dt$. This arrival rate is then added to the arrival rate in normal conditions to get the total arrival rate using Equation 3. Figure 6b shows the mean total arrival rate during the first 96 hr. of 30 simulations for each intensity level if an earthquake occurs on Monday, which is the critical day.

Table 2. Average number of victims estimated by Hazus in the city of Iquique for earthquakes of different intensities IM

IM (g)	ISL_1	ISL_2	ISL_3	ISL_4
0.05	0	0	0	0
0.16	5	0	0	0
0.26	85	11	1	1
0.37	299	57	7	14
0.47	642	151	23	45
0.58	1,121	297	48	95
0.68	1,722	491	82	163
0.79	2,407	722	124	246
0.89	3,179	989	173	343
1.00	3,968	1,268	224	443

DES MODEL OF PATIENTS

A DES model was developed using the Python SimPy library (Müller and Vignaux 2003) to dynamically reproduce the treatment of patients arriving at the ED of the hospital. A DES model is a model based on the queuing theory of stochastic processes such as the arrival time or the time spent in one station within the ED. While in the ED, patients may go through seven types of health care stations and stay there for a certain time, which is sampled from the statistical distributions described in Table 3. This table presents the station, distribution, and sources on the first, second, and third columns, respectively. Two types of sources were used: (1) available literature (Duguay and Chetouane 2007, Zeinali et al. 2015), and (2) the fit of fieldwork data, which was collected in the ED of Iquique. The fieldwork consisted of several activities: extracting the database of the ED patients' attention records at the hospital statistical office (private communication), collecting expert judgment information concerning the typical times a patient stays in each of the ED health care stations, and manually timing and observing patient stays in each ED health care station over several days.

The stations within the ED are: (1) an identification station and (2) triage station with a staying time following a Weibull distribution Weibull(2.2,1.4) (min) and a Gamma distribution Gamma(4.5,0.7) (min), respectively, both obtained after fitting the collected data; (3) three reanimation rooms equipped to provide cardiopulmonary resuscitation with a staying time following a triangular distribution Tri(30,45,60) (min) (Zeinali et al. 2015); (4) 13 examination stations, where patients are assisted by a physician for a staying time following a triangular distribution Tri(15,45,90) (min) (Zeinali et al. 2015); (5) laboratory tests available in a time window following a triangular distribution Tri(30,75,120) (min) and no queue expected to be created at this stage (i.e., an artificial infinite capacity is set in the DES model); (6) two ORs with a staying time following a lognormal distribution LN(0.5,0.6) (hr.); and (7) 16 observation stations, where patients use a bed for ambulatory recovery periods with a staying time following a triangular distribution Tri(0,120,360) (min).

Patients in the ED are treated differently depending on their injury severity level, as shown in Figure 7. Patients are classified into five categories of decreasing severity, ranging from C1 to C5; in the ED, this process is referred to as categorization. Categories C1 and C2

Table 3. Statistical distributions for the time spent in each of the ED units

ED unit (#)	Distribution	Source
Identification (1)	Weibull(2.2,1.4) (min)	Fit of fieldwork collected data[a]
Triage (1)	Gamma(4.5,0.7) (min)	Fit of fieldwork collected data[a]
Reanimation (3)	Tri(30,45,60) (min)	Zeinali et al. (2015)
Examination (13)	Tri(15,45,90) (min)	Zeinali et al. (2015)
Medical tests (∞)	Tri(30,75,120) (min)	Adaption of Duguay and Chetouane (2007)
Operations (2)	LN(0.5,0.6) (hr.)	Fit of fieldwork collected data[a]
Observation (16)	Tri(0,120,360) (min)	Fit of fieldwork collected data[a]

[a] Source: own calculation.

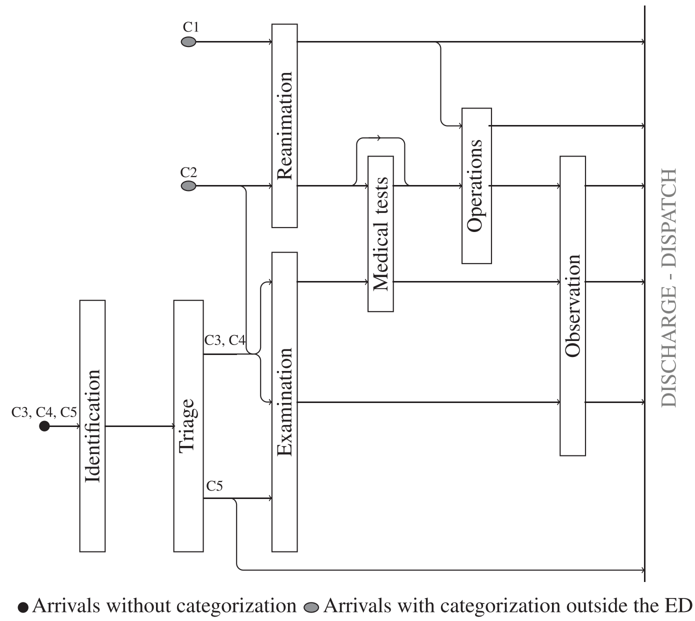


Figure 7. Flow of patients inside the ED depending on their injury categorization from C1 to C5.

are assigned to patients needing immediate and quick attention, respectively. They are classified outside the hospital, typically while in the ambulance. Categories C3, C4, and C5 are assigned to patients needing attention within 1.5 hr. or 3 hr. or no urgent attention, respectively. Based on a well-documented statistical report from the public health service of a Chilean region during a 2-year period, the model sets the normal condition categorization probability of each patient entering the ED as 0.45%, 10.60%, 52.20%, 31.95%, and 4.8% for C1, C2, C3, C4, and C5, respectively (MINSAL 2013). In the case of an earthquake, the ISL = 1, 2, 3, and 4 patients estimated by the casualty model are assigned C4, C3, C2, and C1 categories, respectively. No C5 categorizations are assigned from the earthquake casualty model. The model correctly assumes that C1 and C2 patients skip the identification and triage stations in the ED, and C1 patients go directly to a reanimation room for vital emergency care. It is then assumed from the collected data that half of the C1 patients go to an OR, while the remaining half are transferred to another critical health care department within the hospital. Based on historical data, it is assumed that 22% of C2 patients go to a reanimation room and then undergo surgery. Furthermore, C5 patients go through the identification and triage stations, with 75% immediately redirected to other health care centers and 25% undergoing deeper examination with a medical doctor. Finally, it is assumed from the collected data that 24% of C2, C3, and C4 patients need laboratory medical tests.

VALIDATION OF THE DES MODEL IN NORMAL CONDITIONS

The model was validated in normal conditions by comparing the time elapsed between the arrivals and departures of patients with the historical records of the hospital in Iquique.

The DES model was run 15,000 times and each 24-hr. sample obtained from the model was compared with a 24-hr. sample of the available data. The two-sample Mann-Whitney U-test (Mann and Whitney 1947) was implemented in order to assess whether these two samples, the one from the model and the one from the historic data, came from different continuous distributions. Results show that, considering the 15,000 tests, 80% of them prove that the samples from the model and data were from the same continuous distribution. The significance level of the test, that is, the threshold of rejection of the null hypothesis H_0 (e.g., Cowan 1998), was set to $\alpha = 5\%$. Figure 8 shows the mean cumulative distribution function of the realizations of 1 thousand 24-hr. samples from the model and one from the data and the envelope delimited by the 2.5th and 97.5th percentiles of the thousand cumulative distribution functions. Also, an expert validation with the ED stakeholders was done in parallel. Indeed, the assumptions of the model were deeply discussed and modified several times following the opinions of the medical staff in charge of the ED at the hospital in Iquique.

SCALAR PERFORMANCE QUANTIFICATION

The performance of the ED hospital was defined by the waiting time of patients because it is regarded as being one of the most relevant variables in assessing the overall performance of an ED (Sørup et al. 2013, Welch et al. 2011). The waiting time is calculated herein as the sum of the idle times during which the patient is not assisted by any staff member of the ED. For example, for a patient who successively goes through the identification, triage, and examination units and then leaves the ED, the corresponding waiting time is the sum of the time spent waiting to be identified, categorized, and examined. Hence the performance variable is

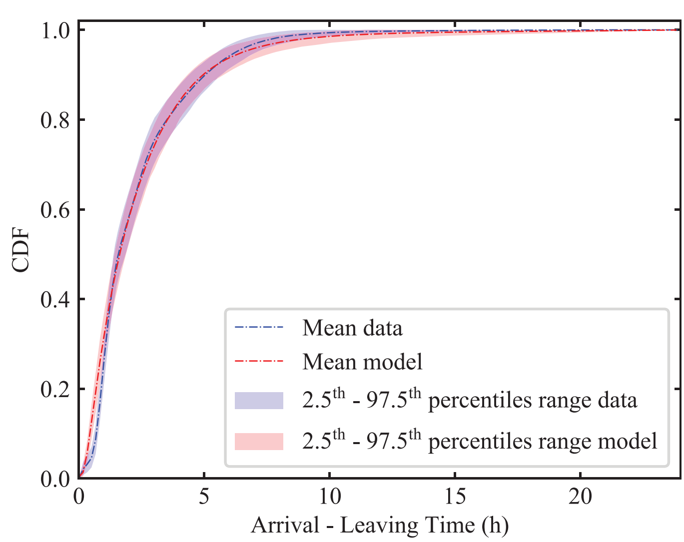


Figure 8. Comparison of the patients' daily cumulative distribution function of time inside the ED between 1,000 realizations of the DES model in normal conditions and experimental data from the hospital in Iquique.

the increase of the total waiting time induced by the earthquake, and it is estimated as the following product summation:

$$PV = \sum_{d=d_i}^{d_f} p_d^l \times \left(\overline{WT_d} - \overline{WT_{d_n}} \right), \tag{7}$$

where $\overline{WT_d}$ is defined as the mean waiting time of all patients leaving the ED during the d^{th} day, $\overline{WT_{d_n}}$ is the average daily mean waiting time under normal condition, and p_d^l is the number of people leaving the ED during the d^{th} day. It is assumed that the earthquake effects on the ED functionality extend from day d_i through day d_f, where d_i is defined as the first day in which the day average waiting time is greater than the mean waiting time under a normal condition, while d_f is the last day where this condition is met. Therefore, d_i must be greater than or equal to the earthquake occurrence day.

RESULTS AND ANALYSIS

STRUCTURAL RESPONSE

Figure 9 shows the two main structural responses considered in the analyses, peak interstory drift along the longitudinal direction (see Figure 9a) and total floor acceleration (see Figure 9b), both calculated for the first story at the center of mass of the building. The boxplots (Tukey 1977) of Figure 9 are depicted after 30 runs of the structure model for each of the ten intensities. Figure 9a shows a significant increasing trend of the first, second (median), and third quartiles' drift responses as $IM = im$ increases, whereas in Figure 9b,

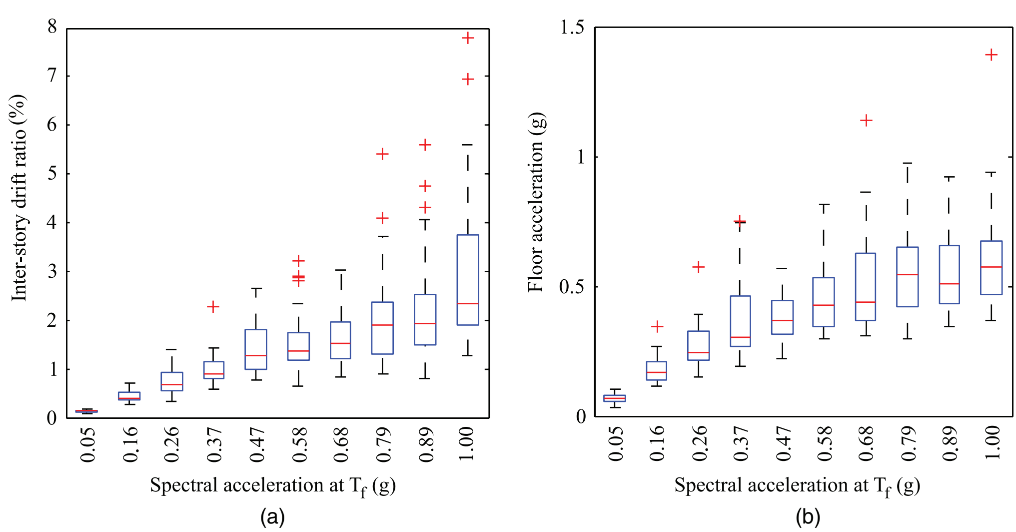


Figure 9. Boxplots of the peak structural responses of the first story at the center of mass: (a) interstory drift ratio along the longitudinal direction; and (b) total floor acceleration. Symbols (+) are values strictly higher than the upper quartile plus 1.5 times the interquartile range.

those quartiles for acceleration tend to saturate. This asymptotic behavior of the acceleration for high ground motion intensities, say intensities greater than 0.79 g, is probably due to the inelastic effects of the structural model, as plastic hinges are formed at columns' ends, and the lateral resistance of the structure reaches a limit as well as the accelerations. It is also apparent that the uncertainty tends to grow initially for increasing *im* and then stabilize for accelerations greater than about 0.79 g.

ED ROOM FUNCTIONAL DOWNTIME

The mean downtime of the two ORs and 13 examination stations for the ten IMs are presented in Table 4. Both ORs and examination stations have no downtime at the two lower intensity levels, i.e., $IM = 0.05\,\text{g}$ and 0.16 g. The earthquake starts to affect functionality at the third intensity level, with mean downtimes of 0.6 hr. for examination stations and 7 hr. for ORs. Even though the downtime of each component is sampled from a small number of distributions (one for examination stations and two for ORs), the average downtimes shown in Table 4 increase throughout the whole intensity range because of the uncertainty considered in the structural response and component damage states and the averaging of all the components of the same type. The highest IM ($IM = 1.0\,\text{g}$) generates a mean downtime for examination rooms greater than the median of the distribution defined previously as 0.5 days in Table 1. The highest estimated mean value of downtime in ORs is 69 hr. (2.9 days) when $IM = 1.0\,\text{g}$. This OR downtime of 69 hr. could be problematic because most new earthquake-induced patients are expected to reach the ED during the first 48 hr. (see Figure 6b), which means that any patient with an urgent vital surgery would need to wait for an OR with possible fatal consequences.

PERFORMANCE VARIABLE RISK

The patient DES model was run 500 times for each of the 300 ground motions in order to estimate the conditional probability curves of Equation 2. The accuracy of the Monte Carlo simulations was assessed by computing the 95% confidence interval half-widths of the mean waiting time of each ground motion, which were always found to be less than 7% of the

Table 4. Mean downtimes for each intensity level of the two ORs dedicated to the ED and the 13 examination stations

IM (g)	ORs (hr.)	Examination stations (hr.)
0.05	0	0.0
0.16	0	0.0
0.26	7	0.6
0.37	25	2.6
0.47	30	2.7
0.58	42	6.0
0.68	50	7.0
0.79	63	10.8
0.89	62	11.1
1.0	69	13.1

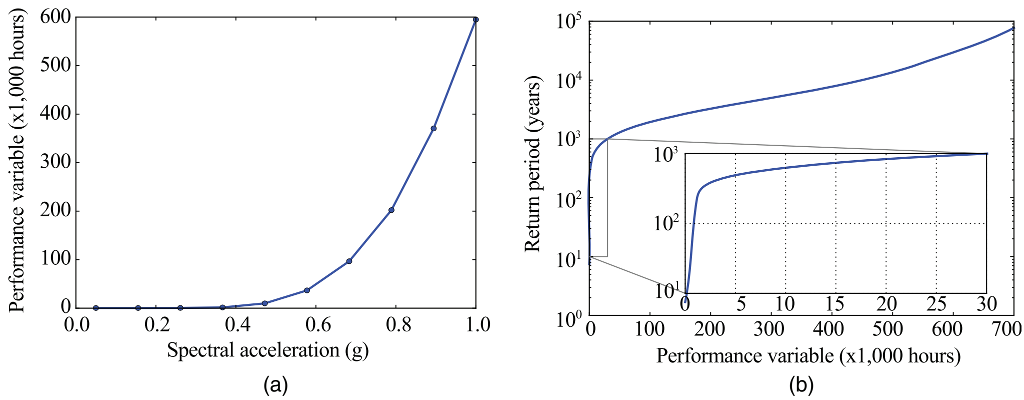


Figure 10. Estimated waiting times: (a) mean performance values in thousands of hours for each intensity level selected; and (b) seismic risk expressed as return periods of events exceeding certain values of the performance variable measured in thousands of waiting hours.

estimated mean. The accuracy improves further for ground motions with intensities greater than 0.5 g, for which the half-widths were less than 2% of the estimated mean.

Figure 10a presents the mean performance variable for each $IM = im$, which shows an exponential behavior. As should be expected, the two lower intensity levels ($IM = 0.05$ and $IM = 0.16\,g$) do not impact the waiting times, because there is no downtime and the patient arrival rates are similar to those under normal conditions. Although Table 4 shows that the next two intensity levels ($IM = 0.26\,g$ and $IM = 0.37\,g$) generate downtime, their associated waiting times are also very small. At intensity $IM = 0.47\,g$, the earthquake begins to show a significant impact on the ED performance. This number is interesting because it may help decision makers anticipate a sudden increase of demand at the ED simply by using the ground motion data, which can be readily available. Although this number is only for this hospital in Iquique, it may be relevant to record.

The return period of events corresponding to different values of the performance variable are given by Figure 10b and were calculated as the inverse of the mean annual rate in Equation 2. In the semi-log plot, the curve shows two distinct behaviors: first, the curve rapidly increases for the performance variable between 0 and 2,000 hr., and then, for higher values, the slope of the curve decreases steadily to about 200 thousand hr. to increase again from 300 thousand hr. and larger. More specifically, for the hospital in Iquique, a performance value PV of 1,000 hr. has a return period of 100 years, and a performance value PV of 30,000 hr. has a return period of 1,000 years.

CONCLUSIONS

This study quantified the seismic risk in the ED of the regional hospital in the coastal city of Iquique, North Chile. The seismic performance of the ED was measured in terms of the total waiting time of patients there exclusively because of an earthquake. This patient-oriented performance variable goes further than just a physical or functional quantification and takes into account the resilience of the system by explicitly using the downtime and recovery of the relevant ED units. The methodology considers successive models that assess the inelastic structural response of the ED building, nonstructural damage, downtime of ED spaces, changes in patient arrival rates, and patient waiting times. The results are presented in terms of the return period of events that exceed certain levels of additional waiting time.

As it should be, the quartile values of the distributions of drift ratio and acceleration increase with the earthquake IMs; however, the values of floor acceleration tend to saturate for IMs greater than 0.79 g because of the inelastic response of the structural model. It is apparent that the mean downtimes of the OR can reach critical values (e.g., 69 hr. when IM = 1.0 g), which are much larger than the 48-hr. time window of the arrival of earthquake casualties. Furthermore, results show that an event with 140 thousand hr. of accumulated additional waiting time has approximately 2% probability of exceedance in 50 years, i.e., a return period of about 2,500 years. Naturally, results provided for this seismic patient-oriented performance study are restricted to this public hospital in Iquique because the exposure, geographical setting, and each submodel is specific to the case study. However, the methodology used can be extended to other EDs in different seismic settings.

In trying to move research forward, there are still gaps in the literature to characterize the distribution of loss of functionality for examination rooms and ORs, distribution of functional downtimes for ED spaces, and patient arrival rates and injury categorizations. Particular efforts were made herein to integrally tackle these gaps and propose a quantification model that makes some progress in the field. Indeed, quantifications of the loss of functionality for examination rooms and ORs was done using data and results adapted from the existing literature and on-site data collected by the authors of functional downtime for ED rooms. Furthermore, the estimation of patient arrival rates and injury categorization was done using a combination of a recent case study of Iquique using Hazus and the adaptation of well-documented past observational data of patient arrivals.

In terms of some limitations of this methodology, more research is needed to develop more complete system models that take into account interruptions of utility services and hospital supply chains, evolution in times of staff attendance, effects of aftershocks, and total or partial building collapses. Future studies should include some of these aspects in the methodology and incorporate observations of past earthquakes to better calibrate final results. The significant time necessary to carefully develop each of the model components is also a limitation, i.e., the detailed Hazus implementation, inelastic structural model of the hospital, and hospital organizational model. These models are time consuming and, though relevant, make this study difficult to reproduce and scale up in the short term. For instance, the study could be extended to the larger health care network only if some parts of the model are less refined.

Finally, it is important to emphasize that the results presented in terms of patient-oriented variables, such as waiting time, can be easily communicated to different hospital stakeholders (e.g., public health decision makers and hospital managers or stakeholders). Associating return periods to these performance variables (e.g., waiting time) is quite promising for future patient-oriented risk management and risk reduction. Please note that from the results of this particular hospital, there is a clear threshold of IM required to impact the performance variable of the system, and hence an early warning or alert system may be established to anticipate the peak demand arrival for the ED. Moreover, approaches as the one presented herein can be used to assess the direct effect of possible mitigation actions on patients, such as retrofitting the existing building, improving the condition of nonstructural components, rearranging the location of health care units, or any other process to decrease the service performance and downtime. These mitigation actions could also be designed in conjunction with optimization procedures to maximize the operation continuity subject to budgetary constraints.

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